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Volatility Transmission and Conditional Correlation between Oil prices, Stock Market and Sector Indexes: Empirics for Saudi Stock Market

Ahmed Almohaimeed[1] and Nizar Harrathi[2]

Abstract

This paper investigates the volatility transmission effect and conditional correlations among crude oil, stock market and sector stock indexes in Saudi Arabia. Using daily data from January 3, 2009 to March 21, 2012 and VAR-BEKK specification, we find significant volatility transmission between oil prices and Saudi stock market. Furthermore, our findings show that sector stock returns significantly react to oil prices changes. In addition, except telecom sector, the results show the presence of volatility transmission between stock market and sector stock market returns. Our results are important for understanding how oil prices changes affect Saudi stock market. Indeed, our findings offer insights to investors to know how the value of their portfolios may be affected by large variations observed in oil prices. Our results may have crucial implications for market participants whose optimal portfolio decisions and the risk management policy depend on the characteristics and behavior of conditional volatility.

JEL classification numbers: C12, C32, G12, Q43
Keywords: Volatility transmission, Causality in Variance, Conditional Correlations, Multivariate GARCH, Oil prices, Sector indexes, Portfolio decisions.

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[1] Associate Professor of Economics, Department of Economics, College of Business Administration, King Saud University, Saudi Arabia.
[2] Associate Professor of Economics, Department of Economics, College of Business Administration, King Saud University, Saudi Arabia.

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1 Introduction

The review of the active academic survey on the oil market and the macroeconomic activity (e.g. see Hamilton (1983), Gisser and Goodwin (1986), Mork et al. (1994), Jones et al. (2004) and Jimenez and Sanchez (2005)), revealed that there is evidence of a significant negative relationship between oil prices and the measurements of employment and output growth. By reference to the International Monetary Fund, it is suggested that the increase in oil prices has negative repercussions on the global economy. Consequently, the impact of oil prices changes on stock market has been the subject of much attention from the finance practitioners and academic. Many empirical studies have investigated the behavior of oil prices and conclude the sensitivity of economic growth and stock market returns to oil prices volatility (e.g. see Jones and Kaul (1996), Sadorsky (1999), Papapetrou (2001), Park and Ratti (2008) and Apergis and Miller (2009). Indeed, it is important to understand how volatility is transmitted between stock market. Furthermore, given the high degree of major financial markets, the oil prices changes and stock markets shock occurred in one market is transmitted to other market suggesting the existence of volatility spillovers over time.

Otherwise, a number of studies include, Malik and Hammoudeh (2007), Lescaroux and Mignon (2008), Arouri et al. (2011a) and Arouri et al. (2012) report a significant volatility spillover from the oil prices to the Gulf Corporation Council (GCC) stock market. Malik and Hammoudeh (2007) found that oil prices receive volatility spillover only from Saudi. The sensitivity of the GCC stock market to changes in oil prices can be explained by the importance of these countries in the global oil market. These countries produce about 20% of all the oil in the world, accounting for 36% of world oil exports, and have 47% of proven oil reserves in the world. Oil exports are the primary determinants of government revenues, expenditures and aggregate consumption demand[3].

It is well documented that there is a strong relationship between the Saudi economy and oil prices where considered the primary source of income, which has a significant impact on Saudi joint stock companies. We note that when oil prices slumped between 1997 and 1999 due to the global economic recession, particularly in East Asia, it has been shown that Saudi stock market was negatively affected (e.g. see Tuluca and Zwick (2001) and Manning (2002)). While, improving oil prices positively affects the stock market. However, there are exceptions in this comparison where we may find the oil prices increase between mid-2002 and early 2003, was not associated to a significant increase in the stock market prices. Obviously, oil is playing a significant role in the development of Saudi economy. Furthermore, Saudi is an oil-producing country and one of the main decision makers in the Organization of the Petroleum Exporting Countries (OPEC)[4].

In this paper, GARCH-type model are used for investigating of shock and volatility forecasting. Additionally, the GARCH-BEKK parameterization introduced by Engle and Kroner (1995 allows to capture the own shock and volatility effect on the return series. On the other hand, the MGARCH-BEKK specification, which does not impose the restriction of constant correlations among markets, permits to capture cross-market shock and volatility effect between return time-series and may provide more insights to the

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[3]See Arouri et al. (2011a) for a detailed characteristics of GCC stock market

[4]Saudi Arabia represent 29% of the OPEC and almost 20% of the world total reserves (see http://www.gulfbase.com).

interactive relationship between oil prices volatility and stock market behaviour. Moreover, the constant conditional correlations model and the dynamic conditional correlations model are used in order to investigate conditional correlations between selected markets.

The main purpose of this paper is to investigate the volatility transmission effect between oil prices volatility shocks and the Saudi stock market dynamics. Compared to previous works devoted to this main research issue, we employed sector based-data for the period from January 3, 2009 to March 21, 2012. The remainder of the paper is structured as follows. The following section reviews some previous work on the volatility transmission. Section 3 provides methodology and econometric framework. Data and their preliminary analysis are reported in section 4. The empirical results are presented and discussed in section 5, while Section 6 relates the main concluding comments.

