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- Investigating the Effects of Lower Oil Prices on Aggregate U.S. Output and Household Consumption -

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Master's Thesis

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Abstract

In the last decade, there has been a gradual structural shift occurring in the U.S. economic landscape. Decreasing oil imports coupled with a booming oil sector and increased crude oil exports, implies that the oil sector now represents an increasingly larger part of total U.S. GDP. In light of the fracking revolution and the recent oil price decline of 2014, this thesis utilizes a SVAR model to study the effects of lower oil prices on U.S. real GDP and PCE. In so doing, we aim to investigate whether the transmission of an oil shock to U.S. economic activity has changed. Our analysis of the historical decomposition with data ranging from 1975-2016 suggests that the transmission of an oil shock remains unchanged. This is in line with findings made by Baumeister and Kilian (2016). Despite these findings, the effects of an oil price decline on U.S. real GDP and PCE are different when considering the recent changes in the U.S. economic landscape. Our findings suggest that an oil price decline has a significantly negative effect on both GDP and PCE post 2000. This is attributed to a number of changes; The increased importance of the oil sector as a contributor to U.S. GDP implies that reduced investments in the oil sector, as a consequence of lower oil prices, adversely affect GDP growth. Further, following the financial crisis, the FED rate was reduced close to the zero lower bound, effectively constraining the power of the FED to influence economic activity. Finally, a general cooldown of global economic activity implies reduced demand for American goods.

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1.0 – Introduction

The impact of oil price fluctuations on macroeconomic activity is well documented. The established literature, such as Hamilton (1983), Kilian (2009) and Aastveit et.al (2012), features extensive analysis on the effects of oil price movements on economic activity. Despite this attention, there has been significantly less focus on the effects of oil price declines[1], possibly because there have been fewer historically significant cases of this occurring.

Since June 2014 the real price of oil has seen a significant decline. A drop in the oil price of this magnitude is usually accompanied by an increase in global economic activity. Consequently, macroeconomists have viewed changes in the price of oil as an important source of economic fluctuations (Blanchard and Gali, 2010). The conventional idea has been that a decline in the price of oil tends to boost global economic activity. The negative relationship between oil prices and GDP growth has been confirmed by a number of studies including Hamilton (1983, 2003) and more recently by Awerbuch & Sauter (2003). Therefore, when considering the current sharp decline in oil prices, one would expect aggregate economic activity to pick up. However, the recent oil price decline differs in one significant aspect; global economic activity has not seen the expected benefit of lower oil prices, growth has all but stagnated. In fact, IMF (2016) numbers point out that the global GDP growth went from 3.4 percent to 3.2 percent during the year 2014 to 2015. Their official forecasts for 2016 and 2017 are 3.1 percent and 3.4 percent respectively. These figures suggest that there has been no boost to GDP growth from the recent oil price decline.

A recent paper by Baumeister and Kilian (2016) showed that the overall growth in the U.S. economy has been marginal at best[2]. In theory, lower oil prices are expected to increase demand for other goods and services as disposable income previously used

[1] One notable exception is the literature that focuses on the asymmetric relationship between a decline and an increase in oil prices, see for instance Mork (1989).

[2] Following the 2014 oil price decline, Baumeister & Kilian report that the U.S. economy experienced only a slight increase in economic growth from 1.8 percent in 2012Q1 to 2014Q2 to 2.2 percent in 2014Q3 to 2016Q1

on energy is freed up. The increase in demand would further be expected to accelerate overall economic activity and cause a shift in U.S. domestic aggregate supply curves. However, Baumeister and Kilian's findings indicate a global economic slowdown as one of the main reasons for the lower than expected GDP growth rate. This challenges the generally accepted view that lower oil prices are good for the U.S. economy. Interestingly, Bernanke (2017) also suggests that the positive correlation between the stock market and the price of oil indicates a softening of global aggregate demand, which in turn hurts corporate profit and the demand for oil. Falling oil prices might therefore not necessarily be generally good news for global economic activity.

Historically, when OPEC cuts production, the supply of oil is reduced. Because OPEC countries draw on their oil inventories to supplement any decrease in oil production, this delays a market price reaction until inventories are depleted. Once inventories are drawn down, prices are usually expected to rise. The fracking revolution however is believed to have introduced a paradigm shift in global oil production. In the last decade, the market has become increasingly flooded with American oil as a result of the increased shale oil production. This trend continued past the initial decline in oil price, with several rigs operating despite oil prices being as low as $30 per barrel. This has resulted in the U.S. becoming an oil exporter as of 2015 (Stlouisfed.org, 2017).

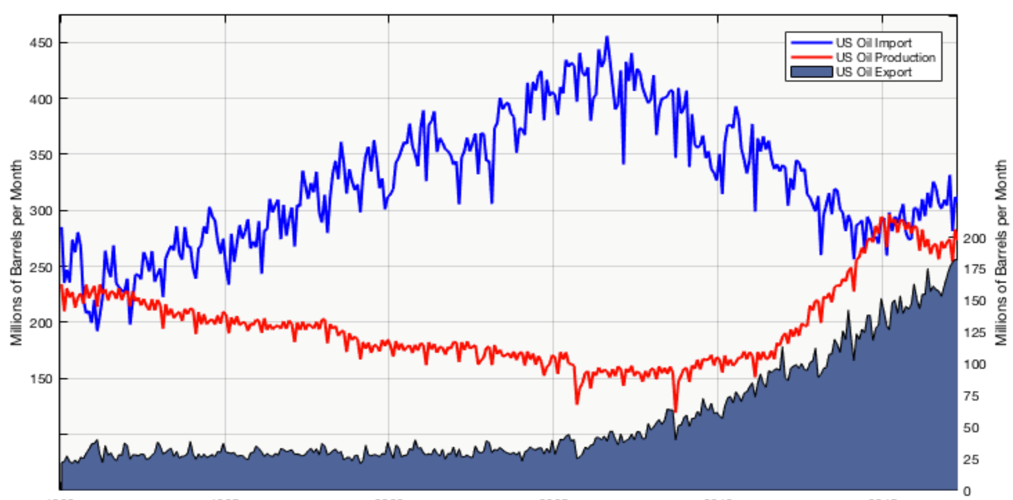

Figure 1: U.S. oil import vs U.S. oil production (left-hand side) U.S. oil export (right-hand side) 1990-2017.

Source: EIA

Figure 1 shows the evolution of U.S. oil imports, exports and production. A clear, gradual shift can be observed starting after the financial crisis (2007); the dawn of the fracking revolution. Oil imports gradually decline while production and consequently, exports increase. As a result of increased domestic oil production and crude oil exports, oil makes up a larger percentage of overall U.S. economic output. This begs the question, “Has the U.S. become more sensitive towards oil price fluctuations?”

In light of the recent oil price decline, the stagnation in GDP growth that followed and the paradigm shift resulting from the shale oil revolution, the aim of this investigation is to analyse the effects of an oil price shock on the U.S. economy. By constructing a six-variable SVAR model it is possible to analyse the sensitivity of U.S. economic activity to oil price fluctuations and thus the transmission of an oil shock. This can be achieved through incorporating a global component consisting of global demand and the real price of oil, and a domestic component consisting of U.S. oil production, GDP, personal consumption expenditure and the FED rate. Using data ranging from 1975 to 2016, with a separate model for the years 2000 to 2016, and separating global activity and oil related shocks, this analysis aims to investigate whether the transmission of an oil shock has changed. This also allows for an investigation into whether the increased importance of the oil sector has led the U.S. economy to more closely resemble that of an oil exporting country.

An asymmetric relationship between oil price increases and decreases has been demonstrated by Mork, (1989) among others. This study however assumes a symmetric relationship. Incorporating an asymmetric model might yield more accurate results, but a symmetric relationship is sufficient for determining whether the effects of an oil price shock has changed over time. Moreover, it removes any unnecessary complications from the model.

Three structural shocks will be simulated in order to investigate the relationship between oil prices and macroeconomic activity in the United States. First, a global demand shock normalized to reduce global demand, which should cause a decline in demand for oil and thus reduce oil prices. Second, an oil shock normalized to reduce the oil price. This shock should have a positive effect on global demand. And last, a production shock to U.S. crude oil production. These are the main structural shocks of importance for determining the effects of oil price fluctuation on economic activity. An analysis of impulse responses facilitates an estimation of how a system of variables is affected when there is a shock to one of the variables. Historical decomposition allows insight into the evolution of the structural shocks over the course of the sample data, and the forecast error variance decomposition helps with quantifying the impact of the structural shock on the variables in question. With this investigation, we hope to uncover whether the shale oil revolution has induced a structural shift in the U.S. economic landscape and thus changed how the United States reacts to a shock that reduces the price of oil.

The paper is constructed in the following way: Section 2 is a literature review that includes a discussion of several papers written about the relationship between oil prices and the macro economy. Section 3 describes the methodology used in the analysis and the theory behind the SVAR model. Section 4 introduces the data, which will be used in the analysis and provides a short description of each variable. Section 5 starts with a model diagnostics before presenting an analysis of the impulse response functions, variance decomposition and historical decomposition of the data with section 5.5 providing a robustness test of the baseline model. Finally, section 6 presents the conclusion and thoughts about the limitations of the study.

2.0 – Literature Review

Hamilton (1983) found that sharp oil price increases during the period 1948 to 1972 were usually followed by reductions in real GDP growth. This growth reduction was not anticipated by previous behaviour in output, prices or the money supply. In other words, most U.S recessions prior to 1973 were directly preceded by a hike in oil prices. Hamilton found little evidence to support the notion that *"some third set of influences were responsible for both the oil price increases and the subsequent recessions"*. Hamilton did not include any discussion of oil shocks after 1973 because of non-stationarity in the data. He did however, conclude that oil shocks were a contributing factor in at least some of the pre-1973 recessions.

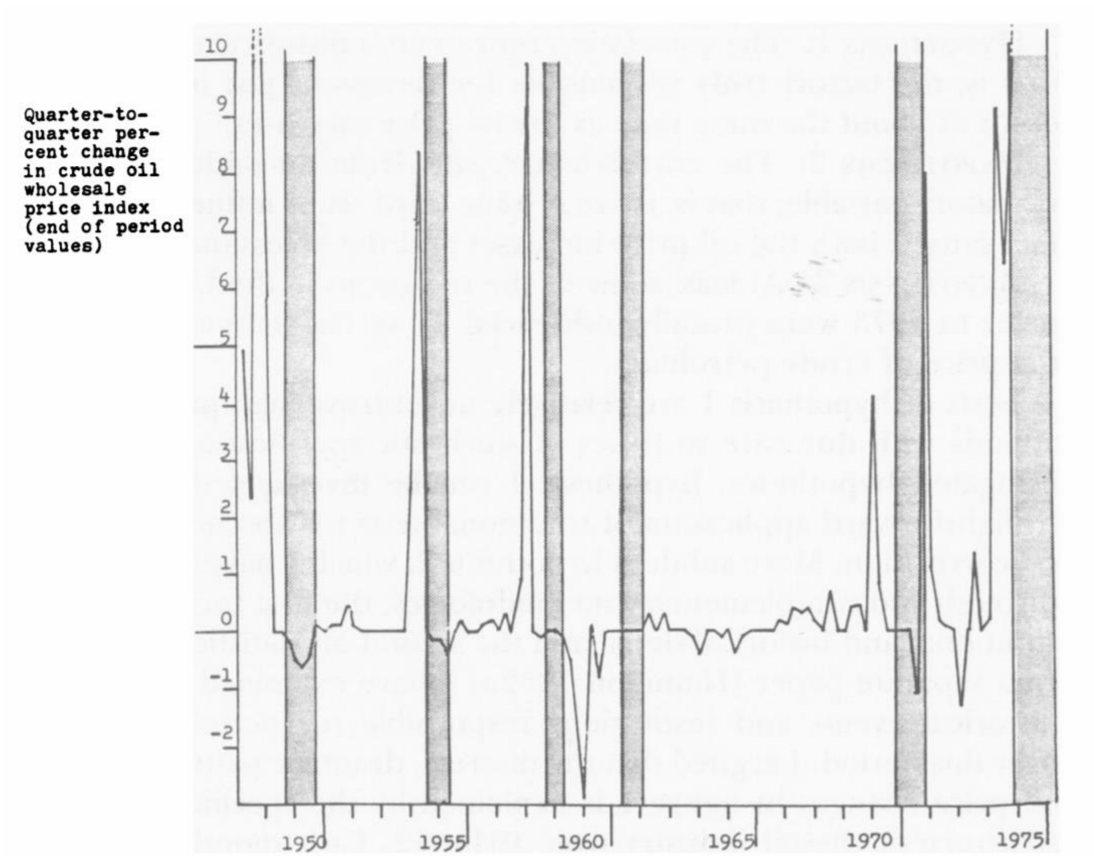

Figure 2: Changes in crude oil prices (solid lines) and U.S. recessions (shaded area), 1947-75.
Source: Hamilton 1983

Building on the work of Hamilton (1983), both Burbidge & Harrison (1984) and Gisser & Goodwin (1986) support Hamilton's findings. They show similar results for the 1973-74 oil shock when looking at data from 1962-1982. Several others, including Rasche and Tatom (1977, 1981) also found a clear negative relationship between energy prices and aggregate measures of output. Findings by Mork (1989) suggest asymmetry in the relationship between oil and the macro economy. Based on Hamilton's work, Mork's study showed that when increases and decreases in the price of oil are entered separately in a VAR framework, the coefficients are significantly different. Further, his results showed that oil price increases Granger-Cause output, while price decreases did not.

Hooker (1996) analysed the aspect of asymmetry and tried to re-establish a robust link in the relationship between the macro economy and oil prices by re-specifying the oil price. He found that when post-1980 data are included, the *"original specifications of oil price in log levels or differences break down".* Moreover, he found that since 1972, the significance of oil shocks has decreased and that oil prices fail to Granger-Cause the most important macroeconomic indicators such as real GDP, the unemployment rate and aggregate employment. Hooker examined three possible explanations. The first being that there were significant breaks in most U.S. macro series around 1973. Second, that the oil price was no longer exogenous and last, that there was asymmetry between oil price increases and decreases. He concluded that while there appears to be a structural break in the GDP growth rate around 1973, it was not due to oil price interactions. He went on to say that the price of oil did not appear to be any more endogenous post-1973 than in the period immediately prior and finally, that *"transformations of oil prices consistent with asymmetric responses also fail to Granger cause macro indicators after 1973 and in the full sample."*

Hamilton (1996), however, rejected Hooker's conclusion and argued that since 1986 the majority of oil price increases occurred after even larger price decreases. Hence, to measure the real effect of an oil price increase on consumer and corporate spending, one should compare current oil prices with previous year, not with the previous quarter. He proposed a new measure that he called "net oil price increase" (NOPI). NOPI is defined as the difference between the current price of oil and the maximum observed value from the last four quarters. This new measurement removes any increases in the price of oil that acted solely as a direct correction of a previous price decline. Contrary to Hooker's findings, Hamilton's results showed that the relationship between NOPI and GDP growth was still statistically significant and oil price increases tend to induce recessions in the United States.

Lee, Ni & Ratti (1995) argued that innovations to the price of oil are more likely to have a greater impact on real activity in an environment where oil prices have been stable, than an environment where the oil price has been more volatile. Consequently, the *"uncertainty hypothesis"* provides another explanation for how fluctuations in oil prices affect economic activity. The hypothesis suggests that increased volatility in the price of oil can have a negative effect on output. This explanation suggests that both positive and negative oil price shocks can have a negative effect. The reasoning behind this hypothesis is that uncertainty makes investors wary. Hence, activity will be lower when volatility increases. Hamilton (2003) states that: *"the suggestion that oil price shocks contribute directly to economic downturns remains controversial".* He attributes this to the fact that the correlation between the price of oil and economic activity becomes much weaker in data post-1985, as reported by Hooker (1996).

More recently, Awerbuch & Sauter (2003) finds that oil price volatility is more significant in its effect on economic activity than the oil price level alone. They conclude that a volatile environment weakens the effect of price changes because the "surprise effect" of an oil price change diminishes in a more volatile environment. However, as Hamilton (2003) concluded, *"There is no doubt about the negative impact of oil price increases and oil price volatility on economic growth during the last decades".* Later, Kilian (2009) would emphasize the importance of the specifics of the shock. He was both supported and critiqued by Hamilton (2012) among others.

Variations in the price of oil influence real activity. The literature defines three kinds of shocks that are important when describing fluctuations in the price of oil: oil supply shocks, global demand shocks and oil market-specific demand shocks. Supply shocks are defined as shocks caused by disruptions in supply proliferated by geopolitical events and developments. Global demand shocks are identified as shocks caused by fluctuations in demand that cannot be explained by changes in oil supply. Oil market-specific demand shocks are defined as changes to the oil price that occur when controlling for demand and supply shocks. The latter is a shock to prices that is caused by the market's expectations of future oil disruptions (Kilian 2009). Previous assumptions about disruptions in the oil supply due to political unrest or conflict in oil-producing nations could be explained as a demand shock initiated by expectations about supplies running low in the near future.

Kilian (2009) further argues that fluctuations in the price of oil have different effects on real activity depending on the specific underlying reasons for the shock. An adverse supply shock causes minimal increase in prices because other suppliers are quick to adjust their productions to fill the gap in the market. Hence, disruptions to supply do not cause any significant changes in real activity and fluctuations in oil prices are primarily driven by "precautionary demand shocks". Hamilton agrees that the underlying cause of the shock is important but criticizes Kilian's approach to the problem. He argues that Kilian is attaching too little importance to the effect of supply disruptions and claims that if one were to measure precautionary demand as changes in inventories, then the outcome would change. He put forth the notion that at the time of the sharpest price movements, inventories tend to decrease and suggested that, *"inventory changes were serving to mitigate rather than aggravate the magnitude of the price shocks"* (Hamilton 2012). This argument suggests that oil supply shocks have a significant effect on the price of oil and thus on global activity. Another aspect of Kilian's argument, that demand plays a larger role than supply, is based on an example from the Iranian revolution. During that period, the surge in oil prices was mainly driven by increased precautionary demand and increased global activity. Kilian's claim is backed by an impulse response analysis that shows that shocks related to precautionary demand and global aggregate demand cause a persistent increase in price. On the other hand, the impulse response function for an adverse supply shock causes an insignificant increase in price that quickly dies out.

Aastveit et. al. (2012) analysed the importance of demand from emerging and developed economies as drivers of the price of oil. Much like Kilian (2009) who emphasized the importance of demand shocks, their results suggested that the combined demand accounted upwards of 50 percent of the fluctuation in the real price of oil. Further, the demand from emerging countries, most notably in Asia, was twice as important as the demand from developed countries when accounting for the fluctuation in both the oil price and global oil production. Moreover, their evidence revealed that adverse oil market shocks had different impacts in different regions. Emerging economies were less exposed to adverse oil related shocks than developed countries. Even those with high investment shares in GDP were less affected by the increase in oil prices.

Using structural VAR models, Blanchard & Gali's 2010 study concluded that the effect of oil price shocks on macroeconomic variables has changed over time. The study compared the effect of an oil specific shock before and after 1984 across several industrialized nations, including the United States. Their findings revealed noteworthy changes in prices, wages, production and employment. The effects were significantly larger pre-1984. They cited three plausible causes: a decrease in real wage rigidities, increased credibility of monetary policy and the decrease in the share of oil in consumption and production.

