



Impact Of Oil Price Shocks On Stock Returns In Turkey: A Sectoral Analysis Based On Hilbert-Huang Transform And Event Study

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Abstract

Purpose of the study: This paper intended to analyze the sectoral index which can possibly be affected by oil price shocks in Turkey.

Research method: The study used Hilbert-Huang transform (HHT) to quantify oil price shock intensities based on daily West Texas Intermediate spot prices obtained from energy information administration website for the year 2000 to 2019 and target shocks were selected for event study. Later event study methodology was used to assess the impact of oil price shocks on sectoral indexes of six sectors in Istanbul stock exchange of Turkey based on data collected from investing.com website.

Findings: Empirical results show that oil price shocks negatively affect real estate sector (XGMYO), financials (XUMAL) and transportation (XULAS), but positively affects industrials (XUSIN) and food and beverage (XGIDA) sectors.

Originality/Value: The study contributes to theoretical and empirical literature. It also demonstrated that it is reasonable to combine HHT and event study to evaluate sectoral effects of oil price shocks on Turkey.

1 Introduction

Oil has always been in the society but became a necessity when people craved illumination and transportation. As such demand for oil and supply led to oil booms and oil busts. These Oil booms and oil busts are both crises that disrupt market stability and create confusion in economic, political and industrial circles. Oil price changes and oil price shock impact have been looked into by many researchers. Most of them looked into the impact of oil price shocks in the macro economy. Since oil is a basic commodity linked to nearly all of our activities, oil market volatility is expected to quickly be transferred to other sectors of society as well. In determining what an oil shock is, (Hamilton, 2003) concluded that those exogenous disruptions in petroleum supplies which lead one to predict lower GDP are the same disruptions that are an important factor in causing economic downturns. (Sadorsky, 2008) focused on the relationship between oil price movements and stock prices for different firm sizes. Using a multifactor model, they concluded that increases in oil prices reduce stock price returns and have a greater effect than decreases in oil prices. (Driesprong, Jacobsen, & Maat, 2008), investigates if changes in oil prices predict stock returns using data from 48 countries. According to their findings changes in oil prices forecast stock returns meaning that higher oil prices predict lower stock returns. This is in line with Sadorsky's findings of stock returns turn to be lower after oil price increases and higher if the oil price falls in the previous month. Even though G. Driesprong et al. took into consideration as many as 48 countries, they were mostly developed countries, implying that developing countries were not taken into consideration. Since most researchers are based on the macro economy, there are not many studies that go in details to investigate which sectors could be affected by oil price shocks. This paper aims to analyze those sectors which can possibly be affected by oil price shocks in Istanbul stock exchange so that investors can be aware of which sectors are impacted before investing in that sector. In the remaining paper, section 2 describes the data and methodology, section 3 presents the findings and discussions and last but not the least section 4 concludes.

2 Data and Methodology

2.1 Data

The Energy Information Administration (EIA) website¹ is well known for its well documented database on oil prices and the history of oil price fluctuations. As such, daily oil price data of West Texas Intermediate (WTI) oil have been freely extracted and used as a benchmark for the analysis. Oil price data from 1986 till 2020 was extracted and the HHT method was used to analyze and quantify the shocks that occurred within the oil price fluctuations. For our study, only the oil prices for the period 01:2001 – 03:2019 were taken into consideration. Sectors analyzed for Turkey include Real Estate Invest Trust (XGMYO), Industrials (XUSIN), Financials (XUMAL), Food and Beverage (XGIDA), Transportation (XULAS), and Tourism (XTRZM) sectors, and Istanbul Stock Exchange (BIST 100 (XU100)) as market proxy. Daily data on sectoral index is taken from www.investing.com website.

2.2 Methodology

In this study, Hilbert-Huang Transform (HHT) and Event study methodology are used to quantify oil price shocks and analyze the impact it has on abnormal returns of six sectors in Turkey simultaneously just as was used by (Ju, Zhou, Zhou, & Wu, 2014).

2.2.1 Hilbert - Huang Transform (HHT)

HHT uses the empirical mode decomposition method to decompose a signal into Intrinsic Mode Functions (IMF) with a trend. Let's say $X = (x(1), x(2), \dots, x(T))^T$ denote the original oil price data series.

Firstly, all the local maxima (extrema) of X are identified and connected by a cubic spine line as the upper envelope. Similarly, the lower envelop can be connecting all the local minima of X i.e., the procedure is repeated for the local minima to produce the lower envelope. Denote m_{11} as the mean of the upper and lower envelopes. Then the difference between X and m_{11} can be calculated as:

¹ www.eia.gov

$$X - m_{11} = h_{11} \quad (1)$$

Ideally, if h_{11} satisfies the conditions of an IMF, we can denote it as the first IMF. Otherwise, we need to repeat the procedure as described in Eq. (2) by k times until h_{1k} satisfies the conditions of IMF.

$$h_{1(k-1)} - m_{1k} = h_{1k} \quad (2)$$

We call h_{1k} IMF1 and designate it as c_1 , i.e.

$$c_1 = h_{1k} \quad (3)$$

Next, we need to separate c_1 from the remaining part of X by

$$X - c_1 = r_1 \quad (4)$$

Unless the residue r_1 does not contain longer period components, it will be treated as the new data series which will be processed by the same procedures from Eq. (1). Without loss of generality, we assume that the procedure is repeated by n-1 times i.e.

$$r_1 - c_2 = r_2, \dots, r_{n-1} - c_n = r_n \quad (5)$$

The process will end when the residue r_n becomes a constant a monotonic function, or a function with only one maximum and minimum. In the circumstances, no IMF can be extracted anymore.

