The Effects of Oil Price Uncertainty on China's Economy*

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Abstract

This paper studies the effects of world oil price uncertainty on China's economy from both empirical and theoretical angles. First, we use a vector autoregression model with stochastic volatility in mean to explore the relation between world oil price uncertainty and real economic activity of China. We find that one standard deviation higher uncertainty shock of world oil price reduces electricity production by almost 0.2 percentage. Then we use a canonical New-Keynesian small open economy model solved by third-order perturbation method to explain this phenomenon, in which consumer's precautionary saving channel distresses real activity when oil price uncertainty is higher.

Keywords: Oil price uncertainty; China economy; Stochastic volatility.

JEL Codes: C32; E32; Q43.

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1 Introduction

Along with the rapid and persistent economic growth in the last four decades, China's crude oil demand and crude oil import dependence are higher and higher. Since 1994, China has been a net oil importer, and oil import dependence has risen to a new height in recent years, reaching almost 80%[1]. The heavy dependence on external oil supply makes China's economy sensitive to international crude oil price. Meanwhile, in the past two decades, oil price has become extremely volatile. What effects are this higher international oil price uncertainty on China's economy? We answer this question in this paper by applying a vector autoregression model with stochastic volatility in mean (SVM-VAR) for China's macroeconomy and find that higher uncertainty of world oil price reduces China's real activity in the short run. Then we use a structural dynamic stochastic general equilibrium (DSGE) model with oil sector to explain this finding.

In the literature, the effect of oil price level (first-order) shock on China's macroeconomy has been studied sufficiently (Tang et al. (2010), Du et al. (2010), Wei and Guo (2016) and Cross and Nguyen (2017)). But the effect of oil price uncertainty (second-order) shock has never been explored. To our best knowledge, this paper is the first one to study the effect of international oil price uncertainty on China's economy both in the assumption-free VAR model and in the structural DSGE model.

Uncertainty is defined as the logarithm of the second moment of random variable. To investigate the effects of oil price uncertainty, we first use the econometric framework of SVM-VAR to study the relationship between oil price uncertainty and macroeconomic activity. Vector autoregression model is the workhorse for exploring the relationship between oil and macroeconomy. SVM-VAR model allows volatilities of structural shocks to enter the VAR system acting as exogenous variables, which helps to explain the dynamics of endogenous variables of the VAR (Mumtaz and Zanetti (2013)). In this paper the VAR model includes three monthly endogenous variables: world crude oil production, world crude oil price and China real economic activity, proxied by electricity production. We find that the monthly growth rate of China economic activity slows by nearly 0.2 percentage when oil price volatility rises one standard error. The slowdown of real economic activity leads to a decline in crude oil production, and a fall in crude oil price.

To understand how oil price volatility affects economic output, we construct a New-Keynesian small open economy model with an oil sector. Up to higher international oil price

[1] Oil import dependence = 1 − domestic oil production/oil consumption. Data source: Easy Professional Superior, http://olap.epsnet.com.cn.

volatility, households save precautionarily to insure possible risks, and both consumption and investment decrease. Firms reduce output and demand less for oil. Further sensitivity analysis indicates that if China's economy is more dependent on external oil supply, the effect of oil price uncertainty shock is nonlinearly enhanced; a larger intermediate product substitution elasticity can also amplify the effect of oil price volatility shock.

Our work is related to two bunches of literature. First, this study of international oil price volatility's effect on China's economy is an application of macroeconomy uncertainty. Bloom (2009) starts this line of research of macroeconomy uncertainty. He constructs a partial equilibrium model with a time-varying second moment and find that macro uncertainty shock induces a rapid drop in employment and aggregate output. Fernandez-Villaverde et al. (2011), Fernandez-Villaverde et al. (2015) and Basu and Bundick (2017) explore the uncertainty of interest rate, fiscal policy, and household discount rate respectively in the DSGE model. Mumtaz and Zanetti (2013), Mumtaz and Theodoridis (2015) and Mumtaz and Theodoridis (2019) develop the SVM-VAR model to study the relations between uncertainty and macroeconomy empirically.

Second, our work links with a vast body of literature that focus on the relationship between oil price uncertainty and macroeconomy. Hamilton (1983) starts the modern empirical research on this topic. Kilian (2009) uses a structural vector autoregression model to identify the oil supply shock, aggregate demand shock and oil specific–demand shock. Some studies (Lee et al. (1995), Ferderer (1996) and Elder and Serletis (2010)) consider the oil price volatility in generalized autoregression conditional heteroskedasticity model (GARCH) or GARCH-in-Mean model. Jo (2014) proposes a SVM-VAR model instead of a GARCH-in-Mean process to investigate the world oil market and the world economic activity, and finds that the increase in oil price uncertainty has a negative and persistent impact on global economy. Baskaya et al. (2013) study oil price uncertainty in a small open economy theoretically. Punzi (2019) is concerned with a similar issue about energy price volatility, but we use a different VAR model, and both of our empirical and theoretical findings are opposite to that paper. Our findings support the conclusion of macroeconomy uncertainty literature that higher uncertainty reduces aggregate output.

We contribute to the literature by exploring the effect of oil price uncertainty on China's economy from both empirical and theoretical angles. This study is the first attempt to use the SVM-VAR model which incorporate the volatilities of structural shocks as exogenous variables in the VAR to study China's macroeconomy. Our theoretical model also explains the effect of oil price uncertainty on China's economy through precautionary saving channel.

The rest of the paper is structured as follows. Section 2 introduces the SVM-VAR model and discusses the data, identification, estimation method, and results. Section 3 constructs a New-Keynesian small open economy model with oil sector and explains the empirical finding theoretically through this model. Section 4 concludes.

2 Empirical Analysis

The vector autoregression model considers the endogenous variable vector as a function of its own lags and reduced-form innovations, which is flexible and commonly used to study macroeconomic dynamics. To investigate the effects of oil price uncertainty, we incorporate monthly world crude oil production, world crude oil price and real economic activity of China, proxied by electricity production, in the VAR model[2]. In this section, we first introduce the SVM-VAR model settings and the identification strategy. Then we describe data and estimation method. Finally, we present the estimation results of the SVM-VAR model and the impulse response results of oil price volatility shock.

2.1 A VAR model with stochastic volatility in mean

Uncertainty is related to the second moment of random variable. To study the impact of oil price uncertainty on China economy, we use a VAR model with stochastic volatility in mean. Following Mumtaz and Theodoridis (2015) and Mumtaz (2018), we set the model as follows:

$$\begin{aligned} y_t &= c + \sum_{j=1}^{12} \beta_j y_{t-j} + \sum_{k=1}^{3} b_k \tilde{h}_{t-k} + u_t && (1) \\ u_t &= \Omega_t^{1/2} e_t, \quad e_t \sim N(0, I_3) && (2) \\ \Omega_t &= A^{-1} \Sigma_t A^{-1'} && (3) \\ \tilde{h}_t &= \alpha + \Theta \tilde{h}_{t-1} + Q^{1/2} \xi_t, \quad \xi_t \sim N(0, I_3) && (4) \end{aligned}$$

y_t is a 3×1 vector of endogenous variables. c is a 3×1 vector of constant terms. β_j and b_k are both 3×3 matrices. The variance of the VAR innovation u_t is stochastic and can be decomposed as equation (3). This decomposition extracts all the covariate information in A and leave the variance information in Σ_t.

[2] Kilian (2009) use a three-variable small scale VAR of monthly oil production, world real activity and oil price to explore the dynamics of oil sector and macroeconomy. Recursive identification is applied because the time convention is a suitable reason that oil production does not respond to demand shock within a month. However, in our study, monthly GDP or industrial production is not available in the period we want to cover. Thus we use monthly electricity production to proxy real activity in China.

A is a 3×3 lower triangular matrix with one in the diagonal, which is the key to recover structural VAR from reduced form VAR.

$$A = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{21} & 1 & 0 \\ \alpha_{31} & \alpha_{32} & 1 \end{bmatrix} \tag{5}$$

$\tilde{h}_t = [h_{1,t}, \ldots, h_{3,t}]'$ is a 3×1 vector of log volatilities of disturbances e_t. $\Sigma_t = diag(exp(\tilde{h}_t))$ is a 3×3 diagonal matrix whose diagonal elements are stochastic volatilities. In equation (4), $\tilde{h}_t$ follows an AR(1) process with an intercept term. α denotes a 3×1 vector of constant terms. Θ is a 3×3 matrix. e_t and ξ_t are disturbances that follow standard normal distribution, and independent of each other. Q is a definite and symmetric matrix.