2 Some Previous Related Research

Recent empirical studies have extensively investigated the volatility transmission between stock market. Hamao et al.(1990), Koutmos and Booth (1995) and Hisashi and Shigeyuki (2009) analyzed the volatility spillover of stock price among three market, Tokyo, Landon and New York. Using daily returns and MGARH-BEKK parameterization, the authors found that there was a volatility transmission among the three markets. Kanas (1998) investigate the volatility spillovers across three European stock markets, London, Frankfurt and Paris based on daily data from January 1, 1984 to December 7, 1993. The implementation of GARCH model suggests that volatility spillover exist between the selected markets.

In line with the aforementioned studies, Lieven (2005) examined the volatility spillovers from the aggregate European and US market to a number of European equity market. Using weekly data from January 1980 to August 2001 and employing regime-switching model, the authors provide evidence of the volatility spillovers effect from European and US market to local European equity market. Francis et al. (2001) examined dynamic interdependence and volatility transmission across selected Asian stock markets during the Asian financial crisis periods. Using a VAR-EGARCH model, they pointed out that volatility transmission exist between Asian markets. The result suggests that Hong Kong played a significant role in volatility transmission to the other Asian markets.

More recent studies investigate the volatility transmission between stock market. Worthington and Higgs (2004) examine the transmission volatility among nine major Asian markets, Hong Kong, Japan and Singapore considered developed markets and Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand as emerging markets using weekly data from January 15, 1988 to October 6, 2000. The obtained results indicate the presence of positive mean and volatility spillovers effect and conclude that the mean spillovers from developed markets to emerging markets were not homogeneous across emerging market. In addition, the result suggests that own volatility spillovers are generally higher than cross volatility spillovers. John et al. (2010) investigate the global and regional volatility spillovers in emerging stock market by using weekly data and employing the multivariate GARCH-in-Mean. They found cross-market mean and volatility spillovers effect. Their results are supporting the presence of a global volatility spillovers effect in Asia and regional volatility spillovers effect in Latin America and

Middle East.

Otherwise, several studies have researched the volatility spillovers effect between oil prices and stock market. Arouri et al. (2011b) investigate the volatility spillovers effect between oil prices and European stock market. Using weekly data from January 01, 1998 to December 31, 2009 and the VAR-GARCH approach, they found the existence of volatility spillovers effect between oil prices and stock market. Also, the results provide evidence of volatility transmission between oil prices and sector stock return. Mali and Ewing (2009) have examined the volatility transmission between oil prices and equity sector returns using weekly data from January 01, 1992 to April 30, 2008. The results showed evidence of volatility spillovers effect between oil prices and some market sector. Malik and Hammoudeh (2007) analyses the volatility transmission between global oil market, Us and Golf equity markets (Saudi Arabia, Kuwait and Bahrain) using daily data from February 14, 1994 to December ,25 2001 and VAR-GARCH specification, they found volatility spillovers effect between US equity and global oil market. Also, the results provide evidence of volatility transmission from oil prices to the three Gulf equity markets. While, only Saudi Arabia has volatility spillovers effect on global oil market.

This research extends previous studies devoted to the interactive relationship between oil prices volatility shocks and stock market behavior including Malik and Hammoudeh (2007) for at least two main points. Firstly, we narrow our attention to the impact of oil prices volatility on Saudi stock market sectors using more recent dataset. Secondly, compared to Malik and Hammoudeh (2007) empirical approach, we investigated the causality in variance between oil prices, general indexes and sector indexes. The underlining idea is the check whether oil prices volatility shocks are transmitted to Saudi stock market sectors. We believe that the VAR-GARCH under dynamic conditional correlations (DCC) model will be useful to assess the dynamic linkage between the selected markets. More precise, the DCC approach allows us to perceive the time-path of the conditional correlations. In addition, it should be noted that our study is the first on the oil prices volatility effects on sector stock indexes in Saudi Arabia.

In this paper, we investigate the volatility transmission between oil prices, stock market and sector market indexes in Saudi Arabia using daily data. The sector used in the analysis are Banking, Telecom, Industrial and Cement. The multivariate GARCH model is used to estimate conditional volatility of returns series. Also, we employ the BEKK specification introduced Engle and Kroner (1995) in order to capture the shock and volatility spillovers effect between oil prices, stock market and sector indexes. We estimate the VAR-GARCH model to investigate the volatility transmission and conditional correlation cross effect between return series. Additionally, the conditional correlations are estimated by the CCC and DCC model in order to examine the dynamic interdependence between the selected markets. Finally, our results are exploited for optimal portfolio designs and risk management.

We deem out this research is distinguishable from the aforementioned studies of at least four points: Firstly, we use recent database covering the main Saudi stock market and four important sector indexes namely Banking, Telecom, Industrial and Cement. Secondly, compared to previous studies we use VAR-GARCH model including simultaneously crude oil, stock market and sector stock market. Thirdly, we expand our study by using CCC model and DCC model in order to investigate conditional correlations between the selected markets. Finally, we provide some financial implications for the optimal portfolio designs and risk management. More precisely, we estimated optimal portfolio weights as well as the Hedge ratio.