Summing up Eqs. (4) And (5), we finally obtain

$$X = \sum_{j=1}^n c_j + r_n \quad (6)$$

Which shows that X is decomposed into n IMFs c_j , $j=1, \dots, n$ plus a residue r_n .

Secondly, Hilbert-Huang spectrum analysis (HSA) is used to get an energy-frequency-time distribution for each IMF. As the derived IMFs have clear instantaneous frequencies, HSA can be used to analyze the data series in a time-frequency-energy space. After the HSA process, the original data series can be expressed as follows:

$$X(t) = RP \sum_{j=i}^n \alpha^j(t) e^{i \int w_j(t) dt} \quad (7)$$

The presentation of HSA is an energy-frequency-time distribution. The energy of the signal is given in Eq. (7), denoted as $H(w, t)$, is termed the Hilbert spectrum. Its marginal spectrum $h(w)$ is then defined as:

$$h(w) = \int_0^t H(w, t) dt \quad (8)$$

Hilbert marginal spectrum offers a measure of total amplitude (or energy) contribution from each frequency value. It represents the cumulated amplitude over the entire data span in a probabilistic sense.

2.2.2 Event study

Assume that sector i is influenced by oil price shock. The abnormal return during the event period can be expressed as

$$AR_{it} = R_{it} - \hat{R}_{it} \quad (9)$$

Where AR_{it} , R_{it} and \hat{R}_{it} are abnormal, actual, and normal returns of sector i at period τ , respectively.

Two models, the constant mean return model and the market model are usually used to compute normal return \hat{R}_{it} . For this study we adopt the market model and it can be described as follows:

$$R_{it} = \alpha_i + \beta_i R_{m\tau} + \epsilon_{it} \quad (10)$$

$$E(\epsilon_{it}) = 0 \quad \text{Var}(\epsilon_{it}) = \sigma_{\epsilon_i}^2$$

To facilitate the measurement and analysis of the abnormal returns, we define the following notations: returns will be indexed in event time using τ . $\tau = 0$ is the event date, $\tau = T_1 + 1$ to $\tau = T_2$ represents the event window, and $\tau = T_0 + 1$ to $\tau = T_1$ constitute the estimation window. $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$ is the length of the estimation window and the event window respectively. Thus, post event window will be from $\tau = T_2 + 1$ to $\tau = T_3$ and of length $L_3 = T_3 - T_2$.

Using the Ordinary Least Squares method to estimate the market model parameters, we have,

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1} (R_{m\tau} - \hat{\mu}_m)^2} \quad (11)$$

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i \hat{\mu}_m \quad (12)$$

$$\hat{\sigma}_{\hat{\alpha}_i}^2 = \left(1/L_1 - 2\right) \sum_{\tau=T_0+1}^{T_1} (R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2 \quad (13)$$

where

$$\hat{\mu}_i = (1/L_1) \sum_{\tau=T_0+1}^{T_1} R_{i\tau}$$

and

$$\hat{\mu}_m = (1/L_1) \sum_{\tau=T_0+1}^{T_1} R_{m\tau}$$

$R_{i\tau}$ and $R_{m\tau}$ are the return in event period τ for sector i and the market respectively.

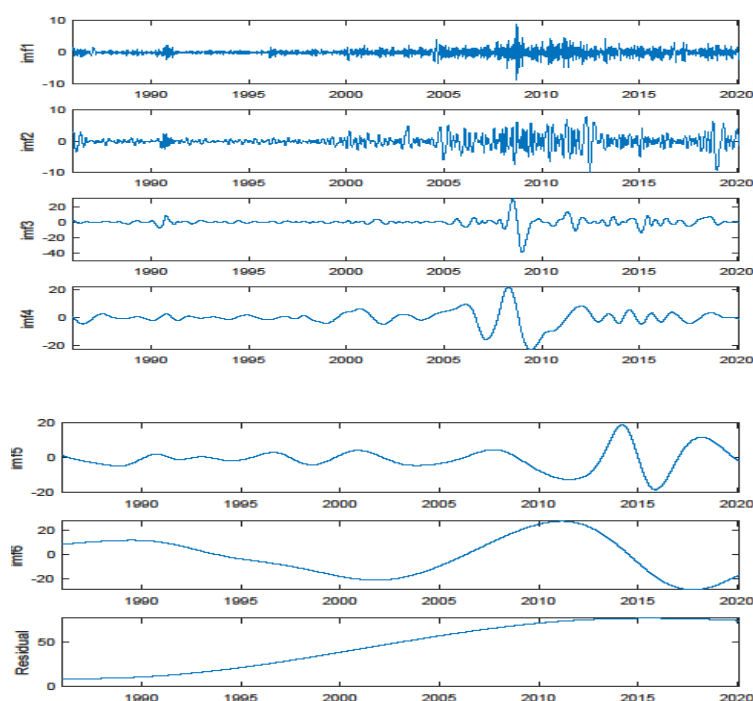
3 Findings and Discussions

To determine the target shocks, the HHT process was followed simultaneously beginning with EMD process performed on weekly WTI² oil price data using equation (1) to equation (6) which yielded six IMF³s and one residual. IMFs with higher frequencies were generated before those with lower frequencies thus they were listed from highest to lowest. The last one which is known as the residue, is often treated as the deterministic long-run behavior of the data set. IMF1 had the highest frequency followed by IMF2. In IMF 1, several shocks occurred between 1980s, 1991, 1996, the period after 2000 especially around 2008 and 2009 with very high shocks as seen on Figure 1.

