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Essays on Fiscal Policy and Oil Price Shocks

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by

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ABSTRACT OF THE DISSERTATION

Essays on Fiscal Policy and Oil Price Shocks

by

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Professor James Hamilton, Chair

In my dissertation, I use cutting-edge time series econometric models to explore how the effects of government spending shocks change with the state of the economy, how to identify the effects of oil price changes induced by different reasons, and why oil price shocks seem to be much less important nowadays than decades ago.

Chapter 1 builds a Markov-switching structural VAR to estimate state-dependent government spending multipliers in the U.S. We show that the multipliers are statistically larger during recessions than during expansions, although smaller than 1 in both periods. Our model has two features. First, we combine quantitative data and qualitative indicators to infer the regimes of the economy across which the multipliers differ. Second, we propose a recursive method to estimate

impulse response functions that allows the economy to switch regimes after the shock. We argue that these two features are important for reconciling the main findings in previous studies.

Chapter 2 estimates a standard structural VAR of the global oil market using both external and internal instrumental variables. I find that a negative oil supply shock leads to a delayed but significant decline in economic activity. Whereas oil consumption demand shocks do not have a significant effect on economic activity, a positive shock to oil inventory demand results in significant declines in oil production and economic activity at the same time. Furthermore, I show that oil price movements are mostly driven by shocks to oil consumption demand.

Chapter 3 revisits the evidence in Blanchard and Galí (2010) that the effects of oil price shocks have diminished since the mid-1980s. I show that the apparent instability in the oil price-macroeconomy relationship they find can be accounted for by the endogeneity of oil price changes and the lower energy share in consumption in recent decades. When these two factors are taken into account, the effects of oil price shocks on real economic activity appear to be stable over time. Nevertheless, the impact of oil prices on inflation has noticeably weakened over time.

Chapter 1

Cyclical Variation in the Government Spending Multipliers: A Markov-Switching SVAR Approach

Measuring the size of fiscal multipliers is a central issue in macroeconomics. Given that many countries used discretionary fiscal policy to combat weak economic growth during the Great Recession, a key question is how effective government purchases are in bad times. Some studies, including Barro and Redlick (2011) and Ramey (2011), find government spending multipliers smaller than 1 on average over a long history, suggesting that increases in government spending crowd out private demand to some extent.

However, there is a long-lasting belief in economics that the effects of fiscal policy are stronger in bad times relative to normal times so that the multipliers for recession could potentially be much larger than 1. The textbook Keynesian theory tells us that the effects of government spending are stronger when there is more slack in the economy because private consumption and investment are less likely to be crowded out when resources are underutilized. Canzoneri et al. (2016) show that a standard business cycle model equipped with costly financial intermediation is capable of generating large fiscal multipliers in recessions and small multipliers in expansions. Michaillat (2014) develops a New Keynesian model in which the effects of government-led stimulation policy differ across the business cycle phases even in the absence of the zero lower bound. He shows that an additional hire in the public sector would crowd out less private employment when unemployment is high.

Recently there has been a growing number of empirical studies investigating the state dependence of the government spending multipliers. However, these studies reach very different conclusions. Auerbach and Gorodnichenko (2012*a*,*b*), Bachmann and Sims (2012), Mittnik and Semmler (2012), and Caggiano et al. (2015) find much larger government spending multipliers for recession than for expansion. Fazzari, Morley and Panovska (2015) also find that the government spending multipliers become larger and more persistent during times of slack. By contrast, Owyang, Ramey and Zubairy (2013) and Ramey and Zubairy (2018) do not observe larger multipliers when there is substantial economic slack in the United States. Bognanni (2013) and Alloza (2016) present evidence that the multipliers could even be smaller in economic downturns than in booms.

Using a U.S. dataset from 1890Q1-2015Q4 developed by Ramey and Zubairy (2018), we document the countercyclical behavior of the government spending multipliers: the multiplier values are larger in recessions than in expansions, and the gaps are statistically significant. More specifically, the mutipliers are around 0.5 in expansions and around 0.9 in recessions. To estimate the state-dependent responses of aggregate output to an unanticipated and exogenous change in government spending, we build a Markov-switching structural VAR that includes government spending, tax revenue, and output as endogenous variables and the military spending news as an exogenous variable. We assume that there are two unobserved regimes of the economy, and the dynamics of the economy vary with the regime. The regime can always shift from one to the other with constant transition probabilities. Then we estimate the model, and as suggested by Ramey and Zubairy (2018), we calculate the government spending multiplier at some specific horizon as the cumulative change in output normalized by the cumulative change in government spending in response to a military spending news shock. We calculate the multipliers for various horizons conditional on the regime when the shock occurs, and compare the multiplier values for different regimes to check if the effects of government purchases depend on the regime of the economy.

Our model has two distinctive features. First, following Jefferson (1998), we use both quantitative and qualitative information to infer the regime of the economy. Whereas economists know that the size of fiscal multipliers may vary with the regime, a consensus on how to measure the regime does not exist. In a typical Markov regime-switching model where the regime is assumed unobserved, one can use quantitative data to estimate the probability of occurrence of each regime for any historical period. We can then relate these inferred probabilities to other indicators. For example, if the probability is substantially different during periods that the Dating Committee of the NBER designates as recession, we can confidently claim that the unobserved regimes correspond to different business cycle phases. Since this inference is a byproduct of the estimation of the model, it is determined entirely by the data used. In addition to this purely data-driven approach, the regime could also be determined directly by some simple qualitative indicators. For example, Alloza (2016) uses the NBER business cycle dates to measure expansion and recession. Owyang, Ramey and Zubairy (2013) and Ramey and Zubairy (2018) assume that the economy is in the non-slack regime if the unemployment rate is below 6.5% and in the slack regime if otherwise. The conclusions of various studies could depend critically on how they measure the regime of the economy.[1] Different inference methods mean different data observations are used to inform the model parameters for each regime, which in turn give different estimates of state-dependent fiscal multipliers.

Both the inference based on quantitative data and the inference based on qualitative indicators have drawbacks. The former method is not accurate if the data quality is not good enough, and the latter is arbitrary to a large extent. Jefferson (1998) proposes a method of combining quantitative and qualitative information to improve inference in a simple Markov regime-switching model. Instead of taking the qualitative indicator as a perfect measure for the regime, he assumes it to be a proxy for the regime with measurement error and we are able to

[1] Bognanni (2013) and Alloza (2016) argue that differences in the methods used to calculate the time-varying probability of occurrence of recession is the main reason why their results differ from Auerbach and Gorodnichenko (2012*a*).

assess how reliable the indicator variable is. We generalize Jefferson's approach to the VAR framework and consider multiple qualitative indicators at the same time. In particular, we use the NBER business cycle dates as well as the indicator variable based on the unemployment rate as in Owyang, Ramey and Zubairy (2013) and Ramey and Zubairy (2018). Our result shows that the effects of government spending are much more likely to change with the official business cycle phases than with the labor market condition. This explains why Owyang, Ramey and Zubairy (2013) and Ramey and Zubairy (2018) do not find significant differences in the government spending multipliers between times of high unemployment and times of low unemployment, although their results are robust to using the NBER dates as an alternative measure for the regime of the economy.

The other important feature of our model is that by taking advantage of the Markov-switching framework, we develop a simple recursive method for estimating the dynamic effects of a government spending shock, allowing the regime of the economy to change naturally after the shock. In contrast, it is hard to construct impulse response functions in existing nonlinear VAR models. For simplicity, many papers, including Auerbach and Gorodnichenko (2012*a*), Bachmann and Sims (2012), Bognanni (2013), and Alloza (2016), compute impulse response functions under the assumption that the regime is fixed permanently. Given the fact that the average duration of U.S. recessions is about only six quarters, their results tend to obscure the true effects of government purchases that happen in recessions. We show that if we prohibit the regime from changing, we will obtain much larger multipliers in recessions. In particular, we estimate the 5-year multiplier for recession to be 1.9. This explains why the leading study by Auerbach and Gorodnichenko (2012*a*) obtains multipliers as high as 2.24 in recessions. As an alternative to the nonlinear VAR approach, Auerbach and Gorodnichenko (2012*b*), Owyang, Ramey and Zubairy (2013), and Ramey and Zubairy (2018) compute impulse response functions using Jordà (2005)'s local projection method, which amounts to a direct forecast of future output in response to a government spending shock conditional on the regime when the shock hits.

Although the local projection method implicitly allows the regime to switch after the shock, it suffers a notable efficiency loss due to its nonparametric property. We show that differences in the methods used to estimate impulse response functions can explain why Ramey and Zubairy (2018) fail to find statistically significant variations in the government spending multipliers even if they use the NBER business cycle dates to measure the regime.

At the end of this paper, we consider a generalization of our model that allows the regime transition probabilities to be dependent on government spending shocks. The rationale is that an expansionary fiscal policy may help the economy escape from recession while a contractionary fiscal policy may end an expansion early. Our result shows that the influence of fiscal policy shocks on the regime is insignificant, which justifies our assumption of constant transition probabilities. We also show that allowing for time-varying transition probabilities does not change our conclusion about the state-dependent effects of government spending shocks.

Our paper is related to three strands of literature. First, we contribute to the literature gauging the size of fiscal multipliers, such as Blanchard and Perotti (2002), Ramey (2011), and Auerbach and Gorodnichenko (2012*a*) among others. Our results corroborate the existing evidence that fiscal policy is more effective in economic downturns than in booms. However, the multipliers in recessions are smaller than 1, which is consistent with the finding in Ramey and Zubairy (2018). The second strand of literature investigates the asymmetric effects of aggregate shocks over the business cycle; see Auerbach and Gorodnichenko (2012*a*), Caggiano, Castelnuovo and Groshenny (2014), and Tenreyro and Thwaites (2016). We contribute by providing a useful framework that could be easily applied to study the cyclical effects of monetary policy shocks or uncertainty shocks. Our model is more convenient than the existing nonlinear VAR models for impulse response analysis and more efficient than the local projection method. The last strand of literature applies Markov-switching models in macroeconomics. Hamilton (2016) serves as an excellent survey. We extend this literature by exploring a Markov-switching structural VAR, which takes advantage of both quantitative and qualitative information for inference about the regime and generates impulse response functions that allow for regime changes.

The remainder of this paper proceeds as follows. We present our econometric model in section 1.1. In section 1.2, we briefly describe the data we use and show our main results. Section 1.3 shows how we reconcile the main findings in previous studies. Section 1.4 discusses the extension of our model that allows for time-varying regime transition probabilities. Section 1.5 concludes.

1.1 Econometric Model

In this section, we present a Markov regime-switching structural VAR used to estimate the state-dependent effects of government spending shocks on aggregate output. We assume there are two regimes of the economy, and the dynamics of the economy change according to the regime. Then we show how to estimate the model and draw probabilistic inferences about the regime. Finally we illustrate how we compute the government spending multipliers for different regimes.

1.1.1 A Markov-Switching Structural VAR

As is conventional in the literature beginning with Auerbach and Gorodnichenko (2012*a*), we build a structural VAR to describe the behavior of $\mathbf{y}_t$ that includes government spending (G_t), tax revenue (T_t), and output (Y_t).[2] The model is recursively identified so that shocks to tax revenue and output can not affect government spending contemporaneously. Blanchard and Perotti (2002) justify this identification assumption by the observation that it usually takes policymakers more than a quarter to decide how government should change its spending in response to those shocks, pass the decisions through the legislature, and send them to implementation. However, Ramey (2011) argues that the shocks to government spending identified in this way can be predicted by war dates or professional forecasts because there is

[2]The detailed definition of these variables will be discussed in the next section.

usually a lag between the announcement of a fiscal policy and its actual implementation, an issue known as fiscal foresight. From the standpoint of the neoclassical models, an increase in government spending creates a negative wealth effect for the representative household. From this perspective, it is the change in the present discounted value of government purchases that really matters, and households react immediately once they learn the news about future government purchases. Because the conventional VAR as just described captures shocks only when they occur, it misses the initial response of the economy to the news.

To control for the timing of government spending shocks, we follow Ramey (2011) to incorporate the military spending news (N_t), an estimate of changes in the expected present value of military spending, in the VAR. The government spending multiplier then measures the change in output relative to the change in government spending in response to a military spending news shock. Because military spending is very likely to be orthogonal to the U.S. macroeconomic condition and there is no statistical evidence that the value of the news depends on its past values or the other variables, we assume it to be totally exogenous. The fiscal and macroeconomic variables are allowed to react to both current and lagged values of the news.

To allow the effects of government spending shocks to be state-dependent, we model the dynamics of $\mathbf{y}_t$ using a Markov-switching structural VAR (MS-SVAR hereafter)[3]:

$$\mathbf{A}_0(s_t)\mathbf{y}_t = \mathbf{c}(s_t) + \sum_{j=1}^{4} \mathbf{A}_j(s_t)\mathbf{y}_{t-j} + \sum_{j=0}^{4} \Gamma_j(s_t)N_{t-j} + \varepsilon_t \tag{1.1}$$

$$\varepsilon_t \sim \mathbf{N}(\mathbf{0}, \Sigma)$$

The values of the intercept and slope parameters in equation (1.1) vary with the unobserved state variable s_t, which is assumed to be exogenous and follow a two-state Markov chain with

[3]The specification of equation (1.1) is sometimes referred to as VARX in the literature. We show in Appendix A.2 that it can be rewritten as a restricted VAR.

transition probabilities:

$$p_{ij} \equiv p(s_t = j | s_{t-1} = i) \qquad i, j = 1, 2 \tag{1.2}$$

$\mathbf{A}_0(s_t)$ is a lower-triangular matrix with ones on the diagonal. $\mathbf{c}(s_t)$ is the intercept. Σ is a diagonal matrix collecting the variances of structural shocks ε_t. There is no restriction on $\mathbf{A}_j(s_t)$ or $\Gamma_j(s_t)$. Since we use quarterly data, we set the lag order to four to capture any important dynamics.

It is worth mentioning that we follow Gordon and Krenn (2010) and Ramey and Zubairy (2018) to divide all the variables by trend (potential) output instead of taking logarithms of the variables as in many previous studies including Auerbach and Gorodnichenko (2012*a*). With the logged variables in the VAR, it is necessary to convert the estimated impulse responses of government spending and output to multipliers based on the sample average of Y_t/G_t. Ramey and Zubairy (2018) notice that in the post-WWII sample, the value of Y_t/G_t varies modestly with a mean of 5. However, in the full sample from 1890-2015 that is used in our paper, the value of Y_t/G_t fluctuates widely with a mean close to 8. This means that we may overestimate the multipliers relative to the existing results which are mostly based on the post-WWII sample, if we follow the common practice in the literature. In contrast, our approach makes all the variables in the same dollar unit, which allows us to calculate the government spending multiplier directly as the ratio of the response of output to the response of government spending without using the sample average of Y_t/G_t.

1.1.2 Estimation and Inference

Let $\mathbf{x}_t$ denote the vector including all the regressors on the right-hand side of equation (1.1), and $\beta(s_t)$ denote the matrix of the corresponding coefficients. For simplicity, we can write equation (1.1) as:

$$\mathbf{A}_0(s_t)\mathbf{y}_t = \beta(s_t)\mathbf{x}_t + \varepsilon_t \tag{1.3}$$

Let $\mathscr{Y}_t \equiv \{\mathbf{y}_t, \mathbf{y}_{t-1}, \ldots, \mathbf{y}_1\}$ denote observations up to time t. The parameters to be estimated are collected in a column vector θ, including p_{11}, p_{22}, and all the unknown elements in $\mathbf{A}_0(j)$, $\beta(j)$ $(j = 1,2)$ and Σ. The log likelihood function of the observed sample data is:

$$\begin{aligned}\mathscr{L}(\mathscr{Y}_T;\theta) &= \sum_{t=1}^{T} \ln f(\mathbf{y}_t|N_t, \mathscr{Y}_{t-1};\theta) \\ &= \sum_{t=1}^{T} \ln\{\sum_{j=1}^{2} p(s_t = j|\mathscr{Y}_{t-1};\theta) f(\mathbf{y}_t|\mathbf{x}_t, s_t = j;\theta)\}\end{aligned} \tag{1.4}$$

where the conditional likelihood function is:

$$f(\mathbf{y}_t|\mathbf{x}_t, s_t = j;\theta) = \frac{1}{\sqrt{(2\pi)^3|\Sigma|}} \exp\{-\frac{1}{2}[\mathbf{A}_0(j)\mathbf{y}_t - \beta(j)\mathbf{x}_t]'\Sigma^{-1}[\mathbf{A}_0(j)\mathbf{y}_t - \beta(j)\mathbf{x}_t]\} \tag{1.5}$$

The maximum likelihood estimate $\hat{\theta}$ can be obtained through the expectation maximization (EM) algorithm proposed by Hamilton (1990). With the model estimated, we can draw a probabilistic inference about the unobserved state variable s_t using full-sample information, denoted by $p(s_t = j|\mathscr{Y}_T;\hat{\theta})$ $(j = 1,2)$. This probability is called the smoothed inference, and an easy way to implement it has also been introduced in Hamilton (1990).

This inference relies solely on the observed sample data. One valid concern is that the available data is not rich or clean enough to shed much light on s_t. Instead of estimating time-varying probabilities of occurrence of each regime, some studies simply use qualitative indicators to determine the regime of the economy for each period. For example, Alloza (2016) uses the NBER business cycle dates as an indicator of the regime, and Owyang, Ramey and Zubairy (2013) determine the regime by whether the unemployment rate exceeds 6.5%. While extremely simple, the inference method based solely on qualitative information is not innocuous as the choice of qualitative information is somewhat arbitrary. As we will show later in section 4, the conclusion about the state-dependent effects of fiscal policy may depend on the qualitative indicator one chooses. If the indicator variable is not a reliable measure for the true regime, one may fail to observe the state dependence of the government spending multipliers.

Jefferson (1998) proposes a method of combining quantitative data and qualitative information for inference in a simple Markov-switching model. We generalize his method to the VAR framework, and consider various indicators that might be useful at the same time. Suppose there are n different indicator variables $z_t^{(1)},\ldots,z_t^{(n)}$ that can be regarded as independent proxies with measurement error for the unobserved state variable s_t. We define:

$$g_1^{(i)} \equiv p(z_t^{(i)} = 1|s_t = 1), \quad 1 - g_1^{(i)} \equiv p(z_t^{(i)} = 2|s_t = 1) \tag{1.6}$$

$$g_2^{(i)} \equiv p(z_t^{(i)} = 2|s_t = 2), \quad 1 - g_2^{(i)} \equiv p(z_t^{(i)} = 1|s_t = 2) \tag{1.7}$$

for $i = 1,2,\ldots,n$. The parameters $g_1^{(i)}$ and $g_2^{(i)}$ indicate how reliable $z_t^{(i)}$ is on average. If $g_1^{(i)}$ and $g_2^{(i)}$ are close to 1, it suggests that the ith indicator contains much useful information about s_t. We treat $g_1^{(i)}$ and $g_2^{(i)}$ as free parameters, and estimate them along with the other parameters in the model. Let $\mathbf{w}_t \equiv \{\mathbf{y}_t, z_t^{(1)}, z_t^{(2)},\ldots,z_t^{(n)}\}$ denote observations of both quantitative and qualitative variables at time t, and define $\mathscr{W}_t \equiv \{\mathbf{w}_t, \mathbf{w}_{t-1},\ldots,\mathbf{w}_1\}$. The log likelihood function associated with our model then changes into:

$$\begin{aligned}\mathscr{L}(\mathscr{W}_T;\lambda) &= \sum_{t=1}^{T} \ln f(\mathbf{w}_t|N_t,\mathscr{W}_{t-1};\lambda) \\ &= \sum_{t=1}^{T} \ln\{\sum_{j=1}^{2} p(s_t = j|\mathscr{W}_{t-1};\lambda) f(\mathbf{w}_t|\mathbf{x}_t, s_t = j;\lambda)\}\end{aligned} \tag{1.8}$$

where λ contains $g_1^{(i)}$ and $g_2^{(i)}$ $(i = 1,2,\ldots,n)$ in addition to θ. The conditional likelihood function becomes:

$$f(\mathbf{w}_t|\mathbf{x}_t, s_t = j;\lambda) = f(\mathbf{y}_t|\mathbf{x}_t, s_t = j;\theta) \prod_{i=1}^{n} p(z_t^{(i)}|s_t = j; g_1^{(i)}, g_2^{(i)}) \tag{1.9}$$

The first term on the right-hand side of equation (1.9) is exactly the same as equation (1.5), and the following product term is obtained directly from equation (1.6) or (1.7). We adapt the EM algorithm to obtain the maximum likelihood estimate $\hat{\lambda}$, and calculate the smoothed inference $p(s_t = j|\mathscr{W}_T;\hat{\lambda})$ $(j = 1,2)$ that makes use of qualitative information as well. The implementation of the modified EM algorithm and the smoothed inference is described in Appendix A.1. With the information set augmented, the inference about s_t should be more accurate than that based only on quantitative information $\mathscr{Y}_T$.

Within this general framework, two special cases are worth noting. First, we consider $g_1^{(i)} = g_2^{(i)} = 1$. The inference about s_t becomes:

$$p(s_t = j|\mathscr{W}_T;\hat{\lambda}) = \begin{cases} 1 & \text{if } z_t^{(i)} = j \\ 0 & \text{if } z_t^{(i)} \neq j \end{cases} \qquad j = 1,2 \tag{1.10}$$

or equivalently:

$$s_t = z_t^{(i)} \tag{1.11}$$

This is the case in Alloza (2016), Owyang, Ramey and Zubairy (2013) and Ramey and Zubairy (2018) which assume that some indicator variable measures the regime of the economy perfectly. The second special case requires $g_1^{(i)} + g_2^{(i)} = 1$ for any $i = 1,2,\ldots,n$. This implies $p(z_t^{(i)} = 1|s_t = 1) = p(z_t^{(i)} = 1|s_t = 2)$ and $p(z_t^{(i)} = 2|s_t = 1) = p(z_t^{(i)} = 2|s_t = 2)$. Because the value of $z_t^{(i)}$ is totally independent of s_t, the qualitative information is of no use for inference about s_t. It is not hard to prove that in this case, the smoothed inference collapses to the one that uses only quantitative information:

$$p(s_t = j|\mathscr{W}_T;\hat{\lambda}) = p(s_t = j|\mathscr{Y}_T;\hat{\theta}) \quad j = 1,2 \tag{1.12}$$

In our application, we label regime 1 “good regime” and label regime 2 “bad regime” without loss of generality. Based on the literature and data availability, we consider two indicator variables that could be informative about s_t and almost uncorrelated:

$$z_t^{NBER} = \begin{cases} 1 & \text{if period } t \text{ is an NBER dated expansion} \\ 2 & \text{if period } t \text{ is an NBER dated recession} \end{cases}$$

$$z_t^{UNEMP} = \begin{cases} 1 & \text{if the unemployment rate in period } t \leq 6.5\% \\ 2 & \text{if the unemployment rate in period } t > 6.5\% \end{cases}$$

The parameters measuring the reliability of these indicators are denoted by g_1^{NBER}, g_2^{NBER}, g_1^{UNEMP}, and g_2^{UNEMP}. Another indicator variable worth considering is based on the interest rate:

$$z_t^{ZLB} = \begin{cases} 1 & \text{if the interest rate is away from the zero lower bound} \\ 2 & \text{if the interest rate is near the zero lower bound} \end{cases}$$

Some studies argue that the effects of fiscal policy are different in the zero lower bound periods and in the normal periods. For example, Christiano, Eichenbaum and Rebelo (2011) and Miyamoto, Nguyen and Sergeyev (2018), among others, argue that the government spending multipliers are larger than 1 when the nominal interest rate is zero. We obtain very similar results if we replace z_t^{UNEMP} with z_t^{ZLB} for inference.[4]

1.1.3 Computing State-dependent Multipliers

Before calculating the government spending multipliers, we need to calculate impulse response functions based on the estimated model parameters. Since the economic dynamics differs across regimes, the effects of a government spending shock should depend on the regime when the shock hits. Conditional on the regime prevailing at the time of the shock, the impulse response function is proportional to the size and symmetric in the sign of the shock because future regimes of the economy are not affected by it. Due to the assumption that the regime-

[4] We can not put z_t^{UNEMP} and z_t^{ZLB} in the model at the same time because they are highly correlated.

switching process is governed by an exogenous Markov chain, it is easy to allow for regime transition throughout the duration of the responses.

