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# Oil Prices and the Kuwaiti and the Saudi Stock Markets: The Contrast

**Samih Antoine Azar**
Faculty of Business Administration & Economics,
Haigazian University, Mexique Street, Kantari, Beirut, Lebanon.
Telephone/fax: +9611349230. Email: samih.azar@haigazian.edu.lb

**Loucine Basmajian**
Accounting, Internal Operations, and Sales Manager
Printkom, Mar Mikhael, Beirut, Lebanon.
Telephone: +9611444344. Email: loucine.b@gmail.com

**ABSTRACT:** The purpose of this paper is to test the impact of oil price shocks on the stock markets of the two biggest and most liquid GCC equity markets, those of Kuwait and Saudi Arabia. It is expected that the two stock markets react similarly to oil price shocks. Actually the results show heterogeneity in responses. While there is prima facie evidence that both stock markets are influenced positively and linearly by oil price shocks, this evidence disappears when additional variables are added to the regressions. With the larger specification oil price shocks do not impact, neither linearly or non-linearly, Kuwaiti stock markets. By contrast Saudi markets react non-linearly to both oil price shocks and shocks in the US S&P 500. The only common feature for both equity markets is the positive relation with the shocks in the US S&P 500.

**Keywords**: Oil prices; stock markets; Kuwait and Saudi Arabia; US S&P 500; GARCH; non linear relations
**JEL Classifications**: G14; G15; F36; C22

## 1. Introduction

The purpose of this paper is to study the linkage between oil prices and the stock markets of two main members of the Gulf Cooperation Council (GCC) which are Kuwait and Saudi Arabia. High-frequency daily data is analyzed for the period going from January 2, 2008 to October 23, 2012, a period which coincides with the aftermath of the world financial crisis. It is known that correlations between stock markets increase in a downturn. Using daily data means that the relations that are studied are short run in nature, abstracting from long run dependencies that ought to be estimated by cointegration methods, although some researchers have used cointegration techniques with daily data (Hammoudeh and Aleisa, 2004). Daily data are noisier than monthly data, but monthly data may obscure the underlying association if there is one. One feature of the structure of the data that is original and which is necessary in order to enable the researcher to tie movements between US stock markets and the stock markets of these two major oil-exporting countries is to select the three days of the week during which both US and Arab stock markets are open for trading, and these are Mondays, Tuesdays, and Wednesdays. Kuwaiti and Saudi stock markets are closed on Thursdays and Fridays, and the US markets are closed on Saturdays and Sundays. In addition due to time zone differences the Arab markets open usually when US markets are still open for business. Hence there might be lagged reactions by Arab stock markets to US markets. Such reactions are overshadowed with monthly and lower frequency data. The choice of Kuwait and Saudi Arabia is dictated by the fact that both have higher share turnover in their stock markets among the six members of the GCC (Hammoudeh and Choi, 2006).

The relation between oil prices and GCC stock markets is a rather recent addition to the academic literature. The earliest effort is in the year 2004 (Hammoudeh and Aleisa, 2004). Previously the focus of the theoretical and empirical enquiries was on developed countries (Huang et al., 1996; Jones and Kaul, 1996; Sadorsky, 1999). Jones and Kaul (1996) start their analysis by stating that equity is equal to the sum of the discounted value, or present value, of future cash flows. Since oil prices affect the macro-economy, they inevitably affect future corporate profits, which in turn are priced in equity markets. The direction of this pricing is negative: higher oil prices retard business activity, and lead to lower current and expected corporate profits. Unfortunately the same cannot be said for Kuwait and Saudi Arabia. Oil prices may either have a positive or a negative impact. A positive impact is warranted because Kuwait and Saudi Arabia are major oil producers and their earnings, government budget revenues, and aggregate demand are positively influenced by higher oil prices. A negative impact can be rationalized if higher oil prices increase the input cost and price of imported consumer and capital goods by these two Arab countries and result in an increase in domestic inflation. Higher inflation causes higher interest rates and therefore higher discount rates and thus lower share prices. In addition if monetary policy becomes restrictive to reign inflation interest rates and discount rates can edge significantly higher. Since Kuwaiti and Saudi foreign exchange rates are pegged in one way or another to the US dollar, US financial markets may have some bearing on these two markets. So, the ultimate impact is uncertain, and the choice of the independent variables becomes more complicated.

The paper is organized as follows. In section 2 the literature is surveyed. In section 3 the equation models are provided. Section 4 covers the source of the data and reports descriptive statistics of the variables. Section 5 presents the empirical results. In section 6 some robustness tests are provided. The final section summarizes and concludes.

## 2. Survey of the Literature

The survey of the literature is chronological and is centered about Kuwait and Saudi Arabia. In general the evidence in the literature on the connection between GCC stock markets and oil prices is mixed, heterogeneous and contradictory. Hammoudeh and Aleisa (2004) find bi-directional causality between Saudi stock markets and oil futures, while the relation with oil futures is insignificant for the stock markets of the other five GCC countries. They also document that Saudi markets have the most causal linkages with other GCC markets.

