The Transmission of Oil Price Shocks to the Stock Markets: Evidence from the US and Turkey

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ABSTRACT

Oil can be considered as the most prominent and volatile commodity in financial markets all around the world economy. Oil and oil-based products are not only used directly as raw materials by many production sectors but also are used in many service sectors, also traded on stock exchange markets. Due to growing and high demand also constraints on supply, oil has become very valuable and volatile. Therefore, any fluctuation in oil prices has significant regional and worldwide effects. Many other factors including global economic developments, financial crises and political issues have profound effects on oil prices, macroeconomic variables and financial markets. Therefore, the researches have been accelareted focusing on these contributors and their influence.

In the beginning of the thesis, the investigations are industrial based that focus on the magnitude of volatility transmission and the risk spillover mechanism across the oil market, financial market risks, and the oil-related Credit Default Swaps (CDS) sectors in US. The dataset covers 6 January 2004 - 2 February 2016 of seven different measurements of markets, credit risks and daily closing futures prices of West Texas Intermediate (WTI). Four of the vast risk measurements are the oil sector and oil-related sectors' CDSs for auto, chemicals, natural gas as well as utility sectors. Furthermore, three measures of the financial market risk, the one-month expected equity volatility measured by VIX, MOVE and SMOVE are also included. These are not only used as risk measurement tools but also used to represent the volatilities in different markets and sectors. The volatility transmission mechanism across the oil and financial markets and CDS sectors is investigated using the

volatility impulse response model that has the advantage of providing valuable information on the speed of risk transmission. In addition, the shape and sign of the volatility impulse responses also provide significant information on the transmission mechanism. The objectives are (1) to analyze the volatility transmission mechanism across the oil, oil-related CDS sectors and financial markets, using a multivariate conditional volatility model, known as Baba-Engle-Kraft-Kroner (BEKK) model and (2) to discern how major global events affect the volatility of the oil and oil-related CDS markets by employing the newly introduced Volatility Impulse Response Function (VIRF) analysis. We evaluate the risk transmission due to several recent events around the world and the results show complicated transmission mechanisms that spread over long periods. Among these events, the Lehman Brothers bankruptcy has destabilizing effects on all oil-related sectors. Findings also show that all oil market related shocks have significant risk transmission effects.

For the second part of the thesis the perspective is chosen as to investigate on the general index of stock exchange market. This part analyzes the impacts of real Brent crude oil price and macroeconomic variables namely, real effective exchange rate, industrial production index and short-term real interest rate on the Turkish stock market. To this aim, a time varying parameter vector autoregression model (TVP-VAR) is estimated for the time period from February 1988 to March 2017 which is monthly data. The time-varying responses and forecast error decompositions computed from this model indicates that the influence of each macroeconomic variable on the stock market return differs substantially over time. Time-varying responses imply lower influence of real crude oil price shocks compared to those of exchange rate and interest rate. Output shock has a positive influence on the stock

returns, as expected. The time-varying forecast error decomposition results suggest that stock returns have been largely explained by the variations in exchange rate and interest rate.

Keywords: Risk, Sectoral CDS, VIX, MOVE, SMOVE, Volatility Impulse Response, Oil prices, Stock returns, TVP-VAR model, Turkey.

ÖZ

Petrol; tüm dünya ekonomilerinde, finansal piyasalarda en öne çıkan ve fiyat açısından çok dalgalanan bir ticari mal olarak düşünülebilir. Petrol ve petrol bazlı ürünler sadece bir çok üretim sektöründe direk hammadde olarak kullanılmakla kalmayıp, bir çok servis sektöründe de kullanılır; aynı zamanda borsalarda işlem görür. Yüksek olan ve sürekli artan talep ve aynı zamanda arzdaki kısıtlar nedeniyle, petrol çok değerli ve fiyat olarak oynak hale gelmiştir. Böylelikle, petrol fiyatlarındaki herhangi bir dalgalanma, bölgesel çapta ve dünya çapında önemli etkiye sahiptir. Küresel ekonomik gelişmeler, finansal krizler ve politik olayları içeren diğer faktörler petrol fiyatları, makroekonomik değişkenler ve finansal marketler üzerinde derin etkilere sahip olmuştur. Aynı zamanda ters yönlü etki de söz konusudur. 1997 Asya Finansal Krizi, 2003 Irak Savaşı, 2007 sonlarında ABD yüksek riskli konut kredisi krizi, 2009 sonlarından beri Avrupa ülke borçları krizi bir çok araştırmaya katalizör olmaktadır.

Tezin ilk kısmında; petrol piyasası, finansal piyasa riskleri ve ABD'deki petrol ile ilgili Kredi Temerrüt Swap (CDS) sektörleri arasındaki volatilite iletiminin ve risk dağılma mekanizmasının büyüklüğüne odaklanan araştırmalar endüstriyel bazdadır. Veri seti 6 Ocak 2004 ile 2 Şubat 2016 arasında West Texas Intermediate (WTI) günlük kapanış vadeli fiyatları ve yedi farklı piyasa ve kredi riski ölçümlerini içermektedir. Geniş risk ölçümlerinden dördü, otomobil, kimyasal, doğalgaz ve hizmet sektörleri için petrol ve petrolle ilgili CDS'lerdir. Buna ek olarak, finansal piyasa riskinin üç ölçümü, VIX, MOVE ve SMOVE tarafından ölçülen bir aylık beklenen sermaye hareketliliği de dahil edilmiştir. Bunlar sadece risk ölçüm araçları

olarak değil, aynı zamanda farklı pazar ve sektörlerdeki dalgalanmaları temsil etmek için de kullanılmaktadır. Petrol ve finansal piyasalar ile CDS sektörleri arasındaki oynaklık iletim mekanizması, risk iletiminin hızı hakkında değerli bilgiler sunma avantajına sahip olan volatilite etki tepki fonksiyonu (VIRF) kullanılarak incelenmektedir. Buna ek olarak, volatilite etki tepkilerinin şekli ve işareti iletim mekanizması hakkında önemli bilgiler sağlar. Amaçlar, (1) Baba-Engle-Kraft-Kroner (BEKK) modeli olarak bilinen çok değişkenli bir koşullu volatilite modeli kullanılarak, petrol, petrol ile ilgili CDS sektörleri ve finansal piyasalar arasındaki oynaklık iletim mekanizmasını incelemek ve (2) yeni bulunan Volatilite Etki Tepki Fonksiyonu (VIRF) analizini kullanarak, büyük küresel olayların petrol ve petrolle ilişkili CDS pazarlarının oynaklığını nasıl etkilediğini ayırt etmektir. Dünya çapında son zamanlarda gerçekleşen birçok olayın risk iletimini değerlendirdik ve sonuçlar uzun sürelere yayılmış olan karmaşık iletim mekanizmalarını göstermektedir. Bu olaylar arasında, Lehman Brothers'ın iflası, petrol ile ilgili tüm sektörler üzerinde istikrarı bozucu etkilere sahiptir. Bulgular ayrıca, petrol piyasasına ilişkin şokların önemli risk iletim etkilerine sahip olduğunu göstermektedir.

Tezin ikinci bölümünde, seçilen perspektif borsanın genel endeksi üzerine inceleme yapmaktır. Bu kısım, Brent ham petrolün ve makroekonomik değişkenlerin şöyle ki, reel efektif döviz kuru, kısa vadeli reel faiz oranı ve endüstriyel üretim endeksi, Türkiye borsası üzerine etkilerini analiz etmeyi amaçlar. Bu amaçla, zamanla değişen katsayılı vektör otoregresyon modeli (TVP-VAR) Şubat 1988'den Mart 2017'ye kadar olan zaman periyodunu kapsayan aylık veri kullanılarak tahmin edilmiştir. Bu modelle hesaplanmış olan, zamanla değişen tepkiler ve tahmini hata ayrıştırmaları, her bir makroekonomik değişkenin hisse senedi getirileri üzerindeki etkisinin zamanla ciddi derecede değiştiğini gösterir. Zaman içindeki tepkiler, reel ham petrol fiyat şoklarının etkisinin döviz kuru ve faiz oranlarına kıyasla daha düşük olduğunu ima etmektedir. Üretim çıktısı şoku; beklendiği gibi, hisse senedi getirileri üzerinde olumlu bir etkiye sahiptir. Zamanla değişen tahmini hata ayrıştırma sonuçları; hisse senedi getirilerinin, döviz kurundaki ve faiz oranındaki değişimler tarafından büyük ölçüde açıklandığı görüşündedir.

Anahtar Kelimeler: Risk, Sektörel CDS, VIX, MOVE, SMOVE, Volatilite Etki Tepkisi, Petrol fiyatları, Hisse Senedi Getirileri, TVP-VAR Modeli, Türkiye.

DEDICATION

To my love Dr. M. Burak Toparlı, my little boy Ahmet Selim and to all my family

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LIST OF ABBREVIATIONS

Δ	Difference Operator
ADF	Augmented Dickey and Fuller Unit Root Test
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
BEKK	Baba, Engle, Kraft, Kroner
BIST	The Stock Exchange of Istanbul
BIST100	Turkish General Stock Price Index
BRIC	Brazil, Russia, India, China
BVAR	Bayesian Vector Autoregression
CBOE	Chicago Board Options Exchange
CD	Convergence Diagnostics
CDS	Credit Default Swap
CPI	Consumer Price Index
DCC-GARCH	Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroskedasticity
DCC-GARCH-GJR	Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroskedasticity- Glosten, Jagannathan, and Runkle
DJIA	Dow Jones Industrial Average
ECB	European Central Bank
EU	European Union
GARCH	Generalized Autoregressive Conditional Heteroscedasticity

GCC	Gulf Cooperation Council
GDP	Gross Domestic Product
GIRF	Generalized Impulse Response Function
IFS	International Financial Statistics
IMF	International Monetary Fund
ISDA	The International Swaps and Derivatives Association
JB	Jarque&Bera Langrange multiplier test
KPSS	Kwiatkowski, Philips, Schmidt and Shin Unit Root Test
LM	Lagrange Multiplier
ln	Natural Logarithm
MCMC	Markov Chain Monte Carlo
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroscedasticity
MOVE	Merrill Lynch Option Volatility Estimate Index
MSCI	Morgan Stanley Capital International
MS-VAR	Markov-Switching Vector Autoregressive
NIEs	Newly Industrializing Economies
NYMEX	New York Mercantile Exchange
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
OPEC	The Organization of the Petroleum Exporting Countries
OTC	Over-the-Counter
PCC	Pearson Correlation Coefficient
PP	Phillips and Perron Unit Root Test
Q	Ljung-Box Q Test

REITs	US Real Estate Investment Trusts
RMB	Chinese yuan
S&P 500	The Standard & Poor's 500 index
S.D.	Standard Deviation
SDSVaR	State-dependent Sensitivity Value-at-risk
SMOVE	Swaption Move Expected Volatility Index
SVAR	Structural Vector Autoregressive
TVP-R	Time Varying Parameter Autoregression
TVP-VAR	Time Varying Parameter Vector Autoregression
US	The United States
VAR	Vector Autoregressive
VAR-BEKK	Vector Autoregressive Baba-Engle-Kraft-Kroner
VAR-GARCH	Vector Autoregressive- Generalized Autoregressive Conditional Heteroscedasticity
VDC	Generalized Forecast Error Variance Decomposition
VEC	Vector Error Correction
VECM	Vector Error Correction Model
VIRDF	Volatility Impulse Response Density Function
VIRF	Volatility Impulse Response Function
VIX	CBOE Volatility Index
WTI	West Texas Intermediate

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Chapter 1

INTRODUCTION

Crude oil is based on fossil fuels which takes millions of years to form. After the discovery of combustion engines about mid-1800s, the demand of the crude oil and its derivatives such as petroleum products have been dramatically increased. Owing to the increase in demand, crude oil has become one of the most valuable assets of the local and global economies. Therefore, the price of the crude oil plays an important role for all countries importing and exporting the crude oil and its derivatives.

One of the most important factors that determines the price of the crude oil is the law of supply and demand. The Organization of the Petroleum Exporting Countries (OPEC) significantly affects the crude oil price by controlling the crude oil production by setting production targets to member countries. According to US Energy Information Administration, as of September 2018, OPEC countries control approximately 81.5% of the world's total proved oil reserves and produced 44% of the world's total crude oil. And in 2020, for Middle Eastern OPEC countries' supply ratio would be expected as 40% of the world crude oil. The US supplies more than 10% of the world crude oil need. Therefore, the supply has considerable influence over the crude oil price, as expected.

In addition to supply-demand relation, local and worldwide geopolitical and economical events have also remarkable influence on the crude oil prices. As shown in Figure 1.1, the geopolitical and economical events particularly those related to the crude oil producers or OPEC countries, can induce steep price change, i.e. shocks. Considering the Figure 1.1, the steep rise of crude oil price in the beginnings of 1980s was triggered by Iran-Iraq war and similar behavior was observed during the invasion of Kuwait by Iraq. As known, Iraq, Iran and Kuwait are OPEC member countries. In addition, significant events with global impact also affect the crude oil price such as 9/11 attacks happened in the US and global financial collapse, inducing significant but short-term price changes.

Fluctuations in oil price influence stock exchange market prices owing to the impact on future cash flows. Having direct effect on stock exchange market, change in oil price can also create an effect on interest rate by depreciating the future cash flows. In addition to crude oil price, other macroeconomic variables have also strong impact on stock exchange markets. S. A. Basher & Sadorsky (2006) argue that oil price volatilities introduce significant impacts on the emerging markets, inducing risks and uncertainty on stock returns. Hence, S. A. Basher & Sadorsky (2006) claim that the stock exchange market is affected negatively. S. A. Basher & Sadorsky (2006) also argue that depreciation in stock market prices reduces the wealth and future investments.

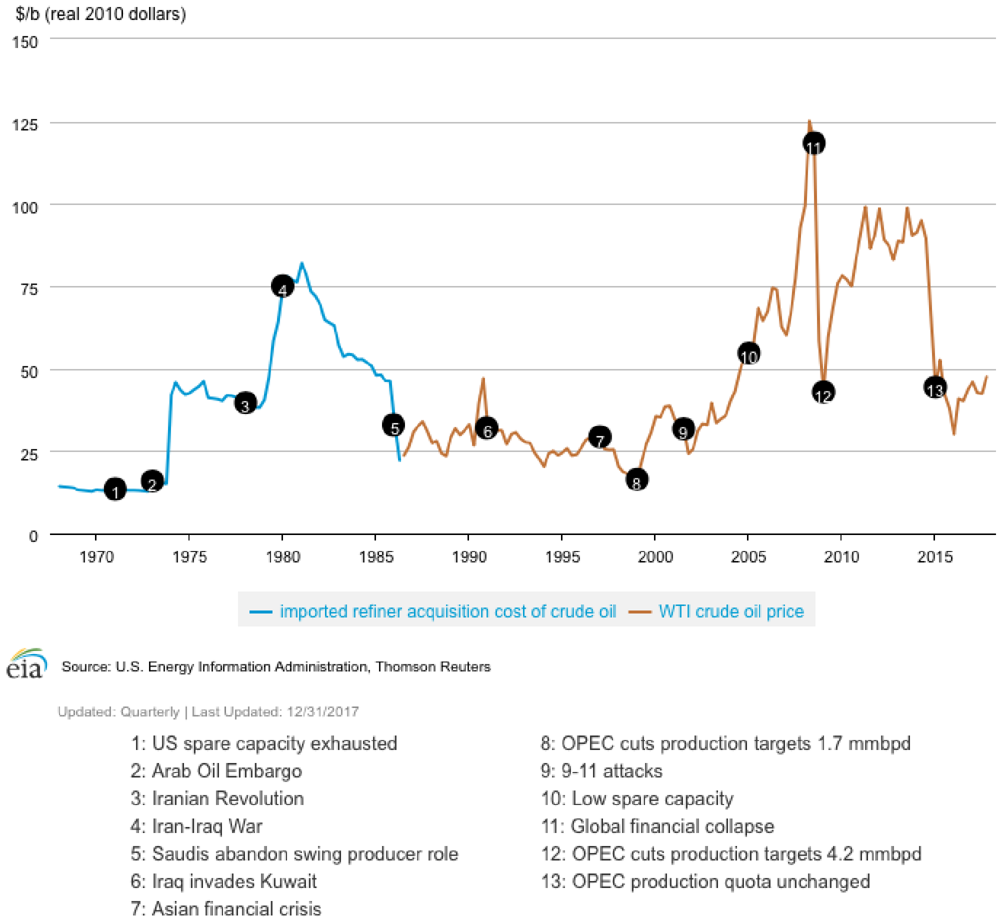

Figure 1.1: Crude oil price vs. time. The effects of major political and economic events can be seen. Courtesy: US Energy Information Administration, Thomson Reuters

Other macroeconomic variables for instance industrial production, real effective exchange rate and interest rate have also very significant contribution to wellness of local economies and global financial markets. Economists are particularly interested in their relation to each other, and they employ various models to predict the relation among them. Exchange rate is the conversion power of any local currency against other currencies and foreign exchange rate is the one representing the home currency. In the economic theory, the interrelation between the price of stock market and exchange rate is accepted as positive. Exchange rate determines the purchasing power at home country and the ability of domestic investors by changing the cash flow in and out. Any upward trend in domestic exchange rate makes investors move to financial markets. In other words, appreciation of the home currency will increase the purchasing power, leading to local and global investors to explore the investment opportunities. Owing to the increase in demand for investments, stock prices will also increase. For investor companies, stock price means present value of future cash flows. Furthermore, exchange rate impresses international competitiveness by affecting cash flows and stock prices. Any appreciation in stock prices will be motivated for domestic assets having an impact on domestic currency. Motivation for domestic asset and currency create demand for money that leads to higher exchange rate and interest rate, which creates capital flows into the country.

Any volatility in interest rate also influences stock demand and stock prices. Low interest rate means lower opportunity cost for borrowing. This situation motivates investors to economic activities, such as new investments. Therefore, equity shares become valuable in stock market. When interest rate decreases the dividend income's present value appreciates. Then, stock prices increase leading to an opposite relation across interest rate and stock price. Furthermore, any upward trend in interest rate attracts shareholders to invest on the earnings of interest and move away from stock market therefore decrease in stock value.

The short-term changes in the volume of production in industrial sectors for one month is represented by industrial production index. It is also named as the measure of output level of an economy. Forecasting future economic performance, this is a valuable macroeconomic variable, affected by consumer demand and interest rates. High amounts of industrial production could cause excess supplies and high inflation periods. Central banks of the countries are accounted these levels to measure inflation rate. In macroeconomic theory, the expectation of the connection between stock return and industrial production index is positive.

Being the world’s biggest oil consuming country, the US and its economy is very attractive for researchers to investigate the oil price and its response to important local and global political and financial events. And, Turkey is one of the most important emerging economies owing to its geopolitical importance as well as young population and growing economy. Therefore, both countries and their economical parameters are investigated in this thesis.

In this study, Chapter 2 covers the literature review part. In the following chapters, the crude oil price is investigated according to two different scenarios. Initially, the magnitude of volatility transmission and the risk spillover mechanism across the oil market, financial market risks, and the oil-related CDS sectors in US are examined as the first scenario placed in Chapter 3. In the second scenario, the investigation of the effects of crude oil price and selected macroeconomic variables: interest rate, industrial production index and exchange rate on Turkish stock market by employing TVP-VAR model is placed in Chapter 4. The conclusions of two scenarios and recommendation for future work are presented in Chapter 5. Furthermore, Appendix part includes additional figures related to the study presented in Chapter 4.

Chapter 2

LITERATURE REVIEW

Fluctuations in oil price and its effects on local and global economies have become one of the most attractive topics for economists. Particularly for the last two decades, the relations between the international financial markets activity and oil price have been investigated. Empirical studies about the influence of macroeconomic variables on different stock markets are examined in detail. The studies yield inconclusive results suggesting that the nature of the correlation and interrelation varies across selected variables, country, time horizon and the frequency of the data.

The crude oil price and influences on the stock return has been examined widely for developed countries, especially for the United States (US) according to literature. Huang, Masulis, & Stoll (1996) argue the interaction among daily oil future returns and the US stock prices for the sample from 1979 to 1990. By using VAR approach, the findings show that oil future returns do not have significant influence on the US aggregate indices of stock market. Sadorsky (1999) employs a VAR model to evaluate the effects of variables on stock market of US namely oil price, industrial production as a measure of output and short-term interest rate. The model covers monthly data of 1947, January – 1996, April. Contrary to Huang et al. (1996), the US market real stock return of S&P 500 has been negatively and significantly influenced by the shocks in oil prices. Oil price influence on stock returns is significantly higher after 1986 compared to interest rates associated with the oil market turbulence. Oil price impacts become largest from January 1986 to April 1996. The findings also show that the volatility of oil price shocks have asymmetric impacts on the US economy due to changes in oil price dynamics. In addition, it is declared that the price and price volatility of oil have significant roles on the aggregate stock market. Besides this, the changes in the variables of economic activity play minor influence on oil price and oil price volatility. Positive oil price shocks lead stock returns in a negative manner and induce a decrease in industrial production as well as interest rate.

The long-run equilibrium relationships exist among exchange rate, interest rate, industrial production, inflation and aggregate stock price in the paper by Kim (2003). The data that covers 30 days for the period between January 1974 and December 1998 in the US. The results indicate the presence of a negative influence of the interest rate, inflation and real exchange rate on the US general stock prices in the long run. It is asserted that S&P 500 is positively affected by the economic activity. The relation among oil price futures and real stock returns of US is also examined by Ciner (2007). The S&P 500 stock index data and the oil futures contracts' daily closing prices trade on the New York Mercantile Exchange (NYMEX) are analyzed for the years between 1990-2000. The results obtained from VAR model shown that there existed statistically significant non-linear causality in the selected variables.

According to Kilian & Park (2009), due to demand or supply oriented shocks, the oil price and so the US economy is affected in various ways. Using structural VAR model for monthly data covering the period of 1973-2006, the correlation among the stock market and the oil price is investigated. According to this study, for the long term, global crude oil market's supply-demand shocks explain 22% of the volatility in the US market real stock return.

The correlations between stock market and economic activities over the period January 1961 - October 2006 are investigated by Hamrita, Ben Abdallah, & Ben Ammou (2009) by using the industrial production index and the Dow Jones Industrial Average (DJIA) stock price index for the US. Findings of the study on multi-scale interactions between exchange rate, interest rate and stock prices show that stock market returns have the tendency in leading the economic activities.

Daily data from 1999 to 2011 is examined to investigate the link between the US stock returns including equity VIX volatility, inflation expectations, the USD/Euro exchange rate, gold prices, interest rates and oil prices by Mollick & Assefa (2013). GARCH and Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) models are employed for their study. It is shown that oil price and exchange rate affect negatively the US stock exchange market. On the contrary, these interactions are positive after mid-2009 for the subsample. As a result, it is shown that positive US stock responses are observed for the expectations of worldwide recovery after the financial crisis.

In addition to the US, there are studies concentrating on the developed countries. Mok (1993) studies stock return prices, interest rate and exchange rate of Hong Kong stock market covering 1986 - 1991. The daily data is employed to capture the dynamic fluctuation in the market by using autoregressive integrated moving average (ARIMA) model. It is concluded, the market efficiently incorporates much of the exchange rate and interest rate information.

Yu (1996) examines the interaction among exchange rate and stock price on the daily data of Singapore, Hong Kong and Tokyo between 3 January 1983 and 15 June 1994. Depending on the country, the relations between stock prices and exchange rates show different behaviors. In Tokyo market, bidirectional causal relations among stock returns and change in exchange rates are observed. Besides, no significant relation among exchange rate and changes in stock prices is found in Singapore. The exchange rate's predictive power on stock returns is found as higher for the Hong Kong stock market.

