Oil Price Shocks and China's Economy:

Reactions of the Monetary Policy to Oil Price Shocks

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Abstract

The paper empirically analyzes the effect of oil price shocks on China's economy with special interest in the response of the Chinese interest rate to those shocks. Using different econometric models, i) a time-varying parameter structural vector autoregression (TVP SVAR) model with short-run identifying restrictions, ii) a structural VAR (SVAR) model with the short-run identifying restrictions, and iii) a VAR model with ordering-free generalized impulse response VAR (GIR VAR), we find the response of the Chinese interest rate to the oil shocks is not only time-varying but also showing quite different signs of responses. Specifically, in the earlier sample period (1992:4-2001:10), the interest rate shows a negative response to the oil shock, while in the latter period (2001:11-2014:5) it shows a positive response to the shock. Given the negative response of the world oil production to an oil price shock in the earlier period, the shock is identified as a negative supply shock or a precautionary demand shock, thereby the negative response the interest rate the oil shock is deemed as economy-boosting. The positive response of interest rate the oil shock in the later period, given that this shock is identified as a positive world oil demand shock, gives evidence that stabilization of inflation is one of the main objectives of China's monetary authority, even though the current main objective of the monetary policy is characterized as "maintaining the stability of the value of the currency and thereby promoting economic growth." Finally, the variance decomposition results reveal that the oil price shock becomes an increasingly important source in the volatility of China's interest rate.

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1.   Introduction

According to BP (2014), China is the second largest oil consumer in the world, consuming 10.77 million barrels per day or about 12% of the world oil demand in 2013. This puts China second to the United States which consumes 18.89 million barrels per day or 19.9% of the world demand. By consuming 18.72 million barrels per day in 2035 as forecasted by the U.S. Energy Information Administration (EIA, 2014), China would surpass the U.S. which is forecasted to consume 18.46 billion barrel per day by that year. Given China's increasing future consumption of oil, it would be interesting and useful to see how China's economy responds to changes in the oil market. There are several studies that examine the relationship between changes in oil prices and the responses of the Chinese economy. There seem to be no clear explanations of why the signs of responses of China's macroeconomic variables to an oil price shock should be that way. For example, the result in some studies of having a positive response of industrial production to a positive oil price shock seems puzzling, particularly when the source of the shock is not specified.

Ou et al. (2012) analyze how China's macroeconomy responds to the world oil price shocks, using a structural dynamic factor model. They find that various price indices, industrial production, investment and interest rate rise while stock prices fall in response to a positive oil price shock. These authors however do not specify whether the oil price shock is demand shock or not.

Qianqian (2011), on the other hand, finds that positive oil price shocks cause China's real output to fall but interest rate and CPI to rise. Tang et al. (2010) also find that a positive oil price shock has a negative impact on output and investment but positive effects on inflation and interest rate. Du et al. (2010) note that there is a structural break in the model because of

recurrent reforms in China's oil pricing mechanism, and find that the effects of the oil price shock on China's macroeconomic variables are non-linear. However, those asymmetric responses are found to be statistically insignificant. Wu and Ni (2011) test a Granger causality between the oil price and China's inflation, interest rate and money supply and find that the oil price affects inflation contemporaneously and also with lags.

China's price regulations on oil prices are well documented in Du et al. (2010). In 1981, the State Council of China introduced a dual-track pricing system through which the Ministry of Petroleum was required to sell the first 100 million tons at a regulated low price, while the production that exceeds more than 100 million tons was allowed to be sold at the higher market prices. However, the government deregulated its domestic pricing mechanism in 1998. The dual-track pricing system was abolished and the current month's price of crude oil was determined on the basis of the average world price of similar quality of the last month. Still the petroleum products were still required to follow the government's guideline price and the retail prices were allowed to fluctuate within 5% from the guideline. In 2000, the pricing mechanism of the petroleum products of China was further deregulated and the monthly prices of the petroleum products were determined on the basis of the average closing prices of the Singapore futures market of the last month. Finally, in October 2001, the prices were revised to combine the futures prices of New York, Rotterdam and Singapore of the last month. Those price regulation events could be useful in identifying structural breaks in the relationship between the Chinese economy and oil prices.

Therefore, what is an oil price shock? Archanskaïa et al. (2012) identify the main driving force behind oil price shocks in the period 1970-2006. Their identification strategy relies on a simple premise: supply-driven oil price shocks negatively impact global economic activity, while

demand-driven oil price shocks do not have negative effects. They find that the oil price shocks between 1970 and 1992 were adverse supply-driven shocks, while between 1992 and 2006 they were favorable global oil demand shocks. The former is also confirmed by Hamilton (1983, 1996, and 2009) and the latter is confirmed by Hamilton (2009), Kilian (2008a, 2008b) and Kilian (2009).

We basically are interested in addressing three questions. The first question is: How do China's industrial production and interest rate respond to positive oil shocks? The second question is: Are the positive oil price shocks always the same, thereby they can be characterized as positive demand shocks. The third question is: How important is the oil price shock in the volatility of China's interest rate in two different subperiods which are separated by the last oil price regulations near the end of 2001.

Therefore, we attempt to invoke several explanations of why the literature comes up with different and sometimes contradicting signs of China's macroeconomic responses to a positive oil shock, particularly the role played by the Chinese monetary policy and the conduct of interest rate in response to the shock. Our explanations depend partially on the degree the various types of models capture the time variations in response to the positive oil shock. They also relate to the regulatory state of the Chinese crude oil and refined products markets, thereby structural breaks and subperiod separations matter in those explanations. The type of the positive oil shock whether it is a negative supply shock or a positive shock matters in governing the responses.

The results also cooperate with our research scheme well. They show that the responses of the macroeconomic variables including the interest rate are not only time-varying but also different in different subperiods. Before the regulatory structural break, the responses are negative in response to the positive oil shock, while interest rate drops, indicating that the shock

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is negatively supply-driven. However, in the subperiod following the structural break the responses are positive, underscoring that the shocks are demand-driven. These findings have important implications for the conduct of China's monetary policy and the responsive trajectory of its interest rate once the type of the oil price is identified.

The remainder of the paper is organized as follows. Section 2 presents the empirical methods that will be used. Section 3 discusses the results produced by the various models employed in this study. Section 4 concludes.

