

2013 | 10

# Working Paper

Monetary Policy

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ISSN 1502-8143 (online)

ISBN 978-82-7553-744-5 (online)

# Oil Price Shocks and Monetary Policy in a Data-Rich Environment

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April 4, 2013

## Abstract

This paper examines the impact of different types of oil price shocks on the U.S. economy, using a factor-augmented VAR (FAVAR) approach. The results indicate that when examining the effects of oil price shocks, it is important to account for the interaction between the oil market and the macroeconomy. I find that oil demand shocks are more important than oil supply shocks in driving several macroeconomic variables, and that the origin of demand shocks matter. Specifically, the U.S. economy and monetary policy respond differently to global demand shocks that have the effect of raising the price of oil and to oil-specific demand shocks.

**Keywords:** Oil demand shocks, Oil supply shocks, Business cycle, Monetary policy, Factor model, FAVAR

**JEL Classification:** C3, E31, E32, E4, E5, Q43

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\*I have received helpful comments from Anindya Banerjee, Michael Bergman, Hilde C. Bjørnland, Fabio Canova, Vasco Carvalho, Jordi Gali, Lutz Kilian, Kristoffer Nimark, Ragnar Nymoen, Gonçalo Pina, Francesco Ravazzolo, Terje Skjerpen and Thijs van Rens as well as conference participants at The 14th Spring Meeting of Young Economists in Istanbul, The 5th NHH-UiO Workshop on Economic Dynamics in Bergen, The 5th Conference on Growth and Business Cycles in Theory and Practice in Manchester, The 5th Dynare Conference in Oslo, The 25th Annual Congress of the European Economic Association in Glasgow and seminar participants at BI Norwegian School of Management, Federal Reserve Bank of New York, University of Oslo and Universitat Pompeu Fabra. I also thank Lutz Kilian for providing an updated version of the index of global real economic activity in industrial commodity markets used in Kilian (2009). The views expressed in this paper are those of the author and should not be attributed to Norges Bank. E-mail: Knut-Are.Aastveit@norges-bank.no.

# 1 Introduction

Since the large oil price shocks in the 1970s, changes in the price of oil have been widely seen as an important source of macroeconomic fluctuations. Hamilton (1983) showed that all U.S. recessions except one since World War II were preceded by a spike in oil prices. Subsequent to Hamilton's work, a large body of research has suggested that oil price variations have strong and negative effects on both the U.S. economy and those of other oil importing countries (see, e.g., Burbidge and Harrison (1984), Mork, Olsen, and Mysen (1994), Bjørnland (2000), Jiménez-Rodríguez and Sanchez (2005) and Hamilton (1996, 2003, 2009), among many others).

The most common approach in studies of oil price shocks is to evaluate responses of macroeconomic variables to exogenous changes in the price of oil (see Hamilton (1996, 2003)). An implicit assumption of such studies is that oil price innovations result from oil supply shocks.<sup>1</sup> More recently, this view has been challenged by Barsky and Kilian (2002, 2004) and Kilian (2009). Fluctuations in the price of oil, like those of any other price, are driven by both demand shocks and supply shocks.

Kilian (2009) proposes a structural vectorautoregressive (SVAR) model of the global crude oil market and its interaction with global real economic activity. Assuming a recursive structure, he identifies three different kinds of shocks to the global crude oil market: a crude oil supply shock, a global demand shock and a global demand shock specific to the crude oil market.<sup>2</sup> His results suggest that the implications of higher oil prices for U.S. real GDP and CPI inflation depend on the cause of the oil price increase. However, his model does not account for interactions between the global oil market, the U.S. macro economy and monetary policy.

As first argued by Sims (1980), it is crucial, when studying the response of macroe-

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<sup>1</sup>The effect of oil supply shocks has been studied extensively in the literature. Recent research by Kilian (2008a,b) documents that oil supply shocks (measured in terms of disruption to global crude oil production) alone cannot explain the bulk of oil price fluctuations. His results also suggest that this type of shock does not have a substantial effect on real economic growth in any of the G7 countries.

<sup>2</sup>Baumeister and Peersman (2013) and Peersman and Van Robays (2009, 2012) suggest an alternative identification approach in which the different kinds of oil price shocks are identified by applying sign restrictions on the implied impulse responses of the different variables.

conomic variables to various structural shocks, to jointly model the interactions among endogenous variables. The different oil price shocks are not the only relevant sources of macroeconomic fluctuations. Hence, if the main focus of study is how macroeconomic variables are affected by different types of oil price shocks, one should control for other macroeconomic variables. This becomes especially important when studying the response of monetary policy, as monetary policy does not react to oil price movements per se, but to how the macro economy responds to different oil price shocks. If shocks that are important to macroeconomic fluctuations are ignored, the identified monetary policy response is likely to be contaminated.

Furthermore, oil price movements have historically posed a difficult challenge for policy makers seeking to balance the trade-off between higher inflation and higher unemployment. Bernanke, Gertler, and Watson (1997, 2004) suggest that monetary policy makers have historically leaned toward keeping inflation low at the cost of greater slowdowns in economic activity. That is, the systematic component of monetary policy accounts for a large portion of the decline in GDP growth following an oil price shock. This view was challenged by Hamilton and Herrera (2004) and Bachmeier (2008), and more recently by Kilian and Lewis (2011).<sup>3</sup> Only the latter paper takes into account the endogeneity of the real price of oil and allows policy responses to depend on the underlying cause of an oil price shock. They find no evidence that endogenous monetary policy responses have caused large aggregate fluctuations in the U.S. economy.

In this paper, I study the impact of different types of oil price shocks on the U.S. macro economy and monetary policy. I jointly model the interaction between the oil market, the U.S. macro economy and monetary policy, by extending the factor-augmented VAR (FAVAR) model in Bernanke, Boivin, and Elias (2005) to explicitly include measures of global oil production, an index of global real activity and the real price of oil. The advantages of using a FAVAR model are two-fold. First, it incorporates the large infor-

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<sup>3</sup>Kilian and Vigfusson (2011) also argues that the impulse response estimates obtained by Bernanke, Gertler, and Watson (1997) are inconsistent because their model includes censored changes in the nominal oil price, which implies that the underlying structural model cannot be represented as a VAR.

mation set typically monitored by policy makers. This ensures a proper identification of the monetary policy response. As argued in Sims (1992), if the information processed by the central bank is not reflected in the model, the measurement of the policy shock is likely to be contaminated. Second, impulse responses of a wide range of U.S. macroeconomic variables, following different types of oil price shocks, can be analyzed. This ensures a broad understanding of the potentially heterogeneous effects of different types of oil price shocks.<sup>4</sup> I apply the model to a large dataset of 114 monthly U.S. macroeconomic variables, over the sample period 1974M1 - 2008M6.

To the best of my knowledge, this is the first paper to examine the effects of different types of oil price shocks on a wide range of U.S. macroeconomic variables. While Lippi and Nobili (2012) and Peersman and Van Robays (2009, 2012) also study the impact of different types of oil price shocks on the U.S. economy, they study the responses of only a few macroeconomic variables. By contrast, I study the impact of oil supply and oil demand shocks on a broad range of U.S. macroeconomic variables, including disaggregated measures of industrial production and prices, a wide selection of labor market variables and financial variables. Such an approach yields a broad understanding of how different types of oil price shocks affect the U.S. macroeconomy.

I find considerable differences in the responses of both nominal and real variables to the different types of oil price shocks, robust to numerous robustness checks. First, I show that positive oil-specific demand shocks strongly increase the real price of oil and various price measures, and have a broad negative effect on the labor market and the production side of the economy. These findings are consistent with the negative effect on GDP and the positive effect on CPI inflation, reported in Peersman and Van Robays (2009, 2012) and Lippi and Nobili (2012). My results indicate that oil-specific demand shocks yield the well-known trade-off between higher unemployment and higher inflation, often associated with negative supply shocks. Hence, oil-specific demand shocks have an effect

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<sup>4</sup>Few papers have examined the impact of oil price shocks on a broad selection of U.S. macroeconomic variables. One exception is Lee and Ni (2002), who studied the effects of exogenous oil price shocks, using U.S. industry level data.

on the macroeconomy similar to that of an aggregate supply shock. Kilian and Lewis (2011) and Peersman and Van Robays (2009, 2012) find strong but conflicting monetary policy responses to oil-specific demand shocks. While Kilian and Lewis (2011) find that such a shock causes a significant monetary tightening, Peersman and Van Robays (2009, 2012) find the opposite, namely, a significant monetary loosening following a positive oil-specific demand shock. When controlling for a large set of macroeconomic variables, I show that the federal funds rate remains almost unchanged after an oil-specific demand shock, which indicates that the Federal Reserve (Fed) has not systematically responded to oil-specific demand shocks.

Second, I find that positive global demand shocks have a large and persistent positive effect both on the real price of oil and on various price measures. I find empirically that this causes a monetary tightening in the short run, in line with the findings of Kilian and Lewis (2011) and Peersman and Van Robays (2009). The effect on the U.S. labor market and on the production side of the economy is almost negligible during the first year, but becomes significantly negative after approximately two years. In other words, shocks to global aggregate demand that increase the real price of oil also negatively affect the U.S. economy. However, in contrast to an oil-specific demand shock or an oil supply shock, the negative effect on the real economy is delayed.

Third, the estimated effect of a negative oil supply shock on the U.S. economy is rather small. While such a shock increases the price of oil in the short run, I find only a weak negative effect on the real economy and that prices are almost unaffected. This is in line with responses for GDP and CPI inflation in Kilian (2009), but contrasts with the findings of a significant negative impact on the real economy in Lippi and Nobili (2012) and Peersman and Van Robays (2009, 2012). Consequently, I also find that an oil supply shock has a negligible effect on the federal funds rate, while Peersman and Van Robays (2009, 2012) find indications of a monetary tightening. A possible reason for the conflicting findings may be that Peersman and Van Robays (2009, 2012) identifies the different types of oil price shocks by applying sign restrictions, while I follow Kilian

(2009) and Kilian and Lewis (2011) in using a recursive identification scheme. The former approach has been criticized by Kilian and Murphy (2012), who show that imposing sign restrictions alone, as opposed to applying a recursive identification scheme, is not sufficient to resolve the question of the relative importance of different types of oil price shock.

To illustrate the implications of the FAVAR model, I compare impulse responses in the preferred FAVAR model to impulse responses in a three-variable SVAR model (similar to Kilian (2009)) and a six-variable SVAR model. The latter model includes industrial production, the consumer price index and the federal funds rate, in addition to the variables related to the oil market (see Kilian (2009)). The comparison shows considerable differences in the responses of macroeconomic variables between the three-variable SVAR model and the FAVAR model. Such differences show that it is important to account for interactions between the oil market, the U.S. macro economy and monetary policy. The differences between the six-variable SVAR model and the FAVAR model are smaller.

This paper is organized as follows: In the following section, I present the FAVAR model and the dataset. Empirical results are discussed in section 3, while robustness results for various data and model specifications are presented in section 4. Finally, section 5 summarizes and concludes.

## 2 Modeling Framework

The empirical framework that I consider is based on the factor-augmented vector autoregressive (FAVAR) model described in Bernanke, Boivin, and Elias (2005). One of its key features is that it provides estimates of the macroeconomic factors that affect the variables of interest by efficiently exploiting all the information from a large set of economic indicators (see Boivin, Giannoni, and Mihov (2009)). In this application, I estimate an empirical model by exploiting information from a large set of macroeconomic indicators. This framework allows me to characterize the responses of all variables to macroeconomic



disturbances, including different types of oil price shocks and monetary policy shocks.

Assume that the state of the economy is captured by a few common components, represented by the vector  $C_t$ . I am interested in characterizing the effects of different types of oil price shocks and monetary policy shocks on the macroeconomy. Thus, I include observable variables that are associated with these shocks. For the global oil market, I follow Kilian (2009) in including three observable variables: the percent change in global crude oil production ( $\Delta prod_t$ ), an index of real economic activity that drives demand for industrial commodities in global industrial commodity markets ( $rea_t$ )<sup>5</sup> and the real price of oil ( $rpo_t$ )<sup>6</sup>. In addition, I include the federal funds rate ( $R_t$ ) as the observable measure of the Fed's monetary policy stance. These four variables are assumed to have pervasive effects throughout the economy and will thus be considered to be common components of all variables entering the dataset. In addition, I extract some unobservable common factors ( $F_t$ ) from a large dataset and include  $F_t$  in  $C_t$ . I assume that the dynamics of the common components are modeled as a VAR and given by

$$C_t = \Phi(L) C_{t-1} + u_t \quad (1)$$

where

$$C_t = \begin{bmatrix} \Delta prod_t \\ rea_t \\ rpo_t \\ F_t \\ R_t \end{bmatrix}, \quad (2)$$

and  $\Phi(L)$  is a conformable lag polynomial of finite order. The error term,  $u_t$ , is assumed to be i.i.d., with zero mean. The system (1) is a VAR in  $C_t$ .<sup>7</sup> The additional difficulty with respect to a standard VAR is that the factors represented by the vector  $F_t$ , of

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<sup>5</sup>This is the index developed by Kilian (2009). It is based on dry cargo single ocean freight rates and is explicitly designed to capture shifts in the demand for industrial commodities in the global business markets. See Kilian (2009) for more details about this index.

<sup>6</sup>The real price of oil series is based on U.S. refiner acquisition costs of imported crude oil. The nominal oil price has been deflated by the U.S. consumer price index.

<sup>7</sup>All variables in  $C_t$  are standardized. Hence, no constant term is needed.

dimension  $K \times 1$ , are unobservable. These factors are extracted from a large number of macroeconomic variables,  $X_t$ , of dimension  $N \times 1$ . I assume that  $X_t$  can be described by an approximate dynamic factor model given by

$$X_t = \Lambda C_t + e_t, \quad (3)$$

where  $\Lambda$  is a  $N \times (K + 4)$  matrix of factor loadings and  $e_t$  is a vector of series-specific components that are uncorrelated with the common component  $C_t$ . The series-specific components are allowed to be serially correlated and weakly correlated across indicators (see Chamberlain and Rothschild (1983), Forni, Hallin, Lippi, and Reichlin (2000) and Stock and Watson (2002) for details). However, note that, in contrast to a standard dynamic factor model, I assume that some of the factors are observable.

## 2.1 Data

I use a balanced panel of 114 monthly series for the U.S. economy. The sample period is 1974M1 - 2008M6.<sup>8</sup> The dataset contains 110 macroeconomic indicators, covering a broad spectrum of the U.S. economy, including series for prices, industrial production, the labor market, stock prices and interest rates, among others. The variables are mainly similar to, but updated from, those used in Stock and Watson (2002) and Bernanke, Boivin, and Elias (2005). The 110 macroeconomic indicators are collected in  $X_t$ , and all series were initially transformed to induce stationarity and then standardized. In addition, I include the effective federal funds rate ( $R_t$ ), the percentage change in global crude oil production ( $\Delta prod_t$ ), an index of real economic activity ( $reat_t$ ), and the real price of oil ( $rpo_t$ ). A description of all series in the dataset and their transformations is given in Appendix A.

