

## **The impact of oil prices on sectoral returns: an empirical analysis from Borsa Istanbul**

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**Abstract.** *Oil prices affecting production costs, inflation rates and therefore economic growth have a direct impact on stock market returns. In the last two decades sharp increases in oil prices led way to stock market collapses which were transmitted to the global economy as downturns. This paper examines the relationship between crude oil prices and sectoral returns of 18 sub-indices from Borsa Istanbul. We use monthly data for the period between January 2002 and April 2013. We apply multivariate time series analysis by conducting VAR (Vector Auto-Regression) and VECM (Vector Error Correction Model) methodology to explore the short-run and the long-run dynamics for the series under investigation. We also employ impulse response and Granger causality methods to investigate the structural relationship between the variables. We figure out a long-run equilibrium relation and a uni-directional causality from oil prices to chemical-petroleum-plastic sub-index as oil prices directly affect the revenues of the companies operating in this sector. For the other sub-indices the empirical results suggest no long-run equilibrium relation.*

**Keywords:** sector indices; vector autoregression; vector error correction; impulse-responses; forecast error variance decompositions.

**JEL Classification:** C32; G10.

**REL Classification:** 15F.

## 1. Introduction

The world has experienced extant financial crises for the last two decades, namely the Mexican crisis (1994), the Asian crisis (1998), the Russian crisis (1998), the Brazilian crisis (1999), the Argentine crisis (2002), the US subprime crisis (2008) and the Greek crisis (2010) which diverted the stock markets to excessive volatility and to turmoil. Stock markets are of significant importance in any economy as a medium through which capital allocation to real economy is enhanced fostering economic growth. Stock markets also provide a mechanism to increase efficiency through reallocation of funds from the ones with weak performance to the more profitable ones. The discounted cash flow approach in stock pricing suggest that future expected corporate earnings determine the stock prices, which are directly linked to economic activities.

Oil prices affecting production costs, inflation rates and therefore economic growth have a direct impact on stock market returns. Huang et al. (1996) argue that oil prices, acting as a major determinant of production costs, affect firm profitability, hence dividend payments, and stock prices. In a microeconomic view, rising oil prices negatively impacts earnings of firms which use oil directly or indirectly in the production process. From the macroeconomic perspective, increasing oil prices brings inflationary pressures and central banks increase interest rates to control the inflation. Rising interest rates leads to stock price decreases as the interest rates have direct effects on the discount rates in the equity pricing formulation. Many researchers evidence significant and profound impact of oil prices on stock returns; however at varying magnitudes between different industries (Hamilton, 2003, Lee, Ni, 2002, Davis, Haltiwanger, 2001).

Hamilton (1983), documents that sharp rises in oil prices cause worldwide recessions and stock market collapses. The last two decades have witnessed unprecedented swings in the price of oil. The fluctuations in oil prices are the results of the global demand shocks, the demand growth of China and India and the recession in the US and European economies due to the sub-prime mortgage crises; or the supply shocks mainly stemming from the US invasion of Iraq and the output decisions of OPEC countries.

There is a vast literature amplifying the asymmetric and adverse effects of oil price shocks on the stock markets, distinguishing between the effects of demand-side shocks and supply-side shocks. A demand-side shock is eventuated by an increasing demand for oil in the world in general, like the one in 2008, which arose from the growing demand of China. A wealth transfer from the oil-importing countries to oil-exporting countries eventually slows down demand and attenuates economic activity in oil-importing countries which also deteriorates the cash flows to oil-exporting countries. A supply-side shock results from major

supply decisions of oil producing countries, which are highly affected by political actions. The US invasion of Iraq in 2001 induced a supply-side shock where rising oil prices reduces the availability of a key input, aggrandizing uncertainty and distress (Sadorsky, 1999, Brown et al., 2002, Arouri, 2011, Park, 2007, Scholtens, Wang, 2008).

Although there is a vast body of literature implying that oil price rises adversely affect stock prices, some studies argue that oil prices have no significant impact on stock prices or the effect may even be positive. In line with this school of thought, Al-Fayomi (2009) examine the impacts of oil prices on stock returns in Turkey, Tunisia and Jordan, which are all net oil-importing countries and find that oil price changes have no significant effect on stock returns in these countries. Moreover, some studies point out that oil price hikes are seen as signals of stronger business performance and are associated with booming economy, as the rising global demand stimulates global economic activity through increased demand for resources such as labor. Rising demand for labor brings higher wages and more spending which contributes to the growth of overall economy. Thus an increase in oil prices along with economic growth has a positive effect on stock returns (Yurtsever, Zahor, 2007, Gogineni, 2010). Narayan and Narayan (2010) also argue that oil prices have a positive and statistically significant effect on stock prices in Vietnam.

Different time spans included in various studies provide different repercussions. Welch and Goyal (2008) assert that positive predictability results may depend on samples that include the 1974 oil shock resulting from the output decisions of OPEC countries. Jones and Kaul (1996), Sadorsky (1999) and Park and Ratti (2008) provide evidence of a negative relationship. Fan and Jahan-Parvar (2012) distinguish between the first and the second order impacts of oil price fluctuations on stock index returns. According to the authors, fluctuations in oil prices as a direct factor of production have a first-order impact on the profitability of various sectors, furthermore, they argue that because of the predictive power of oil prices on GDP, oil price variations have second or higher order impact on the cash flows to all businesses.