2.   Empirical methods

To analyze the effect of oil price shocks on China's macroeconomy and monetary policy (i.e., interest rate), we consider a six-variable VAR model for $\Delta z_t = (\Delta oy, \Delta op, \Delta y, \Delta p, \Delta q, \Delta i)'$, where Δoy is the log-differenced global crude oil production, Δop is the log-differenced real oil price where it is defined as the US refiner acquisition cost of imported crude oil deflated by U.S. CPI, Δy is the log-difference of China's industrial production, Δp is the log-difference of China's CPI, Δq is the log-difference of China's real exchange rate, defined as $q = \frac{S\left(\frac{CN}{US}\right) \times CPI(US)}{CPI(CN)}$, Δi is the difference of China's interest rate. The structural VAR representation is

$$A_0 \Delta z_t = \alpha + \sum_{i=1}^{p} A_i \Delta z_{t-i} + u_t , \tag{1}$$

where u_t is the vector of serially and mutually uncorrelated structural innovations and $Eu_t u_t' = I$. Assume that A_0^{-1} has a following structure such that the reduced-form errors ε_t , where $E\varepsilon_t \varepsilon_t' = \Sigma$ can be decomposed according to $\varepsilon_t = A_0^{-1} u_t$:

$$\varepsilon_t \equiv \begin{pmatrix} \varepsilon_t^{\Delta oy} \\ \varepsilon_t^{\Delta op} \\ \varepsilon_t^{\Delta y} \\ \varepsilon_t^{\Delta p} \\ \varepsilon_t^{\Delta q} \\ \varepsilon_t^{\Delta i} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{pmatrix} \begin{pmatrix} u_t^{\text{oil production shock}} \\ u_t^{\text{oil price shock}} \\ u_t^{\Delta y} \\ u_t^{\Delta p} \\ u_t^{\Delta q} \\ u_t^{\Delta i} \end{pmatrix}. \tag{2}$$

Our objective is to identify a structural oil price shock, and therefore we adopt a partial identification strategy. It is well-known that a unique oil price shock (and an oil production shock) can be identified as long as the oil production and the oil price have a recursive structure as above. None of results (responses of macroeconomic variables to an oil price shock) are sensitive to altering the ordering of China's industrial production, CPI, real exchange rate and interest rate while keeping the oil production and the oil price ordered first and second, respectively. The recursive ordering between oil production and oil price is consistent with the VAR based empirical literature on analyzing oil shocks.

Kilian (2009) defined an oil price shock as the oil-specific demand shock which is generated from a precautionary demand that is driven by uncertainty about future oil supply shortfalls. Given that the oil price shocks may be time-varying, alternative explanations in determining the cause of the oil price shock may be may be useful, as we will suggest below.

Our identification strategy of finding driving the source of the oil price shock is based on how the world oil production responds to a positive oil price shock in a VAR framework. If the world oil production falls in response to a positive oil price shock, the oil price shock is referred as negative supply shock or a precautionary demand shock according to Kilian (2009). If, however, the world oil production rises in response to a positive oil price shock, the oil price shock is referred to as positive demand shock. Our identification strategy of the driving forces of the oil price shock is summarized in <Figure 1>.

<Figure 1> Causes of oil price increases
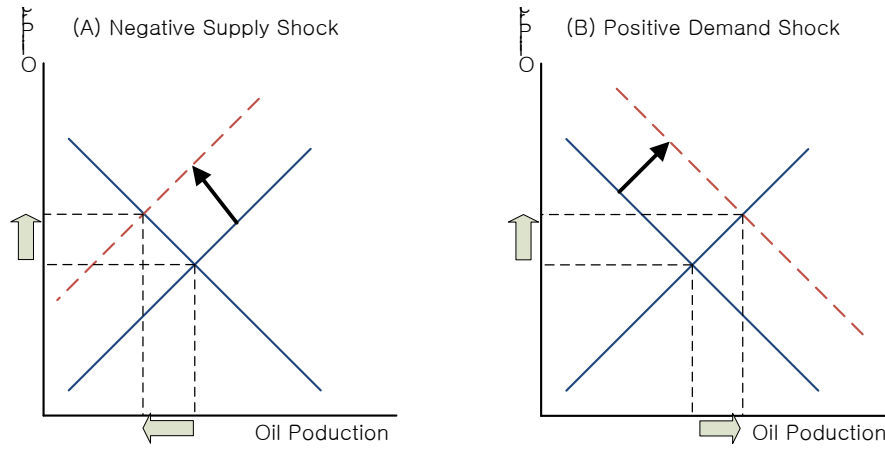
3. Empirical results

3.1. Data

Based on data availability, the monthly sample period is January 1992 – May 2014. Following the recent trend in the oil-price literature (see, for example, Baumeister and Peersman (2013) and references cited therein), the real oil price is defined as the U.S. refiner acquisition cost of crude oil sourced from the Energy Information Administration (EIA), and deflated by U.S. CPI accessed from U.S. Bureau of Labor Statistics (BLS). Oil production is also taken from EIA and denotes the world crude oil production (defined as the monthly average value of thousand barrels per day). China's industrial production and consumer price index data are obtained from China's National Bureau of Statistics. China's interest rate is the one-year lending rate and is taken from the Peoples' Bank of China (PBOC). Its real exchange rate is defined as the nominal exchange rate (CN/US) sourced from the Peoples' Bank of China, multiplied by the U.S. CPI and divided by China's CPI. A rise in this real exchange rate means a real depreciation of

Chinese yuan. All the variables are seasonally adjusted.

<Table 1> reports the summary statistics. During 1992.2-2014.5, the world oil production on average has increased by 0.087% per month (or 1.04% annually), and the real oil price has risen by 0.445% per month (or 5.34% annually). On the other hand, China's industrial production on average has grown by 1.046% per month (or 12.55% annually), while its average real exchange rate has appreciated by 1.22% annually and its interest rate dropped over the sample period.

<Table 1> Summary Statistics (1992:2-2014:5)

Name	Obs.	Mean	S.E.	Min.	Max.
Oil Production	268	0.00087	0.00694	-0.01976	0.02678
Real Oil Price	268	0.00445	0.06898	-0.32598	0.17994
Industrial Production	268	0.01046	0.02512	-0.09402	0.19723
CPI	268	0.00363	0.00609	-0.00913	0.02809
Real Exchange Rate	268	-0.00102	0.02370	-0.04704	0.36194
Interest Rate	268	-0.01028	0.21260	-1.48019	1.39437