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<sup>8</sup>Alquist, Kilian, and Vigfusson (2013) show that data before 1974 are not amenable to time-series analysis because the price of oil was regulated. A structural break in the process governing the real price of oil in 1973 has also been documented by Dvir and Rogoff (2009). Furthermore, monthly data on refiner acquisition costs of imported crude oil are first available for 1974, while monthly observations on global crude oil production are first available for 1973.

## 2.2 Estimation

I estimate the model, using a two-step principal components approach, similar to Bernanke, Boivin, and Elias (2005) and Boivin, Giannoni, and Mihov (2009). In the first step, I extract principal components from the large dataset in order to obtain consistent estimates of the common factors. In the second step, I add the three observable variables related to the oil market,  $\Delta prod_t, rea_t, rpo_t$ , and the federal funds rate, and estimate a structural VAR. In this step, I impose the constraint that the four observable variables are four of the factors in the first-step estimation. This guarantees that the estimated latent factors will recover dimensions of the common dynamics not already captured by the four observable variables. More specifically, I follow the iteration procedure used in Boivin and Giannoni (2007) and Boivin, Giannoni, and Mihov (2009). I start with an initial estimate of  $F_t$ , denoted by  $F_t^{(0)}$  and obtained as the first  $K$  principal components of  $X_t$ . I then iterate through the following steps:

- (i) Regress  $X_t$  on  $F_t^{(0)}$  and the observed factors  $Y_t = [\Delta prod_t, rea_t, rpo_t, R_t]'$  and obtain  $\hat{\lambda}_Y^{(0)}$ .
- (ii) Compute  $\tilde{X}_t^{(0)} = X_t - \hat{\lambda}_Y^{(0)} Y_t$ .
- (iii) Estimate  $F_t^{(1)}$  as the first  $K$  principal components of  $\tilde{X}_t^{(0)}$ .
- (iv) Repeat the procedure multiple times.

Having estimated the factors,  $F_t$ , and the factor loadings,  $\Lambda$ , I can now estimate the VAR in equation (1), using OLS, and then seek a more structural representation of the system.

## 2.3 Identification

Once the factors are consistently estimated by principal components, equation (1) can be considered as a standard VAR. The errors in equation (1) are assumed to be correlated and therefore cannot be interpreted as structural shocks. Equation (1) has the following

moving average representation:

$$C_t = B(L) u_t. \quad (4)$$

Assume that the reduced form innovations ( $u_t$ ) can be written as linear combinations of the underlying orthogonal structural disturbances ( $\varepsilon_t$ ), i.e.  $u_t = S\varepsilon_t$ , where  $S$  is a  $((K + 4) \times (K + 4))$  contemporaneous matrix. Equation (4) can then be written as

$$C_t = B(L) S\varepsilon_t = D(L)\varepsilon_t \quad (5)$$

where  $B(L)S = D(L)$ .

To orthogonalize the shocks, I order the vector of shocks recursively, using the Cholesky decomposition. That is, I choose an ordering for the variables in the system that allows for only a contemporaneous correlation between certain series. Specifically, I assume the following recursive identifying restrictions:

$$C_t = \begin{bmatrix} \Delta prod_t \\ rea_t \\ rpo_t \\ F_t \\ R_t \end{bmatrix} = B(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{OS} \\ \varepsilon_t^{GD} \\ \varepsilon_t^{OD} \\ \varepsilon_t^F \\ \varepsilon_t^{MP} \end{bmatrix}, \quad (6)$$

where  $F_t$  is a  $(K \times 1)$  vector.

This allows me to identify three different structural shocks related to the oil market, in addition to U.S. monetary policy shocks and shocks to the U.S. macroeconomic factors. The shocks to the U.S. macroeconomic factors are not given any structural interpretation. For the oil market part of the model, I follow the identifying assumptions in Kilian (2009), while the identifying assumptions for the unobservable factors and for the monetary policy part of the model follow Bernanke, Boivin, and Elias (2005). This implies the following identifying assumptions: First, crude oil supply shocks, ( $\varepsilon_t^{OS}$ ), are defined as unpredictable innovations to global oil production. In other words, I assume a vertical short-run supply curve for crude oil. Crude oil supply is therefore assumed not

to respond within the same month to demand shocks in the crude oil market, shocks to U.S. macroeconomic factors or to shocks in U.S. monetary policy. As argued in Kilian (2009), this is plausible, as oil producing countries will be slow to respond to demand shocks, given the cost of adjusting oil production, in addition to uncertainty about the state of the global oil market. Kilian and Murphy (2013) also estimate the price elasticity of oil supply to be about 0.02 on impact, consistent with the view that the short-run oil supply curve is nearly vertical.

Second, innovations to global real economic activity that cannot be explained by global oil supply shocks are referred to as global demand shocks ( $\varepsilon_t^{GD}$ ). It is assumed that shocks specific to the global oil market, as well as shocks to U.S. macroeconomic factors and to U.S. monetary policy, cannot affect global real economic activity within the same month.

Third, innovations to the real price of oil that cannot be explained by oil supply shocks or global demand shocks are referred to as oil-specific demand shocks ( $\varepsilon_t^{OD}$ ). Kilian (2009) argues that this type of structural shock will particularly reflect fluctuations in the precautionary demand for oil, driven by uncertainty with regard to future oil supply shortfalls. It is assumed that the real price of oil cannot be affected contemporaneously by U.S. macroeconomic factors or by U.S. monetary policy.

Innovations to U.S. factors that cannot be explained by the three types of oil price shock are referred to as U.S. factor shocks ( $\varepsilon_t^F$ ). It is assumed that such shocks cannot affect global oil production, global real economic activity or the real price of oil within the same month. In this way, the U.S. factors can be interpreted as indicators that recover the most important aspects of the U.S. economy not already captured by the three oil related variables. In particular, only shocks to the U.S. economy that can affect global real economic activity within the same month can contemporaneously affect the real price of oil. This specification exploits the conventional assumption that oil prices are predetermined with respect to domestic macroeconomic aggregates (see Kilian and Vega (2011)).

Finally, to identify the monetary policy shock ( $\varepsilon_t^{MP}$ ), the federal funds rate is allowed to respond to contemporaneous fluctuations in the U.S factors and in the oil related variables. However, none of these variables are allowed to respond within the same month to unanticipated changes in monetary policy. Note that all of the indicators included in  $X_t$  are allowed to respond to contemporaneous monetary policy shocks, even though the latent U.S. factors  $F_t$  are assumed to remain unaffected during the current month. Such contemporaneous responses thus relate directly to changes in the federal funds rate (see Boivin, Giannoni, and Mihov (2009) for more details on this point). The above restrictions concern only contemporaneous effects. After one month, all variables can react to all shocks.

## 2.4 Model Specification

In factor models, the number of factors is usually exogenously determined.<sup>9</sup> The dataset I use to extract the factors is an updated version of the dataset used in Bernanke, Boivin, and Elias (2005). In addition, I include three additional observable variables,  $\Delta prod_t$ ,  $rea_t$  and  $rpo_t$ , representing the oil market and the federal funds rate. I choose a maximum number of  $K = 7$  factors, then reduce the number of factors and determine whether the impulse responses are thereby affected. A similar strategy is used in Boivin, Giannoni, and Mihov (2009). This leads me to choose  $K = 5$ , which is the same number of factors as in Bernanke, Boivin, and Elias (2005). I checked for robustness of my results to different numbers of factors. In particular, none of my conclusions were affected by including more factors.

I estimate the system (1) and (3), for the period 1974M1 - 2008M6, using the data described above and assuming five latent factors in the vector  $F_t$ . I use 13 lags in estimating equation (1).

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<sup>9</sup>Bai and Ng (2002) provide different information criteria to determine the number of factors present in a large dataset.

### 3 Results

One of the advantages of using a FAVAR model is that the responses for a large number of variables to different structural shocks can be analyzed with a minimal number of identifying restrictions. In particular, it is possible to calculate impulse responses for all of the variables included in  $X_t$ . Note that for each variable in  $X_t$ , equation (3) implies that

$$x_{it} = \Lambda'_i C_t + e_{it}, \quad (7)$$

where  $x_{it}$  is an element of  $X_t$ . This formulation implies that each variable in  $X_t$  is allowed to react contemporaneously to all structural shocks, despite the recursive ordering in equation (1). For example, financial variables included in  $X_t$  are allowed to react to contemporaneous changes in the federal funds rate. Thus we see the flexibility of the FAVAR model.

#### 3.1 Effects of oil shocks

I now examine the transmission of different types of oil price shocks through the U.S. macroeconomy. I focus particularly on the responses of the following six variables: global oil production, real global economic activity, the real price of oil, industrial production, the consumer price index and the federal funds rate. As noted above, I compare the impulse responses of my chosen FAVAR model with those of two other models. I first consider a monetary SVAR model extended to include the oil market, as modeled in Kilian (2009). The model includes the following variables:  $Y_t = [\Delta prod_t, rea_t, rpo_t, \Delta ip_t, \Delta cpi_t, R_t]'$ , where  $\Delta ip_t$  denotes the first difference of the logarithm of industrial production and  $\Delta cpi_t$  denotes the first difference of the logarithm of the consumer price index. I use the same recursive structure for identification as in the FAVAR model and denote this as the *SVAR model*.

Next, I compare the responses observed in the three models noted above with those of a version of the model in Kilian (2009).<sup>10</sup> This is a SVAR model that includes the

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<sup>10</sup>This model differs slightly from the model specified in Kilian (2009). I use 13 instead of 24 lags to

three oil-related variables,  $\Delta prod_t$ ,  $rea_t$  and  $rpo_t$ . The responses of industrial production, consumer prices and the federal funds rate are obtained by separately regressing each variable on the contemporaneous and lagged values of the extracted shock of interest. I refer to this model as the *Kilian model*.<sup>11</sup> In addition, I will also use the FAVAR model to produce impulse responses for a broad set of industrial production, price and labor market variables, as well as several other selected variables of interest. All shocks are normalized to have a positive effect on the real price of oil and represent a one standard deviation shock from the Kilian model.

### 3.1.1 Oil supply shock

Figure 1 shows the responses of global oil production, real economic activity, the real price of oil, industrial production, consumer prices and the federal funds rate to a one standard deviation structural shock of the Kilian model.<sup>12</sup> In the FAVAR model, an unexpected oil supply disruption causes a sharp and significant decline in oil production upon impact, followed by a partial but slow reversal within the next few years. This shock triggers a transitory increase in the real price of oil and a decline in global real economic activity. The first effect is weakly significant, while the latter is insignificant. Further, the shock causes a temporary but insignificant decline in industrial production, while consumer prices are almost unaffected. The monetary policy authority does not seem to react to the negative oil supply shock, as the federal funds rate remains unchanged.

There are considerable differences in the responses of the FAVAR model and the Kilian model. Notably, the response of the federal funds rate differs, with the Kilian model implying a surprisingly strong monetary tightening. There are also large differences in the responses of consumer prices and, to some extent, industrial production. This

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make the model compatible with the preferred FAVAR model. My sample is also slightly different, as Kilian (2009) uses data from 1973M1 to 2007M12. However, the results are very similar.

<sup>11</sup>Note that Kilian (2009) does not investigate the responses of industrial production and the federal funds rate. However, he uses a similar approach to calculate impulse responses of quarterly GDP and the CPI.

<sup>12</sup>The error bands in all figures below represent 95 percent confidence intervals for the FAVAR model, calculated using the bootstrap method in Kilian (1998). This procedure accounts for the uncertainty in the factor estimation.



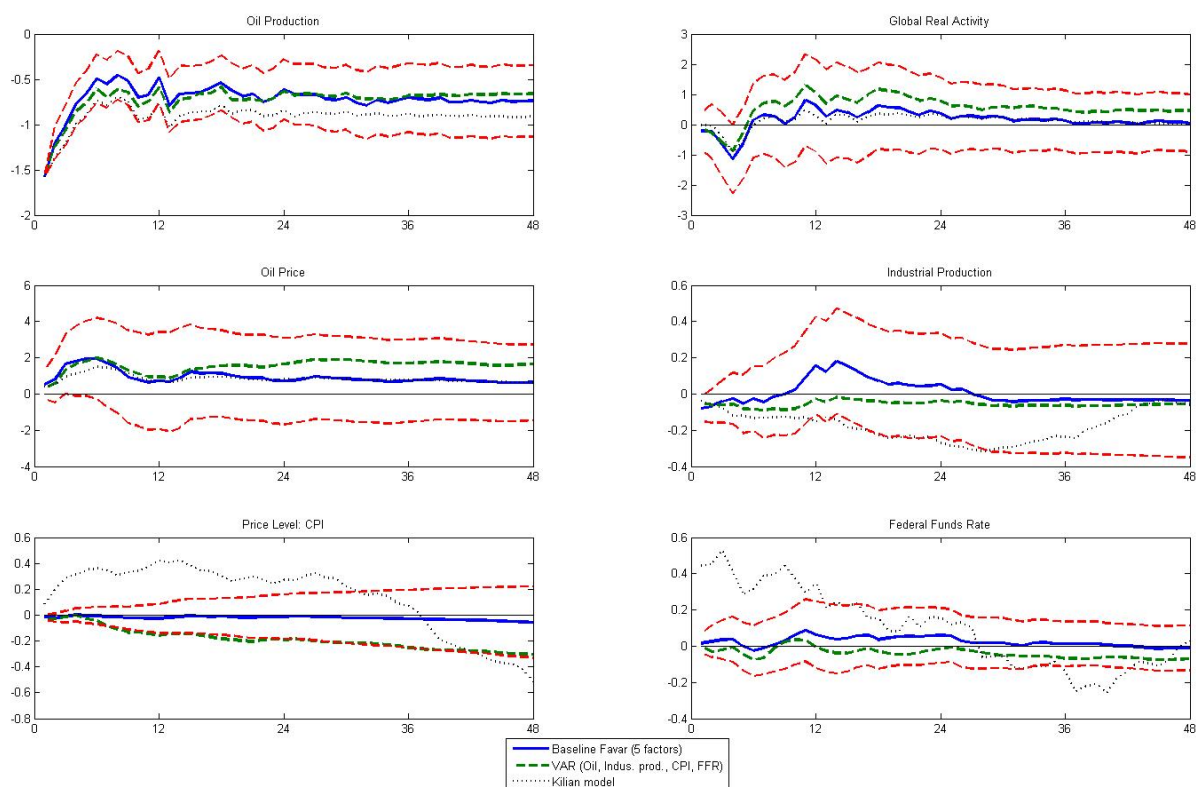


Figure 1: *Comparison of responses in the FAVAR model, the SVAR model and the Kilian model to a one standard deviation oil supply shock. 95 percent error bands for the FAVAR model. All variables are expressed in log levels, except the federal funds rate and the global real activity index.*

supports the view that it is important to account for the full interaction between the oil market, the U.S. macro economy and monetary policy, when estimating the effects of an oil supply shock on the macro economy. There are smaller differences between the responses of the FAVAR model and the SVAR model. One exception is the response of consumer prices. The SVAR model indicates a somewhat surprising fall in consumer prices after a negative shock to global oil production, while consumer prices are almost unaffected in the FAVAR model.

