Oil Price and Stock Market Synchronization in Gulf Cooperation Council Countries

Rosmy Jean Louis and Faruk Balli

ABSTRACT: Knowing that the Gulf Cooperation Council (GCC) economies are dichotomous in nature, and growth in the non-oil sector is tributary to the oil sector, we document the extent of synchronization between crude oil prices and stock markets for each of the GCC markets and for the GCC as an economic bloc. We use both the bivariate and multivariate nonparametric synchronicity measures proposed by Mink et al. (2007) to assess that linkage. We find a low to mild (mild to strong) degree of synchronization between oil price and stock market returns (volatilities). In a very few instances, we find very strong (above 80 percent) associations between these variables. These results hold irrespective of whether we assume that stock market participants form adaptive or rational expectations about the price of oil. Dynamic factor results confirm that shocks to volatility are more important than shocks to oil price returns for the GCC stock markets.

KEY WORDS: GCC stock markets, oil price, synchronicity measures.

It is well known that crude oil is the backbone of the Gulf Cooperation Council (GCC) economies, namely, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates. A change in the price of oil, however, may produce quite ambiguous effects on these economies. As oil is a main source of energy, a rise in its market price boosts profits for oil companies while increasing costs for goods-producing companies if other cost-cutting measures are not implemented. Since most of the GCC oil companies are government owned, the resulting boost in oil-export revenues serves as a means of fostering investment in education, infrastructure, tourism, and other sectors. An increase in the price of oil also brings the misfortune of raising the cost of imported capital goods and therefore hampers growth in the GCC markets. This line of reasoning is akin to the macro view that oil prices can influence the real sector of the economy mainly via its effects on consumption as firms shift a portion of their costs to consumers, production, and government budgets (see, e.g., Basher 2010; Basher and Sadorsky 2006; Ravichandran and Alkhathlan 2010). Research in this strand of the literature has linked fluctuations in key macroeconomic indicators to stock market performance. This research includes the work of Chen et al. (1986), Hamao (1988), and Kaneko and Lee (1995) for Japan; El-Wassal (2005) for oil-exporting countries in Asia, Africa, and Latin America; Ferson and Harvey (1995) for eighteen stock markets; Jones and Kaul (1996) for Canada, the United States, Japan, and the United Kingdom; King et al. (1994) for a sample of developed and emerging markets; Papapetrou (2001) for Greece; and Sadorsky (2003) for the United States,

---

Rosmy Jean Louis (rosmy.jeanlouis@viu.ca) is a professor in the Department of Economics and Finance, Faculty of Management, Vancouver Island University, Nanaimo, BC, Canada. Faruk Balli (f.balli@massey.ac.nz) is a senior lecturer in economics at the School of Economics and Finance, Massey University, Palmerston North, New Zealand, and an associate professor in the Department of Business Administration, Suleyman Sah University, Istanbul, Turkey. The authors thank the editor, Ali M. Kutan, and two anonymous referees for their valuable comments, which helped improve the quality of the paper, and Eninim Ekon of the MBA/MScIB program at Vancouver Island University for excellent research assistance. The usual disclaimer applies.

Emerging Markets Finance & Trade / January–February 2014, Vol. 50, No. 1, pp. 22–51.

ISSN 1540–496X (print)/ISSN 1558–0938 (online)
DOI: 10.2753/REE1540-496X500102

among others. Their overall findings are in line with what Cuñado and Pérez de Gracia (2005), Hamilton (1983, 1996, 2003), Hamilton and Herrera (2004), and Kilian (2008a) have documented: oil price shocks affect key macroeconomic variables in both developed and emerging markets with different intensities and through different mechanisms. Not surprisingly, given the newness of the GCC stock markets and the lack of high-frequency macroeconomic data, this line of research has not been exploited.[1]

Another strand of the literature has focused on the differing effects that unanticipated changes in the price of oil can have on the share prices of oil and non–oil companies as expectations about future dividends are factored into investors' portfolio decisions. To this end, researchers have conducted two types of inquiry at the cross-country level: (1) assessment of the state of stock market integration, and (2) investigation into the linkages between oil price returns (volatilities) and national stock indexes. Several methodological approaches have been followed, and data of various frequencies from various sources have been used. Early studies on stock market linkages include the work of Abraham et al. (2001), Darrat et al. (2000), Girard and Ferreira (2004), Girard et al. (2003), Harvey (1995a, 1995b), and Omran and Gunduz (2001) for the Middle East and North African region; Al-Khazali et al. (2006) and Hammoudeh and Aleisa (2004) for a sample of the GCC markets; and Bley and Chen (2006) for all the GCC markets.

Research on the linkages between oil prices and stock market prices for the GCC countries has gained impetus following early contributions by Hammoudeh and Aleisa (2004), who use the Johansen cointegration technique and daily data and find that oil future prices can help forecast stock market returns for Saudi Arabia only. Abu Zarour (2006) uses the vector autoregression (VAR) technique and concludes that only the Saudi Arabia and Oman stock markets can be predicted with oil price innovations. Hammoudeh and Choi (2006) use a vector-error correction model to investigate the short-run bilateral causal relationships among the GCC weekly stock index returns and their relationships with oil prices, among other factors. They find no direct impact of oil prices on these markets. Maghyereh and Al-Kandari (2007), by contrast, find that the impacts of oil price changes on GCC stock prices are significant over the long run.

Arouri and Fouquau (2009) investigate the relationship between oil prices and GCC stock markets using a nonparametric method. Their results show that stock markets in Qatar, Oman, and the United Arab Emirates exhibit asymmetric and regime-switching linkages with changes in oil price. Arouri et al. (2011) provide further evidence that the effects of oil prices on GCC stock prices differ across member countries. Arouri and Rault (2010) use panel data analysis to study the sensitivity of GCC stock markets to oil prices. They show that the causal relationship is bidirectional for Saudi Arabia only when the data are either weekly or quarterly. For other GCC countries, however, they find strong statistical evidence that oil price disturbances Granger cause stock price changes. They therefore surmise that investors in the GCC stock markets should pay close attention to fluctuations in oil prices, while investors in oil markets should follow the Saudi stock market closely. Fayyad and Daly (2011) consider a VAR with the United States, the United Kingdom, and all GCC countries except Saudi Arabia to investigate the time-varying nature of that relationship. Their results show that the sensitivity of GCC stock returns to oil price increases due to a rise in the price of oil increased during the recent global financial crisis. They also find that of all the stock markets, Qatar and the United Arab Emirates stock returns are the most responsive to oil shocks.

The empirical literature on the feedback effects between GCC stock markets and oil markets has thus far been concentrated on the performance of national stock indexes, which are weighted averages of sectoral stock indexes. However, little was known about the relationship between GCC sectoral stock market disturbances and oil price innovations until the publication of Mohanty et al. (2011). These authors assess the relationship between changes in crude oil prices and stock returns using both country-level and industry-level stock market data. At the country level, they show that, except for Kuwait, GCC stock markets have significant positive exposure to oil price shocks. At the industry level, they find that the responses of industry-specific returns to oil shocks are significantly positive for only twelve of the twenty industries. Their study also provides evidence that oil price changes have asymmetric effects on stock market returns at both levels. However, Mohanty et al. do not consider stock market and oil price volatilities in their study.

Focusing on disaggregated stock market data in analyzing the impact of oil price shocks on stock returns is a sensible approach since it allows us to factor in speculators' sentiments in buying and selling stocks on a daily basis. Instinctively, an investor contemplating a quick return will closely follow movement in various stocks to capitalize on any relationship that might exist. For example, if the performances of oil and industry sectors are inversely correlated, expectations of an increase in the price of oil may prompt investors to purchase oil company stocks while selling industrial company shares. Heterogeneity of industries makes it possible for these potential gains to materialize as risks are being minimized (Fama and French 1993). Therefore, a study of the relationship between stock market returns at the industry level and oil price movements is of utmost importance to market participants. Recent studies by Kilian (2008b, 2009) and Kilian and Park (2009) have established that the effects of oil price shocks on the real economy depend on whether these shocks are driven by global demand or supply factors. Killian and Park have also shown that the effects of oil price shocks on stock market returns hinge on the underlying causes of the oil shocks, and these effects vary across industries. Their findings suggest that sectoral analysis is the most appropriate for capturing the relationship between oil prices and stock market disturbances.

In this paper, we make three major contributions to the existing literature on the linkages between oil price movement and stock prices. First, we use both the bivariate and multivariate nonparametric approach proposed by Mink et al. (2007) to measure the synchronicity between oil market returns (volatilities) and sectoral/national/regional stock market returns (volatilities) in the GCC. Second, we document the extent of synchronization between past or future oil prices and GCC stock prices. Third, in search of robustness, we investigate whether GCC stock market dynamics at all levels are governed by a common factor and whether oil price return and volatility can explain this common factor.[2] To this end, we estimate variants of the dynamic factor model proposed by Stock and Watson (1989, 1991). In terms of coverage, our paper follows Mohanty et al. (2011) in using industry-level stock price data for the GCC. Mohanty et al.'s study covers only Bahrain, Kuwait, Oman, and Qatar because data covering a sufficiently long period are not available for Saudi Arabia and the United Arab Emirates in the Thomson Reuters database; however, due to its flexibility, our methodology, which differs from theirs, allows for the inclusion of all of the GCC countries in our analysis. We are not aware of other papers similar to ours in the literature; Mohanty et al.'s (2011) is the closest.

The results can be summarized as follows: As per the data analysis on sectoral stock price returns, we find that only investments in hotel and tourism stocks in Bahrain, banks in Kuwait, and industry in Oman are more profitable than the crude oil market; investment in industry stocks in United Arab Emirates–Abu Dhabi is as good as investment in crude oil. Hence, we conjecture that a portfolio made up of these stocks would be more desirable than any other GCC portfolio of similar risk levels. This finding is good news for the typical risk-averse GCC investor who can freely participate in these markets. We also find that the crude oil market is less volatile than sectors such as food (Kuwait), energy (United Arab Emirates–Abu Dhabi), and utilities (United Arab Emirates–Dubai). In terms of relative risk, the portfolio that emerges for the average daily return analysis also performs quite well. Higher risk with higher return is only confirmed for the industry sector; the remaining stocks in the portfolio have lower risk attached than other stocks within the same market. Granger causality and pairwise correlation tests between the daily stock market return and oil price return provide strong evidence that oil price returns can help forecast stock market returns in most GCC countries and for most sectors. Two-way Granger causality between the two variables is detected for most sectors in Saudi Arabia. Most sectoral stock returns are positively and highly correlated and significant at the 1 percent level. In only very few cases could we detect a negative correlation. The link with the oil price returns, however, is weak, but significant, at the 10 percent level. These results suggest that a movement in crude oil prices is not a strong signal when it comes to watching fluctuations in sectoral and national stock prices for speculative purposes.

