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Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010

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ABSTRACT

In this paper, we test for mean and variance causality between world oil prices and sectoral equity returns in Jordan before and after the Arab Uprisings that started in 2010. The testing methodology is based on the sample of cross-correlation functions that are computed from the standardized residuals of a GARCH process. Our results show that the influence is not uniform across the equity sectors. The oil return shocks significantly impact the Financials and the Services sectors, while its effect is insignificant on the Industrials sector. This result is more pronounced in the period that follows the Arab Uprisings. In terms of risk transfer, we find that oil is a negligible risk factor. However, there is still a significant evidence of risk transmission to the Industrials sector particularly during the Arab Uprisings period. These results represent a unique information transmission mechanism that is useful for risk management and portfolio diversification.

1. Introduction

Studies of energy economics have increasingly focused on the role of crude oil prices in influencing stock markets' returns (Arouri et al., 2012; Cuando and de Garcia, 2014; Kang et al., 2015). A crucial issue in this strand of research is related to the effect of oil price return and volatility on stock market activities. Building on cash flow models which state that a stock price depends on expected discounted earnings, previous empirical studies have initially examined aggregate stock market return and volatility but have ignored the impact of oil prices on sectoral stock returns (see, inter alia, Arouri et al., 2011a; Ma et al., 2014; Bouri, 2015a). Given that crude oil is an intermediate input in the production process, not all equity sectors are affected equally by an oil price/volatility shocks. For instance, one would naturally expect that the oil and gas sector, and to a lesser extent the industrial and the manufacturing sectors, to be the most affected by the international oil market conditions. However, the services and financials sectors are expected to be much less affected by oil price returns and volatilities. Focusing on the cross-sector heterogeneity can help portfolio managers better diversify their portfolios across different equity sectors within a particular market to maximize returns and minimize risks. This may also help regulators formulate appropriate frameworks at the sector level.

The few studies that have focused on sectoral indices have mainly examined data from the US (Elyasiani et al., 2011; Qinbin and Mohammad, 2012; Broadstock and Filis, 2014) and Europe (Arouri and Nguyen, 2010; Arouri et al., 2012). In view of that, these studies have been based on the context of large oil-importing countries, with quite limited evidence provided on small oil-importing countries (Bouri, 2015a, 2015b). However, there is considerable evidence that stock markets in emerging countries, such as MENA (Middle East and North Africa) countries, are different from those of US and European countries in many important ways (see, inter alia, Mohanty et al., 2011). First, emerging countries in general, and MENA oil-importing countries in particular, are more vulnerable to oil price shocks than industrialized countries because they experience a rapid economic growth and are highly energy intensive (Bhar and Nikolova, 2009). Second, MENA oil-importing countries are largely segmented from developed stock markets (e.g. Yu and Hassan, 2008), suggesting that global investors in oil-importing countries' stocks are likely to achieve better

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risk-adjusted returns through international diversification. Third, the stock markets in MENA oil-importing countries are sensitive to regional political developments. Fourth, some prior studies have focused on oil-intensive industries such as the oil and the gas sector (El-Sharif et al., 2005; Ghouri, 2006; Boyer and Filion, 2007) and the airline and the transportation sectors (Luft, 2006; Morrell and Swan, 2006; Mohanty, 2011), while ignoring the less- and the non-oil-intensive sectors such as the industrials and the services sectors that can also be subject to oil shocks (Arouri et al., 2012). The few studies that have focused on sectoral indices in the MENA region have only considered oil-exporting countries in the GCC (The Gulf Cooperation Council)[1] region (Mohanty et al., 2011; Jouini, 2013). In major suppliers of oil, such as the GCC countries, the stock market reaction to changes in oil prices is usually stronger and bi-directional to some degree (Arouri et al., 2011b). This is due to the dominating role of the energy and gas sectors in those oil exporters compared to non-oil-related sectors such as consumer goods, services, and financials. Accordingly, the relationship between oil price changes and stock market returns is expected to be different (weaker) for sectoral indices in MENA oil-importing countries which have less oil-intensive sectors. Our paper differs from those conducted on GCC sectoral indices in using a different methodology that is based on mean and variance causalities and takes into account the effects of the political unrest that agitated most of the MENA region and affected oil supplies. In particular, we explore linkages between oil prices and sector level data from an oil-importing country, in our case, Jordan. This provides more nuanced conclusions about sectoral stock returns that capture some of the main heterogeneity across these equity sectors. Using different methodological framework and study periods, we address the voids presented in the abovementioned literature and argue that the effect of oil mean and variance on the country-level aggregate market index in Jordan tends to mask the heterogeneity of sector sensitivity to oil price returns and volatilities. In addition, the analysis evaluates the impact of the recent political uncertainty (Arab uprisings) that agitates the MENA region on the linkages between international oil market and Jordanian sectoral indices.

This paper complements a growing literature on the oil-stock nexus from a sectoral perspective, even though other global and macroeconomic factors could potentially affect the price discovery process and volatility of the Jordanian equity sector returns.

To proceed with the analysis, a methodology approach based on (CCF) cross-correlation function tests from Cheung and Ng (1996) and Hong (2001) is employed. Unlike the traditional causality test of Granger (1980) which suffer from a number of shortcomings that include the inability to test for causality in variance, the model building requirements, and the possible bias akin to omitted variables (Nakajima and Hamori, 2013), our methodology is simpler and allows for testing causalities both in the mean and the variance. More importantly, the CCF-based approach is conducted on standardized residuals and squared residuals of univariate ARMAX-EGARCH[2] models that account easily for the non-normality of the return series and the asymmetric responses to positive and negative shocks, making the construction of less flexible multi-dimensional models unnecessary. Similar CCF-based tests were employed by Nakajima and Hamori (2013) in testing causal relationships between wholesale electricity prices, natural gas prices, and crude oil prices.[3] In addition, we conducted several model selection criteria to decide which model has a superior fit, where usually an ad hoc approach has been used. This can help us to more accurately capture the causal relationship in both mean and variance between international oil prices and sectoral stock returns in Jordan. According to Javed and Mantalos (2011), misspecification in fitting a GARCH-based model can undermine the efficiency of the related estimators, leading to spurious results and potentially missed causalities.

This paper makes three main contributions. Firstly, unlike prior studies that generally focused on MENA oil-exporting countries, this paper considers the case of Jordan whose economy is not only heavily dependent on oil imports, but also has one of the most diversified and developed stock market in the MENA region (Bouri, 2014, 2015b). In this regard, the case of Jordan provides an adequate setting to assess oil-stock linkages as compared to other less diversified and less developed stock markets in MENA oilimporters (Bouri, 2014). This suggests a lower barrier to possible mean and volatility linkages between oil and Jordanian equity market sectors. Recognized by the groups of MSCI (Morgan Stanley Capital International) and Standard and Poor as a frontier market, Jordan is also on the watch list for potential future reclassification as an emerging market. As shown in Table 1, the stock market of Jordan is virtually fully accessible to foreign investors and has 234 listed companies belonging to three main sectors, namely, Financials, Industrials, and Services. The high ratio of market capitalization to GDP (gross domestic product) emphasized the importance of the Jordanian stock market in terms of the local economy (Bouri, 2014). As of December 2014, foreign holdings of Jordanian stocks reached 43.20%. Secondly, this paper uncovers hidden relationships between the oil market and sectoral stock returns, suggesting that investors need to be aware of the heterogeneity of equity sectors in Jordan in order to maximize cross-sector asset allocation decisions. Only few studies have already established that equity sectors tend to respond differently to oil price/volatility shocks in some MENA oil-exporting countries (Mohanty et al., 2011; Jouini, 2013). Nevertheless, these studies have not focused on the effect of the Arab uprisings on the relationship between the international oil market and sectoral stock returns. In this respect, and to the best of our knowledge, this is the first study examining the effect of the Arab uprisings on the sensitivity of sectoral indices to oil price and volatility movements in the MENA region using the causality in mean and variance tests in line with the procedures presented in Cheung and Ng (1996) and Hong (2001). Thirdly, this paper focuses on the events that had begun in Tunisia in December 2010 and have since then stirred the Arab world. In this regard, the sample period is divided equally into two periods around that time to investigate the asymmetrical impact of the Arab uprisings events on the relationships between the returns and the volatilities of international oil prices and the main sectoral indices in Jordan.