² West Texas Intermediate

³ Intrinsic Mode Functions

Figure 1. IMFs of Weekly Oil Prices



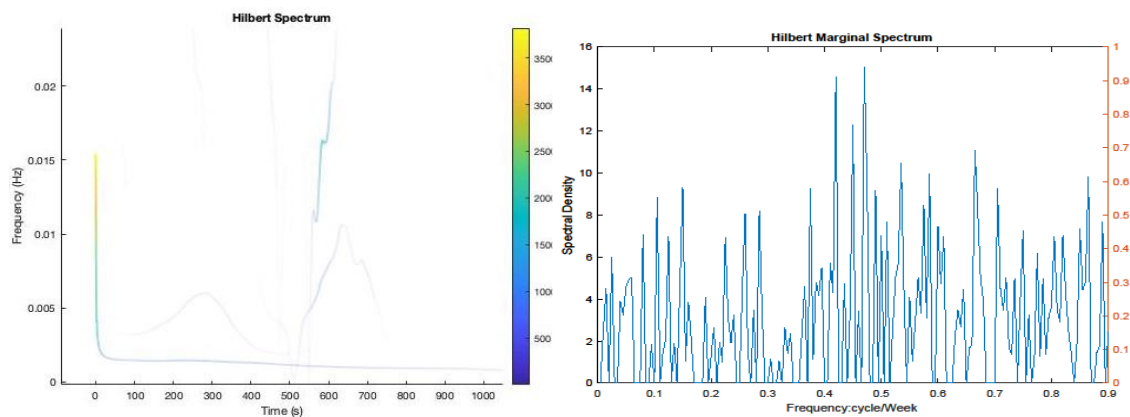
In order to understand the characteristics of shock intensities in different time scales, the values of IMFs were individually analyzed using statistical measures. Three measures were calculated: Mean Period (MP) which is the ratio of the total number of points to the number of peaks for each IMF; Maximal Amplitude (MA) which is the maximum of each IMF and can be directly obtained from the Empirical Mode Decomposition process; and finally, the Correlation Coefficient (CC) which was used to measure the coefficient relationship between each intrinsic mode function and the original data series as seen on table 1.

Table 1: Three Measurements of six IMFs

IMF	Mean Period MP, week	Maximal Amplitude MA	Correlation Coefficient - CC
1	3.5815	9.0618	0.032442
2	10.854	7.9292	0.096095
3	30.69	29.904	0.22318
4	93.684	21.88	0.14524
5	254.29	18.86	0.096225
6	890	27.719	0.35284

It should be noted that the frequencies and amplitudes of an IMF may change continuously with time, as such, the periods are not constant. As seen on the Table 1, IMF 6 is the most important IMF because it had the largest correlation coefficient value. Normally, lower frequencies would imply that each up and down movement changes gradually with the trend lasting a long time before a fluctuation occurs. As such if this should happen, it therefore means there is highly volatile shocks happening to the oil prices.

Figure 2: Hilbert Spectral Analysis



From the Hilbert Marginal Spectrum on Figure 2. It can be seen that the peak of the price fluctuations occurred at 0.48 cycle/week or nearly six weeks per cycle. This therefore means that oil price shocks lasted about six (6) weeks.

3.1 Calculating shock probabilities and deriving shock intensities.

To get the shock intensities, we took into consideration the shock probabilities. If we consider the probability of each oil price shock as equal to the probability of each IMF, then as there were six IMFs, the Hilbert Marginal Spectrum (HMS) was divided into six parts.

From a mathematical perspective, the curve of the HMS is represented by $I = G(f)$. The shock probability SP_i of IMF_i was calculated as:

$$SP_i = \left(\int_{f_i} I df / \sum_{i=1}^7 \int_{f_i} I df \right) * 100\%$$

$$\frac{1}{f_i} \in [MP(IMF_i), MP(IMF_{i+1})] \tag{14}$$

Where l and f denoted the likelihood and frequency of oil price shocks. f_i stood for the i th frequency range, and $MP(IMF_i)$ stood for the mean period of IMF_i . Using equation 11, the shock probabilities of six IMFs were computed and represented in Table 2 below:

Table: 2 Shock Probabilities of each IMF

IMFs	SHOCK PROBABILITIES
1	13.63%
2	11.32%
3	14.5%
4	22.33%
5	16.9%
6	17.4%

Sub-shocks were calculated after obtaining shock probabilities which depended on three indicators: The Mean Period (MP), Maximal Amplitude (MA) and Shock Probability (SP) which can be obtained from Table 2 and equation 14.

