

# **How Well Can a New Keynesian Model with Oil Price Shocks Explain the Behavior of the Chinese Economy?**

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## **Abstract**

By the year of 2013, China has become the second largest oil consumer in the world with an annual consumption of 20.74 quadrillion Btu. In contrast with numerous studies for developed countries, the research focusing on the relation between the oil price and developing countries, such as China, is just getting started. In order to analyze the impact of the oil price shocks on the Chinese economy, Jian, Li and Zheng (2010) construct a New Keynesian model with oil price shocks. However, since their study is mainly focusing on the theoretical mechanisms, the cyclical properties of that model are not reported in their paper. In this study, I simulate the model of Jian, Li and Zheng (2010) and conduct a comparison of the cyclical properties between this model and the Chinese actual data, to see how well such a New Keynesian model can explain the behavior of the Chinese economy. The results show that the differences between the model and the Chinese actual data are significant in terms of the predicted correlations. In order to improve this model, three possible approaches are suggested based on the facts of the modern energy industry.

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## **1. Introduction**

The Chinese economy has been growing rapidly in the recent decades since the beginning of the economic reforms 1978. According to the World Bank, the Chinese Gross Domestic Product (GDP) has reached 9240.27 billion U.S. dollars by the year of 2013, with the average annual growth rate of 9.89% (1979-2013), thereby making China the second largest economy in the world. Since modern industries are highly dependent on the crude oil as the main energy source, the Chinese oil consumption also increases dramatically along with the development of the economy. According to the U.S. Energy Information Administration (EIA), by the year of 2013, China has also become the second largest oil consumer in the world with an annual consumption of 20.74 Quadrillion Btu. Considering the fact that China is an oil net importer since 1992 and adjusts its oil price according to international markets, the relation between the international oil price and the Chinese economy has attracted the interest of economists in recent years.

Although there are numerous studies based on the developed countries, the research focusing on the relation between oil prices and developing countries, such as China, is just getting started. Among these researches, a notable job is done by Jian, Li and Zheng (2010). In order to analyze the impact of the oil price shocks on the Chinese economy, they construct a New Keynesian model with oil price shocks, based on a standard sticky price business cycle model outlined in Ireland (2003). According to the impulse response analysis and the variance decomposition based on this model, Jian, Li and Zheng (2010) conclude that the exogenous oil price shock is one of the main causes of the Chinese economic fluctuations. Furthermore, they find that positive oil price shocks decrease output and consumption, meanwhile increase the inflation in the Chinese economy.

From a modern prospective, Jian, Li and Zheng (2010)'s model is quite well-developed. It includes many ingredients, which are coincidentally important for many notable studies in the macroeconomic field. The parameter estimation of their model is conducted by the maximum likelihood method using the Chinese actual data. However, since their study is mainly focusing on the theoretical mechanism through which the oil price shock may impact the whole economy, the cyclical properties of that model are not reported in their paper.

Cyclical properties, such as standard deviations, autocorrelations and cross-correlations, play an essential role in evaluating a theoretical model. Specifically, a standard deviation measures the volatility of an economic series; an autocorrelation measures the persistence of the series and a cross-correlation measures the direction of the comovement between different variables. In order to examine how well the model in Jian, Li and Zheng (2010) explains the behavior of the Chinese economy, I conduct a comparison of the cyclical properties between this model and the Chinese actual data. Particularly, six variables are chosen from the model as the observable variables. They are output, consumption, oil price, money supply, inflation and government expenditure. On the other hand, six time series data are selected as the counterparts of these observable variables in the real world. They are real GDP, household final consumption, price of West Texas Intermediate (WTI), narrow money supply M1, Consumer Price Index (CPI) and government expenditure. All of them are the Chinese data except the international oil price WTI. After that, standard deviations, first-order autocorrelations and cross-correlations are calculated based on the simulation results of Jian, Li and Zheng (2010)'s model and these real world data respectively for this comparison.

The comparison results show that the first-order autocorrelations of these six observable variables are very similar between the model and reality, which means the model depict the Chinese economy properly in term of persistence. However, when it comes to the standard deviations and cross-correlations, the differences between the simulated and the actual data are

significant. To be specific, the economic system described by Jian, Li and Zheng (2010) is more volatile than the Chinese economy. And the counter-cyclical comovement between output and the oil price in the model is contrary to the real world. According to this result, I conclude that the model in Jian, Li and Zheng (2010) cannot explain the Chinese economy well in terms of the standard cycle properties, and further amendments are still needed. Furthermore, with the aim of improving this model, three possible approaches are suggested based on the facts of modern energy industry.

The remaining parts of this paper are organized as following. Part 2 is a brief literature review introducing the theoretical development of studying oil price shock. Part 3 presents Jian, Li and Zheng (2010)'s model in detail and discusses the main characteristics of this model. Part 4 is a detailed description of the methodology adopted by this study. The comparison results and the discussion based on these results can be found in Part 5. Part 6 is the conclusion.

## **2. Literature Review**

Although the history of exploiting crude oil can be tracked back to the ancient Egypt, when people started using such black liquid in construction and pharmacy, it is in the 1970's that the crude oil triggered people's serious attentions globally. Two worldwide oil crises happened in 1973 and 1979, which caused tremendous shocks to the western world's economy. Since then, numerous efforts have been devoted to studying the transmission mechanisms of the oil price's impact, and more importantly, what people should do to alleviate the negative effects brought by the drastically changes of oil prices.

Some early analyzes were done by Hamilton (1983). He found the fact that the substantial increases of oil price always followed by recessions in the postwar U.S. economy. This phenomenon could not be simply explained as a statistical coincidence. Furthermore, there was little evidence indicated that the oil price and total output were simultaneously affected by

another macroeconomic variable in the U.S. economy. Therefore, Hamilton argued that there might be an endogenous mechanism in the U.S. economy so that at least part of these recessions was triggered by the increases of oil price through such mechanism. From the modern perspective, Hamilton (1983)'s work is extremely meaningful since a considerable amount of the following studies is inspired by it. However, the six-variable model he used, which was based on Sims (1980), is questionable to some people. Since Sims (1980)'s model is an aggregate model and lacks micro-foundations, Hamilton's work is arguably subject to Lucas (1976) critique.

In the 1980's, the real business cycle revolution happened in the academia of macroeconomics, triggered by Kydland and Prescott (1982). In their study, Kydland and Prescott showed that if a stochastic technology shock was introduced into the neoclassical growth model, such model would be able to replicate many features of modern business cycles. Kydland and Prescott (1982)'s work demonstrated that the aggregate fluctuations in macroeconomics could be explained by a competitive model without any externalities. Since then, their work has been extended on numerous dimensions by the following researchers.

One of the most debatable points in Kydland and Prescott's theory is that, besides the technological innovations, there might be other potential factors that can be considered as the main forces of driving the macroeconomic fluctuations. The price of energy is one of these potential factors. In 1992, Kim and Loungani first extended the basic real business cycle model by taking the energy price shock into account. They treated the energy as an input of the firm sector and assumed that the exogenous energy price would follow an Autoregressive-Moving-Average (ARMA) stochastic process. In their study, the RBC model with technology and energy price shocks was compared with the model with only technology shocks and the model with only energy price shocks. Their result showed that, comparing with the basic model which only took the technology shocks into account, the RBC model with both the technology and energy price shocks could explain more of the volatility in output. However, such increment was only modest.

When it came to the model only with energy price shocks, the simulation results failed to replicate the main cyclical properties of the actual U.S. data. In conclusion, Kim and Loungani's (1992) research indicated that, the energy price did play a role in explaining the aggregate fluctuations and had impacts on macroeconomics. However, comparing with the impact of technology shocks, the impact of oil price shocks was not equally significant.

Another important research focusing on the role of energy price shocks was done by Finn (1995). Finn argued that when researchers wanted to introduce the energy price shocks in their models, a special attention was required to be paid on the method of such an introduction. Giving the fact that the growth rate of the real energy price and the aggregate Solow residual in the U.S. economy were highly correlated, Finn built his RBC model to demonstrate how the productivity of an economy could be affected by the energy price shocks. Instead of directly putting the energy usage into the production function as an input, Finn multiplied the capital input by a utilization rate. By his assumption, the energy usage in each period would affect the ratio of energy to capital. The change of such ratio would further lead to the variations of the capital utilization rate. In this way, the linkage between the energy price and the productivity was established. According to Finn's results, this RBC model with energy price shocks, combining with the technology shocks and the government expenditure shocks, could generally mimic the cyclical properties of the postwar U.S. economy.

With the further development of the business cycle research, economists have found that real business cycle models with complete, flexible prices conflict with the large amount of empirical evidence which indicates that monetary disturbances have substantial real effects. In order to build a general equilibrium model which can well explain the business cycle phenomenon both qualitatively and quantitatively, the New Keynesian assumptions, such as the monopolistic competition, nominal rigidities and short-run non-neutrality of monetary policy have been introduced.

Taking the New Keynesian model as the paradigm of analyzing economic shocks, Leduc and Sill (2004) did another meaningful work in studying the impact of oil price shocks. The basic research question of their work was that whether it was the oil price shock itself or the endogenous monetary policy which led to the phenomenon that recessions are always preceded by the increase of the oil price in the postwar U.S. economy. In order to compare the effects of different monetary policies, Leduc and Sill built a New Keynesian model with oil price shocks. The oil usage was introduced into this model through the capital utilization rate, which was similar to Finn (1995). Instead of defining a single monetary policy for the central bank, Leduc and Sill gave three optional policies to let the central bank target the price level, the inflation rate or the interest rate. They found that the impulse responses of the oil price shock were substantially different among these three monetary policies. The monetary policy targeting the price level gave the best performance in abating the negative effect of oil price shocks. On the contrary, the monetary policy targeting the inflation rate seemly could only make the situation worse. Therefore, their study concluded that the central bank's monetary policy did play a crucial role in the reaction to oil price shocks.

Similarly, Jian, Li and Zheng (2010)'s work is also based on a New Keynesian model like Leduc and Sill (2004). In order to study the impact of oil price shock on China's economy, Jian, Li and Zheng (2010) constructed their New Keynesian model with the elements of the adjustment cost of capital accumulation, consumption habit, capital utilization rate, sticky prices and monopoly competition, which are same as in the previous discussion. Further, instead of only examining oil price shocks, Jian, Li and Zheng also introduced preference shocks, technology shocks, government expenditure shocks, tax rate shocks and monetary policy shocks to obtain a sufficient stochastic structure. Such a well-developed model seemingly can well explain the behavior of the Chinese economy, at least at the theoretical level. It is intriguing to examine whether such a model will quantitatively match the cyclical properties of the Chinese actual data.

### **3. The Model**

To start my research, it is necessary to describe the New Keynesian model, which is outlined in Jian, Li and Zheng (2010), first. Please notice that, in order to be consistent with Jian, Li and Zheng's previous analysis, I do not make any change on the original model. The following description of this part is almost exactly taken from Jian, Li and Zheng (2010). Please refer to this paper for further information.

In order to build a well-developed model, Jian, Li and Zheng choose the standard sticky price dynamic stochastic general equilibrium model, constructed by Ireland (2003) as their framework. With the purpose of introducing the exogenous oil price shock into the system, they add the capital utilization rate into the production function of intermediate firms. The capital utilization rate is determined by the ratio of the firm's oil usage to capital input, which is same as in Finn (1995). Besides that, Jian, Li and Zheng also modify the endogenous money supply function of the central bank. In particular, the money supply function in this model responds to not only the fluctuations of inflation and output, but also the oil price shocks. Further, Jian, Lin and Zheng give this model the feature of nominal rigidity by assuming the intermediate firms can only adjust their price by a staggering manner according to the rule of Calvo (1983). In addition, the adjustment cost of capital accumulation and consumption habit assumptions are also included in this model.

To sum up, Jian, Li and Zheng (2010)'s model has five agents. They are the representative household, the representative finished goods-producing firm, the representative intermediate goods-producing firm, the government and the central bank. Further, six exogenous shocks are included in this model. All these shocks are listed in Table 3.1 for the convenience of reference. The following part describes each agent in this model in detail.