Our analysis yields interesting results: The sensitivity of the Jordanian stock market to oil price movements differs across industries and covers the two periods in question. Those results can help investors allocate their capital more efficiently during turbulent periods. In particular, our analysis refines the understanding on the timing and direction of the transmission of information between the crude oil market and Jordanian equity sectors during a period characterized by political instability. This can facilitate the assumption of hedge positions in response to external information shocks and improve the mean and variance forecasting in the Jordanian sectoral stock market.

Table 1
The Jordanian stock market in 2014.

Year of establishment	1999
Number of listed firms	234
Market capitalization (US$ bn)	25.12
Market capitalization/GDP	0.739
Turnover ratio%	12.270
Net foreign assets/GDP	0.270
Oil imports/GDP	0.112
Foreign ownership	0.432
Accessibility	Fully accessible

Notes: Listed stocks are the number of domestic listed companies. Turnover ratio corresponds to total value of shares traded during the period divided by the average market capitalization for the period. Source: Reuters DataStream.

[1] The GCC includes the following countries: Saudi Arabia, Bahrain, Qatar, Kuwait, United Arab Emirates, and Oman.

[2] ARMAX denotes the autoregressive-moving-average with an external input, whereas EGARCH denotes the exponential GARCH process.

[3] Numerous studies have employed the CCF tests, see, among others, Bhar and Hamori (2005), Stolbov (2014), Tamakoshi and Hamori (2014).

The rest of the paper proceeds as follows. The background and evolvements of the Arab uprisings are briefly described in the next section, which is followed by a section containing the econometric method. The subsequent section discusses the empirical results and conducts robustness analysis. The final section concludes with policy implications.

2. The Arab Uprising

Before proceeding with the study, it is pertinent to introduce the background and evolvements of the political and civil uprisings which constitute one of the most dreadful events in the history of the MENA region. The Arab world has been stirred, 1 month before the end of 2010, by unprecedented protests and movements that began in Tunisia by the so-called 'Jasmine Revolution' and led to the fall of the local political regime. These uprisings then spread to Egypt and Libya and brought down long-standing rulers from power before moving to Yemen and Syria, where the movements have dramatically heightened, inflaming ongoing and devastating armed conflicts. Less severe and less persistent protests reached the Kingdom of Bahrain located in the GCC oil-rich region. The rest of the MENA countries have however been relatively spared, with limited forms of protests. Undoubtedly, depressed socio-economic and socio-political foundations were behind the uprisings from poor economic conditions, high unemployment rates, soaring food prices, and persistent corruption (Chau et al., 2014). Despite their tendencies to offer hope for freedom and democracy, those movements have however provoked severe economic and financial challenges at high costs. The uprisings have intensified an already shaky economic recovery coming out of the global financial crisis of 2008. The high level of risk associated with these uprisings has adversely affected the stock market activities, fiscal/trade balance, labor market, capital flows, and tourism. While the political risk is not new for market participants and policy-makers in this turbulent region of the world, the intensity of the conflicts has been critical.

3. Methodology

The methodology employed in this paper is based on the test approach from Cheung and Ng (1996) and Hong (2001) which allows for the causalities both in mean and in variance between Brent oil prices and sectoral equity indices in Jordan. Earlier studies on the causal relation between oil and stock markets have relied on the traditional Granger causality in mean test (Granger, 1980), which is highly sensitive to the lag length choice and is known not to be robust to common features of financial series (i.e. heteroscedasticity, autocorrelation, non-normality). Later studies employed tests within multivariate GARCH models that allow for the analysis of causality both in mean and variance (Hafner and Herwartz, 2008). However, these tests typically inherit the curse of dimensionality from multivariate models, potentially leading to spurious or missed causalities. In the Cheung and Ng (1996) and Hong (2001) approach, testing for the causality in mean and variance is based on the cross-correlation function (CCF) of standardized residuals and the squared standardized residuals extracted from the estimation of univariate GARCH-type models. In this view, the CCF procedure is straightforward and thus does not require the simultaneous modeling of intra- and inter-series dynamics as with multivariate GARCH-based tests. The CCF procedure is applied in two steps. First, a univariate GARCH-based model is employed in studying the time-varying in both conditional mean and variance of each return series. In this paper, this first step is broadened by applying different univariate specifications of GARCH-type models to account for non-normality, conditional heteroscedasticity, and asymmetric responses to positive and negative shocks. In this context, extensive specification tests are conducted for the most appropriate GARCH process and its corresponding error distribution. For all return series, the best univariate ARMAX-EGARCH or ARMAX-GARCH model specifications is selected on the basis of the Schwarz Bayesian Information Criterion (SIC) which is known for leading to a parsimonious specification (Beine and Laurent, 2003), instead of an ad hoc selection. Next, the standardized residuals and standardized squared residuals series from each univariate models are generated and then used to calculate the CCF. For each pair of standardized residuals (standardized squared residuals), the CCF is used to test the null hypothesis of no causality in mean (variance). This richer methodological framework, as compared to the one employed by Nakajima and Hamori (2013), allows us to seize many of the salient features of the data and to more properly model the conditional mean and variance of the returns series. Misspecification in fitting a GARCH-type model together with an imprecise assumption of the error-term distribution may substantially undermine the efficiency of the related estimators. Such misspecification can give rise to a wrong assessment of mean and variance causal relationships and, eventually, to invalid input into the decision-making process. Analytically, the CCF approach is summarized below in accordance with Cheung and Ng (1996) and Hong (2001).