Figure 2 and figures B.1 - B.3 in Appendix B show impulse responses in the FAVAR model for a selection of key macroeconomic variables, as well as various industrial production, price and labor market variables, to an oil supply shock. The responses generally have the expected signs, but are mostly insignificant. An unanticipated reduction in oil supply causes real activity measures to decline on impact. The unemployment rate

increases significantly after approximately six months, while other labor market measurements decrease, though the effects are insignificant. Furthermore, the dollar appreciates and the effect on the stock market is negative, but insignificant. Somewhat surprisingly, the commodity price index falls on impact. However, the effect is insignificant and is reversed after about one year.

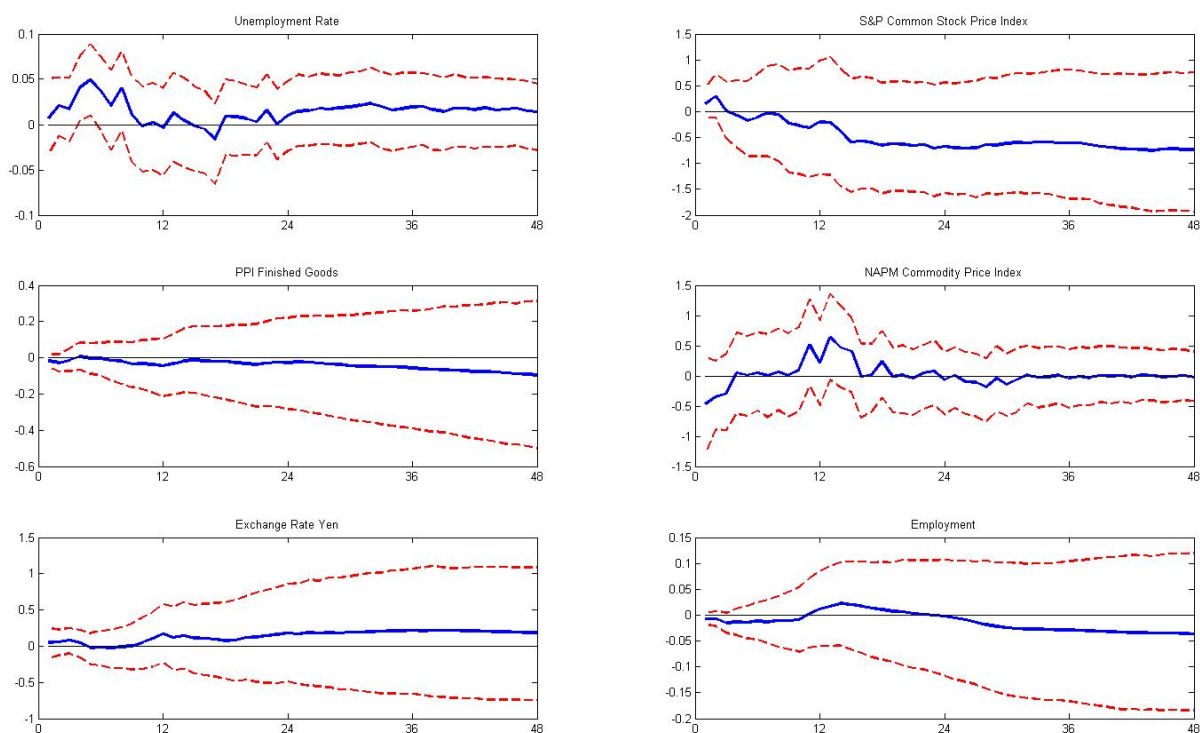


Figure 2: *Response of the FAVAR model to a one standard deviation oil supply shock. 95 percent error bands. The stock price index, PPI, the exchange rate and employment are expressed in log levels. All other variables are expressed in original units.*

The contributions of all shocks considered to the variances of selected variables are shown in Table C.1 in Appendix C. The table shows that oil supply shocks are important primarily in explaining variations in oil production. Even so, such shocks also explain roughly 3-6 percent of the variation in the real price of oil, the unemployment rate and industrial production after one to two years. The contribution of oil supply shocks to variations in the federal funds rate is almost negligible. The results above support the finding in Kilian (2008b) that oil supply shocks are not very important in explaining

fluctuations in U.S. macroeconomic variables.

### 3.1.2 Global demand shock

An unanticipated global demand expansion has a persistent and positive effect on global real economic activity. Figure 3 shows that such a shock temporarily increases production of global crude oil, with only a short delay. The effect is insignificant and reversed after about 18 months. A global commodity demand expansion causes a large and persistent significant increase in the real price of oil, with a maximum effect after approximately two years. Moreover, the increase in the real price of oil causes a persistent and significant increase in prices, while the effect on the real economy is more muted in the short run. This leads to a significant monetary tightening after six months, which, together with the higher price of oil, has a significant negative impact on real economic activity in the U.S. after about one to two years. The negative impact on the U.S. real economic activity is somewhat surprising, as the positive effect on global real activity is persistent, which might be expected to have a stimulating effect on the U.S. economy. The results thus indicate that the negative impact of higher oil prices is larger for the U.S. economy than for other countries. Aastveit, Bjørnland, and Thorsrud (2012) show that demand from emerging economies, in particular Asia, has been more than twice as important as demand from developed countries, in accounting for fluctuations in the real price of oil since the early 1990s.<sup>13</sup> This may explain the negative effect on U.S. real activity, despite the positive shock to global real activity.

Again, there are differences between the responses of the macroeconomic variables in the FAVAR and Kilian models, while the differences are smaller between the FAVAR and SVAR models. In particular, the response of the federal funds rate in the Kilian model differs from that in the two other models, as it involves an immediate monetary loosening, while the responses in the SVAR and FAVAR models involve a significant

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<sup>13</sup>Hicks and Kilian (2012) also show that the recent surge in the real price of oil, from mid-2003 to mid-2008, was driven by repeated shocks to the demand for industrial commodities, due to unexpectedly high growth in emerging Asian countries.

monetary tightening. Additionally, compared with the FAVAR model, the response of consumer prices seems too strong in the SVAR model (given the negative delayed effect on industrial production) and too weak in the Kilian model.

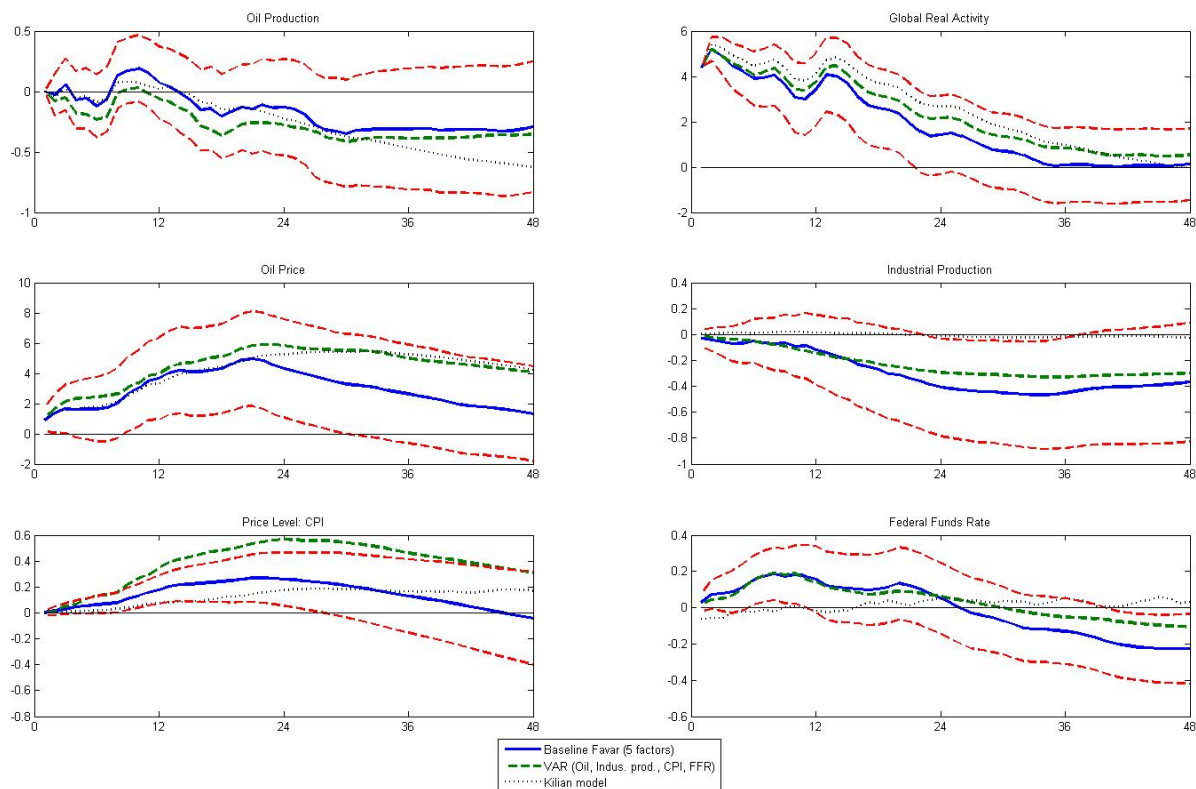


Figure 3: Comparison of responses in the FAVAR model, the SVAR model and the Kilian model to a one standard deviation global demand shock. 95 percent error bands for the FAVAR model. All variables are expressed in log levels, except the federal funds rate and the global real activity index.

A global aggregate demand expansion has negligible effects on U.S. production and the labor market (see figures B.4 and B.6). One exception is the significant decrease, in the first few months, in the unemployment rate, shown in figure 4. After about one year, the effect on the labor market and on various industrial production measures turns negative, as interest rates and prices increase. The increase in the federal funds rate is significant after 6-12 months, and the unemployment rate increases significantly after about two years, in addition to significant reductions in other labor market variables. Additionally, the shock positively affects the U.S. stock market on impact and leads to an appreciation of the dollar, though only the latter effect is significant. The commodity

price index increases significantly on impact, as expected.

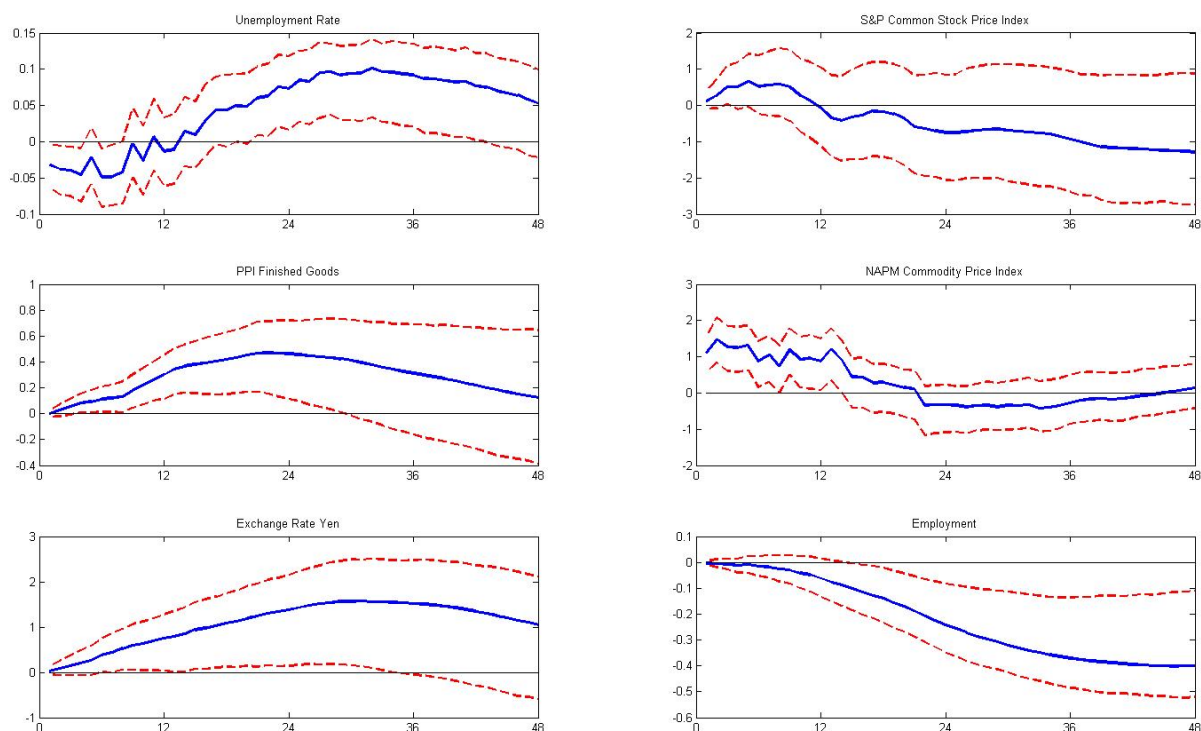


Figure 4: *Response in the FAVAR model to a one standard deviation global demand shock. 95 percent error bands. The stock price index, PPI, the exchange rate and employment are expressed in log levels. All other variables are expressed in original units.*

Table C.1 in Appendix C shows that global demand shocks explain more than 10 percent of the variation in the real price of oil and in the commodity price index after one year. In addition, these shocks explain more than 5 percent of the variation in the federal funds rate, in consumer and producer prices, in the unemployment rate and in employment after one to two years. The results indicate that global demand shocks that raise the real price of oil play an important role in U.S. macroeconomic fluctuations.

### 3.1.3 Oil-specific demand shock

Unanticipated oil-specific demand shocks have immediate, large and persistently significant effects on the real price of oil, as shown in Figure 5. Kilian (2009) argues that this type of shock captures shifts in the price of oil driven by a higher precautionary demand associated with market concerns about future oil supplies. These shocks are associated

with a strong and temporarily significant increase in global real activity and a transitory decline in oil production, with the latter effect insignificant. The oil-specific demand shock has a strong and persistent positive effect on consumer prices and a negative effect on industrial production. The first effect is strongly significant, while the latter is significant after about one year. There is evidence of monetary tightening following the positive oil-specific demand shock, indicating that the Fed has leaned towards stabilizing the inflation rate rather than stabilizing the real economy. However, the response is small and insignificant.