**Table 3.1 Shocks Manual**

Name	Symbol
Preference Shock	$a_t$
Technology Shock	$Z_t$
Oil Price Shock	$P^o_t$
Government Expenditure Shock	$G_t$
Tax Rate Shock	$\tau_t$
Monetary Policy Shock	$M_t$

### 3.1 The Representative Household

Jian, Li and Zheng (2010) assume that there is a continuum of infinitely lived households indexed by  $i \in [0, 1]$ .  $C$ ,  $M$  and  $L$  denote consumption, money and labor supply. The representative household solves the intertemporal utility maximization problem in each period:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, \frac{M_t}{P_t}, L_t),$$

where  $E_0$  is the expectation operator and  $0 < \beta < 1$  stands for the discount factor of the representative household.  $P_t$  is the aggregate price level.

In period  $t$ , the representative household holds  $M_{t-1}$  units of money, and earns a labor income of  $W_t L_t$ , given the nominal wage  $W_t$ . In addition, he/she also gains the revenue of renting capital  $K_t$  to firms at the rate of  $R_t^k$ .  $B_t$  denotes the one period riskless bond and  $R_t$  is the riskless return of that bond. Further,  $\Pi_t$  stands for the dividends of firms that owned by this household,  $T_t$  is the lump-sum tax and  $X_t$  is the transfer payment conducted by government. Hereby, the budget constraint of the representative household can be described as following.

$$\frac{B_{t-1} + M_{t-1} + W_t L_t + R_t^k K_t + \Pi_t + X_t}{P_t} \geq C_t + I_t + T_t + \frac{B_t / R_t + M_t}{P_t}$$

The accumulation of the representative household's capital follows the rule below where  $0 < \delta < 1$  denotes the depreciation rate of capital.

$$I_t = K_{t+1} - (1 - \delta) K_t + S \left( \frac{K_{t+1}}{K_t} \right) K_t$$

The further assumption is that the capital adjustment cost is measured as following and  $S(I) = 0$ ,  $S'(I) = 0$ ,  $S''(I) = \phi_k > 0$ .

$$S \left( \frac{K_{t+1}}{K_t} \right) K_t = \frac{\phi_k}{2} \left( \frac{K_{t+1} - K_t}{K_t} \right)^2$$

According to the assumption of Jian, Li and Zheng (2010), the instantaneous utility function of the representative household is

$$U(C_t, \frac{M_t}{P_t}, L_t) = a_t \ln(C_t - bC_{t-1}) + \ln\left(\frac{M_t}{P_t}\right) - \frac{L_t^{1+\eta}}{1+\eta},$$

where  $\eta > 0$  is the elasticity of labor supply, and  $b$  stands for consumption habit. Notice that the real money balance,  $M_t/P_t$  is included in this utility function, making it is a money-in-the-utility-function (MIU) form. Unlike the frictionlessly neoclassical model, the money in the New Keynesian model plays an important role as a medium of exchange. In the MIU form utility function, households are willing to hold real money and can obtain utility from it directly. This assumption can be understood in the way like that the convenience of money in transaction reduces the time and efforts of households. Besides that, by Jian, Li and Zheng (2010)'s assumption, the preference shock  $a_t$  follows an autoregressive process like

$$\ln a_t = \rho_a \ln a_{t-1} + \varepsilon_t^a,$$

where  $0 < \rho_a < 1$  and the stochastic disturbance  $\varepsilon_t^a$  is serially uncorrelated and has zero mean.

### 3.2 The Representative Finished Goods-producing Firm

Two types of firms are included in Jian, Li and Zheng (2010)'s model: a representative finished goods-producing firm and a continuum of intermediate goods-producing firms. Specifically, the representative finished goods-producing firm exists in a perfectly competitive market. This firm has a constant returns to scale (CRS) technology like below.

$$Y_t = \left[ \int_0^1 Y_t(i)^{\frac{\theta-1}{\theta}} di \right]^{\frac{\theta}{\theta-1}}$$

Notice that in order to produce  $Y_t$  units of finished goods,  $Y_t(i)$  amount of intermediate goods are needed, and  $\theta > 0$  by assumption.

Taking the final goods price  $P_t$  and intermediate goods price  $P_t(i)$  as given, the demand function of the representative finished goods-producing firm for intermediate goods is like following, where  $\theta$  denotes the price elasticity of demand for intermediate goods  $i$ :

$$Y_t(i) = \left( \frac{P_t(i)}{P_t} \right)^{-\theta} Y_t$$

Since the market of the representative finished goods-producing firm is perfectly competitive, the following zero profit condition of  $P_t$  needs to be satisfied.

$$P_t = \left[ \int_0^1 P_t(i)^{1-\theta} di \right]^{\frac{1}{1-\theta}}$$

### 3.3 The Representative Intermediate Goods-producing Firm

Taking the labor, capital and oil as inputs, various intermediate goods are produced by different intermediate goods-producing firms respectively. Jian, Li and Zheng (2010) assume the following production function for these intermediate goods-producing firms:

$$Y_t(i) = Z_t [u_t(i) K_t(i)]^\alpha [L_t(i)]^{1-\alpha},$$

where  $0 < \alpha < 1$ ,  $K_t(i)$  and  $L_t(i)$  stand for capital and labor inputs.

As mentioned previously, the oil usage of the representative intermediate goods-producing firm,  $O_t(i)$ , is linked with the capital utilization rate  $u_t(i)$  in this model, which is the same as Finn (1995). The capital utilization rate function is assumed to have the following format,

$$\frac{O_t(i)}{K_t(i)} = \frac{u_t(i)^\nu}{\nu}$$

where  $\nu \geq 1$  denotes the elasticity of capital utilization. According to this formula, it is clear that the representative intermediate goods-producing firm can benefit more from its capital input if it increases the amount of oil usage. However, along the increase of the oil usage, the increment of the capital utilization rate is diminishing. Further, an exogenous oil price shock can change the firm's inputs demand through the income and substitution effects, hence, can change the amount of its total output.

Moreover, the oil price  $P_t^o$  and the technology shock  $Z_t$  are exogenous by assumption and follow the autoregressive processes described below.

$$\ln P_t^o = (1 - \rho_p) \ln P^o + \rho_p \ln P_{t-1}^o + \varepsilon_t^p$$

$$\ln Z_t = (1 - \rho_z) \ln Z_t + \rho_z \ln Z_{t-1} + \varepsilon_t^z$$

Here  $0 < \rho_p < 1$ ,  $0 < \rho_z < 1$  and both  $\varepsilon_t^p$  and  $\varepsilon_t^z$  are zero mean, serially uncorrelated innovations.

Besides that, because the market of intermediate goods-producing firms is imperfectly competitive, we can deduce the optimal conditions of the representative intermediate goods-producing firm by cost minimization. They are

$$u_t = \left( \frac{\nu}{\nu-1} \frac{r_t^k}{p_t^o} \right)^{\frac{1}{\nu}}$$

$$\frac{K_t}{L_t} = \frac{\nu-1}{\nu} \frac{\alpha}{1-\alpha} \frac{w_t}{r_t^k}.$$

After we introduce the real prices  $r_t^k = R_t^k / P_t$ ,  $w_t = W_t / P_t$  and  $p_t^o = P_t^o / P_t$ , the real total cost of the representative intermediate goods-producing firm can be written as

$$S_t(Y) = r_t^k u_t K_t + w_t L_t + p_t^o O_t.$$

Furthermore, in order to import the New Keynesian sticky price feature into the model, Jian, Li and Zheng (2010) assume the representative intermediate goods-producing firm adjusts its price in a staggering manner, which is the same as in Calvo (1983). Specifically, in period  $t$ , each intermediate goods-producing firm has the probability of  $(1 - \theta_p)$  to reset its price, and this price adjustment behavior is independent between different periods. It means in period  $t$ , an intermediate goods-producing firm will seek to maximize its profit according to

$$\Pi_t(i) = E_t \left\{ \sum_{k=0}^{\infty} (\theta_p)^k \Lambda_{t,t+k} \left( \tilde{P}_t(i) Y_{t+k}(i) - S_{t+k}(i) P_{t+k} \right) \right\}$$

where

$$\Lambda_{t,t+k} = \beta^k \frac{\lambda_{t+k}}{\lambda_t} \frac{P_k}{P_{t+k}}$$

stands for the discount factor. Notice that  $\lambda_{t+k} / P_{t+k}$  represents the increment of utility for one unit of profit and  $\tilde{P}_t(i)$  is the new price of the intermediate goods-producing firm, which can reset its price at period  $t$ . Hereby, the dynamics of the aggregate price level are described by

$$P_t = \left[ (1 - \theta_p) \tilde{P}_t^{1-\theta} + \theta_p (P_{t-1})^{1-\theta} \right]^{\frac{1}{1-\theta}}.$$

### 3.4 The Government

According to Jian, Li and Zheng (2010), the government in this model has two missions. First, the government gives the transfer payments  $X_t$  to households, which equals to the net increment of the central bank's currency supply.

$$X_t = M_t - M_{t-1}$$

Second, the government spends its expenditure  $P_t G_t$ , which is financed by issuing bonds and levying taxation.

$$P_t G_t = P_t T_t + \left( \frac{B_t}{R_t} - B_{t-1} \right)$$

Here  $T_t = \tau_t Y_t$  and  $\tau_t$  stands for the proportion of total output that is levied by the government.

The tax rate shock  $\tau_t$  and the government expenditure shock  $G_t$  are assumed to follow the autoregressive processes as below.

$$\ln \tau_t = (1 - \rho_\tau) \ln \tau_t + \rho_\tau \ln \tau_{t-1} + \varepsilon_t^\tau$$

$$\ln G_t = (1 - \rho_g) \ln G + \rho_g \ln G_{t-1} + \varepsilon_t^g$$

Notice that both  $\varepsilon_t^\tau$  and  $\varepsilon_t^g$  represent the independent and identically distributed (i.i.d.) shocks,  $\rho_\tau$  and  $\rho_g$  are the shock persistence parameters.

### 3.5 The Central Bank

According to the assumption of Jian, Li and Zheng (2010), the central bank in this model carries a monetary policy that targets not only output and inflation, but also the exogenous oil price shock. The endogenous money supply mechanism can be described as below

$$\ln M_t = (1 - \rho_m) \ln M + \rho_m \ln M_{t-1} + \phi_\pi (\ln \pi_t - \ln \pi) + \phi_y (\ln Y_t - \ln Y) + \phi_p \varepsilon_t^p + \varepsilon_t^m,$$

where  $\varepsilon_t^m$  is a zero mean, serially innovation,  $\pi$  and  $Y$  stand for the steady state values of the inflation and output. Notice that  $\phi_y$ ,  $\phi_\pi$  and  $\phi_p$  are the money supply coefficients on output, inflation and the oil price shock respectively. If the central bank is willing to react to the change of output in a pro-cyclical manner and to increase the money supply to offset the oil price increase, the signs of  $\phi_y$  and  $\phi_\pi$  are supposed to be positive. If the central bank is intended to alleviate inflation by reducing the money supply,  $\phi_p$  is supposed to be negative.

In the end, a market-clear condition is indispensable to close the model.

$$Y_t = C_t + I_t + G_t + p_t^o O_t$$

This equation means that total output of this economic system is used up for the household's consumption, investment, government expenditure and energy spending. In order to conduct further analysis, all equilibrium conditions are derived and log-linearized. In Appendix A, the total of twenty two log-linearized equilibrium conditions are listed for reference.

### **3.6 Discussion**

Comparing this model with Leduc and Sill (2004), it is clear that although both of these two models can be categorized as New Keynesian models and use Finn's (1995) capital utilization rate to introduce oil usage, there are still some differences. For example, instead of using the MIU form utility function, Leduc and Sill (2004) impose a cash-in-advance constraint on the household. This constraint means the consumption spending of the representative household cannot exceed his/her remaining money balance in each period. In this way, the role of money as a medium of exchange is addressed in this model. Another difference lies in the way of introducing the nominal rigidity. Besides that, there is only one type of firm in Leduc and Sill (2004), which does not adjust its price through the staggering manner. The only mechanism of making price sticky in their model is the non-zero price adjustment cost.

However, in my opinion, the most important difference between these two models is the assumption of the monetary policy. In Leduc and Sill (2004), the monetary policy of the central bank follows a Taylor rule, in which the interest rate is the operational objective. In contrast, Jian, Li and Zheng (2010)'s model, the operational objective is the money supply. This difference is mainly based on the divergence of the different countries' policies. Further, in order to see whether the central bank will respond to oil price directly, the oil price factor is also added into the monetary policy equation in Jian, Li and Zheng (2010).

