PhD THESIS

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Essays on the Effects of Oil Price Shocks on Financial Markets and Industries

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Abstract

The aim of this dissertation is to extend the literature on the connection between oil and the economy, by investigating the impacts of oil price shocks on financial markets and industries.

The first chapter of my thesis is devoted to give a new look to the relation between the stock market return and the oil price shocks in the US stock markets. This study empirically models oil price changes as driven by speculative demand shocks along with consumption demand and supply shocks in the oil market. It also takes into account all the factors that affect stock market price movements over and above the oil market, in order to quantify the pure effects of oil price shocks on returns. The results show that stock returns respond to oil price shocks differently, depending on the causes behind the shocks. Consumption demand shocks are the most relevant drivers of the stock market return, relative to other oil market shocks. Industry level analysis is performed to control for the heterogeneity of the responses of returns to oil price changes. The results show that both cost side and demand side effects of oil price shocks matter for the responses of industries to oil price shocks.

The second chapter investigates the effects of oil price shocks, including oil specific and macroeconomics shocks to the oil market, on volatility of selected agricultural and metal commodities. The investigation is divided into two subsamples, before and after 2006 for agricultures taking into account the 2006-2008 food crisis, and before and after 2008 for metals considering the global financial crisis. The results show that the response of volatility of each commodity to an oil price shock differs significantly depending on the underlying cause of the shock for the both pre and post-crisis periods. moreover, the explanatory power of oil shocks becomes stronger after the crisis. The different responses of commodities are described in detail by investigating market characteristics in each period.

The third chapter studies the relationship between investment and uncertainty in a panel of U.S. firms in oil and gas industry. The paper decomposes oil price uncertainty to be driven by the shocks to supply of oil, global consumption demand for oil and all industrial commodities and other oil market-specific demands, to investigate whether and how investment-uncertainty relationship depends on the causes behind uncertainty. The findings show that oil market uncertainty lowers investment only when it is driven by global demand shocks. When it is driven by oil supply shocks and oil market-specific demand shocks, it has no significant effect on investment. Stock market uncertainty found to negatively affect investment. The results show no positive relation between investment and uncertainty but the negative relation is not always correct. This is in line

with the option theory of investment and shows that the irreversibility effect of increased uncertainty dominates the traditional convexity effect.

Chapter 1

Global Oil Market and the U.S. Stock Returns

1.1 Introduction

The impacts of oil price changes on the economic indicators are very important in studying the connection between oil and the economy. The prevailing approach in the literature is to analyze this connection by investigating the impacts of oil price shocks on macroeconomic and financial variables such as stock market returns. Several empirical studies document strong evidence connecting oil price shocks and stock market returns. For example, Charles and Gautam [1996] and Kling [1985] find a negative effect of an oil price increase on aggregate real stock returns. Ciner [2001] concludes that the connection between oil price and stock market returns is nonlinear. Some studies have done sector analysis and concluded that the oil-related industries appreciate after an oil price increase while oil using industries depreciate after the same change (see e.g. Arouri and Nguyen [2010], Arouri [2011] and Scholtens and Wang [2008]). On the other hand, there are studies concluding that there is not a significant connection between oil market and stock market (for example Chen et al. [1986], Huang et al. [1996] and Scholtens and Boersen [2011]).

There is a consensus in the literature that oil price is not exogenous and its determining factors are supply and demands for oil and for other industrial commodities (see e.g. Hamilton [2009], Kilian [2009a], Alquist and Kilian [2010], Galloa et al. [2010], Askaria and Krichene [2010] and Kilian and Murphy [2014]). Kilian and Park [2009], Hamilton [2009] and Kilian [2009a] argue that the endogeneity of the price of oil with respect to macroeconomy is essential in studying the effect of oil price on any economic variable. In particular Kilian and Park [2009] study the effects of oil price changes on the U.S. stock market return taking into account the determining factors of the oil market, including supply and demand. The results they document suggest that the response of the stock market returns to oil price shocks caused by the demand side of the economy is the most significant one. What is missing in the current literature assessing the effects of oil market shocks on the stock market returns is taking into account the underlying factors driving returns in the stock market. According to the Gordon and Shapiro [1956], the price of a share is equal to the discounted sum of expected future dividends. Miller and Modigliani [1961] argue that the underlying source of a firm's value is the firm's earnings as it fund dividends. Therefore, the systematic factors influencing stock prices are those impacting expected earnings and the discount rate (Fama [1990]). Accordingly, numerous number of papers studied the effect of various macroeconomic and/or stock market related variables on stock market return. Goyal and Welch [2008] comprehensively study the performance of the variables that are suggested in literature to be stock market return predictors in explaining the future values of the returns.

This paper tries to fill this gap by taking into account the determinant factors of stock market return along with those of oil market in studying the connection between the two markets. The econometric framework of this paper is based on a structural vector autoregressive(SVAR) model developed by Kilian and Murphy [2014] that enables the identification of the speculative demand component of the oil price shocks along with supply and consumption demand components by considering the determining variables of the global market for crude oil, including the global production of oil, consumption demand for oil, inventory demand for oil and the real price of oil. We augment this framework by including the determining factors of the stock market return to the structural VAR model to capture any fluctuation of the return that is driven by stock market related variables which are unrelated to oil market.

Stock market related variables are taken from the long list of predicting factors documented by Goyal and Welch [2008] which includes dividend price ratio, stock return volatility, default spread, long term rate of return, corporate bond returns and net equity expansion. These variables are shown to have very significant explanatory power towards stock market return. The results documented by this paper suggest that the effect of oil market on stock market return is indeed overestimated if the enogeneity of stock market return with respect to stock market related variables is not taken into account. The findings show that there is a negative relation between stock market return and oil price changes driven by a shock to speculative demand for oil. An oil price increase due to an oil supply shock does not significantly affect stock market return while its effect is mixed when global demand shock raises the price of oil. It raises the market return for ten months and lowers it afterwards. According to results from forecast error variance decomposition(FEVD) of the stock market return, in the long-run on average, 16% of the variations of the U.S. real stock return is explained by the structural shocks in the global crude oil market. However, if we exclude the stock market related variables from the model, the explanatory power of oil market shocks towards the variations in stock return raises to more than 18% in FEVD analysis. This result reflects how a misspecified model would overestimate the role of oil market in explaining variations in stock market.

In this study, industry level analysis is performed to control for the heterogeneity among sectors in response to oil price changes and to better investigate the transmission channels of oil market shocks to stock market. However, this paper is not the first to preform such an analysis. For example, Arouri and Nguyen [2010], Arouri [2011], Kilian and Park [2009], Scholtens and Yurtsever [2012], Lee and Ni [2002], among others, have examined the effects of oil price changes on sector level returns in the U.S. and Europe stock markets using various econometric techniques. The consensus in the literature is that an oil price increase affects industries through the supply for industry inputs and the demand for final product. On the supply side, this shock increases the input cost of industries as well as the transportation cost. On the demand side, depending on the cause behind the shock and on the sectors, it could increase or decrease the demand for the industries' output. If the oil price increase is driven by better economic activity, it raises the demand for all industrial commodities, while a speculative demand shock decreases the demand for manufacturing industries and increase the demand for substitutionary energy sectors like coal, as well as precious metals as being a safe haven to avoid increasing risk from uncertainty in the oil market.

The common practice in the empirical studies examining the effect of oil market on sectors of stock market is to analyze a specific sector in the stock market in isolation of the other sectors or the market as a whole. The conclusion of such studies is therefore based on the connection between the oil market and an industry's return in the stock market (e.g.Kilian and Park [2009]) or the commodity market (e.g. Wang et al. [2014]). This view is particularly of high importance since it provides a clearer image of the transmission channel through industries as opposed to the outcome effect on the stock market where positive or negative effects on the sectors counterbalance. However, the results of such analyses are heavily postulated on the presumption that the return of a sector in stock market only responds to the shocks occurred in oil market and is uncorrelated to the return of other sectors or market wide shocks. This presumption does not seem to be credible in the presence of supply-demand chain for input-output among sectors (see for example Linn [2006]), or market wide systematic shocks like global financial crisis. The latter is particularly very important as concluded by KiHoon et al. [2014], who investigated the impacts of industry level and market wide shocks in equity markets. We argue that industry specific shocks as well as market wide shocks should be taken into account in the sectoral analysis. For this objective, we augment the structural VAR model where oil market variables are included as well as an industry's return, by adding an index of market return. For each industry we construct the index for market return by making a weighted average of the returns of all the selected industries, excluding the industry in question, where weights are proportional market values of each industry.

The findings from sector level analysis show that industries are affected through both the cost side and the demand for final product. Therefore, although the total cost of energy matters, it is not enough to explain differences in the responses of stock returns across industries. This result is in contrast to the interpretation of oil price shocks as input cost shocks. For many industries, specially less oil intensive ones, the transmission of oil price shocks to their returns is driven more by shifts in the demand for goods and services, rather than the cost of production. Examples are consumer goods and services, entertainments and retail industries. More interestingly, the results imply that in response to an oil price increase that is due to a speculative demand shock in oil market, auto, consumer goods and steel industries depreciate while precious metals appreciates and oil industry is unaffected. This result could be interpreted as a re-balance in market participants' investment portfolio, followed by an unexpected increase in the speculation in the oil market. All the industries appreciate if the reason of oil price increase is global demand shock.

The rest of the paper is set out as follows. Section 2 reviews literature related to the current research. Section 3 describes the data. In section 4 the structural VAR methodology is described. The results of estimation of the structural VAR model for the U.S. aggregate stock market return are discussed in section 5. In section 6 sectoral analysis is carried out by assessing the impulse responses and forecast error variance decomposition. Some concluding remarks are given in Section 7.

1.2 Literature review

The relationship between oil price shocks and stock market returns is studied broadly in the literature. A group of studies applying econometric models assesses the link between the stock market return and different variables including oil price. Charles and Gautam [1996], test the response of stock market return to oil price changes based on the cash-flow dividend valuation model on quarterly data for the U.S., Canada, UK and Japan. They find that in the post-war period, the effects of an oil price shock on stock market return in Canada and the U.S. are through its impact on real cash flows, while the results for Japan and the UK are not conclusive. Sadorsky [1999] develops a Vector Autoregressive (VAR) model with GARCH effects to American monthly data of oil price, stock market return, short-term interest rate and industrial production over the period 1947-1996. He shows that oil price plays an important role in variations of the U.S. aggregate real stock market return. Odusami [2009] analyzes the relationship between oil price and the U.S. stock market by employing an asymmetric GARCH-jump model. Using daily data from January 1996 to December 2005 he finds a nonlinear negative relationship between oil price shocks and the U.S. stock market return. Using an unrestricted vector autoregressive (VAR) model, Huang et al. [1996] find no relationship between oil price and the S&P500 market index. Park and Ratti [2008] use an unrestricted VAR with the four variables and find that, over 1986:1-2005:12, an oil price shocks has a negative impact on real stock market return in the U.S. and 12 European countries and a positive impact in Norway as an oil exporter. Dhaoui and Khraief [2008] employ an EGARCH-in-M model to examine whether oil price shocks impact stock market return. They use monthly data for eight developed countries from January 1991 to September 2013 and find that an oil price shock negatively affects stock market return in the U.S., Swiss, France, Canada, U.K., Australia and Japan. However they find no impact of oil price changes on stock market of Singapore.

Some studies, consider the endogeneity of the price of oil with respect to macroeconomic and global oil market variables . They take into account the determining factors of the real price of oil in the analysis of the effects of oil price shocks on stock market returns. Kilian and Park [2009] and Apergis and Miller [2009] assess the effects of oil price shocks on real stock market returns by employing a structural vector autoregressive model to decompose oil price changes into three components including oil supply shock, oil-specific demand shock and global demand shock. Kilian and Park [2009] consider the U.S. real stock market returns from 1973:2 to 2006:12 and document that the response of the U.S. real stock market return to an oil price shock depends on the underlying shock that drives the oil price shock. According to their results, the response of the U.S. stock market return to an oil supply shock is not significant while a global demand shock has positive and an oil-specific demand shock has negative impacts on real stock market return. Apergis and Miller [2009], using data for the period from 1981 to 2007 of eight countries, Australia, Canada, France, Germany, Italy, Japan, the U.K. and the U.S., find that international stock market returns do not respond in a large way to oil market shocks. Oil supply shocks, global demand shocks and oil-specific demand shocks have significant but small effects on stock-market return in most countries. Ready [2013] develops a method for classifying oil price changes as supply or demand driven and documents that demand shocks are strongly positively correlated with market returns, while supply shocks have a strong negative correlation.

Moreover, many studies focus on industry level data to provide a clearer understanding of the transmission channel through which oil price shocks affect stock market returns. Lee and Ni [2002] study the effects of oil price shocks on demand and supply in the U.S. industries by applying a structural vector auto regressive model. They conclude that oil price shocks have negative effects upon the U.S. industries. For more oil intensive industries, like industrial chemicals, oil price shocks mainly reduce supply while for many other industries oil price shocks mainly reduce demand. Kilian and Park [2009] investigate the impacts of oil price shocks on the return of four industries: petroleum and natural gas, automobiles and trucks, retail and precious metals industries. They find that the effects of oil price shocks on the U.S. industries' returns differ across industries and also depending on the cause of the shock. They suggest that oil price shocks are shocks to the demand for industries rather than being supply shocks. Arouri and Nguyen [2010], Arouri [2011] and Scholtens and Yurtsever [2012] using European data with different econometric techniques, find that the responses of stock returns to oil price shocks differ greatly depending on the sectors. On his industry level analysis, Ready [2013] concludes that the negative effects of supply shocks are concentrated in industries which produce consumer goods, and are also strongest for oil importing countries.

This paper extends the previous literature by taking into account the endogeneity of the real price of oil and the real stock market return with respect to macroeconomic and their own market variables. We investigate the link between oil price and the U.S. real stock market return in the aggregate and industry levels. The econometric framework is based on a structural vector autoregressive model. Our object is to provide a comprehensive analysis of the effects of supply and demands components of an oil price shock on the

U.S. stock market return in the presence of stock market determinants. Structural VAR framework has two advantages for this object. First, it allows to identify the speculative demand component of the oil price shocks along with supply and consumption demand components and second, we can include the determining factors of the stock market return to the analysis. The latter is to capture any fluctuation of the return that is driven by stock market related variables which are unrelated to the oil market.

1.3 Data

The data we use in this study is monthly and covers the period 1973:3 to 2013:12. As described in the previous section, two types of variables are employed, variables related to the U.S. stock market and variables related to the global oil market.

Global oil market variables consist of global crude oil production, global crude oil inventories, real price of crude oil and finally a measure for global trade. Data on global crude oil production is available in the monthly energy review of the Energy Information Administration (EIA). The real price of crude oil is the U.S. refiners' acquisition cost for imported crude oil and is reported by the EIA. We extrapolate this series from 1974:1 back to 1973:3 to cover the whole sample period following Barsky and Kilian [2002], and deflate it by the U.S. consumer price index. Given the lack of data on crude oil inventories for all countries, following Kilian and Murphy [2014] and Kilian and Lee [2014], we employ the data for the U.S. crude oil inventories scaled by the ratio of OECD petroleum stocks over the U.S. petroleum stocks as a proxy for global crude oil inventories[1]. We use a measure of global industrial activity, introduced by Kilian [2009a], to proxy global demand for crude oil. This measure is based on the global dry cargo shipping rates which reflects the global business cycle and measures consumption demand for oil and all industrial commodities.

Stock market variables consist of the U.S. aggregate stock market and industries return as well as other related variables. The aggregate U.S. stock return is from is from the Center for Research in Security Prices (CRSP) which is a value-weighted market portfolio including NYSE, AMEX, and Nasdaq stocks. The real stock market return is obtained from the aggregate U.S. stock return deflated by the U.S. consumer price index. The industry level returns are available by Kenneth French[2]. This data is derived from the CRSP database and therefore are consistent with the aggregate stock return series. The industries we analyse include precious metals, steel, consumer goods (household), aircraft, automobile and trucks, transportation, chemicals and petroleum and natural gas. We intend to satisfy a set of criteria to choose these industries. First, any industry chosen is supposed to be affected by oil market through either of the channels mentioned above.

[1] The data for this proxy of the global crude oil inventories, and for other three oil market variables are also available in Journal of Applied Econometrics data archive.

[2] Available at $http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

Second, the selected industries account for relatively high (more than thirty percent) fraction of the market value. Data on other stock market variables, including dividend price ratio, stock return volatility, default spread, long term rate of return, corporate bond returns and net equity expansion are available by Amit Goyal[3].

1.4 Methodology

A structural vector autoregressive (SVAR) model is used in this paper to investigate the impact response of the U.S. stock market returns to oil market shocks, namely, oil supply shock, global demand shock and speculative demand shock. The structural VAR model is the following:

$$A_0 y_t = \alpha + \sum_{i=1}^{24} A_i y_{t-i} + BX_t + \varepsilon_t \tag{1.1}$$

Where y_t is the vector of endogenous variables including the percent change in global crude oil production, global real economic activity, the change in global crude oil inventory, the real price of crude oil and the U.S. real stock return. X_t is the vector of stock market variables that are main drivers of stock returns including dividend price ratio, stock return volatility, default spread, long term rate of return, corporate bond returns and net equity expansion. This vector is treated as an exogenous variable to the VAR system. Following Kilian and Murphy [2014], we assume that the vector of structural shocks, ε_t, consists of the following shocks. The first shock, oil supply shock, is an unanticipated shift in the percentage change of the global production of crude oil. The Second shock, consumption demand shock (global demand shock), is a sudden change in the demand for crude oil and other industrial commodities. The third shock, speculative demand shock, is the shock to the demand for the above-ground oil inventories. This shock captures the changes in speculative demand for oil inventories that arises when the future oil supply is uncertain. The forth shock is called the residual shock and captures the short-run unanticipated change in the real price of oil which is not driven by the first three shocks. An example would be an abrupt change in the weather which increases the oil price in the short-run but it does not affect the other driving factors of the oil market. Finally, the last shock captures innovations in the real stock returns which is not driven by the factors operating inside the financial markets.