Let O_t and S_t be oil and sector returns in day t, respectively, the ARMAX-EGARCH process is then can be written as

$$\begin{cases} O_t = C + \sum_{i=1}^{k} a_1 O_{t-1} + \sum_{i=1}^{l} a_2 \varepsilon_{t-1} + d_1 + d_2 + d_3 + d_4 + \varepsilon_t \\ \log\left(\sigma_{O,t}^2\right) = \omega + \sum_{i=1}^{q} b_1 \log\left(\sigma_{O,t-1}^2\right) + \sum_{i=1}^{p} b_2 \left| \frac{\varepsilon_{t-i}}{\sigma_{o,t-i}} \right| + \gamma \frac{\varepsilon_{t-i}}{\sigma_{o,t-i}} \end{cases} \tag{1}$$

$$\begin{cases} S_t = C + \sum_{i=1}^{k} a_1 S_{t-1} + \sum_{i=1}^{l} a_2 \varphi_{t-1} + d_1 + d_2 + d_3 + d_4 + \varphi_t \\ \log\left(\sigma_{S,t}^2\right) = \omega + \sum_{i=1}^{q} b_1 \log\left(\sigma_{S,t-1}^2\right) + \sum_{i=1}^{p} b_2 \left| \frac{\varphi_{t-i}}{\sigma_{s,t-i}} \right| + \gamma \frac{\varphi_{t-i}}{\sigma_{s,t-i}} \end{cases} \tag{2}$$

where ε_t and φ_t are independent white noise processes with zero mean and unit variance for O_t and S_t, respectively; d_1, d_2, d_3, and d_4 are dummy variables for the day of the week effect; $\log(\sigma_{o,t}^2)$and $\log(\sigma_{s,t}^2)$- represent the log of conditional variances of oil and sector returns, respectively; γ is the parameter that measures the asymmetric responses of the conditional variance to positive and negative shocks of equal magnitude. Finally, k, l, p, and q are lag parameters that are chosen on the basis of the SIC information criteria.

Now suppose that I_t and J_t are two information sets defined by $I_t = (O_{t-j}; j \geq 0)$ and $J_t = (O_{t-j}; S_{t-j}; j \geq 0)$. Then O_{t-1} causes S_t in mean and variance if:

$$\mathrm{E}\,(O_t \mid I_{t-1}) \neq \mathrm{E}(O_t \mid J_{t-1}) \tag{3}$$

$$\mathrm{E}\left\{ \left(O_t - \mu_{o,t}\right)^2 \mid I_{t-1} \right\} \neq \mathrm{E}\left\{ \left(O_t - \mu_{o,t}\right)^2 \mid J_{t-1} \right\} \tag{4}$$

where $\mu_{o,t}$ is the mean of O_t conditional on the filter I_t.

We also suppose that $h_{o,t}$ and $h_{s,t}$ represent the conditional variances of the EGARCH models, and compute the standardized residuals $\hat{u}_t = \{(\varepsilon_t - \mu_{\varepsilon,t})^2/h_{o,t}\}$ and the squared standardized residuals $\hat{z}_t = \{(\varphi_t - \mu_{\varphi,t})^2/h_{s,t}\}$ from models (1) and (2) in order to calculate the M sample CCF which is then used for testing the null hypothesis of no causality-in-variance. To test this null hypothesis, Cheung and Ng (1996) has developed the following S-statistic:

$$S = \mathrm{T} \sum_{j=i}^{M} \hat{\rho}_{uz}^2(j) \tag{5}$$

where the sample cross correlation $\hat{\rho}_{uz}^2(j)$ is specified as $\hat{\rho}_{uz}^2(j) = \hat{C}_{uz}(j)\,\{\hat{C}_{uu}(0)\hat{C}_{zz}(0)\}^{-1/2}$ and the sample cross-covariance function is given by $\hat{C}_{uz}(j) = \begin{cases} T^{-1}\sum_{t=j+1}^{T} \hat{u}_t \hat{z}_{t-j}, & j \geq 0 \\ T^{-1}\sum_{t=-j+1}^{T} \hat{u}_{t+j} \hat{z}_t, & j < 0 \end{cases}$ and $\hat{C}_{uu}(0) = T^{-1}\sum_{t=1}^{T} \hat{u}_t^2$; $\hat{C}_{zz}(0) = T^{-1}\sum_{t=1}^{T} \hat{z}_t^2$.

Table 2
Summary statistics on variables

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque Bera	Probability	Obs.
Before the Arab uprisings (December 18, 2004 - May 15, 2007)									
Brent	0.0801	5.7195	−7.2428	1.9519	−0.0876	3.3500	3.6461	0.1615	571
Financials	0.0359	5.2514	−4.7631	1.5943	−0.1949	3.5663	11.247	0.0036	571
Industrials	0.0082	13.107	−13.464	1.3140	−0.2962	38.630	30212	0.0000	571
Services	0.0242	4.3089	−3.6329	1.2067	0.1196	4.2331	37.543	0.0000	571
After the Arab uprisings (December 18, 2010–June 18, 2013)									
Brent	0.0156	4.7249	−8.2452	1.5548	−0.4239	4.7817	92.635	0.0000	571
Financials	−0.0293	2.3111	−2.1313	0.4757	−0.3551	5.7132	187.14	0.0000	571
Industrials	−0.0305	3.4959	−3.0635	0.7362	−0.0029	6.2225	247.07	0.0000	571
Services	−0.0321	3.579	−3.3603	0.6021	0.1925	7.3240	448.36	0.0000	571

The *S*-statistic has a chi-square distribution with $(M - i + 1)$ degrees of freedom. The null hypothesis is that there is no causality relationship in mean (variance) at all lags. However, Cheung and Ng (1996) give equal weight for each M cross-correlation even though the cross-correlation between two financial time-series diminishes with the increase of lags. Hong (2001) extends the *S*-statistic of Cheung and Ng (1996) by introducing non-uniform kernel weighting functions. He also demonstrates that his modified test is able to outperform the *S*-statistic in Monte Carlo experiments. The test proposed by Hong (2001) is given by

$$Q = T\sum_{l=1}^{T-1} k^2\left(\frac{l}{M}\right)\hat{\rho}^2_{uz}(l) - C_{1,T}(k)/\{2D_{1T}(k)\}^{\frac{1}{2}} \tag{6}$$

where k^2 (l /M) is the squared truncated Bartlett Kernel and $C_{1T}(k) = \sum_{l=1}^{T-1}(1-|l|/T)k^2\left(\frac{l}{M}\right)$ and $D_{1T}(k) = \sum_{l=1}^{T-1}(1-|l|/T)\{1-(|l|+1)/T\}k^4\left(\frac{l}{M}\right)$.

The *Q*-statistic is computed and compared to the upper-tailed critical value of the Gaussian distribution at an appropriate level. The null hypothesis of no causality is rejected if *Q* is larger than the critical value.

However, the model discussed above may suffer from size distortions in the presence of a structural break in the conditional variance process (Rodrigues and Rubia, 2007), or in case the causality-in-mean effects are not incorporated into the causality-in-variance tests. Therefore, we conduct pre-testing for structural breaks in the variances along the lines of Bai and Perron's (1998, 2003). In addition, we eliminate the causality-in-mean effects on the causality-in-variance tests by including lagged returns in the conditional mean equation of the ARMAX-(E)GARCH model. This is hoped to eliminate any Granger causality in mean effect on the residuals as pointed out by Tamakoshi and Hamori (2014).

4. Empirical results

4.1. Data set and preliminary estimates

The data employed in this paper are daily, and the sample period covers two sub-periods whereby each contains two and a half years before and after the political turmoil that started in the Arab world on December 18, 2010. While the post-Uprising period extends from December 18, 2010, to June 18, 2013, the pre-Uprising period is chosen to be sufficiently remote to reveal the impact of the uprisings and the social dislocations on the mean and the variance linkages between crude oil prices and the Jordanian sector indices.[4] Accordingly, the pre-Uprising spans the period from December 18, 2004, to May 15, 2007. It is worth noting here that the use of a less remote period would intersect with the global financial crisis period, during which the relationship between oil and stock markets, among others, has strengthened.