Bjørnland & Thorsrud (2014) investigated the potential spill-over effects from the resource sector in Australia and Norway following a resource boom. Their findings revealed that a thriving resource sector stimulates productivity and production in both countries and showed significant evidence of positive productivity spill-overs on non-resource related sectors. Further, the study found that increases in the price of commodities, particularly those related to increased global activity, also stimulate the economy. However, price increases unrelated with a boom in global activity, yield less positive results. Exchange rate appreciation and reduced competitiveness were pointed out as an explanation for this. Employment and the value added from the resource sector in Norway, temporarily increases due to increased government spending and technological advancements required to effectively extract the resource. This results in spill-over effects within other technology intensive service sectors and helps to reduce the overall negative effect on the economy. Australia, on the other hand experiences an effect that resembles the phenomenon known as "Dutch disease" when productivity in the resource sector declines.

Baumeister & Kilian (2016) studied how the recent oil price decline affected the U.S. economy. Their results suggest that the U.S. has not had the expected activity increase after the oil price decline. They question whether the transmission of an oil shock to the U.S. economy has shifted due to fundamental and structural changes in the U.S. and the emergence of the shale oil sector. Their findings indicate that consumer spending increased after June 2014. If this influx of funds from lower energy prices did not increase consumer spending where did it go? Neither did their savings rate increase[3], nor did they use this opportunity to deleverage. Their estimates are somewhat consistent with the IMF (2016) report. They found that private real consumption and non-oil related investments increase by about 0.9 percentage points of real GDP growth and that oil-related real investments fell dramatically. The U.S. oil industry has seen an impressive upturn and oil production has doubled in the last 5 years. The increased importance of the oil sector in the U.S. could explain why the "expected" upturn did not occur following the oil price drop. Furthermore, they find no evidence to indicate that the transmission of an oil shock on the U.S. economy has changed, but rather that the lower GDP growth rate could be attributed to the slower growth of non-petroleum based exports and a global economic slowdown.

[3] Baumesiter and Kilian point to data from the Bureau of Economic Analysis showing that the personal savings rate of U.S. households declined from 5.9 percent on average between January 2009 and June 2014, to 5.8 percent on average between July 2014 and March 2016. The savings rate dropped further from 5.8 percent to 5.3 percent during the bulk of the oil price decline before recovering in 2015.

3.0 – Methodology

Early studies on the relationship between oil and the macro economy were primarily based on oil importers. In these studies, Real Business Cycles (RBC) models were used to study the macroeconomic outcome of shocks to the price of oil.

The structural vector autoregressive (SVAR) model was introduced by Sims (1980) and has gained widespread use in applied macroeconomic research ever since. The model replaced the rather out-dated large-scale macro econometric models. In these models, the identification issue is solved by excluding variables, typically lagged exogenous variables, in lack of any theoretical or statistical justification. The idea was to construct a model where the variables are treated as either endogenous or exogenous. The latter was determined outside the model, and could thus be treated independently of the other variables. A sensible way of handling the problem was by imposing exclusion restrictions on the lags of certain variables. This method was criticised by Sims (1980). He questioned the idea of using models identified by unjust exclusion restrictions that were neither innocuous nor essential for the construction of a model that could be used for policy analysis and forecasting. According to Sims, only the a priori knowledge of which variables should enter the system in the reduced form is required in order to utilize the SVAR approach. Only after this first step can the lag length, choice of the deterministic components, and how to handle the non-stationary components be determined (Bjørnland and Thorsrud 2015, 214). Thereafter, the effects of a shock to the system of variables can be assessed by computing the impulse response functions (IRF) and forecast error variance decompositions (FEVD). Sims argued that through the use of this method, economic hypotheses and the historical dynamics of the data could be tested and examined more accurately than with the old large scale macro models.

3.1 – Choice of model

This thesis utilizes the VAR approach to analyse the effects of an oil price decline on the U.S. economy. The model is easy to implement and often provides better results than older conventional large-scale macro econometric models (Sims 1980, Bjørnland & Thorsrud 2015). All variables are treated symmetrically as endogenous variables in the system and there is no causal relationship between the variables. This means that one allows the different variables in the VAR to directly and indirectly affect each other. The high flexibility of the VAR to test the effects on different variables in a system makes the VAR approach an ideal choice for this type of analysis, particularly with regards to testing how a shock to one variable affects the other variables in the system.

3.2 – Vector Autoregressive Model

A VAR model is a multivariate version of the univariate AR model. The model is in essence a system of equations that collectively and individually depend on the other variables in the system. As a consequence, using the OLS method to estimate the system of equations would yield biased results essentially making it impossible to make a good inference from the results. Estimating the reduced form of the system from the standard VAR solves this problem. The VAR model has the following reduced form of order p:

$$Y_t = \mu + A_1 y_{t-1} + A_2 y_{t-1} + \cdots + A_p y_{t-p} + e_t \quad (1)$$

$$Y_t = \mu + \sum_{i=1}^{p} A_t y_{t-1} + e_t \quad (2)$$

Where A is a (K x K) coefficient matrix, μ is a (K x 1) vector of intercept terms, and e_t denotes a (K x 1) vector of error terms, which are assumed to be white noise and has the following properties:

$\mathrm{E}\,[e_t] = 0$

$$\mathrm{E}\,[e_t, e'_s] = \begin{cases} \Sigma e & \text{for } t = s \\ 0 & \text{otherwise} \end{cases}$$

A key difference between the reduced form VAR and a univariate AR model is that the VAR model relates the k'th variable in the vector Y_t to all past values of all other variables in the model and not only of itself. However, the error terms may be correlated in the reduced form VAR. Thus, estimating how a shock to one variable affects the other variables in the system would produce misleading results. Further, the properties of the data are determined by the reduced form VAR parameters. This implies that any attempt to determine the structural parameters from the properties of the data would lead to indeterminacy. The solution is to impose $\frac{(n-a)n}{2}$ identifying restrictions (Bjørnland and Thorsrud 2015, 219).

For the model to work it is important that it is stable, i.e. covariance-stationary, meaning that the effects of the shocks eventually die out. The stability of the model is discussed in section 5.1 Diagnostics.

3.3 – Identification: Cholesky Decomposition

Three methods of identification are suggested in the literature: contemporaneous restrictions, long-run restrictions and sign restrictions. Contemporaneous restrictions are represented by the Cholesky decomposition, the chosen approach in this thesis. This decomposition brings to light the importance of the ordering of the variables in the system, due to how the individual variables respond to shocks in other variables. Further, Cholesky Decomposition ensures that all error terms are orthogonal. The orthogonality condition is critical to achieve a valid result. Without orthogonality, the error terms would be correlated, meaning that a shock to one variable is accompanied by shocks to the other variables in the system, leading to biased results.

To achieve orthogonal shocks, the Cholesky Decomposition assumes a lower triangular matrix with positive elements on the diagonal:

$$y_t = \sum_{j=0}^{\infty} B_j P P^{-1} e_{t-j} = \sum_{j=0}^{\infty} C_j v_{t-j} \tag{3}$$

Where $C_j = B_j P$ and $v_t = P^{-1} e_t$ and $\Sigma = PP'$

This identification method ensures that the shocks are uncorrelated and assumes a recursive relationship between variables. As a result, a shock to any one variable does not affect the variable above it contemporaneously, i.e. all other shocks can be set to zero if one imposes a shock to one variable. With this in place, any equation in the system can only contain the contemporaneous value of the variables ordered above it in the system. However, one important step remains. In order for the model to yield viable results from which to make a good inference about the contemporaneous effects, the ordering of the variables in the Cholesky decomposition needs to be determined.

3.4 – Model specification

The VAR model will be constructed to describe how the U.S. economy is affected by an oil price shock. More specifically, the effects of a global activity shock and oil related shocks on U.S. output and household consumption. This allows an investigation into the impact of lower oil prices on the U.S. economy. To capture fluctuations in the price of oil through the oil market, the model includes the two global variables: global activity and the real price of oil. One could argue that in order to accurately represent the oil market, one would need to add global oil supply as well. However, findings made by Kilian (2009), and supported by Aastveit et.al. (2012), show that global oil supply has little effect on total fluctuations in the price of oil. The subsequent variables are chosen to depict the U.S. domestic economy, represented by U.S. oil production, U.S. output (GDP), U.S. personal consumption expenditure (PCE) and the FED rate. This study is focused around the assumption that there has been a shift in the U.S. economic landscape brought about by the shale oil revolution. Thus, U.S. oil production is ordered as the first domestic variable to measure whether this shift has caused significant changes with regards to the transmission of an oil shock. The following two variables: U.S. GDP and PCE, are the two variables of prime concern in this thesis when measuring the effects of an oil price decline. Finally, the FED rate is included as a control variable to adjust for how the reaction of monetary policy affects the non-oil related domestic variables.

Thus, the Cholesky ordering is as follows:

Global Activity	*Non-Oil Related*	*Global*
Real Oil Price	*Oil Related*	
U.S. Oil Production		*Domestic*
U.S. Real GDP	*Non-Oil Related*	
U.S. Real PCE		
FED Rate		

Which results in this model:

$$\begin{pmatrix} Gact_t \\ Real\ oil\ price_t \\ Oil\ production_t \\ US\ rGDP_t \\ Consumption_t \\ MP_t \end{pmatrix} = K + \begin{pmatrix} \theta_{11,0} & 0 & 0 & 0 & 0 & 0 \\ \theta_{21,0} & \theta_{22,0} & 0 & 0 & 0 & 0 \\ \theta_{31,0} & \theta_{32,0} & \theta_{33,0} & 0 & 0 & 0 \\ \theta_{41,0} & \theta_{42,0} & \theta_{43,0} & \theta_{44,0} & 0 & 0 \\ \theta_{51,0} & \theta_{52,0} & \theta_{53,0} & \theta_{54,0} & \theta_{55,0} & 0 \\ \theta_{61,0} & \theta_{62,0} & \theta_{63,0} & \theta_{64,0} & \theta_{65,0} & \theta_{66,0} \end{pmatrix}$$

$$\begin{pmatrix} \varepsilon_{Gact,t} \\ \varepsilon_{Real\ oil\ price,t} \\ \varepsilon_{Oil\ production,t} \\ \varepsilon_{Us\ rGDP,t} \\ \varepsilon_{Consumption,t} \\ \varepsilon_{MP,t} \end{pmatrix} \Theta_1 \varepsilon_{t-1} + \cdots \qquad (4)$$

where K is a vector of intercepts.

Through this structural relationship, a change in the oil price will not affect global activity contemporaneously. This is a common assumption when conducting this type of empirical study. Further, it is assumed that the price of oil does not react contemporaneously on impact with any of the variables ordered below it in the system. This assumption seems reasonable as the price of oil does not necessarily react on impact with variables like domestic consumption and other country specific variables (Bjørnland 2009). Moreover, the real price of oil affects oil production contemporaneously, but oil production only affects the price of oil with a lag.

This thesis investigates the macroeconomic effects of an oil price shock and how oil related shocks affect U.S. output and consumption. Even though the ordering of the variables in a SVAR can be somewhat arbitrary, the ordering ultimately determines the validity of the results. As such, it is an important and necessary step towards understanding how an oil shock affects macroeconomic variables. Cholesky ordering implies that any variable in the system can only contemporaneously affect the variables that are ordered below it in the system. Hence, in order to study the effects of an oil price increase, global demand and the real price of oil needs to be ordered first in the system. This ordering of the two first variables implies a modification from Kilian (2009) and instead follows Bjørnland and Thorsrud (2016). The reason for this is the differences in scope. Kilian looked specifically at the effects of a global oil supply shock to the price of oil, while this paper is focusing on the effects of a demand shock and oil related shocks on the U.S. domestic economy. For the remaining variables, this thesis assumes that to reflect the changes in U.S. output and consumption, the variables should be ordered in terms of their causal relationship. U.S. crude oil production is ordered between the oil price and GDP, because oil production is heavily dependent on the real price of oil. Output is a determining factor in consumption. A decline in output implies fewer available consumer goods and thus lower consumption. Hence, consumption is ordered below GDP. Finally, the FED rate is ordered last in the system to act as a control variable. Note that all variables can only react after one lag to an exogenous shock to any of the other variables in the system.

4.0 – Data description

A model consisting of six different variables is used to estimate the effects on U.S. economic activity; a proxy for global activity, the real price of oil, U.S. oil production, U.S. output, U.S. consumption and the FED rate. When first inspecting the data, one can clearly see that U.S. oil production has rapidly increased since 2007. It is thus natural to split the data set and estimate whether there are any significant differences before and after the increase in the oil production. However, this would leave too little data to give viable results. Thus, in order to make a good inference from the results, the data sets will be split from 2000 Q1 to 2016 Q4 in order to investigate potential differences. Seasonally adjusted data will be used where applicable.

4.1 – Indicator for Global Activity

To measure global activity (Gact), a variable that predicts changes in demand for commodities over time and can be used as a proxy for global demand needs to be identified. Kilian's Index of Global Real Economic Activity is the main indicator for Gact used in this paper while the two others are used to test the model for robustness. These three variables are:

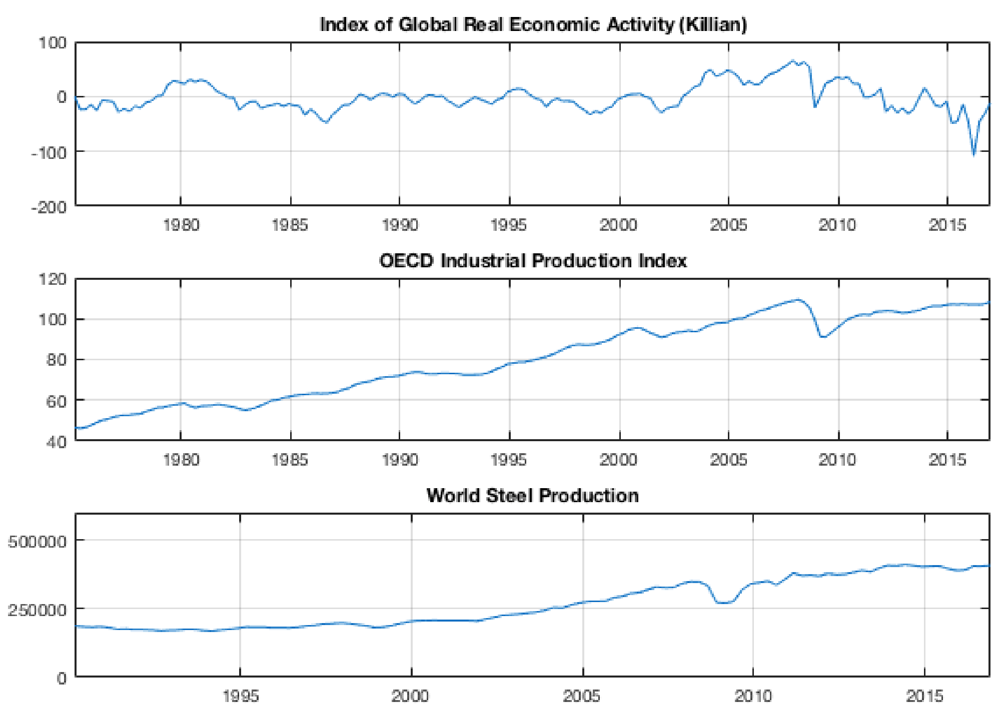

Figure 3: Three Different Proxys for Global Economic Activity

4.1.1 – Kilian's Index of Global Real Economic Activity

Kilian's "index of global real economic activity in industrial commodity markets" has been the preferred measure for global activity since its inception and is widely used in the literature despite its shortcomings. Kilian claims that this index, which is based on a dry cargo freight rate index, is designed to accurately capture fluctuations in demand for industrial commodities on a global scale. Using Kilian's indicator for global demand, it is possible to model the great moderation (1985 - 2007) and the global financial crisis (Ravazzolo and Vespignani, 2015). However, there are some limitations with this indicator. Limitations in the data makes it difficult to accurately measure the weights for commodities and routes. Hence, in his index, Kilian weighed everything equally. Because routes and individual commodities are expected to change over time, weighting everything equal may introduce the possibility for the index to become biased over time. This shift in the global trade routes and global demand for commodities over time has been noted by several authors, including Kilian himself[4]. One observation from the data is a negative trend in the indicator since around 2011. This could possibly be attributed to a global economic cooldown following a rapid increase in the real price of oil. Kilian's index of real global economic activity is available from: http://www-personal.umich.edu/~lkilian/ and is estimated on a monthly basis. For the purpose of this study, the series will be converted to quarters.

4.1.2 – The OECD Industrial Production Index

The OECD Industrial Production Index is a measure for the total industrial output of all OECD countries and is available from the OECD monthly economic indicators (MEI) running all the way from 1975. The data will be converted from months to quarters. It was a popular indicator for economic activity prior to 2009 mainly because there were few other alternative series available at the time. The use of this series as a proxy for global economic activity relies on two assumptions; The industrial sector is a good representation of the full economy and the OECD countries are a good representation of the World economy. The introduction of China into the WTO in December of 2001 and the increasing importance of emerging economies on

[4] See Kilian (2008), Kilian (2009) and Hamilton (2013).

Global aggregate output pulls into question the validity of the second assumption. Further, Steindel (2004) among others argue that the relationship between industrial output and GDP has been diverging since 2001. Moreover, by using this indicator to measure global demand, we would neglect the fact that the macroeconomic environment is changing. Emerging economies are now leading global demand with China as a prime example. China and India have become major contributors to world output since 2003. Hence, using the OECD industrial activity as a measure for global demand the model would not reflect this change in global aggregate demand and could possibly give biased results.

4.1.3 – World Steel Production

A Norges Bank working paper from 2015 by F. Ravazzolo and J. L. Vespignani suggest an alternative to the two indicators discussed above, World Steel Production. The series is available in months and will be converted to quarters for the purpose of this study. They argue that the importance of crude steel as a key input resource in many industries implies that a measure of world steel production would be a good proxy for global activity. Further, the series is already in real numbers so there is no need to deflate it. The weighting issue one encounters with the OECD industrial production index and Kilian's real activity index does not apply to steel production because the production of steel by countries can be weighted and updated monthly by actual production output. However, there are some obvious drawbacks with using world steel production as a proxy for global activity. First, the series is relatively new, only dating back to 1990, limiting the scope of studies using this series. Further, the series is based on one single commodity. When constructing a measure for global demand, it would be preferable to have a data series that accounts for the intricacies of the global economy. Hence, one could argue that this indicator would not accurately capture the all the complexities of the global economy.

4.2 – Oil Price: U.S. Refiner Acquisition Cost

This study follows Kilian (2009) among others, and utilize U.S. refinery acquisition cost to reflect the price of oil available from eia.gov. The series is a weighted average of domestically produced and imported crude oil costs. U.S. refiners acquisition cost is more accurately described as "The cost of crude oil, including transportation and other fees paid by the refiner. The refiner acquisition cost does not include the cost of crude oil purchased for the Strategic Petroleum Reserve (SPR)". CPI for U.S. urban goods has been used to deflated the series to reflect the real price of oil. One advantage of using this series is the historic data that is available. The series reaches back to 1974, and allows the estimation of past and present phenomenon with regards to changes in the oil price.