We estimate the VAR system with 24 lags. Applying 24 months of lags is consistent with Hamilton and Herrera [2004] and Kilian and Park [2009] who argue that allowing for high lag order is crucial in capturing the transmission of the structural shocks in the oil market. They provide evidence that moving cycles in the oil market are very slow and a low number of lag would fail to capture the whole dynamics of the cycle. The

[3] http://www.hec.unil.ch/agoyal/

alternative way of setting the lag order is testing the goodness of fit using information criteria. However, some researchers argue against the validity of such methods specially when there is a prior on the number of lags. For example Leeb and Potscher [2006] argue that any lag order selection based on data used in the analysis invalidates inference. Ivanov and Kilian [2005] conclude that where one has no prior information about lag length, for structural impulse responses in monthly VAR models, the AIC could be a good approach. However, according to Hamilton and Herrera [2004] there are strong claims about the value of lag order in the oil market based on prior studies and the AIC estimates would make a lower bound.

The reduced-form representation of equation 1.1 is given by:

$$y_t = A_0^{-1}\alpha + \sum_{i=1}^{24} A_0^{-1}A_i y_{t-i} + A_0^{-1}BX_t + e_t$$

and the vector of residuals, e_t, has the following relation with the vector of structural shocks, ε_t:

$$e_t = A_0^{-1}\varepsilon_t.$$

In order to identify structural innovations from the reduced-form residuals, we impose short-term exclusive restrictions on the matrix A_0^{-1} as follows.

$$\begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{3t}^{\Delta global\ oil\ inventory} \\ e_{4t}^{real\ price\ of\ oil} \\ e_{5t}^{real\ stock\ return} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ supply\ shock} \\ \varepsilon_{2t}^{global\ demand\ shock} \\ \varepsilon_{3t}^{speculative\ shock} \\ \varepsilon_{4t}^{residual\ shock} \\ \varepsilon_{5t}^{stock\ market\ shock} \end{pmatrix} \quad (1.2)$$

The identifying restrictions are based on the four assumptions. First, we assume that in short-run, that is within a month after a shock, changes in global oil production do not respond to global demand shock and other oil market shocks, as well as stock market shocks. This assumption complies with the real world because adjustment in oil production plan is very costly. The second assumption is that within a month, the increase in price of oil that is caused by speculative demand shock or other oil market shocks does not affect global real economic activity. The third assumption is that, in short-run, global oil inventory responds only to supply, global demand and speculative demand shocks. Finally, we assume that oil market variables do not respond to the shocks in the stock market.

In order to see how the results change if the stock market related variables are excluded from the model, we compare the results of the model 1.1 with the second model:

$$A_0 y_t = \alpha + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t, \tag{1.3}$$

where all the variables are defined as in model 1.1. Model 1.3 is the typical model applied in literature in the sense that it assumes that all the fluctuations in the stock market return are caused by the oil market. The results presented in the next sections will illustrate how this presumption leads to overestimation of the role of the oil market in expiating the stock market.

Model 1.1 is augmented and applied to analyze the connection between industries and the oil market. We modify model 1.1 in two directions. The first change is obviously adding the real return of the selected industries to the vector of endogenous variables, y_t, in model 1.1. Each industry is analyzed separately by estimating the model using the industry's return data. The second modification is that for each industry we construct an index to proxy the market return. The aim of this procedure is to exclude the contribution of the industry under consideration from the market return and facilitate the identification of the market wide shocks and the industry specific shocks. The index is constructed as the weighted average of the real return of all the industries excluding the industry under consideration, where the weights are the relative market value of each industry. The identification scheme is described in relation 1.4.

$$\begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{3t}^{\Delta global\ oil\ inventory} \\ e_{4t}^{real\ price\ of\ oil} \\ e_{5t}^{real\ stock\ return} \\ e_{6t}^{real\ industry\ return} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ supply\ shock} \\ \varepsilon_{2t}^{global\ demand\ shock} \\ \varepsilon_{3t}^{speculative\ shock} \\ \varepsilon_{4t}^{residual\ shock} \\ \varepsilon_{5t}^{stock\ market\ shock} \\ \varepsilon_{6t}^{industry\ specific\ shock} \end{pmatrix} \tag{1.4}$$

The identification assumptions in relation 1.2 are preserved in relation 1.4. The additional identifying restriction in relation 1.4 compared to relation 1.2 is that industry specific shocks do not affect aggregate market return within a month after the shock. The constructed index to proxy market return legitimizes such assumption because now any possible correlation between the market return index and an industry return should be driven by market wide shocks, like a surprising shift in the interest rates set by government and not industry specific shocks, like technological breakthroughs.

1.5 Estimation results

Figure 1.1 depicts the impulse responses of the U.S. real stock market return to the structural shocks in the crude oil market and the stock market shock resulted from estimation of the model 1.1. The impulse responses imply that an unexpected oil supply disruption does not significantly affect the real stock market return. On the other hand, an unanticipated positive shock in the global demand for oil has a positive effect on the real stock return which is persistent for about 9 months. This result is expected as a positive global demand shock is caused by an increase in real economic activity, reflected as a positive change in the real stock return. Therefore, in the short run, the U.S. stock market appreciates even though the real price of oil increases. The only cause of an oil price increase that makes a depreciation in the U.S. aggregate real stock return is speculative demand shock. A positive speculative demand shock causes a significant and persistent negative effect on the U.S. real stock return. This result is not surprising since investors decrease their demand for stocks as they rebalance their portfolios against the stock market by investing more on the oil market.

Table 1.1 reports the contribution of each shock to variations in the stock market return. Forecast error variance decomposition analysis indicates that in the long run, the explanatory power of all oil market shocks are larger than in the short run. In the long run (30 months after the shock), 16% of the variations of the U.S. real stock market return is explained by the structural shocks in the global crude oil market. Consumption demand shock with 5% and speculative demand shock with 4% show the largest contributions to the variability of returns and oil supply shocks explain only 2.5%.

To see how the presence of the stock market determinants is important in studying the connection between the stock market and the oil market, figure 1.2 and table 1.2 present the impulse responses and the results of variance decomposition resulted from model 1.3. The results of model 1.3 suggest that the dynamics of the responses of the stock returns to the oil market shocks is similar to the results obtained from model 1.1. Compared to oil supply shocks, consumption demand and speculative demand shocks play more important role in explaining the variation of the U.S stock returns. However, the important difference is that the contribution of all oil market shocks is larger in model 1.3 compared to model 1.1. In the long-run (30 months after the shock), more than 18% of the variations of the U.S. real stock market return is explained by the shocks in the oil market. This result provides evidence that omitting stock market variables leads us to overestimate the role for oil market shocks in explaining the variations in the stock market return.

1.6 Industries and the oil market

In this section, the structural analysis in performed based on the industry level data for both oil intensive and non-oil intensive sectors. This analysis is crucial to find out the channels through which oil price shocks affect aggregate stock market returns. As industries do not respond homogeneously to oil price shocks, aggregate stock market responses may mask the performance of different sectors which are not necessarily uniform. Some sectors may be affected more severely by these shocks due to the high level of oil usage as an input for manufacturing, or the change in demand for their output.

To see the importance of market return index in explaining industry returns, the results from regressing each industry return on driving variables of stock market are shown in tables 1.3 and 1.4. In both tables the odd columns show the regression results of the industry return on the stock market variables excluding the index for aggregate stock market return and the even columns show the results from the same regression including aggregate return index. The coefficients on aggregate stock return are highly significant, both statistically and economically. It varies from as low as 0.5 for the case of gold to 1.3 for the case of steel. Interestingly, except for auto industry, the results show that including aggregate return in the regressions makes the coefficient on other variables statistically insignificant, while in the absence of it they are mostly statistically significant. This result confirms the importance of including aggregate return to the model that analyzes the responses of industries to oil market shocks.

Figure 1.3 depicts the impulse response of the selected industries to a negative oil supply shock. The figure suggests that the industries that have negative response to supply shocks are not necessarily the oil intensive industries. The responses of industries to a positive global demand shock are graphed in figure 1.4. As shown in this figure, all the selected industries respond positively to a global demand shock. This finding is consistent with the fact that this shock is driven by an increase in the real economic activity which increases the demand for all industrial commodities. This figure also suggests that after a period, the return of all industries decreases to its initial level. This is because the higher price of oil decreases real economic activity and hence the demand for the industrial commodities declines. A positive shock to the speculative demand for oil, as shown in figure 1.5, affects negatively almost all of the industries with a delay. The exceptions are oil and precious metals industries. Overall, the results form impulse response analysis imply that the total cost of energy it is not enough to explain differences in the responses of real returns across industries, which is against the interpretation of oil price shocks as aggregate cost shocks.

Table 1.5 presents the FEVD, the contribution of each structural shock in forecasting industries return. The industries are sorted in their cost of oil for each dollar of their output. No systematic pattern in terms of oil use and the responses to an oil supply shock is seen. This suggests that the transmission of oil market shocks to the industries returns is driven not only by shifts in the the cost of production but also by shifts in final demand for goods and services.

1.6.1 Automobile and trucks

The automobile and trucks industry is considered in the literature as being very responsive to oil price shocks and it is known as the most relevant channel through which oil shocks affect the economy (see e.g., Hamilton [1988] and Ramey and Vine [2010]). The consensus in the literature is that, specially in the long-run, the oil market affects the manufacturing industries through the demand for final product by shifting toward high fuel efficiency. This is because an increase in gasoline price reduces demand for these industries through income effect. As these industries are not oil intensive, oil price shocks are shocks to the demand for their goods and services. For example, Lee and Ni [2002] and Ramey and Vine [2010] provide evidence that the demand for full-size cars with low fuel efficiency collapses in response to an oil price increase. They explain that a permanent increase in gasoline price causes households to cut back on vehicle travel in the short run and then to make appropriate adjustments to their vehicle stock in the long run. Hughes et al. [2008] report that the long-run price elasticity of gasoline consumption is seven times larger than the short-run elasticity. According to their empirical evidence, households drive more compared to early 1970s, but they do so in vehicles that are more fuel efficient.

The empirical results of this paper show that, contrary to the common perception, depending on the cause behind the oil price increase, some of the strongest responses to oil shocks are found not only in the auto industry, but also in other industries like consumer goods and services. This result is in contrast with the view that oil price shocks are mostly cost shocks. The impulse responses show that an increase in the price of oil due to the production disruption has no significant effect on automobile stock price movements. An increase in global demand causes automobile shares to appreciate for about ten months. The effect of a positive shock to speculative demand for oil is negative after about 5 months of delay.

1.6.2 Petroleum and Natural Gas

Ready [2013] argues that oil industry enjoys a natural hedge against the negative supply shock since after a supply disruption the lower production and the higher price net out. This view is consistent with figure 1.3 where a small positive response to an oil supply shock could be noticed. After about 8 months, the response turns negative and still very small which could be justified with a reduction in demand for crude oil resulted from increased energy conservation. In contrast, a positive global demand shock causes a persistent increase in the petroleum and natural gas stock return. A speculative demand shock has a delayed negative effect on the value of this industry's stock. The small positive response to supply shocks and the negative response to speculative demand shocks could be an evidence that the oil industry does not appreciate from political disturbances driving production disruptions.

1.6.3 Precious Metals

The impulse responses show that gold and silver industries appreciate significantly in response to a positive shock to global economic activity. An unanticipated increase in global demand driven by higher economic activity is taken as a signal of inflation and as a result the demand for gold and finally the gold industry appreciates. The other view about the effect of demand shock of gold industry which seems to be less strong is, during periods of high economic activity, investment in gold (increasing gold reserve) decreases as stock prices increase. However, unlike most of industries, this industry does not depreciate after a speculative demand shock. This result is consistent with the view that when stock prices fall in times of political uncertainty, investors increase their demand for precious metals.

1.6.4 Steel

Although metals are usually considered as highly energy intensive the main energy source for these industries is coal. For example, the total cost of coal for each dollar of revenue of iron and steel is eight cents, about twice as much as the cost of oil for this industry (Lee and Ni [2002]). Therefore, the cost effect of oil price shock on the steel industry is not as high as expected. On the demand side, an increase in price of oil raises the demand for steel in sectors like rig and pipeline building. This could explain why steel industry does not depreciate after a negative oil supply shock. The negative response to a positive speculative demand shock is due to the reduction in demand for steel and aluminum given the lowering effect of this shock on auto sales.

1.7 Conclusion

This paper provides a comprehensive analysis of the response of the U.S. real stock market return to the structural shocks in the global market for crude oil. On the aggregate level, the findings show that the responses to oil price shocks differ depending on the causes behind the shocks. The only underlying cause of an oil price shock that depreciates aggregate stock market is the shock to speculative demand for oil. A positive global demand shock raises the market return for ten months and lowers it afterwards. An oil supply shock does not affect significantly the aggregate stock market return. We argue that it is important to consider both stock and oil markets determinant variables in the analysis of the link between the two markets as omitting the stock market determinants from the analysis leads us to overestimate the contribution of oil shocks in the variations of the stock market return.

On the industry level, the estimation results show that the way oil price fluctuations affect each industry depends on the cause that drives the oil price shock, as well as on the industry characteristics. All industries appreciate after a global demand shock. This is because a positive global demand shock increases global real economic activity and also increases the demand for almost all industries. We did not find a systematic pattern for the responses of industries to an oil supply shock in terms of the level of oil-intensity of the industries. This could be an evidence that an increase in oil price due to a negative oil supply shock works through consumer spending as well as higher cost for production.

The results show that most of the industries depreciate in response to a speculative demand shock with some months of delay. The exception are precious metals and oil industries. This is consistent with the fact that speculative demand shocks are driven by expectations about the availability of future oil supplies. The results imply that the responses of industries' returns to an oil supply shock and to a speculative demand shock are positively correlated with the cost of oil for those industries. This suggests that cost side effect matters for the differences in the responses of real stock returns across industries. However, this effect is not enough to explain those differences since no such relation is found regarding the responses to a global demand shock. The estimation results suggest that both cost side dependence and demand side dependence on oil are important in explaining the sensitivity of industries' returns to oil price changes. More interestingly the demand side effect appears to be stronger.

Table 1.1: Variance decomposition of the U.S. real stock market return from estimation of model 1.1

Horizon	Oil supply shock	Global demand shock	Speculative demand shock	Other oil market shocks	other stock market shocks
2	.52	.16	.14	1.08	98.09
3	.51	.71	.44	2.031	96.31
12	2.26	6.07	3.46	2.85	85.36
13	2.23	6.31	3.65	3.32	84.49
15	2.99	6.39	5.08	3.68	81.86

Table 1.2: Variance decomposition of the U.S. real stock market return from estimation of model 1.3

Horizon	Oil supply shock	Global demand shock	Speculative demand shock	Other oil market shocks	other stock market shocks
2	.59	.15	.63	1.88	96.75
3	.61	1.08	.77	2.62	94.92
12	2.20	5.13	3.27	3.06	86.34
13	2.18	5.11	3.66	3.36	85.69
15	2.58	5.15	4.25	3.83	83.92

Table 1.3: Results of regressing each industry return on the stock market variables without and with inclusion of the index for aggregate stock market return.

	hshld	hshld	steel	steel	autos	autos	aero	aero
mrkt ret		0.774***		1.270***		1.045***		1.093***
		(22.04)		(23.80)		(19.27)		(22.40)
dividend	-0.0186***	-0.00715	-0.0259**	-0.00696	-0.0256**	-0.0102	-0.0173*	-0.000867
price ratio	(-3.43)	(-1.85)	(-3.04)	(-1.19)	(-3.28)	(-1.72)	(-2.29)	(-0.16)
return	-3.176***	-0.531	-5.174***	-0.844	-5.081***	-1.544**	-4.383***	-0.653
volatility	(-7.18)	(-1.59)	(-7.44)	(-1.67)	(-7.94)	(-3.00)	(-7.11)	(-1.41)
default	1.771**	0.615	2.147*	0.233	3.485***	1.960**	2.121**	0.472
spread	(3.11)	(1.51)	(2.39)	(0.38)	(4.23)	(3.13)	(2.67)	(0.84)
long term	-0.146	0.229*	-1.210***	-0.608***	-1.118***	-0.622***	-0.593**	-0.0760
rate of ret	(-1.03)	(2.25)	(-5.43)	(-3.96)	(-5.46)	(-3.98)	(-3.00)	(-0.54)
corporate	0.590***	-0.104	1.417***	0.283	1.394***	0.461*	0.929***	-0.0431
bond ret	(3.74)	(-0.90)	(5.71)	(1.62)	(6.11)	(2.59)	(4.23)	(-0.27)
net equity	-0.126	-0.0578	0.0344	0.150	0.0271	0.125	-0.0690	0.0293
expansion	(-1.12)	(-0.73)	(0.20)	(1.25)	(0.17)	(1.02)	(-0.44)	(0.27)
constant	-0.0756**	-0.0316	-0.101**	-0.0274	-0.115***	-0.0557*	-0.0669*	-0.00306
	(-3.19)	(-1.87)	(-2.71)	(-1.08)	(-3.36)	(-2.14)	(-2.03)	(-0.13)
r2	0.1770	0.5902	0.1909	0.6280	0.2157	0.5569	0.1493	0.5833

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.4: Results of regressing each industry return on the stock market variables without and with inclusion of the index for aggregate stock market return.

	gold	gold	oil	oil	trans	trans
market ret		0.497***		0.647***		1.022***
		(4.22)		(12.91)		(27.28)
dividend price ratio	-0.0163	-0.00881	-0.0136*	-0.00338	-0.0153*	0.0000306
	(-1.25)	(-0.68)	(-2.12)	(-0.61)	(-2.36)	(0.01)
ret volatility	-2.706*	-1.006	-2.772***	-0.511	-3.627***	-0.133
	(-2.54)	(-0.90)	(-5.29)	(-1.05)	(-6.86)	(-0.37)
default spread	3.052*	2.300	0.621	-0.470	1.797**	0.255
	(2.22)	(1.69)	(0.92)	(-0.80)	(2.64)	(0.59)
long term rate of ret	-0.477	-0.240	-0.563***	-0.262	-0.484**	0.00365
	(-1.40)	(-0.71)	(-3.36)	(-1.79)	(-2.86)	(0.03)
corporate bond ret	0.855*	0.411	0.815***	0.232	0.855***	-0.0567
	(2.25)	(1.06)	(4.36)	(1.38)	(4.54)	(-0.46)
net equity expansion	0.170	0.215	-0.106	-0.0523	-0.132	-0.0404
	(0.63)	(0.81)	(-0.80)	(-0.46)	(-0.99)	(-0.48)
constant	-0.0847	-0.0557	-0.0417	-0.000875	-0.0606*	-0.00112
	(-1.49)	(-0.99)	(-1.49)	(-0.04)	(-2.14)	(-0.06)
r2	0.0388	0.0731	0.1100	0.3386	0.1545	0.6677

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.5: Long-run variance decomposition of selected industries' return

	oil use	oil supply shock	global demand shock	speculative demand shock	other oil market shocks	other stock market shocks	industry shock
oil	0.0	5.0687	6.5499	2.5521	8.5068	21.3156	56.007
aero	0.011	6.7125	5.3515	5.5317	5.0433	37.0748	40.2862
auto	0.015	3.8152	10.0918	7.546	7.2716	35.2333	36.0422
hshld	0.021	4.5404	7.0714	6.3848	6.5545	35.2036	40.2453
steel	0.023	5.0056	5.5713	7.1523	5.2367	42.8745	34.1596
gold	0.046	5.136	5.3152	5.3772	5.036	6.5946	72.541
trans	0.050	6.0408	4.8956	10.2999	5.4709	40.5653	32.7276
Chems	0.103	7.4778	6.1056	8.3571	4.6688	44.0234	29.3674

Figure 1.1: Structural impulse responses of stock market return from estimation of Model 1.1.