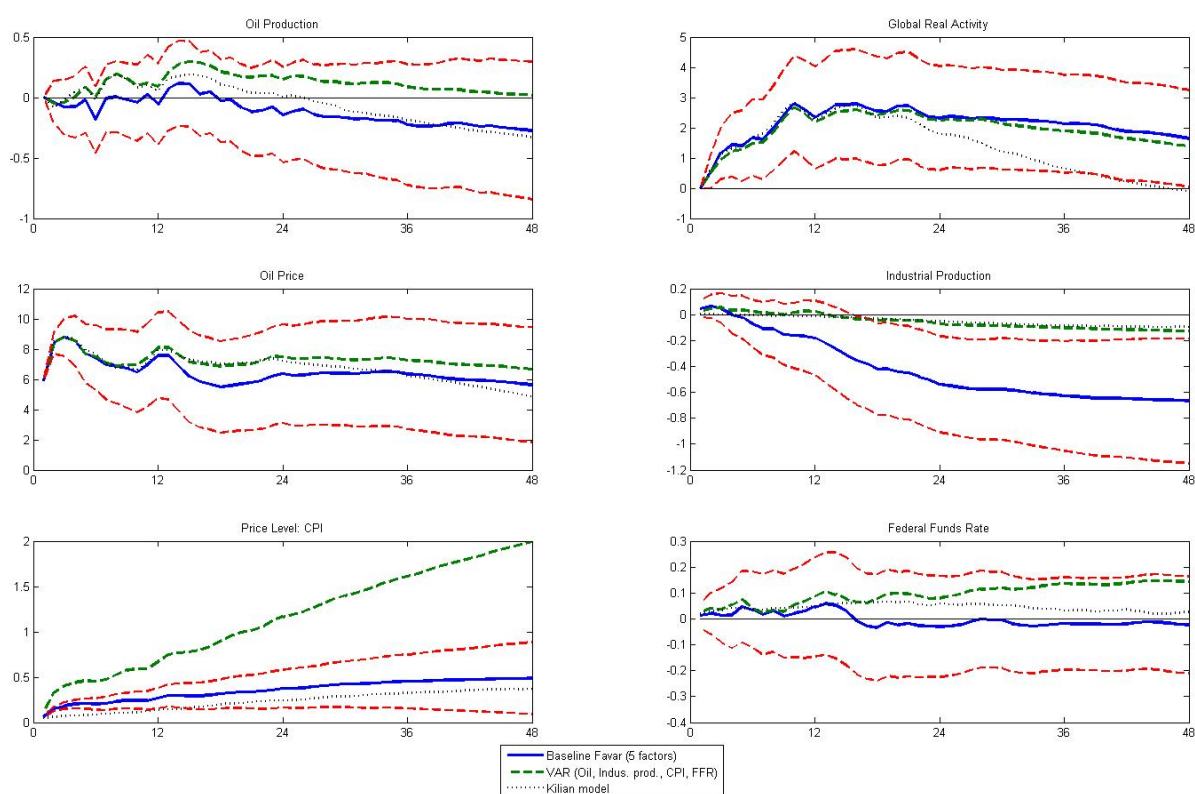


Figure 5: Comparison of responses in the FAVAR, SVAR and Kilian models to a one standard deviation oil-specific demand shock. 95 percent error bands for the FAVAR model. All variables are expressed in log levels, except the federal funds rate and the global real activity index.

There are several differences between the responses in the three models. First, both the Kilian and SVAR models appear to produce stronger and more persistent responses in the real price of oil and global real economic activity than the FAVAR model. Second, the response of industrial production differs among the three models. In particular, the

FAVAR model shows a stronger and more rapid slowdown in economic activity than the other two models. The opposite is the case for consumer prices, where the SVAR model yields a much stronger positive response than the FAVAR model. The FAVAR model uses additional information not present in the VAR and Kilian models. According to Sims (1998), two different models will yield accurate and equal estimates of impulse responses to various shocks, if they are both conditioned on the relevant information set. The differences we observe in the responses exhibited by the models indicate there is important information in the FAVAR model not captured by the other two models.

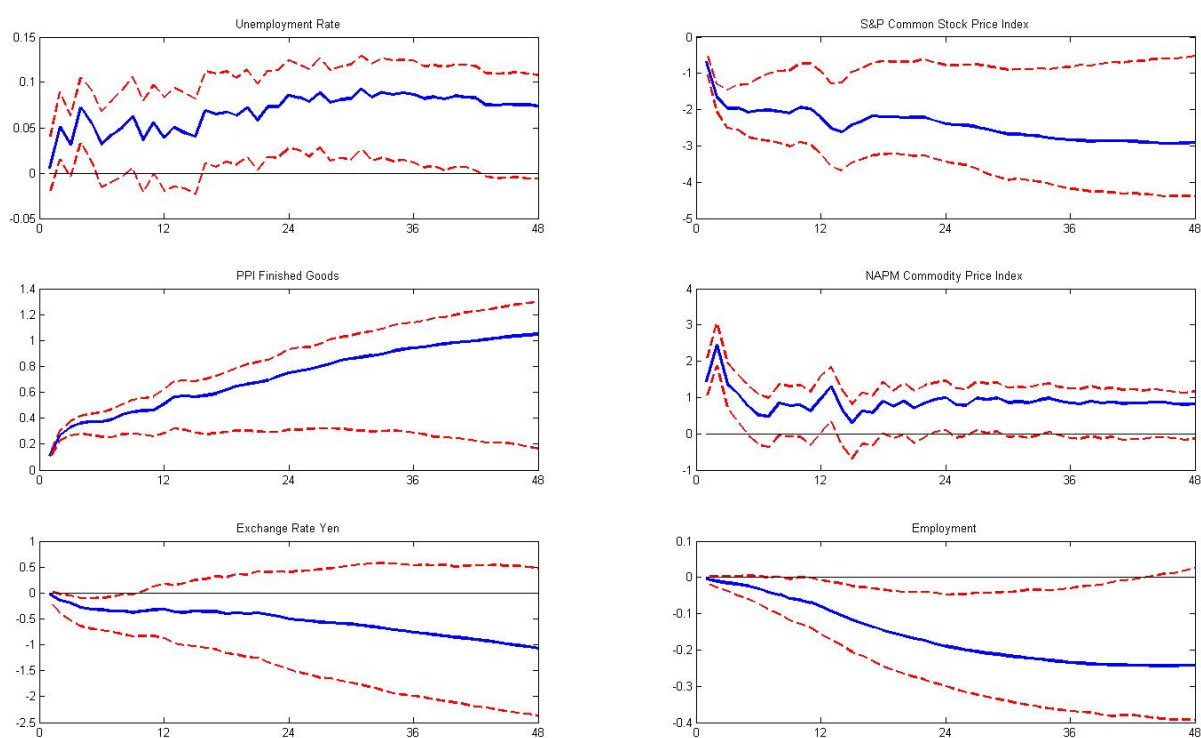


Figure 6: *Response in the FAVAR model to a one standard deviation oil-specific demand shock. 95 percent error bands. The stock price index, PPI, the exchange rate and employment are expressed in log levels. All other variables are expressed in original units.*

Figure 6 and figures B.7 and B.9 in Appendix B show that a positive oil-specific demand shock causes real economic activity and labor market variables to decrease. The effect is significant for the unemployment rate over most horizons and for several other labor market measures after one year or so. There is a strong and persistent increase

in a wide range of consumer and producer price indices, and the commodity price index increases significantly for the first six months. Moreover, a shock to the real price of oil has a significant negative impact on consumer expectations and a significant negative impact on stock prices. This confirms the finding in Kilian and Park (2009) that only higher oil prices caused by an oil-specific demand shock yield lower stock prices.<sup>14</sup>

The net result is that oil-specific demand shocks have a negative impact on the U.S. economy, although these shocks are associated with temporary increases in global real economic activity. In particular, this type of shock negatively affects U.S. real economic activity, while pushing prices higher. Hence, it leads to the well-known trade-off between higher unemployment and higher inflation, often associated with supply shocks. This indicates that if the oil-specific demand shock identified in our model really is a demand shock in the oil market, it has an effect on the macro economy similar to that commonly associated with a supply shock.

The variance decomposition in table C.1 shows that oil-specific demand shocks are the main driving force behind fluctuations in the real price of oil, as they explain almost 80 percent of the variation in the real price of oil after one year. Additionally, these shocks are an important driving force behind several of our macroeconomic variables of interest. These shocks explain more than 20 percent of the variations in consumer prices, producer prices, consumer expectations and commodity prices, both in the short and long run, as well as more than 15 percent of the variation in stock prices over most time horizons and in global real activity over time horizons longer than one year. Oil-specific demand shocks also significantly affect the real economy, as they contribute to more than 5 percent of the variation in the unemployment rate, the employment measure and industrial production over horizons longer than one year. The contribution of oil-specific demand shocks to variations in the federal funds rate and other variables is more modest.

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<sup>14</sup>Several other papers have found that oil price increases have a negative effect on stock market prices in oil importing countries. See Jones and Kaul (1996), Sadorsky (1999) and Nandha and Faff (2008), among others. On the other hand, Bjørnland (2009) finds that oil price increases have a positive effect on the Norwegian stock market. Norway is an oil-exporting country. However, none of these papers distinguish between different types of oil price shocks.



## 3.2 Monetary Policy Shock

This paper focuses on the transmission of different types of oil price shocks on the U.S. macro economy and their interaction with monetary policy. For the sake of completeness, in this section I will briefly discuss the effects of a monetary policy shock on the U.S. economy. This topic has already been studied in detail, in a FAVAR model, by Bernanke, Boivin, and Elias (2005) and Boivin, Giannoni, and Mihov (2009). Nonetheless, these papers do not explicitly model the interaction between the U.S. macro economy and the global oil market.

Figure 7 shows the responses of different macroeconomic variables to an unexpected 25 basis point increase in the federal funds rate. Interestingly, a negative monetary policy shock causes a significant reduction in global oil production after approximately six months. This somewhat surprising finding may suggest that OPEC reacts to surprises in Fed policy. There are also positive (but insignificant) movements in both the global demand for commodities and in the real price of oil. In addition, a monetary tightening has the expected negative effect on industrial production, and it causes a fall in prices. Note that, as highlighted in Bernanke, Boivin, and Elias (2005), the FAVAR model removes the “price puzzle” evident in most standard SVAR models. By and large, the impulse responses are similar to the ones in Bernanke, Boivin, and Elias (2005) and Boivin, Giannoni, and Mihov (2009).

Table C.1 shows that the explanatory power of monetary policy shocks is as expected. Monetary policy shocks explain more than 10 percent of the variation in stock prices and more than 5 percent of the variation in various price measures, the unemployment rate and employment for time horizons longer than six months. As expected, it has a negligible effect on global real activity and the real price of oil.

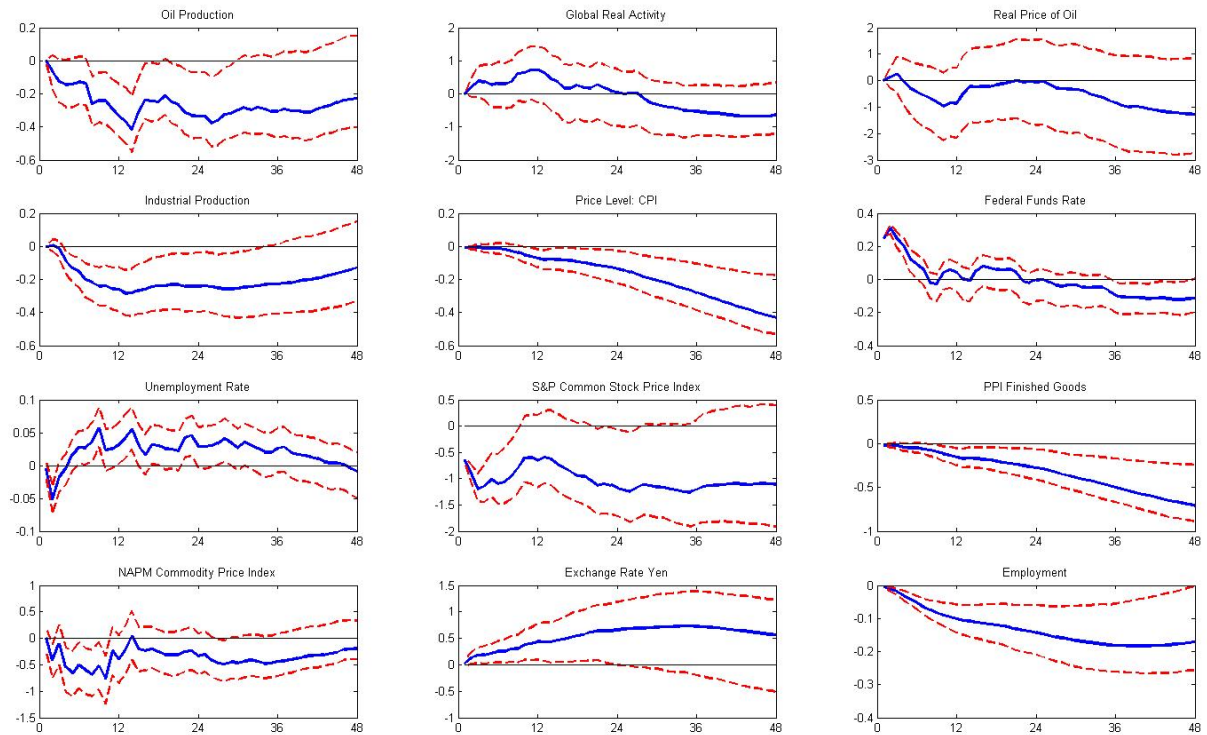


Figure 7: *Response in the FAVAR model to an unexpected 25 basis point increase in the federal funds rate. 95 percent error bands. All variables are expressed in log levels, except the federal funds rate, the global real activity index, the unemployment rate, the NAPM commodity price index and the exchange rate.*

## 4 Results of robustness tests

I check for robustness in three ways. First, I check the robustness of my results with respect to the number of factors included in the FAVAR and then with respect to the lag length of the VAR in equation (1). Finally, I check for robustness with respect to the starting the estimation in 1984.

### 4.1 Different number of factors

The figures in Appendix D compare the impulse responses of several variables to different types of oil price shock, as well as monetary policy shocks, choosing one, three, five and seven factors, respectively. The figures show that for most of the variables, the results are robust to the number of factors. However, two exceptions are worth noting. First, results obtained when one factor is selected appear to differ from those obtained when more

than one factor is selected. This indicates that one factor is not enough to capture the appropriate dimensions of the U.S. economy. Second, for some of the financial variables, the results differ when fewer than five factors are selected. Consequently, if responses to financial variables are of particular interest, one should choose at least five factors.

## **4.2 Different lag length**

The figures in Appendix D compare the results for different numbers of lags in equation (1). Hamilton and Herrera (2004) criticized the results in Bernanke, Gertler, and Watson (1997) as not robust to the choice of lag length. Bernanke, Gertler, and Watson (1997) specified a monthly VAR model with seven lags, using U.S. macroeconomic data. However, Hamilton and Herrera (2004) showed that the econometric evidence favored a longer lag length. For model specifications of 12 to 16 lags, the results in Bernanke, Gertler, and Watson (1997) no longer hold. Several papers have shown that the maximum effects of oil shocks on macroeconomic variables occur with lags of around one year. Thus, one should use at least 12 lags for monthly data. Kilian (2009) argues that the dynamics are even more persistent and includes 24 lags in his monthly VAR model. I check the robustness of my results to 7, 13, 18 and 24 lags, respectively. The figures show that the results are very similar for different choices of lag length.