For the synchronicity between oil price and sectoral/national stock markets, we find the bivariate synchronicity measures range (1) from low (less than 40 percent) to mild (40–60 percent) for the return cycles; and (2) from borderline mild and strong to strong (low 60 percent range to a high of 78 percent).[3] The multivariate synchronicity measures are, on average, lower than the mean of the bivariate measures, with the ten-day volatility showing a tighter link. It is worth noting that the aggregate GCC sectors follow similar patterns, but the energy sector based on the fifty-day volatility is at the borderline of mild and high (59 percent) synchronization with the oil price. Saudi Arabia's stock sectors are the most tied to oil price in terms of volatility whether we consider a ten- or a fifty-day horizon. In general, there is less association between individual stock return and oil cycles than there is between their volatility cycles. These results hold whether we consider the lagged or lead values of the oil price. The dynamic factor models reveal that sectoral as well as national stock markets in the GCC are governed by a common underlying factor, which is weakly explained by disturbances in oil markets.

Methodology

Measuring Synchronicity

The starting point toward documenting the synchronicity (or lack thereof) between sectoral/national stock markets and oil markets is the determination of a measure of the cyclical fluctuations in both the return and return volatilities of these assets. A number of alternative techniques are available in the literature to extract and investigate the extent of comovement of the cycles. These include Markov-switching vector autoregression decomposition, cointegration analysis, testing for common features, and tests for common trends and common cycles. Nonetheless, due to its simplicity and popularity, we use the Hodrick and Prescott (1997) nonparametric filter to decompose returns and volatilities into a trend (the permanent component) and a cycle (a transitory component) in which the trend is the long-term return and the cycle is the deviation of the actual return from its trend, which may arise due to speculation and uncertainty.[4] The gap between the two returns (volatility) is calculated as the ratio of the cycle over the trend for each sector or national stock index and the oil price. In addition to the conventional correlation, a few nonparametric tests have recently been developed to measure the synchronization of the cycles. These measures (SYNCH) can be easily tailored to the variables at hand. For example, Giannone et al.'s (2008) synchronicity measure can be redefined as the negative of the absolute value of the differential between stock market returns (volatilities) (S) and oil price returns (volatilities) (O) over time, where the oil price variables serve as the reference in the bilateral setup.

$$SYNCH1_{i,o,t} \equiv -\left|\left(\ln S_{it} - \ln S_{it-1}\right) - \left(\ln O_t - \ln O_{t-1}\right)\right|. \tag{1}$$

A second measure in the vein of Morgan et al. (2004) is to regress returns (volatilities) (Y) on sector/country fixed effects (γ_i) and period fixed effects (ϕ_t) for each sector/country to obtain a residual whose absolute value is used to construct a proxy for synchronization.[5] This measure is defined as the negative of the absolute value of the differential between sector i's residual ($v_{i,t}$) and the oil variable residual ($v_{o,t}$).

$$\ln Y_{i,t} - \ln Y_{i,t-1} = \gamma_i + \phi_t + v_{i,t}\ \forall i,o. \tag{2}$$

These residuals account for cross-country and across-year mean return/volatility fluctuations:

$$FLUCT_{i,t} \left|\equiv v_{i,t}\right| \text{ and } FLUCT_{o,t} \equiv \left|v_{o,t}\right|. \tag{3}$$

Therefore,

$$SYNCH2_{i,o,t} \equiv -\left|v_{i,t} - v_{o,t}\right|. \tag{4}$$

Simply put, this index measures how similar returns/volatilities are between each sector/country and the oil sector in any given year when we account for the average return/volatility in each country and in each year.

The third measure, $SYNCH3_{i,o,t}$, consists of computing the five-year correlation of the cyclical component of return/volatility, which can be obtained via any filtering method or the Baxter and King (1999) band-pass filter (Baxter and Kouparitsas 2005; Imbs 2006).

Kalemli-Ozcan et al. (2011) take the average of each of the three bilateral synchronicity measures described above in their investigation of the linkages between financial integration and business cycle synchronization ($SYNCH_{i,j,t}$) for the twenty Organization for Economic Cooperation and Development countries considered in their study. Although the first two measures are relatively easy to implement and are not subject to the shortcomings of various filtering methods, their drawback is that they are most useful when the objective is to explain rather than to determine the extent of synchronicity. As can be gleaned from Equations (1) and (4), all the values are negative. Therefore, it is difficult to tell whether the synchronicity between a sector of the stock market and the oil market is, for example, 50 percent or 60 percent.

We choose the nonparametric methodology proposed by Mink et al. (2007) as the second-best alternative available to answer our research question. This measure is as flexible as Kalemli-Ozcan et al.'s (2011) in that it is easy to use and can be calculated at every point in time in a bivariate or multivariate setting within/across sectors or countries to indicate whether cycles are synchronized. However, it first requires filtering to obtain the return/volatility gap, and it is bounded between –1 and 1. The main issue that sometime arises when dealing with cross-country data is the choice of an appropriate reference cycle against which synchronization can be assessed with individual cycles.[6] As Basher

(2010) points out, this problem does not necessarily exist in sectoral analysis since the choice of the reference cycle is, at times, fairly straightforward. In this paper, cyclical fluctuations in oil price return and volatility are used as the references. The shortcoming of fixing the reference cycle is that spillovers from other sectors cannot be factored into computation of the bivariate synchronicity measure.

In its simplest form, the bivariate version of the synchronicity measure between the reference cycle ($g_{r,t}$) and the individual cycle ($g_{i,t}$) as proposed by Mink et al. (2007) is represented as follows:

$$\phi_{i,r,t} = \frac{g_{i,t} g_{r,t}}{\left|g_{i,t} g_{r,t}\right|}. \tag{5}$$

This synchronicity measure takes a value of 1 when the reference cycle and the individual cycle have the same sign and –1 when they move in opposite directions. The percentage of time that $\varphi_{i,r,t} = 1$ is a number that lies in the interval [0, 1]. We use three benchmarks to assess the extent of synchronicity. First, as a soft approach, we classify the synchronicity as low if $\varphi_{i,r,t} < 0.40$, mild if $0.40 \leq \varphi_{i,r,t} \leq 0.60$, and strong if $\varphi_{i,r,t} > 0.60$. Second, we use a cold-turkey approach in adopting a cut-off point of 0.50, above (below) which the cycles are synchronous (asynchronous), and at which the cycles are neither one nor the other. The number of times $\varphi_{i,r,t} > 0.50$ divided by the total number of $\varphi_{i,r,t}$ values is the overall measure of synchronicity between the individual cycles and the oil price cycle for a country. Third, we produce an average of all $\varphi_{i,r,t} > 0.50$.

The multivariate version of the synchronicity measure, as per Mink et al. (2007), is given by

$$\varphi_t = \frac{1}{N} \sum\nolimits_{t=1}^{N} \frac{g_{i,t} g_{r,t}}{\left|g_{i,t} g_{r,t}\right|}, \tag{6}$$

where N is the number of cycle pairs. This equation tells us the average synchronicity of the individual countries' cycles with the reference cycle at each point in time. Positive values of ϕ_t indicate the dominance of synchronous cycles over asynchronous cycles in relation to the reference for a given day. We use both versions of Mink et al.'s synchronicity measure in our investigation of the linkage between GCC stock markets and the international oil market.

Dynamic Factor Model

Although the nonparametric method of Mink et al. (2007) is quite flexible in accommodating even small data samples, there is the possibility that the synchronicity observed may be spurious in that cycles that are not related may show comovement without any underlying common component. We attempt to overcome this issue by reformulating the research question without deviating from the main objective. We ask whether GCC stock markets at both the industry and the country level are governed by a common factor and whether oil price return and volatility cycles can explain the dynamics of that factor.

The dynamic factor (DF) models as developed by Geweke (1977), Sargent and Sims (1977), Stock and Watson (1989, 1991), and Watson and Engle (1983) consist of estimating a vector of n endogenous variables as linear functions of $k < n$ unobserved factors and some exogenous covariates. The model assumes that the vector Y_t of stock indexes can be modeled as consisting of an intercept, α; a sector/country/overall GCC sector-specific autoregressive component of order one, AY_{t-1}; k unobservable factors $F_t = [F_{1,t}, \ldots, F_{k,t}]$ that are common to all series, which follow a first-order autoregressive process; and a normally distributed disturbance term, e_t. Generally, the model estimated can be represented as follows:

$$Y_t = a + AY_{t-1} + BF_t + e_t, F_t = DF_{t-1} + v_t, \tag{7}$$

where B is an $n \times k$ sensitivity matrix that captures the contemporaneous effects of changes in the common factor on each series Y_i; v_t is also a white noise disturbance. The variance–covariance matrix of e_t is assumed to be diagonal, with diagonal elements equal to σ_i^2. We estimate the basic DF model proposed by Stock and Watson by setting the following: Model 1: $\alpha = 0$ and $A = 0$; Model 2: $A = 0$ and $e_t = \delta e_{t-1} + u_t$; Model 3: $\alpha = 0$; Model 4's specification is in fact Equation (7) with the autocorrelated error term.

Once a set of common factors has been obtained for each country and for the GCC as a bloc, we then ask whether oil price returns and volatilities (not their cyclical components) have any explanatory power. To this end, we estimate the following equation generally:

$$FT = \gamma_o + \textstyle\sum_{j=1}^{n} \gamma_j O_{t+1-j} + u_t. \tag{8}$$

The sign and significance of the slope coefficients indicate to what extent the return or volatility of oil prices can explain the dynamics of the common factor underlying the GCC stock markets. Thus far, our focus has been on the common factor that underlies the sectoral stock markets in each country, the GCC sectors as a group, and the country-level indexes. Although the overall GCC stock sectors are weighted averages of the individual countries' stock sectors, it is, in our view, not convincing enough to argue that the same holds for the common factors. To that effect, we expand the analysis by investigating whether the industry-level common factors across GCC countries share a common component that is also associated with oil price returns and volatility. This layer of the analysis is motivated by the uneven number of sectors across countries that we can obtain from the Thomson Reuters database. This layer also allows us to capture the depth and breadth of the research question at hand.