It is noteworthy that, according to the forecast error variance decomposition in Jian, Li and Zheng (2010), which is showed in Table 3.2 below, oil price shocks make the largest contribution to the aggregate volatility of output, following by tax rate shocks and technology shocks. In contrast, the government expenditure shocks, preference shocks and monetary policy shocks only account for a very small amount of the total fluctuations in output and consumption.

Further, based on the results in Table 3.2, the monetary policy shocks only play a minor role even in explaining the fluctuations in the money supply itself. Considering that fact that the oil price shock coefficient is also not significant, the influence of the two stochastic elements in the money supply function is small. It is reasonable to conclude that the money supply in the Chinese economy is mainly determined endogenously.

**Table 3.2 Forecast Error Variance Decomposition (In Percentage)**

	Output ( $Y$ )	Consumption ( $C$ )	Inflation ( $\pi$ )	Money Supply ( $M$ )
Preference Shock	0.60	24.76	0.92	0.27
Technology Shock	11.46	6.28	6.64	18.15
Oil Price Shock	54.57	39.51	23.94	63.19
Government Expenditure Shock	1.37	0.19	2.57	0.31
Tax Rate Shock	31.96	29.25	65.88	11.35
Monetary Policy Shock	0.04	0.01	0.05	6.73

Source: Jian, Li and Zheng (2010)

#### 4. Methodology

Because Jian, Li and Zheng (2010)'s study is mainly focusing on the theoretical transmission mechanisms of the oil price shocks, the cyclical properties of this model are not reported in their paper. With the purpose of examining how well this New Keynesian model can explain the behavior of the Chinese economy, the object of this study is to conduct a comparison between the simulations of this model and the Chinese actual data.

In order to simulate the model, all the parameters in this model need to be assigned. In this study, I assign these parameters according to the estimation and the calibration results in Jian, Li and Zheng (2010). However, the values of three parameters are missing in the published version of their paper. They are the elasticity of the representative household's labor supply ( $\eta$ ), the probability for the representative intermediate goods-producing firm to keep its price

unchanged ( $\theta^p$ ) and the coefficient of the price adjustment cost ( $\phi_k$ ). To overcome this difficulty, I check the reference of Jian, Li and Zheng (2010) and find those papers, in which the same formulas and parameters are outlined as Jian, Li and Zheng (2010). After that, I adopt the estimations of those parameters from their studies. Specifically,  $\eta$  is assigned to be 0.4 to match Duval and Jesk (2008).  $\theta^p$  is assigned to be 0.5, as in Blanchard and Gali (2007), and  $\phi_k$  is assigned to be 32.1346, as in Ireland (2003). The final parameter-assigning results are listed in Appendix B (Table B.1, Table B.2 and Table B.3).

For the purpose of my simulations, I choose Matlab R2014a as the software environment and the IRIS Toolbox as a modeling tool. IRIS is a free and open-source toolbox for Matlab, and specifically designed for modeling macroeconomic models and forecasting. Comparing with other macroeconomic plugins, IRIS is more flexible and easier to understand. The original IRIS code, which describes the model, and the original Matlab code, which simulates the model and calculates all the statistical moments, are included in Appendix D.

On the other hand, for the purpose of comparing the model with the real world, Chinese actual data are necessary. In order to conduct the estimation, Jian, Li and Zheng (2010) chose six time series data to represent six observable variables. The names and sources of these data are listed in Table 4.1. However, due to the issue of the database's accessibility, the actual data that are applied in this study and their sources are listed in Table 4.2.

**Table 4.1 Original Data and Source**

Variable	Data	Source
$Y$ (Output)	Real GDP (1992-2009)	China Center for Economic Research (CCER) database
$C$ (Consumption)	Total retail sales of consumer goods (1992-2009)	CCER database
$P^o$ (Oil Price)	Chinese Oil price (1992-2009)	Economagic.com
$M$ (Money Supply)	M1 (1992-2009)	CCER database
$\pi$ (Inflation)	CPI (1992-2009)	CCER database
$G$ (Government Expenditure)	Real amount of budget expenditures (1992-2009)	CCER database

**Table 4.2 Applied Data and Source**

Variable	Data	Unit	Source
$Y$ (Output)	Real GDP (1992-2013)	Billions of 2000 Yuan	China National Bureau of Statistics / Haver Analytics
$C$ (Consumption)	Household final consumption expenditure (1992-2013)	Yuan	World Bank national accounts data
$P_o$ (Oil Price)	WTI crude oil price (1992-2013)	Dollars per Barrel	MacroTrends.org
$M$ (Money Supply)	M1 (1999-2013)	Billions of Yuan	People's Bank of China / Haver Analytics
$\pi$ (Inflation)	CPI (1992-2013)	1	China National Bureau of Statistics / Haver Analytics
$G$ (Government Expenditure)	Government expenditure (2007-2013)	Billions of Yuan	China National Bureau of Statistics / Haver Analytics

In this study, the Chinese actual data are mainly provided by Haver Analytics database. Haver is a professional globe research data provider and experts in time series database of macroeconomics and finance. The data of the Chinese household final consumption expenditure

are downloaded from the World Bank database. The historical WTI oil prices are available publicly on MacroTrends.org.

It is noteworthy that all these applied data are the Chinese data except the oil price. There was no accessible dataset that could provide me the historical data of the oil prices in China in time for my research. Alternatively, the empirical oil price data in this study are the historical prices of the WTI crude oil. The reason of making such a choice is based on the fact that China is an oil importer and the Chinese oil price targets on the prices of the international oil markets. Besides that, the WTI crude oil is the underlying commodity of the Chicago Mercantile Exchange's oil futures contracts and the price of it is one of the most important benchmarks in the international oil markets. Further, the oil price in Jian, Li and Zheng (2010)'s model is assumed to be exogenous. Therefore, it is reasonable to use the WTI price to reflect the oil price in this model. Moreover, since the unit of the WTI prices is the U.S. dollars per barrel, in order to obtain the real oil prices in international markets, the historical WTI prices are inflation-adjusted by the headline CPI of the U.S.. In this way, the U.S. inflation's effect on the price unit is eliminated.

It is also necessary to mention that all these data are the quarterly data and has been seasonal adjusted by the Census X12 method, with an exception of the household final consumption expenditures. Due to the issue of availability, the original data from the World Bank database are annual. In order to consistent with other data, the annual household final consumption expenditures are converted into quarterly data through the method of constant growth rate interpolation.

Another noteworthy thing is that, due to the issue of availability, the length of each time series data is not equal. The data of inflation and consumption have the relatively complete record and hence have the longest time series. On the other hand, the earliest data of the government expenditures are from 2007 and the earliest data of the money supply are from 1999, which make

these time series relatively shorter than the others. For this reason, I only select output, consumption, oil price and inflation as the observable variables in comparing the cross-correlations between the model and the real data. The data samples for these four variables are long enough for a meaningful calculation of the empirical statistics. Besides that, I also extended the latest data's period. In Jian, Li and Zheng (2010), these time series data are censored at 2009Q3. In this study, the period of the latest data is 2013Q4.

The first step in processing the data is taking logarithms so that we can calculate the percentage deviation from their trends. In empirical studies, suppose that  $X_t$  stands for the value of variable  $X$  in period  $t$ ,  $X^*$  presents the value of  $X$ 's trend and  $\Delta X_t$  denotes the deviation of  $X_t$  from  $X^*$ . When  $\Delta X_t / X^*$  is small enough, we can demonstrate that

$$\hat{X}_t = \log X_t - \log X^* = \log \left( \frac{X_t}{X^*} \right) = \log \left( 1 - \frac{\Delta X_t}{X^*} \right) \approx \frac{\Delta X_t}{X^*} \times 100\%.$$

In this way the percentage deviation from the trend can be computed.

The second step in processing the data is detrending, a process that separates the business cycle component from the economic growth path. In order to justify the detrending process is necessary for all these six variables, I conduct the unit root (Augmented Dickey-Fuller) test on all these time series. The test results are included in Appendix C (Table C.1-C.6). According to the p-values of the test results, the null hypothesis, which is the time series has a trend, cannot be rejected at the significant level of 1% for all these six variables. Hereby, detrending process is appropriate and necessary for these time series data in this research.

It is well known that there are various ways to detrend a time series, and the detrending results will be different according to the chosen process. For the purpose of consistence, I choose the Baxter and King (1999)'s Band Pass (BP) filter to detrend all six time series, which is identical to Jian, Li and Zheng (2010). Specifically, the minimum and maximum cycle periods

are set to be 6 and 32. That means the cyclical components between 6 and 32 quarters can be retained after detrending. The detrending results of all six time series are plotted and included in Appendix C (Figure C.1-C.6).

In order to evaluate how well the theoretical model in Jian, Li and Zheng (2010) explains the business cycle phenomenon in the Chinese economy, three types of statistical moments are computed based on both the model's simulation results and the real time series data. These three moments are standard deviation, first-order autocorrelation and cross-correlation.

Firstly, the standard deviation measures the volatility of a variable's fluctuations. A small standard deviation means the variable is moving forward smoothly around its growth path. On the contrary, a large standard deviation implies the variable fluctuates intensely. Moreover, for the purpose of comparing the relative volatility, the relative standard deviations between total output and other variables are also calculated. The relative standard deviation is an important indicator in examining whether a variable is more sensitive or less sensitive than output.

Secondly, the first-order autocorrelation is a measure of how much a variable's current value is dependent upon its history value. For instance, if the data of total output has a value of first-order autocorrelation that is close to 1, this means the current level of output is highly dependent on the output amount of the previous periods. Therefore, the business cycle in this economic system is persistent.

Thirdly, the cross-correlation measures the comovement of different variables over the time. The value of a cross-correlation lies between -1 and 1. If two variables move together in the same direction, the value of their cross-correlation is positive and close to 1. On the contrary, if a value of cross-correlation is close to -1, it means that these two variables move in the opposite direction. Additionally, a zero cross-correlation means the movements of these variables are unrelated.

In summary, these three statistical moments capture the cyclical properties of the business cycle phenomenon in different dimensions. It is reasonable to say that if a model can explain the business cycle in the real world well, the values of these statistical moments based on the model's simulation must be similar to these based on the real world data.

In this study, the statistical moments of the real data are computed by Matlab. In order to conduct a comparison between the real data and the model, firstly, the model in Jian, Li and Zheng (2010) is described in the IRIS code. Secondly, such IRIS model file is loaded and simulated by Matlab. In order to extract the cyclical components, I put the simulation series through the Baxter and King (1999)'s BP filter, which is identical to the actual data processing method in Jian, Li and Zheng (2010). Specifically, each simulation starts in the steady state and contains 188 periods. The first 100 periods are censored in order to eliminate the dependence on the initial condition. The quantity of the remaining periods after detrended by BP filter is 64, which is consistent with the periods of output (real GDP) after detrending. After each simulation, all the statistical moments (standard deviations, relative standard deviations, first-order autocorrelations and cross-correlations) are calculated and stored. In order to stabilize the results and avoid the randomness of a single simulation, the previous processes are repeated 500 times. Eventually, the displayed statistical moments of the model are the average value of the results of these 500 different simulations. Further, in order to reveal the comovements between the observable variables in responding to the oil price shocks, I plot the oil price impulse response paths of these variables. Moreover, in order to eliminate the distraction of other types of shocks and focusing on the impact of the oil price shocks. I repeat the simulation processes above with the model with the oil price shocks alone. All these results are exhibited and discussed in Part 5. The original Matlab codes are included in Appendix D.

## 5. Comparison Results and Discussion

First, the standard deviations of output, consumption, oil price, money supply and government expenditure in the models (with all shocks and with only oil price shocks) are listed in Table 5.1. This table also presents the values of standard deviations of the actual data. Notice that the sample periods of the money supply and the government expenditure are relatively shorter than the others (36 and 16 periods). For the rest of the observable variables, the number of the sample periods is 64.

