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Volatility Spillovers between World Oil Market and Sectors of BIST

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Abstract

Nowadays, enormous increase of production and service sectors leads to increase in demand for energy consumption. Therefore, energy and oil consumption in a variety of countries are considerably effected by energy and oil prices. International oil prices are crucial for both oil exporting countries and capital market investors as a means of volatility spillovers. This paper aims to analyze whether volatility spillovers exist between world oil market and several sector indices operating in Borsa Istanbul (BIST) 100 including energy, non-metal mineral products, and transportation using bivariate GARCH (1, 1) model. Estimation results suggest that except for non-metal mineral products sector, there are interactions between oil returns and the underlying sectors in terms of both shocks and conditional variance.

Keywords: volatility spillover, bivariate GARCH model, BIST, Turkey

1. Introduction

Oil price shocks have been induced for economic recessions, financial crisis in different industries, unemployment, depression of investment through uncertainty, high inflation, low equity and bond values, trade deficits and famine. Hamilton (1983) argued that except for one, all of U.S. recessions since World War II have been taken precedence of a dramatic increase in oil crude petroleum price, typically with a lag of almost three-fourths of a year (Lizardo & Mollick, 2010). Furthermore, in the globalized era, along with the rapid increase in the information and the communication technologies, economic interaction among developed and emerging countries has been inevitable. Therefore, moving markets including oil has come into prominence as a crisis and risk transmission channel in the international arena. No doubt, this subject is more important for oil exporting countries. To this end, the crucial role of volatility spillovers revisit for investors operating in the capital markets. A recent study (Basher & Sadorsky, 2006) noticed the association between oil demand of developed and emerging countries and growth on industrial production which explicitly identifies this vital impact on modern economies. According to BP Statistical Review of World Energy (2012) data, Turkey consumes average 0.8% of the world oil annually between 2001 and 2011. During the same period; the annual oil consumption of Japan, China, India, the U.S. and the Russian Federation refers to 6%, 8.6%, 3.3%, 23.5%, and 3.2%, respectively. Statistically, the U.S. consumes nearly one-quarter of oil in the world and it is more affected by the volatility spillovers of oil prices.

Over the past decade, there is a rapidly growing literature which addresses the linkages among oil prices, stock market indices and volatility spillovers using a variety of econometric estimation methods. A number of studies focused on the comparison between the Asian, namely, Japan, Hong Kong, Saudi Arabia, China, or ASEAN-5 countries and the U.S. and the U.K. stock markets and generally found evidence of volatility spillover linkages especially in the post-crisis periods (Kim, 2005; In, 2007; Alsubaie & Najand, 2009; Moon & Yu, 2010; Arifin & Syahruddin, 2011; Gebka, 2012; Haixia & Shiping, 2013; Zheng & Zuo, 2013). There is also overwhelming evidence corroborating the significance of volatility spillovers of European stock markets in the light of oil prices (Giannellis, Kanas, & Papadopoulos, 2010; Arouri, Jouini, & Nguyen, 2011, 2012; Antonakakis, 2012; Tamakoshi & Hamori, 2013; Reboredo, 2014). More comprehensive studies carried out extensive volatility spillover comparisons among different countries (Serra, 2011; Korkmaz, Çevik, & Atukuren, 2012; Krause &

Tse, 2013; Nazlioglu, Erdem, & Soytas, 2013; Salisu & Mobolaji, 2013; Valadkhani, Harvie, & Karunanayake, 2013). Some recent studies examined the behavior of the U.S. stock markets and sector indices depending on oil prices and found evidence of significant transmission of volatility and shocks between oil prices and relevant sectors (Hammoudeh, Li, & Jeon, 2003; Malik & Ewing, 2009; Du, Yu, & Hayes, 2011; Diebold & Yilmaz, 2012; Ji & Fan, 2012; Trujillo-Barrera, Mallory, & Garcia, 2012; Liu, Ji, & Fan, 2013). Most recent studies successfully established the comparison of econometric methodology in terms of their accuracy during the measurement of volatility spillovers, asymmetric effects across and within the oil and the other selected markets (Chang, McAleer, & Tansuchat, 2010; Sadorsky, 2012; Wang & Wu, 2012; Ewing & Malik, 2013). As a result, GARCH models take their respectable place through their usefulness and estimation accuracy.

