# Oil Price Shocks and the Monetary Policy

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*Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.*
*Duke University*
*Durham, North Carolina*
*2010*

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## Acknowledgments

I am especially grateful to my thesis advisor, Kevin D. Hoover, for his indispensible advice throughout my research, and for his patience throughout numerous weekly meetings and email correspondences. I'd like to also thank my Davies Fellowship faculty advisors, Professor Juan Rubio-Ramirez and Professor Gale A. Boyd, who introduced me to the subject and provided insightful feedback on the project proposal. I am indebted to Daisy Yizhuo Lu, Chung-Ying Lee, Harry Jiasheng Lee and Marcelo Ochoa for their support and kind help in time-series analysis, computer programming and software implementation. All errors are my own.

## 0. Abstract

Essentially all US recessions have been preceded by oil price shocks and subsequently tighter monetary policies. (Bernanke, Gertler and Watson, 1997). Whereas some scholars, including Herrera and Hamilton (2001) claimed that such oil price shocks contributed to the recession that followed, others, including, Bernanke *et al*. (1997), believed that the Fed's endogenous reaction to the monetary policy, rather than oil price per se, led to the contraction of the economy. Which had a greater influence on gross domestic product (GDP) — oil price shocks or a change in monetary policy—has been debated for years. One of the most prominent debates is between Bernanke *et al.* (1997), and Herrera and Hamilton (2001). In the debate, Bernanke *et al.* and Herrera and Hamilton used the same model but with different lag lengths and came to different conclusions. In the current study, we contribute to the resolution of this issue by using a new methodology to examine the effects of monetary policy to the economy in response to oil price shocks. Specifically, we determine the contemporaneous causal order empirically in structural vector-autoregression (SVAR). We then examine the economic responses in counterfactual schemes where the Fed does not respond to the oil price shocks. Contrary to Bernanke *et al.*'s finding, in which the economy would have done better had the Fed not held its interest rate constant during an oil price shock, we found that the Fed's response generates higher output but a less steady price level. This suggests that the results are dependent upon prior assumptions of the model specifications.

# 1. Introduction

## *1.1 Oil price, GDP and federal funds rate*

Historical data show that, every major increase in oil price was followed by a recession (Hamilton, 1983). It has also been observed that the Federal Reserve tightens monetary policy in response to oil price shocks (Bernanke, Gertler and Watson, 1997). Figure 1 shows the historical data of oil prices, corresponding federal funds rate, and the level of industrial production. We document four major oil price shocks recorded by Blanchard and Gali (2007), as shown in the shaded time periods in Figure 1: 1973:3-1974:1; 1979:1-1980:2, 1999:1-2000:4 and 2002:1-2007:3. Each shaded region corresponds to a slowdown in the industrial production and a rise in the federal funds rate.

Oil prices have been believed to be recessionary to the economy through two channels. One is through the supply-side: oil prices increase the cost of production. The other is through the demand side: increases in oil prices reduce the real purchasing power of households.  In addition, as the majority of the oil in the United States comes from overseas, the rise in oil price increases the nominal value of imports and decreases net exports. This subsequently decreases aggregate demand. Kilian (2009) argued that while theoretically a rise in oil prices unambiguously decreases output, the effect on the price level could be inflationary or deflationary, depending on whether supply or demand shocks dominate.

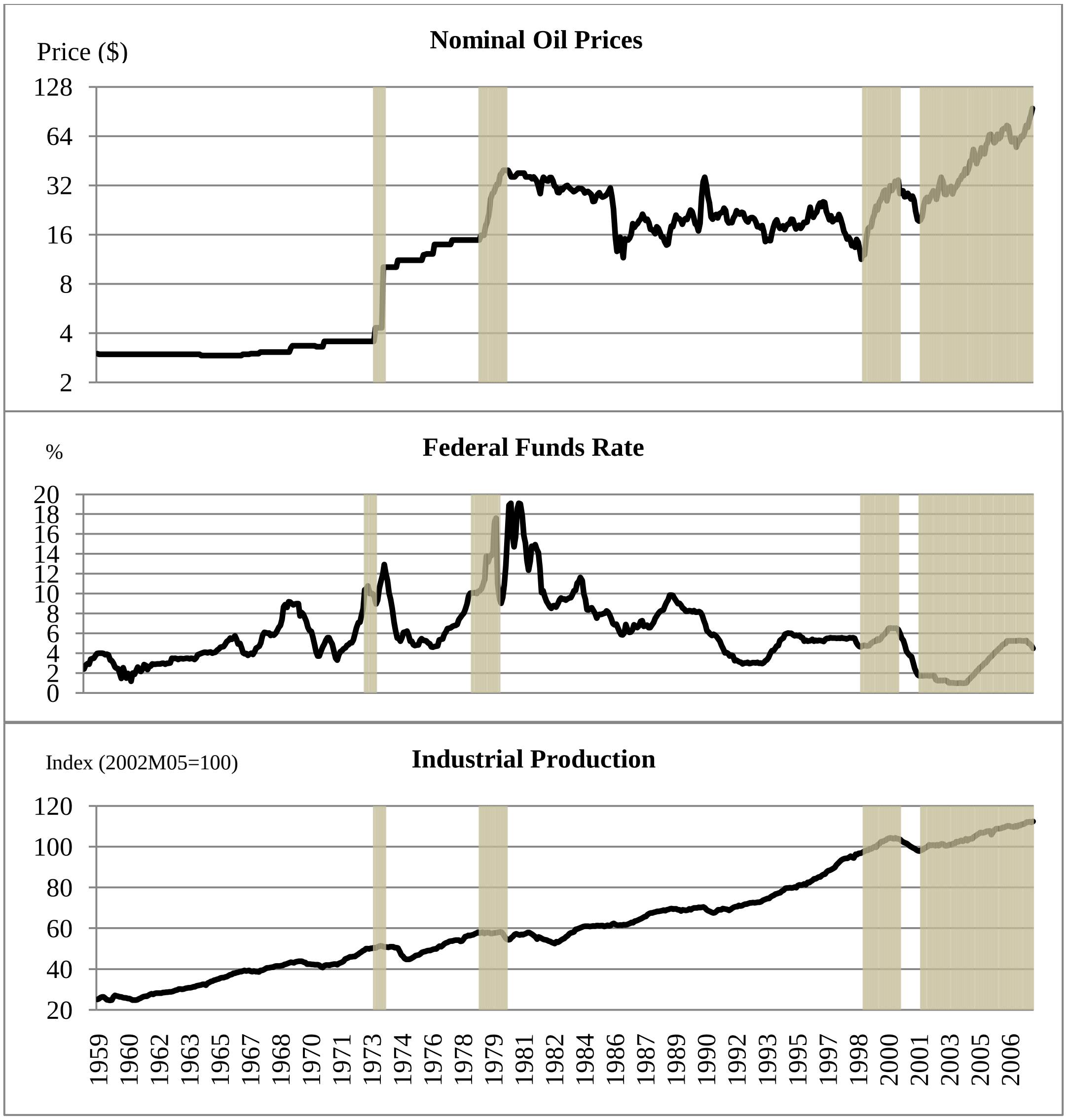


Figure1: Nominal oil prices, federal funds rate and industrial production from 1959 to 2007

Although the oil price shocks could be either inflationary or deflationary, Bernanke *et al.* (1997) claimed that the Fed has typically raised its interest rate in response to an oil price shock – a counter inflationary policy. As a matter of policy, the goal was to ensure price stability by counteracting an overall increase in prices originating with the rise in oil prices. However, the ambiguous effect that oil price shocks have on price levels raises the question of whether the Fed's response was correct. If the dominant effect of an oil price shock is on the supply side, creating an inflationary and recessionary effect, then the Fed's tighter monetary policy would serve its purpose – it could reduce inflation. However, if the dominant effect of an oil price shock is on the demand side, then its effect on the economy would be recessionary and deflationary. As a result, the Fed's tighter monetary policy would be counterproductive. Moreover, tighter monetary policy puts downward pressure on GDP by discouraging investment and lending. Therefore, it is possible that the GDP slump originates from the tighter monetary policy in conjunction with oil prices.

Since the slump in GDP comes from two possible channels, directly, through a hike in the oil price, or indirectly, through tighter monetary policy, we aim to assess whether the Fed responded wisely to the oil price shocks. Specifically, we ask the following questions:

- Does the Federal Reserve really respond to oil shocks?
- What is the effect of an oil price shock on production and the price level?
- Did the monetary response reorient the economy in a helpful way? Specifically, did it successfully ensure price and output stability?

*1.2 A prominent debate: Bernanke versus Hamilton*

The question of how oil price shocks affect the economy and how effective a tighter monetary policy is in ensuring price and output stability during an oil price shock is still debated and no consensus has emerged. On the one hand, Hamilton (1983, 1996) pinpointed oil as the main cause for recession. On the other hand, a number of economists suggested that something else was going on that contributed to the recession. Barsky and Kilian (2002) showed that exogenous changes in monetary expansions in the United States coincided with the rise in oil prices. Bohi (1991) examined data in Germany, Japan, the United Kingdom and the United States and argued that tighter monetary responses to rises in oil prices, rather the oil prices per se, may have contributed to subsequent recessions. Bernanke *et al.* (1997) also pointed to a tighter monetary policy as the prime culprit for the recessions.

Bernanke *et al.* (1997) argued that declines in output and employment in the 1970s were the result of the rise in interest rates – the Fed's endogenous response to the higher inflation induced by oil shocks. Bernanke conducted counterfactual simulations wherein the Fed did not react to the oil price shocks, and the results showed that the slump in GDP could have been completely avoided had the Fed not tightened monetary policy. In their view, it was not the oil price per se, but the resulting monetary tightening that contributed to the recession.

Herrera and Hamilton (2001) challenged Bernanke *et al.*'s (1997) result and argued that these results were a statistical artifact of specifying too short a lag length in the VAR. First, Bernanke *et al*'s empirical result could be undermined if additional lags are adopted. With longer lags, the counterfactual simulation would still show a decrease in GDP in response to an oil price shock even without the monetary policy tightening. Secondly, Herrera and Hamilton argued that Bernanke *et al*'s proposed response, wherein the Fed adopted a constant federal funds rate policy, was not credible in light of Lucas critique, which claimed that such a policy would require consistently setting the federal funds rate lower than predicted for three months in succession. Because rational expectations theory states that the forecast errors should be white noise, the probability of such policy happening is extremely low, namely, one in 100 billion. The second argument is later acknowledged by Bernanke *et al.* (2004).

The debate between Bernanke *et al.* (1997) and Herrera and Hamilton (2001) suggested that few agreements emerged on the actual effect of oil prices on the economy. We believe a neutral and innovative revisit to the question will shed some light to the long-held debate. First, we attempt to improve an issue pertaining to the methodology proposed by Bernanke *et al.*(1997): the contemporaneous causal structure used in SVAR was arbitrarily determined. To resolve this issue, we aim to avoid *a priori* assumptions on SVAR made by Bernanke *et al*.(1997) that federal funds rates do not *directly* affect output and prices, that macroeconomic variables are Wold-causally prior to interest rates, and that federal funds rates are Wold-causally prior to other interest rates. Unlike Bernanke *et al.*'s model specification, we include lagged values of all variables in our regression, and we use a graph-theoretical causal search algorithm (the PC algorithm) to empirically identify the contemporaneous causal order of the SVAR. Graph-theoretic search algorithms originated in the work of philosophers and computer scientists (Spirtes, Glymour, and Scheines, 2001; Pearl, 2000). They were introduced to SVAR analysis by Swanson and Granger (1997). Demiralp, Hoover and Perez (2008) offer a bootstrap method for accessing the reliability of causal orders selected by using the PC algorithm.

### *1.3 Structural vector-autoregression and Cholesky ordering*

Suppose we have a vector of *n* of variables at period *t* $\mathbf{Y_t=[y_{1,t}, y_{2,t}\ldots,y_{n,t}]'}$. The SVAR can be written as

$$\mathbf{A_0 Y_t = A(L) Y_{t-1} + E_t} \tag{1}$$

$\mathbf{A_0}$ is the *n x n* matrix with ones on the main diagonal and non-zero at some off-diagonal entries. **A(L)** is the lag operator, and $\mathbf{E_t}$ is an *n x* 1 diagonal matrix with error terms. The covariance matrix $\sum = E(\mathbf{EE'})$ is diagonal. This diagonal matrix allows practitioners to assign shocks individually. $\mathbf{A_0}$ defines Wold-causal order of contemporaneous variables. $\mathbf{A_0}$ is just-identified if $\frac{n(n-1)}{2}$ restrictions are imposed on the matrix; over-identified if more than $\frac{n(n-1)}{2}$ restrictions are imposed on the matrix.

If we premultiply equation (1) by $\mathbf{A_0^{-1}}$, then equation (1) becomes reduced-form or vector autoregression (VAR) :

$$\mathbf{Y_t = A_0^{-1} A(L) Y_{t-1} + A_0^{-1} E_t = B(L) Y_{t-1} + U_t} \tag{2}$$

Equation (2) could be easily estimated using OLS, yet, the error term, $\mathbf{U_t}$, in general, will have a covariance matrix $\Omega=E(\mathbf{UU'})$ not diagonal. This non-diagonal matrix hinders practitioners from evaluating effects from a shock of a single variable, because the shock of one variable also triggers the change of other variables through correlations among the variables. To evaluate a single, uncorrelated shock therefore requires estimation of SVAR, which requires that we know the $\mathbf{A_0}$ matrix. Typically, $\mathbf{A_0}$ has simply been imposed *a priori* on the basis of loose and informal reasoning.