If equal weights are assigned to the three indicators, the intensity of IMF can be calculated as:

$$Int_{IMF_i} = MP/3 + MA/3 + SP/3 \tag{15}$$

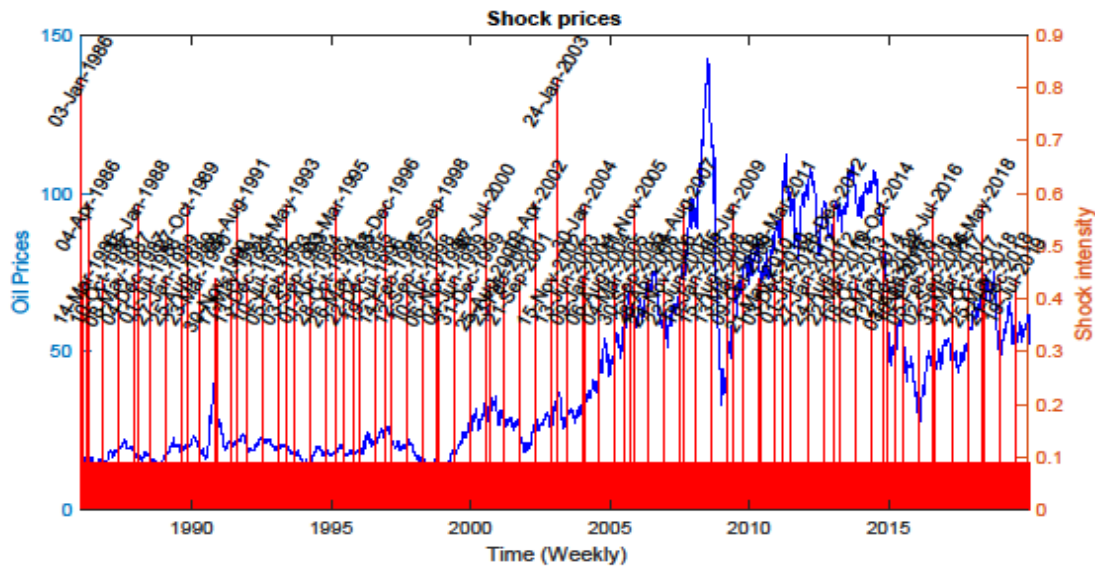
The intensities of the seven sub-shocks are sorted as follows:

$$IMF_2 < IMF_1 < IMF_5 < IMF_3 < IMF_4 < IMF_6$$

(0.0027) (0.0871) (0.4287) (0.4395) (0.5788) (0.8164)

The shock intensities of each sub-shock are represented in the brackets. Every sub-shock occurs according to its own mean period, and the total oil shock intensity of one period can be integrated by simply summing up the intensities. The integrated intensities of oil price shocks of each period are shown below on Figure 3.

Figure 3: Intensity of oil price shocks



3.2 Ranking oil price shock intensities

Based on Figure 3. There were several shock intensities which occurred over time. To perform an event study, these shocks were classified into ranks from Rank I through Rank IV based on their degree of intensities. Shocks with higher intensities were put under rank I through rank IV and target dates were selected from each rank as the event date. On a measuring scale of $0 - 1$, Rank I shock range from $0.8 - 1$ shock intensity, Rank II shocks range from $0.6 - 0.79$ shock intensity, Rank III shock range from $0.5 - 0.59$ shock intensity and last but not the least, Rank IV shocks range from $0 - 0.49$ shock intensity. From these ranks, selected target dates include: **24/01/2003**, **21/05/2010**, **10/102014** and **25/05/2018** from Rank I to Rank IV respectively.

3.3 Event study results interpretation

Firstly, for each event date, an event window of 21 days and an estimation period of 252 trading days was used in our analyses of the shock impact on the sectoral indexes of Turkey.

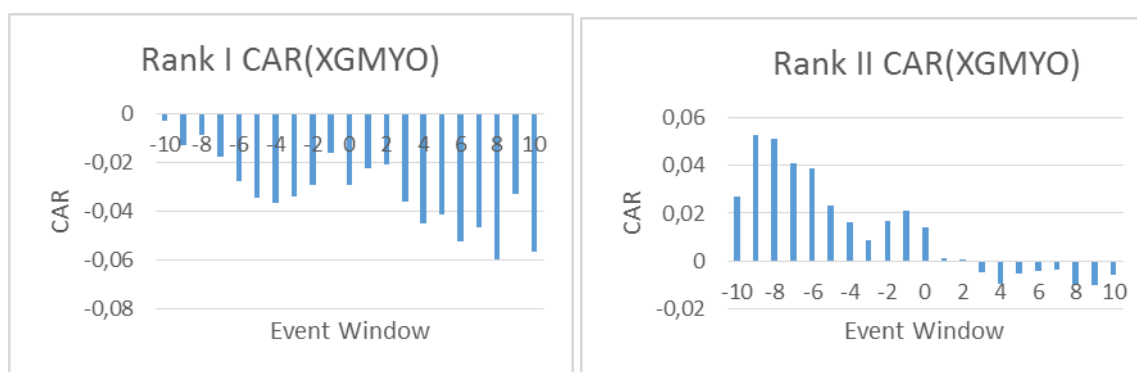
Table 3: Cumulative Abnormal Returns (CAR) values of Turkey’s sectors caused by oil price shocks