Global oil prices, which are represented by the Brent crude oil spot prices (Bouri, 2015a, 2015b), are obtained from the US Energy Information Administration and they are expressed in US dollars per barrel. Sector indices are gathered from the Amman stock exchange and they are denominated in domestic currency (Jordanian Dinar). Specifically, we consider three sectoral indices constructed by the local exchange: Financials, Industrials, and Services. All variables are expressed in percentages using the first differences of the natural logarithms of the price multiplied by 100.

The summary statistics of daily return series in both periods are reported in Table 2. In the period before the Arab uprisings, all return series have a positive mean, whereas Brent has this privilege only in the period following the Arab uprisings. In addition, Brent has the highest standard deviation on average in both periods. Among the sectoral indices, Financials has the highest standard deviation in the pre-Uprising period, whereas Industrials has highest standard deviation in the period post the Arab uprisings. As for the third and fourth moments, all return series exhibit non-zero skewness and excess kurtosis in both periods. There is a negative mean skewness for Brent, Financials, and Industrials, indicating that the return of these three series have long left tail; for Services, there is a positive mean skewness in the two samples, indicating that the return has long right tail. All return series have more peaked data distribution than a normal distribution.

To check stationarity of the conditional mean, the analyzed series have to be examined to determine whether or not they contain a unit root. This step is required to ensure that the parameters estimates in the GARCH-type process and causality models are reliable. Using the augmented Dickey and Fuller (1981) (ADF) approach and the Kwiatkowski et al. (1992) (KPSS) test, we ensured that the null hypothesis of the existence of a unit root is rejected at conventional levels in both periods and for all returns series (see Table 3).

Table 3
Tests of unit roots.

	ADF tests		KPSS tests
	No intercept	Intercept	Test with intercept and 1 lag
Before the Arab uprisings (December 18, 2004–May 15, 2007)			
Brent	-25.5398^a	-25.5580^a	0.0683^a
Financials	-18.1997^a	-18.1870^a	0.6760^b
Industrials	-20.5570^a	-20.5390^a	0.3002^a
Services	-18.3060^a	-18.3010^a	0.4379^c
After the Arab uprisings (December 18, 2010–June 18, 2013)			
Brent	-23.7302^a	-23.7101^a	0.1689^a
Financials	-21.4790^a	-21.5201^a	0.4190^c
Industrials	-25.4102^a	-25.4491^a	0.2375^a
Services	-22.6689^a	-22.7108^a	0.2167^a

Notes: ADF (Augmented Dickey-Fuller); KPSS (Kwiatkowski Philips Schmidt Shin); For both tests, a, b, c indicate that the null hypothesis of a unit root is rejected at 1%, 5%, and 10% significance levels, respectively.

[4] We thank the reviewer for this suggestion.

Table 4
Estimation results for the best GARCH-based process

	Brent	Financials	Industrials	Services
Before the Arab uprisings (December 18, 2004–May 15, 2007)				
	ARMAX(1,1) EGARCH(1,1)	ARMAX(1,1) GARCH(1,1)	ARMAX(0,1) EGARCH(1,1)	ARMAX(0,0) EGARCH(1,1)
Mean equation				
Constant	0.3965^{b}	0.1305	0.0365	−0.6367
d_1	−0.5856^{b}	0.0218	0.0161	0.1911
d_2	−0.2848	−0.3125^{c}	−0.1406	−0.0895
d_3	−0.6015^{b}	−0.0503	−0.0504	0.0865
d_4	−0.1453	0.0282	−0.0480	0.0998
AR(1)	−0.9377^{a}	−0.4239^{a}	–	–
MA(1)	0.9208^{a}	0.6465^{a}	0.1980^{a}	–
Variance equation				
Constant	0.2095^{c}	0.0225	−0.3801^{a}	−0.2072^{a}
ARCH	−0.0827	−.1005^{a}	0.5083^{a}	0.2753^{a}
GARCH	0.8875^{a}	0.8927^{a}	0.8412^{a}	0.9505^{a}
Asymmetric term	−0.0577	–	−0.1288^{c}	−0.0729^{b}
GED parameter	1.7590^{a}	–	1.2931^{a}	1.5477^{a}
Diagnostic				
Q(10)	8.5618	16.8230^{b}	7.8790	14.1640
Q(20)	17.2930	25.1850	20.3620	22.3090
$Q^2(10)$	5.4297	16.1820^{c}	1.1623	11.9340
$Q^2(20)$	23.1440	25.8670	1.4846	17.4650
After the Arab uprisings (December 18, 2010–June 18, 2013)				
	ARMAX(0,0) GARCH(1,1)	ARMAX(0,0) GARCH(1,1)	ARMAX(0,0) GARCH(1,1)	ARMAX(0,0) GARCH(1,1)
Mean equation				
Constant	−0.0995	0.0784^{b}	−0.0218	0.0316
d_1	0.2395	−0.0662	−0.0023	−0.1993^{a}
d_2	0.2747^{c}	−0.1715^{a}	−0.0513	−0.1010^{c}
d_3	0.1198	0.1013^{b}	−0.0404	−0.0432
d_4	0.1319	0.0818^{c}	0.0547	0.0366
Variance equation				
Constant	0.0461	0.0306	0.0681^{b}	0.0579^{b}
ARCH	0.0660^{b}	0.0812^{c}	0.1907^{b}	0.1550^{b}
GARCH	0.9179^{a}	0.7804^{a}	0.6908^{a}	0.6849^{a}
GED parameter	1.3511^{a}	1.2053^{a}	1.1118^{a}	1.1775^{a}
Diagnostic				
Q(10)	7.9708	14.5090	8.4112	3.9298
Q(20)	12.4130	20.3350	12.7320	12.7110
$Q^2(10)$	2.4574	3.7936	8.1820	6.1201
$Q^2(20)$	15.9400	15.1770	17.0980	19.7130

Notes: Q(10), Q(20), $Q^2(10)$, and $Q^2(20)$ are Box-Pierce statistics for autocorrelations of the standardized residuals and the squared standardized residuals, respectively.
^{a} Statistical significance at 1% level.
^{b} Statistical significance at 5% level.
^{c} Statistical significance at 10% level.

The period under study contains two sub-periods that are sufficiently remote from each other.[5] However, we carry out Bai and Perron's (1998, 2003) test of structural break for the period before the Arab uprisings and the period after the Arab uprisings. This test, which discloses the exact number of breaks and their corresponding dates of occurrence, trims the first and the last 15% of return observations of the sample period. The optimal lag length of this test is chosen by using the Akaike Information Criterion (AIC). The results of the structural break test (not reported here) show that all return series have no breaks in the variance during both periods. Therefore, we may safely proceed and estimate GARCH models and CCF causality tests.

Furthermore, to ensure an appropriate fit, an extensive specification testing procedure is conducted for the conditional mean and variance processes of the return series. Specifically, the conditional mean is modeled within an ARMAX process to account for salient features of the data such as autocorrelation and day-of-the-week effects. As for the variance equation, several univariate GARCH-type processes are considered to model the time-varying conditional volatility of the return series as well as to account for asymmetry in stock returns. Table 4 presents the best univariate ARMAX-EGARCH or ARMAX-GARCH model specifications for each of the return series and the resultant parameter estimates. The specifications are chosen on the basis of the SIC information criteria that prefer simple specification (Beine and Laurent, 2003).