Data and Data Analysis

The stock market data for this paper[7] are of daily frequency and were extracted from the Thomson Reuters database. The data are organized by industries or sectors, by country, and by region. We exploit all three dimensions for the GCC region. A perceptible feature of the data shown in Table 1 is that the number of sectors and the sample sizes vary across countries.

Sectors that are common to all are banking, insurance, industry, and services. Since our primary objective is to examine the synchronicity (or lack thereof) between individual stock sectors and the crude oil market, this feature of the data does not constitute an impediment in our search for a general pattern. The crude oil price (or *oil price* for short) is the West Texas Intermediate, which is the most widely used in the world. This data sample was adjusted to match the stock data sample of each country/economic bloc. Figure 1 displays the paths of the stock market indexes and the oil prices for individual GCC countries and for the GCC as a bloc. As can be gleaned from this figure, the two series tend to comove over time whether we focus on sectoral or national stock markets. However, nothing at this point can be said about the strength of that synchronicity.

Table 1. Sectoral and national equity indexes

	Bahrain	Kuwait	Oman	Qatar
Sample	June 30, 2004–December 31, 2010	March 31, 2002–December 31, 2010	January 6, 1999–December 31, 2010	May 14, 2001–December 31, 2010
	Dow Jones^{N} (GG, 0.03)	MSCI Kuwait^{N} (GG, 0.04)	Muscat^{N} (G, 0.09**)	Banking and financial (0.07**)
	Commercial banks (G, 0.05**)	Banks (–0.03)	Banking and investments (G, 0.11**)	Insurance (G, 0.10**)
	Hotel and tourism (–0.03)	Food (-0.01)	Services and insurance (G, 0.10**)	Industrial (G, 0.06**)
	Industry (–0.01)	Insurance (0.00)	Industry (0.08**)	Services (0.07**)
	Insurance (0.03)	Industry (0.05*)		Qatar Exchange Index^{N} (G, 0.08**)
	Investment (0.01)	Investment (–0.02)		
	Services (0.00)	Kuwait companies (G, 0.03)		
	ESTERAD^{N} (G, 0.02)	Real estate (0.04)		
		Non-Kuwait companies (–0.02)		
Observations	1,698	2,241	3,128	2,515

	Saudi Arabia	United Arab Emirates–Dubai	United Arab Emirates–Abu Dhabi	GCC
Sample	April 19, 2007–December 31, 2010	August 27, 2007–December 31, 2010	August 27, 2007–December 31, 2010	January 1, 2007–December 31, 2010
	TADAWUL^{N} (*GG*, 0.16**)	Bank (G, 0.12**)	ADX^{N} (G, 0.11**)	Energy (G, 0.07**)
	Agriculture and food (GG, 0.10**)	Financial investment (G, 0.12**)	Banks and financial services (G, 0.03)	Basic materials (G, 0.04)
	Banks and financial services (0.14**)	Insurance (G, 0.04)	Construction (0.09**)	Industry (G, 0.09**)
	Building and construction (GG, 0.12**)	Materials (0.02)	Consumer goods (G, 0.07**)	Noncyclical consumer goods and services (GG, 0.13**)

(continues)

Table 1. Continued

	Saudi Arabia	United Arab Emirates–Dubai	United Arab Emirates–Abu Dhabi	GCC
	Cement (GG, 0.19**)	Real estate (G, 0.13**)	Telecommunication (0.09**)	Utilities (G, 0.03)
	Energy and utility (G, 0.11**)	Telecommunication (GG, 0.09**)	Health care (0.03)	Telecommunication services (GG, 0.06**)
	Hotel and tourism (GG, 0.08**)	Transportation (GG, 0.07**)	Industry (0.01)	Real estate (G, 0.11**)
	Industrial development (GG, 0.13**)	Utilities (GG, 0.07**)	Insurance (G, 0.03)	Banking and investment services (GG, 0.09**)
	Insurance (GG, 0.13**)	DFM[N] (G, 0.14**)	Real estate (0.05)	Cyclical consumer goods and services (GG, 0.13**)
	Media and publishing (GG, 0.14**)		Energy (0.04)	Transportation (G, 0.06**)
	Multipurpose investment (G, 0.12**)			Industrial services (GG, 0.09**)
	Petrochemicals (GG, 0.14**)			Mineral resources (G, 0.05)
	Real estate development (G, 0.13**)			
	Retail (G, 0.12**)			
	Telecommunications and information technology (G, 0.14**)			
	Transportation (G, 0.13**)			
Observations	967	875	875	1,045

Source: Thomson Reuters Database.

Notes: National equity indexes are denoted with superscript N. Results of oil price return Granger causality and correlation with stock returns are in parentheses. G denotes one-way Granger causality running from oil price return to stock price return. GG denotes two-way Granger causality. Only causalities that are statistically significant are reported here. Causalities that run from stock return to oil price return are significant mostly at the 10 percent level. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

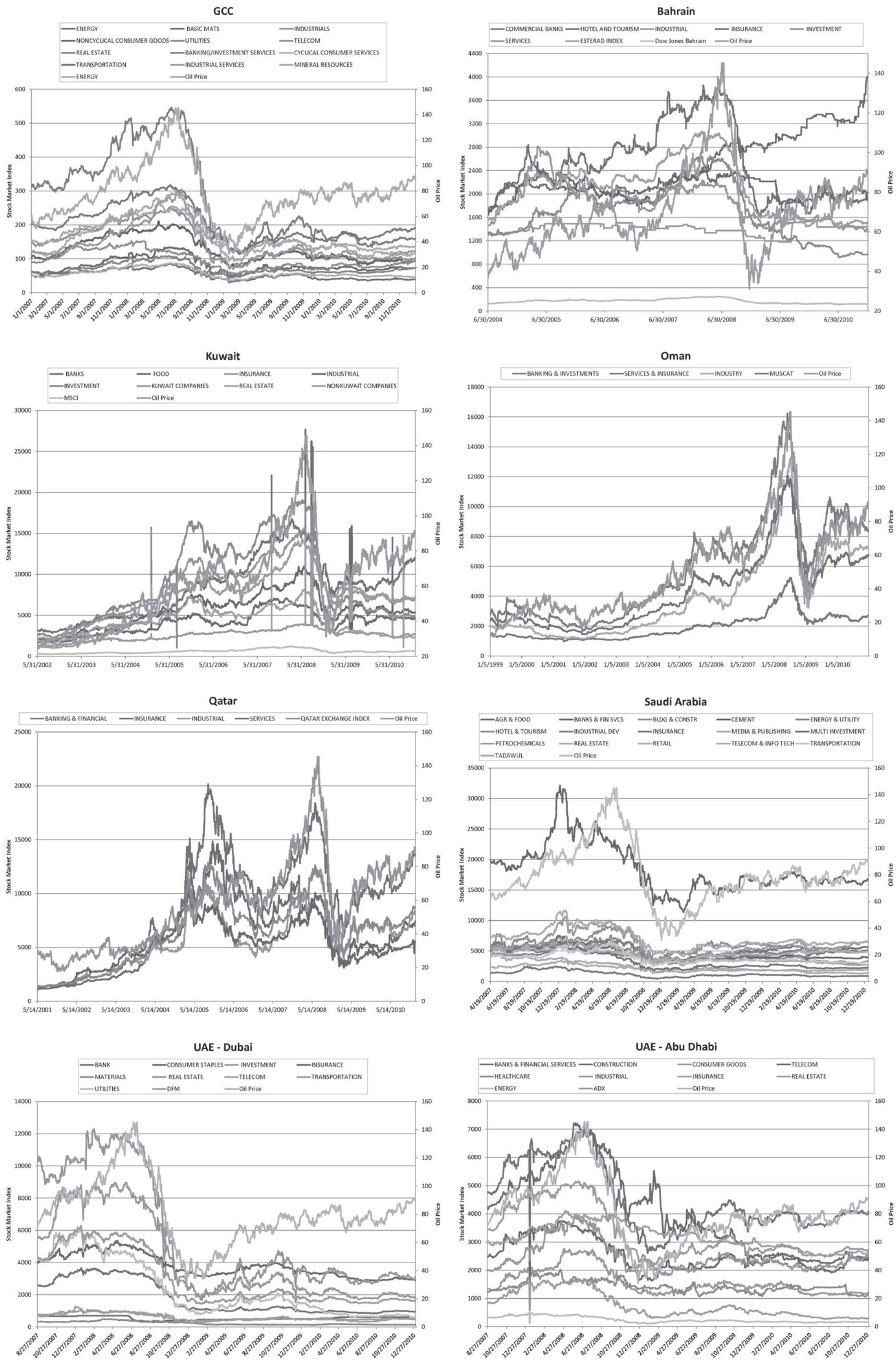

Figure 1. GCC stock market indexes and crude oil prices

We begin the data analysis by computing daily returns as

$$r_t = \ln(P_t / P_{t-1}), \tag{9}$$

where r_t is the daily return of either the stock or the crude oil market, ln is the natural logarithm, and P_t is either the stock index or the oil price at time t. We then compute the annualized historical or N period's rolling window moving-average estimator of the volatility, which corresponds to the product of the square root of the number of trading days and the standard deviation of the window:

$$\sigma_t = T^{1/2} \sqrt{\frac{1}{N-1} \sum_{t=1}^{N} \left(r_t - \bar{r}_t\right)^2}, \tag{10}$$

where $\bar{r}_t$ is the average daily return and T is the number of trading days. Determining the appropriate window size N is difficult because volatility changes over time. A small window size delivers a volatility measure that is reflective of current market sentiment but is quite noisy. However, a larger window size produces a volatility measure that is smooth, but less accurate for forecasting since we may have dug too deep into the past to increase the sample size. For this reason, we explore windows of ten and fifty days to represent, respectively, as close as possible to the period used by most traders and a slight distance into the past. There are two shortcomings in using historical instead of generalized autoregressive conditional heteroskedasticity–based dynamic volatility. The first is that historical volatility is indifferent to fluctuations in the series; for example, continuous increases in a stock price can create high volatility on the upside that investors may not be concerned about. The second disadvantage is that historical volatility assigns equal weights to all daily returns whether the return is for recent times or from deep in the past. Despite these weaknesses, historical volatility is one of the most used measures of volatility due to its simplicity and the fact that it does not impinge on the estimation of a parametric model (Pindyck 2004). A debate is still ongoing as to whether volatility based on autoregressive conditional heteroskedasticity models provides forecasts that are superior to volatility based on the simple standard deviation (Andersen and Bollerslev 1998; Cumby et al. 1993; Suganuma 2000).