Hammoudeh and Choi (2006), using weekly data, do not find empirical evidence on a relation between GCC markets and oil prices and between GCC markets and US stock markets. They argue that this implies no predictability from US oil and US capital markets and the presence of strong cross diversification benefits. They also find no own lagged effects for Kuwaiti and Saudi stock markets. However the US T-bill rate seems to impinge on these two markets in the short run. In a subsequent paper and with weekly data again Hammoudeh and Choi (2007) confirm the weak correlation between oil prices and GCC stock markets, with the highest correlation being found for Saudi Arabia. However the GCC stock markets are found to be highly integrated together, reducing the scope for local diversification benefits. Notably, the correlation is highest between Kuwait and Saudi Arabia. The authors divide total returns of the GCC stock markets into permanent and transitory components, and they show that there exist two volatility regimes for each of these two components, and they conclude that return premiums should be higher during the high volatility regime.

Onour (2007), using daily data between 2004 and 2006, finds that, in the short run, non-observable speculative factors are the driving force of GCC stock markets. Additional support for this hypothesis is the finding of first-order serial correlation in all stock returns. In the long run oil prices are seen to affect stock market returns indirectly.

Arouri and Fouquau (2009) examine both linear and non-linear relationships between weekly oil prices and GCC stock returns. They find evidence that oil prices do not affect the stock markets of Kuwait and Saudi Arabia.

Ravichandran and Alkhathlan (2010), using daily data, conclude that, in the short run, non-observable speculative factors are the driving force of GCC stock returns and that oil price volatility is ineffective in explaining GCC stock returns.

Arouri and Rault (2010) study weekly and monthly panel data of stock indexes of GCC countries with oil prices, using the SUR (Seemingly Unrelated Regressions) econometric procedure. Causality is bidirectional for Saudi Arabia. Causality runs from oil prices to stocks for the other five

GCC countries. Surprisingly Saudi Arabia's stock market negatively Granger-causes oil prices. And oil prices negatively Granger-cause Saudi stock markets on a weekly basis but positively on a monthly basis.

Arouri et al. (2010) use weekly data and non-linear methods to uncover the relation between GCC stock markets and oil prices. World market returns and oil prices impact Saudi stock markets significantly, while there is no discernible linear relation between Kuwaiti stock markets and oil. However there is a significant non-linear relation with oil for the latter country.

Arouri and Fouquau (2011) start their research by recognizing that the relation between oil prices and GCC stocks is non-linear and they estimate an asymmetric cointegration regression with weekly and monthly data. While traditional cointegration tests fail to reject the null of no-cointegration, this hypothesis is rejected with the asymmetric cointegration variant.

Daly and Fayyad (2011) use daily data and estimate a VAR model with four lags. They divide their data into three periods, comprising a normal period, a period of rising oil prices, and a period of falling oil prices. For the first period there is no significant relation between oil prices and GCC stock returns. There is a stronger relation in the second period for two GCC countries out of the total. And for the third period the predictive power of oil on stock prices increases. One drawback of this paper is that the VAR methodology does not take into account contemporaneous effects.

Finally, Arouri et al. (2011) employ daily data with a VAR-GARCH approach which allows for spillover effects in both returns and conditional volatilities. They discover that Gulf Cooperation Council stock markets have lower daily average stock returns and volatilities than the world oil markets. Furthermore, they show that skewness is positive for the oil markets whereas it is negative for all the stock markets and demonstrate that kurtosis coefficients are considerable in both size and significance, indicating leptokurtic distributions. These findings are of great importance to international investors as skewness coefficients are indicative that extreme positive and negative returns can be realized in the oil and stock markets respectively and since both the stock and oil distributions are leptokurtic, investors can gauge themselves from irregular swings in both returns and risk. Thus, though the inclusion of oil in a diversified portfolio might increase the risk of the portfolio, it would definitely induce larger diversification benefits. One of their results is that "past oil shocks have significant effects on stock market volatility in Saudi Arabia while past oil volatility strongly affects stock market volatility in Kuwait."

## 3. Model Equations

Four models will be estimated to explain each of the Kuwaiti stock market log returns and the Saudi stock market log returns. Log returns are calculated by taking the first-difference of the natural logs. Since non-linearity is pervasive in the literature, three types of non-linearity are considered. All models include one kind of non-linear relation which is a GARCH (1,1) process for the conditional variance. In this case the non-linear relation is the temporal dependency of the squared residuals. The first model is with the time period $t$:

$$\Delta(\log(stock_t)) = \alpha + \sum_{i=0}^{s} \delta_i \Delta(\log(oil\ price_{t-i})) + \sum_{j=1}^{p} \beta_j \Delta(\log(stock_{t-j})) + \varepsilon_t \tag{1}$$