4.3 – U.S. Crude Oil Production - Thousand Barrels Per Day Average

Contrary to Kilian (2009), this thesis does not focus on the effect of a global oil supply shock. Killian's results show that said shock has a minuscule effect on oil price, real GDP and inflation. Instead U.S. crude oil production is used as a domestic oil related variable. Following the recent shale oil revolution and a legislation that removed the crude oil export ban that dated back to 1975, oil production in the U.S. is reaching new heights. Thus, U.S. Oil Production is becoming increasingly important. This variable measure average millions of barrels produced per day, in monthly frequency and is available from the U.S. Energy Information Administration's database. The data series dates back to 1920 and is available in both annual and monthly frequencies, but is converted to questers for the purpose of this study.

4.4 – U.S. Real Gross Domestic Product

Real Gross Domestic Product is the inflation adjusted monetary value of the goods and services produced by labor and property located in the United States (Federal Reserve Bank of St. Louis). It is calculated on a quarterly basis. GDP includes all private and public consumption, investments, private inventories, government outlays and the balance of trade. Instead of measuring the value of a finished product, it measures the difference in values of the completed product and the materials used in its construction, i.e. GDP measures value added instead of total value. This implies that the GDP can be broken down into its different components and thus serve as an indicator of the failure or success of economic policy (Segal, 2017).

4.5 – U.S. Personal Consumption Expenditure

U.S. Personal Consumption Expenditure (PCE) measures the price changes of consumer goods and services. The index shares a lot of similarities with the Consumer Price Index (CPI) when analysing the "Economic Health" of the United States. However, in contrast to the CPI which only contains changes in expenditures on goods included in a predetermined "basket of goods", the PCE includes a great variety of household's expenses that the CPI does not consider. Hence, the PCE is the preferred indicator for the Federal Reserve (FED) when they are reviewing economic conditions and charting a course that impacts inflation and employment (Staff, 2017). This study will utilize the PCE to measure changes in households' consumption and economic activity, presenting an opportunity to analyse how households react to a change in the price of oil.

4.6 – FED Rate

The Federal funds rate is the interest rate at which depository institutions lends overnight funds, maintained at the Federal Reserve, to each other. It is one of the most influential interest rates in world economy and certainly in the U.S. Through its impact on monetary and financial conditions, it affects a number of key macroeconomic indicators, such as investments, inflation, employment, output etc. The series is available from The Federal Reserve Bank of St. Louis in a monthly frequency. Since this thesis uses quarterly frequency, the data set is converted by taking the average rate of three months.

5.0 – Results

This section of the paper starts by presenting a diagnostic report of the baseline model before continuing with an analysis of the results. Section 5.2 presents a complete analysis of the full sample baseline model including an analysis of the impulse response functions, forecast error variance decomposition and historical decomposition. Section 5.3 presents a similar analysis for the subsample baseline model. All variables apart from Kilian's global real economic activity index and the FED rate are in log-levels and the shocks are normalized to reduce the oil price. The analysis assumes a symmetric relationship between oil price decreases and increases.

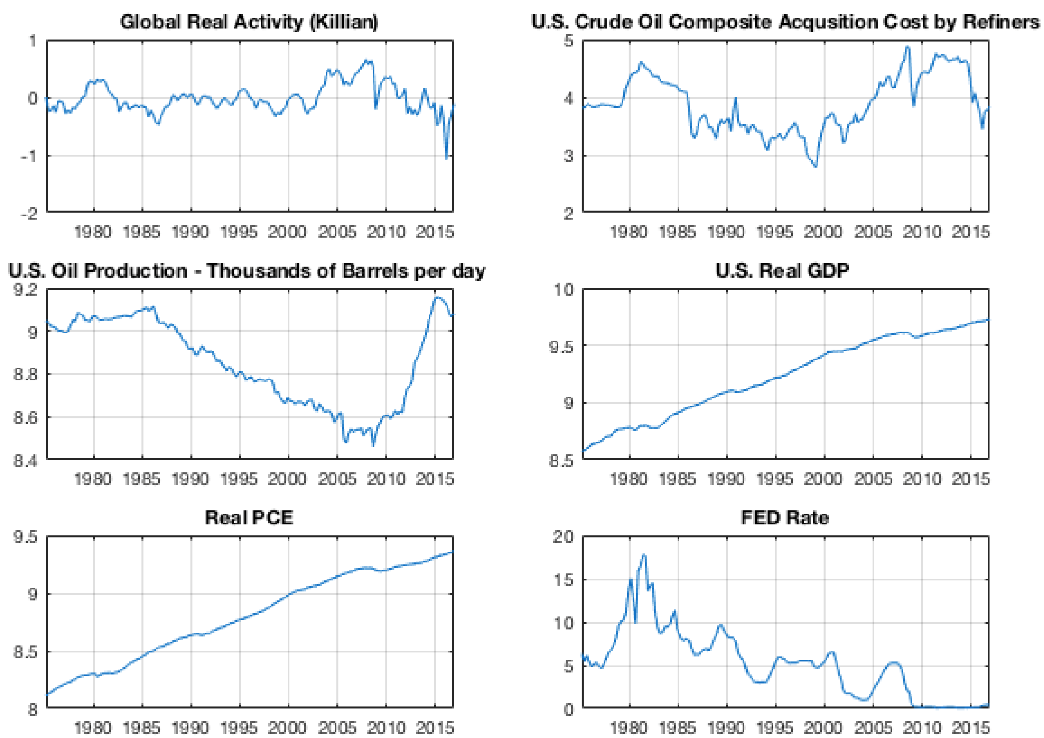

Figure 4: Variables used in the baseline model.
All variables but global activity and the FED rate are in log levels

5.1 – Diagnostics

Statistically, if the variables are skewed, any analysis of correlation or regressions performed will be heavily influenced by outliers. Hence, in order to ensure that the data is not affected in this way, the logs of the variables are used where applicable. Further, taking logs of the variables also reduce the impact of any large changes in the total value of the variables. This implies that all variables apart from the FED rate and Kilian's real activity index will be in log-levels.

Several diagnostics tests have been performed in order to check the integrity and validity of the model. First, an Augmented Dickey Fuller (ADF) test revealed that most of the data is non-stationary. However, model stability is more important than stationarity in the individual time series. Without a stable model, the results would be biased. However, in order to accurately determine whether the model is stable, the lag order must first be determined. Hamilton and Herrera (2004) presents a factual argument for increasing the lag length beyond what is provided by the Akaike Information Criterion and the Bayesian information Criterion[5] when constructing a model with the intention of measuring the effects of an oil price shock. They argue that a minimum lag length of 12 months is required to achieve the most accurate results, and this thesis follows this logic. At 8 lags (24 months), the full sample baseline model is stable. Further, when dividing the dataset from 2000Q1 to 2016Q4, all models are stable at 4 lags (12 months). Finally, tests on the residuals of the model is performed in order to check whether there is evidence of persistence or autocorrelation in the residuals which revealed that there is no evidence of any significant persistence in the any of the variables.

The results of the ADF test, the lag selection process, stability tests and autocorrelation, including the theory behind these tests can be found in the appendix part 2 and the interested reader is directed there for further information.

5.2 – Full Sample Model

The full sample model ranges from 1975 Q1 to 2016 Q4. The model is estimated with 8 lags (24 months) and every shock is normalized to reduce the price of oil. An analysis of all three shocks is provided.

[5] The theory behind both the AIC and BIC is provided in the appendix, part 1

5.2.1 – Impulse Response Functions

The purpose of the impulse response functions are to describe how a given structural shock affects the specified variables in the vector over time. More specifically, the IRF is the reaction of a dynamic system of variables to some external change denoted by a shock to one of the variables in the system. Full theoretical explanation is available in the appendix, part 2.

The IRF presented below are estimated with 68 percent bootstrapped confidence bands, represented by the 32nd and 68th percentile respectively. The shocks are normalized to one unit of the respective variable. For instance, a shock to the oil price implies an oil specific shock equal to one log unit of the oil price. Note that the shocks are specified as negative on impact to emulate an oil price decline driven by an adverse demand shock and a negative oil specific shock.

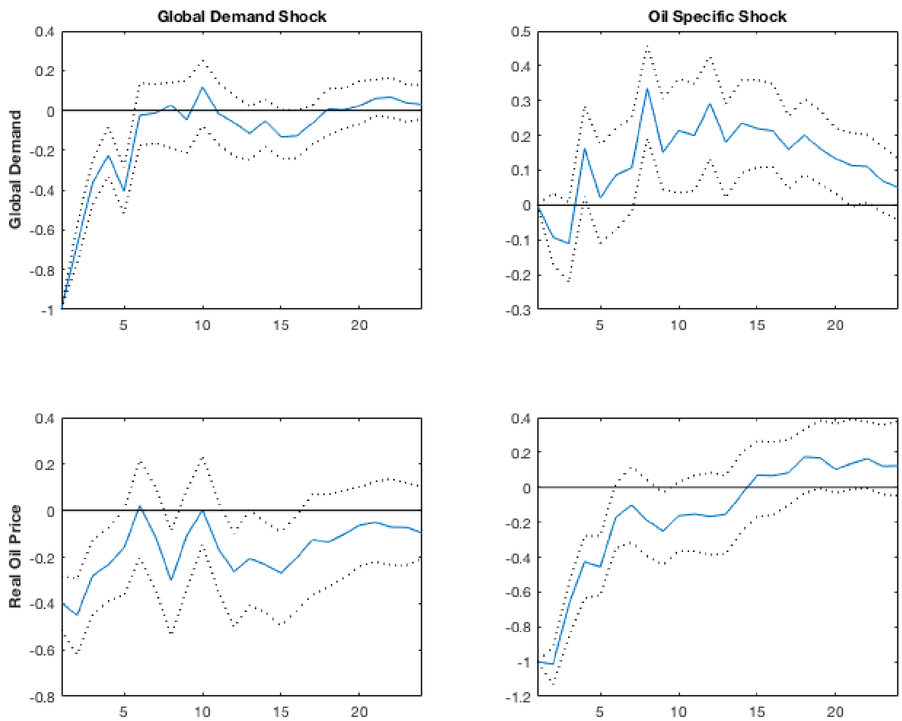

Figure 5: Global Demand shock vs Oil Specific Shock
Shocks normalised to 1 – 68 percent bootstrapped confidence bands - 2000 draws

Figure 5 presents the dynamic of two of the main shocks included in this study. There is a clear distinction between the effect of the two shocks. The adverse demand shock reduces global demand and subsequently the price of oil. The dynamic of an oil specific shock on the other hand, is different. A shock normalized to reduce the oil price without any prior changes to global demand, increases demand for oil, which in turn increases global demand and results in a gradual stabilization of the oil price back to its prior level. This dynamic is important in order to distinguish between these two types of shocks.

The figures posted below display the estimated impulse response functions for the different variables of interest to an oil specific shock normalized to reduce the price of oil.

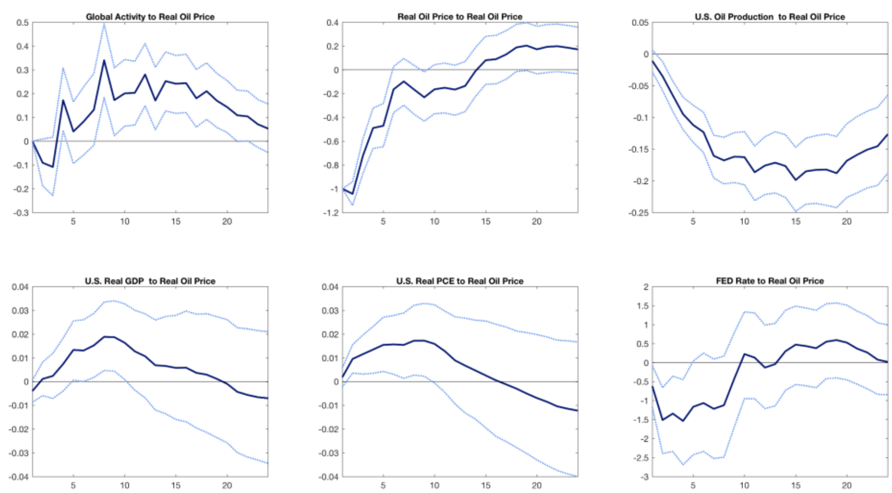

Figure 6: Response to a negative oil price shock
8 lags - 2000 draws – 68 percent bootstrapped confidence bands - 1975-2016

Figure 6 fits with conventional economic theory and exhibits the expected reaction to an oil specific shock. A negative shock to the oil price increases global demand. Further, PCE shifts up significantly on impact, sustaining the level for around 10 quarters. Even though GDP responds contemporaneously negative, the variable experiences a reaction resembling that of the PCE, remaining significantly positive until approximately quarter 10, albeit with a lag. As noted by Baumeister & Kilian (2016), lower energy prices for consumers corresponds to potentially higher consumption of other goods. This positive reaction to consumer demand coupled with lower production cost for firms, supplements a further increase in output. Moreover, the reaction of GDP and PCE is further strengthened by the increased global demand. Oil production declines persistently throughout the whole period. This is as expected, considering the lower profitability in oil production. Even though the oil price eventually recovers, it does not recuperate back to its former level. This could correspond to the development of U.S. oil production, falling from its peak level in 1975 and not fully recovering before the dawn of the shale oil revolution. An interesting observation is the movement of the FED. As a reaction to lower oil prices, the FED reacts negatively on impact, which in turn strengthens the response of both GDP and PCE. From the full sample model, it is easy to simulate additional shocks to both global demand and U.S. oil production. The next paragraph includes an analysis of the three structural shocks, comparing their effects.

On first inspection of Figure 7, one can clearly see that all three shocks have a significant negative impact on the real price of oil. The effect on the other variables in the system however differ somewhat with the shock type. An interesting observation is that an adverse demand shock, and the following contemporaneous negative effect on the oil price, seemingly increases oil production. Moreover, this increased production does not seem to significantly negatively reinforce a continued downward reaction in the price of oil. This is contrary to what happens with the supply shock. In column three one can see that the initial supply shock induces a significant decline in the oil price, and it does not start to recover before the effect of the supply shock wears off. Despite these differences, the two shocks have a relatively similar effect on both GDP and PCE. The variables respond significantly positive to the shocks. However, unlike the oil specific shock discussed in the section above, said variables do not seem to recover. The shocks are persistent, and both GDP and PCE appear to stabilize on a new equilibrium level.[6] The FED rate, which is used as a control variable, seem to be affected in the same way by both of the first two shocks; significantly negative in the first few periods, before stabilizing. The FED rates reaction to the third shock is more or less insignificant over the entire timeframe.

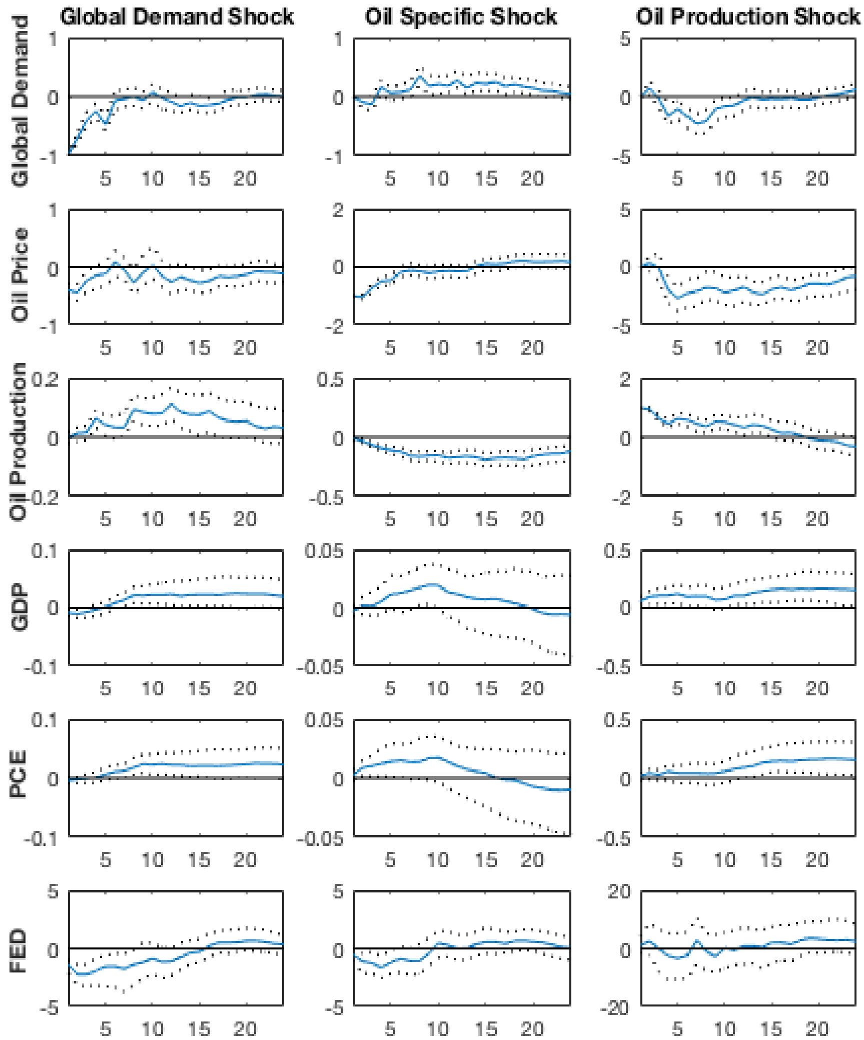

Figure 7: Response to Global demand- Oil specific and U.S. Oil production shocks
(8 lags - 2000 draws – 68 percent bootstrapped confidence bands - 1975-2016)

[6] It is important to keep in mind that the supply shock is only comprised of U.S. crude oil production and not global oil production. If one were to use global supply instead, the shock would most likely look significantly different.

5.2.2 – Forecast Error Variance Decomposition

Table 1 presents the forecast error variance decomposition (FEVD) of the three specified shocks on the two variables of interest. The FEVD decomposes the proportion of forecast error variance in the variables attributed to the variations coming from the respective shocks. More generally, it describes how much of the variation in each variable is explained by the respective shocks. This decomposition can help with quantifying the impact of the structural shocks on the U.S. economy. A theoretical description of the FEVD is provided in the appendix, part 1.