**Table 5.1 Standard Deviation Comparison**

	$Y$	$C$	$P_o$	$M$	$\pi$	$G$
Real Data	0.0044	0.0036	0.0822	0.0156	0.0124	0.0412
Model (All Shocks)	0.0242	0.0229	0.1142	0.0662	0.0149	0.0339
Model (Oil Price Shocks Only)	0.0085	0.0069	0.1151	0.0206	0.0049	0.0000

Note: the sample periods of  $M$  and  $G$  are 36 and 16.

The first notable phenomenon is that the model is apparently more volatile than the real world. The standard deviations of output, consumption, oil price and money supply in the model are larger than these in the real data. Specifically, the fluctuations of the money supply in model are four times larger than in the actual data and for the standard deviation of total output, the value of model is five times larger than the real one. That means the business cycle in Jian, Li and Zheng (2010)'s model is much more choppy and unstable than in the real world. When it comes to the model with the oil price shocks only, the simulation results become significantly less volatile, as expected. The standard deviations for all the observables are decreased, except for the oil prices self. Comparing the model with all shocks, the oil price shocks can explain 35.12% of the fluctuations of output in the model, which is less than the reported value (54.57%) in the variance decomposition results in Table 3.2 from Jian, Li and Zheng (2010). This phenomenon can be attributed to the fact that the adopted historical oil price series in this study is different

from Jian, Li and Zheng (2010)'s analysis. The actual oil price's standard deviation in this study is coming from the WTI historical price. In contrast, the estimation result of  $\sigma_p$  in Jian, Li and Zheng (2010) is based on Chinese historical oil price. Since I use the same value of  $\sigma_p$  as Jian, Li and Zheng (2010) in the simulations, it is expected that there is a difference between the simulation's results and the actual data in term of the standard deviation of the oil. Further, it seems that the Chinese oil price series adopted by Jian, Li and Zheng (2010) is more volatile than the WTI price data series adopted in this study.

**Table 5.2 Relative Standard Deviation Comparison**

	$C/Y$	$P_o/Y$	$M/Y$	$\pi/Y$	$G/Y$
Real Data	0.8013	18.5421	3.5135	2.7888	9.3002
Model (All Shocks)	0.9544	4.9042	2.759	0.627	1.4604
Model (Oil Price Shocks Only)	0.802	13.5327	2.4089	0.5835	0

Note: the sample periods of  $M$  and  $G$  are 36 and 16.

In Table 5.2, the relative standard deviations of consumption, oil price, money supply and inflation to total output in the models (with all shocks and with only oil price shocks) and actual data are calculated and listed. From the results we can see that, although the differences in standard deviations are significant, the relative standard deviation between the consumption and output is relatively similar among the model and the actual data. The value of this relative standard deviation is less than one, which means the consumption is less volatile than output. The phenomenon can be theoretically explained by the Permanent Income Hypothesis, which addresses that the individuals will change their consumptions according to the permanent income, rather than the income in the current period. On the contrary, the relative standard deviation between money supply and output are larger than one in both the model and the actual data. This phenomenon means the central bank adjusts the money supply more heavily than the fluctuations of output. However, besides these two relative standard deviations, the significant quantitative

differences between the model and actual data still exist. It is also interesting to notice that, after I shut off the shocks other than the oil price shock in Jian, Li and Zheng (2010)'s model, the simulation result still indicates that consumption is less volatile than output. In contrast, Kim and Loungani (1992) showed that, if their RBC model with the CES production function was simulated with only the oil price shock turned on, consumption would be more volatile than output.

Second, the comparison results of the first-order autocorrelations of these six observable variables in the models (with all shocks and with only oil price shocks) and the real data are listed in Table 5.3.

**Table 5.3 First-order Autocorrelation Comparison**

	$Y$	$C$	$P_o$	$M$	$\pi$	$G$
Real Data	0.9328	0.9246	0.8584	0.8578	0.928	0.7806
Model (All Shocks)	0.8867	0.9082	0.8704	0.896	0.7831	0.8589
Model (Oil Price Shocks Only)	0.8962	0.9267	0.8714	0.914	0.7901	0.8625

Note: the sample periods of  $M$  and  $G$  are 36 and 16.

From the results in Table 5.3 we can see, on one hand, the values of the first-order autocorrelations of the variables are quite close between the model and the actual data, which means the model does a quite good job in depicting the persistence of the business cycles. On the other hand, according to the results in Table 5.3, the values of the first-order autocorrelations of all these six variables are relative high, closing to 1. This phenomenon implies that the values of these variables in the current period are highly dependent on their history values. The reason for this result can be related to the large persistence of the shocks.

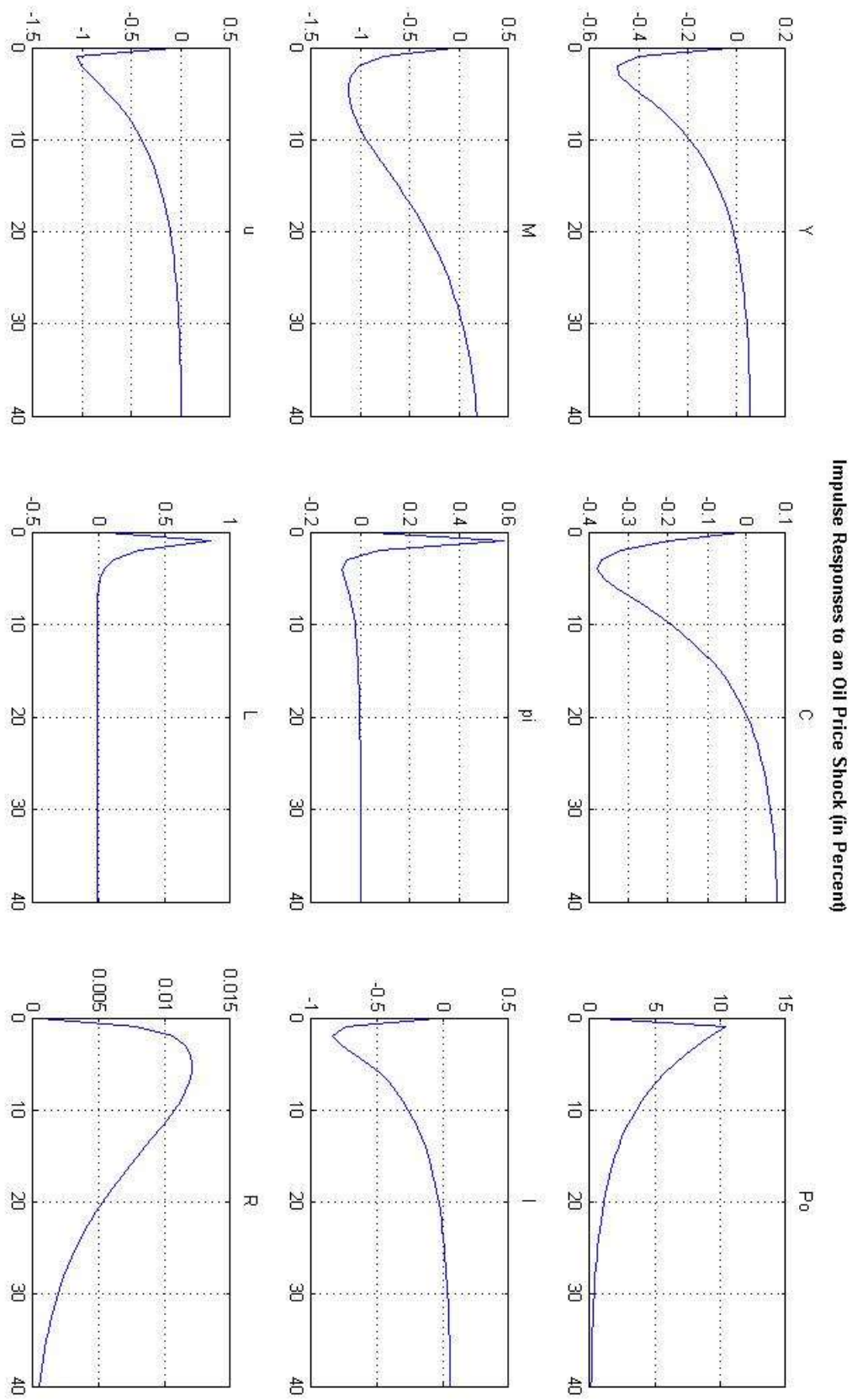
Third, the cross-correlations of the model with all types of shocks, the model with only the oil price shocks and the actual data are listed in Table 5.4

**Table 5.4 Cross-correlation Comparison**

		$Y$	$C$	$P_o$	$\pi$
Real Data	$Y$	1.0000			
	$C$	0.3729	1.0000		
	$P_o$	0.2642	0.4206	1.0000	
	$\pi$	0.5466	0.5490	0.2722	1.0000
Model (All Shocks)	$Y$	1.0000			
	$C$	0.8301	1.0000		
	$P_o$	-0.3343	-0.2655	1.0000	
	$\pi$	-0.1996	-0.1351	0.0791	1.0000
Model (Oil Price Shocks Only)	$Y$	1.0000			
	$C$	0.9735	1.0000		
	$P_o$	-0.9868	-0.9326	1.0000	
	$\pi$	-0.2061	-0.1777	0.2922	1.0000

In Table 5.4, first we can see the cross-correlations between total output, consumption, oil price and inflation in the model. The results are quite expected, since we can find, when comparing with total output, consumption is procyclical and the oil price is countercyclical. Besides that, it is also clear that the oil price is positively correlated with inflation and negatively correlated with consumption. The same comovements can also be identified in the impulse response paths of the oil price shock. In order to generate these impulse response paths, I increase the oil price ( $P_o$ ) by one standard deviation in the first period, then plot the dynamic paths of other variables in the following 40 periods. The result is exhibited in Figure 5.1 on the next page.

Figure 5.1 Impulse Responses to an Oil Price Shock



Impulse Responses to an Oil Price Shock (in Percent)

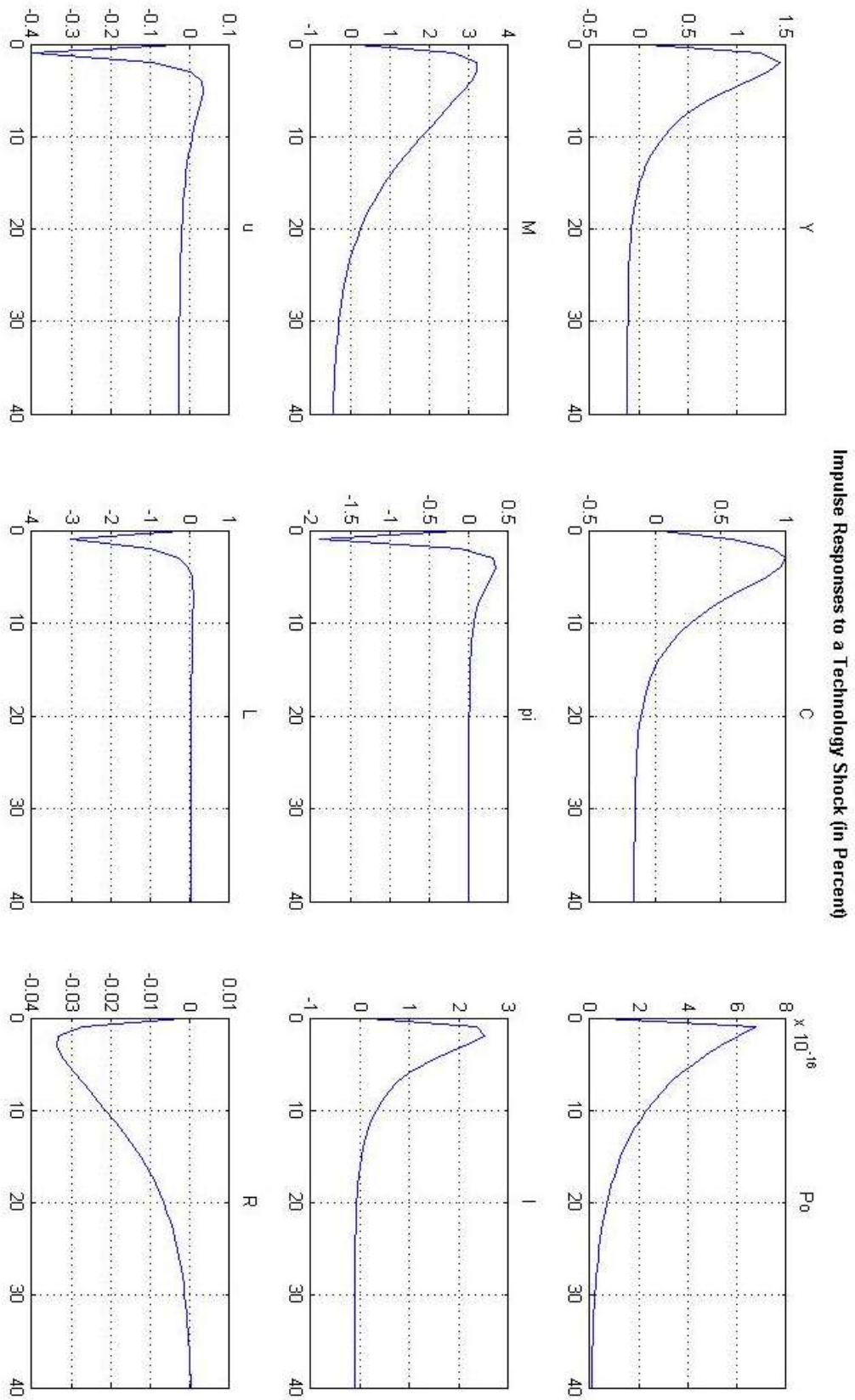
According to Figure 5.1, an unexpected increase in the exogenous oil price ( $P_o$ ) leads to the cost-push inflation ( $\pi$ ) directly and leads to the intermediate goods-producing firm reduce the oil usage. For this reason, the capital utilization rate ( $u$ ) decreases and leads to the reduction of the investment ( $I$ ) and total output ( $Y$ ). The central bank tries to alleviate the inflation by decreasing the money supply ( $M$ ). This monetary policy leads to the increase of interest rate ( $R$ ) simultaneously. For the representative household, on one hand, there is a positive income effect, since the demand of labor ( $L$ ) will increase due to the substitution effect of intermediate goods-producing firm. On the hand, a negative income effect will also occur since the price level goes up. In the end, combining all the effects, the total consumption ( $C$ ) will go down in response to such an oil price impulse.