Jones & Kaul (1996) analyze the US, UK, Japan and Canada's quarterly data from 1947 to 1991 to examine oil price fluctuations on economies of different countries' stock returns depending oil productions and consumption levels of each countries. For the US and Canada, impression of oil prices on aggregate stock return are fully descriped by effects of oil price shocks because of the change of real cash flows in the postwar period. The results of Japan as well as the UK are not very significant.

Papapetrou (2001) adapts multivariate VAR model to find out the dynamic relationship between monthly data of economic activity, employment, real stock price, interest rate and oil price for the period of January 1989 - June 1999 in Greece. The results of this study are well-aligned with the conclusions of Sadorsky (1999). This study shows that oil price changes influence negatively employment and the real economic activity in Greece. This variation has an indirect negative effect on stock prices. However, it is claimed that the stock return changes are not the main influence for variations of employment and real economic activity.

A new perspective based on the influence of oil price fluctuation on real stock market return is introduced by Park & Ratti (2008). The study concentrates on stock return prices of the US and 13 European countries by using multivariate VAR model for January 1986- December 2005 monthly data on variables of stock prices, consumer prices, industrial production and short term interest rate. It is claimed that the effect of oil price fluctuations on real stock market returns depending on whether the country is oil importing or exporting. Norway, as an oil exporter European country, shows significant positive real stock return response to oil price increase. In addition, it is also found that there is asymmetric effect from oil price shocks to real stock returns for Norway and the US. However, considering other oil importing European countries, the asymmetric effects induced by negative and positive oil price shocks are not significant.

The long term relation between international stock exchange and world crude oil price is examined by Miller & Ratti (2009) for six Organization for Economic Co-operation and Development (OECD) countries by employing Vector Error Correction Model (VECM) for the period of 1971-2008. Structural breaks in the correlation are found because substantial negative relationship is disappeared among indices of stock market and oil shocks after September 1999.

The daily data from January 1991 to September 2008 of the US, the UK, Germany, France and Japan’s stock and exchange rate markets are examined using GARCH model in the study of Ning (2010). Despite the previous evidences on the asymmetric relationship, it is claimed that a significant symmetric time-varying association between two markets exists in this study. The dependence becomes weaker; however, it is still significant particularly after the introduction of the Euro.

Filis, Degiannakis, & Floros (2011) research time-varying correlations among oil price and stock markets with Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroskedasticity-Glosten, Jagannathan, and Runkle (DCC-GARCH-GJR) model by grouping countries similar to Park & Ratti (2008) as oil importing countries: Netherlands, Germany, the US and oil exporting countries: Brazil, Mexico and Canada. For the investigated period between 1987-2009, a positive relationship is reported between variables, when there are economic crises or booms. However, non-economic crises lead to strongly negative correlation. Shocks from the supply side do not affect the link among oil prices and stock market. On the other hand, precautionary demand shocks induce negative relationships and aggregate demand side shocks induce positive correlations.

Kal, Arslaner, & Arslaner (2015) estimates a Markov-Switching Vector Autoregressive (MS-VAR) model to investigate the correlation between interest rates, exchange rates and stock markets between 1972 and 2010. The effects of currency depreciation on interest rate as well as stock market are investigated by defining as overvalued or undervalued exchange rates. Economic fundamentals and nominal exchange rates are depended on the influence of the overvaluation or undervaluation of four currencies which are Japanese yen, British pound, Australian and Canadian dollars. Also, results suggest a a time varying interaction between stock index, interest rates and exchange rates.

There are also studies focusing on developing and emerging countries. Abdalla & Murinde (1997) work on the monthly data of exchange rates and stock prices from India, Korea, the Philippines and Pakistan by employing bivariate vector autoregressive model for the period of January 1985 - July 1994. A unidirectional causality to stock markets from exchange rates is obtained except the Philippines.

Stock markets of South Korea, Indonesia, Hong Kong, Japan, Philippines, Malaysia, Singapore, Taiwan and Thailand are researched also by Granger, Huang, & Yang (1998) in empirical analyses. The bivariate causality is examined by using Granger causality model among exchange rates and stock prices. The investigated daily data cover January 1986 - November 1997. Positive correlations among exchange rates and stock prices are obtained for Thailand and Japan. However, Taiwan stock market shows negative link with exchange rate. Strong feedback relations are indicated from Indonesia, Korea, Malaysia, and the Philippines data. It is argued that no significant pattern was found for Singapore.

The analyses of VAR model with five Pacific Basin countries such as the Philippines, Hong Kong, Singapore, Malaysia and Thailand are created over the period 1980 – 1998 about dynamics of long and short runs between stock prices and exchange rates by Phylaktis & Ravazzolo (2005). Positive relation is founded for foreign exchange markets and stock marekts.

Zarour (2006) investigated the interactions between oil price and five Gulf Cooperation Council (GCC) stock markets by employing VAR models for the period 2001 – 2005. According to this study, it is concluded that responses of the stock markets become faster as the oil price is increasing.

S. A. Basher & Sadorsky (2006) examines the link between oil prices and price returns of 21 emerging stock markets covering December 1992 - October 2005 using unconditional and conditional risk analyses. It is concluded that the risk in oil price seriously influences the stock market performance in emerging countries, i.e. Argentina, Brazil, Chile, Colombia, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, South Africa, Sri Lanka, Taiwan, Thailand, Turkey and Venezuela.

Pan, Fok, & Liu (2007) examine time-varying response between exchange rates (local currency per US dollar) and daily stock prices for seven countries in East Asia, including Hong Kong, Korea, Japan, Singapore, Malaysia, Thailand and Taiwan covering January 1988 - October 1998 using VAR model. The study reveals that the relation between countries' stock returns and exchange rates depend on economies according to the equity market size, trade size, degree of capital control and exchange rate regimes.

Malik & Hammoudeh (2007) investigates the volatility and shock transmission in global crude oil markets, Gulf equity and US equity by employing multivariate GARCH (MGARCH) model. The volatility is transmitted from oil markets to Gulf stock markets with the results of the data from 1994 to 2001. In the findings, the significant volatility spillover is only observed from Saudi Arabia market to oil market. This result proves the importance and dominance of the Saudi Arabia, over the global crude oil market.

The interaction between the macroeconomic variables of oil price and exchange rates of BRIC countries: Brazil, India, Russia and China and their stock market index prices are analyzed by D. Gay (2008). A Box-Jenkins ARIMA model is built using the data of 1999 - 2006. The monthly averages of respective stock market indices, oil prices and foreign exchange rates show no significant relationship between each other for these countries. A weak-form of market efficiency is claimed in these countries due to the insignificant relation between present and past stock market returns.

Diamandis & Drakos (2011) are interested in the time-varying interactions among exchange rate and stock market price for Argentina, Brazil, Chile and Mexico. The monthly data covering January 1980 - February 2009 is used as an input to their model. Exogenous shock influences are also examined for these markets. Positively related foreign exchange markets and stock markets are obtained. However, the relationships are instable during the Mexican currency crisis in 1994, 1997 Asian crisis and 2008 global financial crisis.

The effects of fluctuations in local currency Chinese yuan-RMB, the exchange rate and interest rate on Chinese financial market are investigated by Cao (2012) with the daily data covering July 2005 - January 2012. This study is extended time-varying parameter structural vector autoregression VAR (TVP-VAR) and time-varying parameter autoregression (TVP-R) models to the long-memory models. Based on these models, it is shown that the short-term influence of renminbi exchange rate on stock market was sensitive. The influence of interest rate change on stock return is related to 2008 financial crisis. Besides, effects of interest rate on stock returns are very limited for long term period and it is argued that the appreciation of RMB could be considered as a non-negative factor for the Chinese financial market.

With monthly data from January 1988 to December 2008, S. Basher, Haug, & Sadorsky (2012) examine the dynamic relation between interest rates, global stock prices, global oil production, oil prices, exchange rates and real economic activity in Kazakhstan, Qatar, Saudi Arabia, China, Algeria, Singapore, Kuwait, United Arab Emirates, Ecuador and India with six-variable structural VAR model. Their findings show that in emerging countries, positive change in oil price shocks induce a decrease in US dollar exchange rate and stock prices. It is quarreled that the interaction between oil price and oil production is negative. However, link between real economic activity and oil price is observed to be positive for some emerging countries. The most important finding is that the increase in the stock market prices in emerging country lead a rise in oil price.

Awartani & Maghyereh (2013) examine the spillover volatility between WTI oil price and stock market equities and dynamic spillover of return in the GCC countries Qatar, Bahrain, Kuwait, Saudi Arabia, Oman, Abu Dhabi, Dubai. The MGARCH model using weekly data starting from the 2 January 2004 to the 30 March 2012 reveals that the return and volatility transmissions are bidirectional.

The long run relations between Brent oil price, US interest rate and MSCI (Morgan Stanley Capital International) world index and stock markets of the GCC are investigated by Jouini (2013). The dataset of oil price and other variables are weekly from 7 June 2005 to 21 October 2008. A strong evidence of nonlinear long run correlation between movements of global factors including oil price and these countries' stock markets is claimed to be obtained.

Fang & You (2014) concentrate on three BRIC countries; China, India and Russia in their study. Structural vector autoregressive model (SVAR) approach is chosen as a methodology to explore the relationship between the BRIC financial markets and oil price shocks driven by demand or supply. The model employs data from January 2001 to May 2012. Findings show that the influence of oil price shocks on the three large newly industrializing economies' (NIEs') stock prices are different. It is reported that there is relatively low energy efficiency of China. Therefore, it is concluded that the oil prices have insignificant effects. During the 3rd to 6th months of the investigated period, China's demand-driven oil prices have a considerable negative impact. Besides, it is reported that the effect is negative on India's economy. If the oil price movement is driven by Russian oil-specific supply shocks, the impact is found to be significantly positive on Russia's stock returns. As a result, the study shows that three large NIEs' stock markets behaviors are different and they integrate partially with the other oil price shocks as well as stock markets.

Turkey has become one of the most attractive developing country for researchers in the recent years owing to its the political and economic role. Yet, there are few studies covering Turkey's economic indicators in the literature. The short and long-run relationships among the daily time series data of Turkish interest rate, Turkish lira/US dollar exchange rate, The Stock Exchange of Istanbul (BIST) benchmark bond rate, Brent oil price and domestic spot gold and silver prices are examined using VAR model by Soytas, Sari, Hammoudeh, & Hacihasanoglu (2009). Observation period starts in May 2003 and ends in March 2007. Findings show that world oil markets do not have significant influence on Turkish markets in the short run. However, in the long run, Turkish spot precious metals, bond markets and exchange rate are not helpful to forecast world oil price. Predictive power of oil price could not be obtained on the interest rate, exchange rate markets and the precious metal prices in Turkey.

Al-Jafari, Mohammed Salameh, & Habbash (2011) examines the interaction between the macroeconomic variables namely exchange rate, money supply, stock prices, real economic activity, interest rate and inflation between January 2002 and December 2008. The data is elected from 16 developed and 16 emerging markets. (Emerging: Argentina, Malaysia Brazil, India, Chile, China, Colombia, Indonesia, Czech Republic, Thailand, Hungary, Mexico, the Philippines, Poland, Russia and Turkey. Developed: Hong Kong, Australia, the UK, Austria, Belgium, Denmark, Finland, France, Japan, New Zealand, Portugal, Singapore, Sweden, Canada, Switzerland and the US) VAR model results show that long-term interactions between exchange and interest rates and stock prices in developed or emerging markets are not existed, however, between interest rates and stock prices a short-term relationship is claimed to be observed.

Considering the influences of both risks of foreign exchange and interest rates on stock returns of Turkish banks, Kasman, Vardar, & Tunç (2011) study the models of GARCH and ordinary least squares (OLS). The investigation period covers 27 July 1999- 9 April 2009. It is found that on the bank stock returns, variations of interest rate and exchange rates have significant negative impacts. Furthermore, it is concluded that for the volatility of conditional bank stock returns, the interest rate and exchange rate volatilities are very important indicators.

Eryigit (2012) investigates the dynamic relationship between the main index of Turkish General Stock Price Index (BIST100), exchange rate, crude oil price and interest rate by employing VAR model covering January 2005 - October 2008. Dynamic relationship among all variables is discovered. Findings show that the shocks in oil price have impacts on Turkish stock exchange and have immediate negative effect on exchange rates. Oil price shocks explain significant proportion of the interest rate and stock exchange according to findings.

Compared to the study of S. A. Basher & Sadorsky (2006), Aloui, Nguyen, & Njeh (2012) examine 25 emerging countries including Turkey. The stock exchanges with daily data for the period of September 1997- November 2007 are employed for conditional multifactor pricing model and the long-term correlation. The countries are grouped into three as the largest net-oil importing (oil dependent) countries, the moderately oil dependent countries and the largest net-oil exporting countries. The impact of bearish and bullish market conditions on the relation among oil prices and stock returns are analyzed. Findings show that oil price impact is asymmetric and the risk of the oil price is valued in emerging countries' stock markets. However, results for Europe show that volatility spillover among oil price as well as sectoral stock return is important.

Turkyilmaz & Balibey (2013) examine the transmission and spillover of volatility and shocks among stock market prices, interest rates and exchange rates are examined by using BEKK-MGARCH model cover Monthly data for Turkey from January 2002 to January 2009 is used in the analyses. It is shown that investigated variables display both ARCH and GARCH effects, therefore all news has significant impacts on conditional volatilities. In addition, it is argued that all variables are interacted to each other through shocks and volatilities.

Sensoy & Sobaci (2014) study the dynamic correlations between interest rate, exchange rate and BIST100 index in local currencies using the VAR-GARCH model based on the daily data covering January 2003 and September 2013. The results indicate sudden changes in dynamic correlations that can be attributed to volatility shocks in only short terms. However, it is also reported that there might not be considerable contagion effects for long run. A consistent positive correlation between bond and exchange markets is observed and there is a positive correlation between Turkish stock market and exchange rate due to the appreciation of US dollar against Turkish Lira.

Aydogan & Berk (2015) employ VAR methodology to investigate the dynamic interactions among BIST100 stock index and oil price shock. The daily data covering 2 January 1990 - 1 November 2011 are used and the sample period divides into three periods to obtain the influences of oil price variations on stock market. Besides, by including VIX index of Chicago Board of Exchange (CBE)'s S&P 500 into the model, the relation under global liquidity conditions is also investigated. Aydogan & Berk (2015) argue that the oil price variations do not have considerable influences on the Turkish stock market. In addition, the effect of global liquidity conditions on the stock market is found higher compared to oil price.

A research in economies including Turkey, Brazil, Colombia, Chile, India, Mexico, South Africa and Russia is conducted by Reboredo, Rivera-Castro, & Ugolini (2016) to examine risk spillovers from exchange rate to stock. In the results, they show these risk spillovers. The weekly data covering the period of 13 April 2001 to 7 November 2014 is included in the model. Computing upside and downside value-at-risk and conditional value-at-risk, a positive relation between currency values and stock prices in these countries with respect to the Euro and the US dollar is obtained in this study.

Ozcelebi & Yildirim (2017) employ a TVP-VAR model to find the effect of short term interest rate and exchange rate on stock market return of Brazil, Indonesia, Mexico and Turkey. The monthly data from January 2000 to February 2015 uses to study the interactions between these variables. During the periods of economic instability and financial crisis, it is argued that the capital movements might create a considerable amount of variation in stock and exchange markets. Furthermore, the rise in interest rates could lead to decrease in stock returns, which deteriorate Indonesia's real economic activity. In Brazil, Indonesia and Turkey, changes in short term interest rates cannot be used as a tool to stabilize the value of their domestic currencies against the US dollar.

According to literature review, other macroeconomic variables and crude oil price have impacts on the stock market returns. Considering oil prices and their influences on stock market returns, the response of the stock market varies depending on countries whether developed, developing and emerging and dependence to oil, i.e. being an importing or exporting country. In addition, political and economic events may also influence the oil prices therefore other macroeconomic indicators and stock market returns. Furthermore, other macroeconomic variables namely industrial production, interest rate and exchange rate can also contribute to stock return levels. However, their roles mainly depend on the economy of the investigated country and its dependence to the macroeconomic variables. A TVP-VAR model is built in this study to investigate the time-varying influence of real crude oil price, real effective exchange rate, industrial production index and real interest rate on Turkish stock market general index (BIST100). A TVP-VAR model is built since this model uses the advantage of impulse responses and is convenient for the researches on transmission mechanism to capture time-varying relationships, that exist between investigated parameters. Considering the dynamics of Turkish economy, selected macroeconomic variables are the most influential parameters to local economy.

Chapter 3

ON THE RISK SPILLOVER ACROSS THE OIL MARKET, STOCK MARKET, AND THE OIL RELATED CDS SECTORS: A VOLATILITY IMPULSE RESPONSE APPROACH

3.1 Introduction

Oil can be considered as the most prominent and volatile commodity in the world economy and especially in financial markets. Oil and oil-based products are not only used directly as raw materials by many economic sectors but also are used in many service sectors and traded on exchange markets. Due to high and growing demand and constraints on supply, oil has become very valuable and volatile. Therefore, any fluctuation in oil prices results significant regional and worldwide effects on the world's economies. Many factors including supply-demand, global economic developments and political issues have profound effects on oil prices and other connected markets. The researches of the transmission of risk shocks across oil and financial markets have recently gained more attention from researchers, oil industry and policymakers, particularly in the wake of recent major global crisis. The Asian Financial Crisis in 1997, the Iraq War in 2003, the US subprime Crisis at the end of 2007, the European Sovereign Debt Crisis since the end of 2009 have been the catalysts for more research on volatility and the risk transmission mechanism among oil and financial markets. For instance, after Iraq War, WTI (West Texas Intermediate) future price declined to $31.21 on 6 February 2004.

The WTI oil price was $146.12/barrel in July 2008, then nose-dove to $39.72/barrel in the middle of February 2009, as a result of the 2008 global economic crisis. Then, it dropped more than 70% and reached to $29.69[1] in January 2016 because of the excess supply. The ten year nominal bond rates in the United States declined from 275 basis points to 225 basis points in October 2015 and to about 180 basis points in January 2016. The financial market also declined by half over the same period.

The major events affecting the oil and financial markets have associated shocks and these have negative effects on the Credit Default Swap (CDS) spreads reflecting the health of the economy and fluctuations in the risk level of oil-related sectors. Due to mortgage crisis in 2007, the CDS market reached a record level of $60 trillion up from $2 trillion dollars in 2002. This market in December 2010 was $29.9 trillion and finished the year 2012 with the value of $25.1 trillion according to a survey of ISDA[2].

The fear index, CBOE Volatility Index (VIX) measures one-month expected equity volatility of the S&P 500. The Merrill Lynch Option Volatility Estimate Index (MOVE) represents the expected risk in the bond market and the Swaption Move Expected Volatility Index (SMOVE) shows the expected risk in the swap market. In other words, VIX and MOVE are correlated with the equity market and US Treasury securities market, respectively. SMOVE can be considered as a kind of VIX for US

[1] http://www.bloomberg.com/quote/CL1:COM
[2] http://www2.isda.org/attachment/NTY4MQ==/ISDA%20Year-End%202012%20Market%20Analysis%20FINAL.pdf

non-Treasury in swaption markets. MOVE is the measurement of treasury risk, on the other hand SMOVE is counting the business risk and interest rate fear risk is measured by VIX.

The daily closing futures prices of WTI and seven different measures of risk are used in the analysis of this study. Four of the vast risk measures are oil and oil-related sector CDSs, which include auto (AUTO), chemicals (CHE), natural gas (OILGAS), and utility (UTIL) sectors. Others are the one-month expected equity volatility measured by VIX, one-month MOVE and SMOVE indices. The seven variables investigated in this study are not only used as risk measurement tools but also used to represent the volatilities in different markets and sectors.

One of the main aims of this part is to investigate study the volatility transmission mechanism across the oil, oil-related CDS sectors and financial markets, employing a multivariate conditional volatility model. The other main objective is to discern how major global events affect the volatility of the oil and oil-related CDS markets by employing the newly introduced Volatility Impulse Response Function (VIRF) analysis. To examine the risk spillover mechanism within and across the oil market, financial market, and the oil related CDS sectors; eight variables (WTI, four oil and oil-related sector CDSs, VIX, MOVE and SMOVE) are employed for the period from the beginning of January 2004 to February 2016 in the BEKK model, by Engle & Kroner (1995) multivariate conditional volatility model. In addition, the VIRF model uprated by Hafner & Herwartz (2006) is employed to our dataset to assess the magnitude of the volatility transmission. We evaluate the risk transmission on oil and oil-related market volatilities due to following events: US mortgage crisis: Lehman Brothers bankruptcy on 17 September 2008; the Greece debt crisis on 8 December

2009; the fear of Greece's default on 23 April 2010; the Egyptian political unrest (Second Revolution) on 27 May 2011; the European sovereign debt crisis on 18 August 2011; and the US government shutdown on 30 September 2013.

The volatility impulse responses have the advantage of providing valuable information on the speed of risk transmission. In addition, the shape and sign of the volatility impulse responses also provide significant information on the transmission mechanism. Therefore, the study of volatility transmissions within and across the oil sector and oil-related sectors and the determination of the dynamic relationship between the price of oil, oil-related CDS sector indices, VIX, MOVE/SMOVE are valuable to oil companies, market investors, creditors of these sectors, energy regulators and governments for future decisions and actions.

This work aims to contribute to the literature by conducting the first comprehensive analysis of the volatility transmission mechanisms across oil and oil-related sectors CDS' and financial markets. As opposed to previous studies mainly focusing on financial markets, analyses conducted in this study are performed at sectoral level. Sectoral analyses are crucial for policy-makers, energy regulators and investors in financial markets of the energy and energy-related sectors. In addition, according to authors' best knowledge, there is no similar study focusing on the effects of various global historical shocks to oil and oil-related market volatilities on sectoral based by employing VIRF model. In the literature, most of the studies are concentrating on only Global Financial Crisis, triggered after Lehman Brothers bankruptcy.

The remainder of this chapter is organized as follows. The next section includes a literature review. Section 3.3 defines the data and descriptive statistics. The econometric methodology employed in this chapter, i.e. VIRF, is presented in Section 3.4 while the empirical results are in section 3.5 and some remarks for the future studies are discussed in the final section, section 3.6.

3.2 Literature Review

3.2.1 Volatility impulse response function (VIRF) method

The Error Shock Methodology named also as Impulse Response Analysis is employed to understand the effects of a shock on the behavior of time series. Most of the early papers on Impulse Response Analysis in the literature employed linear equations. The first paper about this concept was written by Sims (1980) and improved by Doan, Litterman, & Sims (1983). Sims (1980) studied the analysis of shocks on volatility in linear models. Sims (1980) identified the impulse response analysis providing dynamic effects of an error shock in the system on future economic variables. Single linear equations or Vector Autoregressive (VAR) model were used to show the links between international equity returns. The initial studies of the international finance on spillover effect were conducted by Eun & Shim (1989) and K. G. Becker, Finnerty, & Gupta (1990). Blanchard & Quah (1989) that investigated the persistence of shocks on linear multivariate time series. Engle, Ito, & Lin (1990) introduced two important concepts known as “meteor showers” and “heat waves”. “Meteor showers” showed the transmission of volatility from one market to another and “heat waves” indicated the increased persistence in market volatility using linear equations. Koch & Koch (1991) studied on the regional interdependence by using lead/lag relationships among eight financial markets. Their findings showed at the expense of the US market, the influence of the Japanese market increases and regional interdependence between markets growing over time. They focused only on the return series and correlations, in other words, focused only on interdependence through the mean of the processes.

In the literature, linear time series models were mainly based on basic linear models. However, Beaudry & Koop (1993), Potter (1995), M. Hashem Pesaran & Potter (1997) demonstrated that linear models are not adequate for studying on persistence effects of shocks on time series because of symmetry, since, it is very hard to distinguish differences between the effect of shocks occurring in an expansion period and a recession period in linear models. The early basic models using univariate linear equations were initially improved by models employing linear multivariate equations, offered by M. H. Pesaran, Pierse, & Lee (1993) and also K. C. Lee & Pesaran (1993).