For simplicity, we rewrite our model (1.1) as a typical four-variable VAR that augments $\mathbf{y}_t$ with N_t, with additional restrictions on the autoregressive coefficients, and represent it in companion form:

$$\tilde{\mathbf{y}}_t = \tilde{\mathbf{c}}(s_t) + \Phi(s_t)\tilde{\mathbf{y}}_{t-1} + \mathbf{B}(s_t)\tilde{\varepsilon}_t \tag{1.13}$$

where $\tilde{\mathbf{y}}_t = (N_t, G_t, T_t, Y_t, \ldots, N_{t-3}, G_{t-3}, T_{t-3}, Y_{t-3})'$ and $\tilde{\varepsilon}_t$ collects structural shocks. The expressions for $\tilde{\mathbf{c}}(s_t)$, $\Phi(s_t)$ and $\mathbf{B}(s_t)$ are provided in Appendix A.2. Let $\tilde{y}_{l,t}$ denote the lth element of $\tilde{\mathbf{y}}_t$ for $l = 1, \ldots, 4$. We follow Koop, Pesaran and Potter (1996) to define the generalized impulse response (*GIR*) of the lth variable at date $t+h$ to a shock to the kth variable ($k = 1, \cdots, 4$) at date t conditional on the regime prevailing as:

$$GIR^{k,l}_{t+h|s_t} \equiv E(\tilde{y}_{l,t+h}|\tilde{\varepsilon}_t = \mathbf{e}_k, s_t) - E(\tilde{y}_{l,t+h}|\tilde{\varepsilon}_t = \mathbf{0}, s_t) \tag{1.14}$$

where $\mathbf{e}_k$ is the kth column of the identity matrix $\mathbf{I}_{16}$. Note that in this definition, the response function does not depend on future regimes of the economy $\{s_{t+1}, \ldots, s_{t+h}\}$. It implies that the *GIR* measures on average what will happen in the future given the shock and current regime. Because the *GIR* is hard to estimate in existing nonlinear VAR models such as the smooth-transition VAR and the threshold VAR, many studies instead estimate the regime-dependent impulse response function (*RDIR*):

$$RDIR^{k,l}_{t+h|s_t} \equiv E(\tilde{y}_{l,t+h}|\tilde{\varepsilon}_t = \mathbf{e}_k, s_t = \cdots = s_{t+h}) - E(\tilde{y}_{l,t+h}|\tilde{\varepsilon}_t = \mathbf{0}, s_t = \cdots = s_{t+h}) \tag{1.15}$$

The *RDIR* measures the impact of a structural shock when the economy remains in its current regime for the horizon over which we calculate the impulse response function. The *RDIR* should be close to the *GIR* when the economy is currently in expansion since expansions usually last for long time. However, if the economy is currently in recession, the *RDIR* could be very different from the *GIR* at long horizons since recessions usually last for a short period. While the *RDIR* is much easier to estimate, it is not a good measure for the realistic effects of government spending shocks that happen in recessions at horizons beyond two years. As formalized in the following proposition, the *GIR* can be expressed as a function of $\Phi(s_t)$ and $\mathbf{B}(s_t)$: $GIR^{k,l}_{t+h|s_t} = \mathbf{e}_l' E(\prod_{i=1}^{h} \Phi(s_{t+i})|s_t)\mathbf{B}(s_t)\mathbf{e}_k$ for $h \geq 1$.

Proof. See Appendix A.3. □

This formula is very similar to the one for computing conventional impulse response functions except the expectation operator, which averages out all possible changes in future regimes. The remaining issue is how to compute the expectation. It is not impossible to write out the expectation term analytically, but it would become very complicated when h is large. One may also simulate the path of $\{s_{t+1}, \ldots, s_{t+h}\}$ and then take an average of the simulated values of the endogenous variable to obtain the impulse response function. Although this approach should yield a good estimate with a large number of simulations, it is computationally intensive especially when h is large. Therefore we propose a recursive method to solve out the expectation term and estimate the *GIR*. Let $\Phi_{s_t}^{(h)} \equiv E(\prod_{i=1}^{h} \Phi(s_{t+i})|s_t)$ for $h = 1, 2, \ldots$. We can calculate it recursively as:

$$\Phi_j^{(h)} = p_{j1}\Phi(1)\Phi_1^{(h-1)} + p_{j2}\Phi(2)\Phi_2^{(h-1)}$$

where $\Phi_1^{(0)} = \Phi_2^{(0)} = \mathbf{I}_{16}$ and $p_{ji} = p(s_t = i|s_{t-1} = j)$ for $i, j = 1, 2$. The generalized impulse response function can thus be calculated as:

$$GIR^{k,l}_{t+h|s_t} = \mathbf{e}_l' \Phi_{s_t}^{(h)} \mathbf{B}(s_t)\mathbf{e}_k$$

Proof. See Appendix A.4. □

Following Mountford and Uhlig (2009), Fisher and Peters (2010), Uhlig (2010), and Ramey and Zubairy (2018), we calculate the $H-$quarter cumulative government spending multiplier conditional on s_t as:

$$M_{s_t}^{H} = \frac{\sum_{h=0}^{H} GIR_{t+h|s_t}^{N,Y}}{\sum_{h=0}^{H} GIR_{t+h|s_t}^{N,G}} \tag{1.16}$$

The multiplier measures the cumulative change in output relative to the cumulative change in government spending in response to a military news shock in the first H quarters if the shock happens in regime s_t. Ramey and Zubairy (2018) argue that this cumulative method produces multipliers that are more relevant for policy purposes than the widely used measure originated by Blanchard and Perotti (2002) that defines the multiplier as the ratio of the peak response of output to the initial change in government spending. Ramey and Zubairy (2018) also show that the cumulative method tends to result in lower estimates of the multipliers as compared to the Blanchard-Perotti method.

1.2 Data and Results

We use U.S. quarterly data from 1890Q1-2015Q4 developed by Ramey and Zubairy (2018). Here we briefly describe the construction of this century-long dataset.[5] The military spending news series (N_t) is initially constructed by Ramey (2011) and then extended by Ramey and Zubairy (2018). In order to guarantee that the news series is unanticipated and exogenous, the authors use narrative methods to estimate changes in the expected present discounted value of government spending that are related to military and political events, which are by nature very likely to be independent of the state of the economy. Government spending (G_t) is defined as nominal government purchases including all federal, state, and local purchases, but net of transfer payments. Tax revenue (T_t) is the nominal value of federal government receipts. Output (Y_t) is nominal U.S. GDP. Quarterly data since 1947 is from BEA NIPA. For 1890-1946, historical annual series are interpolated to obtain quarterly series. The other variables, such as

[5] Full details can be found in the data appendix of Ramey and Zubairy (2018).

the GDP deflator and the unemployment rate, are constructed in similar ways. To construct the real trend GDP, Ramey and Zubairy (2018) use a sixth degree polynomial for the logarithm of GDP, from 1890 to 2015 excluding 1930 through 1946. We multiply real trend GDP by the GDP deflator to get nominal trend GDP and use it to scale variables in our model.

We estimate our model as described in the previous subsection. Table 1.1 shows the estimated reliability of z_t^{NBER} and z_t^{UNEMP}. The value of g_1^{NBER} is greater than g_1^{UNEMP} and the value of g_2^{NBER} is greater than g_2^{UNEMP}, suggesting that the official business cycle dates are overall a better proxy for s_t than the labor market condition. In Figure 1.1, we plot the time-varying probabilities of occurrence of regime 2. We declare that the economy is in regime 2 if the probability is above some threshold, say 0.5, and in regime 1 if otherwise.[6] It is clear that the historical periods when the economy is estimated to be in regime 2 correspond closely to the periods designated as recessions by the NBER. The correlation between our estimated regimes and z_t^{NBER}, z_t^{UNEMP} and the real GDP growth rate is 0.48, 0.16 and -0.54, respectively. As a consequence, we interpret regime 1 as expansion and regime 2 as recession without loss of generality. Our estimate of regime 2 misses some NBER recessions such as the one in 1953, 1960, 1970, 1980 and 1990, though. The main reason is that the declines in GDP are mild during these recessions. It is worth noting that our estimated regime 2 includes some periods when the unemployment rate was very high but the real economy was growing, such as a few periods during the Great Depression. Our estimated regime 2 also picks up some war periods such as 1918Q1-1918Q2 and 1943Q1-1943Q3 when the economy was in good shape for sure. This is probably because government purchases are much more stimulative during war years than during tranquil times.

The left panel of Figure 1.2 shows the effects of a military news shock that is normalized to be 1% of potential GDP. We display the generalized impulse responses of government spending, tax, and GDP together with 90% asymptotic confidence intervals. The responses of government spending and GDP are both more muted in expansions than in recessions. The right

[6] Any reasonable choice of the threshold does not affect our result.

Table 1.1. Estimated reliability of the NBER dates and the unemployment rate as proxies for the unobserved regime of the economy

Parameter	Point estimate	Standard error
g_1^{NBER}	0.81	0.03
g_2^{NBER}	0.73	0.07
g_1^{UNEMP}	0.68	0.03
g_2^{UNEMP}	0.54	0.07

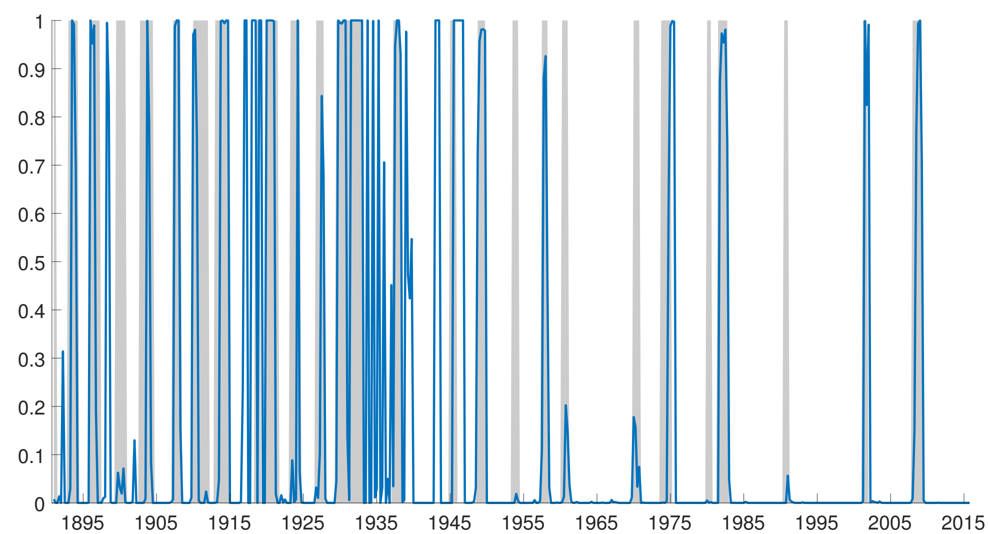

Figure 1.1. Smoothed probability of occurrence of regime 2

Note: The shaded region represents the NBER recession dates. The solid line shows the estimated time-varying probabilities of regime 2.

Table 1.2. Estimates of $H-$quarter cumulative government spending multipliers for expansion and recession

Horizon	Expansion	Recession	Gap
H = 4	0.55	0.97	0.42
	[0.35, 0.74]	[0.78, 1.18]	[0.16, 0.71]
H = 8	0.50	0.82	0.32
	[0.36, 0.63]	[0.66, 1.01]	[0.14, 0.53]
H = 12	0.51	0.79	0.29
	[0.38, 0.63]	[0.63, 0.98]	[0.14, 0.46]
H = 16	0.55	0.81	0.26
	[0.42, 0.68]	[0.64, 1.01]	[0.13, 0.43]
H = 20	0.59	0.84	0.24
	[0.45, 0.74]	[0.65, 1.06]	[0.12, 0.40]

Note: The results are obtained from the MS-SVAR model where both the NBER dates and the unemployment rate are used for inference about the unobserved regime of the economy. The values in brackets give the 90% confidence intervals.

panel of the same figure depicts the gaps in impulse responses between the recession regime and the expansion regime. As can be seen, the gaps are statistically significant.

Table 1.2 shows our estimates of the government spending multipliers at various horizons for different regimes. The first thing we should note is that the multipliers are always smaller than 1, suggesting that government purchases always crowd out private demand to some extent. The multiplier values are stable over horizons. If the shock happens during an expansion, the multiplier values are around 0.55. If the shock happens during a recession, the multiplier values are around 0.9. The 1-year multiplier for recession is very close to 1 and is almost twice as large as the 1-year multiplier for expansion. The second thing to note is that the gaps in the multipliers between recessions and expansions are statistically significant, although it is not obvious whether the gaps are economically significant. Our results indicate that the differences in the effects of government spending between good and bad times may not be as large as some previous studies estimate.

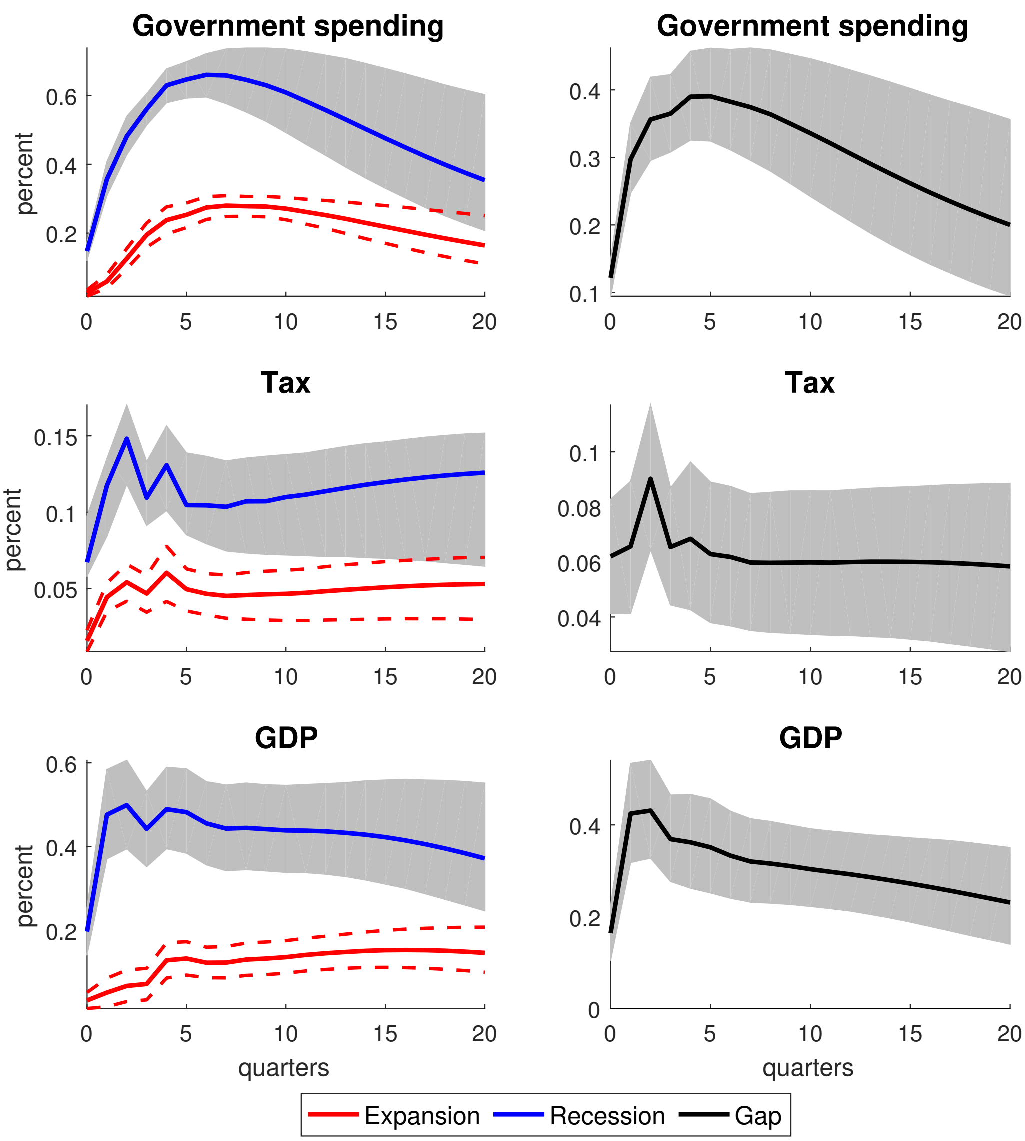

Figure 1.2. Generalized impulse responses (% of potential GDP) of government spending, tax, and GDP to a military news shock for expansion and recession, and differences in impulse responses between the two regimes

Note: The left panel shows the generalized impulse responses of government spending, tax, and GDP to a military news shock that is normalized to be 1% of potential GDP. The red solid lines are impulse responses for regime 1 (expansion) and the blue solid lines are impulse responses for regime 2 (recession). The right panel shows differences in impulse responses between the two regimes. The shaded area and dashed lines represent the 90% asymptotic confidence intervals.

1.3 Reconciling Estimates of the Government Spending Multipliers

Our estimates of the government spending multipliers challenge some existing results in the literature. For example, Auerbach and Gorodnichenko (2012*a*) obtain multipliers as high as 2.24 for recession, whereas we do not observe any multiplier value that is greater than 1. Moreover, our finding of the state dependence of the government spending multipliers is at odds with the extensive evidence provided by Ramey and Zubairy (2018) that the multipliers do not vary with the amount of slack in the economy, although we use the same dataset. In this section, we relate our empirical strategy to these two studies, and explain why we reach different conclusions.

1.3.1 Auerbach and Gorodnichenko (2012a)

The pioneering paper by Auerbach and Gorodnichenko (2012*a*) (AG hereafter) estimates a smooth-transition structural VAR to measure the asymmetric effects of government spending shocks over the business cycle. Although their paper is different from ours in many aspects, such as model specification, identification, and data used, we reach the same conclusion that government spending is more effective in recessions as compared to in expansions.

Nevertheless, AG differ from us in the magnitudes of the multipliers. At the 5-year horizon, AG's estimate of the multiplier for recession is 2.24 whereas our estimate is 0.84. To explain the difference, we focus on the different methods for constructing impulse response functions employed by AG and us. In AG, the authors assume that the economy remains in its current regime throughout the duration of the responses to a government spending shock. In other words, AG estimate the regime-dependent impulse response functions instead of the generalized impulse response functions. Ramey and Zubairy (2018) point out that AG's estimate of the multiplier for recession grows as the horizon grows because their constructed impulse response for GDP keeps increasing while government spending does not. The reason why the response of GDP is so unusual is that AG assumes the economy to remain in recession, and people should forecast future output growth to be higher than current growth during recessions. To verify this explanation, Ramey and Zubairy (2018) estimate AG's model, but allow the regime of the economy to switch endogenously with respect to the history of both the government spending shocks and the nongovernment spending shocks when converting the model parameters into impulse response functions. They find that the multipliers in recessions are around 1, which are very close to our results.

We add to the evidence provided by Ramey and Zubairy (2018) by calculating what the multipliers would be for our maximum likelihood estimates if we were to prohibit the regime from switching. Figure 1.3 shows the result. Under the assumption of non-changing regimes, we obtain much larger multipliers for recession than our benchmark result. The multiplier grows with the horizon and becomes 1.9 after five years, which is in line with AG's finding. We conclude that previous studies constructing the government spending multipliers based on the regime-dependent impulse response functions tend to overestimate the average effects of government purchases in recessions.

1.3.2 Ramey and Zubairy (2018)

Ramey and Zubairy (2018) (RZ hereafter) argue that there are no differences in the effects of government spending shocks between slack regimes and non-slack regimes. Instead of using a structural VAR, they adapt the local projection method proposed by Jordà (2005) to estimate state-dependent impulse responses of government spending and GDP to military news shocks. They estimate the 2-year and 4-year cumulative multipliers to be around 0.6 in both slack periods and non-slack periods.

In line with RZ, we find that the government spending multipliers are always smaller than 1 regardless of the regime of the economy. However, in contrast to RZ, we find statistically significant evidence that the effects of government spending are stronger in recessions than in expansions. We believe the main reason why RZ fail to observe statistically significant

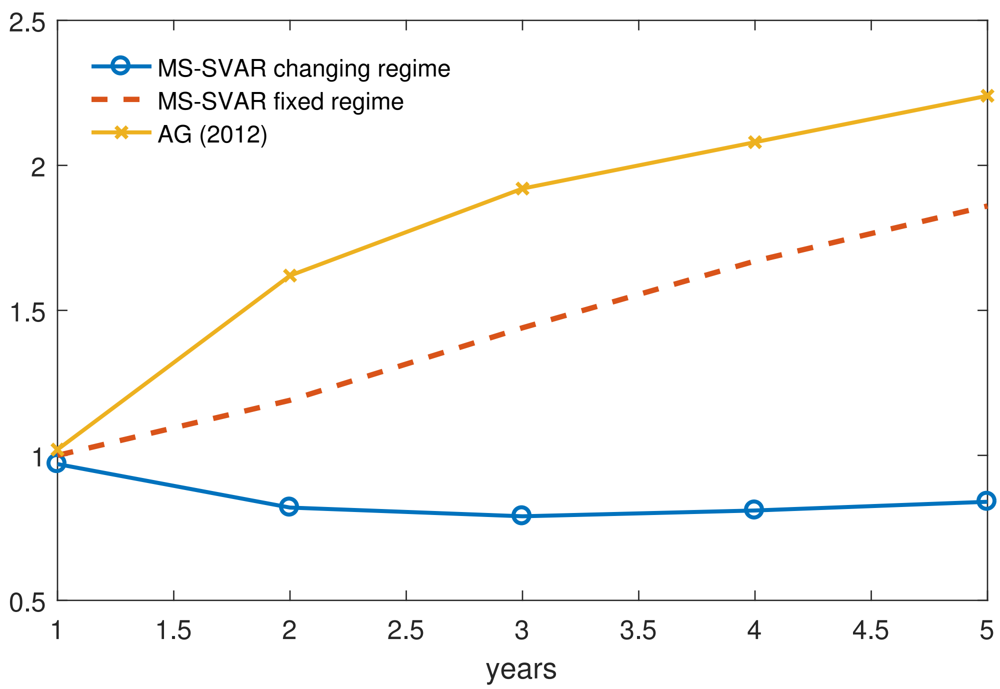

Figure 1.3. Cumulative government spending multipliers for the recession regime for alternative specifications

Note: This figure shows cumulative government spending multipliers for the recession regime at various horizons. The blue line with circles shows the multipliers obtained from our MS-SVAR model that allows the regime to change. The dashed line shows the multipliers obtained from our MS-SVAR model assuming a fixed regime of the economy after the shock. The yellow line with x-marks shows the multipliers obtained by Auerbach and Gorodnichenko (2012*a*).

variations in the multipliers is that the local projection method they use to construct impulse response functions (and the government spending multipliers) is too inefficient to generate precise estimates. Essentially this is a multiperiod direct forecasting method that is subject to efficiency loss relative to the VAR method based on one-period-ahead forecasting. As a result, one may not be able to reject the null hypothesis of constant government spending multipliers using the local projection method, even if the multipliers are truly state-dependent.