Other than different stock markets, different industries should react distinctively, whether oil is used as an input or it is the output of a particular industry. The level of the competition and demand elasticity arbitrate the degree of transmitting rising oil prices to end customers, which in the end determine the cash flows to the industries. Although oil price shocks led to recessions in industrialized economies during the 1970s, “The Great Moderation”, a phenomenon which argues that oil price shocks only have a limited effect on macro-economic indicators, finds support from many researchers. Jimenez-Rodriguez and Sanchez (2005),

Blanchard and Gali (2007), Kilian (2008), Kapetanios and Tzavalis (2010), Nakov and Pescatori (2010), Gomez-Loscos et al. (2011) all evidence the above phenomenon after 1980s. International Energy Agency (2006) asserts that firms are more prone to absorb higher input costs in production without increasing their output prices as the result of increased productivity and investments in renewable energy sources. Furthermore, due to the contemporary conditions in the labour markets, wage flexibility helps to minimize the effects of oil price shocks as suggested by Nordhaus (2007). Thus growing literature in neoclassical theory finds out minor or no effect of oil price shocks on stock markets, especially after 1980's (Hamilton, 1983, Bernanke, Gertner, Watson, 1997, Blanchard, Gali 2007, Lescaroux, Mignon, 2008).

This paper aims to investigate the relation between oil and BIST (Borsa Istanbul) sub-index returns. Previous studies either relate returns or volatilities of aggregate or sectoral market indices in developed economies to oil return shocks, while our effort is in line with these previous studies, by analysing the relationship between oil price shocks and the Borsa Istanbul industry returns by using a VAR (Vector Autoregression) and VEC (Vector Error Correction) models. We use monthly data for 18 industries classified by BIST classification system between the period January 2002 and April 2013. We probe industry responses to oil price shocks by impulse response functions and variance decomposition analyses.

This study contributes to the literature by an extensive analysis of the relationship between oil price shocks and Turkish sectoral indices, with 18 sub-indices under investigation. Previous literature concentrates on developed economies while our concentration is on an emerging market of an oil-importing country. Furthermore, Turkey, as an emerging market, has suffered from high inflation and trade deficits almost for the last four decades and oil price shocks surmount the inflation and interest rates in the Turkish economy pressurizing political authorities to come up with rigid fiscal policies to remedy.

The remainder of this paper is organized as follows: Part II describes the data set and the methodology; Part III presents the empirical results and discusses the findings; Part IV concludes the paper.

## **2. Data and methodology**

### **2.1. Data**

Our data consists of Brent oil prices and 18 selected sub-sector indices from Borsa Istanbul (BIST Banks (XBANK), BIST Electricity (XELKT), BIST Leasing-Factoring (XFINK), BIST Food&Beverage (XGIDA), BIST Real Estate

Investment Trusts (XGMYO), BIST Holding&Investment (XHOLD), BIST Wood, Paper, Printing (XKAGT), BIST Chemical, Petroleum, Plastic (XKMYA), BIST Basic Metal (XMANA), BIST Metal Products , Machinery (XMESY), BIST Wholesale and Retail Trade (XTCRT), BIST Textile, Leather (XTEKS), BIST Tourism (XTRZM), BIST 100 (XU100), BIST Services (XUHIZ), BIST Transportation (XULAS), BIST Industrials (XUSIN) and BIST Technology (XUTEK)). The first data set used for VAR and VEC models is monthly between the period January 2002 and April 2013, hence we have 136 observations for each of the variables. Brent oil data is from International Energy Agency (IAE) and BIST sub-sector index data are from Borsa Istanbul. Sub-sector indices and Brent oil prices that are cointegrated are in levels. The other series are converted to log returns defined as  $R_t = \log(P_t/P_{t-1})$ . Sub-sector indices are value weighted portfolios consisting numerous individual companies, thus each sub-sector index is an aggregate measure.

## 2.2. Methodology

We employ a Vector Autoregressive (VAR) model which was popularized in time series econometrics by Sims (1980) and seen as a natural extension of univariate autoregressive models (Brooks, 2008). All the variables are treated as endogenous variables in the system. Hence the identification problem is avoided.

The mathematical representation of bivariate VAR (1) model is;

$$\begin{aligned} y_{1,t} &= \alpha_{11}y_{1,t-1} + \alpha_{12}y_{2,t-1} + \varepsilon_{1,t} \\ y_{2,t} &= \alpha_{21}y_{1,t-1} + \alpha_{22}y_{2,t-1} + \varepsilon_{2,t} \end{aligned}$$

In matrix notation,

$$y_t = A_1 y_{t-1} + \varepsilon_t$$

$$A_1 = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$$

where,  $y_t$  is a k vector of endogenous variables,  $A_1$  is a matrix of coefficients to be estimated and  $\varepsilon_t$  is a vector of shocks, uncorrelated with their own lagged values and all right-hand side variables. The coefficients of the VAR system can be separately estimated by ordinary least squares (OLS).

Cointegration relationship between oil prices and sector indices is tested using Johansen cointegration test (1991). Applying Johansen's vector error-correction model, we investigate the dynamic association between oil prices and BIST sub indices. As explained by Maysami and Koh (2000), even though Engle and

Granger's (1987) two-step error-correction model may also be used in a multivariate context, the VECM yields more efficient estimators of cointegrating vectors, since it is a full information maximum likelihood estimation model, which allows for testing for cointegration in a whole system of equations in one step and without requiring a specific variable to be normalized. The Johansen vector error correction mechanism prevents carrying over the errors from the first step into the second, with the additional advantage of not restricting any assumptions of endogeneity or exogeneity of the variables. If a linear combination of nonstationary variables is stationary, they are said to be cointegrated. Also, the variables converge to equilibrium through time and this situation implies the presence of long run relationship. If the variables are cointegrated, vector error correction model must be employed in order to capture the variations associated with adjustment to a long term relationship (Chang, Wong, 2003). A significant and negative error correction term implies that any short run variations between the variables will bring a stable long term relationship.