	Global Demand		Oil Specific		Oil Production	
Horizon	**Real GDP**	**Real PCE**	**Real GDP**	**Real PCE**	**Real GDP**	**Real PCE**
4	**.0323**	**.0137**	**.0150**	**.0359**	**.0490**	**.0159**
	[.0091-.0861]	*[.0041-.0430]*	*[.0047-.0404]*	*[.0078-.0939]*	*[.0118-.1203]*	*[.0038-.0558]*
12	**.0658**	**.0511**	**.0431**	**.0441**	**.0534**	**.0268**
	[.0254-.1506]	*[.0154-.1474]*	*[.0135-.1133]*	*[.0122-.1290]*	*[.0167-.1383]*	*[.0071-.0851]*
20	**.0682**	**.0557**	**.0423**	**.0457**	**.0660**	**.0506**
	[.0233-.1804]	*[.0142-.1675]*	*[.0153-.1103]*	*[.0165-.1178]*	*[.0177-.1708]*	*[.0127-.1453]*
36	**.0627**	**.0587**	**.0573**	**.0599**	**.0646**	**.0541**
	[.0201-.1841]	*[.0146-.1883]*	*[.0191-.1608]*	*[.0192-.1726]*	*[.0184-.1791]*	*[.0144-.1652]*

Table 1: The contribution of global demand, oil specific and oil production shock to U.S. GDP and PCE

The 50th percentile of the variance decompositions from a residual bootstrap procedure with 2000 draws. The numbers in brackets are the 32nd and the 68th percentiles respectively – Derived from baseline model

In the short-term, the effect of the three shocks is relatively small. After four quarters, the global demand shock accounts for just 3,23 and 1,37 percent of the variation in real GDP and real PCE respectively. The same is evident for the oil production shock, which accounts for just 1,59 percent of the variation in PCE after 4 quarters. However, the explanatory power increases slightly over the horizon, peaking at 20 quarters for the demand shock, explaining 6,82 percent of the variation in GDP, and at 36 questers for PCE with 5,87 percent. Similarly, the explanatory power of the oil specific shock and the oil production shock increases over the horizon. One clear observation from the table, is that all shocks have a persistent effect on GDP and

PCE. In the long run, between 18 to 19 percent of the variation in GDP and 17 to 18 percent of the variation in the PCE is accounted for by the three structural shocks.

Note that the FEVD is used to describe how much of the variation in the variables is caused by the variability in the structural shock at different time horizons t+s given what is known at time t. This implies that for a large sample of non-stationary time series, one can bring into question the accuracy of the FEVD. Ideally time varying parameters could be used to increase the accuracy, but this is outside the scope of this thesis.

5.2.3 – Historical Decomposition

Figure 8 displays the accumulated effect of the structural shocks through the decomposition accompanying the estimated six-variable SVAR model with data starting from 1975.

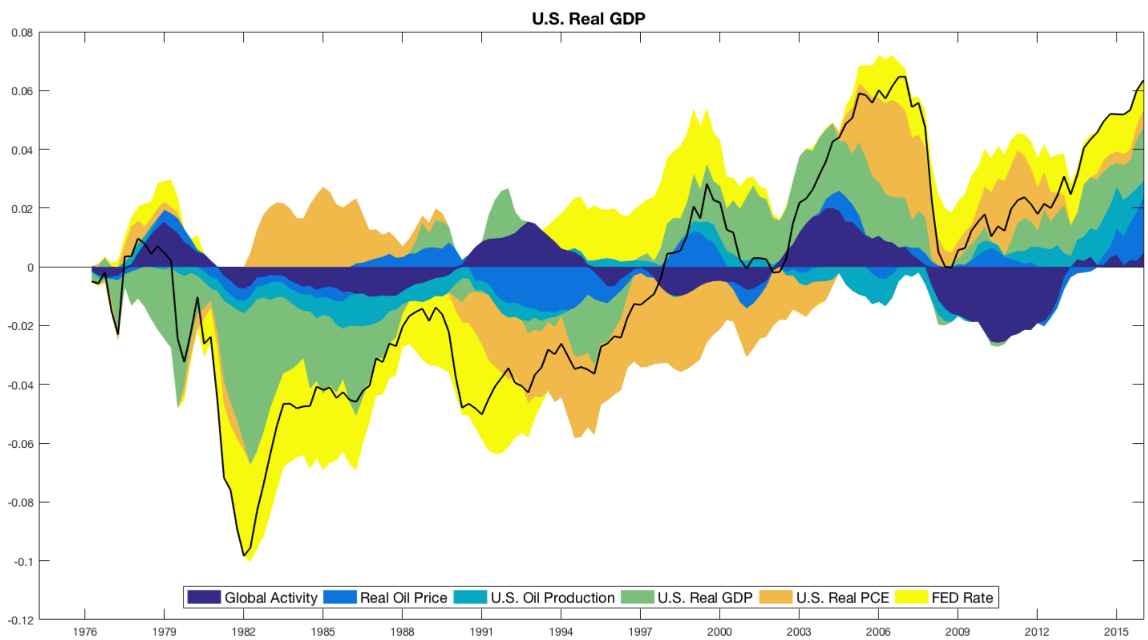

Figure 8: Historical decomposition of U.S. Real GDP – all shocks included

1975-2016 – Derived from the baseline model

The black line corresponds to the observed data series with the constant term subtracted i.e. the sum of the structural shocks over time. This decomposition allows an investigation into the cumulative effect of a given structural shock at any given point in time, thus making it easier to quantify how the response of GDP to a structural shock has changed over time.

The historical decomposition above includes several significant geopolitical events and recessions which culminated in major fluctuations to the price of oil and global activity. These events include the Iranian revolution and the following Iran-Iraq war resulting in the 1979 energy crisis, the 1990 oil price shock occurring in response to the Iraqi invasion of Kuwait, the global financial crisis in 2007, the shale oil revolution and the subsequent oil price increase leading up to the oil price decline of 2014. The increasing oil price as a response to the 1979 energy crisis, where the price of crude oil more than doubled, clearly has a negative effect on GDP. The same pattern is visible around the time of the Iraqi invasion of Kuwait. Following the global financial crisis and the oil price decline of 2014, the lower oil price clearly contributes to increasing U.S. GDP. The results would indicate that the transmission of an oil shock to the U.S. economy remains unchanged. This finding has previously been noted by Baumeister & Kilian (2016) who concluded that the transmission of an oil shock has not changed significantly. Instead, declining investments in the oil sector coupled with a contractionary effect on private consumption and a general cooling of global demand has had a large effect on U.S. GDP growth following the oil price decline. The findings above do however differ from Baumeister and Kilian in the respect that accompanying the lower oil prices, PCE is positively contributing to GDP. As expected, the increased importance of the oil sector and oil production as a consequence of the shale oil revolution, has had a positive effect on GDP. This effect is clearly visible towards the end of the sample starting from around 2010, suggesting that without the boom in shale oil production, the effects of the recent oil price decline on the U.S. economy would have been different.

Figure 9 plots the respective cumulative effects of a global demand shock, an oil specific shock and an oil production shock to U.S. GDP based on a historical decomposition of the data. The first panel, global demand shock, has arguably had the greatest impact. Although, global activity has considerably cooled down towards the end of the sample, it has not directly influenced U.S. output. Still, one can argue that the global cooldown had an indirect effect on GDP through the effect on the price of oil[7]. Interestingly, global demand shocks have caused long persistent swings in U.S. output across the entire sample. On the other hand, the oil price shocks, particularly in the subsample period, have caused more rapid and frequent movements to output. Shocks caused by U.S. oil production have historically made comparatively small contributions to output. However, one can clearly see that the shale oil revolution has contributed positively to output since its conception.

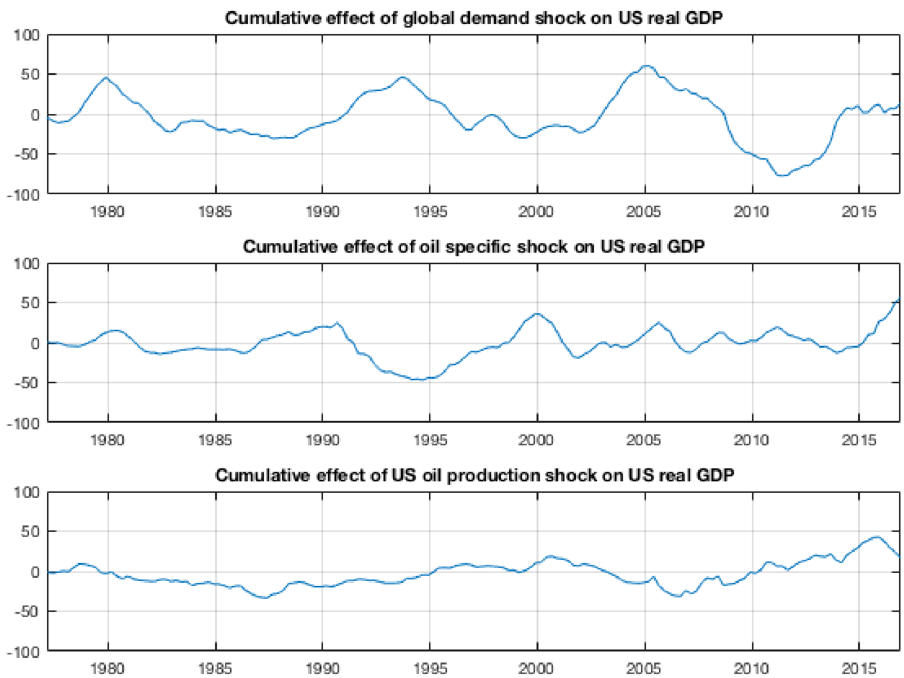

Figure 9: Historical decomposition of U.S. real GDP – First three shocks included

1975-2016 – Derived from baseline model

[7] Kilian 2009 found that global demand had a significantly larger impact on the price of oil than production.

5.3 – Subsample Analysis

The subsample period ranges from 2000 Q1 - 2016 Q4. The break date should ideally have been set at a later stage to minimize the disturbance caused by data prior to the shift observed in the oil sector in the United States. However, this is not possible because shifting the break date closer to the time frame of interest results in an unstable model due to a lack of observations. Note that the sub sample period corresponds to several major events including the dot.com bubble, the great recession (Global Financial Crisis) and the shale oil revolution in the United States. During this period, the united states oil sector has grown significantly to the point where they lifted a 40-year ban on crude oil exports in December of 2015.

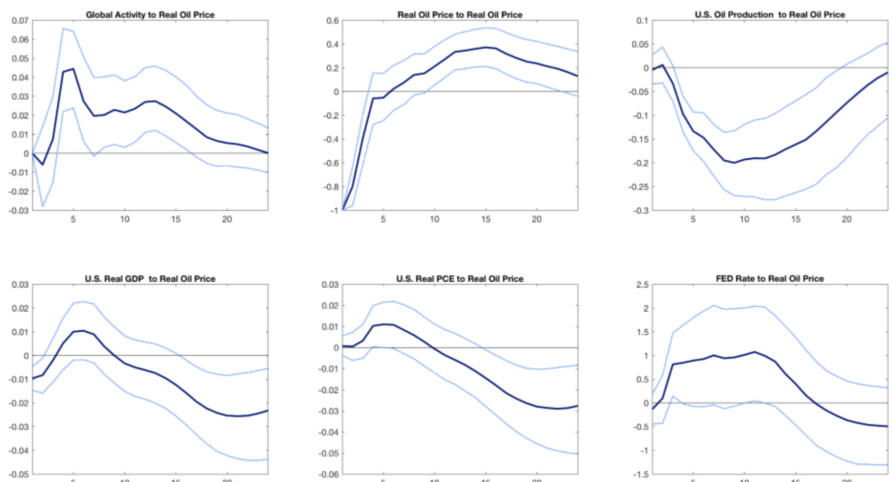

Figure 10: Response to a negative oil price shock

4 lags - 2000 draws – 68 percent bootstrapped confidence bands - 2000-2016

Most relevant for this thesis, the response GDP and PCE is decidedly more negative in the post-2000 period. Both GDP and PCE are less affected by the oil specific shock than in the full sample model, there are no longer any significant and persistent increases in the two variables. After the initial small and insignificant increase, output and consumption shift downwards for the remaining periods, showing a significant decrease in the final two years. Over the observed horizon in the subsample model, these two variables look to react negatively to the oil price shock overall. This is substantially different from the full sample model, where the reaction to output and consumption is overall positive. These changes are somewhat consistent with our initial assumption, which states that output in oil producing countries react negatively to an adverse oil specific shock, suggesting a change in the U.S. economic landscape. An important note is that a large part of the model still includes the period before U.S. oil production picked up pace which introduces a certain amount of uncertainty in the results.

The oil price has a much faster recovery from the initial adverse shock than what is observed in the full sample, where the oil price is relatively stable after the first 10-15 periods. The same is not evident in the subsample, where the oil price does not seem to stabilize before towards the end of the sample. There is even evidence of a significant increase in the oil price after 10 quarters which could provide a partial explanation for the negative reaction in output and consumption.

Similar to the full sample model, the reaction of global activity is significantly positive, while oil production responds with a sharp decline. However, the latter recovers and returns back to normal towards the end. Interestingly, the recovery happens around the same time as the oil price starts to increase and become significantly positive. Although not significant, the FED rate has a completely opposite reaction in the sub sample model compared to the full sample model. However, the monetary policy regime has seen a drastic change since the introduction of the inflation target. As a result, the FED rate is much more stable in the subsample dataset.

Shifting the focus to a positive U.S. oil supply shock, Figure 11 reveals that global activity responds in a similar fashion to the full sample model, exposing a small but significant decrease in the first two years, followed by a steady recover. The initial reaction to the oil price is somewhat unconventional and seems to exhibit a movement similar to the phenomenon commonly known as a price puzzle. However, it quickly becomes significantly negative before gradually returning to its initial level. There is clear evidence of a significant positive impact for both GDP and PCE. The shock seems to be persistent on the two macroeconomic variables, which is also consistent with the variance decomposition in Table 2 below. The reactions of both GDP and PCE to the supply shock seems to provide further evidence for an increased importance of the oil sector following the shale boom.

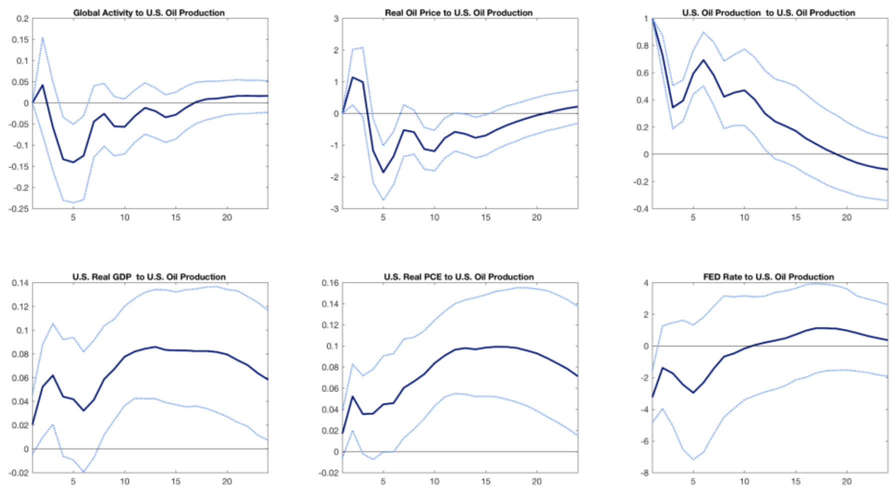

Figure 11: Response to a positive shock in U.S. Oil production
4 lags - 2000 draws – 68 percent bootstrapped confidence bands - 2000-2016

The variance decomposition of the subsample model exhibits some notable differences from the full sample. The explanatory power of the three shocks combined is approximately 48 - and 50 percent after 36 quarters for GDP and PCE respectively. This is a substantial increase from the full sample model where the total impact of the three shocks did not exceed 19 percent in the long run[8]. Further, analogous to the full sample model, all three shocks are persistent. However, the explanatory power of the two oil related shocks increases substantially over the horizon, while the explanatory power of the demand shock somewhat decreases. The oil specific shock alone accounts for approximately 25 and 27 percent of the variation in the two variables in the subsample.

[8] The drastic increase in explanatory power is likely to be due to the large fluctuations in global demand, oil price and U.S. oil production over the course of the subsample. The data includes the global financial crisis which caused considerable changes in both global demand and the real price of oil. The following shale revolution which started in 2007 has increased U.S. oil production back to its former peak levels from 1975 during which the oil price also fluctuated from around $40 per barrel to $120 back down to $30. These large fluctuations in the data implies high volatility in the data over a relatively short timeframe which can drastically increase the uncertainty of the results.

	Global Demand		Oil Specific		Oil Production	
Horizon	Real GDP	Real PCE	Real GDP	Real PCE	Real GDP	Real PCE
4	.1871	.0896	.0623	.0473	.0596	.0529
	[.0723-.3395]	*[.0233-.2348]*	*[.0280-.1279]*	*[.0158-.1397]*	*[.0155-.1461]*	*[.0138-.1492]*
12	.1611	.1221	.0972	.0935	.1051	.1250
	[.0724-.3098]	*[.0372-.3070]*	*[.0440-.1927]*	*[.0328-.2075]*	*[.0405-.2104]*	*[.0423-.2537]*
20	.1388	.1136	.1755	.1891	.1305	.1586
	[.0665-.2607]	*[.0392-.2477]*	*[.0795-.3187]*	*[.0817-.3537]*	*[.0583-.2383]*	*[.0684-.2846]*
36	.1218	.1034	.2454	.2715	.1117	.1242
	[.0552-.2568]	*[.0356-.2493]*	*[.1085-.4253]*	*[.1100-.4693]*	*[.0482-.2202]*	*[.0501-.2506]*

Table 2: The contribution of global demand, oil specific and oil production shock to U.S. GDP and PCE

The 50th percentile of the variance decompositions from a residual bootstrap procedure with 2000 draws. The numbers in brackets are the 32nd and the 68th percentiles respectively – Derived from baseline model

5.4 – Observations from the Empirical Results

The analysis suggests that the effect of a negative oil specific shock is different when comparing the full sample model with the subsample model. Without further investigation into the results one might conclude that the transmission of an oil shock has changed and that the oil price-GDP relationship is (weakly) positive in the subsample period. However, our findings suggest that this is not the case. The IRF analysis of the accumulated effect of an oil price shock on GDP and PCE show a significant negative impact in the subsample relative to the full sample model. In addition, the increased importance of the oil sector has had a considerable effect on the U.S. economy after the shale oil revolution. This is evident from the variance decomposition which shows that the explanatory power of the oil specific shock alone has increased five times, representing a significant increase relative to the full sample model. Moreover, the historical decomposition revealed that the effect of an oil shock to GDP is consistent throughout the sample period. This is also immediately evident when analysing the individual historical decompositions of the structural shocks. Thus, one can argue that without the shale boom, the effect on both GDP and PCE would be different. This observation seems to be supportive of our initial suspicion that there has been a structural shift in the U.S. economic landscape. The increased U.S. dependence on the oil sector as a contributor to GDP growth makes the country more vulnerable to fluctuations in the oil price, while the transmission of the shock itself seems to remain unchanged.

Another noteworthy observation from the results is the evolution of the interest rate. Relative to the full sample model, the explanatory power of the FED rate on the variation in GDP has considerably decreased in the subsample (see table 6 and 10 in appendix 3). Following the financial crisis, the FED rate was lowered close to the zero lower bound. Consequently, the power of the Central Bank to influence economic activity through the FED rate decrease as the interest rate approaches the zero lower bound (Romer, 2012).