3 Methodology and Econometric Framework

Multivariate GARCH approach have been used to investigate the volatility transmission and conditional correlation between oil prices, stock market and sector stock indexes in Saudi Arabia. The multivariate GARCH specifications such BEKK, DCC and CCC are more significant than univariate GARCH model to capture the conditional volatility and volatility spillovers across return series.
In this study, we represent the first and second moments by tri-variate VAR(1)-GARCH(1,1) model[5]:

$$R_t = \alpha + \beta' R_{t-1} + \varepsilon_t \quad (1)$$
$$(1\varepsilon_t / I_{t-1} \sim N(0, H_t)$$

With R_t a 3×1 vector of oil prices returns, stock market returns and sector stock return, α a 3×1 vector of constant terms, β a 3×1vector of autoregressive parameters. ε_t is a 3×1 vector of residual terms $\varepsilon_t = D_t \mu_t$ and has a 3×3 conditional variance-covariance matrix $H_t . \mu_t = (\mu_{1t}, \mu_{2t}, \mu_{3t})'$ is a sequence of independently and identically distributed random vectors and $D_t = diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, h_{33,t}^{1/2}$ where $h_{11,t}, h_{22,t}, h_{33,t}$ are respectively the conditional variance of oil prices returns, stock market returns and sector stock return. The market information available at time $t - 1$ is represented by I_{t-1}. The conditional variance-covariance matrix is given by:

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix} \quad (2)$$

The multivariate GARCH-BEKK (Baba, Engle, Kraft and Kroner) parameterization proposed by Engle and Kroner (1995) guarantees positive semi-definiteness of the conditional variance-covariance matrix H_t . The specification shows that the variance-covariance matrix depends on the squares and cross products of residual terms ε_t and volatility. The conditional variance-covariance matrix takes the following form:

$$H_t = C'C + A'\varepsilon'_{t-1}\varepsilon_{t-1}A + G'H_{t-1}G \quad (3)$$

Where C is a 3×3 lower triangular matrix of constants, A and G are 3×3 matrices. The diagonal parameters of matrices A and G measures the effects of own past shocks and past volatility of return indexes on its conditional volatility. The off-diagonal elements in matrix A and G, a_{ij} and g_{ij} measures respectively the cross effects of shock spillovers and volatility spillovers between returns indexes.
The multivariate GARCH model can be estimated using maximum likelihood method. The log likelihood function of conditional distributions $L(\theta)$ for a sample of T observation and n return indexes is:

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta) \quad (4)$$

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[5]The AIC criterion is used to determine the optimal order of VAR-GARCH model.

$$\mathrm{l_t}(\theta) = -\log(2\pi) - \frac{1}{2}\log|\mathrm{H_t}(\theta)| - \frac{1}{2}\varepsilon'_t \mathrm{H_t^{-1}} \varepsilon_t \tag{5}$$

Where θ denotes the vector of unknown parameters. The parameters of VAR(1)-GARCH(1,1) model can be estimated by quasi maximum likelihood estimation (QMLE), which can be optimized by using the BFGS algorithm.

In order to investigate the conditional correlations between oil prices returns, stock market returns and sector stock return, we use the conditional constant correlation (CCC) model of Bollerslev (1990). The CCC specification shows that the conditional variance covariance matrix is given by:

$$Q_t = D_t \Gamma D_t \tag{6}$$

Where $D_t = diag(h_{11,t}^{1/2}, h_{22,t}^{1/2}, h_{33,t}^{1/2})$ and Γ is a 3×3 constant conditional correlation matrix of the unconditional shocks, $\Gamma = E(\mu_t^{'}\mu_t)$ where $\mu_t = (\mu_{1t}, \mu_{2t}, \mu_{3t})^{'}$. The conditional correlations are assumed to be constant over time. The conditional correlation matrix is defined as $\Gamma = D_t^{-1} Q_t D_t^{-1}$. The CCC model assumes that the conditional variance for each return follows a univariate GARCH process.

Moreover, the assumption that the conditional correlations are constant may seen unrealistic. Engle (2002) proposed a dynamic conditional correlation (DCC) model in order to make the conditional correlation matrix time dependent. The variance covariance matrix takes the following form:

$$Q_t = D_t \Gamma_t D_t \tag{7}$$

Where Γ_t is the dynamic conditional correlation matrix $\Gamma_t = \mathrm{D_t^{-1} Q_t D_t^{-1}}$. Where the symmetric positive definite matrix $\mathrm{Q_t}$ is given by:

$$Q_t = (1 - \theta_1 - \theta_2) Q_0 + \theta_1 \mu'_t \mu_t + \theta_2 Q_{t-1} \tag{8}$$

Where θ_1 and θ_2 are non-negative scalar parameters to capture the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation. μ_t is a sequence of independently and identically distributed random vectors. H_t is a 3×3 conditional variance covariance matrix and Q_0 is a 3×3 unconditional variance-covariance matrix of μ_t.