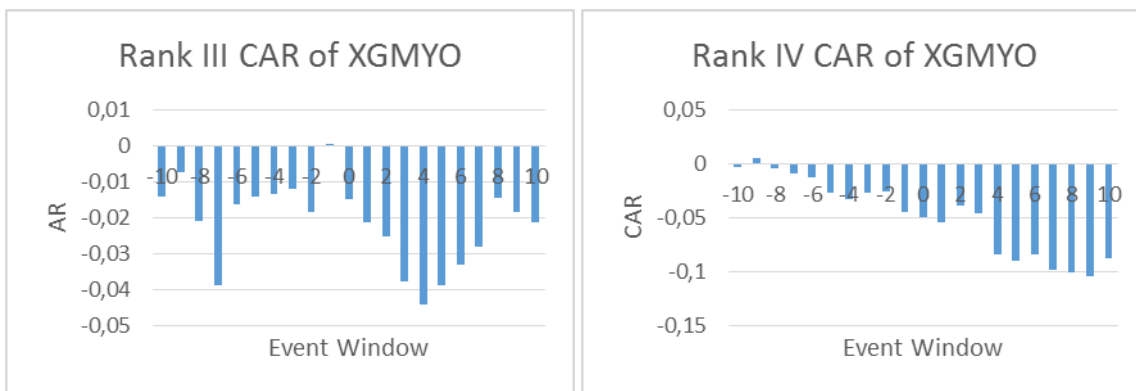
CAR values of Turkey’s sectors caused by oil price shocks						
Sectors	XGMYO	XUSIN	XUMAL	XGIDA	XULAS	XTRZM
Rank I	-0.06	0.03	-0.01	0.06	-0.02	-0.17
Rank II	-0.01	-0.02	0.01	0.04	-0.01	0.06
Rank III	-0.02	0.01	0.00	0.01	0.01	0.01
Rank IV	-0.09	0.04	-0.01	-0.01	-0.08	0.04

3.3.1 Abnormal Return (AR) s and Cumulative Abnormal Return (CAR)s of XGMYO

The CARs of real estate sector showed an increasing downward trend of the cumulative abnormal returns for all ranks. This was an indication that market value of the sector dropped significantly over the event window of 21 days. As such the impact of the four price shocks on Turkey’s real estate sector were ordered based on the CAR values of table 3 as rank II > rank III > rank I > rank IV. The minor (rank IV) and major shocks (rank I) had a greater impact on the sector returns as seen on figure 4.

Figure 4: CARs of Turkey’s Real estate trust funds sector caused by oil price shocks

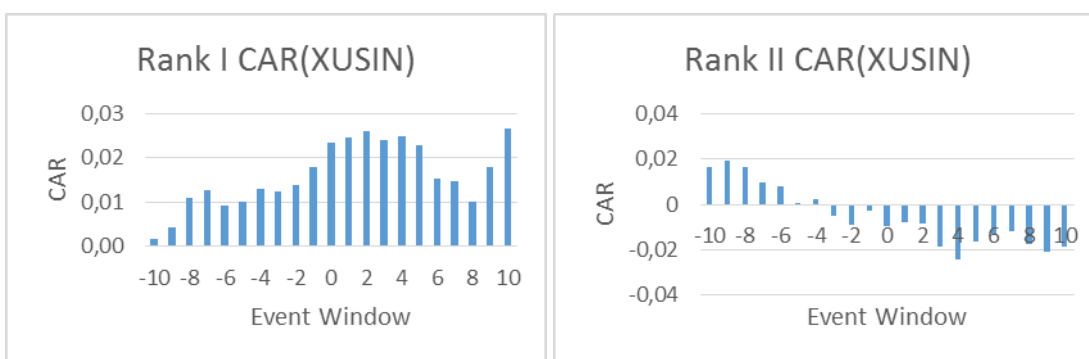


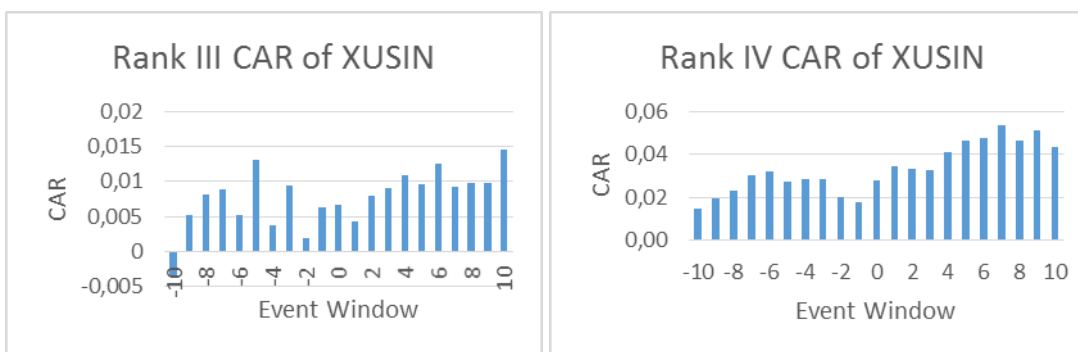


3.3.2 ARs and CARs of XUSIN

The CARs of industrials sector show an increasing upward trend of the abnormal returns for all ranks except for rank two shocks whose returns were increasing steadily before the event day but slightly dropped after the event day as seen on figure 5. Despite this trend, the end return is negative for the event window in rank II. This is an indication that market value of the sector increased significantly over the event window of 21 days. As such the sector was positively impacted overall by the the oil price shocks. Thus, the industrials sector is positively impacted by the overall oil price shocks. This trend can be ordered as rank IV > rank I > rank III > rank II.