The SVM-VAR model we proposed has two noteworthy characteristics. First, it allows the volatilities of structural shocks to enter the equations directly to affect endogenous variables y_t. This setup has a theoretical origin. When making decisions, people need to consider volatilities. Bloom (2009) models uncertainty as the volatility in a general equilibrium model. Fernandez-Villaverde et al. (2011) and Fernandez-Villaverde et al. (2015) adopt a third-order Taylor expansion of the differentiable DSGE model, and the volatility shocks appear alone in the linear approximation solution which are just the reduced-form SVM-VAR. Thus, we can incorporate the volatilities into the VAR model equations directly as exogenous variables.

Second, we abandon the assumption that Θ is a diagonal matrix, which is frequently used in the literature (such as Mumtaz and Zanetti (2013)). This assumption means that the volatility of any shock is only related to its own lags but not influenced by the volatilities of other endogenous variables. However, in the business cycle, the volatilities of endogenous variables may be correlated to each other and comove with each other. Thus, we do not impose the restriction that Θ in equation (4) should be a diagonal matrix.

Univariate SVM-VAR model is first proposed by Koopman and Hol Uspensky (2002). Mumtaz and Zanetti (2013), and Mumtaz and Theodoridis (2015, 2019) extend this to multivariate SVM-VAR model and empirically investigate a wide range of volatility issues. Jo (2014) is the first to apply SVM-VAR model to study the effects of oil price uncertainty on world economic activities in a special case that only one volatility appears in the equation (1). Following these recent empirical contributions, we apply a more generalized SVM-VAR model that incorporates all three volatilities to study the relationship between oil price uncertainty and China's economy.

2.2 Identification

As Kilian (2009), we apply the recursive identification in the three-variable small-scale VAR to identify the level shocks e_t and the uncertainty shocks ξ_t. We use monthly data in this study and oil production is rigid within the same month. It is reasonable to assume that oil production does not respond to oil price shock and real activity shock contemporaneously.

2.3 Data and estimation

According to Kilian (2009) and Kilian and Park (2009), we use the world crude oil market data and China electricity production data from 2000M01 to 2015M12. All data are seasonally adjusted. Let $y_t = [\Delta qoil_t, \Delta poil_t, \Delta ycn_t]'$. $qoil_t, poil_t$ and ycn_t are expressed in logs. The data of world crude oil production $qoil_t$ and prices $poil_t$ come from the US Energy Information Administration (EIA). The world crude oil price $poil_t$ is the refiner acquisition cost of imported divided by the US consumer price index downloaded from S.t. Louis Fed website.

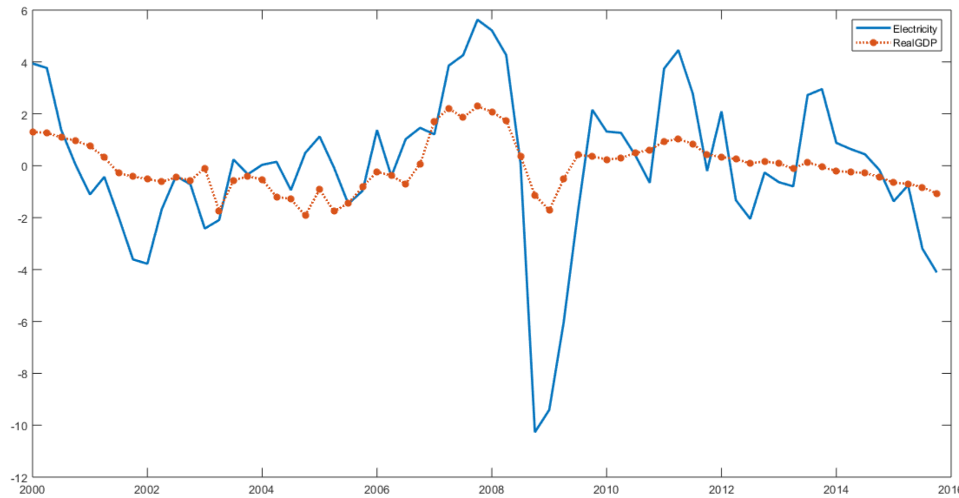
Since mid 2010s, the National Bureau of Statistics of China does not report some monthly economic activities data in January or February due to the Chinese New Year factor. Industrial production data at the monthly frequency, widely used in the research, are not available in China recently. Electricity production, one of the indicators that Chinese Premier Keqiang Li used to gauge Chinese economic activity, is a reasonable proxy for China's economic activity[3]. We apply Fernald et al. (2014)'s method to remove the effect of the Chinese New Year. Figure 1 shows the cyclical fluctuations of the quarterly log electricity production and log real GDP extracted by the Hodrick-Prescott filter. The correlation parameter is 0.66. In the baseline SVM-VAR model, we use monthly electricity production data.

We use Bayesian method to estimate the SVM-VAR model. The lag length of endogenous variables is twelve, and the lag length of volatilities is three following Mumtaz and Theodoridis (2019). The first 60 observations are selected as training sample for priors. Priors, initial values and the Gibbs sampling algorithm of Beyesian estimation are elaborated in Appendix A. We draw 50000 samples from the posterior distribution and discard the first 45000 draws[4]. Convergence diagnostics show the chains converge.

[3]The data of monthly electricity production are from CEIC database

[4]We use and modify Mumtaz and Theodoridis (2019)'s codes to fit the problem studied here. Data and codes can be download from our website.

Figure 1: Electricity Production and Real GDP



Note: We take logarithms of quarterly electricity production and real GDP in China. Then obtain the cyclical fluctuations by Hodrick-Prescott filter with a smoothing parameter 1600. The solid line represents electricity fluctuations and the dotted line is real GDP. Quarterly real GDP data are from Chang et al. (2016).

2.4 Results

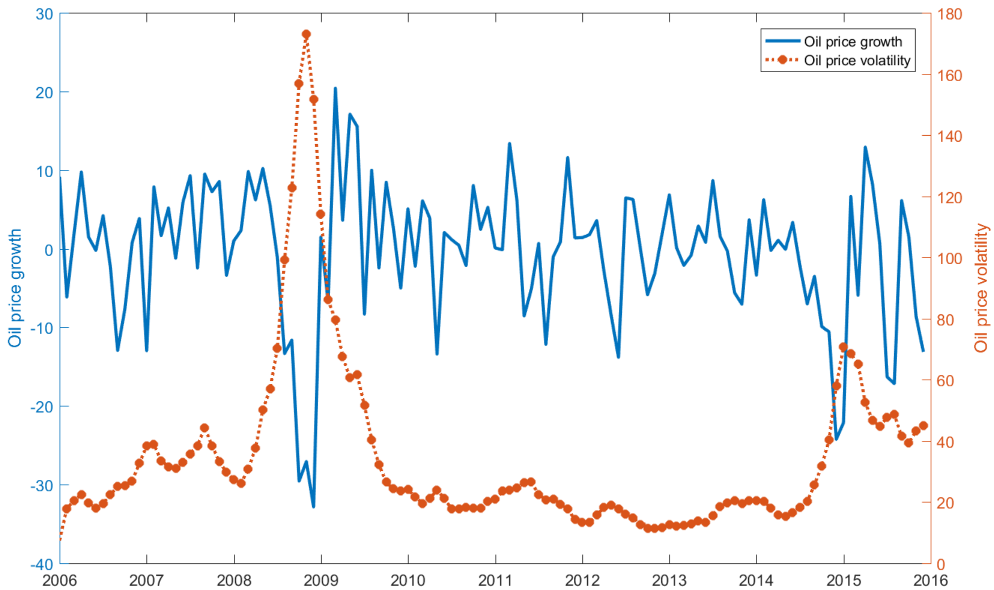
Figure 2 presents the growth rate series of oil price and its median volatility series estimated from the SVM-VAR model. During the 2008-2009 international financial crisis, global oil demand declined and oil prices fell sharply. This period has the highest oil price volatility during the sample period. In 2015, when the shale oil revolution happened in the shadow of the international financial crisis, international oil prices also fell sharply, and oil price volatility rose up. Then oil price volatility returned to low level.

Figure 3 presents the median generalized impulse responses of three endogenous variables to one standard error increase in oil price volatility along with the 68% posterior error band[5]. We find mainly that when the crude oil price growth volatility increase unexpectedly by one standard deviation, China's electricity production growth rate falls by more than 0.2 percentage. And the world crude oil price growth rate falls by nearly 0.3 percentage, the sign of which is contrary to Jo (2014).