We use the vector error correction model (VECM) in the following form;

$$\Delta X_t = \sum_{j=1}^{k-1} \Gamma_j \Delta X_{t-j} + \alpha \beta' X_{t-k} + \mu + \varepsilon_t$$

where variable  $X_t$  is an  $n$  vector of endogenous variables with same order of integration;  $\Delta$  represents the first difference;  $k$  shows the length of lag;  $\Gamma_j$  is an  $n \times n$  matrix of coefficients to be estimated and  $\mu$  and  $\varepsilon_t$  are the intercept vector and i.i.d. error term, respectively. Besides,  $\alpha$  is an  $n \times r$  matrix indicating the speed of adjustment and  $\beta$  represents the cointegrated matrix.

The coefficients of standard VAR and VEC models are difficult to interpret. For this reason, generalized impulse response functions (GIRFs) and variance decompositions (VDCs) can be utilized to summarize the relationship between the variables. Generalized impulse response functions are invariant to the ordering of the variables in the system and show the effect of an exogenous shock of one variable on the other. IRFs can be interpreted as dynamic simulations of the response of an endogenous variable over time. In this way, we use IRFs to investigate the impacts of oil price shocks on sector indices in Turkey.

A VAR can be written in vector form of MA() as;

$$y_t = \mu + \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \dots$$

$$\psi_s = \frac{\partial y_{t+s}}{\partial \varepsilon_t}$$

In the above formula, the row  $i$ , column  $j$  elements of  $\Psi_s$  determines the outcomes of a one unit increase in the  $j$ th variable's shock at date  $t$  ( $\varepsilon_{jt}$ ) for the value of the  $i$ th variable at time  $t+s$  ( $y_{i,t+s}$ ), holding all other shocks at all dates constant.

A plot of the row  $i$ , column  $j$  element of  $\Psi_s$

$$\frac{\partial y_{i,t+s}}{\partial \varepsilon_{jt}}$$

as a function of  $s$  is called as the impulse response function.

Variance decompositions (VDCs) analysis is the complement to impulse response and provides a compact overview of the models' dynamic structures. VDC displays the contribution of each source of shock to the variance of the future forecast error for each endogenous variable. VDC analysis splits the forecast error variance of a variable to its own shock and other variables' shocks in the system. Thus, in our study, it examines the impact of oil price shocks on the variance of sector indices.

Particularly,  $s$ -period ahead forecast error from a VAR can be written as;

$$\hat{y}_{t+s} - y_{t+s|t} = \varepsilon_{t+s} + \psi_1 \varepsilon_{t+s-1} + \psi_2 \varepsilon_{t+s-2} + \dots + \psi_{s-1} \varepsilon_{t+1}$$

The mean square of the forecast is,

$$\begin{aligned} MSE(\hat{y}_{t+s|t}) &= E[(y_{t+s} - \hat{y}_{t+s|t})(y_{t+s} - \hat{y}_{t+s|t})'] \\ &= \Omega + \psi_1 \Omega \psi_1' + \psi_2 \Omega \psi_2' + \dots + \psi_{s-1} \Omega \psi_{s-1}' \\ &= PP' + \psi_1 PP' \psi_1' + \psi_2 PP' \psi_2' + \dots + \psi_{s-1} PP' \psi_{s-1}' = \\ &= \sum_{j=1}^m (p_j p_j' + \psi_1 p_j p_j' \psi_1' + \psi_2 p_j p_j' \psi_2' + \dots + \psi_{s-1} p_j p_j' \psi_{s-1}') \end{aligned}$$

where  $\Omega = E(\varepsilon_t \varepsilon_t')$ ,  $p_j$  is the  $j$ th column of  $P$ . The orthogonalized response at lag  $p$  is  $\psi_p P$  and the row  $i$  column  $j$  element of  $\psi_p P$  is the impact of a one standard deviation orthogonalized shock to  $y_{j,t}$  on  $y_{i,t+p}$  holding each of the other shock at the all dates constant.

As a final step, Granger causality test is implemented to explore unidirectional or bidirectional causal relationship between oil prices and sector returns. A variable  $x$  Granger causes another variable  $y$  if past values of  $x$  help forecast the current value of  $y$  given all other information. Granger causality requires estimating the following two equations:

$$x_t = \alpha + \sum_{i=1}^m \beta_i x_{t-i} + \sum_{j=1}^n \gamma_j y_{t-j} + \varepsilon_t$$

$$y_t = \theta + \sum_{i=1}^k \vartheta_i y_{t-i} + \sum_{j=1}^l \phi_j x_{t-j} + \eta_t$$

### 3. Empirical results

Table 1 represents the descriptive statistics of the monthly data. The mean returns for all series are positive ranging from a minimum of 0.00013 (electricity sub-index, XELKT) to a maximum of 0.017 (main metal industry sub-index, XMANA). For all indices and Brent oil, the standard deviation is noticeably greater than absolute mean values, suggesting that the means are not significantly different from zero. The sample standard deviations show that food and beverages sub-index (XGIDA) is the least volatile with a standard deviation of 0.10 while the financial leasing sub-index (XFINK) can be considered as the most volatile with a standard deviation 0.15. Based on the skewness statistics, all series, except the tourism sub-index (XTRZM), are skewed to the left and the value of kurtosis is greater than 3 for all the series indicating a leptokurtotic distribution which means that return series have heavy tails relative to the normal distribution. Besides, the Jarque-Bera statistics suggest rejection of the null hypothesis of normality at the 1% level of significance.