RZ show that their conclusion is robust no matter whether we use the NBER business cycle dates or the unemployment rate to measure slack and non-slack regimes. We are not surprised that RZ do not find variations in the government spending multipliers across times of high unemployment and times of low unemployment because we have shown that the labor market condition is not a reliable indicator of the regime of the economy across which the multipliers differ. Nevertheless, we do expect to see some variations in the multipliers across official business cycle phases because our estimated regimes have a high correlation with the NBER dates. To verify that, we estimate our MS-SVAR model using only z_t^{NBER} or z_t^{UNEMP} for inference.[7] First, we assume that the NBER dates are a perfect measure for the regime of the economy, namely $s_t = z_t^{NBER}$. Table 1.3 shows the result. While the multipliers in expansions are always smaller than 1, the multipliers in recessions are always larger than 1. The differences in the multipliers between recessions and expansions are statistically significant at the 1-year horizon and the 2-year horizon. Next we assume that the unemployment rate-based indicator variable is a perfect measure for the regime, namely $s_t = z_t^{UNEMP}$. In this case, the multiplier is always smaller than 1 irrespective of the regime or horizon. The multipliers in slack periods and non-slack periods are very similar. The gaps in the multipliers are negligible and statistically insignificant. The magnitudes of the multipliers are also close to RZ's estimates.

To illustrate that the inefficiency of the local projection method explains why RZ fail to observe differences in the government spending multipliers when they use the NBER dates to

[7] In this experiment, the Markov transition probabilities are not identified in the model. We calibrate the values of the transition probabilities using the series of z_t^{NBER} or z_t^{UNEMP}.

Table 1.3. Estimates of state-dependent $H-$quarter cumulative government spending multipliers: regime measured by the NBER dates or the unemployment rate

	NBER dates		
Horizon	Expansion	Recession	Gap
H = 4	0.38	1.20	0.82
	[0.05, 0.71]	[0.33, 2.37]	[0.07, 1.84]
H = 8	0.34	1.17	0.83
	[-0.07, 0.74]	[0.09, 2.60]	[0.01, 2.05]
H = 12	0.30	1.12	0.83
	[-0.17, 0.74]	[-0.11, 2.75]	[-0.09, 2.20]
H = 16	0.25	1.08	0.83
	[-0.25, 0.74]	[-0.25, 2.86]	[-0.15, 2.34]
H = 20	0.20	1.04	0.83
	[-0.34, 0.72]	[-0.37, 2.94]	[-0.18, 2.42]

	Unemployment rate		
Horizon	Low	High	Gap
H = 4	0.50	0.50	0.00
	[-0.15, 1.13]	[0.23, 0.77]	[-0.66, 0.72]
H = 8	0.47	0.47	0.00
	[-0.14, 1.11]	[0.24, 0.72]	[-0.58, 0.57]
H = 12	0.40	0.45	0.05
	[-0.33, 1.17]	[0.21, 0.70]	[-0.61, 0.66]
H = 16	0.36	0.43	0.06
	[-0.36, 1.20]	[0.18, 0.70]	[-0.60, 0.65]
H = 20	0.35	0.41	0.06
	[-0.35, 1.17]	[0.14, 0.71]	[-0.57, 0.62]

Note: The results are obtained from the MS-SVAR model where the regime is measured precisely by the NBER dates or the unemployment rate. The values in brackets give the 90% confidence intervals.

measure the regime of the economy, we show what the multipliers would be if we employ the local projection method for estimation. Following RZ, we estimate the $h-$period cumulative government spending multiplier by regressing the sum of GDP from t to $t+h$ on the sum of government spending from t to $t+h$ and control variables $N_{t-j}, G_{t-j}, T_{t-j}, Y_{t-j}$ ($j = 1, \cdots, 4$), using the military spending news variable N_t as an instrument for the sum of government spending. To allow for state-dependence, the values of the regression coefficients are postulated to depend on the NBER dates. Table 1.4 shows the result. Two things are worth noting. First, the multipliers in recessions are estimated to be negative, which is hard to interpret. The second thing to note is that the estimates are very imprecise. According to the confidence intervals reported, we are unable to reject the null hypothesis that the multipliers in expansions and recessions are equal. However, due to the large standard errors associated with the point estimates, we are also unable to reject the null that the gaps in the multipliers between expansions and recessions equal our estimates based on the MS-SVAR, as shown in Table 1.3.

1.4 Time-varying Transition Probabilities

A key feature of our MS-SVAR model is that the regime transition probabilities are constant. This assumption makes the model more tractable. However, one may think that the regime of the economy is likely to be affected by fiscal policy shocks. Presumably a positive government spending shock can help the economy escape from recession, while a negative government spending shock may end an expansion early. Therefore a natural generalization of our model is to allow the transition probabilities to depend on the values of fiscal shocks. In this section, we first test if the assumption of constant transition probabilities is reasonable, and then check the robustness of our result with the assumption relaxed.

There are many ways to specify time-varying transition probabilities, and we consider a simple one. Motivated by Diebold, Lee and Weinbach (1994) and Kim and Nelson (1999), we assume that the state variable s_t has a logit specification:

$$s_t = \begin{cases} 1 & \text{if } s_t^* < 0 \\ 2 & \text{if } s_t^* \geq 0 \end{cases} \tag{1.17}$$

where s_t^* is a latent variable defined by:

$$s_t^* = a_0 + a_1 \delta_{2,t-1} + \gamma N_{t-1} + \eta_t \tag{1.18}$$

$\delta_{2,t-1} = 1$ if $s_{t-1} = 2$ and 0 otherwise. N_{t-1} is the lagged military spending news shock (divided by potential GDP), and η_t follows a standard logistic distribution.[8] The transition probabilities are then time-varying:

$$p_{11,t} \equiv p(s_{t+1} = 1 | s_t = 1, N_t) = \frac{1}{1 + \exp(a_0 + \gamma N_t)} \tag{1.19}$$

$$p_{22,t} \equiv p(s_{t+1} = 2 | s_t = 2, N_t) = \frac{\exp(a_0 + a_1 + \gamma N_t)}{1 + \exp(a_0 + a_1 + \gamma N_t)} \tag{1.20}$$

If $\gamma = 0$, the transition probabilities become time-invariant and the model collapses to our benchmark model in section 2. Therefore we can test the assumption of constant transition probabilities by the significance of γ.

We estimate our MS-SVAR adapted for time-varying transition probabilities as specified above. Table 1.5 shows the estimates of the parameters in equation (1.19) and (1.20) along with their standard errors. The null hypothesis $\gamma = 0$ can not be rejected, which implies that the regime of the economy is not likely to be affected by fiscal policy shocks and thus justifies our assumption of constant regime transition probabilities.

[8] We assume that the regime of the economy is realized at the beginning of each period, so the military news shock affects the regime of the next period.

Table 1.4. Local projection estimates of $H-$quarter cumulative government spending multipliers for expansion and recession

Horizon	Expansion	Recession	Gap
H = 4	0.50	0.52	0.03
	[0.24, 0.75]	[-0.28, 1.33]	[-0.83, 0.88]
H = 8	0.58	0.11	-0.47
	[0.43, 0.72]	[-1.15, 1.37]	[-1.79, 0.85]
H = 12	0.66	-0.46	-1.12
	[0.56, 0.76]	[-2.39, 1.46]	[-3.08, 0.84]
H = 16	0.66	-0.74	-1.40
	[0.55, 0.76]	[-3.07, 1.59]	[-3.76, 0.97]
H = 20	0.69	-0.74	-1.43
	[0.57, 0.82]	[-3.00, 1.53]	[-3.74, 0.88]

Note: The results are obtained from the local projection estimation. The NBER dates are used as the indicator of the regime of the economy. The values in brackets give the HAC-robust 90% confidence intervals.

Table 1.5. Estimates of parameters in the logit specification of s_t

Parameter	Point estimate	Standard error
a_0	-2.51	0.20
a_1	3.16	0.32
γ	0.11	2.57

Next we show that time variation in the transition probabilities has a negligible effect on our estimates of the fiscal multipliers. If the military spending news shock affects the regime of the following period, the government spending multipliers are supposed to be dependent on the value of the shock. To illustrate, we consider two extreme cases. In the first case, the military spending news shock takes the maximum value over our sample period, which was seen in 1941Q4 due to the direct involvement of the U.S. in WWII. In the second case, the military spending news shock takes the minimum value over our sample period, which was seen in 1945Q3 due to the ending of WWII. Table 1.6 reports the estimated government spending multipliers for both cases. As can be seen, the multipliers are very similar to our benchmark results in Table 1.2. Therefore our conclusion is robust to time variation in the regime transition probabilities.

1.5 Conclusion

This paper proposes a Markov regime-switching structural VAR to study the state-dependent effects of government spending shocks on aggregate output. Using a U.S. dataset, we find that the government spending multipliers are statistically larger in recessions than in expansions, which confirms the existing evidence that fiscal policy is more effective during bad times. However, the multipliers are always smaller than 1, and the differences between recessions and expansions are not as large as some previous studies have claimed.

Our model has two distinctive features that enable us to understand why previous studies reach different conclusions. First, we combine quantitative data and qualitative indicators to infer the regimes across which the government spending multipliers differ. Second, we propose a recursive method to estimate the dynamic effects of a government spending shock that allows the regime of the economy to change after the shock. We show that if we prohibit the regime from switching, we will obtain much larger multipliers for recession. This explains why Auerbach and Gorodnichenko (2012*a*), who assume the economy to remain in its current regime indefinitely,

Table 1.6. Estimates of state-dependent $H-$quarter cumulative government spending multipliers for two extreme cases: allowing for time-varying transition probabilities

	Shock=$max_t N_t$		
Horizon	Expansion	Recession	Gap
H = 4	0.55	0.97	0.42
	[0.36, 0.74]	[0.78, 1.18]	[0.17, 0.71]
H = 8	0.50	0.82	0.32
	[0.37, 0.63]	[0.66, 1.00]	[0.15, 0.53]
H = 12	0.51	0.79	0.29
	[0.39, 0.63]	[0.64, 0.97]	[0.14, 0.45]
H = 16	0.55	0.81	0.26
	[0.43, 0.67]	[0.66, 0.99]	[0.13, 0.41]
H = 20	0.59	0.84	0.24
	[0.46, 0.73]	[0.68, 1.03]	[0.12, 0.39]

	Shock=$min_t N_t$		
Horizon	Expansion	Recession	Gap
H = 4	0.54	0.97	0.42
	[0.35, 0.73]	[0.78, 1.17]	[0.17, 0.70]
H = 8	0.50	0.82	0.32
	[0.36, 0.62]	[0.67, 0.99]	[0.15, 0.52]
H = 12	0.51	0.79	0.29
	[0.38, 0.62]	[0.64, 0.96]	[0.14, 0.44]
H = 16	0.55	0.81	0.26
	[0.42, 0.67]	[0.66, 0.98]	[0.13, 0.41]
H = 20	0.59	0.84	0.24
	[0.47, 0.73]	[0.68, 1.01]	[0.12, 0.38]

Note: We estimate our MS-SVAR model allowing for time-varying transition probabilities, and estimate state-dependent government spending multipliers for two extreme cases. The upper panel shows the results for the case where the military news shock takes the maximum value over our sample period. The lower panel shows the results for the case where the military news shock takes the minimum value over our sample period. The values in brackets give the 90% confidence intervals.

obtain very large multipliers in recessions. Moreover, we argue that the main reason why Ramey and Zubairy (2018) do not find statistically significant differences in the government spending multipliers between good and bad times is that their estimation strategy is inefficient. We show that their method produces much less precise estimates than ours.

Chapter 1, in full is currently being prepared for submission for publication of the material. Lyu, Yifei; Noh, Eul. The dissertation author was a primary investigator and author of this material.

Chapter 2

Disentangling the Effects of Oil Price Shocks

Oil price fluctuations have been regarded as an important driver of the business cycle since the 1970s. There are in general four types of oil price shocks, depending on whether the increase in oil prices is driven by supply shortfalls, stronger economic activity, higher oil consumption demand, or higher inventory demand for oil that mainly reflects concerns about future oil supply shortfalls.[1] Since Kilian (2009), structural vector autoregression (SVAR) models have been widely used to study and compare the effects of oil supply and demand shocks on oil prices and economic activity.

In this paper, I estimate a standard SVAR of the global crude oil market to decompose the effects of oil price shocks. In particular, I estimate each structural equation by two-stage least squares using external or internal instrumental variables. I find that a negative oil supply shock leads to a delayed but significant decrease in global economic activity, proxied by world industrial production. The real price of oil increases and oil inventories decrease significantly. A positive global demand shock leads to significant increases in oil production and oil prices but decreases in oil inventories. While a positive oil consumption demand shock has negligible and insignificant effects, a positive oil inventory demand shock leads to statistically and economically significant falls in oil production and economic activity. Forecast error variance and historical

[1] Oil inventory demand shocks are also referred to as speculative demand shocks in the literature.

decompositions show that most variation in oil price changes are due to oil consumption demand shocks. The results are robust to a battery of sensitivity checks.

This paper contributes to the literature disentangling oil supply and demand shocks. The majority of literature identifies oil price shocks through timing restrictions or sign restrictions; see Kilian (2009), Lippi and Nobili (2012), Baumeister and Peersman (2013), Kilian and Murphy (2012, 2014), and Baumeister and Hamilton (2019) among others. However, the result depends critically on researchers' prior on the short-run price elasticity of oil supply (Baumeister and Hamilton 2019, Herrera and Rangaraju 2018, Kilian and Zhou 2018). By using instruments, I do not need to put any restrictions on model parameters and thus avoid imposing any prior on the elasticity.

This paper is not the first one that exploits external instruments to identify oil market shocks. A novelty of my approach is that I identify four types of oil shocks at the same time, whereas the existing studies usually identify only one type. For example, Hamilton (2003), Stock and Watson (2012), and Caldara, Cavallo and Iacoviello (2018) identify oil supply shocks, and Känzig (2019) identifies oil supply news shocks. In addition, the validity of traditional instruments for oil supply shocks is worth questioning. For example, similar to Hamilton (2003), Caldara, Cavallo and Iacoviello (2018) construct their instrument based on declines in crude oil production (as a percentage of global oil production in previous period) in countries that are experiencing geopolitical events and natural disasters. However, during these exogenous events, the dramatic oil supply shocks may go hand in hand with positive oil inventory demand shocks due to uncertainty about future oil supplies. To illustrate this point, I depict in Figure 2.1 the relationship between the instrument in Caldara, Cavallo and Iacoviello (2018) and the inverse of the 12-month oil futures spread, a measure for oil inventory demand shocks proposed by Alquist and Kilian (2010), during the selected periods. Clearly evident is the fact that episodes of large exogenous declines in oil production are associated with spikes in oil inventory demand.

The remainder of this paper is organized as follows. Section 2.1 presents the empirical

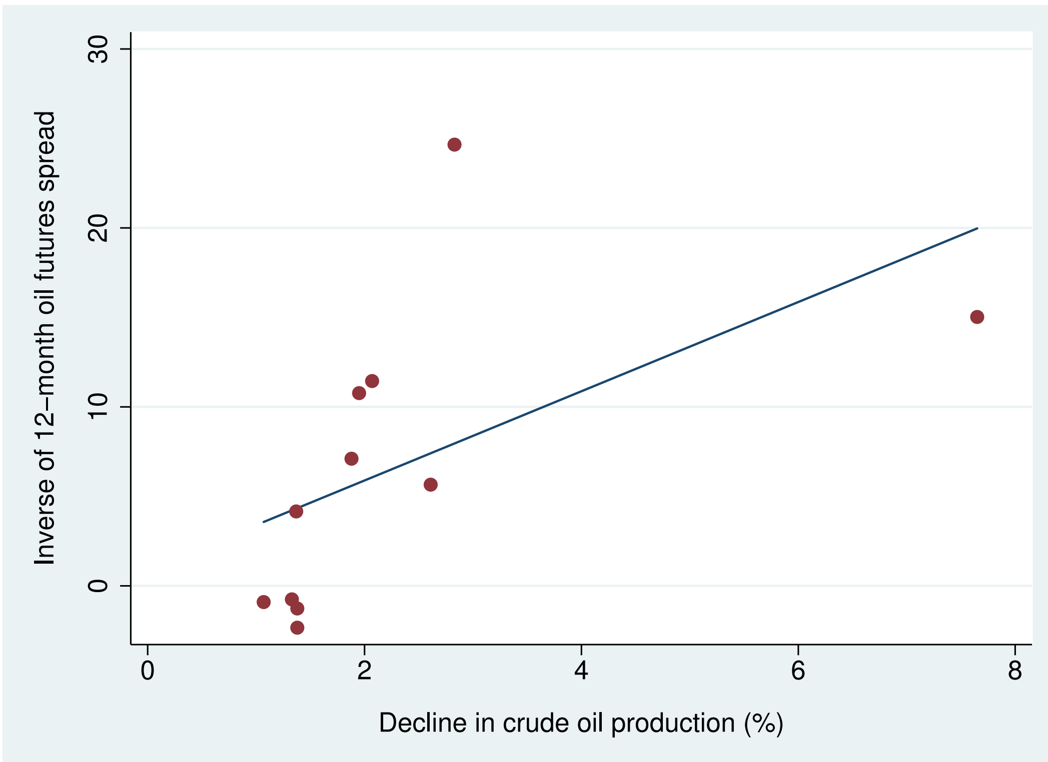

Figure 2.1. Proxies for oil inventory demand shocks and oil supply shocks.

Note: The scatter plot depicts the relationship between proxies for two structural oil market shocks during episodes of geopolitical events and natural disasters from January 1989 to December 2016 selected by Caldara, Cavallo and Iacoviello (2018). The horizontal axis shows the decline in crude oil production (as a percentage of global oil production) in countries that are subject to the event, a proxy for oil supply shocks constructed by Caldara, Cavallo and Iacoviello (2018). The vertical axis shows the inverse of the 12-month oil futures spread, a proxy for oil inventory demand shocks proposed by Alquist and Kilian (2010).

strategy. Section 2.2 shows the main results. Section 2.3 runs robustness checks and section 2.4 concludes.

2.1 Modelling the Global Crude Oil Market

2.1.1 An Oil Market Structural VAR

The following four equations describe the global crude oil market:

$$q_t = \beta_{q,p} p_t + \gamma_q' \mathbf{x}_{t-1} + \varepsilon_{q,t} \tag{2.1}$$

$$y_t = \beta_{y,p} p_t + \gamma_y' \mathbf{x}_{t-1} + \varepsilon_{y,t} \tag{2.2}$$

$$p_t = \beta_{p,q}(q_t - \Delta i_t) + \beta_{p,y} y_t + \gamma_p' \mathbf{x}_{t-1} + \varepsilon_{p,t} \tag{2.3}$$

$$\Delta i_t = \beta_{i,q} q_t + \beta_{i,y} y_t + \beta_{i,p} p_t + \gamma_i' \mathbf{x}_{t-1} + \varepsilon_{i,t} \tag{2.4}$$

where q_t, y_t, p_t are log growths in global crude oil production, world industrial production, and the real price of oil. Δi_t is the change in oil inventories as a percentage of oil production in previous period. $\mathbf{x}_{t-1}$ includes a constant and 24 lags of q_t, y_t, p_t, and Δi_t, as suggested by Kilian and Murphy (2014). This model follows exactly Baumeister and Hamilton (2019), except the number of autoregressive lags and that I do not consider measurement error in oil inventories for simplicity.[2]

Equation (2.1) represents the oil supply curve, where $\beta_{q,p}$ denotes the short-run price elasticity of supply, and $\varepsilon_{q,t}$ is the shock to oil supply. Equation (2.2) determines the global economic activity, where $\varepsilon_{y,t}$ is the shock to global demand. I assume that y_t only reacts to the price of oil within the period, so changes in oil production and oil inventory demand have an indirect contemporaneous effect on economic activity through changes in prices. Equation (2.3) describes the inverse oil demand curve, where $q_t - \Delta i_t$ is the growth in oil consumption and

[2] As far as I know, Baumeister and Hamilton (2019) is the only study in the literature that considers measurement error. Kilian and Zhou (2018) also argue that there is no reason to focus on measurement error in oil inventories exclusively.

$\varepsilon_{p,t}$ measures the shock to oil consumption demand. Equation (2.4) models the determinants of oil inventories, where $\varepsilon_{i,t}$ is the shock to inventory demand. As discussed in Kilian and Murphy (2014), oil inventory demand may change for many reasons, for example, in response to news about future oil supplies or future demand, uncertainty about future supply shortfalls, and changes in traders' perception about what other traders think. In this paper, I do not differentiate further between the sources where inventory demand shocks originate.

2.1.2 Estimation

Without further identifying restrictions on the parameters, we need at least one external instrumental variable (IV) in order to fully estimate the structural model. Suppose there exists an instrument z_t that is correlated with $\varepsilon_{i,t}$ but uncorrelated with shocks to oil supply ($\varepsilon_{q,t}$) and global demand ($\varepsilon_{y,t}$). Then we can estimate equations (2.1) to (2.4) sequentially using two-stage least squares as follows:

(i) estimate equation (2.1) using z_t as the IV for p_t, and get the residual $\hat{\varepsilon}_{q,t}$.

(ii) estimate equation (2.2) using z_t as the IV for p_t, and get the residual $\hat{\varepsilon}_{y,t}$.

(iii) estimate equation (2.3) using $\hat{\varepsilon}_{q,t}$ and $\hat{\varepsilon}_{y,t}$ as IVs for $q_t - \Delta i_t$ and y_t, and get the residual $\hat{\varepsilon}_{p,t}$.

(iv) estimate equation (2.4) using $\hat{\varepsilon}_{q,t}$, $\hat{\varepsilon}_{y,t}$, and $\hat{\varepsilon}_{p,t}$ as IVs for q_t, y_t and p_t, and get the residual $\hat{\varepsilon}_{i,t}$.