For the period that preceded the Uprising, the specification tests indicate that the best models are as follows: ARMAX(1,1)-EGARCH (0,1) is the best fit for Brent returns, ARMAX(1,1)-GARCH (1,1) for Financials, ARMAX(0,1)-EGARCH (1,1) for Industrials, and finally ARMAX(0,0)-EGARCH (1,1) is the most suitable model for Services. Except for the constant term, several of the parameter estimates for the ARMAX model are statistically significant at 5% level, especially for Brent and Financials. The parameter estimates of the GARCH and EGARCH models are also statistically significant at 10% significance level. The GARCH term measures the impact of past volatility on current conditional volatility, whereas the ARCH term measures the impact of past innovations on current conditional volatility. The large magnitude of the GARCH parameter (ranging between 0.9505 and 0.8412) is an indication of persistence in the volatility process. It also suggests slow to gradual fluctuations of the conditional volatility over time. Except for Industrials, further specification test results show that most of the GARCH-based models estimated with the GED (generalized error distribution) outperform the models estimated with either standard normal or even Student *t* distributions. In order to assess whether each of the selected models has succeeded in addressing the problem of autocorrelation in residuals and squared residuals, we focused on the goodness-of-fit in all cases. As shown in last four rows of Table 4, the Box-Pierce statistics indicate that there is no evidence of significant autocorrelation in residuals and squared residuals for up to 4 weeks or 20 lags.

In the period that follows the Arab uprisings, the results of the specification tests show that the ARMAX(0,0)-GARCH (1,1) is uniformly the best fit for all return series. Except for Industrials, several day-of-the-week effects are found to be significant at the 10% level. A part from the constant, all parameter estimates of the GARCH models are statistically significant at 10% level. Compared to the period before the Arab uprisings, the loadings of the GARCH parameters are lower and this indicates a decrease in volatility persistence in all sectoral indices. This suggests slower fluctuations of conditional volatility over time. One more time, the GED outperforms in all cases. Similar to the first sample, diagnostic tests indicate that the selected models are free from autocorrelation.

In Table 5, Panel A and Panel B report the simple correlation coefficient between the standardized residuals of the return series and their

Table 5
Correlations between standardized residuals.

	Brent	Financials	Industrials	Services
Panel A: The level of standardized residuals				
Brent	1.0000	**−0.0648**	**−0.0006**	**−0.0245**
Financials	*0.0525*	1.0000	**0.4552**^{a}	**0.5008**^{a}
Industrials	*−0.0113*	*0.6034*^{a}	1.0000	**0.4343**^{a}
Services	*−0.0182*	*0.6712*^{a}	*0.6503*^{a}	1.0000
Panel B : The squares of standardized residuals				
Brent	1.0000	**−0.0284**	**0.0007**	**−0.0311**
Financials	*−0.0498*	1.0000	**0.2915**^{a}	**0.2628**^{a}
Industrials	*−0.0500*	*0.1331*^{a}	1.0000	**0.3931**^{a}
Services	*−0.0102*	*0.4282*^{a}	*0.1328*^{a}	1.0000

Notes: The period before the Arab uprisings spans from December 18, 2004, to May 15, 2007, whereas the period after the Arab uprisings spans from December 18, 2010, to June 18, 2013. Correlations coefficients for the period before the Arab uprisings are reported in italic, whereas correlations coefficients for the period after the Arab uprisings are reported in bold.
^{a} Statistical significance at 1% level.

[5] The global financial crisis period is omitted to avoid the influence of the crisis on the results. This point has been raised thankfully by one of the referees.

Table 6
P-values for causality in mean and in variance tests.

	Before the Arab uprisings (*December 18, 2004–May 15, 2007*)				*After the Arab uprisings* (*December 18, 2010–June 18, 2013*)			
	Causality in mean		Causality in variance		Causality in mean		Causality in variance	
M	Fin→Brent	Brent→Fin	Fin→Brent	Brent→Fin	Fin→Brent	Brent→Fin	Fin→Brent	Brent→Fin
1	0.3722	0.2383	0.7530	0.3904	0.7393	0.2173	0.6489	0.4118
4	0.3321	0.1797	0.7203	0.3548	0.9017	0.1281	0.7815	0.3910
8	0.2897	0.0809	0.6288	0.3641	0.9578	**0.0161**	0.8776	0.3594
12	0.2375	**0.0320**	0.6089	0.3443	0.9851	**0.0035**	0.9332	0.2834
M	Ind→Brent	Brent→Ind	Ind→Brent	Brent→Ind	Ind→Brent	Brent→Ind	Ind→Brent	Brent→Ind
1	0.7560	0.7436	0.7532	0.3793	0.6533	0.7332	0.4806	0.2653
4	0.9172	0.8972	0.9147	0.2721	0.7939	0.8960	0.4644	0.0965
8	0.9753	0.9603	0.9733	0.1932	0.8770	0.9593	0.4704	**0.0249**
12	0.9905	0.9785	0.9907	0.1558	0.9407	0.9754	0.4055	**0.0057**
M	Serv→Brent	Brent→Serv	Serv→Brent	Brent→Serv	Serv→Brent	Brent→Serv	Serv→Brent	Brent→Serv
1	0.5388	0.2764	0.6881	0.6723	0.7426	0.1290	0.7492	0.6571
4	0.5431	0.1768	0.8302	0.8085	0.8973	0.0809	0.9084	0.7881
8	0.5045	**0.0412**	0.9088	0.9074	0.9676	**0.0359**	0.9701	0.8676
12	0.6114	**0.0007**	0.9249	0.9570	0.9887	**0.0012**	0.9870	0.9159

Notes: This table shows the p-values for causality in mean and in variance tests for M = 1, 4, 8, and 12 days; Figures in bold are statistically significant at 5% level.

squares, respectively. These can be interpreted in terms of contemporaneous causality between oil and equity sectors returns and volatilities. As can be seen in Table 5, correlations of oil are insignificant for all sectors. This result is uniform across the two samples and in both returns and volatilities. The lack of correlation may indicate that the information is not absorbed simultaneously by the international oil market and Jordanian sectoral indices. On the contrary, it may take some time before a possible transmission of risk and return absorbed and subsequently observed.

In order to obtain further information on linkages between oil prices and sector indices and investigate causality at various periods, we estimate the causalities in mean and variance as mentioned previously. We turn to discuss these causality tests in the next subsection.

4.2. Causality tests results

As mentioned previously, the paper employs the CCF approach of Cheung and Ng (1996) and Hong (2001) to make an inference on causality between oil and Jordanian equity sectors. Table 6 reports the p-values for causality tests in mean and variance for 1, 4, 8, and 12 periods. The numbers in the table represents the causality-in-mean and the causality-in-variance tests between Brent prices and each of the three Jordanian sectoral indices for the periods before and after the Arab uprisings.

The scale of Jordan's sectoral market is much smaller than that of Brent oil market. Therefore, it is counter-intuitive that mean and variance information are transmitted from sectoral indices to oil prices. Our results are consistent with these expected outcomes. The effect of causality-in-mean from sector indices to oil returns is insignificant for all periods. However, the causality-in-mean test provides evidence that the mean of Brent returns Granger cause Financials and the Services sectors' returns. The reaction is more delayed in the Financials sector compared to the Services sector. For instance, the information is absorbed with 12 days in the Financials sector, while it takes only 8 days for the effect to be transmitted to the Services sector.

