The Impact of Oil Price Shocks on Stock Returns of European Industries

Jonas von Werder
40762

Yue Lin
40765

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Department of Finance

Stockholm School of Economics

Abstract

Using a VAR approach, we investigate the sensitivity of European industry returns to linear oil price changes and oil price volatility for a period from January 1995 until December 2015. We show that the response to a change in the price of oil is varying across industries and across the sample period. Splitting the data into a period before and after the beginning of the financial crisis, we find evidence that the relationship between industry returns and the oil price has changed. Before the financial crisis, most oil energy consuming industries react negatively to an increasing oil price while the Oil & Gas and the Basic Resources industry show a significant positive response. Since the financial crisis, all 13 investigated European industries respond positively to an increase in the price of oil and negatively to an increase in oil price volatility. We argue that investors interpret the price of oil as an indicator for future economic activity, which can increase investor's confidence. Little evidence of asymmetric effects of oil price changes on industry returns is found.

Keywords: Vector autoregressive model, oil prices, oil price volatility, asymmetric oil price effects, financial crisis

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1 Introduction

During the last decade we have seen immense fluctuations in the price of oil. Until 2008 the oil price surged almost steadily reaching a record high of 145$ per barrel of Brent crude oil in July 2008 before the financial crisis brought oil prices down to a low of 37$ only five months later. After a recovery in the following years that brought notations back to around 100$, we recently experienced another major downturn in the price of oil. In 20 months the cost of Brent crude oil decreased by more than 75% from a value of 115$ per barrel in June 2014 to around 27$ per barrel in February 2016. Despite these strong price movements, surprisingly little research has focused on recent dynamics on the relationship between the oil price and the stock market. This gives us the incentive to reexamine the stock-oil relationship applying a recent dataset.

Oil price shocks are generally thought to have a negative impact on firm values, thereby decreasing stock returns. The literature explains this findings by supply and demand side factors (among other effects). On the supply side, a higher oil price increases the cost base of oil consuming companies, thereby decreasing earnings and depleting cash for possible investments. On the demand side, income is transferred from oil importing countries to oil exporting countries. Customers tend to have less spending power since they pay more for oil and oil related products.

It is quite plausible that changes in the price of oil should affect stock markets. Yet, the sensitivity of stock returns to oil price changes can be expected to be highly varying across industries. Each industry has a different dependence on oil and both supply and demand factors should impact industries in a different way. For example, some industries are highly energy intensive and are likely to be strongly affected by oil price changes. Other industries might be directly or indirectly related to the oil production process. Furthermore, the shift in aggregate demand induced by the change in the price of oil could affect consumer and investment behavior in a way that could benefit some industries and disadvantage others.

In this thesis we estimate the effects of linear oil price changes and oil price volatility on the real stock returns of 13 European industries over the period 1995M01-2015M12. Most prior research on the relationship between oil and stock prices has focuses primarily on broad-based stock indices that do not take into account industry effects. This approach could raise the problem that by taking the “average” across all industries, significant responses of stock returns could be hidden if industry responses are diverse. From a portfolio management point of view, insights about the sensitivities to oil price changes can help investors assess their oil price risk and possibly provide a simple means of diversification.

Using a multivariate VAR approach, our findings show that the response to a change in the price of oil is both varying across industries and across the sample period. Inspired by the results of Tsai (2015), who finds significant positive oil price reactions of U.S. stock returns during and after the financial crisis, we divide our sample period into two sub-periods, which are separated by the Lehman bankruptcy in August 2008. This separation of our data sample enables us to investigate recent developments in the stock-oil relationship, which are of particular interest since we experienced two major oil price downturns since the beginning of the financial crisis in 2008.

Results from the effect of linear oil price changes on industry returns show a strong positive sensitivity of the *Oil & Gas* sector and the *Basic Resources* industry. This finding is robust over all sample periods and confirms the results of prior literature.

For energy consuming industries, the effect of oil price changes on stock returns is ambivalent across the two sample periods. During the first period most energy consuming industries are negatively affected by an increase in the price of oil. This result is expected as higher oil prices should raise operational costs. Since the financial crisis, however, all 13 investigated industries react strongly positively to linear oil price changes and for 11 industries the response is statistically significant. These finding question the predominant view in the literature that stock returns are negatively affected by oil price changes and indicate that oil price dynamics might have changed. We argue that the oil price has a signaling effect for future economic activity that dominates the negative implications of a rising oil price during the second period.

Results from the effect of oil price volatility on industry returns indicate that industries that are highly sensitive to linear oil price changes also show a high sensitivity to oil price volatility. Oil price volatility can be interpreted as a form of uncertainty for companies that are highly dependent on the price of oil. For this reason, it is not unexpected that the effect of oil price volatility on industry returns is mainly negative, but highly varying across industries. The influence of oil price volatility on industry returns also shows differences across both time periods, which is another indicator that oil price dynamics have changed.

Our thesis contributes to the existing literature in various ways. First, we complement the existing research on the stock-oil relationship by estimating the effect of oil price changes on the stock returns of European industries using a recent dataset that includes both the financial crisis and much of the recent drop in oil prices. Second, we investigate changes in the relationship between oil price changes and industry returns over time by allowing for two different sub-samples. Finally, we estimate the effect of oil price volatility on the European industry stock returns. To the best of our knowledge no research has been done with regards to the effect of oil price volatility on the stock returns across different industries.

The remainder of this thesis is organized as follows. In the next section we give a short summary of the existing literature on the relationship between oil price changes and stock returns. In section 3 we develop our research hypothesis. Section 4 describes our data and input variables and shows descriptive statistics. Section 5 describes our methodology. Section 6 presents the results of the effects of oil price changes and oil price volatility on industry returns. Section 7 concludes.

2 Literature review

As discussed in the introduction, this thesis contributes to the broad-based literature on the relationship between oil price changes and stock returns. In particular, we investigate the oil price sensitivity of industry returns and further test for changes in the stock-oil relationship since the financial crisis. The literature review follows this sequence from general to specific. First, we describe the broad-based literature on the influence of oil price shocks on the economy and stock returns. Second, we report the literature on the relationship between oil price shocks and industry returns. Third, we describe recent papers that investigate the oil-stock relationship during and after the financial crisis.

2.1 Oil price shocks, economic activity and stock returns

Following the major oil crisis of the 1970s a rich literature developed on the relationship between the oil price and the economy. One of the first influential studies is Hamilton (1983), who discovers a pattern that postwar recessions were often preceded by dramatic increases in the price of oil. Employing a VAR approach for the time period 1948-72, Hamilton provides evidence that the oil price was a contributing factor for at least some of the recessions occurring after World War II. Hamilton's work stimulated many other studies on the relationship between oil price changes and economic variables that use alternative data and estimation procedures (e.g. Burbidge and Harrison 1984, Gisser and Goodwin 1986, Loungani 1986). In general, Hamilton's results were confirmed and accepted as a fundamental basis. Mork (1989) confirms Hamilton's findings of a negative correlation between oil price increases and economic activity (measured by GNP). He, however, does not find a significant effect of oil price decreases on GNP, concluding that the effect of oil price changes on macroeconomic activity might be asymmetrical. The findings of an asymmetric oil price effect on economic activity received support when the strong oil price decline in 1986 was not followed by an economic expansion.

While a large body of literature focuses on the relationship between oil price shocks and economic activity, fewer papers investigate the relationship between oil price shocks and stock returns. Jones and Kaul (1996) were among the first studies who investigate the effect of oil price changes on stock returns. Using quarterly data from 1947-1991 and focusing on the stock markets in the U.S., Canada, the UK and Japan, the authors find that stock returns are negatively affected by oil price changes. For the U.S. and Canadian stock markets, Jones and Kaul (1996) show that the negative reaction of stock returns can be completely explained by the effects of the oil price on future and current real cash flows.

Sadorsky (1999) investigates the stock-oil relationship by employing a VAR model with the input variables interest rate, real oil price, industrial production and U.S. real stock returns. Using monthly data for the time period 1947M01 to 1996M04, he finds that the oil price significantly negatively affects stock returns. He further reports a negative effect of oil price volatility on stock returns and finds evidence for asymmetric oil price effects. Splitting oil price changes into positive and negative price changes, he shows that positive oil price changes explain more of the forecast error variance in stock returns than negative oil price changes. Sadorsky (1999) further reports that oil price sensitivity of stock returns has increased since 1986.

Park and Ratti (2008) use a VAR model with the same input variables as Sadorsky (1999) and test the relationship between stock returns and equity returns in the U.S. and 13 European countries. With the exception of Norway, an oil exporting country, they find that all stock markets are negatively impacted by an increase in the price of oil. The authors further study the influence of oil price volatility on stock prices. For many European countries, but not for the U.S., they find that an increase in oil price volatility significantly depresses stock returns. Some signs of asymmetric effects of positive and negative oil price shocks are found for the U.S. and Norway, but not for the countries.

2.2 Oil price shocks and industry returns

Although highly relevant for portfolio optimization, surprisingly few studies have researched the impact of oil price changes on the stock returns of individual industries. Moreover, some of these studies only focus on individual sectors in certain countries and thereby do not give a conclusive comparison among the oil price sensitivity of industry returns. As an example, Sadorsky (2001) and El-Sharif et al. (2005) investigate the oil price influence on the returns of the *Oil & Gas* industries in Canada and the UK and find a significant positive reaction to a rising oil price.

In a more comprehensive study, Nandha and Faff (2008) analyze monthly data of 35 DataStream global industry indices for the period from 1983M04 to 2005M09 using a multifactor model approach. Their findings indicate that oil price increases have a negative impact on equity returns for all sectors except *Oil & Gas* and *Mining*. Similar results are reported by Arouri (2011) and Scholtens and Yurtsever (2012), who analyze the oil price sensitivity of European industries using data from DJ Stoxx Europe 600 industry indices. Employing a multifactor model to weekly data from 1998M01 to 2010M06, Arouri (2011) shows that six sectors are negatively influenced (*Financials*, *Food & Beverages*, *Health Care*, *Personal & Household Goods*, *Technology*, *and Telecommunications)* and three sectors are positively influenced by oil price increases (*Oil & Gas*, *Basic Materials*, and *Consumer Services*). Scholtens and Yurtsever (2012) find a significant negative reaction to oil price increases for 33 out of 38 analyzed European industries using an unrestricted VAR model for the sample period 1983M08 to 2007M11. Those sectors showing a significant positive reaction to oil price increases are sub-sectors of the *Mining* and *Oil & Gas* industry.

In general, previous research shows that energy consuming industries react negatively to an oil price increase whereas energy producing sectors, such as the *Oil & Gas* and *Mining* industry, react positively.

2.3 Oil price changes and stock returns during and after the financial crisis

Few studies on the relationship between oil price changes and stock returns are using a recent sample period that spans over the financial crisis and beyond. Those studies that include the most recent sample data, such as Mollick and Assefa (2013) or Tsai (2015), report interesting results.

Investigating the relationship between the oil price and U.S. aggregate stock returns from 1999M01 to 2011M12, Mollick and Assefa (2013) report a negative impact of a rising oil price on stock returns before the financial crisis, which is in line with the previous literature. Interestingly, however, the authors find evidence of a positive and statistically significant effect of a rising oil price on stock returns in the aftermath of the financial crisis.

Similar results are reported in a recent study by Tsai (2015). Focusing on the relationship between oil price changes and U.S. industry returns, Tsai (2015) shows significant changes in the oil-stock relationship since the beginning of the financial crisis. Before the financial crisis almost all industries, except for the *Oil & Gas* and the *Mining* industry respond negatively towards an increasing oil price. During and after the financial crisis every single industry responds positively to an increasing oil price, most of them statistically significant. The authors explain the positive effect of the oil price with the oil price being an indicator of future aggregate demand that influences investor's expectation about future earnings.

3 Data and descriptive statistics

3.1 Input variables and data sources

Following a major strand in the literature on the relationship between oil price changes and stock returns, we employ an unrestricted VAR model using monthly data of interest rate, real oil price, industrial production and real stock returns as input variables. In the second part of our analysis, we replace the real oil price with oil price volatility in our model. The sample period ranges from 1995M01 to 2015M12 and comprises 252 observations for each data series.

Even though our main focus is investigating the impact of oil price changes on stock returns, the inclusion of the remaining input variables in the VAR model is of essence. Without accounting for external factors that could affect stock returns or oil prices, our results of the stock-oil relationship could be biased and show significant relationships that, in fact, result from the influence of an external factor. In the following, we elaborate on the choice of input variables and describe our data sources.

The interest rate is included in the model as it is both related to stock returns and the price of oil. Interest rates can influence stock returns for three reasons as described in Sadorsky (1999). First, interest rates affect the borrowing costs of companies and therefore have a major influence on corporate profits. This influences the price investors are willing to pay for stocks. Second, changes in the interest rate affect competing assets and lead to shifts in investor's portfolio allocation. Third, interest changes affect the desire or the ability of investors to speculate as some stocks are purchased on margin. Beside the tight relation to stock returns, interest rates are also related to the price of oil. Sadorsky (1999) shows that a shock in the price of oil positively affects interest rates. He argues that oil price increases are often a sign of inflationary pressure, thereby indicating future interest rate increases. A positive side-effect of including the interest rate in our model is that it gives us a good comparison of how strong stock returns are affected by changes in interest rates vs. changes in the price of oil. As a proxy for the interest rate, we use the Euro area 19 annualized short-term interest rates (3 months), also described as the money market rate. The data was provided by the OECD.

European industrial production is included in our model as a proxy for economic activity. Both the stock market and the oil price are fundamentally related to the state of the economy. Thus, failing to account for the output might give biased results on the relationship between stock returns and oil price changes as both variables would be influenced by the industrial production. We used the Euro Area 19 Industrial Production Index, which is seasonally adjusted and measures the total aggregate industrial production. The data stems from the ECB database.

The price of oil should reflect the inflation-adjusted cost of oil for European industries in our model. We therefore took the Brent spot price of crude oil as it is the most relevant price for European industries (Crude Oil-Brent FOB U$/BBL), converted it into Euro and deflated it by the European Consumer Price Index. The price of crude oil with the currency conversion was obtained from Datastream[1]. For the consumer price index we use the Harmonized Index of Consumer Prices for the Euro area (changing composition) published by the ECB. The nominal oil price in USD will also be used as a check for robustness. In order to calculate oil price volatility, we use daily data (nominal) of Brent oil prices denominated in Euro. The method we use to calculate volatility will be explained in the next section.

Monthly data for the industry indices "Stoxx Europe" are obtained from Bloomberg. The indices are calculated as total return index with reinvested dividends. The 13 industries in our data set are *Banks, Basic Resources, Oil & Gas, Automobile, Insurance, Healthcare, Telecommunication, Food and Beverages, Utilities, Chemicals, Personal & Healthcare, Construction & Materials* and *Technology*. Furthermore, we use the *Stoxx 600* index as a proxy for the European market return. In order to get the real industry returns, we deflated the total return indices by the European harmonized consumer price index and subsequently used the log difference of levels.

[1] For the period before the Euro was established Datastream uses a weighted basket of exchange rates from the first Euro countries

The notation will be as follows:

r	First log difference in interest rate
$roilp$	First log difference of the real oil price (in €)
$noilp$	First log difference of nominal oil price (in \$)
ip	First log difference of European industrial production
rsr	Real stock return (cont. compounded)
$vol_{€}$	Oil price volatility derived from price changes in Euro
$vol_{\$}$	Oil price volatility derived from price changes in Dollar

3.2 Definition of oil price volatility

Following Park and Ratti (2008), our measurement of monthly oil price volatility will be given by the sum of squared log differences in the daily spot price of crude oil.

$$Vol_t = \sum_{d=1}^{s_t} (Log(P_{t,d+1}/P_{t,d}) \,/\sqrt{s_t})^2 \qquad (1)$$

where s_t is the number of trading days for a given month and $P_{t,d}$ is the daily spot price of Brent crude oil denominated in Euro. For reasons of descriptive clarity we scale up the volatility measure to a range from zero to ten.

We base our volatility measure on oil price changes denominated in Euro, because we expect the oil price volatility in Euro should to be of higher relevance for European industries. We also construct a volatility measure based on the dollar denominated oil price changes and test for differences in the result. The Dollar oil price volatility measure is scaled up by the same factor as the Euro oil price volatility to allow for comparison.

3.3 Limitations of data and critical analysis

For our dataset, we select the most recent data available and, at the same time, try to maximize the sample period. On both sides the limiting factor is data for European Industrial Production, which is only available from January 1995 until December 2015.

We are using total return data from Bloomberg on Stoxx industry indices for a data range from January 1995 until December 2015. The Stoxx industry indices, however, were introduced in 1998. For the three years before the introduction of the indices, Bloomberg creates the data based on backtesting using the same methodology as the indices use. We decide to work with the data from 1995 in order to have a larger range of data available.

Another point worth mentioning is that the recent period of negative short-term interest rates makes a direct log transformation of the data impossible. In order to overcome this problem, we add a constant (+1%) to the interest rate prior to log transformation.

A potential point of criticism could be that we use aggregate European data as a proxy for output, interest rate and inflation. Using European aggregate data has the advantage that all investigated European industries are treated equally and thus only few data series are necessary for the calculations. A problem with this approach could arise if industries are extremely clustered in certain countries and our proxies vary strongly over countries. In contrast to the U.S., the European economy is much more heterogeneous economy, meaning that inflation rate, interest rate and especially output can vary significantly from country to country. If an industry is predominant in one country, it might be the case that the aggregate European data does not adequately represent the conditions for that industry. This could have an effect on the outcome of our analysis. We do not believe, however, that this issue will have a major effect on our analysis for the following reasons: First, the Industries investigated are scattered over many different countries and possible country effects are likely to cancel out. Second, interest rate, inflation and output tend to correlate strongly across European countries. Third, the proxies are there to refine the analysis, but the main focus lies on the relationship between oil real price changes and real stock returns, which is only slightly affected by the choice of proxies.

The Stoxx industry indices represent a capitalization weighted portfolio of the biggest companies in the sector. For this reason, the index covers only the biggest companies in the industries. A possible bias could arise if there are different reactions of stock returns to oil price shocks based on company size as recently investigated by Narayan and Sharma (2011), Tsai (2015) and Phan et al. (2015). If big firms are more negatively affected by an oil price shock, as reported by the studies mentioned, our results could possibly overstate the reaction of price shocks on industry returns.

3.4 Descriptive statistics

Table 1 shows the descriptive statistics of all input variables that will be used in our analysis as well as their respective correlation with real oil price changes and real market returns. The real market returns are approximated by the real returns of the STOXX 600 Index.

Table 1:
Descriptive statistics of data series

	Mean	Med	Max	Min	SD	Skew.	Kurt.	JB	Correlations	
									Roilp	Market
Real stock returns										
Automobile	0.55	0.87	26.01	-32.61	7.91	-0.71	5.15	69.52	0.12	0.75
Banks	0.22	1.29	30.54	-27.44	6.85	-0.60	5.93	105.26	0.15	0.88
Basic Resources	0.28	1.12	18.82	-37.85	7.73	-0.76	5.16	73.72	0.35	0.72
Chemicals	0.75	1.21	15.00	-19.98	5.61	-0.64	4.18	31.90	0.16	0.84
Construction	0.48	1.13	23.99	-19.18	5.71	-0.44	4.64	36.67	0.16	0.85
Food & Bev.	0.71	1.06	10.73	-12.77	3.16	-0.57	3.81	20.73	0.04	0.63
Healthcare	0.79	1.04	11.43	-11.03	3.99	-0.40	3.25	4.08	0.00	0.57
Insurance	0.39	1.36	24.91	-33.61	7.28	-0.91	7.29	228.23	0.02	0.86
Oil & Gas	0.41	0.99	17.81	-16.37	5.40	-0.21	3.64	6.14	0.45	0.66
Pers. Household	0.70	1.15	11.19	-18.32	4.67	-0.78	4.45	47.25	0.17	0.86
Technology	0.33	0.84	32.90	-33.71	8.61	-0.43	5.25	60.63	0.12	0.82
Telecomm.	0.53	0.85	20.46	-23.56	6.20	-0.48	5.20	60.25	0.03	0.70
Utilities	0.49	0.76	11.67	-13.54	4.22	-0.55	3.65	17.05	0.12	0.76
Stoxx 600	0.49	1.41	13.48	-15.23	4.60	-0.78	4.21	40.70	0.20	1
Oil price variables										
$roilp$	0.31	0.96	34.25	-40.18	10.22	-0.40	4.60	33.39	1	0.20
$noilp$	0.40	0.58	33.20	-43.67	10.53	-0.42	4.18	22.30	0.96	0.17
opp	4.03	0.96	34.25	0.00	5.79	1.92	7.53	368.63	0.82	0.16
opn	-3.72	0.00	0.00	-40.18	6.39	-2.53	10.97	932.53	0.86	0.17
$vol_{€}$	1.29	0.95	10.00	0.13	1.18	2.99	16.61	2311.7	-0.17	-0.10
$vol_{\$}$	1.29	0.97	8.77	0.10	1.16	2.68	12.68	1280.9	-0.21	-0.13
Macroeconomic variables										
r	-0.87	-0.38	16.05	-21.66	4.14	-1.17	8.85	414.66	0.11	0.04
ip	0.03	0.01	2.43	-4.13	1.01	0.54	4.09	24.92	0.21	0.14

Notes: Descriptive statistics of input variables and correlations with the real oil price ($roilp$) and the market return (Stoxx 600). Mean, Med, Max, Min and SD are reported in percent. The figures are based on monthly data. opp and opn indicate positive and negative oil price changes and will be used to test for asymmetry.

The statistics show that oil price changes have a higher standard deviation (10.22%) than all industry returns. The industry returns with the highest standard deviation are the *Technology* sector (8.61%) followed by the *Automobile* sector (7.01%). On average, oil experienced lower returns than most industries. The only exceptions are the *Banking* and *Basic Resources* sectors. As expected, all of the industry returns are positively correlated with the market ranging from 56.31% for the *Healthcare* sector to 88.06% for the *banking* sector. Skewness is negative for all return series and the Jarque-Bera test rejects the hypothesis of normality at a 5% confidence level for all return series except the *Healthcare* sector.

The returns of the *Oil & Gas* industry show the highest correlation with oil price changes (43.58%), followed by the returns of the *Basic Resources* sector (34.63%). For both sectors the profitability is strongly driven by the price of the commodity they produce. While the positive correlation between the *Oil & Gas* industry and the oil price can be directly explained by the impact of oil prices on profitability, the positive correlation between the *Basic Resources* sector and the oil price can be explained by a high correlation among oil and basic resources.

The returns of the *Healthcare* sector do not show any correlation with oil price changes. All other industries returns are moderately positively correlated with oil price changes. This result differs from Nandha and Faff (2008) as well as Scholtens and Yurtsever (2012). Nandha and Faff (2008) investigate worldwide reactions of industry returns to oil price changes for a period from 1983M04 to 2005M09 and report negative correlations between sector returns and oil price changes in 31 out of 35 cases. Scholtens and Yurtsever (2012) focus on the relationship between European sector returns and the oil price for a period from 1983M08 to 2007M11 and find a negative correlation in 34 out of 38 cases. In both studies the *Oil and Gas* sector and the *Mining* sector (highly similar to *Basic Resources*) are among the few exceptions.

Table 2:
Correlation between industry returns, market return and oil price changes over different time periods

	1995M01-2008M08		2008M08-2015M11	
Industries	roilp	Market (Stoxx 600)	roilp	Market (Stoxx 600)
Automobile	0.070	0.811	0.219 ↑	0.667
Banks	-0.016	0.895	0.392 ↑	0.889
Basic Resources	0.217	0.675	0.546 ↑	0.798
Chemicals	0.053	0.817	0.347 ↑	0.887
Construction	0.111	0.838	0.238 ↑	0.885
Food & Bev.	-0.111	0.599	0.382 ↑	0.698
Healthcare	-0.078	0.543	0.173 ↑	0.607
Insurance	-0.073	0.856	0.212 ↑	0.876
Oil and Gas	0.370	0.608	0.561 ↑	0.758
Pers. Household	0.062	0.865	0.414 ↑	0.841
Technology	0.059	0.838	0.347 ↑	0.858
Telecommunication	0.001	0.734	0.103 ↑	0.662
Utilities	0.052	0.726	0.205 ↑	0.822

Working with a more recent set of data, our results indicate a positive shift in the correlation between stock returns and oil price changes. Such a shift becomes even more pronounced if we divide our sample period into the two sub-periods described. Table 2 shows that correlation between stock returns and oil price changes has increased for every industry between the two periods. It is interesting to see, if we find evidence for the expected negative relationship between oil prices and the returns of energy consuming industries despite the positive correlation.