## **4.3 Post-1984 sample**

Recent research has provided evidence of widespread instability in many macroeconomic models (see, among others, Stock and Watson (1996, 2003), Gambetti, Pappa, and Canova (2008) and Benati and Surico (2009)). Studies, such as Bernanke and Mihov (1998), Clarida, Gali, and Gertler (2000) and Boivin and Giannoni (2006), have found evidence of changes in monetary policy behavior over my sample period (1974M1 - 2008M6) and of an important reduction in output volatility (The Great Moderation) since around 1984. Herrera and Pesavento (2009) show that the macroeconomic response to an exogenous oil price shock, as well as the response of monetary policy, changed after

1984. Baumeister and Peersman (2013) use a Bayesian time varying VAR, similarly to Primiceri (2005), to show that the effects of oil supply shocks on U.S. GDP and inflation have changed over time. In particular, the effects have changed since the mid-1980s. Kilian (2009), on the other hand, argues that one possible explanation for these changes is that the relative composition of oil supply and oil demand shocks has changed over time.

I have checked whether my results are robust to all these events. The graphs in Appendix D show impulse responses of different variables to the four types of structural shock considered. The models are now estimated using the shorter sample period 1984M1 - 2008M6. The figures indicate some quantitative differences from my original results, but qualitatively the results are almost the same, although there are two exceptions. First, the negative effect on the U.S. real economy following a global demand shock is smaller in the post-1984 sample, while the response of global oil production is stronger. The real price of oil also reacts more strongly to a shock to global oil production in the post-1984 sample. Second, the effects of a monetary policy shock are different for some of the variables of interest. In particular, the responses of industrial production and the unemployment rate are different, while the response of prices is much smaller. In fact, there is evidence of a price puzzle, which is in line with findings of Boivin, Giannoni, and Mihov (2009).

## 5 Conclusion

In this paper, I have investigated the impact of different types of oil price shocks on the U.S. economy, using a factor-augmented vector autoregression (FAVAR) approach. This statistical framework allows me to study the effects of oil price shocks on a large number of U.S. macroeconomic variables.

I find that it is important to account for interactions between the oil market, the U.S. macro economy and monetary policy. Comparing impulse responses in my preferred FAVAR model with those in a three-variable SVAR model (similar to the one used by Kil-

ian (2009)) and a six-variable SVAR model, I find significant differences in the responses of different macroeconomic variables to the different types of oil price shocks.

Estimates of my preferred FAVAR model show that oil demand and oil supply shocks have rather different effects on the dynamics of the real price of oil and on the U.S. macro economy. In particular, I find that positive oil-specific demand shocks lead to increases in the real price of oil and other prices and have negative effects on real economic activity, the labor market and the stock market. Additionally, I find that positive global demand shocks have large and persistent positive effects on the real price of oil and other prices. Shocks of this kind lead to monetary tightening in the short run. Similarly to oil-specific demand shocks, positive global demand shocks also have negative effects on U.S. real economic activity and on the labor market. Nevertheless, the dynamics are different, as these negative effects are delayed. Finally, oil supply shocks have a small effect on the U.S. macro economy and cause negligible movements in the federal funds rate. The results are robust to a series of alternative model specifications.

The results show that there are important differences in the responses of the real price of oil, various macroeconomic variables and monetary policy to different types of oil price shocks. In particular, oil demand shocks appear to be more important than oil supply shocks in fluctuations in the real price of oil. My results indicate that oil demand shocks are an important source of macroeconomic fluctuations, while oil supply shocks are of far less importance. Furthermore, the causes of changes in the demand for oil appear to matter. The U.S. economy responds differently to global demand shocks that raise the price of oil than to demand shocks that are specific to the global crude oil market. This suggests that the causes behind the movements of oil prices are important to consider. Thus, my results suggest that monetary policy should respond differently to movements in the real price of oil, depending on what causes those movements.

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# Appendices

## Appendix A Description of data set

We apply the following transformations to the raw data in order to induce stationarity: 1 = No transformation, 2 = First differences, 4 = Logarithm, 5 = First differences in logs. Below follows a complete description of the data set.

Description	Transformation
<b>OUT ----- real output and income</b>	
1 Industrial Production Index - Products, Total	5
2 Industrial Production Index - Final Products	5
3 Industrial Production Index - Consumer Goods	5
4 Industrial Production Index - Durable Consumer Goods	5
5 Industrial Production Index - Nondurable Consumer Goods	5
6 Industrial Production Index - Business Equipment	5
7 Industrial Production Index - Materials	5
8 Industrial Production Index - Durable Goods Materials	5
9 Industrial Production Index - Nondurable Goods Materials	5
10 Industrial Production Index - Manufacturing (SIC)	5
11 Industrial Production Index - Mining NAICS=21	5
12 Industrial Production Index - Electric and Gas Utilities	5
13 Industrial Production Index - Total Index	5
14 Purchasing Managers' Index (SA)	5
15 NAPM Production Index (Percent)	5
16 Personal Income (Chained) (Bil 2000\$, SAAR)	5
17 Personal Income Less Transfer Payments (Chained) (Bil 2000\$, SAAR)	5
18 Industrial Production Index - Residential Utilities	5
19 Industrial Production Index - Basic Metals	5
<b>EMP ----- employment and hours</b>	
20 Index of Help-Wanted Advertising In Newspapers (1967=100;SA)	5
21 Employment: Ratio; Help-Wanted Ads: No. Unemployed Clf	4
22 Civilian Labor Force: Employed, Total (Thous., SA)	5
23 Civilian Labor Force: Employed, Nonagric. Industries (Thous., SA)	5
24 Unemployment Rate: All Workers, 16 Years & Over (% , SA)	1
25 Unemploy. by Duration: Average(Mean) Duration in Weeks (SA)	1
26 Unemploy. by Duration: Persons Unempl.Less Than 5 Wks (Thous., SA)	1
27 Unemploy. by Duration: Persons Unempl.5 To 14 Wks (Thous., SA)	1
28 Unemploy. by Duration: Persons Unempl.15 Wks + (Thous., SA)	1
29 Unemploy. by Duration: Persons Unempl.15 To 26 Wks (Thous., SA)	1
30 Total Nonfarm Employment (SA) - CES0000000001	5
31 Total Private Employment (SA) - CES0500000001	5
32 Goods-Producing Employment (SA) - CES0600000001	5
33 Natural Resources and Mining Employment (SA) - CES1000000001	5
34 Construction Employment (SA) - CES2000000001	5
35 Manufacturing Employment (SA) - CES3000000001	5
36 Durable Goods Manufacturing Employment (SA) - CES3100000001	5
37 Nondurable Goods Manufacturing Employment (SA) - CES3200000001	5
38 Service-Providing Employment (SA) - CES0700000001	5
39 Trade, Transportation, and Utilities Employment (SA) - CES4000000001	5
40 Retail Trade Employment (SA) - CES4200000001	5
41 Wholesale Trade Employment (SA) - CES4142000001	5
42 Financial Activities Employment (SA) - CES5500000001	5
43 Private Service-Providing Employment (SA) - CES0800000001	5
44 Government Employment (SA) - CES9000000001	5
45 Manufacturing Average Weekly Hours of Production Workers (SA) - CES3000000005	1
46 Manufacturing Average Weekly Overtime of Production Workers (SA) - CES3000000007	1
47 NAPM Employment Index (Percent)	1
<b>HSS ----- housing starts and sales</b>	
48 Housing Starts: Nonfarm (1947-58); Total Farm&Nonfarm(1959-); (Thous. U., SA)	4
49 Housing Starts: Northeast (Thous. U., SA)	4
50 Housing Starts: Midwest (Thous. U., SA)	4
51 Housing Starts: South (Thous. U., SA)	4
52 Housing Starts: West (Thous. U., SA)	4
53 Housing Authorized: Total New Private Housing Units (Thous., SAAR)	4
54 Mobile Homes: Manufacturers' Shipments (Thous. U., SAAR)	4
<b>INV ----- real inventories and inventory-sales ratios</b>	
55 NAPM Inventories Index (Percent)	1
<b>ORD----- orders and unfilled orders</b>	
56 NAPM New Orders Index (Percent)	1
57 NAPM Vendor Deliveries Index (Percent)	1
58 New Orders (Net) - Consumer Goods & Materials, 1996 Dollars (BCI)	5
59 New Orders, Nondefense Capital Goods, In 1996 Dollars (BCI)	5
<b>SPR ----- stock prices</b>	
60 S&P's Common Stock Price Index: Composite (1941-43=10)	5
61 S&P's Common Stock Price Index: Industrials (1941-43=10)	5
62 S&P's Composite Common Stock: Dividend Yield (% Per Annum)	1

63 S&P's Composite Common Stock: Price-Earnings Ratio (% , NSA)	1
64 Common Stock Prices: Dow Jones Industrial Average	5
<b>EXR ----- exchange rates</b>	
65 Foreign Exchange Rate: Switzerland (Swiss Franc Per U.S.\$)	5
66 Foreign Exchange Rate: Japan (Yen Per U.S.\$)	5
67 Foreign Exchange Rate: United Kingdom (Cents Per Pound)	5
68 Foreign Exchange Rate: Canada (Canadian \$ Per U.S.\$)	5
<b>INT ----- interest rates</b>	
69 Interest Rate: Federal Funds (Effective) (% Per Annum, NSA)	1
70 Interest Rate: U.S.Treasury Bills,Sec Mkt,3-Mo.(% Per Ann, NSA)	1
71 Interest Rate: U.S.Treasury Bills,Sec Mkt,6-Mo.(% Per Ann, NSA)	1
72 Interest Rate: U.S.Treasury Const Maturities,1-Yr.(% Per Ann, NSA)	1
73 Interest Rate: U.S.Treasury Const Maturities,5-Yr.(% Per Ann, NSA)	1
74 Interest Rate: U.S.Treasury Const Maturities,10-Yr.(% Per Ann, NSA)	1
75 Bond Yield: Moody's AAA Corporate (% Per Annum)	1
76 Bond Yield: Moody's BAA Corporate (% Per Annum)	1
77 Spread FYGM3 - FYFF	1
78 Spread FYGM6 - FYFF	1
79 Spread FYGT1 - FYFF	1
80 Spread FYGT5 - FYFF	1
81 Spread FYGT10 - FYFF	1
82 Spread FYAAAC - FYFF	1
83 Spread FYBAAC - FYFF	1
<b>MON ----- money and credit quantity aggregates</b>	
84 Money Stock: M1(Curr,Trav.Cks,Dep,Other CK'able Dep) (Bi\$, SA)	5
85 Money Stock:M2(M1+O'nite Rps,Euro\$,G/P&B/D Mmms&SAv&Sm Time Dep (Bi\$, SA)	5
86 MZM (SA) FRB St. Louis	5
87 Monetary Base, Adj for Reserve Requirement Changes (Mil\$, SA)	5
88 Depository Inst Reserves: Total,Adj For Reserve Req Chgs (Mil\$, SA)	5
89 Depository Inst Reserves: Nonborrowed,Adj Res Req Chgs (Mil\$, SA)	5
90 Consumer Credit Outstanding - Nonrevolving(G19)	5
91 Commercial and Industrial Loans at All Commercial Banks (FRED) Billions \$ (SA)	5
<b>PRI ----- price indexes</b>	
92 NAPM Commodity Prices Index (Percent)	1
93 Producer Price Index: Finished Goods (82=100,SA)	5
94 Producer Price Index: Finished Consumer Goods (82=100,SA)	5
95 Producer Price Index: Intermed Mat.Supplies & Components (82=100,SA)	5
96 Producer Price Index: Crude Materials (82=100,SA)	5
97 CPI-U: All Items (82-84=100,SA)	5
98 CPI-U: Apparel & Upkeep (82-84=100,SA)	5
99 CPI-U: Transportation (82-84=100,SA)	5
100 CPI-U: Medical Care (82-84=100,SA)	5
101 CPI-U: Commodities (82-84=100,SA)	5
102 CPI-U: Durables (82-84=100,SA)	5
103 CPI-U: All Items Less Food (82-84=100,SA)	5
104 CPI-U: All Items Less Shelter (82-84=100,SA)	5
105 CPI-U: All Items Less Medical Care (82-84=100,SA)	5
106 Spot Market Price Index: BLS & CRB: All Commodities (1967=100)	5
107 Personal Consumption Expenditures: Chain-type Price Index	5
108 Personal Consumption Expenditures: Chain-Type Price Index Less Food and Energy	5
<b>AHE ----- average hourly earnings</b>	
109 Construction Average Hourly Earnings of Production Workers - Seasonally Adjusted - CES2000000006	5
110 Manufacturing Average Hourly Earnings of Production Workers - Seasonally Adjusted - CES3000000006	5
111 U. of Michigan Index of Consumer Expectations (Bcd-83)	1
<b>Oil market</b>	
112 Crude Oil Production, World Millions Barrels per Day)	5
113 Index of global demand for industrial commodities (from Kilian (2009))	1
114 U.S. Crude Oil Imported Acquisition Cost by Refiners (Dollars per Barrel)	4

# Appendix B Additional Impulse Response Figures

## Oil Supply Shock

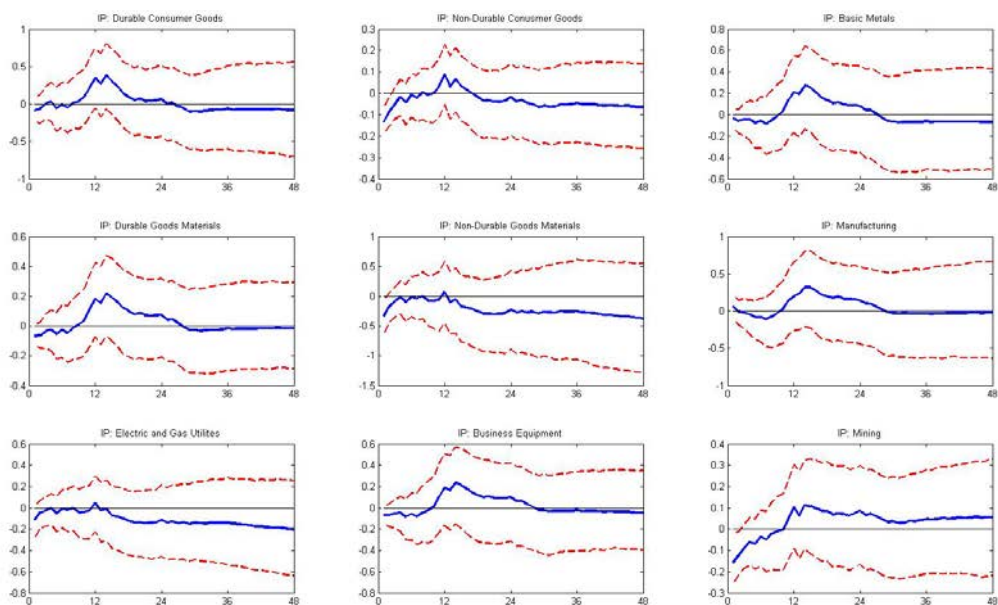


Figure B.1: Responses of various industrial production measures to a one standard deviation oil supply shock. 95 percent error bands. All variables are expressed in log levels.