The impact of the oil prices on the Turkish stock exchange index and several sub-indices (Eryiğit, 2009; Soytas & Oran, 2011; Toraman, Başarır, & Bayramoğlu, 2011) is also prominent in the existing literature. The main objective of the present paper is to explore the volatility spillovers between world oil prices and BIST 100, energy, transportation and non-metal mineral products sectors using GARCH (1, 1) model. The rest of the paper is organized as follows. Section 2 gives information about the data set and the method being used. Section 3 introduces the estimation results and discusses them in terms of implications for policy making.

2. Data Set and Methodology

2.1 Data Set

This paper utilized the data set including the daily close of the session values of BIST National Market-100 index, electricity, transportation, non-metal mineral products sub-sector indices and world oil prices between January 2, 2002 and December 31, 2012. As all the time series have a unit root, daily returns formula with respect to the existing literature can be written as

$$R_t = \log(P_t) - \log(P_{t-1}) \tag{1}$$

where P_t denotes the price index. Table 1 presents the descriptive statistics of the underlying data. As shown in Table 2, all sectors have positive average return. Moreover, since there is an ARCH effect in the time series, the application of the GARCH model is approved.

Table 1. Descriptive statistics

	Oil Price	BIST 100	Electricity	Non-metal mineral products	Transportation
Mean	0.08386	0.08193	0.03408	0.0685	0.0897
Standard Deviation	2.1963	2.4129	2.5836	2.0256	2.6529
Skewness	0.21979	-0.0886	-0.1504	-0.3759	-0.0682
Kurtosis	8.2440	7.4626	8.031657	9.4615	6.3022
Shapiro-Wilk statistic	0.9600	0.9521	0.9382	0.9291	0.958
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH effect	39.350	133.0630	165.4350	137.738	92.0570
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of observations	2,853	2,853	2,853	2,853	2,853

p values are presented in parentheses

Figure 1 illustrates the prior information about the daily returns and volatility spillovers, where clustering phenomenon was observed in parallel with the existing literature. In addition, high kurtosis values of variables in Table 1 also ensure the presence of clustering phenomenon for the underlying time series. Therefore, it can be suggested that time series have a conditional variance.