The descriptive statistics not reported here show that the average daily return in percentage terms varies as shown below:

- from –0.02 (investment) to 0.05 (hotel and tourism) for Bahrain;
- from –0.05 (investment) to 0.05 (banking) for Kuwait;
- from 0.0045 (banking and investment) to 0.04 (industry) for Oman;
- from –0.024 (services) to –0.0032 (banking and finance) for Qatar;
- from –0.11 (media and publishing) to 0.02 (petrochemical) for Saudi Arabia;
- from –0.12 (real estate) to 0.03 (industry) for United Arab Emirates–Abu Dhabi;
- from –0.22 (utilities) to –0.03 (transportation) for United Arab Emirates–Dubai.

In comparison with an average daily return on crude oil of 0.03 percent over the different samples in Table 1, the data suggest that only investments in hotel and tourism stocks in Bahrain, banks in Kuwait, and industry in Oman are more profitable than the crude oil market, whereas investment in industry stocks in United Arab Emirates–Abu Dhabi is as good as investment in crude oil. Hence, a portfolio made of these stocks would be more desirable than any other GCC portfolio of similar risk levels. This finding is good news for the typical risk-averse GCC investor who can freely participate in these markets.

It is customary in the literature to compare the standard deviations of different variables to determine the relative degree of volatility or risk. This measure ranges:

- from 0.60 percent (industry) to 1.14 percent (commercial banks) with hotels and tourism at 0.65 percent for Bahrain;
- from 1.90 percent (Kuwaiti companies) to 13.72 percent (food) with banks at 5.88 percent for Kuwait;
- from 1.17 percent (services) to 1.55 percent (industry) for Oman;
- from 1.76 percent (Qatar exchange) to 2.25 percent (insurance) for Qatar;
- from 1.56 percent (cement) to 2.69 percent (petrochemical) for Saudi Arabia;
- from 0.84 percent (insurance) to 6.89 percent (energy) for United Arab Emirates–Abu Dhabi;
- from 1.14 percent (insurance) to 3.60 percent (utilities) for United Arab Emirates–Dubai.

With the average daily oil price volatility hovering around 3 percent, the crude oil market is less volatile than sectors such as food (Kuwait), energy (United Arab Emirates–Abu Dhabi) and utilities (United Arab Emirates–Dubai). In terms of relative risk, the portfolio that emerges for the average daily return analysis also performs quite well. Higher risk with higher return is only confirmed for the industry sector; the remaining stocks in the portfolio have lower risk attached than other stocks within the same market.

The Granger causality and pairwise correlation results between the daily stock market return and oil price return are incorporated in Table 1. We find strong evidence that oil price returns can help forecast stock market returns in most GCC countries, except in Saudi Arabia where stock market returns also causes oil price returns. Results not presented here show that most sectoral stock returns are positively and highly correlated and significant at the 1 percent level. In only very few cases could we detect a negative correlation. The link with the oil price returns, however, is weak, but significant, at the 10 percent level. The correlation coefficient fluctuates:

- between –0.03 (hotel and tourism) and 0.05 (commercial banks) for Bahrain;
- between –0.03 (banks) and 0.05 (industry) for Kuwait;
- between 0.08 (industry) and 0.11 (banking and investment) for Oman;
- between 0.06 (industry) and 0.10 (insurance) for Qatar;
- between 0.08 (hotel and tourism) and 0.19 (cement) for Saudi Arabia;
- between 0.03 (banking and finance) and 0.11 (Abu Dhabi Securities Exchange) for United Arab Emirates–Abu Dhabi;
- between 0.02 (materials) and 0.14 (Dubai Financial Market) for United Arab Emirates–Dubai;
- between 0.03 (utilities) and 0.13 (cyclical and noncyclical goods) for the overall GCC.

These results suggest that a movement in crude oil prices is not a strong signal when it comes to watching fluctuations in sectoral and national stock prices for speculative purposes.

None of the daily return series is normally distributed as per the Jarque–Bera, Shapiro–Wilk, and Shapiro–Francia normality tests at the 1 percent significance level. The distributions of returns are negatively skewed and leptokurtic (kurtosis is far above

3 in all cases), meaning that they have both higher peaks and fatter tails than a normal distribution.

Empirical Analysis

The Synchronicity Results

To determine the degree of synchronicity between oil prices and GCC stock prices, returns and rolling window volatilities were each decomposed into a permanent component or trend and a transitory component or cycle using the popular Hodrick–Prescott filter with a smoothing parameter, λ, equal to $(90)^4 \times 1{,}600 = 104{,}976{,}000{,}000$ as suggested by Ravn and Uhlig (2002) for daily data. The trend captures long-term returns; the cycle is associated with market sentiments. We use the cycle definition that expresses the cycle as a share of the actual trend. The cyclical component of volatility is assumed to capture transitory noise; the permanent component reflects disturbances to economic fundamentals.

We use a five-step approach to arrive at the synchronicity ratio (SR) for each pairing of the cycles based on Equations (5) and (6). The oil price return (volatility) gap is used as the reference cycle for the nationwide and sector-wide stock price return (volatility) cycles. First, we count the number of synchronized cycles (+1s) and divergent cycles (–1s) and obtain a total equal to the number of cycles over the years for each pairing with the reference cycle. Second, we compute the proportion of +1s within the total. Third, we produce a count of the proportions of +1s that were greater than 0.50. Fourth, we calculate the SR as the count of proportions of +1s that are greater than 0.50 over the total (+1s and –1s) multiplied by 100 and rounded off to the nearest whole number. Fifth, we assess the degree of synchronicity using the three benchmarks described in the above methodology.

For the multivariate synchronicity measures, we compute the horizontal average of the +1s and –1s stemming from the matching of the reference cycle with the individual cycle at every point in time. This calculation produces a column series of T observations between –1 and +1, where T is the sample size. Positive values indicate a tendency toward synchronization; negative values indicate the opposite. The multivariate SR is computed as the count of the positive averages over the total of all averages (positive and negative). The same benchmarks are used for classification. Unless otherwise specified, the synchronicity results hereafter are expressed in percentage terms.

Detailed results of the SR for both the bivariate and the multivariate synchronicity measures based on returns and volatilities are not presented here due to space constraints. We also explore whether expectations of an oil price change or past disturbances to oil prices carry effects into the future that investors should take into consideration in purchasing stocks. To that effect, we discuss the synchronicity results stemming from the association between lead and lagged oil price return cycles with contemporaneous stock market return (volatility) cycles. At the sectoral level, we find contemporaneous synchronicity with oil price based on returns covers a range of values as follows:

- from 49 percent (commercial banks/investment) to 52 percent (insurance) for Bahrain;
- from 47 percent (Kuwait companies) to 50 percent (banks/food) for Kuwait;
- from 50 percent (banking and investment) to 51 percent (services and insurance/industry) for Oman;
- from 48 percent (insurance) to 53 percent (industry) for Qatar;

- from 44 percent (cement) to 54 percent (petrochemicals and retail) for Saudi Arabia;
- from 47 percent (energy and real estate) to 52 percent (health care) for United Arab Emirates–Abu Dhabi;
- from 43 percent (real estate) to 52 percent (consumer staples) for United Arab Emirates–Dubai;
- from 46 percent (real estate) to 53 percent (noncyclical goods/utilities) for the entire GCC.

At the country level, the overall index synchronicity with oil price stands at 50 percent (Bahrain), 49 percent (Kuwait), 50 percent (Oman), 48 percent (Qatar), 49 percent (Saudi Arabia), 46 percent (United Arab Emirates–Abu Dhabi), and 45 percent (United Arab Emirates–Dubai). Results based on lead and lagged oil price return cycles do not differ much from the contemporaneous synchronicity results, which suggests that there is a mild association between the crude oil and stock markets.

Contemporaneous volatility synchronicity results based on ten- and fifty-day rolling windows are, on average, higher than the return synchronicity. We summarize the results using a bracket system in which the first value corresponds to the ten-day volatility and the second value corresponds to the fifty-day volatility. The same applies to the associated industries. We find synchronicity as follows:

- between (48, 49) (insurance, insurance) and (62, 63) (industry, investment) for Bahrain;
- between (60, 56) (food, real estate, and Kuwait companies) and (64, 63) (investment, food) for Kuwait;
- between (60, 57) (services and insurance, industry) and (63, 62) (banking and investments, banking and investments) for Oman;
- between (60, 40) (industry and services, services) and (62, 56) (banking and finance, insurance) for Qatar;
- between (57, 53) (energy and utilities, energy and utilities) and (78, 73) (petrochemicals, agriculture and food/cement) for Saudi Arabia;
- between (42, 27) (insurance, consumer goods) and (66, 53) (real estate, construction) for United Arab Emirates–Abu Dhabi;
- between (52, 35) (insurance, insurance) and (69, 64) (financial investment, consumer staples/financial investment/transport) for United Arab Emirates–Dubai;
- between (64, 59) (cyclical goods, energy) and (76, 75) (banking and investment services, basic materials) for GCC as a whole.

At the country level, the synchronicity values are, respectively, (59, 69), (63, 71), (61, 61), (61, 47), (78, 68), (71, 54), and (67, 63) for Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, United Arab Emirates–Abu Dhabi, and United Arab Emirates–Dubai. A number of insights can be gathered from the results as presented. First, we find evidence that the ten-day volatility association of the cycles is relatively strong, as per our definition, except for Bahrain and Abu Dhabi, for which it is mild. Second, the fifty-day volatility synchronicity fluctuates from low (27 in the case of Abu Dhabi's consumer goods) to strong (75 in the case of the GCC's basic materials). Third, the ten-day volatility associations are greater than the fifty-day volatility associations, except for Bahrain's insurance sector. At the country level, the results suggest that volatility synchronicity ranges from mild to strong, and when the two measures are compared in terms of their relative magnitude, the outcome is mixed. For some countries (Bahrain and Kuwait), the fifty-day volatility dominates; for other countries of the group, the ten-day volatility shows more associations. For Oman, however, there is no difference. The overall results do not differ much when we focus on the synchronicity between the contemporaneous stock market volatility cycle and the oil price return volatility cycle during period $t + 1$ or $t - 1$. Nonetheless, we find a clear dominance of the ten-day volatility over the fifty-day volatility for Qatar, United Arab Emirates–Abu Dhabi, United Arab Emirates–Dubai, and the GCC as a whole.