These results are carried over across the period that followed the Arab Uprising in 2010. During this period, the causality is even more pronounced in terms of higher significance levels and faster influence in the Financials Sector. The influence of oil return innovations is absorbed within 8-day periods instead of the 12 days observed in the period that preceded the Arab Uprising. The faster transmission of influence is indicated by the higher significant levels and by the effect at shorter periods. No significant mean influence of oil on the Industrials is recorded during any period. Hence, we conclude that the Jordanian equity market sectors do react differently to oil return shocks.

As mentioned previously, before making any inference on variance causality, the causality in mean effects should be accounted for. The inference on variance causality is prone to bias if it is drawn in the presence of mean causality effects. To rule out the in mean influence, we re-estimate and compute the residuals after including the lagged returns in the conditional mean equation of the ARMAX-(E)GARCH models. This is done only to make an inference on variance causality of the Financials and the Services sectors where a significant causality in mean effects is found.[6] On the contrary, no lagged returns where included in the Industrials as the causality in mean for this sector is found to be negligible.

Column 5 and Column 9 of Table 6 reports the p-values of the variance causality test. In column 5, we report the test results for the period that preceded the Arab Uprising, while in Column 9 we report results from the post Uprising sample. As can be seen in Column 5, the volatility of oil does not Granger cause the volatilities of Jordanian sectoral indices. Hence, we conclude that the risk transfer from the oil market to equity sectors is weak. However, we find a significant risk cross over from oil to the Industrials sector in the period that followed the Arab Uprising.

Interestingly, Granger-causality-in-variance to the Industrials sector is transmitted also over longer lags. The risk transfer is only significant at the 8 and the 12 day periods, while it is negligible at the 1 and 4 day periods. This indicates that the influence of uncertainty in the oil market is felt within an 8 day period in the Industrials sector.

While several studies reported evidence of faster informational linkages among markets during crisis periods (see, inter alia, Awartani and Maghyereh, 2013; Bouri, 2015b), the evidence of delayed reaction suggests an inefficient processing of information by stock market participants (Bouri, 2015b). The slow processing in return adjustment allows for a possible short-term arbitrage profit opportunities in Jordan. However, this finding contradicts with that reported by Al Janabi et al. (2010) who provide empirical evidence supporting the efficiency of some MENA markets such as the GCC equity markets.

After the Arab uprisings, the mean linkages between Brent prices and the Financials and Services sector indices increased. For the financial sector, this can be explained by the fact that even though Financials are not directly affected by the market conditions of oil as an

6 Cheung and Ng (1996) indicates that the results from the causality-in-variance tests between two variables are biased when there is evidence of causality-in-mean effects.

intermediate input in the production process, the financial sector is sensitive to political uncertainty. The latter has been ushered unwittingly by the Arab uprisings. Probably, the fear of government collapse has adversely influenced banking activities, leading to the expectations that financial firms profitability will decline. The financial sector is also sensitive to macroeconomic changes, such as the expectations about future inflation, the slope of the yield curve, and changes in monetary policy (Rumler and Waschiczek, 2010). This result, which contradicts that reported by Jouini (2013), is however consistent with the view that nature of the firms that make up this sector are indirectly affected by the role of oil prices as a leading economic indicator. It is well accepted that oil prices have macroeconomic impact and they are often seen as representing greater uncertainty in the aggregate level of output especially in oil-importing countries. In this sense, this finding confirms earlier results of Haddow et al. (2013) on that the financial sector is tied to economic uncertainty and, accordingly, it appears that firm performance in the financial sector is not insulated from oil market conditions.

The situation is quite different in the relatively oil-intensive Industrials sector which usually receives considerable government subsidy. It could be that the Industrials sector remains relatively unaffected by oil volatility shocks when the crude oil markets were relatively stable in the pre-Arab uprisings period, while it is more exposed when the crude oil market stability was threatened by the Arab uprisings. This suggests that other factors besides the possible increases in the marginal cost of production may have played a role in establishing the risk linkages. Factors such as demand-side effects, the interaction among oil price changes, economic growth, and aggregate consumption may have all played a role in shaping the relationship. Another possibility is the fear of the government collapse and the suspension of fuel subsidies.

These empirical findings are inconsistent with the findings of Malika and Ewing (2009) and Arouri et al. (2012), who find no evidence of a relationship between oil prices and the industrial equity sector in the US. These authors have reasoned that the development of an effective hedging strategy against unanticipated oil price changes is the most likely explanation of their results. Based on a different explanation, however, our results are somewhat consistent with those reported by Mohanty et al. (2011) in GCC countries.

Our results for the Services sector display a mean effect in both periods, with more pronounced return spillovers in the period that followed the Arab uprisings. Note that this sector contains two big companies that are heavily dependent on oil: these are the Royal Jordanian Airlines and the Jordanian Electric Power Company. Moreover, there is a big transportation subsector within the services sector that depends on oil. The influence in terms of returns may also suggest that the companies composing the sector are unable to pass through the higher cost due to increases in oil prices to final consumers.[7] The increase in oil prices is translated into lower profit margins and equity returns. Hence, we may conclude that equity investment in these companies cannot effectively hedge increases in oil prices. Finally another plausible explanation of the influence particularly during the Arab Uprising is the emergence of some additional challenges resulting from bigger exposures due to the rise in geopolitical risks.

4.3. Robustness analysis

To check the robustness of our results, we employ a bivariate model that jointly estimates the influence of oil mean and volatility on the sectors. In particular, we use the VARMA (1, 1)–BEKK–AGARCH (1, 1) model developed by McAleer et al. (2009).[8] Unlike the CCF method where inference on the oil-equity relationship is derived in two steps, this model simultaneously estimates the return and volatility cross-effects of each market-pair under consideration.[9] The econometric specification of this model has two components: a conditional mean equation which $A=\pi r^2$is specified as a vector autoregressive moving average process (VARMA) and a conditional variance equation that is modeled as asymmetric multivariate GARCH. Accordingly, for each pair, the conditional mean and variance of this empirical model can be written as

$$\begin{cases} R_{it} = \phi_{i0} + d_{1i}+d_{2i} + d_{3i} + d_{4i} + \psi_{ij}R_{jt-1} + \varepsilon_{it} + \vartheta_{ij}\varepsilon_{jt-1} \\ \varepsilon_{it} = D_{it}\eta_{it} \end{cases} \tag{7}$$

where $R_{it}(O_t,S_t)'$ is a vector of daily returns of the oil price index and the stock sector index at time t, respectively; d_1,d_2,d_3,and d_4 are dummy variables for the day of the week effect; ϕ_{i0} is a (2×1) vector of constant terms; ψ_{ij} is a (2×2) matrix of coefficients that allows for cross-sectional dependency between the conditional mean of oil and equity market returns; ε_{it} is a (2×1) vector of error terms from the mean equations; ϑ_{ij} is a (2×2) matrix of coefficients of the lagged residuals and it explains the propagation of shocks between oil and equities; η_{it} is a (2×1) vector of independently and identically distributed $(i.i.d)$ random errors; and finally $D_{it} = diag(\sqrt{h_{o,t}}, \sqrt{h_{s,t}})$ with $h_{o,t}$ and $h_{s,t}$ being the conditional variances of stock and oil returns, respectively, and they are given by.