The selection of the $\mathbf{A_0}$ aims to satisfy one primary goal: to ensure that the covariance matrix $\sum$ is diagonal. There exists a large number of matrices P that $\sum=E(\mathbf{P^{-1}U}(\mathbf{P^{-1}U})')$ is diagonal. Typically, practitioners adopt Cholesky decomposition in choosing $\mathbf{A_0}$. Cholesky orderings select an $\mathbf{A_0}$ that is lower triangular. Since there are no zeros on or below the main diagonal and all zeros are above the main diagonal, Cholesky orderings impose $\frac{n(n-1)}{2}$ restrictions, and are just identified. The variables of interest are ordered based on the assumptions of how the economy functions. The order assumes that variables higher in the order have no contemporary effects on the variable lower in the order, but the lower-ordered variable is assumed to be affected by the variables at the upper order. In a system of *n* variables, the number of feasible Cholesky orderings are *n* permutation, or *n*! orderings. Demiralp, Hoover and Perez (2008) showed that in an SVAR model, different Cholesky orders in the model could change the impulse response functions (IRF) dramatically, and therefore, a justifiable identification of $\mathbf{A_0}$ matrix is especially important when conducting SVAR analysis.

*1.4 Identifying causal structure using PC algorithm*

Unfortunately, in most literature, the assumption of Cholesky order used in SVAR was left casually justified. The same problem also existed in the debate between Bernanke *et al.*(1997) and Herrera and Hamilton (2001) , where the selection of the Cholesky ordering was rather arbitrary.[1] We call into question whether this particular Cholesky order would correctly identify the actual response of the economy. To answer this, we first need a justified $\mathbf{A_0}$ matrix. The innovation is that we use a relatively recent method of empirical identification of the $\mathbf{A_0}$ matrix that was adopted from the graph-theoretic causal search literature to the SVAR by Swanson and Granger (1997), and developed by a variety of economists, including Demiralp, Hoover and Perez (2008). The exposition in the next few paragraphs closely follows Hoover (2005) and Demiralp, Hoover and Perez (2008).

The method uses graph theory to relate causal order to relations of probabilistic dependence and independence among the data. There is a connection between each contemporaneous causal order and the $\mathbf{A_0}$ matrix. Each contemporaneous causal order can be represented as a system of equations with contemporaneous terms and the lagged terms. The system of equations could be transformed to an SVAR wherein the contemporaneous terms are characterized by a unique $\mathbf{A_0}$ matrix. For example, suppose A→B→C, where A, B and C have no time dependence. We can represent the system of equations as:

[1] Bernanke *et al.* and Herrera and Hamilton chose [real GDP, GDP deflator, commodity price, oil price federal funds rate 3-month T-bill rate, 10-year T-bond rate] as their Cholesky ordering with exclusion restrictions on the lagged terms of Federal funds rate to other macro variables (real GDP, GDP deflator, commodity price and oil price). They assume the federal funds rate only affect macro variables through its impacts on short and long interest rates. For details see Bernanke *et al.* (1997) and Herrera and Hamilton (2001).

$$A=\varepsilon_A \quad (3)$$

$$B=\beta A+\varepsilon_B \quad (4)$$

$$C=\gamma B+\varepsilon_c \quad (5)$$

where $\varepsilon_{i,\ i=A,B,C}$ are error terms with mean value 0. The parameters $\beta,\gamma$ are the contemporaneous effects of A to B and B to C, respectively. Written in the matrix form, the equation becomes

$$\begin{bmatrix} 1 & 0 & 0 \\ -\beta & 1 & 0 \\ 0 & -\gamma & 1 \end{bmatrix} \begin{bmatrix} A \\ B \\ C \end{bmatrix} = \begin{bmatrix} \varepsilon_A \\ \varepsilon_B \\ \varepsilon_C \end{bmatrix} \quad (6)$$

or $$\mathbf{A_0 Y} = \mathbf{E}$$

To fix ideas, consider variables with no time dependence. We let arrows represent one-way causes, and edges represent the existence of a one-way cause (arrow) but with unidentified directionality. For example, suppose A→B, it means A causes B, and suppose A−B, it means there is a causal connection between A and B, either A causes B (A→B) or B causes A (B→A). Suppose A→B→C, then A and C are probabilistically dependent, but they are independent conditional on B. In this case, B is said to *screen* A from C. Suppose that A←B→C, then B is said to *common cause* A and C. In this case, A and C will also be dependent, but conditional on B, they will be independent. Lastly, if A→B←C, then B is called the *unshielded collider* on the path ABC.[2] In this case, A and C are unconditionally independent; yet, conditional on B, A and C are conditionally dependent (Hoover 2005). A well-known example of starting a car elicits this relationship: suppose A

[2] On the other hand, if there is a causal edge between A and C, in addition to A→B←C, then B is called a *shielded collider,* in which case A and C are not unconditionally dependent.

is the status of a battery (charged/uncharged), B is whether the car starts or not, and C is the status of a car switch (on/off). The status of a car battery is independent from the status of a car switch, but the start of a car requires both the switch to be on and the battery to be charged. Conditional on the car starting, knowledge that the switch is on conveys the information that the battery is charged. This shows a conditional dependence relationship.

Causal search algorithms use these relationships and facts about conditional dependence and independence relations in the data to work backwards to infer possible causal structures. In practice, the independence is determined through measuring the conditional correlations among variables. Causal search algorithms use these statistical measures, and the basic graphical patterns that can generate them to work backward from these measures to infer the class of graphs compatible with the data. We summarize the fundamental ideas of the causal search algorithm in the following paragraphs, and a detailed description of the algorithm is documented in Hoover (2005), and Demiralp, Hoover and Perez (2008).

The PC algorithm is the most common causal-search algorithm (Spirtes *et al.*, 2001; Pearl, 2000) and has been widely used to determine the causal structure. This algorithm is built upon two assumptions: first, it assumes that the causal order is *acyclical,* meaning that there is no simultaneous causation or causal loop between variables, such as A→B→A, A↔B, or A→B→C→A; second, it assumes *causal sufficiency,* which claims that selected variables include all that explain the economic phenomenon of our interest, and that no variables that have causal links to more than one of the selected variables are left out. Though these two are strong assumptions, they are not stronger than a typical assumption of SVAR with Cholesky ordering.

PC algorithm is composed of three stages: first, statistically eliminating edges; second, orienting edges statistically; and third, orienting edges logically. At the first stage, the graph-searching process begins with an assumption that each variable is connected by an undirected causal edge to all other variables. It then tests for the unconditional independence between each pair of variables, and eliminates the edges that are statistically insignificant. Next, the third variable is tested again for conditional independence, as are pairs, triples and so on, until all unconditionally and conditionally independent edges are eliminated to the greatest extent.

The second stage tries to identify unshielded colliders from the existing edges. In practice, it identifies a pair of conditionally uncorrelated variables that are connected through a third variable (such as the case of A, C in an A−B−C link), and tests whether the pair would be correlated conditional on the connecting variable, C. If so, we orient the edges from A−B−C to A→B←C to make the link an unshielded collider.

The last stage involves logical reasoning based on two assumptions: first, that the structure is acyclical, and second, that no unidentified unshielded colliders exist in the graph. Specifically, if an order of A→B−C is identified, then we orient it to B→C since the other possibility A→B←C contradicts our second assumption. Similarly, when there is a pair of variables A, B connected by an undirected edge and a directed path, from A through other variable(s) to B, then we orient the link as A→B since the other alternative will contradict the assumption of acyclicality.

One caveat of this algorithm is that, in some cases, not all the directionality of edges can be recovered uniquely (Hoover, 2005). The *skeleton* of a graph is the causal linkages between variables ignoring the directionality. The *observational equivalence theorem* (Pearl, 2000) states that graphs with the same skeletons and unshielded colliders have the same probability in representing the actual causal order.[3] For example, A→B←C→D and A→B←C←D are observationally equivalent, because they have one unshielded collider and the same skeleton. As a result, according to the observational equivalence theorem, the PC algorithm is not able to recover Cholesky ordering because all Cholesky orderings have the same skeleton and no unshielded colliders.

Swanson and Granger (1997) argued that conditional on the lagged variables in a VAR, the residual matrix reflects the contemporaneous characteristics of variables. They used the residual terms from the VAR model to identify the contemporaneous ordering by testing the unconditional and conditional relations between variables for which lagged dynamics have been filtered out. This suggests that it is possible to apply PC algorithm to the residual matrix to analyze the contemporaneous causal order of variables.

Demiralp, Hoover and Perez, (2008) developed a bootstrap procedure to give an assessment of the reliability of the PC algorithm applied to the

[3] Pearl, 2000, P.19, Theorem 1.2.8

identification of $\mathbf{A_0}$ matrix of an actual SVAR.[4] The procedure works as follows: it takes the matrix of residuals estimated from the original VAR, forms a "resampled" residual matrix by drawing columns from the residual matrix with replacement, constructs a new set of data using the original VAR coefficients and the "resampled" residual matrix, runs VAR again using new data, and records the new residual matrix. The program draws columns in order to preserve the contemporaneous covariance structure among variables. PC algorithm identifies the causal structure based on the new residual matrix. After a number of repeated simulations, this procedure will generate the distribution of edge orientations identified by the PC algorithm. This serves as a tool in judging our confidence in the orientations selected by the PC algorithm as well as in orienting the undirected edge in the PC algorithm. Here, we use the PC algorithm with bootstrap procedure to evaluate the causal structure for SVAR purposes.

## 2. Data

Data consist of seven monthly variables: federal funds rate (*FFR*), 3-month Treasury bill rate (*T3M*), 10-year Treasury bond rate (*T10M*) and the logarithmic values of commodity price index (*COM*), industrial production (*IND*), consumer price index (*CPI*) and nominal oil prices (*OIL*). The time span is from 1959M02 to 2007M11. Consumer price index and industrial production are seasonally adjusted, while oil prices are non-seasonally

[4] The program is called BootGraph, and can be downloaded from http://econ.duke.edu/~kdh9/Software and Data.html. We run the program using Ox version 6.10 (Doornik, 2007)

adjusted. Detailed information and sources of the data can be found in Appendix I.

## 3. Model Specification

### *3.1 Overview*

The investigation is composed of two parts: first, we estimate and simulate an SVAR and compute the responses of federal funds rate (*FFR*), industrial production (*IND*) and the consumer price index (*CPI*) to a positive, one-standard-error oil price shock. Second, we conduct a counterfactual experiment and analyze how the variables of interest would have behaved if 1) the federal funds rates had not been allowed to respond to the oil price shocks, but instead remained constant and 2) the federal funds rates had not responded to the oil prices directly but had responded to other macroeconomic variables.

The first part of the investigation has been addressed by numerous researchers, but the Cholesky order of those SVAR done previously was rather arbitrary. As we believe different Cholesky orderings could generate different impulse response functions, and such Cholesky ordering could not be tested in the real world, it was difficult to draw a conclusion. It could have been another contemporary ordering that accounts for the actual economy. Therefore, this reexamination adds value to previous discussions because we use an empirically-based search methodology to specify the contemporary causal order of variables. In other words, we specify an $\mathbf{A_0}$ matrix that is the most relevant to what the empirical data suggest.

We also split the data into two periods, with the division of time point corresponding to the Volcker period. It is widely agreed that there is a structural change in the monetary policy regime before and after the Volcker period (Bai and Perron, 1998), and therefore, separating the time span into two periods generates a more realistic picture of the economy in both periods. The first period was from February 1959 to September 1979, and the second period was from January 1984 to November 2007. We intentionally avoided the Volcker monetarist period from September 1979 to December 1982[5].

### *3.2 Selection of lag lengths*

A modified-Akaike Information Criterion has been proven to be effective in correctly identifying lag lengths or VARs (Hurwich and Tsai, 1991). This method suggests a lag length of 2 in both periods. On the other hand, in the debate between Bernanke *et al.*(1997) and Herrera and Hamilton (2001), there was a focus on the selection of lag lengths, with Bernanke *et al.* selecting a lag length of 7 and Herrera and Hamilton selecting a lag length of 12. Therefore, we conduct an exclusion restriction test to see whether the lag length of 2 is a feasible restriction condition on lag lengths of 7 and 12. We

[5] Since there is not a widely agreed date that marked the end of Volcker monetarist period, we pick 1984/1 to ensure the confidence that the Volcker monetarist period is not included in the regression.

also test whether the lag length of 12 could be reasonably restricted to the lag length of 7.

Using the likelihood ratio test below:

$$LR=2[\ln(L_u^{max})- \ln(L_R^{max})]\sim\chi_q^2 \quad (7)$$

where q is the number of restrictions, $\ln(L_u^{max})$ is the log-likelihood of unrestricted lag length, and $\ln(L_R^{max})$ is the log-likelihood of restricted lag length. The results favor a lag length of 12, since for the two alternative lag lengths we chose (2 and 7) we reject the hypothesis that each lag length is a reasonable restriction of the lag length 12 at 1% critical value. Therefore, we pick lag length 12 for our analysis. The selection is reasonable since the lag length of 2 and 7 are nested in lag length of 12.

Table 1: Likelihood ratio test for Period 1 and Period 2

| **Lag length test** | **Period 1** | **Period 2** |
|---|---|---|
| 2 against 7 (q=245) | p<0.01 | p<0.01 |
| 2 against 12 (q=490) | p<0.01 | p<0.01 |
| 7 against 12 (q=245) | p<0.01 | p<0.01 |

### *3.3 Contemporaneous Causal Order*

Period 1: 1959M02-1979M09

An over-identified diagonal $\mathbf{A_0}$ matrix is rejected with $p < 0.001$, suggesting that the contemporary causal matrix plays a role in SVAR. We identify the contemporary causal order between variables using the BootGraph program by Demiralp, Hoover, and Perez (2008). We set the size of the PC algorithm at 0.10.[6] The results of the Bootstrap method for period 1 and period 2 are shown in Table 2 and Table 3, respectively.