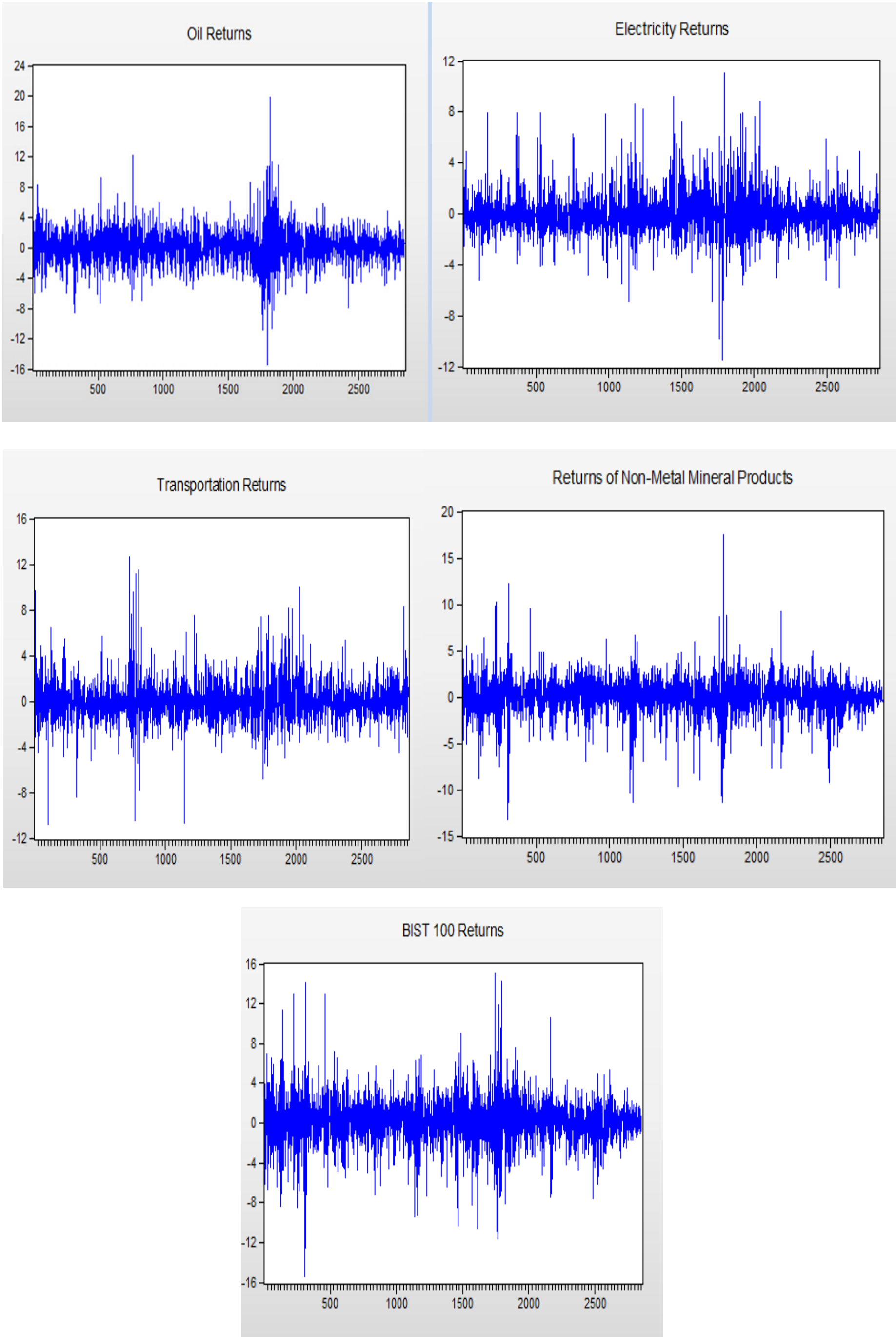

Figure 1. Daily oil returns and BIST 100, electricity, transportation, and non-metal mineral products indices

2.2 Bivariate GARCH (1, 1) Model

Bollerslev, Engle and Wooldridge (1988) extended the bivariate ARCH/GARCH models and conditional variance is defined as

$$vech(H_t) = A + \sum_{i=1}^{p} B_i vech(H_{t-i}) + \sum_{j=1}^{q} C_j vech(\varepsilon_t - j\varepsilon_t' - j) \qquad (2)$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, H_t)$$

where *vech(.)* refers to the column stacking operator of the lower portion of a symmetric matrix and also,

N: Number of observations

A: *(1/2)N(N+1)* dimensional vector of constants;

B_i: i=1,2,...,p and *(1/2)N(N+1)*(1/2)N(N+1)* dimensional constants matrix;

C_j: j=1,2,…q and *(1/2)N(N+1)*(1/2)N(N+1)* dimensional constants matrix.

Furthermore, a simple two-equation GARCH (1, 1) *vec* model without exogenous influences can be illustrated as follows (Engle & Kroner, 1995):

$$h_t = \begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{1,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon^2_{2,t-1} \end{bmatrix} \tag{3}$$

For a time period *t*, the log-likelihood function can be expressed

$$\ln l_t(\theta) = -\frac{N}{2}\ln 2\pi - \frac{1}{2}\ln\left|H_t(\theta)\right| - \frac{1}{2}\varepsilon_t(\theta)' H_t^{-1}(\theta)\varepsilon_t(\theta) \tag{4}$$

where θ denotes the vector of all combined parameters defined in the model. Here, $\frac{1}{2}N(N+1)+\left[\frac{1}{2}N(N+1)\right]^2(p\times q)$ parameters are estimated for only variances and covariances. If the covariances ($h_{jk,t}$) are only defined by their own past values $\left(\varepsilon_{j,t}\varepsilon_{k,t}\right)$, then the number of parameters to be estimated will dramatically decrease. To this end, the diagonality is imposed on the matrices (Bollerslev, Engle, & Wooldridge, 1988). The relevant variance-covariance equations $\left(h_t\right)$ are defined as the following (Engle & Kroner, 1995):

$$h_t = \begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} + \begin{bmatrix} c_{11} & 0 & 0 \\ 0 & c_{22} & 0 \\ 0 & 0 & c_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{1,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon^2_{2,t-1} \end{bmatrix} \tag{5}$$

or

$$\begin{aligned} h_{11,t} &= a_1 + b_{11}h_{11,t-1} + c_{11}\varepsilon^2_{1,t-1} \\ h_{12,t} &= a_2 + b_{22}h_{12,t-1} + c_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ h_{22,t} &= a_3 + b_{33}h_{22,t-1} + c_{33}\varepsilon^2_{22,t-1} \end{aligned} \tag{6}$$

In general, the number of parameters to be estimated of an *N*-variable *vec* model for each B_i and C_j matrices are $((1/2)N(N+1))^2$, and (1/2)*N*(*N*+1) for diagonality. So, the total number of parameters to be estimated for a bivariate *vec* model as shown in Equation (5) and (6) will be twenty-two and nine for diagonality.