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + G'u_{t-1}u'_{t-1}G \tag{8}$$

where C is a (2×2) upper triangular matrix of constants with elements c_{ij}; A is a (2×2) matrix of coefficients α_{ij} that that capture the effects of own shocks and cross-market shock interactions; B is a (2×2) matrix of coefficients β_{ij} that capture the own volatility persistence and the volatility spillover from market to another; G is each a (2×2) matrix of coefficients g_{ij} that capture the asymmetric effect for own markets and the asymmetric spillover from market to another. Finally $C'C$ is the decomposition of the intercept matrix.

The Eqs. (7) and (8) are estimated by using quasi-Maximum Likelihood (QMLE) which provides consistent estimates.[10] Table 7 reports the coefficients obtained for the periods before and after the Arab uprisings.

The estimated parameters of the mean equations in Table 7 show that there is a negative and significant unidirectional shock transmission from oil price to all sectoral returns. The coefficients that measure the impact of oil in the table are denoted ψ_{12} and they are all negative and significant. The influence in the opposite direction is captured by ψ_{21} and as expected it is found to be insignificant.

The implication of these results is similar to the previous analysis. The unanticipated shocks in the oil market are transmitted to the Jordanian sectoral returns. The only difference here is that oil shocks are found to influence the mean return of Industrials as well; the sector which is found to be unrelated to oil innovations in the CCF analysis in the previous section.

The estimated loadings show that the impact is highest on the Services sector (−0.69) followed by the Industrials (−0.58) and then the lowest impact is on the Financials (–0.37). These estimates reflect the fundamentals of the sectors and the extent to which they are dependent on oil. For instance, the Financials sector is the least dependent on oil and therefore it is the least affected. However, the sensitivity of the Services sector reflects the vulnerability of the transportation and the utilities and electricity subsectors that heavily depends on oil. The Industrials should be also sensitive, but as this sector is the least regulated, it is the most able to pass on the increase in energy costs and inflation to final consumers.

[7] The insignificant mean causality in the Industrials may suggest the opposite. The Industrials sector companies are able to pass through increased costs to final consumers in both periods.

[8] This model is an augmented version of VARMA–GARCH process developed by Ling and McAleer (2003).

[9] This procedure has been rapidly adopted in the relevant literature; refer to, for example to research by (Arouri et al., 2011a, 2011b, 2015; Chang et al., 2011; Sadorsky, 2012, 2014; Mensi et al., 2013; Salisu and Oloko, 2015).

[10] The selected lags for the models are based on AIC and BIC information criteria.

Table 7
Asymmetric multivariate GARCH estimation results.

	Before the Arab uprisings (December 18, 2004–May 15, 2007)			*After the Arab uprisings (December 18, 2010–June 18, 2013)*		
	Brent & Financials	Brent & Industrials	Brent & Services	Brent & Financials	Brent & Industrials	Brent & Services
Mean equation						
ϕ_{10}	0.4818[b]	0.1663[a]	0.0232	0.1219	−0.2388[a]	−0.0143[a]
d_{11}	−0.4249[b]	−0.2906	−0.3649	−0.1528[a]	−0.1895[a]	−0.1608[a]
d_{21}	−0.4253[c]	0.0455	0.0581	−0.1283[a]	0.1682	0.1964[a]
d_{31}	−0.4943[c]	−0.6913[a]	−0.3312	−0.2608[a]	−0.5798[a]	−0.3050[a]
d_{41}	−0.4678[a]	−0.3468[a]	−0.0319	−0.2176[a]	−0.2318[a]	−0.0162
ψ_{11}	0.6159[a]	0.5927[b]	0.7194[a]	0.5899[a]	0.3579[a]	0.7906[a]
ψ_{12}	−0.3766[b]	−0.5864[a]	−0.6964[b]	−0.7928[a]	−0.8448[a]	−0.8971[a]
ϑ_{11}	−0.9115[a]	-0.6315[a]	-0.7162[b]	−0.4779[a]	−0.3870[a]	−1.1061[a]
ϑ_{12}	−0.2667[b]	−0.5558[a]	-0.3343[a]	−0.3106[a]	−0.5413[a]	−1.0760[a]
ϕ_{20}	−0.1185[a]	0.1172	−0.2248	−0.0918[a]	−0.0054	−0.0362[a]
d_{12}	−0.0788[a]	0.0414	−0.2884[c]	−0.1259[a]	−0.1418[a]	−0.0060
d_{22}	−0.4197[a]	−0.2357[c]	−0.2116	−0.0215[a]	−0.0423[a]	−0.0772[a]
d_{32}	−0.2458	−0.0448	−0.2543	0.1088[a]	0.0344[b]	−0.0546
d_{42}	0.1836	0.3708[a]	0.3641	0.0153[a]	0.1168[b]	0.2756[a]
ψ_{22}	0.5901[a]	0.0979[b]	0.2557[a]	0.8750[a]	0.9718[a]	0.7185[a]
ψ_{21}	−0.1035	−0.3735[c]	−0.2404	−0.0628	−0.0581	−0.1527
ϑ_{22}	0.1300	0.4489[b]	0.4133[b]	0.0637	0.5366[a]	0.1649
ϑ_{21}	0.5408[a]	0.1385[c]	0.4271[c]	0.9351[a]	0.8417[a]	0.7653[a]
Variance equation						
c_{11}	1.8325[a]	1.6979[a]	0.7606[a]	1.0267	1.0047[a]	0.0128
c_{21}	0.0118	0.2883[a]	−0.2292[a]	0.1758	0.2327[a]	−0.1440[a]
c_{22}	0.0000	−0.0026	−0.0000	0.2137[a]	−0.0445[b]	0.1670[a]
α_{11}	0.0774[b]	0.1650[b]	0.0161[a]	0.0099[c]	0.0737[a]	0.0681[a]
a_{12}	0.0982	0.1739	0.0010	−0.0078	0.0609[b]	0.0358
a_{21}	0.0892	0.0577	0.0170	0.1349	0.02691	0.0842
a_{22}	0.2785[a]	0.3660[a]	0.2644[a]	0.1978[a]	0.4258[a]	0.3783[a]
β_{11}	0.1436	0.1371[a]	0.0843[a]	0.1844[a]	0.1815[a]	0.0803[a]
β_{12}	0.0448	0.2382[c]	0.1346[c]	0.0049	0.1603[b]	0.0083
β_{21}	0.0681	0.0377	0.2952	0.0319	0.0480	−0.0165
β_{22}	0.8909[a]	0.6843[a]	0.8589[a]	0.7290[a]	0.8158[a]	0.8152[a]
g_{11}	0.0979	0.1169	0.2314[a]	0.1690[a]	0.1870[a]	0.1638[a]
g_{12}	−0.0187	−0.2699[c]	−0.0509	−0.0127	0.0209	−0.0414
g_{21}	−0.0355	0.1797[c]	−0.0777	−0.0616	0.2443	−0.0770
g_{22}	0.4344[a]	1.0891[a]	0.4722[a]	−0.6160[a]	0.3264[a]	0.4341[a]

