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Oil supply news shock and Chinese economy

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ABSTRACT

This paper studies the effects of the oil supply news shock on the Chinese economy using a novel approach as newly proposed in Känzig (2021). Specifically, we use the changes of West Texas Intermediate oil futures prices around OPEC meeting announcements as a high-frequency instrument in a structural VAR model to identify the oil supply news shock. Our results suggest that the Chinese domestic economy is not affected significantly by the shock in terms of industrial production and CPI, two important macroeconomic indicators. However, due to the global features of the international trade, China's exchange rate and trade balance respond to the shock.

1. Introduction

China is the world's most populous country with a fast-growing economy that has led it to be the largest energy consumer in the world. The second-largest fuel source is petroleum and other liquids, accounting for about 20% of the country's total energy consumption. Although China is the fifth-largest petroleum and other liquids producer in the world, most of the country's production comes from legacy fields that require expensive enhanced oil recovery techniques to sustain production. As China's oil demand continues to outstrip domestic production and the country continues building its strategic petroleum reserves, oil imports have greatly increased during the past decade. China has been the world's top crude oil importer, surpassing the United States in 2017.

The Organization of the Petroleum Exporting Countries (OPEC) has been the largest crude oil exporter to China. Saudi Arabia alone accounts for 15.9% of China's crude oil imports in 2020. OPEC is a cartel consisting of thirteen of the world's major oil-exporting nations that aims to regulate the supply of the oil in order to set the price in the world market.[1] China's imported crude oil purchases were highly impacted by the price-setting action initiated by OPEC.

It is always intriguing to investigate how the Chinese macroeconomy is affected by the oil price in the international oil market. However, this is a particularly challenging task given the endogenous feature of the oil price, which responds to global economic developments. So, recovering and studying the effects of the unobserved exogenous oil price shock has become an important task for researchers. Recent literature focuses on the structural vector autoregression (VAR) models to isolate the effect of the exogenous oil

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[1] Current members that belong to OPEC include Iran, Iraq, Kuwait, Saudi Arabia, Venezuela (the five founders), Algeria, Angola, the Republic of Congo, Equatorial Guinea, Gabon, Libya, Nigeria, and the United Arab Emirates.

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price shock using different identification methods, such as the zero restriction approach in Kilian (2009), the sign restrictions approach in Kilian and Murphy (2012), Lippi and Nobili (2012), Baumeister and Peersman (2013), Baumeister and Hamilton (2019), and the narrative information approach in Antolín-Díaz and Rubio-Ramírez (2018), Caldara, Cavallo, and Iacoviello (2019) and Zhou (2020).

Oil prices are forward-looking, not only current demand or supply matters but also news or expectations about the future. Recently, Kilian and Murphy (2014) and Juvenal and Petrella (2015) have tried to include global oil inventories in the VAR models to account for future expectations. However, this approach cannot disentangle the oil demand news from the oil supply news. The oil supply news is of particular interest to policymakers due to its stagflation effects.

Exploiting the institutional features of OPEC and information contained in high-frequency data, Känzig (2021) proposes a novel approach to identify the oil supply shock. This approach combines the traditional oil market VAR approach with a high-frequency surprise series as an instrument for identification. OPEC accounts for about 44% of world oil production and thus, its announcements have a significant impact on oil prices. Therefore, changes in oil futures prices around OPEC meeting announcements are an appropriate instrument to identify the oil supply news shock.

In this paper, we use the method proposed by Känzig (2021) to study how the oil supply news shock may affect the Chinese economy. This question is of particular importance given that China is the largest oil importer and has the second-largest economy in the world. We draw two important conclusions from our study. First, our results suggest that the Chinese domestic economy is not significantly affected by the oil supply news shock based on the impulse response functions of industrial production and consumer price index (CPI), two important macroeconomic indicators. We believe this could be mainly due to China's energy mix which depends primarily on coal. Another factor could be the Chinese government's strategic initiative to diversify the oil import sources in recent years. Second, as the international trade plays a vital role in the Chinese economy, we further study the effects of the oil supply news shock on China's international trade. We observe a significant and persistent increase in China's imports. This could be explained by the Chinese yuan's appreciation relative to a broad range of foreign currencies after the shock, but there is no significant change or just a small drop in the exports after the shock. The increase in imports and no change or a small drop in exports together will lead to a decrease in China's trade balance. Our results are robust to excluding the COVID-19 period, the period with the oil price floor in China, and to alternative VAR specifications.