2.1.3 External Instrument: Oil Supply Surprises

The oil supply surprise series constructed by Känzig (2019) serves as a good candidate for the instrument z_t we need. In a nutshell, Känzig (2019) develops a proxy for oil supply news shocks by using changes in oil futures prices around the announcements made by the Organization of the Petroleum Exporting Countries (OPEC), which contributes to nearly half

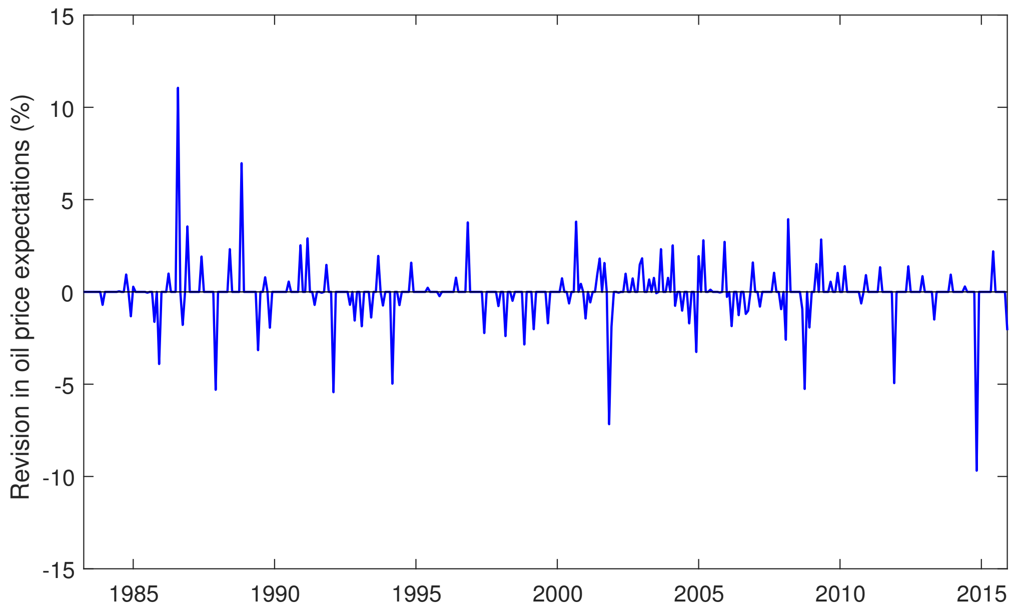

Figure 2.2. Figure 1 in Känzig (2019): the oil supply surprise series constructed from changes in oil futures prices around OPEC announcements.

of world crude oil production and has a remarkable impact on oil prices. More specifically, the author takes the (log) difference between the settlement price of the 6-month West Texas Intermediate crude oil futures contract on the day of each OPEC announcement and the price on the last trading day before the announcement. Then he aggregates the daily surprises into a monthly series. If there is no announcement in a month, the monthly surprise takes zero value. The original series in Känzig (2019), plotted in Figure 2.2, starts in 1983M4 when the futures data is available and ends in 2015M12. In order to match the sample period of the other variables in my model, I extend the series such that it starts in 1968M1 and ends in 2016M12. The missing values are simply censored to zero.

Obviously, the oil supply surprise series is correlated with the oil inventory demand shock $\varepsilon_{i,t}$ and thus also correlated with p_t.[3] On the contrary, as argued by Känzig (2019), the shock to global economic activity $\varepsilon_{y,t}$ is uncorrelated with the surprise series because global

[3] I will test the strength of the surprise series as an instrument for p_t in the next section.

economic conditions are already priced in by the market before the OPEC announcements and are unlikely to change within the tight window used to measure the oil supply surprises. As a result, the surprise series can be regarded as a valid instrument for p_t in equation (2.2).

In order for the surprise series to be valid as an instrument in equation (2.1), it also needs to be uncorrelated with the shock to oil supply $\varepsilon_{q,t}$. Although it is not possible to directly test the exogeneity condition due to the fact that $\varepsilon_{q,t}$ is not observable, I try to establish an assessment indirectly by exploring the relationship between the surprise series and a proxy for oil supply shocks.[4] In particular, I extend the monthly proxy constructed by Caldara, Cavallo and Iacoviello (2018) based on geopolitical events and natural disasters back to 1968M1 by including three additional exogenous events that are quantitatively important: the Arab-Israel war in November 1973, the Iranian revolution lasting from November 1978 to January 1979, and the Iran-Iraq war in October 1980.[5] Then I regress the oil supply surprise series z_t on the extended proxy for supply shocks m_t. The result is as follows (robust standard errors in parentheses):

$$z_t = \underset{(0.05)}{-0.02} + \underset{(0.04)}{0.03}\, m_t \tag{2.5}$$

The slope coefficient is very insignificant, suggesting that the surprise series is not picking up oil supply shocks. This is actually not surprising. As pointed out by Känzig (2019), the surprises should not capture current supply shocks because of the 30 day implementation lag of OPEC decisions.

[4]Piffer and Podstawski (2017) employ a similar method to indirectly test the exogeneity of their constructed proxy for uncertainty shocks.

[5]To be consistent, I follow the methodology in Caldara, Cavallo and Iacoviello (2018) that measures supply shocks by declines in crude oil production (as a percentage of global oil production in previous period) in countries that are involved in the events. Specifically, the total loss of oil production from Algeria, Kuwait, Libya, Qatar, Saudi Arabia, and the U.A.E. in November 1973 is 5.7%; the losses of Iranian oil production in the three months from November 1978 to January 1979 are 3.2%, 1.8%, and 2.7%, respectively; the total loss from Iranian and Iraqi oil production in October 1980 is 5.8%.

2.1.4 Data

Most of the data comes from Baumeister and Hamilton (2019) directly. The world industrial production index is constructed by the authors by including OECD countries plus six major non-OECD countries (Brazil, China, India, Indonesia, Russia, and South Africa). The real price of oil is measured by the refiner acquisition cost of crude oil imports deflated by the US CPI. This measure is widely used in the literature because it reflects the price of oil in global markets and was not subject to price control in the 1970s. The global oil inventories are estimated by multiplying the US crude oil inventories by the ratio of OECD petroleum stocks over US petroleum stocks.[6] More details can be found in the appendix of Baumeister and Hamilton (2019). The sample period is 1968M1-2016M12. The starting date is determined by the availability of oil price data.[7]

2.2 Results

2.2.1 First Stage

The estimation of structural equations (2.1)-(2.4) delivers reliable results only if the external instrument z_t and the internal instruments $\hat{\varepsilon}_{q,t}$, $\hat{\varepsilon}_{y,t}$, and $\hat{\varepsilon}_{p,t}$ are not weak. In Table 2.1, I report a standard first-stage F-statistic (Cragg-Donald Wald F-statistic) and also a robust F-statistic (Kleibergen-Paap Wald F-statistic) which allows for heteroskedasticity for each equation. Because all F-statistics are above the threshold value of 10 that is recommended by Stock, Wright and Yogo (2002), we should be confident that the weak instrument problem is not present. In addition, the robust F-statistics for equation (2.1) and (2.2) are large enough to reject the null of weak instruments for an asymptotic bias of 20% at a signicance level of 10% based on the test proposed by Montiel Olea and Pflueger (2013).

[6]Non-OECD strategic reserves are not counted in due to the lack of data. Nevertheless, the oil inventories of major non-OECD countries are very small in most of my sample period.

[7]The refiner acquisition cost for imported crude oil, as reported by the Energy Information Administration (EIA), is available as of January 1974. The series is extended back to January 1968 by Baumeister and Peersman (2013).

Table 2.1. Tests of the strength of the instruments

	Equation			
	(2.1)	(2.2)	(2.3)	(2.4)
F-stat	14.02	14.02	515.60	13173.25
F-stat (robust)	12.96	12.96	559.41	13527.22

2.2.2 Estimated Shocks

Figure 2.3 shows the estimated structural shocks. In the 1970s and 1980s, there were quite a few large negative oil supply shocks, such as the one in November 1973 due to the Arab-Israel war and the one in October 1980 due to the Iran-Iraq war. However, there seems to be no evidence of a big decline in world oil production associated with the Iranian revolution from November 1978 to January 1979, which is in line with Kilian (2009). The last large negative supply shock happened in August 1990 due to the Persian Gulf war, which Kilian (2009) fails to identify. After then, oil supply shocks become very small. Regarding global demand shocks, there was a large positive one in 1978 and a large negative one in 2008. Oil consumption demand shocks are very volatile. A large negative shock happened in 1986 and a large positive one happened at the beginning of the Persian Gulf war. The last quarter of 2008 was characterized by repeated large negative shocks to oil consumption demand, followed by large positive shocks in the first quarter of 2009. There were also large negative consumption demand shocks in December 2014 and January 2015. Regarding oil inventory demand shocks, the largest one occurred in March 1990, a few months before the Persian Gulf war.

2.2.3 Impulse Responses

Figure 2.4 depicts impulse responses (shown in levels) to one standard deviation structural oil market shocks. The supply shock is negative and the other three shocks are positive. The dashed lines are the 90% confidence intervals based on the moving block bootstrap method

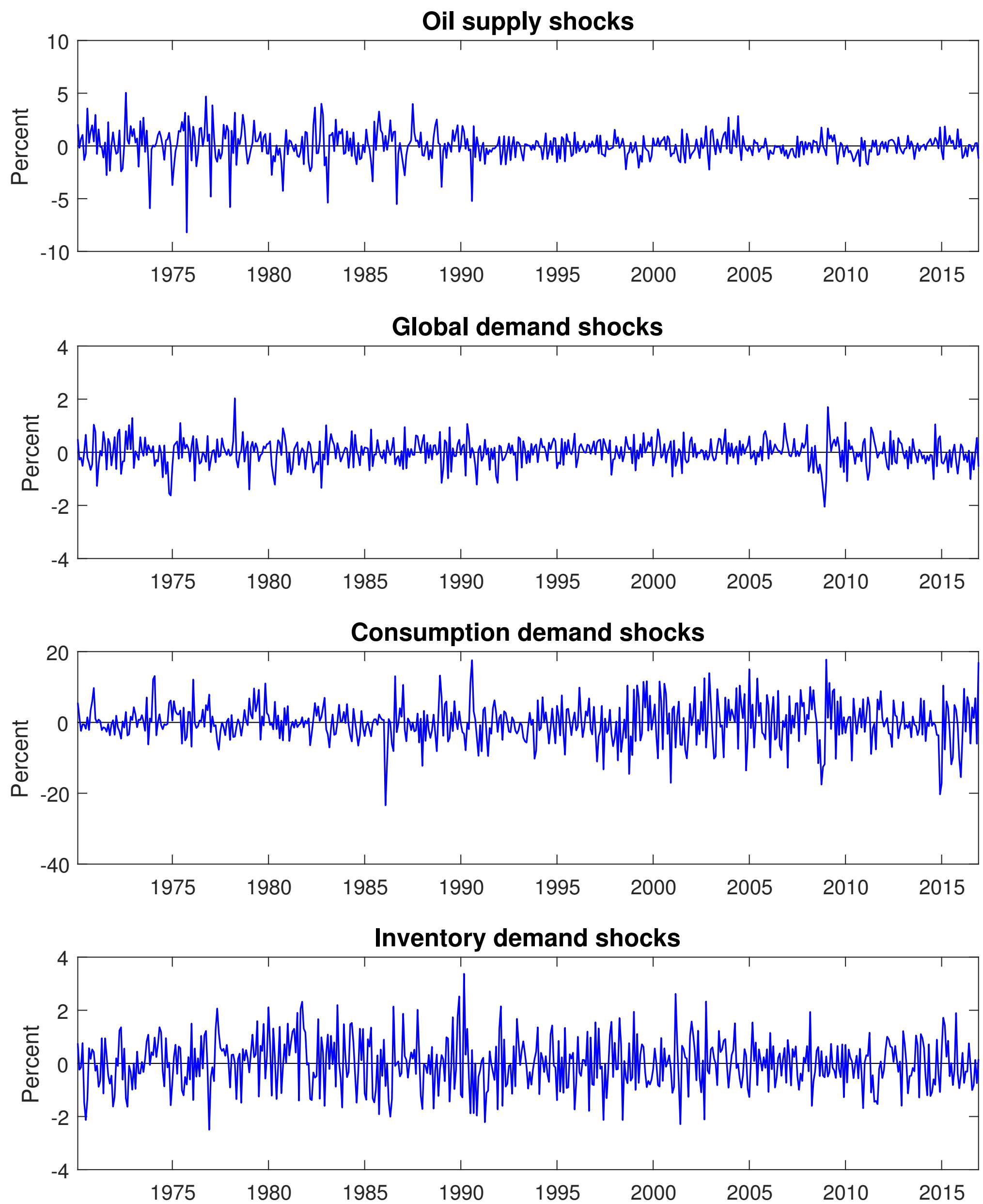

Figure 2.3. Estimated oil shocks.

proposed by Jentsch and Lunsford (forthcoming).[8]

A conventional oil supply shock leads to a significant increase in oil prices and significant declines in global economic activity and oil inventories. It is worth noting that economic activity declines only after about one year. These are all consistent with the findings in the literature such as Kilian and Murphy (2014) and Baumeister and Hamilton (2019). A positive shock to global economic activity leads to a significant increase in oil prices, and therefore a significant increase in oil production and a decrease in oil inventories. In response to a shock to oil consumption demand, changes in oil production and economic activity are very mild and insignificant, while changes in oil prices and oil inventories are significant and persistent. Last but not least, a positive oil inventory demand shock leads to a significant increase in oil prices, and significant declines in oil production and economic activity, which are qualitatively consistent with the effects of oil supply news shocks identified by Känzig (2019). It suggests that the oil inventory demand shocks in my sample mainly capture news about future oil supplies.

2.2.4 Forecast Error Variance and Historical Decompositions

In Table 2.2, I report the 12-month-ahead forecast error variance of each of the four variables attributed to each structural shock.[9] Oil supply shocks, global demand shocks, oil consumption demand shocks, and oil inventory demand shocks are the overwhelming factors driving fluctuations in oil production, world industrial production, oil prices, and oil inventories, respectively. The other factors are almost equally unimportant. In particular, I find that 86% of the variation in the real price of oil can be explained by oil consumption demand shocks, which stands in contrast to Kilian and Murphy (2014) and Känzig (2019) who argue that the majority of the variation in oil prices can be attributed to global demand shocks or oil supply news shocks.

Figure 2.5 depicts the historical decomposition of changes in oil prices. It is obvious

[8]The block length is set to 27. The confidence intervals are based on 1,000 bootstrap replications.

[9]The 24-month-ahead and 36-month-ahead forecast error variance decompositions are similar.

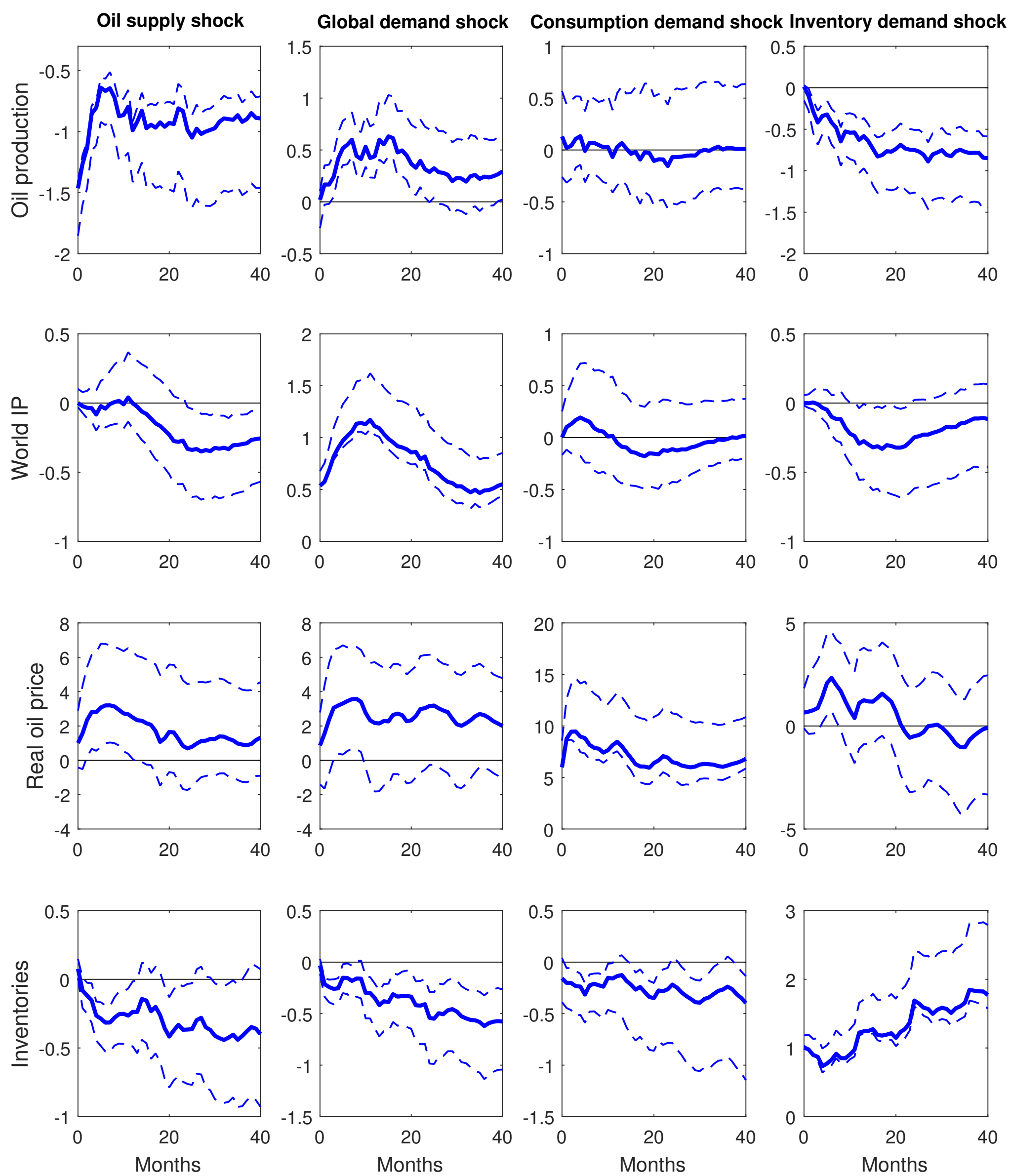

Figure 2.4. Impulse responses to one standard deviation structural shocks: baseline model.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

Table 2.2. Forecast error variance decomposition

	Variable			
Shock	Oil production	World IP	Oil price	Inventories
Oil supply	0.88	0.03	0.04	0.04
Global demand	0.05	0.89	0.06	0.05
Consumption demand	0.03	0.05	0.86	0.04
Inventory demand	0.05	0.03	0.04	0.87

Note: This table shows the fraction of the 12-month-ahead forecast error variance of each variable explained by each structural shock. Each column sums up to 1.

that the price movements are mostly due to oil consumption demand shocks. Oil supply shocks contribute to the price increase in 1974, the drop in 1986 and rebound in 1987, and the spike in 1990. Global demand shocks contribute to the price plummet in 2008 and the following rebound in 2009. Overall, the contribution of oil supply shocks, global demand shocks, and oil inventory demand shocks are very limited.

2.3 Sensitivity Analysis

In this section, I perform a number of robustness checks to investigate how the estimated effects of oil market shocks change with the model specification and the estimation sample.

In the baseline case, I use the refiner acquisition cost of crude oil imports to measure the price of oil, as it is a good proxy for oil prices in global markets and was not price controlled in the early part of the sample. As an alternative, I use the West Texas Intermediate (WTI) spot crude oil price. Next, I allow changes in oil production to have a direct contemporaneous effect on economic activity, as in Kilian (2009) and Caldara, Cavallo and Iacoviello (2018). Then I include a linear time trend in the VAR. The impulse responses shown in Figures B.1 to B.3 suggest that my results are very robust to these modelling choices. In addition, I change the number of autoregressive lags from 24 to 12 as in Baumeister and Hamilton (2019). The results in Figure B.4 remain similar except that some effects become insignificant.

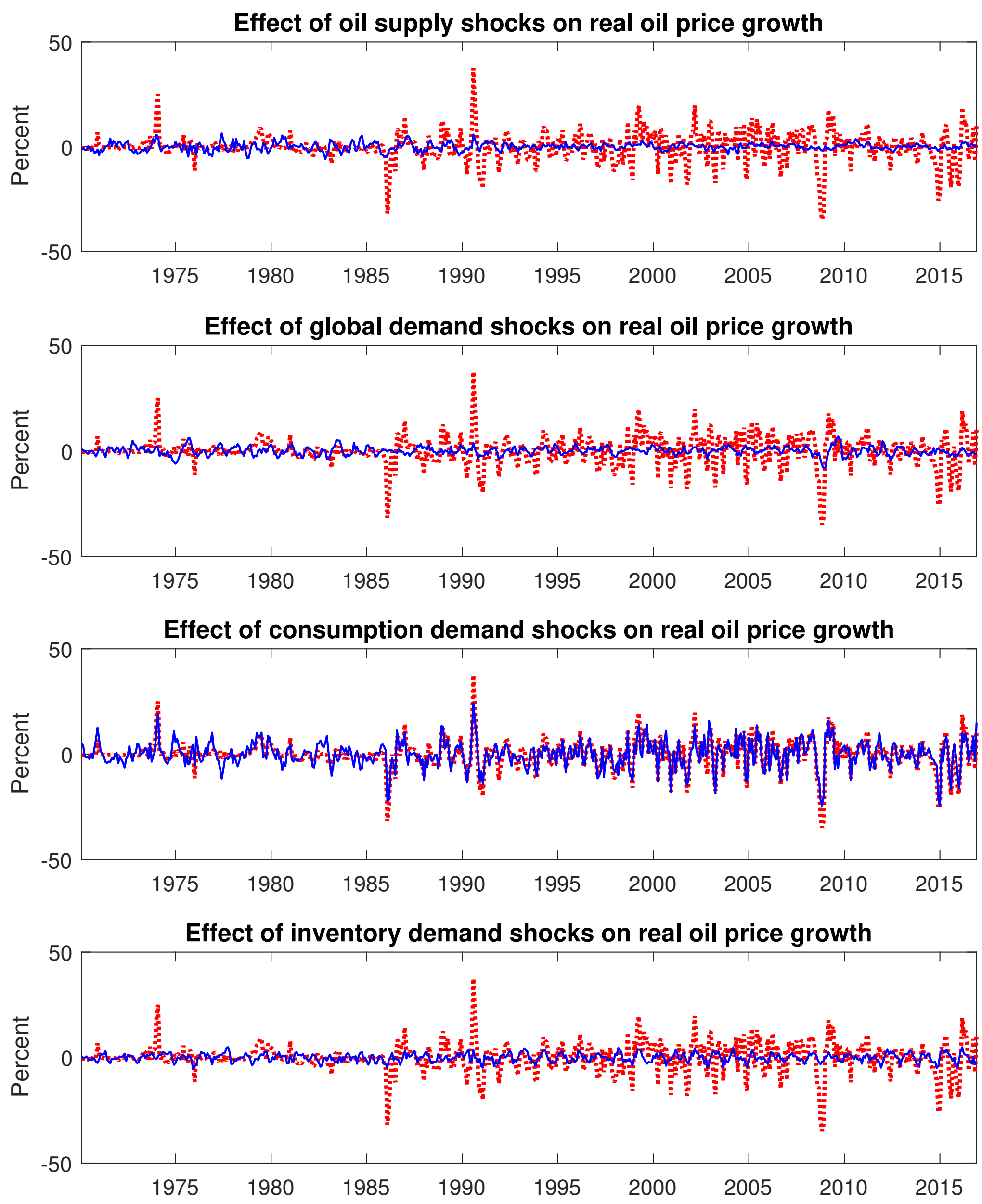

Figure 2.5. Historical decomposition of real oil price growth.

Note: Red dotted lines are growth in the real price of oil. Blue lines are contribution of each structural shock.

Another important choice is how to measure global economic activity. In the baseline model, I use the proxy for world industrial production constructed by Baumeister and Hamilton (2019). A popular alternative indicator of economic activity is constructed by Kilian (2009) based on the cost of shipping. Figure B.5 shows the impulse responses using Kilian's (corrected) indicator. The results are similar, at least qualitatively, to the baseline model. The main difference is that Kilian's measure of economic activity increases significantly as a consequence of a shock to oil consumption demand. This is probably because ship-building and scrapping cycles confound the link between shipping costs and economic activity, as argued by Känzig (2019).