Further improvements were also conducted by employing models using nonlinear equations, which were able to demonstrate more complexities compared to linear models. Two different definitions of Impulse Response Analysis using nonlinear models were offered by Gallant, Rossi, & Tauchen (1993) and Koop, Pesaran, & Potter (1996). Gallant et al. (1993) made use of a semi-nonparametric methodology for nonlinear system in their Impulse Response Analysis and two concepts the “baseline” and the “shocked” were defined. In their paper, the difference between the baseline approach and the shocked was approved as the conditional moment profile and the shock was declared as either estimated or observable. Koop et al. (1996) offered a new method, Generalized Impulse Response Function (GIRF). The difference between the mean that only conditioned on history and the mean of the response vector conditioned on both present shock and history was found so that a new concept of generalized nonlinear impulse response functions for the conditional expectation was introduced and named as the GIRF. Lin (1997) contributed the idea of Gallant et al. (1993) by filling the gap in the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) literature by tracing the dynamics of the conditional variance from past squared innovations for the impulse response function. In that paper, this function for conditional volatility in GARCH model's standard error was found. Then, first-order derivatives of the function and the covariance matrix of the estimated parameters were traced. Monte Carlo analysis was employed to find the standard errors' finite sample properties. It was also concluded that despite the process itself being nonlinear, the conditional variance was linear. In the 1990s, Hamao, Masulis, & Ng (1990), Engle & Ng (1993), Lin, Engle, & Ito (1994), Karolyi (1995), Koutmos & Booth (1995) and Booth, Chowdhury, Martikainen, & Tse (1997) traced the effects of shocks over time using impulse response analysis and investigated whether the volatility was transferred from one market to another. Ewing, Malik, & Ozfidan (2002) studied volatility transmission on oil and gas companies' stock indices. Serletis & Shahmoradi (2006) examined volatility spillovers between prices of electricity and gas in Canada.

Compared to earlier studies, Hafner & Herwartz (2006) investigated the conditional variance rather than the conditional mean. According to their paper, it was considered that two news appearing in different series at the same time are independent. Therefore, it can be assumed that news is independent both over time and across the series. Whenever its distribution is not normal, the method helps to identify shocks. News is claimed as independent and identically distributed, in other words, inherently independent over time. Hafner & Herwartz (2006) created Volatility Impulse Response Function (VIRF) which is an application of the

Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) model, introduced by Koop et al. (1996). The VIRF is employed for checking the influences of independent shocks of a market on volatility of another market and the continuity of spillover influences in multivariate nonlinear models.

The effects of central bank decisions on the foreign exchange market volatility were checked for the independent shocks' effects on volatility through time by ignoring orthogonality and ordering problems. In order to avoid these problems, Jordan decomposition was applied to obtain a realistic and independent shock from the conditional heteroskedastic error terms. Hafner & Herwartz (2006) proved that news is inherently uncorrelated over time because of being a risk source that is independent and unpredictable, which is initially introduced by Gallant et al. (1993). Panopoulou & Pantelidis (2009) investigated the connection between the US and the rest of the G-7 countries and international information flow between these countries by using daily financial market return data based on VIRF analysis for 20 years. According to their findings for post-1995 period, connections between markets were changed significantly, in other words, interdependence in the volatility of the markets increased. Panopoulou & Pantelidis (2009) argued that the VIRF method developed by Hafner & Herwartz (2006) is well suited for the analysis on volatility spillover. According to Panopoulou & Pantelidis (2009), VIRF method helps to show how a shock in one market could affect the other market's dynamic adjustment of volatility to another market and the persistence of these spillover effects. In addition, when shocks occur, VIRF depends on both the state of actual system's volatility and the unexpected returns vector. This shows expected conditional volatility does not always been increased by a given shock. The asymmetric response of volatility can be negative and positive. Furthermore, owing to the application of Jordan decomposition, VIRF approach avoids ordering problems and also typical orthogonalization which is hardly feasible at high frequency financial time series in the presence of highly interrelated. Diebold & Yilmaz (2009) examined interdependence between asset returns and/or volatilities by measuring return spillovers and volatility spillovers.

From the early 1990s to the present, daily nominal local-currency financial market indices of nineteen global equity markets (seven developed financial markets and twelve emerging markets) were analyzed. According to results, in the dynamics of volatility spillovers vs. return spillovers, a divergent behavior was observed. Spillover intensity was time varying and it was different for returns vs. volatilities as the nature of the time-variation. Return spillovers had no bursts but increasing trend, also increasing financial market integration for the last fifteen years. However, volatility spillovers displayed no trend but clear bursts because of the relevance of crisis. Le Pen & Sévi (2010) quantified the effect of shocks on return volatilities in three electricity forward markets: British, Dutch and German. For the analysis of forward OTC (Over-the-Counter) electricity daily price data, they used MGARCH and VIRF models. Limited number of papers investigated the volatility spillovers in energy markets. Jin, Xiaowen Lin, & Tamvakis (2012) investigated the effects of two historical shocks of 2008 Financial Crisis and BP Deepwater Horizon oil spill on Brent, Dubai and WTI futures contracts by VIRF analyses using the daily data from 2005 to 2011 with VAR-BEKK model. Their findings show that Dubai and Brent crude futures are highly responsive to market shocks. Finding a large influence of a shock has lower probability and opposite for observing smaller impact. From small probability case, only a large shock could be derived and show an increase in expected conditional volatilities. Most papers on volatility spillovers in energy markets use the mean of the processes for transmissions than moments. Grobys (2010) investigated the cointegration of European financial markets and studied the volatility spillover effects. A new concept was introduced, the advance of VIRF, to capture the overall impacts of volatility spillovers from one market on to another market named as Volatility Impulse Response Density Function (VIRDF). The sample data was divided into two parts: 1990-2000 and 2000-2010. Grobys (2010) focused on the asset return series and whether returns were correlated with different economies.

The financial markets' mean processes and a method determining changes concerning second-order moments over time were investigated in the model consisting of VAR and MGARCH models. Grobys (2010) suggested that VIRDF presented a precise estimation of the overall volatility spillover effects considering within a certain time window since volatility shocks were continuous random variables. In addition, the probability of shocks was included in this study. Increasing or decreasing volatility spillover effects could be embraced as the difference of the volatility spillover effects between different time windows founded by VIRDF. Consequently, according to the findings of Grobys (2010), there was an increasing volatility spillover impact among countries. Adams, Füss, & Schindler (2015) created a state-dependent sensitivity value-at-risk (SDSVaR) model for quantifying risk spillover among 74 U.S. Real Estate Investment Trusts (REITs). The direction of risk spillover effects from one REIT to another was investigated. For risk spillover size, an estimation of the link between geographic distance and risk spillover was conducted. Therefore, these estimates were not only quantifying the size but also the direction. Their findings showed that vulnerability to risk in other REITs was significantly increased by high leverage, size, and market beta by increasing the probability of contagion during a financial crisis.

3.2.2 Volatility impulse response function (VIRF) method using CDS

Credit Default Swaps (CDS) index spread is a newly introduced concept; therefore, the number of studies is very limited. In addition, the limited availability of data on CDS also affects the study of economic analysis. As far as we know, there is no study related to CDS especially studying on our selected shocks in VIRF analysis. The following studies use cross sectional data while analyzing on CDS spreads (equity and credit markets). Longstaff, Mithal, & Neis (2005) examined the difference between CDS spreads of corporate bond-implied and the actual market CDS therefore found the first spread is being higher than the second one. Das & Hanouna (2006) investigated the change between cash/asset market CDS spread and credit market CDS.

The papers which examined the primary determinants of CDS spreads and investigated the reasons of changes in those can be listed as Alexander & Kaeck (2008), Cremers, Driessen, & Maenhout (2008), Ericsson, Jacobs, & Oviedo (2009a), Annaert, De Ceuster, Van Roy, & Vespro (2013), Galil, Shapir, Amiram, & Ben-Zion (2014) and Chan & Marsden (2014).

CDS spread is thought as a measurement of credit risk in the following papers. The work of Bharath & Shumway (2004) is another example on credit risk study. The links between default swap spreads and theory-based determinants of default risks are investigated by Ericsson, Jacobs, & Oviedo (2009b).

A significant portion of the variation in the data is explained by the theory-based variables. Berndt, Douglas, Duffie, Ferguson, & Schranz (2008) examined the degree of variations in the credit risk premium of CDS spread in oil and gas sectors, health care, broadcasting and entertainment over time. According to the results, variations in the credit risk premium were significantly different. B. Y. Zhang, Zhou, & Zhu (2009) studied the CDS premium; because of high frequency stock prices, jump risks and the volatility of individual firms. In CDS spread levels, the jump risk and volatility risk predicted 19% and 48% of the variation, respectively. By controlling the internal and external influences, they predicted 6% more variation than before. As a result, the credit spreads could be explained by the high frequency-based volatility measures.

CDS is examined by time series in the following studies. Byström (2006) investigated Dow Jones iTraxx CDS indices, i.e. indices of CDS securities of the seven sectors; sub-ordinated financials, technology-media-telecommunications, energy, industrials, autos, consumers and senior financials; covering the European market. Byström (2006) found a connection between the financial market and iTraxx CDS index. The stock price volatility was highly correlated with CDS spreads and there was a significant positive autocorrelation in the iTraxx market.

Similar to findings of Byström (2006); Narayan, Sharma, & Thuraisamy (2014) and Narayan (2015) found the heterogeneity between equity returns and CDS index spreads of the US selected industries. Narayan (2015) investigated the period of July 2004 - March 2012 for CDS of US ten sectors and found time-varying spillover index.

Haibin Zhu (2006) showed the high response of CDS premium to credit conditions by using vector error correction model (VECM) and found a long-run relation between CDS market and credit risk in the corporate bond market. Fung, Sierra, Yau, & Zhang (2008) discovered the links between CDS and stock markets in US and it was shown that the lead/lag relationships between those markets depended on the quality of credit. Forte & Lovreta (2008) found the stronger relationship at lower credit quality levels after examining the link between financial market and company level CDS. Norden & Weber (2009) was also examined the relation between bond, CDS and financial markets. Daily, weekly and monthly lead-lag relationships in VAR models for period from 2000 to 2002 were investigated. According to their findings, stock returns led to a change in CDS and bond spread. In addition, the CDS market was found more sensitive to the financial market than the bond market and this tendency increased for larger bond issues and lower credit quality. It was also shown that the CDS market contributed more to price discovery than the bond market and this was stronger for US firms than for European firms. R. Becker, Clements, & McClelland (2009) evaluated two issues related to volatility index (VIX). The first issue that was discussed in this study was the contribution of historical events to volatility. And, the other one was the possible indication and information that could be inferred from VIX about future events. Their findings showed that VIX included information about both related to incremental information relevant to past and future even contributions on total volatility. It is an important study showing how option markets form volatility forecasts. By using a general VECM representation with a sample of European and North American firms, Forte & Peña (2009) studied financial market relationships and implications on CDS, bond and credit spreads. The empirical results on price discovery indicated the CDS' leading role with respect to bonds. Figuerola-Ferretti & Paraskevopoulos (2011) argued the nature of the relation between credit risk and market risk. It was claimed that long-term relationships in CDS and VIX markets was found for most companies. Figuerola-Ferretti & Paraskevopoulos (2011) revealed the cointegration in VIX and iTraxx/CDS markets. In addition, they stated that in the price discovery process, VIX had a clear lead over the CDS market. When there was a temporary mispricing from the long-run equilibrium, CDS could adjust to market risk. Luo & Zhang (2012) extended the use of VIX to other maturities. Daily term VIX data from 2009 was offered by using two-factor stochastic volatility structure for the VIXs. It was shown that historical volatility contains less information than VIX. According to their results, both the time series dynamics of VIXs and the term structure's rich cross-sectional shape were captured by this framework.

In contrast to the previous studies, Hammoudeh, Liu, Chang, & McAleer (2013) focused on variable interactions at the sector level, not the firm level. Risk migration and transmission of six market and credit risks in US were examined. The data used in the series of analysis were from 2004 to 2011. However; a sub-period of 2009 to 2011 was also used to analyze the effects of shocks in 2007–2008 Great Recession. Four oil exploration and production sectors namely the auto, natural gas, chemicals and utility sectors were investigated. According to the study, there were short run causal relationships and more long-run equilibrium risk relationships between SMOVE, VIX indices and the four oil-related CDS spreads for the full period and the sub-period. In addition, the four oil-related CDS spreads were responded to VIX in the long and short runs, whereas none of the indices were sensitive to SMOVE. The CDS spread of auto sector was the most error correcting in the short and long-run. It was pioneering in the risk discovery process. Furthermore, in the oil-related sectors, the 2007–2008 Great Recession showed “localization” and less migration of market and credit risk.

Papers such as Guo, Chen, & Huang (2011), Sharma & Thuraisamy (2013), Arouri, Hammoudeh, Jawadi, & Nguyen (2014), Lahiani, Hammoudeh, & Gupta (2016) investigated the price of crude oil as a predictive factor for explaining the changes in CDS spreads similar to the work of Hammoudeh et al. (2013).

Fernandes, Medeiros, & Scharth (2014) investigated the time series properties of the daily market VIX from the Chicago Board Options Exchange (CBOE). According to results, there was a positive simultaneous relationship with the volume of the S&P 500 index and VIX displayed long-range dependence as well as a negative interaction between the S&P 500 index and VIX returns. In addition, it was found that because of the high demand for oil in those years, VIX tended to decrease while the long-run oil price increased.

Shahzad, Nor, Ferrer, & Hammoudeh (2017) studied the asymmetry between ten CDS index spreads, major macroeconomic and financial variables for selected industries in the US economy using the NARDL approach. Findings showed that the price of crude oil formed important asymmetric determinants of ten U.S. industry CDS spreads.

Da Fonseca & Ignatieva (2018) examined volatility spillover effects between ten sectors’ CDS indices during April 2007 - January 2012. To the overall market volatility, financial sector was the main contributor along with the consumer goods, consumer services and basic materials sectors. Results of the study showed that during the Global Financial Crisis, there were indirect links between the sectors that conveyed shocks.

In this thesis, we employ VIRF method for MGARCH model introduced by Hafner & Herwartz (2006), which enables our data to examine for any unbiased transmission flow patterns. We focus on sector level for oil and oil related sectors as discussed in Hammoudeh et al. (2013). Focusing on the sector level is important because of the arising interest in the energy and energy-related sectors. We use CDS spreads for all 4 sectors; auto (AUTO), chemicals (CHE), natural gas (OILGAS), utility (UTIL); and indices of VIX, MOVE and SMOVE as variables. Our daily dataset covers the period from the beginning of January 2004 to February 2016. We examine the risk spillover mechanism across the oil market, financial market, and the oil related sectors' CDSs. Different than Hammoudeh et al. (2013), the volatility transmission mechanisms across the oil and financial markets and sector CDS are examined by using the Volatility Impulse Response Function, having the advantage of providing valuable information on the speed of risk transmission. The shape and sign of the VIRF also provide significant information on the transmission mechanism of historical events. The effects of six specific historical events as mentioned before on residuals are researched. This study enables the migration of risk in the markets and four oil exploration and production sectors at a time of volatile oil prices.

3.3 Data and Descriptive Statistics

3.3.1 Data

Our data includes the daily closing futures prices of West Texas Intermediate (WTI), Credit Default Swap (CDS) indices for four sectors (AUTO, CHE, OILGAS and

UTIL), Volatility Index (VIX), one-month Merrill Lynch Option Volatility Estimate Index (MOVE) and Swaption Move Expected Volatility Index (SMOVE). The daily dataset covers the period from 6 January 2004 to 2 February 2016 for five working days. Quoted prices are in the US dollars per barrel and the data is obtained from Datastream.

CDS is a type of swap insured by the swap seller to remove the risk of non-payment on the security's premium and also interest payments at the end of the maturity date of a contract. Therefore, until the maturity date of a contract, swap buyer makes payments to seller. In other words, the credit exposure of fixed income products is transferred between two parties, i.e. buyer of the swap and the seller. The risk is transferred in the way of paying CDS premia determined by current estimated calculations depending on the country risk. CDS spread is smaller for developed countries compared to developing ones. In our study, CDS spread represents the risk, fear, present and future economic health of four oil sector and oil-related sectors including auto, chemicals, natural gas, and utility sectors. The one-month expected equity volatility of the S&P 500 index measured by the VIX. Known as uncertainty or fear index, VIX is used to understand whether there is fear or enthusiasm on the asset and gives an idea about the risk level by showing the volatility of the price of an asset. When the price of a good increases, VIX also increases meaning that the risk becomes higher. The value of VIX greater than 30% is a sign of evolving in the course of the economy and leads to an increase in the risk perception of investors expecting the value of the S&P 500 index fluctuate in next 30 days. However, the value of 20% in VIX represents opposite that diminution in the risk perception and positive future expectations for the course of economy. MOVE is a yield curve weighted index on one-month US Treasury maturities of the normalized implied volatility which are weighted on the 2, 5, 10, and 30 years contracts and represents expected risk in the bond market. On the 10-year Treasury, MOVE is 40% and 20% on the rest of Treasury options. VIX is correlated with equity; MOVE is with US Treasury options. On the other hand, SMOVE index measures expected risk in the swap market. It is a kind of VIX for US non-Treasury in swaption markets and measures volatility on one to ten years US non-Treasury options depending on inflation, deflation, massive rolling of government debts and interest rate movements. MOVE/SMOVE movements are dramatic and responses are in opposite compared to VIX.

We employ the first logarithmic differences for all eight variables in time series analysis. Daily nominal return series are converted from daily prices as shown:

$$R = \ln\left((R_t/R_{t-1})\right) \quad \text{for } t = 1, 2, \ldots, \mathrm{T} \qquad (3.1)$$

where R is the returns for all variables used in the study, R_t is the current level at time t and $R_{t-1}$is previous day's value.

3.3.2 Descriptive statistics and correlations

The descriptive statistics are given in Table 3.1 Panel A, Panel B and Panel C. All variables are in first natural logarithmic differences. For full period, the number of observations is 3151 and the same for all the series. The mean of all the variables are very close to zero. The standard deviation, measure of volatility, varies between 2.09-6.88%. The most volatile measure is VIX, despite the low peak-to-valley difference, i.e. the range of the data obtained from minimum and maximum. The lowest volatility is observed for WTI. Considering the peak-to-valley difference, UTIL and SMOVE have the highest, correlating with high standard deviations.

MOVE, SMOVE and VIX return series are skewed to the right, i.e. positive skewed and the data for the rest of the variables show negative skewness. The skewness values of WTI, SMOVE, MOVE and VIX are very close to zero means that the distributions of the data for these variables are close to normal distribution. The kurtosis values of oil and oil-related sectors are very high particularly for UTIL. Therefore, it can be concluded that there are high leptokurtic distributions for oil and oil-related sectors. SMOVE index also has high value on kurtosis.

All variables are checked by Jarque & Bera (1980) (JB) Langrange multiplier test whether series show normal distribution or not. According to the test results, all variables reject the null hypothesis of not having normal distribution with zero probabilities of the test, which could be also observed from the skewness and kurtosis values. Because of the finding, we employ Student's t-distribution for our analyses. The Box–Pierce Portmanteau Q statistics for lagged 1 and lagged 4 orders are also calculated. All residual series are found to be independently distributed at 5% significance level. Based on statistical results given in Panel A of Table 3.1, it is concluded that implementation of Student's t distribution to the series' error terms are more suitable instead of normal distribution.

For the effects of Autoregressive Conditional Heteroskedasticity (ARCH), all residuals are tested autocorrelation for first [ARCH(1)] and the fourth [ARCH(4)] order by the Lagrange Multiplier (LM) tests. The tests reject the homoscedasticity hypothesis up to 4 lagged orders at the significance level of 1% except UTIL in 1 lagged order.

For full period, the sample is checked for the Pearson Correlation Coefficient (PCC). As can be seen in Table 3.1 Panel B, MOVE is highly interdependent with SMOVE compared to other PCCs, as observed by Hammoudeh et al. (2013). Table 3.1 Panel C represents the PCC estimates for the subprime mortgage crisis period. The correlation coefficient of MOVE and SMOVE is very close to 1 suggesting a high interdependency as found for the full period. However, UTIL and OILGAS have also high PCC, which is not observed for the full period. It can be concluded from Table 3.1 that the correlations between WTI and risk measures are low excluding the correlation between MOVE-SMOVE for both periods. Therefore, we can conclude that risk measures used in this study for the full period give information about different risks.

3.3.3 Dynamic interdependencies in returns: VAR model

We employ a Vector Autoregressive (VAR) model to have an idea about the return behavior for each of the four sectors' CDS indices, WTI, MOVE, SMOVE and VIX. The residuals of the VAR model are used for the following pursuits about volatility. In our model, we estimate the lags via information selection criteria. As shown in Table 3.2, lags are representing for each as p. Diagnostic tests are also shown in Table 3.2 for univariate GARCH (1,1) model. All residuals of time series are tested by ARCH-LM (1) and checked for Jarque-Bera. According to results, ARCH-LM (1) test rejects the null hypothesis because none of the tests is significant. As a result, we can conclude that there is ARCH effect in all series. Jarque-Bera tests are checked for normality assumption and is found that is violated at 1% significance level. The Box–Pierce Portmanteau Q statistics for lagged 10 and lagged 20 orders are also calculated. Only OILGAS and MOVE are independently distributed for lagged 20. In sum, according to statistical results, tests and VAR model demonstration that are more suitable to implement Student's t distribution to the series' error terms instead of normal distribution.

3.3.4 Dynamic interdependencies in volatilities: BEKK model

For modeling vectors of residuals, BEKK model of Engle & Kroner (1995) is used in analyses. In the VAR model, for return behavior of variables we identify error terms, ε_t as:

$$\varepsilon_t = H_t^{1/2} z_t \quad (3.2)$$

where z_t is the 8*1 random vector: $z_t \sim (0, I_N)$. I_N is the identity matrix of order 8. H_t is 8*8 positive definite symmetric matrix and identified in the BEKK (1, 1) model as:

$$H_t = C\,C' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \qquad (3.3)$$

where *C* is upper triangular and *A*, *B* are all 8*8 parameter matrices in the model. Matrix *A* in Equation (3.3) measures the correlation between past squared one-lag unexpected returns and conditional variances. In other words, Matrix *A* shows the effects of the selected shocks on volatilities and Matrix *B* measures whether there exists a correlation across the current level and the past one-lag conditional variance-covariance matrices.

As we discuss earlier, all return series are distributed non-normal as proven in Table 3.1 and Table 3.2. Therefore, we check the distribution of error terms, ε_t, by using Student's t distribution.