4 Data and Preliminary Analysis

To examine the conditional correlations and volatility spillovers between the return of oil prices, stock market and sector stock indexes in Saudi Arabia, we use daily data for oil prices, stock market and four Sector indexes of the real investment in the trading market, accounting for 65% of the transaction volume namely Banking, Telecom, Industrial and Cement. The sample cover the daily period from January 3, 2009 to March 21, 2012 (a total of 806 daily observations). The data are obtained from TADAWUL (Saudi Stock Exchange, www.tadawul.com.sa). The return indexes obtained as the first difference of the natural logarithm.

Table 1 presents some summary statistics for the corresponding return series. The highest daily returns are in oil prices (0.138%), industrial sector (0.085%) and cement sector (0.077%) while the highest volatility is in oil prices (1.9%) and industrial sector (1.5%) as measured by standard deviation. All return series, except banking sector and cement sector, are skewed to the left, while all returns series exhibit considerable excess kurtosis suggesting the presence of asymmetry. As a consequence, the Jarque-Bera statistics reject the null hypothesis of normal distribution. Furthermore, based on the Ljung-Box LB statistic of order 12, we can also reject the null hypothesis of white noise and assert that all series are serial correlated. The ARCH-LM test reveals that all returns exhibit conditional heteroskedasticity.

Table 1: Summary of descriptive statistics of return series

	Oil	Stock Market	Telecom	Banking	Industrial	Cement
Mean	13.8×10^{-4}	5.10×10^{-4}	$2.\times 10^{-4}$	2.3×10^{-4}	$8.\times 10^{-4}$	$7.\times 10^{-4}$
Std.Dev.	0.019	0.012	0.012	0.013	0.015	0.012
Skewness	-0.082	-0.688	-1.082	0.263	-0.712	0.153
Kurtosis	9.246	7.471	7.992	7.130	6.699	7.172
JB	2868.623*	1935.948*	2299.301*	1714.552*	1573.496	1728.516*
LB(12)	6.348*	25.010*	10.658*	39.108*	24.124*	14.536*
$LB^2(12)$	64.9778*	186.1578*	149.728*	203.605*	83.6865*	90.2557*
ARCH-LM	32.717*	58.113*	52.262*	53.413*	17.451*	12.333*
ADF	-17.721*	-15.468*	-15.958*	-14.872*	-16.103*	-14.678*

Notes: (*) denote the significant level at 1%, std.dev. (standard deviation), JB (Jarque-Bera) is the statistics test for normality test, LB (Ljung-Box) is the statistics test for serial correlation of order 12. ARCH-LM is the statistics test for conditional Heteroskedasticity of order 2. ADF is the statistics test for unit root.

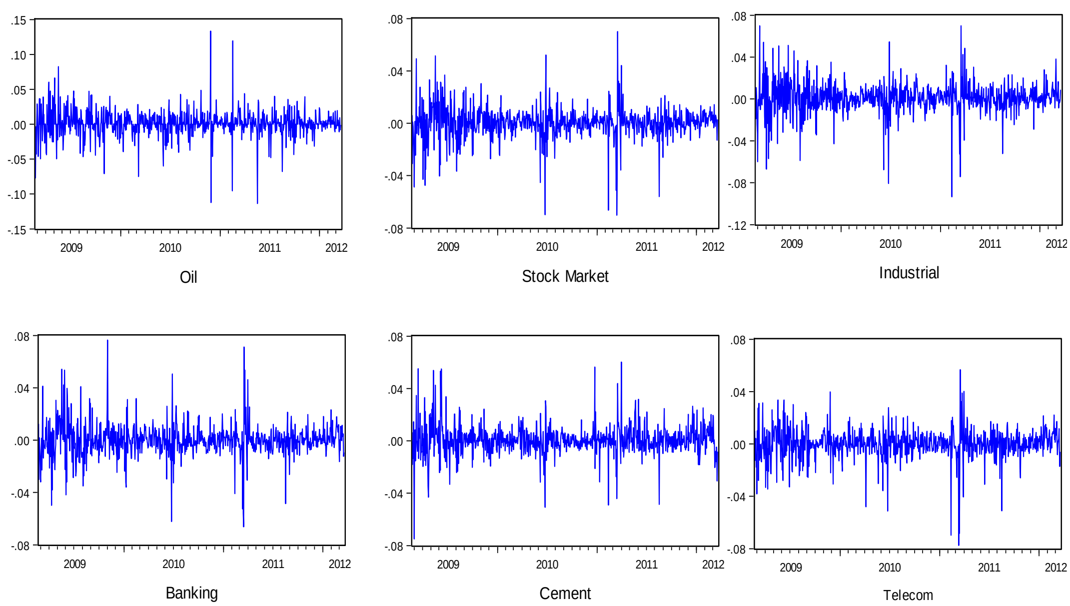

Figure 1: Daily return series

In same table, we present the results of the Augmented Dickey Fuller (ADF) unit root tests. The ADF tests reject the null hypothesis of a unit root for all series under consideration at the 1% significance level. As the result, we can conclude that all returns times series are stationary.
Figure 1 represents the daily returns series. All series are characterized by volatility clustering where large (small) changes tend to be followed by large (small) changes. This suggests the presence of ARCH effect.