The second model introduces another non-linearity which is by separating the oil price series into positive log changes $[\Delta(\log(oil\ price))]^+$ and negative log changes $[\Delta(\log(oil\ price))]^-$:

$$\Delta(\log(stock_t)) = \alpha + \gamma_1 [\Delta(\log(oil\ price_t))]^+ + \gamma_2 [\Delta(\log(oil\ price_t))]^- + \sum_{j=1}^{p} \beta_j \Delta(\log(stock_{t-j})) + \varepsilon_t \tag{2}$$

The third model is an extension of equation (1) and includes two additional variables, the log returns of the US S&P 500 index (SP) and a proxy variable for regional log returns ($\Delta(\log(M))$). Also included are two non-linear variables, the square of the S&P log returns and the square of the oil price log returns. The model becomes:

$$\begin{aligned}\Delta(\log(stock_t)) &= \alpha + \sum_{i=0}^{s} \delta_i \Delta(\log(oil\ price_{t-i})) + \sum_{j=1}^{p} \beta_j \Delta(\log(stock_{t-j})) + \\ &\sum_{d=0}^{q} \theta_d \Delta(\log(SP_{t-d})) + \sum_{c=0}^{v} \lambda_c \Delta(\log(M_{t-c})) + \pi[\Delta(\log(SP_t))]^2 + \omega[\Delta(\log(oil\ price_t))]^2 + \varepsilon_t\end{aligned} \tag{3}$$

The fourth and last model is an extension of equation (2):

$$\Delta(\log(stock_t)) = \alpha + \gamma_1[\Delta(\log(oil\ price_t))]^+ + \gamma_2[\Delta(\log(oil\ price_t))]^- + \sum_{j=1}^{p} \beta_j \Delta(\log(stock_{t-j})) + \sum_{d=0}^{q} \theta_d \Delta(\log(SP_{t-d})) + \sum_{c=0}^{v} \lambda_c \Delta(\log(M_{t-c})) + \pi[\Delta(\log(SP_t))]^2 + \omega[\Delta(\log(oil\ price_t))]^2 + \varepsilon_t \tag{4}$$

## 4. The Data

High-frequency data, weekly or daily, capture the interactions between the independent variables and the dependent variable more accurately than low-frequency data such as monthly or yearly. Moreover, larger sample sizes increase the precision of estimation. Since there is only five years of post-crisis data, the paper investigates the relation between oil prices and the Kuwaiti and the Saudi stock markets using daily data that includes the period from January 2, 2008 to October 23, 2012. The data is structured to include only Mondays, Tuesdays, and Wednesdays, during which time both US and GCC markets are open for trading. This paper is partially based on Basmajian (2013).

The data is collected from various sources. The Brent oil spot prices are obtained from the Energy Information Administration. The values of the S&P 500 index are collected from Google finance. The Saudi all share index and the Kuwait S.E. prices are both collected from the Arab Monetary Fund database. The data consists of 641 observations for each variable in levels, or 640 observations in log returns.

Table 1 provides KPSS stationarity tests for four variables: K, the Kuwaiti stock index, S, the Saudi stock index, SP, the US S&P 500, and B for the Brent oil price in US dollars. The null of stationarity is rejected for all above four variables in log-levels. However the stationarity hypothesis fails to be rejected for the first-differences of the logs. Since, for daily data, cointegration tests are not advisable, all four variables are considered hereafter in their stationary form, i.e. in the first-differences of the logs. In addition the stationarity hypothesis fails to be rejected at the 5% marginal significance level for the two squared variables identified in the previous section: $[\Delta(\log(SP_t))]^2$ and $[\Delta(\log(oil\ price_t))]^2$.

**Table 1. Stationarity tests: Kwiatkowski-Phillips-Schmidt-Shin (1992) with a constant and a trend.**

| X | Log(X) | Δ(log(X)) | Δ(log(X))^2 |
|---|---|---|---|
| B | 0.314228 | 0.106070 | 0.136028 |
| K | 0.414609 | 0.078516 | |
| S | 0.360568 | 0.085197 | |
| SP | 0.342198 | 0.094986 | 0.100611 |

Notes: K is the Kuwaiti stock market index. S is the Saudi stock market index. SP is the US S&P 500 stock market index. B is the Brent oil price in US dollars. The first-difference operator is Δ. The marginal significance levels for the KPSS test are 0.216 (1%), 0.146 (5%), and 0.119 (10%). The null of the test is stationarity.

Table 2 reports descriptive statistics for the four main initial variables. The Brent oil price log returns are the most variable. The least variable are the Kuwaiti log returns. All variables are skewed to the left, except the oil price log returns which are skewed to the right. This suggests that a portfolio that is long oil and short stocks is worthwhile. All four variables are leptokurtic and have therefore fat tails relative to the normal distribution. This means that extreme returns, whether positive or negative, have a higher likelihood, thereby increasing the upside and downside risks of holding these assets. Hence all four variables are non-normally distributed. All this evidence is consistent with Arouri et al. (2011). One can invoke the Central Limit Theorem to carry out a t-test on whether the mean of each one of these four variables is zero. The null hypothesis of a zero mean fails to be rejected for all variables except for the Kuwaiti stock log returns variable. In the latter case the mean is statistically significantly negative.