4 Hypothesis

This thesis intents to answer the following four research hypothesis:

Hypothesis 1: The oil price affects stock returns differently based on their sectoral allocation.

We expect different oil price reactions of energy producing industries and energy consuming industries. An increase in the price of oil raises the operational costs of energy consuming industries. Furthermore, aggregate demand in oil importing countries (Europe is a net importer of oil) declines as income is transferred to oil exporting countries (Scholtens and Yurtsever 2012). Hence, if stock prices reflect the present value of future earnings, we would expect that the returns of energy consuming industries are negatively affected by oil price increases. The degree of the impact should vary across industries based on their dependence on oil and their ability to pass on higher operational costs to the consumer.

The returns of energy producing industries, on the other hand, should be positively affected by an increase in the price of oil. For the oil producing industry the price of oil directly affects profit margins and for other energy producing industries profit margins are indirectly affected due to substitution effects.

Hypothesis 2: The relationship between oil price changes and European industry returns has changed since the beginning of the financial crisis.

Recent studies from Mollick and Assefa (2013) and Tsai (2015) provide evidence that the relationship between oil price changes and stock returns in the U.S. market has changed due to the financial crisis. In this thesis we want to investigate, if a similar change in the oil-stock relationship has occurred for European industries. To the best of our knowledge, no paper has investigated the oil-stock relationship in Europe, by testing sub-samples before and after the start of the financial crisis.

Hypothesis 3: The effect of oil price changes on industry returns is asymmetrical.

Some papers describe an asymmetrical relationship between oil price changes and economic activity by showing that oil price increases have a stronger impact on economic growth than oil price decreases (e.g. Mork 1989, Lardic and Mignon 2008, Cologni and Manera 2009). If financial markets are efficient, the effect of oil price changes on economic activity should be correctly reflected in the stock prices. Therefore, we expect the relationship between oil price changes and industry returns to follow the relationship between economic activity and oil price changes, and also be asymmetrical.

Hypothesis 4: The effect of oil price volatility is varying across industries and negative for those industries that are highly dependent on the price of oil.

Most companies can be expected to have a certain degree of exposure to the price of oil. This exposure can derive form the supply side, if oil is used as an input in the production process, or from the demand side. Subsequently, oil price volatility can be interpreted as a form of uncertainty for most companies. This uncertainty can lead to two negative effects for the stock price. First, uncertainty about the price of oil could postpone capital expenditures and thereby dampen growth opportunities for the company as described by Pindyck (1991). Second, investors are generally risk averse and could avoid stocks with a high exposure to the price of oil during times of high oil price volatility. Since different industries are likely to have different exposures to the price of oil, we expect that the effect of oil price volatility on stock returns is varying across industries.

5 Methodology

5.1 Stationarity and long-term properties of data

Before calculating a VAR model, it is a prerequisite to test the time series properties of the input variables $y_t = [y_{1t} \dots y_{kt}]'$. For this reason, we test for stationarity and subsequently for a possible cointegration relationship among the variables.

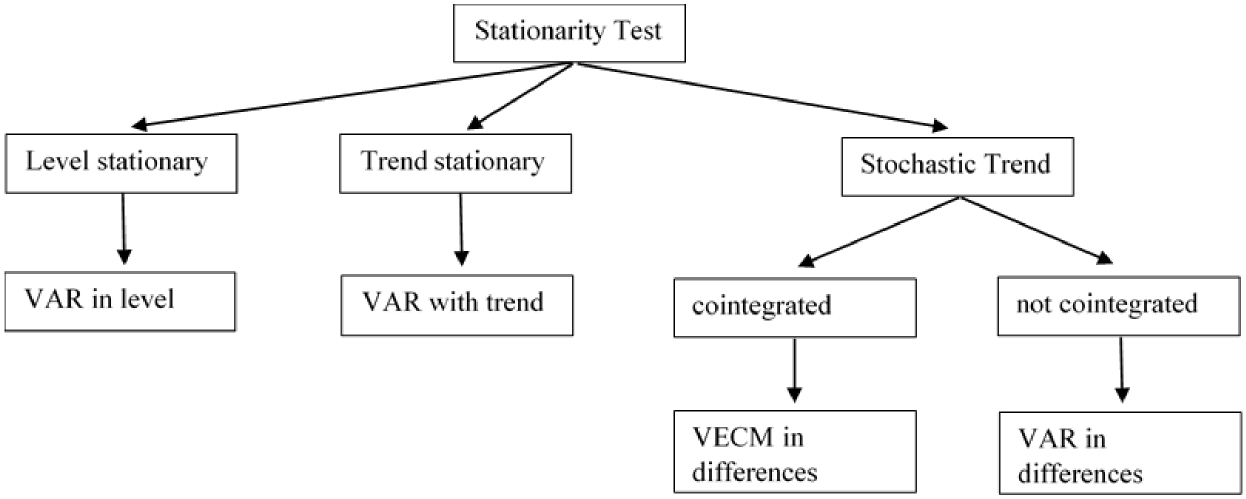
A stationary process has the property that the mean, variance and autocorrelation are constant for each given lag. Unit root tests investigate if a stochastic trend exists in the time series and, if that is the case, the time series is non-stationary. Using non-stationary data can lead to spurious regression results and can distort standard regression measures such as R^2, t-statistics and the significance of the coefficients (Brooks 2014, p.234).

The unit root test employed in this thesis is a standard Augmented Dickey-Fuller (ADF) test. The Dickey–Fuller test was developed by David Dickey and Wayne Fuller (Dickey and Fuller, 1979) and tests, whether a unit root is present in an autoregressive model. The original Dickey-Fuller test is based on the restrictive assumption that the time series y_t follows an AR (1)-process. The ADF test is an augmented version of the Dickey–Fuller test that can be applied to a larger and more complicated set of time series models. The underlying model for the ADF test is specified as follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (1)$$

where $y_t$is the time series of interest, Δ is first difference operator, α is constant, β is the coefficient of a time trend, t is the time index, γ is a coefficient, p is the lag order of the autoregressive process and $\varepsilon_t$is the error term. We will select the lag order p based on the Akaike Information Criterion. The null hypothesis of the ADF test states that the time series is non-stationary. The unit root test is then carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis $\gamma < 0$. If the null hypothesis can be rejected, which means that we accept that the variables are stationary, a VAR model in levels can be estimated. If the time series are non-stationary, the VAR framework has to be modified to get consistent estimation results for the time series relationships.

Figure 1:
VAR modeling with time series data



If the unit root test indicates a stochastic trend for the time series, the following step is to check, whether there is a cointegration relationship between the time series. Cointegration here means that there is a linear combination of two non-stationary time series, which is stationary. The most popular test for integration is the Johansen and Juselius test as it permits more than one existing cointegration relationship between the time series. The test is based on two test statistics that are expressed as below:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} ln\left(1 - \hat{\lambda}_i\right) \tag{2}$$

$$\lambda_{max}(r, r+1) = -T\ ln\left(1 - \hat{\lambda}_{r+1}\right) \tag{3}$$

where r is the number of cointegrating vectors under the null hypothesis, g is the number of variables, $\hat{\lambda}_i$ are the ordered eigenvalues, and T is the number of observations. The null hypothesis of the trace statistic is that the number of cointegrating vectors is less or equal to r, while the alternative hypothesis is that there exist more than r cointegrating vectors between the time series. For the max eigenvalue statistic the null hypothesis is that the number of cointegrating vectors is exactly r against the alternative hypothesis of $r + 1$ cointegating vectors. Johansen and Juselius (1990) provide critical values for the two statistics. If the test statistic is greater than the critical value from Johansen's tables, the null hypothesis gets rejected (Brooks, 2014 p. 387).

In case a cointegration relationship is found between the time series, a vector error correction model might be applied to the differences, which accounts for the cointegration relationship. If no cointegration is found among the time series, the time series can be differenced (by its order of integration) and a VAR model can be applied to the stationary differences of the time series. Figure 1 visualizes the standard approach for testing time series data and applying the appropriate vector autoregressive model.

5.2 The vector autoregressive model

The empirical framework to analyze the relationship between oil price changes and stock returns in our thesis is an unrestricted Vector Autoregressive model. Vector Autoregressive models were pioneered by Christopher Sims (1980) and since then applied in different forms and in various fields of use. The main advantage of VAR models is that they provide a simple approach to model rich dynamics between multiple time series. In the literature on oil price changes and stock returns VARs have frequently been applied since the work of Hamilton (1983). A VAR model consists of a system of n equations that express each variable in the system as a function of its own lagged variables and the lagged variables of the all the other (n-1) variables in the system (Park and Ratti, 2008). For example, a VAR of order p that includes k variables, can be expressed as

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + u_t \tag{4}$$

where p represents the number of lags, $y_t = [y_{1t} \dots y_{kt}]'$ denotes a column vector of all observations of the variables in the model, A_0 describes a column vector of constant terms, A_i is a $k \times k$ matrix of coefficients that will be estimated and u_t is a column vector of errors terms. The error terms u_t are assumed to follow a zero-mean independent white noise process. They are further assumed to be uncorrelated, but may be contemporaneously correlated (Park and Ratti, 2008).

The lag length (p) determines how long changes in the variables take to work through the VAR model. Selecting the appropriate lag length is often a difficult decision as there are several approaches that might lead to conflicting results. For this reason, the selection of the optimal lag length can be seen as a disadvantage of the VAR approach. A common way to select the optimal lag length is to make use of information criteria. In this thesis we follow Ivanov and Kilian (2005) who find that the Akaike Information Criteria (AIC) based estimates for monthly VAR processes are always at least as accurate as those based on other information criteria. The optimal lag length is determined for each VAR process individually by choosing the lowest AIC value and the results are reported Table 16 in the Appendix.

A further weakness of the VAR approach is that the complicated dynamics within the VAR and the large number of parameters involved in the estimation process make the models difficult to interpret. In order to overcome this problem, it is common practice to construct statistics that come with a VAR model such as impulse response functions and variance decompositions. These statistics are generally more informative than the regression coefficients and R^2 statistics of the estimated VAR models, which typically, just as in this thesis, go unreported (Stock and Watson, 2001).

5.3 Impulse response functions

Impulse responses trace out the response of the dependent variables in the Vector Autoregressive model to shocks to each of the input variables. To do this, a unit shock (or standard deviation shock) is applied to the error term of each variable from the VAR equation separately and the effects on the VAR system are described over time. One important assumption is that all other error terms are zero when applying a shock to one error term in the VAR system. This ensures that the responses are solely caused by a shock to a particular variable in the VAR system.

In practice, however, it can be assumed that the error terms in the VAR system are likely to be correlated across equations to some extent. Simply assuming that the error terms would be completely uncorrelated would lead to a misrepresentation of the VAR dynamics (Brooks 2014, p.337). For this reason, impulse response functions as well as variance decompositions require further identifying restrictions so that orthogonal structural shocks can be identified.

As suggested by Sims (1980), we orthogonalize the error terms using Cholesky decomposition to compute impulse response functions and error variance decompositions. This has the consequence that the ordering of the variables in the VAR becomes important.

The input variables should be ordered based on their level of exogeneity with the first variable being the most exogenous. Following Sadorsky (1999) and Park and Ratti (2008), we choose the following order ($r, roilp, ip, rsr$). This ordering assumes that monetary policy shocks are independent of contemporaneous disturbances to the other variables. Furthermore, changes in interest rates are assumed to influence the price of oil and, both interest rate and the oil price are assumed to affect industrial production. Finally, real stock returns are placed last in the ordering as they are assumed to be affected by all three other variables (Sadorsky 1999).

It is also worth noting that the more highly correlated the residuals from the VAR model are, the more the variable ordering will matter. In case the error terms are almost uncorrelated, the ordering of the variables will not have a big influence. Previous studies that use a VAR approach with the same variables report that the empirical results are not very sensitive to the ordering (Sadorsky 1999, Park and Ratti 2008).

To facilitate interpretation, we normalize the size of the shocks to one standard deviation. This ensures that shocks to variables, which are measured in different units can be compared more easily. Since VAR models are linear models, scaling from unit error shocks to one standard deviation error shocks does not influence the marginal effects.

In order to draw inferences about the significance of the impulse responses, Monte Carlo error bands (±2 SD) are created through Bootstrapping with 1000 repetitions. A variable's response to a one standard deviation shock is considered statistically significant if the confidence interval does not include zero for a given time horizon.

5.4 Variance decomposition

The Forecast Error Variance Decomposition explains the percentage of the movements in the dependent variables that are due to the respective variable's own shocks, versus shocks to the other variables. As the name suggests, the Forecast Error Variance decomposition is based on forecasting. Specifically, the variance is decomposed by determining how much of the s-step-ahead forecast error variance of any variable in the system is explained by innovations to each explanatory variable for s = 1, 2,… (Brooks 2014, p. 237). Typically, the shocks of the own series explain most of the error variance, although shocks will affect also other variables in the system. Just as for impulse response functions, the ordering of the variables is important.

6 Empirical results

The following section describes the results of our empirical analysis. All statistics have been computed in Eviews 8.

6.1 Stationarity and long-term properties of data

Table 3 reports the results of the ADF test for stationarity. The lag length is automatically selected based on the Akaike Information Criterion with a maximum of 15 lags. The results show that the null hypothesis of a unit root can be rejected for all real industry stock returns as well as for oil price volatility (measured in € or $). For the log levels of the real oil price, industrial production and interest rate the null hypothesis of a unit root cannot be rejected at the five percent confidence level. Consequently, we test these variables for difference stationarity. The null hypothesis that the first difference of the variables has a unit root can be rejected and we accept that the first differences of the variables are level stationary.

Table 3:
ADF Test Results

	Level		Difference	
Input variables	C	C & T	C	C & T
Real stock returns				
Automobile	-8.309***	-8.318***		
Banks	-7.800***	-7.884***		
Basic Resources	-7.481***	-7.523***		
Chemicals	-14.825***	-14.798***		
Construction	-4.982***	-4.973***		
Food & Bev.	-13.573***	-13.565***		
Healthcare	-14.134***	-14.126***		
Insurance	-4.195***	-4.1841***		
Oil & Gas	-15.624***	-15.710***		
Pers. Household	-15.144***	-15.132***		
Technology	-13.730***	-13.708***		
Telecommunication	-7.046***	-7.0413***		
Utilities	-14.524***	-14.541***		
$Ln\ (Real\ oil\ price)$	-1.894	-3.308*	-15.492***	-15.507***
$Ln\ (industrial\ prod.)$	-2.303	-2.135	-5.2187***	-5.2829***
$Ln\ (interest)$	-0.935	-2.653	-7.3316***	-7.3486***
$vol_{€}$	-6.014 ***	-6.293 ***		
$vol_{\$}$	-5.178 ***	-5.355 ***		

Notes: Difference denotes the first difference of the variables. ADF performed with constant (C) and constant with trend (C&T), automatic lag selection based on the Akaike criterion. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Since we cannot reject the null hypothesis of a unit root for the log levels of interest rate, industrial production and real oil price, we conduct a test of cointegration to see if these non-stationary variables have a common stochastic trend. The test of cointegration that we apply is the Johansen and Juselius (1990) test and the results are listed in Table 4.

Both the trace test as well as the max-eigen statistics indicate that there is no cointegration relationship between the respective variables. The economic interpretation is that there is no long-term relationship between the real oil price, the interest rate and the industrial production. The same result has been reported by Scholten and Yurtsever (2012) and, for most countries investigated, by Park and Ratti (2008). Given these test results, the four variable systems $(r, roilp, ip, rsr)$ or (r, vol, ip, rsr), can be modelled as a vector autoregression. In case we had found evidence for cointegration among the variables, we might have opted for a vector error correction model (VECM) instead.

Table 4:
Johansen Juselius test of cointegration

Variables	Hypothesis	r =0	r <=1	r <=2
$r, roilp, ip$	λ max	11.92	5.45	1.26
(in levels)		[0.55]	[0.68]	[0.26]
	trace	18.64	6.71	1.26
		[0.52]	[0.61]	[0.26]

Notes: The number of cointegrating vectors is indicated by r. P-values are reported in brackets.

6.2 Oil price changes and industry returns

6.2.1 Impulse response functions

We estimate impulse response functions that trace out the response of the dependent variable to shocks to each of the input variables. Since we have four input variables in our VAR model, Eviews delivers 16 impulse response functions for each VAR ($r, roilp, ip, rsr$) model. Our main interest, however, lies on the influence of oil price changes on industry stock returns ($roilp \rightarrow rsr$). Graphical descriptions of impulse response of industry stock returns to shocks in the price of oil are shown in Figure 9 in the Appendix for all time periods.

In order to facilitate interpretation, we focus our analysis on accumulated impulse response functions, which add up the impulse response coefficients up to the considered lag. Stable VAR models have the characteristic that the effect of a shock of one input variable on the other variables in the system declines over time. Hence, looking at the accumulated responses after a certain number of lags gives a good indication of the overall response of a certain variable to a shock. In our models we found that the effect of an oil price shock is largely absorbed after 10 lags and the accumulated responses become stable.

Total period (1995M01-2015M12)

Table 5 reports the accumulated impulse responses of all industry stock returns to a one standard deviation shock to real oil price changes ($roilp$) for the total sample period. The results are surprising as we find a positive influence of oil price shocks on most industry stock returns. For ten out of thirteen industries the accumulated impulse responses to an oil price shock are positive at the 10th lag and only the industries *Telecommunications*, *Personal & Household Goods* and *Construction & Materials* show negative responses to an increase in the price of oil. The results reported stand in contrast to the majority of papers on the stock-oil relationship, which report a significant negative influence of oil prices on stock returns for oil importing countries (e.g. Jones and Kaul 1996, Sadorsky 1999, Park and Ratti 2008).

As we would expect, the *Oil & Gas* industry reacts significantly positive to an oil price shock. Higher oil prices lead to higher profit margins and are likely to incentivize companies to invest and grow. A rise in oil prices therefore increases the value of stock prices of *Oil & Gas* companies, which explains the positive reactions of *Oil & Gas* stock returns to oil price increases.

Table 5:
Cumulative impulse responses of industry returns to shocks in real oil price (1995M01-2015M12)

	Cumulative response at lag				
Industry	1	2	3	5	10
Automobile	0.910	0.263	0.978	1.051	1.140
	(0.561)	(0.750)	(0.966)	(1.224)	(1.381)
Banks	0.653	0.342	**1.704**	1.471	0.808
	(0.393)	(0.631)	(0.757)	(1.010)	(1.237)
Basic Resources	**2.350**	**2.440**	**3.283**	**3.154**	**2.943**
	(0.451)	(0.692)	(0.936)	(1.226)	(1.274)
Chemicals	0.584	0.646	**1.370**	0.972	0.760
	(0.388)	(0.531)	(0.633)	(0.903)	(0.936)
Construction	0.545	-0.117	0.411	-0.394	-0.707
	(0.347)	(0.462)	(0.591)	(0.883)	(1.055)
Food & Bev.	-0.029	0.081	0.255	0.152	0.040
	(0.232)	(0.347)	(0.466)	(0.606)	(0.725)
Healthcare	-0.116	-0.306	0.236	0.357	0.480
	(0.251)	(0.382)	(0.463)	(0.550)	(0.668)
Insurance	0.089	-0.785	0.376	1.006	1.298
	(0.426)	(0.638)	(0.725)	(0.886)	(1.132)
Oil & Gas	**2.543**	**2.596**	**3.110**	**3.120**	**3.164**
	(0.342)	(0.485)	(0.621)	(0.775)	(0.835)
Pers. Household	0.508	0.043	0.323	0.078	-0.110
	(0.294)	(0.408)	(0.483)	(0.744)	(0.855)
Technology	0.636	-0.515	0.992	1.256	1.136
	(0.518)	(0.859)	(0.959)	(1.459)	(1.624)
Telecommunication	-0.001	**-1.219**	-0.505	-1.134	-0.709
	(0.378)	(0.566)	(0.705)	(1.018)	(1.253)
Utilities	0.488	0.327	0.806	**1.166**	**1.661**
	(0.254)	(0.391)	(0.478)	(0.566)	(0.659)
Stoxx 600	0.629	0.095	0.824	0.388	0.088
	(0.289)	(0.416)	(0.549)	(0.749)	(0.945)

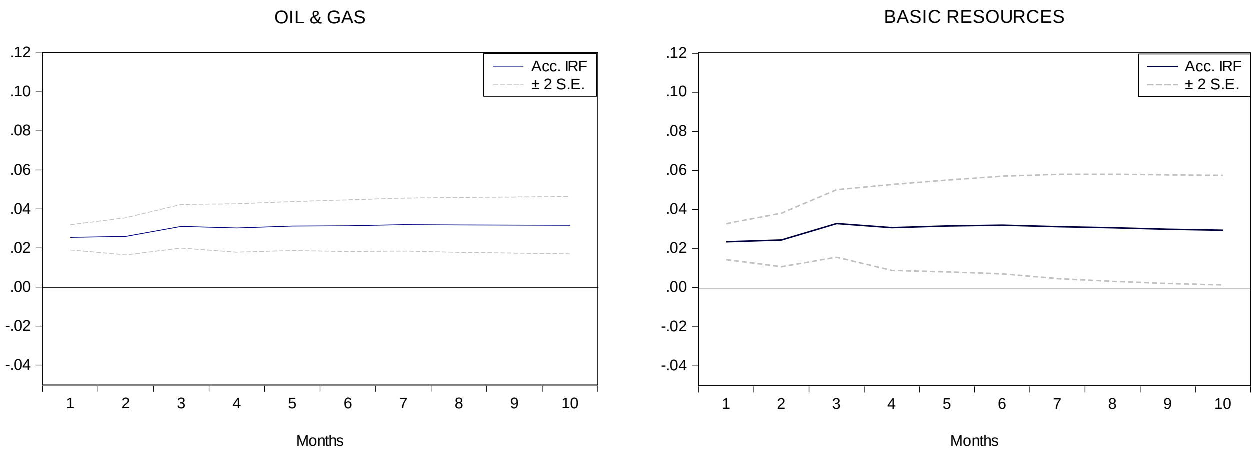
Notes: Cumulative response in percentage of real stock returns at a given lag due to a one standard deviation shock to $roilp$. Standard errors based on Monte Carlo simulation are reported in brackets.

According to our model, a one standard deviation shock to real oil price changes ($roilp$) causes, on average, a 2.54% stock return for the *Oil & Gas* sector at the first lag. Interestingly, the effect of an oil price shock does not seem to be immediately incorporated in the stock prices of *Oil & Gas* companies, since we can see that the accumulated response of an oil price shock grows to 3.16% at lag 10.

Figure 2 gives a graphical representation of the accumulated response of the *Oil & Gas* and the *Basic Resources* sectors. It can be seen that the response of the *Basic Resources* industry to an increase in the price of oil is very similar to the response of the *Oil & Gas* industry, namely positive and significant. It is further noticeable that the standard errors for the *Oil & Gas* industry are smaller than for the *Basic Resources* industry, which likely results from the more direct oil price exposure of the *Oil & Gas* industry.

In our model a one standard deviation shock in real oil price changes causes, on average, a 2.35% return of the *Basic Resources* industry at the first lag and a 2.94% cumulative return until lag ten. This positive reaction is not surprising since the *Basic Resources* sector has similar characteristics to the *Oil & Gas* sector. Both sectors are active in the area of exploration, extraction and refining of resources. Furthermore, the *Basic Resources* sector has exposure to oil prices through the mining of energy sources such as coal or uranium, which, in many cases, can be seen as substitutes to oil. An increase in the price of oil may raise demand and/or prices for various products in the Basic Resources sector. This makes companies in this segment more profitable and raises their stock prices.

Figure 2:
Accumulated impulse responses of the Oil & Gas and Basic Resources industry to a shock in $roilp$ (1995M01-2015M12)



Notes: Accumulated impulse responses to a one standard deviation shock to $roilp$. ±2 Standard error bands are constructed based on Monte Carlo simulation.