3. Results and Discussion

This paper investigates the volatility spillovers between oil market and four sectors using bivariate GARCH (1, 1) model. The relationship between oil returns and the four sectors in terms of average returns can be defined as

$$R_{1,t} = \varphi_{10} + \varphi_{11}R_{1,t-1} + \mu_{1,t}; R_{2,t} = \varphi_{20} + \varphi_{22}R_{2,t-1} + \mu_{2,t} \tag*{(7) \& (8)}$$

where $R_{1,t}$ and $R_{2,t}$ denote oil returns and the returns of other sectors, respectively. Additionally, in Equation (7) and (8), *t*-1 and *u* indicate the delay and the residual, respectively. The bivariate covariance matrix can be defined as the following:

$$\Sigma_t = \begin{pmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{pmatrix} \tag{9}$$

In this context, a *vech* operator enables to transform this matrix into a single column matrix, and the final vectorial form can be described

$$vech(\Sigma_t) = \begin{pmatrix} \sigma^2_{1,t} \\ \sigma_{21,t} \\ \sigma^2_{2,t} \end{pmatrix} \tag{10}$$

where $\sigma^2_{i,t} = \sigma_{ii,t}, i = 1,2$.

Finally, the variance-covariance structure in the underlying bivariate GARCH (1, 1) model can be written as the following:

$$\sigma^2_{1,t} = \omega_1 + \alpha_{11}\mu^2_{1,t-1} + \beta_{11}\sigma^2_{1,t-1} \tag{11}$$

$$\sigma^2_{2,\text{t}} = \omega_2 + \alpha_{22}\mu^2_{2,t-1} + \beta_{22}\sigma^2_{2,t-1} \tag{12}$$

$$\sigma_{12,t} = \omega_{12} + \alpha_{12}\mu_{1,t-1}\mu_{2,t-1} + \beta_{12}\sigma_{12,t-1} \tag{13}$$

Under the assumption that u_t has a conditional normal distribution, it can be estimated by the maximum likelihood method. Then, the log-likelihood will be

$$L(\theta) = -\frac{k}{2}\log(2\pi) - \frac{1}{2}\log\left(\left|\sum_t\right|\right) - \frac{1}{2}\mu'_t \sum_t^{-1} \mu_t \tag{14}$$

where θ is assumed to combine all estimated parameters, $\text{u}_t = Y_t - \mu_t$.

Table 2 represents the interaction results between oil returns and the other four sectors. The convenient average and variance diagonal GARCH (1, 1) equations with respect to the corresponding parameters in Table 2, can be written as the following:

Average Equations (Oil-BIST 100):

$$\begin{aligned} R_{oil,t} &= \underbrace{0.1246}_{t=3.4795} - \underbrace{0.0014}_{t=-0.0717} R_{oil,t-1} + \varepsilon_{oil,t} \\ R_{BIST,t} &= \underbrace{0.1686}_{t=4.7367} + \underbrace{0.0897}_{t=4.5926} R_{BIST,t-1} + \varepsilon_{BIST,t} \end{aligned} \tag{15}$$

Variance Equations (Oil-BIST 100):

$$\begin{aligned} h_{oil,t} &= \underbrace{0.0418}_{t=3.8964} + \underbrace{0.9509}_{t=152.7164} h_{oil,t-1} + \underbrace{0.0393}_{t=7.9370} \varepsilon^2{}_{oil,t-1} \\ h_{oil-BIST,t} &= \underbrace{0.7289}_{t=4.533} - \underbrace{0.4048}_{t=-1.6769} h_{oil-BIST,t-1} + \underbrace{0.0524}_{t=3.4216} \varepsilon_{oil,t-1}\varepsilon_{BIST,t-1} \\ h_{BIST,t} &= \underbrace{0.1767}_{t=6.4587} + \underbrace{0.8476}_{t=83.82} h_{BIST,t-1} + \underbrace{0.1256}_{t=13.7477} \varepsilon^2{}_{BIST,t-1} \end{aligned} \tag{16}$$