**Table 2. Descriptive statistics. The sample size consists of 640 daily observations.**

| | $\Delta(\log(B))$ | $\Delta(\log(K))$ | $\Delta(\log(S))$ | $\Delta(\log(SP))$ |
|---|---|---|---|---|
| Mean | 0.000161 | -0.001216 | -0.000728 | -3.72E-05 |
| Median | 0.000000 | 0.000412 | 0.001004 | 0.000858 |
| Maximum | 0.263543 | 0.058652 | 0.111428 | 0.102457 |
| Minimum | -0.186621 | -0.088500 | -0.209680 | -0.118535 |
| Standard deviation | 0.034474 | 0.013726 | 0.022808 | 0.021279 |
| Skewness | 0.641302 | -1.984386 | -1.651767 | -0.697227 |
| Kurtosis | 11.91340 | 12.66570 | 19.39356 | 8.099994 |
| Jarque-Bera Normality test | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| t-test statistic | 0.1180 (0.4530) | -2.2408 (0.0127) | -0.8072 (0.2099) | -0.0442 (0.4824) |

Notes: See notes under Table 1 for the definition of the variables. The first-difference operator is Δ. The actual p-values of the Jarque-Bera normality tests are provided (Jarque and Bera, 1980, 1987). The t-test is for the null hypothesis that the mean is zero. Below the t-statistics, and in parenthesis, are the upper tail area probabilities for the t-statistics taken in absolute terms.

## 5. The Empirical Results

Table 3 reports the results of estimating model equations (1) and (2) for both the Kuwaiti and the Saudi markets, with a GARCH (1,1) model of the conditional variance. All in all four regressions are specified that include only oil variables together with any lags in the dependent variable. The Kuwaiti regressions include the first-order and the second-order lags of the dependent variable, which are the Kuwaiti stock returns. The following is assumed for the Kuwaiti regressions: s=0, p=2 in equation model (1) and p=2 for equation model (2). The following is assumed for the Saudi regressions: s=0 with no lags for equation model (1), and no lags for equation model (2). The two Saudi regressions do not need any adjustment for serial correlation of the standardized residuals. This is the first contrast between these two Arab markets.

The impact of oil prices on stock log returns is statistically significant for both countries. However, the impact coefficient of oil prices is double for the Saudi market, and is 0.1779, while the impact coefficient for the Kuwaiti market is 0.0684. This is a second contrast. The third contrast is in the estimates of model equation (2). For the Kuwaiti market only negative oil shocks impinge significantly Kuwaiti stock log returns, while, in the Saudi market, both positive and negative changes in oil prices are statistically significant. The impact of negative oil price shocks on stock returns is again double for the Saudi market. Nonetheless the null hypothesis that these two impact coefficients are equal fails to be rejected for both markets, with p-values of 0.3041 and 0.5062 for the two markets, Kuwaiti and Saudi respectively. Finally, all four estimated regression constants are statistically insignificant. Hence there are no excess abnormal returns in the four estimated regressions.

The adjusted R-squares are almost double for the Saudi models. For all four regressions the standardized residuals are free from further serial correlation and conditional heteroscedasticity. For the two Kuwaiti and Saudi regressions, all three information criteria, AIC, Schwarz and Hannan-Quinn, prefer model equation (1) relative to model equation (2). This means that surprisingly the type of non-linearity inherent in model equation (2) does not receive support. As a general conclusion, and at prima facie, oil price shocks do affect significantly and positively stock log returns for both countries, although the dynamics are dissimilar for these two countries.

Table 4 presents the estimates of model equations (3) and (4) for the two Arab countries. As before the Kuwaiti regressions include the first two lags of the dependent variable (s=0, p=2, q=1, and v=0 for both model equations), while the Saudi regressions do not include any lags (s=0, q=1, and v=0 for both model equations). The Kuwaiti stock log returns are statistically significantly explained by the log returns of the once lagged S&P 500, the regional factor variable, and the autoregressive lags in the dependent variable. But surprisingly, for this market, the oil price variable is statistically insignificant in model equation (3), and the positive and negative components of the oil price change are also insignificant for model equation (4). This implies that once adjustment is made in the Kuwaiti regressions by entering the first lags of the S&P 500 log returns, and the regional variable factor, the explanatory power of oil prices disappears. The significance of the first lags of the S&P 500 log returns may be due more to time zone differences than to inefficiency. However the significance of the own lagged log returns is a puzzle and may be due to market inefficiency or to thin trading, and is a common finding in daily data of emerging markets. Anyway if there are arbitrage and abnormal profits to be made these may not be totally risk-free, or they may be lower than transaction costs, or simply they may be due to just sampling errors.