Our paper is closely related to the literature on the macroeconomic effects of oil price shocks. For example, Baumeister and Peersman (2013), Bodenstein, Guerrier, and Killian (2012), Känzig (2021), Kilian and Murphy (2014), and Lippi and Nobili (2012) use a structural VAR approach to examine the effects of oil supply and demand shocks on U.S. macroeconomic aggregates and oil-market price elasticities; Güntner and Linsbauer (2018) investigates how the oil supply and demand shocks affect the U.S. consumer sentiment (ICS); Peersman and Van Robays (2012) compare the economic consequences of several types of oil shocks across a set of industrialized countries; and Herwartz and Plodt (2016) analyze the dynamics in the global crude oil market. Halmilton (2011) provides an excellent review of some of the literature on the macroeconomic effects of oil price shocks with a particular focus on possible nonlinearities in the relationships.

The previous studies find that the responses of macroeconomic aggregates differ across different oil price shocks and different countries. Different from the previous literature that studies the oil price surprise shocks either from the demand side or from the supply side, Känzig (2021) studies the oil supply news shock, which is an expectational shock about future oil supply. Unlike Känzig (2021), who focuses on the U.S. economy, we examine the effects of the oil supply news shock on the Chinese economy. To the best of our knowledge, this is the first attempt in the literature.

The paper proceeds as follows. In Section 2, we discuss the econometric methodology, including the VAR model with proxy (instrument), the construction of the high-frequency instrument, specification of VARs, and data. Section 3 presents the results including the effects of oil supply news on the international oil market and the Chinese macroeconomy, as well as robustness checks. Section 4 concludes.

2. Methodology

To study the effect of the oil supply news shock on the Chinese economy, we use a small-scale proxy Vector Autoregressive (VAR) model as in Gertler and Karadi (2015) and Känzig (2021), identified using a high-frequency instrument. In the next two subsections, we describe this approach and the proxy we use. We also discuss the data, the way we select the number of lags in the VAR model, and how we conduct statistical inference in the last subsection.

2.1. Proxy VAR

Let Y_t be an $n \times 1$ vector of endogenous observable time series variables. A VAR with p lags is given by:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + u_t, \quad (1)$$

where A_i for $i = 1, \ldots, p$ are $n \times n$ coefficient matrices, and u_t is a vector of n reduced-form VAR innovations with covariance matrix $Var(u_t) = \Sigma_u$. Eq. (1) can be rewritten with lag-operator notation in a compact representation as

$$A(L) Y_t = u_t, \quad (2)$$

where $A(L) = I_n - A_1 L - A_2 L^2 - \ldots - A_p L^p$. We assume that the lag order p is known and that the det $(A(z))$ has all roots outside the unit circle so that the data generating process is invertible. This equation characterizes all dynamics of the observable time series variables in the model.

As is standard in the structural VAR literature, we assume that n reduced form VAR innovations u_t are linear combinations of n structural shocks ε_t, so that

$$u_t = H\varepsilon_t = [H_1 \ \dots \ H_n]\begin{bmatrix}\varepsilon_{1t}\\ \vdots \\ \varepsilon_{nt}\end{bmatrix}, \tag{3}$$

where H_1 is the first column of H, ε_{1t} is the first structural shock, and so forth. The structural shocks are assumed to be uncorrelated at all leads and lags, and $Var(\varepsilon_t) = \Sigma_\varepsilon$ is diagonal.

A key object of interest in structural VAR analysis is the impulse response function with respect to a structural shock. From (2) and (3), we have

$$A(L)Y_t = H\varepsilon_{t.} \tag{4}$$

We are interested in disentangling the effect of the oil supply news shock on the economy. In other words, we want to study the effect of the oil supply news shock on the dynamics of the observable series Y_t. Without loss of generality, following Stock and Watson (2012)'s notation, we denote the oil supply news shock as the first shock in the VAR, ε_{1t}.The impulse response function of Y_t with respect to an oil supply news shock is then given by

$$\frac{\partial Y_t}{\partial \varepsilon_{1t}} = A(L)^{-1}H_1. \tag{5}$$

The parameters $A(L)^{-1}$ can be identified directly from Eq. (1), via ordinary least squares estimation. However, H_1 remains to be identified. We use the external instrument (or "proxy") to identify the structural impact factor. As in Stock and Watson (2012) and Mertens and Ravn (2013), identification with an external instrument works as follows. Suppose there is an external instrument, z_t, that fulfills the following assumptions:

$$E(z_t\varepsilon_{1t}) = \alpha \neq 0, \tag{6}$$

$$E\left(z_t\varepsilon_{jt}\right) = 0, \ \text{for}\ j = 2, \dots, n. \tag{7}$$

These two assumptions show that a valid instrument must be correlated with the structural oil supply news shock, which is the relevance requirement, but not with other structural shocks, which is the exogeneity condition.