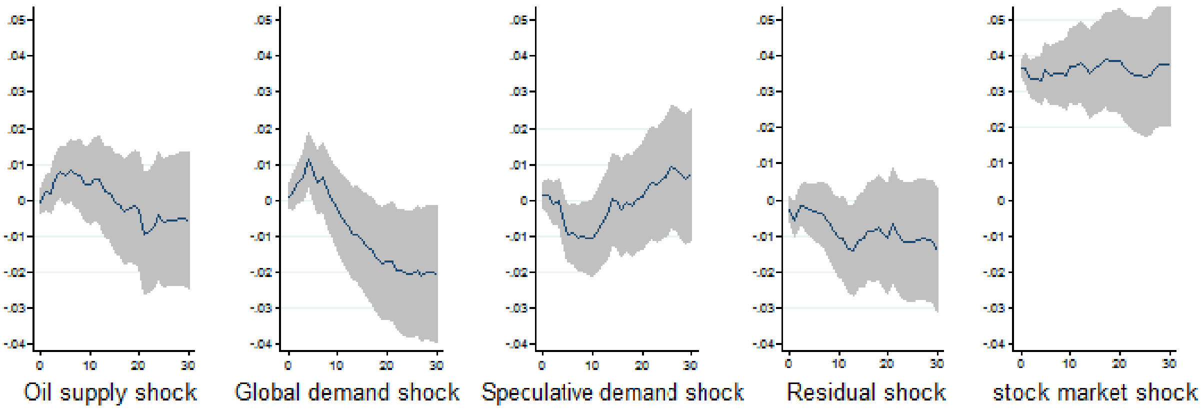


Figure 1.2: Structural impulse responses of stock market return from estimation of Model 1.3.

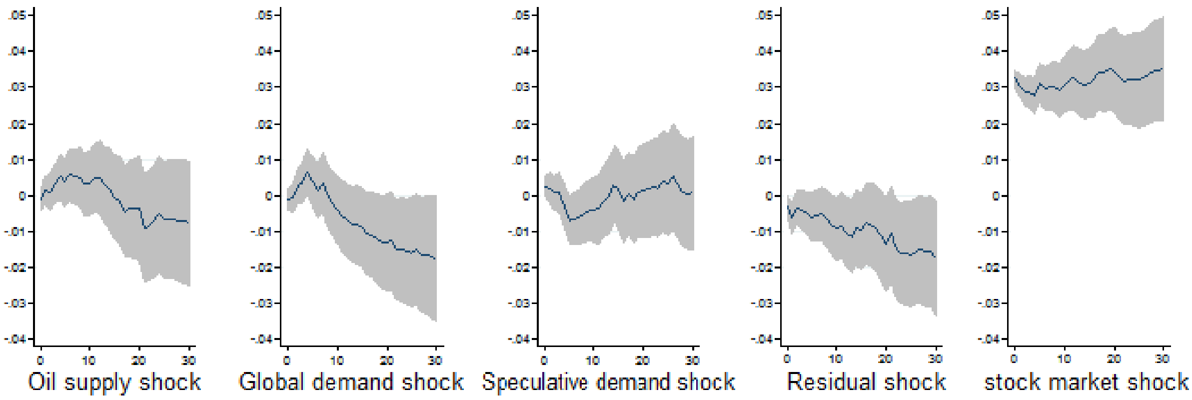


Figure 1.3: Structural impulse responses of selected industries to an oil supply shock: 1973:3-2013:12

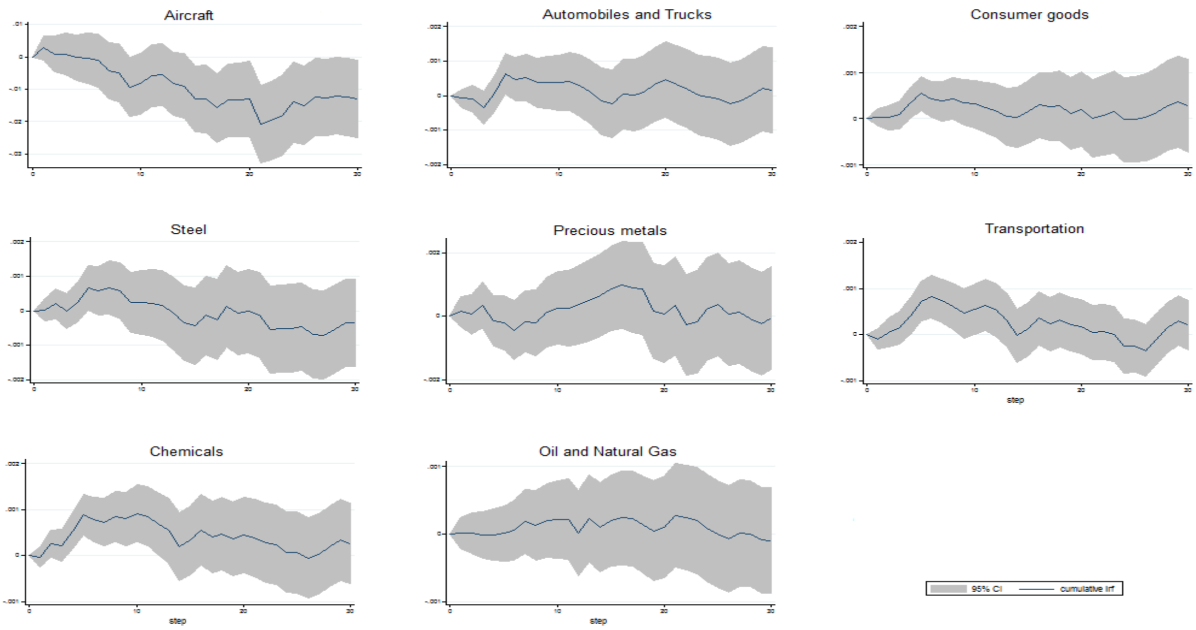
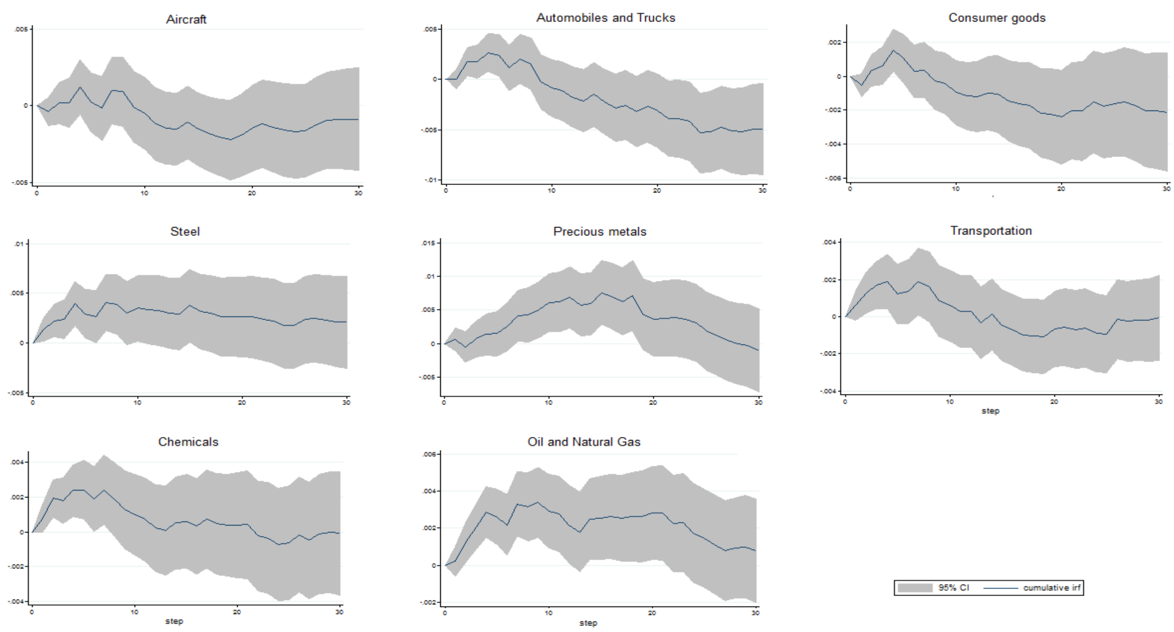


Figure 1.4: Structural impulse responses of selected industries to a global demand shock: 1973:3-2013:12



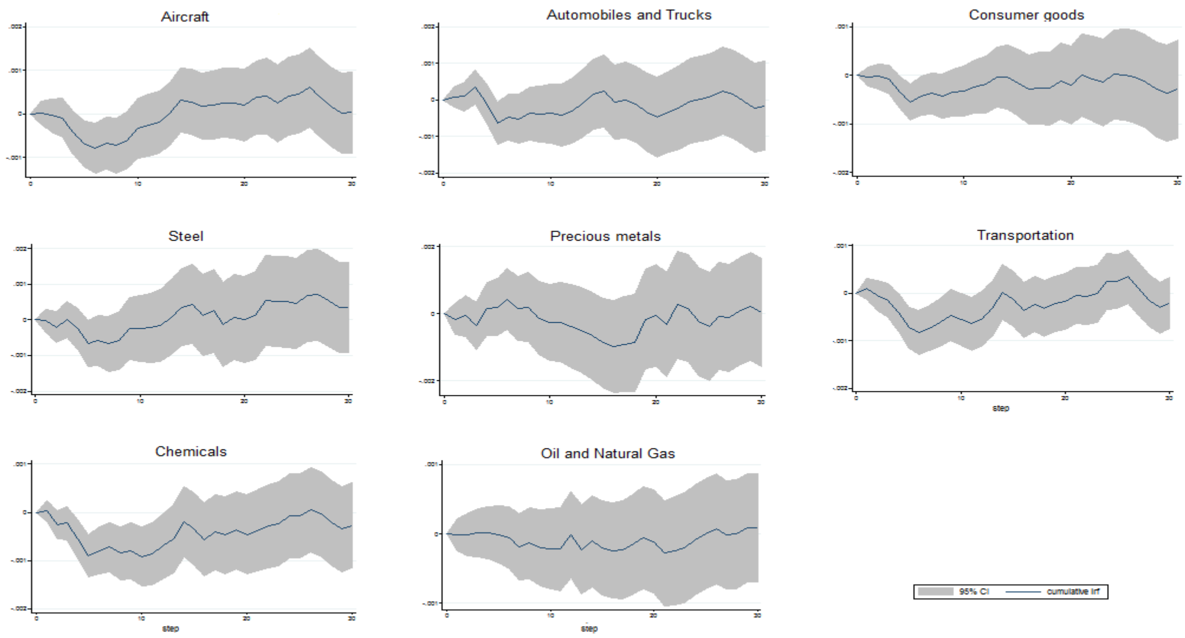


Figure 1.5: Structural impulse responses of selected industries to a speculative demand shock: 1973:3-2013:12

Chapter 2

How is volatility in commodity markets linked to oil price shocks?

2.1 Introduction

In recent years the linkages between oil prices and non-energy commodities prices, including agricultures and metals have increased. This is the result of two main reasons, the substitution of fossil fuels by biofuels as well as the hedge strategies against inflation caused by higher oil prices, (see, Ji and Fan [2012]). The linkage channels between oil and commodity prices are not identical for agricultures and metals. This linkage between agricultures and oil can potentially be explained via three main channels. First, when the increases in the price of oil resulted from a better global economic activity, demand for food increased as well, since the higher income level of emerging economies altered the food consumption pattern. Some authors such as Hochman et al. [2012] and Baumeister and Peersman [2013] assert that this is the most important channel through which oil price shocks affect agricultural commodities. Second, an increase in the price of oil resulting from any kind of shock might trigger demand for biofuels. This increases demand and, consequently, the price of corn, soybeans and other substitute and complementary crops. Furthermore, the increase in production of ethanol after May 2006 caused an additional increase in corn demand for ethanol production, which might have led to a closer link between energy and corn prices. This affects the price of other agricultural products as well, since corn competes with those commodities for fertilizer, scarce water and land sources (Baumeister and Peersman [2013]). The third channel of linkage is that an increase in the price of oil raises the production cost of agricultures, including transportation costs and fertilizers prices, which lead to higher agricultural production prices.

The potential linkage channels between oil and metal prices are rather different from those of agricultures. First, when better economic activity raises global oil demand and enhances oil price, it also increases demand for industrial metals such as copper and silver, as an input to the economy. Second, when oil price increases, the general price level of commodities rises (see, Hunt [2006] and Hooker [2002]). This inflationary effect of oil price is the most important channel of effect on gold price. Third, according to Hammoudeh and Yuan [2008] higher commodity prices resulting from an oil price shock lead to a tightening in monetary policy that enhances the interest rates. The authors argue that the rise in interest rates in interest rates impacts on commodity returns and volatility through multiple macroeconomic channels. For instance, changes in interest rates affect the building construction industry which uses copper and silver heavily, among other metals, and they impact consumer demand for durable goods, which use industrial metals in their manufacturing processes. Fourth, an increase in the price of oil boosts metal prices via the transportation and production costs. However, the question that arises is why after an oil price shock, volatility in commodity markets rises while both commodity and input prices are increasing, despite the fact that an increase in commodity prices is usually good news for producers. This is well described by FAO [2012] for agricultural commodities. It is argued that although price increases are good news for producers, the input prices of oil-based fertilizers, in particular, can increase more quickly than the output prices, which makes producers lose rather than gain benefit. On the other side, there are transport and storage restrictions as well as lack of access to inputs and credit, which prevent producers from investing properly on higher prices. This is a more serious problem for poor food producers, as for them price volatility means uncertainty and higher risk, which prevent enough investments to increase food production and to reduce vulnerability. As a result of these problems, most developing countries experienced a low level of supply response to the high prices of 2007-2008, which led to higher volatility in agricultural market. It is well documented in the relevant literature that an increase of commodity prices is bad news for commodity market consumers and consequently increases the volatility in these markets (see, Carpantier [2010]). Nevertheless, in this study we depart from the previous investigations and we assert that not all oil price shocks identically effect volatility of commodity prices, and the responses of volatility to the oil price shocks depend on the driver behind each shock.

Among the existing literature on this issue, a number of studies focus on the area of volatility spillover between commodity and energy markets using the bivariate or multivariate GARCH-type models, while a number of studies examine the relation between oil and commodity prices applying the cointegration and the Granger causality procedures as well as VAR and structural VAR models to examine this relationship. The relevant literature will be described in details in the next section. The majority of these studies apply the conventional approaches in which commodity prices respond to exogenous changes in oil price. Kilian [2009a] states that these approaches are not completely satisfying as the price of oil is endogenous, and it is driven by its fundamental factors, including demand and supply, and each shock has a different effect on the real price of oil and hence on the economy. Kilian [2009a] performs a structural decomposition of the real price of oil into three components, including oil supply shocks, shocks to global demand for all industrial commodities and other oil-specific demand shocks. Using a structural VAR approach the author analyzed the effects of these shocks on the U.S. GDP and found that the effects depend on the cause of the shocks. Subsequently, Kilian and Park [2009] consider the endogeneity of oil price with respect to the same decomposition and analyze their effects on the U.S. stock market. They obtained the same conclusion for the stock market as the one Kilian [2009a] had obtained for the U.S. GDP. Subsequently, Kilian and Murphy [2014] identify shocks to speculative demand for oil from oil-specific demand shocks in the previous model. This shock is proposed to capture the shifts in oil price caused by higher demand in response to the uncertainty of future oil supply.

Among studies on the linkage between oil and commodity prices, Wang et al. [2014] analyzed the effect of oil price shocks on agricultural prices employing a structural VAR framework. They found that the amount, duration and signs of responses of agricultural prices to an oil price shock differ depending on the reason behind the shock.

The aim of this study is to extend the literature by investigating the effects of different oil-related shocks on the volatility of selected agricultural and metal commodities. The analysis is based on a structural VAR model, which relates oil price to its driving factors, namely oil supply shock, global demand shock and speculative demand shock.

First, we use real daily futures returns for commodities from April 1983 to December 2013, to measure the conditional volatilities applying the GARCH approach. Then, we convert the obtained volatility series to monthly data to use within the structural VAR model.

We apply the data of global oil production as a proxy for global supply, the global real activity index proposed by Kilian [2009a] to quantify the global oil demand and the above-ground oil inventory level to quantify speculative demand in the oil market. Following Baumeister and Peersman [2013] that state that the relationship between oil and agricultural commodity prices had fundamentally changed since May 2006, and in order to take into account the 2006-2008 food crisis, we divide the agricultural data time span into two subsamples, from April 1983 to April 2006 (pre-crisis period) and from May 2006 to December 2013 (post-crisis period). Moreover, to take into account the role of the 2008 global financial crisis for the analysis of metals, we divide its relevant data time span into two subsamples, from April 1983 to December 2007 (pre-crisis period) and from January 2008 to December 2013 (post-crisis period). In order to check for the validity of this time span division, we perform a historical decomposition analysis, to estimate the individual contribution of each shock to the dynamics of volatilities. The historical decomposition demonstrates the relative importance of the shocks in explaining volatility movements, therefore the explanatory power of each individual shock would be observable before and after the crises.