5.5 – Robustness Test of the VAR Model

This section contains a robustness test of the primary VAR model using five different tests of robustness for both the full sample and subsample models. The first test is done using the same model with an additional linear trend added as an exogenous variable. Most of the variables used are non-stationary, adding a linear trend can help reduce the drift in the price of oil. Giordani (2004) argues that rather than entering output in levels in the VAR model, the output gap or the trend level of output should be included instead. This test follows Bjørnland (2009) by including a linear trend and in so doing implicitly modelling the output gap in the VAR. All other variables are the same as in the main VAR model. The second test implies replacing PCE with U.S. real private investment. Similar to the main model, all variables except global activity and FED rate are in log levels. The third test will include year-on-year CPI as the sixth variable in a seven-variable SVAR model ordered above the FED to control for the effect on inflation. Lastly, the fourth and fifth tests will be executed by using the two other variables for global demand, the OECD industrial production index and World Steel Production. A full sample re-estimation will be done using the OECD index, while the sub sample will be re-estimated using both the OECD index and the WSP due to the limited number of observations available in the WSP series. The full sets of impulse response functions are provided in the appendix, part 3.

The tests are run by estimating the impulse response functions of a negative oil specific shock. The robustness tests in the appendix yield familiar results when compared to the main full sample model. In the OECD model and the model with a linear trend, the initial negative oil price shock causes both GDP and PCE to have a significant positive reaction, the reaction is even more significant than in the main model. Replacing PCE with domestic investment yields a different result. Investment reacts contemporaneously significantly downwards. An obvious explanation for this is that oil related investments are affected negatively by the oil price shock. However, after the initial reaction down it increases, although not significantly. This increase corresponds both a partial recovery of the oil price and the increase in GDP. The seven-variable SVAR with CPI included also support the findings of the baseline model, the reaction of CPI in the model does not seem to significantly affect the results. Overall, the results from these models are consistent with the findings from section 5.2, indicating that the baseline model is robust.

Subsample robustness tests yield similar results to the baseline subsample model. The log-levels investment model shows the same contemporaneous result as the full sample version. It is again assumed that the initial negative reaction is a response to declining investments in the oil sector following a negative oil specific shock. Just like the baseline model, GDP in the investments model reacts contemporaneously significantly negative to the oil price shock. The results from the OECD model differs somewhat in the first few periods, in the sense that there is no initial reaction downwards in GDP. However, after those periods both GDP and PCE are consistent with the baseline model, i.e. that both are significantly decreasing. The model which includes CPI is also resembles the baseline model. The only model that yields a slightly different result is the one using WSP as the indicator for global activity. This model yields results similar to the full sample baseline model. This does however not mean that the baseline results are wrong. The WSP indicator consists only of one commodity which means that it might not accurately capture the complexities of global economic activity. Therefore, the WSP is not necessarily a suitable variable for modelling how changes in global activity affects U.S. output. Further, apart from the WSP, all the other robustness tests support the findings from the baseline model. Thus, it is fair to assume that the results are robust.

6.0 – Conclusion

This paper investigates the role of the oil price on the U.S. economy, specifically how lower oil prices affects U.S. aggregate output and household consumption. The premise for the study is the conception of the shale oil revolution in the United States following the financial crisis in 2007, and the recent oil price decline of 2014. Preliminary analysis seemed to indicate that a gradual shift had occurred in the U.S. economic landscape following these two events. The purpose of this study is to analyse this relationship and determine whether the response of GDP to oil price innovations has changed in recent years, making the U.S. act more like an oil exporter towards a negative oil specific shock. We use a six-variable SVAR with structural shocks to global demand, oil price and U.S. oil production. The shocks are normalized to reduce the oil price, and a symmetric relationship between oil price increases and decreases is assumed to generate impulse response functions, forecast error variance decomposition and historical decomposition.

After analysing the results, the main findings of the study are as follows. First, when isolating the effect of the oil price on GDP using the historical decomposition, our analysis suggests that the relationship remains fairly unchanged over the course of the full sample. This supports findings previously made by Baumeister & Kilian (2016), and implies that the transmission of an oil price shock has not changed. However, contrary to Baumeister and Kilian, the effect of an oil specific shock on GDP and PCE has changed when comparing data from 1975 - 2016 and 2000 - 2016. In the full sample, both GDP and PCE react positively to a reduction in the oil price while in the subsample, the effect is opposite, both variables react significantly negative. Moreover, the explanatory power of the shocks related to the total variation in GDP and PCE is significantly larger in the subsample. We believe these results are attributed to a number of changes; The shale revolution has introduced a shift in the U.S. economic landscape with the oil sector now representing a significantly larger part of aggregate U.S. output. This implies that when the oil price declines, and profitability in the oil sector is reduced, which in turn means that oil related investments decline. Furthermore, a general cooldown of global economic activity since 2011 contributes to reduced demand for American goods. Finally, the power of the FED to influence economic activity Has been significantly reduced since the financial crisis due to the interest rate being very close to the zero lower bound. As a result, economic activity following the oil price decline has been lower than expected.

Going forward, it would be interesting to investigate the effect of monetary policy on GDP growth following the financial crisis. Has the zero lower bound constrained policy makers in any way with regards to influencing economic activity in the united states? Further, because of the short timeframe in the subsample model, it would be of interest to revisit this investigation in five years' time. Increasing the number of observations would make it easier to quantify the effects of the shale oil revolution.

6.1 – Limitations of The Study

Although the SVAR model has been influential and much used in the last decades, it has also come under a considerable amount of criticism. The criticism does not typically refer to the methodology of the model, but interpretations and specific applications of the empirical results. The VAR model must be estimated to low order system, meaning that all effects of omitted variables will be in the residuals. This may lead to major distortions in the impulse responses, making them of little use for structural interpretations. Determining the number of lags can be a major issue, when estimating the VAR. A standard dynamic stochastic general equilibrium (DSGE) model suggests an infinite number of lags ($p = \infty$). However, the data sets used in VAR models are finite, which implies that the number of lags must be finite. The truncation of the lags can lead to a specification error, implying a bias in the estimated parameter. Further implications when using a VAR model is that any potential measurement errors or misspecifications could leave unexplained information in the error terms. This makes interpretations of the impulse response functions difficult. This does not however, imply that constructing the IRF is useless, but rather that the emphasis instead should be on a careful empirical analysis of the results.

Throughout this study, the assumptions about the SVAR models and Cholesky decomposition are used to generate results. This implies that there is a margin of error in the results. Thus, any findings and subsequent interpretations must be considered with the limitations of the SVAR model in mind. Moreover, the impulse response functions sensitivity towards omitted variables and all other misspecifications is a cause for concern and must be kept in mind when interpreting any results from a VAR model (Bjørnland & Thorsrud 2015). Despite these shortcomings, the VAR approach is better suited than classic macro models for determining the effects of an oil price decline.

The subsample period includes a lot of data which is not necessarily relevant to the analysis. This study is mostly focusing on how the transmission of an oil shock to the U.S. economy has potentially changed following the shale oil revolution and the subsequent oil price decline starting in 2014. However, it would not be possible to estimate the effects of an oil price decline using only data from the start of the shale oil revolution due to the limited numbers of observations. As such we are aware of the potential uncertainty related to our results from the subsample period. Further, the economic landscape of freight routes and global economic activity is changing with the increased importance of emerging economies on global demand. The fact that Kilian's real economic activity index is based on equal weighting, not taking these changes into account, introduces is a possibility of the index becoming biased over time. This implies a certain amount of uncertainty in the baseline model results that could potentially attribute more of the variations in the variables to changes in Kilian's index when comparing the two sample periods.

Omitting CPI means that we do not control for inflation in the baseline model. This was a conscious choice because it could become problematic to include too many variables in the VAR[9]. Including CPI in the model would lead to a seven-variable SVAR. Hence, the choice to omit CPI came down to the trade-off between what including the extra variable would yield with regards to accuracy in the results and the increased uncertainty from having too many variables. To adjust for this, a seven-

[9] Including more than six variables in a VAR when using macroeconomic data can become troublesome due to having too many parameters to estimate relative to observations in the data. This is known as a degrees of freedom problem and can induce imprecisely estimated variables (Bjørnland and Thorsrud, 2015 p.200)

variable SVAR which includes year-on-year CPI is added in section 6 robustness test to control for inflation.

The quick recovery of the oil price in the subsample period might reinforce the adverse effect on GDP and PCE ref. Baumeister and kilian (2016) who showed that the transmission of an oil shock remains unchanged. Adjusting for this by keeping the oil price on the new lower level, which would simulate what happened in reality, could potentially drastically change the results.

Most of the time series used in this study are non-stationary, i.e. integrated of order 1. In and of itself this is not necessarily problematic. As long as the SVAR models themselves are stable, we can make inferences about the movement of the different variables in the system when introducing a structural shock. However, it is likely that there are several structural breaks in the data. The FED rate is a prime concern given the fact that there have been significant changes to how monetary policy has been conducted throughout the data sample. This study has not taken these potential structural breaks into consideration, meaning that there might be some uncertainty in the results with regards to how the FED responds to a structural shock and how the response of the FED affects U.S. real GDP and PCE.

Finally, this study assumes a symmetric relationship between oil price increases and decreases. Modelling the asymmetry could potentially yield more accurate results. However, a symmetric relationship is believed to be sufficient to determine whether the transmission of an oil shock has changed following the shale oil revolution and would also significantly reduce the complexity of the model. Consequently, the decision to construct the model with a symmetric relationship came down to a trade-off between reducing the complexity of the model against having a more complex model and possibly achieving more accurate results.

7.0 – References

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8.0 – Appendix

This appendix is divided into three parts with the first part consisting of generalized theory and description of theoretical concepts that are used. Part two provides a printout of the different tests used to check the model. Part three will be the full transcripts of the results and robustness tests of the baseline model.

Appendix Part 1: Additional Theory

Stationarity and Random Walk:

The concept of stationarity is a fundamental concept in time series analysis. A process for y_t is said to be covariance (weakly) stationary if neither the mean (μ) nor the covariance cov(y_t, y_{t-j}) are time dependant (Bjørnland and Thorsrud 2015, 54). Hence, for the process to be covariance stationary, then the following must be true for all periods t and lags i:

$$\mathbb{E}[y_t] = \mu \tag{5}$$

$$\mathbb{E}(y_t - \mu)(y_{t-1} - \mu) = Cov(y_t, y_{t-1}) = \gamma(j) \tag{6}$$

If $y_t = a_t + \varepsilon_t$ the process is non-stationary because the mean depends on time.

A random walk is defined as a time series process that depends only on past values of itself and white noise. As an example, the series:

$$y_t = y_{t-1} + \varepsilon_t \; where \; \varepsilon_t \sim i.i.d. N(0, \sigma^2) \tag{7}$$

This time series is a random walk because the best forecast of y_{t+1} at time *t* is simply:

$$E[y_{t+1}|y_t] = y_t \tag{8}$$

A shock to a random walk will persist forever. However, the process is said to be difference stationary because the first difference of the series, $\triangle y_t = \varepsilon_t$, is stationary. This happens because $\varepsilon_t \sim$ *i.i.d.* $N(0,\sigma^2)$ meaning it has a constant mean of zero and a constant variance.

Unit Root:

If a series is non-stationary and the first difference of the series is stationary, it means that the series is integrated of order 1 or I(1) and thus has a unit root (Bjørnland and Thorsrud 2015, 116). Any stationary variable will not have a unit root and will thus be integrated of order 0 or I(0). To test for a unit root, the Augmented Dickey Fuller (ADF) test can be used to check if a series is a random walk or if it is stationary.

Assume AR (1) process;

$$y_t = \phi_1 y_{t-1} + e_t \tag{9}$$

$$\text{can be written as} \rightarrow \Delta y_t = \mu y_{t-1} + e_t \; where \; \mu = \phi - 1$$

The testing for a unit root implies that a null hypothesis of $\phi = 0$ is tested against the alternative hypothesis that $\phi < 0$

This is a t-test where the t-statistics are calculated using:

$$\hat{t}_{DF} = \frac{\hat{\phi} - 1}{SE\hat{\phi}} = \frac{\hat{\mu}}{SE\hat{\mu}} \tag{10}$$

For macroeconomic variables one would want to add a linear trend to the series. This can be done by using:

$$y_t = \alpha + \beta_t + \phi_1 y_{t-1} + \varepsilon_t \tag{11}$$

Which can also be written as:

$$\Delta y_t = \alpha + \beta_t + \mu y_{t-1} + \varepsilon_t \tag{12}$$

$$where\ \mu = \phi - 1$$

This formulation implies that the ADF test allows for serial correlation in the residuals in such a way that Δy_t can follow a higher order AR process (Bjørnland and Throsrud 2015, 118):

$$\Delta y_t = \alpha + \beta_t + \mu y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t \tag{13}$$

where $\mu = \sum_{j=1}^{p} \phi_j - 1$ and $\gamma_j = -\sum_{k=j+1}^{p} \phi_k$, for j = 1, 2, 3,…p.

However, if there is a significant shift in the series, i.e. a structural break, the ADF test may have difficulties discriminating between a stochastic and a deterministic trend (Bjørnland and Thorsrud 2015, 122).

Rejection of the null hypothesis depends on the t-statistics of the test.
If $|\hat{t}_{DF}| > |t_{Critical\ Value}|$ one can reject the null hypothesis of a unit root.

Stability of a Vector Autoregressive (VAR) Model

Determining the stability of a VAR model is essential to the utilization of the model. For the VAR model to be covariance-stationary, the shocks, epsilon, must die out over time. This will be the case if the eigenvalues of the companion form matrix are less than one in absolute value (Bjørnland and Thorsrud 2015, 192)

Starting with VAR (1) model:

$$y_t = \mu + A_1 y_{t-1} + e_t \tag{14}$$

and utilizing recursive substitution, this becomes

$$y_t = \left(1 + A_1 + A_1^2 + \cdots + A_1^j\right)\mu + A_1^{j+1} y_{t-j-1} + \sum_{i=0}^{j} A_1^i e_{t-i} \tag{15}$$

Calculating the eigenvalues can be done by setting $|A_1 - \lambda| = 0$. The resulting eigenvalues must be so that $\lambda < 1$ for the model to be stable.

Autocorrelation test for correlation in the residuals of the model.
The autocorrelation function can be written as:

$$\rho(j) = \frac{\gamma(j)}{\gamma(0)}, \ \ where\, \gamma(j) = cov\ (y_t, y_{t-1}) \tag{16}$$

(Bjørnland and Thorsrud 2015, insert page). Testing for the residual correlation using MatLab is a simple process and requires one a few lines of code to accomplish. Testing for autocorrelation will determine if the residuals are white noise and thus die out over time, or if they are persistent. Results of the autocorrelation test can be found in appendix part 2.

AIC & BIC - lag selection

When estimating the VAR(p) model, one should identify the value of p (i.e. number of lags). It is a delicate process where both too few and too many lags may cause problems. A model with too few lags might omit important information, and the residuals can easily become autocorrelated. Whereas a model with too many lags will estimate more coefficients than needed, thus, further estimation errors into the model is introduced.

Some of the most popular methods, when determining the number of lag to include in autoregressive models, are normally based on minimizing an information criterion. More specifically, there is a trade-off between increased model fit by increasing the number of lags and increased parameter uncertainty by having too large of a model. In time series econometrics, the two most popular information criteria are the Akaike and Bayes information criterion, AIC and BIC, which are easily derived by:

$$\mathrm{BIC(p)} = \ln\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{\ln(T)}{T} \tag{17}$$

$$\mathrm{AIC(p)} = \ln\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{2}{T} \tag{18}$$

where SSR (p) = $\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t$ which is the sum of squared residuals. Computing a basis for choosing the appropriate lag length is achieved by holding the sample length fixed, and running these criteria functions for different lag lengths. The first term on the right-hand side, which is equal for both AIC and BIC, will normally decrease as *p* increases, whereas the second term is subject to increase as the model grows. This second term is also what sets these two information criterions apart. Consequently, the BIC will penalize the size of the model, and typically suggest models with fewer lags than the AIC criterion, and is thus seen as more conservative than the latter.

Impulse response function

The construction and interpretation of the impulse response function (IRF) is a fundamental part of this study. The IRF describes how a given structural shock affects a variable in the y_t - vector over time. As discussed above, if the error terms are correlated, a shock to one variable would be accompanied by a shock to another variable. Thus, calculating the impulse responses from the reduced form moving average discussed above would give problematic and misleading results. In order to make a valid inference, the shocks must be uncorrelated. This is achieved by using Cholesky Decomposition and forwarding the moving average representation s periods forward.

With a VAR model of the moving average form:

$$y_t = v + \sum_{j=0}^{\infty} B_j\, e_{t-j} = v + e_t + B_1 e_{t-1} + B_2 e_{t-2} + \cdots \tag{19}$$

the IRF can be found by forwarding the model s periods forward.

$$y_{t+s} = v + e_{t+s} + B_1 e_{t+s-1} + B_2 e_{t+s-2} + \cdots + B_{s-1} e_{t+1} + B_s e_t + B_{s+1} e_{t-1} + \cdots \tag{20}$$

and the equation becomes:

$$v + \sum_{j=0}^{\infty} C_j\, \varepsilon_{t+s-j} = v + C_0 \varepsilon_{t+s} + C_1 \varepsilon_{t+s-1} + C_2 \varepsilon_{t+s-2} + \cdots + C_s \varepsilon_t + C_{s+1} \varepsilon_{t-1} + \cdots \tag{21}$$

Where $C_j = B_j P$ and $\varepsilon_t = P^{-1} e_t$

The impact of an exogenous shock hitting variable x at time t on the variables at time t+s is represented by the estimates of C_S where $C_S = \frac{dy_{t+s}}{d\varepsilon_t}$ (Favero 2001, 175). By plotting the coefficients of the reduced form VAR, you end up with the Impulse Response Function (IRF). The IFR is commonly used to describe how economic indicators react over time to exogenous impulses, known as shocks. The impact of the different shocks on the variables in the system can be observed over time through the IRF. The infinite sum of the impulse responses captures the cumulative effect of a shock and is useful when making inferences about long-run effects with variables that are specified in first differences (Bjørnland and Thorsrud 2015).

Forecast Error Variance Decomposition

An important question with regards to structural VAR's is how much of the forecast error variance of y_{t+s} at S = 0, 1, . . . ,H is observed with each structural shock. The forecast error matrix of a SVAR is used to describe how much of the forecast error variance is caused by variability in the structural shock (epsilon) at the different time horizons t+s, given what is known at time t. Together with the impulse response functions, the forecast error variance decomposition (FEVD) can be used to describe if the results truly shows the actual effect of the shock, or if it only describes some trivial effect that is caused by the share of the variance on the individual variables (Bjørnland and Thorsrud 2015, 225). For details on how to calculate the FEVD.

When studying the FEVD, the patterns across the horizon and the relative contribution of different shocks at the given horizon is the area of importance. This allows an inference of which shock(s) have had the biggest impact on the variables in the model.