Let $H_1 = (h_{1,1},h_{2,1},\dots,h_{n,1})'$, where $h_{j,1}$ denotes the response of u_{jt} to a unit shock in ε_{1t}. Under assumptions (6)–(7), H_1 is identified up to sign and scale:

$$\widetilde{h}_{j,1} \equiv h_{j,1}/h_{1,1} = E\left(z_t u_{jt}\right)/E(z_t u_{1t}), \ \text{for}\ j = 2, \dots, n, \ (8) \tag{8}$$

provided that $E(z_t u_{1t}) \neq 0$. Note that $\widetilde{h}_{j,1}$ can be thought as the population analog of an IV estimator of u_{jt} on u_{1t} using z_t as an instrument. That is to say, we first obtain estimates of the vectors of reduced-form residuals u_t from the ordinary least square regression of the reduced form VAR. Then we obtain an estimate of the ratio $\widetilde{h}_{j,1} \equiv h_{j,1}/h_{1,1}$ from the two-stage least squared regression of u_{jt} on u_{1t} using z_t as an instrument. Intuitively, the first stage isolates the variation in the reduced form residual u_{1t} that is only due to the oil supply news shock. It does so by regressing u_{1t} on z_t to form the fitted value $\widehat{u}_{1t}$. Given that the variation in $\widehat{u}_{1t}$ is only due to ε_{1t}, the second stage regression of u_{jt} on $\widehat{u}_{1t}$ yields a consistent estimate of $\frac{h_{j,1}}{h_{1,1}}$. Then the structural impact vector $H_1 = (h_{1,1}, h_{2,1}, \dots, h_{n,1})' = (h_{1,1}, \widetilde{h}_{2,1}h_{1,1}, \dots, \widetilde{h}_{n,1}h_{1,1})'$. The scale $h_{1,1}$ is set by a normalization subject to $\Sigma_u = H\Sigma_\varepsilon H'$, where $\Sigma_\varepsilon = diag\,(\sigma_{\varepsilon 1}{}^2\sigma, \dots, \sigma_{\varepsilon n}^2)$. We set $h_{1,1} = x$, which implies that a unit positive value of ε_{1t} has a positive effect of magnitude x on Y_{1t}, the first variable in the VAR model. Following Känzig (2021), we normalize the shock corresponding to a 10% increase in the oil price.

2.2. The proxy

To identify the oil supply news shock, we use high-frequency oil futures price changes around OPEC announcements as a proxy (i.e., the instrument) as in Känzig (2021). The high-frequency feature of the proxy series and the key role of OPEC in the world oil market help the proxy to be an appropriate instrument.[2]

This approach is similar to the one used in Gertler and Karadi (2015), which combines the external instrument approach to the identification of structural shocks with high-frequency event studies around monetary policy announcements as in Kuttner (2001), Gürkaynak, Sack, and Swanson (2005), Hamilton (2008), and Campbell, Evans, Fisher, and Justiniano (2012). Gertler and Karadi (2015) use changes in the three-month-ahead monthly federal funds futures within a 30-minute window around a monetary policy announcement as a valid instrument. The difference before and after a policy announcement represents the change in the expectations of financial market participants due to unanticipated monetary policy action.

[2] Please refer to Känzig (2021) for a more detailed discussion regarding identification. The oil supply surprise series can be downloaded directly from https://www.diegokaenzig.com/research.

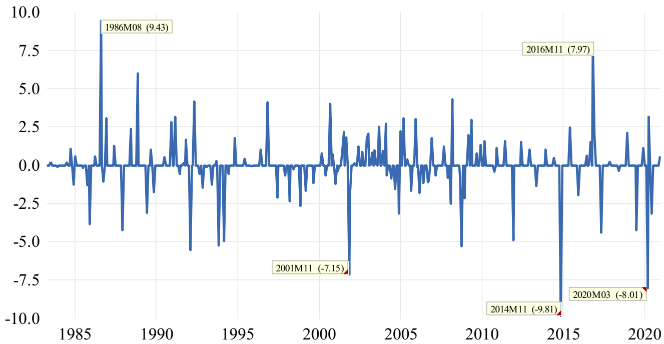

Fig. 1. The Oil Supply Surprise Series.

OPEC does not communicate as clearly as a central bank and the market participants usually need more time to process the implications of OPEC announcements. Moreover, there are no official OPEC announcement times. Given the OPEC announcements' unique features and lack of official announcement times, Känzig (2021) suggests using a daily window instead of a 30-minute window as used in the monetary policy literature.