Table 2: Bootstrap Evaluation of the initial Causal Graph, 1959M02-1979M09

| Causal Order Selected by the PC Algorithm | | | Edge Identification (Percent of bootstrap realizations) | | | | | Summary Statistics | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | − | ← | No edge | → | ↔ | Exists | Directed | Net Direction |
| CPI | → | IND | 60 | 7 | 0 | 30 | 2 | 100 | 40 | 23 |
| T3M | − | T10M | 46 | 33 | 0 | 18 | 4 | 100 | 54 | -15 |
| FFR | ← | T3M | 29 | 47 | 0 | 9 | 15 | 100 | 71 | -38 |
| T10M | → | CPI | 33 | 16 | 27 | 20 | 5 | 73 | 55 | 4 |
| CPI | → | OIL | 37 | 10 | 28 | 22 | 4 | 72 | 49 | 12 |
| FFR | ↔ | CPI | 0 | 23 | 50 | 1 | 26 | 51 | 99 | -21 |
| T3M | − | COM | 14 | 8 | 58 | 14 | 6 | 43 | 67 | 5 |
| T10M | → | OIL | 9 | 10 | 64 | 8 | 10 | 36 | 75 | -2 |
| COM | No edge | IND | 6 | 19 | 68 | 3 | 5 | 32 | 83 | -16 |
| FFR | No edge | IND | 0 | 7 | 86 | 0 | 7 | 14 | 100 | -7 |
| T10M | No edge | COM | 4 | 6 | 86 | 3 | 2 | 14 | 75 | -3 |
| IND | No edge | OIL | 5 | 1 | 87 | 6 | 1 | 13 | 61 | 5 |
| FFR | No edge | COM | 3 | 3 | 91 | 2 | 1 | 9 | 65 | -1 |
| T3M | No edge | OIL | 0 | 3 | 92 | 0 | 6 | 9 | 99 | -3 |
| CPI | No edge | COM | 1 | 1 | 96 | 1 | 1 | 4 | 71 | 0 |
| COM | No edge | OIL | 1 | 1 | 96 | 2 | 1 | 4 | 88 | 1 |
| T10M | No edge | IND | 2 | 1 | 97 | 1 | 0 | 3 | 52 | 0 |
| T3M | No edge | IND | 0 | 1 | 98 | 0 | 1 | 2 | 100 | -1 |
| FFR | No edge | OIL | 0 | 0 | 99 | 0 | 1 | 1 | 91 | 0 |
| FFR | No edge | T10M | 0 | 0 | 100 | 0 | 0 | 1 | 40 | 0 |
| T3M | No edge | CPI | 0 | 0 | 100 | 0 | 0 | 0 | 100 | 0 |

Exists: The percentage that there is a causal edge between two variables
Directed: Out of the samples that have edges, the percentage of those that are directed
Net direction: The differences between the edges oriented to the right and to the left

As an example of how to interpret Table 1, the first row shows that the PC algorithm suggests CPI causes IND. The BootGraph program shows that out of 10,000 replications, PC algorithm identifies this causal relation to be undirected with probability 60%, left-causal (CPI←IND) with probability 7%, no edge with probability 0%, right-causal with probability 30% and bidirected with probability 2%, respectively. The last three cells on the right show the

[6] In the BootGraph specification, we let α=0.025, β=0.10 with 10,000 replications. β is the size of the tests of conditional correlation in the PC algorithm and set to 0.10. We do not use the more common 0.05 as we are more concerned with falsely omitting edges (type II error) than with falsely including edges (type I error). α=0.025, is necessary in replicating a 0.10 size in the PC algorithm. For details please see Demiralp, Hoover, and Perez (2008).

summary of BootGraph identification: All 100% of replications are identified with a causal link; out of the ones that have causal links, 40% are directed, and the right arrow outnumbers the left arrow by 23%. In this case, the BootGraph favors the right arrow (CPI→IND), conforming to PC algorithm.

The PC algorithm selects the existence of the first eight edges (CPI→IND, T3M−T10M, FFR←T3M, T10M→CPI, CPI→OIL, FFR↔CPI, T3M−COM and T10M→OIL), and the Bootgraph program shows that CPI→IND, T3M−T10M, FFR←T3M are the most robust causal links with 100% confidence of existence. The least robust edge among the eight is T10M→OIL, with 36% of confidence by the BootGraph method. Out of the eight edges, five are directed and three are either undirected or with bidirected edges. This method provides a suggestive causal order, and we test over-identifying restrictions to reinforce the confidence of the BootGraph program's selection. To satisfy our assumption of an acyclical order, we need to both direct the bi-directed edge and put edges on non-directed edges. To orient those three edges, we used the likelihood ratio test against the just-identified model (p-value). Since there are three edges and each edge has two directions, there are $2^3=8$ possible combinations to orient those edges. We test all eight combinations and pick the combination that passes the over-identifying restrictions test with the highest p-value. Out of eight possible combinations, three combinations have the highest p-value of 0.354, above our critical value of 0.10.[7] Since BootGraph program also makes suggestions

[7] Those three combinations form an equivalence class

on the directionality of edges (realized through net direction, which suggests the percentage the PC algorithm would prefer the right arrow over the left one), we pick the one that maximizes the suggestions made by BootGraph. A detailed description of p-value tests is in Appendix II.

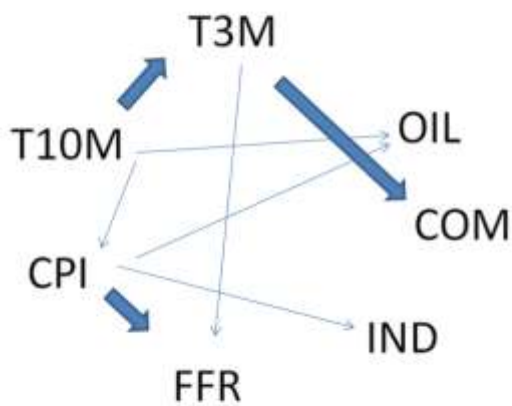


Figure 2: Contemporary causal link between variables. The thin arrows represent the edges identified by the PC algorithm, and the bold arrows represent the edges identified manually through log-likelihood test.

Having identified the causal graph, we can identify the $\mathbf{A_0}$ matrix, which is used for SVAR, and is shown as follows.

$$\mathbf{Y_t}=\begin{bmatrix} FFR_t \\ T3M_t \\ T10M_t \\ OIL_t \\ COM_t \\ IND_t \\ CPI_t \end{bmatrix} \tag{8}$$

$$\mathbf{A_0}=\begin{bmatrix} 1 & \alpha & 0 & 0 & 0 & 0 & \omega \\ 0 & 1 & \beta & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \delta & 1 & 0 & 0 & \gamma \\ 0 & \eta & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & \rho \\ 0 & 0 & \sigma & 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Period 2: 1984M01-2007M11

An over-identified diagonal $\mathbf{A_0}$ matrix is rejected with p value <0.001, suggesting that the contemporary causal matrix plays a role in SVAR. We first use the BootGraph to identify the existence of edges, as shown in Table 3. The PC algorithm selects the existence of seven edges (CPI↔OIL, T3M−T10M, FFR←T3M, T10M−COM, FFR↔OIL, COM→OIL, and CPI←IND), and the Bootgraph program shows that CPI↔OIL, T3M−T10M, FFR←T3M are the most robust causal links with 100% confidence of existence. The least robust edge among the eight is CPI←IND, with 41% of confidence by the BootGraph method. There are four edges that need to be oriented manually[8], thus we test $2^4$=16 possible combinations. Using the same identification methodology as period 1, we determine the contemporaneous causal order as shown on Figure 3. Detailed test results are shown in Appendix II.

[8] CPI↔OIL, T3M−T10M, T10M−COM and FFR↔OIL

| Table 3 : Bootstrap Evaluation of the initial Causal Graph, 1984M01- 2007M11 | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Causal Order Selected by the PC Algorithm | | | Edge Identification (Percent of bootstrap realizations) | | | | | Summary Statistics (%) | | |
| | | | − | ← | No edge | → | ↔ | Exists | Directed | Net direction |
| CPI | ↔ | OIL | 12 | 13 | 0 | 44 | 32 | 100 | 88 | 31 |
| T3M | − | T10M | 24 | 4 | 0 | 69 | 4 | 100 | 77 | 65 |
| FFR | ← | T3M | 54 | 37 | 0 | 6 | 3 | 100 | 46 | -31 |
| T10M | − | COM | 10 | 38 | 9 | 16 | 28 | 91 | 89 | -22 |
| FFR | ↔ | OIL | 1 | 2 | 53 | 10 | 34 | 47 | 99 | 9 |
| COM | → | OIL | 2 | 3 | 55 | 11 | 29 | 45 | 96 | 8 |
| CPI | ← | IND | 1 | 26 | 59 | 0 | 15 | 41 | 98 | -26 |
| T10M | No edge | IND | 0 | 12 | 78 | 0 | 10 | 22 | 99 | -12 |
| COM | No edge | IND | 2 | 8 | 81 | 3 | 6 | 19 | 88 | -5 |
| T10M | No edge | OIL | 0 | 1 | 87 | 0 | 12 | 13 | 100 | -1 |
| IND | No edge | OIL | 1 | 0 | 92 | 4 | 3 | 8 | 94 | 4 |
| FFR | No edge | IND | 1 | 2 | 93 | 1 | 3 | 7 | 92 | -1 |
| T3M | No edge | CPI | 0 | 0 | 95 | 0 | 5 | 5 | 100 | 0 |
| FFR | No edge | T10M | 0 | 0 | 95 | 4 | 1 | 5 | 96 | 4 |
| CPI | No edge | COM | 0 | 0 | 97 | 1 | 2 | 3 | 93 | 1 |
| FFR | No edge | COM | 0 | 0 | 98 | 2 | 0 | 3 | 92 | 2 |
| T3M | No edge | IND | 0 | 1 | 98 | 0 | 1 | 2 | 96 | -1 |
| T3M | No edge | COM | 1 | 0 | 98 | 1 | 0 | 2 | 62 | 0 |
| FFR | No edge | CPI | 0 | 1 | 99 | 0 | 0 | 1 | 91 | -1 |
| T10M | No edge | CPI | 0 | 0 | 99 | 0 | 1 | 1 | 100 | 0 |
| T3M | No edge | OIL | 0 | 0 | 100 | 0 | 0 | 0 | 0 | 0 |

Exists: The percentage that there is n causal edge between two variables

Directed: Out of the samples that have edges, the percentage of those that are directed

Net direction: The differences between the edges oriented to the right and to the left

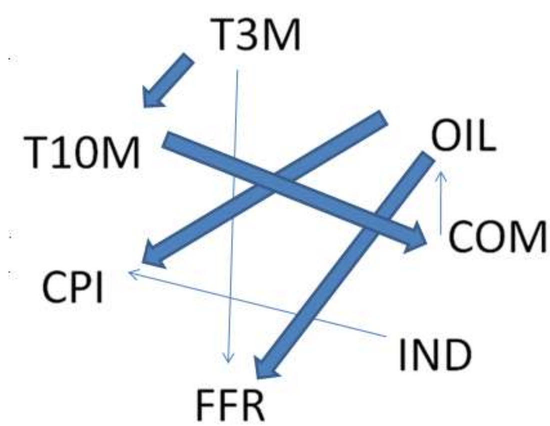


Figure 3: Contemporary causal link between variables. The thin arrows represent the edges identified by the PC algorithm, and the bold arrows represent the edges identified manually through log-likelihood test.

Consequently, the $\mathbf{A_0}$ matrix for period 2, shown as follows, will be used for SVAR in period 2.

$$\mathbf{Y_t}=\begin{bmatrix} FFR_t \\ T3M_t \\ T10M_t \\ OIL_t \\ COM_t \\ IND_t \\ CPI_t \end{bmatrix} \tag{10}$$

$$\boldsymbol{A_0}=\begin{bmatrix} 1 & \alpha & 0 & \beta & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \gamma & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \eta & 0 & 0 \\ 0 & 0 & \delta & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & \sigma & 0 & \kappa & 1 \end{bmatrix} \tag{11}$$

## 4. Impulse Responses and Counterfactual Simulations

### *4.1 IRF of an oil price shock*

We use the $\mathbf{A_0}$ matrices found in both periods to find out impulse response functions for variables of our interest to an oil price shock. We impose a positive, one-standard error oil price shock on other variables and record their impulse response functions. In the following sections we present the SVAR responses of federal funds rates, industrial production, and consumer price index. In addition, a complete IRF of all variables in response to an oil price shock is detailed in Appendix III.

Federal Funds Rate

Obtaining the impulse response functions of the first period (1959M02-1979M09) and the second period (1984M01-2007M11), we see whether the federal funds rates respond to oil price shocks. In our documentation, during major oil price shocks the federal funds rates tend to increase. Our SVAR shows such a behavior, but within a very limited time span, as Figures 4 and 5 show. Dash lines correspond to one standard error bands. In the first period, the federal funds rates increase by a slight 5 basis points 6 months after the oil price shock, but decrease gradually until the 15th month, reaching negative 19 basis points and then finally recover from the 15th month, as Figure 4 shows. In period 2, the federal funds rates increase in the first period, then continuously decrease for 35 consecutive months, and recover after that, as Figure 5 shows. In summary, though the Fed did increase its federal funds rate slightly in the beginning of the oil price shock, after that slight increase, the rates decreased more profoundly. This suggests that the Fed may only use tighter monetary policy when oil prices shocks are above a certain level. In other words, the Fed could possibly respond to extreme oil price shocks in a way that is different from its usual behavior and thus cannot be captured through a normal VAR, which assumes a linear response function of the Federal Reserve to oil price shocks.