Table 3.1: Descriptive statistics and correlations

	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	*Q*(1)	*Q*(4)	ARCH(1)	ARCH(4)
Panel A: Descriptive statistics for log returns (%)											
AUTO	0.01%	4.67%	-141.40%	46.41%	-8.74%	281.68%	10470537.58***	102.62***	131.94***	8.11***	24.64***
OILGAS	0.07%	3.53%	-96.78%	40.23%	-6.40%	210.65%	5854834.47***	29.89***	49.31***	7.84***	10.78*
CHE	0.01%	4.44%	-126.93%	86.65%	-5.18%	283.69%	10593977.62***	13.03***	42.56***	18.15***	25.44***
UTIL	0.02%	5.46%	-241.70%	20.65%	-29.36%	1244.67%	204108753.82***	12.45***	246.59***	0.00	70.16***
WTI	0.00%	2.09%	-10.58%	12.12%	-0.13%	3.09%	1264.83***	11.44***	21.05***	96.75***	415.34***
SMOVE	-0.02%	5.16%	-139.32%	137.89%	0.02%	329.09%	14237272.92***	125.83***	139.69***	776.51***	1279.86***
MOVE	-0.01%	4.02%	-22.21%	30.59%	0.55%	4.97%	3400.14***	6.24**	45.95***	24.76***	73.24***
VIX	0.01%	6.88%	-35.06%	49.60%	0.70%	4.03%	2395.49***	27.79***	47.04***	134.78***	218.72***

Panel B: Pearson correlation coefficient estimates for the full sample

	AUTO	OILGAS	CHE	UTIL	WTI	SMOVE	MOVE	VIX
AUTO	1.000							
OILGAS	0.266	1.000						
CHE	0.179	0.201	1.000					
UTIL	0.141	0.151	0.115	1.000				
WTI	-0.146	-0.176	-0.065	-0.069	1.000			
SMOVE	0.053	0.072	0.056	0.042	-0.046	1.000		
MOVE	0.069	0.079	0.076	0.054	-0.056	0.646	1.000	
VIX	0.259	0.213	0.143	0.108	-0.234	0.163	0.188	1.000

Panel C: Pearson correlation coefficient estimates for the subprime mortgage crises period (Dec 2007-Jun 2009)

	AUTO	OILGAS	CHE	UTIL	WTI	SMOVE	MOVE	VIX
AUTO	1.000							
OILGAS	0.339	1.000						
CHE	0.069	0.202	1.000					
UTIL	0.337	0.831	0.222	1.000				
WTI	-0.145	-0.226	0.004	-0.240	1.000			
SMOVE	-0.062	0.140	0.044	0.132	-0.099	1.000		
MOVE	-0.060	0.139	0.054	0.135	-0.061	0.952	1.000	
VIX	0.103	0.235	0.044	0.214	-0.320	0.210	0.183	1.000

***: one percent significance

**: five percent significance

*: ten percent significance

Note: Panel A presents the log returns' descriptive statistics. The data includes 6/1/2004 – 2/2/2016 with *n*=3151 daily observations. AUTO stands for the five-year US auto sector CDS premium; OILGAS stands for the five-year US auto oil and gas sector CDS premium; CHE stands for the five-year US chemicals sector CDS premium; UTIL stands for the five-year US utilities sector CDS premium; WTI stands for the daily closing price for the West Texas Intermediate (WTI) crude oil futures contract 3 (dollars/gallon) delivered in Cushing, Oklahoma; SMOVE stands for one-month volatility index for swaption; MOVE one-month bond volatility index; and VIX stands for the CBOE SPX volatility.

Mean: Mean of the data

SD: Stadandard deviation

Min: Minimum

Max: Maximum

JB: Jarque-Bera normality test

Q (1): Ljung-Box first test of autocorrelation

Q (4): Ljung-Box fourth test of autocorrelation

ARCH (1): First order LM tests

ARCH (4): Fourth order LM tests

Panel B and Panel C shows the Pearson correlation coefficient (PCC) estimates for the full sample and for the subprime mortgage crises, respectively.

Table 3.2: Univariate AR(*p*)- GARCH (1,1) fit diagnostics

	ARCH-LM(1)	JB	Q (10)	Q (20)	*p*
AUTO	1.722 (0.189)	1776.673*** (< 0.001)	8.736 (0.462)	22.428 (0.263)	4
OILGAS	0.030 (0.862)	4187.452*** (< 0.001)	11.985 (0.214)	27.363* (0.096)	4
CHE	0.102 (0.750)	92736.463*** (< 0.001)	12.633 (0.180)	24.504 (0.178)	1
UTIL	0.025 (0.873)	7645.312*** (< 0.001)	12.066 (0.210)	23.184 (0.229)	4
WTI	2.946 (0.086)	355.697*** (< 0.001)	4.005 (0.911)	8.843 (0.976)	4
SMOVE	0.084 (0.772)	3715.044*** (< 0.001)	8.182 (0.516)	22.492 (0.260)	5
MOVE	0.766 (0.381)	2388.067*** (< 0.001)	5.747 (0.765)	29.374* (0.060)	8
VIX	0.030 (0.864)	3794.099*** (< 0.001)	9.842 (0.363)	25.624 (0.141)	7

***: one percent significance
**: five percent significance
*: ten percent significance

Note: The table reports diagnostic tests for univariate autoregressive GARCH model fits. An AR(*p*)-GARCH (1,1) model is fitted to each series. The AR order *p* is selected by the Akaike Information Criterion (AIC).

ARCH (1): First order LM tests for ARCH
JB: Jarque-Bera normality test
Q (10): Tenth autocorrelation tests of Ljung-Box
Q (20): Twentieth autocorrelation tests of Ljung-Box

The *p*-values of the tests are given in parentheses. The symbol "<" signifies "less than" the number it precedes.

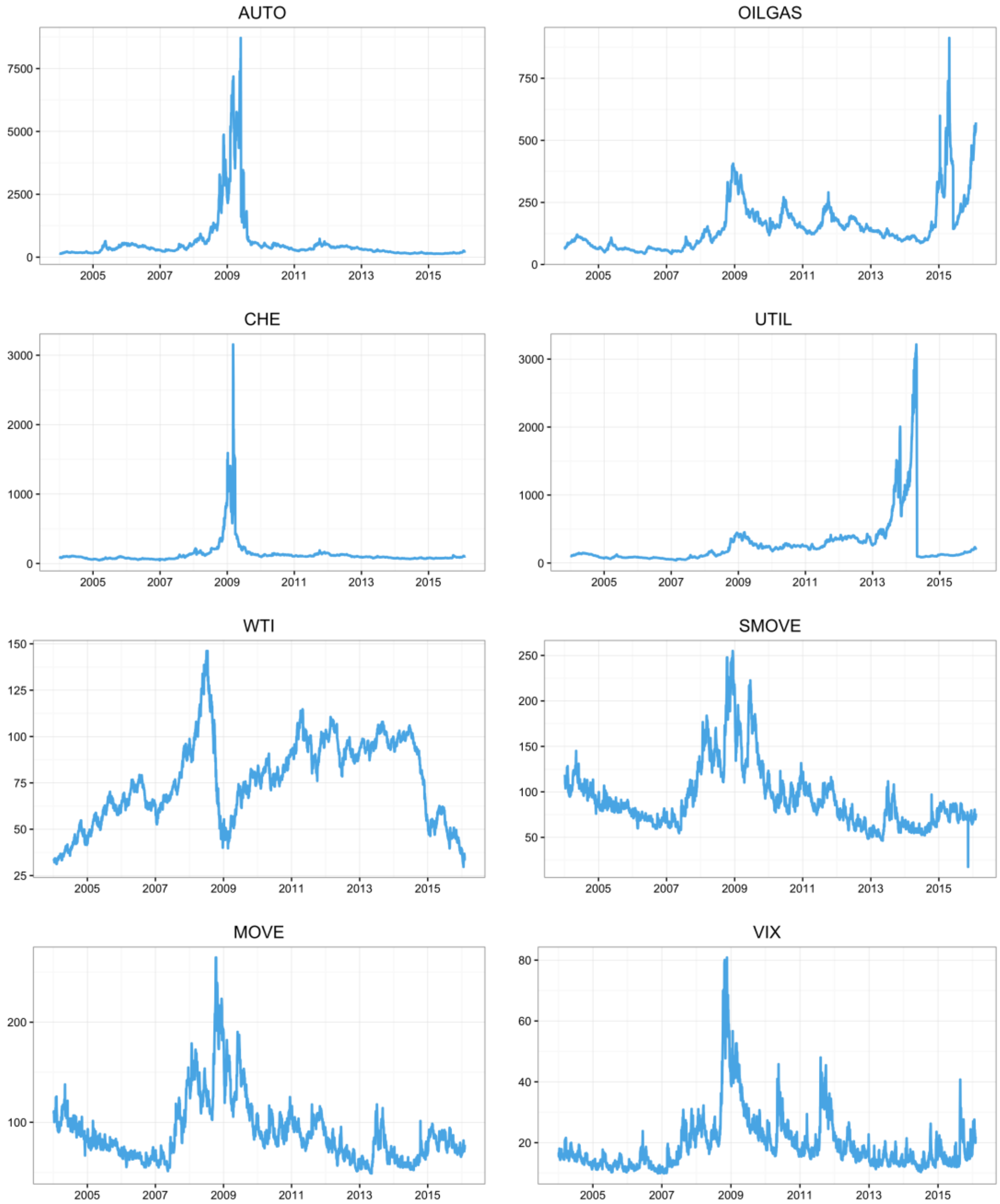

Figure 3.1: Time-series plots of level of the CDS premium, oil price and volatility indices

Note: This figure provides the plots of the daily levels of the indices for the period 6 January 2004 - 2 February 2016. AUTO stands for the five-year US auto sector CDS premium; OILGAS stands for the five-year US auto oil and gas sector CDS premium; CHE stands for the five-year US chemicals sector CDS premium; UTIL stands for the five-year US utilities sector CDS premium; WTI stands for the daily closing price for the West Texas Intermediate (WTI) crude oil futures contract 3 (dollars/gallon) delivered in Cushing, Oklahoma; SMOVE stands for one-month volatility index for swaption; MOVE one-month bond volatility index; and VIX stands for the CBOE SPX volatility.

Figure 3.1 provides the daily levels of the CDS Premiums, oil price and volatility indices for the period 6 January 2004- 2 February 2016. CDS Premium levels of AUTO and CHE have the peak values in 2009 particularly AUTO reaching the highest CDS level. They also show very similar profile over time, suggesting they are affected from the similar events and their responses are similar. On the other hand, OILGAS and UTIL are highly affected from different shocks compared to AUTO and CHE. WTI has the peak value in mid-2008. The rate of change in WTI is very high between 2007 and 2009. After the peak value for the selected time, WTI decreases rapidly from about $145/gallon to $40/gallon in approximately six months. After the effects observed in mid-2008, WTI increases with a rate of change similar to the pre-shocks period until mid-2014. The volatility indices SMOVE and MOVE have very similar profiles during the chosen period. The effects of the shocks and the responses of MOVE and SMOVE are very similar to each other. The interdependency of MOVE and SMOVE are also observed considering the PCC, as observed in Table 3.1. VIX is also affected from the similar shocks i.e. reaching the peak value in 2009, as for the other risk measures. Considering the CDS premiums, WTI and volatility indices; the effects of the different shocks can be clearly seen. However, the influences of the dominant shocks such as observed around 2009 are temporary considering the investigated period except for the CDS of OILGAS so that the values of the risk measures become very similar to pre-shock period, after the shocks.

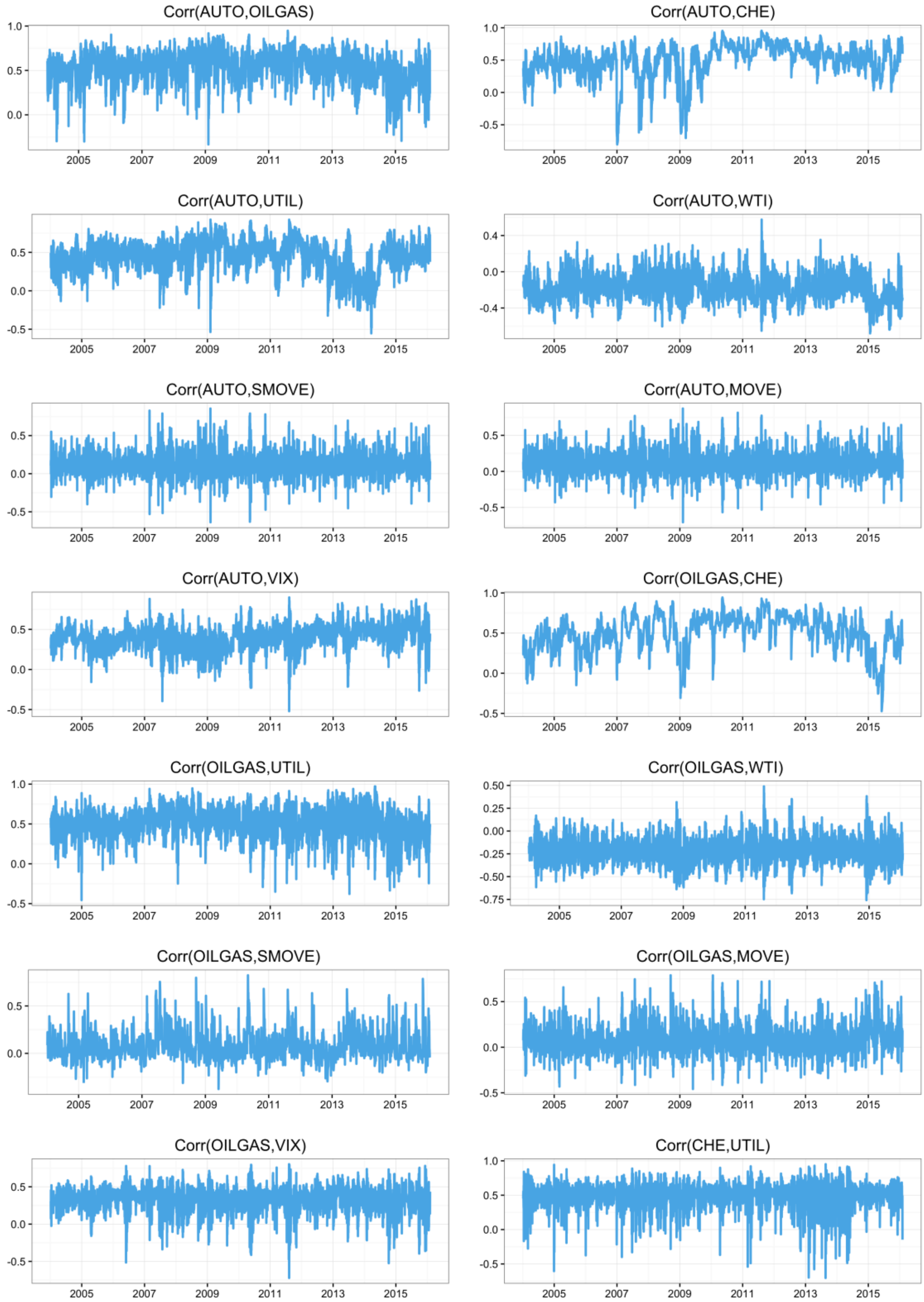

Figure 3.2: Conditional correlations from the BEKK-GARCH model

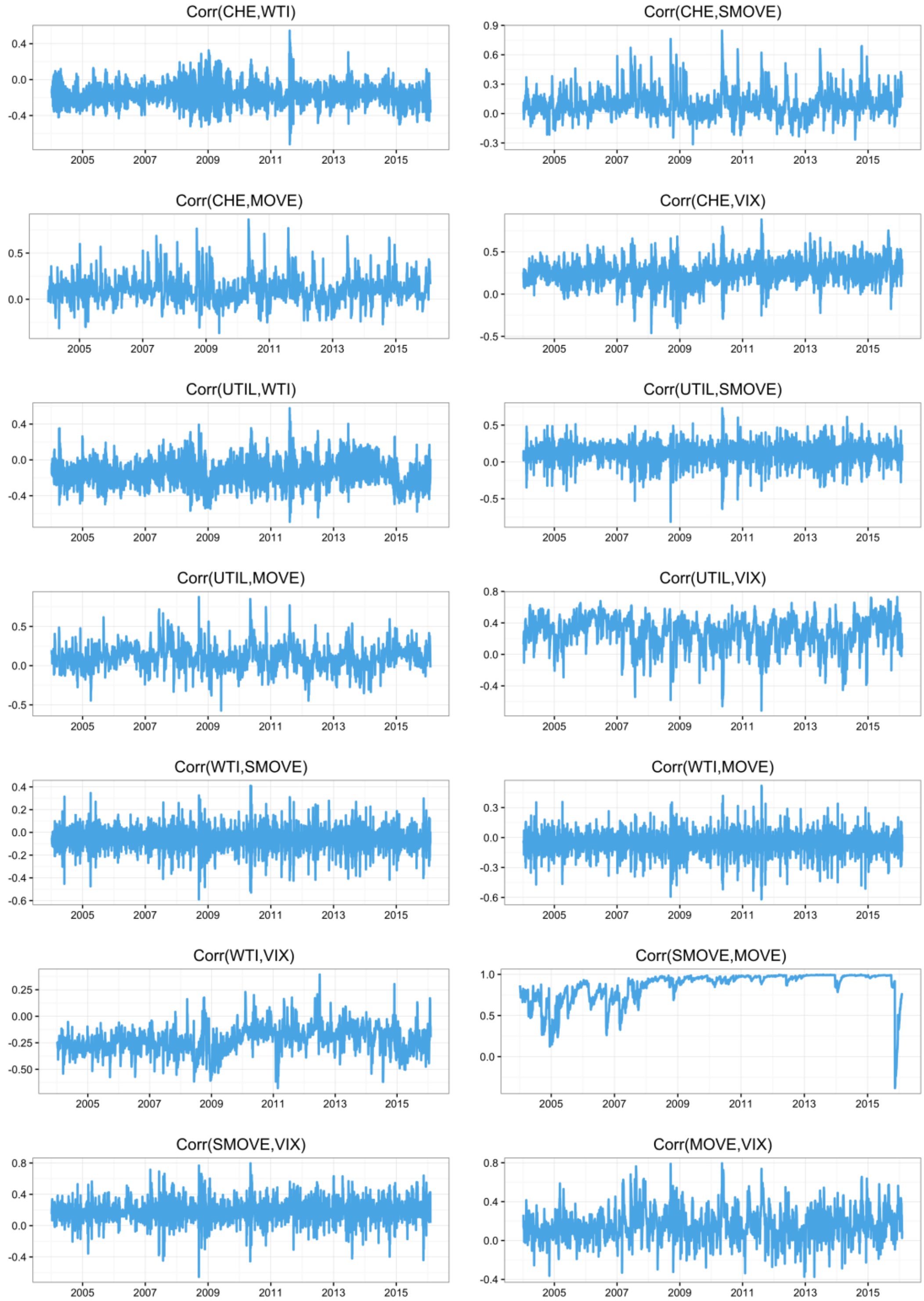

Figure 3.2: Conditional correlations from the BEKK-GARCH model (continued)

Figure 3.2 shows the estimated conditional correlations get from the BEKK-GARCH model using Student's t distribution. All eight variables that we use in our study show signs of volatility clustering. They all have upwards and downwards during the time depending on the different shocks. As can be observed from Figure 3.2, conditional correlation between MOVE and SMOVE is generally close to 1 during the chosen period and volatility is very low compared to other conditional correlations, which can be expected owing to high interdependency between these two risk measures as observed in Table 3.1 and Figure 3.1.

Highest volatility can be seen between AUTO-CHE in 2007 and 2009, and between CHE-UTIL in 2013. Therefore, it can be concluded that high volatilities of AUTO-CHE and CHE-UTIL are due to different shocks, i.e. they have low interdependency. On the other side, lowest volatilities are observed between WTI-SMOVE/MOVE and WTI-VIX, considering the peak-to-valley differences of the conditional correlations.

General conditional correlation trend between four CDS Premiums are positive and their profiles suggest volatility between these measures. Conditional correlations between AUTO and the other CDS Premiums (CHE, OILGAS and UTIL) have high downward peak around 2009, which can be correlated with Lehman Brothers bankruptcy shock. However, same trend between each four CDS Premiums and WTI are negative but close to zero whereas the trend between each four CDS Premiums and VIX is positive, except the steep upwards and downwards due to different responses of the risk measures against different shocks. Conditional correlations between each four CDS Premiums and MOVE/SMOVE are generally close to zero except the responses against the shocks encountered during the period. Slight positive conditional correlation can be observed between MOVE/SMOVE and VIX having similar volatility levels.

3.4 Methodology of VIRF

3.4.1 Independent shocks

In this section, we define our model used to examine the risk spillover mechanism across the oil market, financial market, and the oil related CDS sectors. In addition to showing the magnitude of the volatility transmission, we describe the methodology of the volatility impulse responses. This model is suitable to explore the speed of risk transmission, as well as the shape and sign of the volatility impulse responses also provide significant information.

News or shocks are inherently independent over time as introduced as a new concept by Hafner & Herwartz (2006). A shock is a risk source that is independent and unpredictable. It is also shown that two shocks appearing in different series at the same time are independent. The residuals include the effects of the shocks coming from independent sources. However, to reveal the power of a given shock, the orthogonality conditions of the error terms should be investigated. Otherwise, total effect of one shock on all the components of the residual would be observed. In order to avoid orthogonality problem, Hafner & Herwartz (2006) apply Jordan decomposition to obtain realistic and independent shocks from the conditional heteroskedastic error terms.

The component of our model that shows the effect of a shock is named as z_t in ε_t by Choleski decomposition. Independent news could be identified via Jordan decomposition of H_t. Let $\Lambda_{\mathrm{it}} = \mathrm{diag}\,(\lambda_{1\mathrm{t}}, \dots, \lambda_{\mathrm{Nt}})$ is the diagonal matrix and its components λ_{it}, $i = 1, \dots, N$ denote the eigenvalues of H_t. $\Gamma_{it} = (\gamma_{1t}, \dots, \gamma_{Nt})$ is the matrix N*N whose components Γ_{it}, $i = 1, \dots, N$ denote the corresponding eigenvectors. The symmetric matrix of ${H_t}^{1/2}$can be decomposed as;

$$ {H_t}^{1/2} = \Gamma_t {\Lambda_t}^{1/2} \Gamma_t' \qquad (3.4) $$

As Hafner & Herwartz (2006) identify z_t as past shocks that are able to affect the markets in the future. Therefore, the independent shocks are defined as;

$$ z_t = {H_t}^{-1/2} \varepsilon_t \qquad (3.5) $$

3.4.2 Volatility impulse response function (VIRF)

According to Bollerslev, Engle, & Wooldridge (1988) the BEKK (1,1) model for multivariate GARCH models can be represented by using Vector Error Correction (VEC) model representation as follows:

$$ vech(H_t) = vech(C) + A\ vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B\ vech(H_{t-1}) \qquad (3.6) $$

in which H_t is the conditional covariance matrix at time *t* and $vech(H_t)$ indicates the operator that stacks the lower fraction of an 8*8 matrix into an N*= (N(N+1)/2) dimensional vector. $vech(C)$ is a vector which contains N* coefficients, the parameter matrices A and B are containing $(N^*)^2$ parameters. This VEC model is used to eliminate the variables of the conditional covariance matrix because of appearing twice in the model.

According to Hafner & Herwartz (2006), VIRF is subtraction of the expectation of volatility conditional on an initial shock and history from the baseline expectation that only conditional on history, which can be written as follows;

$$ V_h(z_t) = E\big[\big(vech(H_t)\big|\psi_{t-1,}z_t\big)\big] - E[(vech(H_t)|\psi_{t-1})] \qquad (3.7) $$

where z_t is the specific shock affecting the system at time *t* and ψ_{t-1} is the observed history up to time *t – 1*. $V_h(z_t)$ is the N* = (N (N + 1)/2) vector of the impact of the independent and identical shock components of z_t on the h-step ahead expected conditional variance-covariance matrix components. Therefore, to find the Equation (3.7), the expectation matrix influenced by only history is subtracted from the h-step ahead expected conditional covariance matrix of a given shock and history. As a result, the model of $V_h(z_t)$ shows the reaction of the conditional variance of the eight variables respectively to the shock, z_t that occurred h period ago. One-step ahead VIRF applied to a BEKK (1,1) model is,

$$V_1(z_t) = A\left[vech\left(H_t^{\frac{1}{2}} z_t z_t' H_t^{\frac{1}{2}}\right) - vech(H_t)\right]$$

$$= A\, D_N^{+}\left(H_t^{1/2} \otimes H_t^{1/2}\right) D_N\, vech(z_t z_t' - I_N) \qquad (3.8)$$

where D_N is the duplication matrix defined from the property as:

$$vech\,(Z) = D_N\, vech(Z) \qquad (3.9)$$

for any symmetric N*N matrix $Z$and D_N^{+} is its Moore-Penrose inverse. I_N is the identity matrix and H_t is the conditional variance-covariance matrix representation at time *t*. ⊗ represents the Kronecker product for h>1, the new VIRF is;

$$V_h(z_t) = (A+B)^{h-1}\, A\, D_N^{+}\left(H_t^{\frac{1}{2}} \otimes H_t^{\frac{1}{2}}\right) D_N vech(z_t z_t' - I_N)$$

$$= (A+B)V_{h-1}(z_t) \qquad (3.10)$$

VIRF model defined by Hafner & Herwartz (2006) has the following important properties compared to the traditional Choleski decomposition impulse response function of the conditional mean in linear models:

1) The VIRF is an even, symmetric function of the shock with the property of $V_h(z_t) = V_h(-z_t)$. The impulse responses are odd functions in traditional linear analysis.
2) The VIRF is not a homogenous function of any degree while the traditional linear analyses are.