In particular, the proxy, the oil supply surprise series, is constructed as the log difference of the oil futures price on the day of the OPEC announcement and the price on the last trading day before the announcement, which is:

$$Surprise^{h}_{t,d} = F^{h}_{t,d} - F^{h}_{t,d-1} \tag{9}$$

where d and t indicate the day and month of the announcement, respectively, and $F^{h}{}_{t,d}$ is the log settlement price of the h-month ahead oil prices contract in month t on day d. For the oil futures, we use the international benchmark, the New York Mercantile Exchange (NYMEX)'s West Texas Intermediate (WTI) crude oil futures, the world's most liquid oil contract.[3] WTI is also the go-to measure of the world oil price. To get a more composite measure of the oil supply surprise series, we use the first component based on the WTI crude oil futures contracts with maturities ranging from one month to one year. These contracts are available for a longer period and are more liquid and less subject to risk premia as argued in Baumeister and Kilian (2017). Oil futures prices across different maturities are highly correlated. Therefore, using different contracts with different maturities yields similar surprise series.

The daily surprise series is then aggregated to a monthly series. When there is only one OPEC announcement in a given month, the monthly surprise is equal to the daily one. When there are multiple announcements, the monthly surprise is the sum of the daily surprises in the given month. When there is no announcement, the monthly surprise takes the value of zero.

Fig. 1 plots the oil supply surprise series constructed as described above from 1983M4 when the oil futures data are first available to 2020M12. As we can see, the oil supply surprise series fluctuates irregularly around zero. Negative values indicate surprises that decrease oil futures prices, such as in 2001M11, 2014M11, and 2020M3. The 2001M11 negative surprise is caused by OPEC's conditional pledge to cut production only if other producers cut their production after a significant drop in the oil price after the September 11 attack. In November 2014, despite of low oil prices, OPEC announced to keep its current oil production level instead of a cut as previously expected. In March 2020, COVID-19 spreads globally and became a pandemic. Most of the countries around the world issued stay-at-home or lockdown orders, including closing non-essential businesses, banning travel and gatherings. These measures created a ripple effect that crippled the global economy and the oil market. Amid all the uncertainties, OPEC proposed on March 5, 2020, after its 178th meeting, that oil output be curbed by 1.5 million barrels a day, or 1.5% of world oil supplies, to deal with the effects of the spreading of coronavirus outbreak on demand. The proposed cuts are higher than most analysts expected but seem unlikely to change the gloomy sentiment in the oil market. After the announcement, prices for Brent crude, the international benchmark, fell by about 0.8% to $50.71 a barrel. Similarly, positive values indicate surprises that increase oil futures prices as in 1986M8 and 2016M11. Oil ministers of the OPEC countries reached a unanimous agreement on August 5, 1986 on Iran's proposal for a drastic cut in the production of crude oil in order to raise prices. The cuts amount to about 3.3 million barrels a day, bringing OPEC's daily production down to about 16.7 million barrels from 20 million per day. Oil prices surged at the news. On the New York Mercantile Exchange, contracts for September delivery of West Texas Intermediate, the benchmark of U.S. crude oil, closed at $13.29 a barrel, up by $1.74 over the previous day's closing prices. On November 30, 2016, OPEC announced to curtail oil production for the first time since 2008. OPEC ministers confirmed it had secured a cut in its oil production from 33.8 million barrels a day to 32.5 million in an effort to prop up prices. Oil prices have fallen by more than half since mid-2014 due to global oversupply and the booming U.S. shale production. WTI was up over 8% and trading at approximately $48.97 a barrel.

To justify the use of the supply surprise series as the instrument, we also perform an augmented Dickey-Fuller test. In all specifications, we strongly reject the null hypothesis that the surprise series has a unit root at a 1% significance level.

[3] Ideally, we would use Chinese oil futures. But the Chinese oil futures market is still dwarfed by the dollar-denominated international benchmarks, such as WTI crude oil futures. Renminbi oil futures traded on the Shanghai Stock Exchange was just launched in 2018. Due to its short time span, we cannot use it in this study.

Table 1
Summary Statistics of the Variables.

	Max	Min	Mean	Median	Std
Oil price (WTI)	133.93	12.01	58.83	55.62	26.87
World oil production	84611.27	64307.90	74796.86	74246.34	5010.01
World oil inventories	2734.39	2101.51	2444.25	2493.53	164.96
World industrial production	135.59	80.50	110.55	113.64	16.11
U.S. industrial production	104.17	84.20	96.17	97.26	4.99
U.S. CPI	261.56	164.70	215.12	217.38	27.95
China industrial production	122.91	87.05	110.93	110.02	4.88
China CPI	112.15	69.81	87.67	85.56	13.84
China exports	281.93	10.99	121.08	118.94	72.48
China imports	187.88	11.84	100.95	104.51	57.48
China nominal exchange rate	126.54	83.95	103.16	100.08	11.97
China/US exchange rate	8.28	6.05	7.23	6.89	0.82

Note: The overlapping sample period is from 1999M1 to 2020M12.