With a stationary model, the limit of FEVD, as s → ∞, is the variance decomposition of y_t. This is because the forecast error covariance matrix converges to the unconditional covariance matrix of y_t. This implies that for a stationary system, it is sufficient to construct a mean squared prediction error (MSPE) for the infinite horizon. If the system is integrated, the MSPE diverges on the infinite horizon, but the variance decomposition is accurate with a finite horizon S. The method of constructing the FEVD is similar to constructing the impulse response functions and only the C_j matrices are required.
Starting with a VAR process, the s-step ahead forecast error is:

$$y_{t+s} - y_{t+s|\mathrm{t}} = \sum_{i=0}^{s-1} \phi_i u_{t+s-i} = \sum_{i=0}^{s-1} C_i w_{t+s-i} \ \#(22)$$

Where $u_t = B_0^{-1} w_t$ means one can replace $\phi_i u_{t+s-i}$ by $C_i w_{t+s-i}$

And we get

MSPE(h)

$$\mathrm{MSPE(h)} \equiv \mathbb{E}\big[\big(y_{t+s} - y_{t+s|\mathrm{t}}\big)\big(y_{t+s} - y_{t+s|\mathrm{t}}\big)'\big] = \sum_{i=0}^{h-1} \phi_i \, \Sigma_u \phi'_i \tag{23}$$

$$= \sum_{i=0}^{h-1} C_i \underbrace{\Sigma_w}_{I_k} C'_i$$

$$= \sum_{i=0}^{s-1} C_i C'_i$$

Let $\theta_{kj,h}$ be the kj[th] element of C_h. Then the contribution of shock j to the MSPE of y_{kt},

K = 1,…, K, at horizon h is

$$MSPE_j^k(h) = \theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2 \tag{24}$$

and the total MSPE of y_{kt}, k = 1,…, K, at horizon h is

$$MSPE^k(h) = \sum_{j=1}^{K} MSPE_j^k\,(h) = \sum_{j=1}^{K} (\theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2) \tag{25}$$

Dividing

$$MSPE^k(h) = \sum_{j=1}^{K} MSPE_j^k\,(h) \tag{26}$$

by $MSPE^k(h)$ yields the following decomposition for given h and k:

$$1 = \frac{MSPE_1^k(h)}{MSPE^k(h)} + \frac{MSPE_2^k(h)}{MSPE^k(h)} + \cdots + \frac{MSPE_K^k(h)}{MSPE^k(h)}, \tag{27}$$

$\frac{MSPE_j^k(h)}{MSPE^k(h)}$ which is the fraction of the contribution of shock j to the forecast error variance of variable k (Kilian and Lütkepohl 2017, 112).

Historical Decomposition

Historical decomposition is used to quantify how much a structural shock explains the historical observed fluctuation in each variable of the VAR model. This type of analysis can tell us the cumulative effect of a structural shock on each variable at any given point across the entire operating time frame (Kilian & Lütkepohl 2017). This is a very useful tool when analysing the effect the oil price has on the U.S. economy.

Burbidge, J. and Harrison, A. (1985) explains that the technique of historical decomposition is best explained by reference to the VAR's moving average representation:

$$y_t = C(B)\varepsilon_t = \sum_{i=0}^{\infty} C_i\, \varepsilon_{t-i} \tag{28}$$

Where y_t is a column vector of n endogenous variables, C(B) is a matrix of polynomials in the lag operator B while E, is a vector of innovation (the non-forecastable component of y_t). Consider T as some base period in the sample. For any j =1, 2,..., such that T+j is less than or equal to the first period in the sample, $y_{\gamma+j}$ can be written as the sum of two components:

$$y_{\gamma+j} = \sum_{i=0}^{j-1} C_i\, \varepsilon_{\mathrm{T}+j-i} + \sum_{i=j}^{\infty} C_i\, \varepsilon_{\mathrm{T}+j-i} \tag{29}$$

The first component is the part of the time series that is caused by innovations in the variables since T. From this one can establish the effect of the individual variables on the total innovation. The second component is a "base projection of $y_{\gamma+j}$", which is formed solely from information available at time T. The historical decomposition distinguishes the total effects of the innovations on the series by dividing the responsibility between the base projection and the actual innovations of the variables in the VAR. From the equation above, one can clearly see that innovations to the series introduced since time T yields the actual series. Thus, Burbidge & Harrison (1985) emphasizes that:

"the importance of any one variable, or set of variables, can be determined by examining the extent to which the introduction of the innovations since T in that variable or set of variables closes the gap between the base projection and the actual series".

An important note is that historical decompositions contains an approximation error. This error is a result of the truncated moving average representation that is being used. Consider this, y_{k1}, from equation (x), depends on the structural shock at time 1 in addition to the infinite history of structural shocks. Since a vast portion of the history of shocks is unobserved, the approximation is inevitable going to be insignificant initially. However, an increasingly amount of the recent structural shocks that receive high impulse response weights are captured and the weights of earlier unobserved shocks declines, after continuously updating $\hat{y}_k^{(j)}$.

Constructing historical decomposition involves three steps.

- Compute the structural moving average coefficient matrices $C_0,\ldots,C_{j-1}$
- Compute the structural shocks $\varepsilon_t = B_o u_t$, $t = 1,\ldots,T$
- Match each structural shock, e.g. shock j, with the appropriate impulse response weight, as required by the structural moving average representation, to from Tx1 vectors of fitted values for variable k_1 demoted $\hat{y}_k^{(j)}$ for j=1,…,K,

The VAR model has 6 variables so in this example K = 6. In the thesis, we are interested in finding the historical decomposition of real GDP, which in the VAR model is the 4th variable. The point of interest is the cumulative effect of each of the six-structural shock on the 4th variable of the VAR system

$$\hat{y}_{4t}^{(1)} = \sum_{i=0}^{t-1} \theta_{41,i}\, w_{1,t-1,}$$

$$\hat{y}_{4t}^{(2)} = \sum_{i=0}^{t-1} \theta_{42,i}\, w_{2,t-1,}$$

$$\hat{y}_{4t}^{(3)} = \sum_{i=0}^{t-1} \theta_{43,i}\, w_{3,t-1,}$$

$$\hat{y}_{4t}^{(4)} = \sum_{i=0}^{t-1} \theta_{44,i}\, w_{4,t-1,}$$

$$\hat{y}_{4t}^{(5)} = \sum_{i=0}^{t-1} \theta_{45,i}\, w_{5,t-1,}$$

$$\hat{y}_{4t}^{(6)} = \sum_{i=0}^{t-1} \theta_{46,i}\, w_{6,t-1,}$$

Let $\theta_{jk,i}$ denote the response of variable j to shock k at horizon I and $w_{k,t}$ is the kth structural shock at time t, each vector $\hat{y}_4^{(j)} = (\hat{y}_{41}^{(j)}, \dots, \hat{y}_{4T}^{(j)})'$ shows the cumulative contribution of shock j on the 4th variable in the VAR model over time By construction, the value for $\hat{y}_{4t}$ obtained as the sum

$$\hat{y}_{4t} = \sum_{j=1}^{K} \hat{y}_{4t}^{(j)}$$

Appendix part 2: test results etc.

Augmented Dickey-Fuller test results:

An important step before modelling the variables in a system is to make sure that the variables does not have a unit root, i.e. that the variables are not integrated of order 1, I(1). The Augmented Dicked-Fuller test is a simple way to determine whether a variable has a unit root. The test implies a null hypothesis of a unit root and an alternative hypothesis that the variables is stationary (no unit root). Any variable where the null hypothesis cannot be rejected has a unit root and is believed to be persistent. Stationarity in the variables is required in an AR(p) model. This same requirement in not present in a VAR model. However, it is still of interest to test the different variables. At both levels and log-levels, the ADF test fails to reject the null hypothesis of a unit root against the (trend) stationary alternative for all variables except Kilian's real activity index. This is as expected. However, the standard ADF test may fail reject the null hypothesis if the series is a stationary process around a trend with a structural break (Bjørnland 2000).

Killians Global Real Economic Activity Index

Null Hypothesis: REAL_ACTIVITY__DEMAND_ has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.685044	0.0051
Test critical values:	1% level	-3.469691	
	5% level	-2.878723	
	10% level	-2.576010	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(REAL_ACTIVITY__DEMAND_)
Method: Least Squares
Date: 08/07/17 Time: 13:38
Sample (adjusted): 1975Q2 2016Q4
Included observations: 167 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
REAL_ACTIVITY__DEMAND_(-1)	-0.152491	0.041381	-3.685044	0.0003
C	-0.349440	1.053958	-0.331550	0.7406

R-squared	0.076042	Mean dependent var	-0.070982
Adjusted R-squared	0.070442	S.D. dependent var	14.09043
S.E. of regression	13.58509	Akaike info criterion	8.067727
Sum squared resid	30451.52	Schwarz criterion	8.105068
Log likelihood	-671.6552	Hannan-Quinn criter.	8.082883
F-statistic	13.57955	Durbin-Watson stat	1.984025
Prob(F-statistic)	0.000310		

Oil Price

Null Hypothesis: REAL_PRICE_OF_OIL_2016$ has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.905792	0.3291
Test critical values:	1% level	-3.470179	
	5% level	-2.878937	
	10% level	-2.576124	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(REAL_PRICE_OF_OIL_2016$)
Method: Least Squares
Date: 08/07/17 Time: 13:39
Sample (adjusted): 1975Q4 2016Q4
Included observations: 165 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
REAL_PRICE_OF_OIL_2016$(-1)	-0.044020	0.023098	-1.905792	0.0585
D(REAL_PRICE_OF_OIL_2016$(-1))	0.330085	0.074527	4.429070	0.0000
D(REAL_PRICE_OF_OIL_2016$(-2))	-0.281350	0.075657	-3.718760	0.0003
C	2.408099	1.405943	1.712800	0.0887

R-squared	0.167297	Mean dependent var	-0.008170
Adjusted R-squared	0.151780	S.D. dependent var	8.465277
S.E. of regression	7.796423	Akaike info criterion	6.969151
Sum squared resid	9786.257	Schwarz criterion	7.044446
Log likelihood	-570.9549	Hannan-Quinn criter.	6.999716
F-statistic	10.78204	Durbin-Watson stat	1.938339
Prob(F-statistic)	0.000002		

U.S. oil production

Null Hypothesis: U_S__FIELD_PRODUCTION_OF has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.691882	0.4335
Test critical values:	1% level	-3.470679	
	5% level	-2.879155	
	10% level	-2.576241	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(U_S__FIELD_PRODUCTION_OF)
Method: Least Squares
Date: 08/07/17 Time: 13:40
Sample (adjusted): 1976Q2 2016Q4
Included observations: 163 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U_S__FIELD_PRODUCTION_OF(-1)	-0.014031	0.008293	-1.691882	0.0927
D(U_S__FIELD_PRODUCTION_OF(-1))	0.216079	0.074345	2.906450	0.0042
D(U_S__FIELD_PRODUCTION_OF(-2))	-0.016334	0.076345	-0.213952	0.8309
D(U_S__FIELD_PRODUCTION_OF(-3))	0.084572	0.076929	1.099360	0.2733
D(U_S__FIELD_PRODUCTION_OF(-4))	0.375762	0.075767	4.959443	0.0000
C	100.7206	59.97838	1.679282	0.0951

R-squared	0.231754	Mean dependent var	3.543967
Adjusted R-squared	0.207288	S.D. dependent var	161.3600
S.E. of regression	143.6659	Akaike info criterion	12.80897
Sum squared resid	3240461.	Schwarz criterion	12.92285
Log likelihood	-1037.931	Hannan-Quinn criter.	12.85521
F-statistic	9.472346	Durbin-Watson stat	1.906343
Prob(F-statistic)	0.000000		

GDP

Null Hypothesis: RGDP has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.332780	0.9794
Test critical values:	1% level	-3.469933	
	5% level	-2.878829	
	10% level	-2.576067	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RGDP)
Method: Least Squares
Date: 08/07/17 Time: 13:41
Sample (adjusted): 1975Q3 2016Q4
Included observations: 166 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RGDP(-1)	0.000512	0.001538	0.332780	0.7397
D(RGDP(-1))	0.365912	0.072988	5.013317	0.0000
C	38.41778	17.83663	2.153870	0.0327

R-squared	0.135863	Mean dependent var	69.15723
Adjusted R-squared	0.125261	S.D. dependent var	73.65286
S.E. of regression	68.88569	Akaike info criterion	11.32068
Sum squared resid	773473.7	Schwarz criterion	11.37692
Log likelihood	-936.6165	Hannan-Quinn criter.	11.34351
F-statistic	12.81379	Durbin-Watson stat	2.097116
Prob(F-statistic)	0.000007		

PCE

Null Hypothesis: RPCE has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.876522	0.9950
Test critical values:	1% level	-3.470427	
	5% level	-2.879045	
	10% level	-2.576182	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RPCE)
Method: Least Squares
Date: 08/07/17 Time: 13:43
Sample (adjusted): 1976Q1 2016Q4
Included observations: 164 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RPCE(-1)	0.000941	0.001073	0.876522	0.3821
D(RPCE(-1))	0.263727	0.077630	3.397248	0.0009
D(RPCE(-2))	0.225948	0.078545	2.876680	0.0046
D(RPCE(-3))	0.213290	0.078245	2.725911	0.0071
C	8.588602	8.183441	1.049510	0.2955

R-squared	0.331843	Mean dependent var	49.99573
Adjusted R-squared	0.315034	S.D. dependent var	39.96369
S.E. of regression	33.07502	Akaike info criterion	9.865447
Sum squared resid	173939.2	Schwarz criterion	9.959955
Log likelihood	-803.9667	Hannan-Quinn criter.	9.903814
F-statistic	19.74200	Durbin-Watson stat	1.952549
Prob(F-statistic)	0.000000		

FED

Null Hypothesis: FED has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.500252	0.5312
Test critical values:	1% level	-3.469933	
	5% level	-2.878829	
	10% level	-2.576067	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FED)
Method: Least Squares
Date: 08/07/17 Time: 13:52
Sample (adjusted): 1975Q3 2016Q4
Included observations: 166 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FED(-1)	-0.025977	0.017315	-1.500252	0.1355
D(FED(-1))	0.177204	0.077212	2.295023	0.0230
C	0.111346	0.113382	0.982038	0.3275

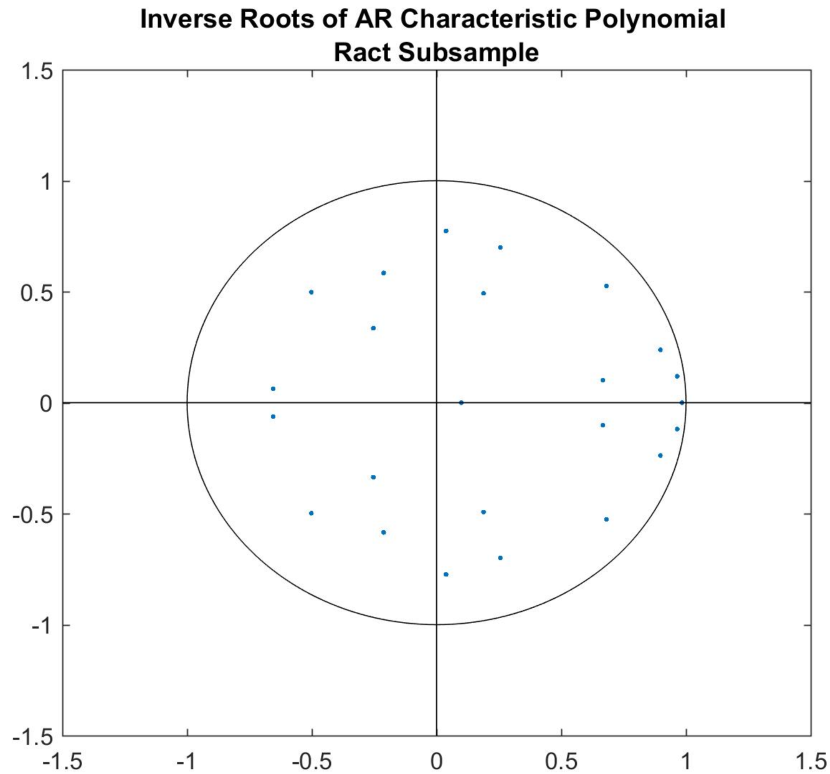
R-squared	0.039667	Mean dependent var	-0.029940
Adjusted R-squared	0.027884	S.D. dependent var	0.894767
S.E. of regression	0.882204	Akaike info criterion	2.605121
Sum squared resid	126.8604	Schwarz criterion	2.661362
Log likelihood	-213.2250	Hannan-Quinn criter.	2.627949
F-statistic	3.366392	Durbin-Watson stat	1.939170
Prob(F-statistic)	0.036930		

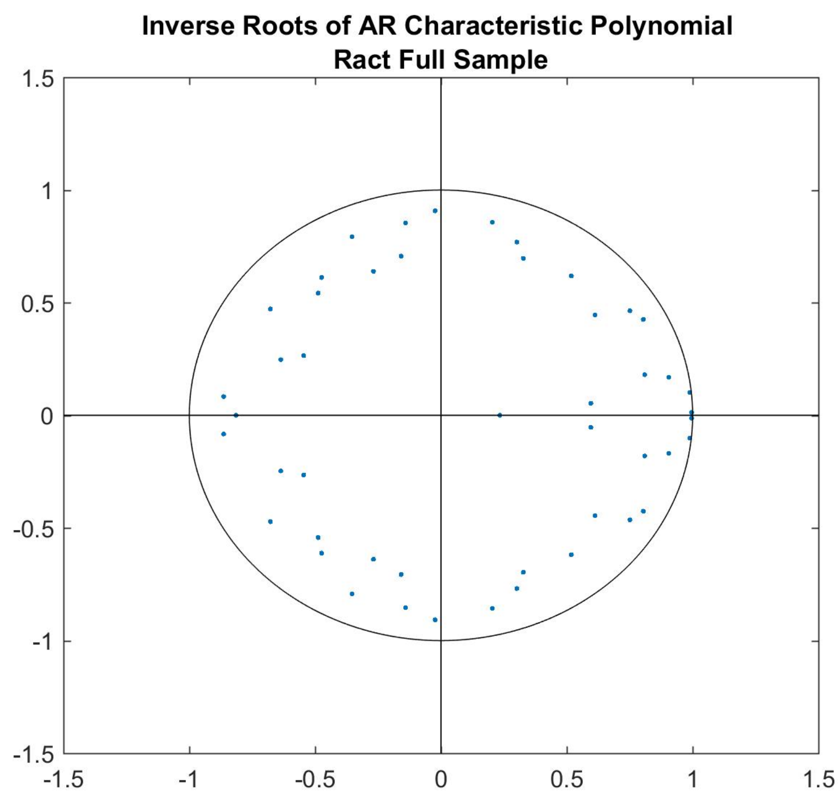
Lag Selection and Stability Test Results:

Before modelling the system, several checks need to be performed, the most important of which is a stability check. This is tested by checking the eigenvalues of the companion form matrix, the A matrix, in the reduced form VAR. If all the eigenvalues are less than one, the model will be stable, i.e. any structural shock will eventually die out. To accurately determine the stability of the system, the lag order must first be determined. There are several different theories about lag length and the most common test for lag length is to perform either the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) test. Kilian (2000) among others argue that using the AIC when choosing lag length is a good approach. However, Hamilton and Herrera (2004) argue that longer lag lengths will provide more robust results. Hence, this paper follows the assumptions made by Hamilton and Herrera about lag length when estimating the effects of an oil price shock on macroeconomic variables and use a minimum lag length of 12 months for all models.

We construct several SVAR models given that there is a total of three different variables that are used as a proxy for global activity, two of them for the purpose of robustness. Log-levels of the variables OECD industrial production index, World Steel Production, Oil price, U.S. crude oil production, GDP and PCE will be used. Kilian's real economic activity index and the FED rate are in levels.