I simulate the model with only the oil price shocks retained, so that all other shocks are removed, and calculate the cross-correlations again. The results are also included in Table 5.4. Comparing with the results of the original model, the signs of all these cross-correlations remain the same in the new results. Moreover, the negative correlations between the output, oil price, consumption and inflation are enhanced. This phenomenon confirms the impulse response analysis above.

However, what is reasonable in theory is not always what will be in the reality. As Table 5.4 shows, the cross-correlations between the output, consumption, oil price and inflation in the real world are quite different from the model's predictions. On one hand, output and consumption are still positively correlated, although the level of correlation is lower in the actual data than that in the model. The oil price is also positively correlated with the inflation, as the model predicts. On the other hand, the oil price in reality is positively correlated with output and consumption, which is the opposite of the results of the model. This phenomenon means that along with the increase of the international oil price, the Chinese total output and consumption also go up.

In order to give Jian, Li and Zheng (2010)'s model more justice, it is meaningful to give a discussion on the effect of technology shock ( $Z_t$ ) in this model. The first reason is that the technology shocks play an important role in explaining the volatilities of different variables. Specifically, the technology shocks in this model can explain 11.46% of the volatility of output and 18.15% of the volatility of money supply (see Table 3.2). The second reason is that when it comes to the standard deviation of the technology shocks ( $\sigma_z$ ), the standard error of the estimation result is relatively high (0.0271, see Table B.3). The third reason is the impulse response paths of output, consumption and inflation corresponding to the technology shock are the opposite of those paths corresponding to the oil price shock. Figure 5.2 on the next page reports the impulse response when the technology is increased by one standard deviation in the first period. Therefore, it is reasonable to question that whether the comovement relations will be changed if a different value of  $\sigma_z$  is adopted.

Figure 5.2 Impulse Responses to a Technology Shock



In order to answer this question, I assign  $\sigma_z$  a smaller value, 0.0128, which is equal to the estimated value minus a half of its standard error. I then simulate the model again and make a comparison between the results with the smaller value and the results with the original value. The comparison results can be found in Table 5.5 and Table 5.6.

**Table 5.5 Standard Deviation Comparison (Different  $\sigma_z$ )**

	$Y$	$C$	$Po$	$M$	$\pi$	$G$
Real Data	0.0044	0.0036	0.0822	0.0156	0.0124	0.0412
Model ( $\sigma_z = 0.0264$ )	0.0242	0.0229	0.1142	0.0662	0.0149	0.0339
Model ( $\sigma_z = 0.0128$ )	0.0142	0.0169	0.1142	0.0463	0.0088	0.0339

(Note: the sample periods of  $M$  and  $G$  are 36 and 16.)

**Table 5.6 Cross-correlation Comparison (Different  $\sigma_z$ )**

		$Y$	$C$	$Po$	$\pi$
Real Data	$Y$	1.0000			
	$C$	0.3729	1.0000		
	$Po$	0.2642	0.4206	1.0000	
	$\pi$	0.5466	0.5490	0.2722	1.0000
Model ( $\sigma_z = 0.0264$ )	$Y$	1.0000			
	$C$	0.8301	1.0000		
	$Po$	-0.3343	-0.2655	1.0000	
	$\pi$	-0.1996	-0.1351	0.0791	1.0000
Model ( $\sigma_z = 0.0128$ )	$Y$	1.0000			
	$C$	0.7071	1.0000		
	$Po$	-0.5773	-0.3616	1.0000	
	$\pi$	-0.1649	-0.0772	0.1468	1.0000

From the results in Table 5.5 and Table 5.6 we can see that, adopting a smaller value of  $\sigma_z$  can reduce the volatilities of output, consumption and money supply. However, such reduction is modest and the new simulation results are still significantly larger than the actual data, as the original results. On the other hand, the values of the cross-correlations between different variables do change after the smaller  $\sigma_z$  is adopted, but the signs of these cross-correlations still remain the

same. Therefore, it is reasonable to say the main cyclical properties of the model will not be affected by adopting a smaller  $\sigma_z$ .

To conclude, after comparing the cyclical properties of Jian, Li and Zheng (2010)'s model with the Chinese actual data, we can find that some of the business cycle's features can be well explained, especially for the persistence of the fluctuations and the relative standard deviations between consumption and output. However, the inconsistency between the model and the actual data is also significant, especially in the variability of total output and the correlation between the oil price and consumption. Therefore, despite the introductions of many sophisticated assumptions, as a result, it is still reasonable to say that there are some components missing in the model of Jian, Li and Zheng (2010). The predictions, based on such model, will possibly be misleading, especially in analyzing the underlying mechanisms of the impact of oil price shocks.

Because of such an important role that the oil price plays in the world's economy, the study on the impact of oil price shocks will definitely not be terminated. There are several possible approaches to improve the model in Jian, Li and Zheng (2010). The first approach is to introduce the international oil market into the model. Currently, the international oil price is mainly determined by two major futures markets, i.e. London's International Petroleum Exchange (IPE) and the New York Mercantile Exchange (NYMEX). The oil futures trades in London are based on the Brent Crude Oil and in New York are based on the WTI. The oil futures' prices, that are determined in these two markets, are often treated as the benchmark of the oil price in other regions, including China. This is why this study chose the WTI as the empirical measure of the oil price. It is obvious that the variation of oil price is determined by the international demand and supply in well-developed financial markets instead of some exogenous stochastic rules. This statement is especially true when the study objects are large oil importers or exporters. The reason is that these larger countries have the international market power, such as the largest oil consumption country, the United States, and the second largest oil user, China.

Some recent work has already focused on this point. In the study of Kilian (2009), a structural vector autoregressive (SVAR) model is constructed to depict the global crude oil market. Hereby, the oil prices shocks are decomposed into three different types of shocks. They are crude oil supply shocks, shocks to the global demand for all industrial commodities and demand shocks in the global crude oil markets. According to the results of the periods from 1975 to 2007, Kilian shows empirically that not all oil price shocks are alike and the theoretical approach of modeling the oil price as an exogenous shock needs to be rethought.

In Bodenstein and Guerrieri (2011), the international oil trade is introduced by a two-country DSGE model. The two countries in their model can be described as domestic and foreign countries or oil importing and exporting countries. In this way, the oil price shocks are further disaggregated into country-specific oil supply shocks and oil efficiency shocks. Their conclusion shows that different types of oil price shocks have different kinds of impacts on the economic systems, and not all the oil price shocks are same. However, Bodenstein and Guerrieri (2011)'s two-country DSGE model is symmetric, based on the assumption that the oil importing country and exporting county have a completely identical structure, which is still questionable.

The second approach is to subdivide the type of oil and add the refined oil usage into the household sector. The most intuitive evidence to justify this suggestion is the fact that individuals in modern society consume refined oil directly in their daily life, such like vehicle refueling, cooking and heating. According to the research of Leung (2008), the oil consumption of the households in China surges from 2.8 million tons in 1990 to 22.7 million tons in 2007, and that amount stands for 6.2% of the total oil consumption of the whole country. Moreover, the refined oil prices also have an effect on people's behaviors directly, such as choosing the forms of transportation, selecting dwelling places and investing the durable goods like vehicles. For these reasons, considering the direct oil usage of the household sector and adding the oil usage into the utility function is likely to be an appropriate modification.

The third approach is to take into account the impact of the development of renewable energy. Oil, combined with coal and natural gas, are often referred as the fossil fuels which are non-renewable and causing environmental pollution. The consistent dependence on non-renewable energy will inevitably lead to an energy crisis and impact the world economy devastatingly. According to Hamilton (2014)'s latest study, in order to have a stable price of oil, the oil's production should have been increased by 19.4% during 2005 – 2013. However, the actual growth rate in the field of crude oil production is 3.1%. The clue of the global-wide crude oil shortage has already emerged and can be considered as the main force behind the doubling of the real oil price phenomenon. In order to avoid the tragedy of the global-wide oil shortage, many countries devote numerous efforts to developing the renewable clean energy, such as the wind power, hydropower, solar energy, geothermal energy and biofuel. According to the statistics of the EIA, the total amount of the usage of renewable energy in the United States has reached 8.83 quadrillion Btu by the year of 2012. Such amount accounts for 9.28% of the total energy consumption in that whole country. More importantly, this proportion is growing continuously. It is predictable that along with the technological development of the renewable energy, the dependency of the conventional fossil fuel, such as oil, will be reduced, and therefore, the significance of the effect of oil price shock to world economy will be weakened. Taking all these facts into consideration, a modification based on the impact of the developing of renewable energies will be prospective and meaningful.

## **6. Conclusion**

Throughout the history, the crude oil has played an essential role in human's society. Numerous efforts have been devoted to studying the relations between the crude oil and the economic systems. The rapid development of China and its huge consumption of oil in the recent decades have attracted economists to focus on studying the oil price change on the Chinese economy.

In Jian, Li and Zheng (2010), in order to study the theoretical mechanisms of oil price shocks on the Chinese economy, a well-developed New Keynesian model is constructed, based on many famous assumptions in this field. In order to analysis whether this model can well explain the Chinese economy in terms of cyclical properties, I conducted a comparison between the model and the actual data. The comparison results show that, despite the fact that the model included many theoretically reasonable assumptions, the inconsistency of the cyclical properties between the model and the actual data is still significant, especially in the standard deviation of total output and the cross-correlations among the oil price, consumption and output. Therefore, I conclude that some components are missing in this model in explaining the impact of oil price shocks on the Chinese economy and further modifications are still necessary.

In order to improve the ability of Jian, Li and Zheng (2010)'s model and describe the real world more properly, three different approaches are suggested based, on the facts of current world's energy industry. They are (1) introducing international oil market, (2) subdividing the oil usage and (3) taking the impact of the developing of renewable energy into account. Of course, these suggestions only provide a few possible ways to improve the model. Considering the complication of the world and the profound impact of the oil in people's life, further studies in this field are still imperative.