We do three robustness checks for the main conclusion in the benchmark. First, we change the training sample period from 60 to 30 and 90. Second, we change the lags of equation (1) from (12,3) to (24,6) and (12,12). Third, we use quarterly world oil production, world oil price, and real GDP data of China to estimate the SVM-VAR model. The main

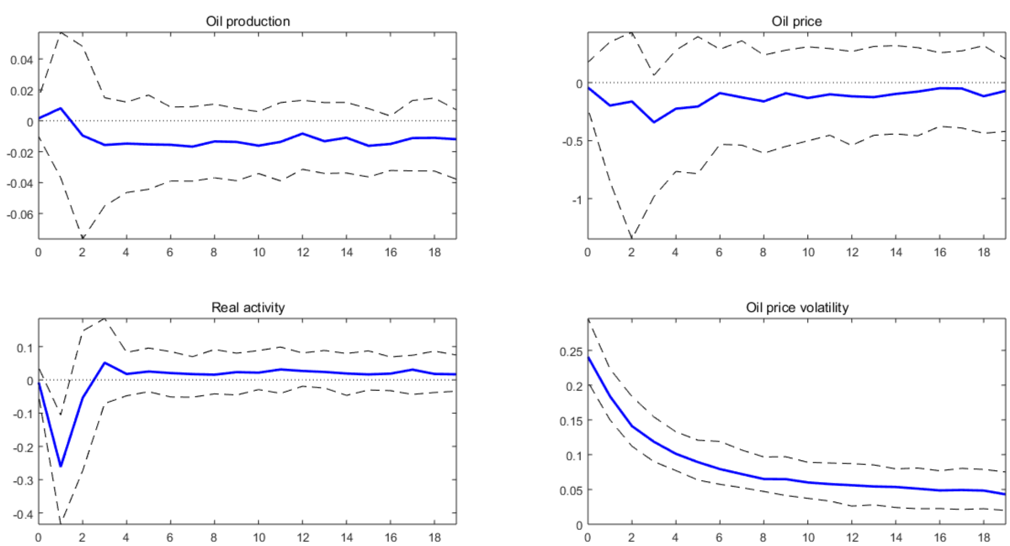
[5] We follow Koop et al. (1996) to calculate the generalized impulse response function.

Figure 2: Oil Price Growth and Oil Price Volatility



Note: The solid line is oil price growth rate, and the dotted line is the median exponent of oil price volatility estimated in the SVM-VAR model. When oil price growth fluctuates acutely, the oil price volatility becomes high.

Figure 3: Impulse Response to an Oil Price Uncertainty Shock



Note: The dotted line is the median generalized impulse response of endogenous variables to one standard error increase in oil price volatility. The dashed lines are the 68% posterior error band. Real economic activity proxied by electricity production has a significant drop in short run when oil price volatility shock occurs.

result in the benchmark that higher international oil price volatility depresses real activity of China is robust to all three alternative changes. The graphs of impulse response functions are shown in Appendix B.

3 Theoretical Analysis

What is the mechanism of the impact of oil price uncertainty on China's economy? To answer this question, we establish a parsimonious New-Keynesian DSGE model with oil sector. Oil price is exogenous and oil price volatility obeys an AR(1) process. Our model is close to Kim and Loungani (1992), Baskaya et al. (2013), Bjornland et al. (2018) and Bachmeier and Plante (2018) but we add the stochastic volatility to simulate the behavior of time-varying oil price volatility. China has independent monetary policy, and we model this feature and incorporate price rigidity in the DSGE model, different from Baskaya et al. (2013).

3.1 Household

There is a continuum of representative households in the economy. Each household consumes $c_{j,t}$ and provides labor $l_{j,t}$. The representative household preference is expressed as:

$$E\sum_{t=0}^{\infty}\beta^t\left[ln(c_{j,t}-h*c_{j,t-1})-\psi_L\frac{l_{j,t}^{1+\gamma}}{1+\gamma}\right] \tag{6}$$

E is the expectation operator. β is the utility discount factor. h denotes the degree of consumption habit formation. ψ_L is the labor utility coefficient. γ is the inverse of Frisch labor supply elasticity.

The representative household's income includes: labor wage $w_{j,t}$, capital rent r_t, gross interest R_{t-1} of the previous period bond $B_{j,t-1}$, transfer payment from government $T_{j,t}$, and profit from the enterprises $F_{j,t}$. The representative household's expenditure includes: current consumption $c_{j,t}$, investment $i_{j,t}$, purchase of government bonds $B_{j,t}$. P_t represents the consumer goods price level. Therefore, the budget constraint faced by the representative household is:

$$c_{j,t}+i_{j,t}+\frac{B_{j,t}}{P_t}=w_{j,t}l_{j,t}+r_tk_{j,t-1}+\frac{B_{j,t-1}R_{t-1}}{P_t}+T_{j,t}+F_{j,t} \tag{7}$$

Households invest in each period to form new capital. δ is depreciation rate of capital. The capital accumulation equation is:

$$k_{j,t}=(1-\delta)k_{j,t-1}+\left[1-S(\frac{i_{j,t}}{i_{j,t-1}})\right]i_{j,t} \tag{8}$$

Investment is irreversible, and adjusting investment plan creates friction. Suppose $S(\frac{i_{j,t}}{i_{j,t-1}}) = \frac{\kappa}{2}(\frac{i_{j,t}}{i_{j,t-1}} - 1)^2$ is investment adjustment cost function satisfying the conditions $S(1) = 0$, $S^{'}(1) = 0$, and $S^{''} > 0$.

3.2 Final goods entrepreneur

Under perfect competition, the final goods entrepreneur purchases the intermediate product $y_{i,t}$ to produce final product y_t^d, and its production function is:

$$y_t^d = \left(\int_0^1 y_{i,t}^{\frac{\varepsilon_f - 1}{\varepsilon_f}} di \right)^{\frac{\varepsilon_f}{\varepsilon_f - 1}} \tag{9}$$

ε_f is the substitution elasticity between different intermediate goods.

Solve the first-order condition of the profit optimization problem of final goods entrepreneur, and we get the demand function for each intermediate product:

$$y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\varepsilon_f} y_t^d \tag{10}$$

This is a decreasing function about relative prices $P_{i,t}/P_t$. $P_{i,t}$ and P_t are the intermediate and final product prices respectively.

Completely competitive market leads to zero profit for the final product producer, which derives a relationship between the price level P_t and the intermediate product price $P_{i,t}$:

$$P_t = \left(\int_0^1 P_{i,t}^{1-\varepsilon_f} di \right)^{\frac{1}{1-\varepsilon_f}} \tag{11}$$

3.3 Intermediate goods entrepreneur

Price rigidity is introduced by intermediate goods entrepreneur's pricing process. In the monopolistic competitive market environment, the production function of intermediate product producer is

$$y_{i,t} = A_t \left(O_{i,t}^{\rho} K_{i,t-1}^{1-\rho} \right)^{\alpha} \left(l_{i,t}^d \right)^{1-\alpha} \tag{12}$$

$\alpha(1-\rho)$ is the share of capital income. $\alpha\rho$ is the share of oil expenditure. $1-\alpha$ is the share of labor income.

Intermediate goods producers are subject to Calvo pricing. In each period, there are a probability of θ_p that producers cannot freely set new price and only automatically adjust the price according to the previous inflation rate. If the nominal price of the period t is $P_{i,t}$, correspondingly, the nominal price of the period $t+s$ is $\Pi_t P_{i,t}/(\Pi_{t+s}P_t)$. There are a probability of $1-\theta_p$ that producers can freely set new optimal prices. Optimization details are in Appendix C.

3.4 Oil price

To explicitly represent the volatility of oil prices in the model, we assume that oil price is determined by the international market and exogenous to China economic system as in Kim and Loungani (1992) and Bjornland et al. (2018). Oil price follows an AR(1) process with stochastic volatility. This model setup is simplified, but enough for the issue we are studying.

$$\begin{aligned} ln\frac{p_{oil,t}}{p_{oil}} &= \phi_{oil} * ln\frac{p_{oil,t-1}}{p_{oil}} + exp(\sigma_{oil,t})\xi_{oil,t} \quad (13) \\ \sigma_{oil,} &= (1-\gamma_{oil})\sigma_{oil} + \gamma_{oil}\sigma_{oil,t-1} + \eta_{oil}\xi_{\sigma_{oil,t}} \quad (14) \end{aligned}$$

p_{oil} is the oil price at steady state. $\xi_{oil,t}$ represents the oil price level shock, and $\xi_{\sigma_{oil},t}$ represents the oil price volatility shock. Both of these shocks are independent of each other and obey the standard normal distribution.