Contrary to the common belief that crude oil is the main driver of the GCC economies, we find that the linkage is not strong for most sectors and for most countries. However, Saudi Arabia, which is understandably the largest oil producer and the largest country in the group, relies more heavily on oil revenues to foment growth in other sectors. This feature is quite evident when we peruse the ten-day volatility results: Saudi Arabia sectoral stock market synchronicity is, on average, larger than that of any other country and of the GCC as a whole. The decoupling of the non–oil sector from the oil sector that has taken place in most GCC countries may be the reason underlying the extent of association of the cycles we have observed (see Basher 2010). As Balli et al. (2009, 2011) have argued, the repatriation of capital to the Middle East after September 11 may be a contributing factor to economic diversification.

The Dynamic Factor Results

The synchronicity results have thus far shown that there is comovement between crude oil and stock markets. However, this comovement could be the result of chance. To overcome the potential problems of spurious synchronicity, we reformulate the research question with a twist by asking whether there is a common underlying factor driving sectoral stock markets in each GCC country and, should this be so, whether oil price return/volatility can explain such a factor.[8] Tables 2, 3, 4, and 5 show the dynamic factor results for the returns and the ten-day volatility. We have made the fifty-day volatility results available online. We report and discuss only coefficients that are statistically significant. Tables 2 and 3 contain the results for all GCC countries except Saudi Arabia; Tables 4 and 5 display results for Saudi Arabia and the two major groups. Tables 2 and 4 present the parameter estimates for Model 3 using sectoral stock returns for each country, the entire GCC, and national stock returns.[9] We find the idiosyncratic autoregressive coefficient, a_i, is significant for investment in Bahrain; all sectors in Oman; all sectors except services in Qatar; consumer goods only in United Arab Emirates–Abu Dhabi; bank, consumer staples, and telecommunications in United Arab Emirates–Dubai; building and construction and energy and utilities in Saudi Arabia; cyclical and noncyclical goods in the GCC. At the national level, a_{i} is significant for Saudi Arabia and United Arab Emirates–Abu Dhabi. This indicates that for each country/bloc/group, there are stock market return dynamics that are not fully captured by the dynamics of the common factor but rather by their autoregressive components or own dynamics. The factor loadings, b_i, which capture the sensitivity of individual stock market returns to the common factor, are statistically significant for most sectors within countries, the GCC-wide sectors, and national stock markets. The only exceptions are for industry in Bahrain, insurance in United Arab Emirates–Abu Dhabi, and consumer staples and materials in United Arab Emirates–Dubai. Thus, there is evidence of a common factor driving the growth dynamics of stock market returns in the GCC. The degree of persistence of this common factor, however, varies across countries, as captured by the value of d.

Table 2. Common factors based on returns

Bahrain	Commercial banks	Hotels and tourism	Industry	Insurance	Investment	Services			
a_i					0.07**				
b_i	0.005***	0.001***		0.001 (2.91)	0.002***	0.003***			
Oman	**Banking and investments**	**Services and insurance**	**Industry**						
a_i	0.11***	0.10**	0.13***						
b_i	0.01***	0.01***	0.01***						
Qatar	**Banking and financial services**	**Insurance**	**Industrial**	**Services**					
a_i	0.26***	0.07***	0.15***						
b_i	0.01***	0.01***	0.02***	0.01***					
UAE–Abu Dhabi	**Banks and financial services**	**Construction**	**Consumer goods**	**Telecom**	**Health care**	**Industry**	**Insurance**	**Real Estate**	**Energy**
a_i			-0.17***						
b_i	0.04***	0.01***	0.03***	0.03***	0.01***	0.01***		0.05***	0.06***
UAE–Dubai	**Banks**	**Consumer staples**	**Financial investment**	**Insurance**	**Materials**	**Real estate**	**Telecom**	**Transportation**	**Utilities**
a_i	0.10**	0.34***					0.10*		
b_i	0.01***		0.03***	0.01***		0.03***	0.02***	0.02***	0.03***
d	Bahrain = 0.44***; Oman = 0.25***; Qatar = 0.25***; UAE–Abu Dhabi = 0.05*; UAE–Dubai = –0.01								

Notes: Model estimated: $Y_{i,t} = a_i Y_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

Table 3. Common factor results based on ten-day volatility

Bahrain	**Commercial banks**	**Hotels and tourism**	**Industry**	**Insurance**	**Investment**	**Services**			
b	0.07***	0.03***	0.002***	0.005***	0.005***	0.006***			
d_1 (d_2)	1.68***	(-0.69 ***)							
Kuwait	**Banks**	**Food**	**Insurance**	**Industry**	**Investment**	**Kuwait companies**	**Real estate**	**Non–Kuwait companies**	
b	0.07***	0.44***	0.40***	0.15***	0.11***	0.02***	0.20***	0.25***	
d_1 (d_2)	1.31***	(–0.35***)							
Oman	**Banking and investments**	**Services and insurance**	**Industry**						
b	0.02***	0.01***	0.02***						
d_1 (d_2)	1.52***	(–0.53***)							
Qatar	**Banking and financial services**	**Insurance**	**Industrial**	**Services**					
b	0.013***	0.014***	0.014***	0.012***					
d_1 (d_2)	1.71***	(–0.72***)							
UAE–Abu Dhabi	**Banks and financial services**	**Construction**	**Consumer goods**	**Telecom**	**Health care**	**Industry**	**Insurance**	**Real estate**	**Energy**
b	0.14**	0.06**	0.12**	0.13**	0.08**	0.07**	0.02**	0.22**	0.26**
d_1 (d_2)	1.20**	(–0.24)							
UAE–Dubai	**Banks**	**Consumer staples**	**Financial investment**	**Insurance**	**Materials**	**Real estate**	**Telecom**	**Transportation**	**Utilities**
b	0.012***	0.02***		0.01***	0.013***	0.03***	0.02***	0.02***	0.03***
d_1 (d_2)	1.74***	(–0.75***)							

Notes: NCCGS = noncyclical consumer goods and services; C = cyclical consumer goods and services. Results are based on the estimation of Model 2: $Y_{i,t} = b_i Z^t + e_{i,t}$, $Z_t = d_1 Z_{t-1} + d_2 Z_{t-2} + v_t$. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

Table 4. Common factors based on returns

Saudi Arabia	Agriculture and food	Banks and financial services	Building and construction	Cement	Energy and utilities	Hotels and tourism	Industrial development	Insurance
a_i			0.21***		–0.26***			
b_i	0.02***	0.01***	0.02***	0.01***	0.01***	0.02***	0.02***	0.02***
	Media and publishing	**Multipurpose investment**	**Petrochemicals**	**Real estate development**	**Retail**	**Telecom**	**Transportation**	
a_i								
b_i	0.02***	0.02***	0.02***	0.02***	0.02***	0.01***	0.02***	
GCC	**Energy**	**Basic materials**	**Industry**	**NCCGS**	**Utilities**	**Telecom**	**Real estate**	**Banking and investment services**
a_i				–0.1***				
b_i	0.01***	0.02***	0.01***	0.01***	0.01***	0.01***	0.02***	0.01***
	CCGS	**Transportation**	**Industrial services**	**Mineral resources**				
a_i	–0.08**							
b_i	0.01***	0.02***	0.01***	0.01***				
Nationals	**DJ–Bahrain**	**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi**	**UAE–Abu Dhabi**	**UAE–Dubai**
a_i						–0.10*	–0.33***	
b_i	0.003***	0.002***	0.006***	0.01***	0.01***	0.01***	0.01***	0.01***
d	Saudi Arabia = 0.06; GCC = 0.14***; Nationals = 0.36**							

Notes: NCCGS = noncyclical consumer goods and services; CCGS = cyclical consumer goods and services. Model estimated: $Y_{i,t} = a_i Y_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$.
* Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

Table 5. Common factor results based on ten-day volatility

Saudi Arabia	Agriculture and food	Banks and financial services	Building and construction	Cement	Energy and utilities	Hotels and tourism	Industrial development	Insurance
b	0.02***	0.02***	0.03***	0.02***	0.02***	0.03***	0.03***	0.03***
d_1 (d_2)	1.49***	(–0.49***)						
	Media and publishing	**Multipurpose investment**	**Petrochemicals**	**Real estate development**	**Retail**	**Telecom**	**Transportation**	
b	0.03***	0.03***	0.03***	0.02***	0.02***	0.02***	0.03***	
d_1 (d_2)								
GCC	**Energy**	**Basic materials**	**Industry**	**NCCGS**	**Utilities**	**Telecom**	**Real estate**	**Banking and investment services**
b	0.01***	0.02***	0.01***	0.01***	0.02***	0.01***	0.02***	0.01***
d_1 (d_2)	1.65***	(–0.65***)						
	CCGS	**Transportation**	**Industrial services**	**Mineral resources**				
b	0.02***	0.02***	0.02***	0.01***				
d_1 (d_2)								
Nationals	**DJ–Bahrain**	**Bahrain**	**Kuwait**	**Oman**	**Qatar**	**Saudi**	**UAE–Abu Dhabi**	**UAE–Dubai**
b	0.004***	0.004***	0.01***	0.008***	0.011***	0.01***	0.008***	0.012***
d_1 (d_2)	1.75***	(–0.65***)						

Notes: NCCGS = noncyclical consumer goods and services; CCGS = cyclical consumer goods and services. Results are based on the estimation of Model 2: $Y_{i,t} = b_i Z_t + e_{i,t}$, $Z_t = d_1 Z_{t-1} + d_2 Z_{t-2} + v_t$. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

We collapse the daily data into quarterly data to plot the estimated common factors. The figure not reported here but reported online reveals that sectoral and national stock markets shared the recent major financial crisis in which the stock market crash of 2008 lasted until 2009, a span of seventeen months, as per the common factors. United Arab Emirates–Dubai is the only stock market that showed a spike during that period, but it fell dramatically in 2009 when investors became concerned that Dubai might not be able to meet its debt requirements in November of that year. For as long as the sample period allows, the common factor is able to show that sectoral markets in the GCC were affected by the dot-com burst in early 2000s, the September 11, 2001, attack, the war in Iraq starting in 2003, heightened nuclear tensions between Western nations and Iran in 2005–6, and the stock market crash of 2005–6.

Does a common factor underlie the volatility of stock market returns in the GCC countries? We answer this question by estimating similar dynamic factor models. One impediment encountered, however, is that the optimization algorithm fails to converge for some model specifications. Since our primary objective is not to find a common factor that embraces all GCC sectors, we report the model that works for each country, but we refrain from making cross-country comparisons. For the ten-day rolling volatility series, we find that Model 1, with a common factor that follows a second-order autoregressive process, works for all countries; for the fifty-day rolling volatility, the same model works for most markets/groups except Kuwait, Oman, and Qatar.