**Table 3. Evidence on the prima facie impact of oil log returns on the Kuwaiti and Saudi market stock log returns.**

| | Kuwaiti market stock log returns | | Saudi market stock log returns | |
|---|---|---|---|---|
| *Conditional mean equation* | | | | |
| Constant | -0.000299 (-0.878582) | 0.000185 (0.354994) | 0.000110 (0.211915) | 0.000626 (0.746651) |
| Oil log returns | 0.068430 (3.440058) | | 0.177863 (6.944583) | |
| Positive oil log returns | | 0.044575 (1.523376) | | 0.152808 (3.882983) |
| Negative oil log returns | | 0.094840 (2.833258) | | 0.204301 (3.897189) |
| First autoregressive lag | 0.153764 (3.710985) | 0.151647 (3.676391) | | |
| Second autoregressive lag | 0.094433 (2.037391) | 0.094537 (2.021756) | | |
| *Conditional variance equation* | | | | |
| Constant | 5.79E-06 (1.740953) | 5.82E-06 (1.787776) | 9.78E-06 (1.732957) | 9.54E-06 (1.716607) |
| ARCH(-1) | 0.132130 (3.324188) | 0.133851 (3.416769) | 0.127638 (2.886400) | 0.127793 (2.901612) |
| GARCH(-1) | 0.830221 (17.14730) | 0.828313 (17.69387) | 0.843809 (19.68114) | 0.844531 (19.75888) |
| *Econometric diagnostics* | | | | |
| Adjusted R-Square | 0.049728 | 0.057124 | 0.083159 | 0.081502 |
| Log Likelihood | 1996.266 | 1997.066 | 1715.464 | 1715.900 |
| Durbin-Watson statistic | 2.119153 | 2.129771 | 1.814335 | 1.819770 |
| Akaike information criterion | -6.235944 | -6.235316 | -5.345200 | -5.343436 |
| Schwarz criterion | -6.187028 | -6.179412 | -5.310345 | -5.301610 |
| Hannan-Quinn criterion | -6.216955 | -6.213614 | -5.331671 | -5.327201 |
| Serial correlation test | k=3: 0.289 k=6: 0.056 | k=3: 0.277 k=6: 0.060 | k=3: 0.221 k=6: 0.430 | k=3: 0.272 k=6: 0.457 |
| Heteroscedasticity test | k=3: 0.393 k=6: 0.793 | k=3: 0.356 k=6: 0.753 | k=3: 0.651 k=6: 0.553 | k=3: 0.642 k=6: 0.523 |
| Normality test | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| Hypothesis test H1 | | 0.3041 | | 0.5062 |

Notes: t-statistics in parenthesis. The serial correlation test reports the p-value of the Ljung-Box Q-statistic on the standardized residuals with a lag length k (Ljung and Box, 1978). The heteroscedasticity test reports the p-value of the Ljung-Box Q-statistic on the squares of the standardized residuals with a lag length k. The normality test records the p-value of the Jarque-Bera test on the standardized residuals. Hypothesis H1 is for the F-test on the equality of slope coefficients. The upper-tailed p-values of this F-test on H1 are reported. Robust standard errors are calculated following the Bollerslev-Wooldridge adjustment (Bollerslev and Wooldridge, 1992).

The regional factor variable is taken to be the Saudi stock log returns. This variable is a noisy measure of regional conditions, and incorporates a measurement-error econometric problem. This problem makes the coefficient on the regional factor biased downwards towards zero (Verbeek, 2012). The bias seems to be minor as the two t-statistics are respectively 5.317 and 5.306 for the two model equations (3) and (4) respectively, which means that the two coefficients remain statistically different from zero at very low marginal significance levels.

Finally, the squared variables in model equations (3) and (4) are always statistically insignificant. So are the two constants, implying no residual abnormal returns.

**Table 4. Evidence on the illusionary linear impact of oil log returns on the Kuwaiti and Saudi market stock log returns**