To the best of our knowledge, this is the first study that considers the endogeneity of oil prices in order to assess the effects of oil shocks on volatility of commodity prices, and the first which distinguishes the impacts of oil factors, including supply and speculative shocks from the impacts of macroeconomic factors. We use the measure of volatility rather than price, as the growing role of commodities in financial markets and of financialization in commodity markets has increased the importance of volatility in these markets. The results of this study provide advantages for investors in terms of hedge strategies and risk management to lower the risk of investment during oil price shocks.

This article is structured as follows. Section 2 provides a review of the literature. Section 3 describes the data. Section 4 presents the applied econometrics methodology. Section 5 reports the empirical results and discussion. Section 6 shows a robustness check. The conclusion is provided in section 7.

2.2 Literature review

There is a vast number of studies that examine the relationship between oil and non-energy commodity markets. In what follows we describe the existing literature and we provide the contribution of this study.

The first group of studies examines the relationship between oil and commodity markets using cointegration and error correction, VAR and structural VAR models. Among studies related to the agriculture-oil nexus, Campiche et al. [2007] apply a Johansen cointegration test during the 2003-2007 period, and reveal no cointegration between agricultures and oil during the 2003-2005 period, however corn and soybean are cointegrated with oil during the 2006-2007 time period. Hammoudeh et al. [2010] use the ARDL model during the 2005-2008 period, and indicate that the grain price is significantly affected by the price of oil and other grain prices. Saghaian [2010] applies the Johansen cointegration and VECM procedure during the 1996-2008 period, and finds that oil and agricultures are cointegrated and causality runs from oil to agricultural prices. Serra

et al. [2010] use a smooth transition VEC model and Generalized impulse response functions in the US from 2005 to 2007, and confirm that a shock to oil and corn prices causes a change in ethanol price. Nazlioglu and Soytas [2012] use the Toda-Yamamoto causality procedure and Generalized impulse response function during the 1994-2010 period, and reveal that the Turkish agricultural prices do not significantly react to oil price and exchange rate shocks. Nazlioglu and Soytas [2012] use the Pedroni panel cointegration test during the time 1980-2010 period, and show that oil price significantly affects agricultural prices. Esmaeili and Shokoohi [2011] apply a principal component analysis between 1961-2005, and find that oil price affects the food production index. Cha and Bae [2011] employ a structural VAR model with sign restriction in the US during the 1986-2008 period, and show that an increase in oil price raises the demand for corn as well as its price. Ciaian and Kancs [2011] apply the Johansen cointegration test during the 1994-2008 period, and reveal that energy prices affect prices for agricultural commodities and that the interdependencies between the energy and food markets are increasing over time. Reboredo [2012] uses copulas approach during the 1998-2011 period, and finds weak oil-food dependences and no extreme market dependence. Liu [2014] applies the ARDL cointegration test, the Granger causality model and the Generalized forecast error decomposition. He finds that there is no strong long-run equilibrium relationship between oil and agricultural volatility indices.
Furthermore, among studies related to metals-oil markets nexus, Hammoudeh et al. use the Toda Yamamoto causality procedure during the 2003-2007 period, and find that oil price does not Granger cause the precious metals prices in Turkey. Sari et al. [2010] apply the Johansen-Juselius, the ARDL cointegration approaches and the generalized impulse response functions between 1999 and 2007. They confirm the positive responses of gold, silver and platinum to oil price increases. Zhang and Wei [2010] apply the Engle-Granger cointegration and the VECM procedure during the 2000-2008 period, and reveal that the oil price Granger causes the gold price, but not vice versa.

In a new generation of studies, following Kilian [2009a]'s structural VAR model based on oil price decomposition methodology, Qiu et al. [2012] use the structural VAR model to decompose supply-demand structural shock effects on corn and fuels prices. The fuels prices include oil, ethanol and gasoline during the 1994-2010 period. The results reveal that fuels market shocks do not spillover into the corn market, however the fundamental market factors of corn are the main drivers of corn prices. Applying the same methodology Wang et al. [2014] use the structural VAR model to decompose oil price shocks during the 1980-2012 period. Their findings show that the responses of agricultural commodity prices to an oil price shock depend on drivers behind the shock. Moreover, they find that oil market shocks have stronger effects on agricultural commodity price variations after the food crisis in 2006-2008 than the period before.

The second group of studies examines volatility spillover between non-energy commodities and oil markets employing the univariate and multivariate GARCH-type models. In this context, Hammoudeh and Yuan (2008) apply the univariate GARCH-type models during the 1990-2006 in favor of the impact of oil price on return, and find strong evidence in favor of the impact of oil price on return and volatility of silver, weak evidence of effect on volatility of gold and no effect on copper. Choi and Hammoudeh [2010] use a DCC-GARCH model during the 1990-2006 period, and find an increasing correlation between oil and industrial commodities since the 2003 Iraq war but decreasing correlations with the S&P 500 index. Du et al. [2011] use stochastic volatility models to oil, corn and wheat prices in 1998-2009, and confirm volatility spillover among oil, corn and wheat after the fall of 2006. Serra [2011] uses the semi-parametric GARCH model with data in 2000-2008. He considers price links between oil, ethanol and sugar in Brazil and finds strong volatility links between them. Ji and Fan [2012] use the EGARCH model over the 2006-2010 period and consider the US dollar index as an exogenous shock. They divide the sample into before and after the 2008 financial crisis and find that the oil market has significant volatility spillover effects on non-energy commodity markets and that the influence of the US dollar index on commodity markets has weakened since the 2008 crisis. Nazlioglu et al. [2013] apply newly developed causality in the variance test on the period from 1986 to 2011. Based on impulse response functions they show that in the post 2006 food crisis oil market volatility is transmitted to agricultural markets, with the exception of sugar, while there was no risk of transmission in the pre-food crisis period. Gardebroek and Hernandez [2013] use the VAR-GARCH approach during the 2000-2008 period. The results show a higher correlation between ethanol and corn markets particularly after 2006, and significant volatility spillover from corn to ethanol price but not the converse. However they do not find major cross market volatility effects running from oil to corn. Wu and Li [2013] analyze volatility spillovers in China's oil, corn and ethanol markets during the 2003-2012 period, employing the univariate EGARCH and the BEKK-MVGARCH models. The results indicate a higher interaction among oil, corn and fuel ethanol markets after September 2008. Liu [2014] investigates cross-correlations between oil and agricultural commodity markets in 1994-2012, using a de-trended cross-correlations statistical analysis, and provides that volatility cross-correlations are highly significant. And finally Mensi et al. [2014] apply the VAR-BEKK-GARCH and the VARDCC-GARCH models, and find evidence in favor of significant linkages between energy and cereal markets. Moreover, the OPEC news announcements are found to exert influence on oil markets and on oil-cereal relationships.

In this study we extend the above described literature examining the effects of oil price shocks on the volatility of commodity prices from a different point of view. We distinguish the impacts of oil specific factors, including oil supply and speculative demand shocks from the macroeconomic factor. Moreover, we consider the measure of volatility rather than the price of commodities, in order to provide a perspective of risk in commodity markets during different oil price shocks.

2.3 Data description

We use real daily futures closing prices for commodities. First we obtain nominal three months ahead futures prices for metals, including copper, gold and silver traded on NYMEX, nominal one months ahead futures prices for agricultures, including coffee traded on NYBOT, corn, soybean, sugar and wheat traded on CBOT, and WTI crude oil traded on NYMEX. Then, nominal prices are divided to the U.S. CPI (2010=100) obtained from the WDI to achieve real prices. The real prices are converted to log returns by means of $R_t = \log(\frac{P_t}{P_{t-1}})$, where R_t is the corresponding return and P_t is the corresponding price series.

All the return series have a Kurtosis statistic greater than three. Therefore the series contain fat tails and have a negative skewness statistic suggesting the presence of a left fat tail, expect for coffee and sugar that show a right tail. Moreover the Jarque-Bera statistics indicate non-linearity for all return series at the 1% level of significance.

The residual diagnostics tests suggest existence of an ARCH effect for all returns at the 1% level of significance; thus the returns of metals suffer from heteroskedasticity, up to one lag, and according to the Ljung-Box Q-test for residuals, there are enough evidences for presence of serial correlation up to 10 lags. In order to check for stationary properties of series we apply the Augmented Dickey and Fuller (1979) (ADF) and the Phillips and Perron(1988) unit root tests. According to both tests the level of commodity prices contain unit roots and their returns are stationary. The description of returns are shown in table 2.1. According to the above described specifications the returns of commodities are suitable for applying the GARCH approach to measure volatility. The GARCH estimations are shown in table 2.2.

In the next step, we convert the obtained volatility series to monthly data, to investigate the effects of different oil price shocks on volatility of selected commodities. The applied data for the crude oil market include the percent change in global crude oil production, a measure of global real economic activity, the change in above ground oil inventory and the change in the real price of oil. Following Kilian and Murphy [2014] we use inventory data to quantify speculation in the oil market. The relevant data for global crude oil production is obtained from the Monthly Energy Review of the Energy Information Administration (EIA). Data for global real activity, introduced by Kilian [2009a] is based on data for global dry cargo shipping rates, as a new measure of global business cycle. It is stationary by construction and and it is available on a monthly basis since the early 1970s.. This measure captures shifts in the global use of industrial commodities. Furthermore, due to the lack of data on global crude oil inventories, following Kilian and Lee [2013] and Kilian and Murphy [2014] we apply a proxy for global crude oil inventories, which is the ratio of OECD petroleum stocks over the U.S. petroleum stocks. Those data are obtained from the Energy Information Administration (EIA).

The time span is from April 1983 to December 2013, which is based on data availability for all series. This has the advantage of covering the 1997 Asian financial crisis, the 2006-2008 food crisis, the 2008 stock market crash, the 2008 global financial crisis and the 2008 and 2012 oil price shocks.

2.4 Methodology

We estimate the effects of oil shocks on volatility of commodities within the framework of SVAR.

To achieve this goal, first we calculate the conditional volatility of commodities within a GARCH framework developed by Bollerslev [1986]:

$$y_t = \beta' x_t + \varepsilon_t \tag{2.1}$$

$\varepsilon_t = z_t\sqrt{h_t}, \quad \varepsilon_t \sim N(0, \sqrt{h_t}), \quad z_t \sim i.i.d.N(0,1)$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-j} \tag{2.2}$$

Where ε_{t-i}^2 denotes the ARCH term and h_{t-i} denotes the GARCH term. We select the appropriate models based on the ARCH test, serial correlation and the Akaike Information Criteria (AIC). Accordingly, the chosen model for corn, soybean, sugar and wheat is the AR(1)-GARCH(1,1) model and the chosen model for coffee, copper, gold and silver is the AR(1)-GARCH(2,1) model. The parameters should satisfy $\alpha_0 > 0,\ \sum_{i=1}^{p} \alpha_i \geq 0\ and\ \sum_{i=1}^{q} \beta_i \geq 0$, to guarantee the non-negative conditional variance. Bollerslev [1986] shows that the necessary and sufficient condition for the second order stationarity of the GARCH(p,q) model is $\sum_{i=1}^{p} \alpha_i + \sum_{i=1}^{q} \beta_i < 1$, which is satisfied for all estimations of this study. The results of the variance equation of the GARCH model, the second moment condition and the relevant diagnostic tests are shown in table 2.2.

In the next step, we convert the daily volatility series to monthly, in order to investigate the effects of different oil price shocks on volatility of commodities. A structural vector autoregressive (SVAR) model is used to investigate the time-varying impact response of volatility of different commodities to different oil market shocks, namely, oil supply shock, global demand shock and speculative demand shock. The analysis is based on a dynamic simultaneous equation model in the form of a structural VAR as follows.

$$A_0 y_t = \alpha + \sum_{i=1}^{12} A_i y_{t-i} + \varepsilon_t \tag{2.3}$$

Where y_t is the vector of endogenous variables including the percent change in global crude oil production, a measure of global real economic activity, the change in global crude oil inventories above the ground, the change in the real price of crude oil and volatility of the commodity that is under study. ε_t is the vector of structural shocks that is assumed to be unconditionally homoscedastic, and its variance-covariance matrix is normalized such that $E(\varepsilon_t \varepsilon_t') = \Sigma_u = I$. The first shock, the oil supply shock, is the shock to the global production of crude oil. The Second shock, the global demand shock, is the shock to consumption demand for crude oil and other industrial commodities. The third shock captures the changes in speculative demand for oil in response to increased uncertainty about future oil supply shortfalls. The fourth shock is residual shock that captures other oil market shocks that are not captured by the first three shocks, like weather shocks. Finally, the last shock is the shock to volatility of each commodity.

2.4.1 Identification

The reduced-form of representation of equation 2.3 is given by

$$y_t = A_0^{-1}\alpha + \sum_{i=1}^{12} B_i y_{t-i} + e_t \tag{2.4}$$

where $B_i = A_0^{-1} A_i$ and $e_t = A_0^{-1}\varepsilon_t$, the vector of residuals, are estimated from the reduced form VAR model (2.4). The elements of A_0^{-1} can be obtained from

$$\Sigma_e = E(e_t e_t') = A_0^{-1}\Sigma_\varepsilon A_0^{-1'},$$

if the number of unknown parameters of A_0^{-1} is not larger than the number of equations. Therefore in order to uniquely identify the elements of A_0^{-1} we need to impose some restrictions on it. Following Kilian [2009a] we employ short-term recursive exclusive restrictions.

$$\begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{3t}^{\Delta global\ oil\ inventory} \\ e_{4t}^{\Delta real\ price\ of\ oil} \\ e_{5t}^{volatility} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ supply\ shock} \\ \varepsilon_{2t}^{global\ demand\ shock} \\ \varepsilon_{3t}^{speculative\ shock} \\ \varepsilon_{4t}^{residual\ shock} \\ \varepsilon_{5t}^{volatility\ shock} \end{pmatrix}$$

There are five assumptions that are discussed in the following.
First, we assume that, within a month, crude oil supply responds only to the oil supply shocks among all the shocks in the model. This assumption is made based on the high production adjustment cost and the fact that the price elasticity of crude oil supply in the short-term is extremely low, due to the long-lead time and capital intensive nature of production projects (Kilian [2009a] and Mu and Ye [2011]).
Second, the increases in the real price of oil driven by shocks to the speculative demand for oil and other residual shocks to the oil market do not affect global economic activity within the same month of the shock. This restriction is consistent with the sluggishness of global real economic activity(Kilian [2009a]).
The third assumption is that within a month the level of above ground oil inventories is affected by oil supply shocks, global demand shocks and oil speculative demand shocks. The last assumption is that any shock that is specific to the commodity market may affect the oil market variables only with the delay of at least one month. While volatility of price of each commodity is allowed to respond to oil market shocks in the same month. This assumption corresponds to the four exclusion restrictions in the last column of the matrix A_0^{-1}, and is implied by the standard approach of treating innovations to the price of oil as predetermined with respect to the economy (Kilian and Park [2009], Lee and Ni [2002]).

In order to take into account the role of the food crisis for the analysis of agricultural commodities, we follow Baumeister and Peersman [2013] by dividing the whole sample into two subsamples: $1983:4-2006:4$ (pre-crisis period) and $2006:5-2013:12$ (post-crisis period). And to take into account the role of the financial crisis, for the analysis of metals, we divide the whole sample into two subsamples: $1983:4-2007:12$ (pre-crisis period) and $2008:1-2013:12$ (post-crisis period). In order to check for the validity of this time span division, we perform a historical decomposition analysis, to estimate the individual contribution of each shock to the dynamics of volatility. Historical decomposition is a very strong econometric tool that enables us to analyze the cumulative effect of structural shocks on volatility of commodities. Historical decomposition methodology is applied to analyze the observed series of the endogenous variables in terms of the structural shocks and the evolution of the exogenous variables. The strength of this tool is that it takes the series of structural shocks that evolve through time rather than assuming that structural shocks are one time shocks. This allows us to make a judgement over what has actually happened to the series of interest in the sample period.

2.5 estimation results

The results of historical decomposition of each commodity's volatility show that the role of some oil price shocks in explaining the dynamics of volatilities increases considerably after a specific time. This time is the mid 2006 for most agricultural commodities and around 2007-2008 for metals. This confirms the time division taking into account food crisis for agricultures and global financial crisis for metals. Figures 2.1 and 2.2 represent the results of historical decomposition for some commodities.[1] We analyze the effects of three oil related shocks, namely, oil supply shock, global demand shock and speculative demand shock on volatility of commodities prices in the agricultural and metal markets[2]. The results are presented in the form of impulse responses and variance decompositions. The latter represents the share of variations in volatility of each commodity resulting from each structural shock. Figures 2.3a and 2.3b show the impulse responses of different agricultural products to different oil related shocks for the time periods before and after May 2006, respectively. Moreover the responses of metals to different oil shocks are shown in figures 2.4a and 2.4b, for the time periods before and after January 2008. From the impulse responses one realizes that the responses of volatility of all commodities to an oil price shock differ depending on the underlying cause of the shock. Furthermore the responses differ in the pre-crisis and post-crisis periods. According to the variance decomposition of volatility of all commodities in tables 2.3 and 2.4 the explanatory power of oil shocks to all volatility variations becomes stronger after the crisis corresponding to their market. This can be seen also from impulse responses in figures 2.3a, 2.3b, 2.4a and 2.4b. The estimation results are analyzed in more details in the following. Our findings are consistent with the view that the link between oil and agricultural commodity markets has been stronger since 2006 (see Kristoufek et al. [2012], Nazlioglu [2011], Nazlioglu et al. [2013] and Reboredo, 2011).

2.5.1 Agricultural commodities

Figures 2.3a and 2.3b show the responses of agricultural commodities volatility to the structural shocks underlying the price of oil, for the periods before and after May 2006.