Figure 5: CARs of Turkey’s industrials sector caused by oil price shocks

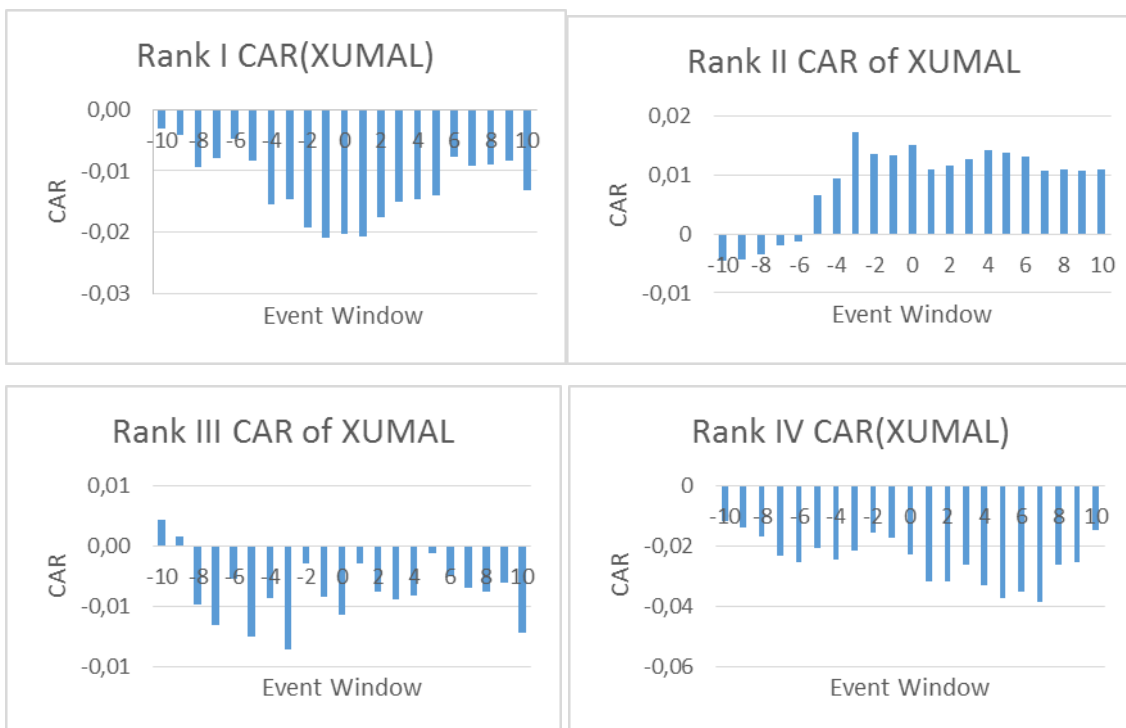




3.3.3 ARs and CARs of XUMAL

Ranks I, III and IV shocks portrayed a downward trend in cumulative abnormal returns except rank II shocks which portray an increasing trend in return values as seen on figure 6. Therefore, it can be concluded that the oil price shocks had a negative impact on Turkey’s financials sector given that the market values of majority of the ranks were negative throughout the event window. Therefore, the shocks can be ordered as rank II > rank III > rank I > rank IV.