| | Kuwaiti market stock log returns | | Saudi market stock log returns | |
|---|---|---|---|---|
| *Conditional mean equation* | | | | |
| Constant | -6.01E-05 (-0.155484) | -000741 (-1.181582) | -0.000283 (-0.660505) | 0.000363 (0.531429) |
| Oil log returns | 0.033332 (1.931156) | | 0.043306 (2.193138) | |
| Positive oil log returns | | 0.084698 (1.788790) | | -0.004079 (-0.081958) |
| Negative oil log returns | | -0.017994 (-0.382863) | | 0.088499 (2.153993) |
| S&P 500 log returns | 0.015303 (0.598980) | 0.015769 (0.611971) | 0.298226 (9.175651) | 0.297886 (9.126355) |
| S&P 500 lagged log returns | 0.057463 (2.979015) | 0.058904 (3.042489) | 0.174909 (6.742024) | 0.171194 (6.672906) |
| Kuwaiti log returns | | | 0.328333 (5.095030) | 0.334127 (5.097124) |
| Saudi log returns | 0.155225 (5.317023) | 0.156358 (5.305967) | | |
| Square of oil log returns | -0.294445 (-0.901926) | -0.706386 (-1.382683) | 0.896823 (4.668065) | 1.230012 (4.782536) |
| Square of S&P 500 log returns | -0.347073 (-0.747796) | -0.390783 (-0.837350) | -1.358679 (-3.089165) | -1.271359 (-2.752929) |
| First autoregressive lag | 0.114233 (3.053157) | 0.114260 (3.065968) | | |
| Second autoregressive lag | 0.106840 (2.525543) | 0.106106 (2.541981) | | |
| *Conditional variance equation* | | | | |
| Constant | 3.60E-06 (1.405057) | 3.36E-06 (1.368910) | 5.35E-06 (1.524950) | 5.29E-06 (1.539060) |
| ARCH(-1) | 0.095959 (2.926006) | 0.090828 (2.884569) | 0.138564 (2.965844) | 0.138806 (2.944007) |
| GARCH(-1) | 0.875372 (20.83845) | 0.882272 (21.45603) | 0.844602 (18.49262) | 0.844558 (18.35932) |
| *Econometric diagnostics* | | | | |
| Adjusted R-Square | 0.239035 | 0.252403 | 0.343919 | 0.344732 |
| Log Likelihood | 2037.349 | 2038.501 | 1810.475 | 1811.160 |
| Akaike information criterion | -6.349055 | -6.349532 | -5.635291 | -5.634303 |
| Schwarz criterion | -6.265199 | -6.258688 | -5.565496 | -5.557528 |
| Hannan-Quinn criterion | -6.316502 | -6.314266 | -5.608198 | -5.604501 |
| Serial correlation test | k=3: 0.438 k=6: 0.069 | k=3: 0.488 k=6: 0.092 | k=3: 0.589 k=6: 0.709 | k=3: 0.636 k=6: 0.726 |
| Heteroscedasticity test | k=3: 0.394 k=6: 0.747 | k=3: 0.381 k=6: 0.728 | k=3: 0.685 k=6: 0.595 | k=3: 0.688 k=6: 0.582 |
| Normality test | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| Hypothesis test H2 | 0.0914 | | | |
| Hypothesis test H3 | | 0.0697 | | |
| Hypothesis test H4 | | | 0.0636 | |
| Hypothesis test H5 | | | | 0.0506 |

Notes: Refer to notes under Table 1. Hypothesis H2 is a joint significance F-test on the intercept, the coefficient on oil log returns, the coefficient on the S&P 500 log returns, and the two coefficients on the squared terms. Hypothesis H3 is a joint significance F-test on the intercept, the two coefficients on the positive and negative oil log returns, the coefficient on the S&P 500 log returns, and the two coefficients on the squared terms. Hypothesis H4 is a joint significance F-test on the intercept and the slope coefficient on oil log returns. Hypothesis H5 is a joint significance F-test on the intercept and the two coefficients on the positive and negative oil log returns. The upper-tailed p-values for these four F-tests, for hypotheses H2 to H5, are reported.

For model (3), a joint significance F-test on the intercept, the coefficient on the oil log returns, the coefficient on the current S&P 500 log returns, and the two coefficients on the squared variables, carries an upper-tailed p-value of 0.0914, failing to reject the null that all these coefficients are jointly zero. The only significant variables are the regional factor variable, and the lagged S&P 500 log returns. For model (4) a joint significance F-test on the intercept, the two non-linear coefficients on oil log returns, the coefficient on the current S&P 500 log returns, and the two coefficients on the squared variables, carries an upper-tailed p-value of 0.0697, failing to reject the null that all these coefficients are jointly zero. Again, the only significant variables are the regional factor variable, and the lagged S&P 500 log returns, besides the two autoregressive variables. The two adjusted R-squares are around 24% much higher than their corresponding adjusted R-squares in Table 3. While the standardized residuals are non-normal, they are still independently and identically distributed. The Central Limit Theorem can be invoked for rendering hypothesis testing feasible.

While oil prices are not significant contributors to the variation in Kuwaiti stock log returns, the same is not true for the Saudi regressions. This is an additional contrast in behavior between Kuwaiti and Saudi markets. For model equation (3), the Saudi stock log returns are explained with statistical success by oil price shocks, the current and first lags of the S&P 500 log returns, the regional factor variable, and the two squared variables. The regional factor variable is taken to be the Kuwaiti stock log returns. This variable is again a noisy measure of regional conditions, and incorporates a measurement-error econometric problem. This problem makes the coefficient on the regional factor biased downwards towards zero (Verbeek, 2012). The bias seems to be minor as the two t-statistics are respectively 5.095 and 5.097 for the two model equations (3) and (4) respectively, which means that the two coefficients remain statistically different from zero at very low marginal significance levels. The regression constant is statistically insignificant denoting no residual abnormal returns. For model (3), a joint significance F-test on the intercept, and the slope coefficient on oil log returns carries an upper-tailed p-value of 0.0636, failing to reject the null of zero joint coefficients. For model (4), a joint significance F-test on the intercept, and the two slope coefficients on the non-linear oil log returns carries an upper-tailed p-value of 0.0506, failing to reject the null of zero joint coefficients. The two adjusted R-squares are around 34%, much higher than their corresponding adjusted R-squares in Table 3, and much higher than those for the Kuwaiti stock market. While the standardized residuals are non-normal, they are still independently and identically distributed. The Central Limit Theorem can be invoked for rendering hypothesis testing feasible.