3.5 Government

Monetary policy follows Taylor rule and is set as follows:

$$ln\frac{R_t}{R} = \phi_R * ln\frac{R_{t-1}}{R} + (1-\phi_R)\left(\gamma_\pi * ln\frac{\Pi_t}{\Pi} + \gamma_y * ln\frac{y_t^d}{y^d}\right) \quad (15)$$

R is gross interest rate at the steady state. Π is inflation rate target. y^d is output at the steady state.

The government finances current transferring payments and bond payments by issuing new bonds. The government runs a balanced budget.

$$T_t = \frac{B_t}{P_t} - B_{t-1}\frac{R_{t-1}}{P_t} \quad (16)$$

3.6 Calibration

We calibrate the model by using China's macroeconomic time series statistical data from 2000 to 2016 and some parameters are calibrated as those in the literature.

China's quarterly average inflation rate is 0.56%, and the quarterly average interest rate is 0.68%. Thus we obtain the household discount factor $\beta = \Pi/R$ according to the steady state. The capital depreciation rate is 2.5%. According to Chang et al. (2015), the substitution rate of intermediate product ε_f is 10, correspondingly the intermediate product price markup about 11%. China's capital income ratio is relatively high. According to Song et al. (2011), α is 0.5. The labor at the steady state is 0.33 and so the labor utility coefficient ψ_L is 21.38. The price rigidity coefficient does not have a consistent value. We simply assume that the average periods that intermediate firm's price can not change are four quarters, thus θ_p is 0.75. The inverse of Frisch labor supply elasticity γ is 2. The consumption habit formation parameter is set to 0.6, close to 0.61 in Zhang (2009). The constant term κ of the investment adjustment cost function is 5. In the monetary policy equation (15) , the coefficient ϕ_R takes a value of 0.96, γ_π is 1.2, and γ_y is 0.2.

According to CEInet Statistical Database[6], the average ratio of crude oil consumption value to GDP is 0.0312 in the period between 2010 and 2018. We use this data to calibrate $\rho = 6.72\%$. As Kim and Loungani (1992), we set the Chinese energy/capital input ratio to 0.02. Then the steady state real oil price p_{oil} is 0.0940. We estimate the equations (13) and (14) using Fernandez-Villaverde et al. (2011)'s particle filtering method. The coefficients in these two equations equal to the medians of the estimation results.

3.7 Results

For the economic dynamic system obtained in the New-Keynesian DSGE model, we use the perturbation method to approximate the solution. Due to the nonlinearity of the oil price equation, the first-order Taylor expansion cannot obtain an equation system containing the volatility shock $\xi_{\sigma_{oil,t}}$. In the second-order expansion, only the interaction term of $\xi_{\sigma_{oil,t}}$and $\xi_{oil,t}$ appears. After the third-order expansion, an independent term of $\xi_{\sigma_{oil,t}}$ appears (see Fernandez-Villaverde et al. (2011)). Although the higher order expansion can bring more accurate results, the amount of calculations increases rapidly. The third-order Taylor expansion can satisfy the needs of this paper.

Additionally, the high-order Taylor expansion will quickly complicate the dynamic sys-

[6]Website: http://tjk.cei.cn/

Table 1: Parameters

Parameter	value	Description
α	0.50	Capital income share
β	0.9988	Household discount factor
δ	0.25	Depreciation rate
ε_f	10	Substitution elasticity between intermediate goods
γ	2	Inverse Frisch elasticity of labor
h	0.6	Consumption habit formation
p_{oil}	0.0940	Oil price at steady state
ψ_L	21.38	Labor utility coefficient
R	1.0068	Bond gross interest rate
ρ_{oil}	0.0672	Oil expenditure share
θ_p	0.75	Probability of not adjusting price
κ	5	Coefficient of investment adjustment cost function
γ_R	0.96	Coefficient on lagged interest rate in the monetary rule
γ_{pi}	1.20	Coefficient on inflation in the monetary rule
γ_y	0.20	Coefficient on output in the monetary rule
ϕ_{oil}	0.53	Coefficient on lagged oil price
σ_{oil}	-1.97	Oil price volatility at the steady state
γ_{oil}	0.52	Coefficient on lagged oil price volatility
η_{oil}	0.56	Standard error of oil price volatility shock

tem. In general, a stable linear dynamic system can be obtained in the first-order expansion, but the dynamic system obtained in the high-order expansion is often no longer stable and explosive. Kim et al. (2008) suggest that after obtaining the dynamic system by approximation, in the forward iteration process, the higher-order items beyond the approximate order should be continuously pruned to avoid the emergences of explosive evolutionary paths. For this purpose, we follow the pruning algorithm of Andreasen et al. (2018), and use the algorithm of Fernandez-Villaverde et al. (2011) to calculate impulse responses.

In this part, we first report impulse responses and analyze the underlying mechanism how oil price volatility shock affects economic activities. Then, through two simulation experiments, we examine the sensitivity of the results to alternative calibrations.

3.7.1 Impulse responses

Figure 4 presents impulse responses of endogenous variables to oil price uncertainty shock in twenty horizons. Output, consumption and investment are expressed as percentage deviations from their ergodic means. When the economic system is impacted by an oil price volatility shock, the volatility of oil price rises and output declines. This is consistent with the direction obtained in the empirical SVM-VAR model. In Figure 4, the decline in output is followed by declines in consumption and investment. The economic intuition here is similar to Fernandez-Villaverde et al. (2011). When the uncertainty of oil price rises, households will increase savings to cope with the rise of uncertainty in the future. Then investment and consumption decrease and households are willing to work more. The declines in consumption and investment add to a decrease in output. In this case, firms will reduce the demand for production inputs, labor, capital and oil. Labor demand by firms falls more than labor supply increase by households increase from the precautionary saving motive, then the equilibrium labor decreases and wage declines. In the capital market, demand reduction brings about a decline in capital and rents.

In summary, the higher oil price volatility reduces China's aggregate output in the short run. This conclusion is consistent with the mainstream uncertainty literature (Bloom (2009), Fernandez-Villaverde et al. (2011), Fernandez-Villaverde et al. (2015), Basu and Bundick (2017), and Bloom et al. (2018)).

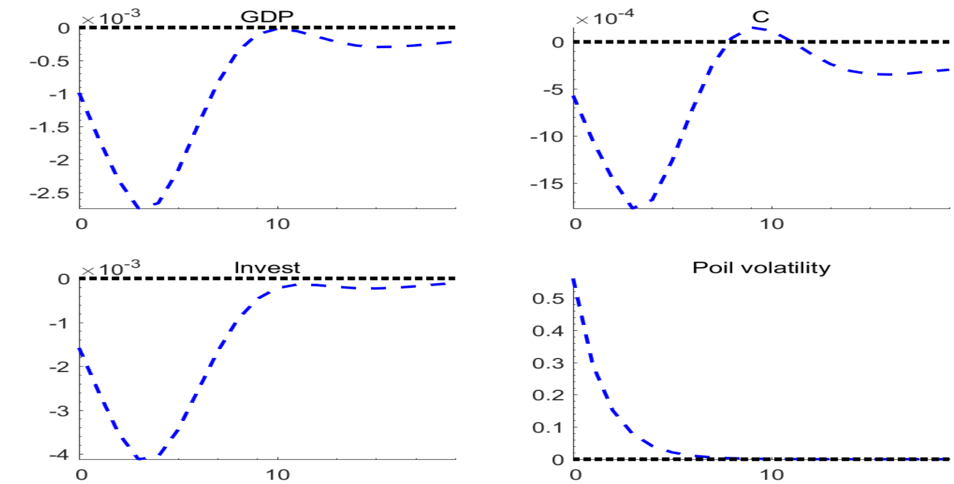
In Figure 4, the magnitude of impulse response is small. This is because only the precautionary saving effect is considered in the DSGE model. Bloom (2014) summarizes that there are two main sources of negative effects of uncertainty shock on output: real options and precautionary savings. Bloom et al. (2018) explore the real option effect in a DSGE model with heterogeneous firms and generate a 2% drop in output when uncertainty shock happens. But the discontinuity of the real option effect is incompatible with the perturbation method we apply here. We leave the real option effect of oil price volatility in a DSGE model for future research.

3.7.2 Sensitivity analysis

China's demand for crude oil probably continues to increase in the future and the oil expenditure's share rises. Thus first we double the value of ρ_{oil} which is the oil expenditure's share. Figure 5 shows that if ρ_{oil} is doubled, the drop in output is nearly 4 times of the benchmark result. When oil input increases, the macroeconomy is more sensitive to oil price uncertainty shock.