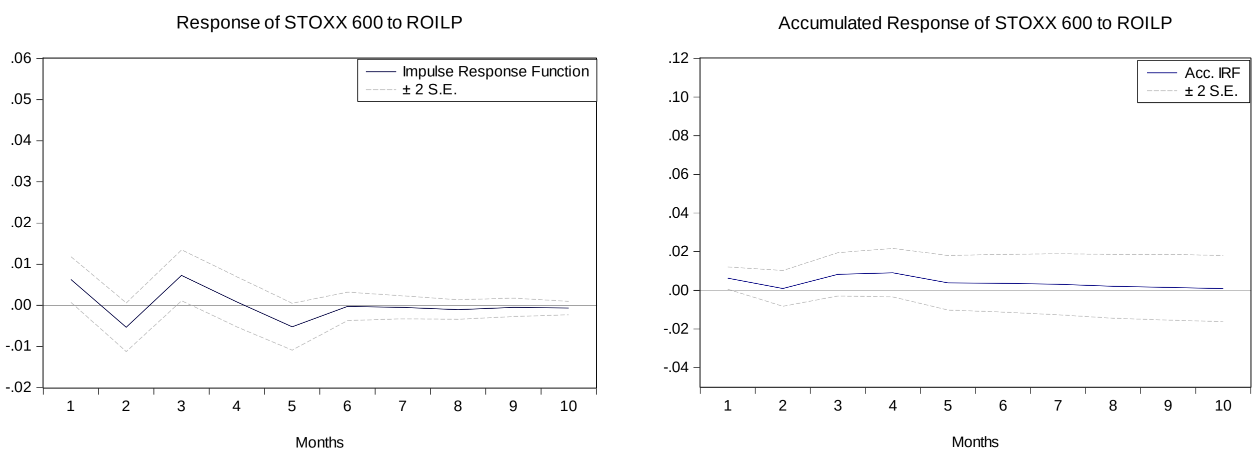
Significant positive responses of the *Basic Resources* and *Oil & Gas* industries have been reported in several papers (e.g. Sadorsky 2001, Nandha and Faff 2008, Scholtens and Yurtsever 2012), which investigated various countries.

The surprising result, however, is that the Stoxx 600 as well as most energy consuming industries also show a positive response to an increase in the price of oil. In the case of the *telecommunication*, *utilities* and *banking* sector, the accumulated responses are even statistically significant at certain lags. These results stand in stark contrast to other studies that investigate sector responses to oil price changes. Most papers report significant negative reactions to an oil price shock for all industries except *Mining*[2] and *Oil & Gas*. The explanation is straight forward: an increase in the price of oil raises the operational costs for energy consuming industries. Furthermore, a high oil price should negatively affect the demand for companies' products. Consumers as well as energy consuming companies have to spend more resources on oil and oil-related products and have less available income to spend for other products or to invest.

Figure 3 shows both the impulse response as well as the accumulated impulse response of the European market return (Stoxx 600) to a shock in the price of oil. The two graphs basically convey the same information. The only difference is that the impulse response function can give better insights about the statistical significance of individual lags while the accumulated impulse response function gives a better overview about the overall effect of a shock.

It can be seen that the individual lag responses of the impulse response function are highly varying between positive and negative, but the overall accumulated response of the European market return is slightly positive.

Figure 3:
Impulse response and accumulated impulse response of Stoxx 600 to a shock in $roilp$ (1995M01-2015M12)



Notes: Impulse response and accumulated impulse response of Stoxx 600 to a one standard deviation shock to roilp. ±2 Standard error bands are constructed based on Monte Carlo simulation.

[2] The Basic Resources sector and the mining sectors have similar characteristics. In fact, the mining sector is part of the Basic resources sector.

Since the reported oil-stock relationship differs to a great extent from the previous literature, we check our model by testing the economic validity of the other impulse responses of the VAR model. Results of the impulse response functions of the four variable VAR with the real stock returns of the Stoxx 600 index are reported in Figure 8 in the Appendix.

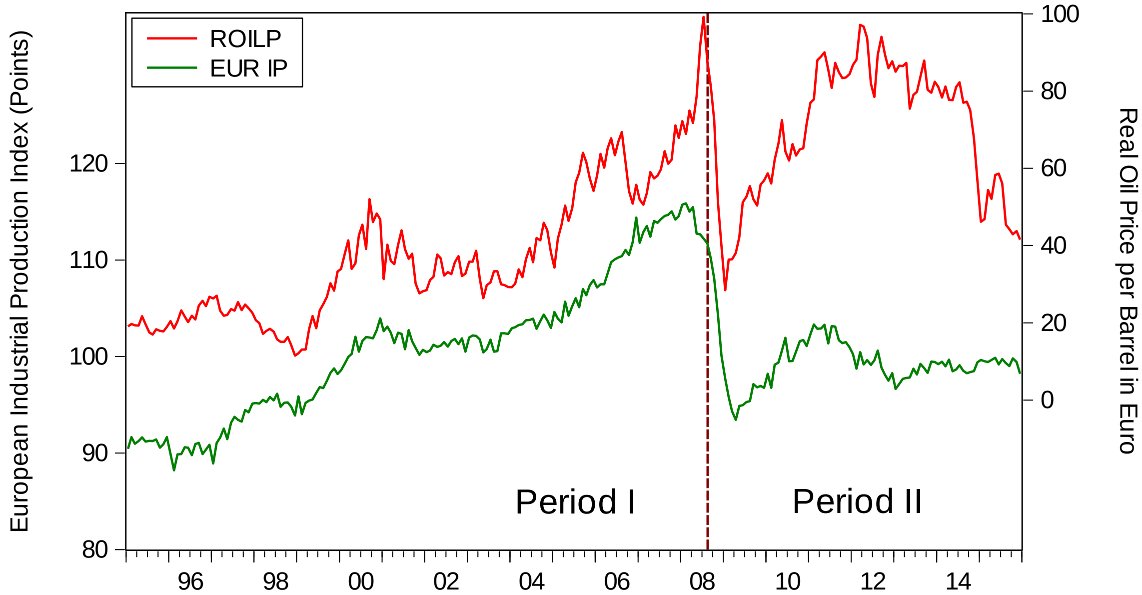
We find strong similarities to the results of Sadorsky (1999), who also applied a VAR ($r, roilp, ip, rsr$) model to test the relationship between oil price shocks and market activity for the United States. In line with Sadorsky (1999), we find a negative influence of interest rate increases on stock returns (in 9 out of 13 cases). Increased interest rates mean higher borrowing cost for companies and can result in reduced earnings or a cut in growth spending. All else being equal, this will tend to lower stock returns. We further find that oil price shocks have a positive initial impact on interest rates. Sadorsky (1999) argues that increases in oil prices are often a sign of inflationary pressure, thereby indicating future interest rate increases. Both an increase in production as well as an increase in real stock returns are found to have a positive impact on interest rates. Increases in stock returns and industrial production are indicators of a strong economy and are often followed by interest rate increases. Furthermore, our results show that industrial production reacts positively to stock return shocks. This finding is consistent with Sadorsky (1999) and the suggestions made by Fama (1981) and Geske and Roll (1983) that the stock market is an indicator for future economic activity. We conclude that the economic relationships described by the remaining impulse response functions of our VAR make economic sense, which increases our confidence in the results of the stock-oil relationship.

Besides minor differences in the methodology, the main difference between our approach and previous research is that we employ a recent dataset that includes the financial crisis and a considerable time beyond. With respect to the results of Tsai (2015), who finds a significant positive reaction of US stock returns to oil price changes during and after the financial crisis, we divide our data series into two periods. The first period is a pre-crisis period beginning in January 1995 and ending in August 2008, directly before the bankruptcy of Lehman Brothers. The second period starts in September 2008 and ends in December 2015.

In contrast to Tsai (2015) and Mollick and Assefa (2013), who choose January 2008 as the start date of the crisis period, we choose the months August/September 2008 to divide our two periods. We argue that the financial crisis hit Europe later than the United States and we see the collapse of Lehman Brothers as the date when the financial crisis seriously started to affect Europe.

Figure 4 illustrates graphically that both the price of oil and the European industrial production slumps in the aftermath of the Lehman collapse. Our hypothesis is that the stock-oil relationship has changed since the financial crisis.

Figure 4:
Crude Oil Price and European Industrial Production



Period before the Lehman bankruptcy (1995M01-2008M08)

Table 6 shows the response of industry real stock returns to an oil price shock for the first sub-period. The results are to a great extent in line with previous research on the stock-oil relationship.

The *Oil & Gas* sector shows a strong and significant positive response to an oil price increase and also the *Basic Resources* sector shows a positive reaction. An explanation for this reaction was given in the previous paragraph. Most energy consuming industries respond negatively to an oil price increase.

The *Automobile* industry shows a moderate negative reaction. A negative reaction can expected as the automobile industry is affected both by supply and by demand effects. On the supply side, higher oil prices directly affect operational costs and thereby affect the firm's profitability. On the demand side, higher oil prices make driving more expansive. This could lead to a reduced demand in cars or to a shift towards more energy efficient cars. Even though the automobile industry is affected by both demand and supply effects, the reaction is relatively weak, which was also reported by Arouri (2013). Possible reasons that the effect is not stronger could be effective oil price hedging that is common in the Automobile industry as well as European legislation that incentivizes the sale of fuel-efficient vehicles (Cameron and Schnusenberg 2009).

Table 6:
Cumulative impulse responses of industry returns to shocks in real oil price (1995M01-2008M08)

	Cumulative response at lag				
Industry	1	2	3	5	10
Automobile	0. 495	-0. 936	-0. 774	-1.140	-1.107
	(0.660)	(0.913)	(1.181)	(1.488)	(1.690)
Banks	-0. 324	**-1.454**	-0.778	-1.659	-1.848
	(0.485)	(0.687)	(0.922)	(1.281)	(1.537)
Basic Resources	**1.513**	0.875	1.128	0.776	0.854
	(0.531)	(0.707)	(0.869)	(1.047)	(1.140)
Chemicals	0.079	-0.086	0.794	0.253	0.139
	(0.421)	(0.657)	(0.825)	(1.043)	(0.998)
Construction	0.375	-0.618	-0.317	-1.038	-1.116
	(0.433)	(0.722)	(0.901)	(1.181)	(1.263)
Food & Bev.	-0.451	-0.211	-0.102	-0.661	-0.725
	(0.331)	(0.480)	(0.649)	(0.800)	(0.841)
Healthcare	-0.285	-0.061	-0.001	-0.084	-0.107
	(0.258)	(0.359)	(0.482)	(0.618)	(0.630)
Insurance	-0.671	**-2.072**	-1.187	-1.158	-0.778
	(0.551)	(0.753)	(1.010)	(1.073)	(1.170)
Oil & Gas	**2.169**	**2.036**	**2.458**	**2.327**	**2.291**
	(0.391)	(0.630)	(0.800)	(0.756)	(0.785)
Pers. Household	0.036	-0.644	-0.359	-1.027	-1.153
	(0.395)	(0.581)	(0.806)	(1.067)	(1.162)
Technology	0.136	-1.899	0.033	-0.218	0.062
	(0.683)	(1.098)	(1.371)	(1.762)	(1.980)
Telecommunication	-0.482	**-2.431**	-1.610	-2.911	-2.744
	(0.540)	(0.832)	(1.194)	(1.548)	(1.964)
Utilities	0.188	-0.444	-0.306	-0.284	-0.024
	(0.320)	(0.468)	(0.584)	(0.706)	(0.834)
Stoxx 600	0.208	-0.744	-0.010	-0.610	-0.818
	(0.360)	(0.628)	(0.785)	(1.061)	(1.050)

Notes: Cumulative response in percentage of real stock returns at a given lag due to a one standard deviation shock to $roilp$. Standard errors based on Monte Carlo simulation are reported in brackets.

We discover a negative response of the *Banking* and *Insurance* industries towards an increasing oil price. Even though these sectors are not directly involved with oil production or consumption, the price of oil can affect industries' profitability through various channels. Banks can have an exposure to the oil price through their lending to companies with significant oil price risk, through their speculative position in oil-related derivatives and through portfolio readjustments by market participants in response to oil price changes (Elyasiani et al. 2011). Both banks and insurance companies can further be affected by oil price changes through the value of their portfolio holdings. Finally, low oil prices can possibly increase the demand for financial and insurance products as individual investors should generally have more disposable income to allocate.

Our findings show a very weak negative response of the *Food & Beverage* sector to changes in the price of oil. We expected a stronger response as the oil price directly affects food production costs as well as costs for transportation and commercialization of Food & Beverage products. In an empirical study, Alghalith (2010) shows that a higher oil price leads to increases in food prices while an increase in the oil supply reduces food prices. Our results suggest that the Food & Beverage sector is able to pass along the main part of the increases in production costs to the consumer. Our results differ from Arouri (2011), who finds a significant negative relationship between the Food & Beverage industry and the oil price. The differences might be explained by the different models used. Arouri (2011) employs weekly data in a multifactor model and thereby investigates the immediate reaction of the sector returns to oil price changes. Our VAR-approach investigates longer relationships between the variables.

For the *Chemicals* industry, we find a weak positive response to a change in the price of oil. This result is rather surprising as we expected a negative impact of an oil price increase on the chemical sector. Many of the key chemical building blocks (such as aromatics, ethylene, and propylene) for the industry's products are produced from oil or oil-derivatives. An increase in the oil price should therefore directly affect the cost structure and the returns of chemical companies negatively. Furthermore, a change in the price of oil is likely to affect the demand for chemical products as spending patterns for individual consumers and companies will change. While a declining oil price will initially increase spending on consumables, a persistent low oil price will increase companies' investments in durables and fixed assets. This will lead to an increased demand for chemical products in order to make these products. Both the described supply side and demand side effects of an oil price increase should tend to affect the chemical industry negatively. Reasons why we do not find a significant negative oil price reaction could be effective oil price hedging or the ability to pass on price increases in the cost structure to the customers.

The *Construction & Materials* sector shows a negative oil price sensitivity. This result could be expected as the construction and building materials industry, in particular the cement industry, is extremely energy intensive. For the cement industry energy costs of fuel and electricity account, on average, for 40% of the manufacturing costs (Schorcht et al. 2013).

For the *Technology* sector, we find a significant negative response to an oil price shock at the second lag, which is offset by a positive shock at lag three. Even though the technology sector shows significant responses to an oil price shock at different lags, the accumulated effect of an oil price shock on stock returns of the technology sector is weak and insignificant. The technology sector is not an oil-intensive sector and the cost structure depends little on changes in the oil price. Possible stimulating demand factors through increased economic activity based on oil price decreases could be offset by companies' investments in research in energy efficiency as well as renewable energies.

The *Utilities* sector mainly contains electricity and water companies. These firms are dependent on oil and oil-related products as an input. Like other companies in the industrials sector, however, firms in the utility sector frequently make use of futures and other derivatives to hedge the exposure of oil price changes on their profitability (Arouri 2011). This could be an explanation, why we find a weak negative effect of oil price changes on Utilities stock returns.

The *Personal & Household Goods* sector shows a relatively weak negative reaction towards an increasing oil price. A high oil price affects both, the supply side as well as the demand side for personal and household goods negatively. However, as mentioned by Arouri (2011), firms in the Personal & Household Goods sector seem to be able to pass on a part of the effects to the consumer, thereby minimizing the impact on profitability.

For the *Telecommunication* sector, we find a strong negative reaction towards the oil price. Being a low energy sector, the relative strengths of the reaction is surprising, but has been previously reported in the literature (Henriques and Sadorsky, 2008; Pierdzioch and Schertler, 2008).

The *Healthcare* sector shows a very weak negative oil price reaction. This finding is not surprising as the supply side is little affected by the oil price. The weak negative reaction could be explained by the exposure of the healthcare sector to the market.

In summary, the results confirm our first research hypothesis that the response to oil price changes differs across industries. The industry responses are, for the most part, in line with previous literature and can be explained by supply and demand factors. We do, however, not find a direct one-to-one relationship between oil intensity of oil consuming industries and stock price sensitivity. This result is consistent with Scholtens and Yurtsever (2012).

Period after the Lehman bankruptcy (2008M09-2015M12)

Table 7 reports the impact of oil price changes on industry returns since the Lehman bankruptcy. The results show strong positive responses of all thirteen industry stock return series to an increase in the price of oil. For all industries, except the *Telecommunication* and *Construction & Materials* sector, the accumulated impact of an oil price change is statistically significant (as measured by a ±2 SE confidence band) at a certain lag.

Table 7:
Cumulative impulse responses of industry returns to shocks in real oil price (2008M08-2015M12)

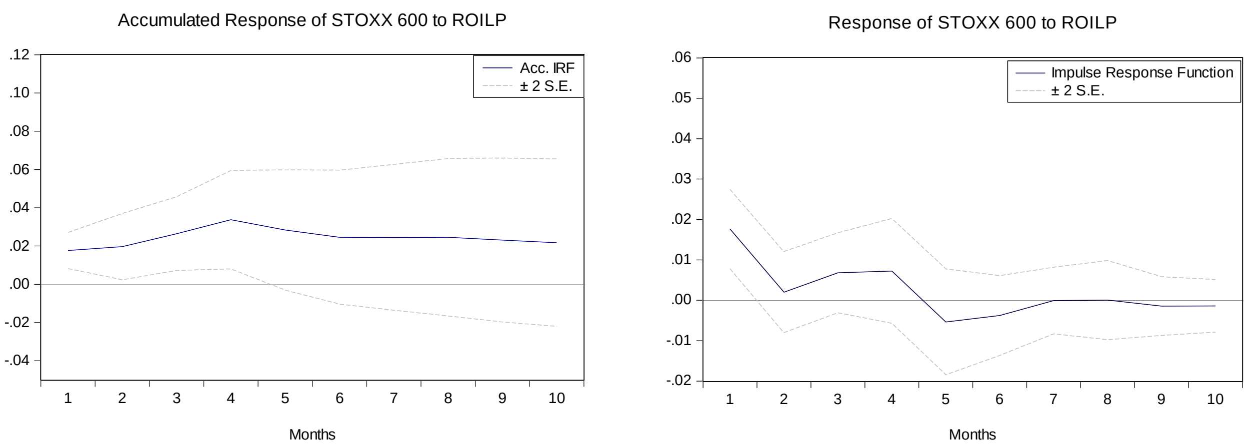
	Cumulative response at lag				
Industry	1	2	3	5	10
Automobile	1.170	1.942	**3.555**	**4.578**	4.538
	(0.961)	(1.429)	(1.660)	(2.431)	(3.359)
Banks	**2.485**	**3.018**	**5.183**	**6.3952**	3.869
	(0.792)	(1.315)	(1.570)	(2.436)	(2.991)
Basic Resources	**4.004**	**4.881**	**6.542**	**6.613**	5.635
	(1.008)	(1.603)	(2.164)	(3.047)	(4.760)
Chemicals	**1.761**	**2.355**	2.610	2.624	2.064
	(0.713)	(1.067)	(1.315)	(1.924)	(2.271)
Construction	1.274	1.004	1.801	1.335	0.262
	(0.656)	(0.974)	(1.056)	(1.663)	(2.516)
Food & Bev.	**1.412**	**1.400**	1.409	2.175	2.1041
	(0.356)	(0.596)	(0.726)	(1.177)	(1.914)
Healthcare	**0.809**	0.759	**1.502**	**2.097**	**2.455**
	(0.375)	(0.562)	(0.709)	(0.927)	(1.075)
Insurance	**1.587**	1.768	3.147	**5.344**	4.710
	(0.728)	(1.227)	(1.719)	(2.202)	(3.490)
Oil & Gas	**3.606**	**4.023**	**4.821**	**4.816**	**4.887**
	(0.491)	(0.733)	(0.995)	(1.496)	(1.942)
Pers. Household	**1.889**	**1.871**	1.899	2.594	2.400
	(0.441)	(0.673)	(0.709)	(1.251)	(1.728)
Technology	**1.643**	**2.718**	**3.342**	**4.202**	3.426
	(0.609)	(1.028)	(1.387)	(1.739)	(1.980)
Telecommunication	0.402	0.452	0.785	1.255	1.901
	(0.439)	(0.592)	(0.725)	(0.981)	(1.457)
Utilities	**0.928**	1.374	**2.142**	**3.324**	3.656
	(0.441)	(0.736)	(0.859)	(1.423)	(2.533)
Stoxx 600	**1.764**	**1.967**	**2.647**	2.835	2.172
	(0.440)	(0.668)	(0.855)	(1.428)	(2.120)

Notes: Cumulative response in percentage of real stock returns at a given lag due to a one standard deviation shock to $roilp$. Standard errors based on Monte Carlo simulation are reported in brackets.

In line with the previous period, we find positive responses of the *Oil & Gas* sector as well as the *Basic Resources* sector to an increase in the price of oil. Compared to the previous period, the reactions are even stronger in magnitude and the *Basic Resources* sector shows a slightly higher oil price response than the *Oil & Gas* sector.

For energy consuming industries the results differ strongly from the results of the previous period. All energy consuming industries react positively to an oil price increase and the economic dependence on the factor oil does not seem to explain the different stock reactions. Industries such as *Banking* or *Insurance*, which react negatively to an oil price increase during the first period show significant positive reactions during the second period. The aggregate European market return also reacts significantly positive to an oil price shock as Figure 5 shows.

Figure 5:
Impulse response and accumulated impulse response of Stoxx 600 to a shock in $roilp$ (2008M09-2015M12)



Notes: impulse response and accumulated impulse response to a one standard deviation shock to $roilp$. ±2 Standard error bands are constructed based on Monte Carlo simulation.

The European market return shows a significant positive first-lag reaction to a shock in the price of oil. The accumulated response grows for the first four lags and declines weakly thereafter.

In general, the results support our research hypothesis that oil price dynamics have changed. Since the financial crisis all industries react positively to an increase in the price of oil, even industries that are highly dependent on oil in the production process. The strong positive stock-oil relationship since the financial crisis is a possible reason why our overall results differ from previous studies, such as Jones and Kaul (1996) or Park and Ratti (2008), who report a negative effect of oil price increases on stock returns.

It is challenging to explain why an increase in the price of oil should cause stock returns of oil energy consuming industries to increase. All else being equal, a rise in the price of oil should reduce corporate earnings due to higher operational costs and cause stock returns to decline.

We argue in line with Mollick and Assefa (2012) and Tsai (2015) that the oil price has some signaling effect for future aggregate demand that investors react upon. Both, oil prices and stock prices are affected by the expectations of future economic activity. Investors might interpret a rising oil price as a sign that the economy will gather momentum and, as a consequence, increase their equity holdings. This way a rise in the price of oil could strengthen investor's confidence in the economy and in the financial markets. Given our results for the second period, the positive signaling effect of a rising oil price must have been stronger than the negative implications of a high oil price that investors expect for companies.

The question remains, why a positive signaling effect of oil price changes should be more pronounced during the second sample period than the first. Tsai (2015) argues that during and in the aftermath of the financial crisis oil prices and stock markets moved in unison, because they were both being affected by the expectations of future economic activity. Thus, Tsai (2015) regarded the oil price as a proxy for the expectations of future economic recovery and expected that the relationship between oil prices and stock returns would normalize after the financial crisis.

Using a sample that spans several years past the financial crisis, we still find significant results for a positive stock-oil relationship for European industry returns. We see two possible explanations for that phenomenon. On the one hand, it could be that the financial crisis has such a pervasive effect that the complete sample shows a positive stock-oil relationship.[3] On the other hand, one could argue that Europe is still in a recovery phase since the output gap, the difference between GDP and potential GDP, has not been closed since the financial crisis.

6.2.2 Variance decomposition

The Forecast Error Variance Decomposition describes the percentage of variation in real industry returns due to shocks in the explaining variables of the VAR model, namely interest rate, real oil price and industrial production. The results are reported in Table 8 and support the finding that the influence of oil price changes on real stock returns varies by sector as well as over time.

[3] Due to the number of data points necessary for our VAR approach, it was not possible to test this hypothesis by separating a sample only for the financial crisis period.