Although oil prices do not affect Saudi stock log returns in model equation (3) the square of oil log returns do. Therefore the marginal effect of oil prices in the Saudi stock market depends on oil price shocks and is equal to:

$$0.043306 \;+\; 1.793646\left[\Delta\left(\log\left(oil\ price_t\right)\right)\right] \tag{5}$$

This marginal effect implies that its minimum of a zero effect is attained when the oil price shock is -2.414%. A more negative value of the oil price shock makes the marginal effect negatively related to this shock. A higher value makes the marginal effect positively related to the oil price shock.

The marginal effect of oil prices on Saudi log returns is more complicated for the model equation (4), depending on the sign of the oil price shock. A negative oil price shock has the following marginal effect:

$$0.088850 \;+ 2.460024\left[\Delta\left(\log\left(oil\ price_t\right)\right)\right]^{-} \tag{6}$$

A positive oil price shock has the following marginal effect:

$$-0.004079 \;+\; 2.460024\left[\Delta\left(\log\left(oil\ price_t\right)\right)\right]^{+} \tag{7}$$

There is also a variable marginal effect for the S&P 500 log stock returns on Saudi log returns, S&P 500 log returns which enter in quadratic form in model equations (3) and (4). For model equation (3) the marginal contemporaneous effect of the S&P 500 is:

$$0.298226 \;-\; 2.717358\left[\Delta\left(\log\left(SP_t\right)\right)\right] \tag{8}$$

And the long run marginal effect is:

$$0.473135 \;-\; 2.717358\left[\Delta\left(\log\left(SP_t\right)\right)\right] \tag{9}$$

For model equation (4) the marginal contemporaneous and long run effects of the S&P 500 are respectively:

$$0.297886 \ - \ 2.542718\left[\Delta(\log(SP_t))\right] \tag{10}$$
$$0.469080 \ - \ 2.542718\left[\Delta(\log(SP_t))\right] \tag{11}$$

All these four marginal effects have maxima but the important feature is that these marginal effects are negatively related to shocks in the US S&P 500 log returns. This partially corroborates the evidence in Arouri and Rault (2010) for a negative Granger-causation.

## 6. Some Robustness Tests

The variables in the sample have day breaks. The most notable break is the break between Wednesdays and the following Mondays. Other breaks arise when there are holidays. The total samples are divided into two subsamples. The first is the sample with at most one day break (subsample # 1), and the second is the sample that includes at least two days break (subsample # 2). Table 5 presents descriptive statistics on the two subsamples for each one of the four main variables. Series related to oil price changes are most variable. Series related to Kuwaiti stock log returns are least variable. All eight series are skewed to the left, except for $\Delta(\log(B))$ in subsample # 2, which is skewed to the right. All eight series are leptokurtic, i.e. they have fatter tails than the normal distribution. Hence all series are non-normal as evidenced by the Jarque-Bera normality test which considers both skewness and kurtosis. The p-values for the t-test on the means for the null hypothesis that each mean is zero are larger from 5% in all eight cases except for subsample # 2 of $\Delta(\log(K))$, which has statistically significant negative log returns.

**Table 5. Descriptive statistics for the two subsamples. The first subsample (# 1) is for the log returns that have at most one day break in the data, and the second subsample (# 2) is for the log returns that have at least two days break in the data. Samples # 1 have 397 observations while samples # 2 have 243 observations.**

| | $\Delta(\log(B))$ | | $\Delta(\log(K))$ | | $\Delta(\log(S))$ | | $\Delta(\log(SP))$ | |
|---|---|---|---|---|---|---|---|---|
| | Subsample # 1 | Subsample # 2 | Subsample # 1 | Subsample # 2 | Subsample # 1 | Subsample # 2 | Subsample # 1 | Subsample # 2 |
| Mean | -0.000499 | 0.001239 | 0.000350 | -0.003774 | -0.000967 | -0.000336 | 0.000301 | -0.000590 |
| Median | 0.000146 | -0.000219 | 0.000631 | -0.001225 | 0.000428 | 0.003409 | 0.000310 | 0.002581 |
| Maximum | 0.083551 | 0.263543 | 0.027329 | 0.058652 | 0.051707 | 0.111428 | 0.102457 | 0.081979 |
| Minimum | -0.114621 | -0.186621 | -0.044706 | -0.088500 | -0.072893 | -0.209680 | -0.094695 | -0.118535 |
| Standard deviation | 0.023824 | 0.046983 | 0.007585 | 0.019818 | 0.013017 | 0.033107 | 0.017550 | 0.026289 |
| Skewness | -0.582439 | 0.742932 | -1.080225 | -1.311454 | -1.606598 | -1.297975 | -0.275520 | -0.808333 |
| Kurtosis | 5.923091 | 8.420590 | 8.345699 | 6.665260 | 10.53827 | 11.20718 | 9.742820 | 5.968192 |
| Normality test | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| t-test statistic | -0.4172 (0.3384) | 0.4110 (0.3407) | 0.9199 (0.1791) | -2.9686 (0.0016) | -1.4802 (0.0698) | -0.1583 (0.4372) | 0.3417 (0.3664) | -0.3496 (0.3635) |

Notes: See notes under Tables 1 and 2.