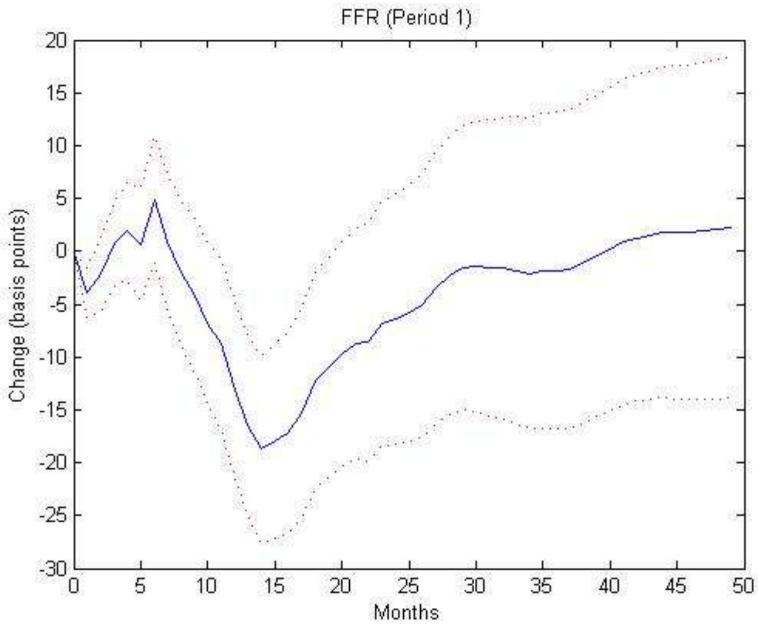


Figure 4: Federal funds rates (FFR) in the first period increase slightly in the first 6 months, and then drop until the 15th period, and then recover afterwards.

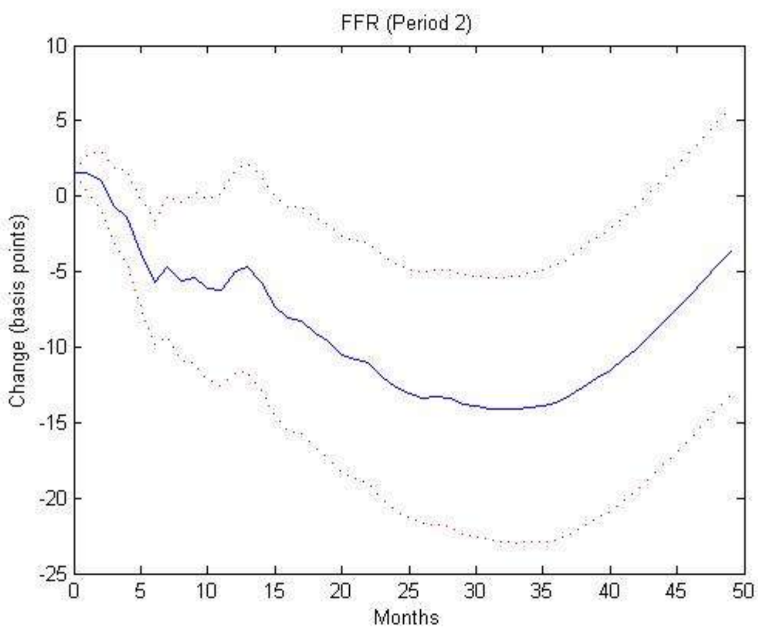


Figure 5: Federal funds rates (FFR) in the second period increase 0.02% in the first period, then drop continuously for 35 months, and then recover onward.

Industrial Production

The industrial production, on the other hand, shows a similar pattern in both periods –an unambiguous decrease in response to oil prices shocks at first, and then recovery, as Figures 6 and 7 show. The effect of an oil price increase on the economy is swifter: the industrial production reaches its trough faster and also recovers faster than the second period. It reaches its trough in the 15th month and then recovers from the 16th month, whereas in the second period, the industrial production declines more gradually but has a more pronounced adverse effect. It reaches its trough in the 30th period with a monthly drop of 0.3% (annualized drop of 5%), compared with a monthly drop of 0.4% (annualized drop of 3%) in the first period.

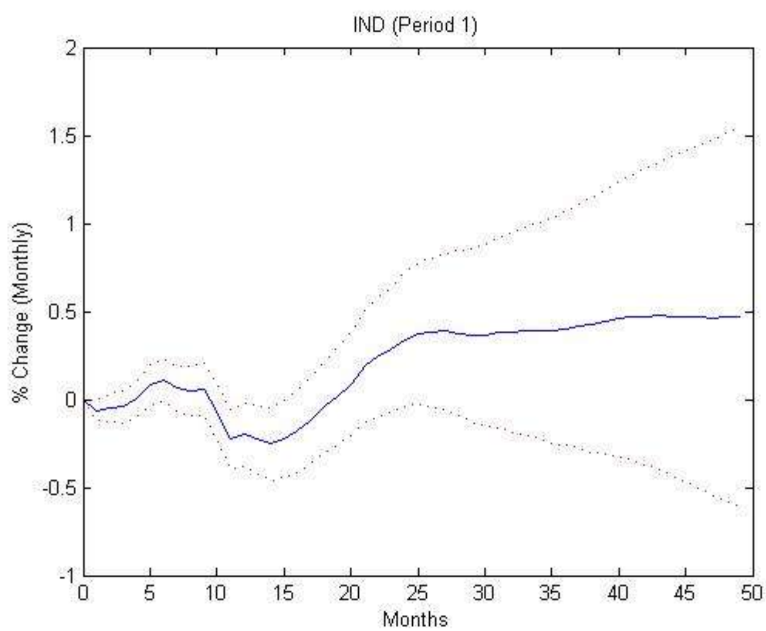


Figure 6: Industrial production (IND) in the first period posts a slump from the 9th month to the 14th month, and recovers after the 15th month.

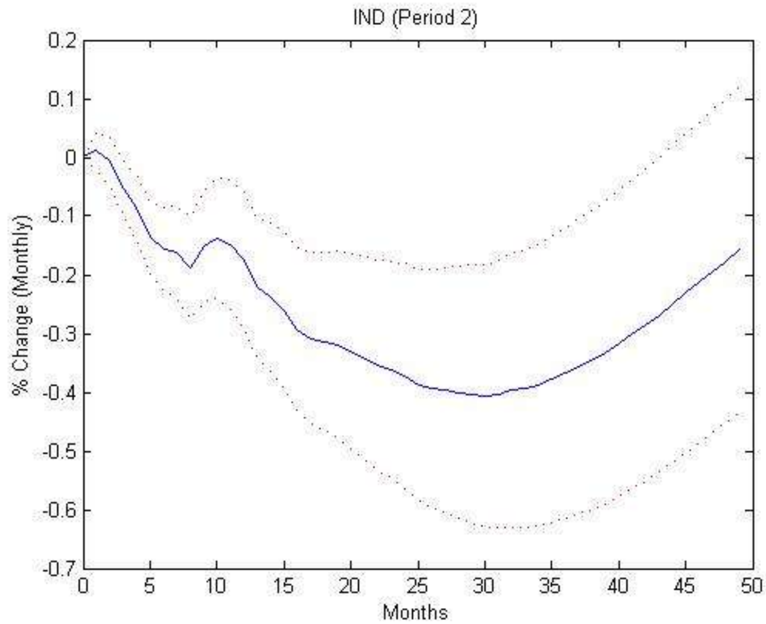


Figure 7: Industrial production in the second period posts a continuous drop through the 30th month, after which it recovers.

<u>Consumer Price Index</u>

Lastly, we look at the price level in response to the oil price shocks. Whereas an oil price shock has a deflationary effect in period 1, it has an inflationary effect in period 2. In the first period, the CPI remains relatively stable until the 10th month after which the CPI starts to decrease, reaching the bottom at the 30th period, with a monthly inflation rate of -0.2% (annualized rate of -2.7%), as Figure 8 shows. Conversely, in the second period, oil prices report an inflationary effect as the price level increases in period 2, hovering around a monthly rate of 0.2% (annualized rate of 2.4%), as shown in Figure 9.

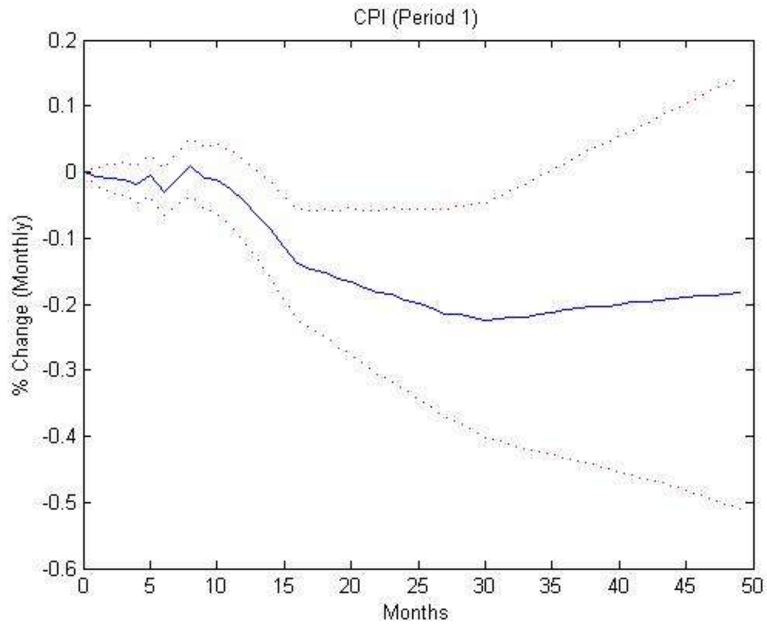


Figure 8: Consumer Price Index (CPI) in the first period remains relatively stable until the 10th month after which the CPI starts to decrease, reaching the bottom at the 30th period with an annualized inflate rate of -2.73%.

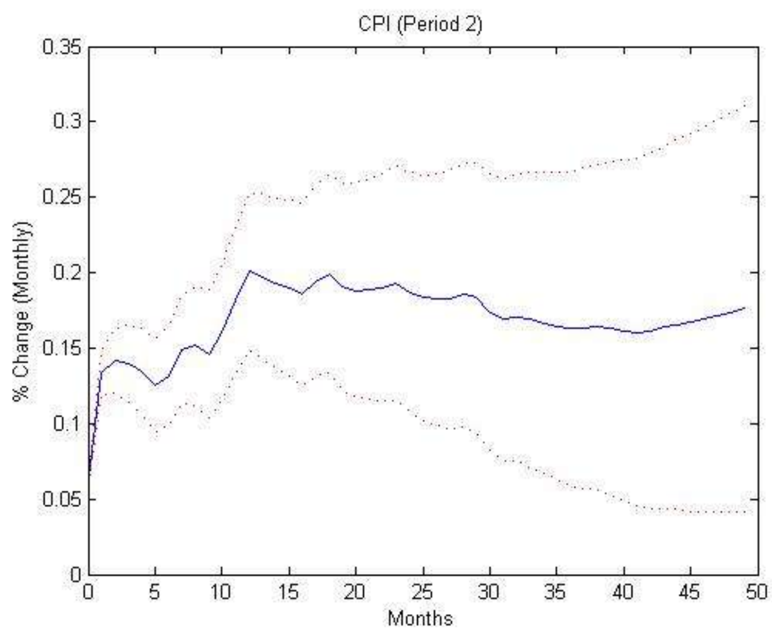


Figure 9: Consumer Price Index in the second period increases in period 2, hovering around an annualized rate of 2.43%.

### *4.2 Counterfactual Experiment*

To answer the question of whether the monetary policy actually worsened the economy, we conduct two cases of counterfactual experiments:

Case I: the federal funds rates had not been allowed to respond to the oil price shocks, but instead remained constant

Case II: the federal funds rates had not responded to the oil prices but had responded to other macroeconomic variables.

In practice, in Case I, we restrict the coefficients of six other variables on the federal funds rate to 0, in both contemporaneous and lagged terms; in Case II, we restrict the coefficients of oil on the federal funds rate to 0 in both contemporaneous and lagged terms. We then impose a positive, one-standard error oil price shock in both cases and record the IRF.[9]

#### Case I: A Constant Federal Funds Rate

We set the federal funds rates to be a constant, with oil prices still affecting the economy through other channels. Figures 10 and 11 show the response of industrial production with and without the response of the federal funds rate in periods 1 and 2, respectively. Without the responses of the Federal Reserve, production has an inferior performance in period 1, as Figure 10 shows. The change is significant and reaches out of the one-standard error band of the normal case from the 17$^{th}$ month onward.

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[9] We obtained IRF from STATA and Eviews, and conducted counterfactual IRF in Matlab. The STATA and Matlab codes are available upon request.

Comparing this with the federal funds rate schedule, we notice that the time point when two simulations diverge is approximately when the Fed has the lowest federal funds rate, as shown on Figure 4. In the $17^{th}$ month after the oil price shock, the federal funds rate reaches its trough by 20 basis points. It is clearly shown that such a decrease in the federal funds rate is necessary for a faster economic recovery, since without such a reduction in the federal funds rate (the counterfactual case), the industrial production falls below the normal case.

In the second period, after restricting the federal funds rate, the economy becomes highly unstable. The industrial production plummets and does not come back to the normal stage, as Figure 11 shows.[10] From the $23^{rd}$ period onwards, the counterfactual response reaches out of range of y-axis, unilaterally decreases and then never recovers. This suggests that the Federal Reserve's response is necessary in achieving economic stability. In both periods, without the Federal Reserve's response, the economy would feel a more profound and adverse effect than with its response.