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## Appendix A. Log-linearized Equilibrium Conditions

The first-order conditions for the household optimization problem:

$$\hat{I}_t = \frac{1}{\delta} \hat{K}_{t+1} - \frac{1-\delta}{\delta} \hat{K}_t$$

$$\hat{\lambda}_t = \frac{1}{1-\beta b} [\hat{a}_t - \frac{1}{1-b} (\hat{C}_t - b\hat{C}_{t-1})] - \frac{\beta b}{1-\beta b} E_t \{ \hat{a}_{t+1} - \frac{1}{1-b} (\hat{C}_{t+1} - b\hat{C}_t) \}$$

$$\eta \hat{L}_t = \hat{\lambda}_t + \hat{w}_t$$

$$\hat{m}_t + \hat{\lambda}_t = -\beta / (1-\beta) \hat{R}_t$$

$$E_t \{ (\frac{1}{\beta} - 1 + \delta) \hat{r}_{t+1}^k + \phi_k (\hat{K}_{t+2} - \hat{K}_{t+1}) \} = \frac{1}{\beta} E_t \{ \hat{\lambda}_t - \hat{\lambda}_{t+1} + \phi_k (\hat{K}_{t+1} - \hat{K}_t) \}$$

$$E_t \{ \hat{\lambda}_{t+1} - \hat{\lambda}_t - \hat{\pi}_{t+1} \} = -\hat{R}_t$$

The first-order conditions for the firm profit maximization problem:

$$\hat{Y}_t = \hat{Z}_t + \alpha (\hat{u}_t + \hat{K}_t) + (1-\alpha) \hat{L}_t$$

$$\hat{O}_t = \hat{K}_t + \nu \hat{u}_t$$

$$\hat{u}_t = 1 / \nu (\hat{r}_t^k - \hat{p}_t^o)$$

$$\hat{K}_t - \hat{L}_t = \hat{w}_t - \hat{r}_t^k$$

$$\hat{\pi}_t = \frac{(1-\theta_p)(1-\beta\theta_p)}{\theta_p} [(1-\alpha) \hat{w}_t + \frac{\alpha(\nu-1)}{\nu} \hat{r}_t^k + \frac{\alpha}{\nu} \hat{p}_t^o - \hat{Z}_t] + \beta E_t \{ \hat{\pi}_{t+1} \}$$

The government's budget constraint:

$$\beta(\hat{b}_t - \hat{R}_t) = (\hat{b}_{t-1} - \hat{\pi}_t) + \frac{G}{b} \hat{G}_t - \frac{T}{b} \hat{T}_t$$

$$\hat{T}_t = \hat{\tau}_t + \hat{Y}_t$$

The central bank's monetary policy:

$$\hat{M}_t = \rho_m \hat{M}_{t-1} + \phi_\pi \hat{\pi}_t + \phi_y \hat{Y}_t + \phi_p \varepsilon_t^p + \varepsilon_t^m \quad \text{— Money supply shocks}$$

$$\hat{M}_t - \hat{M}_{t-1} - \hat{\pi}_t = \hat{m}_t - \hat{m}_{t-1}$$

$$\hat{P}_t^o - \hat{P}_{t-1}^o - \hat{\pi}_t = \hat{p}_t^o - \hat{p}_{t-1}^o$$

The market clear condition:

$$\hat{Y}_t = \frac{C}{Y} \hat{C}_t + \frac{I}{Y} \hat{I}_t + \frac{G}{Y} \hat{G}_t + \frac{P^o O}{Y} (\hat{p}_t^o + \hat{O}_t)$$

The exogenous shocks:

$$\hat{a}_t = \rho_a \hat{a}_{t-1} + \varepsilon_t^a \quad \text{— Preference shocks}$$

$$\hat{Z}_t = \rho_z \hat{Z}_{t-1} + \varepsilon_t^z \quad \text{— Technology shocks}$$

$$\hat{P}_t^o = \rho_p \hat{P}_{t-1}^o + \varepsilon_t^p \quad \text{— Oil price shocks}$$

$$\hat{G}_t = \rho_g \hat{G}_{t-1} + \varepsilon_t^g \quad \text{— Government expenditure shocks}$$

$$\hat{\tau}_t = \rho_\tau \hat{\tau}_{t-1} + \varepsilon_t^\tau \quad \text{— Tax rate shocks}$$

## Appendix B. Calibration and Estimation Results

**Table B.1 Value of Steady State Ratio**

Steady state ratio	$G/Y$	$p^o O/Y$	$C/Y$	$T/b$	$G/b$
Steady state value	0.1570	0.0001	0.4190	10.8540	10.8437

Source: Jian, Li and Zheng (2010)

**Table B.2 The Calibration Results**

Parameter	Calibration Value
$\beta$	0.9897
$\delta$	0.0250
$\alpha$	0.8000
$\theta$	6.0000
$\nu$	9.0455
$\eta$	0.4000 <sup>[1]</sup>
$\phi_k$	32.1346 <sup>[2]</sup>
$\theta_p$	0.5000 <sup>[3]</sup>

Source: Jian, Li and Zheng (2010)

[1]: Duval and Jesk (2008) [2]: Ireland (2003) [3]: Blanchard and Gali (2007)

**Table B.3 The Estimation Results**

Parameter	Estimation Value	Standard Error	t Statistic
$b$	0.6433	0.0255	25.1905
$\rho_z$	0.8085	1.1996	0.6740
$\rho_a$	0.7611	1.2399	0.6139
$\rho_p$	0.8869	1.5277	0.5806
$\rho_g$	0.8101	0.6455	1.2551
$\rho_t$	0.8310	0.8041	1.0335
$\sigma_m$	0.0282	0.0037	7.5795
$\sigma_z$	0.0264	0.0271	0.9759
$\sigma_a$	0.0222	0.0090	2.4597
$\sigma_p$	0.1043	0.0092	11.3419
$\sigma_g$	0.0325	0.0076	4.2870
$\sigma_t$	0.0892	0.2368	0.3769
$\phi_\pi$	0.9922	0.0404	24.5444
$\phi_y$	0.5962	0.0058	102.2094
$\phi_p$	0.0049	0.0258	0.1914
$\rho_m$	0.8532	0.0076	111.6273

Source: Jian, Li and Zheng (2010)

## Appendix C. Unit Root Tests and Detrending Results

### C.1 The Unit Root Test and the Detrending Results of $\log Y$

Null Hypothesis: LOGY has a unit root  
 Exogenous: Constant  
 Lag Length: 0 (Automatic - based on SIC, maxlag=11)

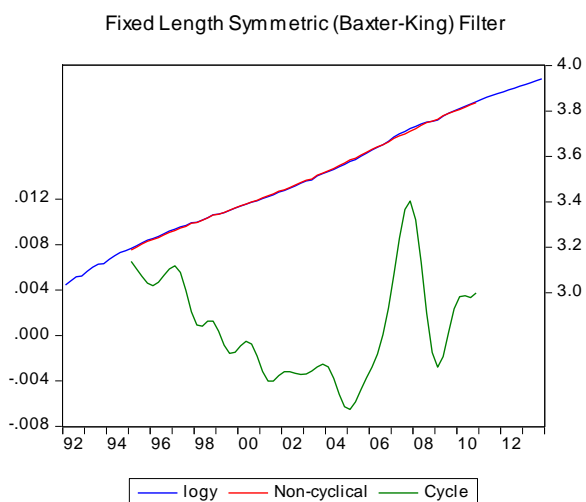
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.863756	0.3478
Test critical values:		
1% level	-3.507394	
5% level	-2.895109	
10% level	-2.584738	

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

Augmented Dickey-Fuller Test Equation  
 Dependent Variable: D(LOGY)  
 Method: Least Squares  
 Date: 10/29/14 Time: 22:22  
 Sample (adjusted): 1992Q2 2013Q4  
 Included observations: 87 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGY(-1)	-0.002884	0.001547	-1.863756	0.0658
C	0.020523	0.005431	3.779024	0.0003

R-squared	0.039261	Mean dependent var	0.010429
Adjusted R-squared	0.027958	S.D. dependent var	0.003789
S.E. of regression	0.003736	Akaike info criterion	-8.319138
Sum squared resid	0.001186	Schwarz criterion	-8.262450
Log likelihood	363.8825	Hannan-Quinn criter.	-8.296311
F-statistic	3.473585	Durbin-Watson stat	1.782196
Prob(F-statistic)	0.065809		



## C.2 The Unit Root Test and the Detrending Results of $\log C$

Null Hypothesis: LOGHFCE has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=11)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	0.654349	0.9905
Test critical values:		
1% level	-3.508326	
5% level	-2.895512	
10% level	-2.584952	

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

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LOGHFCE)

Method: Least Squares

Date: 11/29/14 Time: 23:21

Sample (adjusted): 1992Q3 2013Q4

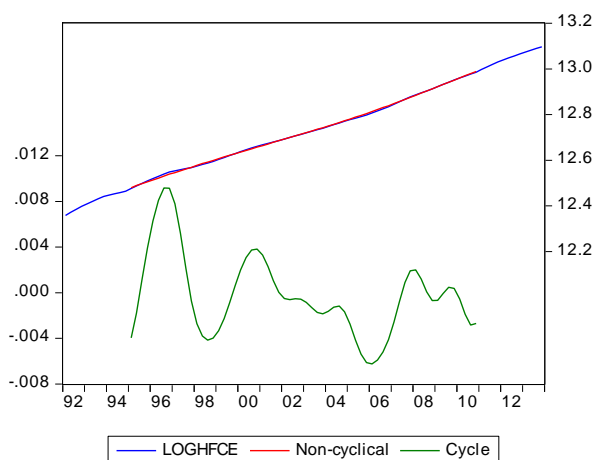
Included observations: 86 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGHFCE(-1)	0.000426	0.000651	0.654349	0.5147
D(LOGHFCE(-1))	0.767604	0.063263	12.13361	0.0000
C	-0.003513	0.008288	-0.423938	0.6727

R-squared	0.640786	Mean dependent var	0.008431
Adjusted R-squared	0.632130	S.D. dependent var	0.001993
S.E. of regression	0.001209	Akaike info criterion	-10.56395
Sum squared resid	0.000121	Schwarz criterion	-10.47834
Log likelihood	457.2500	Hannan-Quinn criter.	-10.52950
F-statistic	74.03010	Durbin-Watson stat	1.857897
Prob(F-statistic)	0.000000		

Fixed Length Symmetric (Baxter-King) Filter



### C.3 The Unit Root Test and the Detrending Results of $\log Po$

Null Hypothesis: LOGWTI has a unit root

Exogenous: Constant

Lag Length: 4 (Automatic - based on SIC, maxlag=11)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-0.504480	0.8841
Test critical values:		
1% level	-3.511262	
5% level	-2.896779	
10% level	-2.585626	

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

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LOGWTI)

Method: Least Squares

Date: 11/30/14 Time: 15:27

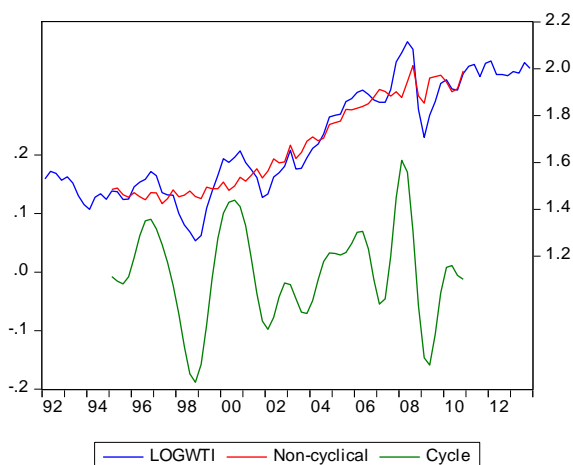
Sample (adjusted): 1993Q2 2013Q4

Included observations: 83 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGWTI(-1)	-0.011964	0.023715	-0.504480	0.6154
D(LOGWTI(-1))	0.500074	0.106509	4.695143	0.0000
D(LOGWTI(-2))	-0.415420	0.118677	-3.500434	0.0008
D(LOGWTI(-3))	0.255075	0.117818	2.165001	0.0335
D(LOGWTI(-4))	-0.377488	0.107631	-3.507237	0.0008
C	0.025618	0.040119	0.638549	0.5250