**Table 1.** Descriptive statistics

	<i>DBRENT</i>	<i>DXBANK</i>	<i>DXELKT</i>	<i>DXFINK</i>	<i>DXGIDA</i>	<i>DXGMYO</i>	<i>DXHOLD</i>
<i>Mean</i>	0.613556	0.014596	0.000138	0.011972	0.016445	0.007394	0.009639
<i>Std. Dev.</i>	6.193187	0.145126	0.130310	0.155715	0.101911	0.142266	0.140740
<i>Skewness</i>	-1.249097	-0.466637	-0.551367	-0.663354	-0.610175	-0.838999	-0.879631
<i>Kurtosis</i>	5.894974	4.052321	4.834260	6.400262	4.233760	6.043951	5.554639
<i>J-B.</i>	82.24788	11.12840	25.76550	74.93587	16.93922	67.95739	54.11916
<i>Probability</i>	0.000000	0.003833	0.000003	0.000000	0.000210	0.000000	0.000000
	<i>DXKAGT</i>	<i>DXKMYA</i>	<i>DXMANA</i>	<i>DXMESY</i>	<i>DXTCRT</i>	<i>DXTEKS</i>	<i>DXTRZM</i>
<i>Mean</i>	0.011034	0.013006	0.017150	0.014046	0.016832	0.006844	0.003010
<i>Std. Dev.</i>	0.134210	0.122789	0.138933	0.133903	0.111813	0.117556	0.153529
<i>Skewness</i>	-0.664320	-0.762312	-0.789661	-1.023173	-1.575774	-1.103797	0.033391
<i>Kurtosis</i>	4.273274	5.823624	4.598519	6.418437	9.213353	6.017572	5.735154
<i>J-B.</i>	19.04913	57.92249	28.40355	89.28701	273.0263	78.63307	42.10608
<i>Probability</i>	0.000073	0.000000	0.000001	0.000000	0.000000	0.000000	0.000000
	<i>DXU100</i>	<i>DXUHIZ</i>	<i>DXULAS</i>	<i>DXUSIN</i>	<i>DXUTEK</i>		
<i>Mean</i>	0.013293	0.013102	0.015036	0.014415	0.008891		
<i>Std. Dev.</i>	0.124632	0.103578	0.144234	0.113655	0.131659		
<i>Skewness</i>	-0.813821	-1.193970	-0.843079	-0.999111	-0.675797		
<i>Kurtosis</i>	4.929787	5.475614	5.252539	5.897288	3.813306		
<i>J-B.</i>	35.84981	66.54896	44.53347	69.67783	13.99654		
<i>Probability</i>	0.000000	0.000000	0.000000	0.000000	0.000913		



We conduct the augmented Dickey-Fuller (ADF) test to examine the stationarity of the series. Table 2 shows that all the variables are non-stationary in levels and stationary in their first differences at the 1% significance level. We also crosscheck our results by the PP (Philips-Perron, 1988) and KPSS (Kwiatkowski, Philips, Schmidt, Shin, 1992) for all series. For the sake of brevity we don't recite the results but they are available upon request.

In this study cointegration analysis investigates whether there exists a common stochastic trend between oil prices and sector indices. If the variables are cointegrated they converge to equilibrium through time. Table 3 represents Johansen cointegration test results with the null hypothesis of no cointegration.

**Table 2.** ADF test results

<i>Variable</i>	<i>Levels</i>	<i>p-value</i>	<i>First Diff.</i>	<i>p-value</i>
<i>BRENT</i>	-1,956	0.3057	-8,253	0.0000
<i>XBANK</i>	-2,113	0.2400	-1,031	0.0000
<i>XELKT</i>	-2,114	0.2396	-8,942	0.0000
<i>XFINK</i>	-2,202	0.2069	-8,803	0.0000
<i>XGIDA</i>	-0,408	0.9026	-1,129	0.0000
<i>XGMYO</i>	-2,266	0.1849	-9,248	0.0000
<i>XHOLD</i>	-2,169	0.2189	-10,000	0.0000
<i>XKAGT</i>	-2,325	0.1663	-9,810	0.0000
<i>XKMYA</i>	-1,363	0.5975	-1,000	0.0000
<i>XMANA</i>	-2,154	0.2246	-8,454	0.0000
<i>XMESY</i>	0,909	0.9636	-9,017	0.0000
<i>XTCRT</i>	-0,250	0.9271	-9,466	0.0000
<i>XTEKS</i>	-1,182	0.6799	-8,485	0.0000
<i>XTRZM</i>	-1,806	0.3760	-9,797	0.0000
<i>XU100</i>	-1,720	0.4181	-1,015	0.0000
<i>XUHIZ</i>	-1,343	0.6070	-1,053	0.0000
<i>XULAS</i>	-0,006	0.9551	-7,141	0.0000
<i>XUSIN</i>	-1,179	0.6811	-9,652	0.0000
<i>XUTEK</i>	-0,697	0.8418	-9,487	0.0000