Average Equations (Oil-Electricity):

$$\begin{aligned} R_{oil,t} &= \underbrace{0.1187}_{t=3.3354} - \underbrace{0.0108}_{t=-0.5507} R_{oil,t-1} + \varepsilon_{oil,t} \\ R_{electricity,t} &= \underbrace{0.0707}_{t=1.9788} + \underbrace{0.0922}_{t=4.6719} R_{electricity,t-1} + \varepsilon_{electricity,t} \end{aligned} \tag{17}$$

Variance Equations (Oil-Electricity):

$$\begin{aligned} h_{oil,t} &= \underbrace{0.0369}_{t=3.8302} + \underbrace{0.9548}_{t=174.84} h_{oil,t-1} + \underbrace{0.0364}_{t=8.3228} \varepsilon^2{}_{oil,t-1} \\ h_{oil-electricity,t} &= \underbrace{0.0670}_{t=3.6320} + \underbrace{0.8197}_{t=28.3136} h_{oil-electricity,t-1} + \underbrace{0.0622}_{t=5.8494} \varepsilon_{oil,t-1}\varepsilon_{electricity,t-1} \\ h_{electricity,t} &= \underbrace{0.4605}_{t=11.16} + \underbrace{0.7520}_{t=52.14} h_{electricity,t-1} + \underbrace{0.1890}_{t=14.89} \varepsilon^2{}_{electricity,t-1} \end{aligned} \tag{18}$$

Average Equations (Oil-Non-Metal Mineral Products):

$$\begin{aligned} R_{oil,t} &= \underbrace{0.1147}_{t=3.1992} - \underbrace{0.0015}_{t=-0.0719} R_{oil,t-1} + \varepsilon_{oil,t} \\ R_{non-metal,t} &= \underbrace{0.1421}_{t=4.7319} + \underbrace{0.1175}_{t=6.1021} R_{non-metal,t-1} + \varepsilon_{non-metal,t} \end{aligned} \tag{19}$$

Variance Equations (Oil-Non-Metal Mineral Products):

$$\begin{aligned} h_{oil,t} &= \underbrace{0.0378}_{t=3.6146} + \underbrace{0.9521}_{t=154.49} h_{oil,t-1} + \underbrace{0.0392}_{t=7.86} \varepsilon^2{}_{oil,t-1} \\ h_{oil-non-metal,t} &= \underbrace{-0.0332}_{t=-0.6896} + \underbrace{0.4460}_{t=0.7822} h_{oil-non-metal,t-1} + \underbrace{0.0164}_{t=0.9228} \varepsilon_{oil,t-1}\varepsilon_{non-metal,t-1} \\ h_{non-metal,t} &= \underbrace{0.2010}_{t=11.127} + \underbrace{0.7910}_{t=94.05} h_{non-metal,t-1} + \underbrace{0.1692}_{t=17.57} \varepsilon^2{}_{non-metal,t-1} \end{aligned} \tag{20}$$

Average Equations (Oil-Transportation):

$$\begin{aligned} R_{oil,t} &= \underbrace{0.1182}_{t=3.2950} - \underbrace{0.0049}_{t=-0.2484} R_{oil,t-1} + \varepsilon_{oil,t} \\ R_{transportation,t} &= \underbrace{0.1105}_{t=2.4860} + \underbrace{0.0952}_{t=5.0762} R_{transportation,t-1} + \varepsilon_{transportation,t} \end{aligned} \tag{21}$$

Variance Equations (Oil-Transportation):

$$\begin{aligned} h_{oil,t} &= \underbrace{0.0384}_{t=3.7681} + \underbrace{0.9521}_{t=161.41} h_{oil,t-1} + \underbrace{0.0388}_{t=8.14} \varepsilon^2{}_{oil,t-1} \\ h_{oil-transportation,t} &= \underbrace{0.0676}_{t=3.0374} + \underbrace{0.7623}_{t=22.08} h_{oil-transportation,t-1} + \underbrace{0.0520}_{t=5.55} \varepsilon_{oil,t-1}\varepsilon_{transportation,t-1} \\ h_{transportation,t} &= \underbrace{0.2612}_{t=7.58} + \underbrace{0.8743}_{t=116.06} h_{transportation,t-1} + \underbrace{0.0902}_{t=13.97} \varepsilon^2{}_{transportation,t-1} \end{aligned} \tag{22}$$

For all four models being fitted, present returns of every sector were significantly affected by their own past returns. Furthermore, the relevant conditional variances were also affected by both their own past shocks and past conditional variances. In this manner, it can be suggested that volatility spillover of oil prices would play an important role on determining the future oil prices. Particularly, this situation depends on the degree of possible future shocks and volatility. Therefore, future behavior of volatility of variance will inevitably shaped by the oil production or demand. This is also valid for BIST100 and the other three sub-sectors, where their conditional variances are effected by both their own shocks and conditional variances. This interaction means that present returns may be affected by past shocks and variance volatility.