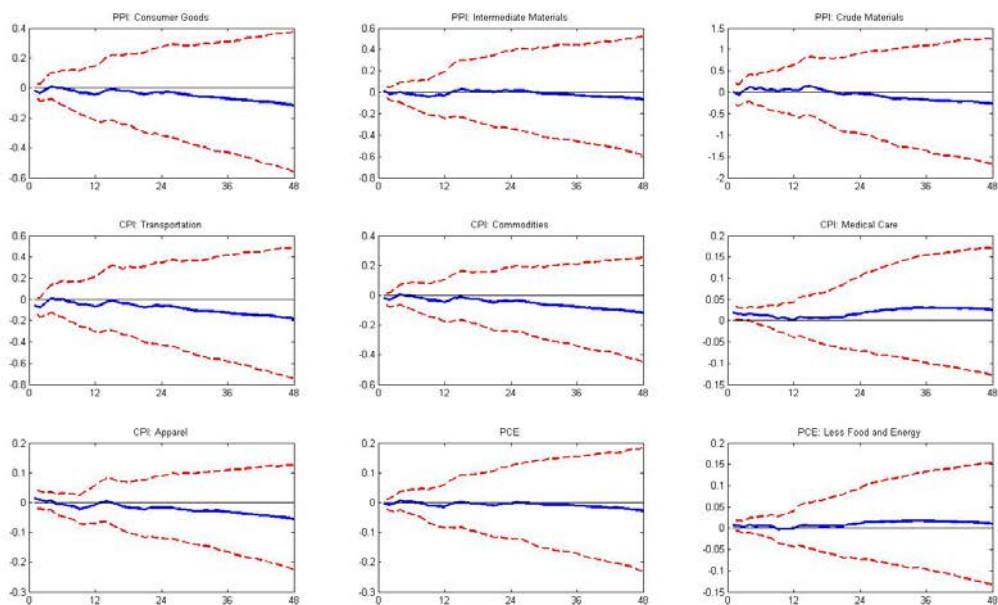


Figure B.2: Responses of various disaggregated price measures to a one standard deviation oil supply shock. 95 percent error bands. All variables are expressed in log levels.

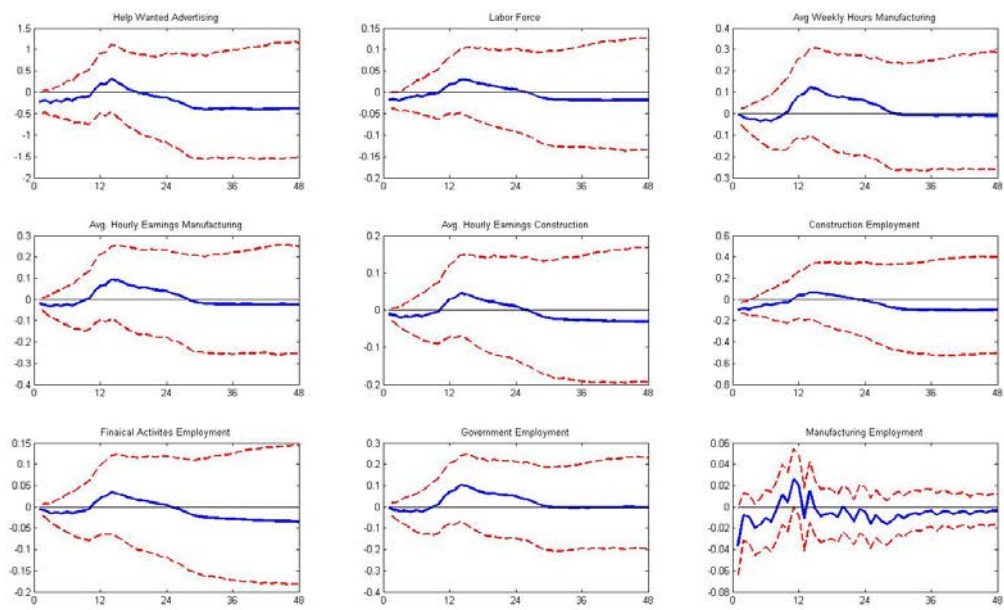


Figure B.3: *Responses of various labor market measures to a one standard deviation oil supply shock. 95 percent error bands. All variables are expressed in log levels, except average weekly hours in manufacturing.*

## Global Demand Shock

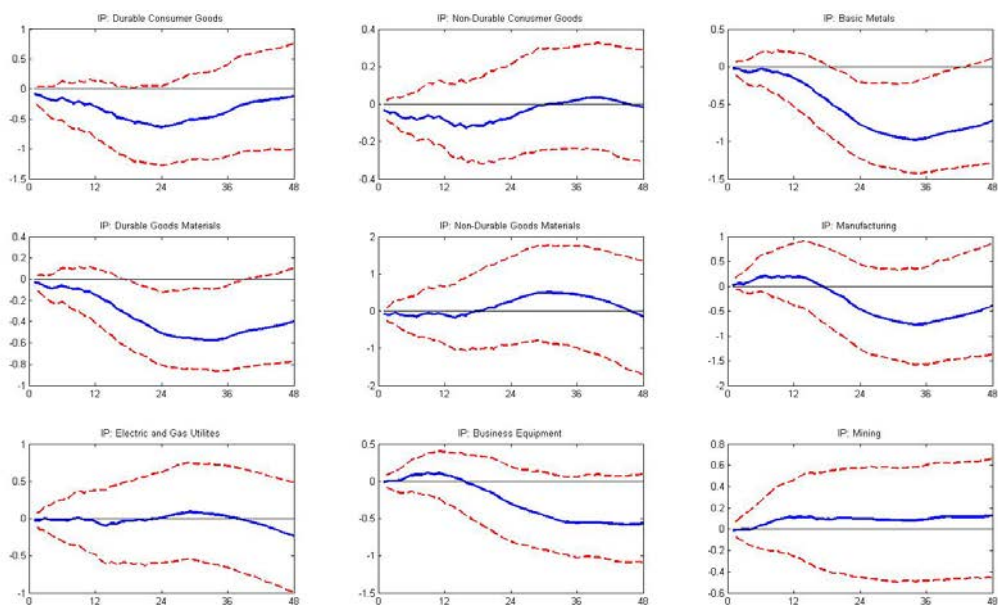


Figure B.4: *Responses of various industrial production measures to a one standard deviation global demand shock. 95 percent error bands. All variables are expressed in log levels.*

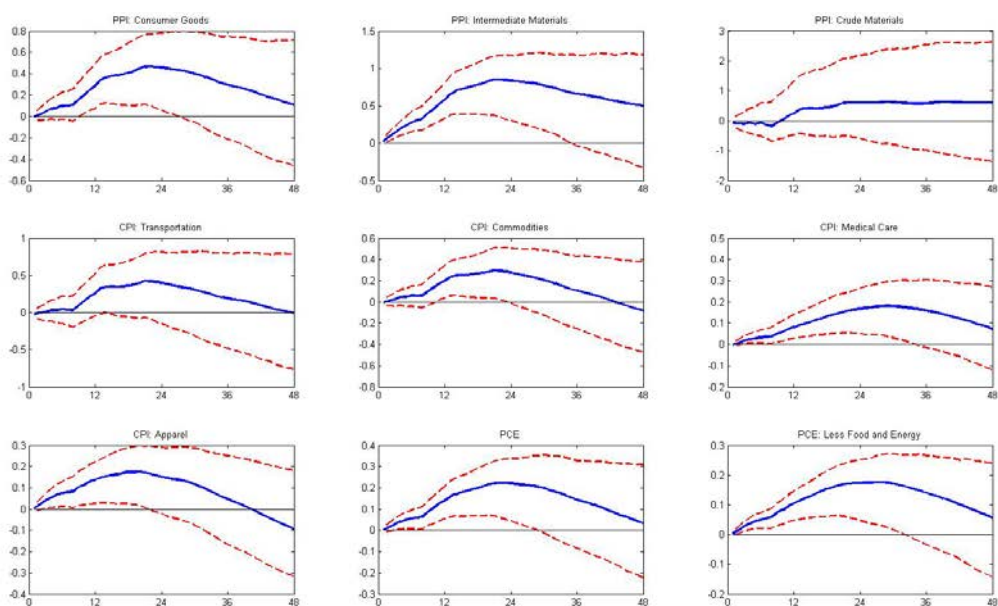


Figure B.5: *Responses of various disaggregated price measures to a one standard deviation global demand shock. 95 percent error bands. All variables are expressed in log levels.*



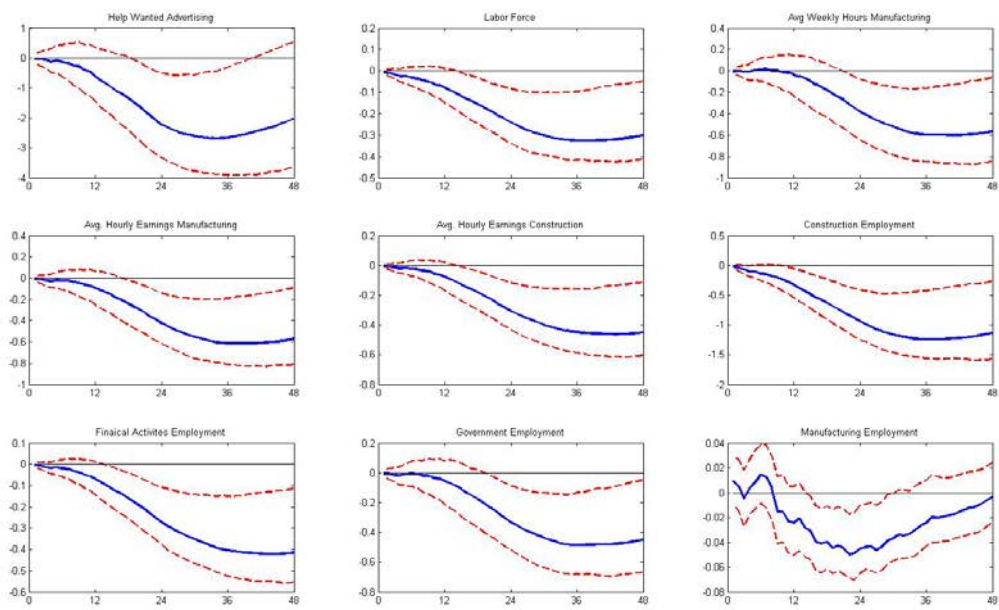


Figure B.6: *Responses of various labor market measures to a one standard deviation global demand shock. 95 percent error bands. All variables are expressed in log levels, except average weekly hours in manufacturing.*

## Oil-Specific Demand Shock

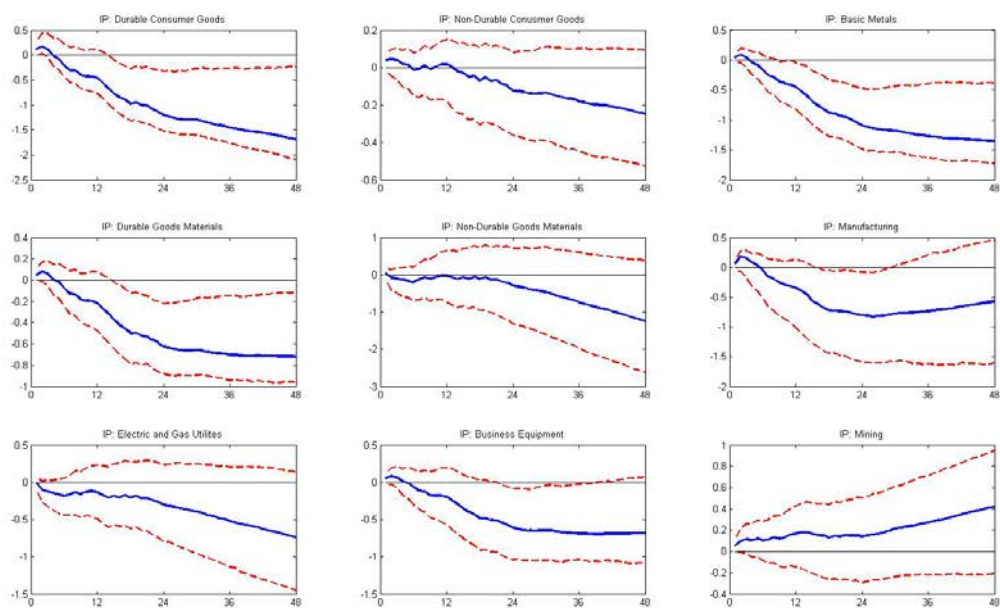


Figure B.7: *Responses of various industrial production measures to a one standard deviation oil-specific demand shock. 95 percent error bands. All variables are expressed in log levels.*

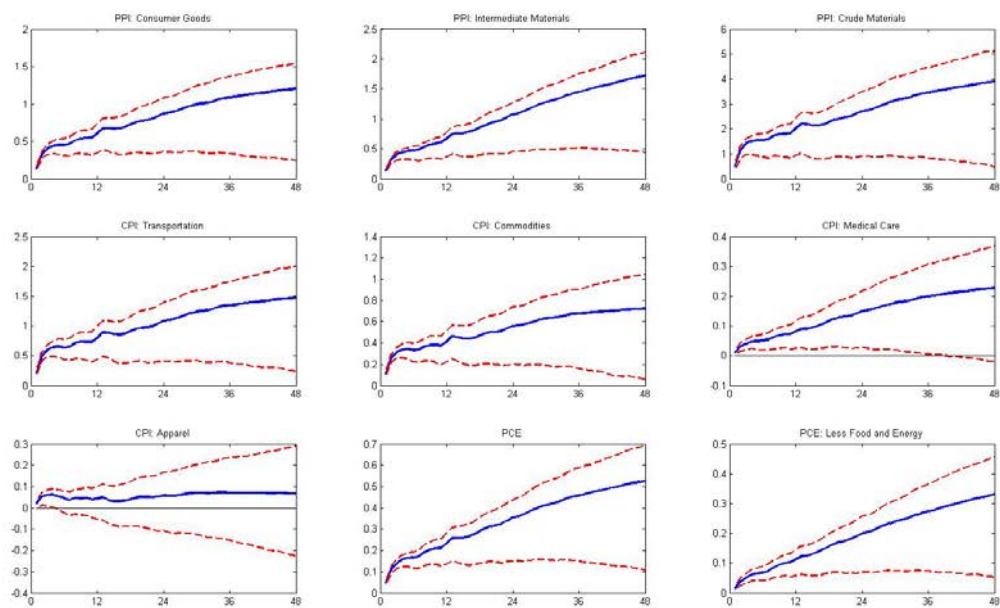


Figure B.8: *Responses of various disaggregated price measures to a one standard deviation oil-specific demand shock. 95 percent error bands. All variables are expressed in log levels.*