[10] The IRF shows that other variables (IND, CPI, T3M, T10M, COM, OIL) would unilaterally decline.

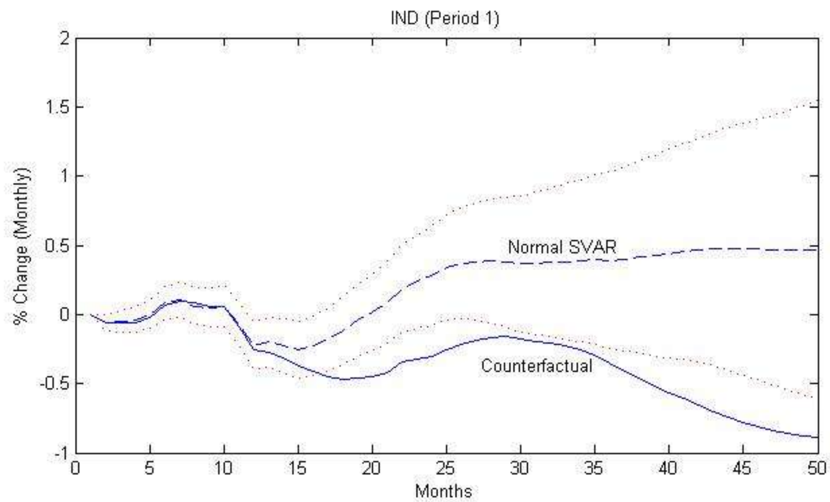


Figure 10: The IRFs of industrial production in period 1 in response to an oil price shock. The dashed line is the normal SVAR and the solid line is the counterfactual simulation, where the federal funds rates are fixed throughout the shock. Had the federal funds rate been fixed, the economy would have worsened without recovery.

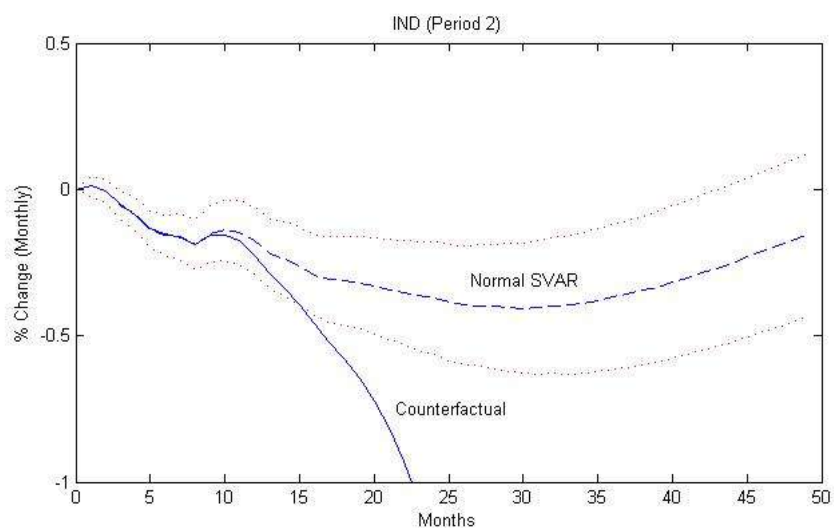


Figure 11: The IRFs of industrial production in period 2 in response to an oil price shock. The dashed line is the normal SVAR and the solid line is the counterfactual simulation with fixed federal funds rates. In the counterfactual scenario, the industrial production response becomes highly unstable and plummets.

We then look at the response of the price level. In period 1, the price level responses in the counterfactual and normal scenarios are steady and lie within the one- standard error band. Yet, the price level would be steadier and undergo less deflation if the Fed did not fix the federal funds rates, as shown in Figure 12. It is reasonable to infer that the Fed makes slight compromise on the price level in order to pave the road for recovery in industrial production.

In the second period, the economy becomes unstable if the federal funds rates remain constant, as shown in Figure 13. From the 18$^{th}$ period onward, the counterfactual impulse response reaches out of bound, unilaterally decreases and then never recovers. This suggests that without the response of the Federal Reserve, the economy would become highly unstable in period 2. This is consistent with our aforementioned observation about industrial production. A complete Case I IRF of all variables in response to an oil price shock can be found in Appendix IV.

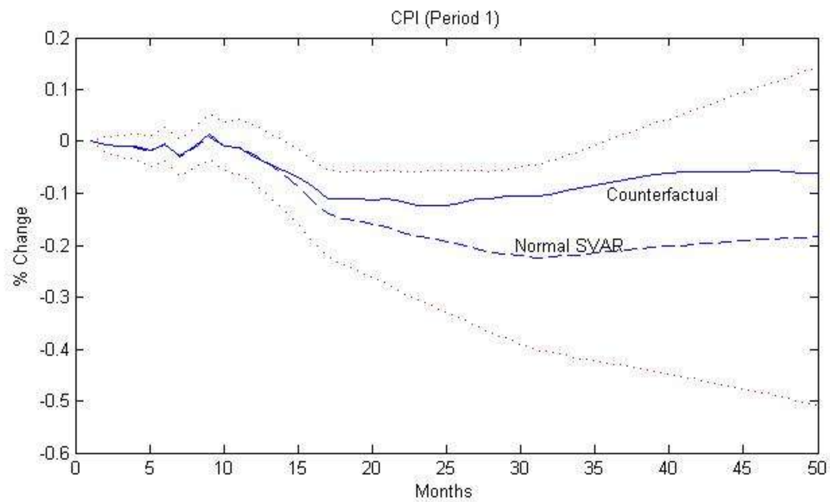


Figure 12: The IRFs of Consumer Price index in response to an oil price shock in period 1. The dashed line is the normal SVAR and the solid line is the counterfactual simulation where the federal funds rates are fixed throughout the oil price shock. Without the Fed's response the price level is steadier.

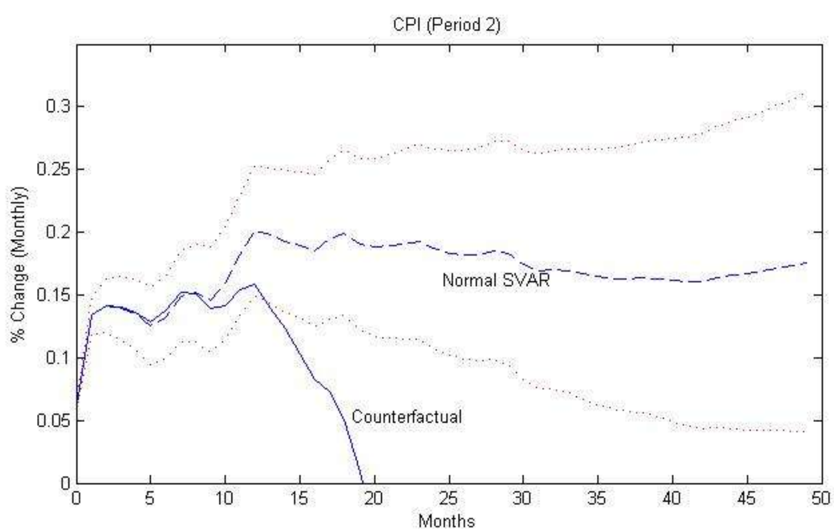


Figure 13: The IRFs of Consumer Price index in response to an oil price shock in period 2. The dashed line is the normal SVAR and the solid line is the counterfactual simulation with fixed federal funds rates. Without the Fed's response the price level becomes highly unstable and plummets.

Case II: Federal Funds Rate Not Directly Responding to Oil

We also examine how the economy would behave if the Federal Reserve was not allowed to respond to oil prices directly. Figures 14 and 15 plot the industrial production in periods 1 and 2, respectively, and Figures16 and 17 show the price level in periods 1 and 2, respectively. The results are not statistically different from the normal case since their response functions are in the one-standard error band of the normal case and lie closely with it. This suggests that whether the Federal Reserve directly responds to the oil prices or not does not alter the economy in a significant way. Yet, we observe that the industrial production performs better in the normal scenario than it does in the counterfactual scenario in both periods, as shown in Figures 14 and 15. On the other hand, the price levels are steadier in the counterfactual scenario since they are less volatile and closer to a zero inflation target. These two patterns are in keeping with our observation in Case I. A complete Case II IRF of all variables in response to an oil price shock is in Appendix V.

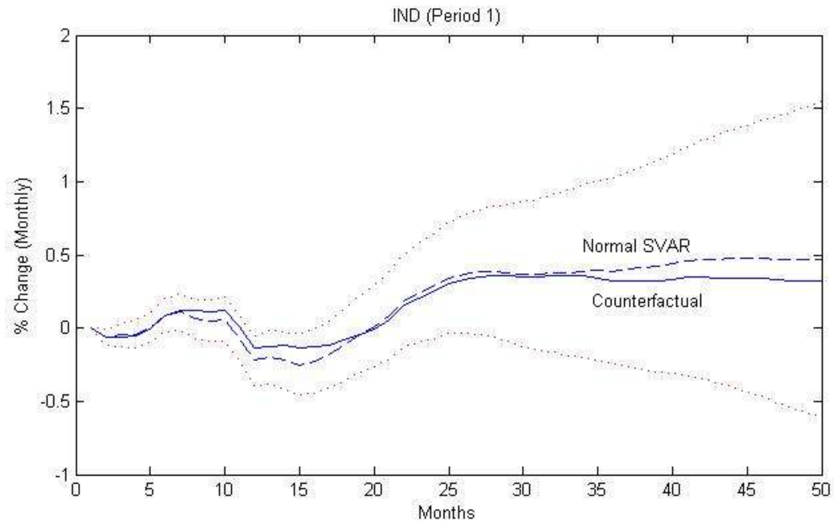


Figure 14: The IRFs of industrial production in period 1 in response to an oil price shock. The dashed line is the normal SVAR and the solid line is the counterfactual simulation, where the federal funds rate does not respond to oil prices directly. The two scenarios are not statistically different, but the counterfactual scenario performs a bit worse than the normal scenario.

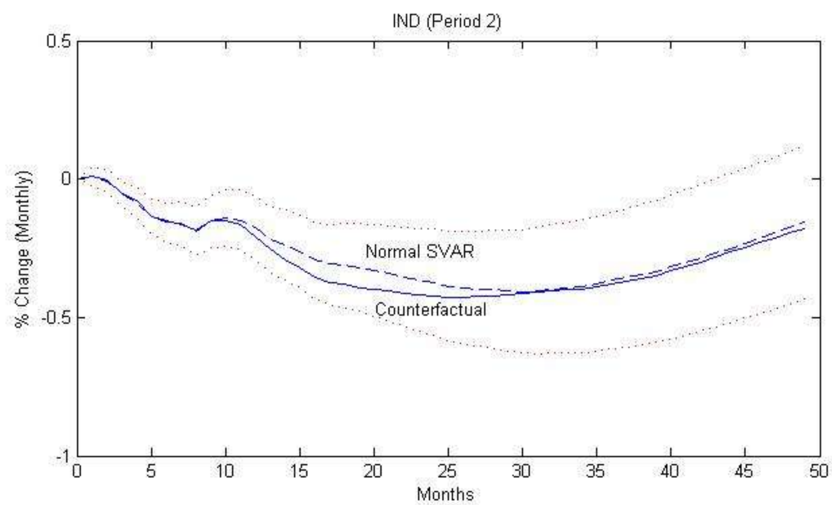


Figure 15: The IRFs of industrial production in period 2. The dashed line is the normal SVAR and the solid line is the counterfactual simulation, where the federal funds rates do not respond to oil prices directly. The two scenarios are not statistically different, but the industrial production in the counterfactual scenario performs worse than the normal scenario.

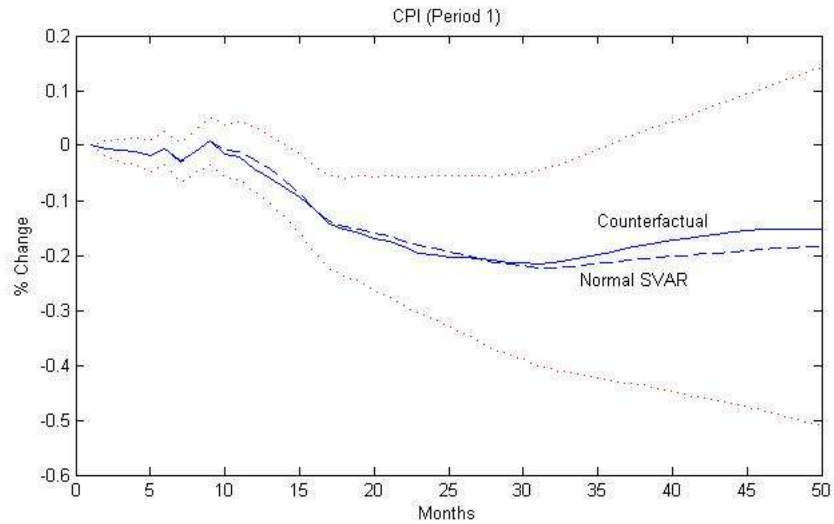


Figure 16: The IRFs of CPI in period 1. The dashed line is the normal SVAR and the solid line is the counterfactual simulation, where the federal funds rates do not respond directly to the oil price. The two scenarios are not statistically different, but the price level in the counterfactual scenario is steadier than the normal scenario.