After May 2006 the responses of volatility of agricultural products, in figure 2.3b, seem to be greater than in the period before the break, as shown in figure 2.3a. The results from variance

[1] To save space, the results of historical decomposition are shown only for corn and silver as examples and the remaining results are available from the authors upon request.

[2] The contribution of the residual shock is not included because it is difficult to interpret this shock economically. Also, this shock does not play an important role in determining the real price of oil as documented by Kilian and Murphy [2014]

decomposition in table 2.3 confirm this finding. This result is not surprising given the increase in production of ethanol after May 2006 that implies an additional increase in demand for corn. This also affects the price of other agricultural products since corn competes with other agricultural commodities for fertilizer, scarce water and land resources (Baumeister and Peersman [2013]). As the impulse responses in figures 2.4a and 2.4b show, the volatility of each product responds differently to each of the structural shocks to oil price. This leads us to investigate how each product reacts to each oil market structural shock.

An increase in the real price of oil due to a positive global demand shock, the second rows of figures 2.3a and 2.3b, decreases volatility of corn for both pre and post break periods, increases volatility of soybeans significantly only before the break with a delay of about one year, makes a short-lived small increase in volatility of wheat only after the break, makes an increase in volatility of sugar only after the break with a four-month delay and leads to a short-lived significant increase in volatility of coffee only after the break as well. When the increase in oil price is triggered by an economic activity growth, there are two conflicting types of expectations. First, we expect a decline in volatility of crops given a positive shock to economic activity and hence a demand side effect on commodity markets, if there is enough inventory. Second, we expect an increase in volatility of crops given that higher oil price leads to higher commodity prices, and given that this is bad news for commodity markets, which according to the literature (e.g. Hammoudeh and Yuan [2008], Carpantier [2010] and Chkili et al. [2014]) leads to an increase in volatility in these markets as an inverse leverage effect. Nevertheless, our results indicate that the effects of this shock are mixed and are more in favor of increasing volatility. The reason of these reactions can be summarized as follows. This shock leads to a demand-side effect in commodity markets. Hence, it makes an increase in human consumption demand for all crops and an increase in demand for meat, which leads to a higher demand for some of these crops, as animal feed. Moreover, this shock leads to a higher demand for biofuels and therefore higher demand for corn, soybeans, wheat and sugar as inputs to biofuels production. On the other side, it is difficult for farmers to respond quickly to the fluctuations of the market. For instance, it takes four years for coffee and five to six years for sugar plants to produce fruits. Consequently this demand surplus reduces their inventory level, and enhances their price volatility. The only exception is corn that has shown a calmer and less volatile market resulting from increasing oil price due to global demand shock. Given that the demand and the net return of producing corn is higher than wheat and soybeans (Antonakakis and Filis [2013], Baumeister and Peersman [2013] and Hart [2005]), and given that these three crops can be produced in the same land, after a positive global demand shock there might be a supply shift in favor of corn. This decreases the inventory level of two other crops in order to smooth consumption, which increases their volatility even in a good economy period (IIF [2011], Roberts and Schlenker [2010] and Pietola et al. [2010]). Thus, the decline in volatility of corn is due to a better economy combined with a fundamental equilibrium in its market. After the 2006 break, since the demand for these crops was higher than the period before (Hochman et al. [2012] and Baumeister and Peersman [2013]) it is not surprising to see that the global demand shock had a stronger effect on the crops volatility.

In the third rows of figures 2.3a and 2.3b we see the responses to a speculative demand shock.

It is noteworthy to mention that a speculative demand shock occurs as a result of possibility of uncertainty in the oil market, such as predicting conflicts in oil exporting countries, low level of oil inventories, and misspecification of oil prices in financial markets, which all lead to predicting a surge in future oil prices. Hence, when oil price increases resulting from a speculative demand shock, our expectations are as follows.

First, it increases the demand for biofuel and therefore acts like a positive demand shock for corn, soybean, sugar and wheat, as inputs to biofuel production. We expect a decrease in volatility of these markets, if there are enough inventory levels. Second, an inverse leverage effect is expected, as earlier in this section. However, our results show a short-lived increase in volatility of corn, soybeans and sugar after the break, and no statistically significant response of volatility of wheat for the both pre and post break periods. This can be explained by the fact that an increase in demand for these crops after this shock is not as high as in the case of a global demand shock. Given that ethanol is mostly produced by corn and biodiesel by soybeans and sugar, and given that after the 2006 break demand for biofuel is higher than before, the increase in demand for biofuel leads to an increase in the price of the input crops, and the inverse leverage effect dominates. Finally, the first rows of figures 2.3a and 2.3b show the responses to an oil price increase due to a negative oil supply shock. This shock also makes expectations in two opposite channels of effects on agricultural markets, as we described above.

Our results show that a negative oil supply shock does not have a statistically significant effect on volatility of corn and wheat for both periods before and after the 2006 break, it makes a short-lived small increase in soybean volatility only after the break, makes a longer-lived increase in volatility of coffee only after the break with five months of delay, and lastly it decreases volatility of sugar before the break and increases its volatility after the break.

This could be evidence that this shock did not matter much for the volatility of these crops before 2006. However with the increasing role of biofuels after 2006 its effect became significant, as the higher oil price leads to a higher demand for biofuel inputs production after 2006.

2.5.2 Metals

In this section we analyze how the structural shocks driving the price of oil affect the volatility of gold, silver and copper. Gold is a precious metal and its demand is mostly for investment to hedge against inflationary effects of economic shocks (Narayan et al. [2010]). Demand for copper mirrors manufacturing and economic growth. And silver has a dual nature, being a precious metal as well as having multiple applications in industry and medicine.

Table 2.4 presents the share of each structural oil related shock in the variation of metals volatility in the form of variance decomposition, based on the structural VAR model responses. These results indicate that the responses of metals to oil related shocks are larger after the 2008 financial crisis than before.

Figures 2.4a and 2.4b show the responses of metals volatility to different oil price shocks for the time periods before and after the 2008 financial crisis.

The first rows of figures 2.4a and 2.4b show the responses of metals volatility to an oil supply shock for the pre-crisis and post-crisis periods, respectively. The results indicate that the responses to oil supply shocks are not statistically significant for all three metals. The insignificant responses hold for both the pre- and post-crisis periods.

The second rows of figures 2.4a and 2.4b represent that all the three metals respond positively to a positive global demand shock before the crisis, while after the crisis this shock decreases their volatility. When the increase in the price of oil is due to a positive global demand shock, the consumption demand for metals increases, as they are inputs for the economy, which increases their prices as well. However, the surprising question is why does this shock affect the volatility of metals in a totally different way before and after the 2008 crisis. This can be explained as below. Along with persistent rapid increase in consumption demand for commodities, their investment demand has also been rising from 2000 to 2008. According to Christian [2009], during that time period the returns available on stocks and bonds were no longer attractive, and volatility of returns in these asset groups was rising. Moreover, at the same time some academic and market-related research publications asserted that commodities compete with stocks and bonds effectively over time in terms of investment, which led the investment demand for metals to increase both physically and financially. It is well known that well-informed and rational commodity investors should add liquidity to the commodity derivatives market, buying when prices are low and selling when prices are high, they should help to clear the market (IIF [2011]). Nevertheless, ill-informed investors exhibiting herding behavior could add to price volatility (Mayer [2009]), which has happened to metal markets, and increased volatility in those markets before the 2008 crisis. This herding behavior decreased after 2008. The other factor that affects the different volatility responses to a positive global demand shock before and after the 2008 is that, the supply of base metals has responded to rising demand slowly due to slow development in mining capacity and rising energy costs. But the presence of inventory and the smoother increase in demand, after the crisis, have declined the gap between demand and supply and reduced volatility in metal markets. The results confirm the view that after the 2008 crisis investment interest decreased in commodities and it became more supply/demand fundamentals-based (see for instance Narayan et al. [2010]).

The third rows of figures 2.4a and 2.4b show the responses of metals volatility to the oil price increase derived by speculative demand for oil.

Before the 2008 break, the speculative demand shock for oil did not significantly affect the volatility in gold, silver and copper markets. After the break, this shock significantly affects only the volatility of silver. It decreases the volatility in the silver market for about 8 months, this decline being statistically significant for the first 4 months. This can be explained by the very high increase in demand for silver for the production of solar panels relative to the pre-2008 period. Since 2008, considering the enormous increase in production of solar panels to be used in solar as an alternative source of energy[3], an increase in the price of oil after this shock would increase the industrial demand of silver. But given that the very slow response of supply of silver[4]

[3]In 2000, only 1 million ounces of silver were used in PV fabrication and by 2008 this had increased to 19 million and then increased again to 64.5 million ounces in 2013. (Berry [2014])

[4]see Opdyke [2014] and `www.silver-coin-investor.com/silver-supply.html`

leads to a decline in silver inventory the decline in silver volatility is short-lived. Furthermore, we find that the responses of volatility of copper to this shock are not statistically significant for the both pre and post-crisis periods. This could be due to the fact that copper is mainly industrial and very sensitive to business cycles, and that the speculative demand shock for oil does not significantly affect the real economic activity in the short run, consequently it does not affect the copper market (Hammoudeh et al., Hammoudeh et al. [2010]).

2.6 Robustness check

2.6.1 Alternative volatility measurement

In order to check the robustness of the results we apply realized volatility as an alternative measurement of volatility within the same structural VAR model. The results confirm that the signs of volatility's responses mainly remain robust to oil related impulses.[5]

2.6.2 Alternative model and proxies for oil related shocks

As the second robustness check, we employ the unrestricted VAR model to assess the effect of structural shocks on the price of oil on the volatility of each commodity. We perform this by estimating the VAR model

$$\begin{pmatrix} u_{it} \\ vol_{jt} \end{pmatrix} \sim VAR(p) \tag{2.5}$$

where $u_{it}, \quad i = 1, 2, 3$ denotes the structural shocks to the oil market including oil supply, global demand and oil speculative demand shocks. The time series for oil market structural shocks are derived from the estimation of the structural VAR model for crude oil market developed by Kilian and Murphy [2014], and $vol_{jt}, \quad j = 1, 2, ..., 8$ denotes the time series for the volatility of each commodity under this study.

The responses mainly remain robust with those from the structural VAR model estimated in the previous section. As the global demand shock is the most important source of effect on volatilities, we represent the impulse responses related to this shock. The related graphs are shown in figure 2.5a for agricultural commodities and in figure 2.5b for metal commodities.

2.7 conclusion

In this paper, we analyze the effects of oil price shocks on selected agricultural and metal commodities price volatility. The sample data is from 1983:04 to 2013:12. To account for the food crisis for the analysis of agricultural commodities, the sample is divided into before and after the 2006 food crisis subsamples. And to take into account the role of financial crisis, for the analysis of metals, we divide the whole sample into before and after the 2008 financial crisis subsamples.

[5]These graphs are not included in the appendix due to the limitation on length of the paper, however they are available upon request from the authors.

Our analysis makes two contributions to the literature. First, we decompose the oil price shock to its driving components, oil supply shock, global demand shock and oil speculative demand shock, which is very important to understand how volatility in commodity markets responds to oil market shocks. Second, we investigate each selected commodity market characteristics to better understand the channels through which oil price shocks affect commodity markets.

The implication of the results on the effect of oil related shocks on commodities price volatility, whether in terms of the direction and duration of the effects over different time spans, or the evolution of the effects before and after the food and financial crises, are important to all beneficiaries of investigations in commodity markets. The underlying beneficiaries include policymakers, industrial manufacturers, crops producers and financial traders. According to our results it is proper for them to consider that: a) The responses of volatility of commodities to an oil price shock significantly differ depending on the underlying cause of the shock for the both pre and post-crisis periods. b) The explanatory power of oil shocks to the variations of volatility of all commodities becomes stronger after the crisis. c) For the both pre and post-2006 crisis, global demand and speculative demand for oil, significantly affect volatility of crops in contrast with very small role of oil supply shock. d) Before 2008 in all three metals volatility increases in response to a global demand shock while after the break they all decrease in volatility in response to the same shock. e) Volatilities of metals respond totally different to oil supply and speculative demand shocks in each period.

Table 2.1: Data description

	Data description			Diagnostics		ADF	P-P	ADF	P-P
Commodity	Skewness	Kurtosis	Jarque-Bera	ARCH	Serial correlation	Levels		Returns	
				F-stat	Q-stat	t-stat		t-stat	
Coffee	0.04184	11.06076	21097.74	182.45*	2.080**	-2.90	-2.91	-88.58*	-88.58*
Corn	-16.065	32.11544	278574.8	6.83*	2.53*	-2.89	-2.96	-85.61*	-85.59*
Soybean	-0.9628	13.18267	34867.58	27.79*	3.29*	-2.55	-2.55	-85.84*	-85.87*
Sugar	0.04309	9.649809	10365.88	64.88*	2.75*	-3.13	-3.08	-65.61*	-90.52*
Wheat	-0.61641	13.96244	32716.69	18.79*	2.470**	-3.25	-3.25	-87.83*	-87.85*
Copper	-0.32016	8.094391	8583.30	369.15*	7.07*	-2.21	-2.34	-94.94*	-94.84*
Gold	-0.19928	9.946727	15763.40	152.32*	2.46*	-1.68	-1.63	-89.87*	-89.92*
Silver	-0.72619	9.937221	16355.51	237.74*	2.94*	-2.72	-2.73	-90.30*	-90.37*

ADF decotes Augmented Dickey Fuller unit root test.
P-P denotes Phillips Perron unit root test.
*, ** and *** indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.2: GARCH model estimations

AR(1)-GARCH(p,q)	Variance equation			Information criteria	Diagnostic tests	
Commodities	$\alpha_1 + \alpha_2$	$\beta_1 + \beta_2$	Second Moment Condition	AIC	ARCH	Serial correlation
					F-stat	Q-stat
Coffee	0.039	0.9599	0.9998	-49.757	0.835	15.35
Corn	0.081	0.9127	0.9940	-56.654	0.429	12.22
Soybean	0.068	0.9234	0.9914	-58.105	1.973	23.00
Sugar	0.033	0.9656	0.9995	-48.650	2.052	26.28
Wheat						
Copper	0.036	0.9633	0.9998	-57.567	4.211**	15.172
Gold	0.030	0.9695	0.9999	-64.738	4.168**	16,187
Silver	0.032	0.9645	0.9966	-53.761	0.032	19.169

AIC denotes Akaike Information Criterion.
*, ** and *** indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.3: Variance decomposition of volatility of crops based on the estimation of model 2.3

	Before Crisis					After Crisis				
	supply shock	global demand shock	speculative shock	residual shocks	volatility shocks	supply shock	global demand shock	speculative shock	residual shocks	volatility shocks
Corn	4.20	7.29	5.28	3.86	79.36	6.93	10.35	15.13	18.54	49.045
Soy	6.37	16.11	2.26	6.47	68.79	13.27	21.00	14.15	17.61	33.96
Wheat	8.36	6.02	1.88	3.15	80.59	16.02	15.65	8.87	33.99	25.4
Sugar	4.57	6.04	7.70	21.75	59.94	12.10	54.79	6.45	7.01	19.65
Coffee	3.60	4.42	10.18	4.81	76.99	36.10	26.61	3.66	10.46	23.17

Table 2.4: Variance decomposition of volatility of metals based on the estimation of model 2.3

	Before Crisis					After Crisis				
	supply shock	global demand shock	speculative shock	residual shocks	volatility shocks	supply shock	global demand shock	speculative shock	residual shocks	volatility shocks
Gold	4.35	3.88	8.18	6.14	77.45	19.06	20.05	11.69	25.42	23.78
Silver	3.88	11.50	7.01	4.1	73.51	40.25	25.89	11.57	5.81	16.48
Copper	5.63	5.96	2.41	12.28	73.73	19.98	27.52	11.21	23.04	18.24

Figure 2.1: Historical decomposition of volatility of the price of Corn 1983:04-2013:12

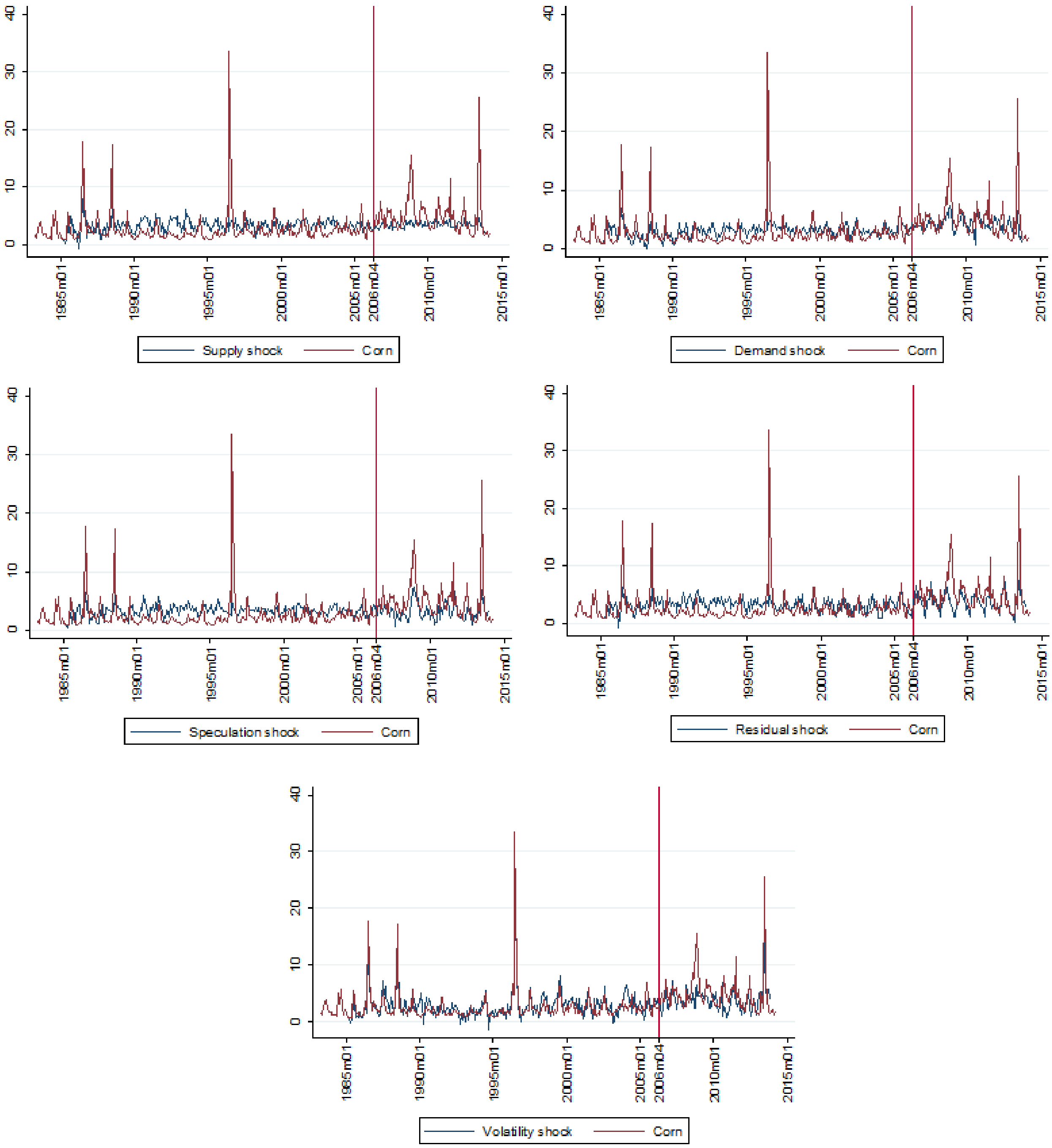


Figure 2.2: Historical decomposition of volatility of the price of Silver 1983:04-2013:12