Note: All the variables, except interest rate, are log differenced. Interest rate is first differenced.
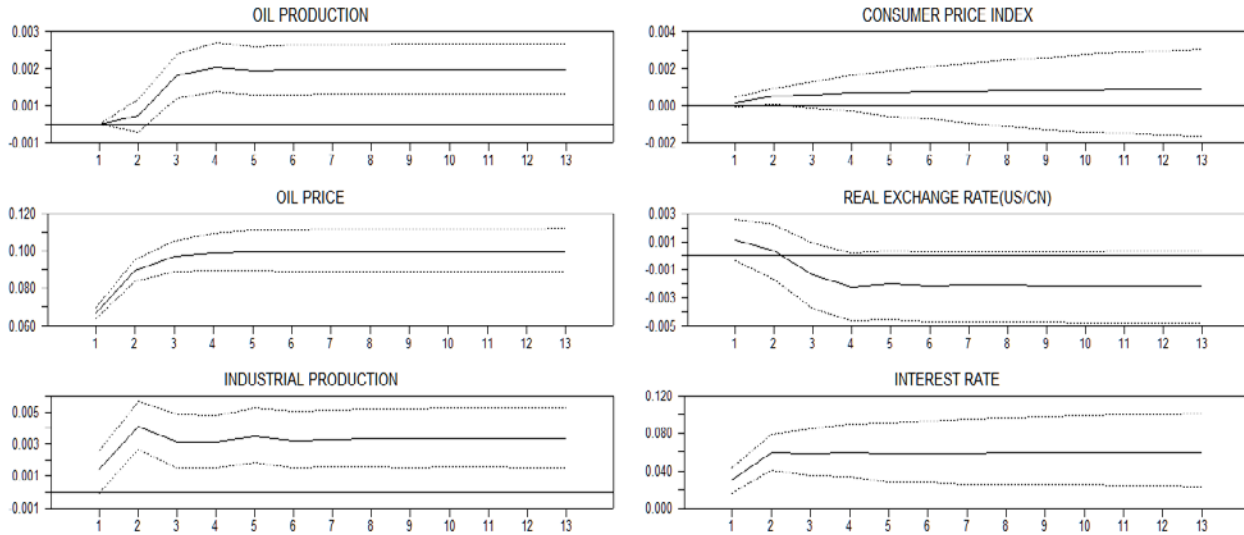
The unit-root test results reveal that all the variables are I(1), except China's CPI which shows I(0). Therefore, we first proceed with a structural VAR with short-run identifying restrictions. This approach is consistent with Kilian (2009) who imposes a recursive short-run identifying restrictions and arranges the ordering of the variables as world oil production, global demand proxied by an international cargo price, and real oil price. We choose a lag length of two based on the Akaike information criteria applied to a stable constant parameter VAR. Since we convert the variables into their growth rates and use two lags, the effective estimation of our analysis starts in 1994:4.

3.2.   Estimation results

<Figure 2> reports the accumulated impulse responses of each of the levels of the variables to a positive oil price shock for the entire sample period (1992:4-2014:5) in the standard SVAR. This figure also includes a one-standard error band for each response generated from a Monte Carlo integration simulation with 1000 replications. In response to the oil price shock, the world oil production rises both in the short-run and in the long-run. Therefore, the oil price shock for the entire period can be thought to be a global oil demand shock, reflecting on average strong global economic conditions, as shown in Figure 1. Both China's industrial production and interest rate rise in response to the positive oil shock. China's consumer price index rises as well, and there is a real appreciation of the Chinese yuan in the long run in response to the shock, even though the responses are not statistically significant. A possible explanation of the positive responses of China's industrial production and interest rate would be that, given the oil price shock is thought to be a global oil demand shock, a rise in global demand for oil implies an improvement in global economic activity. As a result, China's export and industrial production rise and there is a real appreciation of the Chinese yuan. Therefore, the Chinese monetary authority's response to the oil shock is to raise the interest rate to suppress inflation, which is the major objective of the People's Bank of China, among others (Zhou, 2012).

<Figure 2> Accumulated responses to a positive oil price shock: SVAR

Note. The responses are generated with the standard SVAR model for the entire sample period (1992:4-2014:5).

Then the next question is: Are the positive oil price shocks always the same, thereby they can be characterized as positive demand shocks? To answer this question, we utilize a time-varying parameter (TVP) VAR model with stochastic volatility. By allowing all parameters to vary over time in this model, this study examines the assumption of parameter constancy for the VAR's structural shocks based on the standard recursive identification procedure (see the appendix). Du et al (2010), for example, find that there is a structural break in China's oil market in 2002:1 because the last China's oil price reform took place at the end of 2001. However, we would like to see how the world oil production responds to an oil price shock in this model to identify whether the oil price shock is supply-driven or demand-driven. Primiceri (2005) developed the TVP-VAR model. The flexibility and robustness of this model capture the time-varying properties underlying the structure of the economy. More recently, Nakajima (2011) argues that the TVP-VAR model with constant volatility probably produces biased estimates due to the variation in the volatility of the disturbances, thus emphasizing the role of stochastic

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volatility. The TVP-VAR model with stochastic volatility avoids this misspecification issue by accommodating the simultaneous relationships among variables as well as the heteroskedasticity of the innovations. Therefore, we follow Nakajima (2011) in adopting the TVP-VAR model with stochastic volatility. [1] The accumulated impulse responses to the oil shock within the structural TVP-VAR model are reported in <Figure 3> - <Figure 5>. The short-run identifying restrictions are the same as in Equation (2). The error bands are computed using the Monte Carlo Markov Chain (MCMC) algorithm based on keeping 10,000 draws after 1,000 burn-ins. [2]
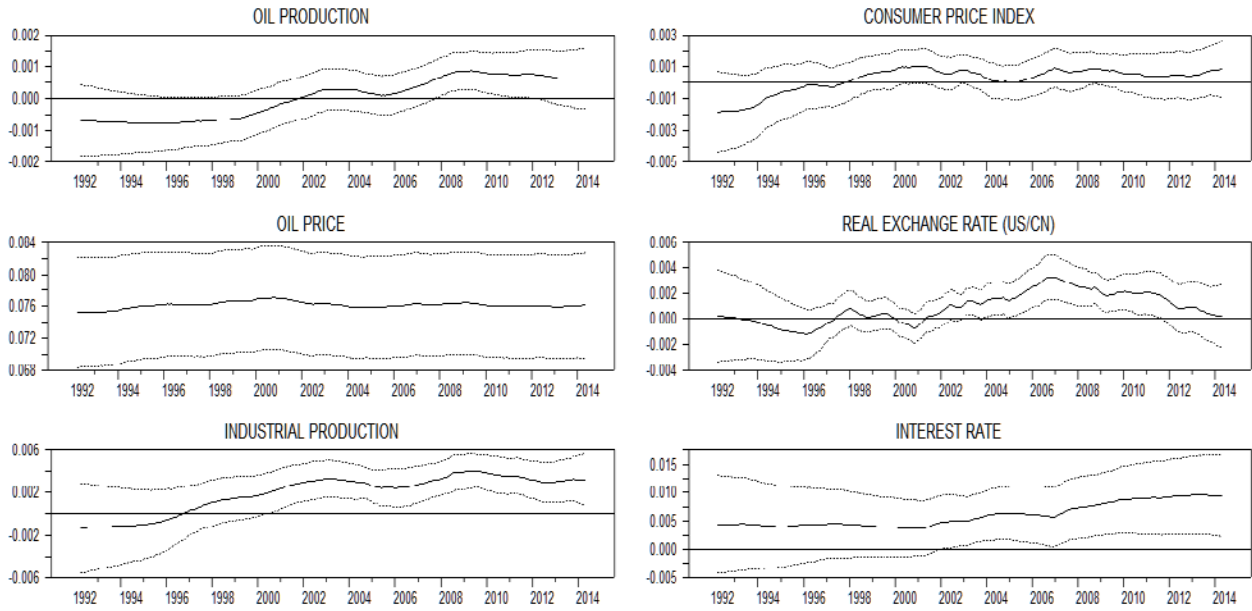
    <Figure 3> - <Figure 5> confirm that the driving force of the oil price shock changes from a negative supply shock (or precautionary demand shock) to a positive demand shock either late 1990s or early 2000s, depending on different response horizons . Specifically, <Figure 3> shows that the world oil production falls one month after the oil price shock until October 2001 and then rises afterward over the sample period. <Figure 4> displays that the world oil production falls three months after the oil price shock until Mary 1999 and then rises afterward. Finally, <Figure 5> illustrates that the world oil production falls twelve month (one year) after the oil price shock until April 1999 and then rises afterward. Generally speaking, it appears that China's industrial production and interest rate fall when the world oil production falls in response to an oil price shock and vice versa.