**Table 3.** Johansen cointegration test results

<b>Indices</b>	<b>Test Statistics</b>	<b>Probability</b>	<b>Results</b>
XBANK	14,56	0.0449	1 cointegration equation
XELKT	8,13	0.3653	No cointegration equation
XFINK	11,89	0.1150	No cointegration equation
XGIDA	16,97	0.0182	1 cointegration equation
XGMYO	10,52	0.1802	No cointegration equation
XHOLD	10,02	0.2109	No cointegration equation
XKAGT	10,25	0.1963	No cointegration equation
XKMYA	16,07	0.0256	1 cointegration equation
XMANA	8,00	0.3789	No cointegration equation
XMESY	10,78	0.1654	No cointegration equation
XTCRT	12,17	0.1043	No cointegration equation

Indices	Test Statistics	Probability	Results
XTEKS	12,56	0.0913	No cointegration equation
XTRZM	6,23	0.5841	No cointegration equation
XU100	14,95	0.0388	1 cointegration equation
XUHIZ	16,34	0.0231	1 cointegration equation
XULAS	8,89	0.2957	No cointegration equation
XUSIN	15,79	0.0285	1 cointegration equation
XUTEK	10,05	0.2085	No cointegration equation

As can be seen from the above table there are at least one cointegrating relationship between oil prices and six of the sub-sector indices. These indices are Banks (XBANK), Food and Beverage (XGIDA), Chemical, Petroleum, Plastic (XKMYA), BIST 100, Services (XUHIZ) and Industrials (XUSIN) indices. Thus we employ vector error correction methodology to these series in order to explore the long run dynamic relationships with oil prices. For the remaining indices, vector autoregressive model is applied to capture the dynamics of the short-run relationships.

Before implementing VAR and VEC models, we need to determine the optimal lag length using Akaike Information Criteria (AIC), Schwart Criterion (SC) and Final Prediction Error (FPE). XBANK and XKMYA are found to have optimal lag length orders of 3 and 2 respectively, while all the other series are tested with 1 lag.

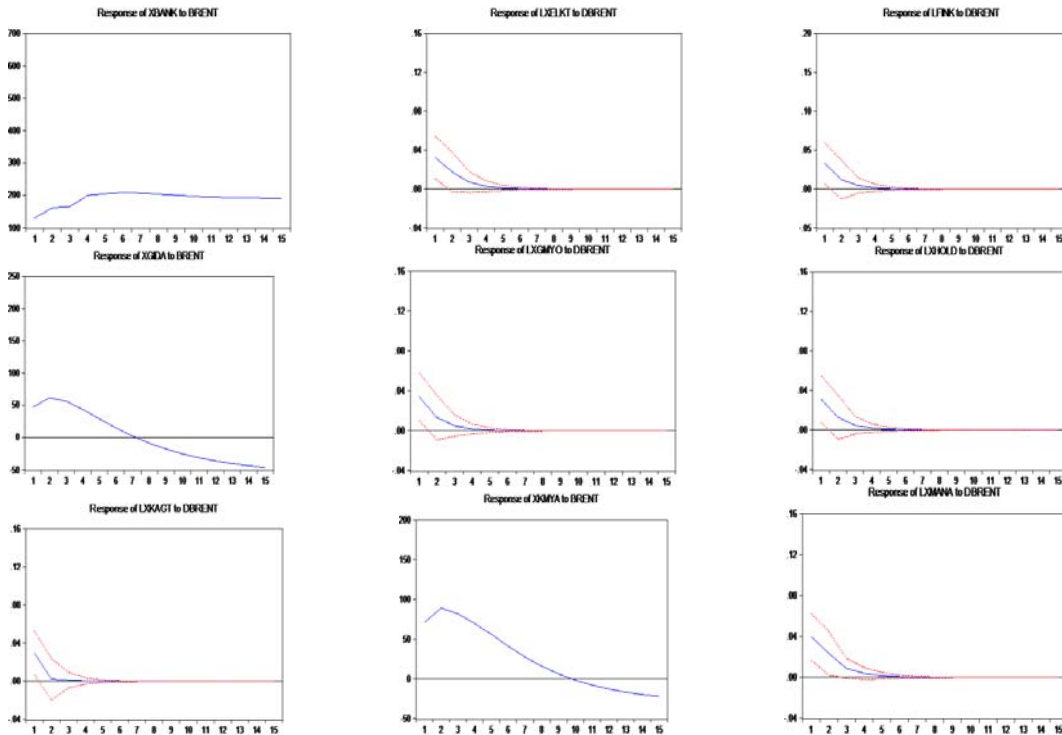
In this empirical work, the direct interest is the impulse response functions (IRFs) and variance decompositions (VDCs) generated from the models. Thus the coefficient estimates except for error correction terms are not included in the paper but can be available upon request.