Beyond model specifications, I also explore whether the results are sensitive to the estimation sample. First, I estimate the structural model using a sample that starts in 1974M1 when the original series for the refiner acquisition cost is available. This allows me to avoid using extrapolated oil price data. Next, to avoid the confounding effects of the Great Recession and the shale oil revolution, I estimate the model based on a sample that ends in 2007M12. Figure B.6 and B.7 show that the results are robust. Finally, I estimate the model based on a sample that starts in 1981M3 when the original oil supply surprise series is available (corrected for autoregressive lags). This also checks whether the effects of oil shocks in recent decades are different from the 1970s and early 1980s. Figure B.8 shows that the results are similar to the baseline model, except that economic activity increases in response to a positive oil inventory demand shock. This finding suggests that oil inventory demand shocks mainly capture news about future global demand in more recent data.

2.4 Conclusion

This paper decomposes the effects of oil price shocks. To achieve this goal, I estimate a structural VAR of the global crude oil market using instrumental variables. My method allows me to put no restrictions on the parameters and thus avoid imposing any prior on the short-run price elasticity of oil supply, which could affect the result much. Compared to the existing studies that use external instrumental variables to identify a specific oil market shock, I identify various types of oil market shocks at the same time.

I find that a negative oil supply shock leads to a significant increase in oil prices and a delayed but significant decline in economic activity. Whereas a positive shock to oil consumption demand does not have a significant effect on economic activity, a positive shock to oil inventory demand results in declines in oil production and economic activity at the same time in my sample. Furthermore, evidence shows that the overwhelming majority of oil price movements are driven by shocks to consumption demand.

Chapter 2, in full is currently being prepared for submission for publication of the material. Lyu, Yifei. The dissertation author was the sole author of this material.

Chapter 3

Accounting for the Declining Economic Effects of Oil Price Shocks

Since the 1970s, there have been large fluctuations in energy prices which possibly contributed to economic fluctuations. A large body of literature suggests that positive oil price shocks have negative effects on the economy; see Barsky and Kilian (2004) and Baumeister and Kilian (2016) for surveys. However, a number of recent studies, including Blanchard and Galí (2010), Edelstein and Kilian (2009), Herrera and Pesavento (2009), Baumeister and Peersman (2013), and Katayama (2013), argue that the effects on the US economy have been much more muted since the mid-1980s.[1] This paper in particular reexamines the finding of Blanchard and Galí (2010) (BG hereafter), one of the most influential works in the literature. By estimating a six-variable structural VAR for two samples individually, they show that the impact of oil price shocks on US inflation and economic activity has declined by more than half since 1984.

Two important changes in the economy since the mid-1980s may explain the apparent instability in the oil price-macroeconomy relationship found by BG. First, changes in oil prices have been driven by global demand to a large extent since the 1990s when emerging economies began to thrive (Edelstein and Kilian 2009, Kilian 2009). Kilian (2009) points out that a positive global demand shock may have a positive direct effect on the US economy (e.g., higher imports from the US) as well as a negative indirect effect through higher oil prices. As a result, the

[1]Some other studies, such as Hamilton (2009), Ramey and Vine (2011), Wu and Cavallo (2012), and Stock and Watson (2012), argue that oil price shocks still play an important role in driving economic fluctuations.

negative effect of increases in oil prices is likely to be cushioned by the stimulative effect of stronger global economic activity in recent decades. The second reason why the economy seems to be less vulnerable to oil price fluctuations is that the energy share in consumption has become much lower. As noted by Hamilton (2008), the key mechanism whereby higher energy prices slow economic growth is through reductions in consumer spending on non-energy goods and services. Hamilton (2009) argues that given the size of an increase in oil prices, when the expenditure share of energy is small, people tend to ignore the price change and cut spending little because they can afford to do so. Since the energy budget share was much lower after the mid-1980s, this can partly explain why BG find a smaller effect of oil shocks in the more recent period.

To the best of my knowledge, this paper is the first to document empirical evidence that the two factors discussed above can account for the diminishing effects of oil price shocks on the US real economy. I extend the VAR analysis in BG in two ways. First, based on the agreement in the literature that the surging oil prices in the 2000s were primarily caused by the strong demand of emerging economies and are thereby endogenous (Hamilton 2009, Aastveit, Bjørnland and Thorsrud 2015), I construct a measure of non-OECD oil demand and augment the VAR in BG with it. Second, to capture the effect of the changing energy share in consumption, I weight the growth of oil price by the lagged energy share as in Edelstein and Kilian (2009) and Hamilton (2009). Then I show that the extended model implies a stable impact of oil price shocks on US GDP and employment. However, the impact of oil price shocks on inflation is still much more muted after 1984. Furthermore, I show that neither of the two factors alone can explain the diminishing effects of oil shocks very well.

The remainder of this paper is organized as follows. Section 3.1 reviews the empirical analysis in BG. Section 3.2 discusses in more detail about the role of the endogeneity of recent oil price fluctuations and the changing energy share. Section 3.3 extends the analysis in BG taking into account these two factors and shows new result. Section 3.4 concludes.

3.1 Review of Blanchard and Galí (2010)

As the pioneering work in the literature, BG use a simple model to demonstrate the declining effects of oil price shocks on the aggregate economy. To describe the dynamics of the US economy, they estimate a quarterly structural vector autoregression (VAR):

$$\mathbf{y}_t = \mathbf{B}\mathbf{x}_t + \sum_{j=1}^{4} \mathbf{A}_j \mathbf{y}_{t-j} + \mathbf{u}_t \tag{3.1}$$

where $\mathbf{y}_t$ includes (in order) the nominal price of oil, the CPI, the GDP deflator, the nominal wage, GDP, and employment. The oil price, the wage, and employment are measured by the price of West Texas Intermediate crude (WTI), nonfarm business compensation per hour, and nonfarm business hours, respectively. All the variables enter in first-order log differences. The lag order is set to 4. The system is partially identified using the Cholesky decomposition so that the oil price shock is defined as the innovation in the first equation. $\mathbf{x}_t$ includes a constant term and a quadratic trend fitted measure of productivity growth.

BG estimate the VAR for two samples: the first spans 1960Q1-1983Q4 and the second spans 1984Q1-2007Q3.[2] The breaking date roughly corresponds to the start of the Great Moderation. I perform the same analysis and report the result in Figure 3.1. The impulse responses to a 10% oil price shock are shown in levels and one-standard deviation confidence intervals are demonstrated as in BG. In both samples, the inflation increases, while GDP and employment decrease significantly. However, the responses are much more muted in the second sample than in the first one. In particular, the decline of GDP and employment after three years is around 0.7% in the first sample, which is in sharp contrast to only 0.3% in the second sample. In Figure 3.2, I show the differences in the impulse responses between the two samples. It is clear that the differences are both economically and statistically significant.

[2] BG end their sample in 2007 because using data for 2008 on would overestimate role of the price of oil in depressing output.

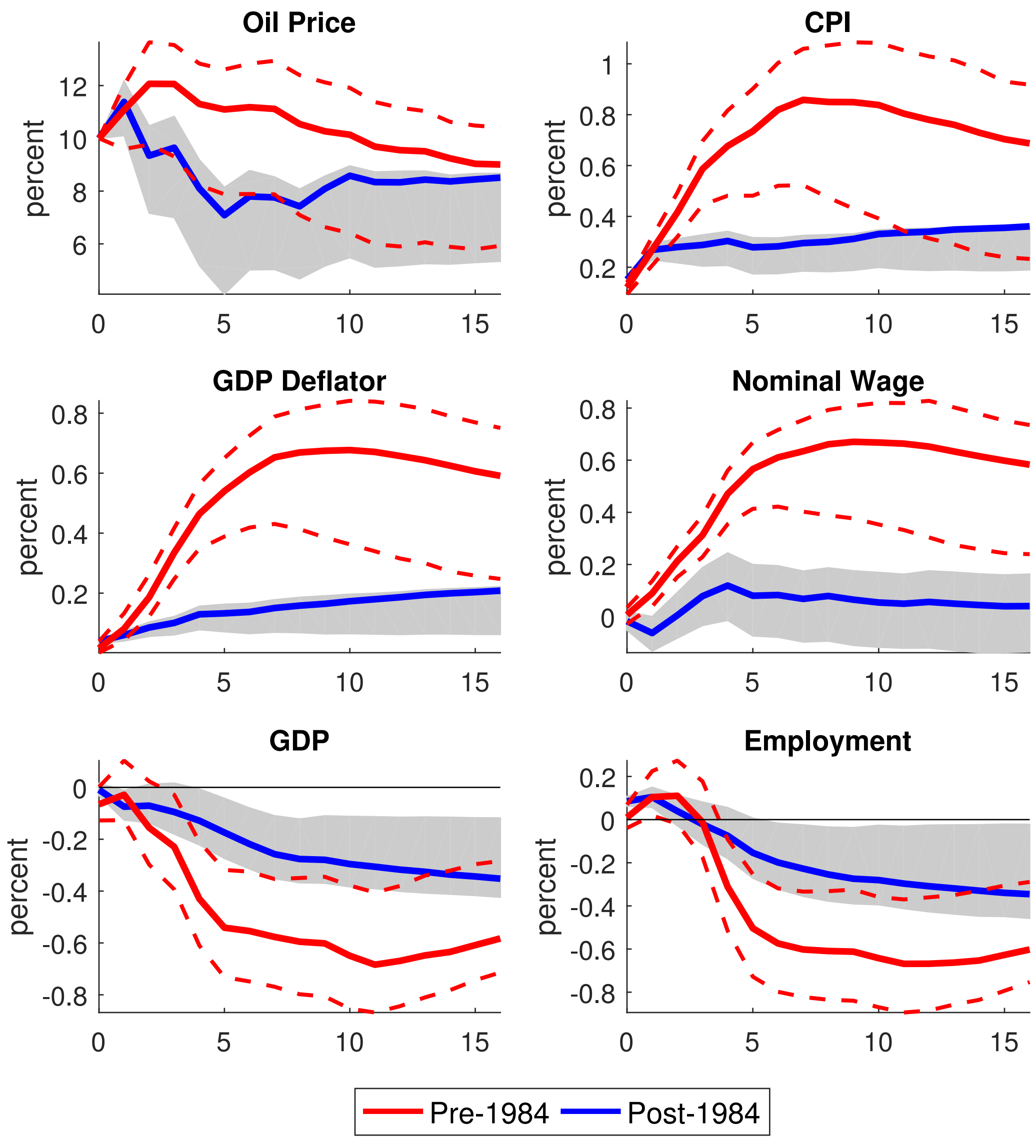

Figure 3.1. Impulse responses to a 10% oil price shock.

Note: Results are based on the VAR in BG. Responses are shown in levels. Dashed lines and shaded areas give one-standard deviation confidence intervals through bootstrapping.

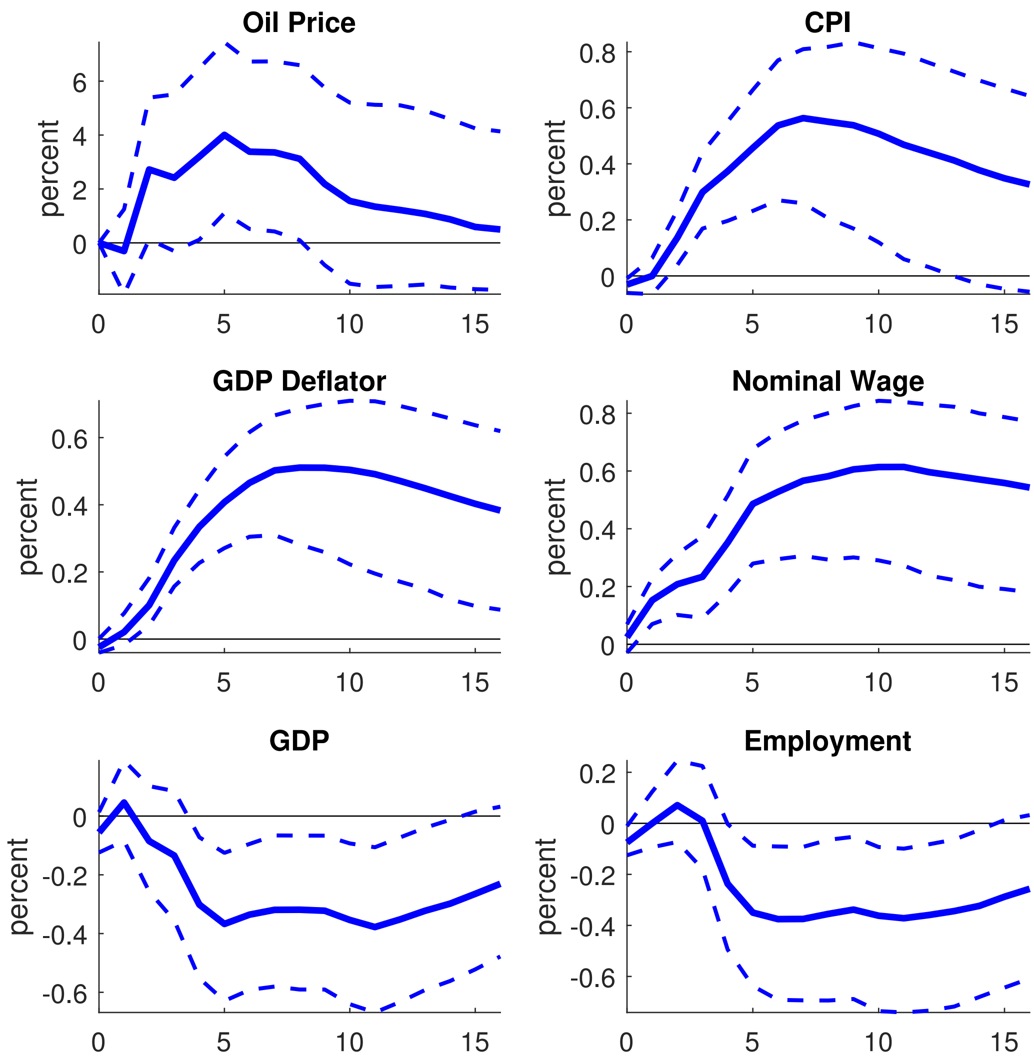

Figure 3.2. Differences in impulse responses to a 10% oil price shock between the two samples.

Note: Results are based on the VAR in BG. Dashed lines give one-standard deviation confidence intervals through bootstrapping.

3.2 Two Important Changes since the Mid-1980s

3.2.1 Endogeneity of Recent Oil Price Shocks

The first important change in the economy which may explain the smaller role of oil prices is that recent oil price fluctuations have become much more endogenous. The literature has become aware that the oil price changes in the 2000s were mainly caused by the strong demand of emerging economies (Hamilton 2009, Kilian 2009, Kilian and Hicks 2013, Aastveit, Bjørnland and Thorsrud 2015). BG notice this problem, but they claim that the price surges as a result of higher global demand, mainly Chinese demand, should have the same effects as exogenous oil supply shocks on the US economy under the assumption that the US economy is not much affected by the emerging markets directly. However, Kilian (2009) shows that oil shocks driven by demand have remarkably different dynamic effects from those driven by supply disruptions. Kilian also points out that the most important reason for the global decline in the responses to oil price shocks is that the negative effects of more recent shocks have been cushioned by the stimulative effects of stronger global economic activity.

Before the early 1980s, oil prices were overall very stable except for several spikes, which usually came after exogenous events such as wars. In particular, the 1973-74 oil shock was likely to originate from the Arab-Israeli War and the following oil embargo imposed by OPEC, and the 1979-80 oil crisis was likely to stem from the Iranian Revolution as well as the Iran-Iraq War.[3] During this period, the world oil production capacity was able to adjust to meet world oil demand as well as stabilize oil prices (Hamilton 2009). In fact, Saudi Arabia has been dedicated to this goal for a long time.

Nevertheless, the big picture has changed dramatically since the late-1990s. The world oil production has been quite stable for a protracted period, and oil prices begin to surge as

[3] As opposed to this conventional view, Barsky and Kilian (2002) argue that these two major oil price shocks were endogenous responses to the booming economic conditions. BG claim that their result remains nearly identical even if the price of oil is allowed to respond contemporaneously to current GDP and employment.

a consequence of strong excess demand of non-OECD countries.[4] Aastveit, Bjørnland and Thorsrud (2015) find that demand from emerging economies is far more important than demand from developed economies in explaining the fluctuations in the real price of oil during the last two decades. The oil consumption of OECD countries actually declined between 2000 and 2010, while non-OECD oil consumption increased by more than 40 percent in the same period.[5] In the meantime, the specular development of non-OECD countries, especially China, has had direct influences on the US economy. These facts make the endogeneity of recent oil price shocks a potentially big issue, and the failure to consider it may lead to a serious omitted variable bias.

3.2.2 Declining Energy Share in Consumption

There is much evidence that higher energy prices slow economic growth mainly through reductions in consumer spending and thus work as demand shocks; see Lee and Ni (2002), Hamilton (2008), and Edelstein and Kilian (2009) among others. As pointed out by Edelstein and Kilian (2009), higher energy prices directly reduce consumer expenditures on non-energy goods and services as consumers need to pay higher energy bills. Households may curtail their consumption further as they increase their precautionary savings due to their fear for the economic outlook. In particular, the consumption of some specific durable goods like motor vehicles that are complementary in use with energy will decline much more than other goods. If it is costly or takes time for workers to retrain or relocate from oil-impacted sectors like the auto industry to the other sectors where jobs are available, these workers may be temporarily unemployed. Therefore the unemployment rate will rise and aggregate output will be suppressed, as argued by Hamilton (1988).

Given the size of an unanticipated increase in oil prices, the smaller the energy share in consumption, the smaller the impact. There are a few reasons. First, households suffer less loss in discretionary income. Second, higher oil prices will not generate much pessimism and

[4] This is true at least until the mid-2000s when the Great Recession and the US shale revolution were yet to come.

[5] Numbers are from the Energy Information Administration.

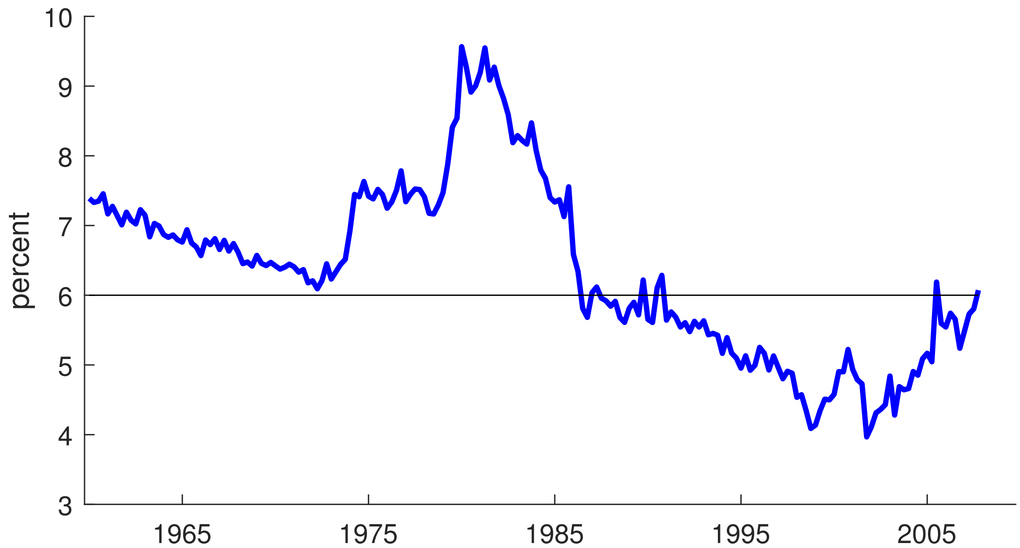

Figure 3.3. Energy share in consumption.

hence not much spending cut driven by a precautionary savings motive. Third, if purchases for automobiles do not decline much, the sectoral imbalance described above may not be very severe. As a result, the declining share in consumer expenditures on energy could potentially contribute to the instability in the oil price-macroeconomy relationship. Figure 3.3 plots the energy budget share between 1960 and 2007. It is apparent that the share before the mid-1980s never fell below 6 percent, which is a ceiling for the rest of time except for 1990 and 2005 when there were dramatic increases in oil prices.

In fact, some studies have already explored the role of the changing energy share in consumption in explaining why the economy responds to some oil shocks more aggressively than to the others. BG and Katayama (2013) build theoretical models to show that the smaller share of oil in consumption after 1984 makes the economy less vulnerable to oil shocks. Sexton, Wu and Zilberman (2012) argue that the unanticipated increases in gas prices between late-2005 and mid-2008 increased the costs of work commutes, lowering the value of houses in zip codes far from the city center. In addition, higher energy expenses left families less income to make mortgage payment and housing demand was depressed. These factors pushed mortgage delinquency to a high level and finally triggered the housing crisis. It is an interesting question whether the crisis would still happen if energy occupied a small budget share during that period. Hamilton (2009) agrees that the relatively lower share of energy in 2004-05 compared to that in 2007-08 can explain why the oil price shock of 2004-05 did not have a negative effect on the economy as large as that of 2007-08.

3.3 Can the Two Changes Explain the Declining Economic Effects of Oil Price Shocks?

3.3.1 An Extended VAR

In order to investigate whether the two changes in the economy discussed above are able to account for the declining effects of oil price shocks on the economy, I extend the VAR in BG in two ways. To control for the effect of the changing energy share, I weight the log growth of oil price in the VAR by the lagged energy share in consumer expenditures.[6] The result in this section is robust to using the energy share in value added. To control for the endogeneity of oil price changes, I construct a new series of non-OECD oil demand, and augment the VAR in BG with the log growth of it. Since the quarterly data on non-OECD oil demand going back to 1960 is not available, I construct it by interpolation.[7] Full details can be found in the appendix.

It might seem more appropriate to use non-OECD output growth instead of oil demand. I do not do that for two reasons. First, quarterly GDP data for major non-OECD countries is not available until the 1990s. For example, data for China is available since 1992. Second, there is a stable relationship between oil demand and economic development, so these two measures should be equally good for my purpose (Csereklyei, Rubio Varas and Stern 2016). Existing evidence shows that the income elasticity of oil demand for non-OECD countries is close to 1, which is about twice as big as that for OECD countries (Gately and Huntington 2002, Dargay

[6]Similar exercises have been done by Hooker (2002), Edelstein and Kilian (2009), and Hamilton (2009).

[7]The most relevant data, collected by the International Energy Agency, starts in 1991. Moreover, this data set is gathered from various sources and the data collection does not follow uniform definitions, with the timeliness and degree of detail highly variable.

and Gately 2010, Hamilton 2009).

I put the non-OECD oil demand as the first variable in the augmented VAR and use the Cholesky decomposition for identification, although the result looks very similar if I order the non-OECD oil demand last in the model. The assumption that non-OECD oil demand does not react to changes in oil prices within a quarter is in fact not unreasonable. Dargay and Gately (2010) show that oil demand in non-OECD countries has grown as rapidly as income but is almost unaffected by prices. The assumption is also supported by the fact that oil inventories in many non-OECD countries are small during my sample period.[8] As a result, without enough storage capacity, non-OECD countries can be regarded as price-takers.