2.3. VAR specification

To estimate the proxy VAR model described above, we use six or seven variables in the VARs. The first four variables are a common set of variables used in the oil market VAR models as in Känzig (2021). They are the real oil price, world oil production, world oil inventories, world industrial production. Specifically, the real oil price is defined as the WTI spot price deflated by the U.S. consumer price index (CPI). World oil production data are obtained from U.S. Energy Information Administration (EIA).[4] World oil inventories are proxied by OECD oil inventories as in Killian and Murphy (2014) and Hamilton (2009). Given the lack of data on crude oil inventories for other countries, we use the data for total U.S. crude oil inventories provided by the EIA. These data are scaled by the ratio of OECD petroleum stocks over US petroleum stocks, also obtained from the EIA. Petroleum stocks as measured by the EIA include crude oil (including strategic reserves), unfinished oils, natural gas plant liquids and refined products. World industries production is Baumeister and Hamilton's (2019) index for OECD and six other major economies.[5] We first augment these four variables with two U. S. variables, i.e., U.S. industrial production and U.S. CPI, to identify the oil supply news shock and get the benchmark results. This setup also allows us to compare the effects between the U.S. and China. To examine the effects of the oil supply news shock on the Chinese economy, we then augment the VAR with each of the following Chinese economic indicator variables: China industrial production, CPI, values of exports, values of imports, the nominal broad exchange rate of Chinese yuan, and the nominal exchange rate of Chinese yuan against the U.S dollar.[6]

All these variables are monthly variables, which are more frequent than the quarterly or annual data and may be more responsive to the shocks. Following Gertler and Karadi (2015), Dias and Duarte (2019) and Känzig (2021), we select the number of lags, p, in the VAR model to be 12 given the monthly data frequency. All variables in the VAR are in natural logarithm and seasonally adjusted as in Känzig (2021).

Similar to Gertler and Karadi (2015) and Känzig (2021), we use a longer sample for the estimation, spanning the period from 1974M1 to 2020M12. A shorter sample from 1983M4 to 2020M12 is used for the identification of the oil supply news shock, i.e., oil supply expectation shock, given the availability of the oil futures data in the baseline model. For the VARs augmented with one of the Chinese economic indicator variables, the sample starts from 1999M1. China's monthly CPI was first available from 1993M1, industrial production from 1999M1, China exports and imports series from 1992M1, the nominal broad exchange rate of Chinese yuan from 1994M1 and the nominal exchange rate of Chinese yuan against the U.S dollar from 1981M1. To make the sample size more consistent across VARs, we use the sample starting from 1999M1. Table 1 provides the summary statistics of the variables in the VARs for the overlapping sample period from 1999M1 to 2020M12.

A very important component of the methodology is statistical inference. Brüggemann, Jentsch, and Trenkler (2016) and Jentsch and Lunsford (2016) show that in the presence of heteroskedasticity, it is incorrect to use a wild bootstrap method to estimate the distribution of impulse responses in the context of proxy VARs. Following this result, we then use a moving block bootstrap method to estimate the distribution of impulse responses as in Jentsch and Lunsford (2016) with 10,000 bootstrap replications.[7]

3. Results

3.1. World oil market

In the baseline results, we first show the effects of the oil supply news shock series identified through the proxy VAR approach using

4 Source: https://www.eia.gov/international/data/world.
5 Source: https://econweb.ucsd.edu/~jhamilto/.
6 Data source: https://fred.stlouisfed.org/.
7 See Jentsch and Lunsford (2016) for a more detailed description of the algorithm as well as for theoretical results concerning the consistency of the moving block bootstrap procedure.