Residual diagnostics for independent series

	Brent	Financials	Brent	Industrials	Brent	Services	Brent	Financials	Brent	Industrials	Brent	Services
$Q(10)$	11.43	5.81	5.24	8.40	8.58	6.98	8.72	2.12	10.47	1.929	8.34	2.21
$Q(20)$	21.36[b]	12.74	8.29	1.07	7.73	14.58	13.47	4.95	9.34	8.18	4.069	4.70
$Q^2(10)$	19.14	20.16	15.82	19.33	20.87	18.37	14.45	14.15	15.64	12.24	12.96	14.71
$Q^2(20)$	30.78[b]	17.62	22.54[c]	2.40	14.01	20.43[c]	20.48[c]	25.50[c]	16.81	19.99	12.53	25.99[c]

Notes: The model is estimated by the quasi-maximum likelihood (QMLE) method which can be optimized by implementing the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. The oil Brent is ordered (1) and each stock sector (2). In the mean equation, ϕ_{ij} represents constant terms, d_{1i},d_{2i},d_{3i} ,and d_{4i} represent the day of the week effect, ψ_{ij} represents AR(1) terms; and ϑ_{ij} represents MA (1) terms. The coefficient ψ_{12} , for example, represents the effect of a one-period lag Brent returns on current period stock sector returns. In the variance equations, C_{ij} represents constant terms, a_{ij} represents the ARCH effect, β_{ij} represents the GARCH effect, and g_{ij} represents the asymmetric effect. The coefficient a_{12} for example represents the short-term volatility spillover from Brent oil to stock sector, β_{12} represents the long-term volatility spillover from Brent oil to stock sector, and g_{12} represents the asymmetric effect from Brent oil to stock sector. Q(10), Q(20), $Q^2(10)$, and $Q^2(20)$ are Box-Pierce statistics for autocorrelations of the standardized residuals and the squared standardized residuals, respectively.

[a] Statistical significance at 1% level.
[b] Statistical significance at 5% level.
[c] Statistical significance at 10% level.

It is worth to mention here that the sensitivity of sector returns has increased following the Arab Uprising in magnitude and significance. This was uniform across the three sectors. The increase in sensitivity is most pronounced in the Financials. This reflects an increased association with the oil market during periods which is characterized with political and economic uncertainty.[11]

The coefficients associated with ARCH and GARCH terms inform on volatility linkages and risk transfer. In terms of risk transfer, the results from the model also mirror the findings from the CCF analysis. In particular, we find low risk transfer from oil to all of the three sectors in the period that preceded the Arab Uprising. The parameters a_{12} and β_{12} are statistical insignificant and hence we may conclude that there is no short or long term volatility impact from oil to other sectors. The only exception is the Industrials where there is a significant long term effect but the short term influence is negligible. As for the period after the Arab uprisings however, there is significant long and short term risk transfer from oil to the Industrials sector only.

Overall, the results from the asymmetric multivariate GARCH model confirm the previous results in that the stock market at the sectoral level in Jordan is an oil price- and volatility-taker.[12]

[11] Increased association among financial variables during periods of stress is extensively reported in the literature.

[12] In addition, we have also estimated three multivariate GARCH models. These are full BEKK-GARCH, the VARMA–BEKK–GARCH, and the VARMA–DCC–AGARCH. The models are estimated to check robustness and also for comparison purpose. The AIC and SIC criteria show that all these models are inferior to the VARMA–BEKK–AGARCH model. However, the main results of these models are consistent with the VARMA–BEKK–AGARCH model. To economize on space, we do not present the estimation results and they are only available from the authors upon request.

5. Conclusion and policy implications

In principle, oil shocks are not expected to influence economic sectors in the same way. Therefore and unlike most of the prior studies that focus on the impact of oil on aggregate market indexes, we investigate causalities at the sectoral level. The analysis is hoped to be more informative and instructive to market participants in terms of oil impact and risk transfer to equities. Our study focuses on Jordan as a model country in the MENA region that has a well- diversified equity market and an economy that is sensitive to oil. The nature of the oil equity relationship has been investigated in two samples that cover the critical time periods surrounding the Arab uprisings that started in Tunisia in December 18, 2010.

To investigate the oil equity association, we computed the CCF tests between oil and sectoral indices as in Cheung and Ng (1996) and Hong (2001). These tests are conducted at varying scales of 1, 4, 8, and 12 days for both the mean and the variance association tests of oil with each of the three sectors composing the Jordanian stock exchange market. These sectors are the Financials sector, the Industrials sector, and the Services sector. The robustness of the test results are checked by employing a bivariate VARMA (1, 1)-BEKK-AGARCH (1, 1) model that simultaneously estimate the mean and the variance impact across the variables. As expected, our results illustrate that the impact of oil on equity sectors is heterogeneous and it varies across the two samples surrounding the Arab Uprising. For instance, the influence of oil shocks is significant on the returns of the Financials and the Services sectors, while it is insignificant on the Industrial sector. This holds to be true in both of the periods that surround the Arab Uprising. However, it is worth to mention here that the impact is more pronounced and it occurs at a faster scale in the second period that follows the Arab Uprising.

In terms of risk transfer, we found that the impact of oil volatility is negligible and that it can be safely ignored in assessing the volatility of the Financials and the Services sectors. However, there is significant evidence of risk transfers from the oil market to the Industrial sector in the period following the Arab Uprising.

The robust analysis based on multivariate GARCH confirms these results. The parameters of the mean equation are all negative and significant indicating the depressing influence of oil shocks on the performance of the three sectors including the Industrials. The loadings of the parameters show that the influence is even stronger in the period that followed the Uprising. Similarly, apart from the risk transfer to the Industrials in the second period, the evidence on volatility transmission is weak.

These findings highlight the importance of oil in assessing the attractiveness of these sectors. Oil is a factor that impacts the returns and the volatility of the three sectors and therefore, oil risk and return should be accounted for in formulating performance expectations for the purpose of investment and asset allocation in either domestic portfolios or in global portfolios that include Jordanian equities. In worldwide recovery when oil prices are increasing, the Services sector is expected to respond faster and outperform compared to the other two sectors. Because there is no risk transfer to Services, the sector will also outperform on a risk adjusted basis. Hence, an increase in allocation to Services on the account of the other two sectors may enhance portfolio efficiency.

Similarly, our results are also important to formulate risk expectations regarding the sectors. The risk transfer from oil to Industrials is significant while it is negligible to Services and to Financials. This indicates that forecasting the risk of Industrials can be improved by accounting for oil volatility. On the contrary, oil risk can be safely ignored in modelling and forecasting the expected volatility of Services and Financials.

The risk transfer information from oil to Industrials can be also useful in managing the risk of portfolios. For instance, in the face of uncertainty in the oil market, portfolios may increase allocation to Financials and decrease allocations to Services and Industrials in order to alleviate the negative impact on portfolio returns and volatility.

Overall, our results shows that the Industrials sector is the least exposed to oil return shocks while it is the most exposed to oil volatility information spills particularly following the Arab Uprising. Therefore, in global portfolios that contain oil, the Industrials sector is the most diversifying in terms of returns while it is the least diversifying in terms of volatility products. Therefore, in these portfolios, the Industrials provide another source of return exposure and the Services and the Financials provide a different source of volatility exposures. These results can be important in diversifying the sources of returns and risk and in managing portfolios that contain oil.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2016.03.021.

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