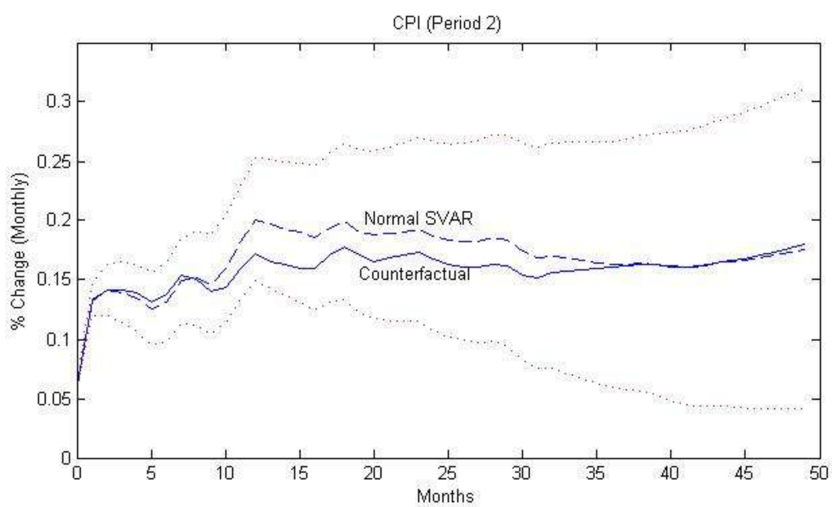


Figure 17: The IRFs of CPI in period 2 in response to an oil price shock. The dashed line is the normal SVAR and the solid line is the counterfactual simulation where the federal funds rates do not respond directly to the oil price. The two scenarios are not statistically different, but similar to period 1, the price level in the counterfactual scenario is steadier than the normal scenario.

## 5. Discussions

### *5.1 Oil price shock and monetary policy*

Our results show several intriguing observations. The oil price shock has an adverse effect on industrial production pre- and post-Volcker periods, but it has the opposite effects on the price level in these two periods. An oil price shock is deflationary in period 1, suggesting a dominant demand shock that characterizes the oil price shocks in the pre-Volcker period. But in period 2, it is inflationary, suggesting a dominant supply shock in the post-Volcker period.

In examining whether the Federal Reserve responds to oil price shocks, we show that the Fed does respond to oil price shocks in an optimal way when compared with other counterfactual scenarios. Yet it is difficult to offer SVAR evidence that the Fed responds to oil price shocks directly, since the economy behaves in much the same way when we shut down the Fed's direct response to oil. This suggests that even though the Fed does not respond to the oil price shocks directly, it indirectly responds through the oil price shocks' effects on other variables, such as price level and industrial production.

The monetary response not only ensures economic stability but also paves the way for economic recovery. Without the monetary response, industrial production declines more, and the price level becomes steadier than with the monetary policy response. In Case I, with a constant federal funds rate during an oil price shock, the industrial production would not be able to recover and grow on its own, but the price level would undergo less deflation. This is also consistent with Case II where the federal funds rate does not respond to oil directly in both contemporaneous terms and lagged terms, and only responds to the oil price shock through oil's impact on other variables. Though the results are statistically insignificant, the observation of Case II is consistent with Case I in that the counterfactual case generates higher price stability but inferior output performance. This suggests that the Federal Reserve is reasonably compensating for a mild deflation with a higher industrial production during recovery.

### *5.2 Revisiting Bernanke and Hamilton*

We also attempt to add a new perspective to the long-held debate between Bernanke *et al* .and Herrera and Hamilton. To ease the comparison of our results with theirs, we include the results of counterfactual experiments that Bernanke *et al.* and Herrera and Hamilton conducted in Appendix VI and VII, respectively. In our results, the industrial production does not show a superior performance with fixed federal funds rates. This contrasts the commonly held observation of Bernanke *et al*. and Herrera and Hamilton. Yet our responses to the price level conform to observations by both groups of scholars, in that the price levels stay higher in the counterfactual scenario than the normal scenario, although the magnitude of the difference varies due to differences in the model.

The disparity in the results could be attributable to two things: 1) data and period selection and 2) causal structure of the economy, in both contemporaneous and lagged terms. Our model differs with their model in the SVAR structure, data, the selection of time periods, and the exclusion restrictions on the lagged variables. Rather than interpolating GDP into monthly data, we use industrial production as our proxy for output; we use consumer price index rather than GDP deflator to proxy the price level; and we use the nominal price of oil rather than the Hamilton oil price series. Also, contrary to Bernanke *et al.* and Herrera and Hamilton's one period model with a time span from 1965-1995, we enclose longer time spans and separate the model into two periods so as to circumvent the Volcker period.[11] This separation, with a break on the Volcker period, has been proposed and commonly practiced (Bai and Perron, 1998).

Secondly, rather than determining the SVAR structure with arbitrary Cholesky orderings, we empirically determine the contemporaneous causal structure. Furthermore, our model imposes no exclusion restrictions on lagged terms, whereas their model imposes exclusion restrictions on the lagged terms of the federal funds rate to macro variables such as GDP, price deflator, commodity price and oil price.

[11] Period 1: 1959M02-1979M09; Period 2:1984M01-2007M11

If the data and time periods are robust to different selections, it means that the effects of an oil price shock are highly dependent on the presumed causal structure of the economy. We attempt, to the best of our ability, to avoid arbitrary assumptions, and we believe that we provide a fair assessment of the economy without being biased towards certain assumptions.

### *5.3 Future directions*

One limitation of our research is that our model assumes that the economy responds to oil prices linearly. Yet, in reality, the Fed could respond to rising oil prices more aggressively than to dropping prices – an asymmetric response of the federal funds rates. The Fed could also respond to oil prices shocks in a nonconventional way when oil prices rise above certain thresholds – a nonlinear response of the federal funds rates. Further research could entail transformation of nominal oil prices to nonlinear or asymmetric oil prices so as to examine the robustness of our result.

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# Appendix I: Data

The data are all monthly and cover 1959M02 to 2007M11. Consumer price index and industrial production are seasonally adjusted, and oil prices are non-seasonally adjusted. All data are available on the website as shown in Table A.1.

Table A.1: Data, details and sources

| Data | Details and Sources |
|---|---|
| Federal Funds Rate (FFR) | Units: percent per year<br>Source: Federal Reserve, Division of Monetary Affairs, Reserve Analysis Division<br>(www.federalreserve.gov) |
| 3-month Treasury Bill Rate (T3M) | Description: Treasury bills (secondary market), 3 months<br>Units: percent per year<br>Source: Board of Governors of the Federal Reserve Statistical Release H.15 Selected Interest Rates<br>(www.federalreserve.gov/releases/H15/data.htm) |
| 10-year Treasury Bond Rate (T10M) | Description: Treasuries constant maturities, Nominal, 10 year<br>Units: percent per year<br>Source: Board of Governors of the Federal Reserve Statistical Release H.15 Selected Interest Rates<br>(www.federalreserve.gov/releases/H15/data.htm) |
| Consumer Price Index (CPI) | Description: Consumer price index, all urban consumers (CPIU), US. All Items (SA)<br>Units: index number, 1982-84=100<br>Source: U.S. Bureau of Labor Statistics<br>(www.bls.gov) |
| Commodity Price Index (COM) | Units: index number, 1967=100<br>Source: U.S. Bureau of Economic Analysis<br>(www.crbtrader.com/crbindex/) |
| Industrial Production (IND) | Description: Industrial production, total index (SA)<br>Units: index number, 2002 = 100<br>Source: Federal Reserve Statistical Release G.17 Industrial Production and Capacity Utilization<br>(www.federalreserve.gov/releases/g17/download.htm) |
| Oil Price (OIL) | Description: Prices of West Texas Intermediate Crude, Monthly (NSA)<br>Units: dollar per barrel<br>(www.economagic.com) |

## Appendix II: Identifying Contemporaneous Causal Order

Period 1: 1959M02-1979M09

The three edges that we are to orient are T3M−T10M, FFR↔CPI, and T3M−COM. To simplify our notation, we represent each combination as a coordinate (*i*,*j*,*k*), where *i*,*j*,*k*=1,2 and represent the directionality of those three edges. The BootGraph program recommended (2,1,1). The coordinate system can be translated to the causal order by Table A.2.

Table A.2: Notations of i,j,k

| | 1 | 2 |
|---|---|---|
| *i* | T10M←T3M | T10M→T3M |
| *j* | FFR←CPI | FFR→CPI |
| *k* | T3M→COM | T3M←COM |

Table A.3 shows the p-value for each possible combinations. (2,1,1), as suggested by the BootGraph program, also maximizes the p-value. We thus select this causal order for SVAR simulation.

TableA.3: Over-identifying tests for each possible combinations

| Directionality | p-value |
|---|---|
| (1,1,1) | 0.354 |
| (1,1,2) | 0.354 |
| (1,2,1) | 0.233 |
| (1,2,2) | 0.233 |
| (2,1,1)* | 0.354* |
| (2,1,2) | 0.221 |
| (2,2,1) | 0.233 |
| (2,2,2) | 0.138 |

Period 2: 1984M01-2007M11

With a similar methodology in period 1, we orient four edges (CPI↔OIL, T3M−T10M, T10M−COM and FFR↔OIL). We also represent each possible combination with a coordinate system (*i*,*j*,*k*,*l*) where *i*,*j*,*k*,*l*=1, 2.

The BootGraph program selects the order of (2,1,1,1). We again picked the combination that has the highest p-value and maximizes the suggestions made by the BootGraph program. The coordination system can also be translated to the causal order in Table A.4.

Table A.4: Notations of i,j,k,l

| | 1 | 2 |
|---|---|---|
| *i* | T3M←T10M | T3M→T10M |
| *j* | T10M←COM | T10M→COM |
| *k* | OIL←CPI | OIL→CPI |
| *l* | OIL←FFR | OIL→FFR |

Table A.5: Over-identifying tests for each possible combinations

| Directionality | p-value |
|---|---|
| (1,1,1,1) | 0.067 |
| (1,1,1,2) | 0.095 |
| (1,1,2,1) | 0.167 |
| (1,1,2,2) | 0.214 |
| (1,2,1,1) | 0.067 |
| (1,2,1,2) | 0.095 |
| (1,2,2,1) | 0.167 |
| (1,2,2,2) | 0.214 |
| (2,1,1,1) | 0.007 |
| (2,1,1,2) | 0.010 |
| (2,1,2,1) | 0.020 |
| (2,1,2,2) | 0.028 |
| (2,2,1,1) | 0.067 |
| (2,2,1,2) | 0.095 |
| (2,2,2,1) | 0.167 |
| (2,2,2,2)* | 0.214* |

## Appendix III: IRF under Normal SVAR

Period 1: 1959M02-1979M09

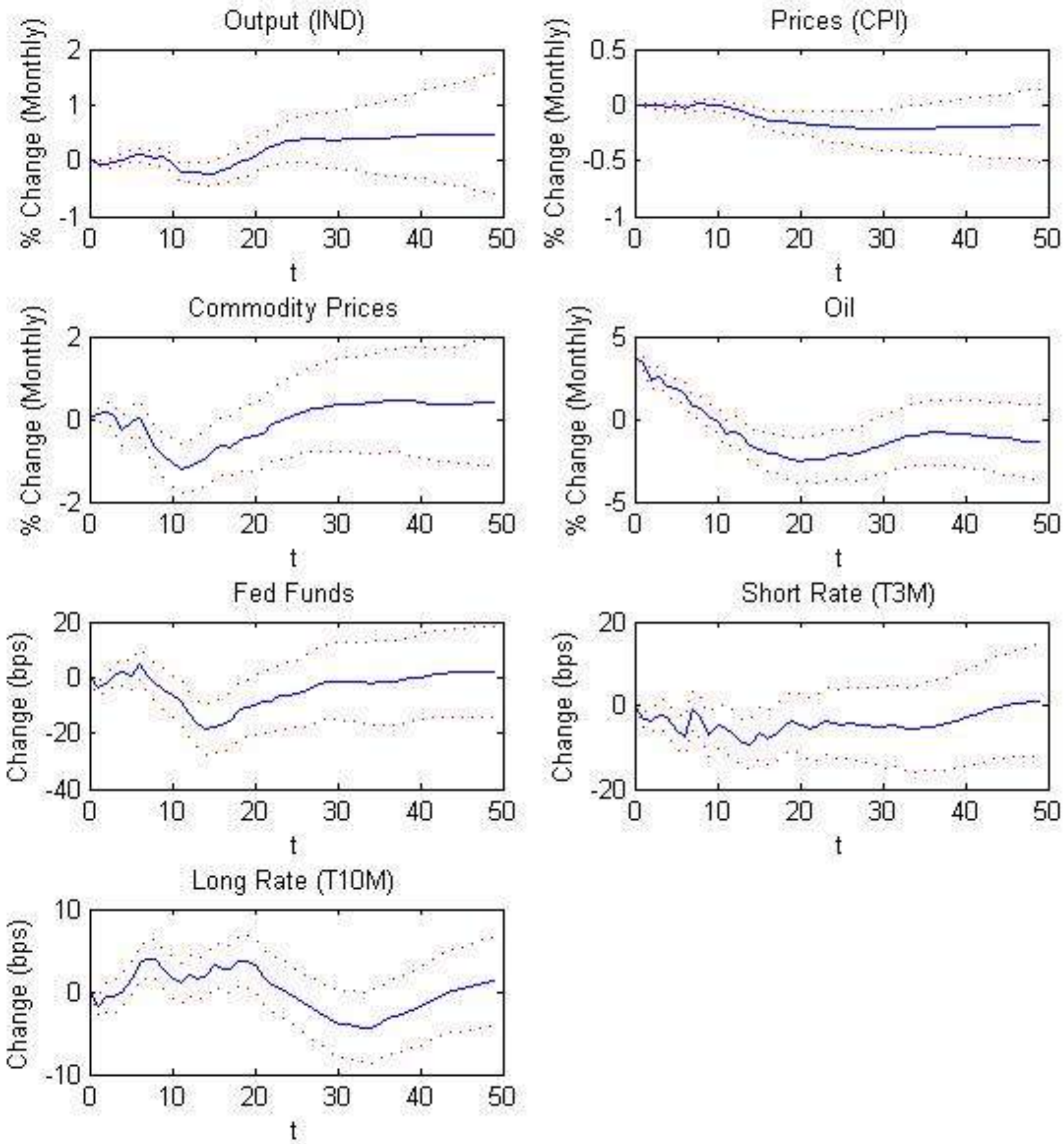


Figure A.1: Impulse response functions of 12 lags in period 1. Dotted lines represent one-standard error band.