5 Empirical Results and Discussions

We will discuss the empirical results to investigate the volatility transmission and conditional correlation between the oil prices return, stock market and sector stock returns in Saudi Arabia. We estimate the tri-variate VAR(1)-GARCH(1,1) model presented in section 3.

5.1 The Volatility Transmission

As the first step, we estimate a VAR model with one lags. The estimated results reported in table 2 show that the autoregressive parameter of oil prices return equations are statistically significant in all case, suggesting that the oil prices return depend on their first lags. The autoregressive parameter of stock returns equations are statistically significant in most cases. Concerning the sector return, the autoregressive parameter in mean equations are statistically significant for all sector except telecom sector. Thus suggesting some evidence of short-term predictability in sector indexes changes.
The estimate results of conditional variance equation (eq.(3)) show evidence of own ARCH and GARCH effect. The diagonal elements in matrix A capture the own ARCH effect, while the diagonal elements in matrix G measure the own GARCH effect. From the estimated results, we can conclude that the diagonal parameters are all statistically significant at the 1% level[6], implying the presence of ARCH effect and a strong GARCH(1,1) process driving conditional volatility of all return series.
Furthermore, we find that the own volatility presented by GARCH parameter (g_{ii}) are greater than the own past shocks presented by ARCH parameter (a_{ii}) for all cases, suggesting that own volatility are more important in predicting than past shocks. The large magnitudes of GARCH parameter suggest that own volatility largely affect their conditional variance.

[6]To save space, the estimated diagonal parameters c_{ij}, a_{ii} and g_{ii} are not reported in table 3 but available frum the authors upon request.

Table 2: Parameter estimates for mean equation

	Bank	Telecom	Industrial	Cement
c	0.00091	0.00089	0.00106***	0.0007
	(0.00062)	(0.0006)	(0.0006)	(0.001)
Oil	0.0858**	0.07186**	0.0821**	0.1161**
	(0.03741)	(0.0347)	(0.0328)	(0.051)
c	0.0006**	0.00071*	0.0006**	0.0004
	(0.00031)	(0.0003)	(0.0003)	(0.0005)
Stock	0.03532	0.0006**	0.07166**	0.0827
	(0.02659)	(0.00032)	(0.0291)	(0.0501)
c	0.00005	0.00062**	0.0011*	0.0006
	(0.0003)	(0.00030)	(0.0004)	(0.0004)
Sector	0.0676**	0.02967	0.0632**	0.0953***
	(0.02766)	(0.0264)	(0.04296)	(0.0532)

Notes: c is the constant terms in mean equations, (.) denote standard deviation. *, ** and *** indicate the rejection of null hypothesis at the 1%, 5% and 10% levels respectively.

The estimate results show that all sectors exhibit the highest sensitivity to the past own volatility except banking sector. In contrast, the banking sector has the highest shocks sensitivity, suggesting that the past news sensitivity is caused by the interconnection with global financial sector. The overall persistence of sector indexes volatility is highest in cement sector (1.117) and lowest for banking sector (0.574). Moreover, the results indicate that the oil prices returns has the same volatility behavior for all sector, except cement sector. While, the stock market returns has the highest sensitivity to the past own volatility (1.116).

The obtained results related the volatility transmission between oil prices, stock market and sector indexes are displayed in table 3. The off-diagonal element of matrix A and G capture the cross effect such as the shock spillovers and volatility spillovers among the return of oil prices, stock market and sector indexes.

From these results, we can perceive strong evidence of volatility transmission between stock market and sector indexes. In fact, the off-diagonal parameter a_{23} are statistically significant for banking sector and industrial sector suggesting that shock spillovers from stock market to these sectors. On the other hand, we reveal that all off-diagonal parameter g_{23} are significant suggesting the volatility spillovers from stock market to sector indexes. It indicates that the conditional variance of stock market affect the volatility of sector indexes. Additionally, all off-diagonal parameter a_{32} are not statistically significant except telecom sector. While, the off-diagonal parameter g_{32} are statistically significant only for banking sector and cement sector. These results point out a strong connection between stock market and sector stock returns. Hence, we note that the volatility of stock market has a positive effect on banking sector volatility and Telecom sector volatility and a negative effect on Industrial sector volatility and Cement sector volatility. Furthermore, the sector stock returns volatility has a negative effect on stock market volatility, except the cement sector volatility.