Table 8:
Forecast Error Variance Decomposition VAR (r,roilp,ip,rsr)

	1995M01-2015M12			1995M01-2008M08			2008M09-2015M12		
	R	Roilp	IP	R	Roilp	IP	R	Roilp	IP
Automobile	0.98	2.67	2.27	0.67	4.14	0.84	4.75	5.59	5.97
	(1.81)	(2.19)	(1.95)	(2.13)	(3.04)	(1.85)	(5.50)	(5.10)	(5.07)
Banks	3.84	**6.23**	**6.97**	1.91	5.78	4.63	6.52	**21.01**	10.17
	(2.24)	(2.61)	(2.58)	(2.61)	(3.60)	(3.83)	(5.67)	(7.14)	(6.91)
Basic Resources	1.39	**10.04**	2.21	1.06	5.78	1.87	3.82	**20.89**	6.21
	(1.62)	(3.27)	(2.45)	(2.30)	(3.44)	(2.65)	(5.07)	(7.20)	(5.40)
Chemicals	1.95	3.30	5.99	2.36	3.05	5.66	3.94	11.15	13.56
	(1.77)	(2.49)	(2.48)	(2.70)	(3.31)	(4.05)	(5.52)	(5.93)	(7.45)
Construction	3.56	4.72	5.21	2.50	4.89	5.64	4.99	10.13	11.57
	(2.46)	(2.75)	(3.14)	(2.57)	(3.31)	(3.89)	(5.70)	(5.90)	(5.90)
Food & Bev.	1.27	0.67	5.45	2.55	0.98	3.45	5.33	**17.04**	11.92
	(1.46)	(1.51)	(2.85)	(2.92)	(2.15)	(3.25)	(5.37)	(6.93)	(5.79)
Healthcare	2.67	2.18	2.26	2.71	2.90	0.51	5.99	8.67	12.75
	(2.03)	(2.49)	(1.99)	(3.48)	(3.16)	(1.79)	(4.55)	(5.67)	(6.51)
Insurance	0.17	4.63	3.77	1.29	5.60	1.73	2.48	12.65	10.05
	(1.01)	(2.52)	(2.46)	(2.23)	(3.87)	(2.51)	(4.39)	(6.79)	(6.01)
Oil & Gas	2.92	**22.09**	1.28	4.94	**15.81**	0.94	2.15	**40.74**	2.99
	(2.09)	(4.87)	(1.56)	(3.03)	(4.70)	(2.19)	(3.86)	(6.88)	(4.32)
Pers. Household	0.74	4.28	2.79	0.18	2.66	0.74	1.86	**20.05**	15.38
	(1.29)	(2.36)	(1.96)	(1.61)	(2.69)	(1.83)	(3.81)	(6.83)	(6.24)
Technology	0.70	5.45	2.16	0.51	7.83	0.65	1.42	12.44	**16.05**
	(1.43)	(2.56)	(2.07)	(1.95)	(3.66)	(2.43)	(3.73)	(6.78)	(7.05)
Telecommunication	1.94	5.60	0.83	2.94	**9.97**	0.93	1.97	2.68	7.79
	(2.10)	(3.09)	(1.52)	(2.56)	(4.33)	(2.18)	(3.67)	(4.42)	(5.63)
Utilities	1.12	3.31	4.39	1.98	2.71	2.71	4.74	11.62	11.07
	(1.67)	(2.40)	(2.92)	(2.68)	(2.48)	(2.51)	(5.28)	(6.80)	(6.16)
Stoxx 600	2.86	**6.64**	5.88	2.10	6.67	3.52	4.06	**18.12**	**17.29**
	(2.46)	(3.02)	(3.03)	(2.58)	(4.00)	(3.13)	(4.83)	(6.67)	(7.98)

Notes: Percentage of variation in real stock returns due to shocks in interest rate, real oil price and industrial production (10 month horizon). Standard errors are constructed through Monte Carlo simulation with 1000 repetitions and reported in brackets.

Over the complete sample period the real oil price, on average, accounted for 5.41% of the variance of industry returns. In comparison, the interest rate explained 1.79% while the industrial production explained 3.67% of the variation in real stock returns. This result is consistent with Park and Ratti (2008) who find that oil price shocks explain more of the variation in real stock returns than the interest rate for most of the countries they investigated. For them, the median result is that oil price shocks account for about 6% of the variability in real stock returns.

As expected, the returns of the *Oil & Gas* industry and the *Basic Resources* industry are most sensitive to oil price changes. For the Oil & Gas industry 22.09% and for the Basic Resources industry 10.04% of the variation in stock returns can be explained by changes in the price of oil. For both industries the small standard errors, which were constructed based on Monte Carlo simulation with 1000 repetitions, indicate that the influence is highly significant. For most other industries the oil price explains between 3-6% of the variation in stock returns. In 11 out of 13 industries the effect of the oil price is higher than the effect of the interest rate and in 6 industries it explains even more of the variation of real stock returns than industrial production. These findings underline that oil price changes are an important factor in explaining stock returns.

The results of the variance decomposition confirm the assumption that the influence of oil price changes on industry returns is time varying and has changed over the total sample period. Before the financial crisis the oil price explained, on average, 5.88% of the variation of industry returns. Since the financial crisis, on average, 14.97% of the variation of industry stock returns can be explained by changes in the price of oil.

Except for the *Telecommunication* sector, the sensitivity to oil price changes, measured by the variance decomposition, increased for every industry. It should be noted, however, that it is not only the oil price that gains explanatory power, but also the interest rate as well as the industrial production.

6.2.3 Test for asymmetry

In this section we investigate whether the effect of linear oil price changes on European industry returns is asymmetric. Following Mork (1989), we test for asymmetry by separating the log difference of the real oil price (op_t) into positive and negative oil price changes. The positive and negative oil price changes are defined as follows:

$$opp_t = max(0, op_t) \; and \; opn_t = min(0, op_t)$$

Over the full sample period 53.78% of the oil price shocks were positive and 46.22% were negative. The average positive shock was 4.03% while the average negative shock was -3.72%. These summary statistics show that positive oil price shocks happen more frequently and are, on average, larger in absolute value.

We test for asymmetry in two different ways. First, we investigate the explanatory power of positive and negative oil price changes based on forecast error variance decomposition. Second, we will apply a traditional Wald coefficient test as suggested by Nandha and Faff (2007), which compares the coefficients of oil price increases and decreases. Both tests complement each other since they test differences in the effects of positive and negative oil price changes based on magnitude and direction.

Variance Decomposition

An asymmetric oil price effect suggests that the influence of oil price decreases and oil price increases are different. We test this assumption within the VAR framework. We create a 5 variable VAR (r, opp, opn, ip, rsr) that includes a variable for positive and negative oil price changes. Subsequently, we decompose the variance of real industry returns to see how much of the total variance can be explained by positive and negative oil price changes. One drawback of this approach is that the results vary depending on which oil price variable is placed first in the variable order. To overcome this problem, we took the average of the results from both variable orders [VAR (r, opp, opn, ip, rsr) and VAR (r, opn, opp, ip, rsr)].

Table 9:
Variance decomposition of forecast error variance in real industry returns due to positive and negative oil price shocks

	1995M01-2015M12		1995M01-2008M08		2008M09-2015M12	
	opp	opn	opp	opn	opp	opn
Automobile	0.96	2.60	1.23	7.55	5.36	5.75
Banks	2.03	5.91	1.74	7.08	10.47	17.77
Basic Resources	5.45	5.07	4.63	4.19	7.75	14.23
Chemicals	1.47	2.85	1.76	3.58	2.99	10.25
Construction	1.57	4.14	2.08	7.53	4.58	6.74
Food & Bev.	0.55	2.15	0.94	1.45	8.04	12.59
Healthcare	0.91	2.16	1.29	3.07	7.92	9.39
Insurance	1.63	4.56	1.45	5.55	3.99	12.43
Oil & Gas	14.11	9.65	13.39	6.64	18.64	24.50
Pers. Household	1.81	4.22	1.09	5.36	14.38	12.13
Technology	2.53	5.00	2.72	8.01	5.91	11.71
Telecommunication	3.22	3.28	5.47	4.99	0.91	3.36
Utilities	1.57	4.02	1.65	2.80	4.47	10.86
Stoxx 600	2.58	5.81	2.38	7.12	8.21	14.99

Notes: Percentage of variation in real stock returns due to positive and negative oil price shocks (10 month horizon). The numbers represent the average values from the results of the variance decomposition of two VAR specifications: VAR (r, opp, opn, ip, rsr) and VAR (r,opn,opp,ip,rsr). Based on the Akaike information criterion, all VAR models were estimated with a lag length of 3.

Table 9 shows the results of the forecast error variance decomposition of industry stock returns due to positive and negative oil price shocks after a 10 months horizon. Besides the discussed pattern that oil price changes seem to have a stronger effect on industry stock returns since the financial crisis, it is noticeable that for most industries negative oil price shocks explain more of the forecast error variance in real stock returns than positive oil price shocks. Over the total sample period 11 out of 13 industries react stronger to negative oil price shocks and only the *Basic Resources* and the *Oil & Gas* sectors show a stronger sensitivity to positive oil price shocks. On average, negative oil price shocks show a higher contribution to the variance of industry stock returns during every investigated time period.

Our results contrast the results of Sadorsky (1999), who reports a stronger effect of positive oil price shocks on stock returns for the U.S. Our findings are closely in line with Scholtens and Yurtsever (2012), who find a stronger influence of negative oil price shocks than positive oil price shocks on European stock returns. The authors further report that asymmetric oil price patterns differ across industries and over time, which can also be observed in our results.

Coefficient Test for asymmetry

Our second test for asymmetry is a conventional Chi-squared test, which tests the null hypothesis that the coefficients of positive and negative oil price changes are equal at all lags. The underlying regression is chosen to reflect the five variable VAR (r, opp, opn, ip, rsr) equation that explains stock returns by its own past values and the lagged values of all other variables in the system.

$$rsr_t = \alpha_0 + \sum_{i=1}^{3} \alpha_{1i} r_{t-i} + \sum_{i=1}^{3} \alpha_{2i} opp_{t-i} + \sum_{i=1}^{3} \alpha_{3i} opn_{t-i} + \sum_{i=1}^{3} \alpha_{4i} ip_{t-i} + \sum_{i=1}^{3} \alpha_{5i} rsr_{t-i} + u_t$$

In the regression the lag length is chosen based on the Akaike information criterion, which suggests an optimal lag length of three for the VAR (r, opp, opn, ip, rsr) models. The results of the Chi-square-test are obtained from a Wald coefficient test and are reported in the Table 10.

For most industries we do not find strong evidence of asymmetrical effects of oil price changes on industry returns when we regard the total sample period. This result is consistent with Scholtens and Yurtsever (2012) as well as Nandha and Faff (2007) who find little evidence of asymmetric oil price effects on industry returns. Only for *Construction & Material* and *Technology* we find significant asymmetric effects at the 10% level.

For the second sub-period we see significant effects of asymmetry for four industry indices (*Food & Beverages*, *Healthcare*, *Personal & Household Goods* and *Technology*) as well as the Stoxx 600 index. Taking a closer look at the regression output, we find similarities across the results. For all indices the asymmetric effect of oil price changes on stock returns derives mainly from the first lag coefficients. The regression results for all five indices show a negative coefficient for positive oil price shocks (opp) and a positive coefficient for negative oil price shocks (opn).

Table 10:
Chi-Square coefficient test of asymmetry

	1995M01-2015M12		1995M01-2008M08		2008M09-2015M12	
	Chi-square	P-Value	Chi-square	P-Value	Chi-square	P-Value
Automobile	1.263	0.738	7.547	0.056 *	3.718	0.294
Banks	4.116	0.249	4.946	0.176	6.156	0.104
Basic Resources	1.510	0.680	3.865	0.277	3.605	0.307
Chemicals	0.968	0.809	3.794	0.285	2.253	0.522
Construction	7.503	0.058 *	8.452	0.038 **	3.973	0.264
Food & Bev.	2.979	0.395	1.094	0.779	6.783	0.079 *
Healthcare	1.421	0.701	2.143	0.543	12.61	0.006 ***
Insurance	2.405	0.493	3.032	0.387	3.909	0.271
Oil & Gas	4.788	0.188	4.556	0.207	5.031	0.170
Pers. Household	2.666	0.446	5.648	0.130	10.24	0.017 **
Technology	7.054	0.070 *	5.133	0.162	6.785	0.079 *
Telecommunication	0.845	0.839	1.023	0.796	1.343	0.719
Utilities	3.762	0.288	2.888	0.409	2.888	0.409
Stoxx 600	4.967	0.174	5.401	0.145	6.412	0.093 *

Notes: Chi-square test results testing the null hypothesis $H_0\colon \alpha_{2i} = \alpha_{3i}$; $i = 1, ..3.$ The subscripts *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

At first sight, these results might seem contradictory to the results from the previous chapter, where a positive oil-stock relationship is described for the second sub-period. However, the interpretation is not as straightforward since a positive coefficient for negative oil price shocks indicates that stock returns increase the less negative the oil price shock becomes. In other words, the intuition behind the test is to see whether oil price changes in the negative area (e.g. a one percent increase from -10% to -9%) have statistically different effects on industry returns than oil price changes in the positive area (e.g. a one percent increase from 9% to 10%).

A possible interpretation for the results could be that an increase in opn, which means a less negative oil price change, could have a strong positive effect on stock returns as investors see the increase as a turning point in both the price of oil and economic activity. An increase in opp, which is equivalent to a higher oil price increase, might have lost this signal effect and the negative effects of increased operational cost might overweigh.

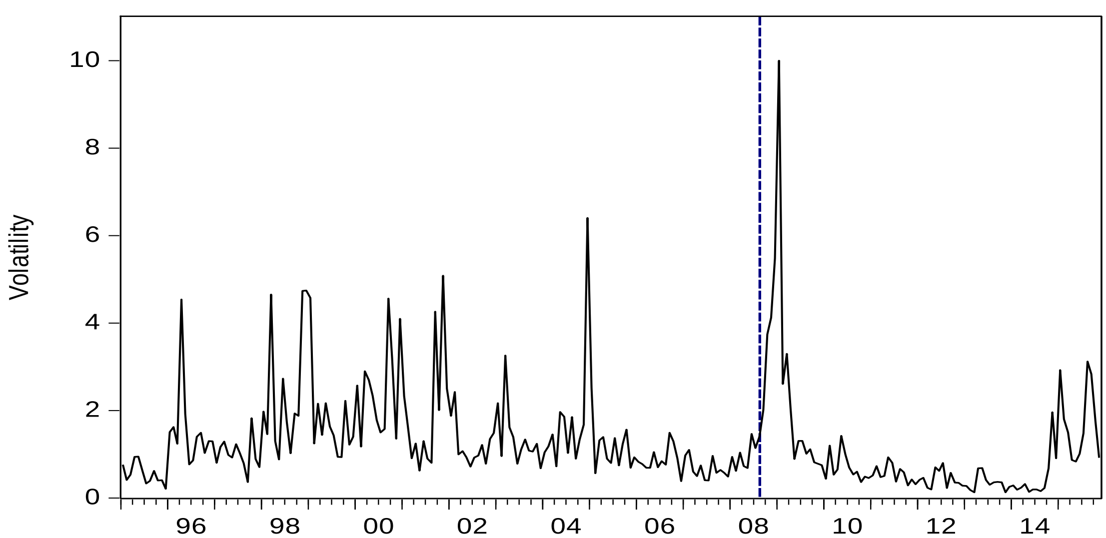
We conclude that there are some signs of asymmetry in the relationship between oil price changes on stock returns. We can, however, not generally confirm our third research hypothesis of an asymmetric effect of oil price changes on stock returns since asymmetric patterns seem to vary across industries and over time.

6.3 Oil price volatility and industry returns

We described various reasons why the price of oil is important for firms and how it could affect stock returns. In the following, we go one step further and estimate how oil price volatility affects stock returns across industries.

Oil price volatility can be interpreted as a form of uncertainty for companies that are dependent on the price of oil. This uncertainty could derive from the supply side, if oil is an input in the production process, or from the demand side, if changes in the price of oil affect product demand. Since investors tend to be risk averse, we would expect a negative influence of oil price volatility on stock returns. The sensitivity to oil price volatility should differ among industries according to the industry's dependence on the price of oil.

Figure 6:
Monthly Oil Price Volatility



Notes: Volatility is measured by the sum of squared first log differences of EUR denominated daily spot prices and scaled up to a volatility range from zero to ten.

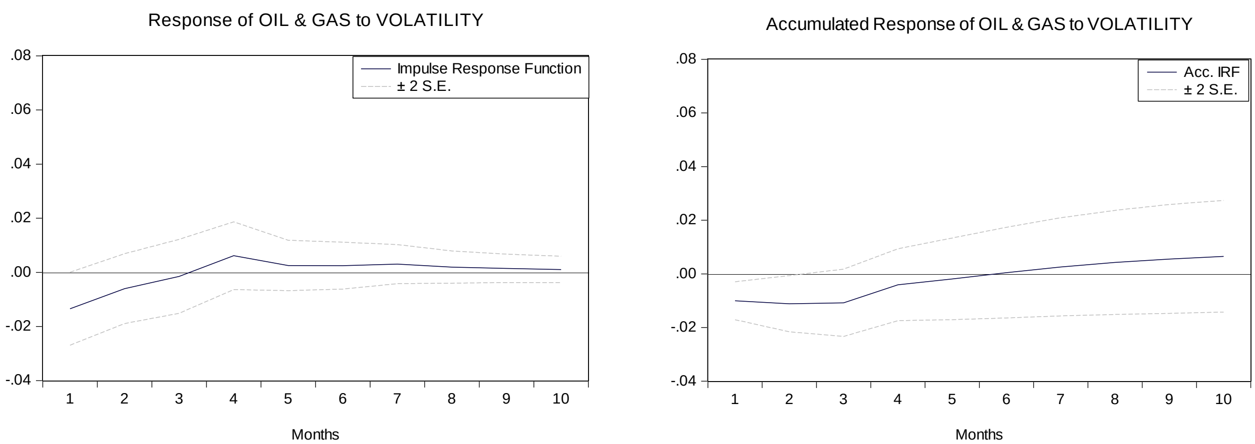
Figure 6 displays our calculated measure of oil price volatility (derived from price changes in Euro) over the sample period. It clearly shows that oil price volatility was strongly varying over time with a peak during the financial crisis. The two sub-periods are graphically divided by the dotted line and the second period starts directly before the sharp increase in volatility.

In the following, we replace the linear oil price changes ($roilp$) from our basic model with our measure for oil price volatility ($vol_€$). The unit root test indicates that oil price volatility is stationary and the relationship between the four variables ($r, vol_€, ip, rsr$) can therefore be modeled in a vector autoregression. The lag length is chosen based on the Akaike information criterion and is three for all industries (see Table 17).

6.3.1 Impulse response functions

The results of the impulse response analysis are particularly difficult to interpret since the sign of the accumulated response often differs across lags. Short-term responses (1st lag) to oil price volatility are often different to long-term responses (10th lag). Figure 7 gives an example.

Figure 7:
Accumulated impulse response of the Oil & Gas industry to a shock to oil price volatility (1995M01-2015M12)



Notes: Impulse response and accumulated impulse response of *Oil & Gas* to a one standard deviation shock to oil price volatility ($vol_€$). ±2 Standard error bands are constructed based on Monte Carlo simulation.

Based on economic expectations and the transitory nature of volatility, we are more confident with the results of short-term responses. Graphical representations of accumulated impulse response functions of all industry returns to a shock in oil price volatility are shown in Figure 10 in the Appendix.

Total period (1995M01-2015M12)

Table 11 describes the impact of oil price volatility on European industry returns for the total sample period. We find a significant negative response to oil price volatility for the *Oil & Gas* industry as well as the *Basic Resources* industry at the first lag. This result is not surprising as we have previously shown that these two sectors have the highest sensitivity to changes in the price of oil. For industries that are highly sensitive to the price of oil, we can interpret an increase in oil price volatility as an increase in uncertainty.

Table 11:
Cumulative impulse responses of industry returns to shocks in oil price volatility (1995M01-2015M12)

	Cumulative response at lag				
Industry	1	2	3	5	10
Automobile	-0.512	-0.829	-0.979	-0.450	0.147
	(0.488)	(0.727)	(0.884)	(1.039)	(1.407)
Banks	-0.790	-1.220	-1.741	-0.655	0.554
	(0.415)	(0.630)	(0.897)	(1.211)	(1.830)
Basic Resources	**-0.989**	-0.939	-0.661	0.447	2.063
	(0.477)	(0.672)	(0.855)	(1.213)	(1.924)
Chemicals	-0.796	-0.963	-0.961	-0.727	-0.379
	(0.362)	(0.509)	0.704)	(0.903)	(1.209)
Construction	-0.568	-0.522	-0.613	0.116	0.969
	(0.370)	(0.537)	(0.653)	(0.871)	(1.244)
Food & Bev.	-0.001	-0.283	-0.340	-0.561	-0.505
	(0.244)	(0.390)	(0.492)	(0.578)	(0.773)
Healthcare	0.257	-0.114	-0.233	-0.602	-0.861
	(0.269)	(0.399)	(0.525)	(0.652)	(0.919)
Insurance	-0.547	-0.913	-1.289	-1.181	-0.978
	(0.524)	(0.733)	(0.926)	(1.154)	(1.641)
Oil & Gas	**-1.002**	**-1.114**	-1.080	-0.190	0.653
	(0.372)	(0.478)	(0.614)	(0.767)	(1.089)
Pers. Household	-0.207	0.035	-0.322	-0.162	-0.016
	(0.289)	(0.460)	(0.552)	(0.662)	(0.932)
Technology	-0.165	0.236	-0.569	-0.242	-0.154
	(0.576)	(0.927)	(1.211)	(1.547)	(2.126)
Telecommunication	0.546	1.141	0.550	0.332	-0.406
	(0.411)	(0.026)	(0.758)	(1.046)	(1.626)
Utilities	-0.096	-0.270	-0.571	-0.6344	-0.687
	(0.269)	(0.425)	(0.526)	(0.664)	(0.943)
Stoxx 600	-0.351	-0.358	-0.679	-0.396	-0.020
	(0.320)	(0.392)	(0.502)	(0.639)	(1.005)

Notes: Cumulative response in percentage of real stock returns at a given lag due to a one standard deviation shock in oil price volatility ($vol_{€}$). Standard errors based on Monte Carlo simulations are reported in brackets.

The *Oil & Gas* industry is directly affected by oil price volatility as it increases uncertainty about future profit margins. For the *Basic Resources* industry, the interpretation is not as straightforward. We previously argued that an increase in the price of oil indicates a higher future demand for *Basic Resources* products. As such, increased oil price volatility could be interpreted as increased uncertainty about the expectations of future demand.

Uncertainty about profitability or product demand could harm stock returns through two channels. First, it could lay off capital investments and thereby cut down companies' growth potential, which should decrease the stock price (Pindyck 1991). Second, it could chase off risk-averse investors and put selling pressure on the stock.

For both the *Oil & Gas* as well as the *Basic Resources* industry the impulse response functions suggest that the stock returns recover quickly from the shock in oil price volatility. Surprisingly, the accumulated impulse response functions even become positive at high lags, but wide error bands indicate that the long-term response is insignificant.

The remaining industries are not significantly affected by oil price volatility. It is, however, remarkable that 11 out of 13 industries show a negative reaction to oil price volatility at the first lag. Only the *Telecommunication* sector and the *Healthcare* sector show positive first lag coefficients.

Period before the Lehman bankruptcy (1995M01-2008M08)

Table 12 shows the cumulative response of industry returns to a one standard deviation shock in oil price volatility for the first sub-period.

We find that the first-lag coefficients confirm a negative short-term response of most industries to a shock in oil price volatility. Over the following lags, however, the sign of the cumulative impulse responses turns around, which makes it difficult to interpret the responses. In line with the results from the total sample period, the *Oil & Gas* sector reacts significantly negative to an increase in oil price volatility. Surprisingly, we find a significant positive reaction of the *Telecommunications* sector to a shock in oil price volatility.

Table 12:
Cumulative impulse responses of industry returns to shocks in oil price volatility (1995M01-2008M08)

	Cumulative response at lag				
Industry	1	2	3	5	10
Automobile	-0.167	0.760	0.857	0.938	0.918
	(0.546)	(0.854)	(1.038)	(1.293)	(1.617)
Banks	-0.228	0.548	0.489	0.995	1.448
	(0.416)	(0.721)	(0.946)	(1.220)	(1.625)
Basic Resources	-0.710	-0.072	0.397	0.994	1.461
	(0.466)	(0.779)	(0.929)	(1.228)	(1.813)
Chemicals	-0.380	-0.219	0.144	0.354	0.495
	(0.465)	(0.604)	(0.806)	(0.941)	(1.198)
Construction	-0.190	0.718	1.064	1.456	1.889
	(0.472)	(0.738)	(0.863)	(1.088)	(1.585)
Food & Bev.	-0.022	-0.1469	0.229	0.139	0.220
	(0.280)	(0.445)	(0.567)	(0.774)	(1.059)
Healthcare	0.264	0.371	0.306	0.001	-0.2277
	(0.359)	(0.533)	(0.711)	(1.027)	(1.496)
Insurance	-0.047	0.746	0.743	0.525	0.574
	(0.655)	(0.983)	(1.230)	(1.534)	(2.082)
Oil & Gas	**-0.905**	-0.884	-0.649	0.182	0.682
	(0.380)	(0.596)	(0.790)	(0.899)	(1.222)
Pers. Household	-0.099	0.580	0.581	0.722	0.926
	(0.369)	(0.566)	(0.684)	(0.881)	(1.191)
Technology	0.148	1.554	0.535	0.585	0.293
	(0.743)	(1.303)	(1.512)	(2.039)	(2.819)
Telecommunication	**1.204**	**2.281**	1.425	0.966	-0.224
	(0.563)	(0.849)	(1.060)	(1.636)	(2.599)
Utilities	0.179	0.517	0.359	-0.188	-0.519
	(0.324)	(0.414)	(0.640)	(0.846)	(1.150)
Stoxx 600	-0.093	0.512	0.391	0.440	0.530
	(0.378)	(0.560)	(0.757)	(0.935)	(1.296)

Notes: Cumulative response in percentage of real stock returns at a given lag due to a one standard deviation shock in oil price volatility ($vol_{€}$). Standard errors based on Monte Carlo simulations are reported in brackets.