Period 2: 1984M01-2007M11

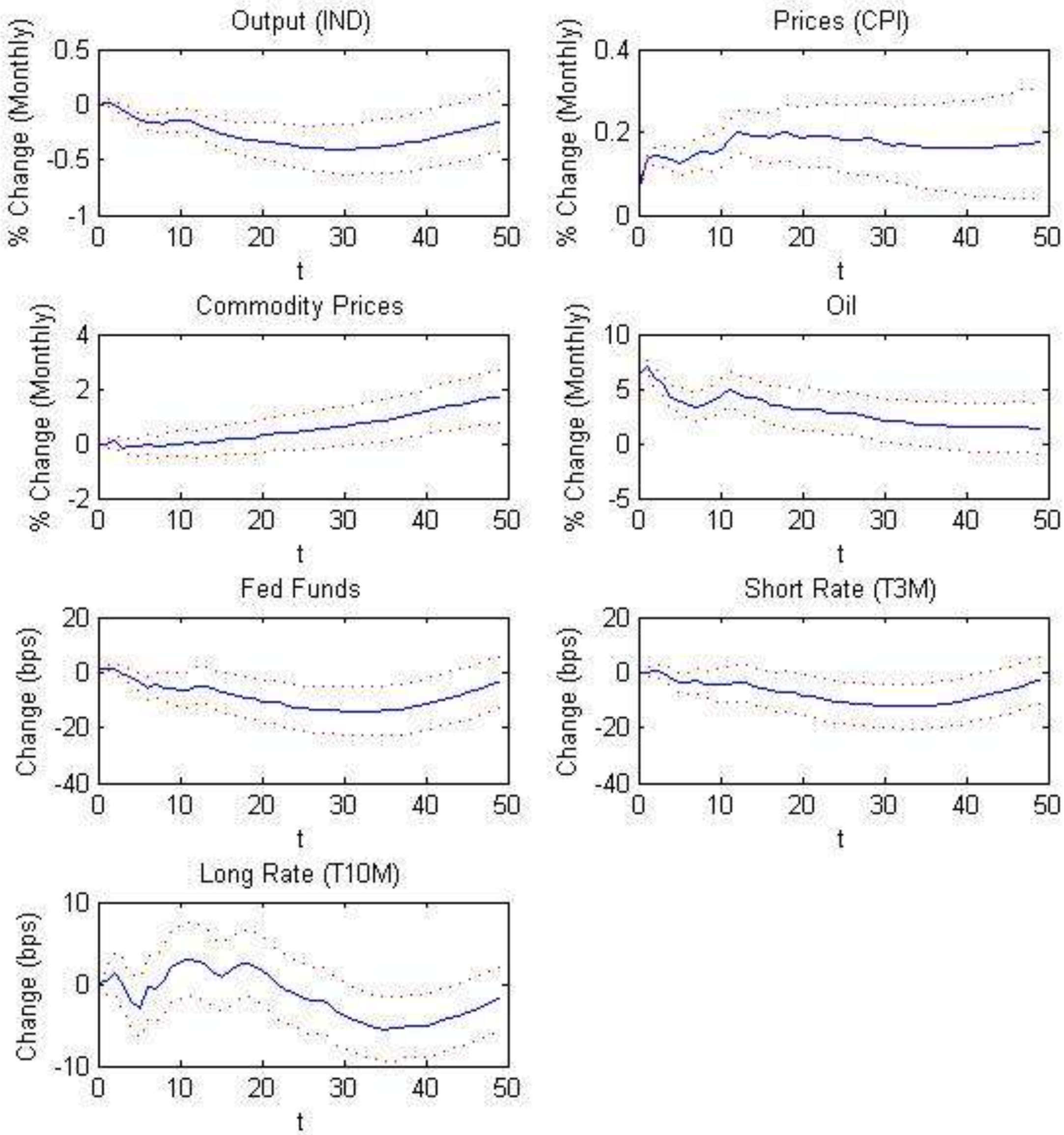


Figure A.2: Impulse response functions of 12 lags in period 2. Dotted lines represent one-standard error band.

## Appendix IV: IRF under Normal and Case I Counterfactual SVAR

Period 1: 1959M02-1979M09

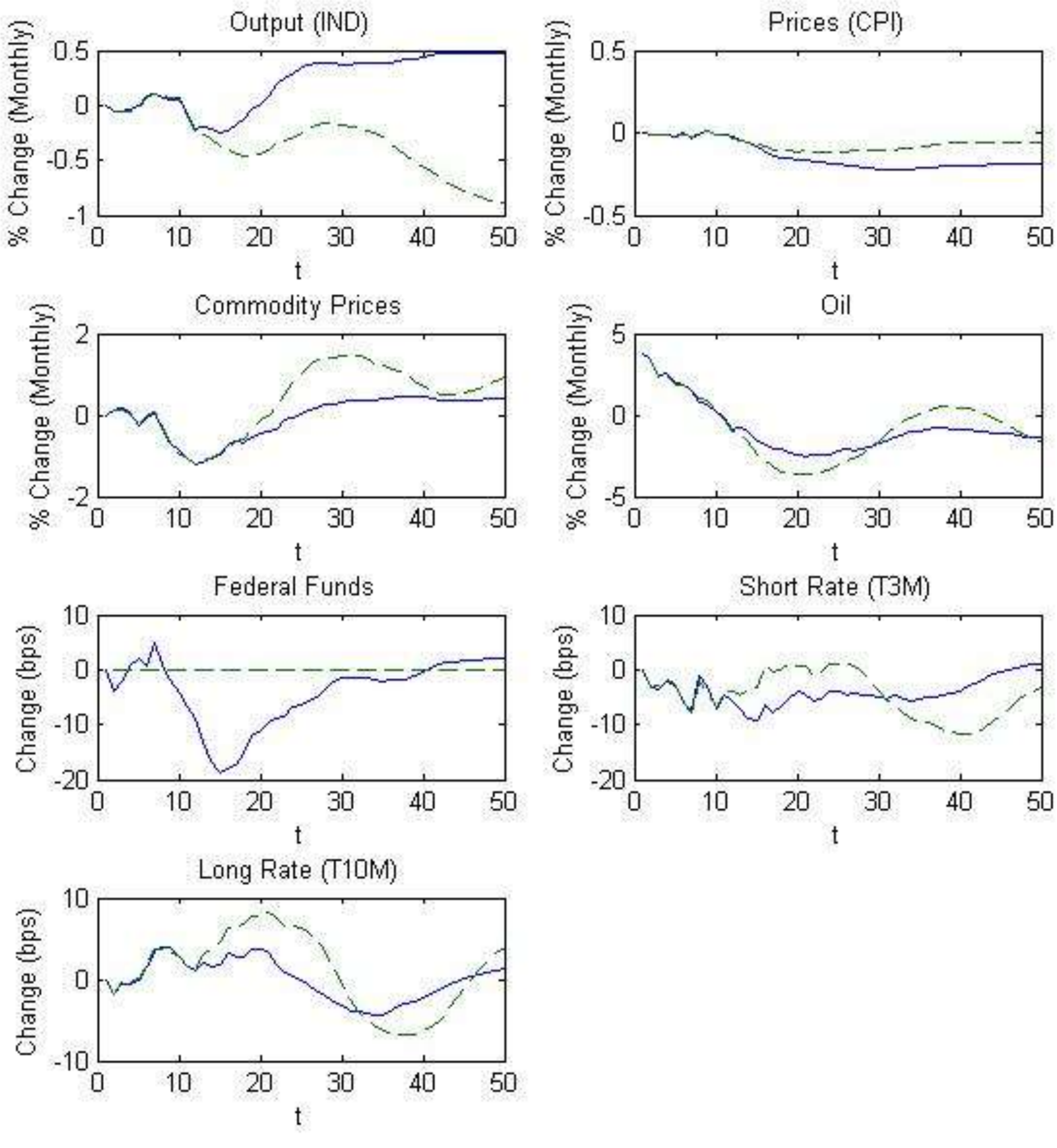


Figure A.3: Impulse response functions of 12 lags in period 1. Dashed lines represent the counterfactual experiment where the federal funds rate is constant during an oil price shock.

Period 2: 1984M01-2007M11

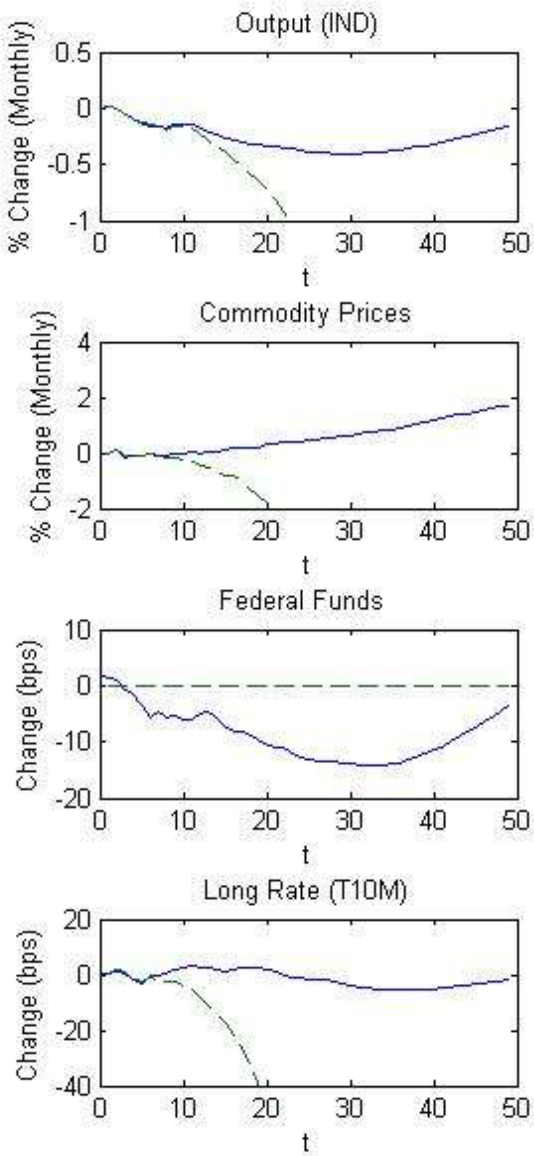


Figure A.4: Impulse response functions of 12 lags in period 2. Dashed lines represent the counterfactual experiment where the federal funds rate is constant during an oil price shock.

## Appendix V: IRF under Normal and Case II Counterfactual SVAR

Period 1: 1959M02-1979M09

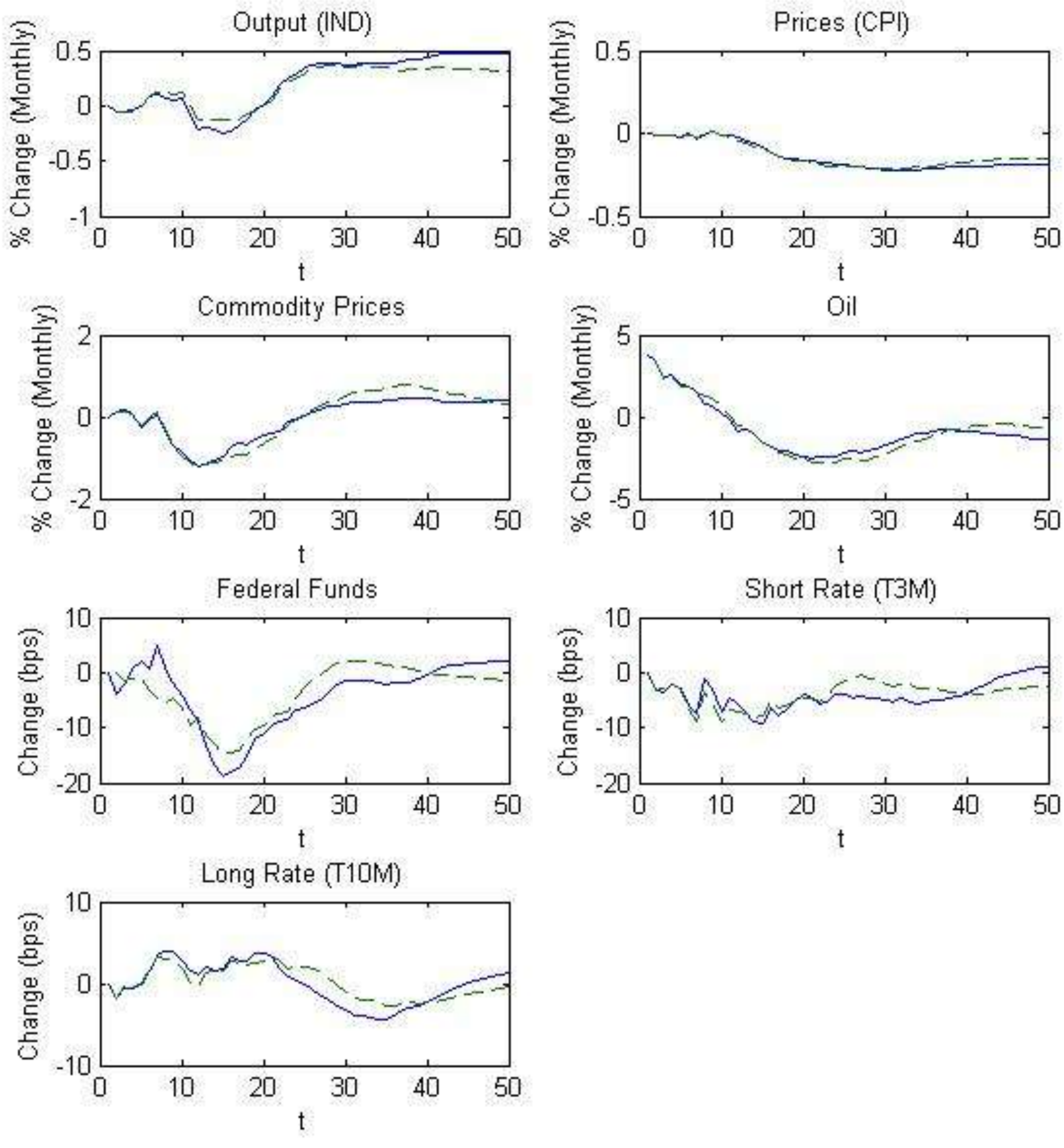


Figure A.5: Impulse response functions of 12 lags in period 1. Dashed lines represent the counterfactual experiment where the federal funds rate responds to the oil price shock indirectly through oil's effect on other variables.