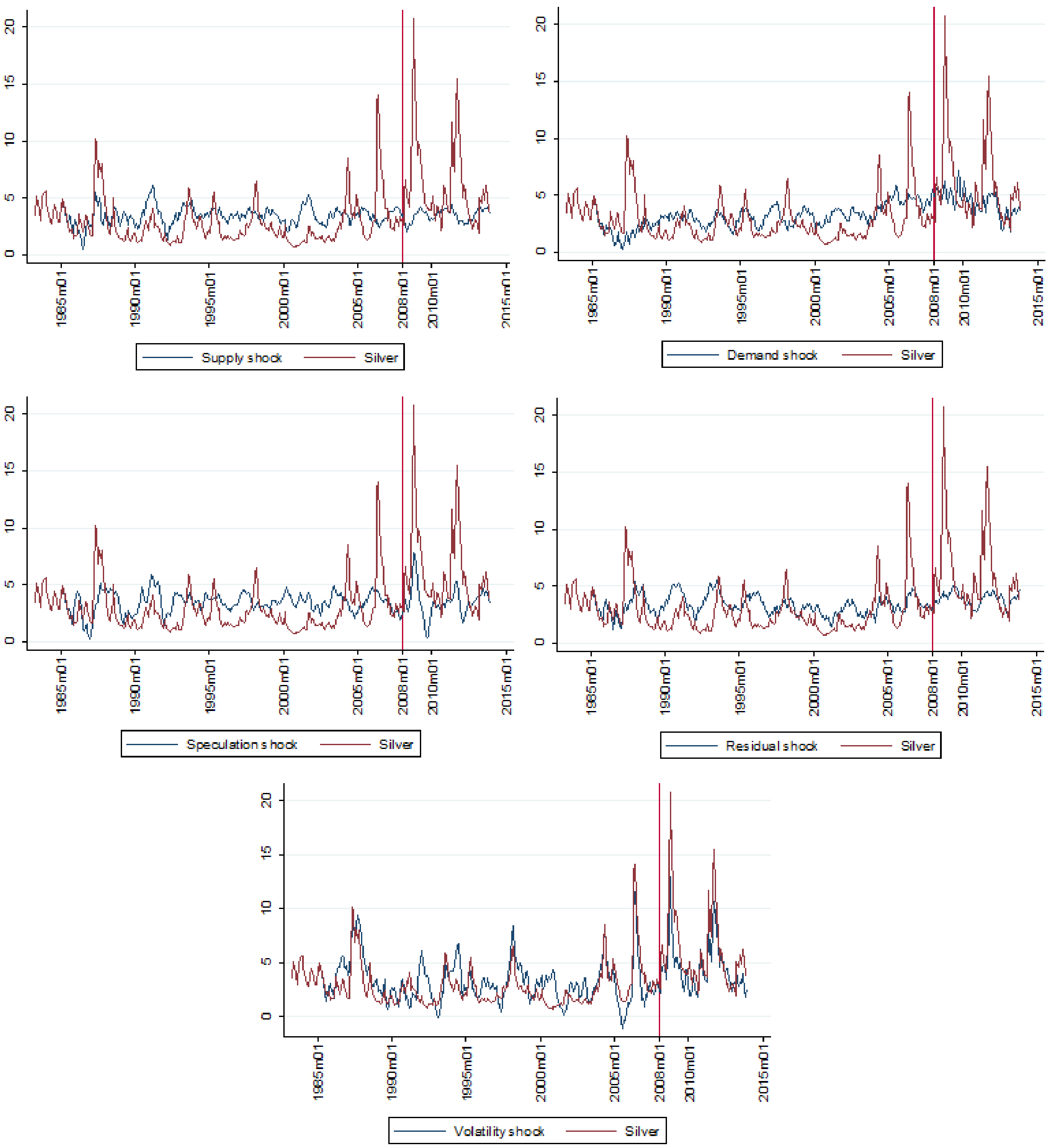


Figure 2.3a: Impulse responses of volatility of crops to the structural shocks in oil market for the time period of 1983:04-2006:04

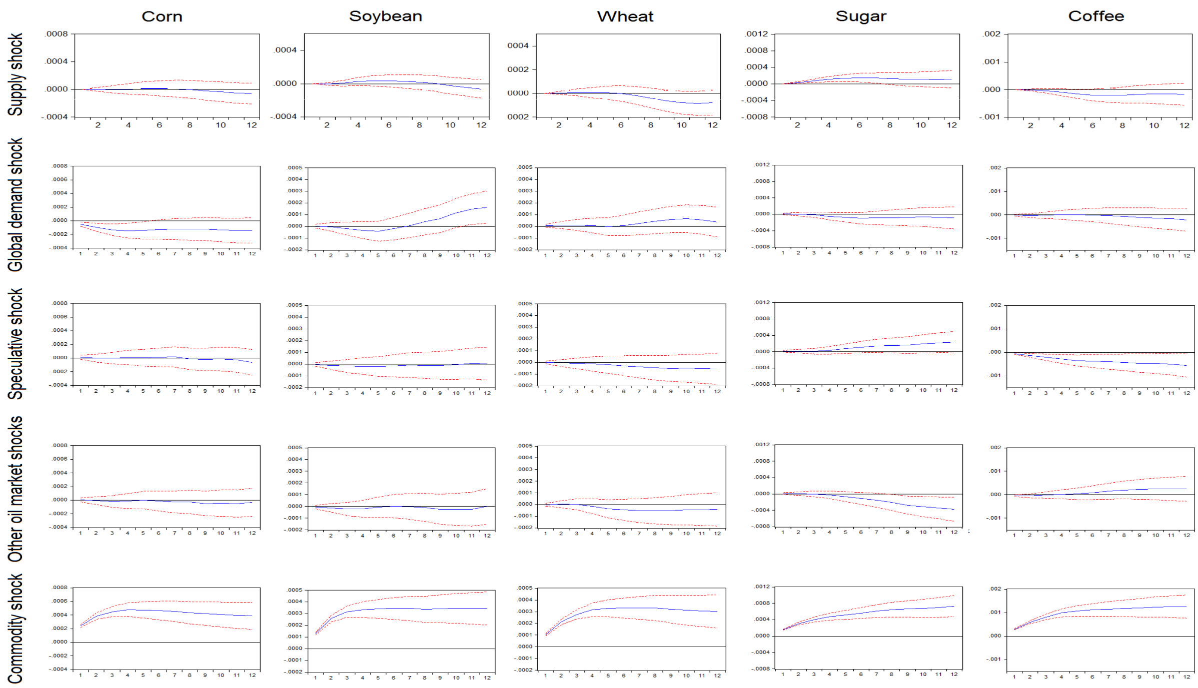


Figure 2.3b: Impulse responses of volatility of crops to the structural shocks in oil market for the time period of 2006:05-2013:12

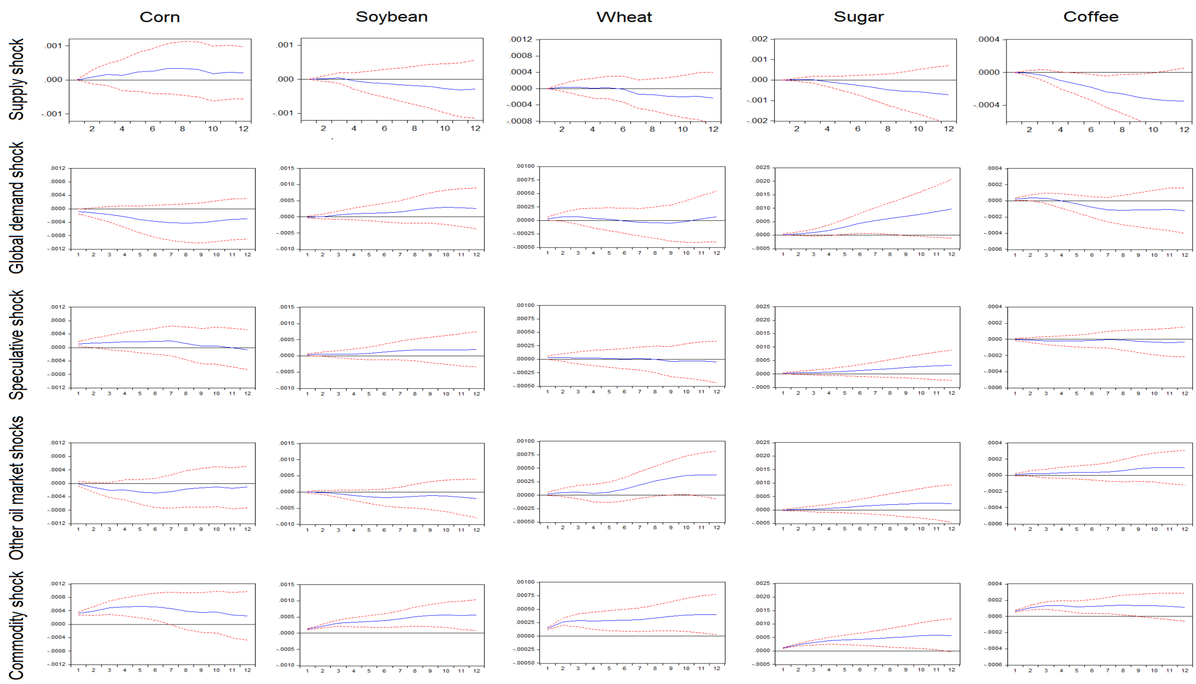


Figure 2.4a: Impulse responses of volatility of metals to the structural shocks in oil market for the time period of 1983:04-2007:12

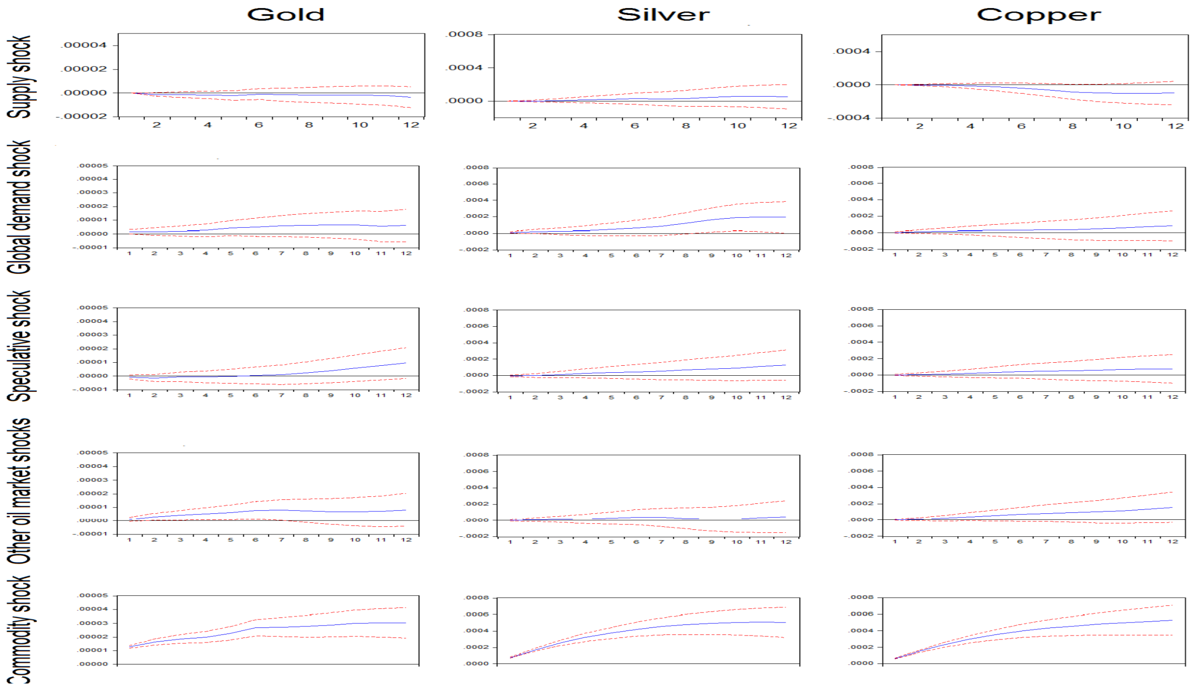


Figure 2.4b: Impulse responses of volatility of metals to the structural shocks in oil market for the time period of 2008:01-2013:12

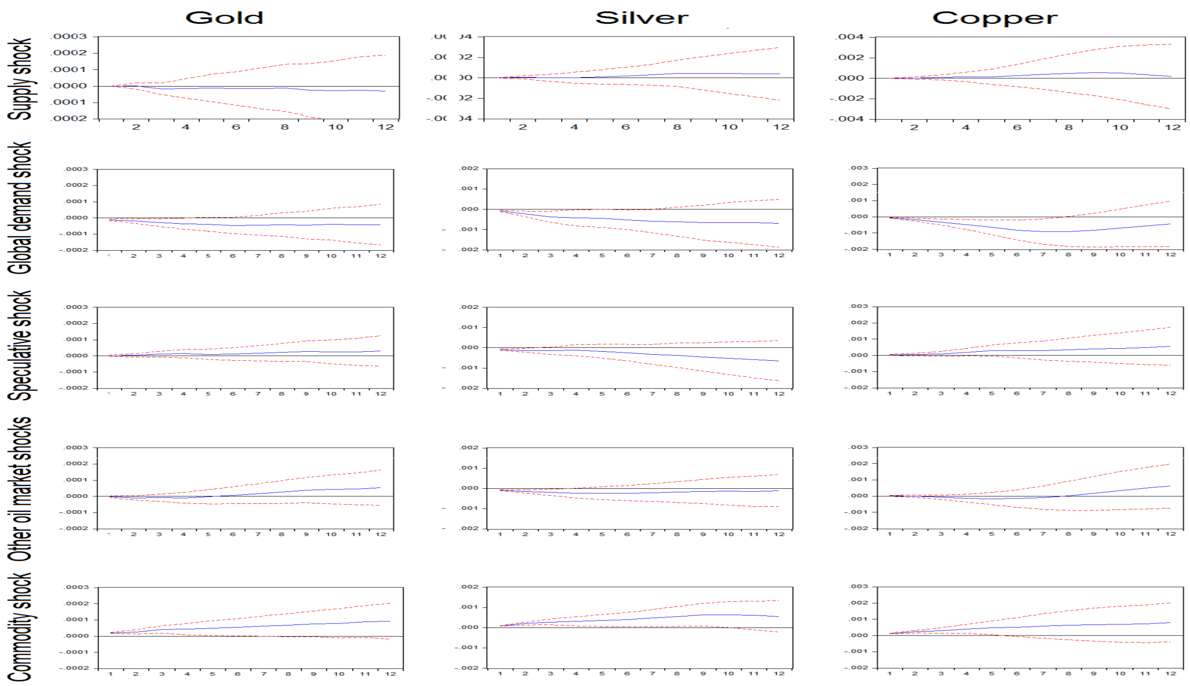


Figure 2.5a: Impulse responses of volatility of crops to global demand shock for the time period of 1983:04-2013:12

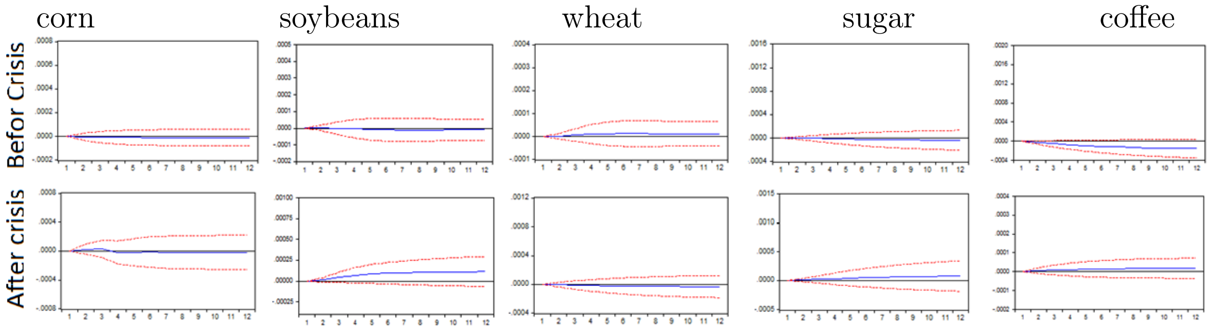
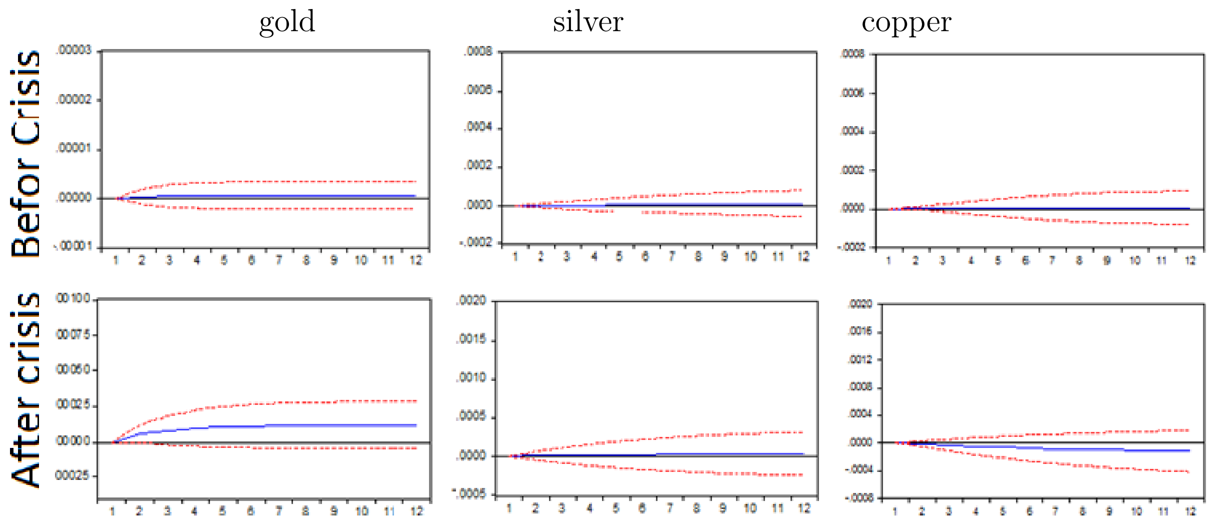


Figure 2.5b: Impulse responses of volatility of metals to global demand sock for the time period of 1983:04-2013:12



Chapter 3

Investment-Uncertainty Relationship in Oil and Gas Industry

3.1 introduction

Investment decisions have three characteristics. First, the cost of investment is at least partially Irreversible. Second, there is uncertainty over future profits. And the third characteristic is the timing of investment that is, the investors postpone their investment decisions to get more information.(Dixit and Pindyck [1994])

The orthodox theory of investment, based on the assumption of reversible investment expenditure, calculate the net present value of investment and see if it is positive. The other approach of this theory compares the capitalized value of the marginal investment to its purchase cost (Tobin [1969]). If Tobin's Q, the ratio of the market value of a firm to the replacement value of its assets, is greater than one, the firm's stock is more expensive than the replacement cost of its' recorded assets and this encourages the firm to invest in capital since its stock is overvalued. If q is less than one, the market value of the firm is less than the cost to replace the firm's assets and therefore its stock is undervalued and the firm will not invest on capital.