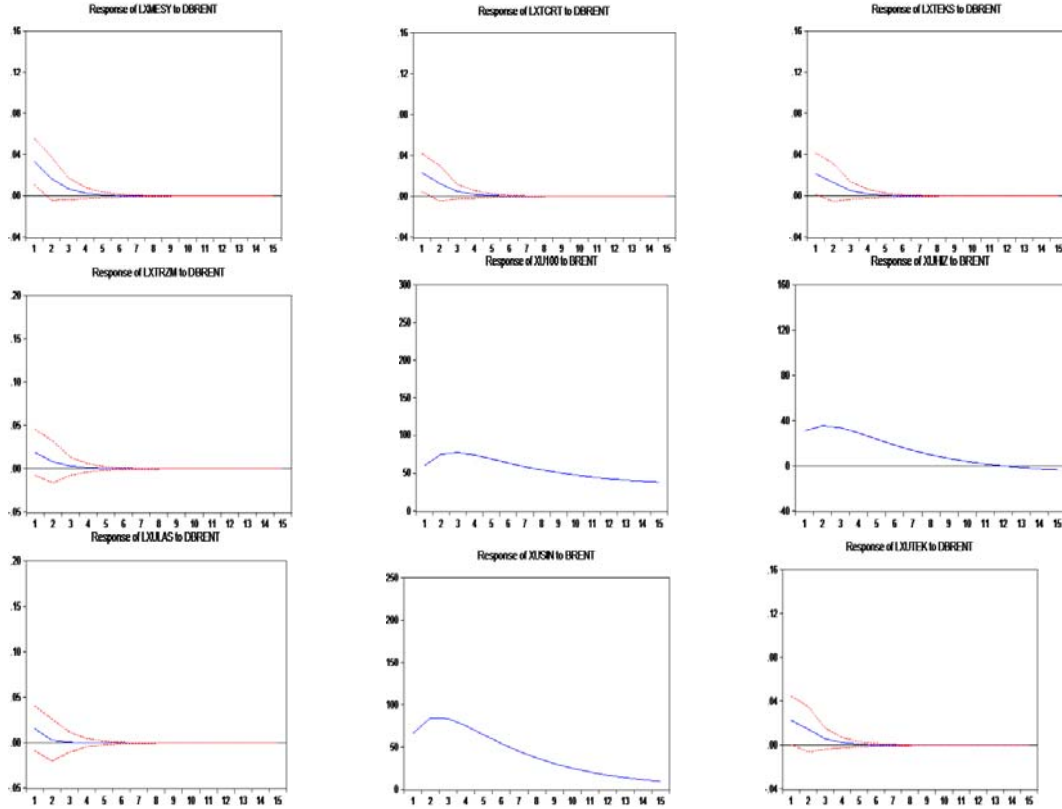
Figure 1 represents the impulse response functions showing the impact of oil price shocks on sub-sector indices, revealing that all 18 industries give positive responses to oil price shocks contemporaneously, however, the reactions are at varying magnitudes. The shocks die away in about six months for the electricity (XELKT), the real-estate investment trusts (XGMYO), holding (XHOLD) and basic metal sub-indices (XMANA) and in about four months for the metal products, machinery (XMESY), the wholesale and retail trade (XTCRT), the tourism (XTRZM), the textile and leather (XTEKS), the leasing and factoring (XFINK) and the technology (XUTEK) sub-sector indices. We find that the effect of oil price shocks on the transportation (XULAS) and the wood, paper and printing (XKAGT) sub-indices fade away only in two months.

As previously mentioned, the cointegrating relationship between oil prices and the banking sub-index requires a VEC model to capture the dynamics of the long-run relationship. A shock to oil prices leads to an increase in the banking sector index

(XBANK) up to four months and then the effect stabilizes over the long-run. One standard deviation shock in oil prices has an immediate positive effect on the food and beverage sub-index (XGIDA), however the index gives a negative response after the eighth month. A shock to the innovations in oil prices leads to an immediate positive response both in the chemical, petroleum, plastic (XKMYA) and the services (XUHIZ) sub-indices, however after a lag of ten and twelve months respectively, the oil shock causes a negative response which stabilizes thereafter. A shock in oil prices causes a positive impact on the BIST 100 index firms which becomes steady in about a year. The response of the industrials index (XUSIN) to oil price shocks is positive and the influence sharply fades away in six months.