It is expected that log returns in subsample # 1 are statistically significantly lower than log returns in subsample # 2, which is characterized by longer day breaks. Therefore, and since the two subsamples are independent, the appropriate test is a t-test on the difference between two means in two independent populations. While the null hypothesis is for a zero difference between means, the one-sided alternative hypothesis is that mean log returns of the series in subsamples # 2 are higher than those in subsamples # 1. First, testing for equality of the variances across respective subsamples is necessary. Table 6 reports that the variances of subsamples # 2 are statistically significantly higher than those of subsamples # 1 for all four series. Hence the t-tests on the means should assume inequality of variances. The upper tail area probabilities do not produce sufficient evidence to reject the null hypothesis. Hence there is not enough evidence that the means are different, and the results in the previous section are robust in this regard. It must be mentioned that in one case, for $\Delta(\log(K))$, the alternative hypothesis that the difference between the two means is negative, instead of positive, is supported strongly, implying that the log returns for this series are significantly lower in subsample # 2.

**Table 6. Comparing subsamples # 2 to subsamples # 1.**

| | $\Delta(\log(B))$ | $\Delta(\log(K))$ | $\Delta(\log(S))$ | $\Delta(\log(SP))$ |
|---|---|---|---|---|
| Variance F-tests | 3.8891 (0.000000) | 6.8267 (0.000000) | 6.4687 (0.000000) | 2.2439 (0.000000) |
| Means t-tests | 0.5360 (0.2962) [320] | -3.1075 (0.9990) [285] | 0.2840 (0.3883) [288] | -0.4683 (0.6801) [374] |

Notes: See notes under Tables 1 and 2. Since the variances for the variables in subsamples # 2 are statistically significantly greater than those for subsamples # 1 the tests on the means assume that variances are unequal. The alternative hypotheses for the four means t-tests are that the means of the variables in subsamples # 2 are higher than those in subsamples # 1. That is why the actual upper-tailed p-values are reported in parenthesis. The degrees of freedom for the means tests are reported in square brackets. The numerator and denominator degrees of freedom for the F-tests of the variances are respectively 242 and 396 for all four tests.

## 7. Conclusion

The purpose of this paper is to determine the impact of oil prices on Kuwaiti and Saudi stock markets. Three types of non-linearity are accounted for. The first is by estimating a GARCH (1,1) model on the regression residuals. The second is to divide oil price shocks into two components, a positive one and a negative one. And the third is to test quadratic functional forms. It is expected that both equity markets react similarly to all identified shocks. This expectation is not materialized as there are different dynamics for each stock market. Another expectation fails to stand. This is that oil price shocks explain linearly equity returns.

When the oil price shock is the only explanatory variable of equity log returns, besides lag feedback effects, then this variable enters significantly both linearly and non-linearly. The hypothesis that the impact of positive oil price shocks is equal to that of negative shocks invariably fails to be rejected. At prima facie oil price shocks seem to explain statistically significantly equity log returns of these two Arab countries. However this is just an illusion because when additional independent variables are included in the regressions, oil prices fail to explain equity returns linearly. These additional variables include regional effects, the effect of the US stock market, and two quadratic terms. While oil prices do not explain non-linearly Kuwaiti stock markets, they have significant non-linear effects on Saudi stock markets. In addition, the two quadratic terms enter statistically insignificantly in the Kuwaiti regressions, but enter statistically significantly in the Saudi regressions. The latter implies that the marginal effects of oil price shocks and of shocks in the US stock market on Saudi equity returns depend on oil price, and on the US capital market respectively.

One common feature for the two Arab countries is that US stock market shocks lead equity log returns. This may seem to be against the Efficient Market Hypothesis (Fama, 1970, 1991), but can be directly explained by time zone differences. A pervasive feature of the regressions for Kuwaiti log returns is that these are dependent on own lagged log returns. Again this may seem against the Efficient Market Hypothesis, but can be explained by thin trading, or just sampling error. In addition lag feedback effects are important in most emerging markets, especially with daily data. Finally, if indeed there are abnormal and arbitrage profits to be made these may not be totally risk-free, or even may be below transaction costs.

As a general conclusion, the two equity markets of Kuwait and Saudi Arabia have different dynamics and react differently to oil price shocks. This is surprising. In fact, once other variables are included in the analysis, oil price shocks do not have any effect on Kuwaiti stock markets, neither linearly or non-linearly. Oil prices have non-linear effects on Saudi log returns. Again this differential effect is surprising. This supports the main finding in this paper, that there is a contrast between the response of the Kuwaiti and Saudi stock markets to oil price shocks. All this explains the reason for the title of this paper.

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