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[1] Recently, Baumeister and Peersman (2013) analyzed the effects of the oil supply shocks on the US economy by using TVP-VAR with stochastic volatility.
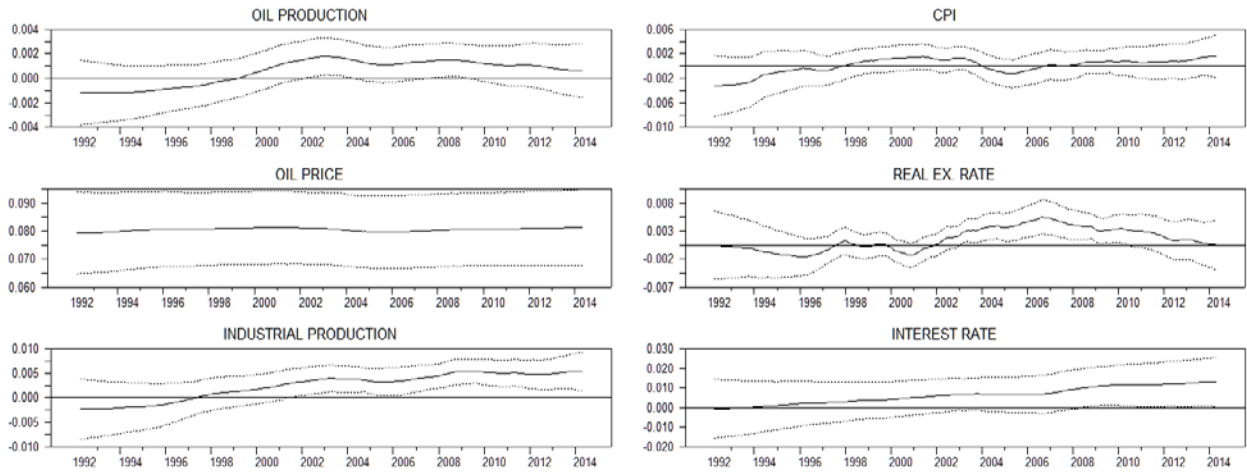
[2] See Nakajima (2011) and Pimiceri (2005) for further details on the TVP-VAR method. We also perform diagnostic tests for convergence and efficiency. We cannot reject the null hypothesis of convergence to the posterior distribution at the conventional level of significance. In addition, we observe low inefficiency factors, confirming the efficiency of the MCMC algorithm in replicating the posterior draws. These results indicate that all the parameters do change over time. See also the Appendix for more details regarding the TVP-VAR estimation results.

<Figure 3> Accumulated responses to an oil price shock with TVP-VAR (after 1 month)
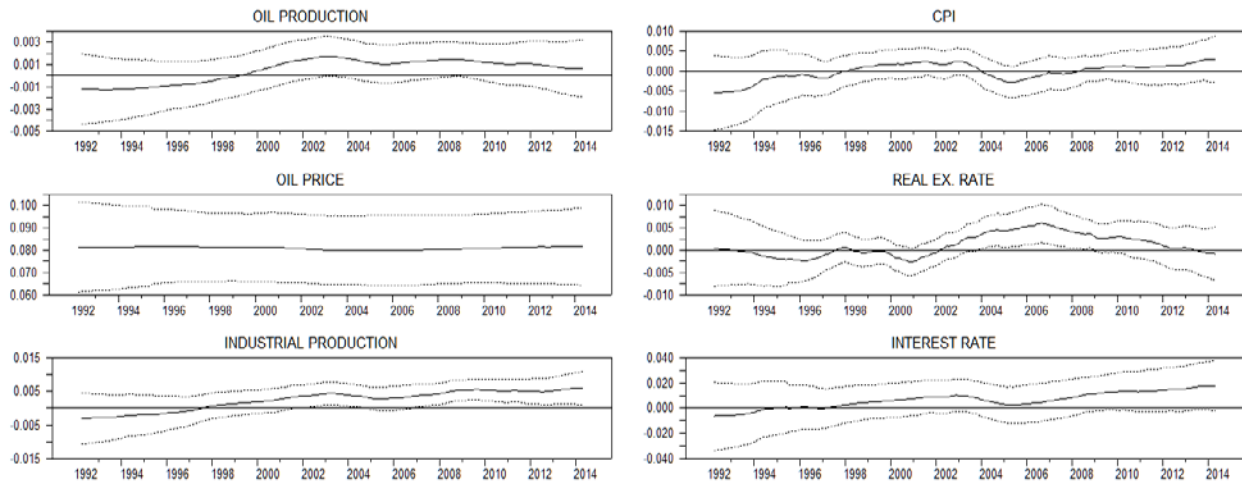

Note. We use the TVP-VAR with stochastic volatility in this figure and following figures.

<Figure 4> Accumulated responses to an oil price shock with TVP-VAR (after 3 months)

<Figure 5> Accumulated responses to oil price shock with TVP-VAR (after 12 months)
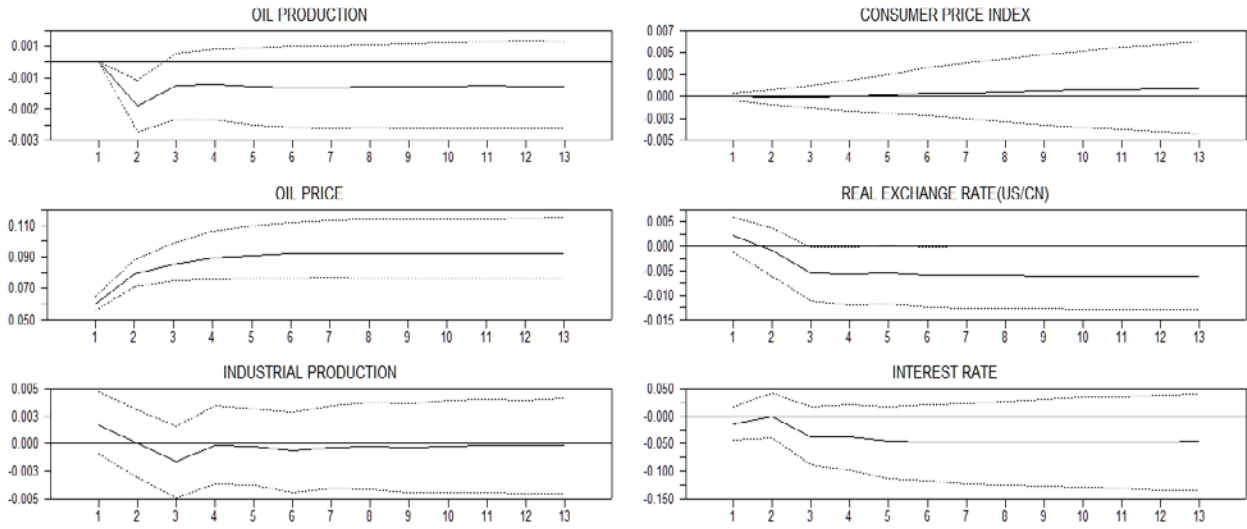

We now re-estimate a conventional structural VAR by dividing sample period into two subperiods.[3] Specifically, based on the results from <Figure 3>, we divide sample period into the subperiod 1992:4-2001:10 (the subperiod when the oil production shows a negative response to an oil shock) and the subperiod 2001:11-2014:5 after that. This period separation is generally consistent with Du et al. (2010) who separated the periods before and after 2001:12.