3.3.2 Impulse Responses

I estimate the extended VAR and report the impulse responses to a 10% weighted oil price shock (together with one-standard deviation confidence intervals) in Figure 3.4. Not surprisingly, the inflation increases, and GDP and employment decrease significantly. While the responses of inflation are still much more muted in the second sample, the responses of GDP and employment in the two samples are almost identical, which is in sharp contrast to the result in section 2. Figure 3.5 shows that the differences in the impulse responses of GDP and employment between the two samples are statistically insignificant. As a consequence, I conclude that the endogeneity of recent oil price changes and the changing energy share can fully account for the declining effects of oil shocks on real economic activity, but we need some extra effort to explain the less responsiveness of inflation.

Following the analysis above, a natural question is whether both the modifications to BG are necessary. I conduct two experiments to answer this question. First, I keep the non-OECD oil demand in the VAR but do not weight the growth of oil price. Second, I keep weighting the growth of oil price, but exclude the non-OECD oil demand from the VAR. The results are

[8] For example, Chinese strategic oil inventories have been less than 100 million barrels by the end of 2014, according to officially released information.

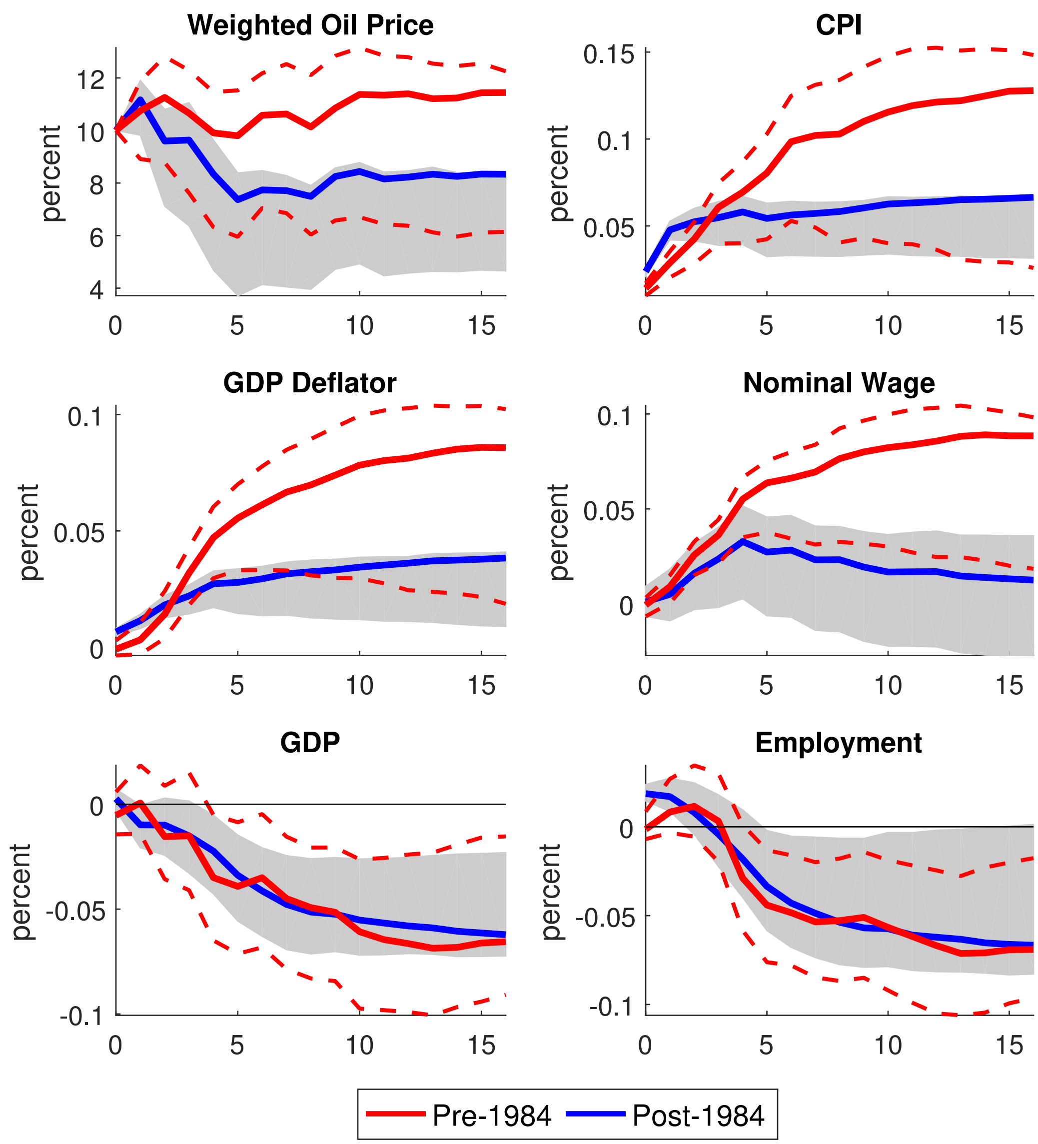

Figure 3.4. Impulse responses to a 10% weighted oil price shock: VAR augmented with non-OECD oil demand.

Note: Results are based on the extended VAR that weights the growth of oil price by the lagged energy share and includes the non-OECD oil demand. Responses are shown in levels. Dashed lines and shaded areas give one-standard deviation confidence intervals through bootstrapping.

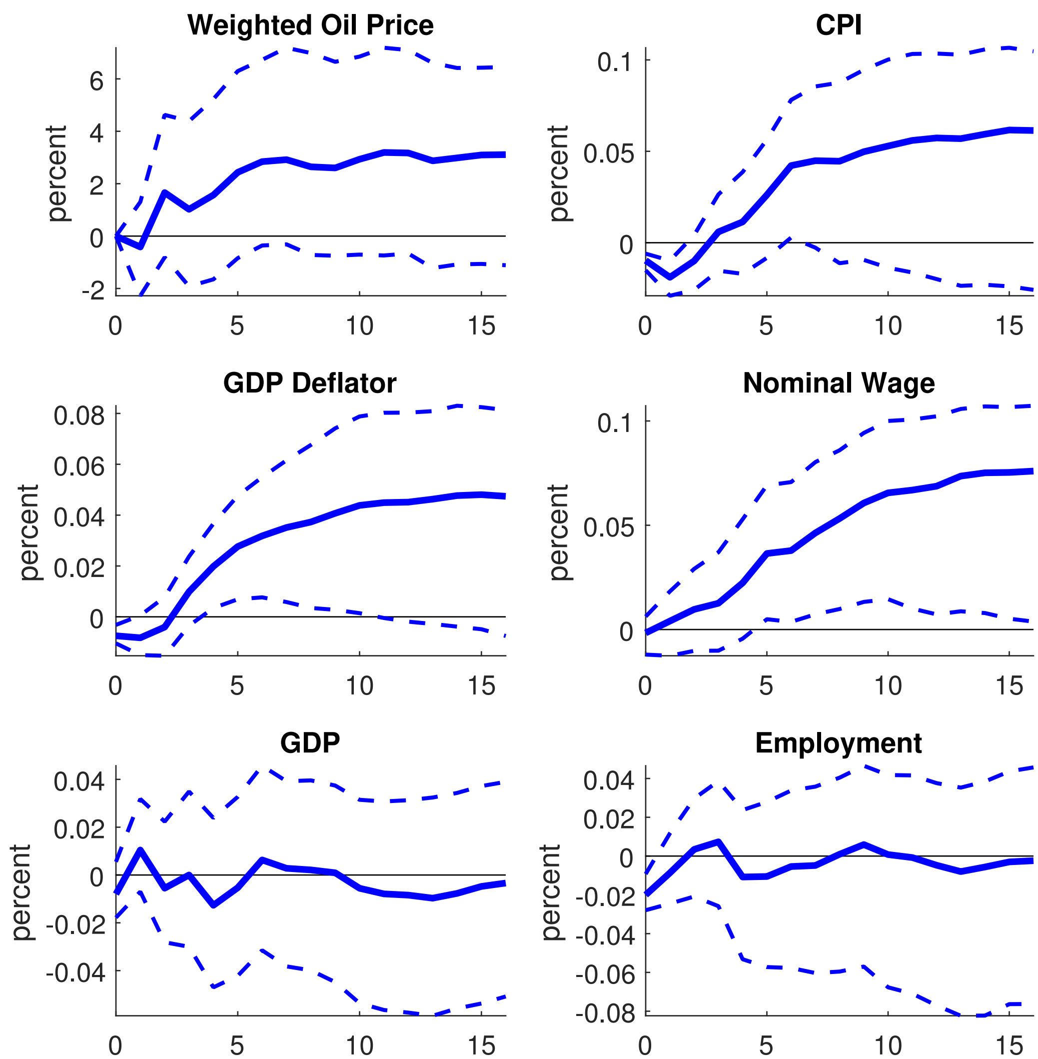

Figure 3.5. Differences in impulse responses to a 10% weighted oil price shock between the two samples.

Note: Results are based on the extended VAR that weights the growth of oil price by the lagged energy share and includes the non-OECD oil demand. Dashed lines give one-standard deviation confidence intervals through bootstrapping.

shown in Figure 3.6 and 3.7, respectively. It is obvious that neither of the two changes alone can account for the entire differences in the impulse responses of GDP and employment between the pre and post-1984 samples, although the endogeneity issue seems to be more important.

3.4 Conclusion

This paper reexamines the finding of Blanchard and Galí (2010) that the impact of oil price shocks on the US aggregate economy has declined by more than half since 1984. By extending the VAR in their paper, I provide evidence that the decline in the effects on real economic activity can be accounted for by the endogeneity of oil price changes and the lower energy share in consumption in recent decades.

My result indicates that exogenous oil price fluctuations can still matter much for the US economy, especially when oil prices are already high such that energy takes a large share in consumer expenditures. A direct implication of my finding is that the Great Moderation may not be explained by an economic structural change such that output is less sensitive to aggregate shocks. Another important implication is that the Federal Reserve should be cautious about bearing inflationary pressures associated with rising commodity prices. If they choose not to take up their monetary policy weapon, we may be in danger of falling into another recession.

Chapter 3, in full is currently being prepared for submission for publication of the material. Lyu, Yifei. The dissertation author was the sole author of this material.

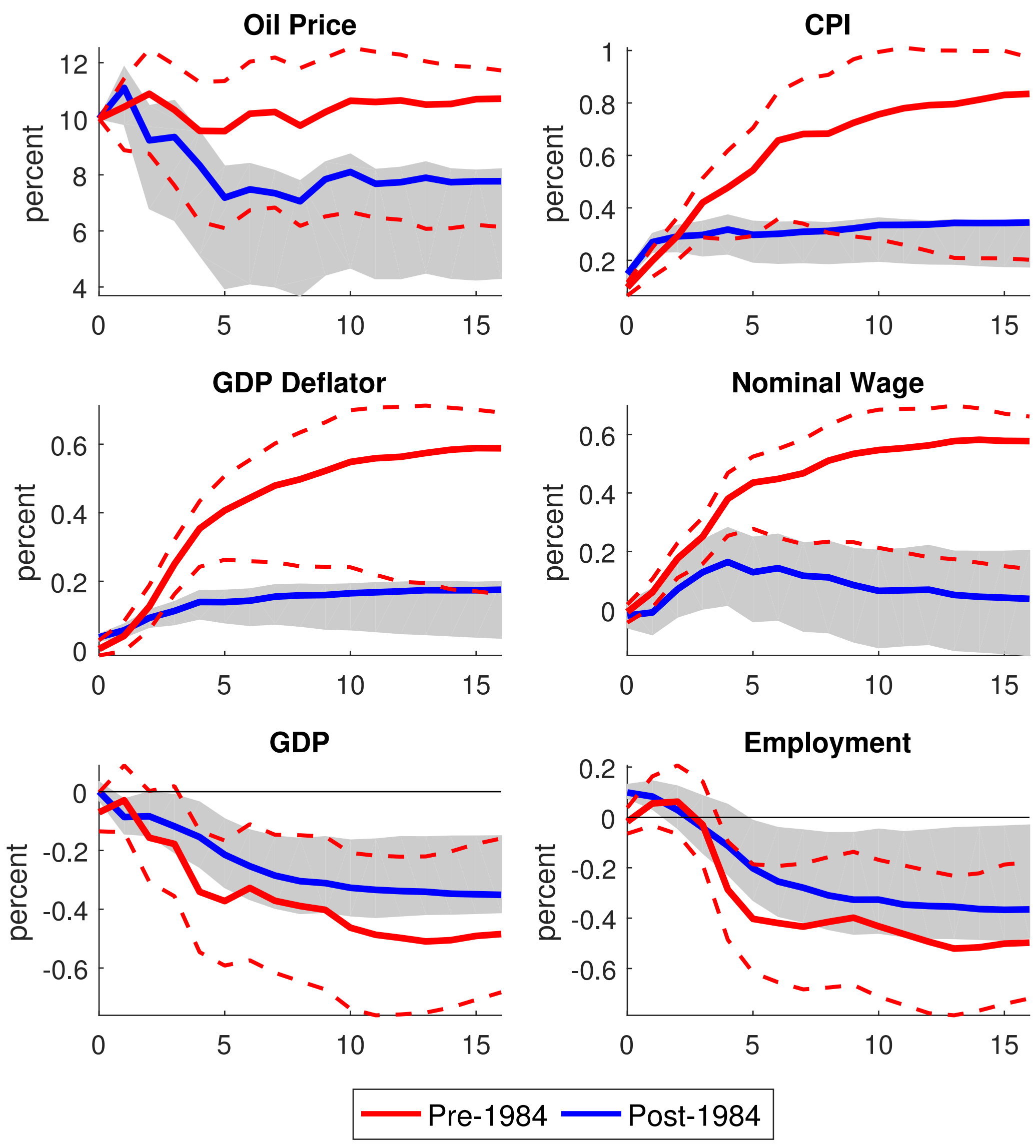

Figure 3.6. Impulse responses to a 10% oil price shock: VAR augmented with non-OECD oil demand.

Note: Results are based on the extended VAR that includes the non-OECD oil demand but does not weight the growth of oil price. Responses are shown in levels. Dashed lines and shaded areas give one-standard deviation confidence intervals through bootstrapping.

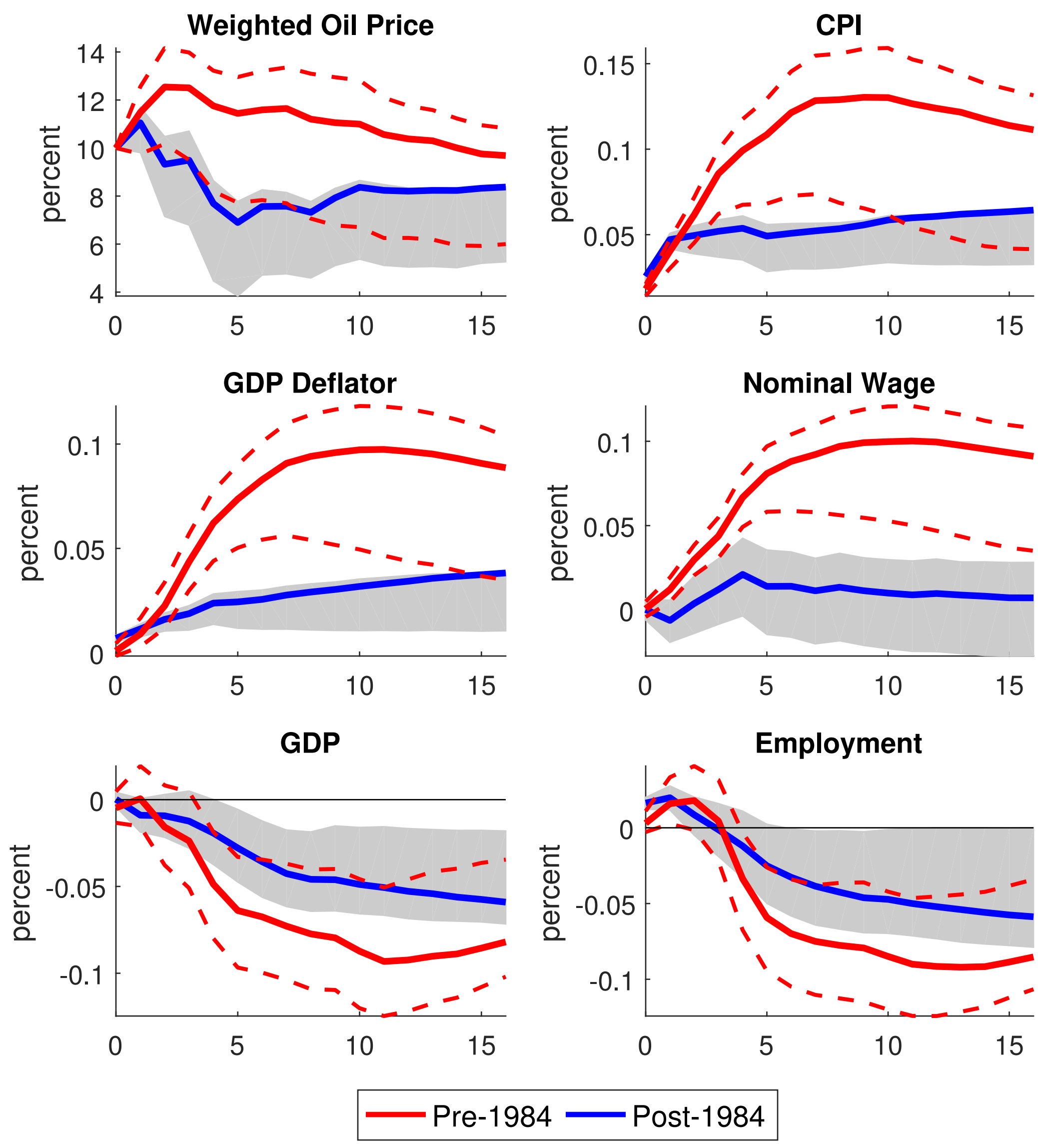

Figure 3.7. Impulse responses to a 10% weighted oil price shock.

Note: Results are based on the extended VAR that weights the growth of oil price by the lagged energy share but excludes the non-OECD oil demand. Responses are shown in levels. Dashed lines and shaded areas give one-standard deviation confidence intervals through bootstrapping.

Appendix A

Chapter 1

A.1 Algorithm for Estimation and Inference

The expectation maximization (EM) algorithm is introduced in Hamilton (1990) for obtaining maximum likelihood estimates of parameters in Markov regime-switching models. To implement the EM algorithm in our application, we only need to evaluate the smoothed probability $p(s_t|\mathscr{W}_T;\lambda)$ for $t = 1,2\ldots,T$. Given old estimates of parameters λ, we calculate smoothed probabilities and use them to reweight the observed data. Then some simple calculations based on the weighted data generate new estimates of λ. The likelihood value increases after each such iteration, and iteration continues until a fixed point for λ is obtained.

Calculating smoothed probabilities Given estimates $\hat{\lambda}$, we first calculate the filtered probability $p(s_t|\mathscr{W}_t;\hat{\lambda})$ for $t = 1,2,\ldots,T$ using the Hamilton filter introduced in Hamilton (1989) as the basis for calculating smoothed probabilities. The Hamilton filter accepts as input $p(s_{t-1}|\mathscr{W}_{t-1};\hat{\lambda})$ and produces $p(s_t|\mathscr{W}_t;\hat{\lambda})$. It runs as follows. First, we calculate

$$p(s_t,s_{t-1}|\mathscr{W}_{t-1};\hat{\lambda}) = p(s_t|s_{t-1})p(s_{t-1}|\mathscr{W}_{t-1};\hat{\lambda}) \tag{A.1}$$

Then we calculate

$$f(\mathbf{w}_t|\mathscr{W}_{t-1};\hat{\lambda}) = \sum_{s_t=1}^{2}\sum_{s_{t-1}=1}^{2} f(\mathbf{w}_t|\mathbf{x}_t,s_t;\hat{\lambda})p(s_t,s_{t-1}|\mathscr{W}_{t-1};\hat{\lambda}) \tag{A.2}$$

where $f(\mathbf{w}_t|\mathbf{x}_t, s_t; \hat{\lambda})$ can be found in equation (1.9). Finally, the output is obtained from

$$p(s_t|\mathscr{W}_t; \hat{\lambda}) = \sum_{s_{t-1}=1}^{2} \frac{f(\mathbf{w}_t|\mathbf{x}_t, s_t; \hat{\lambda}) p(s_t, s_{t-1}|\mathscr{W}_{t-1}; \hat{\lambda})}{f(\mathbf{w}_t|\mathscr{W}_{t-1}; \hat{\lambda})} \tag{A.3}$$

After calculating filtered probabilities, we can calculate smoothed probabilities according to Hamilton (1990). Note that for any $\tau > t$, we have

$$p(s_\tau, s_t|\mathscr{W}_\tau; \hat{\lambda}) = \sum_{s_{\tau-1}=1}^{2} \frac{p(s_\tau|s_{\tau-1}) f(\mathbf{w}_\tau|\mathbf{x}_\tau, s_\tau; \hat{\lambda}) p(s_{\tau-1}, s_t|\mathscr{W}_{\tau-1}; \hat{\lambda})}{f(\mathbf{w}_\tau|\mathscr{W}_{\tau-1}; \hat{\lambda})} \tag{A.4}$$

When $\tau = t$, $p(s_\tau, s_t|\mathscr{W}_\tau; \hat{\lambda})$ equals the filtered probability $p(s_t|\mathscr{W}_t; \hat{\lambda})$. For any t, we can start from the filtered probability and then iterate on the above expression for $\tau = t+1, t+2, \ldots, T$. The smoothed probability is finally obtained from

$$p(s_t|\mathscr{W}_T; \hat{\lambda}) = \sum_{s_T=1}^{2} p(s_T, s_t|\mathscr{W}_T; \hat{\lambda}) \tag{A.5}$$

Updating parameters The EM algorithm solves a sequence of optimization problems (indexed by $l = 0, 1, \ldots$). Let $Q(\lambda_{l+1}; \lambda_l, \mathscr{W}_T)$ denote the expected log-likelihood:

$$Q(\lambda_{l+1}; \lambda_l, \mathscr{W}_T) = \int_{\mathscr{S}} \log p(\mathscr{W}_T, \mathscr{S}; \lambda_{l+1}) \cdot p(\mathscr{W}_T, \mathscr{S}; \lambda_l) \tag{A.6}$$

where $\mathscr{S} = \{s_T, s_{T-1}, \ldots, s_1\}$. Let $\hat{\lambda}_l$ denote estimates of parameters from our previous iteration. We choose as $\hat{\lambda}_{l+1}$ the value of λ_{l+1} that maximizes $Q(\lambda_{l+1}; \hat{\lambda}_l, \mathscr{W}_T)$. Hamilton (1990) proves that $\hat{\lambda}_{l+1}$ is associated with a higher likelihood value than is $\hat{\lambda}_l$, so the sequence of $\{\hat{\lambda}_l\}_{l=0}^{\infty}$ converges to a local MLE. In our application, given $\hat{\lambda}_l$, we run the iteration by first scaling the observed sample data by the square root of smoothed probabilities

$$\mathbf{y}_t^{(l+1,j)} = \mathbf{y}_t \cdot \sqrt{p(s_t = j|\mathscr{W}_T;\hat{\lambda}_l)} \qquad j = 1,2$$
$$\mathbf{x}_t^{(l+1,j)} = \mathbf{x}_t \cdot \sqrt{p(s_t = j|\mathscr{W}_T;\hat{\lambda}_l)} \qquad j = 1,2$$

Then simple OLS regressions based on $\mathbf{y}_t^{(l+1,j)}$ and $\mathbf{x}_t^{(l+1,j)}$ yield new estimates $\hat{\mathbf{A}}_0^{(l+1)}(j)$, $\hat{\beta}^{(l+1)}(j)$ and $\hat{\Sigma}^{(l+1)}$. The remaining new parameters are calculated as

$$p_{jj}^{(l+1)} = \frac{\sum_{t=2}^{T} p(s_t = j, s_{t-1} = j|\mathscr{W}_T;\hat{\lambda}_l)}{\sum_{t=2}^{T} p(s_{t-1} = j|\mathscr{W}_T;\hat{\lambda}_l)} \qquad j = 1,2 \tag{A.7}$$

$$g_1^{NBER}(l+1) = \frac{\sum_{t=1}^{T}(2 - z_t^{NBER})p(s_t = 1|\mathscr{W}_T;\hat{\lambda}_l)}{\sum_{t=1}^{T} p(s_t = 1|\mathscr{W}_T;\hat{\lambda}_l)} \tag{A.8}$$

$$g_2^{NBER}(l+1) = \frac{\sum_{t=1}^{T}(z_t^{NBER} - 1)p(s_t = 2|\mathscr{W}_T;\hat{\lambda}_l)}{\sum_{t=1}^{T} p(s_t = 2|\mathscr{W}_T;\hat{\lambda}_l)} \tag{A.9}$$

$$g_1^{UNEMP}(l+1) = \frac{\sum_{t=1}^{T}(2 - z_t^{UNEMP})p(s_t = 1|\mathscr{W}_T;\hat{\lambda}_l)}{\sum_{t=1}^{T} p(s_t = 1|\mathscr{W}_T;\hat{\lambda}_l)} \tag{A.10}$$

$$g_2^{UNEMP}(l+1) = \frac{\sum_{t=1}^{T}(z_t^{UNEMP} - 1)p(s_t = 2|\mathscr{W}_T;\hat{\lambda}_l)}{\sum_{t=1}^{T} p(s_t = 2|\mathscr{W}_T;\hat{\lambda}_l)} \tag{A.11}$$

It is worth mentioning that the EM algorithm enables us to find a local maximum of the likelihood function, however, the global maximum is not guaranteed. We explore many different starting values $\hat{\lambda}_0$, and select the local maximum that delivers the highest likelihood value. To confirm that we have reached the global maximum, we use the simulated annealing (SA) algorithm, a widely used global optimization algorithm, to search for the MLE as an alternative. We obtain the same result using the EM algorithm and the SA algorithm. To construct asymptotic standard errors, we numerically calculate second derivatives of the log likelihood.