The option theory of investment, on the other hand, builds on the assumption of irreversible investment under uncertainty. The irreversibility provides the firms with an option to postpone investment (McDonald and Sigel [1986], Pindyck [1991], Ingersoll and Ross [1992] and Dixit and Pindyck [1994]). McDonald and Sigel [1986] show that the value of the investment includes the value of the waiting option, that is valued using option pricing theory. According to Favero et al. [1992] an investment project is adopted if the expected payoff is greater than the cost of investment plus the value of the waiting option. This option value of waiting has shown in the literature to be increasing in uncertainty and this implies an impact of uncertainty on the timing of investments so that even risk-neutral firms may decide to postpone investment when there is uncertainty about future prices (See e.g. Favero et al. [1992], Carruth et al. [1998] and Bond and Cummins [2004]).

There are different sources for uncertainty in industries. Examples are exchange rate uncertainty, output price uncertainty and input price uncertainty. One important source of uncertainty is uncertainty about the price of oil. The effect of oil price changes on investment is analyzed in some empirical studies (e.g. Glass and Cahn [1987] and Uri [1980]). They find that oil price change is an important factor in investment decisions in the aggregate level and in the oil intensive firms. Some other studies relating oil price to investment, investigate the role of oil price uncertainty (e.g. Bernanke [1983], Misund and Mohn [2009] and Ratti and Yoon [2011]). According to these studies, increased oil price uncertainty raises the option value of waiting to invest and therefore firms postpone their investment decisions.

The missing point in the existing literature on assessing the effects of oil price changes on investment is considering the endogeneity of the price of oil with respect to the macroeconomic variables. There is a consensus in the literature that oil price is not exogenous with respect to the macroeconomic variables and its determining factors are supply and demands for oil and for other industrial commodities (see e.g. Hamilton [2009], Kilian [2009a], Dvir and Rogoff [2010], Alquist and Kilian [2010] and Kilian and Murphy [2014]). Kilian and Park [2009], Hamilton [2009] and Kilian [2009a] argue that the endogeneity of the price of oil with respect to macroeconomy is essential in studying the effect of oil price on any economic variable. Kilian [2009a] propose a structural decomposition of oil price shocks into three underlying components: crude oil supply shock, the shock to the global (consumption) demand for oil and all industrial commodities and oil market-specific demand shock. The latter shock captures the fluctuations in the price of oil associated with increased uncertainty about the future oil supply.

The aim of this paper is to fill this gap in studying the relationship between uncertainty and investment in oil and gas industry. This is done by taking into account the underlying factors that drive an oil price change along with other factors represented in the literature as determinants of investment. The Structural Vector Autoregressive framework is used in this study to model the global market for crude oil. The reason to use this framework is that it provides us with historical decomposition methodology. By means of historical decomposition, the real price of oil is decomposed into three paths, each one simulated under the counterfactual assumption that only one of the oil market structural shocks hits the price of oil. I use the volatility of the simulated series to proxy oil price uncertainty driven by each of the oil market shocks, namely, oil supply shock, global demand shock and oil market-specific demand shock. I apply the constructed series to the Q model of investment applied in this study. The Q model of investment relates investment to the firm's stock market valuation that is measured by Tobin's Q. In this paper, the Q model is augmented with oil price uncertainty driven by structural shocks to the price of oil, and aggregate stock market uncertainty. The inclusion of aggregate stock market uncertainty is to account for market uncertainty along with oil industry uncertainty. Stock market uncertainty is measured by the volatility of aggregate stock market return. To avoid endogeneity between oil price and stock return, I exclude the effects of oil price shocks from stock market return and simulate the market return assuming the absence of oil market shocks through sample period. This is done by applying historical decomposition methodology from the estimation of Structural VAR model applied to model the relationship between oil price shocks and aggregate stock return. The volatility of the simulated path for stock market return is used to measure stock market uncertainty.

The rest of the paper proceeds as follows. section 2 gives a brief review of the literature related to current research. In section 3 the data is describes. The Structural VAR model and the augmented Q model of investment used in this paper are described in section 4. Section 5 presents the estimation results and discussion and section 6 concludes.

3.2 Literature review

The relationship between investment and uncertainty has been analyzed in a vast number of studies. A number of theoretical studies apply the standard neoclassical investment models and predict a positive relationship between uncertainty and investment. According to these models a firm invests when the present value of the project's expected cash flow is at least as large as its costs. Oi [1961], Hartman [1972] and Abel [1983], under the assumptions of risk neutrality, perfect competition and constant returns to scale technology, find a positive effect of output price uncertainty on investment. This result, however, depends on the convexity of expected profit in output price.

Some studies follow option theory of investment and show that when investment is irreversible, firms have option to postpone investment (e.g., Cukierman [1980], Bernanke [1983], Pindyck [1991] and Dixit and Pindyck [1994]). In these models firms invest if the net present value of investment is greater than the option value of waiting. They find that when uncertainty increases, the value of the waiting option to invest raises and consequently firms find it profitable to postpone their investment decisions. Therefore according to these models investment responds negatively to increased uncertainty.

The empirical studies on the uncertainty-investment relationship, using different proxies for uncertainty and different models, is mixed. Ogawa and Suzuki [2010] use a panel data set to investigate the impact of uncertainty (measured by the conditional standard deviation of the sales growth rate) on the investment decisions of Japanese firms. They find that aggregate uncertainty and industry uncertainty negatively affect investment. Bond and Cummins [2004], using a panel of U.S. companies, find that uncertainty over future profits has a significant negative impact on firm investment even after controlling for other factors (like Tobin's q). Bulan [2005], using a panel of U.S. companies, finds that uncertainty (based on the volatility of stock returns) has a strong negative impact on firm level investment that is robust to the inclusion of Tobin's q or cash-flow variables. Leahy and Whited [1996] study the effects of uncertainty on the investment in a panel of U.S. manufacturing firms. They find a negative effect of uncertainty (based on the within-year variance of the daily share returns of each company) on investment. However this effect disappears when they include Tobin's q to their model and also when they control for the effects of output and cash flow. They conclude that, since there is a strong negative correlation between q and their measure of uncertainty, uncertainty affects investment through its effect on Tobin's Q. Bond and Cummins [2004], on the other hand, using a panel of publicly traded U.S. firms, finds that the negative effect of uncertainty on investment is robust to the inclusion of Q and to control for the effect of expected future profitability. Shaanan [2005], employs a panel data set of U.S. manufacturing firms and finds that irreversibility reduces investment in two of the four groups of firms studied.

Several empirical studies assess the importance of oil price changes in investment decisions and the effects of oil price uncertainty on investment. Glass and Cahn [1987] study the relationship between energy price changes and investment. They develop a firm level theoretical investment equation from a two-period model that maximizes net present value of the firm's cash inflows and sum the resulting investment equation for the firm over all firms to produce an aggregate investment equation. They find that energy price increases affect negatively aggregate investment. They do not examine whether there is a role for uncertainty as a channel to transmit this effect. Uri [1980] develops a simple model to study the role of energy price changes as a determinant of investment behavior. He finds that the price of energy is an important factor in adequately explaining investment decisions at the aggregate level and energy intensive industries. Bernanke [1983] using the theory of irreversible choice under uncertainty, show that when uncertainty about the future price of oil increases, firms must postpone their irreversible investment decision that is to choose between energy-efficient capital or energy-inefficient capital. Increased oil price uncertainty raises the option value of waiting to invest. Ratti and Yoon [2011] estimate an error correction model of capital stock adjustment with data on U.S. manufacturing firms. They find that higher energy price uncertainty declines the responsiveness of investment to sales growth. Their findings suggest that stability in energy prices would be conducive to greater stability in firm-level investment.

While the number of studies working on the effects of uncertainty on investment in oil and gas fields is not many, the empirical findings are mixed. Favero et al. [1992] develop a theoretical model and derives the determinants of the decision to develop an oilfield and then use duration analysis to evaluate the importance of the variables suggested by the theory to explain the lengths of development lags on the UK oil and gas fields. Their results imply that the effect of uncertainty is a function of the expected price level, and the volatility of prices has a positive impact on the duration of investment appraisal when prices are low and a negative impact when prices are high. Misund and Mohn [2009] estimate the effect of oil price volatility on investment in the oil and gas sector. The panel regression is estimated using generalized method of moments (GMM) accounting for firm fixed effects, fixed time effects, and possible endogeneity between the variables. They find that Q is a poor investment indicator for the international oil and gas industry, and that uncertainty measures contribute significantly to the explanation of investment. Hurn and Wright [1994], using data from operations in the oil fields in the North Sea, apply discrete-time hazard regression models to see the influence of economic variables, the expected price of oil, the variance of the price of oil and the level of reserves, on the lag between the discovery of a field and the decision to develop the field. They find that the expected price of oil and the level of reserves are important in influencing the appraisal duration but that the variance of the oil price is not. Elder and Serletis [2010] apply bi-variate GARCH models to study how oil price uncertainty affect investment and economic growth for the US economy. They find that increases in oil price volatility reduce aggregate investment in the United States. Similar result is found in Elder and Serletis (2010b) for Canada. Sadath and Acharya [2015] by estimating an Error Correction Model (ECM) using Generalized Method of Moments (GMM) show that energy price rise has negative effect on the investment of firms in the manufacturing sector in India. Lee et al. [2011] apply a standard investment model to analyze the joint effect of an oil price shock and a firm's uncertainty on that firm's investment using firm level panel data. They conclude that an oil price shock has a greater effect on delaying a firm's investment the greater the uncertainty faced by that firm.

This study extends the described literature by taking into account the endogeneity of the real price of oil with respect to macroeconomic and its own market variables. It analyzes the relationship between oil price uncertainty driven by structural shocks to the oil price and the U.S. firm level investment in oil and gas industry. The aim of this paper is to assess how uncertainty in oil market affects investment in oil and gas industry. By decomposing the shocks to oil prices into their deriving factors we can see whether the underlying cause of an oil price increase matters for the relationship between oil price and investment. The advantage of using Structural VAR framework is that it allows to decompose oil price to its underlying components. It also makes it possible to compare the different effects of an oil price shock, due to its driving factors, on firm-level investment. Stock market volatility is imposed to the investment model to capture market uncertainty.

3.3 Data

There are three types of variables used in this study. Global oil market variables include global crude oil production, a measure for global trade, to capture global demand for oil and all industrial variables, and real price of crude oil, which are all available in monthly frequency. Data on global crude oil production is from the monthly energy review of the Energy Information Administration (EIA). The real price of crude oil is the U.S. refiners' acquisition cost for imported crude oil and is available in the EIA. The price of oil is deflated by the U.S. consumer price index. A measure of global real economic activity, introduced by Kilian [2009a], is used in this study to proxy global demand for crude oil. This measure is based on the global dry cargo shipping rates that captures the global business cycle and is used to measure consumption demand for oil and all industrial commodities.

The U.S. aggregate stock market return is obtained from the Center for Research in Security Prices (CRSP) which is a value-weighted market portfolio including NYSE, AMEX, and Nasdaq stocks. The real stock return is constructed by subtracting the consumer price index (CPI) from the log returns. The volatility of each of the oil market variables and stock market return is then converted to annual data, to investigate the effects of oil market and stock market uncertainties on investment decisions of firms in oil and gas industry.

A panel of 60 U.S. oil and gas companies that covers the period 2000 to 2013 is used in this study. It includes the following variables: market value of equity, long term debt, total assets and capital expenditure. Following previous literature, Tobin's Q is measured as the sum of market value and long term debt divided by total assets. Firm investment is measured by capital expenditure and capital stock is measured by total assets. The annual firm-level data is sourced from CAMPUSTAT.

3.4 Methodology

3.4.1 Uncertainty measures

Oil price uncertainty

To get the oil price uncertainty driven by each of the oil market structural shocks, this paper applies a Structural Vector Autoregressive framework to decompose oil price shocks to their underlying components. The structural VAR model, following Kilian [2009a], is the following:

$$A_0 y_t = \alpha + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t \tag{3.1}$$

Where y_t is the vector of endogenous variables including the percent change in global crude oil production, global real economic activity and the real price of crude oil. The vector ε_t is the vector of structural oil market shocks, namely, oil supply shock, global demand shock and oil market-specific shock. The last shock is to capture the changes in precautionary demand for crude oil in response to increased uncertainty about future oil supply shortfalls. The structural shocks are identified from the reduced form VAR model, $e_t = A_0^{-1}\varepsilon_t$ by imposing short run restriction on A_0, following Kilian [2009a], as follows:

$$\begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{3t}^{\Delta real\ price\ of\ oil} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ supply\ shock} \\ \varepsilon_{2t}^{global\ demand\ shock} \\ \varepsilon_{3t}^{oil-specific\ shock} \end{pmatrix} \tag{3.2}$$

The identifying restrictions are based on the following assumption. The first assumption is that within a month after a shock, changes in global oil production do not respond to global demand shock and to other oil market-specific shocks. This assumption is due to the fact that adjustment in oil production plan is very costly. The second assumption is that the increase in price of oil that is caused by precautionary demand shocks in oil market, does not affect global real economic activity within a month after the shock. And the final assumption is that, any shock to the real price of oil that cannot be explained by oil supply or aggregate demand shocks are specific to the oil market that is mostly driven by uncertainty about future crude oil supply shortfalls.

One advantage of this framework is that it allows us to perform historical decomposition of the real price of oil that is performed by simulating the real price of oil from the Structural VAR model under the counterfactual assumption that there is only one shock hitting the price of oil. The historical decomposition does not assume one-time structural shocks, but it takes the series of structural shocks that evolve through time. This allows us to make a judgement over what has happened to the series of interest through the sample period, by decomposing the real price of oil into three paths each one derived by one of the oil market structural shocks. Figure 3.1 shows the historical decomposition of the log return of the price of oil with respect to oil supply, global demand and precautionary demand shocks. The conditional volatility of each simulated path is calculated by applying the GARCH framework developed by Bollerslev [1986]. The resulting series are our measures of oil price uncertainty driven by oil sully shocks(σ_{supply}), oil price uncertainty driven by global demand shocks(σ_{demand}) and oil price uncertainty driven by precautionary demand shock to oil market($\sigma_{oi-specific}$).

stock market uncertainty

To account for the effects of market uncertainty on the firm-level investment, aggregate stock market uncertainty is included to the investment model. The volatility of stock market return is used to proxy stock market uncertainty. To exclude the contribution of the oil market shocks from the aggregate stock market return and facilitate the identification of the market wide uncertainty, an index is constructed to proxy the market return. This proxy is the simulated series for stock return under the assumption that the oil market shocks are zero through the period under study.

This is done by performing historical decomposition of the stock market return from estimating model 3.1 for the stock market return, where y_t includes stock market return as the forth variable after the three oil market variables, namely, percent change in global crude oil production, global real economic activity and the real price of crude oil. The vector of structural shocks, ε_t, consists of oil supply shock, global demand shock, precautionary demand shock and the last shock, that captures any shock to real stock returns not driven by oil market shocks. The identification assumptions are described in the following:

$$\begin{pmatrix} e_{1t}^{\Delta global\ oil\ production} \\ e_{2t}^{global\ real\ activity} \\ e_{3t}^{real\ price\ of\ oil} \\ e_{4t}^{real\ stock\ return} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_{1t}^{oil\ supply\ shock} \\ \varepsilon_{2t}^{global\ demand\ shock} \\ \varepsilon_{3t}^{uncertainty\ shock} \\ \varepsilon_{4t}^{stock\ market\ shock} \end{pmatrix} \tag{3.3}$$

The identification assumptions in relation 3.2 are preserved in relation 3.3. The additional restriction is that oil market variables do not respond to stock market shocks within a month after the shocks. By applying historical decomposition of the aggregate real stock market return from the estimation of SVAR model for stock market return, the real stock return is decomposed into two series, one derived by all the oil market shocks and one derived by all the shocks to the stock market excluding oil shocks. This is to exclude the effects of oil market shocks from fluctuation of stock market return to be able to analyze the pure effect of stock market uncertainty on investment. Figure 3.2 shows historical decomposition of real stock market return with respect to oil market and stock market shocks. By applying the GARCH framework developed by Bollerslev [1986], the conditional volatility of the simulated stock market return is used to proxy aggregate stock market uncertainty from which the effects of oil industry shocks are excluded, σ_{stock}.