Table 3: Parameter Estimates of VAR(1)-GARCH(1,1) model

	Bank	Telecom	Industrial	Cement
a_{12}	-0.0489**	-0.0303*	-0.0338**	0.0027
g_{12}	-0.0216*	-0.0138	0.0164	-0.2247*
a_{21}	-0.3642	-0.4158*	-0.4130***	-0.3590
g_{21}	0.5832**	0.6613*	0.5045*	0.6272*
a_{13}	-0.0208	-0.0302	-0.0191**	-0.0198
g_{13}	-0.0893*	-0.0203**	-0.0236*	-0.1964*
a_{31}	-0.2970	-0.0142	-0.0675	0.1021
g_{31}	-0.1328	-0.3446	-0.1058	-0.2578
a_{23}	0.2690*	-0.0424	0.1755*	0.0490
g_{23}	0.3293*	0.0843***	-0.1028*	-0.2931*
a_{32}	-0.0890	0.0413	-0.0329***	-0.0116
g_{32}	-0.2172*	-0.0323	0.0740	0.3599*

Notes: The oil prices return is denoted 1, stock return is denoted 2 and sector stock returns is denoted 3. The full set of results is available from the authors upon request. Reject of null hypothesis at 1%, 5% and 10% is denoted by *,**,***.

The statistically significant of parameter a_{12}, a_{21}, g_{12} and g_{21} indicate volatility spillovers between oil prices and stock market returns. The estimated results provide evidence for volatility transmission between them. The off-diagonal parameter a_{12} are significant for all sectors except cement sector implying negative shock spillovers effect. However, the parameter a_{21} are significant for all sector, except banking sector suggesting a negative shock spillovers effect. For the volatility spillovers, the significance of the parameter g_{21} implies that the stock market volatility has a positive effect on oil prices volatility. While the oil prices volatility has a negative volatility spillovers effect on stock market volatility. The interdependence between oil prices and stock market may be explained by the major role that Saudi Arabia plays in the oil market. Our results are more consistent than Malik and Hammoudeh (2007) who found that the Saudi stock market is only indirectly affected by volatility from the oil prices.
From the reported results, we can depict the existence of unidirectional shock and volatility spillovers from oil prices to sector indexes. The result show that there is no cross spillovers from sector volatility to oil prices volatility. Also, we find that the oil prices volatility has a negative shock spillovers effect only for cement sector. In addition, the oil price has a negative volatility spillovers effect on all sectors volatility. This result supports the main conclusion of a volatility transmission from oil market to sector stock returns.

5.2 The Causality in Variance

Now we test the causality in variance between oil prices, stock market and sector indexes. The presence of causality in variance indicates the volatility spillovers effect between them and can be examined by testing the validity of restrictions: $a_{ij} = g_{ij} = 0, \forall i \neq j, i, j = 1,2,3$. The reject of the null hypothesis suggests the presence of causality in variance (volatility spillovers). In order to examine the causality in variance, we use the following Wald test:

$$W_{ald} = [R\hat{\theta}]' [RV(\hat{\theta})R'] [R\hat{\theta}] \quad (9)$$

Where R is the $q \times k$ matrix of restrictions, with q equal to the number of restrictions and k equal to the number of regressors. θ is a $k \times 1$ vector of the estimated parameter and $V(\hat{\theta})$ is the robust consistent estimator for the variance covariance matrix of the parameter estimates.

Table 4: Wald test statistics for no Causality in Variance

	Oil VS Sector		Oil VS Stock		Stock VS Sector	
	$a_{13}=g_{13}=0$	$a_{31}=g_{31}=0$	$a_{12}=g_{12}=0$	$a_{21}=g_{21}=0$	$a_{32}=g_{32}=0$	$a_{23}=g_{23}=0$
Bank	22.521*	2.715	62.056*	4.4.147	66.547*	27.603*
Telecom	5.356*	3.009	7.339*	24.388*	3.857	1.179
Industrial	5.776*	1.244	5.027**	8.821**	66.233*	5120.758*
Cement	5.207*	1.846	8.092**	3.142	166.428*	185.039*

Notes: The oil price return is denoted 1, stock return is denoted 2 and sector stock returns is denoted 3. The chi-squared critical values at 1%, 5% and 10% with 2 degree of freedom are respectively 9.210, 5.991 and 4.605. *, ** and *** indicate the rejection of null hypothesis at the 1%, 5% and 10% levels respectively.

The results reported in table 4 indicate the presence of causality in variance from oil prices to all sectors indexes. The null hypothesis is rejected for all sectors suggesting the unidirectional volatility spillovers from oil prices to sector indexes. While, there is no causality in variance from sector stock to oil prices. Also, our test rejects the null hypothesis of no causality in variance between oil prices and stock market in most case. Furthermore, we find evidence of causality in variance between stock market and sector stock indexes except telecom sector. This result confirms the strong interdependence between stock market and sector indexes.

5.3 The Conditional Correlations

To examine the conditional correlations between oil prices, stock market and sector stock indexes, we estimate the CCC model introduced by introduced (1990) and the DCC model introduced by Engle (2002). The estimated result is displayed in table 5.