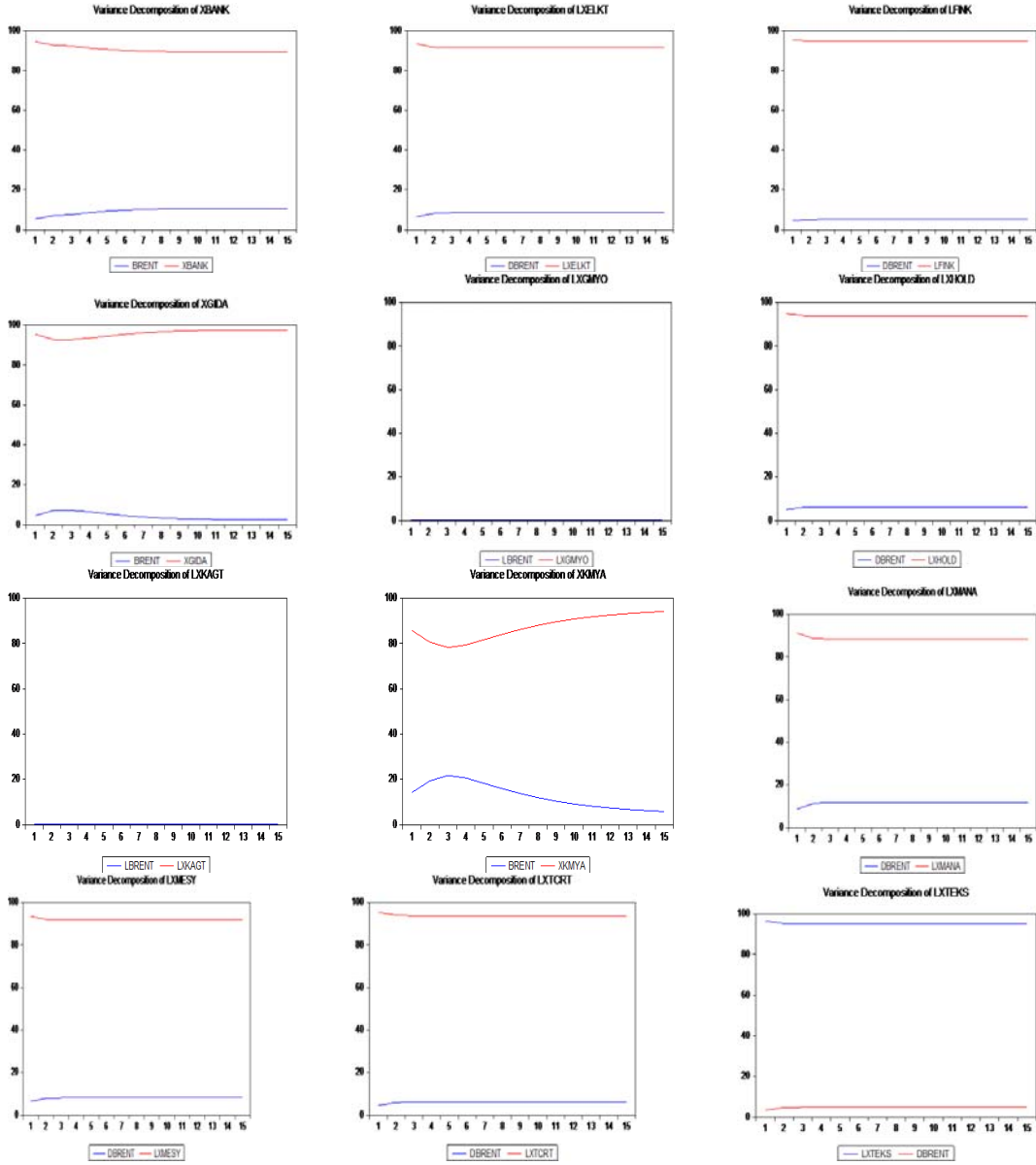
The results of the generalized impulse response functions can be attributed to demand side shocks in oil prices, where oil price increases are taken as signals of output growth in the global economy. Turkish economy has performed at record high growth rates since 2003 and positive effects of this growth may seem to offset the negative effects of oil price shocks. Additionally in recent years, capital inflows to Turkey have significantly increased as a consequence of sustained political stability, structural reforms, sound monetary and fiscal policies.

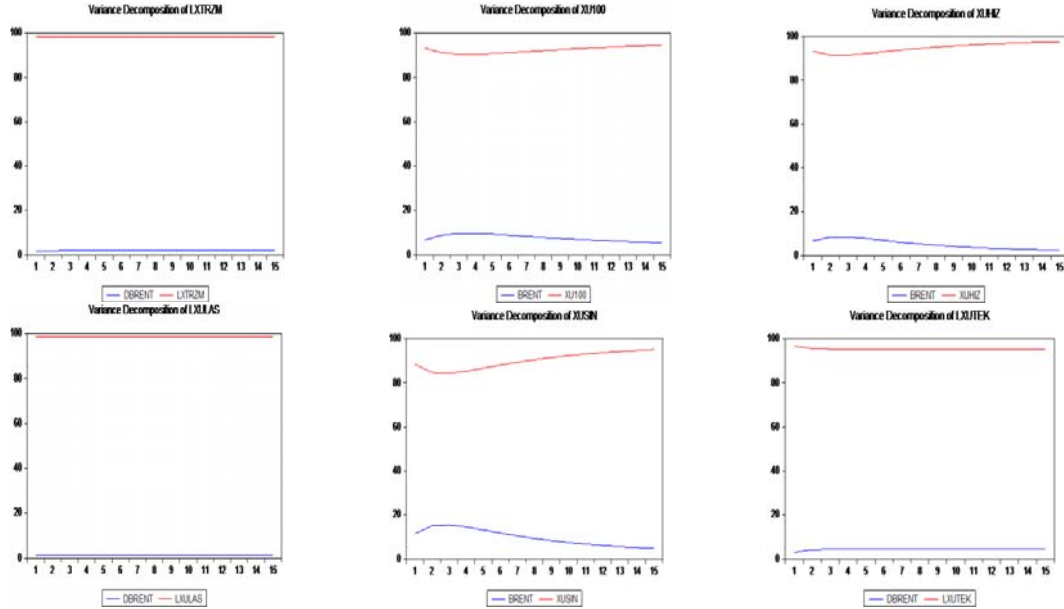




**Figure 1.** *Impulse response functions*

In Figure 2, the VDC analysis depicts that an oil price shock is not a major source of volatility for the sub-sector indices, most forecast error variance is due to each variables' own shock. The contribution of oil price shocks to the variance decompositions ranges from 1% for the transportation (XULAS) index to 21% for the chemical, petroleum, plastic (XKMYA) sub-index. The forecast error variances of the industrials (XUSIN), banking (XBANK), BIST 100 (XU100) are the highest following the chemical, petroleum, plastic (XKMYA) sub-index.