Period after the Lehman bankruptcy (2008M08-2015M12)

Table 12 reports the accumulated impulse responses of industry returns to a one standard deviation shock to oil price volatility for the second sub-period. It seems that industry returns react stronger to oil price volatility than during the first sub-period. The coefficients are, on average, higher in absolute value and we find more evidence for statistically significant responses. This finding is consistent with our previous results that document increased oil price sensitivity since the financial crisis.

The results indicate that all industries react negatively to a shock in oil price volatility. First-lag reactions are significantly negative for *Oil & Gas*, *Basic Resources*, *Banks* and C*hemicals*. In contrast to the previous period, we find statistically significant negative reactions of industry returns at higher lags. The accumulated impulse responses seem to grow for the first three lags, which suggests that a shock takes several lags to be completely incorporated in the stock prices. Subsequently, stock returns seem to recover to a certain extent, which can be seen by the decreasing cumulative responses at higher lags.

Comparing our results of linear oil price changes and oil price volatility, we see that stock returns across all industries are positively affected by an increase in the price of oil, whereas negatively affected by an increase in oil price volatility for the second sub-period. As discussed previously, the oil price could be interpreted by investors as an indicator for future economic activity. As such, high oil price volatility would signal a high uncertainty about the future state of the economy. This could explain the strong negative reaction of stock returns to a shock in oil price volatility.

Table 13:
Cumulative impulse responses of industry returns to shocks in oil price volatility (2008M09-2015M12)

	Cumulative response at lag				
Industry	1	2	3	5	10
Automobile	-0.939	**-3.372**	**-3.581**	-2.395	-0.889
	(0.988)	(1.408)	(1.766)	(2.542)	(3.992)
Banks	**-1.426**	**-4.462**	**-5.863**	-4.048	-1.949
	(0.712)	(1.404)	(1.697)	(2.457)	(3.476)
Basic Resources	**-1.653**	**-2.782**	-2.829	-1.884	0.560
	(0.820)	(1.336)	(1.776)	(2.818)	(4.256)
Chemicals	**-1.282**	**-2.049**	-2.441	-2.200	-1.525
	(0.519)	(0.955)	(1.399)	(1.796)	(2.702)
Construction	-0.775	**-2.480**	**-3.338**	-1.908	-0.398
	(0.594)	(1.121)	(1.281)	(1.699)	(2.439)
Food & Bev.	-0.057	-0.592	-1.123	-1.186	-0.954
	(0.380)	(0.599)	(0.728)	(1.017)	(1.552)
Healthcare	0.213	-1.093	-1.180	-1.527	-1.641
	(0.376)	(0.516)	(0.638)	(0.895)	(1.588)
Insurance	-0.717	**-3.231**	**-4.197**	-3.281	-3.159
	(0.729)	(1.144)	(1.410)	(1.795)	(2.826)
Oil & Gas	**-1.345**	**-1.948**	-2.097	-1.236	-0.251
	(0.629)	(0.937)	(1.218)	(1.585)	(2.344)
Pers. Household	-0.166	-0.718	-1.487	-1.049	-0.590
	(0.478)	(0.717)	(0.925)	(1.292)	(1.955)
Technology	-0.589	**-2.366**	**-2.814**	-1.886	-1.068
	(0.651)	(1.025)	(1.331)	(1.676)	(2.388)
Telecommunication	-0.430	-0.672	-0.717	-0.755	-0.493
	(0.422)	(0.663)	(0.923)	(1.227)	(1.936)
Utilities	-0.637	**-1.941**	**-2.704**	-2.333	-2.234
	(0.434)	(0.670)	(0.927)	(1.239)	(2.115)
Stoxx 600	-0.609	**-1.955**	**-2.435**	-1.839	-0.923
	(0.455)	(0.792)	(1.091)	(1.623)	(2.656)

Notes: Cumulative response in percentage of real stock returns at a given lag due to a one standard deviation shock in oil price volatility ($vol_{€}$). Standard errors based on Monte Carlo simulations are reported in brackets.

In summary, we find evidence that supports our fourth research hypothesis. We can confirm that the influence of oil price volatility on stock returns is varying across industries and is more pronounced for industries that have a tight connection to the price of oil. For every sample period, we find a significant negative reaction of the *Oil & Gas* sector to an increase in oil price volatility. Other industries that are also tightly related to changes in the price of oil (*Basic Resources*, *Chemicals*, *Automobile*) do also show a negative (short-term) reaction, even though not statistically significant over all periods.

Those industries that do not show a significant reaction to oil price volatility in any period are industries that do not seem to have a tight connection to the price of oil. Such industries are *Technology*, *Personal & Household Goods* and *Healthcare*.

6.3.2 Variance decomposition

Table 14 reports the results of the forecast error variance decomposition of industry returns to shocks in the variables interest rate, oil price volatility and industrial production. Our results suggest that oil price volatility can explain stock returns to a considerable extent. Over the total time period oil price volatility can explain, on average, more of the percentage of the total variation of stock returns than the interest rate, but less then industrial production.

In comparison to linear oil price changes (see Table 8), oil price volatility explains, on average, less of the variation of total stock returns. This finding is expected as we would assume that the level of oil price affects companies more than its volatility.

The results of the variance decomposition confirm most of the results from the impulse response analysis, but also reveal some differences. In general, we can see that industries that show a strong response to a shock in oil price volatility do also show that a high percentage of return variation can be explained by oil price volatility. During the total period, the *Oil & Gas* sector is most strongly affected by oil price volatility and the standard error suggests that the influence of oil price volatility on *Oil & Gas* returns is significantly different from zero. This result confirms our findings from the impulse response analysis. In some cases, however, the significance of the results (measured by ±2 SE bands) of the impulse response functions and forecast error variance decomposition differ. As an example, we do not find a significant effect of oil price volatility on the Basic Resources sector based on the results of the variance decomposition.

Just as for linear oil price changes, the variance decomposition with oil price volatility as an input shows strong differences across the sample periods. While oil price volatility explains, on average, 2.58% of the total variance of industry stock returns during the first sub-period, it explains 9.88% during the second.

Table 14:
Forecast Error Variance Decomposition VAR (r, vol, ip, rsr)

	1995M01-2015M12			1995M01-2008M08			2008M09-2015M12		
	R	Vol	IP	R	Vol	IP	R	Vol	IP
Automobile	0.01	0.95	0.02	0.58	2.16	0.41	4.44	9.90	8.50
	(0.02)	(1.46)	(0.01)	(2.02)	(3.15)	(2.14)	(4.37)	(5.76)	(5.46)
Banks	0.87	4.13	6.23	0.48	2.13	1.54	5.09	**22.23**	13.93
	(1.30)	(2.67)	(3.05)	(2.24)	(2.89)	(2.34)	(5.71)	(7.23)	(6.47)
Basic Resources	0.91	3.62	3.20	1.15	2.70	1.17	2.64	6.16	12.57
	(1.57)	(2.63)	(2.55)	(2.08)	(2.45)	(2.40)	(4.44)	(4.85)	(6.54)
Chemicals	0.23	2.05	3.28	0.83	1.01	0.94	2.20	6.58	14.88
	(1.39)	(2.24)	(2.53)	(1.72)	(2.63)	(2.19)	(4.33)	(4.91)	(6.83)
Construction	0.51	2.26	2.85	0.64	3.58	1.45	1.04	14.19	8.34
	(1.29)	(2.20)	(2.17)	(2.18)	(2.85)	(2.46)	(3.29)	(7.41)	(6.28)
Food & Bev.	1.31	0.79	5.66	2.20	1.14	3.62	5.68	3.98	17.28
	(1.61)	(1.65)	(2.93)	(3.24)	(2.49)	(2.96)	(4.33)	(5.33)	(7.09)
Healthcare	0.00	1.87	0.01	2.66	0.82	0.35	4.95	11.21	11.55
	(0.01)	(2.02)	(0.01)	(2.67)	(2.63)	(1.48)	(4.57)	(6.32)	(6.64)
Insurance	0.09	0.96	3.60	1.75	1.26	1.01	2.37	**14.87**	12.30
	(1.06)	(1.57)	(2.03)	(2.20)	(2.80)	(2.41)	(3.68)	(6.72)	(5.99)
Oil & Gas	2.91	**5.47**	3.00	5.08	4.55	0.73	2.06	8.32	8.37
	(2.62)	(2.71)	(2.05)	(2.95)	(3.14)	(1.89)	(3.99)	(5.45)	(5.26)
Pers. Household	0.48	1.08	3.38	0.12	2.00	0.58	1.36	5.11	21.88
	(1.41)	(1.494)	(2.62)	(1.60)	(2.43)	(1.81)	(3.44)	(5.54)	(6.80)
Technology	0.33	1.14	1.80	0.19	2.95	0.17	1.32	11.67	20.50
	(1.08)	(1.60)	(2.02)	(1.84)	(2.84)	(1.47)	(4.05)	(6.28)	(7.27)
Telecommunication	1.75	2.84	0.90	3.17	6.92	1.55	2.61	1.42	9.30
	(1.70)	(2.58)	(1.69)	(2.69)	(3.55)	(2.45)	(4.28)	(3.72)	(6.05)
Utilities	1.17	0.77	4.91	2.27	2.32	1.87	4.86	12.84	12.92
	(1.74)	(1.28)	(2.40)	(2.99)	(3.00)	(2.65)	(5.00)	(7.35)	(5.68)
Stoxx 600	0.31	1.33	4.00	0.74	1.70	0.70	1.01	12.41	19.19
	(1.24)	(1.60)	(2.29)	(1.80)	(2.51)	(1.77)	(2.77)	(6.47)	(8.04)

Notes: Percentage of variation in real stock returns due to shocks in interest rate, oil price volatility and industrial production (10 month horizon). Standard errors constructed through Monte Carlo simulation with 1000 repetitions are reported in brackets.

Interestingly, we find that seven industries show a stronger reaction to oil price volatility than the *Oil & Gas* sector since the financial crisis. Especially the banking (22.23%) and insurance (14.87%) sectors were highly influenced by oil price volatility since the financial crisis. The fact that industries that do not have a close relationship to the price of oil show a strong and significant effect to oil price volatility suggests that volatility in the oil market can represent uncertainty in the aggregate economy. This would supports our argument that the price of oil reflects views about future economic activity.

6.4 Robustness tests

In this section we test the sensitivity of our results with regards to model extensions and changes in the underlying assumptions.

6.4.1 Optimal lag selection

The first assumption that is likely to have an impact on the results of our VAR models is the selection of the optimal lag length of our VAR models. As described in the methodology section, we select the optimal number of lags for our VAR models based on the Akaike Information Criterion. The optimal number of lags is found to be three or four, depending on the industry. There are various information criteria that could be used to select the optimal lag length and the outcome is likely to differ accordingly. We test the robustness of our results concerning the lag length by applying another commonly used information criterion, the Schwarz information criterion. According to the Schwarz criterion, the optimal lag length is one for all industries. Even though a lag selection of one does not seem to be in line with previous research on the stock-oil relationship, we investigate how our results would differ if we were to use the Schwarz criterion.

Table 15, which summarizes the several tests of robustness, shows the accumulated impulse responses of industry returns to an oil price shock for VAR models based on both information criteria. The results indicate that the sign and the statistical significance of most industry responses are identical. Similar results can be seen in Table 18 in the Appendix, where we show the response to oil price volatility based on both information criteria.

We conclude that our main results have a certain robustness to changes in the lag length and suggest that the first lag effect of the VAR model is dominant.

6.4.2 Order of variables

In order to calculate impulse response functions and variance decompositions, we make assumptions about the ordering of the input variables. We test the sensitivity of the variable ordering by reversing the order and subsequently re-compute impulse response functions and variance decompositions.

In contrast to other studies, such as Park and Ratti (2008) or Sadorsky (1999), we find that the variable order has a strong effect on our results. To give an example, Figure 11 shows the effect of oil price changes on the returns of the A*utomobile* sector for the total sample period for two inverse variable orders. One can clearly see that the level of the accumulated impulse response graph shows a negative shift if the inverse ordering is applied.

By testing different possible variable orders, it becomes clear that our results are quite robust to changes in the variable order as long as the variable real oil price ($roilp$) is placed before the variable real industry stock returns (rsr). This ordering seems natural as one would assume that the oil price influences stock prices rather than the other way round. Assuming further that the interest rate (r) influences industrial production (ip) leads to the three remaining variable orders that make the most economic sense to us [VAR ($r, roilp, ip, rsr$); VAR ($roilp, r, ip, rsr$) and VAR ($r, ip, roilp, rsr$)].

Table 19 compares the impulse responses of industry stock returns to changes in the price of oil based on all three variables orders. We can see that the results are highly similar. Changes in the sign do only occur in cases where the influence of oil price changes on industry returns is insignificant and very weak.

In general, we are confident with our chosen variable order as it is economically motivated and follows various papers that have researched the relationship between oil price changes and stock returns. It should, however, be noted that the results are sensitive to certain changes in the ordering.

6.4.3 Exchange rate and market spillover effects

In our analysis we use oil prices denominated in Euro to calculate our input variables for linear oil price changes and oil price volatility. The reason for that is that we think that the real oil price in Euro is the most relevant oil price for European industries. We test this assumption by repeating our analysis with oil prices denominated in Dollar. For linear oil price changes, we replace the log changes of the real price of oil ($roilp$), which were denominated in Euro, with the log changes of the nominal price of oil in USD ($noilp_{\$}$). Since the inflation rate should not have a strong effect on monthly data, this comparison enables us to see whether the exchange rate has a strong impact on the outcome of our results.

Table 14 shows that our main results on the influence of oil price changes on industry stock returns are robust to both measures of oil price changes. The impulse response functions are highly similar and only in few cases does the sign or the statistical significance differ with regards to both measures.

The results of the variance decomposition, which are reported in Appendix 20, show that changes in both oil price measures roughly account for roughly the same percentage of the total variance of industry returns. Since the financial crisis the nominal oil price in USD ($noilp_{\$}$), on average, even explains a higher percentage of the total variance of industry stock returns than the real oil price ($roilp$) in Euro (18.43% vs. 14.97%).

Comparing the results of oil price volatility denominated in Euro and oil price volatility denominated in Dollar, we find that the first lag responses of industry stock returns are very similar for both measures of volatility (see Table 18 in the Appendix). For longer horizons, the differences naturally become larger as the exchange rate plays a bigger role. Interestingly, we find more significant responses to Dollar price volatility than Euro price volatility. This result is supported by the variance decomposition, which shows that oil price volatility in USD, on average, explains more of the total variance of European industry returns than oil price volatility in Euro (see Table 21 in the Appendix).

This result is surprising as we assume that the oil price denominated in Euro should be the most relevant price for European industries. A possible explanation for our findings is that the oil price is traditionally denominated in Dollar and changes in the Dollar denomination gain far more attention than oil price changes calculated in any other currency. Even though the oil price in Euro should be the more relevant price for European companies, investors might be more influenced by the dollar price of oil.

As a final test of robustness, we follow Park and Ratti (2008) and allow for spillover effects between the market return (Stoxx 600) and the different industry returns. We do this by extending our VAR model by the real Stoxx 600 return, which is a proxy for the European market return. In the five-variable VAR ($r, roilp, ip, rmr, rsr$) the real market return is denoted by rmr and the ordering ensures that spillover effects from the market to the industry returns are possible.

Table 15 shows that our main results for the influence of oil price changes on industry stock returns are robust, even if we account for possible spillover effects from the market.

Table 15:
Test of robustness - Impulse Responses to shock in oil price with different VAR specifications

	AU	BA	BR	CH	CO	FO	HE	IN	OI	PE	TEC	TEL	UT
Total Period													
Akaike													
$VAR\ (r, roilp, ip, rsr)$	p	p#	p#	p#	n	p	p	p	p#	n	p	n#	p#
$VAR\ (r, noilp_{\$}, ip, rsr)$	p	p	p#	p	n	n	n	p	p#	n	p	n#	p
$VAR\ (r, roilp, ip, rmr, rsr)$	p	p#	p#	p#	n	n	p	p	p#	n	p	n#	p
$VAR\ (r, noilp_{\$}, ip, rmr, rsr)$	p	p	p#	p	n	n	n	p	p#	n	p	n#	p
Schwarz													
$VAR\ (r, roilp, ip, rsr)$	p	p	p#	p	p	n	n	n	p#	p	n	n#	p
Sub-period I													
Akaike													
$VAR\ (r, roilp, ip, rsr)$	n	n#	p#	p	n	n	n	n#	p#	n	p	n#	n
$VAR\ (r, noilp_{\$}, ip, rsr)$	n	n#	p	n	n	n	n#	n#	p#	n	n	n#	n
$VAR\ (r, roilp, ip, rmr, rsr)$	n	n	p#	n	n	n	n	n#	p#	n	p	n#	n
$VAR\ (r, noilp_{\$}, ip, rmr, rsr)$	n	n#	p#	n	n	n	n	n#	p#	n	n	n#	n#
Schwarz													
$VAR\ (r, roilp, ip, rsr)$	n	n#	p	n	n	n	n	n#	p#	n	n	n#	n
Sub-period II													
Akaike													
$VAR\ (r, roilp, ip, rsr)$	p#	p#	p#	p#	p	p#	p#	p#	p#	p#	p#	p	p#
$VAR\ (r, noilp_{\$}, ip, rsr)$	p#	p#	p#	p#	p#	p#	p#	p#	p#	p#	p#	p	p#
$VAR\ (r, roilp, ip, rmr, rsr)$	p#	p#	p#	p#	p#	p#	p#	p#	p#	p#	p#	p	p#
$VAR\ (r, noilp_{\$}, ip, rmr, rsr)$	p#	p#	p#	p#	p#	p#	p#	p#	p#	p#	p#	p	p#
Schwarz													
$VAR\ (r, roilp, ip, rsr)$	p#	p#	p#	p#	p	p#	p	p	p#	p#	p#	p	p

Notes: n (p) denotes negative (positive) effects of a shock in oil prices on industry returns (abbreviated in alphabetical order in the top row) based on accumulated response functions with a ten month horizon. # denotes statistical significance based on Monte Carlo constructed ±2 SE bands. Five different VAR specifications are tested. $Noilp$ denotes the nominal oil price of Brent in USD. Rmr denotes the real market return (Stoxx 600) and allows for spillover effects. Schwarz and Akaike are the information criteria the lag-selection was based on. For the Schwarz criterion the lag selection was one for all industries. For the Akaike criterion the lag selection was three or four, depending on the industry.

7 Conclusion

This thesis investigates the effects of linear oil price changes and oil price volatility on real stock returns of European industries over the period 1995M01-2015M12. Using a VAR approach, we show that the oil price affects stock returns differently based on their sectoral allocation. As expected, we find a strong and significant positive response to changes in the price of oil for the *Oil & Gas* sector. The price of oil affects the profitability of *Oil & Gas* companies directly, which explains the positive influence on stock returns. In line with previous research, we find that the *Basic Resources* sector responds positively to changes in the oil price, suggesting that a higher oil price increases expectations about future profitability in this segment. For the remaining industries the stock-oil relationship varies strongly across different sub-periods, which indicates that oil price dynamics have changed.

Before the financial crisis (1995M01-2008M08) linear oil price changes could explain, on average, 5.88% of the total forecast error variance of industry returns. Most energy consuming industries react negatively to an increase in the price of oil, which is in line with previous research. Since the financial crisis (2008M09-2015M12) oil price sensitivity has increased strongly and changes in the price of oil can explain, on average, 14.97% of the total forecast error variance of industry returns. All industries show a positive response to an increase in the price of oil, which is statistically significant in 11 out of 13 cases.

Our findings challenge the general view in the literature that oil price changes affect stock returns negatively. Despite the fact that rising oil prices increase operational costs for oil consuming industries, the increase in the price of oil seems to strengthen investor’s overall confidence in the stock market. We argue in line with Mollick and Assefa (2013) and Tsai (2015) that the markets interpret the increase in the price of oil as an indicator of an increase in future aggregate demand. Both stock prices and oil prices are influenced by expectations about future economic activity and an increase in the price of oil could be understood as a positive economic signal. Since all industries are to some extent dependent on the overall state of the economy[4], this would explain why the positive oil price effect is found across all industries.

[4] which is supported by the positive reaction of industry returns to industrial production in our VAR model

We further test for asymmetric effects of oil price changes on industry returns. According to e.g. Mork (1989) and Sadorsky (1999), oil price increases have a more significant effect on the economy and financial markets than oil price decreases. Based on our results, we arrive at a different conclusion. Over all time periods investigated oil price decreases explain, on average, more of the forecast error variance of industry returns than oil price decreases. This result is consistent with Scholtens and Yurtsever (2012), who also investigate asymmetric oil price effects on European industries. In line with Scholtens and Yurtsever (2012), we find that asymmetric patterns can vary across industries and over time. Even though we find signs of asymmetry, for most industries and most time periods the evidence of asymmetry is not statistically significant.

Another important part of our analysis is the relationship between oil price volatility and industry returns. In general, we show that a response to a shock in oil price volatility is higher for industries that strongly react to linear changes in the price of oil. This finding is expected and validates that the effect of oil price volatility on industry stock returns is caused by the factor oil and is not a random relationship.

We show that industries that are highly dependent on the price of oil react negatively to an increase in oil price volatility. For these industries, oil price volatility can be interpreted as uncertainty about future profitability, which could scare away risk-averse investors and delay capital expenditures. In line with this argument, it is not surprising that the *Oil & Gas* and the *Basic Resources* industries showed the strongest (negative) reactions to a shock in oil price volatility over the total sample period.

The influence of oil price volatility on industry returns also differs across the time periods. Before the financial crisis the impact of oil price volatility on stock returns is weak and for most industries insignificant. Since the financial all industries react negatively to an increase in oil price volatility and for nine industries the response is statistically significant. This supports our finding that oil price sensitivity of stock returns has increased since the financial crisis. The fact that all industries show a negative response to oil price volatility since the financial crisis suggest that oil price volatility represents uncertainty in the aggregate economy. This strengthens our hypothesis that the oil price can be an indicator for economic activity that investors might act upon.

The main contribution of our thesis is that the effect of oil price changes on European stock returns is not straightforward and varies across industries and time periods. For investors, our results are important in two ways. First, they give an overview about the sensitivity of different European industries to changes in the price of oil that can be used by investors to assess their own oil price exposure. Second, we show that oil price sensitivity can vary over time. This means that oil price risk is not static and should be reassessed by investors over time.

We suggest that future research should investigate recent developments in the oil-stock relationship using daily or weekly data. Working with higher frequency data allows a closer look into recent oil price dynamics, but requires a different methodological setup since data on industrial production is only available on a monthly basis. We argue for the use of a multifactor model that includes a dummy variable for the period of the financial crisis. This way it could be tested if oil-stock dynamics have changed since the financial crisis or if it was the financial crisis that had such a pervasive effect on the results of our second sub-sample.