Period 2: 1984M01-2007M11

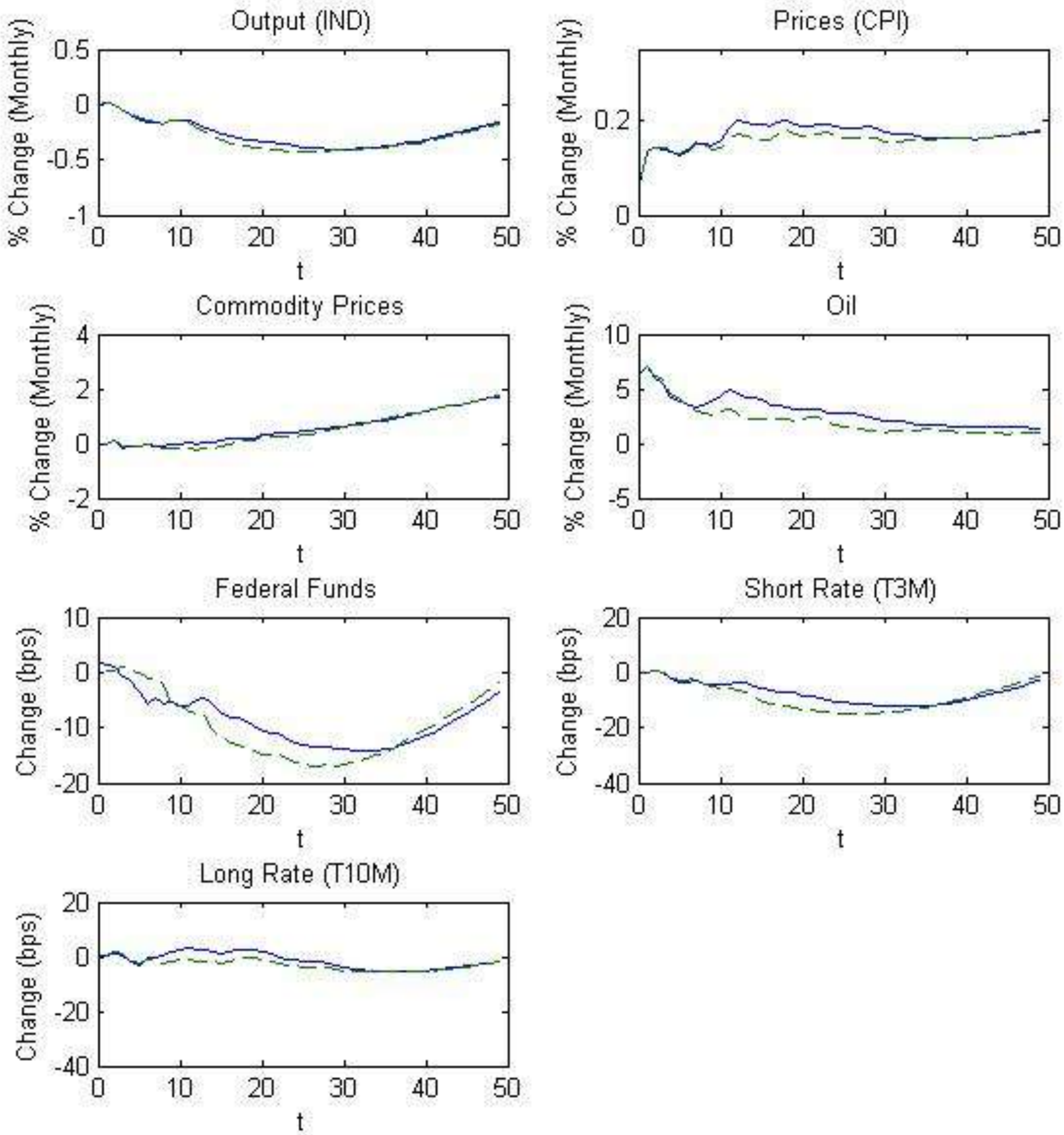


Figure A.6: Impulse response functions of 12 lags in period 2. Dashed lines represent the counterfactual experiment where the federal funds rate responds to the oil price shock indirectly through oil's effect on other variables.

## Appendix VI: Bernanke *et al.:* IRF Counterfactual SVAR

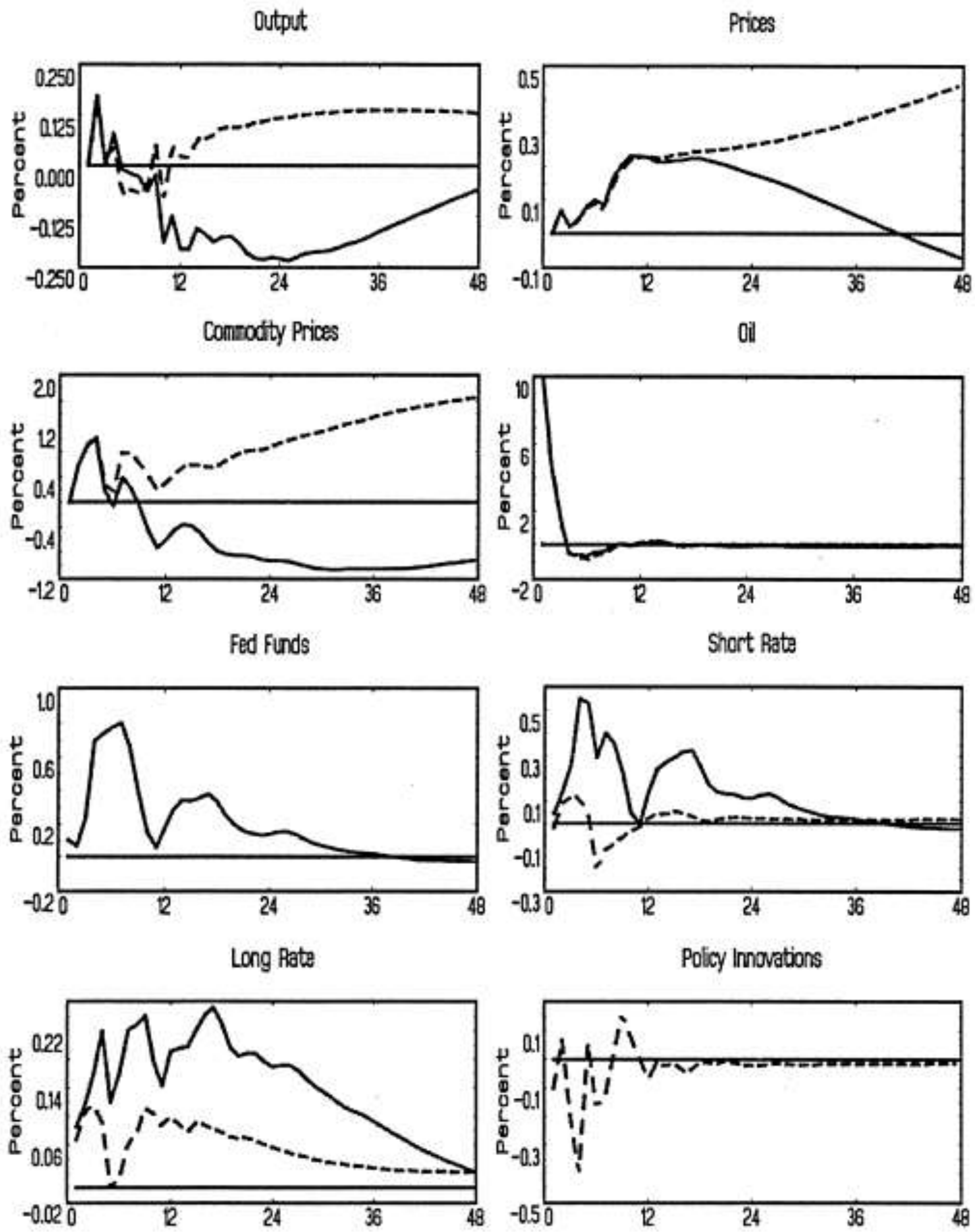


Figure A.7: Impulse response functions of 7 lags by Bernanke *et al*.'s model specifications. Dashed lines represent the counterfactual experiment where the federal funds rate is constant. The figure is extracted from Herrera and Hamilton (2001), page 268.

## Appendix VII: Herrera and Hamilton: IRF Counterfactual SVAR

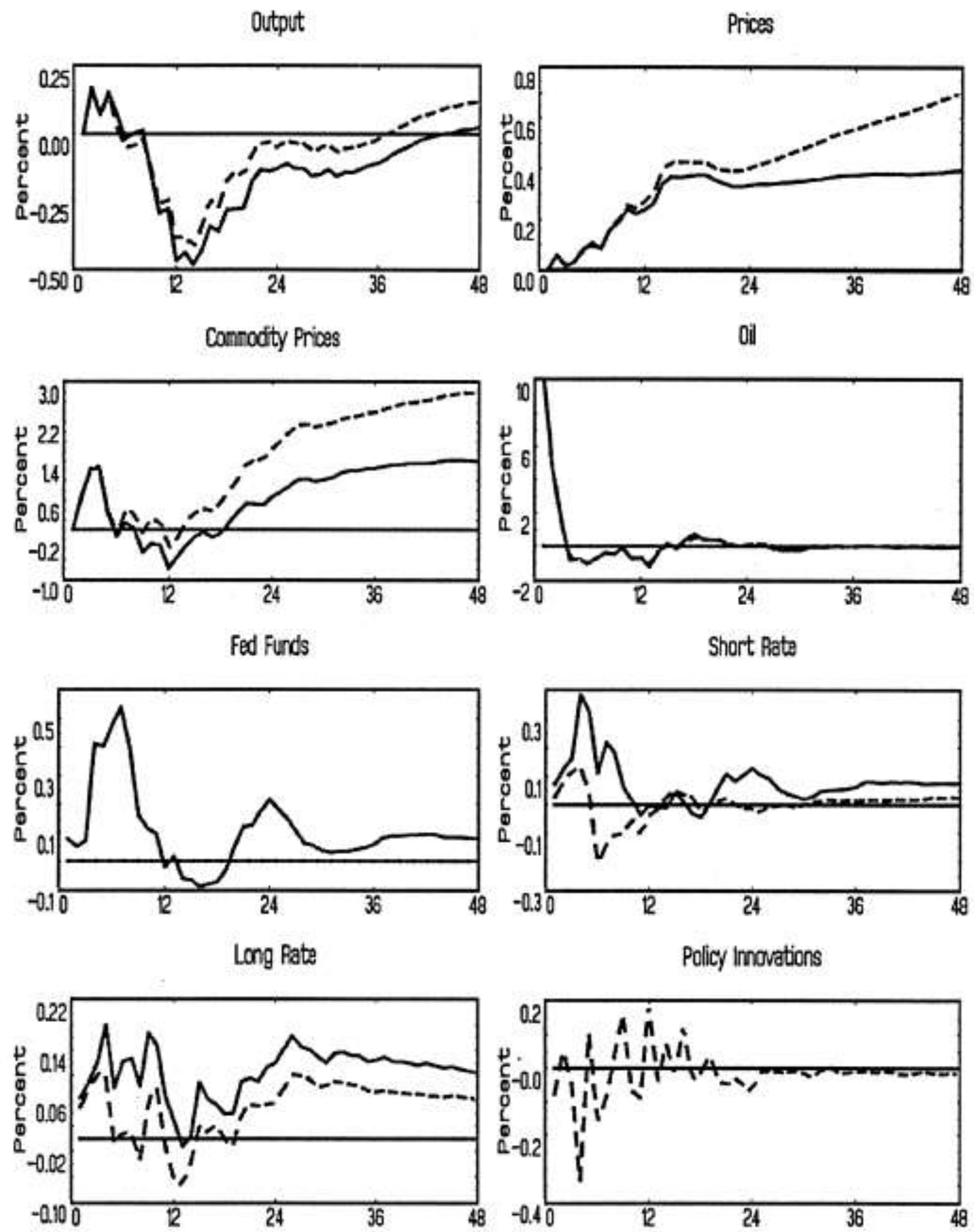


Figure A.8: Impulse response functions of 12 lags by Herrera and Hamilton's model specifications. Dashed lines represent the counterfactual experiment where the federal funds rate is constant. The figure is extracted from Herrera and Hamilton (2001), page 282.