There is no evidence of instability in either model at 8 lags and 4 lags for the full sample and subsample models respectively, when using Kilian's real economic activity index. All AR roots are inside the unit circle, indicating a stable model. The transcripts of the stability test for each model is attached below:


Inverse Roots of AR Characteristic Polynomial
Ract Subsample
1.5
1
0.5
0
-0.5
-1
-1.5
-1.5
-1
-0.5
0
0.5
1
1.5


Inverse Roots of AR Characteristic Polynomial
Ract Full Sample
1.5
1
0.5
0
-0.5
-1
-1.5
-1.5
-1
-0.5
0
0.5
1
1.5

Autocorrelation test results:

Another important step is to perform tests on the residuals of the model. If there is some third unobserved variable that is correlated with one or more of the variables in the system, then this will be reflected in the residuals of these variables and we end up with a simultaneity problem. In such a case, the OLS assumptions break down and give biased results. Hence, it is important to check the residuals for autocorrelation. The test for autocorrelation in the residuals of the reduced form matrix is run for each of the variables in the system to test the 20 first autocorrelation coefficients on the 6 different equations in the model. This is then done for each model.

The test results show that the there are no evidence of significant autocorrelation in any of the estimated residuals in the two models, despite of there being some minor signs of autocorrelation in some of the lags. The black lines in the figures represents the lower and upper bounds, given by two standard deviations from the mean. (95 percent confidence)

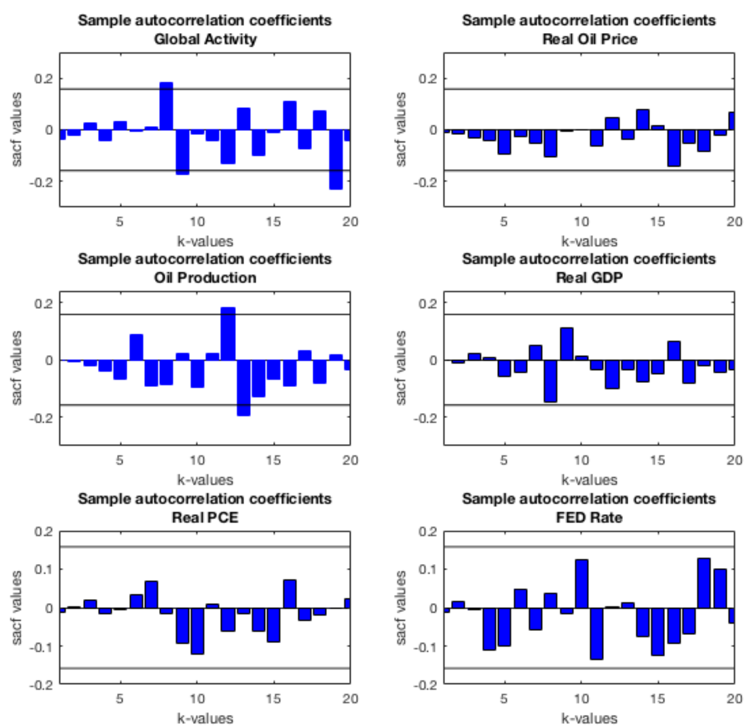


Figure 12: Residual autocorrelation test full sample

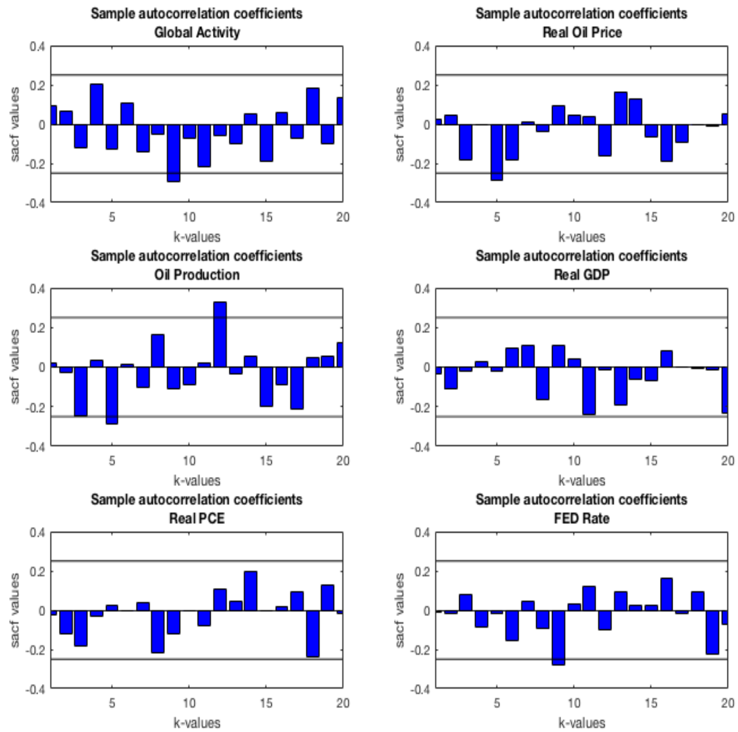


Figure 13: Residual autocorrelation test subsample

Appendix part 3: SVAR model results

Forecast Error Variance Decomposition – 1975-2016

Global Demand Shock						
Horizon	Global Act.	Oil Price	Oil Prod.	Real GDP	Real PCE	Fed Rate
4	.7781	.1459	.0612	.0323	.0137	.1103
	[.6945-.8491]	*[.0655-.2616]*	*[.0276-.1249]*	*[.0091-.0861]*	*[.0041-.0430]*	*[.0490-.2008]*
12	.4592	.1203	.1104	.0658	.0511	.1356
	[.3690-.5576]	*[.0634-.2035]*	*[.0384-.2304]*	*[.0254-.1506]*	*[.0154-.1474]*	*[.0561-.2594]*
20	.4057	.1239	.0969	.0682	.0557	.1329
	[.3193-.5012]	*[.0676-.2114]*	*[.0324-.2283]*	*[.0233-.1804]*	*[.0142-.1675]*	*[.0630-.2481]*
36	.3638	.1212	.0955	.0627	.0587	.1319
	[.2791-.4583]	*[.0659-.2038]*	*[.0362-.2026]*	*[.0201-.1841]*	*[.0146-.1883]*	*[.0648-.2456]*

Table 3: Global Demand shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

Oil Specific Shock						
Horizon	Global Act.	Oil Price	Oil Prod.	Real GDP	Real PCE	Fed Rate
4	.0323	.7054	.1608	.0150	.0359	.0425
	[.0150-.0581]	*[.5923-.0834]*	*[.0823-.2648]*	*[.0047-.0404]*	*[.0078-.0939]*	*[.0114-.1057]*
12	.1028	.3824	.4860	.0431	.0441	.0608
	[.0515-.1825]	*[.2776-.4936]*	*[.3437-.6243]*	*[.0135-.1133]*	*[.0122-.1290]*	*[.0229-.1316]*
20	.1518	.3104	.5710	.0423	.0457	.0734
	[.0809-.2505]	*[.2170-.4295]*	*[.4109-.7034]*	*[.0153-.1103]*	*[.0165-.1178]*	*[.0297-.1428]*
36	.1674	.3017	.4439	.0573	.0599	.0915
	[.0930-.2649]	*[.2003-.4251]*	*[.3053-.5891]*	*[.0191-.1608]*	*[.0192-.1726]*	*[.0406-.1677]*

Table 4: Oil Specific shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

U.S. Oil Production Shock						
Horizon	Global Act.	Oil Price	Oil Prod.	Real GDP	Real PCE	Fed Rate
4	.0327	.0312	.6865	.0490	.0159	.0126
	[.0146-.0654]	*[.0133-.0668]*	*[.5781-.7820]*	*[.0118-.1203]*	*[.0038-.0558]*	*[.0040-.0376]*
12	.1065	.1225	.2454	.0534	.0268	.0303
	[.0495-.1859]	*[.0544-.2156]*	*[.1571-.3637]*	*[.0167-.1383]*	*[.0071-.0851]*	*[.0132-.0741]*
20	.0999	.1506	.1538	.0660	.0506	.0396
	[.0525-.1721]	*[.0729-.2570]*	*[.0922-.2496]*	*[.0177-.1708]*	*[.0127-.1453]*	*[.0187-.0816]*
36	.1187	.1471	.1802	.0646	.0541	.0497
	[.0649-.1950]	*[.0740-.2475]*	*[.1050-.2771]*	*[.0184-.1791]*	*[.0144-.1652]*	*[.0239-.0955]*

Table 5: U.S. Oil Production shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

Monetary policy Shock						
Horizon	Global Act.	Oil Price	Oil Prod.	Real GDP	Real PCE	Fed Rate
4	.0938	.0237	.0090	.0241	.0582	.5959
	[.0430-.1669]	[.0059-.0625]	[.0026-.0268]	[.0106-.0531]	[.0228-.1070]	[.4855-.6983]
12	.1438	.1562	.0190	.1795	.1762	.5105
	[.0812-.2314]	[.0810-.2555]	[.0078-.0580]	[.0857-.3041]	[.0743-.3092]	[.3871-.6270]
20	.1385	.1379	.0264	.2177	.1969	.4499
	[.0796-.2152]	[.0701-.2304]	[.0095-.0816]	[.0980-.3631]	[0773-.3439]	[.3342-.5696]
36	.1329	.1306	.0548	.1947	.1867	.4119
	[.0770-.2091]	[.0674-.2199]	[.0164-.1284]	[.0779-.3485]	[.0674-.3417]	[.3042-.5311]

Table 6: Monetary policy shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

Forecast Error Variance Decomposition – 2000-2016

Global Demand Shock						
Horizon	Global Act.	Oil Price	Oil Prod.	Real GDP	Real PCE	Fed Rate
4	.6854	.1247	.1424	.1871	.0896	.0369
	[.5802-.7843]	[.0531-.2454]	[.0764-.2310]	[.0723-.3395]	[.0233-.2348]	[.0100-.1202]
12	.4912	.1614	.0848	.1611	.1221	.0966
	[.3739-.6052]	[.0950-.2526]	[.0377-.1924]	[.0724-.3098]	[.0372-.3070]	[.0321-.2372]
20	.4455	.1532	.0954	.1388	.1136	.1009
	[.3282-.5712]	[.0894-.2402]	[.0361-.2314]	[.0665-.2607]	[.0392-.2477]	[.0377-.2357]
36	.4226	.1519	.1013	.1218	.1034	.1027
	[.3050-.5504]	[.0881-.2463]	[.0358-.2341]	[.0552-.2568]	[.0356-.2493]	[.0396-.2404]

Table 7: Global Demand shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

Oil Specific Shock						
Horizon	Global Act.	Oil Price	Oil Prod.	Real GDP	Real PCE	Fed Rate
4	.0766	.6142	.1353	.0623	.0473	.0615
	[.0299-.1477]	[.4921-.7302]	[.0669-.2433]	[.0280-.1279]	[.0158-.1397]	[.0197-.1699]
12	.1797	.4504	.4796	.0972	.0935	.1379
	[.0971-.2950]	[.3384-.5573]	[.2929-.6340]	[.0440-.1927]	[.0328-.2075]	[.0438-.3002]
20	.2072	.4696	.4742	.1755	.1891	.1675
	[.1139-.3345]	[.3436-.5836]	[.2831-.6440]	[.0795-.3187]	[.0817-.3537]	[.0668-.3278]
36	.2182	.4491	.4478	.2454	.2715	.1956
	[.1191-.3502]	[.3226-.5718]	[.2655-.6248]	[.1085-.4253]	[.1100-.4693]	[.0834-.3675]

Table 8: Oil Specific shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

U.S. Oil Production Shock						
Horizon	**Global Act.**	**Oil Price**	**Oil Prod.**	**Real GDP**	**Real PCE**	**Fed Rate**
4	**.0424**	**.0566**	**.5782**	**.0596**	**.0529**	**.0345**
	[.0158-.0893]	*[.0233-.1082]*	*[.4643-.6810]*	*[.0155-.1461]*	*[.0138-.1492]*	*[.0108-1066]*
12	**.0714**	**.1087**	**.2327**	**.1051**	**.1250**	**.0413**
	[.0385-.1254]	*[.0609-.1790]*	*[.1297-.3809]*	*[.0405-.2104]*	*[.0423-.2537]*	*[.0130-.1132]*
20	**.0711**	**.1007**	**.1647**	**.1305**	**.1586**	**.0491**
	[.0386-.1232]	*[.0572-.1676]*	*[.0789-.3040]*	*[.0583-.2383]*	*[.0684-.2846]*	*[.0180-.1197]*
36	**.0741**	**.0999**	**.1521**	**.1117**	**.1242**	**.0542**
	[.0399-.1254]	*[.0582-.1686]*	*[.0753-.2859]*	*[.0482-.2202]*	*[.0501-.2506]*	*[.0227-.1212]*

Table 9: Oil Production Shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

Monetary policy Shock						
Horizon	**Global Act.**	**Oil Price**	**Oil Prod.**	**Real GDP**	**Real PCE**	**Fed Rate**
4	**.0786**	**.0474**	**.0184**	**.0377**	**.0438**	**.4161**
	[.0374-.1418]	*[.0193-.0954]*	*[.0058-.0505]*	*[.0125-.0891]*	*[.0127-.1007]*	*[.2906-.5622]*
12	**.0854**	**.0667**	**.0273**	**.0883**	**.0625**	**.2140**
	[.0469-.1418]	*[.0334-.1181]*	*[.0097-.0675]*	*[.0465-.1513]*	*[.0288-.1192]*	*[.1251-.3526]*
20	**.0841**	**.0636**	**.0342**	**.0824**	**.0626**	**.1879**
	[.0462-.1385]	*[.0327-.1094]*	*[.0114-.0888]*	*[.0423-.1407]*	*[.0289-.1188]*	*[.1106-.3142]*
36	**.0839**	**.0661**	**.0378**	**.0683**	**.0526**	**.1721**
	[.0465-.1387]	*[.0344-.1163]*	*[.0131-.0945]*	*[.0326-.1307]*	*[.0219-.1157]*	*[.0994-.2953]*

Table 10: Monetary Policy Shock

68 percent bootstrapped confidence bands in brackets – Derived from baseline model

Robustness tests: Full Sample models

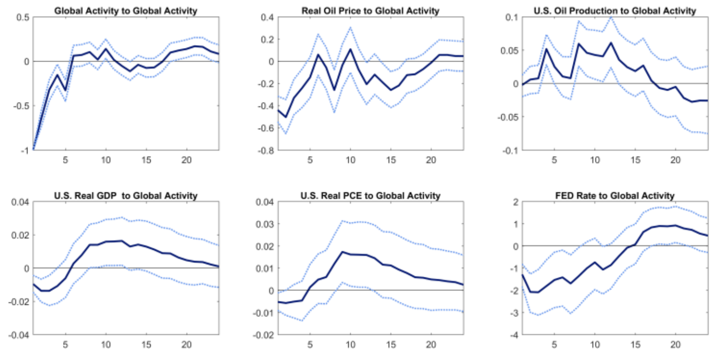


Figure 14: Baseline model included linear trend, 8 lags, 2000 draws – Activity Shock, Full Sample

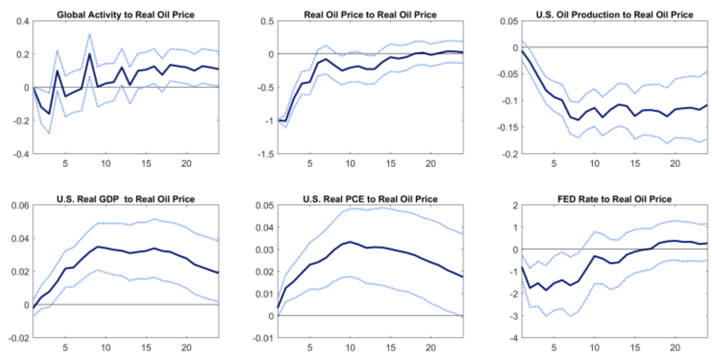


Figure 15: Baseline model included linear trend, 8 lags, 2000 draws – Oil Shock, Full Sample

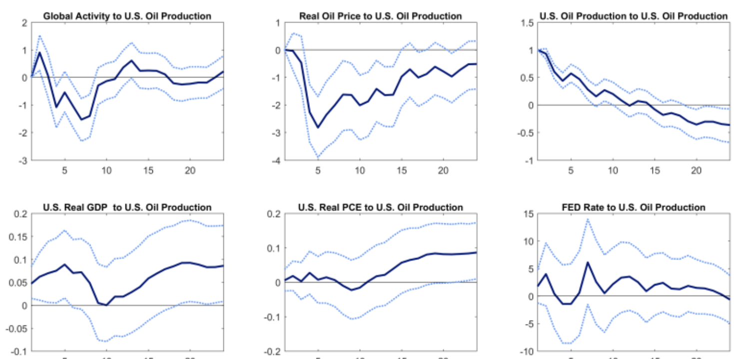


Figure 16: Baseline model included linear trend, 8 lags, 2000 draws – Oil production Shock, Full Sample

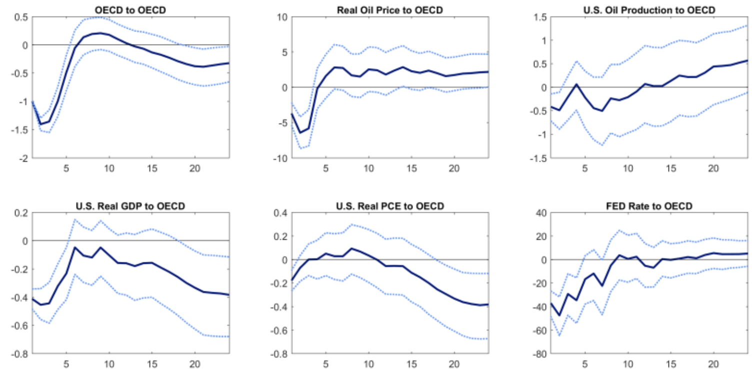


Figure 17: OECD model, 8 lags, 2000 draws – Activity Shock, Full Sample

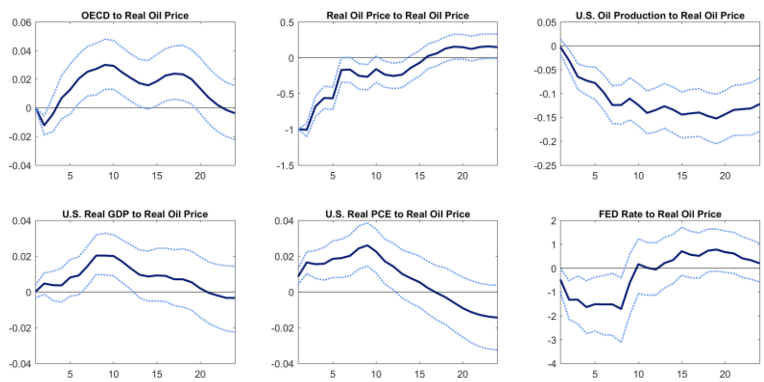


Figure 18: OECD model, 8 lags, 2000 draws – Oil Shock, Full Sample

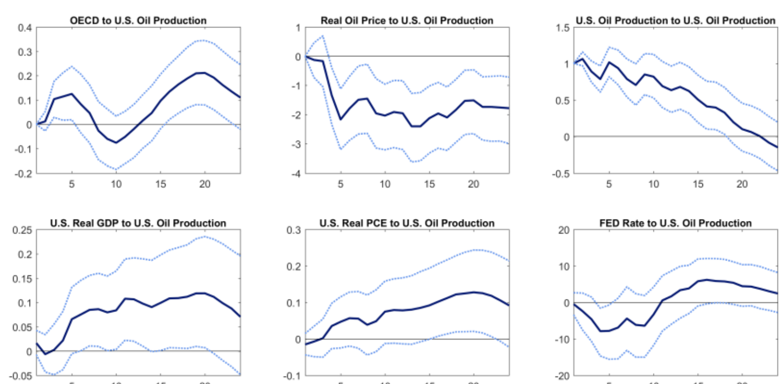


Figure 19: OECD model, 8 lags, 2000 draws – Oil Production Shock, Full Sample

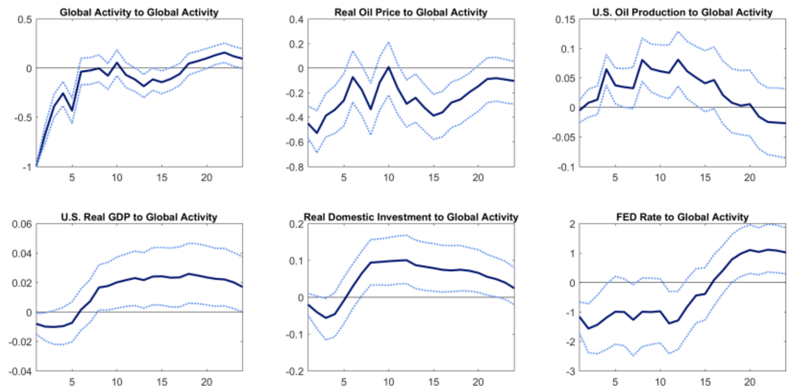


Figure 20: Replaced PCE with Investments, 8 lags, 2000 draws – Activity Shock, Full sample