Tables 3 and 5 show the results pertaining to the DF model using the ten-day volatility series. Except for Dubai's financial investment sector, the common factor coefficient estimates are statistically significant at the 5 percent level for all sectors and main indexes. The common factor is quite persistent, as indicated by the sum of d_1 and d_2, and shows signs of explosion in certain cases in response to shocks. These features are also evident for the common factors that emerge from the fifty-day volatility series. We find the slope coefficients for the common factor to be negative but statistically significant for all sectors in Kuwait (for the documentation, see StataCorp 2011, p. 93). Therefore, irrespective of whether one uses a ten- or fifty-day horizon, there is a common unobservable variable influencing the evolution of the return volatility series.

Given the finding that GCC stock markets are all driven by a common factor, the interesting question is whether crude oil price returns/volatility can explain such a factor. We tackle this question by estimating Equation (8) with robust standard errors while including contemporaneous values and up to eight lags, as per the general-to-specific approach. Tables 6 and 7 report the results. Table 6 shows that while contemporaneous oil price returns have no effect on the common factor, the lagged effects are statistically significant for most models. However, we only present results pertaining to Model 4 to conserve space. We find statistically significant negative impacts when the common factor is extracted from Model 1 for Bahrain; Models 2, 3 and 4 for United Arab Emirates–Dubai; and Model 1 for United Arab Emirates–Abu Dhabi. The R-squares are quite small, varying from 1 percent to 11 percent, thereby indicating that oil price return is one of the variables underlying the common dynamic of stock markets in the GCC, but it is not the principal driver.

Table 7 presents the regression results linking the common factors to the ten-day rolling volatility in oil price returns. For common factors originating from Models 1 and 3 only, the contemporaneous effects, as well as past effects after eight days, are positive and statistically significant. The only exception is for Model 3, in the case of Oman, where the effects are negative and statistically significant. The R-squares fluctuate from 62 percent

Table 6. Regression results of equity return–based common factors on the daily returns of oil prices

	Lags	0	1	2	3	4	5	6	7	8	R^2	RMSE
Bahrain	Model 4			0.008**	0.015***	0.008**	0.1***	0.01***			0.04	0.31
Oman	Model 4		0.008**	0.01***	0.007**	0.006**	0.008***	0.004			0.03	0.24
Qatar	Model 4		0.007**	0.01***	0.006**	0.004*	0.006**			0.005**	0.03	0.24
Saudi Arabia	Model 4								0.003**	0.002**	0.04	0.06
UAE–Dubai	Model 4		–0.0005***	–0.0004**			–0.0004**	–0.0003**			0.04	0.01
UAE–Abu Dhabi	Model 4		0.001**	0.001**		0.001*					0.01	0.05
GCC–wide sectors	Model 4		0.006*	0.01***	0.007**	0.09**	0.006**			0.005*	0.06	0.2
GCC–national indexes	Model 4		0.02***	0.023***	0.012***	0.011**	0.014***	0.012**			0.11	0.34

Notes: RMSE = root mean square error. The common factors used as dependent variables were extracted from the following models: Model 1: $Y_{i,t} = b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 2: $Y_{i,t} = \alpha + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 3: $Y_{i,t} = a_i Y_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 4: $Y_{i,t} = \alpha + a_i Y_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$. Only coefficients that are statistically significant are reported for Model 4 to conserve space. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

Table 7. Regression results of equity return–based common factors on the ten-day historical volatility of oil prices

	Lags	0	8	R^2	RMSE
Bahrain	Model 1	0.24**	0.24**	0.75	12.11
Kuwait	Model 1	0.03*		0.07	3.93
Oman	Model 1	0.1***	0.1***	0.62	6.27
	Model 3	–0.08***	–0.1***	0.69	5.16
Qatar	Model 1	0.21***	0.21***	0.70	10.92
	Model 3	0.11***	0.12***	0.70	5.63
Saudi Arabia	Model 1	0.13*		0.71	6.6
	Model 3	0.09**		0.71	4.38
UAE–Dubai	Model 1	0.15*	0.15**	0.71	9.93
	Model 3	0.07*	0.08**	0.72	4.78
GCC–wide sectors	Model 1	0.2**		0.79	8.33
	Model 3	0.11***		0.79	4.31
GCC–national indexes	Model 1	0.23**	0.2*	0.79	12.1
	Model 3	0.1**	0.11**	0.10	12.76

Notes: RMSE = root mean square error. The common factors used as dependent variables were extracted from the following models: Model 1: $Y_{i,t} = b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 2: $Y_{i,t} = \alpha + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 3: $Y_{i,t} = a_i Y_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 4: $Y_{i,t} = \alpha + a_i Y_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$. Only coefficients that are statistically significant are reported, * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

to 79 percent with two outliers: Kuwait (Model 1: 7 percent) and GCC national indexes (Model 3: 10 percent). When we turn to the impact of the fifty-day rolling volatility, we find the contemporaneous effects to be significant only for Qatar, Saudi Arabia, United Arab Emirates–Dubai, the GCC-wide sectors, and the national indexes. There are no impacts after the eighth lag, except for the GCC-wide sectors when the common factor is taken from Model 4. The *R*-squares lie between 54 percent and 84 percent with two exceptions: GCC-wide sectors and GCC national indexes (Model 4: 15 percent each). These results suggest that the volatility of oil price returns is the main driver of the common factor observed for each GCC stock market.[10]

In Table 8, we display the results of the investigation into a common component underlying the industry-level common factors across the GCC countries and the common component's association with oil price returns and volatility.[11] We find, irrespective of the model estimated, that the common component is positive and statistically significant in each country's common factor equation and is quite persistent. This layer of the analysis thus suggests the existence of an overall common driver of the GCC stock markets that is linked to national and sectoral markets' dynamics despite their inherent differences.

The regression analysis, using robust standard errors of the overall common factor $(CF)_t$, of the contemporaneous and past effects of up to eight lags of the oil price returns confirms that oil price returns are among the factors that are capable of explaining the dynamics of the GCC stock markets, but they are not the most important factor.

$$\underset{}{CF_t} = \underset{(3.16)}{0.020_t} + \underset{(4.34)}{0.030_{t-1}} + \underset{(2.95)}{0.020_{t-2}} + \underset{(2.63)}{0.0160_{t-3}}\ \underset{(2.86)}{0.0180_{t-1}}\ \underset{(4.34)}{0.010_{t-5}} \qquad (11)$$

$R^2 = 0.14$, RMSE = 0.43, and *t*-statistics are in parentheses.

Table 8. The common component of the sector-based common factors

	Bahrain	Oman	Qatar	Saudi Arabia	UAE–Abu Dhabi
Model 1					
b	0.15***	0.26***	0.19***	0.02***	0.01***
d	0.47***				
Model 2					
b	0.15***	0.26***	0.19***	0.02***	0.01***
d	0.46***				
Model 3					
a	0.36***			–0.13**	0.03*
b	0.11***	0.26***	0.21***	0.03***	0.01***
d	0.43***				
Model 4					
a	0.36***			–0.13**	0.03*
b	0.11***	0.26***	0.21***	0.03***	0.01***
d	0.43***				

Notes: The dependent variables and common factors were extracted from the following models: Model 1: $F_{i,t} = b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 2: $F_{i,t} = \alpha + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 3: $F_{i,t} = a_i F_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$; Model 4: $F_{i,t} = \alpha + a_i F_{i,t-1} + b_i Z_t + e_{i,t}$, $Z_t = dZ_{t-1} + v_t$. Only coefficients that are statistically significant are reported. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

Results based on the historical volatility of ten- and fifty-day rolling windows, oil price did not produce any statistically significant coefficients, thereby indicating that oil price volatility, though quite important in explaining the dynamics of industry-level common factors, does not influence the dynamics of the common component of these factors.

Given that GCC countries have been actively participating in world capital markets and that service sectors may be more prone to financial shocks, in the search for robustness, we take the analysis one step further by investigating the importance of world interest rates and returns from major stock markets in explaining the common factor.[12] To that end, we estimate several regression equations and vector autoregression models. The results are presented in Table 9. By looking at the *R*-squares across the board, we find that idiosyncratic shocks explain the bulk of the movement in stock price returns. Lagged oil price returns continue to explain the common factor. Returns in major stock markets such as the United States, the United Kingdom, and Japan are not statistically significant in explaining the common factor driving GCC stock prices. European Monetary Unit (EMU) returns have positive influence only after a three-day lag. Libor-U.S. and Libor-UK have both positive and negative effects while Libor-Japan and fund rate are only statistically significant at the 10 percent level after one lag with opposite impact on the common factor. Libor-EMU was not statistically significant at any level. We repeat the estimation using VARs of different sizes and find that returns in major markets are statistically significant at different lag periods; Libor-Japan, Libor-EMU, and fund rate are not significant at the 5 percent level. The dynamic of the common factor and lagged oil prices are statistically significant mostly at the 1 percent level across models. Sensitivity analysis with various lags does not produce any major difference from the results reported here.

The forecast-error variance decompositions of the VARs are also estimated. We find that, despite the influence that major stock market returns, world interest rates, and oil

Table 9. Importance of world interest rates and major stock market returns in explaining the common factor

	OLS	VAR			
R^2	0.41	0.45	0.4	0.36	0.2
Dependent variable	**Common factor**				
Common factor					
L1		0.27***	0.30***	0.30***	0.34***
L2		0.01	0.03	0.03	–0.01
L3		–0.01			
L4		–0.11***			
Oil price return					
L0	0.004				
L1	0.004	0.002	0.01***	0.01***	0.02***
L2	0.012*	0.01**	0.01**	0.01***	0.005
L3	0.013***	0.01**			
L4	0.009**	0.01**			
Return U.S.					
L0	–0.06				
L1	–0.79	–0.35	–1.15	–1.03	
L2	–1.19	–1.12	–2.48***	–2.13**	
L3	1.98	2.27**			
L4	1.26	0.73			
Return UK					
L0	–0.95				
L1	–0.88	0.10*	0.56	0.19	
L2	2.09	2.47	2.32*	2.60*	
L3	–1.28	–2.27*			
L4	–1.08	–0.34			
Return Japan					
L0	0.44				
L1	1.06	0.68	1.87**	1.80**	
L2	4.95	5.06***	6.86***	6.77***	
L3	0.48	–0.63			
L4	0.91	0.22			
Return EMU					
L0	0.87				
L1	0.77	0.22	0.39	0.57	
L2	1.54	1.50	2.49**	2.42**	
L3	4.01***	3.57***			
L4	0.76	–0.38			
Libor-U.S.					
L0	6.20				
L1	–27.13	–18.13	–18.18***		–30.00***
L2	29.39**	33.02***	20.63***		28.72***
L3	–26.04**	–31.84***			
L4	25.29**	23.78***			

(continues)

Table 9. Continued

	OLS	VAR			
R^2	0.41	0.45	0.4	0.36	0.2
Dependent variable	**Common factor**				
L1	39.55	6.78	15.83		34.82***
L2	–36.67*	–48.31***	–10.82		–27.21**
L3	63.90**	70.51***			
L4	–19.61	–23.37**			
Libor-Japan					
L0	–44.46				
L1	–1.33*	8.37	12.30		9.23
L2	33.64	–8.93	–1.29		–2.77
L3	43.46	44.08*			
L4	–46.62	–62.13***			
Libor-EMU					
L0	12.02				
L1	–17.00	–13.40	–14.75*		–14.02
L2	–3.65	2.84	4.68		2.19
L3	–3.15	–2.44			
L4	3.77	4.81			
Fund rate					
L0	4.03				
L1	0.19*	0.25	2.98		4.47
L2	–2.01	–2.84	–3.13		–2.46
L3	–3.68	–1.46			
L4	–1.72	0.32			

Source: Data come from Thomson Reuters Database.