Figure 6. CARs of Turkey’s Financials sector caused by oil price shocks

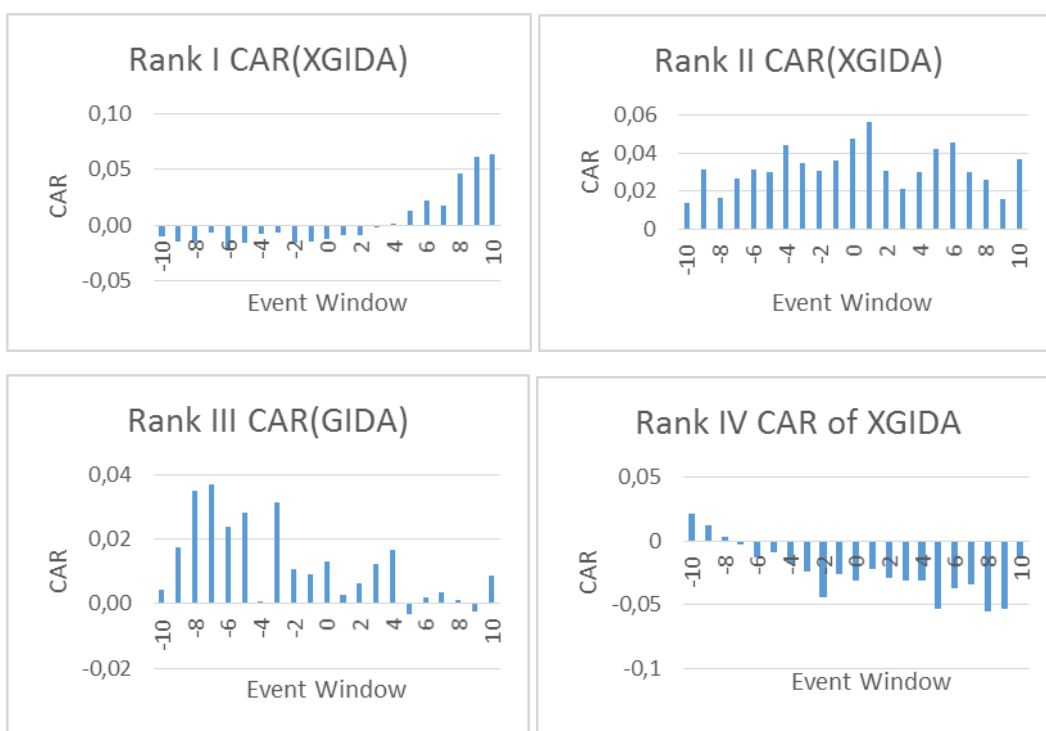


3.3.4 ARs and CARs of XGIDA

The values of the CARs for rank I showed a straight downward trend which rose on the 5th day after the event day on the event window which is the opposite of the

values of rank IV which were decreasing at an increasing rate throughout the event window as seen on figure 7. This implies oil price shocks positively affected the Food and Beverage sector in Turkey because majority of the ranks have a positive value at the end of the event window. The oil price shock effects on all ranks can be ordered as rank I > rank II > rank III > rank IV based on the cumulative abnormal return values on table 3.

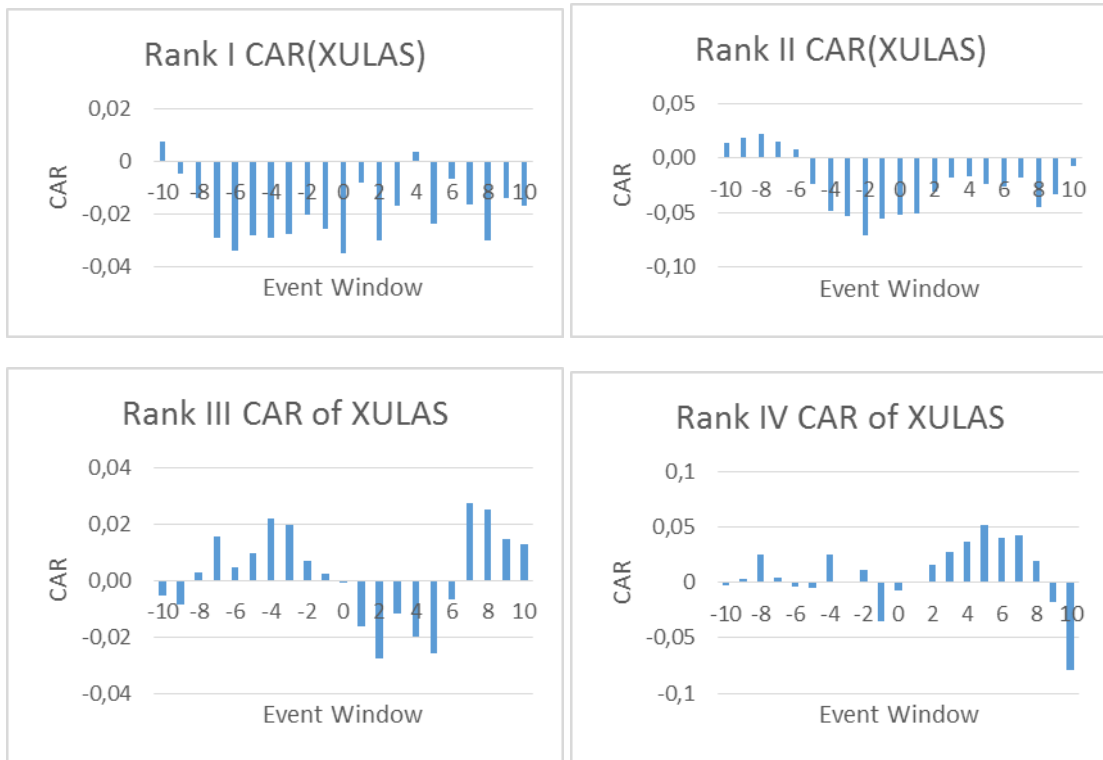
Figure 7. CARs of Turkey’s Food and Beverage sector caused by oil price shocks



3.3.5 ARs and CARs of XULAS

Results showed a downward trend in abnormal return values for ranks I and II but for ranks III and IV shocks the after effects were seen to be negative a week after the event date and positive close to two weeks after the event date on the ranks respectively. Thus, the market value dropped significantly over the event window for all ranks except rank IV as seen on figure 8. The impact of the shocks can be ordered as rank III > rank II > rank I > rank IV based on the values of figure 3.