<Figure 6> illustrates that, in response to an oil price shock in the first subperiod, 1992:4-2001:10, the world oil production falls by 0.14% one month after the shock and this fall stabilizes at 0.08% in the long run. Therefore, an oil price shock in this subperiod can be thought of as a negative supply shock or precautionary demand shock. Oil price instantly rises by 6.96% and its rise stabilizes at 9.03%. China's industrial production and interest rate generally fall to an oil price shock even though the responses are not statistically significant in this subperiod.
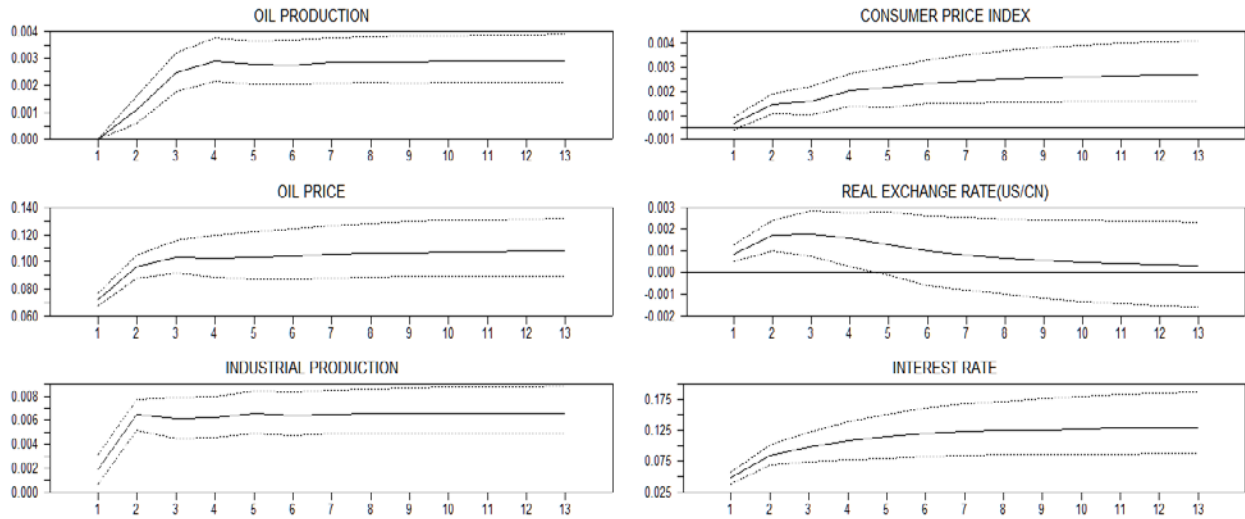
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[3] TVP-VAR clearly reveals that oil production rises in response to an oil price shock after October 2001. This is used to separate the subperiods before and after October 2001.

<Figure 6> Accumulated responses to an oil price shock with the SVAR (1992:4-2001:10)

Using the conventional VAR, <Figure 7> demonstrates that the oil price shock in the subperiod (2001:11-2014:5) has positive and significant effects on the world oil production, China's industrial production, CPI and interest rate. The statistically significant and positive response of the world oil production in this second subperiod confirms that the positive oil price shock can be thought of as a positive oil demand shock. The world oil production increases by 0.011% one month after the shock and its rise stabilizes at 0.29% in the long run. The oil price rises by 7.19% at the instant of the shock and then its rise stabilizes at 10.71%. In the long run, China's industrial production, CPI and interest rate rise by 0.66%, 0.21% and 0.129%p, respectively. The PBOC seems to have increased interest rate to deal with the rising CPI.

<Figure 7> Accumulated responses to an oil price shock with the SVAR (2001:11-2014:5)

Our final question is: How important is the oil price shock in the volatility of China's interest rate in the two different subperiods? This question can be answered with the use of the variance decomposition analysis. The results are reported in <Table 2> and <Table 3>. <Table 2> reports the variance decomposition results for the first subperiod, 1992:3-2001:10. In the earlier part of this subperiod, both the oil production shock and the oil price shock contribute little to explain the volatility of China's interest rate. In the long run (12 months after the shock), the world oil price shock explains only 1.11% of the volatility of the interest rate and the effect is statistically insignificant. Other than its own shock, the volatility of interest rate is affected with statistical significant by China's CPI shock (16.95%) in the long run. In the later subperiod (2001:11-2014:5), the oil price however explains a sizable portion of the volatility of China's interest rate, as shown in <Table 3>. The oil price shock explains 24.52% of the volatility of the interest rate and it is statistically significant.

<Table 2> Variance decomposition (subperiod 1992:4-2001:10)

SHOCKS RESPONSES	STEP	OY		OP		IP		P		Q		I	
		VDC	SE	VDC	SE	VDC	SE	VDC	SE	VDC	SE	VDC	SE
OIL PROD (OY)	3	95.82	4.45	1.60	2.86	0.34	1.33	1.93	2.27	0.27	1.43	0.05	1.39
	6	96.44	5.70	1.64	3.93	0.31	1.54	1.37	2.86	0.18	1.62	0.06	1.87
	12	97.10	8.00	1.62	4.87	0.31	1.95	0.78	5.04	0.11	1.89	0.08	2.31
OIL PRICE (OP)	3	0.41	2.81	97.70	4.03	0.13	1.05	1.57	2.02	0.07	1.28	0.13	1.44
	6	0.30	3.22	98.23	5.07	0.16	1.31	1.09	2.68	0.07	1.65	0.15	2.08
	12	0.21	3.50	98.73	7.27	0.27	1.77	0.57	4.91	0.04	2.03	0.18	2.57
IND. PROD. (Y)	3	0.70	2.79	0.38	2.65	95.36	5.30	2.46	2.73	1.03	2.13	0.07	1.53
	6	0.77	3.23	0.25	3.63	92.46	7.66	5.08	5.28	1.37	2.67	0.07	1.94
	12	0.83	3.60	0.13	4.66	86.99	11.99	10.14	9.90	1.87	3.41	0.04	2.31
CPI (P)	3	2.35	3.94	0.01	2.25	5.18	5.11	90.35	6.57	1.95	2.26	0.16	1.09
	6	1.66	4.10	0.03	3.25	5.89	5.61	89.06	7.61	3.07	3.43	0.30	1.83
	12	1.21	4.32	0.10	4.49	6.23	5.94	88.05	8.73	4.01	4.39	0.41	2.50
REAL. EX. (Q)	3	0.60	2.87	2.02	3.86	4.28	4.52	1.84	3.12	91.25	7.10	0.01	1.51
	6	0.46	3.16	2.97	5.59	4.43	4.84	1.56	4.08	90.56	8.77	0.02	1.93
	12	0.35	3.46	3.78	7.00	4.78	5.26	1.70	6.68	89.35	11.44	0.03	2.26
INT. RATE (I)	3	0.80	2.87	0.60	3.24	0.23	2.27	2.50	3.94	0.77	2.92	95.10	6.40
	6	0.66	3.49	1.07	4.77	0.16	2.37	7.28	7.19	1.56	3.74	89.27	9.45
	12	0.42	3.86	1.11	5.60	0.42	2.82	16.95	12.47	2.64	4.55	78.46	14.15