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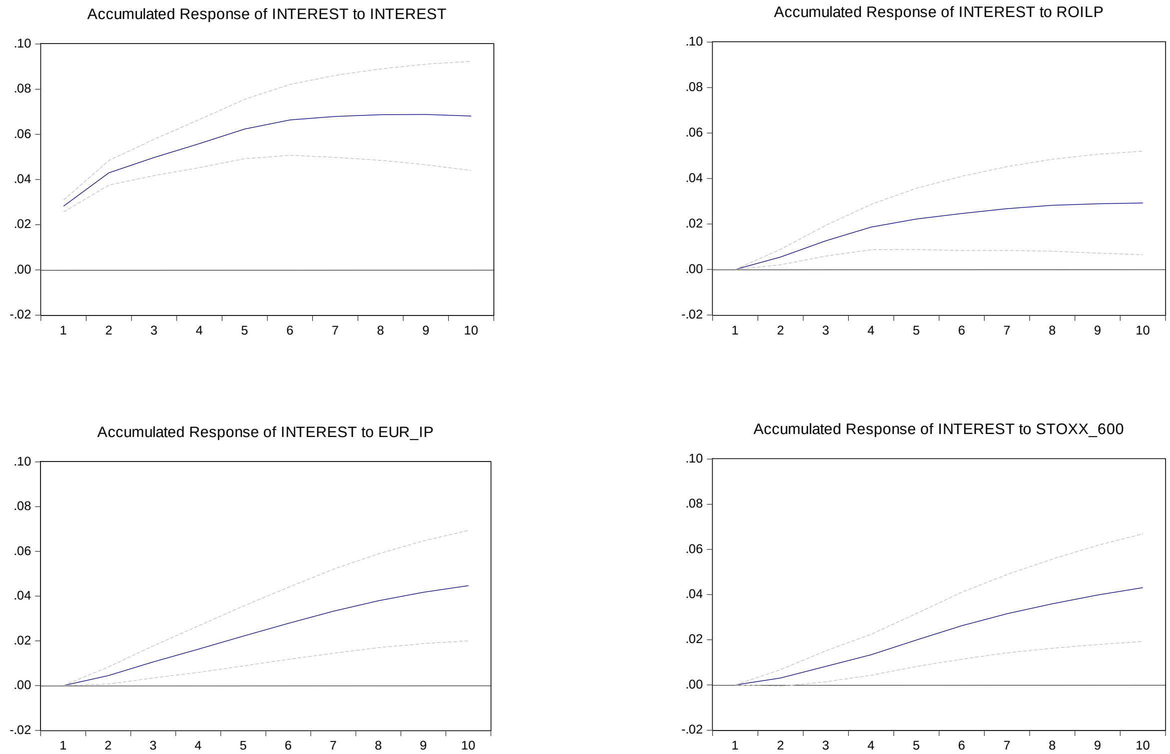
Appendix

Table 16:
Lag length selection VAR ($r, roilp, ip, rsr$)

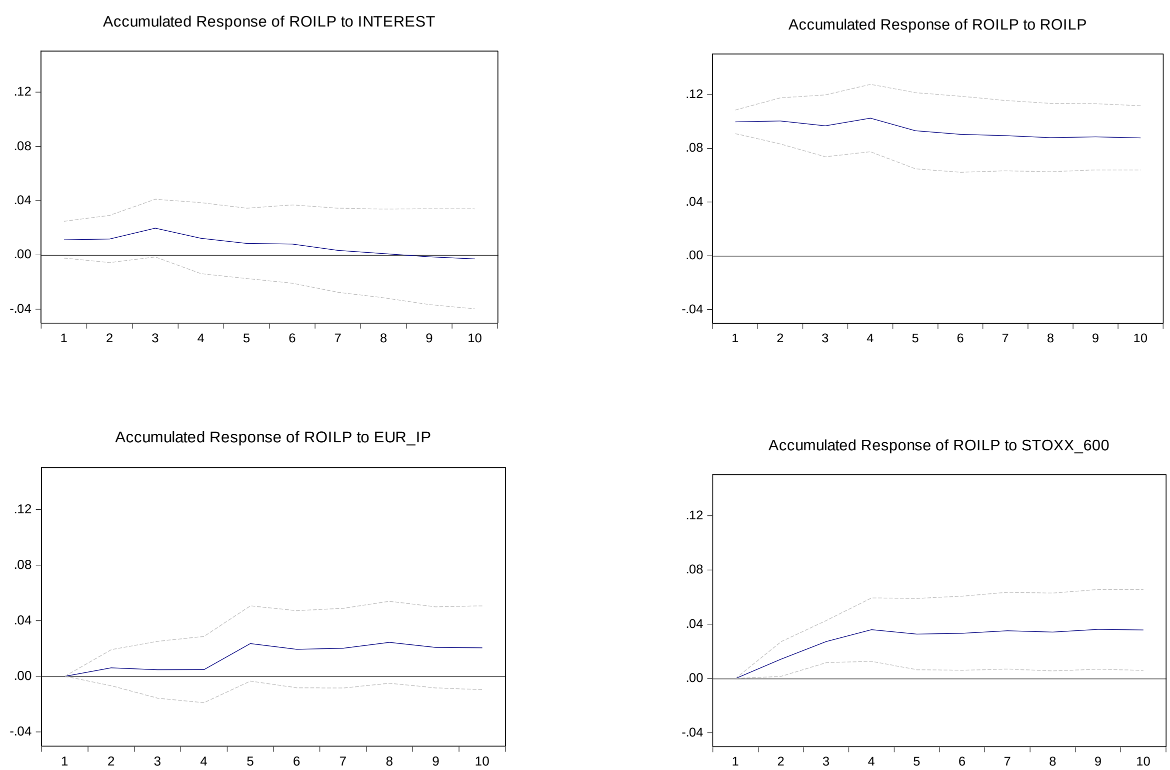
	Number of optimal lags based on AIC			
	2	3	4	5
Automobile	-11.649	-11.798	-11.803	-11.774
Banks	-12.085	-12.208	-12.233	-12.182
Basic Resources	-11.975	-12.126	-12.101	-12.084
Chemicals	-12.403	-12.538	-12.543	-12.459
Construction	-12.402	-12.533	-12.570	-12.506
Food & Bev.	-13.127	-13.270	-13.233	-13.149
Healthcare	-13.030	-13.175	-13.149	-13.087
Insurance	-11.869	-11.990	-11.983	-11.939
Oil & Gas	-12.638	-12.810	-12.791	-12.746
Pers. Household	-12.740	-12.891	-12.904	-12.821
Technology	-11.577	-11.711	-11.684	-11.615
Telecommunication	-12.222	-12.408	-12.369	-12.273
Utilities	-12.962	-13.087	-13.060	-12.983
Stoxx 600	-12.881	-12.999	-13.009	-12.941

Notes: The lowest (underlined) values indicate the optimal number of lags.

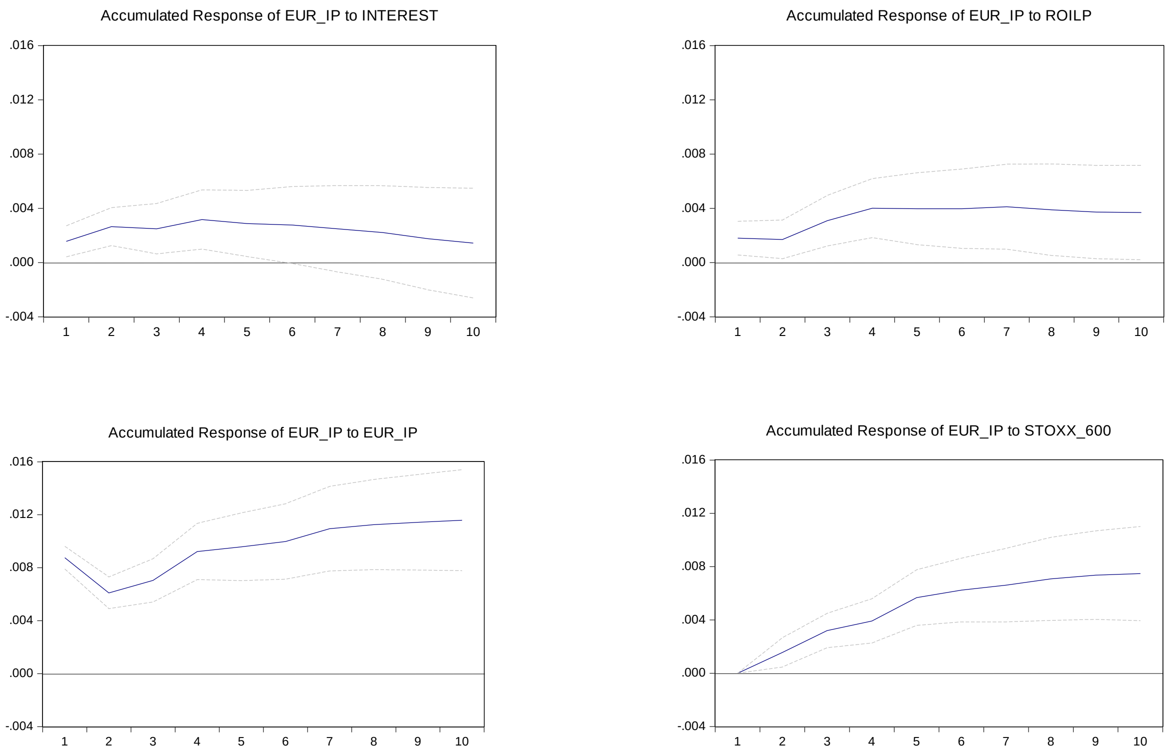
Figure 8:
Accumulated impulse response functions due to shocks in interest rate, real oil price, industrial production and real stock returns



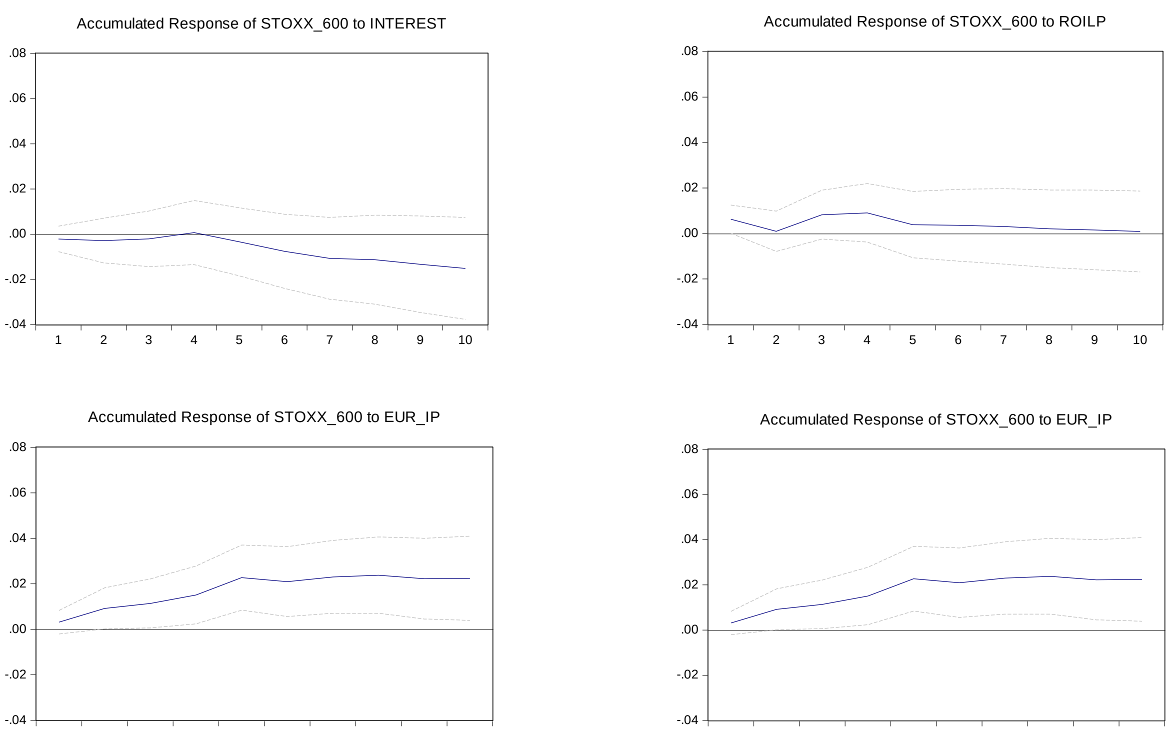
Response to a one standard deviation interest rate shock



Response to a one standard deviation oil price shock



Response to a one standard deviation shock in industrial production

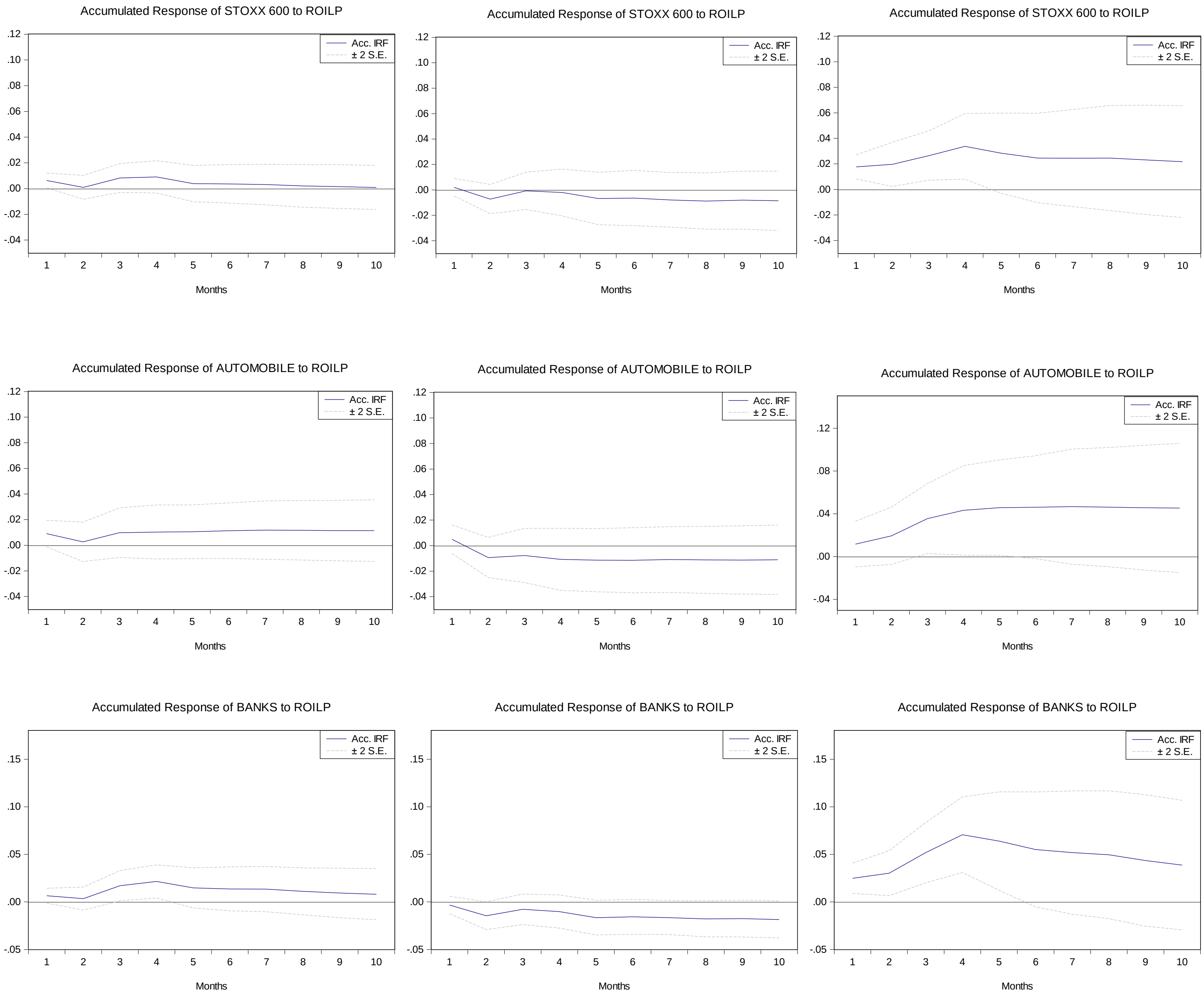


Response to a one standard deviation shock in real stock returns (Stoxx 600)

Notes: Accumulated impulse responses to one standard deviation shocks to $r, roilp, ip$ and rsr. ±2 Standard error bands are constructed based on Monte Carlo simulation.

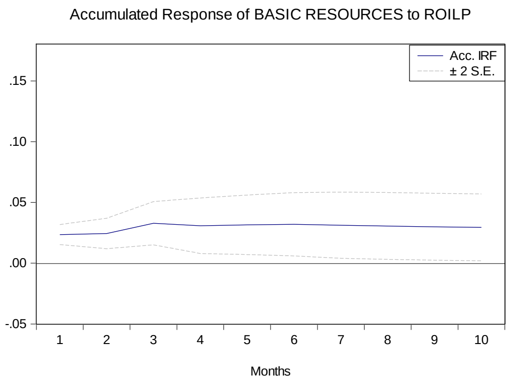
Figure 9:
Accumulated impulse response functions of industry returns to oil price shocks

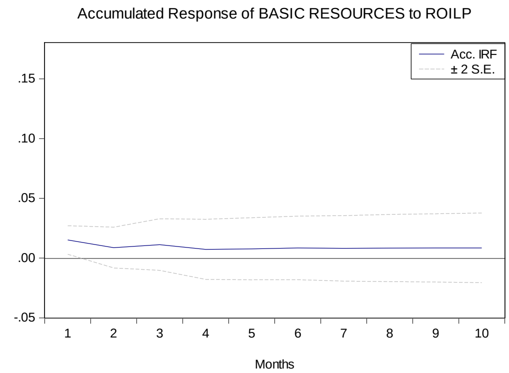
1995M01-2015M12 | 1995M01-2008M08 | 2008M09-2015M12

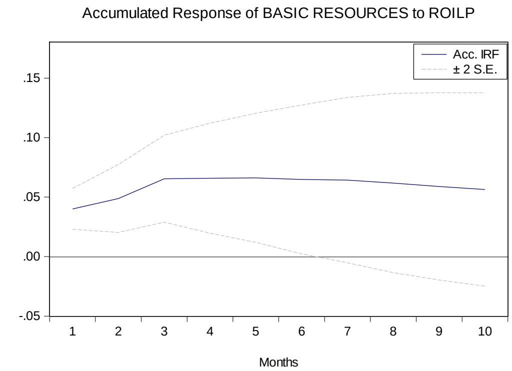


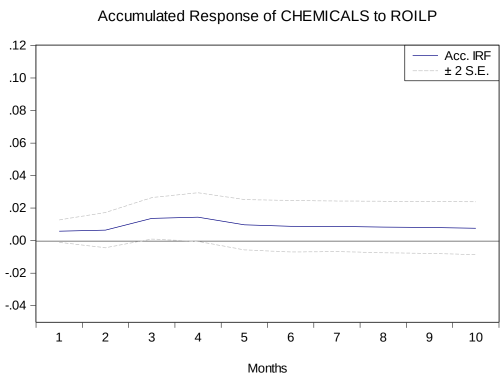
Appendix

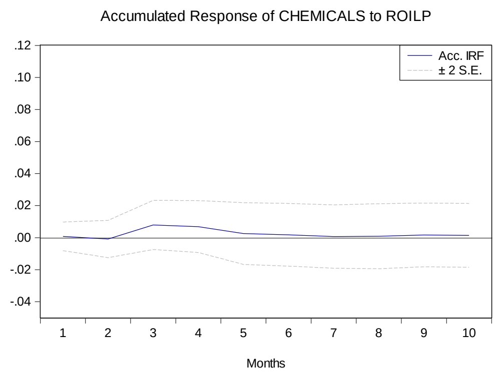
1995M01-2015M12 | 1995M01-2008M08 | 2008M09-2015M12

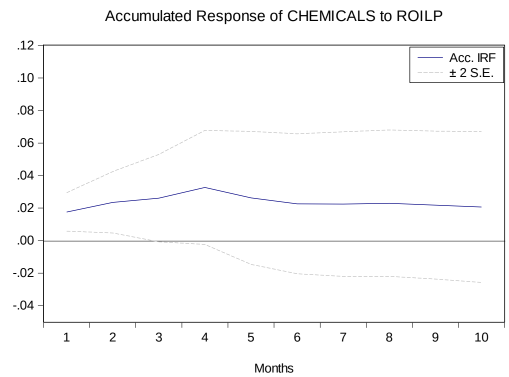


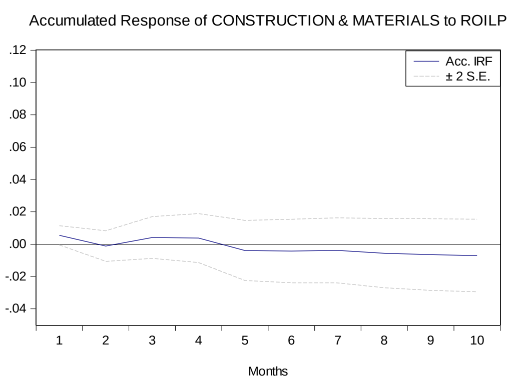


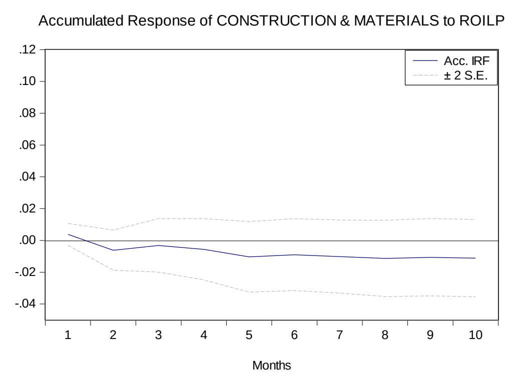


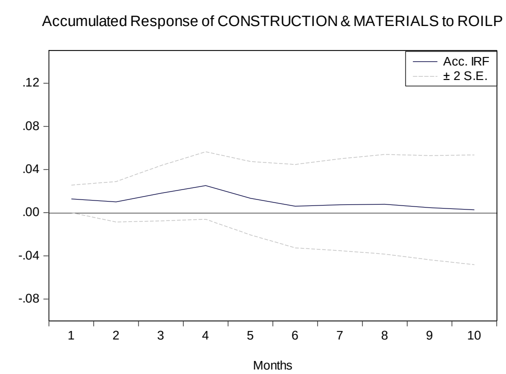


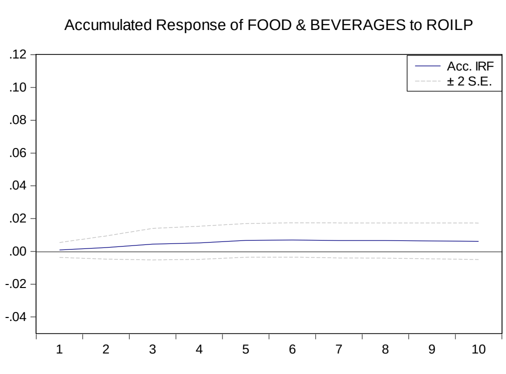


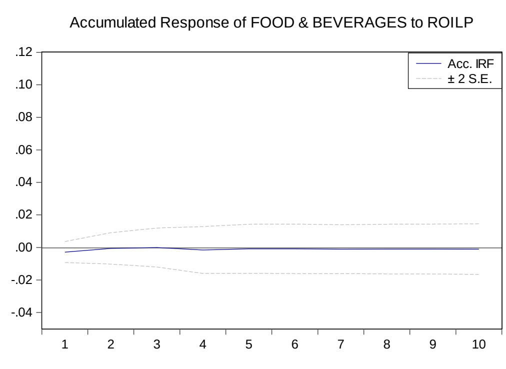


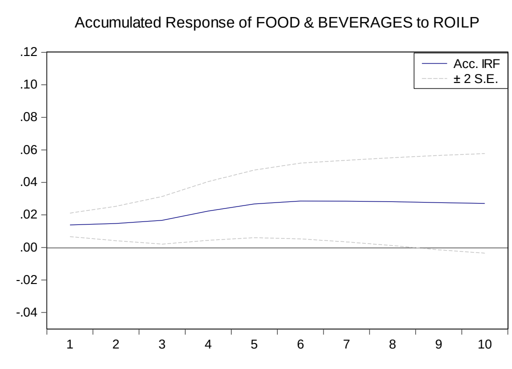






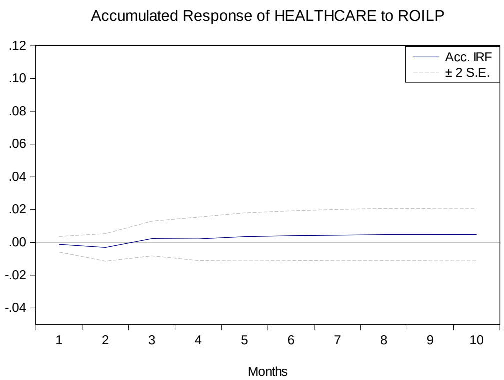


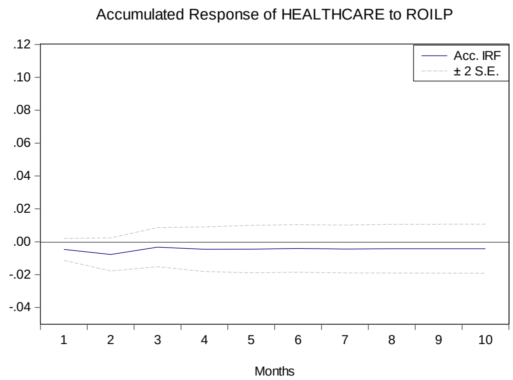


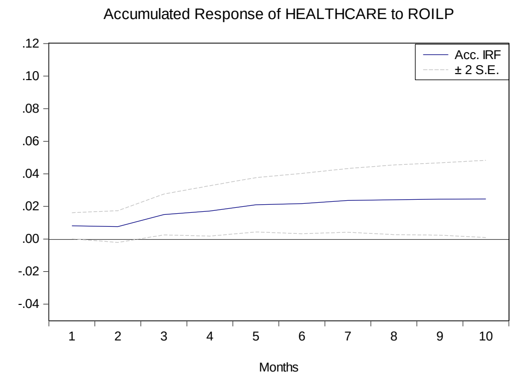


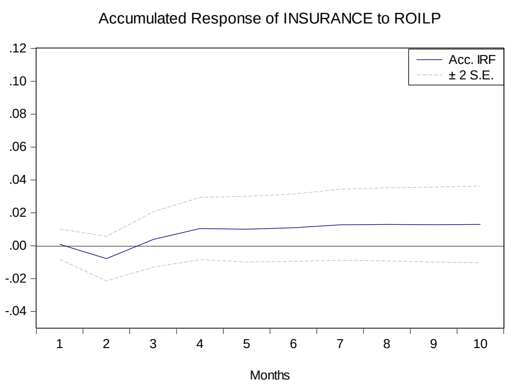
Appendix

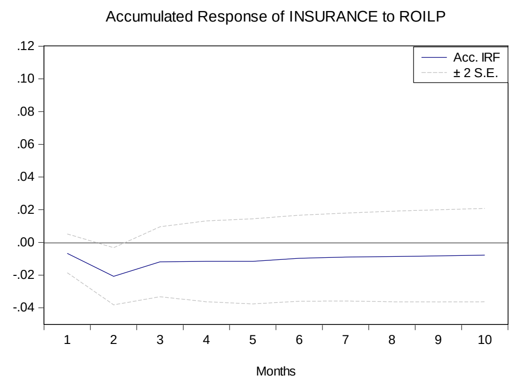
1995M01-2015M12	1995M01-2008M08	2008M09-2015M12