3.4.2 Investment model

The effects of oil price uncertainty, driven by each of the oil market shocks, on firm-level investment are estimated by using an augmented Tobin's Q model (Tobin [1969]). Tobin's Q model relates investment to the firm's stock market valuation, that reflects the present discounted value of expected future profits. The Q-model of investment is represented by the following simple relationship:

$$\frac{I_t}{K_t} = a + \frac{1}{b}(Q_t) + \varepsilon_t \tag{3.4}$$

where Q is the ratio of the market value of the firm to the replacement value of its assets. I_t is the firm's gross investment in period t, K_t is the firm's net capital stock and ε_t is a random error term. The parameters a and b are structural parameters of the adjustment cost function. To take into account the factors that has been shown in the literature to have impact on investment, the Q model of investment is usually augmented with those explanatory variables. In this paper, additional variables include oil market uncertainty driven by oil supply shock, σ_{supply}, oil market uncertainty driven by global demand shock, σ_{demand}, oil market uncertainty driven by precautionary demand shock, $\sigma_{oil-specific}$, and aggregate stock market uncertainty, σ_{stock}. These variables are included to the model to capture industry and market risks and to compare the different effects of an oil price uncertainty on investment.

Given that the panel data set contains 13 years of observations, following Misund and Mohn [2009], to avoid serially correlated error term ε_t is assumed to follow an AR(1) process:

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + \nu_{it} \tag{3.5}$$

with ν representing white noise. Substituting the additional variables to equation 3.4 and then by substituting it into equation 3.5 we reach to the following dynamic firm investment model:

$$\frac{I_t}{K_t} = b_0 + b_1(\frac{I_t}{K_t})_{it-1} + b_2Q_t - b_3Q_{it-1} + B_1X_{it} - B_2X_{it-1} + \eta_t^* + \zeta_t^* + \nu_t \tag{3.6}$$

where, X_t is a vector of variables containing σ_{supply}, σ_{demand}, $\sigma_{oil-specific}$ and σ_{stock}. The empirical model 3.6 relates the investment to capital ratio to its one period lag, Tobin's Q, different oil price volatility series, and stock market volatility.

Panel unit root test

To determine the order of integration of the model's variables, I apply panel unit root tests. The reason to use panel unit root tests is the consensus in the literature that panel unit root tests have higher power to reject the null hypothesis of no unit root test than traditional tests such as Augmented Dickey-Fuller (ADF), especially in the short time span. Therefore, in this study, Im et al. [2003] and Levine et al. [2002] panel unit root tests are performed.
The description is started by using the following autoregressive process for panel data:

$$y_{it} = \rho_i y_{it-1} + X_{it}\delta_i + \varepsilon_{it}$$

where $i = 1, 2, ..., N$ denotes cross section and $t = 1, 2, ..., T$ denotes time period. X_{it} contains the model's exogenous variables, including any fixed effect or individual trends and ε_{it} is the vector of mutually independent error terms. If ρ_i, the autoregressive coefficient, is less than 1 then y_i is weakly stationary and if $\rho_i = 1$, then y_i has a unit root.
The general structure for testing panel unit root is the following:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{l=1}^{pi} \beta_{ij}\Delta y_{it-j} + X_{it}^{'}\delta + \varepsilon_{it}$$

Levine et al. [2002]' test, (L.L.), is based on the assumption of homogeneity among the cross sections' unit roots, meaning that ρ_i is identical. It allows for the different lag orders (p_i) across the cross sections. The null hypothesis is that each individual time series has a unit root, $H_0 : \alpha = 0$, and the alternative hypothesis is that each time series is stationary, $H_1 : \alpha < 0$. For a panel unit root test without the assumption of identical correlation under the alternative, Im et al. [2003]'s panel unit root test, (I.P.S.), is also performed in this study. This test allows for heterogeneity across the cross sections' unit roots therefore each cross section has an individual unit root process and ρ_i can vary across the cross sections. This test specifies an ADF regressions for each cross section. The null hypothesis, $H_0 : \alpha = 0$, is that there is a unitary unit root and the alternative hypothesis, $H_1 : \alpha < 0$ for some i, is that some individuals can have a unit root.

Model estimation

The empirical augmented Q model of investment in equation 3.6, relates the ratio of investment to capital to a one period lag of itself, Tobin's Q, our measures of oil price uncertainty and aggregate stock market uncertainty. The model is estimated using a panel data of 60 U.S. firms in oil and gas industry over a period of 13 years. The panel regression is estimated by applying two-step system generalized method of moments (system GMM) proposed by Blundell and Bond [1998]. The reasons to use system GMM model are as follow. First, it allows to control for possible endogeneity between model's variables and predetermined regressors that are independent of current disturbances but can be influenced by past disturbances.[1] Second, when some series in the model have near unit root properties, according to Bond and Cummins [2004] an Blundell and Bond [1998] the lagged levels of the regressors, used in difference GMM model in Arellano and Bond [1991], may be poor instruments for the first-differenced regressors and therefore difference GMM performs poorly. The persistence of the series for our model variables is shown in table 3.3. System GMM, developed by Blundell and Bond [1998], includes level equations in the estimated system of equations and by applying instruments with lags of both first-differences and levels of the dependent and predetermined variables, improves efficiency of the Arellano and Bond [1991]'s difference GMM model (Misund and Mohn [2009]). Third, the two-step estimation is asymptotically more efficient than one-step estimation and the standard covariance matrix is robust to panel-specific autocorrelation and heteroskedasticity. However the standard errors reported in two-step estimation can be severely downward biased (Arellano and Bond [1991] and Blundell and Bond [1998]). A finite-sample correction of the covariance matrix of two-step GMM estimators is proposed by Windmeijer [2005] that results in larger standard errors that are much more reliable in finite samples. In this paper, the Windmeijer [2005] methodology is applied to the reported standard errors in two-step estimation.

In the GMM regressions on panels, when lags are used as instruments, it is very important to test for autocorrelation. Arellano and Bond [1991] drive an appropriate test for first order and second order autocorrelation in the first-differenced errors. The null hypothesis is that there is no autocorrelation in the first-differenced errors. If the residuals are independent and identically distributed, i.i.d, the first order statistic is significant, meaning that the first differenced errors are first order serially correlated. The higher order serial correlations should be insignificant. To test for over-identifying restrictions, Arellano and Bond [1991]'s Sargan test is a relevant one but it could incorrectly reject the null, when there is heteroskedasticity. Therefore, following

[1] Both the lagged dependent variable and the Q ratio are treated as endogenous variables in the estimation model. There is a consensus on endogeneity bias for the lagged dependent variable in panel data models in the literature (see e.g., Arellano [2003]). Also Q may not be strictly exogenous since it has market valuation is the numerator. (Misund and Mohn [2009]).

Rodman [2005], Hansen test is performed to test for over identifying-restrictions with the null of validity of the restrictions.

3.5 Estimation results

The unit root test results in table 3.2 prove that, according to the both tests, there are strong evidences showing that all the variables are stationary in their levels. Hence, their order of integration is zero, I(0). Accordingly, we do not need to perform the cointegration test and our data are appropriate to adopt the system GMM methodology.

The estimation results of the investment model 3.6 are reported in table 3.4. The results show that the investment-uncertainty relationship depends greatly on the causes behind uncertainty. When uncertainty is driven by shocks to oil supply or oil specific demand for oil, there is no significant relationship between investment and uncertainty. On the other hand, when uncertainty comes from global demand shock, it significantly lowers investment. Stock market uncertainty is found to impact negatively on investment decisions in oil and gas industry. However, the negative response of investment to uncertainty coming from both oil market and stock market is dampened over time and as we see in table 3.4 the effects of lagged oil price uncertainty caused by global demand shock and lagged stock market uncertainty are both insignificantly positive. The temporary significant effect in both cases suggest that any change in uncertainty is taken by oil companies as being transitory. However the results indicate that there is no significant positive relationship between uncertainty and investment in oil and gas industry. This is in line with the option theory of investment and that the irreversibility effect of increased uncertainty dominates the traditional convexity effect.

The coefficient of the lagged investment, reported in the first row of table 3.4, is positive and statistically significant at the 1% level. Tobin's Q positively impact current investment but no significant relation is found between lagged Q and investment. The findings of this paper is in line with the previous literature that Q is not a sufficient statistic to explain investment and consistent with option theory of investment in that there is important role for uncertainty in investment decisions of firms.

The results from Arellano and Bond [1991] postestimation specification tests are presented in the last rows of table 3.4. There is no significant evidence of serial correlation at second order in the first-differenced errors. According to the results of Hansen test for over-identifying restrictions, the validity of the over-identifying restrictions is not rejected.

3.6 Conclusion

This paper studies the relationship between investment and uncertainty in a panel of 60 U.S. firms in oil and gas industry. A Q model of investment is augmented with measures of industry-level uncertainty and aggregate stock market uncertainty. This study contributes to the literature in two ways. First, to capture industry-level uncertainty, I proxy oil market uncertainty, by taking into account the underlying causes behind oil price fluctuations. This is very important to investigate how investment depends on oil market uncertainties. Second, oil market effects are excluded from aggregate stock market uncertainty, to have the pure effect of stock market uncertainty in our investment model.

The results show that the impact of oil market uncertainty on investment greatly depends on the underlying causes of uncertainty. When uncertainty in oil price is due to the shocks to oil supply and oil market specific demand, there is no significant impact on firms' investment decisions. On the other hand, if oil price uncertainty is driven by global demand shock, investment responds negatively significant to oil price uncertainty. Therefore, according to the results, the consumption demand component of oil price is the main oil market variable affecting investment in oil and gas industry. Stock market uncertainty has a statistically significant negative impact on the firms' investment decisions. The findings of this paper show no significant positive relationship between uncertainty and investment in oil and gas industry. Therefore the irreversibility effect of increased uncertainty dominates the traditional convexity effect.

The findings of this paper is in line with the previous literature that Q is not a sufficient statistic to explain investment behavior of firms and consistent with option theory of investment by finding an important role for uncertainty in investment decisions of firms.

Table 3.1: Data description

	Mean	Maximum	Minimum	Std. Dev.
$\frac{I}{K}$	0.251	0.082	0.266	0.359
Q	1.000	1.000	0.999	1.000
σ_{demand}	0	-1.90E-08	-3.82E-05	-0.001
σ_{supply}	0.149	0.049	0.300	0.320
$\sigma_{oil-specific}$	0.482	1.004	0.005	0.304
σ_{stock}	0.489	0.999	-0.004	0.318

Table 3.2: Panel unit root tests results

	without trend		with trend	
	IPS	LL	IPS	LL
σ_{demand}	-1.989**	-11.012*	-5.518*	-19.340*
σ_{supply}	-9.217*	-21.689*	5.862	-8.388*
$\sigma_{oil-specific}$	7.607	7.362	-16.083*	-21.193*
$\sigma_{stock\ market}$	-2.621*	-3.385*	0.827	4.199
$\frac{I}{K}$	-10.091*	-14.266*	-8.649*	-16.591*
Q	-7.763*	-10.561*	-5.640*	-11.527*

IPS: represents Im et al. (2003) panel unit root test,
LL: represents Levin, Lin, and Chu (2002) panel unit root test,
*, ** and *** indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3.3: The estimation results from a linear regression model of each variable on its one period lag.

	$\frac{I}{K}$	Q	σ_{supply}	σ_{demand}	$\sigma_{oil-specific}$	σ_{stock}
$\frac{I}{K}(-1)$	.515* (.030)					
$Q(-1)$		.399* (.022)				
$\sigma_{supply}(-1)$			.864* (.004)			
$\sigma_{demand}(-1)$				.560* (.030)		
$\sigma_{oil-specific}(-1)$					.510* (.0354)	
$\sigma_{stock}(-1)$						.605* (.030)

*, ** and *** indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3.4: Stimation results from investment model using two-step system GMM estimation methodology

	Coefficient	Corrected Standard Error	Prob
$\frac{I}{K}(-1)$	0.392*	(0.062)	0.000
Q	0.633**	(0.253)	0.012
Q(-1)	0.254	(0.207)	0.220
σ_{supply}	0.044	(0.101)	0.663
$\sigma_{supply}(-1)$	-0.065	(0.106)	0.539
σ_{demand}	-0.165*	(0.028)	0.000
$\sigma_{demand}(-1)$	0.039	(0.029)	0.181
$\sigma_{oil-specific}$	-0.028	(0.033)	0.397
$\sigma_{oil-specific}(-1)$	-0.021	(0.027)	0.442
σ_{stock}	-0.067*	(0.020)	0.001
$\sigma_{stock}(-1)$	0.032	(0.030)	0.284
_cons	0.167*	(0.033)	0.000
AR(1)	-3.53		0.000
AR(2)	1.53		0.125
Hansen	55.01		0.994

Values in parenthesis are standard errors,
*, ** and *** indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure 3.1: Historical decomposition of oil price return

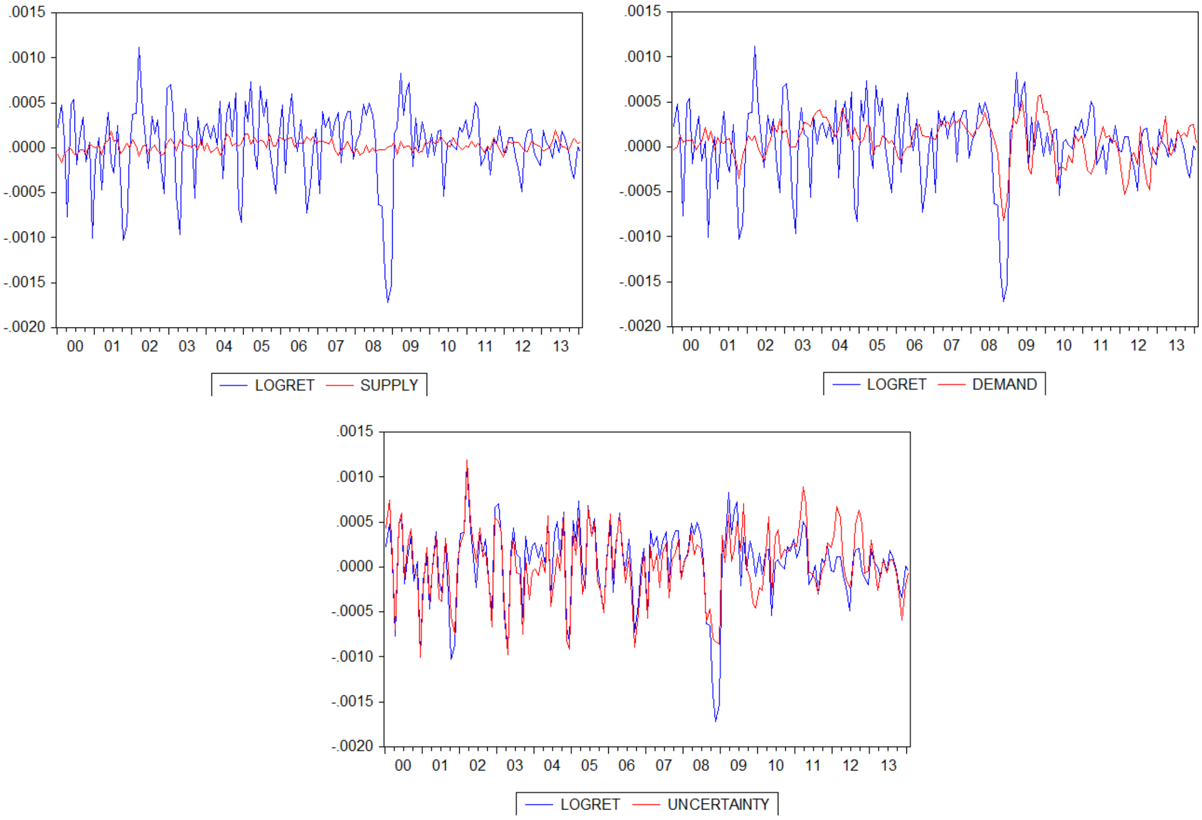
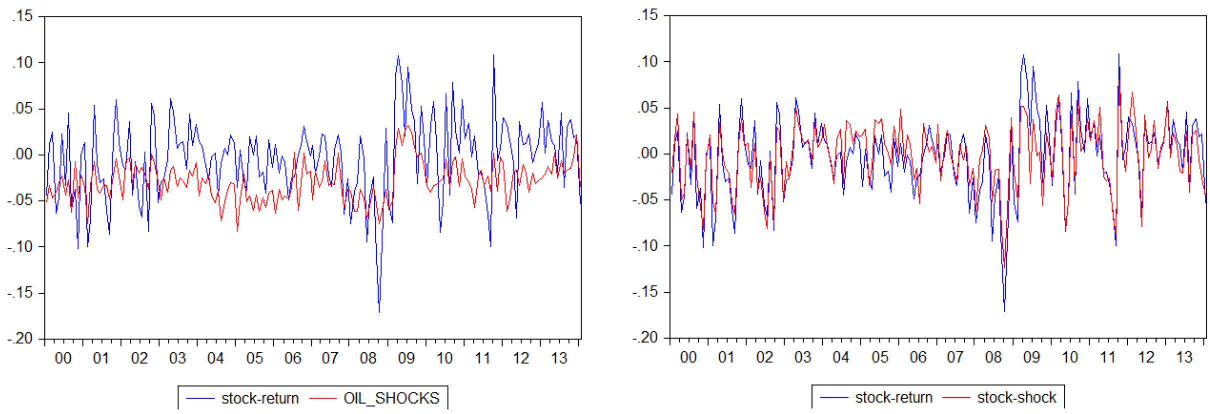


Figure 3.2: Historical decomposition of aggregate stock market return



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