3) At the time of the initial shock occurs, the VIRF will be depended on the history through H_t , the volatility state. However, the traditional analysis on linear systems does not depend on the historic shocks.
4) The persistence of shocks is calculated in moving average part same in the traditional, $(A + B)^{h-1} A$.

In our study, z_t is chosen as a shock with an independent and identically distributed random variable. The impact of a historical random shock is calculated by the observed volatility when a shock occurs. However, we are interested in the past events that have an impact on today and future. In the next part, the impact of observed historical shocks with observed volatilities will give information about past events.

3.5 Emprical Results

This chapter contains the results of the impacts of historical shocks on volatilities. In the sample period, several shocks and effects are witnessed owing to our VIRF analysis. We make an investigation on several historical shocks: the US mortgage crisis: Lehman Brothers bankruptcy, Greece debt crisis, fear of Greece's default, Egyptian political unrest (Second Revolution), European sovereign debt crisis and US government shutdown that have significant effects on our variables. According to our best knowledge, the impacts of the listed six shocks within and across the oil related markets and financial market risks have not been considered in VIRF analyses in the literature.

Figure 3.3 reports the responses of shocks as impulse response to covariances of eight variables used in this study. Nonzero positive impulse responses imply risk transmission. We note that some of the shocks might be negative at the date of shock and the impulse response might be negative. However, negative impulse responses still imply risk transmission. This is due to the fact that the shocks are not normalized in terms of the sign and the size.

3.5.1 The US mortgage crisis: Lehman Brothers bankruptcy on 17 September 2008

Lehman Brothers, one of the financial services firms in US, declared bankruptcy on 15 September 2008. This is the largest bankruptcy announcement in US history. The main reason for the bankruptcy can be associated with large decline of home prices after the collapse in mortgage market. The starting point of US mortgage crisis is accepted as the announcement of the bankruptcy of Lehman Brothers. This event influenced all the markets significantly not in the US but also worldwide. In our analysis, 17 September 2008 is accepted as the base point and we investigate the effects of this event, named also as shock, on our risk transmission and correlation analysis after this date.

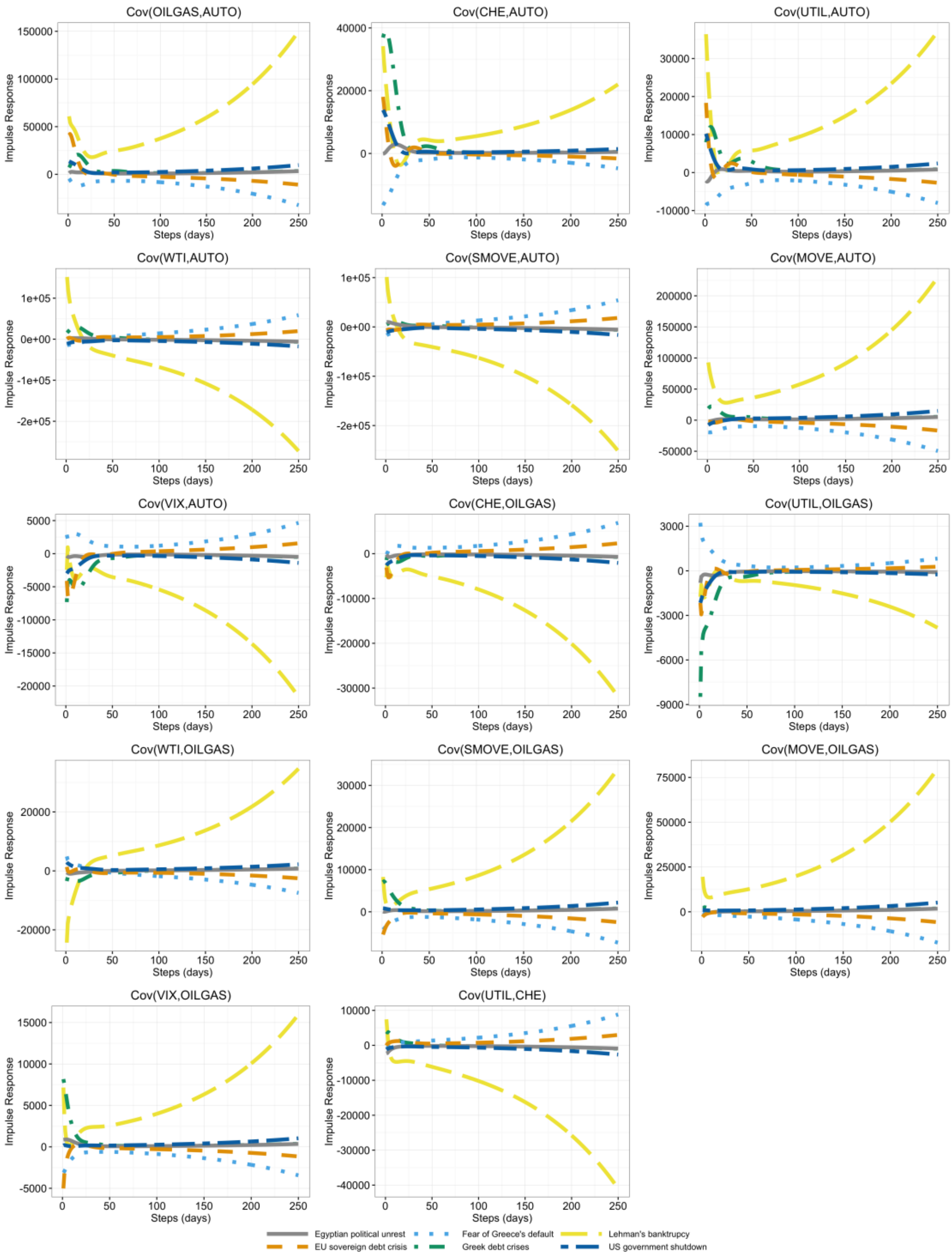

Figure 3.3: Responses of covariances to various shocks

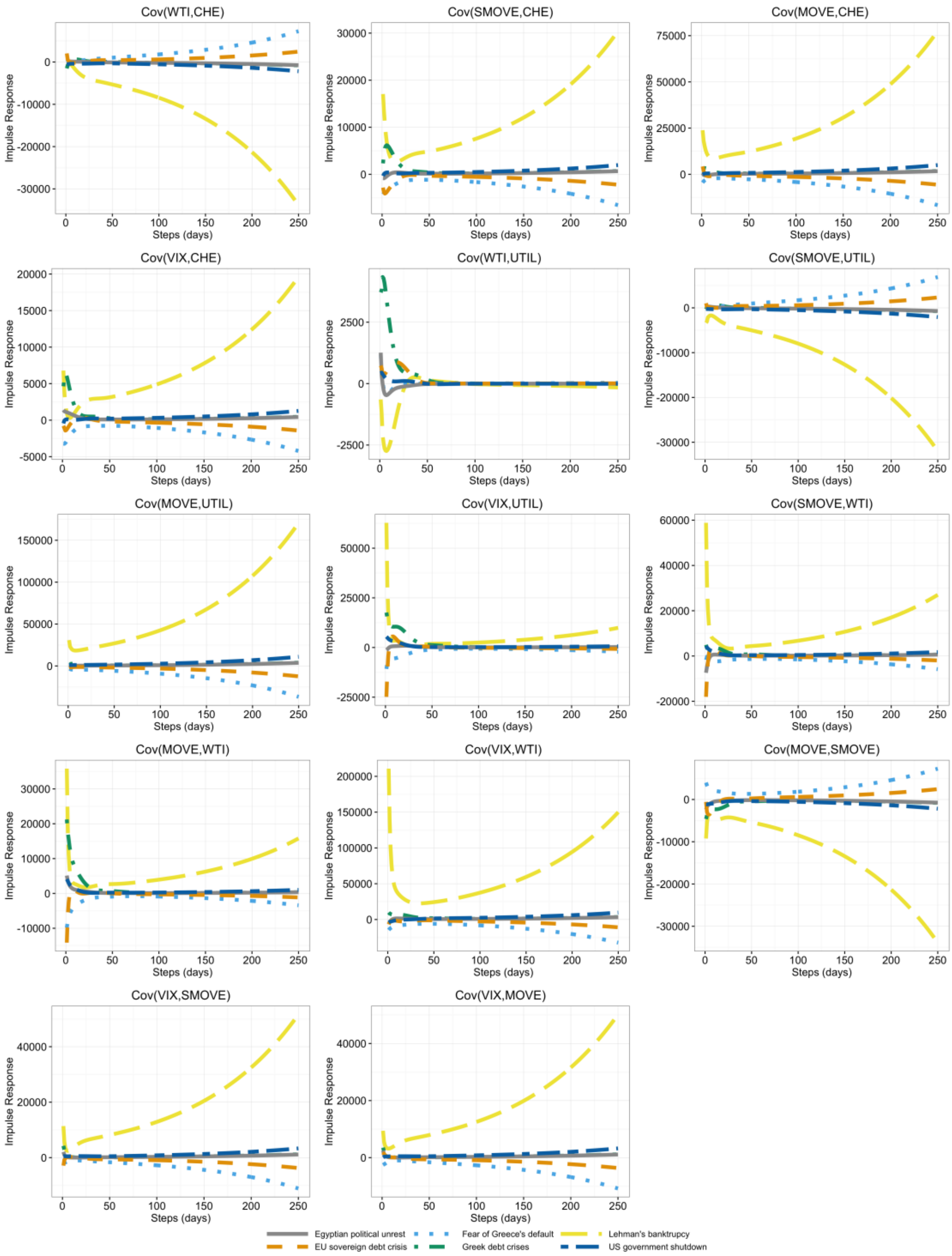

Figure 3.3: Responses of covariances to various shocks (continued)

Note: The figure reports the response of the covariances to the shock due to following events: Lehman Brothers bankruptcy on 17 September 2008; Greece debt crisis on 8 December 2009; Fear of Greece's default on 23 April 2010; Egyptian political unrest (Second Revolution) on 27 May 2011; European sovereign debt crisis on 18 August 2011; and the US government shutdown on 30 September 2013.

As can be seen in Figure 3.3, significant but various types of responses are observed for all the covariances due to Lehman Brothers bankruptcy. This event or shock has the highest influence on the reported covariances compared to other five events. Since all the variables used in this study are US-based, higher influence of Lehman Brothers bankruptcy to response of covariances can be expected.

Our findings are similar to Narayan (2015), as in this study it was also found that while CDS shocks explained most of the forecast error variance of the sectoral equity returns over the crisis period, the effect was the mostly dominated during the post-Lehman crisis period. Hammoudeh et al. (2013) also prove the local impact of financial crisis to the specific US sectors.

Covariances of VIX-AUTO, CHE-OILGAS, UTIL-OILGAS, WTI-CHE, SMOVE-UTIL and MOVE-SMOVE have negative responses to Lehman Brothers bankruptcy shock and negative responses tend to be higher in the long run. Covariances of WTI-AUTO, SMOVE-AUTO and UTIL-CHE shift their response from positive to negative whereas the change of covariance of WTI-OILGAS is vice-versa. The change in response occurs after a very short time from Lehman Brothers bankruptcy. The rest of the covariances show positive response to this shock, however, their profiles are different. In addition, right after the shock, the covariances have slight positive response, which tend to become zero in the short run and have increase in the long run except CHE-AUTO, UTIL-AUTO, VIX-UTIL, SMOVE-WTI, MOVE-WTI and VIX-WTI.

3.5.2 Greece debt crisis on 8 December 2009 and fear of Greece's default on 23 April 2010

Greece was accepted to the European Union on 1 January 1981. Gross domestic product (GDP) per capita reached the highest values in 2008, as around $31,700 after adapting to the currency of Euro in 2001. The second shock we select is “Greece debt crisis” started officially on 8 December 2009 when Fitch the country’s credit rating from A− to BBB+. On 4 March 2010; government announced austerity plan. On 23 April 2010, third shock in our analysis, “fear of Greece’s default” is assumed to be started after George Papandreou, the Prime Minister of that time, called for an EU/IMF rescue package of €500 bn for 3 years. This rescue package was not enough and second Greek crisis began because of Greek budget deficit was declared as higher than expected in April 2011. After that, credit rating of Greece was decreased from B to CCC. Second bailout loan was confirmed for €130 bn. Therefore, interest rate increased and bond prices decreased. Banks and Greek Stock Exchange Market closed for a month in June 2015. Unemployment rate rose to 24.5% in November 2015. As a result, confidence in Government services was at a low point.

After Lehman Brothers bankruptcy, the second highest influential shock is the Greece debt crisis in Figure 3.3. This shock has slight effects on covariances in short and medium terms tends to become zero. Substantial positive responses of covariances of OILGAS-AUTO, CHE-AUTO, WTI-AUTO, MOVE-AUTO, VIX-UTIL and MOVE-WTI as well as slight negative response of covariance UTIL-OILGAS can be observed right after the shock. However, all the responses diminish in the long run. Another remarkable feature is that covariances tend to show higher response to fear of Greece's default compared to European sovereign debt crisis and US government shutdown in the long term.

3.5.3 Egyptian political unrest (Second Revolution) on 27 May 2011

In Egypt, thousands of people protested for the step down of Husni Mubarak, the President for 30 years, and for changing the regime to democracy. Police used violence to stop protestors on the streets resulting injuries and deaths. First revolution of Egypt named as the Arab Spring was placed on 25 January 2011. Muslim Brotherhood was a large crowd of faces of the protests. Demonstrators filled Gharbeya, Alexandria, Suez, Ismailia and also Tahrir Square in Cairo on 27 May 2011, which was accepted as the base point in our analysis. The demands of the crowd were for civilians not to be judged in military trials, all members of the Mubarak regime and those who killed protestors to be put on trial. And before parliament elections, demonstrators wanted the restoration of the Egyptian Constitution.

Covariances of the all the risk measures are almost insensitive to Egyptian political unrest in Figure 3.3. WTI-UTIL and SMOVE-WTI have the greatest responses which straightly become zero. The lowest response is to Egyptian political unrest. Furthermore, the covariance of WTI-UTIL has no significant response to all reported shocks since utilities are a local monopoly that is regulated by policymakers. Moreover, utilities do not use oil as a fuel.

3.5.4 European sovereign debt crisis on 18 August 2011

European sovereign debt crisis started at the end of 2009 around European Union because of having difficulties in refinancing government debts or repayments of loans to Eurozone countries, European Central Bank (ECB) and International

Monetary Fund (IMF). Increase in government expenditures and investments, troubles in housing market therefore in banking system, low economic growth and also low productivity were main reasons for crisis especially around these Eurozone member countries; i.e. Greece, Portugal, Ireland, Spain and Cyprus. The impress of sovereign debt crisis was not only on the entire Eurozone but also on European Union countries and worldwide.

The transmission process between different sectors in financial markets through which the crisis had spread were studied by Chudik & Fratzscher (2011). The results demonstrated that the global transmission of the crisis was complex and could not be reduced to a single dimension.

European sovereign debt crisis has slight effect on covariances in the short-run, which tends to become zero in the medium term. However, the responses of the covariances of the risk measures slightly change as time passes. As can be seen in Figure 3.3, the highest response to this shock is observed for OILGAS-AUTO covariance. After an initial positive response, it decreases to 0 in a very short time and becomes slightly negative. Considering the rest of the covariances, after an initial shock, the response approaches to zero and becomes either positive or negative in the long run. Another remarkable feature is that covariances tend to show higher response to fear of Greece's default compared to European sovereign debt crisis in the long term.

3.5.5 The US government shutdown on 30 September 2013

The two chambers of US Congress could not be agreed on the offer of increasing the federal government's debt ceiling or called extra fund to finance Patient Protection and Affordable Care Act known as Obamacare signed in 2010. As a result, US government was shut down on 1 October until 16 October 2013. Non-compulsory expenditures were stopped and government postponed payments. Approximately 800,000 federal employees were forced for an unpaid leave. This event influenced financial agents and markets negatively, as can be expected. The base shock date chosen for our analyses is a day ago from the beginning of shutdown.

Figure 3.3 shows that the US government shutdown has slight effect on covariances in the short-run, which tends to become zero in the medium term. However, the responses of the covariances of the risk measures slightly increase as time passes. The general trend suggests an initial shock followed by a very slightly positive or negative response in the long run. The covariances are less responsive to US government shutdown and Egyptian political unrest compared to other historical shocks.

3.6 Conclusion

This study examines the volatility transmission mechanism across the oil and financial markets and sector CDSs, using eight different measures of risks during the period 6 January 2004 – 2 February 2016. In addition to assessing the magnitude of the volatility transmission, the volatility impulse responses have the advantage of providing valuable information on the speed of risk transmission. The shape and sign of the volatility impulse responses also provide significant information on the transmission mechanism. We also evaluate the risk transmission due to global shocks related to the US mortgage crisis: Lehman Brothers bankruptcy, Greece debt crisis, fear of Greece's default, Egyptian political unrest (Second Revolution), European sovereign debt crisis and US government shutdown and observe that most of these events lead to significant risk transmission. Among these events, the Lehman

Brothers bankruptcy has destabilizing effects on all the oil-related sectors. We also find that all oil market related shocks have significant risk transmission effects. Finally, the results show complicated transmission mechanisms that spread over long periods.

Chapter 4

THE IMPACTS OF OIL PRICES AND MACROECONOMIC VARIABLES ON THE STOCK RETURNS IN TURKEY: A TVP-VAR APPROACH

4.1 Introduction

The role of oil price movements in the explanation of stock exchange market fluctuations has been attracted a great deal of attention since the seminal papers by Jones & Kaul (1996) and Huang et al. (1996). The empirical evidences indicate that the response of the stock returns varies across the type of countries, i.e. oil importer or oil exporter as well as the methodology and estimation sample under consideration. The studies have widely concentrated on developed countries; e.g. Jones & Kaul (1996), Sadorsky (1999), Huang et al. (1996), Park & Ratti (2008) and Kilian & Park (2009). Jones & Kaul (1996) analyze the effect of oil price fluctuations on the stock market returns of Japan, Canada, the UK and the US. The results suggest that oil price shocks significantly affect stock market returns for Canada and the US whereas the impacts on the UK and Japan stock markets are found to be less significant. Sadorsky (1999) also validates a negative and significant impact of oil price shocks on the stock returns in the US. However, Huang et al. (1996) find that oil future returns do not have a sizable impact on aggregate US stock market indices and only affect some individual stock returns of oil companies. Park & Ratti (2008) focus on the stock returns of the US and 13 European countries. The results indicate that the impact of oil price returns on equity returns depends on the extent to which these countries are net importers or net exporters of oil. As the only oil exporter in the sample, Norwegian stock returns respond positively to oil price shocks whereas negative and instantaneous impact of oil price increases are reported for net oil importing European countries and the US. Kilian & Park (2009) argue that the US economy is affected by oil price shocks in different ways whether the reason is because of demand or supply shocks in the oil market. Global crude oil market's supply and demand shocks explain a considerable amount of volatility in the real stock returns.

Regarding developing countries, the number of studies investigating the effect of oil price shocks on the stock returns have remained relatively limited compared to developed ones. Studies on this issue also present mixed evidences about the significant impacts of oil shocks on the stock returns. For example, Maghyereh (2004) analyzes the impact of crude oil price shocks on the stock market returns of 22 emerging economies and finds that oil price changes do not have a significant influence on all countries under consideration. However S. Basher et al. (2012) investigate dynamic relationship among exchange rates, stock prices and oil prices in ten emerging countries and report the presence of a negative relationship between all the emerging market returns and oil prices. Bhar & Nikolova (2009) analyze the relationship between oil price and equity returns of BRIC countries therefore find that as oil importer countries, China and India are more affected by the fluctuations in the global oil market compared to Brazil. Conversely, Cong, Wei, Jiao, & Fan (2008) and D. Zhang & Cao (2013) find that on the most of the Chinese stock market returns, oil price shocks do not have significant effects.

Although the studies corroborate the strong and negative influence of oil prices on the stock returns, most of them also report the significant time-variations and structural breaks in the relationship. For example, Sadorsky (1999) finds that the impact of oil prices has become more apparent when the model is estimated for the period after 1986. Miller & Ratti (2009) also report that negative and significant impact of oil shocks observed in the long run has disappeared after September 1999. Huiming Zhu, Guo, & You (2015) confirm that the sensitivity of Chinese stock returns to the oil price changes can be ascribed to the existence of structural breaks in the relationship. Those authors have argued that the bubbles in crude oil markets and asset markets and the change in the degree of oil dependence and improvements in the energy efficiency over time might explain the instabilities in the relationship.

Recent studies have attempted to uncover the reasons for the evidence on the inconclusive results by introducing nonlinearity through the estimation of asymmetric or time-varying parameter models. These studies mostly confirm the evidence that the influences of oil price shocks to the stock markets varies across the estimation sample. By utilizing an asymmetric GARCH model, Chang & Yu (2013) confirm the regime-dependent influences of oil price shocks between the turbulent and stable periods in the US. In line with the findings of Miller & Ratti (2009), Jammazi & Aloui (2010) corroborate the presence of structural breaks for the stock markets of France, Japan and the UK using a Markov regime-switching vector autoregressive (MS-VAR) model. The results also indicate that the influence of crude oil shocks on the stock returns varies across the phases of stock markets, crude oil shocks have a significant impact only when the stock markets are in the expansionary period. Using a similar approach, Jammazi & Nguyen (2015) confirm the presence of asymmetric behavior of stock markets for the oil importer countries, i.e. Japan, the US, the UK, Germany and Canada. Huiming Zhu, Su, You, & Ren (2017) also employ MS-VAR model by using the data of the ten oil importing and oil exporting countries; the UK, Russia, Mexico, Canada, Brazil, South Korea, Japan, India, China and the US. The results suggest that oil supply and demand shocks have statistically significant impacts in a high-volatility regime and in a low-volatility regime, these shocks do not have considerable influence on stock returns.

Moya-Martínez, Ferrer-Lapeña, & Escribano-Sotos (2014) estimate a time-varying parameter multifactor market model with a state-space specification to analyze the effect of change in oil price on stock returns in Spain at industry level. The results indicate that as compared to 1990s the interaction between price of stock and crude oil seems to have increased during the 2000s and become mostly positive. This implies that the global real economic activity and aggregate demand-side oil price shocks play key roles in the explanation of the effects of oil price fluctuations. Boldanov, Degiannakis, & Filis (2016) analyze the time-varying conditional correlation between stock market volatility and oil price for six major oil exporting and oil importing countries utilizing a Diagonal-BEKK model. The results suggest that the correlation between stock market volatilities and the oil price changes over time fluctuating at both negative and positive values. There are also remarkable differences between in the time-varying correlations of the oil exporting and importing countries. Major economic and geopolitical events, i.e. global financial crises, the 9/11 terrorist attacks and 2000 recession are found to have considerable impacts on the time-varying correlations. B. Zhang (2017) investigates the impacts of two great shocks; 2003 Iraq War and 2008 Global Financial Crisis on the correlations between stock markets and oil using a mixed asymmetry dynamic conditional correlation model (MADCC). Similar to the findings of Boldanov et al. (2016), the results suggest that those events increase the correlation between US/Chinese stock market returns and oil price.