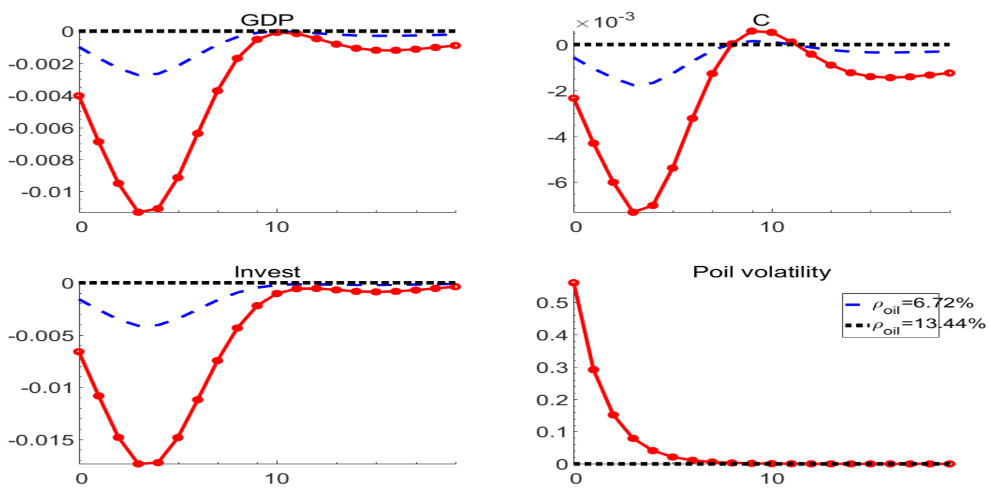
Second we change the value of the substitution elasticity of intermediate producers ε_f. When the economic system is at steady state, the marginal cost of the intermediate goods producer $mc = (\varepsilon_f - 1)/\varepsilon_f$. The substitution elasticity ε_f of the intermediate goods deter-

Figure 4: Impulse Response to an Oil Price Uncertainty Shock



Note: The dashed lines are the impulse responses of endogenous variables to one standard error increase of oil price uncertainty shock. GDP drops in short run when oil price volatility shock occurs.

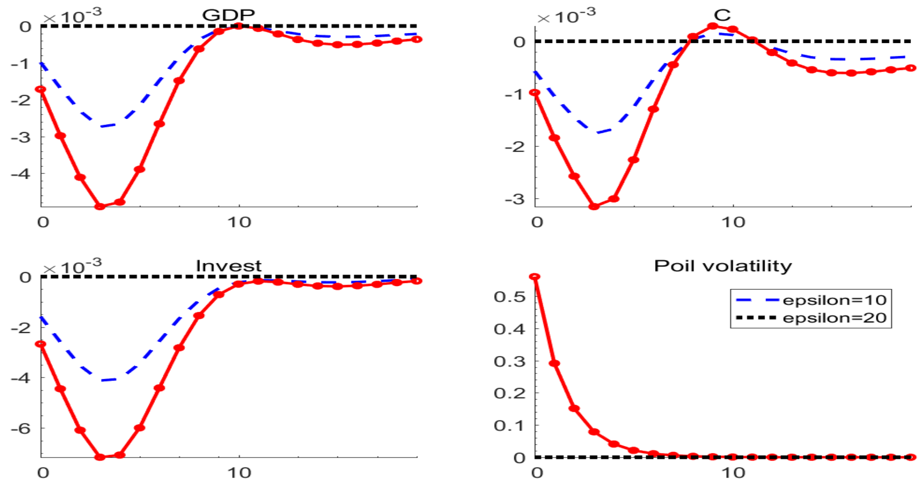
Figure 5: Effect of Double Oil Expenditure's Share



Note: The dashed lines are the impulse responses of endogenous variables to one standard error increase of oil price uncertainty shock in the baseline when the oil expenditure share $\rho_{oil} = 6.72\%$. The dotted lines are the impulse responses of endogenous variables to one standard error of oil price uncertainty shock when ρ_{oil} doubles. GDP drops more in the economy with a larger oil expenditure share when the same amount of oil price uncertainty shock occurs.

mines the marginal cost at the steady state. When the substitution elasticity increases, the marginal cost mc rises. In the baseline model, $\varepsilon_f = 10$. When $\varepsilon_f = 20$, it can be seen from Figure 6 that the amplitude of the impulse response of all variables becomes larger. The reason is that the increase in marginal cost leads to a decline in the markup, a smaller profit margin for companies. Firms response more fiercely to the same demand decline brought about by precautionary savings.

Figure 6: Effect of Double Intermediate Goods Substitution Elasticity



Note: The dashed lines are the impulse responses of endogenous variables to one standard error increase of oil price uncertainty shock in the baseline when the substitution elasticity of the intermediate goods $\varepsilon_f =$ 10*. The dotted lines are the impulse responses of endogenous variables to one standard error of oil price uncertainty shock when* ε_f *doubles. GDP drops more in the economy with a larger substitution elasticity of the intermediate goods when the same amount of oil price uncertainty shock occurs.*

4 Conclusion

This paper investigates the relationship between oil price uncertainty and China's macroeconomy. First, we apply the VAR model with stochastic volatility in mean that makes the volatility of oil price affect the endogenous variables directly. We find that a positive shock to oil price uncertainty results in a decrease in China's real economic activity, world oil production and world oil price.

Second, we use a New-Keynesian small open economy model with time-varying oil price volatility to explain the outcomes in the SVM-VAR model. We find that the sign of output impulse response function is consistent with the SVM-VAR model, though the magnitude is smaller for only precautionary saving channel is included in the theoretical model. How to construct a model with real option effect of oil price uncertainty is an issue for future research.

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Appendix A SVM-VAR model estimation

A.1 Priors and initial values

1. VAR coefficients Γ. $\Gamma = vec([c; \beta_j; b_k])$. The prior is assumed to be $N(\Gamma_0, P_0)$. We choose the first 60 observations as a training sample. Σ_d is a vector of AR(1) variance of each endogenous variables in the training sample. We follow Banbura et al. (2010)'s dummy observation method and get the dummy dependent variable y_d and independent variable x_d. $\Gamma_0 = [x_d^{'}x_d]^{-1}[x_d^{'}x_d]$ and $P_0 = \Sigma_d \bigotimes [x_d^{'}x_d]^{-1}$.

2. Elements of $\tilde{h}_t$. The prior of lnh_0 is assumed to be $N(ln\hat{\sigma}_0, I_n)$. $\hat{\sigma}_0$ is a vector of the diagonal elements of $Cholesky(\hat{\Sigma}_{ols})$. $\hat{\Sigma}_{ols}$ is the OLS covariance of the training sample.

3. Elements of A. The prior is assumed to be $N(\hat{a}_{ols}, 100I_n)$. Each row of $\hat{\Sigma}_{ols}$ is scaled by this row's diagonal element, and then the off-diagonal elements construct the vector $\hat{a}_{ols}$.

4. Elements of α, Θ and Q. Set the prior of the elements of Θ and Q also by dummy observation method and Q follows a inverse Wishart distribution.

Initial values of the estimated variables are the mean of their priors respectively.

A.2 Gibbs sampling algorithm

To obtain the posterior draws, we partition the unknown parameters into five parts and sample each part sequentially by Gibbs sampling with $\tilde{h}_t$ sampled from particle Gibbs.

1. $p(A|\Gamma, \alpha, \Theta, Q, \tilde{h}_t)$. We can sample A following the procedures in Cogley and Sargent (2005) conditional on $\Gamma, \alpha, \Theta, Q, \tilde{h}_t$.

2. $p(\Gamma|\alpha, \Theta, Q, \tilde{h}_t, A)$. We can sample Γ from the posterior normal distribution conditional on $\alpha, \Theta, Q, \tilde{h}_t, A$ using the Carter and Kohn (1994) algorithm.

3. $p(\alpha, \Theta|Q, \tilde{h}_t, A, \Gamma)$. The posterior distribution of α, Θ is a normal distribution given $Q, \tilde{h}_t, A, \Gamma$.