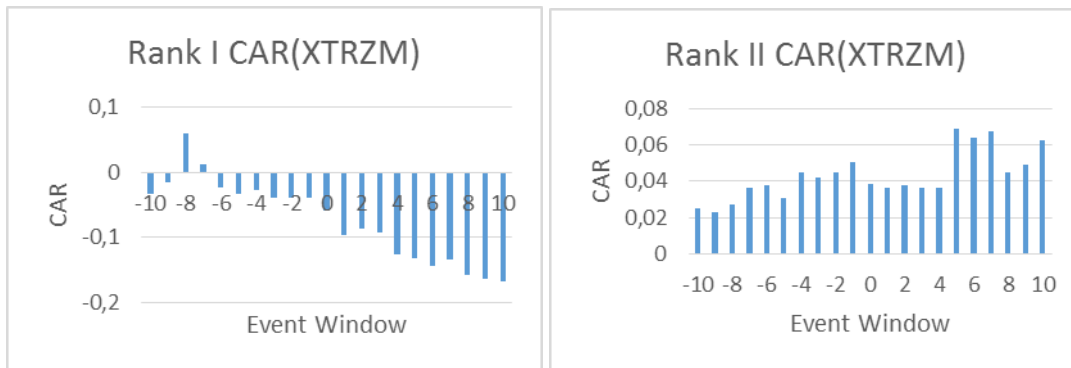
Figure 8. CARs of Turkey’s Transportation sector caused by oil price shocks

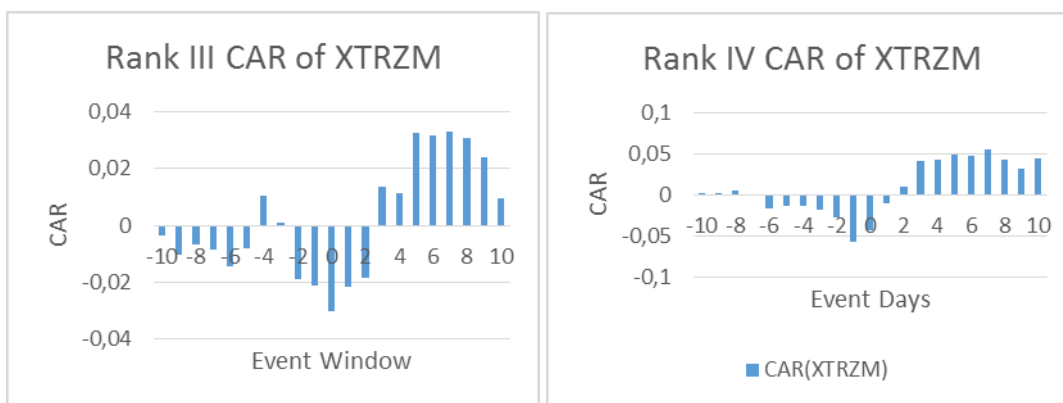


3.3.6 ARs and CARs of XTRZM

Rank I showed a decreasing trend in abnormal returns, rank II had positive cumulative abnormal returns throughout the event window, rank III and IV had positive cumulative abnormal returns only after the event date as seen on figure 9. In that regard, the impact of oil price shocks can be ranked as rank II > rank IV > rank III > rank I based on the results of the cumulative abnormal returns on table 3.

Figure 9. CARs of Turkey’s Tourism sector caused by oil price shocks





3.4 Comparison of results with other researchers.

Similar to our research is a study conducted by (Bouri, Awartani, & Maghyereh, 2016:213) on crude oil prices and sectoral stock returns in Jordan using GARCH process. Our results are consistent with theirs which states that oil shocks are significant in the returns of financials sector but insignificant in the industrial sector. In this paper, oil price shocks positively affect XGIDA and XUSIN but negatively affect XGMYO and these results are consistent with those of (Gencer, 2013:16) and they went further to justify why as expected oil price shocks did not have a negative impact on Turkey's XUSIN sector by attributing it to its growth since 2003.

4 Conclusion

This study combined HHT and event study methodology to model the impact of oil price shocks on selected sectors in the Istanbul stock exchange in Turkey. Firstly, the HHT method is used to compute oil price shock intensities and target shocks are later selected based on their degree of intensity, for event study purposes. Event study methodology is later used to assess the effects of these shock intensities on the sectoral indexes. Results showed that oil price shocks negatively affected Turkey's real estate sector, financials and transport sector. While there is a positive impact towards the industrials and food and beverage sector. Due to the fact that our results are in general consistent with existing researches, it implies that modeling the relationship between oil prices and sectoral returns is reasonable using HHT and event study. This paper answered the question that there is a relationship between oil prices and sectoral returns.

References

- Bouri, E., Awartani, B., & Maghyreh, A. (2016). Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010. *Energy Economics*, Vol. 56, pp. 205–214. <https://doi.org/10.1016/j.eneco.2016.03.021>
- Driesprong, G., Jacobsen, B., & Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics*, 89(2), 307–327. <https://doi.org/10.1016/j.jfineco.2007.07.008>
- Gencer, G. (2013). The impact of oil prices on sectoral returns: an empirical analysis from Borsa Istanbul. *Theoretical and Applied Economics*, XX(12), 7–24.
- Hamilton, J. D. (2003). What is an oil shock? *Journal of Econometrics*, 113(2), 363–398. [https://doi.org/10.1016/S0304-4076\(02\)00207-5](https://doi.org/10.1016/S0304-4076(02)00207-5)
- Ju, K., Zhou, D., Zhou, P., & Wu, J. (2014). Macroeconomic effects of oil price shocks in China: An empirical study based on Hilbert-Huang transform and event study. *Applied Energy*, 136, 1053–1066. <https://doi.org/10.1016/j.apenergy.2014.08.037>
- Sadorsky, P. (2008). Assessing the impact of oil prices on firms of different sizes: Its tough being in the middle. *Energy Policy*, 36(10), 3854–3861. <https://doi.org/10.1016/j.enpol.2008.07.019>