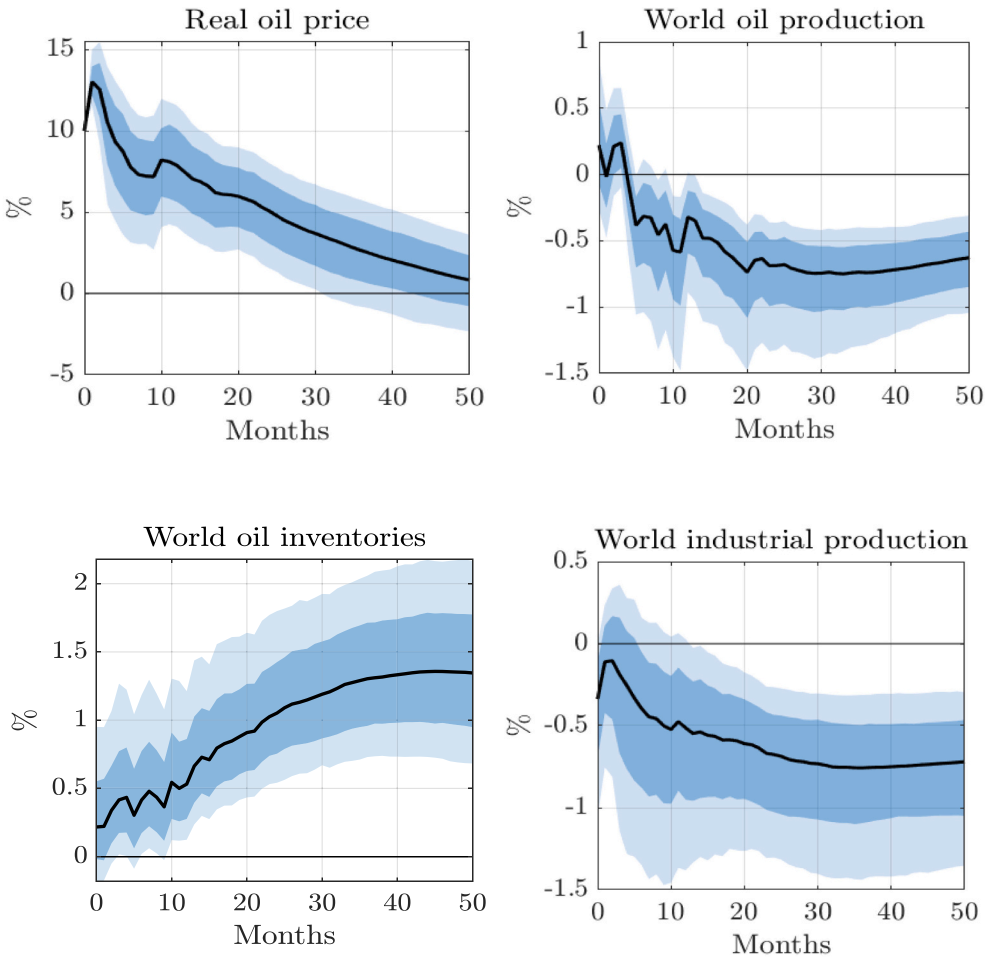

Fig. 2. Four Standard Oil Market Variables Impulse Response Functions to an Oil Supply News Shock.

the oil supply surprise series as the instrument on the real oil price, world oil production, world oil inventories, world industrial production. The oil supply news shock is normalized to increase the real oil price by 10%. Fig. 2 shows the impulse response functions with 68% confidence interval and 90% confidence interval. We observe that an oil surprise news shock that increases the real oil price by 10% initially has a persistent and lasting positive impact on the real oil price. According to the 68% confidence interval, the real oil price increases significantly within the first forty months. The largest impact happens in about two months after the shock, and the impact diminishes slowly and gradually. World oil production does not show a significant response upon impact, but in about five months it starts to decrease significantly and persistently. The behavior is consistent with the response to an oil supply news shock or an oil supply expectation shock that increases the oil price. Next, let us turn to the response of world oil inventories. Unlike the response of world oil production, given the expectation of lower oil supply, world oil inventories increase immediately after the shock and continue to increase over the next few years. This response is expected because when countries anticipate lower oil production, they will build up their inventories to deal with the anticipated change. Lastly, word industries production does not show a significant response immediately, but within a year, the oil supply news shock that increases the oil price begins to have a toll on the industrial production as oil is an important input in many industries. Increases in input prices slow down the industrial production level in the world. Overall, our impulse response results are consistent with the ones in Känzig (2021), in which the sample period ends in 2017. Adding three more years data, which include the COVID-19 period in 2020, does not change the basic responses of the world oil market to an oil supply news shock.

3.2. *Chinese economy*

In this subsection, we discuss the macroeconomic effect of the oil supply news shock on the Chinese economy. The top panel of Fig. 3 shows the impulse response functions of China industrial production and China CPI, two major macroeconomic indicators. As a comparison, in the bottom panel, we show the impulse functions of U.S. industrial production and U.S. CPI to an oil supply news shock. We notice the industrial production in China does not fall over the entire fifty-month period after the oil supply news shock, which