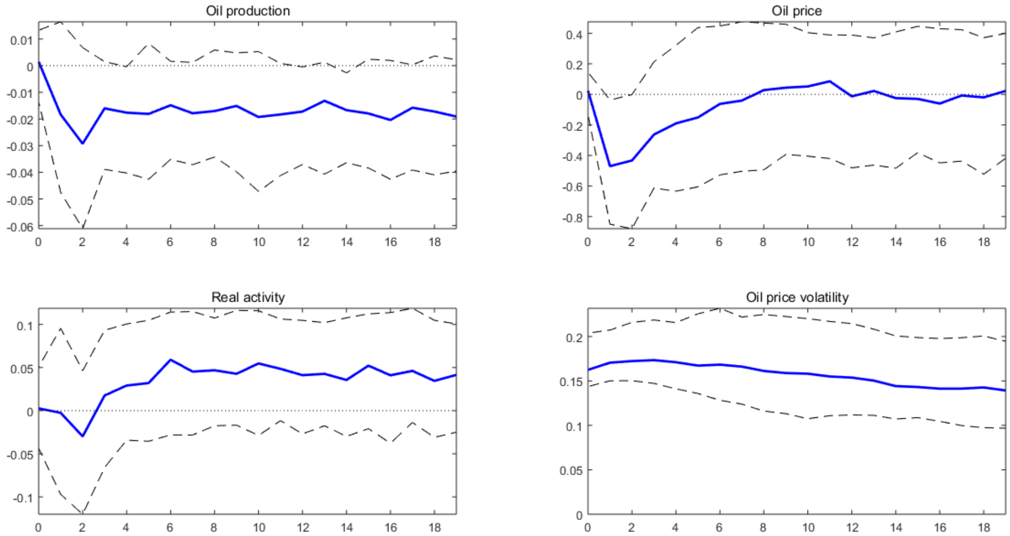
4. $p(Q|\tilde{h}_t, A, \Gamma, \alpha, \Theta)$. We can sample Q from the posterior inverse Wishart distribution conditional on $\tilde{h}_t, A, \Gamma, \alpha, \Theta$.

5. $p(\tilde{h}_t|A, \Gamma, \alpha, \Theta, Q)$. The posterior distribution of $\tilde{h}_t$ is not standard so we can not sample $\tilde{h}_t$ from a built-in procedure. We use a particle Gibbs step to draw $\tilde{h}_t$ following Andrieu et al. (2010) and Lindsten et al. (2014).

For more algorithm details, please refer to Appendix 1.2 of Mumtaz and Theodoridis (2019).

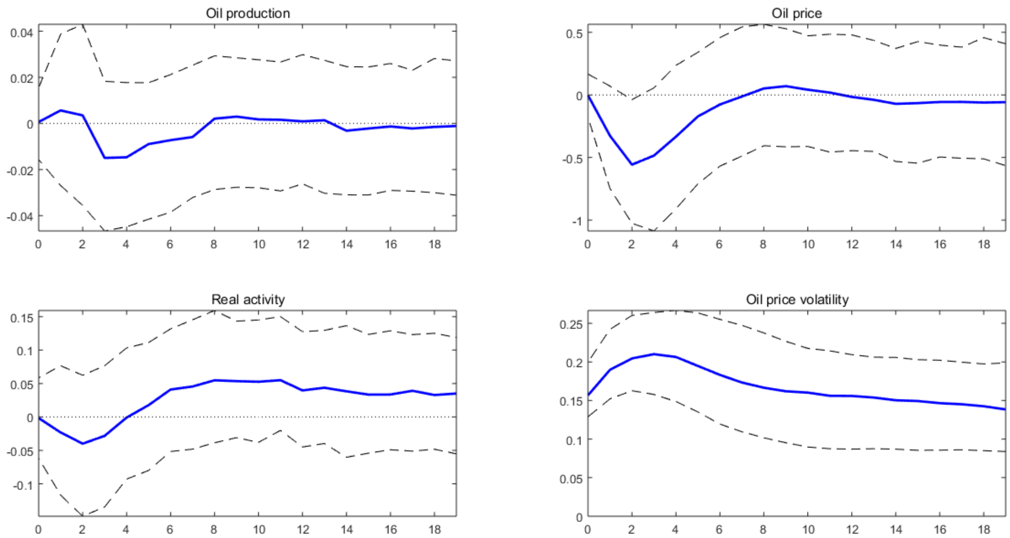
Appendix B Robustness Checks

Figure B-1: IRF to an Oil Price Uncertainty Shock: 30-Period Training Sample



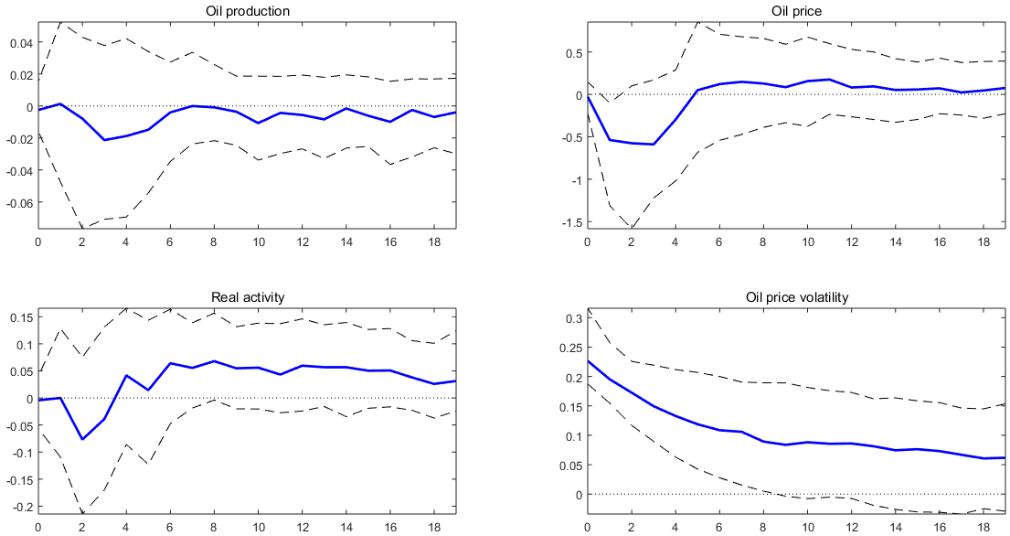
Note: We use the data of the first 30 months as a training sample to calculate priors and initial values. The solid line is the median generalized impulse response of endogenous variables to one standard error increase in oil price volatility. The dashed lines are the 68% posterior error band. GDP proxied by electricity production drops in short run when oil price volatility shock occurs.

Figure B-2: IRF to an Oil Price Uncertainty Shock: 90-Period Training Sample



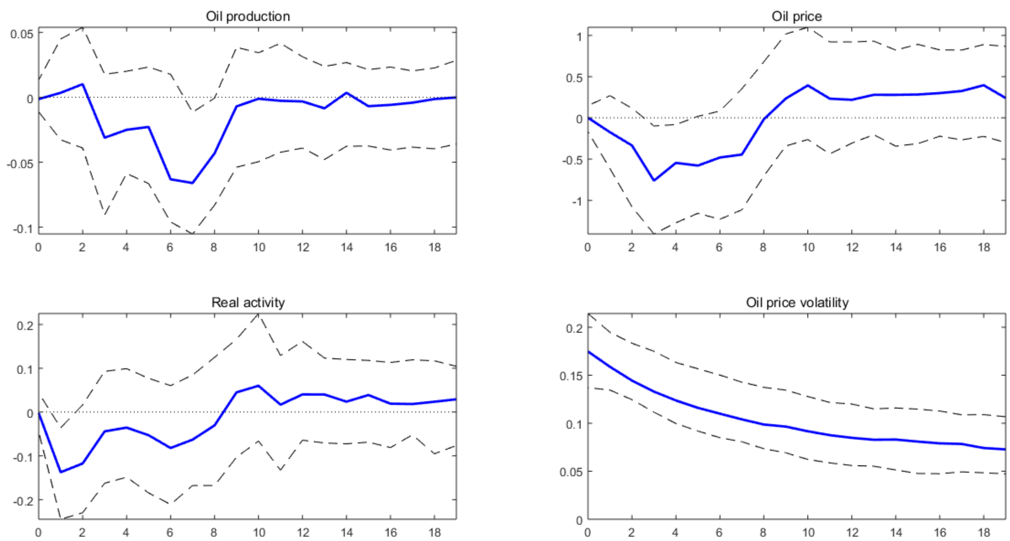
Note: We use the data of the first 90 months as a training sample to calculate priors and initial values. The solid line is the median generalized impulse response of endogenous variables to one standard error increase in oil price volatility. The dashed lines are the 68% posterior error band. GDP proxied by electricity production drops in short run when oil price volatility shock occurs.