Note: 'VDC' denotes variance decomposition result and 'SE' denotes one-standard errors computed using 1,000 bootstrap replications of the model.

<Table 3> Variance decomposition (subperiod 2001:11-2014:5)

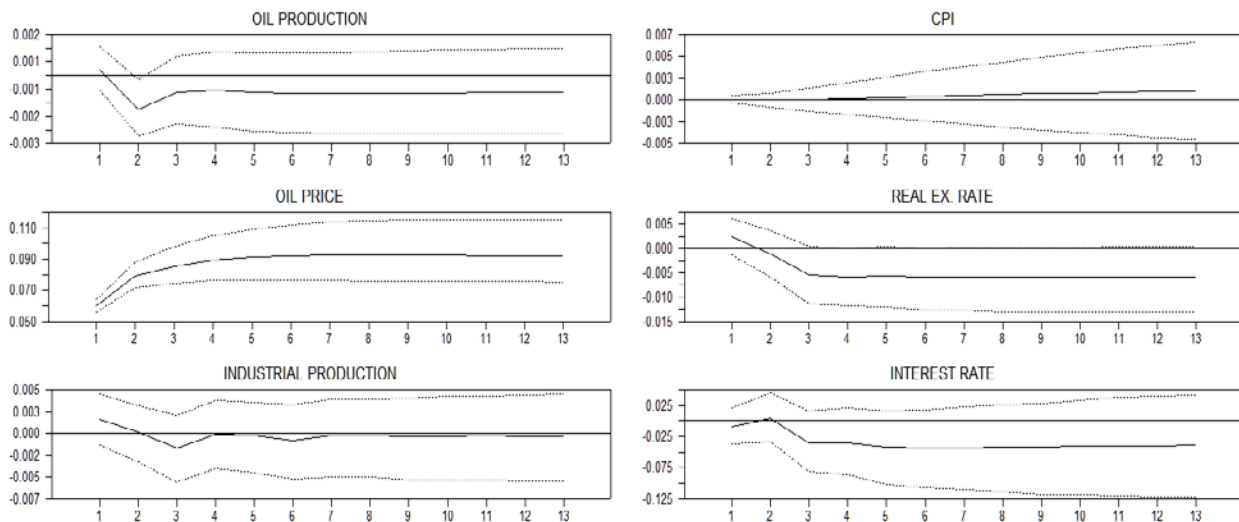| SHOCKS RESPONSES	STEP	OY		OP		IP		P		Q		I	
		VDC	SE	VDC	SE	VDC	SE	VDC	SE	VDC	SE	VDC	SE
OIL PROD (OY)	3	81.28	7.10	12.35	6.11	0.58	0.97	4.57	3.44	1.07	2.17	0.15	1.35
	6	74.32	9.43	17.52	7.94	0.77	1.23	5.44	4.38	1.81	3.42	0.13	2.02
	12	69.08	11.54	21.40	9.35	0.92	1.49	6.14	5.55	2.31	4.53	0.15	3.04
OIL PRICE (OP)	3	1.98	3.19	94.13	4.77	0.79	1.07	1.27	2.00	0.18	1.28	1.65	2.22
	6	1.98	3.33	90.84	7.05	1.05	1.38	2.50	3.28	0.41	2.37	3.22	3.89
	12	1.91	3.37	87.74	9.65	1.29	1.65	3.79	4.55	0.53	3.25	4.73	5.58
IND. PROD. (Y)	3	2.82	2.70	25.02	7.45	66.87	7.40	0.27	1.01	1.85	1.80	3.17	2.53
	6	2.95	3.21	31.69	9.18	59.46	8.95	0.17	1.37	1.33	2.16	4.40	3.92
	12	2.83	3.55	36.27	10.36	54.34	10.15	0.10	2.06	0.94	2.88	5.52	5.43
CPI (P)	3	0.02	1.40	6.24	5.41	1.89	1.66	80.16	7.06	3.96	3.34	7.73	4.09
	6	0.01	1.57	8.14	6.94	1.74	2.20	74.14	9.30	3.47	4.24	12.51	6.35
	12	0.01	1.72	9.73	8.13	1.80	2.55	69.57	11.05	3.01	4.98	15.88	8.10
REAL. EX. (Q)	3	0.01	1.48	4.11	4.30	0.74	1.50	30.21	8.64	59.62	9.17	5.31	3.55
	6	0.01	1.65	2.42	4.07	0.85	1.97	33.92	10.12	53.05	11.20	9.75	5.98
	12	0.02	1.76	1.21	3.91	1.10	2.36	36.97	11.20	46.82	13.06	13.88	8.01
INT. RATE (I)	3	0.21	1.83	24.77	8.80	2.99	2.84	7.78	5.16	1.38	2.48	62.87	9.25
	6	0.12	1.97	24.69	10.16	3.38	3.11	10.47	6.58	1.00	2.96	60.33	10.72
	12	0.08	2.07	24.52	11.20	3.61	3.27	12.54	7.68	0.76	3.67	58.49	11.83