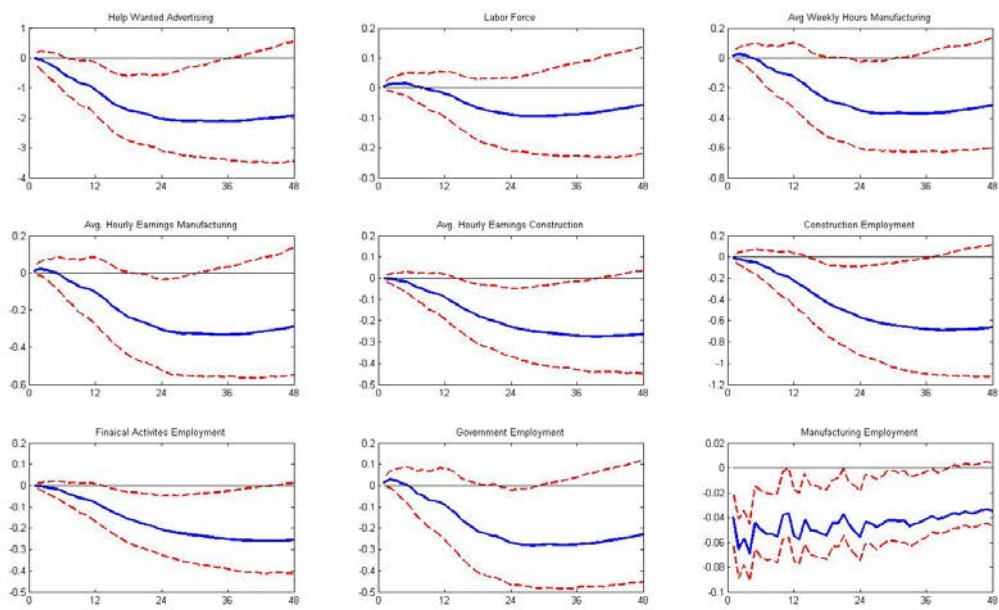


Figure B.9: *Responses of various labor market measures to a one standard deviation oil-specific demand shock. 95 percent error bands. All variables are expressed in log levels, except average weekly hours in manufacturing.*

## Appendix C Variance Decomposition

<b>Oil Production</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	0	99	0	0	1
6	1	87	1	2	10
12	2	78	2	3	15
24	3	72	3	3	15
48	3	71	3	3	15
120	3	71	3	3	15
<b>Global Real Activity</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	0	0	98	1	0
6	1	1	87	7	5
12	2	1	71	15	11
24	2	1	61	25	11
48	3	1	45	33	17
120	4	1	36	32	28
<b>Real Price of Oil</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	0	1	3	94	2
6	0	4	4	88	4
12	1	2	9	79	8
24	1	2	20	68	9
48	2	2	17	69	10
120	3	1	14	64	18
<b>Interest Rate</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	62	0	1	0	37
6	32	0	5	0	63
12	16	1	7	0	76
24	11	1	6	0	82
48	12	1	11	0	76
120	13	0	13	4	70
<b>Consumer Prices</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	1	1	11	25	62
6	6	1	18	21	54
12	8	1	19	20	52
24	7	1	16	21	55
48	9	1	11	24	55
120	6	1	15	31	48
<b>Industrial Production</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	0	2	0	1	97
6	7	3	1	2	87
12	6	5	1	3	85
24	6	6	3	5	80
48	6	6	3	5	80
120	7	6	4	5	78

Table C.1: Contribution of all the shocks to the variance of selected variables.

<b>Unemployment rate</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	5	0	2	2	91
6	4	3	5	6	82
12	7	2	4	7	80
24	9	2	9	14	66
48	7	1	20	21	51
120	15	1	16	20	48
<b>Stock Prices</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	14	1	0	19	66
6	14	2	2	17	65
12	14	2	3	15	66
24	14	2	4	16	64
48	14	2	4	15	65
120	14	2	4	15	65
<b>Producer Prices</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	1	0	1	41	57
6	2	1	3	40	54
12	5	1	9	35	50
24	6	1	9	32	52
48	12	1	9	27	51
120	12	1	11	27	49
<b>Commodity Price Index</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	1	1	11	25	62
6	6	1	18	21	54
12	8	1	19	20	52
24	7	1	16	21	55
48	9	1	11	24	55
120	6	1	15	31	47
<b>Exchange Rate (Yen)</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	6	1	1	3	91
6	6	2	6	4	82
12	7	3	7	4	79
24	7	3	10	4	76
48	7	3	12	5	73
120	8	3	14	7	68
<b>Employment</b>					
Horizons/Shocks	$\varepsilon_t^{MP}$	$\varepsilon_t^{OS}$	$\varepsilon_t^{GD}$	$\varepsilon_t^{OD}$	$\varepsilon_t^F$
1	2	1	0	1	96
6	12	1	1	2	82
12	12	2	5	5	79
24	10	2	15	7	76
48	9	2	17	6	73
120	12	2	19	6	68

Table C.1: *Continued.*

# Appendix D Robustness

## Different factor combinations

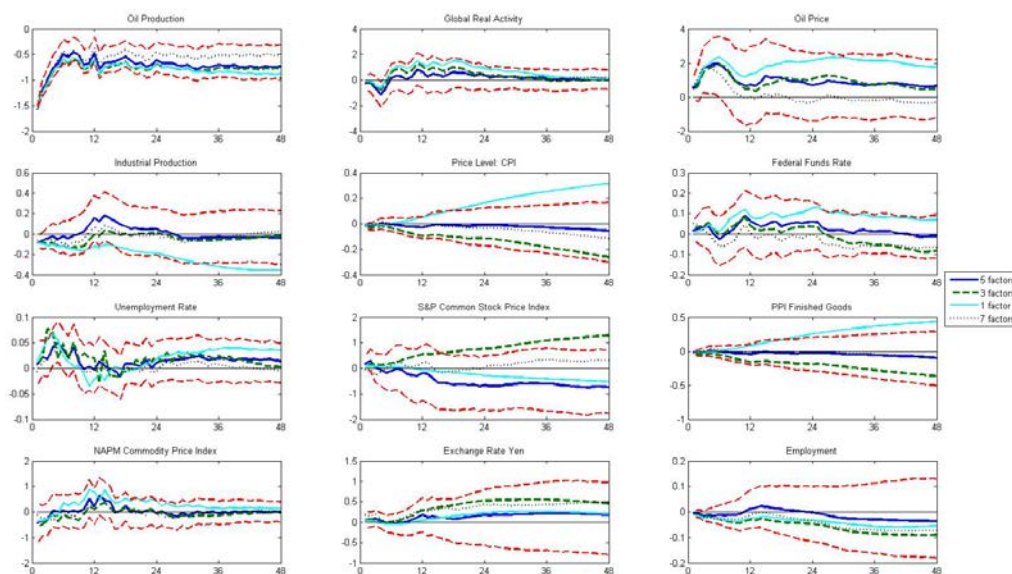


Figure D.1: *Robustness with respect to number of factors. Response to a one standard deviation oil supply shock with, respectively, 1, 3, 5 and 7 factors. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

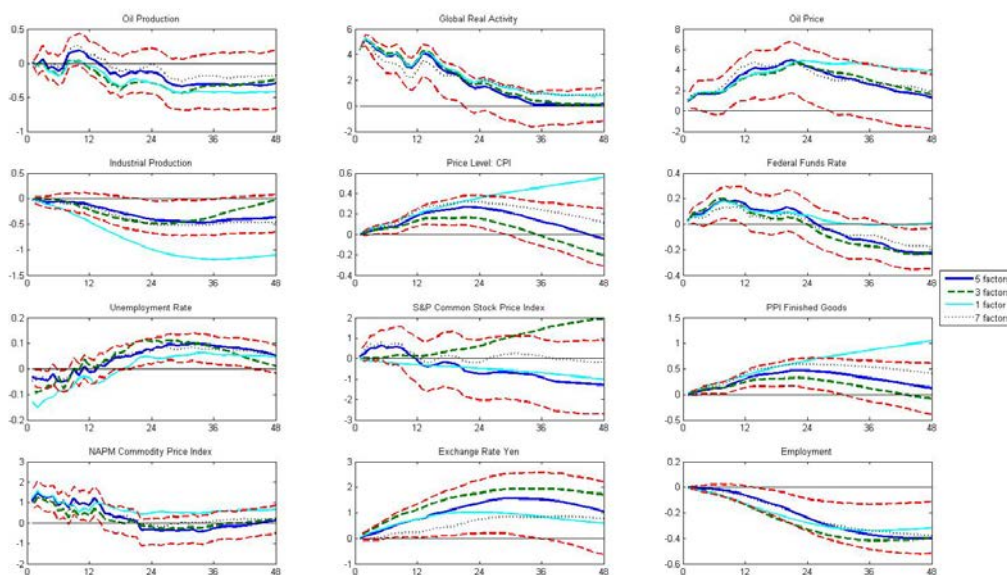


Figure D.2: *Robustness with respect to number of factors. Response to a one standard deviation global demand shock with, respectively, 1, 3, 5 and 7 factors. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

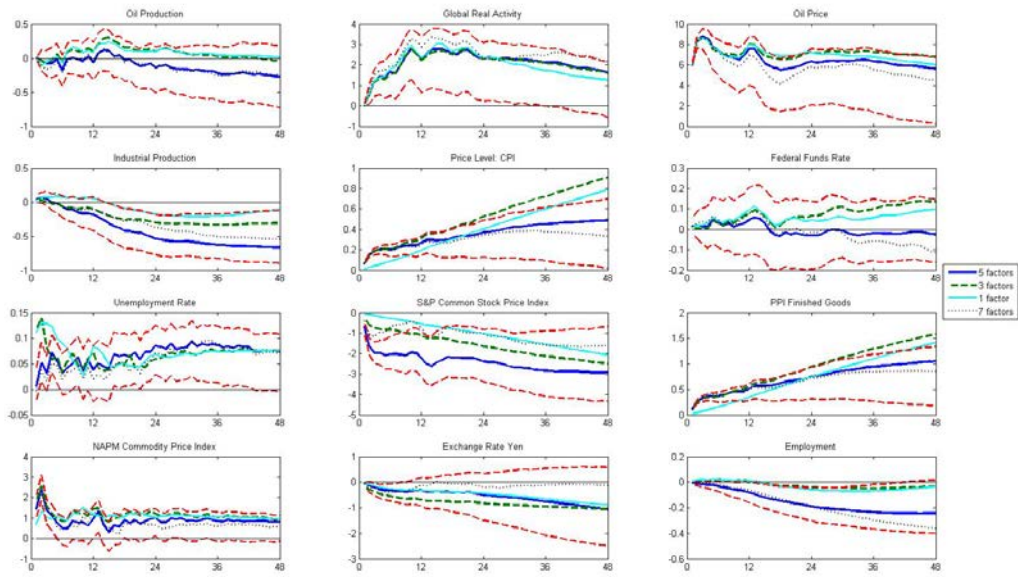


Figure D.3: *Robustness with respect to number of factors. Response to a one standard deviation oil-specific demand shock with, respectively, 1, 3, 5 and 7 factors. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

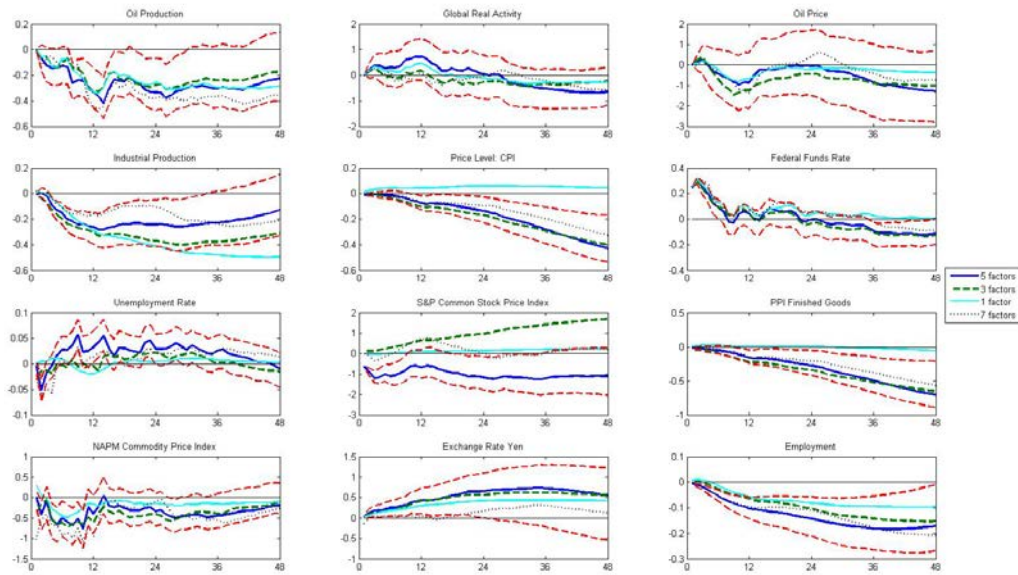


Figure D.4: *Robustness with respect to number of factors. Response to a 25 basis points unexpected increase in the Federal funds rate with respectively 1, 3, 5 and 7 factors. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

## Different lag length

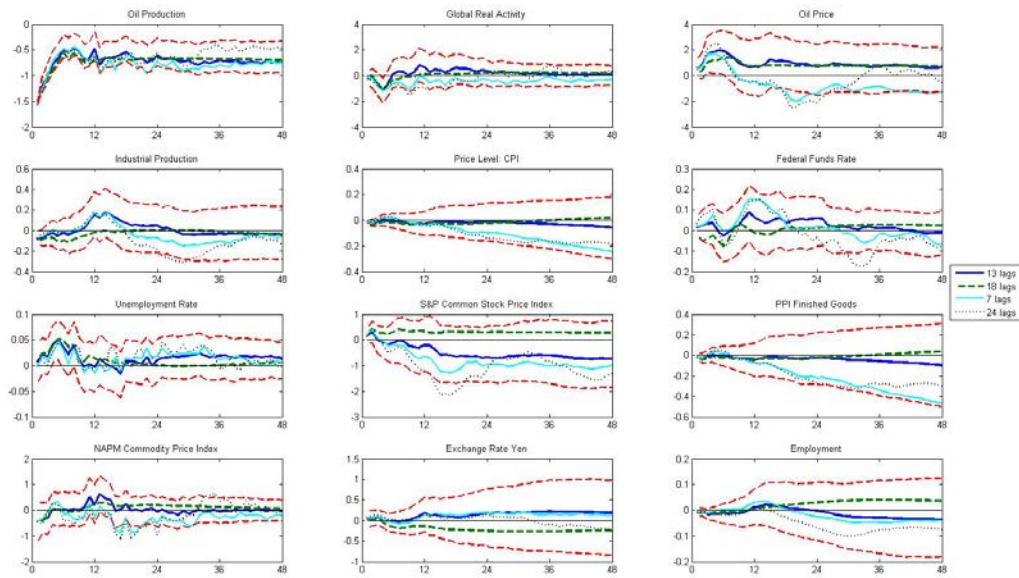


Figure D.5: *Robustness with respect to lag length in equation (1). Response to a one standard deviation oil supply shock with, respectively, 7, 13, 18 and 24 lags. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