Figure B-3: IRF to an Oil Price Uncertainty Shock: Lags Change (24,6)



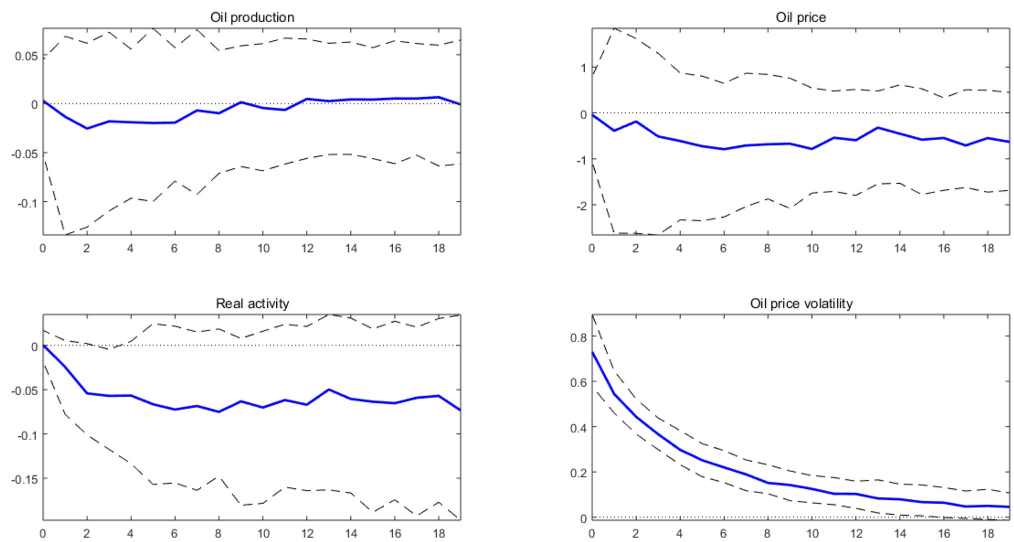
Note: The lag number of endogenous variables is 24 and the lag number of volatilities is 6. The solid line is the median generalized impulse response of endogenous variables to one standard error increase in oil price volatility. The dashed lines are the 68% posterior error band. GDP proxied by electricity production has a significant drop in short run when oil price volatility shock occurs.

Figure B-4: IRF to an Oil Price Uncertainty Shock: Lags change (12,12)



Note: The lag number of endogenous variables is 12 and the lag number of volatilities is 12. The solid line is the median generalized impulse response of endogenous variables to one standard error increase in oil price volatility. The dashed lines are the 68% posterior error band. GDP proxied by electricity production has a significant drop in short run when oil price volatility shock occurs.

Figure B-5: IRF to an Oil Price Uncertainty Shock: Quarterly Data



Note: We use quarterly data of 2000Q1-2017Q4, especially quarterly real GDP, to estimate the model. The data of world oil production and prices are the averages of the monthly data. The data of China's quarterly real GDP are from Chang et al. (2016). The lag of endogenous variables is four, and that of volatilities is one. The solid line is the median generalized impulse response of endogenous variables to one standard error increase in oil price volatility. The dashed lines are the 68% posterior error band. Real GDP has a significant drop when oil price volatility shock occurs.

Appendix C DSGE model

C.1 Household

The representative household preference is:

$$E\sum_{t=0}^{\infty}\beta^t\left[ln(c_{j,t}-h*c_{j,t-1})-\psi_L\frac{l_{j,t}^{1+\gamma}}{1+\gamma}\right] \tag{C.1}$$

The budget constraint faced by representative households is:

$$c_{j,t}+i_{j,t}+\frac{B_{j,t}}{P_t}=w_{j,t}l_{j,t}+r_tk_{j,t-1}+B_{j,t-1}\frac{R_{t-1}}{P_t}+T_{j,t}+F_{j,t} \tag{C.2}$$

The capital accumulation equation is:

$$k_{j,t}=(1-\delta)k_{j,t-1}+\left[1-S(\frac{i_{j,t}}{i_{j,t-1}})\right]i_{j,t} \tag{C.3}$$

$S(\frac{i_{j,t}}{i_{j,t-1}})=\frac{\kappa}{2}(\frac{i_{j,t}}{i_{j,t-1}}-1)^2$ is investment adjustment cost function, and satisfy the conditions $S(1)=0$, $S^{'}(1)=0$, and $S^{''}>0$.

The first-order conditions for consumption, bonds, capital stock, investment and labor are:

$$\lambda_{j,t} = \frac{1}{c_{j,t}-hc_{j,t-1}}-h\beta E_t\frac{1}{c_{j,t+1}-hc_{j,t}} \tag{C.4}$$

$$\lambda_{j,t} = \beta E_t\frac{\lambda_{j,t+1}R_t}{\pi_{t+1}} \tag{C.5}$$

$$q_{j,t} = \beta E_t\left[\frac{\lambda_{j,t+1}}{\lambda_{j,t}}r_t+\frac{\lambda_{j,t+1}}{\lambda_{j,t}}q_{j,t+1}(1-\delta)\right] \tag{C.6}$$

$$1 = q_{j,t}\left[1-S(\frac{i_{j,t}}{i_{j,t-1}})-S^{'}(\frac{i_{j,t}}{i_{j,t-1}})\frac{i_{j,t}}{i_{j,t-1}}\right]+\beta E_t\left[q_{j,t+1}\frac{\lambda_{j,t+1}}{\lambda_{j,t}}S^{'}(\frac{i_{j,t+1}}{i_{j,t}})\frac{i_{j,t+1}^2}{i_{j,t}^2}\right] \tag{C.7}$$

$$\lambda_{j,t} = \frac{\psi_L l_{j,t}^{\gamma}}{w_{j,t}} \tag{C.8}$$

$\lambda_{j,t}$ is the Lagrangian multiplier of the budget constraint equation. $Q_{j,t}$ is the Lagrangian multiplier of the capital accumulation equation. $q_{j,t}=\frac{Q_{j,t}}{\lambda_{j,t}}$.

C.2 Final goods entrepreneur

Under perfect competition, the final goods entrepreneur's production function is:

$$y_t^d = \left(\int_0^1 y_{i,t}^{\frac{\varepsilon_f - 1}{\varepsilon_f}} di \right)^{\frac{\varepsilon_f}{\varepsilon_f - 1}} \tag{C.9}$$

Profit maximization problem is:

$$\max_{y_{i,t}} P_t \left(\int_0^1 y_{i,t}^{(\varepsilon_f - 1)/\varepsilon_f} di \right)^{\varepsilon_f/(\varepsilon_f - 1)} - \int_0^1 p_{i,t} y_{i,t} di \tag{C.10}$$

Via first order conditions, we get the demand function for each intermediate goods:

$$y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\varepsilon_f} y_t^d \tag{C.11}$$

Zero profit condition under complete competition:

$$P_t \left(\int_0^1 y_{i,t}^{(\varepsilon_f - 1)/\varepsilon_f} di \right)^{\varepsilon_f/(\varepsilon_f - 1)} - \int_0^1 p_{i,t} y_{i,t} di = 0 \tag{C.12}$$

and with the equation (C.11) eliminate $y_{i,t}$, we get the relationship between the price level and the intermediate good prices:

$$P_t = \left(\int_0^1 P_{i,t}^{1-\varepsilon_f} di \right)^{1/(1-\varepsilon_f)} \tag{C.13}$$

Solve the first-order condition of final goods entrepreneur profit optimization problem, and we get the demand function for each intermediate product:

$$y_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\varepsilon_f} y_t^d \tag{C.14}$$

Completely competitive market leads to zero profit for the final product producer, which derives a relationship of the price level and the intermediate product price:

$$P_t = \left(\int_0^1 P_{i,t}^{1-\varepsilon_f} di \right)^{\frac{1}{1-\varepsilon_f}} \tag{C.15}$$

C.3 Intermediate goods entrepreneur

In the monopolistic competitive market environment, the production function of intermediate product producer is

$$y_{i,t} = A_t \left(O_{i,t}^{\rho} K_{i,t-1}^{1-\rho}\right)^{\alpha} \left(l_{i,t}^{d}\right)^{1-\alpha} \tag{C.16}$$

First, minimize the cost of the unit intermediate product:

$$\min_{k_{i,t-1}, l_{i,t}^{d}} w_t l_{i,t}^{d} + r_t k_{i,t-1} + p_{oil,t} O_{i,t} \tag{C.17}$$

$$s.t. \quad y_{i,t} = A_t (O_{i,t}^{\rho} k_{i,t-1}^{1-\rho})^{\alpha} (l_{i,t}^{d})^{1-\alpha} \tag{C.18}$$