3.3.   Robustness checks

There is a concern that the results may be sensitive to the ordering imposed on the SVAR to orthgonalize the shocks. Thus, we apply Pesaran and Shin (1998) to see if our results are sensitive to different orderings. Pesaran and Shin (1998) developed the generalized impulse response analysis which negates the relevance of the ordering of the variables to the responses. Their approach does not require orthgonalization of shocks and is invariant to the ordering of the variables in the VAR.
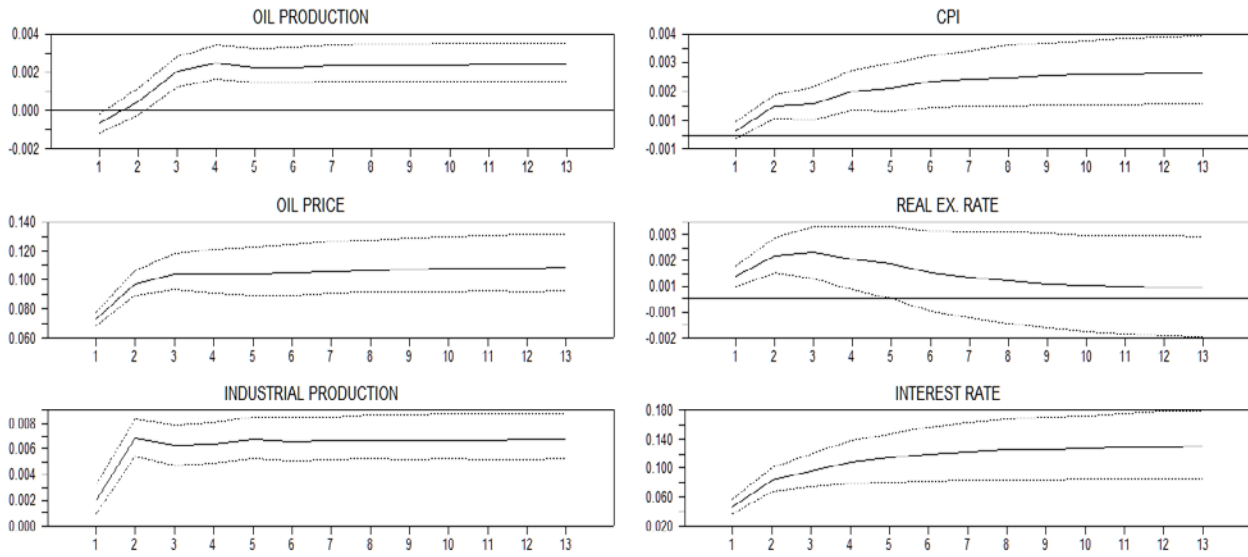
<Figure 8> shows the generalized impulse responses to an oil price shock for the subperiod 1992:4-2001:10. When it is compared with <Figure 6>, there seems to be not much difference at least in terms of signs of the responses of the variables to an oil price shock.

<Figure 8> Generalized impulse responses to an oil price shock (subperiod 1992:4-2001:10)

Finally, <Figure 9> shows the generalized impulse responses to an oil price shock for the period 2001:11-2014:5. There seems not much differences in the responses of the variables to an oil price shock between <Figure 9> and <Figure 7>.

<Figure 9> Generalized impulse responses to an oil price shock (subperiod 2001:11-2014:5)

4. Conclusion

The paper empirically analyzes the effect of positive oil price shocks on the Chinese macroeconomy, with a special interest in the response of China's interest rate to those shocks. Using the different econometric models - i) a time-varying parameter structural vector autoregression (TVP-SVAR) model with stochastic volatility and short-run identifying restrictions, ii) a structural VAR (SVAR) model with the short-run identifying restrictions and iii) an VAR model with ordering-free generalized impulse response VAR (GIR-VAR) – we find that the China's interest rate response to the oil price shock is not only time-varying but also shows quite different signs of responses.

Specifically, in the earlier sample subperiod (1992:4-2001:10), China's interest rate shows a negative response to the oil price shock, implying that the PBOC was working in a period of high aspirations for stronger economic growth. However in the second subperiod (2001:11-2014:5), the interest rate shows a positive response to the oil price shock. Given the

negative response of the world oil production to a positive oil price shock in the first subperiod, the oil price shock can be identified as a negative supply shock or a precautionary demand shock. Therefore, the negative response of China's interest rate to the positive oil price shock amounts to boosting the Chinese economy. The objectives of China's monetary policy are defined in the PBOC's Act (Chapter I General Provisions, Article 3) (promulgated by the order No. 46 of the President of the People's Republic of China on March 18, 1995) as "to maintain the stability of the value of the currency and thereby promote economic growth". According to Sun (2013), the GDP growth target is set each year by the central government of China to guarantee high-level job creation. One of the major tasks of the PBOC is to implement a monetary policy in line with this growth target. Therefore, the negative response of interest rate to an oil shock in the earlier subperiod may imply that PBOC is focusing more on the economic growth than inflation.

The positive response of China's interest rate to the oil price shock in the second subperiod, given that the oil price shock is identified to be a positive world oil demand shock, gives evidence that stabilization of domestic inflation is the main objectives of China's monetary authority. The pressure on domestic inflation became stronger over time due to continuing ascending in income from the increased export and industrial production as well as due to increases in oil prices. Finally, the variance decomposition results reveal that the oil price shock becomes an increasingly important source of volatility in China's interest rate in the later subperiod.

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Appendix: The TVP-VAR Method and Results

A1.   TVP-VAR method

The TVP-VAR model emerges from the basic structural VAR model defined as follows:

$$A\Delta z_t = F_1 \Delta z_{t-1} + ... + F_s \Delta y_{t-1} + u_t, t = s+1, ..., n, \tag{A1}$$

where Δz_t denotes a $k \times 1$ vector of observed variables, and $A, F_1, ..., F_s$ denote the $k \times k$ matrices

of coefficients. The disturbance vector u_t is a $k \times 1$ structural shock assumed to follow a normal

distribution of the form $\mathbf{u_t} \sim N(0, \Sigma)$ where

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}. \tag{A2}$$

To specify the simultaneous relations of the structural shock by recursive identification,

matrix *A* takes on a lower-triangular structure as follows:

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix}. \tag{A3}$$

The model in Equation (A1) is solved for the following reduced form specification:

$$\Delta z_t = B_1 \Delta z_{t-1} + ... + B_s \Delta z_{t-s} + A^{-1}\Sigma \varepsilon_t \quad \varepsilon_t \sim N(0, I_k), \tag{A4}$$

where $B_i = A^{-1}F_i$ for $i = 1, ..., s$. Stacking the elements in the rows of the $B_i s$ to form β

$(k^2 s \times 1 \text{ vector})$, and defining $X_t = I_k \otimes (\Delta z_{t-1}', ..., \Delta z_{t-s}')$, where $\otimes$ denotes the Kronecker

product, we can rewrite the model as follows:

$$\Delta z_t = X_t \beta + A^{-1}\Sigma \varepsilon_t \tag{5}$$

By allowing the parameters in the equation to change over time, we can rewrite the model in the following specification:[4]

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \varepsilon_t \qquad t = s+1, ..., n ,$$ (A6)

where the coefficients β_t, and the parameters A_t and Σ_t are all time-varying. To model the process for these time-varying parameters, Primiceri (2005) assumes the parameters in Equation (6) follow random-walk processes. Let $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, ..., a_{k,k-1})'$ denote a stacked vector of the lower-triangular elements in A_t and $h_t = (h_{1t}, ..., h_{kt})'$ with $h_{jt} = \log \sigma_{jt}^2$ for $j = 1, ..., k$, $t = s+1, ..., n$. Thus,

$$
\begin{aligned}
\beta_{t+1} &= \beta_t + u_{\beta_t}, \\
a_{t+1} &= a_t + u_{a_t}, \\
h_{t+1} &= h_t + u_{h_t},
\end{aligned}
\qquad
\begin{pmatrix} \varepsilon_t \\ u_{\beta_t} \\ u_{a_t} \\ u_{h_t} \end{pmatrix}
\sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta_t} & 0 & 0 \\ 0 & 0 & \Sigma_{a_t} & 0 \\ 0 & 0 & 0 & \Sigma_{h_t} \end{pmatrix} \right)
$$ (A7)

for $t = s+1, ..., n$, where $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$ and $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$.