Notes: OLS = ordinary least squares; VAR = vector autoregression models. * Significance at the 10 percent level; ** significance at the 5 percent level; *** significance at the 1 percent level.

prices have in explaining the driving forces underlying the common dynamics of GCC stock prices, idiosyncratic shocks remain the major explanatory variables; they account for a minimum of 64 percent of the common factor's total variance. Oil price disturbance accounts for 2 percent on average, while disturbances to U.S. returns have the most substantial impact among all variables included in the various models. In general, this analysis confirms that our findings are robust.

Conclusion

The vast literature on risk sharing provides the rationale for investors to hold a diversified portfolio of assets as opposed to purely domestic assets, though some research has shown that home biasness is still a reality in a number of markets due to uncertainty, high transaction and transportation costs, capital flow restrictions, and the high cost of gathering reliable information. The GCC is quite peculiar in this case. Most GCC stock markets are fairly new and emerging with returns far above those of mature markets; therefore, the GCC stock markets are attracting a huge volume of foreign portfolio inflow.

The rise in oil export revenues has given birth to sovereign wealth funds invested in major foreign emerging and/or developed markets as savings for a rainy day, while efforts toward economic diversification have led to massive investment in different economic sectors. The important questions for GCC and foreign investors are as follows: (1) Given the opportunities available, what portfolio mix stochastically dominates the crude oil market performance? (2) Given the reliance on oil revenues to finance development projects, how are returns and volatility in the crude oil market linked to sectoral stock price returns and volatility? (3) How do disturbances from major markets alter the dynamics of the GCC stock markets? The response to these questions are the contributions of this paper to all stakeholders, be they finance practitioners, academics, speculators, long-term investors, government bodies, pension funds managers, and so on.

We find that only investments in hotel and tourism stocks in Bahrain, banks in Kuwait, and industry in Oman are more profitable than the crude oil market; investment in industry stocks in United Arab Emirates–Abu Dhabi is as good as investment in crude oil. Hence, we conjecture that a portfolio made of these stocks would be more desirable than any other GCC portfolio of similar risk levels. This finding is good news for the typical risk-averse GCC investor who can freely participate in these markets. We also find that the crude oil market is less volatile than sectors such as food (Kuwait), energy (United Arab Emirates–Abu Dhabi), and utilities (United Arab Emirates–Dubai). In terms of relative risk, the portfolio that emerges for the average daily return analysis also performs quite well. Higher risk with higher return is confirmed only for the industry sector; the remaining stocks in the portfolio have lower risk attached than other stocks within the same market. Granger causality and pairwise correlation tests between the daily stock market return and oil price return provide strong evidence that oil price returns can help forecast stock market returns in most GCC countries and for most sectors. The converse is true for most but not all sectors of the Saudi Arabia market. Most sectoral stock returns are positively and highly correlated and significant at the 1 percent level. In only very few cases could we detect a negative correlation. The link with the oil price returns, however, is weak, but significant, at the 10 percent level. These results suggest that a movement in crude oil prices is not a strong signal when it comes to watching fluctuations in sectoral and national stock prices for speculative purposes.

We document the degree of synchronicity between crude oil and stock markets in the GCC in line with the commonly held view that oil constitutes the backbone of these economies. We use the bivariate and multivariate synchronicity measures proposed by Mink et al. (2007) and daily data on sectoral, GCC-wide sectoral, and national stock market data. The results show that cyclical fluctuations in oil prices and stock market returns are mildly synchronized (between 40 percent and 60 percent), whereas the fluctuations of volatility fall between mild and strong (above 60 percent). These results suggest that shocks to oil price volatility matter more than shocks to oil price returns for the GCC stock markets. Upon this finding, we reformulate the research question with a twist: If we were to leave oil price return and volatility in standby, would we be able to find an underlying common factor driving the dynamics of the different GCC stock market groupings, and—if and when we find that common factor—can its dynamics be explained by oil price return and volatility?

We have shown that a distinct common factor underlies sectoral stock markets within each GCC country and the GCC-wide and GCC national stock markets. Shocks to oil price return explain the dynamics of each common factor, with no clear evidence supporting the view that oil price is the main driver of the dynamics of the stock market for any of the groupings. Shocks inducing changes in oil price volatility, by contrast, are quite important. Further research into the underlying common component of the industry-level common factors confirms the existence of such an overall common driver, which is positively correlated with the common factors of the GCC-wide sectoral and the GCC national stock markets. For this unique industry-level common factor, representative of all sectors in the GCC, although the importance of shocks to oil price return does not change, volatility no longer carries any explanatory power.

Notes

1. For example, macroeconomic data on inflation and output are available on a yearly basis for all GCC countries except Saudi Arabia. Data on interest rates and unemployment are not available. Although stock trading began as far back as 1935 (Saudi Arabia), 1952 (Kuwait), and 1957 (Bahrain), electronic trading started in the late 1980s for Bahrain and Saudi Arabia, the mid- to late 1990s for Oman and Kuwait, and the early 2000s for the United Arab Emirates and Qatar. For a chronology of the GCC stock market and its economic characteristics, see Arouri et al. (2011) and Bley and Chen (2006).

2. The motivation is to avoid spurious synchronicity. Two variables may comove just because of chance. Our contention is that for synchronicity to be meaningful, the dynamics of both variables must be driven by a common factor. This is the idea embodied in cointegration and correlation analyses.

3. A mild association of the fifty-day volatility cycles is noted for the Dubai Financial Market (DFM) and the Abu Dhabi Exchange (ADX). The ADX is also more sensitive to oil price disturbances than the DFM.

4. The notion of decomposing returns into a trend and a cycle is in line with market participants' behavior toward risks and returns. Some investors purchase shares for retirement or as long-term investments and therefore are not concerned with day-to-day fluctuations in stock prices. Their goal is to collect dividends over time while waiting for the share price to reach a certain level. Others, however, make a living off the market by monitoring share prices closely.

5. The variable Y stands for either oil price or stock market returns/volatilities here.

6. The methodology of our paper is similar to Basher's (2010), but the nature and scope of our work is different. Basher's investigation into the decoupling of the oil sector from the non–oil sector covers only three of the six GCC countries (Kuwait, Qatar, and Saudi Arabia) for the real sector; our paper, which focuses on the financial sector, covers the aggregate GCC sectors, individual stock sectors, and the country-level stock index for each of the six countries.

7. A more detailed version of the paper is available at http://web.viu.ca/rosmyjl/papers.htm.

8. As Sturm and Siegfried (2005) noted, sectoral diversification is marked by sharp differences across GCC countries. Bahrain has put efforts toward becoming a financial hub for the region and, along with the United Arab Emirates, has invested heavily in tourism, transport, manufacturing, and other services. These two economies are the least reliant on oil. Kuwait has been developing its finance sector while Oman and Saudi Arabia have been diversifying into manufacturing. Saudi Arabia has become a major producer of petrochemicals. The construction/real estate sector has stagnated in the United Arab Emirates (mostly in Dubai) but has been growing in other GCC countries. Qatar has invested heavily in the extraction of natural gas while making large investment in infrastructure. Underlying the financing of all these initiatives is the power of crude oil export revenues.

9. Although we are able to estimate all four types of models for the return, due to space constraints, we present only results pertaining to the estimation of Model 3, which is equivalent to Model 4 when $\alpha = 0$. These are the most complete of the models. However, when assessing the importance of oil price returns, we use common factors from all four models. Dynamic factor results based on Models 1, 2, and 4 are available upon request. Kuwait was left out in the estimation of most models because of nonconvergence of the algorithm.

10. It is important to note that the common factors used as dependent variables are related to stock price returns, not stock price return volatility, because we could not find a single model that works for all countries or groupings. In addition, since we report only coefficients that are statistically significant, models that are not listed in Tables 6 and 7 do not deliver such coefficients when we regress their common factors on either the oil price return or volatility.

11. Pairwise correlations among the industry-based common factors show a negative relationship between United Arab Emirates–Dubai and the rest of the GCC markets. Therefore, the United Arab Emirates–Dubai common factor is dropped. Kuwait, for which a common factor cannot be estimated due to algorithm nonconvergence issues, is also dropped. The common factor used for each country comes from Model 2. The results do not differ much when common factors from other models are used instead.

12. We thank an anonymous referee for making this and many other suggestions that led to the improvement of our work.

References

Abraham A.; F.J. Seyyed; and A. Al-Elg. 2001. "Analysis of Diversification Benefits of Investing In the Emerging Gulf Stock Markets." *Managerial Finance* 27, nos. 10/11: 47–57.

Abu Zarour, B. 2006. "Wild Oil Prices, but Brave Stock Markets! The Case of GCC Stock Markets." *Operational Research: An International Journal* 6, no. 2: 145–162.

Al-Khazali, O.; A. Darrat; and M. Saad. 2006. "Intra-Regional Integration of the GCC Stock Markets: The Role of Market Liberalization." *Applied Financial Economics* 16, no. 17: 1265–1272.

Andersen, T., and T. Bollerslev. 1998. "Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts." *International Economic Review* 39, no. 4: 885–905.

Arouri, M.; M. Bellalah; and D. Nguyen. 2011. "Further Evidence on the Responses of Stock Prices in GCC Countries to Oil Price Shocks." *International Journal of Business* 16, no. 1: 89–103.