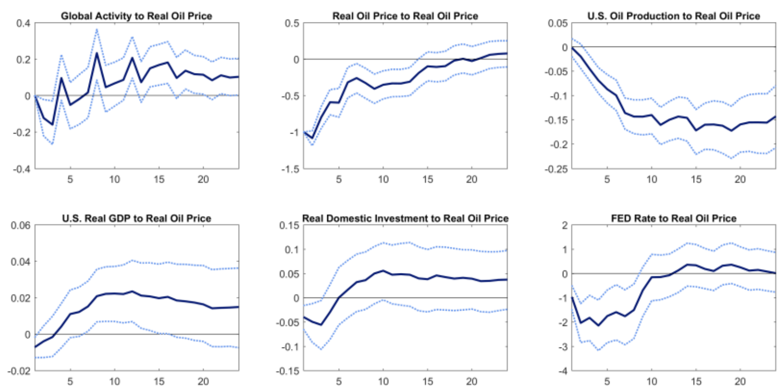


Figure 21: Replaced PCE with Investments, 8 lags, 2000 draws – Oil Shock, Full Sample

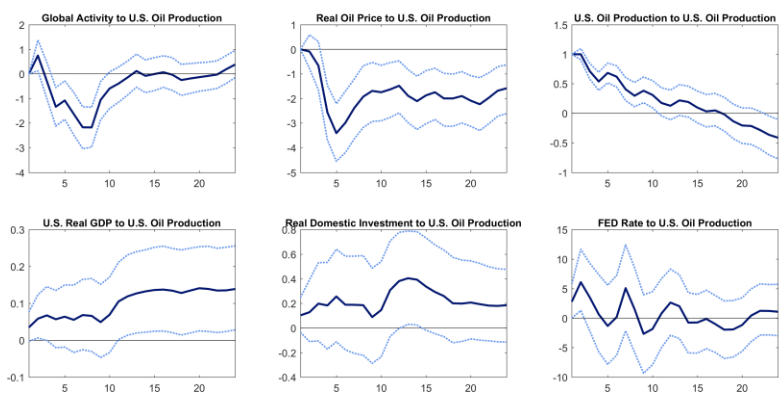


Figure 22: Replaced PCE with Investments, 8 lags, 2000 draws – Oil Production Shock, Full Sample

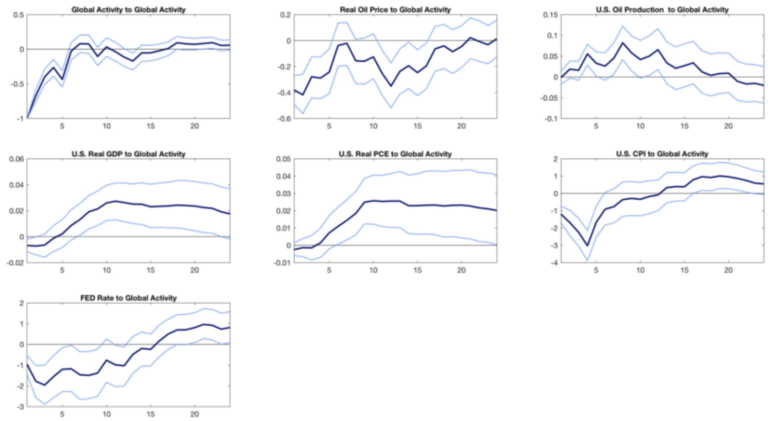


Figure 23: Seven-Variable Model with CPI, 8 lags – Activity Shock, Full Sample

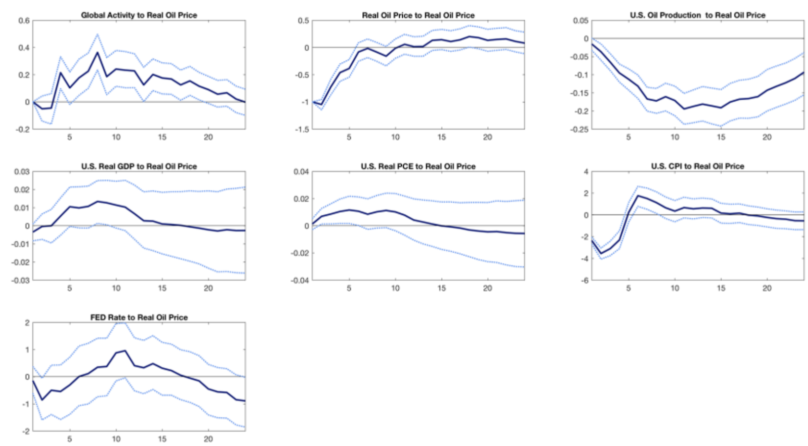


Figure 24: Seven-Variable Model with CPI, 8 lags – Oil Shock, Full Sample

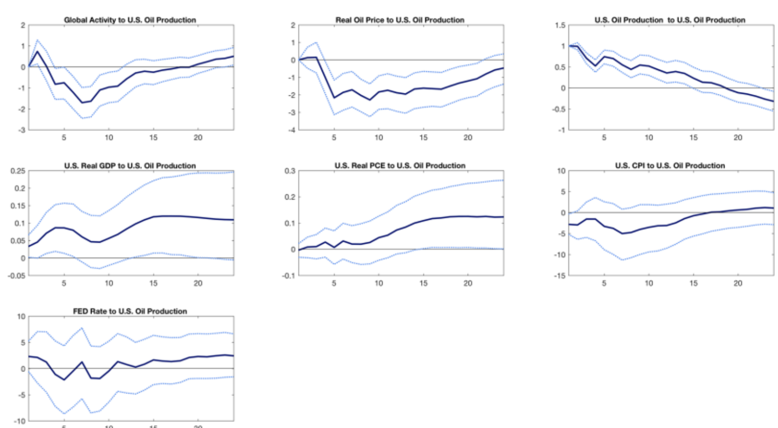


Figure 25: Seven-Variable Model with CPI, 8 lags – Oil Production Shock, Full Sample

Robustness tests: Subsample models

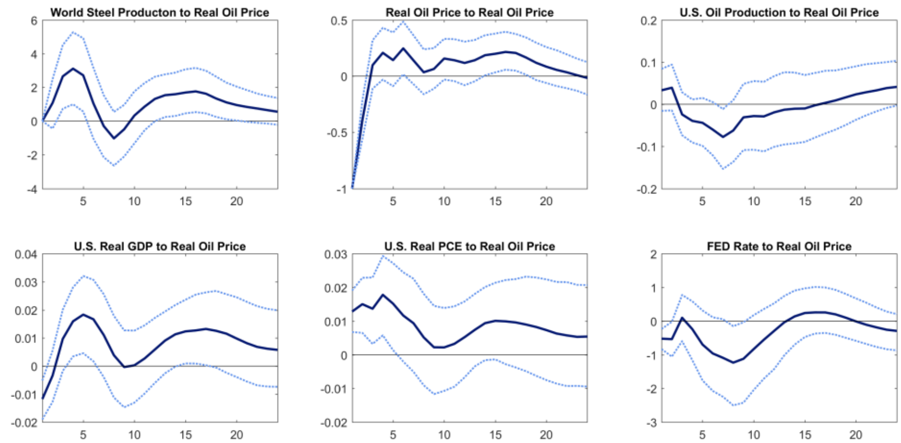


Figure 26: WSP model, 4 lags, 2000 draws – Oil Shock, Subsample

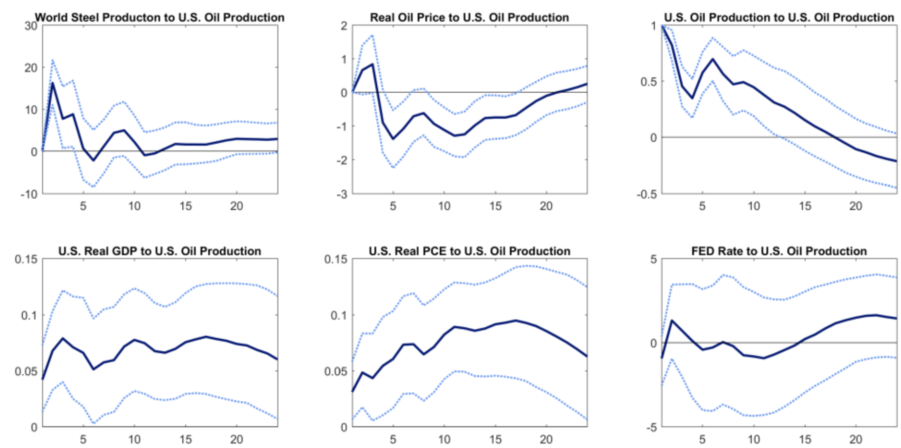


Figure 27: WSP model, 4 lags, 2000 draws – Oil Production Shock, Subsample

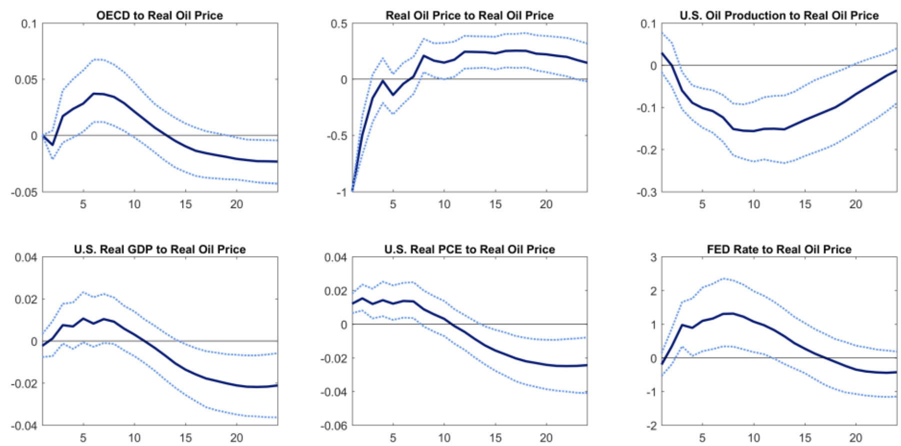


Figure 28: OECD model, 4 lags, 2000 draws – Oil Shock, Subsample

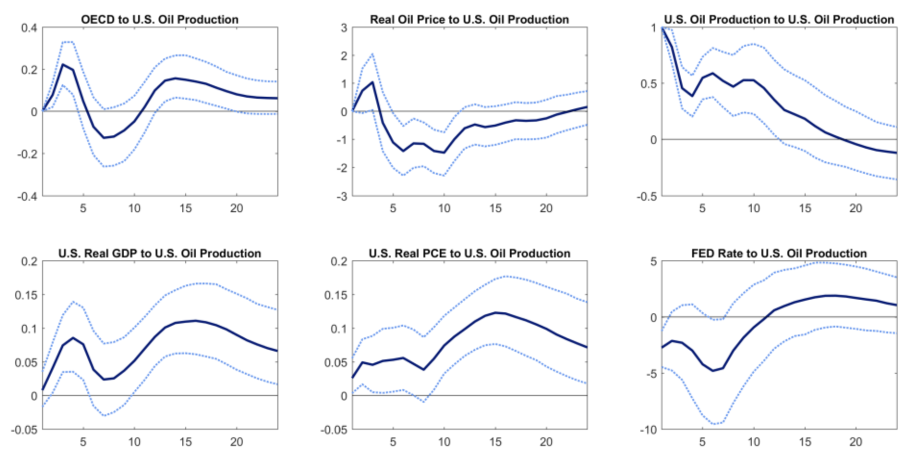


Figure 29: OECD model, 4 lags, 2000 draws – Oil Production Shock, Subsample

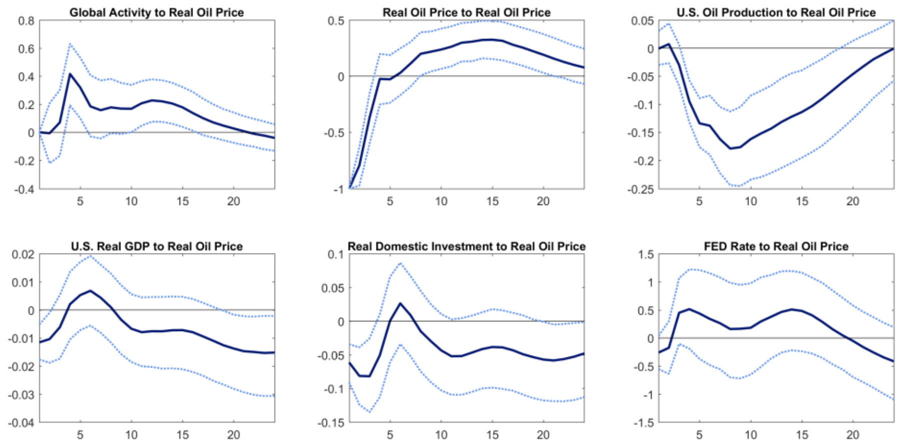


Figure 30: Replaced PCE with Investments, 4 lags, 2000 draws – Oil Shock, Subsample

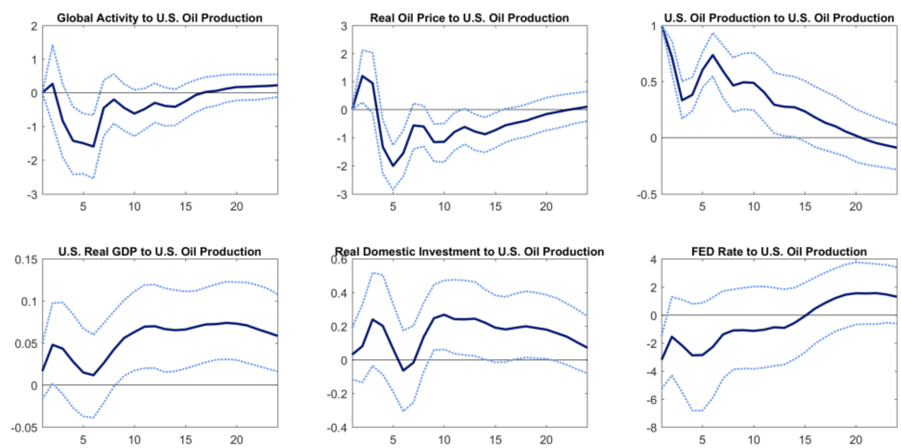


Figure 31: Replaced PCE with Investments, 4 lags, 2000 draws – Oil Production Shock, Subsample

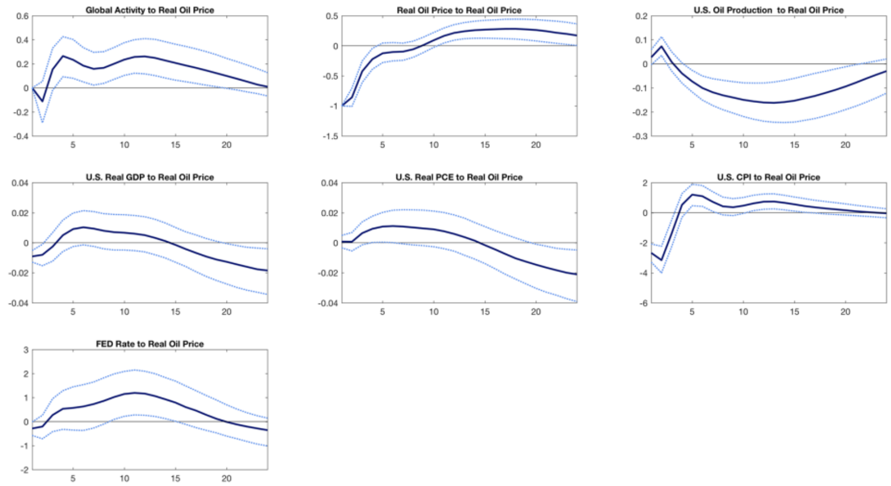


Figure 32: Seven-Variable Model with CPI, 4 lags, 2000 draws – Oil shock, Subsample

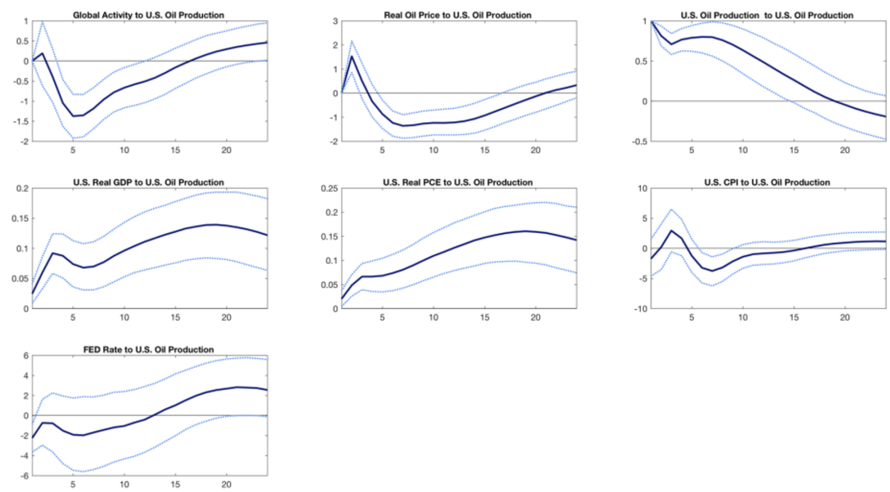


Figure 33: Seven-Variable Model with CPI, 4 lags, 2000 draws – Oil production Shock, Subsample