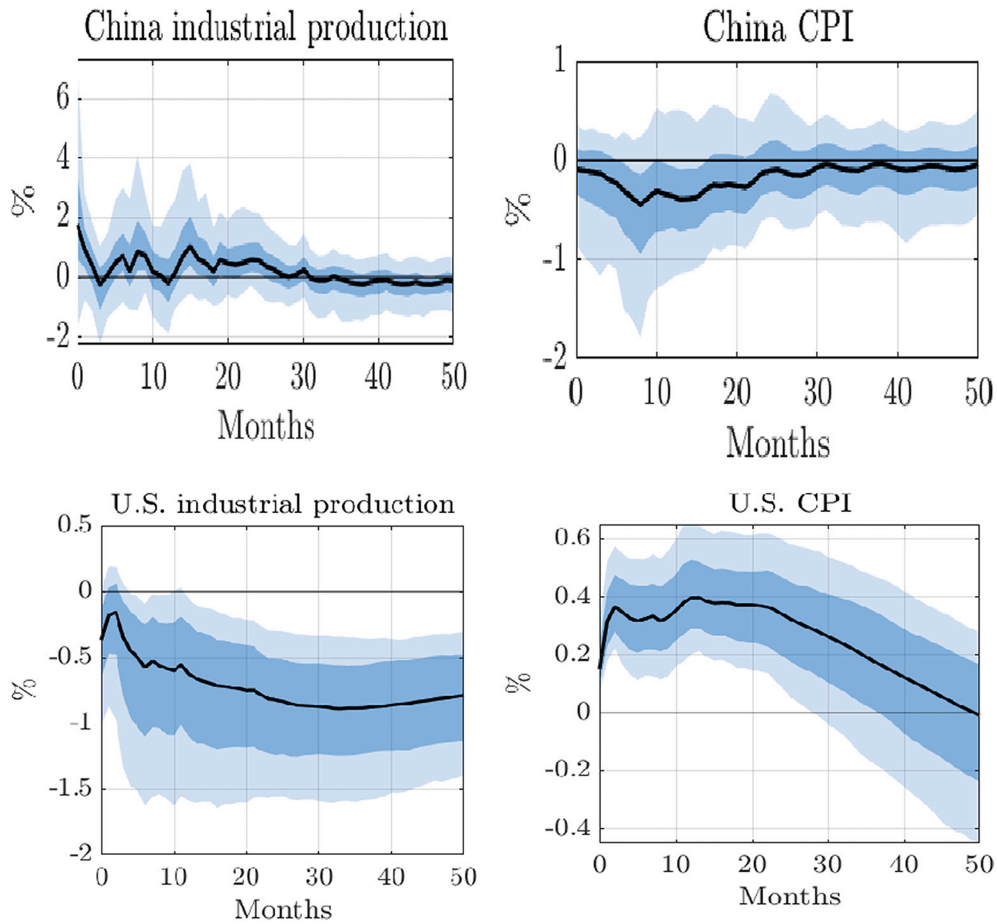

Fig. 3. Macroeconomic Indicators Impulse Response Functions to an Oil Supply News Shock.

suggests that China's real economy is quite robust and not sensitive to the negative oil supply news shock. This is quite different from the U.S. economy. The U.S. industrial production falls significantly by 0.5% to 1% most of the time after a negative oil supply news shock, similar to the world industrial production proxied by the OECD and six major economies. Turning to CPI, we also observe the sharp differences. China CPI shows no significant response upon impact after the oil supply news shock, decreases slightly afterwards and back to the original level in less than twenty months, while U.S. CPI increases significantly by about 0.2% upon impact, and the positive effect on U.S. CPI lasts for almost three years based on the 68% confidence interval.

Overall, these two macroeconomics indicators suggest that the Chinese domestic economy is not significantly affected by the oil supply news shock, which is identified through changes in oil futures prices around OPEC meeting announcements. This could be mainly due to China's energy mix which depends primarily on coal, whose share has been declining over the years but still remains above 60% recently, while oil accounts for only about 20–25% of the overall energy consumption. Another factor could be the Chinese government's strategic initiative to diversify the oil import sources and the declining share of Chinese crude oil imports from OPEC countries in recent years. In 1993, China became a net importer of oil. China surpassed the United States in annual gross crude oil imports for the first time in 2017, importing 8.4 million barrels per day compared with 7.9 million for the United States. China has become the world's largest net importer (imports minus exports) of total petroleum and other liquid fuels since 2013. However, the share of Chinese crude oil imports from OPEC countries has been declining over the years, from a peak of 67% in 2012 to about 56% in 2017. The share further decreased to 55% in 2019, the smallest share since at least 2005. Meanwhile, China imports from other non-OPEC countries have been increasing. These countries include Russia, Brazil, the United Kingdom, Malaysia, the United States and Norway. Russia has become the China's largest source of foreign crude oil since 2016, totaling 1.2 million barrels per day in 2017 from 9% to 14%, and Saudi Arabia only counts for 1 million barrels per day. Russia remained the largest non-OPEC source of China's crude oil imports in 2019, averaging 1.6 million barrels per day, or 15% of total crude oil imports. In 2020, forty-nine countries supplied crude oil to China. More than half of them are non-OPEC countries. The purpose of the Chinese government's initiative to diversify