This methodology exploits the salient features of the VAR model with time-varying coefficients to estimate a six variable VAR model (world oil production, real oil price, China's industrial production, China's CPI, China's real exchange rate, and China's interest rate), focusing on the dynamics of the interest rate adjustments in relation with both the world oil production and the oil price. By allowing all parameters to vary over time, this paper examines the assumption of parameter constancy for the VAR's structural shocks based on the standard recursive identification procedure known as the Choleski decomposition. We achieve

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[4] See Nakajima (2011) and Pimiceri (2005) for further details on the TVP-VAR methodology.

identification by imposing a lower triangular representation on matrix A_t. However, it is worth noting that, as long as the world oil production is ordered first and the oil price ordered second, which are standard assumptions as in Kilian (2009), changes of ordering between China's variables do not the affect identifying unique oil production and the oil price shocks.

A2.   TVP-VAR results

Table 1 reports the posterior estimates computed using the MCMC algorithm based on keeping 10,000 draws after 1,000 burn-ins.[5] We perform diagnostic tests for convergence and efficiency. The 95-percent credibility intervals include the estimates of the posterior means and the convergence diagnostic (CD) statistics developed by Geweke (1992). We cannot reject the null hypothesis of convergence to the posterior distribution at the conventional level of significance (see Table A1). In addition, we also observe low inefficiency factors, confirming the efficiency (see Figure A1) of the MCMC algorithm in replicating the posterior draws. These results indicate that all three sets of parameters $(\Sigma_{\beta_t}, \Sigma_{a_t}, \Sigma_{h_t})$, as described in Equation (A7), do change over time.

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[5] The MCMC method assesses the joint posterior distributions of the parameters of interest based on certain prior probability densities that are set in advance. This paper implements the code of Nakajima (2011) by assuming the following priors: $\Sigma_\beta \sim IW(25, 0.01I)$, $(\Sigma_a)_i^{-2} \sim G(4, 0.02)$, $(\Sigma_h)_i^{-2} \sim G(4, 0.02)$, where $(\Sigma_a)_i^{-2}$ and $(\Sigma_h)_i^{-2}$ are the ith diagonal of elements of Σ_a and Σ_h, respectively. IW and G denote the inverse Wishart and the Gamma distributions, respectively. We use flat priors to set initial values of time-varying parameters such that: $\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0} = 0$ and $\Sigma_{\beta_0} = \Sigma_{a_0} = \Sigma_{h_0} = I$.
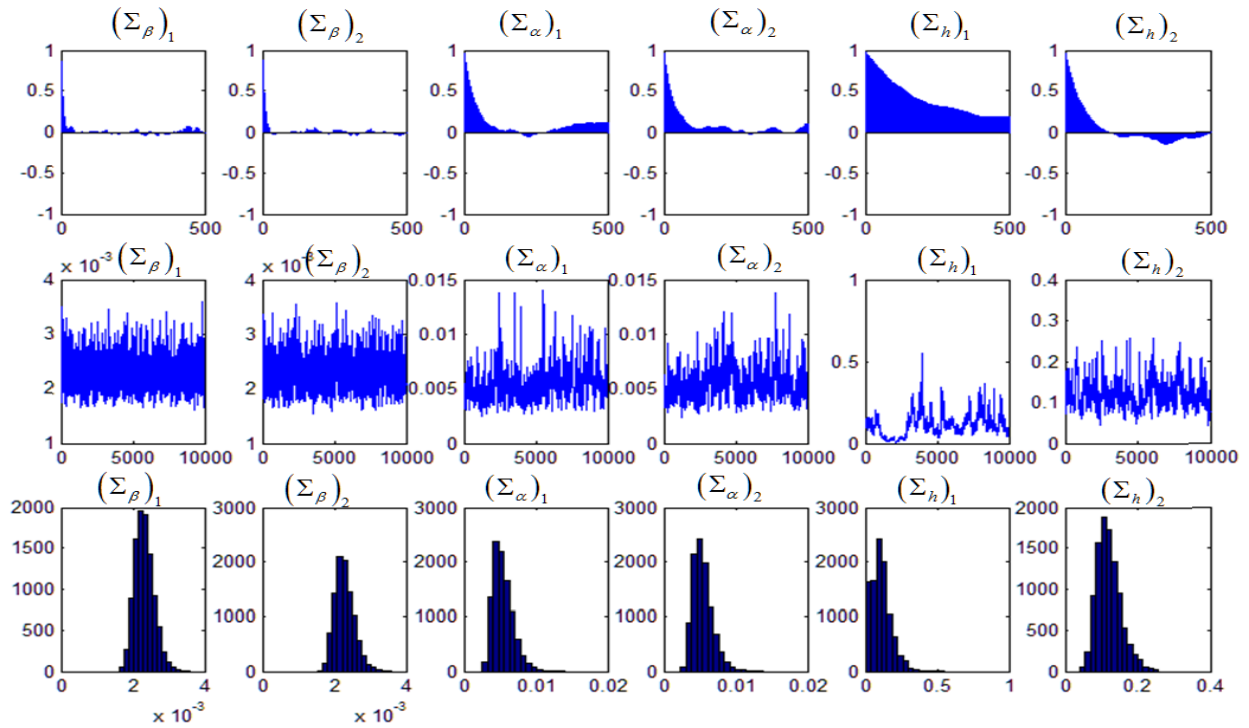
Table A1:   **Posterior estimates results**

Parameters	Mean	Std Dev.	95% Intervals	Geweke CD	Inefficiency
$(\Sigma_\beta)_1$	0.0023	0.0003	[0.0019, 0.0029]	0.047	16.85
$(\Sigma_\beta)_2$	0.0023	0.0003	[0.0018, 0.0029]	0.170	16.45
$(\Sigma_a)_1$	0.0054	0.0015	[0.0034, 0.0089]	0.004	72.69
$(\Sigma_a)_2$	0.0055	0.0014	[0.0034, 0.0088]	0.023	75.15
$(\Sigma_h)_1$	0.1131	0.0690	[0.0137, 0.2746]	0.444	228.31
$(\Sigma_h)_2$	0.1204	0.0331	[0.0686, 0.1999]	0.442	83.12

Note: The estimates of Σ_β and Σ_a are multiplied by 100.

Figure A1.   **Estimates of the moments and posterior distributions of the model**

Figure A2:   Posterior estimates for the stochastic volatility of the structural shock