The estimated results of the CCC model show that all conditional correlations between oil prices indexes, stock market and sector indexes are statistically significant at 1%. These results provide convincing evidence of comovement between them. Furthermore, we find high conditional correlations between stock market and sector indexes suggesting a strong interdependence between them. Also, the results make evidence of conditional correlation between oil prices and sector indexes. Indeed, these results are consistent with our previous finding related to volatility transmission between oil prices and sector indexes. It is worthy to note that, for each sector, the conditional correlations are below 0.4. As expected, the estimated results suggest the presence of conditional correlations between oil prices and stock market supporting the volatility linkages between them.

Table 5: Results estimates of conditional correlations

	Bank	Telecom	Industrial	Cement
	Constant conditional correlations: CCC Model			
R_{12}	0.364*	0.361*	0.360*	0.358*
R_{13}	0.300*	0.229*	0.305*	0.200*
R_{23}	0.901*	0.742*	0.853*	0.671*
$LogL$	7762.101	7441.874	7437.407	7376.437
AIC	-19.264	-18.467	-18.456	-18.305
	Dynamic conditional correlations: DCC Model			
θ_1	0.034*	0.062*	0.060*	0.063*
θ_2	0.950*	0.878*	0.896*	0.440**
$LogL$	7773.736	7467.057	7473.024	7382.645
AIC	-19.295	-18.532	-18.547	-18.323

Notes: R_{ij} the constant conditional correlations between return i and return j. θ_1 and θ_2 the DCC parameter in Eq.8. $LogL$ the log likelihood and AIC the Akaike Information Criteria. *, ** and *** indicate the rejection of null hypothesis at the 1%, 5% and 10% levels respectively.

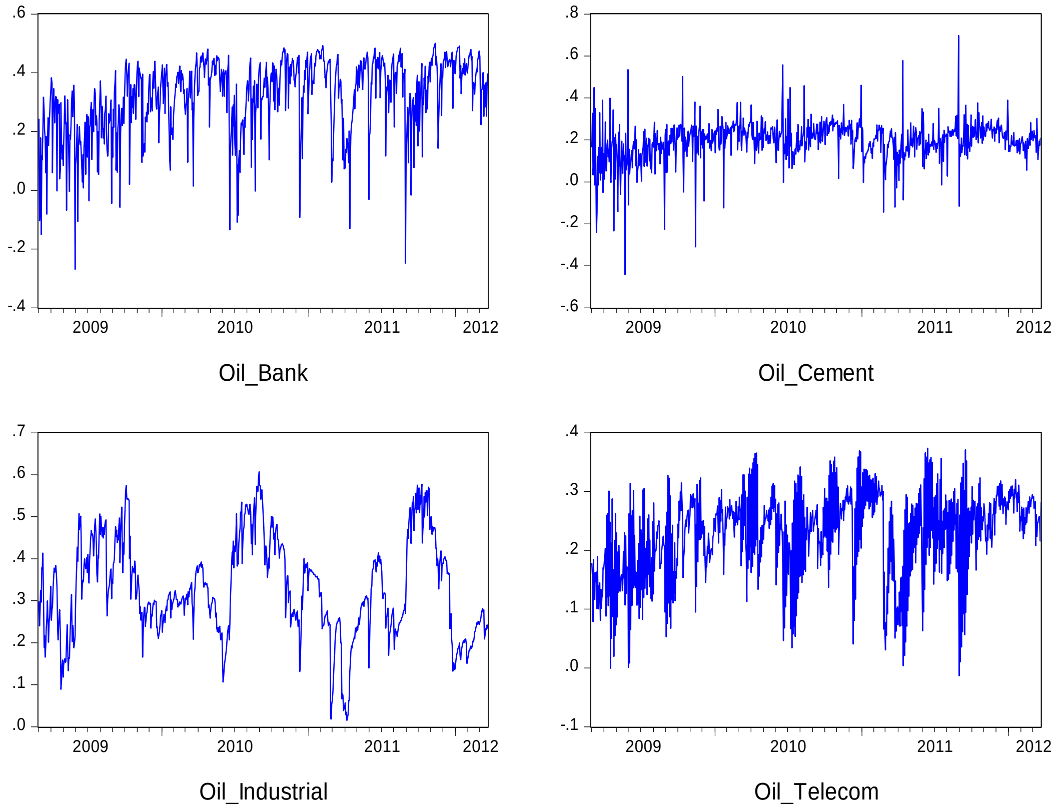

Figure 2: Dynamic conditional correlations

Concerning the dynamic conditional volatility, we find that all DCC parameters are statistically significant. These results support again the presence of conditional correlations between oil prices, stock market and sector indexes. The estimate of both $\hat{\theta}_1$, measures the impact of past shock on current conditional correlations, and $\hat{\theta}_2$, measures the impact of past dynamic conditional correlations are statistically significant. This indicates that the assumption of CCC is not supported empirically implying that the conditional correlations cannot be constant. Also, we find that $\hat{\theta}_1$ coefficient is low and close to zero and $\hat{\theta}_2$ coefficient are high and close de unity except for the cement sector suggesting that Q_t in eq.8 is close to Q_{t-1}. In addition, the time-varying conditional correlations between oil prices and sector stock indexes given in Figure 2 show significant variation in the conditional correlations over time.