Some recent studies, e.g. Kang, Ratti, & Yoon (2015), Nasir, Razvi, & Rossi (2017) utilize time varying parameter VAR (TVP-VAR) model with stochastic volatility introduced by Primiceri (2005) to account for the dynamic effect oil price shocks on the returns of stock market. Kang et al. (2015) examine the impact of oil price shocks on the stock market returns of US and find an evidence in favor of time variation both in terms of parameters and the variance-covariance matrix. The results indicate that the oil shocks are able to explain a considerable portion of the variation in real stock returns; in line with the findings of the studies analyzing time-varying conditional correlations, the contribution of oil market specific demand price shocks has reached its maximum value during the period of global financial crisis. Nasir et al. (2017) analyze the impact of oil price shocks on the aggregate and energy sector returns in the UK with a TVP-VAR model. However, the energy sector stock has always reacted positively to oil price shocks, the results suggest that the oil price shocks have negatively affected the stock market. It is also evidenced that a shift to net oil importer from net oil exporter does not have a substantial effect on the association between the UK stock market and the oil shocks. The results further suggest that global financial crisis has led to a positive and symmetric response to oil shocks at aggregate and energy sector levels.

In this context, this study aims to examine the effects of oil prices on the stock market prices for Turkey in a time-varying framework. The previous studies analyzing the effects of oil price shocks on the stock market for Turkey are very limited, moreover the existing studies are based on the application of linear models.

Even though Turkey is regarded as one of the important emerging economies in the world, the number of studies are remained very limited and existing studies are mainly based on the applications of linear models. Among them, Soytas et al. (2009) and Aydogan & Berk (2015) find that oil price variations do not have significant effects on the Turkish stock market in the short run. On the other hand, using a linear estimates of multifactor asset-pricing model S. A. Basher & Sadorsky (2006), Aloui et al. (2012) examine the effect of oil price changes and find the serious impact of oil price on the emerging stock markets including Turkey. The results also support the asymmetric impact of oil prices and the risk of the oil price is valued in emerging countries' stock markets. Eryigit (2012) investigates the dynamic relationship between exchange rate, crude oil price, interest rate and the main index of Turkish General Stock Price Index: BIST100 for the period January 2005 and October 2008. VAR model estimates indicate that the oil price shocks have negative, significant and immediate impacts on stock returns and exchange rates. The results further suggest that the highest portion of the variations in the stock returns and interest rates are explained by oil price shocks.

The main objective of this part is to contribute to the previous literature by first investigating the effects of oil prices on stock market returns in a time-varying framework. We prefer TVP-VAR methodology among the other alternative specifications allowing for the evolution of parameters between subsamples based on the following reasons: First, the previous studies on Turkey have failed to determine how the interaction among the oil prices and stock markets evolved over time.

Second, our estimation sample covers the period where Turkish economy has experienced local and global financial crises leading to sudden and gradual shifts in the designation of macroeconomic policies. Therefore**,** we argue that TVP-VAR model might offer us a more flexible and robust tool to account for the impact of those structural changes on the underlying dynamics between stock returns and oil prices. The results from the estimated TVP-VAR model composed of oil prices, stock returns, interest rate and exchange rate variables indicate that oil price shocks are found to have a lesser effect on stock returns compared to exchange rate and interest rate shocks.

The remainder of this chapter is organized as the followings. The data employed in the study are described in Section 4.2. The methodology of the TVP-VAR model is illustrated in Section 4.3 and Section 4.4 discusses the empirical results obtained from time-varying impulse response and forecast error decompositions. Finally, this chapter of the thesis ends with concluding remarks.

4.2 Data

The data are monthly and cover the period from February 1988 to March 2017 for investigating the dynamic interaction among stock returns, interest rate, industrial production, exchange rate and oil price. The data are collected from International Financial Statistics Database of IMF. Following Sadorsky (1999), this study uses the following vector of endogenous variables Y_t in the estimation of the VAR model,

$$Y_t' = [poil_t \; rer_t \; ip_t \; rint_t \; ret_t] \qquad (4.1)$$

where $poil_t$ represents the log of real crude oil prices per barrel calculated as Brent crude oil spot prices in terms of Turkish Lira deflated by consumer price index with 1987 base year. rer_t is the log of real effective exchange rate, ip_t is the log of industrial production index, $rint_t$ is real interest rate calculated from three-month treasury discount rate.[3] Lastly, ret_t represents the real stock return of Turkish stock exchange market index calculated as the log first difference of the Turkish General Stock Price (BIST100) index deflated by consumer prices.

Integration properties of the variables are investigated before proceeding to estimation. The linear unit root tests presented in Table 4.1, i.e. Augmented Dickey and Fuller ADF Dickey & Fuller (1981), and Phillips and Perron PP Phillips & Perron (1988) and Kwiatkowski, Phillips, Schmidt, & Shin (1992) KPSS imply that real stock returns and real interest rate are stationary at level, whereas industrial production, real exchange rate and real oil prices are stationary at first difference. Therefore, all variables can be treated as I(1) except for $rint_t$ and ret_t.

J. Lee & Strazicich (2003) unit root test is also applied to take into consider the impacts of the possible structural breaks on the stationarity of the variables. The LM test results allowing for one and two endogenous structural breaks in the intercept and trend (crash model and trend shift model) are presented in Table 4.2 with their breaking time obtained from break fractions λ_j. The results based on the LM unit root tests with endogenous breaks support the linear unit root tests that all variables except real interest rate and real stock returns are first-difference stationary.

[3] Short-term real interest rate is calculated using the formula $rint = \frac{(1+i_t)}{(1+\pi_t)} - 1$ where i_t is the three-month treasury discount rate and π_t is year on year inflation rate calculated from CPI with base year 1987.

Table 4.1: Unit root test results

Variables	ADF		PP		KPSS	
	Intercept	**Trend and Intercept**	**Intercept**	**Trend and Intercept**	**Intercept**	**Trend and Intercept**
poil	-1.744	-2.676	-2.711*	-3.578**	1.490***	0.187**
Δ*poil*	-5.848***	-5.835***	-12.386***	-12.361***	0.038	0.034
rer	-1.841	-1.988	-2.514	-3.095	0.305	0.190**
Δ*rer*	-5.902***	-5.971***	-13.372***	-13.369***	0.077	0.039
ip	0.123	-2.417	-0.549	-7.923***	2.445***	0.421***
Δ*ip*	-5.130***	-5.121***	-13.758***	-13.739***	0.038	0.034
rint	-2.438	-3.229*	-5.484***	-5.825***	0.773***	0.263***
ret	-5.736***	-5.748***	-17.796***	-17.769***	0.023	0.022

***: one percent significance
**: five percent significance
*: ten percent significance

Note: The lag length is chosen based on the Akaike information criterion (AIC) for the ADF test. On the basis of the Parzen-Kernel, the PP and KPSS tests are estimated using the Newey-West and Andrews bandwidths respectively. The null hypothesis is that the series is nonstationary for the ADF and PP tests. For the KPSS test, opposite of the PP test hypothesis is accepted as the null hypothesis.

Table 4.2: Lee and Strazicich unit root with break tests

	One Endogenous Break					**Two Endogenous Breaks**							
	Model A (Crash Model)		**Model C (Trend Shift Model)**			**Model A (Crash Model)**			**Model C (Trend Shift Model)**				
	LM-Stat	**Breaking Time**	**LM-Stat**	$\boldsymbol{\lambda_1}$	**Breaking Time**	**LM-Stat**	**Breaking Time**		**LM-Stat**	$\boldsymbol{\lambda_1}$	$\boldsymbol{\lambda_2}$	**Breaking Time**	
		$\boldsymbol{D_{1t}}$			$\boldsymbol{D_{1t}}$		$\boldsymbol{D_{1t}}$	$\boldsymbol{D_{2t}}$				$\boldsymbol{DT_{1t}}$	$\boldsymbol{DT_{2t}}$
poil	-2.820	2004:04 (2.256)	-3.754	0.39	1999:07 (2.824)	-3.291	1991:11 (-1.903)	2005:02 (1.314)	-5.659**	0.39	0.90	1999:07 (3.267)	2014:05 (-4.607)
Δ*poil*	-4.215**	1999:08 (1.254)	-6.984***	0.37	1998:11 (6.128)	-4.747***	1998:03 (0.286)	2004:07 (1.174)	-11.469***	0.50	0.60	2002:11 (-3.656)	2005:10 (3.994)
rer	-4.193**	2001:04 (4.959)	-4.853**	0.63	2006:06 (1.888)	-4.433**	2001:04 (4.983)	2004:12 (1.353)	-6.416***	0.20	0.68	1994:01 (-4.134)	2008:02 (3.854)
Δ*rer*	-12.438***	2002:05 (-2.628)	-12.218***	0.44	2004:03 (2.063)	-12.900***	1994:05 (1.881)	2001:07 (-1.074)	-12.460***	0.46	0.69	2001:06 (5.992)	2008:03 (-5.819)
ip	-3.611**	2004:02 (0.759)	-3.438	0.55	2004:02 (-1.475)	-4.420**	1999:12 (-1.502)	2003:02 (0.783)	-5.100	0.51	0.70	2003:01 (4.423)	2008:08 (-4.786)
Δ*ip*	-6.755***	2007:03 (-0.365)	-7.623***	0.43	2000:09 (-5.467)	-7.091***	1996:07 (-1.443)	2007:05 (-0.718)	-8.619***	0.2	0.62	1993:11 (-7.622)	2006:03 (8.031)

rint	-5.647***	1992:12 (1.678)	-7.624***	0.21	1994:03 (3.908)	-6.092***	1992:12 (1.672)	2002:10 (-0.579)	-8.826***	0.21	0.45	1994:04 (-8.355)	2001:04 (8.491)
ret	-4.549***	1999:04 (-0.874)	-17.283***	0.71	2008:10 (-9.406)	-5.213***	1998:11 (0.236)	2006:04 (-1.397)	-17.493***	0.20	0.44	1994:02 (-5.899)	2000:02 (-1.806)

***: one percent significance
**: five percent significance
*: ten percent significance

Note: A maximum of 12 lags to find the optimum lag length is allowed. The parentheses (.) represent t-statistics. These are J. Lee & Strazicich (2003)'s critical values. Model A allows for breaks in the intercept and Model C allows for breaks in both the trend and the intercept. D_{1t} and D_{2t} show the first and second break dates, while DT_{1t} and DT_{2t}, when allowing for the trend and intercept together, show the first and second break dates. λ_1 and λ_2 are the first and second breakpoints, respectively ($\lambda = D_t/T$ for Model A and $\lambda = DT_t/T$ for Model C, where T is the sample size). LM-Stat represents the unit root test of Lagrange Multiplier, reported by Schmidt & Phillips (1992).
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The results indicate that most of the estimated breaking times are significant, the variables contain at least one important structural break. The timing of breaks also suggests that the crises experienced during the investigation period have important implications on the evolution of the variables. The significant breaking date for $poil_t$ around the midst of 1999 seems to be connected with more than twofold decline in the crude oil prices due to increase in OPEC supply. Another significant breakpoint seems to be associated with the 2008 Global financial crisis, on that time oil prices hit their highest value with $133.9 in July 2008. The significant break is observed in the midst of 2014. On that time oil prices have declined by more than half (from 111.87 in June 2014 to $48.42 in January 2015), due to the decision of OPEC to increase production and the expansion of supply from non-OPEC countries investigated by Baffes, Kose, Ohnsorge, & Stocker (2015). The two-identified significant breaking dates of stock returns are found to be associated with 1994 local and 2008 global financial crises.

To sum up, the results obtained from unit root tests in general suggest that oil price, exchange rate and industrial production are integrated of order one, therefore those variables are introduced in their first difference form in the VAR model. On the other hand, variables of stock return and interest rate are used in their level form in the VAR model.

4.3 Methodology - TVP-VAR Model

In this chapter; the influence of oil price, exchange rate, output, interest rate on the stock price returns in Turkey with the estimation of a TVP-VAR model developed by Primiceri (2005) is investigated. This model includes both time-varying variance covariance matrices and time-varying coefficients of the additive innovation. The time-varying structure of the model enables the data to detect whether the time variation of the linear structure derives from changes in the propagation mechanism (response) or from changes in the size of the shocks (impulse) (Primiceri (2005), 823).

The TVP-VAR model can be represented as in Equation (4.2). The measurement equation of the state-space model is given by,

$$y_t = B_{0,t} + B_{1,t}\, y_{t-1} + \cdots + B_{p,t} y_{t-p} + u_t = X_t' \Theta_t + u_t \,, \qquad (4.2)$$

$$X_t' = \left[1, y_{t-1}', \dots, y_{t-p}'\right] \qquad (4.3)$$

where y_t is an $(n \times 1)$ vector of observed dependent variables and $B_{0,t \dots p,t}$ are $(n \times n)$ time-varying coefficients matrices rewritten as Θ_t matrix. X_t is the $(n \times k)$ matrix including intercepts and lags of the endogenous variables. The independent structural shock in the regression equation is by u_t with $(n \times 1)$ dimension presumed to be normally distributed heteroskedastic disturbance term with time-varying variance covariance matrix Ω_t and zero mean. The relationships among Turkish stock market return and crude oil price, exchange rate, industrial production index, interest rate are modeled by Ω_t , the variance-covariance matrix of disturbances which can be decomposed as,

$$\Omega_t = A_t^{-1} H_t (A_t^{-1})' \qquad (4.4)$$

where A_t is a lower triangular matrix measures the simultaneous relationships among the variables. H_t is a matrix where stochastic volatilities are located on the diagonals.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix}, \; H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & 0 & 0 \\ 0 & h_{2,t} & 0 & 0 & 0 \\ 0 & 0 & h_{3,t} & 0 & 0 \\ 0 & 0 & 0 & h_{4,t} & 0 \\ 0 & 0 & 0 & 0 & h_{5,t} \end{bmatrix}$$

On the basis of the following transition Equations (4.5), (4.6) and (4.7) (Primiceri (2005) and Nakajima (2011)); time-varying parameters are assumed to change in represented state space model. as follows[4]:

$$\Theta_t = \Theta_{t-1} + v_t \quad v_t \sim N(0,Q) \qquad (4.5)$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \quad \zeta_t \sim N(0,S) \qquad (4.6)$$

$$\ln h_{i,t} = \ln h_{i,t-1} + \sigma_i \eta_{i,t} \quad \eta_{i,t} \sim N(0,1) \qquad (4.7)$$

As indicated by Equations (4.5) and (4.6) time-varying parameters of Θ_t and α_t follow a random walk processes, whereas Stochastic volatilities h_t defined by Equation (4.7) follows independent geometric random walk. In addition, following Primiceri (2005) it is presumed that in each equation, the coefficients of contemporaneous relations among variables evolve independently in order to simplify the inference and increase the estimation's efficiency. This suggests that the transition equations and the error terms of the measurement equation which are the parameters of A_t matrix are assumed to be independent.

4.4 Empirical Results

Before proceeding to TVP-VAR estimation, we check stability of the model. To this aim, first we estimate linear version of the VAR model presented in Eq. (4.2) and

[4] Because of the non-stationary random walk model by its structure, following Cogley & Sargent (2005) way, the stability constraint is imposed on the evolution of the time-varying parameters.

then check the stability based on the plots of recursive residuals and the application of VAR Chow Breakpoint test. The results suggest the presence of serious parameter instabilities in the linear VAR model.[5] These results of various statistical tests support the presence of nonlinearity in the residual generating mechanism and favor the use of time-varying model.

After checking stability of the parameters, the TVP–VAR model is estimated based on Bayesian estimation procedures. To estimate the time-varying parameters in terms of unobserved latent variables, Markov chain Monte Carlo (MCMC) method is used. Following the method of Nakajima, Kasuya, & Watanabe (2011), Watanabe & Omori (2004) developed the multi-move sampler that is utilized to draw sample from the exact posterior density of the stochastic volatility.[6] To draw 50.000 sample from

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[5] The recursive residuals of the linear VAR model and Chow Breakpoint test results are presented in Figure A1 and A2 in the Appendix A respectively.

[6] For determining the lag numbers, we estimate the model from one to six lags and select the appropriate lag with the lowest Akaike Information Criterion in the VAR model. As a result, while the model is estimated with two lags, the minimum value is achieved. Nakajima et al. (2011)'s same following priors are used in the Bayesian estimation of the TVP-VAR model $\Sigma_\beta \sim IW(25, 0.01I)$, $(\Sigma_\alpha)_i^{-2} \sim G(5, 0.02)$, $(\Sigma_h)_i^{-2} \sim G(5, 0.02)$. $(\Sigma_\alpha)_i^{-2}$ and $(\Sigma_h)_i^{-2}$ are i^{th} diagonal elements of the Σ_α and Σ_h matrices, respectively. *G* represents the respective inverse Gamma distributions and *IW* represents the respective inverse Wishart. We use assumption of the following flat priors: $\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0} = 0$ and $\Sigma_{\beta_0} = \Sigma_{a_0} = \Sigma_{h_0}$ in the determination of the initial values of the time-varying parameters. Based on MCMC algorithm, it is possible to be found the details about the estimation of the TVP-VAR model in Nakajima et al. (2011) work.

Table 4.3: Estimation Results of Selected Parameters of the TVP-VAR Model

Parameter	Mean	S.D.	95%L	95%U	CD	Inefficiency
$(\boldsymbol{\Sigma}_{\boldsymbol{\Theta}})_1$	0.044	0.0103	0.0286	0.0681	0.606	75.79
$(\boldsymbol{\Sigma}_{\boldsymbol{\Theta}})_2$	0.0421	0.0094	0.0275	0.0639	0.53	71.49
$(\boldsymbol{\Sigma}_{\boldsymbol{\alpha}})_1$	0.1714	0.0188	0.1388	0.2125	0.289	13.29
$(\boldsymbol{\Sigma}_{\boldsymbol{\alpha}})_2$	0.1714	0.0188	0.1388	0.2125	0.289	13.29
$(\boldsymbol{\Sigma}_{\mathbf{h}})_1$	0.0524	0.0065	0.0415	0.0672	0.857	28.76
$(\boldsymbol{\Sigma}_{\mathbf{h}})_2$	0.0543	0.0068	0.0428	0.0696	0.111	27.37

Note: For the parameters, this table shows the means and the standard deviations. 95%L and 95%U are the lower and upper 95% confidence intervals of the parameters. CD represents convergence diagnostics from Geweke (1992) and Inefficiency represents inefficiency factors of selected parameters.

the posterior distribution, the multi-move sampler is used and we discard the initial 5.000 as burn-in sample. Table 4.3 reports the standard deviations, lower and upper 95 % confidence intervals and the posterior means of the selected parameters based on the MCMC estimation of the TVP-VAR model. Convergence diagnostics (CD) and the inefficiency factors are also reported. These results based on Geweke (1992) show that for the parameters at five percent level of significance, the null hypothesis of the convergence to the posterior distribution is not rejected. Convergence of the time-varying parameters is achieved successfully as proven from the diagnostic tests. Showing the numbers of iterations are sufficient for the stable estimation of the TVP-VAR model, most of the inefficiency factors are also found to be low.[7]

The stochastic volatility of the shock of each variable employed in this study is presented in Figure 4.1. The graphs include posterior mean with corresponding one standard deviation error bands. Considering the plots of each variable, they give similar response, i.e. after the 2001 crisis stochastic volatility of all the variables are tended to be zero. Having said that, after 2010 all the variables are held about their minimum except the stochastic volatility of the oil price, which increases to the

[7] The sample autocorrelation functions, for selected parameters, the posterior densities and the sample paths show that the simulation produced stable and uncorrelated samples as highlighted in Figure A3.

levels of pre-financial crisis. In addition, the stochastic volatilities of industrial production, exchange rate and oil price are affected from 1994 financial crisis and show similar pattern, i.e. spikes in the graphs, as for 2008 global financial crisis. As can be seen in Figure 4.1, the stochastic volatilities of the variables show different patterns for the same time period.

The responses of stock returns computed from the variance covariance matrix of the TVP-VAR model are reported in Figure 4.2 for the time horizons t = 0,1,2,…,12. Following Nakajima et al. (2011), the responses of each variable are obtained by equating the initial shock size to the time-series average of stochastic volatility over the data period and employing the simultaneous relations at each point in time. This allows us to compare the impacts of the shocks on each variable over time. Along with the cumulated three-dimensional representation for the horizon h=1 to h=12 and the cumulated responses at the horizon h=12 with their two standard error bands are also presented to evaluate the significance of the shocks over the sample period.[8] The time-varying responses presented in Figure 4.2 indicate that the responses of stock returns differ markedly across time. As far as time-varying responses are considered, it is observed that the effect of the shocks occurs instantaneously and mostly disappear within three or four months.

[8] In addition, the VAR model linear responses of stock returns for selected time periods are given in Figure A4. The time periods are selected up to three significant events, i.e. 1991 Gulf War, 2001 financial crisis, 2008 global financial crisis. As shown in the plots, the linear responses of stock returns depend on selected subsamples and the prominence of the responses changes across the varied estimation time horizons. Therefore, it can be concluded that the constant parameter VAR model may not be a convenient tool for modelling the relationship among the variables.