Table 2. Bivariate GARCH (1, 1) model estimation results between oil returns and BIST100, electricity, transportation, and non-metal mineral products sectors

Variable	**Oil-BIST 100 Index**		**Oil-Electricity**		**Oil-Non-metal mineral products**		**Oil-Transportation**	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
φ_{10}	0.1246*** (0.0358)	3.4795	0.1187*** (0.0356)	3.3354	0.1147*** (0.0359)	3.1992	0.1182*** (0.0359)	3.2950
φ_{11}	-0.0014 (0.0197)	-0.0717	-0.0108 (0.0196)	-0.5507	-0.0015 (0.0203)	-0.0719	-0.0049 (0.0198)	-0.2484
φ_{20}	0.1686*** (0.0356)	4.7367	0.0707** (0.0357)	1.9788	0.1421*** (0.0300)	4.7319	0.1105*** (0.0445)	2.4860
φ_{22}	0.0897***	4.5926	0.0922***	4.6719	0.1175***	6.1021	0.0952***	5.0762

Variable	Oil-BIST 100 Index		Oil-Electricity		Oil-Non-metal mineral products		Oil-Transportation	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
	(0.0195)		(0.0197)		(0.0193)		(0.0188)	
ω_1	0.0418*** (0.0107)	3.8964	0.0369*** (0.0096)	3.8302	0.0378*** (0.0105)	3.6146	0.0384*** (0.0102)	3.7681
α_{11}	0.0393*** (0.0050)	7.9370	0.0364*** (0.0044)	8.3228	0.0392*** (0.0050)	7.8671	0.0388*** (0.0048)	8.1398
β_{11}	0.9509*** (0.0062)	152.7164	0.9548*** (0.0055)	174.8402	0.9521*** (0.0062)	154.4999	0.9521*** (0.0059)	161.4134
ω_2	0.1767*** (0.0274)	6.4587	0.4605*** (0.0413)	11.1584	0.2010*** (0.0181)	11.1269	0.2612*** (0.0345)	7.5832
α_{22}	0.1256*** (0.0091)	13.7477	0.1890*** (0.0127)	14.8945	0.1692*** (0.0096)	17.5755	0.0902*** (0.0065)	13.9751
β_{22}	0.8476*** (0.0101)	83.8286	0.7520*** (0.0144)	52.1423	0.7910*** (0.0084)	94.0553	0.8743*** (0.0075)	116.0636
ω_{12}	0.7289*** (0.1608)	4.5339	0.0670*** (0.0184)	3.6320	-0.0332 (0.0481)	-0.6896	0.0676*** (0.0222)	3.0374
α_{12}	0.0524*** (0.0153)	3.4216	0.0622*** (0.0106)	5.8494	0.0164 (0.0178)	0.9228	0.0520*** (0.0093)	5.5568
β_{12}	-0.4048* (0.2414)	-1.6769	0.8197*** (0.0289)	28.3136	0.4460 (0.5701)	0.7822	0.7623*** (0.0345)	22.0841
LogL	-12262.99317867		-12443.71267470		-11775.61684958		-12671.13843135	

Standard deviations are shown in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Another important evidence is the significant joint conditional shocks and volatility between oil returns and electricity and transportation sectors, although no significant interaction was determined between oil returns and returns of non-metal mineral products. However, there was an interaction between oil returns and BIST100, but relatively weak interaction was observed in terms of volatility. It can be noticed that all sectors including oil returns were positively affected by their shocks and their conditional variances, which demonstrates the non-negativity of variances and a positive change will reflect the present the conditional variance in the same way. Although negative interaction was also observed, conditional variance shocks of mutual interactions and the corresponding changes on conditional covariances generally positively reflected the present covariance of returns. The analysis results may provide information for current investors to minimize their portfolio risks with respect to these interactions between oil returns and the underlying sectors.

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