A.2 Companion Form of the MS-SVAR

Because the news variable N_t by construction is unforecastable, we can augment the vector of endogenous variables $\mathbf{y}_t$ with N_t and rewrite equation (1.1) as:

$$\mathbf{A}_0^*(s_t)\mathbf{y}_t^* = \mathbf{c}^*(s_t) + \sum_{j=1}^{4} \mathbf{A}_j^*(s_t)\mathbf{y}_{t-j}^* + \varepsilon_t^* \tag{A.12}$$

where $\mathbf{y}_t^* = (N_t, G_t, T_t, Y_t)'$, $\mathbf{c}^*(s_t) = (c^N, \mathbf{c}(s_t)')'$, $\varepsilon_t^* = (\varepsilon_t^N, \varepsilon_t')'$, and

$$\mathbf{A}_0^*(s_t) = \begin{pmatrix} 1 & \mathbf{0} \\ -\Gamma_0(s_t) & \mathbf{A}_0(s_t) \end{pmatrix}$$

$$\mathbf{A}_j^*(s_t) = \begin{pmatrix} 0 & \mathbf{0} \\ \Gamma_j(s_t) & \mathbf{A}_j(s_t) \end{pmatrix}$$

for $j = 1, \ldots, 4$. c^N is the mean of the military spending news that is assumed to be constant over time. ε_t^N is the shock to the military spending news. With both sides premultiplied by $\mathbf{A}_0^*(s_t)^{-1}$, equation (A.12) becomes:

$$\mathbf{y}_t^* = \mathbf{A}_0^*(s_t)^{-1}\mathbf{c}^*(s_t) + \sum_{j=1}^{4} \mathbf{A}_0^*(s_t)^{-1}\mathbf{A}_j^*(s_t)\mathbf{y}_{t-j}^* + \mathbf{A}_0^*(s_t)^{-1}\varepsilon_t^* \tag{A.13}$$

Then we can express this VAR(4) system in companion form:

$$\tilde{\mathbf{y}}_t = \tilde{\mathbf{c}}(s_t) + \Phi(s_t)\tilde{\mathbf{y}}_{t-1} + \mathbf{B}(s_t)\tilde{\varepsilon}_t \tag{A.14}$$

where $\tilde{\mathbf{y}}_t = (\mathbf{y}_t^{*\prime}, \mathbf{y}_{t-1}^{*}{}', \mathbf{y}_{t-2}^{*}{}', \mathbf{y}_{t-3}^{*}{}')'$, $\tilde{\mathbf{c}}(s_t) = ((\mathbf{A}_0^*(s_t)^{-1}\mathbf{c}^*(s_t))', \mathbf{0}_{1\times 12})'$, $\tilde{\varepsilon}_t = (\varepsilon_t^{*\prime}, \mathbf{0}_{1\times 12})'$, and

$$\Phi(s_t) = \begin{pmatrix} \mathbf{A}_0^*(s_t)^{-1}\mathbf{A}_1^*(s_t) & \mathbf{A}_0^*(s_t)^{-1}\mathbf{A}_2^*(s_t) & \mathbf{A}_0^*(s_t)^{-1}\mathbf{A}_3^*(s_t) & \mathbf{A}_0^*(s_t)^{-1}\mathbf{A}_4^*(s_t) \\ \mathbf{I} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I} & \mathbf{0} \end{pmatrix}$$

$$\mathbf{B}(s_t) = \begin{pmatrix} \mathbf{A}_0^*(s_t)^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix}$$

A.3 Proof of Proposition 1

Starting from the companion form

$$\tilde{\mathbf{y}}_t = \tilde{\mathbf{c}}(s_t) + \Phi(s_t)\tilde{\mathbf{y}}_{t-1} + \mathbf{B}(s_t)\tilde{\varepsilon}_t \tag{A.15}$$

we obtain the following expression for $h \geq 1$ using recursive method:

$$\tilde{\mathbf{y}}_{t+h} = \tilde{\mathbf{c}}_{t+1,t+h} + \left(\prod_{i=1}^{h}\Phi(s_{t+i})\right)(\tilde{\mathbf{c}}(s_t) + \Phi(s_t)\tilde{\mathbf{y}}_{t-1} + \mathbf{B}(s_t)\tilde{\varepsilon}_t) + \mathbf{u}_{t+1,t+h} \tag{A.16}$$

where

$$\tilde{\mathbf{c}}_{t+1,t+h} = \begin{cases} \tilde{\mathbf{c}}(s_{t+h}) + \sum_{m=1}^{h-1}\left(\prod_{j=0}^{m-1}\Phi(s_{t+h-j})\right)\tilde{\mathbf{c}}(s_{t+h-m}) & \text{if } h \geq 2 \\ \tilde{\mathbf{c}}(s_{t+h}) & \text{if } h = 1 \end{cases}$$

and

$$\mathbf{u}_{t+1,t+h} = \begin{cases} \mathbf{B}(s_{t+h})\tilde{\varepsilon}_{t+h} + \sum_{m=1}^{h-1}\left(\prod_{j=0}^{m-1}\Phi(s_{t+h-j})\right)\mathbf{B}(s_{t+h-m})\tilde{\varepsilon}_{t+h-m} & \text{if } h \geq 2 \\ \mathbf{B}(s_{t+h})\tilde{\varepsilon}_{t+h} & \text{if } h = 1 \end{cases}$$

Note that given a path of future regimes $\{s_{t+1}, s_{t+2}, \cdots, s_{t+h}\}$, $\mathbf{u}_{t+1,t+h}$ has zero mean:

$$E\left(\mathbf{u}_{t+1,t+h}\middle| s_{t+1}, s_{t+2}, \cdots, s_{t+h}\right) = \mathbf{0} \tag{A.17}$$

The conditional expectation of $\tilde{y}_{l,t+h}$ is:

$$E\left(\tilde{y}_{l,t+h}\middle| \tilde{\varepsilon}_t, s_t\right) = \mathbf{e}_l' E\left(E\left(\tilde{\mathbf{y}}_{t+h}\middle| \tilde{\varepsilon}_t, s_t, s_{t+1}, \cdots, s_{t+h}\right)\middle| \tilde{\varepsilon}_t, s_t\right) \tag{A.18}$$

where $\mathbf{e}_l$ is the lth column of $\mathbf{I}_{16}$. Combining A.16-A.18, we have

$$E\left(\tilde{y}_{l,t+h}\middle| \tilde{\varepsilon}_t, s_t\right) = \mathbf{e}_l' E\left(\tilde{\mathbf{c}}_{t+1,t+h}\middle| s_t\right) + \mathbf{e}_l' E\left(\prod_{i=1}^{h} \Phi(s_{t+i})\middle| s_t\right)\left(\tilde{\mathbf{c}}(s_t) + \Phi(s_t)\tilde{\mathbf{y}}_{t-1} + \mathbf{B}(s_t)\tilde{\varepsilon}_t\right)$$

which leads to proposition 1 in the main text:

$$\begin{aligned} GIR_{t+h|s_t}^{k,l} &\equiv E\left(\tilde{y}_{l,t+h}\middle| \tilde{\varepsilon}_t = \mathbf{e}_k, s_t\right) - E\left(\tilde{y}_{l,t+h}\middle| \tilde{\varepsilon}_t = \mathbf{0}, s_t\right) \\ &= \mathbf{e}_l' E\left(\prod_{i=1}^{h} \Phi(s_{t+i})\middle| s_t\right) \mathbf{B}(s_t)\mathbf{e}_k. \end{aligned}$$

A.4 Proof of Proposition 2

We define $\Phi_j^{(h)} \equiv E\left(\prod_{i=1}^{h} \Phi(s_{t+i})\middle| s_t = j\right)$, so

$$\begin{aligned} \Phi_j^{(h)} &= E\left\{E\left(\prod_{i=1}^{h} \Phi(s_{t+i})\middle| s_{t+1}\right)\middle| s_t = j\right\} \\ &= E\left\{\Phi(s_{t+1})\, E\left(\prod_{i=1}^{h-1} \Phi(s_{t+1+i})\middle| s_{t+1}\right)\middle| s_t = j\right\} \\ &= E\left(\Phi(s_{t+1})\Phi_{s_{t+1}}^{(h-1)} | s_t = j\right) \\ &= p(s_{t+1} = 1 | s_t = j)\Phi(1)\Phi_1^{(h-1)} + p(s_{t+1} = 2 | s_t = j)\Phi(2)\Phi_2^{(h-1)} \\ &= p_{j1}\Phi(1)\Phi_1^{(h-1)} + p_{j2}\Phi(2)\Phi_2^{(h-1)} \end{aligned}$$

Appendix B

Chapter 2

B.1 Additional Figures for Sensitivity Analysis

This section shows the impulse response functions based on alternative specifications and estimation samples. In particular, I use the West Texas Intermediate (WTI) spot crude as an alternative measure of oil price, allow changes in oil production to have a direct contemporaneous effect on economic activity, include a linear time trend, change the number of autoregressive lags, measure global economic activity using Kilian's (2009) indicator, and change the estimation sample so that it starts in 1974M1 or 1981M3 or ends in 2007M12.

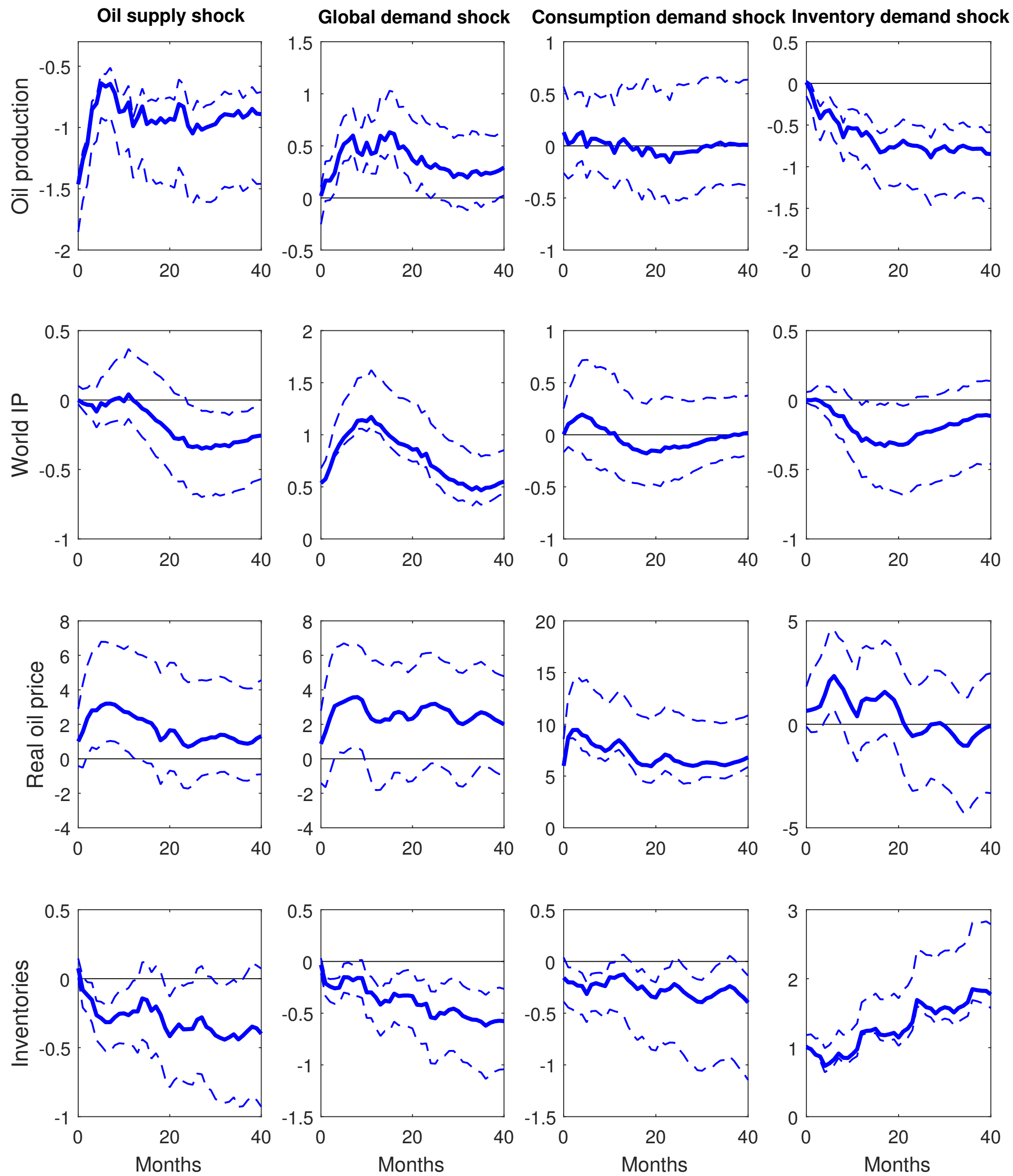

Figure B.1. Impulse responses to one standard deviation structural shocks: West Texas Intermediate as oil price measure.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

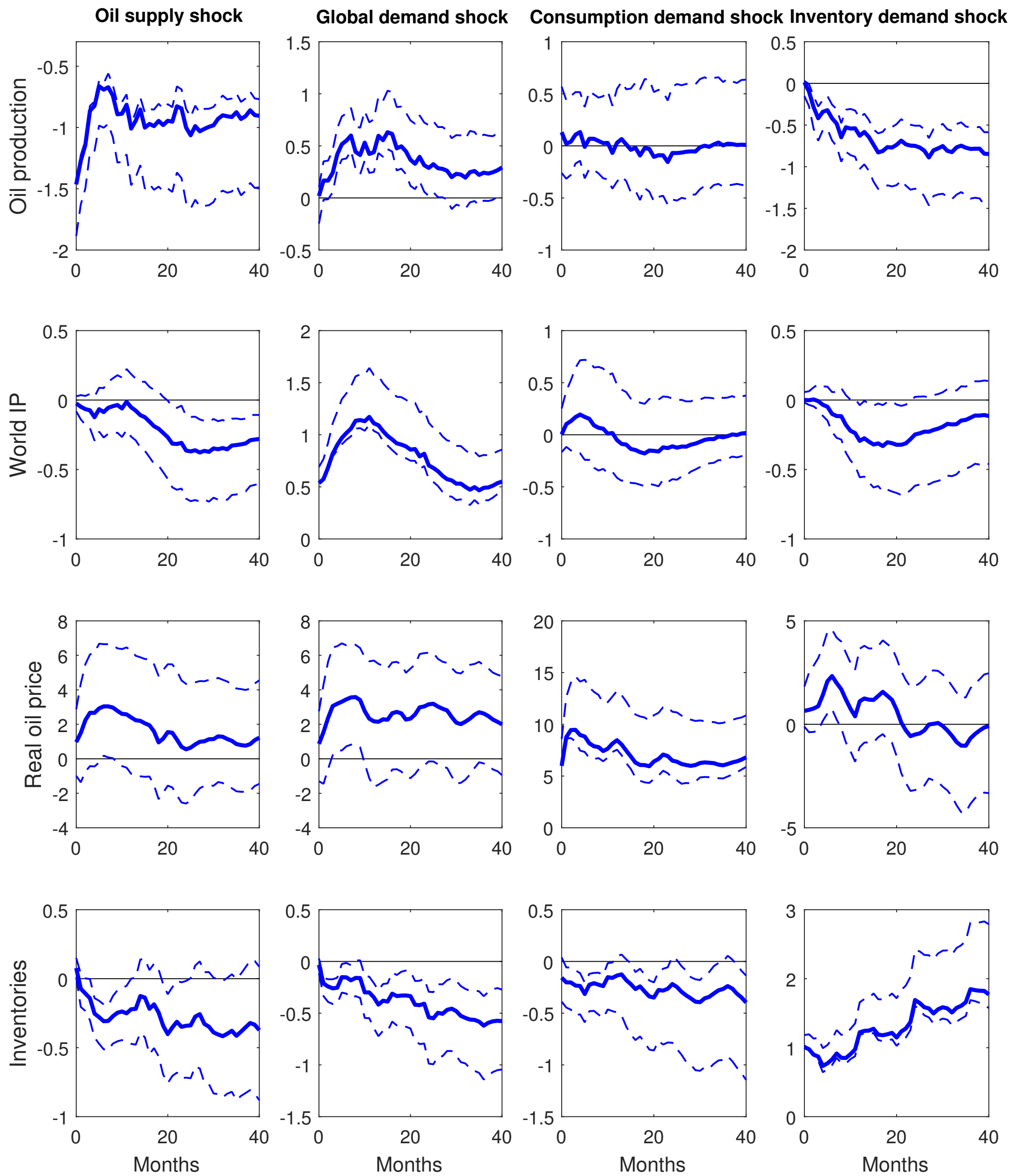

Figure B.2. Impulse responses to one standard deviation structural shocks: oil production allowed to have a direct contemporaneous effect on economic activity.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

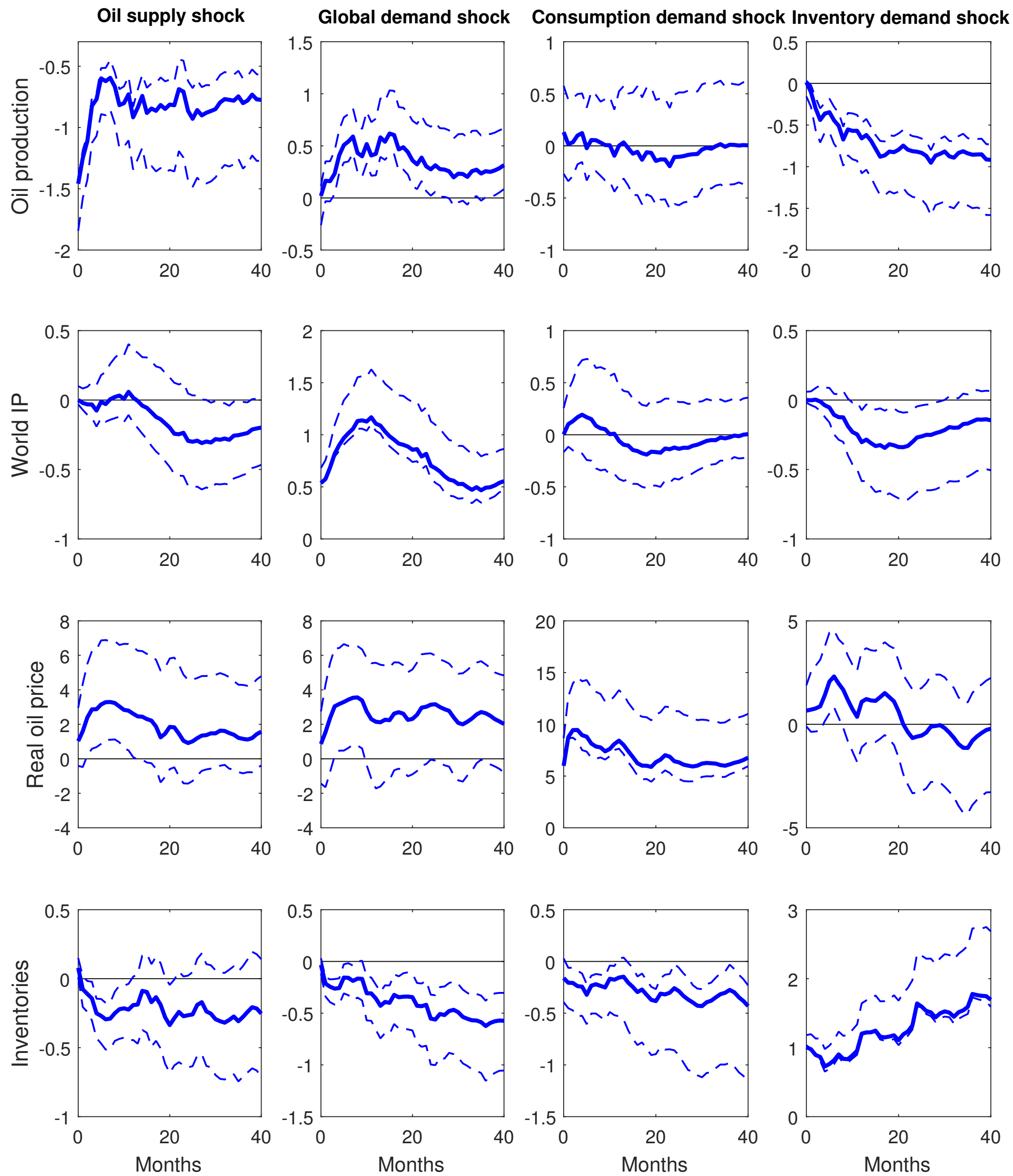

Figure B.3. Impulse responses to one standard deviation structural shocks: linear time trend included.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