R-squared	0.311547	Mean dependent var	0.005580
Adjusted R-squared	0.266842	S.D. dependent var	0.054816
S.E. of regression	0.046936	Akaike info criterion	-3.210508
Sum squared resid	0.169632	Schwarz criterion	-3.035652
Log likelihood	139.2361	Hannan-Quinn criter.	-3.140261
F-statistic	6.968983	Durbin-Watson stat	1.924890
Prob(F-statistic)	0.000020		

Fixed Length Symmetric (Baxter-King) Filter



### C.4 The Unit Root Test and the Detrending Results of $\log M$

Null Hypothesis: LOGM has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=10)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.664975	0.4434
Test critical values:		
1% level	-3.548208	
5% level	-2.912631	
10% level	-2.594027	

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

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LOGM)

Method: Least Squares

Date: 10/29/14 Time: 22:53

Sample (adjusted): 1999Q3 2013Q4

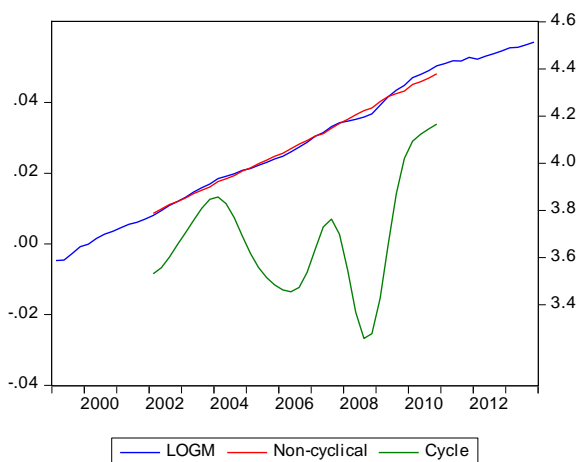
Included observations: 58 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGM(-1)	-0.006066	0.003643	-1.664975	0.1016
D(LOGM(-1))	0.293039	0.122822	2.385877	0.0205
C	0.036062	0.015317	2.354339	0.0222

R-squared	0.153473	Mean dependent var	0.015948
Adjusted R-squared	0.122691	S.D. dependent var	0.008139
S.E. of regression	0.007623	Akaike info criterion	-6.864872
Sum squared resid	0.003196	Schwarz criterion	-6.758297
Log likelihood	202.0813	Hannan-Quinn criter.	-6.823359
F-statistic	4.985691	Durbin-Watson stat	1.929486
Prob(F-statistic)	0.010236		

Fixed Length Symmetric (Baxter-King) Filter



### C.5 The Unit Root Test and the Detrending Results of $\log\pi$

Null Hypothesis: LOGCPI has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=11)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.123219	0.0285
Test critical values:		
1% level	-3.508326	
5% level	-2.895512	
10% level	-2.584952	

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

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LOGCPI)

Method: Least Squares

Date: 11/29/14 Time: 23:29

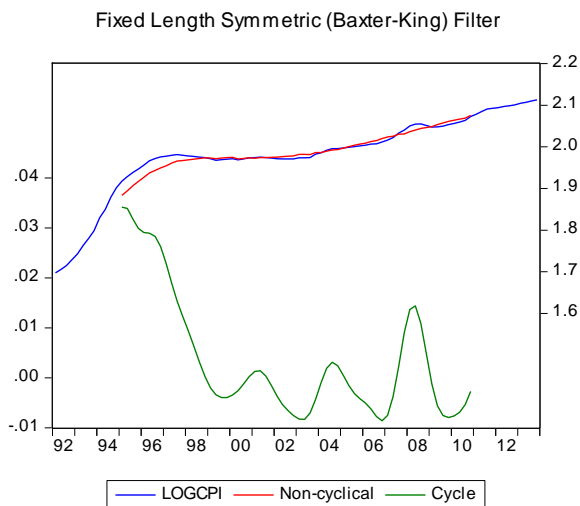
Sample (adjusted): 1992Q3 2013Q4

Included observations: 86 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGCPI(-1)	-0.014578	0.004668	-3.123219	0.0025
D(LOGCPI(-1))	0.766194	0.060813	12.59919	0.0000
C	0.029945	0.009420	3.178994	0.0021

R-squared	0.786068	Mean dependent var	0.004739
Adjusted R-squared	0.780913	S.D. dependent var	0.006882
S.E. of regression	0.003221	Akaike info criterion	-8.603796
Sum squared resid	0.000861	Schwarz criterion	-8.518179
Log likelihood	372.9632	Hannan-Quinn criter.	-8.569339
F-statistic	152.4866	Durbin-Watson stat	2.443209
Prob(F-statistic)	0.000000		



## C.6 The Unit Root Test and the Detrending Results of $\log G$

Null Hypothesis: LOGG has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=6)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.343987	0.5934
Test critical values:		
1% level	-3.711457	
5% level	-2.981038	
10% level	-2.629906	

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

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LOGG)

Method: Least Squares

Date: 10/29/14 Time: 23:01

Sample (adjusted): 2007Q3 2013Q4

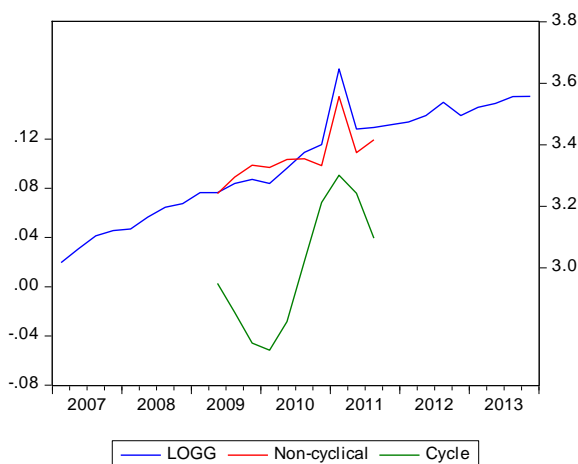
Included observations: 26 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGG(-1)	-0.097452	0.072509	-1.343987	0.1921
D(LOGG(-1))	-0.400728	0.182399	-2.196985	0.0384
C	0.353672	0.242693	1.457284	0.1586

R-squared	0.240701	Mean dependent var	0.019092
Adjusted R-squared	0.174675	S.D. dependent var	0.065864
S.E. of regression	0.059836	Akaike info criterion	-2.686265
Sum squared resid	0.082347	Schwarz criterion	-2.541101
Log likelihood	37.92145	Hannan-Quinn criter.	-2.644463
F-statistic	3.645550	Durbin-Watson stat	2.159324
Prob(F-statistic)	0.042145		

Fixed Length Symmetric (Baxter-King) Filter



## Appendix D. Matlab Codes

### D.1 The Matlab Code for Calculating the Statistical Moments of the Actual Data

```

%% This Matlab code calculates the statistical moments of the actual
data for comparison.
%% Created by Mingche Wu for ECO6999 Major Paper.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%
clear all;
close all;
clc;

%% Import real data from MS Excel.
Y_real = xlsread('E:\Academic\MRP\Data\RealData','B14:B77');
C_real = xlsread('E:\Academic\MRP\Data\RealData','C14:C77');
Po_real = xlsread('E:\Academic\MRP\Data\RealData','D14:D77');
M_real = xlsread('E:\Academic\MRP\Data\RealData','E42:E77');
pi_real = xlsread('E:\Academic\MRP\Data\RealData','F14:F77');
G_real = xlsread('E:\Academic\MRP\Data\RealData','G68:G83');

%% Calculate standard deviation.
sd_Y = std(Y_real);
sd_C = std(C_real);
sd_Po = std(Po_real);
sd_M = std(M_real);
sd_pi = std(pi_real);
sd_G = std(G_real);

Stdrd = [sd_Y sd_C sd_Po sd_M sd_pi sd_G];
disp('Standard Deviation (Real Data)')
disp('      Y      C      Po      M      pi      G')
Stdrd

%% Calculate relative standard deviation.
RelStd = [sd_C/sd_Y sd_Po/sd_Y sd_M/sd_Y sd_pi/sd_Y sd_G/sd_Y];
disp('Relative Standard Deviation (Real Data)')
disp('      C/Y      Po/Y      M/Y      pi/Y      G/Y')
RelStd

%% Calculate first-order autocorrelation.
auto_Y = autocorr(Y_real,1);
auto_C = autocorr(C_real,1);
auto_Po = autocorr(Po_real,1);
auto_M = autocorr(M_real,1);
auto_pi = autocorr(pi_real,1);
auto_G = autocorr(G_real,1);

disp('First-order Autocorrelation (Real Data)')
fprintf('  auto_Y = %6.4f\n  ',auto_Y(2));
fprintf('auto_C = %6.4f\n  ',auto_C(2));
fprintf('auto_Po = %6.4f\n  ',auto_Po(2));

```

```

fprintf('auto_M = %6.4f\n  ',auto_M(2));
fprintf('auto_pi = %6.4f\n  ',auto_pi(2));
fprintf('auto_G = %6.4f\n  ',auto_G(2));

%% Re-import data and calculate cross-correlation.
Y_realc = xlsread('E:\Academic\MRP\Data\RealData','B14:B77');
C_realc = xlsread('E:\Academic\MRP\Data\RealData','C14:C77');
Po_realc = xlsread('E:\Academic\MRP\Data\RealData','D14:D77');
pi_realc = xlsread('E:\Academic\MRP\Data\RealData','F14:F77');

crord = corrcoef([Y_realc C_realc Po_realc pi_realc]);
disp('Cross-correlation (Real Data)')
disp('      Y      C      Po      pi')
crord

```

## D.2 The IRIS Code for Describing the Model in Jian, Li and Zheng (2010)

```

%% This IRIS code describes the New Keynesian model in Jian, Li and
Zheng (2010).
%% Created by Mingche Wu for ECO6999 Major Paper.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
!variables
Y, I, K, lambda, C, L, w, m, R, rk, pi, u, O, b, po, T, a, Z, Po, G,
tau, M

!shocks
ea, ez, ep, eg, etau, em

!parameters
delta, hb, beta, eta, alpha, nu, thetap, G_hb, T_hb, fik, fipi, fiy,
fip, C_Y, I_Y, G_Y, PoO_Y, rhoa, rhoz, rhop, rhog, rhotau, rhom, sa, sz,
sp, sg, stau, sm

!equations
I = (1/delta)*K{+1}-((1-delta)/delta)*K;
lambda = (1/(1-beta*hb))*(a-(1/(1-hb))*(C-hb*C{-1}))- (beta*hb/(1-
beta*hb))*(a{+1}-(1/(1-hb))*(C{+1}-hb*C));
eta*L = lambda+w;
m+lambda = -beta/(1-beta)*R;
((1/beta)-1+delta)*rk{+1}+fik*(K{+2}-K{+1}) = (1/beta)*(lambda-
lambda{+1}+fik*(K{+1}-K));
lambda{+1}-lambda-pi{+1} = -R;
Y = Z+alpha*(u+K)+(1-alpha)*L;
O = K+nu*u;
u = 1/nu*(rk-po);
K-L = w-rk;
pi = (((1-thetap)*(1-beta*thetap))/thetap)*((1-alpha)*w+((alpha*(nu-
1))/nu)*rk+(alpha/nu)*po-Z)+beta*pi{+1};
beta*(b-R) = (b{-1}-pi)+G_hb*G-T_hb*T;
T = tau+Y;
M = rhom*M{-1}+fipi*pi+fiy*Y+fip*100*ep+100*em;
M-M{-1}-pi = m-m{-1};

```

```

Po-Po{-1}-pi = po-po{-1};
Y = C_Y*C+I_Y*I+G_Y*G+PoO_Y*(po+O);
a = rhoa*a{-1}+100*ea;
Z = rhoz*Z{-1}+100*ez;
Po = rhop*Po{-1}+100*ep;
G = rhog*G{-1}+100*eg;
tau = rhotau*tau{-1}+100*etau;