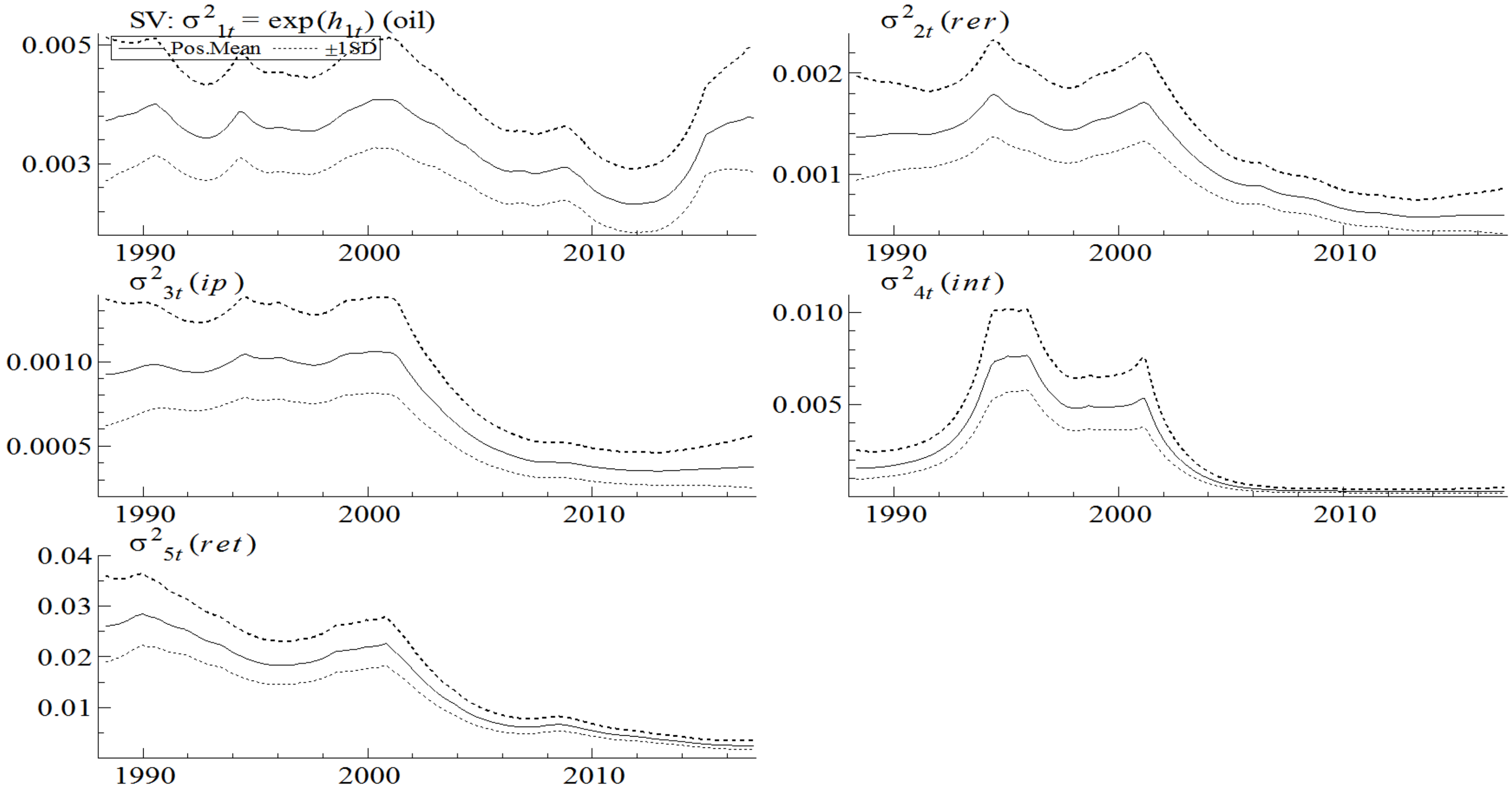

Figure 4.1: Posterior estimates for stochastic volatility of structural shock

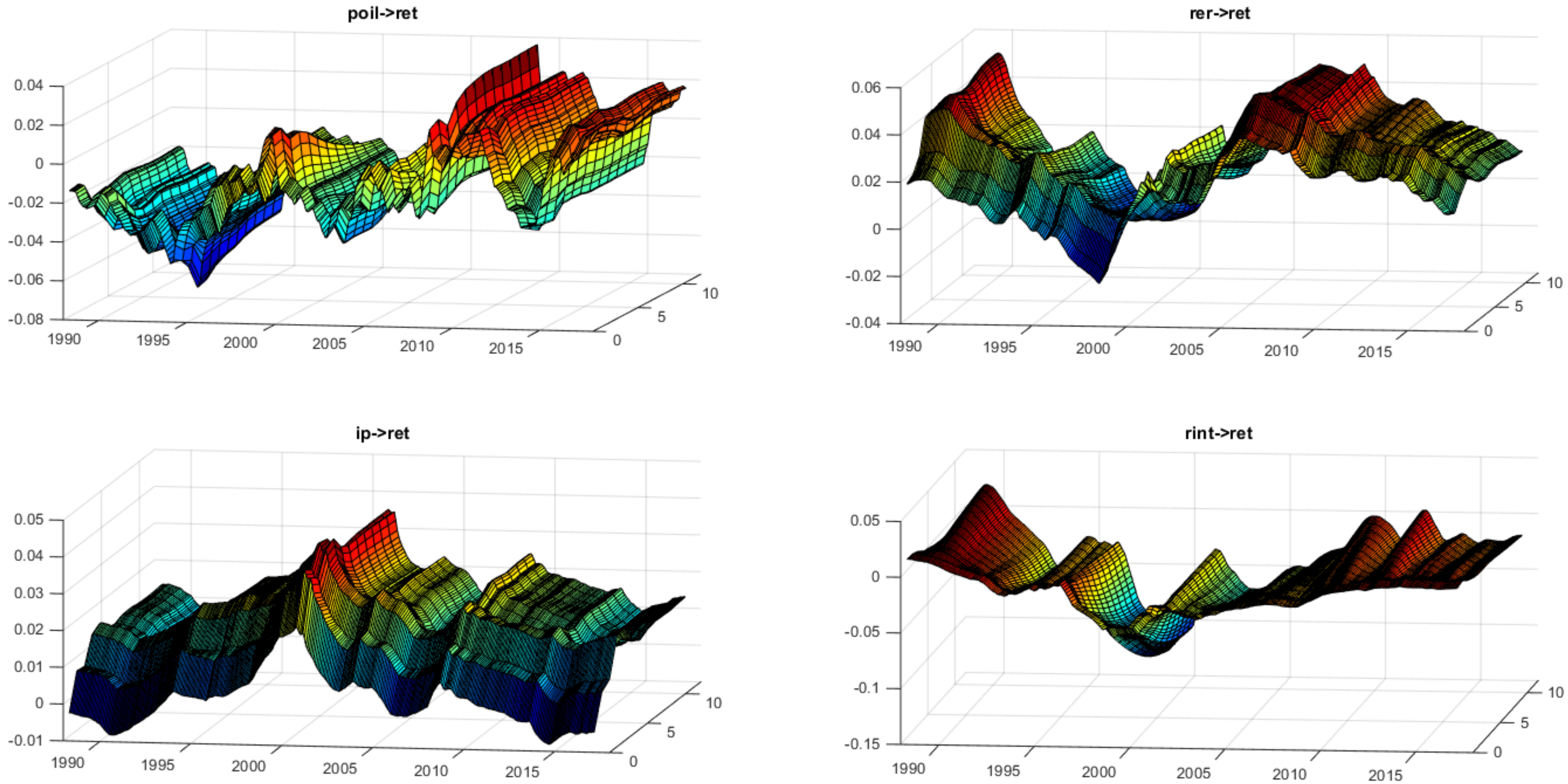

Figure 4.2 (a): Time-varying cumulative responses of stock returns

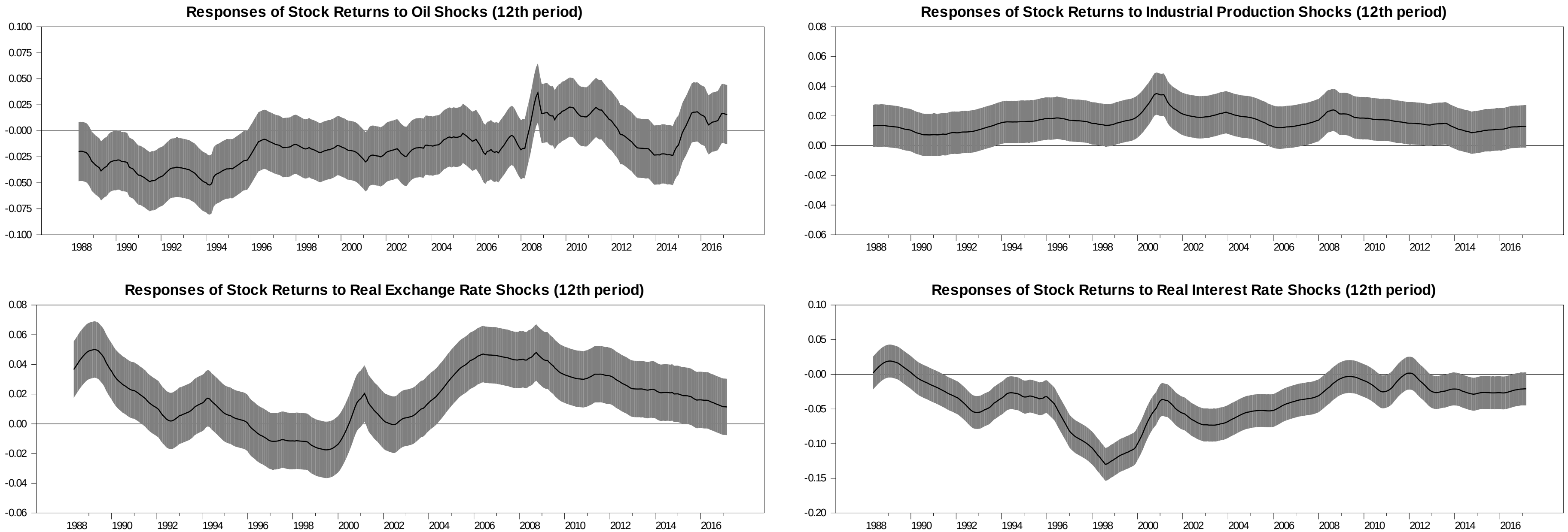

Figure 4.2 (b): Cumulative time-varying responses of stock returns at h=12 having ±2 standard error bands

The influence of oil price shocks on the real stock returns are found to be insignificant in the majority of the estimation sample, however significant responses are reported in some periods. The first significant and negative impact of oil prices are observed for the period between November 1990 and June 1992 attributable to the possible impact of increases in the nominal prices of oil due to Gulf War. On that time the influence of oil price shocks is reported as – 4.9 percent as of July 1991. The largest effects of oil prices covering the period June 1993 and November 1994 seem to be associated with the 1994 financial crisis, positive real oil price shocks lead to decline in stock returns by 5.1 percent on April 1994 attributable to more than one hundred percent depreciation of Turkish Lira against the US Dollar. After 1994, the significant effects of oil prices have not been observed till the end of the investigation period.

In contrast to oil prices, real interest rate; $rint_t$ and real exchange rate; rer_t turns out to be the most important variables in terms of its effects on stock price returns. Among the variables, the highest impacted variable on the stock returns is found to be real interest rate. The responses to interest rate shocks are initially insignificant, however negative and significant impacts are sighted thenceforth the early 1991. The highest influence of the interest rate shocks is obtained just before the 2001 crisis period (with -4.3 percent in November 1999). The impact of real interest rate shocks declines remarkably over the last four years of the investigation period. On that time the response of stock returns fluctuates between -2.1 and -2.9 percent. At the end of the investigation period, the cumulated impact of interest rate shocks remains significant and realized as -2.1 percent.

A positive shock to real exchange rate, i.e. appreciation of domestic currency, significantly rises stock returns in the beginning of the investigation period and reached one of its peak point in 1989 with 4.9 percent then its significance disappears between 1992-2002. After that time significant responses are observed, especially for the period between 2006 and 2009. The highest cumulated effect in that period obtained in November 2008 with 4.8 percent, attributable to the appreciation of the domestic currency during 2008 global financial crisis.

Stock returns' responses to the industrial production shocks are found to be positive as expected, it is also notable that the responses follow relatively stable pattern as compared to the shocks of other variables. However, the cumulated responses plotted with their standard error bands suggest that the impact of positive output shocks are not significant in the beginning of the investigation period. The highest impact of industrial production shocks is observed in the last period of 2001, during which the local economy was trying to recover from the financial economic crisis. Second significant response obtained in July 2008 is again coincided with the Global financial crisis.

In addition to impulse responses, time-varying forecast error decompositions are also computed to evaluate the relative importance of the oil prices and macroeconomic variables in the explanation of stock returns over the investigated period. The variance decompositions of stock returns at the 1, 4, 6 and 12 months horizons are presented in Figure 4.3. The results are in line with the time-varying responses. The first notable thing is that most of the variation in the stock returns are explained by their own shocks at all forecast horizons. However, the portion explained by the own shocks has declined significantly as the forecast horizon is increased from h=1 to *h*=12. For instance, at *h*=1, 95.0 percent of the variation in the stock returns is explained by the own shock of the variable by the end of 1988, however at *h*=12 the own contribution of stock returns declines to 87.0 percent in the same period. At the end of the investigation period, the self-explanatory power of stock returns is still high at h=1 with 92.2 percent, however it falls as low as about 60 at the end of the analysis period at h=12.

The contribution of oil prices to the variations in the stock returns remain initially below 5 percent similar to that of other variables, however due to the possible effect of Gulf crisis it becomes a major contributor in the beginning of 1992 (with 8.9 percent in January 1992). Oil prices has continued to remain the main contributor up to the midst of 1996 the highest explanatory power of real oil prices is obtained in April 1994 with 11.2 percent connected with 1994 financial crisis. After that time real interest rate becomes the main contributor of stock returns after the own shock of the variable the highest forecast error decomposition results for the real interest rate are obtained just before the 2001 crisis (with 22.2 percent in December 1999). However explanatory power of $rint_t$ has declined remarkably, oil prices again become the major contributor of stock returns after the own shocks in December 2002 with 9.4 percent. The portion explained by oil prices is lagging behind the other variables by the end of the investigation period with 6.0 percent in March 2017.

The contribution of exchange rate is low in the beginning however it becomes the most important contributor of the variation in the stock prices since the early 2004, by June 2007 real exchange rate can explain 20.1 percent of the variation in stock returns. By the end of the period, real exchange rate is still the most important contributor of the stock returns after its own shocks with 15.4 percent. On that time, oil prices and real interest rate are able to explain 5.86 and 4.66 percent of the variation respectively at the 12th month forecast horizon, h=12.

It is also notable that the contribution of industrial production is increasing over time. In the beginning industrial production can only account for less than 3 percent of the variation in the stock returns. However, the portion explained by this variable has remarkably increased especially after 2001 and reached to 13.48 percent by the end of the investigation period.

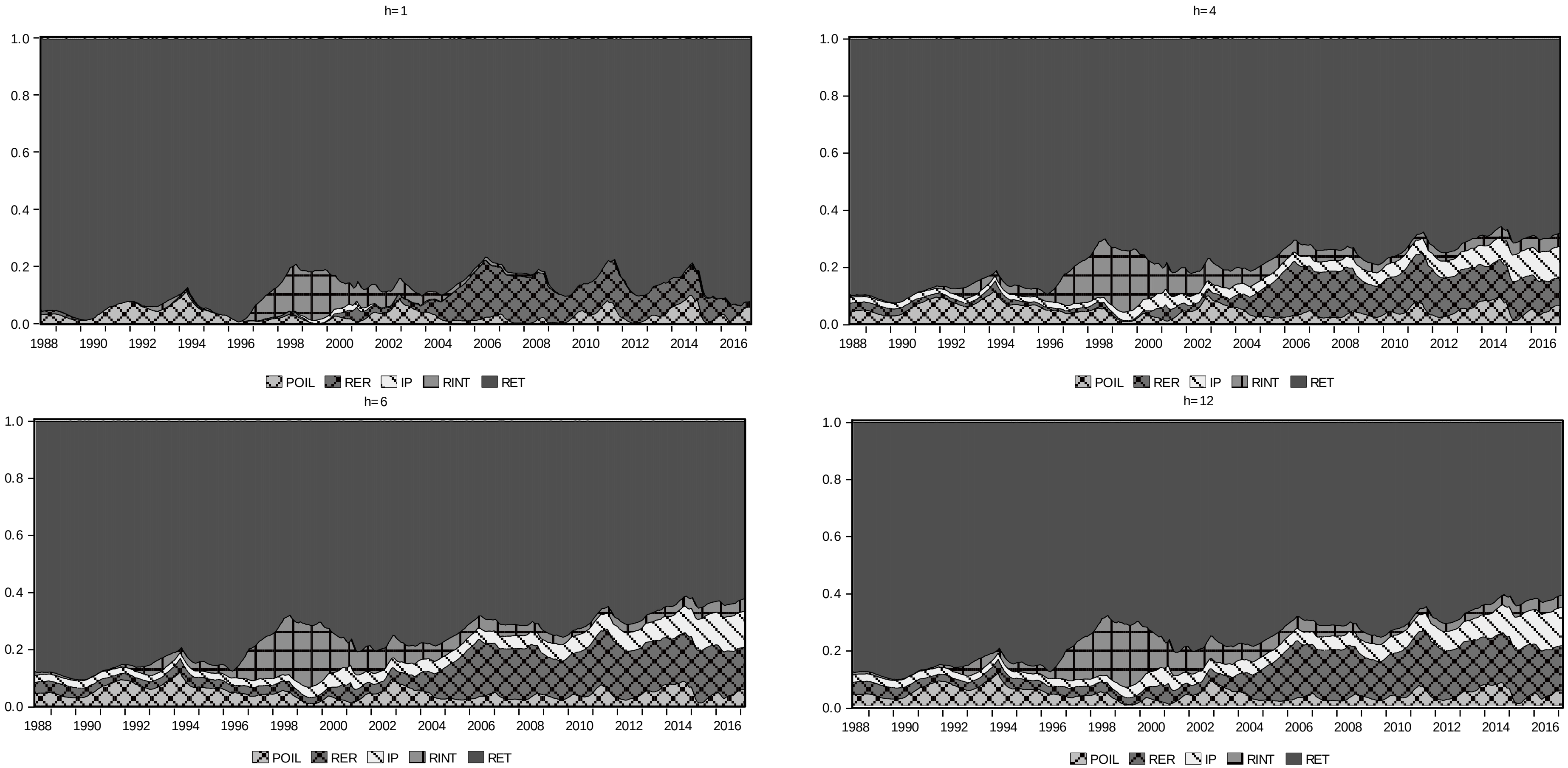

Figure 4.3: Time-varying forecast error decompositions

4.5 Conclusion

This chapter has examined the impacts of oil prices and economic activity on the Turkish stock market in a time-varying framework. To this aim we estimate a TVP-VAR model by using monthly data covering the period from February 1988 to March 2017 and time-varying impulse responses and forecast decomposition analyses have been conducted.

The results in general support the view that the impression of variables on the stock returns differ markedly over the investigation period. Impulse response results imply that real stock returns are largely influenced by the shocks in exchange rate and interest rate. However, oil price shocks have a lesser impact compared to those variables and their effects are only significant during the period of Gulf War and 1994 local financial crisis periods. In line with the findings of the previous studies, e.g. Sensoy & Sobaci (2014) and Ozcelebi & Yildirim (2017), positive exchange rate shocks, e.g. appreciation of domestic currency, make increases in stock price returns. There is also an evidence that output shocks generally have positive and stable effects on the stock prices. The time-varying forecast error decompositions support the results of impulse-responses by suggesting that exchange rate and interest rate significantly explain changes in stock returns, and the contributions of oil price remain relatively low during the analysis period.

Significant and negative impact of interest rates on the stock market returns imply that policymakers may utilize interest rates as a policy tool to control the prices of domestic assets. However, TVP-VAR estimates also indicate that global and local financial crises might extend impression of real exchange rate shocks on the stock returns. Therefore, the authorities should also consider the fluctuations in the exchange rate market since they may create a potential threat on the stability of asset prices.

Chapter 5

CONCLUSIONS

The Turkish and the US financial markets with respect to crude oil prices are investigated in this dissertation thesis. In the first part, the study focuses on the magnitude of volatility transmission and the risk spillover mechanism across the oil market, financial market risks, and the oil-related CDS sectors in the US. The dataset includes seven different measures of markets and credit risks and daily closing futures prices of WTI. Four of the vast risk measures are oil and oil-related sector CDSs, which include auto (AUTO), chemicals (CHE), natural gas (OILGAS) and utility (UTIL) sectors. In addition, three measures of the financial market risk that are VIX, MOVE and SMOVE indices. The fear index, CBOE Volatility Index (VIX) measures one-month expected equity volatility of the S&P 500. The expected risk in the bond market is represented by the Merrill Lynch Option Volatility Estimate Index (MOVE). The Swaption Move Expected Volatility Index (SMOVE) measures the expected risk in the swap market. In other words, VIX and MOVE are correlated with the equity market and the US Treasury securities market, respectively. SMOVE can be considered as a kind of VIX for the US non-Treasury in swaption markets. The seven variables investigated in this study are not only used as risk measurement tools but also used to represent the volatilities in different markets and sectors. The daily dataset is from 6 January 2004 to 2 February 2016.

One of the main aims of this part is to research the volatility transmission mechanism across the oil, oil-related CDS sectors and financial markets, employing a multivariate conditional volatility model. The other objective is to discern how major global events affect the volatility of the oil and oil-related CDS markets by employing the newly introduced Volatility Impulse Response (VIRF) analysis. The volatility transmission mechanism across the oil and financial markets and CDS sectors is investigated using the VIRF model. To analyze the risk spillover mechanism within and across the oil market, financial market, and the oil related CDS sectors; eight variables (WTI, four oil and oil-related sector CDSs, VIX, MOVE and SMOVE) are employed in the multivariate conditional volatility model, known as BEKK model, by Engle & Kroner (1995). In addition, the VIRF model uprated by Hafner & Herwartz (2006) is employed to dataset to assess the magnitude of the volatility transmission. We evaluate the risk transmission on oil and oil-related market volatilities due to several recent shocks or events around the world: the US mortgage crisis: Lehman Brothers bankruptcy on 17 September 2008; the Greece debt crisis on 8 December 2009; the fear of Greece's default on 23 April 2010; the Egyptian political unrest (Second Revolution) on 27 May 2011; the European sovereign debt crisis on 18 August 2011; and the US government shutdown on 30 September 2013. The volatility impulse responses have the advantage of providing valuable information on the speed of risk transmission. In addition, the shape and sign of the volatility impulse responses also provide significant information on the transmission mechanism. Therefore, the study of volatility transmissions within and across the oil sector and oil-related sectors are valuable to oil companies, market investors, creditors of these sectors, energy regulators and governments. The determination of the behavior between oil prices, oil-related CDS sector indices, VIX, MOVE/SMOVE will guide for future decisions and actions.

In the results of this part, it is observed that most of these events lead to significant risk transmission. Among these events, the Lehman Brothers bankruptcy has destabilizing effects on all the oil-related sectors. Findings also show that all oil market related shocks have significant risk transmission effects. Finally, the results show complicated transmission mechanisms that spread over long periods.

In the following part of the thesis, the power of Brent crude oil prices and macroeconomic variables: real effective exchange rates, industrial production indices and real short-term interest rates on Turkish stock market general index (BIST100) is explored. Previous studies on Turkey employ linear VAR models, which are not able to capture time-varying effects of macroeconomic variables. Therefore, a TVP-VAR model is utilized based on Primiceri (2005) to capture the time-varying effects with non-constant coefficient parameters of oil price and other macroeconomic variables on the stock returns using monthly data covering the period from January 1988 to March 2017. According to time-varying responses and forecast error decompositions, it can be concluded that the influences of each variable to stock returns largely depend on the horizons and the investigated time periods.

It is also shown that the most important variables influencing the stock market returns are real effective exchange rates and real interest rates compared to real crude oil prices and industrial productions. In addition, it is revealed that stock returns have been dominated by the variations in exchange rate. The influence of real crude oil price is lower compared to exchange rate and interest rate. The industrial production index has positive effect on stock returns in Turkey, as expected. Exchange rate significantly explains changes in stock returns particularly after 2002 and the contributions of oil price and interest rate remain relatively low during this time period. This may be associated with the appreciation of domestic currency and the external investors. Significant positive relation between stock returns and real exchange rate are observed similar to Sensoy & Sobaci (2014). However, the positive relation is revealed, particularly during local and global financial crises. The contribution of the interest rate to stock return is significant compared to other variables during 1996-2002, however, the effect is temporary. The impact of oil price is obtained as negative for the period of 1988-1995, which is well-correlated with Sadorsky (1999). However, the effect is found to be insignificant for the other investigated periods. Industrial production indices generally have positive and stable influences on stock market prices. Having said that, the cumulative responses of industrial production to stock returns are increased after 2012.

The findings imply that stock returns in Turkey have been affected particularly by real exchange rate, i.e. foreign-dependent and hard-to-control variable. The effects of real crude oil prices are lower. Therefore, in addition to implementation of all measures to control the real exchange rate and oil prices effects, policy makers are advised to regulate the interest rate to stabilize the economy. In addition, industrial production has positive effects as expected, so it has to be promoted by policy makers to increase the stock market prices. As a conclusion, this study provides significant and valuable information to academicians, policymakers and investors interested in Turkey.

To sum up, according to the findings of the thesis, it is shown that the impacts of variables on the Turkish and United States financial markets differ substantially over time. In addition, local and global financial and political events have various degree of influence.

Considering the number of studies on US, I want to go towards emerging countries. The number of studies is scarce on emerging or developing countries. One of the most important and effective one is Turkey for me with the political and geopolitical situation. The object of the future work considering the second part of the thesis is that Turkish stock exchange market could be investigated by the sectoral perspective. Parallel to the study of first part, oil sector and oil-related sectors will be examined and control for the impacts of oil prices. This sectoral study could be conducted on new Fragile Five countries namely Turkey, Argentina, Pakistan, Egypt and Qatar because of there is few investigations on this. Because of tighter monetary policies and higher interest rates, these countries named as new Fragile Five by S&P Global Ratings.