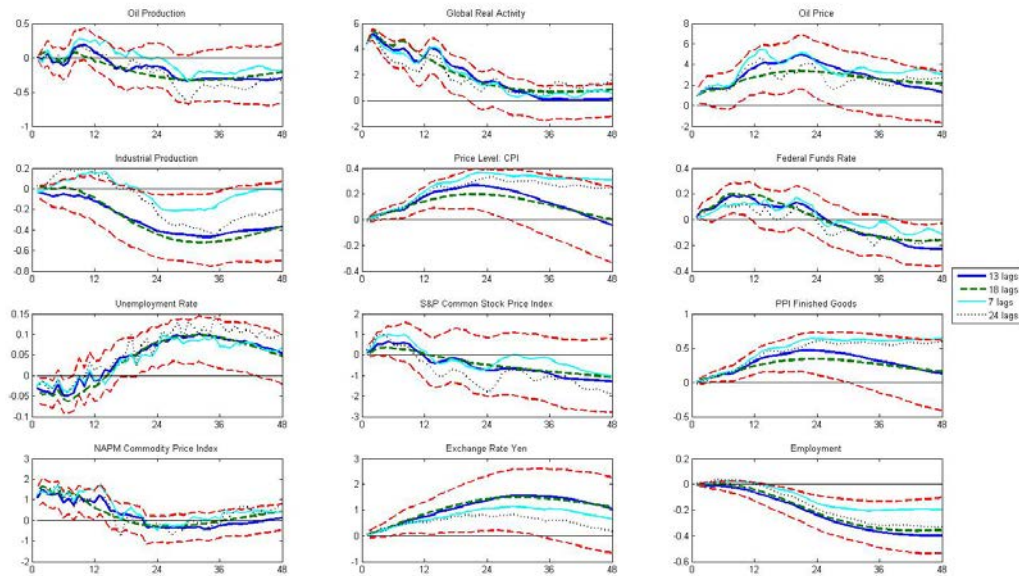


Figure D.6: *Robustness with respect to lag length in equation (1). Response to a one standard deviation global demand shock with, respectively, 7, 13, 18 and 24 lags. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*



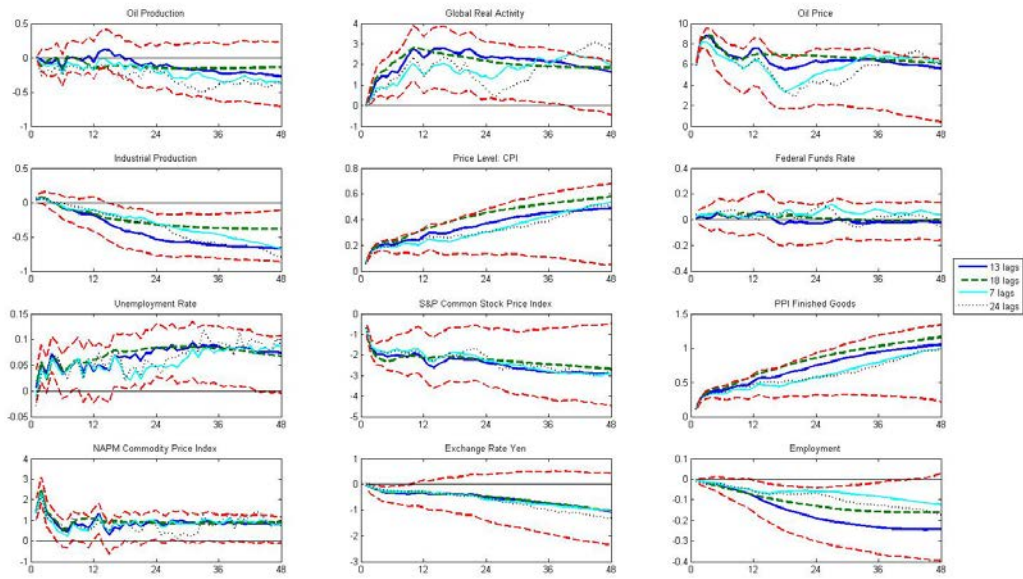


Figure D.7: *Robustness with respect to lag length in equation (1). Response to a one standard deviation oil-specific demand shock with, respectively, 7, 13, 18 and 24 lags. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

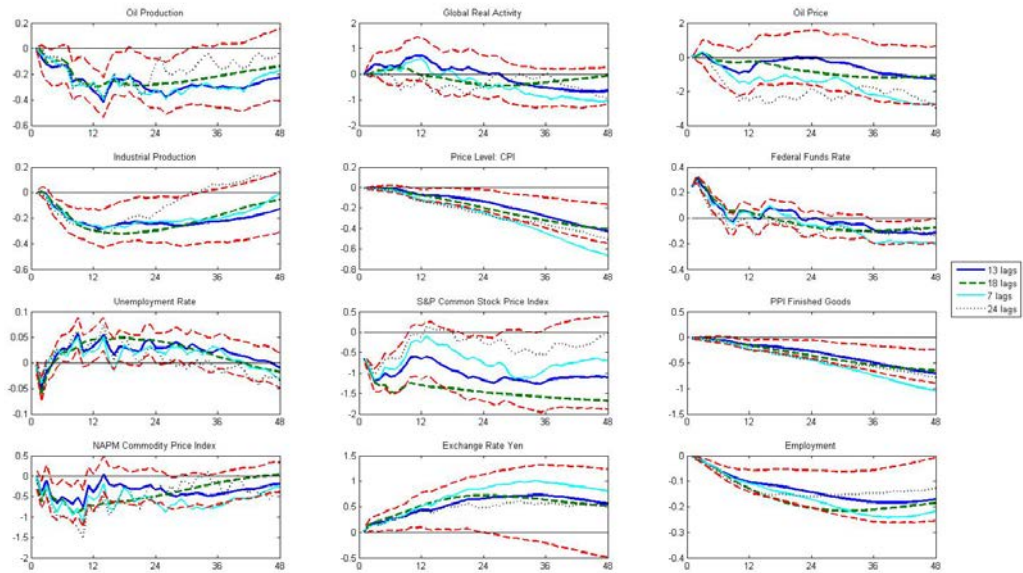


Figure D.8: *Robustness with respect to lag length in equation (1). Response to a 25 basis points unexpected increase in the Federal funds rate with respectively 7, 13, 18 and 24 lags. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

## Post 1984

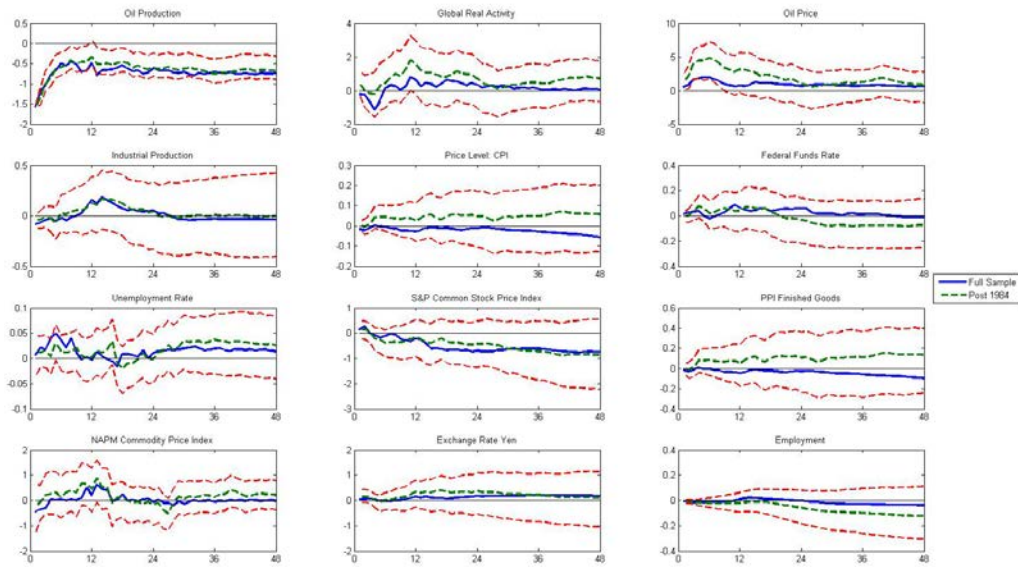


Figure D.9: *Robustness with respect to starting the estimation in 1984. Response to a one standard deviation oil supply shock. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

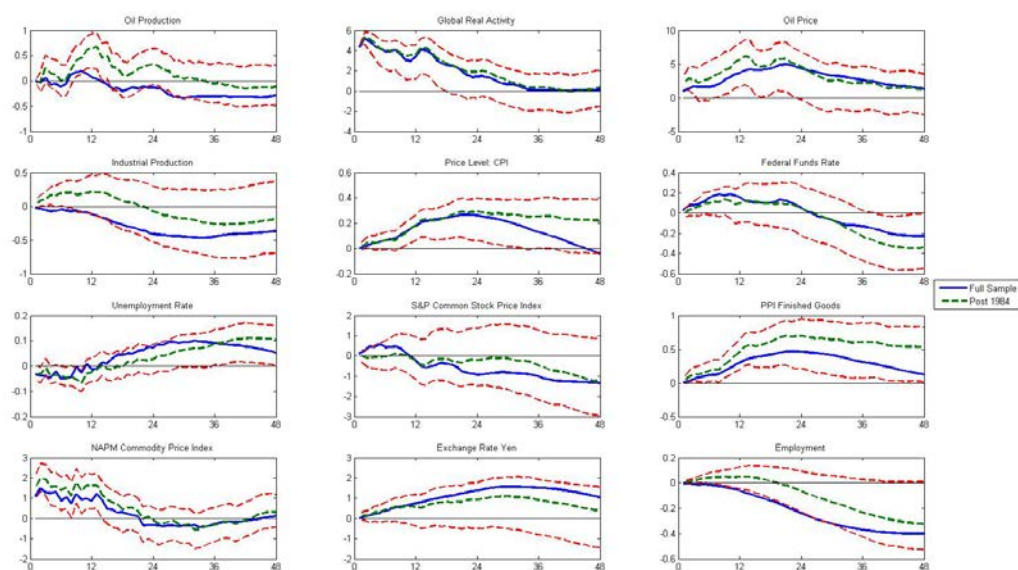


Figure D.10: *Robustness with respect to starting the estimation in 1984. Response to a one standard deviation global demand shock. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

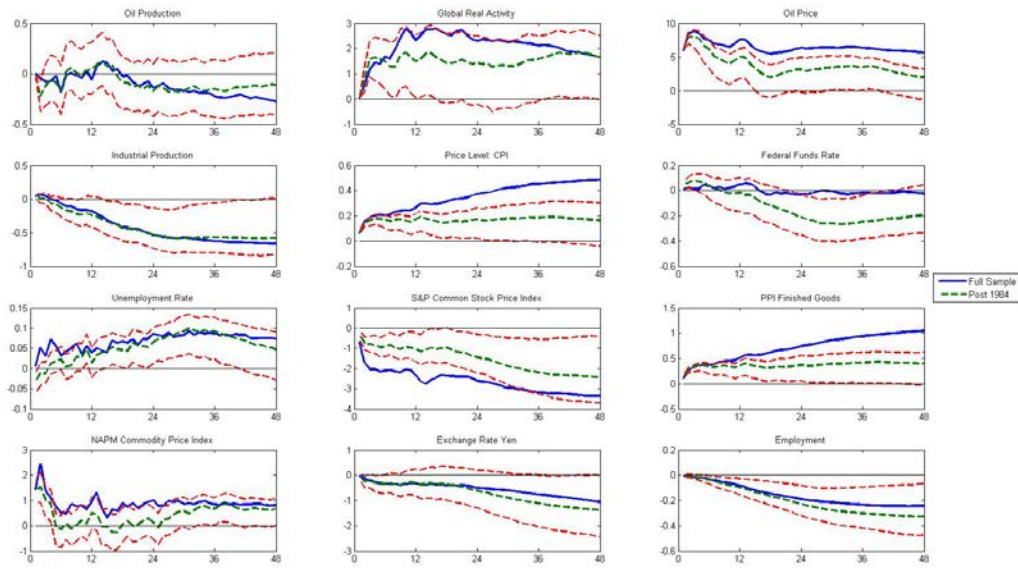


Figure D.11: *Robustness with respect to starting the estimation in 1984. Response to a one standard deviation oil-specific demand shock. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*

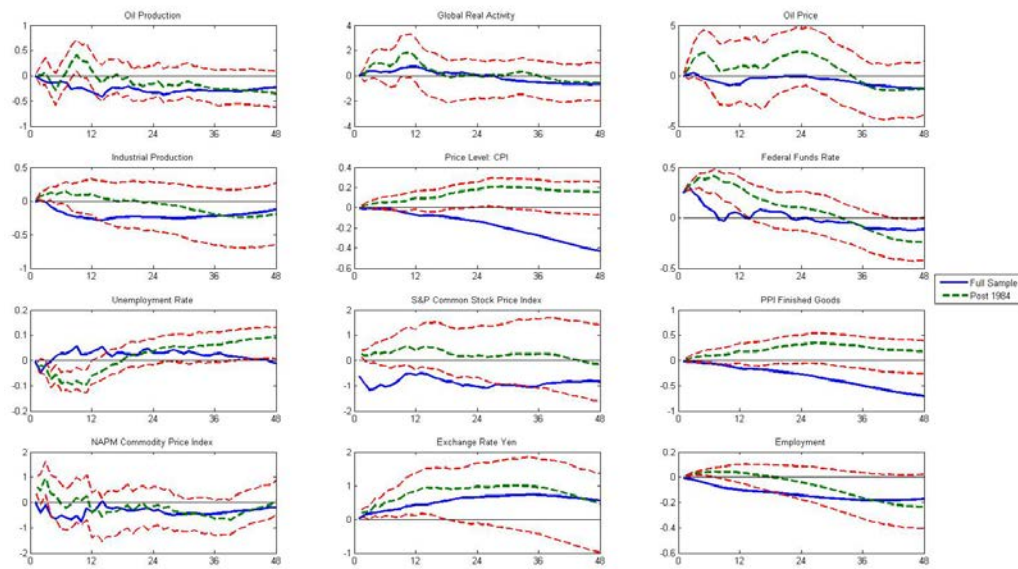


Figure D.12: *Robustness with respect to starting the estimation in 1984. Response to a 25 basis points unexpected increase in the Federal funds rate. Point estimates and 95 per cent error bands for the standard FAVAR model, constructed using bootstrap after bootstrap method.*