```

### D.3 The Matlab code for Simulating the Model with All Types of Shocks and Computing

#### the Statistical Moments

```

%% This Matlab code simulates the New Keynesian model in Jian, Li and
Zheng (2010).
%% Created by Mingche Wu for ECO6999 Major Paper.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%
clear all;
close all;
clc;

%% Setup IRIS.
addpath C:\IRIS_Tbx; irisstartup

%% Load IRIS model file and create a model object.
m = model('IRISModel.model');

%% Assign values to parameters.
m.delta = 0.025;
m.hb = 0.6433;
m.beta = 0.9897;
m.eta = 0.4;           % to match Dhawan and Jeske (2008)
m.alpha = 0.8;
m.nu = 9.0455;
m.thetap = 0.5;       % to match Blanchard and Gali (2007)
m.fik = 32.1346;      % to match Ireland (2003)
m.fipi = -0.9922;
m.fiy = 0.5962;
m.fip = 0.0049;
m.G_hb = 10.8437;
m.T_hb = 10.854;
m.C_Y = 0.419;
m.I_Y = 0.4239;
m.G_Y = 0.157;
m.PoO_Y = 0.0001;
m.rhoa = 0.7611;
m.rhoz = 0.8085;
m.rhop = 0.8869;
m.rhog = 0.8101;
m.rhotau = 0.8310;
m.rhom = 0.8532;
m.sa = 0.0222;
m.sz = 0.0264;

```

---

```

m.sp = 0.1043;
m.sg = 0.0325;
m.stau = 0.0892;
m.sm = 0.0282;

%% Find the steady state and check its validity.
m = sstate(m);
chksstate(m);

%% Solve the model.
m = solve(m);

%% Creat matrixes for collecting statistic moments' results.
StdDev = [];
RelStd = [];
AutCor = [];
CroCor = [];

%% Creat loops for calculating statistic moments.
for SimNum = 1:500

%% Create an input database for simulation and enter a random shock.
d = sstatedb(m,1:188, 'randomShocks=',true);
d.ea = m.sa*d.ea;
d.ez = m.sz*d.ez;
d.ep = m.sp*d.ep;
d.eg = m.sg*d.eg;
d.etau = m.stau*d.etau;
d.em = m.sm*d.em;

%% Simulate the model.
s = simulate(m,d,1:188, 'deviation=',true, 'dbextend=',true);

%% Detrend by BP filter and plot cycles.
Ycycle = BK([s.Y(101:end)], 6, 32,12);
Ccycle = BK([s.C(101:end)], 6, 32,12);
Pocycle = BK([s.Po(101:end)], 6, 32,12);
Mcycle = BK([s.M(101:end)], 6, 32,12);
picycle = BK([s.pi(101:end)], 6, 32,12);
Gcycle = BK([s.G(101:end)], 6, 32,12);

%% Compute standard deviation.
Stdm = std ([Ycycle Ccycle Pocycle Mcycle picycle Gcycle]);
StdDev(SimNum,:) = Stdm;

%% Compute relative standard deviation
for i = 1:5

    if i == 1
RelStd(SimNum,i) = Stdm(1,2)/Stdm(1,1); % Std C/Y
    end

    if i == 2
RelStd(SimNum,i) = Stdm(1,3)/Stdm(1,1); % Std Po/Y

```

```
end

    if i == 3
RelStd(SimNum,i) = Stdm(1,4)/Stdm(1,1); % Std M/Y
    end

    if i == 4
RelStd(SimNum,i) = Stdm(1,5)/Stdm(1,1); % Std pi/Y
    end

    if i == 5
RelStd(SimNum,i) = Stdm(1,6)/Stdm(1,1); % Std G/Y
    end

end

%% Compute first-order autocorrelation.
AutoYm = autocorr(Ycycle,1);
AutoCm = autocorr(Ccycle,1);
AutoPom = autocorr(Pocycle,1);
AutoMm = autocorr(Mcycle,1);
Autopim = autocorr(picycle,1);
AutoGm = autocorr(Gcycle,1);

for i = 1:6

    if i == 1
AutCor(SimNum,i) = AutoYm(2);
    end

    if i == 2
AutCor(SimNum,i) = AutoCm(2);
    end

    if i == 3
AutCor(SimNum,i) = AutoPom(2);
    end

    if i == 4
AutCor(SimNum,i) = AutoMm(2);
    end

    if i == 5
AutCor(SimNum,i) = Autopim(2);
    end

    if i == 6
AutCor(SimNum,i) = AutoGm(2);
    end

end

%% Compute cross-correlation.
```

---

```

Crom = corrcoef([Ycycle Ccycle Poycycle picycle]);

for i = 1:6

    if i == 1
    CroCor(SimNum,i) = Crom(2,1); % Cro Y_C
    end

    if i == 2
    CroCor(SimNum,i) = Crom(3,1); % Cro Y_Po
    end

    if i == 3
    CroCor(SimNum,i) = Crom(4,1); % Cro Y_pi
    end

    if i == 4
    CroCor(SimNum,i) = Crom(3,2); % Cro C_Po
    end

    if i == 5
    CroCor(SimNum,i) = Crom(4,2); % Cro C_pi
    end

    if i == 6
    CroCor(SimNum,i) = Crom(4,3); % Cro Po_pi
    end

end

end

%% Calculate the average value and display the results.
mStdDev = mean(StdDev);
mRelStd = mean(RelStd);
mAutCor = mean(AutCor);
mCroCor = mean(CroCor);
mStdDev
mRelStd
mAutCor
mCroCor

%% Plot the cycles
figure(1);

subplot(3,2,1);
plot(1:64', [Ycycle]);
title('Y cycle', 'FontSize', 12);
xlim([0, 64]);
grid on;

subplot(3,2,2);
plot(1:64', [Ccycle]);
title('C cycle', 'FontSize', 12);

```

---

```

xlim([0, 64]);
grid on;

subplot(3,2,3);
plot((1:64)', [Pocycle]);
title('Po cycle', 'FontSize', 12);
xlim([0, 64]);
grid on;

subplot(3,2,4);
plot((1:64)', [Mcycle]);
title('M cycle', 'FontSize', 12);
xlim([0, 64]);
grid on;

subplot(3,2,5);
plot((1:64)', [picycle]);
title('pi cycle', 'FontSize', 12);
xlim([0, 64]);
grid on;

subplot(3,2,6);
plot((1:64)', [Gcycle]);
title('G cycle', 'FontSize', 12);
xlim([0, 64]);
grid on;

subplot(3,2,1);
plot((1:64)', [Ycycle]);
title('Y cycle', 'FontSize', 12);
xlim([0, 64]);
grid on;

%% Impulse responses to oil price shock (ep)
dp = zerodb(m,1:40);
dp.ep(1)= m.sp;
impp = simulate(m,dp,1:40,'deviation=',true,'dbextend=',true);
dbplot(impp,0:40,{'Y','C','Po','M','pi','I','u','L','R'},'zeroline=',true);
ftitle('Impulse Responses to Oil Price Shocks (in Percent)');

%% Impulse responses to a technology shock (ez)
dz = zerodb(m,1:40);
dz.ez(1) = 1*m.sz;
impz = simulate(m,dz,1:40,'deviation=',true,'dbextend=',true);
dbplot(impz,0:40,{'Y','C','Po','M','pi','I','u','L','R'},'zeroline=',true);
ftitle('Impulse Responses to a Technology Shock (in Percent)');

```

## D.4 The Matlab code for Simulating the Model with Oil Price Shocks Only and Computing the Statistical Moments

```

%% This Matlab code simulates the New Keynesian model in Jian, Li and
Zheng (2010) with oil price shocks only.
%% Created by Mingche Wu for ECO6999 Major Paper.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
clear all;
close all;
clc;

%% Setup IRIS.
addpath C:\IRIS_Tbx; irisstartup

%% Load IRIS model file and create a model object.
m = model('IRISModel.model');

%% Assign values to parameters.
m.delta = 0.025;
m.hb = 0.6433;
m.beta = 0.9897;
m.eta = 0.4;
m.alpha = 0.8;
m.nu = 9.0455;
m.thetap = 0.5;
m.fik = 32.1346;
m.fipi = -0.9922;
m.fiy = 0.5962;
m.fip = 0.0049;
m.G_hb = 10.8437;
m.T_hb = 10.854;
m.C_Y = 0.419;
m.I_Y = 0.4239;
m.G_Y = 0.157;
m.PoO_Y = 0.0001;
m.rhoa = 0.7611;
m.rhoz = 0.8085;
m.rhop = 0.8869;
m.rhog = 0.8101;
m.rhotau = 0.8310;
m.rhom = 0.8532;
m.sa = 0;           % Shut down preference shocks
m.sz = 0;           % Shut down technology shocks
m.sp = 0.1043;      % Remain oil price shocks
m.sg = 0            % Shut down government expenditure shocks
m.stau = 0          % Shut down tax rate shocks
m.sm = 0            % Shut down money supply shocks

%% Find the steady state and check its validity.
m = sstate(m);
chksstate(m);

%% Solve the model.

```

```

m = solve(m);

%% Creat matrixes for collecting statistic moments' results.
StdDev = [];
RelStd = [];
AutCor = [];
CroCor = [];

%% Creat loops for calculating statistic moments.
for SimNum = 1:500

%% Create an input database for simulation and enter a random shock.
d = sstatedb(m,1:188,'randomShocks=',true);
d.ea = m.sa*d.ea;
d.ez = m.sz*d.ez;
d.ep = m.sp*d.ep;
d.eg = m.sg*d.eg;
d.etau = m.stau*d.etau;
d.em = m.sm*d.em;

%% Simulate the model.
s = simulate(m,d,1:188,'deviation=',true,'dbextend=',true);

%% Detrend by BP filter and plot cycles.
Ycycle = BK([s.Y(101:end)], 6, 32,12);
Ccycle = BK([s.C(101:end)], 6, 32,12);
Pocycle = BK([s.Po(101:end)], 6, 32,12);
Mcycle = BK([s.M(101:end)], 6, 32,12);
picycle = BK([s.pi(101:end)], 6, 32,12);
Gcycle = BK([s.G(101:end)], 6, 32,12);

%% Compute standard deviation.
Stdm = std ([Ycycle Ccycle Pocycle Mcycle picycle Gcycle]);
StdDev(SimNum,:) = Stdm;

%% Compute relative standard deviation
for i = 1:5

    if i == 1
RelStd(SimNum,i) = Stdm(1,2)/Stdm(1,1); % Std C/Y
    end

    if i == 2
RelStd(SimNum,i) = Stdm(1,3)/Stdm(1,1); % Std Po/Y
    end

    if i == 3
RelStd(SimNum,i) = Stdm(1,4)/Stdm(1,1); % Std M/Y
    end

    if i == 4
RelStd(SimNum,i) = Stdm(1,5)/Stdm(1,1); % Std pi/Y
    end
end

```

```
    if i == 5
RelStd(SimNum,i) = Stdm(1,6)/Stdm(1,1); % Std G/Y
    end

end

%% Compute first-order autocorrelation.
AutoYm = autocorr(Ycycle,1);
AutoCm = autocorr(Ccycle,1);
AutoPom = autocorr(Pocycle,1);
AutoMm = autocorr(Mcycle,1);
Autopim = autocorr(picycle,1);
AutoGm = autocorr(Gcycle,1);

for i = 1:6

    if i == 1
AutCor(SimNum,i) = AutoYm(2);
    end

    if i == 2
AutCor(SimNum,i) = AutoCm(2);
    end

    if i == 3
AutCor(SimNum,i) = AutoPom(2);
    end

    if i == 4
AutCor(SimNum,i) = AutoMm(2);
    end

    if i == 5
AutCor(SimNum,i) = Autopim(2);
    end

    if i == 6
AutCor(SimNum,i) = AutoGm(2);
    end

end

%% Compute cross-correlation.
Crom = corrcoef([Ycycle Ccycle Pocycle picycle]);

for i = 1:6

    if i == 1
CroCor(SimNum,i) = Crom(2,1); % Cro Y_C
    end

    if i == 2
CroCor(SimNum,i) = Crom(3,1); % Cro Y_Po
```

```
end

    if i == 3
CroCor(SimNum,i) = Crom(4,1); % Cro Y_pi
end

    if i == 4
CroCor(SimNum,i) = Crom(3,2); % Cro C_Po
end

    if i == 5
CroCor(SimNum,i) = Crom(4,2); % Cro C_pi
end

    if i == 6
CroCor(SimNum,i) = Crom(4,3); % Cro Po_pi
end

end

end

%% Calculate the average value and display the results.
mStdDev = mean(StdDev);
mRelStd = mean(RelStd);
mAutCor = mean(AutCor);
mCroCor = mean(CroCor);
mStdDev
mRelStd
mAutCor
mCroCor
```