By the first order conditions, we get:

$$\frac{w_t l_{i,t}^{d}}{1-\alpha} = \frac{r_{k,t} k_{i,t-1}}{\alpha(1-\rho)} \tag{C.19}$$

$$\frac{p_{oil,t} O_{i,t}}{\alpha\rho} = \frac{r_{k,t} k_{t-1}}{\alpha(1-\rho)} \tag{C.20}$$

mc_t is the aggregate cost of a unit $y_{i,t}$, thus we can get:

$$mc_t = \frac{1}{A_t} \left(\frac{w_t}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} \left[\left(\frac{p_{oil,t}}{\rho}\right)^{\rho} \left(\frac{r_{k,t}}{1-\rho}\right)^{1-\rho}\right]^{\alpha} \tag{C.21}$$

Intermediate goods producers are subject to Calvo pricing. The profit maximization problem of Intermediate goods entrepreneur is:

$$\max_{P_{i,t}} E_t \sum_{s=0}^{\infty} (\beta\theta_p)^s \frac{\lambda_{t+s}}{\lambda_t} \left[\left(\prod_{\tau=1}^{s} \pi_{t+\tau-1}\right) \frac{P_{i,t}}{P_{t+s}} - mc_{t+s}\right] y_{i,t+s} \tag{C.22}$$

$$s.t. \quad y_{i,t+s} = \left[\left(\prod_{\tau=1}^{s} \pi_{t+\tau-1}\right) \frac{P_{i,t}}{P_{t+s}}\right]^{-\varepsilon_f} y_{t+s}^{d} \tag{C.23}$$

Then the first order conditions are:

$$\varepsilon_f g_t^1 = (\varepsilon_f - 1) g_t^2 \tag{C.24}$$

$$g_t^1 = \lambda_t mc_t y_t^d + \beta\theta_p E_t g_{t+1}^1 \left(\frac{\pi_t}{\pi_{t+1}}\right)^{-\varepsilon_f} \tag{C.25}$$

$$g_t^2 = \lambda_t \frac{P_t^*}{P_t} y_t^d + \beta\theta_p E_t g_{t+1}^2 \frac{P_t^* P_{t+1}}{P_{t+1}^* P_t} \left(\frac{\pi_t}{\pi_{t+1}}\right)^{1-\varepsilon_f} \tag{C.26}$$

For the symmetric equilibrium that the optimal price of each intermediate goods firm is consistent, this price is expressed as P_t^*. With $1-\theta_p$ proportion of P_t^*, equation (C.15) becomes

$$P_t = [\theta_p(\pi_{t-1}P_{t-1})^{1-\varepsilon_f} + (1-\theta_p)(P_t^*)^{1-\varepsilon_f}]^{1/(1-\varepsilon_f)} \tag{C.27}$$

C.4 Oil price

Oil price follows an AR(1) process with stochastic volatility.

$$\begin{aligned} ln\frac{p_{oil,t}}{p_{oil}} &= \phi_{oil} * ln\frac{p_{oil,t-1}}{p_{oil}} + exp(\sigma_{oil,t})\xi_{oil,t} && \text{(C.28)} \\ \sigma_{oil,} &= (1-\gamma_{oil})\sigma_{oil} + \gamma_{oil}\sigma_{oil,t-1} + \eta_{oil}\xi_{\sigma_{oil,t}} && \text{(C.29)} \end{aligned}$$

C.5 Government

Monetary policy follows Taylor rule and is set as follows:

$$ln\frac{R_t}{R} = \phi_R * ln\frac{R_{t-1}}{R} + (1-\phi_R)\left(\gamma_\pi * ln\frac{\Pi_t}{\Pi} + \gamma_y * ln\frac{y_t^d}{y^d}\right) \tag{C.30}$$

The government budget balance equation is:

$$T_t = \frac{B_t}{P_t} - B_{t-1}\frac{R_{t-1}}{P_t} \tag{C.31}$$

C.6 Equilibrium system

Aggregate all the representative entities, we get the equilibrium system:

Households:

$$\begin{aligned} \lambda_t &= \frac{1}{c_t - hc_{t-1}} - h\beta E_t\frac{1}{c_{t+1} - hc_t} && \text{(C.32)} \\ \lambda_t &= \beta E_t\frac{\lambda_{t+1}R_t}{\pi_{t+1}} && \text{(C.33)} \\ q_t &= \beta E_t\left[\frac{\lambda_{t+1}}{\lambda_t}r_t + \frac{\lambda_{t+1}}{\lambda_t}q_{t+1}(1-\delta)\right] && \text{(C.34)} \\ 1 &= q_t\left[1 - S(\frac{i_t}{i_{t-1}}) - S'(\frac{i_t}{i_{t-1}})\frac{i_t}{i_{t-1}}\right] + \beta E_t\left[q_{t+1}\frac{\lambda_{t+1}}{\lambda_t}S'(\frac{i_{t+1}}{i_t})\frac{i_{t+1}^2}{i_t^2}\right] && \text{(C.35)} \\ \lambda_t &= \frac{\psi_L l_t^\gamma}{w_t} && \text{(C.36)} \end{aligned}$$

Firms:

$$\begin{aligned}
\varepsilon_f g_t^1 &= (\varepsilon_f - 1) g_t^2 && \text{(C.37)}\\
g_t^1 &= \lambda_t mc_t y_t^d + \beta\theta_p E_t g_{t+1}^1 \left(\frac{\pi_t}{\pi_{t+1}}\right)^{-\varepsilon_f} && \text{(C.38)}\\
g_t^2 &= \lambda_t \frac{P_t^*}{P_t} y_t^d + \beta\theta_p E_t g_{t+1}^2 \frac{P_t^* P_{t+1}}{P_{t+1}^* P_t} \left(\frac{\pi_t}{\pi_{t+1}}\right)^{1-\varepsilon_f} && \text{(C.39)}\\
\frac{w_t l_t^d}{1-\alpha} &= \frac{r_{k,t} k_{t-1}}{\alpha(1-\rho)} && \text{(C.40)}\\
\frac{p_{oil,t} O_t}{\alpha\rho} &= \frac{r_{k,t} k_{t-1}}{\alpha(1-\rho)} && \text{(C.41)}\\
mc_t &= \frac{1}{A_t} \left(\frac{w_t}{1-\alpha}\right)^{1-\alpha} \left(\frac{1}{\alpha}\right)^{\alpha} \left[\left(\frac{p_{oil,t}}{\rho}\right)^{\rho} \left(\frac{r_{k,t}}{1-\rho}\right)^{1-\rho}\right]^{\alpha} && \text{(C.42)}\\
P_t &= [\theta_p(\pi_{t-1}P_{t-1})^{1-\varepsilon_f} + (1-\theta_p)(P_t^*)^{1-\varepsilon_f}]^{1/(1-\varepsilon_f)} && \text{(C.43)}
\end{aligned}$$

Monetary policy:

$$ln\frac{R_t}{R} = \phi_R * ln\frac{R_{t-1}}{R} + (1-\phi_R)\left(\gamma_\pi * ln\frac{\Pi_t}{\Pi} + \gamma_y * ln\frac{y_t^d}{y^d}\right) \tag{C.44}$$

Market clearing:

$$\begin{aligned}
y_t &= c_t + i_t + p_{oil,t} O_t && \text{(C.45)}\\
GDP_t &= c_t + i_t && \text{(C.46)}\\
y_t &= \frac{A_t \left(O_t^{\rho} k_{t-1}^{1-\rho}\right)^{\alpha} \left(l_t^d\right)^{1-\alpha}}{\nu_t^p} && \text{(C.47)}\\
\nu_t^p &= \left(\frac{\pi_{t-1}}{\pi_t}\right)^{-\varepsilon_f} \theta_p \nu_{t-1}^p + 1 - \theta_p \left(\frac{P_t^*}{P_t}\right)^{-\varepsilon_f} && \text{(C.48)}\\
\pi_t^* &= \frac{P_t^*}{P_t} && \text{(C.49)}\\
l_t^d &= l_t && \text{(C.50)}\\
k_t &= (1-\delta)k_{t-1} + \left[1 - S(\frac{i_t}{i_{t-1}})\right] i_t && \text{(C.51)}
\end{aligned}$$

Exogenous processes:

$$\begin{aligned}
ln\frac{p_{oil,t}}{p_{oil}} &= \phi_{oil} * ln\frac{p_{oil,t-1}}{p_{oil}} + exp(\sigma_{oil,t})\xi_{oil,t} && \text{(C.52)}\\
\sigma_{oil,} &= (1-\gamma_{oil})\sigma_{oil} + \gamma_{oil}\sigma_{oil,t-1} + \eta_{oil}\xi_{\sigma_{oil,t}} && \text{(C.53)}
\end{aligned}$$