Arouri, M., and J. Fouquau. 2009. "On the Short-Term Influence of Oil Price Changes on Stock Markets in GCC Countries: Linear and Nonlinear Analyses." *Economics Bulletin* 29, no. 2: 795–804.

Arouri, M.; A. Lahiani; and D.K. Nguyen. 2011 "Return and Volatility Transmission Between World Oil Prices and Stock Markets of the GCC Countries." *Economic Modelling* 28, no. 4: 1815–1825.

Arouri, M., and C. Rault. 2010. "Oil Prices and Stock Markets: What Drives What in the Gulf Cooperation Council?" Working Paper no. 2934, CESifo Group, Munich.

Balli, F.; R. Jean Louis; and M.A. Osman. 2009. "International Portfolio Inflows to GCC Markets. Are There Any General Patterns?" *Review of Middle East Economics and Finance* 5, no. 2: 45–65.

———. 2011. "The Patterns of Cross-Border Portfolio Investments in the GCC Region: Do Institutional Quality and the Number of Expatriates Play a Role?" *Journal of Economics and Finance* 35, no. 4: 434–455.

Basher, S.A. 2010. "Has the Non-Oil Sector Decoupled from Oil Sector? A Case Study of Gulf Cooperation Council Countries." MPRA Paper no. 21059, University Library of Munich (available at http://mpra.ub.uni-muenchen.de/21059/).

Basher, S.A., and P. Sadorsky. 2006. "Oil Price Risk and Emerging Stock Markets." *Global Finance Journal* 17, no. 2: 224–251.

Baxter, M., and R.G. King. 1999. "Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time-Series." *Review of Economics and Statistics* 81, no. 4: 575–593.

Baxter, M., and M. Kouparitsas. 2005. "Determinants of Business Cycle Co-Movement: A Robust Analysis." *Journal of Monetary Economics* 52, no. 1: 113–157.

Bley, J., and K.H. Chen. 2006. "Gulf Cooperation Council (GCC) Stock Markets: The Dawn of a New Era." *Global Finance Journal* 17, no. 1: 75–91.

Chen, N.-F.; R. Roll; and S.A. Ross. 1986. "Economic Forces and the Stock Market." *Journal of Business* 59, no. 3: 383–403.

Cumby, R.; S. Figlewski; and J. Hasbrouck. 1993. "Forecasting Volatility and Correlations with EGARCH Models." *Journal of Derivatives* 1, no. 2 (Winter): 51–63.

Cuñado, J., and F. Pérez de Gracia. 2005. "Oil Prices, Economic Activity and Inflation: Evidence for Some Asian Countries." *Quarterly Review of Economics and Finance* 45, no. 1: 65–83.

Darrat, A.F.; K. Elkhal; and S.R. Hakim. 2000. "On the Integration of Emerging Stock Markets in the Middle East." *Journal of Economic Development* 25, no. 2 (December): 119–129.

El-Wassal, K. 2005. "Stock Market Growth: An Analysis of Cointegration and Causality." *Economic Issues* 10, no. 1: 37–58.
Fama, E.F., and K.R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33, no. 1: 3–56.
Fayyad, A., and K. Daly. 2011. "The Impact of Oil Price Shocks on Stock Market Returns: Comparing GCC Countries with the UK and USA." *Emerging Markets Review* 12, no. 1: 61–78.
Ferson, W., and C. Harvey. 1995. "Predictability and Time-Varying Risk in World Stock Markets." *Research in Finance* 13: 25–88.
Geweke, J. 1977. "The Dynamic Factor Analysis of Economic Time Series." In *Latent Variables in Socio-Economic Models,* ed. D.J. Aigner and A.S. Goldberger, pp. 365–383. Amsterdam: North-Holland.
Giannone, D.; M. Lenza; and L. Reichlin. 2008. "Explaining the Great Moderation: It Is Not the Shocks." *Journal of the European Economic Association* 6, no. 2–3: 621–633.
Girard, E., and E. Ferreira. 2004. "Long Term Stochastic Trends in MENA Capital Markets." *International Journal of Business and Economics Research* 3, no. 2: 23–45.
Girard, E.; M. Omran; and T. Zaher. 2003. "On Risk and Return in MENA Capital Markets." *International Journal of Business* 8, no. 3: 285–314.
Hamao, Y. 1988. "An Empirical Examination of the Arbitrage Pricing Theory: Using Japanese Data." *Japan and the World Economy* 1, no. 1: 45–61.
Hamilton, J.D. 1983. "Oil and the Macroeconomy Since World War II." *Journal of Political Economy* 91, no. 2: 228–248.
———. 1996. "This Is What Happened to the Oil Price-Macroeconomy Relationship." *Journal of Monetary Economics* 38, no. 2: 215–220.
———. 2003. "What Is an Oil Shock?" *Journal of Econometrics* 113, no. 2: 363–398.
Hamilton, J.D., and A.M. Herrera. 2004. "Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy." *Journal of Money, Credit and Banking* 36, no. 2: 751–782.
Hammoudeh, S., and E. Aleisa. 2004. "Dynamic Relationship Among GCC Stock Markets and NYMEX Oil Futures." *Contemporary Economic Policy* 22, no. 2: 250–269.
Hammoudeh, S., and K. Choi. 2006. "Behavior of GCC Stock Markets and Impacts of US Oil and Financial Markets." *Research in International Business and Finance* 20, no. 1: 22–44.
Harvey, C.R. 1995a. "Predictable Risk and Returns in Emerging Markets." *Review of Financial Studies* 8, no. 3: 773–816.
———. 1995b. "The Risk Exposure of Emerging Equity Markets." *World Bank Economic Review* 9, no. 1: 19–50.
Hodrick, R.J., and E.C. Prescott. 1997. "Postwar U.S. Business Cycles: An Empirical Investigation." *Journal of Money, Credit and Banking* 29, no. 1: 1–16.
Imbs, J. 2006. "The Real Effects of Financial Integration." *Journal of International Economics* 68, no. 2: 296–324.
Jones, C., and G. Kaul. 1996. "Oil and the Stock Markets." *Journal of Finance* 51, no. 2: 463–491.
Kalemli-Ozcan, S.; E. Papaioannou; and J.L. Peydró. 2011. "Financial Regulation, Financial Globalization and the Synchronization of Economic Activity." Working Paper no. 14887, National Bureau of Economic Research, Cambridge, MA.
Kaneko, T., and B.-S. Lee. 1995. "Relative Importance of Economic Factors in the U.S. and Japanese Stock Markets." *Journal of the Japanese and International Economies* 9, no. 3: 290–307.
Kilian, L. 2008a. "The Economic Effects of Energy Price Shocks." *Journal of Economic Literature* 46, no. 4: 871–909.
———. 2008b. "Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy?" *Review of Economics and Statistics* 90, no. 2: 216–240.
———. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *American Economic Review* 99, no. 3: 1053–1069.
Kilian, L., and C. Park. 2009. "The Impact of Oil Price Shocks on the U.S. Stock Market." *International Economic Review* 50, no. 4: 1267–1287.
King, M.; E. Sentana; and S. Wadhwani. 1994. "Volatility and Links Between National Stock Markets." *Econometrica* 62, no. 4: 901–933.

Maghyereh, A., and A. Al-Kandari. 2007. "Oil Prices and Stock Markets in GCC Countries: New Evidence from Nonlinear Cointegration Analysis." *Managerial Finance* 33, no. 7: 449–460.

Mink, M.; J. Jacobs; and J. de Haan. 2007. "Measuring Synchronicity and Comovement of Business Cycles with an Application to the Euro Area." Working Paper no. 2112, CESifo Munich.

Mohanty, S.K.; M. Nandha; A.Q. Turkistani; and M.Y. Alaitani. 2011. "Oil Price Movements and Stock Market Returns: Evidence from Gulf Cooperation Council (GCC) Countries." *Global Finance Journal* 22, no. 1: 42–55.

Morgan, D.P.; B. Rime; and P. Strahan. 2004." Bank Integration and State Business Cycles." *Quarterly Journal of Economics* 119, no. 4: 1555–1585.

Omran, M., and L. Gunduz. 2001. "Stochastic Trends and Stock Prices in Emerging Markets: The Case of Middle East and North Africa Region." *Istanbul Stock Exchange Review* 5: 3–16.

Papapetrou, E. 2001. "Oil Price Shocks, Stock Market, Economic Activity and Employment in Greece." *Energy Economics* 23, no. 5: 511–532.

Pindyck, R.S. 2004. "Volatility in Natural Gas and Oil Markets." *The Journal of Energy and Development* 30, no. 1: 1–20

Ravichandran, K., and K.A. Alkhathlan. 2010. "Impact of Oil Prices on GCC Stock Market." *Research in Applied Economics* 2, no. 1: 1–12 .

Ravn, M.O., and H. Uhlig. 2002. "On Adjusting the Hodrick–Prescott Filter for the Frequency of Observations." *The Review of Economics and Statistics* 84, no. 2: 371–375.

Sadorsky, P. 2003. "The Macroeconomic Determinants of Technology Stock Price Volatility." *Review of. Financial Economics* 12, no. 2: 191–205.

Sargent, T.J., and C.A. Sims. 1977. "Business Cycle Modeling Without Pretending to Have Too Much *A Priori* Economic Theory." In *New Methods in Business Research*, ed. C.A. Sims, pp. 45–109. Minneapolis: Federal Reserve Bank of Minneapolis.

StataCorp. 2011. *Stata Time-Series Reference Manual: Release 11.* College Station, TX: Stata Press.

Stock, J.H., and M. Watson. 1989. "New Indexes of Coincident and Leading Economic Indicators." In *NBER Macroeconomics Annual 1989,* vol. 4, ed. O.J. Blanchard and S. Fischer, pp. 351–394. Cambridge: MIT Press.

———. 1991. "A Probability Model of the Coincident Economic Indicators." In *The Leading Economic Indicators: New Approaches and Forecasting Records*, ed. K. Lahiri and G.H. Moore, pp. 63–89. Cambridge: Cambridge University Press.

Sturm, M., and N. Siegfried. 2005. "Regional Monetary Integration in the Member States of the Gulf Cooperation Council." Occasional Paper no. 31, European Central Bank, Frankfurt.

Suganuma, R. 2000. "Reality Check for Volatility Models." Working Paper no. 0508, University of California, San Diego.

Watson, M.W., and R.F. Engle. 1983. "Alternative Algorithms for the Estimation of Dynamic Factors, MIMIC, and Varying Coefficient Regression Models." *Journal of Econometrics* 23, no. 3: 385–400.