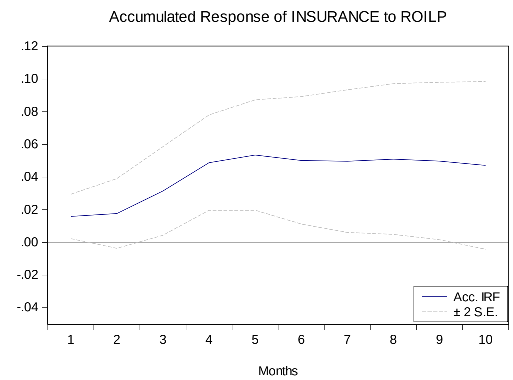


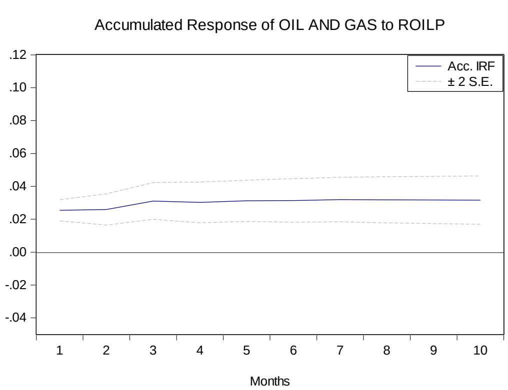


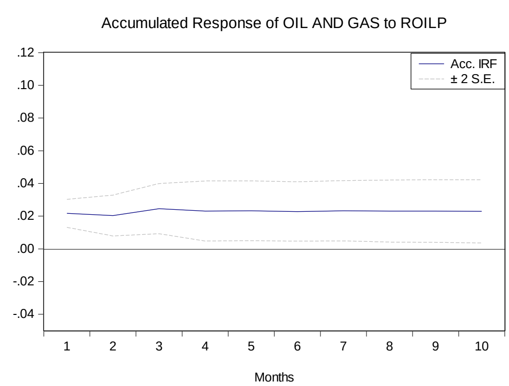


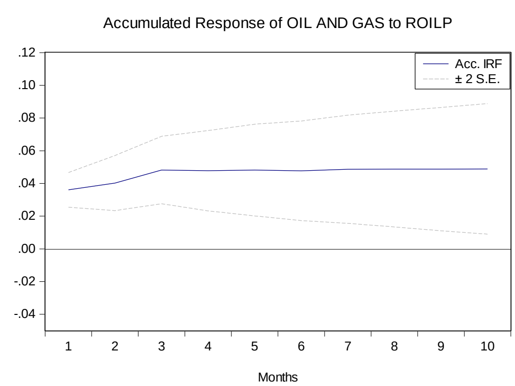


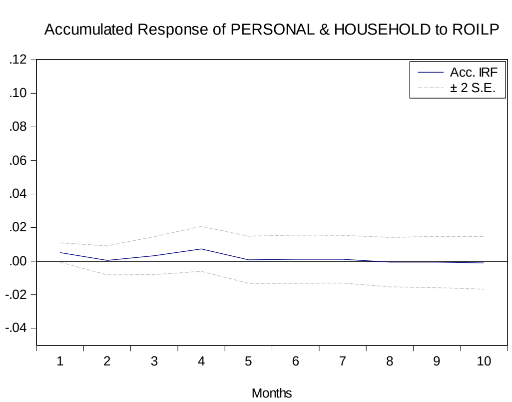


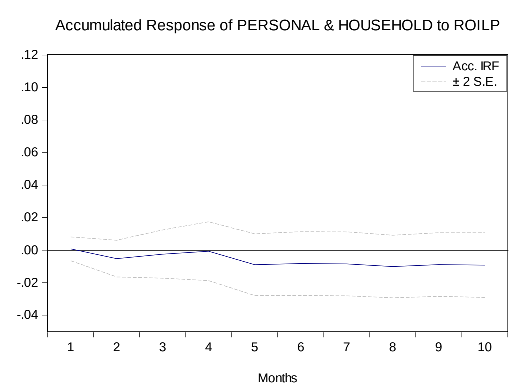


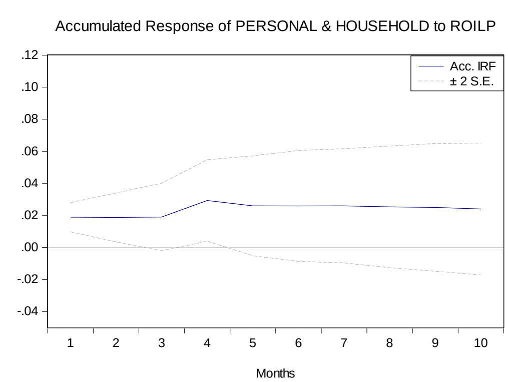






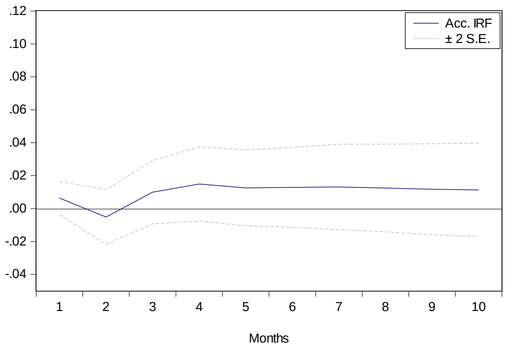




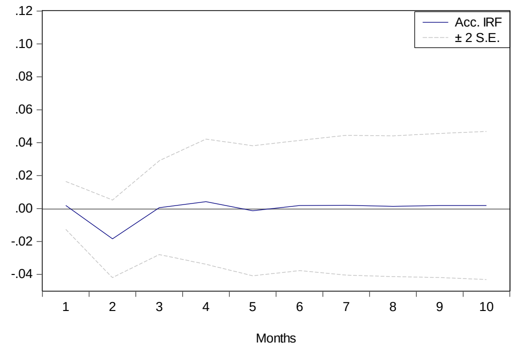


1995M01-2015M12 | 1995M01-2008M08 | 2008M09-2015M12

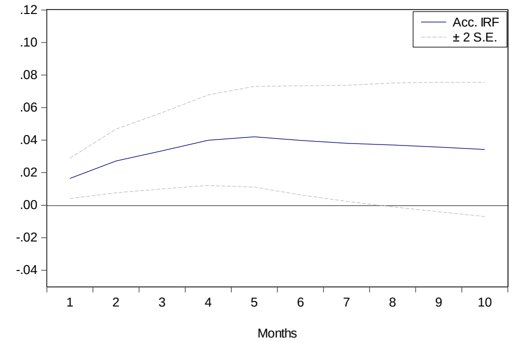
Accumulated Response of TECHNOLOGY to ROILP



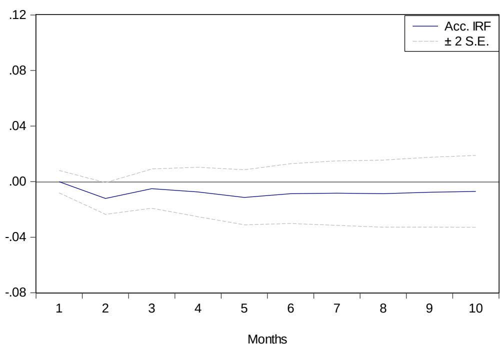
Accumulated Response of TECHNOLOGY to ROILP



Accumulated Response of TECHNOLOGY to ROILP



Accumulated Response of TELECOMMUNICATION to ROILP



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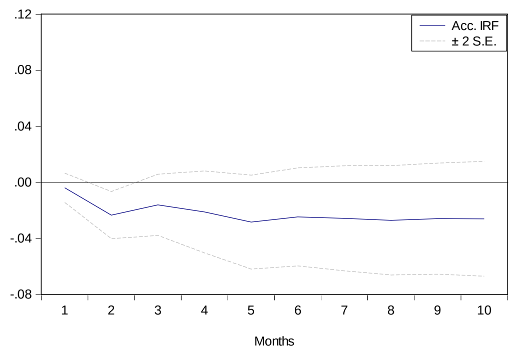
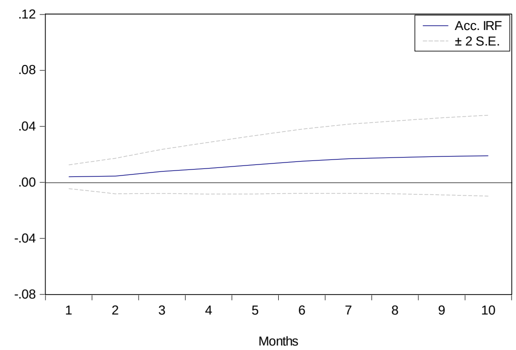
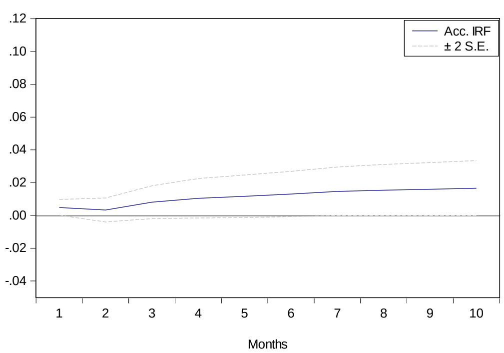


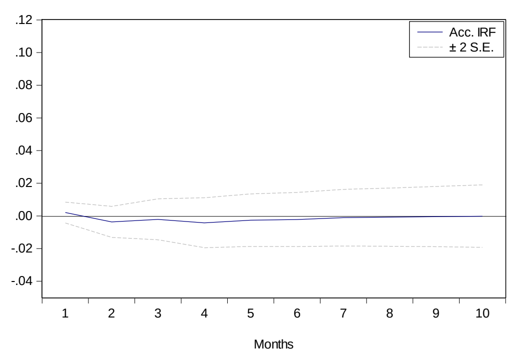
Accumulated Response of TELECOMMUNICATION to ROILP



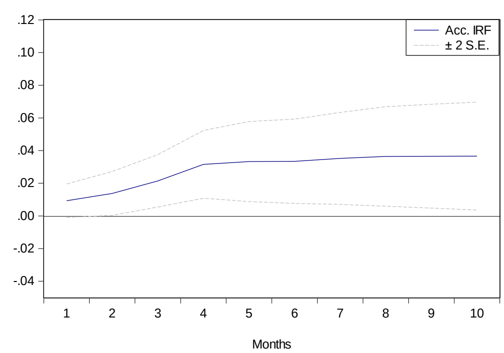
Accumulated Response of UTILITIES to ROILP



Accumulated Response of UTILITIES to ROILP



Accumulated Response of UTILITIES to ROILP



Notes: Accumulated impulse responses of industry returns to a one standard deviation shocks to $roilp$. ±2 Standard error bands are constructed based on Monte Carlo simulation with 1000 repititions.

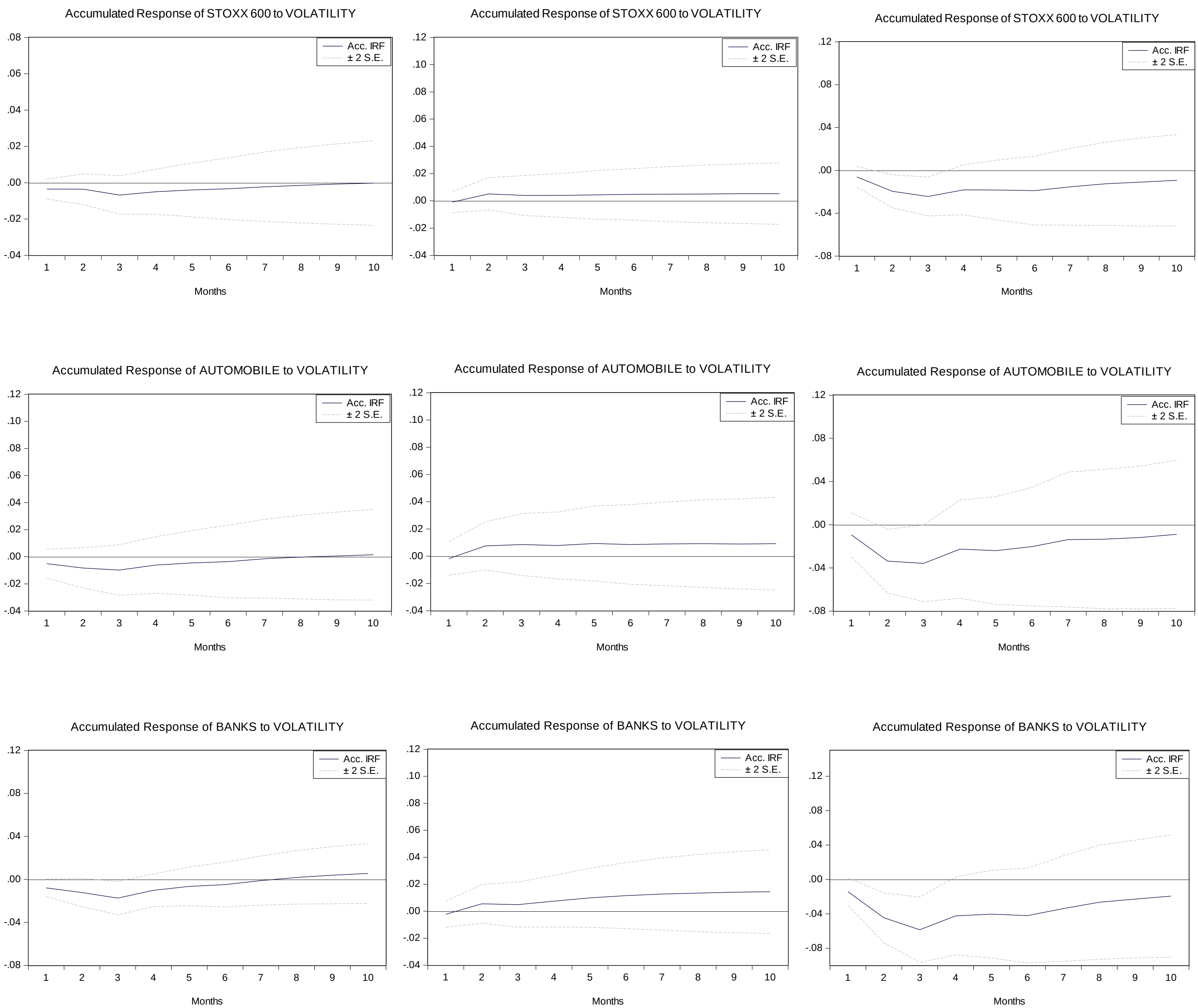
Table 17:
Lag length selection VAR (r, vol, ip, rsr)

	Number of optimal lags based on AIC			
	2	3	4	5
Automobile	-9.910	<u>-9.973</u>	-9.953	-9.882
Banks	-10.346	<u>-10.397</u>	-10.376	-10.291
Basic Resources	-10.209	<u>-10.278</u>	-10.242	-10.183
Chemicals	-10.686	<u>-10.741</u>	-10.726	-10.633
Construction	-10.662	<u>-10.710</u>	-10.697	-10.607
Food & Bev.	-11.435	<u>-11.496</u>	-11.463	-11.352
Healthcare	-11.304	<u>-11.364</u>	-11.314	-11.242
Insurance	-10.101	<u>-10.146</u>	-10.102	-10.026
Oil & Gas	-10.773	<u>-10.849</u>	-10.798	-10.694
Pers. Household	-11.020	<u>-11.082</u>	-11.057	-10.955
Technology	-9.7776	<u>-9.8344</u>	-9.769	-9.696
Telecommunication	-10.474	<u>-10.589</u>	-10.543	-10.445
Utilities	-11.225	<u>-11.277</u>	-11.235	-11.122
Stoxx 600	-11.107	<u>-11.145</u>	-11.109	-11.017

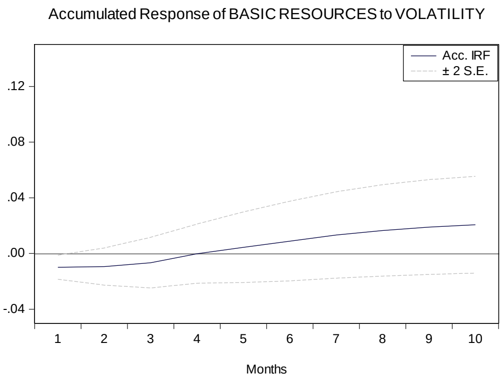
Notes: The AIC values presented come from the VAR model with the volatility measurement based on the EUR denominated price of crude oil. The lowest (underlined) values indicate the number optimal of lags.

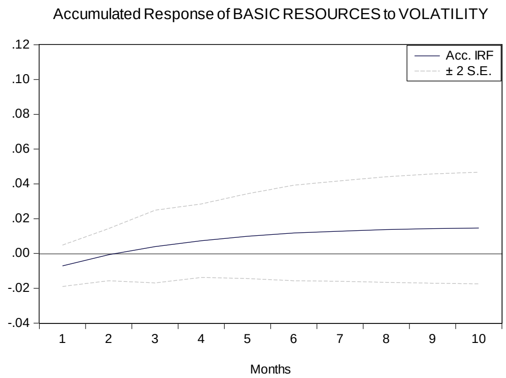
Figure 10:
Accumulated impulse response functions of industry returns to oil price volatility shocks

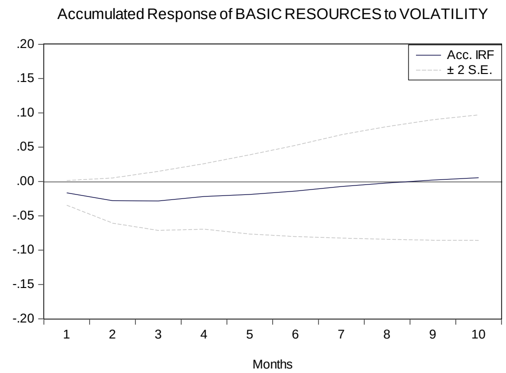
1995M01-2015M12 1995M01-2008M08 2008M09-2015M12

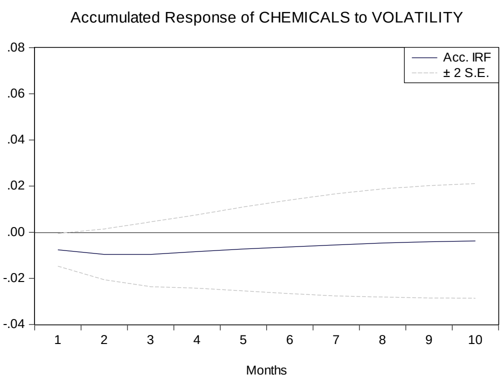


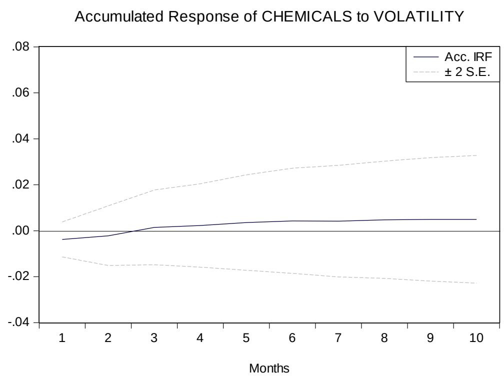
1995M01-2015M12	1995M01-2008M08	2008M09-2015M12