5.4 Portfolio Management and Hedging Strategies

Our estimate results show significant volatility spillovers effect between oil prices and stock sector indexes suggesting some financial implication for the portfolio decision and risk management. More precisely, the estimated conditional volatility using multivariate GARCH model can be exploited to make portfolio optimal allocation decision. Following Kroner and Ng (1989), the risk minimizing portfolio of the two assets is given by:

$$w_{13,t} = \frac{h_{33,t} - h_{13,t}}{h_{11,t} - 2h_{13,t} + h_{33,t}} \qquad (10)$$

Where w_{13t} is the portfolio weight of the oil relative to the sector at time t and $h_{11,t}$ and $h_{33,t}$ are the conditional variance of oil prices and sector indexes respectively. $\mathrm{h}_{13,\mathrm{t}}$ is the conditional covariance between oil prices and sector indexes. Assuming a mean-variance utility function, the optimal portfolio holdings of the oil portfolio is given as: $0 \; if \; w_{13,t} < 0$, $w_{13,t} \; if \; \leq w_{13,t} \leq 1$ and $1 \; if \; w_{13,t} > 1$. The optimal weight of the sector in the considered portfolio is $1 - w_{13,t}$.

Table 6 reports the optimal weights (average value, $w_{13,t}$) for each sector. These results reveal that optimal weights vary from 19% for the bank sector to 31% for the industrial sector suggesting that the optimal holding of oil in \$100 of oil-bank sector portfolio is \$19, compared with \$81 for the bank sector. Our results suggest that investors in Saudi Arabia should own more bank sector's stocks than oil in the corresponding portfolio in order to minimize the risk without reducing the expected return. For the industrial sector, a portfolio weights of 31% implies that an investor willing to invest \$100 will get a minimum risk from a portfolio comprising of oil and industrial sector if the investor holds 31% in oil futures and 69% in industrial futures.

Table 6: Optimal Portfolio weights and hedge ratio

Portfolio	Weights $w_{13,t}$	hedge ratio $\beta_{13,t}$
Oil-Bank	0.19	0.45
Oil-Telecom	0.20	0.36
Oil-Industrial	0.31	0.43
Oil-Cement	0.20	0.37

Otherwise, we can determine the optimal hedge ratio for this portfolio by using the multivariate GARCH model results. Kroner and Sultan (1993) show that to minimize the risk of a portfolio an investor should short $\$\beta$ of the oil portfolio that is $\$1$ long in the stock sector. The hedge ratio is given by:

$$\beta_{13,t} = \frac{h_{13,t}}{h_{11,t}} \tag{11}$$

Where $h_{13,t}$ the conditional covariance between the oil prices and sector indexes and $h_{11,t}$ is the conditional variance of the oil prices. The average values hedge ratio are reported in table 6 and suggest that the bank sector has the highest hedge ratio (45%), while telecom sector has the lower hedge ratio (36%). The results show that $100 long in oil should be shorted by $45 of bank stocks, while $100 long in oil should be shorted by $36 of Telecom stocks.

Our findings show how our estimated results could be used by financial market participants for making portfolio allocation decisions and risk management.

6 Conclusions

This paper investigated the volatility transmission effects and conditional correlations between oil prices and Saudi stock market and sector stock indexes using VAR-BEKK specification for daily dataset covering the period from January 3, 2009 to March 21, 2012. The results pointed out revealed the existence of own past shock and volatility effect on all return under consideration. Moreover, we reveal a bidirectional volatility transmission between oil price and stock market. The results indicate that oil prices has a negative volatility spillovers effect on stock market, while the stock market has a negative shock effect and positive volatility effect on oil prices. Concerning the volatility transmission effect between oil prices and sector stock returns, our findings showed that only oil prices volatility affect sector stock returns. We conclude that an oil price has a negative volatility spillovers effect on sector stock returns. Otherwise, we found evidence of volatility transmission effect between stock market and sector stock returns, except telecom sector.

The estimated models under CCC and DCC show significant dynamic conditional correlations between all return. The conditional correlation between oil prices and stock market is significant and closed to 0.36. Also, the conditional correlation is significant and less than 0.3 between oil prices and sector stock returns. However, the results confirm the existence of high conditional correlations between stock market and sector stock return. In addition, the DCC model supports the main conclusion time-varying conditional correlations between all returns.

Our results may be useful for understanding how shock and volatility are transmitted between oil prices and Saudi stock market. Also, the results may offer insights to investors to know how the value of their portfolios will be affected by large variations observed in oil prices. We believe that our findings are crucial for market participants whose optimal portfolio's decisions and the risk management policy depend on the characteristics and the behavior over time of conditional volatility.

Finally, this study pave the way for several issues such as including structural breaks in volatility (volatility shift) related financial crisis that may affect the interactive relationship between market.

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