**Figure 2.** Forecast error variance decompositions

In the context of efficient markets, oil price predictability may seem to have irrational outcomes; however, in the finance literature, researchers as Hong and Stein (1996), Schiller (2000), Hong et al. (2007) vindicate oil effect by the assumptions of the underreaction hypothesis which states that investors are “boundedly rational”, they have limited understanding of the dynamics affecting asset prices, so they procrastinate immediate action to instantaneous flow of public information. In line with this branch of literature, Driesprong et al. (2008) evidence that industries where oil prices exhibit a “dominant first-order impact” are less predictable compared to the industries where oil has a “second-order impact”. They suggest the latter having a more “pronounced” oil effect. Our findings for the chemical, petroleum, plastic (XKMYA) index are contrary to those of Driesprong et al. (2008), Fan and Jahan-Parvar (2012), Hong and Stein (1996), Hong et al. (2007) who adduce that sectors which are highly “sensitive” to oil prices incorporate oil price information instantaneously into stock prices; thus they are not oil predictable. Industries that are not in direct relation with the energy sector are found to be oil predictable with the justification of the underreaction hypothesis in their studies. The transportation sector (XULAS) is not oil predictable supporting the literature above.

In order to explore the speed of adjustment from short run to long run dynamics, Table 4 represents the error correction terms.

**Table 4.** *Estimated error correction terms*

Dependent variables	ECT <sub>t-1</sub>	p-value
XBANK	1.100	0.7127
XGIDA	-2.291	0.1201
XKMYA	-3.067*	0.0462
XU100	-0,679	0.6119
XUHIZ	-0,873	0.2453
XUSIN	0.051	0.2061

Table 4 provides an empirical evidence of a short run adjustment to long term dynamics in the relationship between Chemical, Petroleum, Plastic sub-index (XKMYA) and Brent oil prices. The statistically significant and negative error correction term above (-3.067) shows the adjustment speed to the long run equilibrium.

Tables 5 and 6 represents Block Exogeneity Wald test and standard Granger causality tests, respectively. Block Exogeneity Wald test is applied for the variables which have a cointegrating relationship. Standard Granger causality test is conducted for the variables in the VAR system. Block Exogeneity Wald test is an F-test which evaluates the impact of the lags of independent variables on dependent variables and indicates the short term causality.

**Table 5.** *VECM Granger causality/Block exogeneity Wald test*

Dependent Variable	$\chi^2$	p-value	Results
<i>XBANK</i>	0.666	0.881	BRENT does not Granger cause to XBANK
<i>XGIDA</i>	3.807	0.051	BRENT does not Granger cause to XGIDA
<i>XKMYA</i>	8.845	0.012	BRENT does Granger cause to XKMYA
<i>XU100</i>	1.348	0.245	BRENT does not Granger cause to XU100
<i>XUHIZ</i>	1.661	0.197	BRENT does not Granger cause to XUHIZ
<i>XUSIN</i>	3.667	0.055	BRENT does not Granger cause to XUSIN

According to the results based on the Table 5 above, we reject the null hypothesis that Brent oil price does not Granger cause to Chemical, Petroleum and Plastic sub-index (XKMYA). Hence, Brent oil prices can help predict the current value of the index, which is also consistent with the significant error correction term. No causal relation is found to exist between Brent oil prices and other remaining cointegrated sub-indices. Since Granger (or short term) causality can be found through the vector error-correction model derived from the long-term cointegrating vectors. Table 6 provides an evidence of significant short run uni-directional causal link from oil prices to the basic metal sub-index (XMANA) only.

**Table 6.** *Standard Granger causality*

<i>Null Hypothesis</i>	<i>F-statistics</i>	<i>p-value</i>	<i>Decision</i>
BRENT does not Granger cause to XELKT	1.322	0.270	Accept
BRENT does not Granger cause to XFINK	0.780	0.460	Accept
BRENT does not Granger cause to XGMYO	1.055	0.351	Accept
BRENT does not Granger cause to XHOLD	2.248	0.109	Accept
BRENT does not Granger cause to XKAGT	1.257	0.287	Accept
BRENT does not Granger cause to XMANA	3.195	0.044	Reject
BRENT does not Granger cause to XMESY	2.239	0.110	Accept
BRENT does not Granger cause to XTCRT	2.588	0.079	Accept
BRENT does not Granger cause to XTEKS	1.094	0.337	Accept
BRENT does not Granger cause to XTRZM	0.332	0.717	Accept
BRENT does not Granger cause to XULAS	0.554	0.575	Accept
BRENT does not Granger cause to XUTEK	1.127	0.327	Accept

## Conclusions

In this study we analyzed both short-term and long-term relations between oil prices and 18 selected sub-sector indices from Borsa Istanbul for the period between January 2002 and April 2013. We have found cointegrating relationship between oil prices and banks (XBANK), food and beverage (XGIDA), chemical, petroleum, plastic (XKMYA), BIST 100, services (XUHIZ) and industrials (XUSIN) indices. Vector error correction methodology is employed to these indices in order to explore the long run dynamic relationships with oil prices. In the context of vector autoregressive models, we apply generalized impulse responses and forecast error variance decomposition analysis to measure the sensitivity of sectoral returns to the oil price shocks. The results of the analyses reveal that sector indices respond positively to oil price shocks. We document mixed results compared to previous literature. We provide an empirical evidence of oil price predictability for the XKMYA sub-index, where oil prices have a first-order impact. However, the transportation sector (XULAS) is not oil predictable.

The results of the multivariate GARCH model suggest uni-directional volatility spillover from oil market to four of the sectors. We observe that Turkish firms have an oil risk exposure and they should implement more effective hedging strategies in this regard. Our findings are indicative for policy makers and portfolio managers.



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