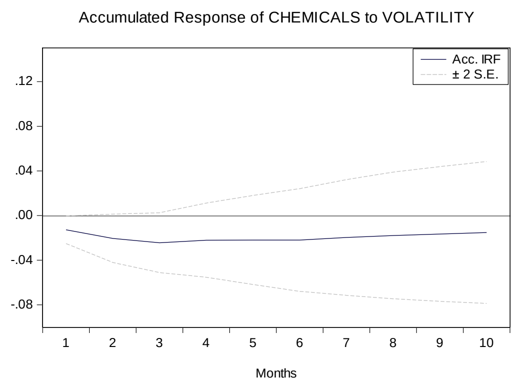


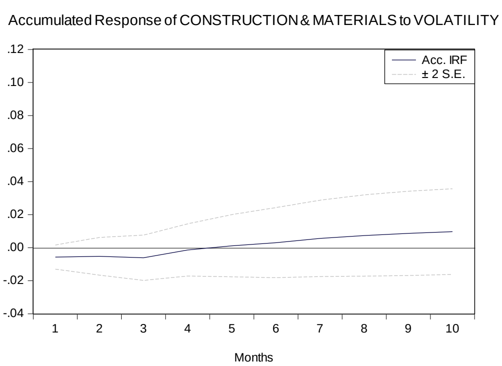


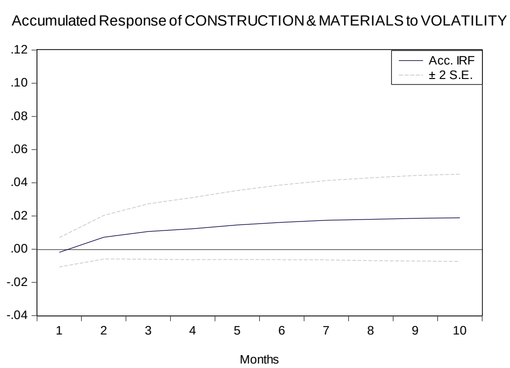


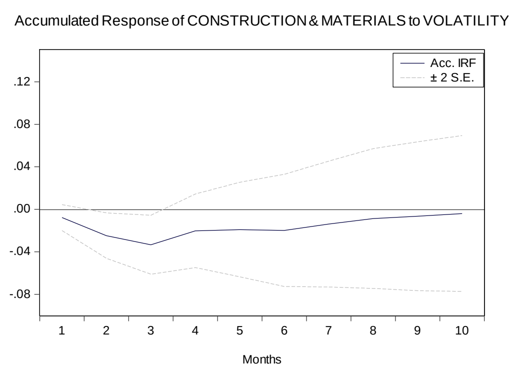


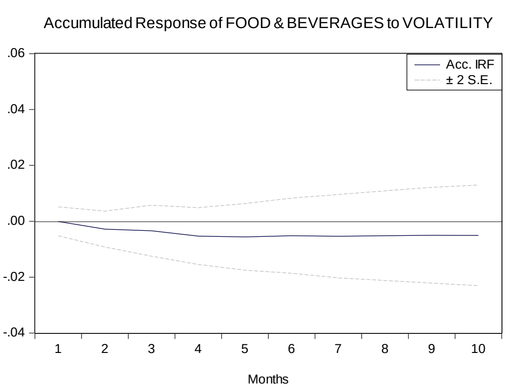


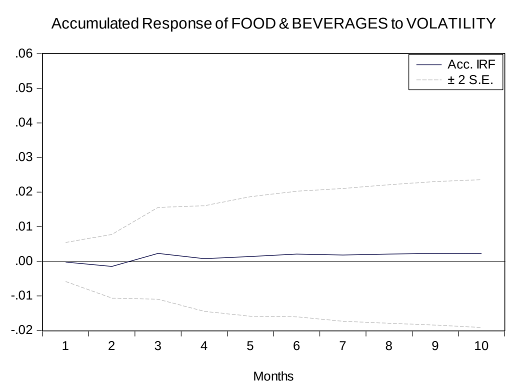


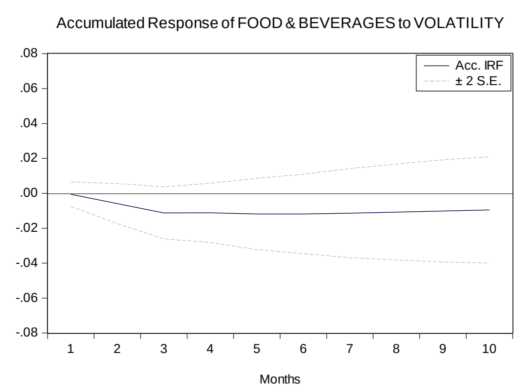






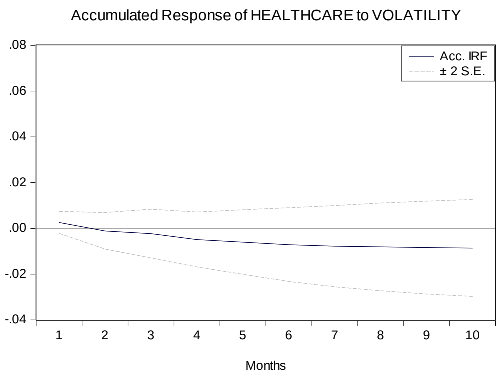


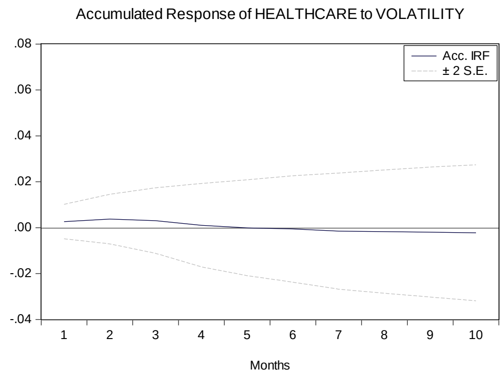


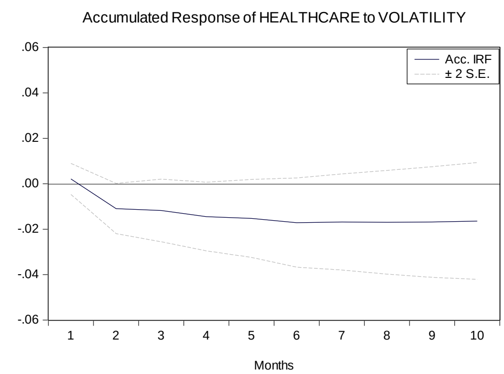


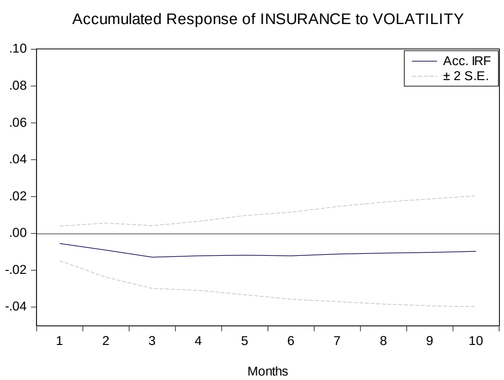
Appendix

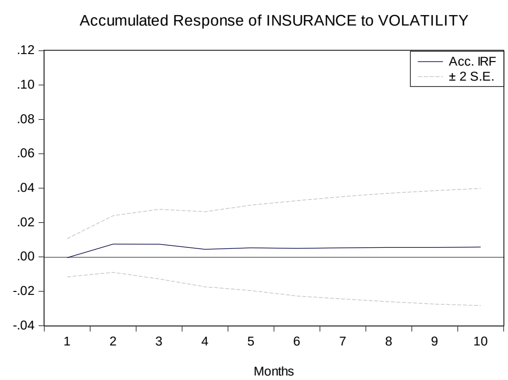
1995M01-2015M12 | 1995M01-2008M08 | 2008M09-2015M12

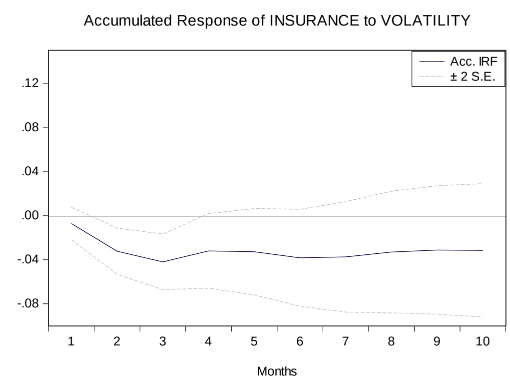


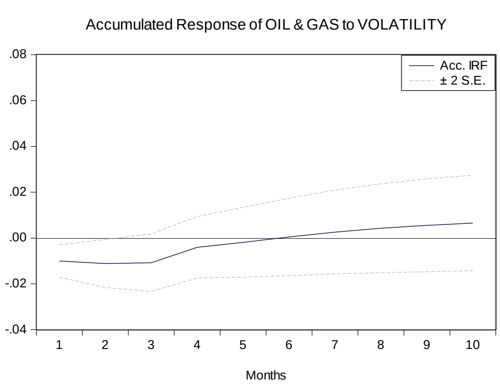


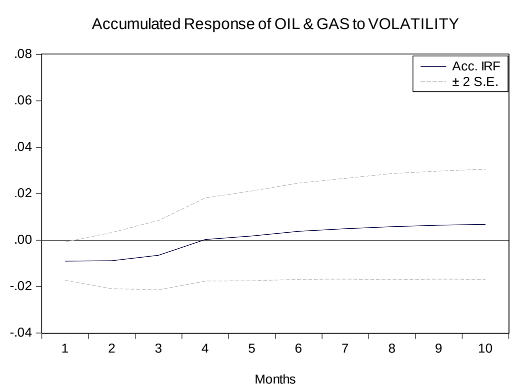


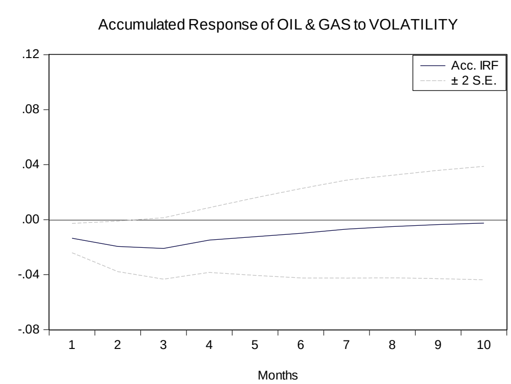


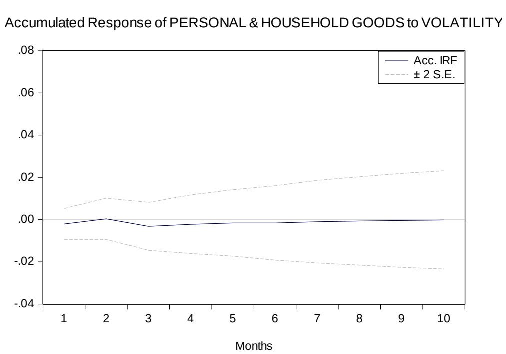


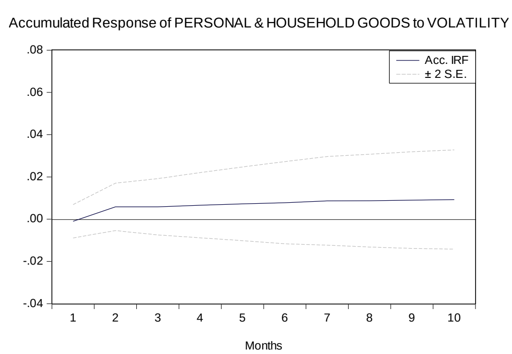


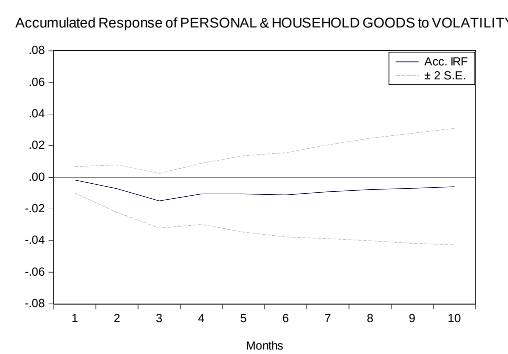






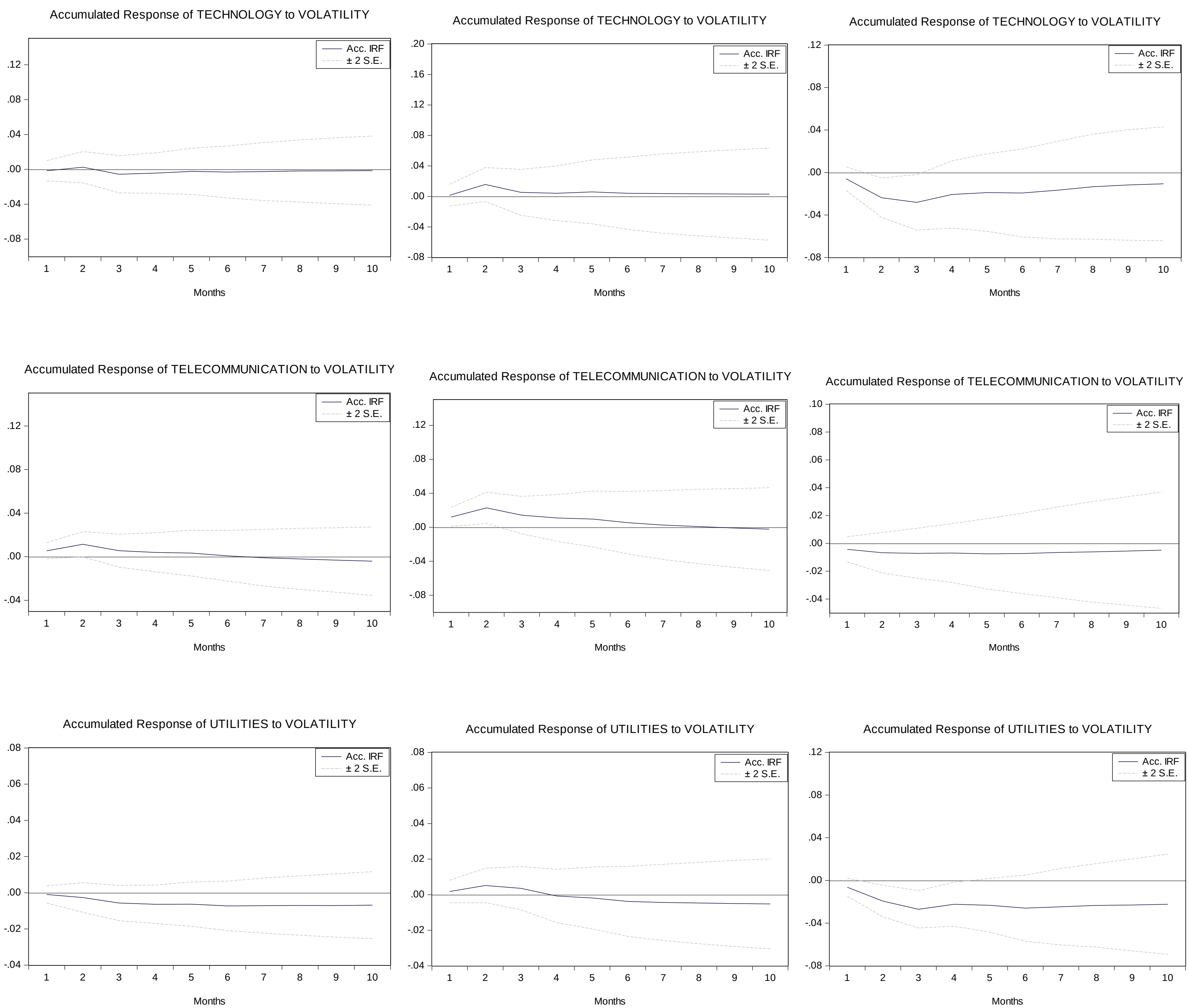






Appendix

1995M01-2015M12 | 1995M01-2008M08 | 2008M09-2015M12



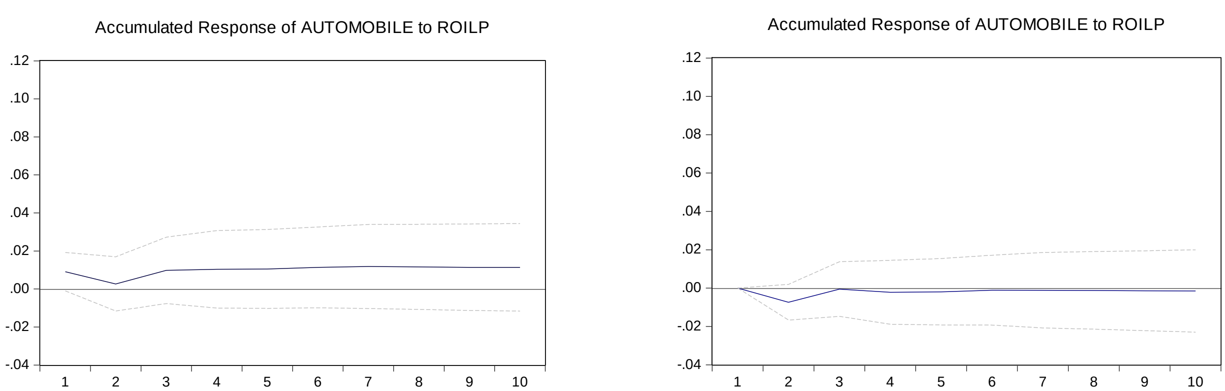
Notes: Accumulated impulse responses of industry returns to a one standard deviation shocks to oil price volatility ($vol_{€}$). ±2 Standard error bands are constructed based on Monte Carlo simulation with 1000 repititions.

Table 18:
Test of robustness - Impulse Responses to shock in oil price volatility with different VAR specifications

	AU	BA	BR	CH	CO	FO	HE	IN	OI	PE	TEC	TEL	UT
<u>Total Period</u>													
Akaike													
$VAR\ (r, vol_{€}, ip, rsr)$	n	n	n#	n	n	n	p	n	n#	n	n	p	n
$VAR\ (r, vol_{\$}, ip, rsr)$	n	n#	n#	n#	n	n	p	n	n#	n	n	p	n
Schwarz													
$VAR\ (r, vol_{€}, ip, rsr)$	n	n	n#	n#	n	n	p	n	n#	n	n	p	n
<u>First sub-period</u>													
Akaike													
$VAR\ (r, vol_{€}, ip, rsr)$	n	n	n	n	n	n	p	n	n#	n	p	p#	p
$VAR\ (r, vol_{\$}, ip, rsr)$	n	n	n	n	n	n	p	n	n#	n	p	p#	p
Schwarz													
$VAR\ (r, vol_{€}, ip, rsr)$	n	n	n	n	n	n	p	n	n	n	n	p	p
<u>Second sub-period</u>													
Akaike													
$VAR\ (r, vol_{€}, ip, rsr)$	n	n#	n#	n#	n	n	p	n	n#	n	n	n	n
$VAR\ (r, vol_{\$}, ip, rsr)$	n	n#	n#	n#	n	n#	p	n	n#	n	n	n	n
Schwarz													
$VAR\ (r, vol_{€}, ip, rsr)$	n	n#	n#	n#	n#	n	p	n	n#	n	n	p	n

Notes: n (p) denotes negative (positive) effects of a shock in oil prices volatility on industry returns (abbreviated in alphabetical order in the top row) based on accumulated response functions with a one month horizon. # denotes statistical significance based on Monte Carlo constructed ±2 SE bands. Schwarz and Akaike are the information criteria the lag-selection was based on.

Figure 11:
Accumulated impulse response with different variable order



VAR $(r, roilp, ip, rsr)$

VAR $(rsr, ip, roilp, r)$

Table 19:
Test of robustness - Sign of accumulated impulse response for different VAR orders

	AU	BA	BR	CH	CO	FO	HE	IN	OI	PE	TEC	TEL	UT
<u>Total Period</u>													
$VAR\ (r, roilp, ip, rsr)$	p	p#	p#	p#	n	p	p	p	p#	n	p	n#	p#
$VAR\ (roilp, r, ip, rsr)$	p	P#	p#	p#	n	p	p	p	p#	n	p	n#	p#
$VAR\ (r, ip, roilp, rsr)$	p	p#	p#	p#	n	n	p	p	p#	n	p	n#	p
<u>Sub-period I</u>													
$VAR\ (r, roilp, ip, rsr)$	n	n#	p#	p	n	n	n	n#	p#	n	p	n#	n
$VAR\ (roilp, r, ip, rsr)$	n	n	p#	p	n	n	n	n	p#	n	p	n#	n#
$VAR\ (r, ip, roilp, rsr)$	n	n	p#	p	n	n	n	n#	p#	n	p	n#	n
<u>Sub-period II</u>													
$VAR\ (r, roilp, ip, rsr)$	p#	p#	p#	p#	p	p#	p#	p#	p#	p#	p#	p	p#
$VAR\ (roilp, r, ip, rsr)$	p#	p#	p#	p#	n	p#	p#	p#	p#	p#	p#	p	p#
$VAR\ (r, ip, roilp, rsr)$	p	p#	p#	p#	n	p#	p#	p#	p#	p#	p#	p	p#

Notes: n (p) denotes negative (positive) effects of a shock in oil prices on industry returns (abbreviated in the top row) based on accumulated response functions with a ten month horizon. # denotes statistical significance based on Monte Carlo constructed ±2 SE bands. The Akaike information criterion was used for lag length selection.

Table 20:
Forecast Error Variance Decomposition for different oil price specifications

	VAR $(r, roilp_{€}, ip, rsr)$			VAR $(r, noilp_{\$}, ip, rsr)$		
Industry	1995M01-2015M12	1995M01-2008M08	2008M09-2015M12	1995M01-2015M12	1995M01-2008M08	2008M09-2015M12
Automobile	2.67	4.14	5.59	1.22	3.02	6.72
	(2.19)	(3.04)	(5.10)	(1.68)	(2.89)	(5.19)
Banks	**6.23**	5.78	**21.01**	4.37	5.03	**27.60**
	(2.61)	(3.60)	(7.14)	(2.63)	(3.05)	(8.09)
Basic Resources	**10.04**	5.78	**20.89**	**8.34**	3.07	**29.35**
	(3.27)	(3.44)	(7.20)	(3.75)	(2.83)	(8.63)
Chemicals	3.30	3.05	**11.15**	2.53	1.05	16.77
	(2.49)	(3.31)	(5.93)	(2.21)	(2.12)	(8.60)
Construction	4.72	4.89	10.13	2.58	3.26	11.24
	(2.75)	(3.31)	(5.90)	(2.06)	(3.12)	(6.89)
Food & Bev.	0.67	0.98	**17.04**	0.97	2.45	**17.11**
	(1.51)	(2.15)	(6.93)	(1.65)	(2.58)	(7.33)
Healthcare	2.18	2.90	8.67	3.09	6.20	6.99
	(2.49)	(3.16)	(5.67)	(2.27)	(3.97)	(4.98)
Insurance	4.63	5.60	12.65	3.60	6.96	15.75
	(2.52)	(3.87)	(6.79)	(2.54)	(3.70)	(8.04)
Oil & Gas	**22.09**	**15.81**	**40.74**	**17.73**	**10.85**	**44.75**
	(4.87)	(4.70)	(6.88)	(4.22)	(4.08)	(7.13)
Pers. Household	4.28	2.66	**20.05**	2.62	2.47	**20.30**
	(2.36)	(2.69)	(6.83)	(2.37)	(2.95)	(7.50)
Technology	**5.45**	**7.83**	12.44	4.99	8.08	**15.65**
	(2.56)	(3.66)	(6.78)	(2.58)	(4.17)	(6.62)
Telecomm.	5.60	**9.97**	2.68	6.15	**11.02**	4.04
	(3.09)	(4.33)	(4.42)	(3.60)	(4.42)	(3.93)
Utilities	3.31	2.71	11.62	2.31	2.68	**14.62**
	(2.40)	(2.48)	(6.80)	(2.07)	(2.70)	(7.05)
Stoxx 600	**6.64**	6.67	**18.12**	4.30	5.02	**23.34**
	(3.02)	(4.00)	(6.67)	(2.70)	(3.07)	(7.98)

Notes: Percentage of variation in real stock returns due to real oil price shocks in Euro and nominal oil price shocks in USD (10 month horizon). Standard errors constructed through Monte Carlo simulation with 1000 repetitions are reported in brackets.

Table 21*:*
Forecast Error Variance Decomposition for different oil price volatility specifications

	VAR $(r, Vol_{€}, ip, rsr)$			VAR $(r, Vol_{\$}, ip, rsr)$		
Industry	1995M01-2015M12	1995M01-2008M08	2008M09-2015M12	1995M01-2015M12	1995M01-2008M08	2008M09-2015M12
Automobile	0.95	1.60	9.85	0.71	2.16	7.86
	(1.46)	(2.50)	(5.10)	(1.48)	(2.97)	(5.18)
Banks	4.14	2.13	**22.23**	3.61	2.46	**24.20**
	(2.67)	(2.89)	(7.23)	(2.39)	(2.26)	(7.75)
Basic Resources	3.62	2.70	6.17	4.37	3.31	**13.18**
	(2.63)	(2.45)	(4.85)	(2.78)	(2.66)	(6.32)
Chemicals	2.05	1.02	6.58	2.25	1.23	9.16
	(2.24)	(2.64)	(4.91)	(2.01)	(2.46)	(5.57)
Construction	2.26	3.58	14.19	2.09	4.25	10.86
	(2.20)	(2.85)	(7.41)	(1.60)	(3.33)	(6.67)
Food & Bev.	0.79	1.14	3.98	0.97	1.16	6.42
	(1.65)	(2.49)	(5.33)	(1.50)	(2.46)	(5.21)
Healthcare	1.87	0.82	11.21	1.96	1.05	**14.59**
	(2.02)	(2.63)	(6.32)	(2.04)	(2.76)	(6.04)
Insurance	0.96	1.26	**14.87**	1.62	1.95	**14.08**
	(1.58)	(2.80)	(6.72)	(1.79)	(2.59)	(6.25)
Oil & Gas	**5.47**	4.55	8.32	**5.41**	4.26	**12.23**
	(2.71)	(3.13)	(5.45)	(2.56)	(2.99)	(6.01)
Pers. Household	1.08	2.00	5.11	1.39	3.07	7.40
	(1.49)	(2.43)	(5.54)	(1.40)	(3.07)	(7.34)
Technology	1.14	2.95	11.67	1.01	2.68	15.42
	(1.60)	(2.84)	(6.28)	(1.53)	(2.88)	(8.12)
Telecomm.	2.84	6.93	1.42	3.40	6.66	1.69
	(2.58)	(3.55)	(3.72)	(2.76)	(3.52)	(4.21)
Utilities	0.77	2.32	12.84	1.11	2.02	**15.78**
	(1.28)	(3.00)	(7.35)	(1.99)	(2.38)	(7.17)
Stoxx 600	1.33	1.70	12.41	1.40	2.01	**15.56**
	(1.60)	(2.51)	(6.47)	(1.63)	(2.44)	(7.47)

Notes: Percentage of variation in real stock returns due to oil price volatility measured in Euro and USD (10 month horizon). Standard errors constructed through Monte Carlo simulation with 1000 repetitions are reported in brackets.