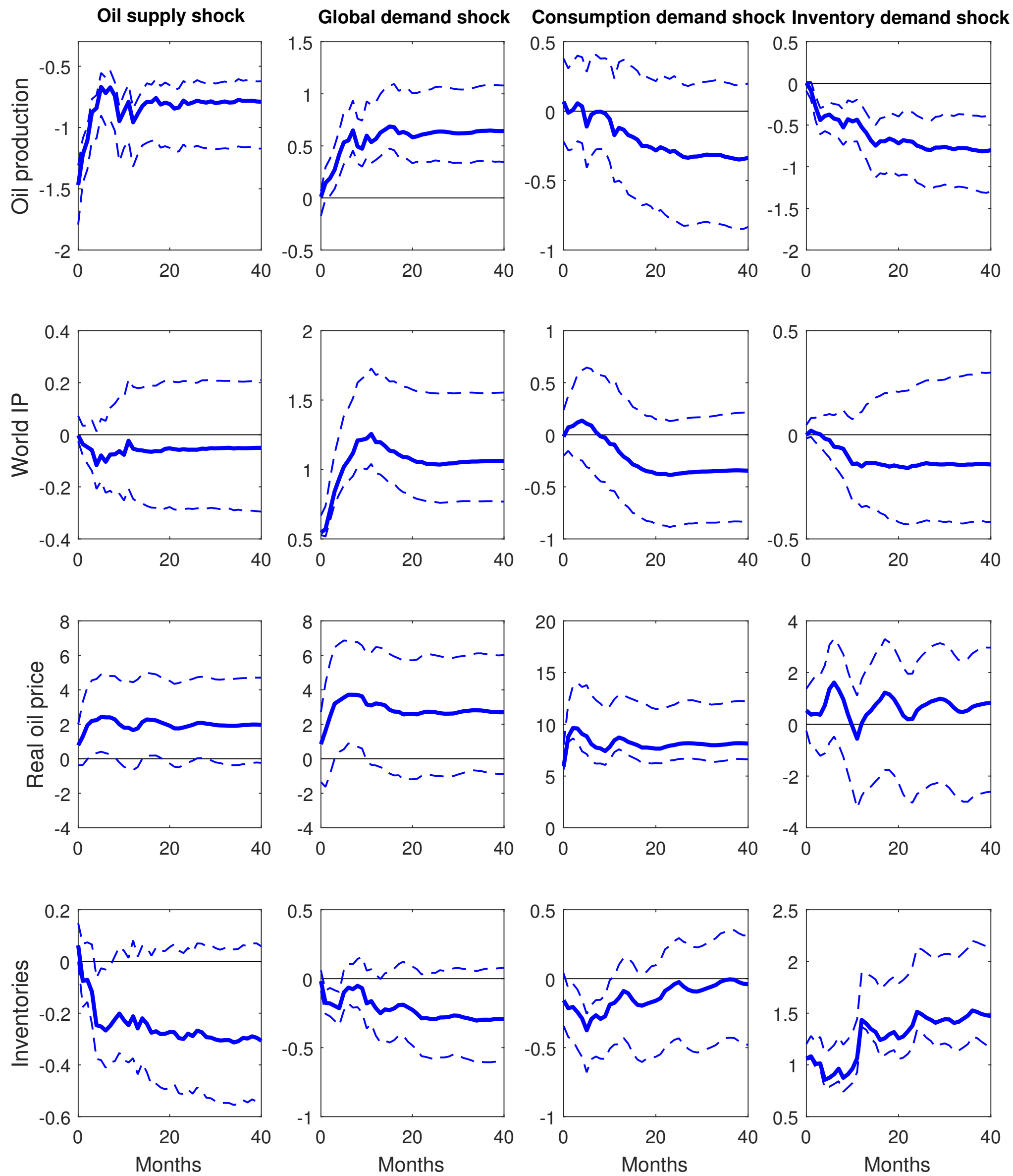

Figure B.4. Impulse responses to one standard deviation structural shocks: 12 autoregressive lags.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

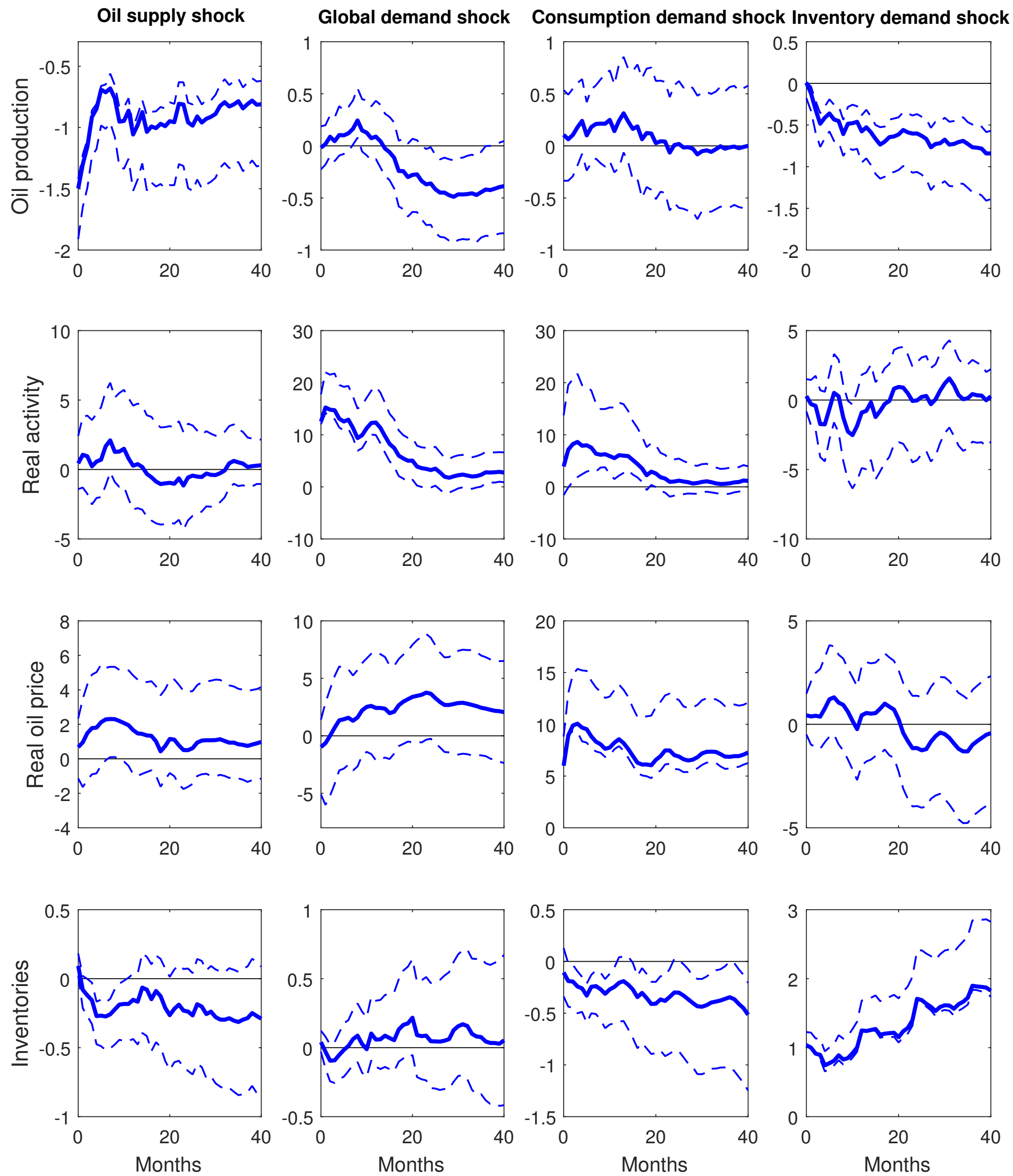

Figure B.5. Impulse responses to one standard deviation structural shocks: global economic activity measured by the index constructed by Kilian (2009).

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

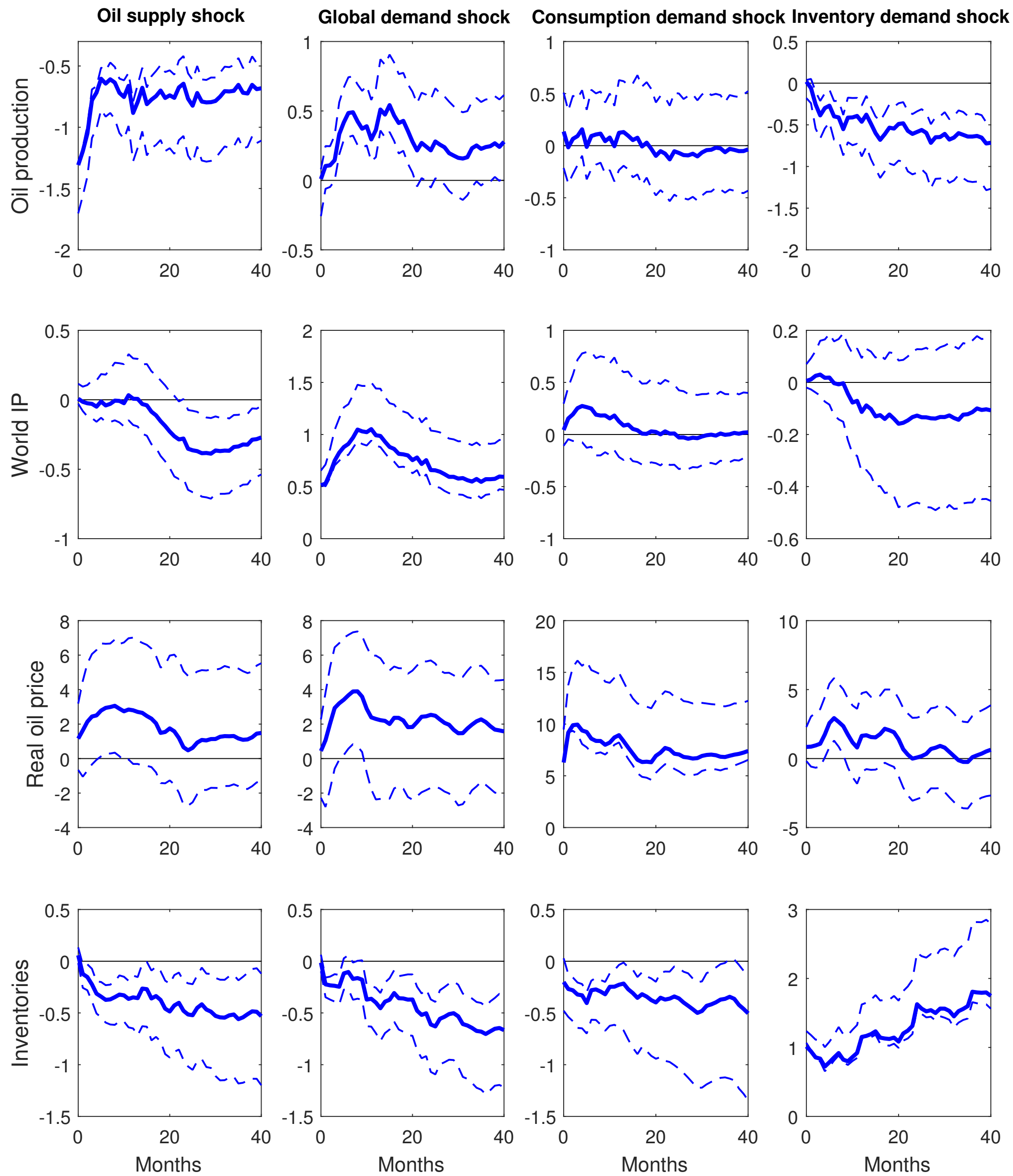

Figure B.6. Impulse responses to one standard deviation structural shocks: 1974M1-2016M12.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

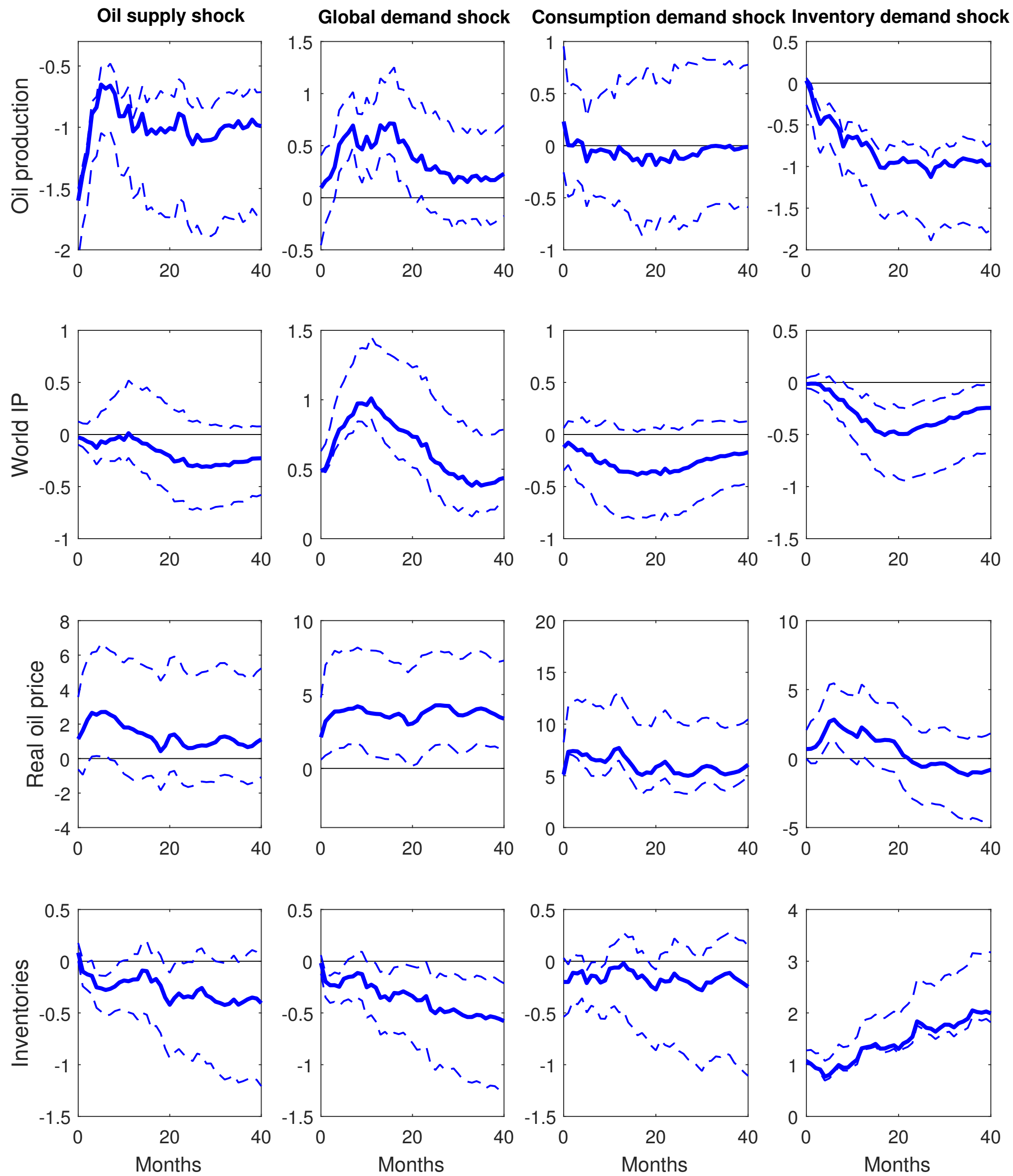

Figure B.7. Impulse responses to one standard deviation structural shocks: 1968M1-2007M12.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

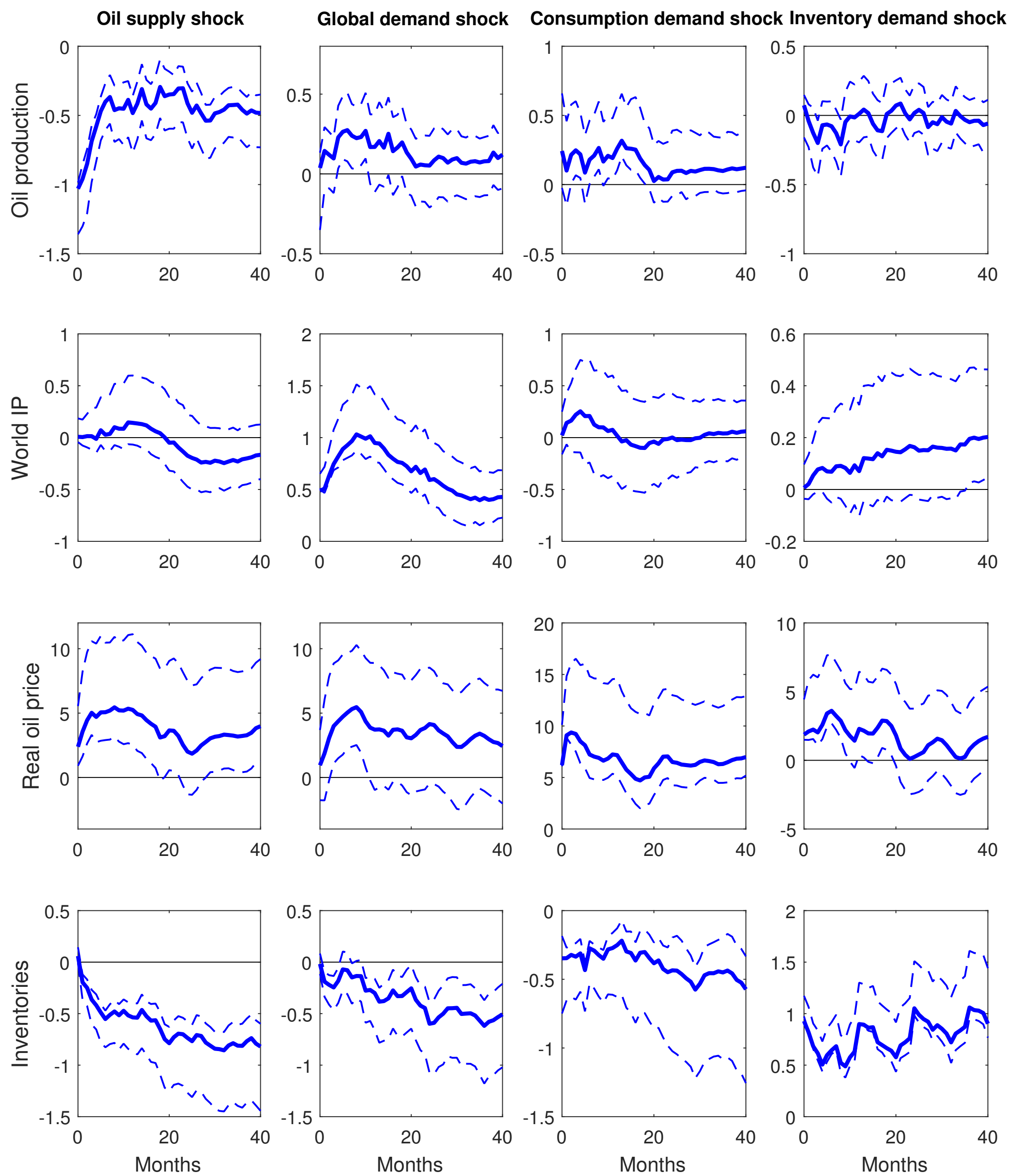

Figure B.8. Impulse responses to one standard deviation structural shocks: 1981M4-2016M12.

Note: Solid lines are impulse response estimates shown in levels. Dashed lines give 90% confidence intervals based on 1,000 moving block bootstrap replications.

Appendix C

Chapter 3

C.1 Construction of Non-OECD Oil Demand

Since it is almost impossible to collect high-quality data on non-OECD oil demand directly, the best alternative is to calculate it as world oil production minus OECD demand.[1] The Energy Information Administration (EIA) provides quarterly data on OECD consumption of petroleum products as well as stocks spanning 1984Q1-2007Q3, hence for this period we just need to find quarterly data on world production of petroleum products. While quarterly production data is available for 1994Q1-2007Q3, only annual production data is available for 1984-1993. A natural idea is to construct a quarterly series of world production of petroleum products for 1984Q1-1993Q4 by disaggregating the annual one. Because crude oil is the key input for creating petroleum products and quarterly data on crude oil production is available, I use it for interpolation.

Suppose the period of our interest covers m years, then the quarterly series to be constructed has $n = 4m$ values. I follow the approach in Fernandez (1981) that amounts to minimizing a quadratic loss function in the difference between the series to be created and a linear transformation of the related high frequency series:

$$(\mathbf{X} - \mathbf{Z}\beta)'\mathbf{A}(\mathbf{X} - \mathbf{Z}\beta) \tag{C.1}$$

[1] Here demand includes both consumption and changes in inventories.

subject to the the constraint that:

$$\mathbf{Y} = \mathbf{B}'\mathbf{X} \tag{C.2}$$

X is quarterly production of petroleum products to be estimated, **Z** is the observed quarterly production of crude oil and **Y** is the observed annual production of petroleum products. Both **X** and **Z** are $n \times 1$ vectors, and **Y** is an $m \times 1$ vector. As the production data is denoted in thousand barrels per day, **Y** is a simple average of the quarterly production within the year. This relationship is represented by the constraint equation (C.2) where

$$\mathbf{B} = \begin{bmatrix} \mathbf{j} & 0 & \cdots & 0 \\ 0 & \mathbf{j} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \mathbf{j} \end{bmatrix}$$

B is an $n \times m$ matrix where **j** is a 4×1 column vector in which each element is 0.25. In equation (C.1), $\mathbf{A} = \mathbf{D}'\mathbf{D}$ and

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ . & . & . & \cdots & . & . \\ . & . & . & \cdots & . & . \\ . & . & . & \cdots & . & . \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix}$$

The estimators for β and **X** are then given as:

$$\hat{\beta} = [\mathbf{Z}'\mathbf{B}(\mathbf{B}'(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B})^{-1}\mathbf{B}'\mathbf{Z}]^{-1}\mathbf{Z}'\mathbf{B}(\mathbf{B}'(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B})^{-1}\mathbf{Y} \tag{C.3}$$

$$\hat{\mathbf{X}} = \mathbf{Z}\hat{\beta} + (\mathbf{D}'\mathbf{D})^{-1}\mathbf{B}(\mathbf{B}'(\mathbf{D}'\mathbf{D})^{-1}\mathbf{B})^{-1}[\mathbf{Y} - \mathbf{B}'\mathbf{Z}\hat{\beta}] \tag{C.4}$$

I use equation (C.3) and (C.4) to estimate quarterly world production of petroleum products for 1984Q1-1993Q4 and connect it with the quarterly production data for 1994Q1-2007Q3 provided by EIA. Then I calculate quarterly non-OECD oil demand for 1984Q1-2007Q3 by subtracting OECD consumption and changes in OECD stocks from world production.[2]

For the period of 1960-1983, quarterly data on OECD consumption of petroleum products is unavailable, thus we can not calculate quarterly non-OECD oil demand using the method above. However, annual data on non-OECD consumption of petroleum products is collected by EIA. For this reason, I estimate quarterly non-OECD oil demand directly by interpolating the annual series. According to Boot, Feibes and Lisman (1967), which is a special case of Fernandez (1981), I minimize the sum of squares of the difference between successive quarterly values:

$$\sum_{i=1}^{4n} (x_i - x_{i-1})^2 \tag{C.5}$$

subject to the constraint that the quarterly values average up to the annual one:

$$\sum_{i=4k-3}^{4k} x_i = t_k \quad (k = 1, 2 \cdots, n) \tag{C.6}$$

where x_i is the ith quarterly value to be estimated, and t_k is the observed annual value in the kth year.

[2]Note that the estimated non-OECD oil demand includes both consumption and changes in inventories. However, as inventories of non-OECD countries are very small, the estimate almost totally reflects their consumption demand.

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