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APPENDICES

Appendix A: Tables of VAR Model

Table A1: Time-varying variance decompositions

h=1	poil	rer	ip	rint	ret	h=4	poil	rer	ip	rint	ret	h=6	poil	rer	ip	rint	ret	h=12	poil	rer	ip	rint	ret
1988	0.034	0.013	0.000	0.003	0.950	**1988**	0.047	0.028	0.020	0.009	0.895	**1988**	0.05	0.04	0.02	0.01	0.88	**1988**	0.05	0.04	0.03	0.01	0.87
1989	0.012	0.005	0.000	0.001	0.982	**1989**	0.027	0.026	0.019	0.006	0.922	**1989**	0.03	0.04	0.02	0.01	0.90	**1989**	0.03	0.04	0.03	0.01	0.90
1990	0.048	0.002	0.002	0.000	0.948	**1990**	0.059	0.020	0.021	0.006	0.894	**1990**	0.06	0.03	0.03	0.01	0.88	**1990**	0.06	0.03	0.03	0.01	0.87
1991	0.077	0.002	0.000	0.001	0.919	**1991**	0.091	0.013	0.017	0.012	0.866	**1991**	0.09	0.02	0.02	0.01	0.85	**1991**	0.09	0.02	0.02	0.01	0.85
1992	0.046	0.000	0.000	0.018	0.936	**1992**	0.062	0.013	0.017	0.037	0.871	**1992**	0.06	0.03	0.02	0.04	0.85	**1992**	0.06	0.03	0.02	0.04	0.85
1993	0.085	0.005	0.001	0.014	0.895	**1993**	0.096	0.020	0.019	0.035	0.830	**1993**	0.10	0.03	0.02	0.03	0.81	**1993**	0.10	0.04	0.02	0.04	0.81
1994	0.047	0.002	0.001	0.007	0.943	**1994**	0.065	0.017	0.018	0.034	0.865	**1994**	0.06	0.04	0.02	0.03	0.85	**1994**	0.06	0.04	0.02	0.03	0.84
1995	0.027	0.001	0.000	0.000	0.972	**1995**	0.064	0.010	0.019	0.034	0.874	**1995**	0.06	0.03	0.02	0.03	0.85	**1995**	0.06	0.03	0.02	0.03	0.85
1996	0.010	0.001	0.000	0.046	0.944	**1996**	0.042	0.008	0.019	0.095	0.835	**1996**	0.04	0.03	0.03	0.10	0.81	**1996**	0.04	0.03	0.03	0.10	0.81
1997	0.018	0.005	0.001	0.111	0.866	**1997**	0.042	0.014	0.017	0.156	0.770	**1997**	0.04	0.03	0.02	0.16	0.75	**1997**	0.04	0.03	0.02	0.16	0.74
1998	0.016	0.005	0.006	0.161	0.811	**1998**	0.033	0.013	0.022	0.204	0.728	**1998**	0.03	0.03	0.03	0.21	0.70	**1998**	0.03	0.03	0.03	0.21	0.70
1999	0.004	0.002	0.016	0.168	0.810	**1999**	0.013	0.004	0.035	0.213	0.736	**1999**	0.01	0.03	0.04	0.22	0.70	**1999**	0.01	0.03	0.04	0.22	0.70
2000	0.015	0.031	0.020	0.071	0.862	**2000**	0.019	0.035	0.052	0.102	0.793	**2000**	0.02	0.05	0.06	0.10	0.77	**2000**	0.02	0.06	0.06	0.10	0.76
2001	0.040	0.024	0.005	0.070	0.861	**2001**	0.044	0.028	0.033	0.095	0.801	**2001**	0.04	0.04	0.04	0.09	0.79	**2001**	0.04	0.04	0.04	0.09	0.78
2002	0.083	0.019	0.001	0.058	0.838	**2002**	0.097	0.025	0.028	0.082	0.768	**2002**	0.09	0.04	0.03	0.08	0.75	**2002**	0.10	0.04	0.04	0.08	0.75
2003	0.040	0.030	0.005	0.036	0.889	**2003**	0.058	0.036	0.039	0.065	0.803	**2003**	0.06	0.05	0.05	0.06	0.78	**2003**	0.06	0.06	0.05	0.07	0.78
2004	0.009	0.087	0.002	0.025	0.878	**2004**	0.023	0.086	0.036	0.058	0.797	**2004**	0.02	0.11	0.04	0.06	0.77	**2004**	0.02	0.11	0.05	0.06	0.77
2005	0.011	0.166	0.001	0.019	0.804	**2005**	0.023	0.155	0.034	0.052	0.736	**2005**	0.02	0.17	0.04	0.05	0.71	**2005**	0.02	0.17	0.04	0.05	0.71
2006	0.030	0.166	0.001	0.013	0.790	**2006**	0.041	0.159	0.035	0.044	0.722	**2006**	0.04	0.17	0.04	0.04	0.70	**2006**	0.04	0.17	0.04	0.04	0.69
2007	0.001	0.163	0.001	0.015	0.820	**2007**	0.021	0.162	0.037	0.042	0.737	**2007**	0.02	0.18	0.05	0.04	0.71	**2007**	0.02	0.18	0.05	0.04	0.71
2008	0.003	0.130	0.000	0.008	0.858	**2008**	0.039	0.129	0.040	0.037	0.756	**2008**	0.04	0.15	0.05	0.04	0.73	**2008**	0.04	0.15	0.05	0.04	0.73
2009	0.019	0.093	0.000	0.001	0.887	**2009**	0.026	0.112	0.049	0.029	0.784	**2009**	0.02	0.14	0.06	0.03	0.75	**2009**	0.03	0.14	0.06	0.03	0.75
2010	0.039	0.131	0.000	0.000	0.830	**2010**	0.041	0.151	0.053	0.025	0.731	**2010**	0.04	0.18	0.06	0.02	0.70	**2010**	0.04	0.18	0.06	0.02	0.70
2011	0.020	0.140	0.000	0.001	0.839	**2011**	0.030	0.166	0.053	0.029	0.721	**2011**	0.03	0.19	0.06	0.03	0.69	**2011**	0.03	0.19	0.06	0.03	0.68
2012	0.013	0.093	0.000	0.001	0.894	**2012**	0.037	0.129	0.061	0.034	0.739	**2012**	0.04	0.16	0.07	0.03	0.70	**2012**	0.04	0.17	0.07	0.03	0.69
2013	0.055	0.106	0.000	0.000	0.838	**2013**	0.078	0.129	0.067	0.039	0.688	**2013**	0.07	0.16	0.07	0.04	0.65	**2013**	0.08	0.17	0.08	0.04	0.64
2014	0.079	0.103	0.008	0.000	0.811	**2014**	0.072	0.133	0.083	0.041	0.670	**2014**	0.07	0.18	0.10	0.04	0.62	**2014**	0.07	0.18	0.10	0.04	0.61
2015	0.028	0.058	0.004	0.001	0.908	**2015**	0.044	0.122	0.096	0.045	0.692	**2015**	0.04	0.17	0.11	0.04	0.63	**2015**	0.04	0.17	0.12	0.04	0.62
2016	0.054	0.021	0.003	0.001	0.921	**2016**	0.059	0.098	0.108	0.050	0.686	**2016**	0.05	0.15	0.12	0.05	0.63	**2016**	0.06	0.15	0.13	0.05	0.61

h=1	poil	rer	ip	rint	ret	h=4	poil	rer	ip	rint	ret	h=6	poil	rer	ip	rint	ret	h=12	poil	rer	ip	rint	ret
2017	0.056	0.018	0.003	0.001	0.922	**2017**	0.062	0.099	0.109	0.050	0.681	**2017**	0.06	0.15	0.13	0.05	0.62	**2017**	0.06	0.16	0.13	0.05	0.60

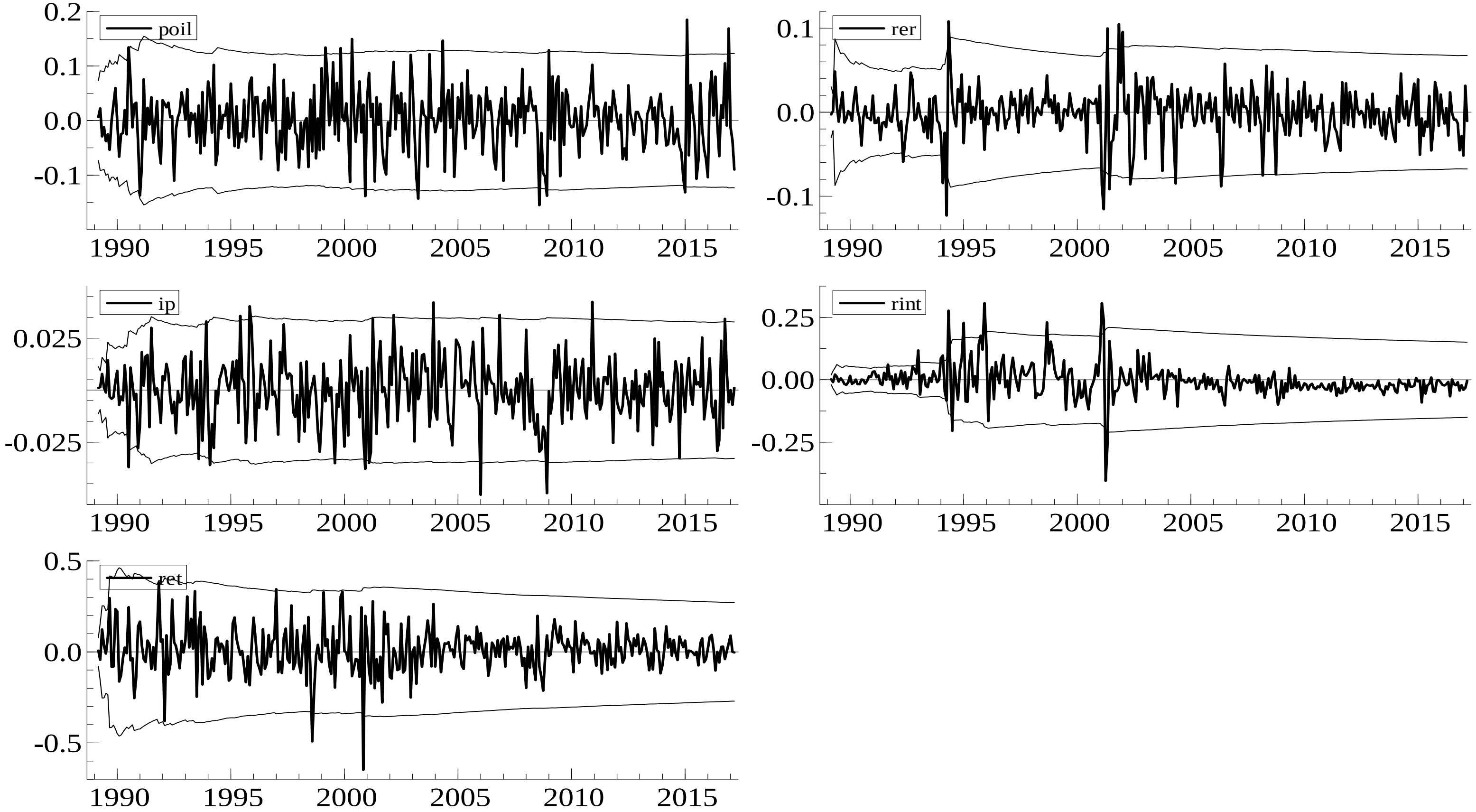

Figure A1: Recursive residuals of the linear VAR model

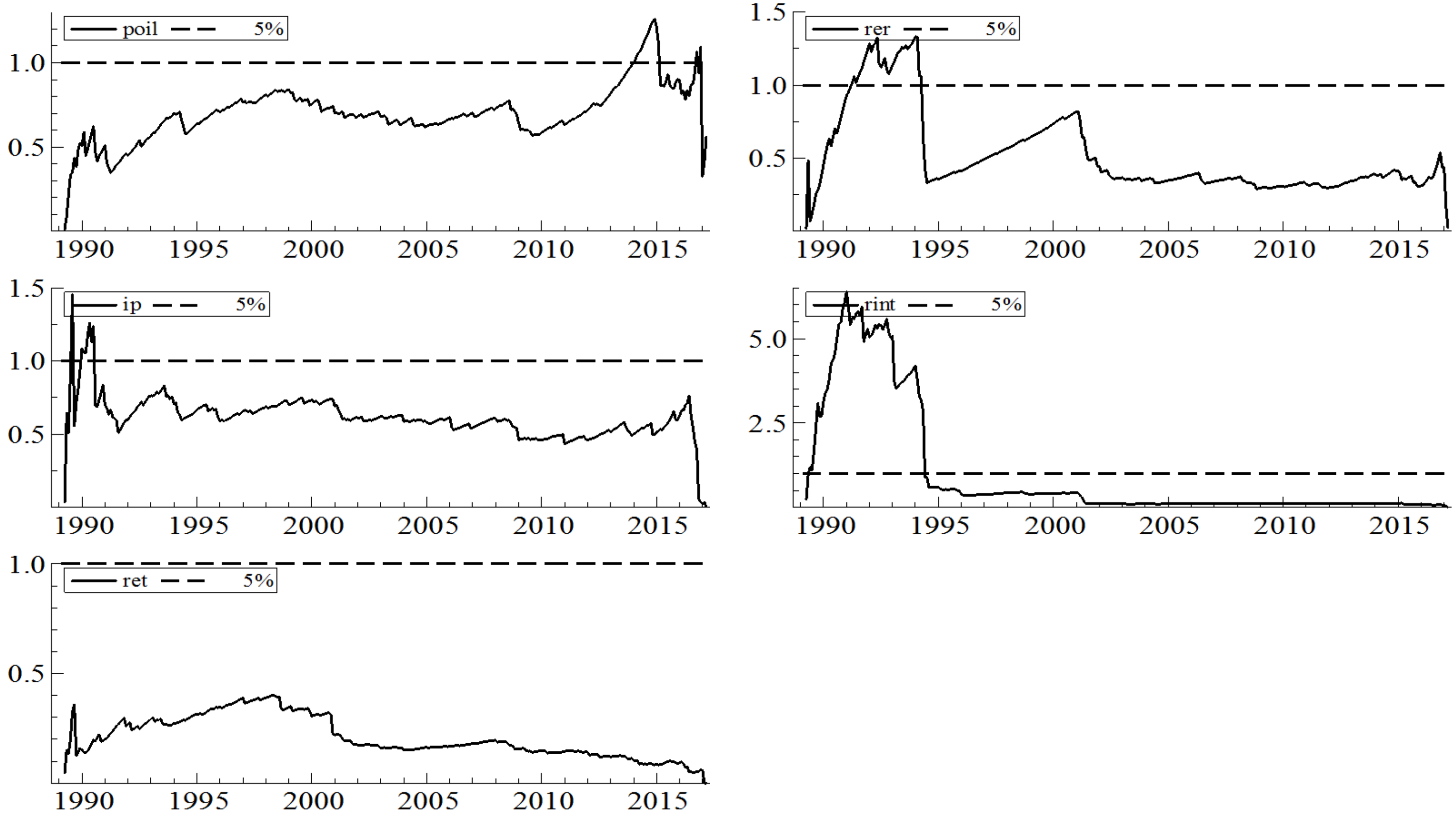

Figure A2: Chow Breakpoint test results based on linear VAR model

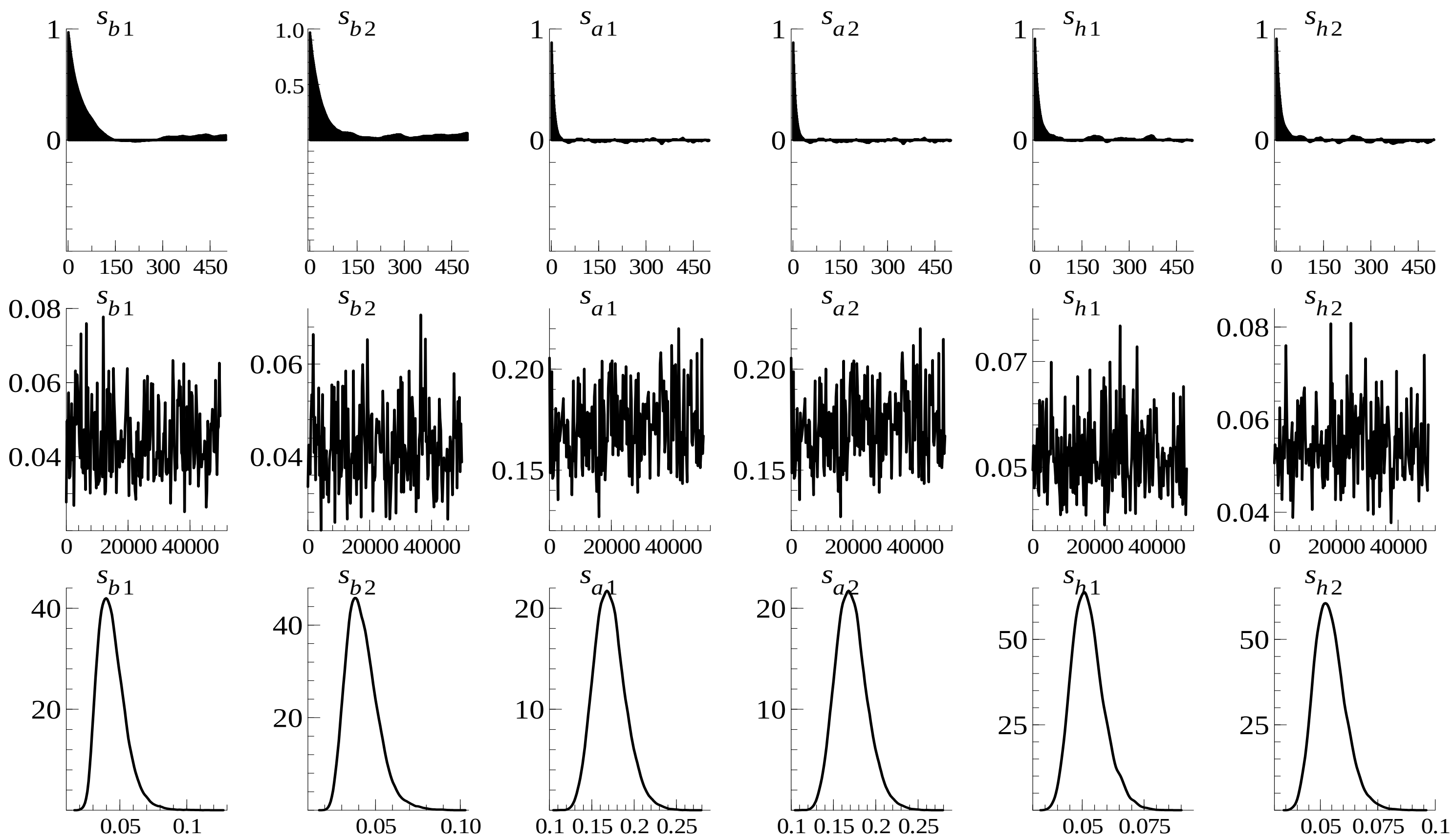

Figure A3: Sample autocorrelation functions, the sample paths and the posterior densities for selected parameters

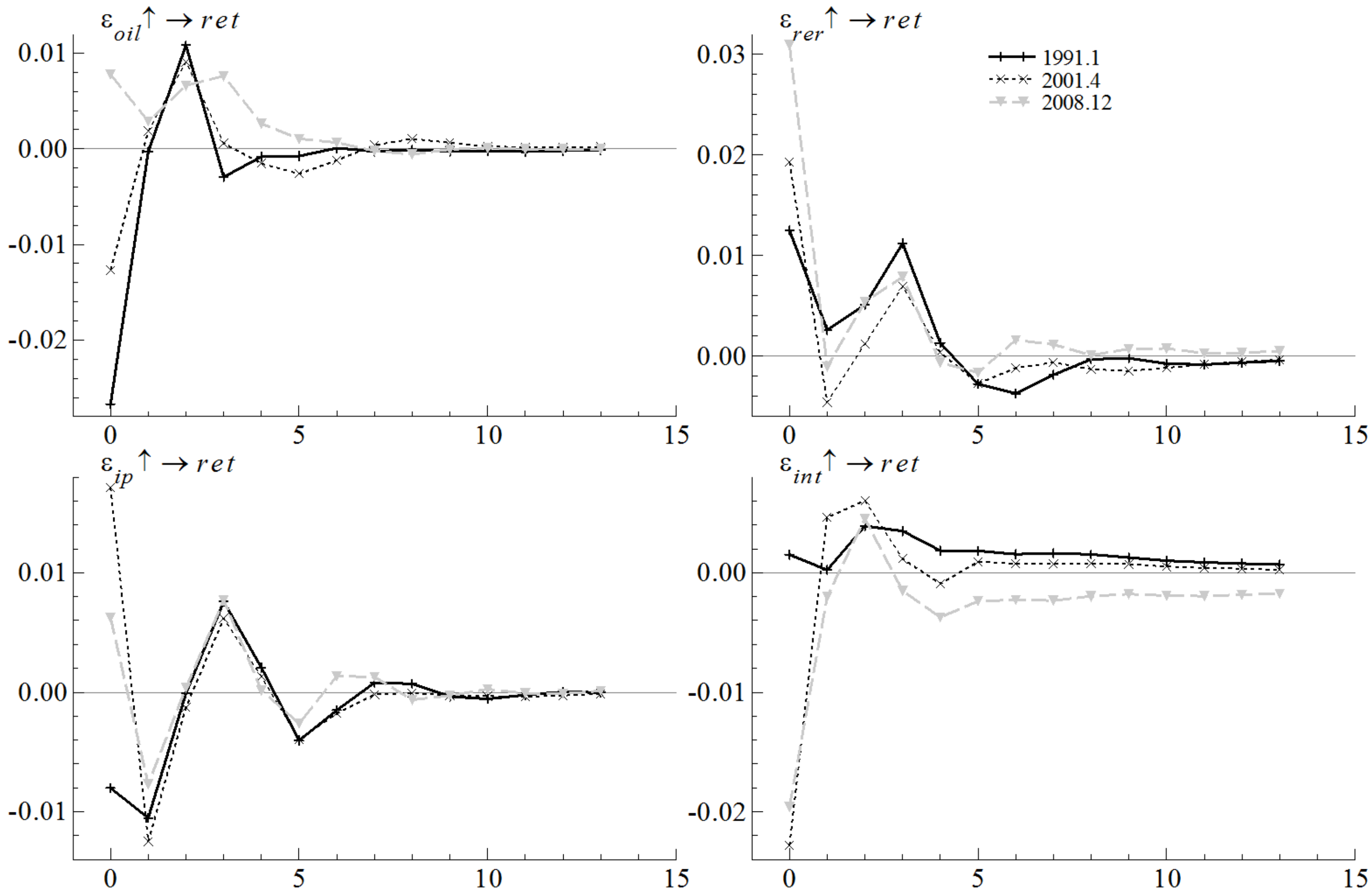

Figure A4: Linear responses of stock returns for selected dates

Appendix B: Explanation of Short Term Interest Rate

Short-term real interest rate is calculated using the following formula:

$$\text{rint} = \frac{(1 + i_t)}{(1 + \pi_t)} - 1$$

where i_t is the three-month treasury discount rate and π_t represents year on year inflation rate calculated from CPI with base year of 1987.

The effective exchange rate is an index that describes the strength of a currency relative to a basket of other currencies. Suppose a country has *N* trading partners and denote $Trade_i$ and E_i as an exchange rate with country i. Then the effective exchange rate is calculated as:

$$E_{effective} = E_1 \frac{Trade_1}{Trade} + \cdots + E_N \frac{Trade_N}{Trade}$$