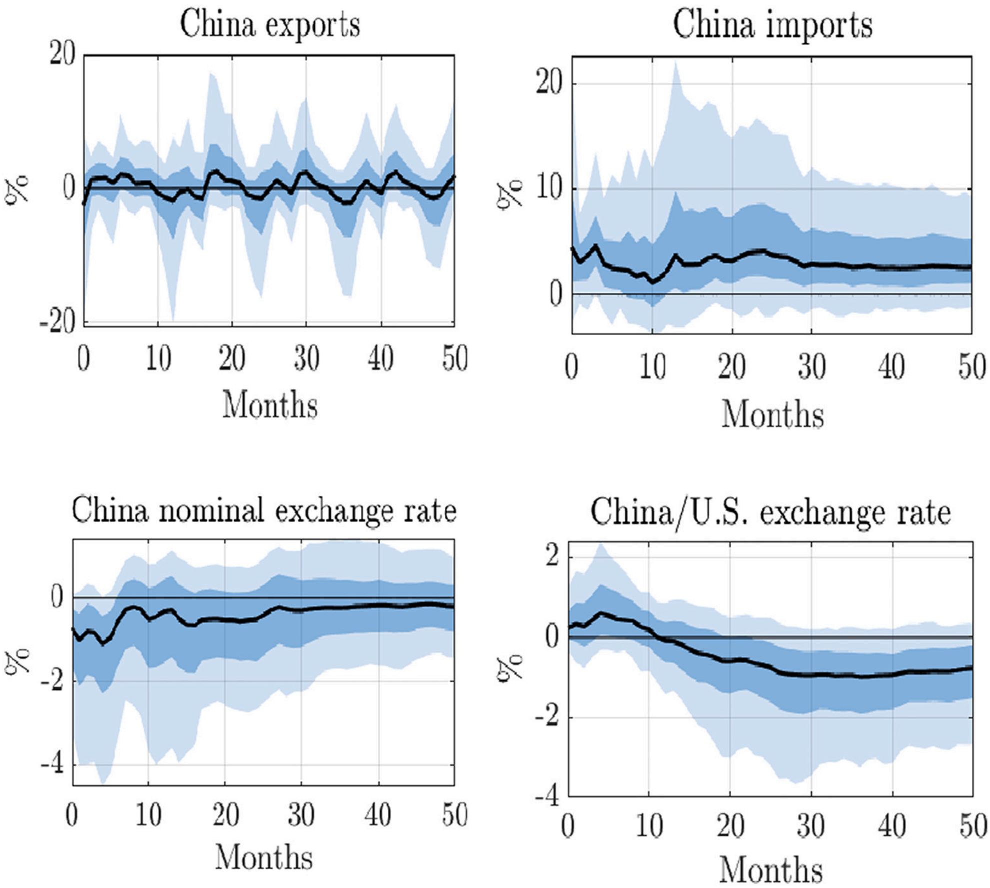

Fig. 4. International Trade Variables Impulse Response Functions to an Oil Supply News Shock.

crude oil import sources is to weaken China's energy and economic dependence on OPEC.[8]

Given the vital role of international trade in the Chinese economy, we next study the effects of the oil supply news shock on China's imports, exports, the broad nominal exchange rate, and the bilateral Chinese yuan/ U.S. dollar nominal exchange rate.[9] The impulse response functions are shown in Fig. 4. We notice that there is no significant change in China's exports after the shock. However, China's imports increase significantly by about 4% upon the impact, and the increase lasts persistently over the next fifty months according to the 68% confidence interval. To better understand the reason behind the change, we dig further into the exchange rates. We notice a significant decrease in the Chinese yuan's broad nominal exchange right after the shock, which indicates the Chinese yuan's appreciation against a broad range of foreign currencies. The strong purchasing power of the Chinese yuan allows China to buy more from other countries, which increases the imports. As the U.S. is China's largest exporting country, we examine in particular the bilateral exchange rate of the Chinese yuan/U.S. dollar. We observe a significant and persistent drop in the exchange rate after the shock, which suggests a depreciation of the U.S. dollar against the Chinese yuan. Känzig (2021) has a similar finding that there is a significant and persistent depreciation of the U.S. dollar after the shock. However, the weaker dollar does not decrease China's exports according to the impulse response function shown in Fig. 4. Overall, our findings suggest that an oil supply news shock causes an appreciation of the Chinese yuan, which increases China's imports but does not affect China's exports. As a result, there is a negative impact on China's trade balance. Our results are robust and almost identical when using the real exchange rates.

3.3. *Robustness checks*

In this subsection, we perform several robustness checks. We first check if the results on the Chinese economy are affected by the COVID-19 pandemic by dropping the data in 2020. The results are shown in Fig. 5. Next, we consider the effect of the Chinese

[8] The Chinese government sets retail gasoline and diesel prices, adjusting those prices every ten working days in line with fluctuations in global oil prices. But such delay should not affect our monthly impulse response functions.

[9] The broad nominal exchange rate is an average of the bilateral exchange rates between China and each of its trading partners, weighted by the respective trade shares of each partner.

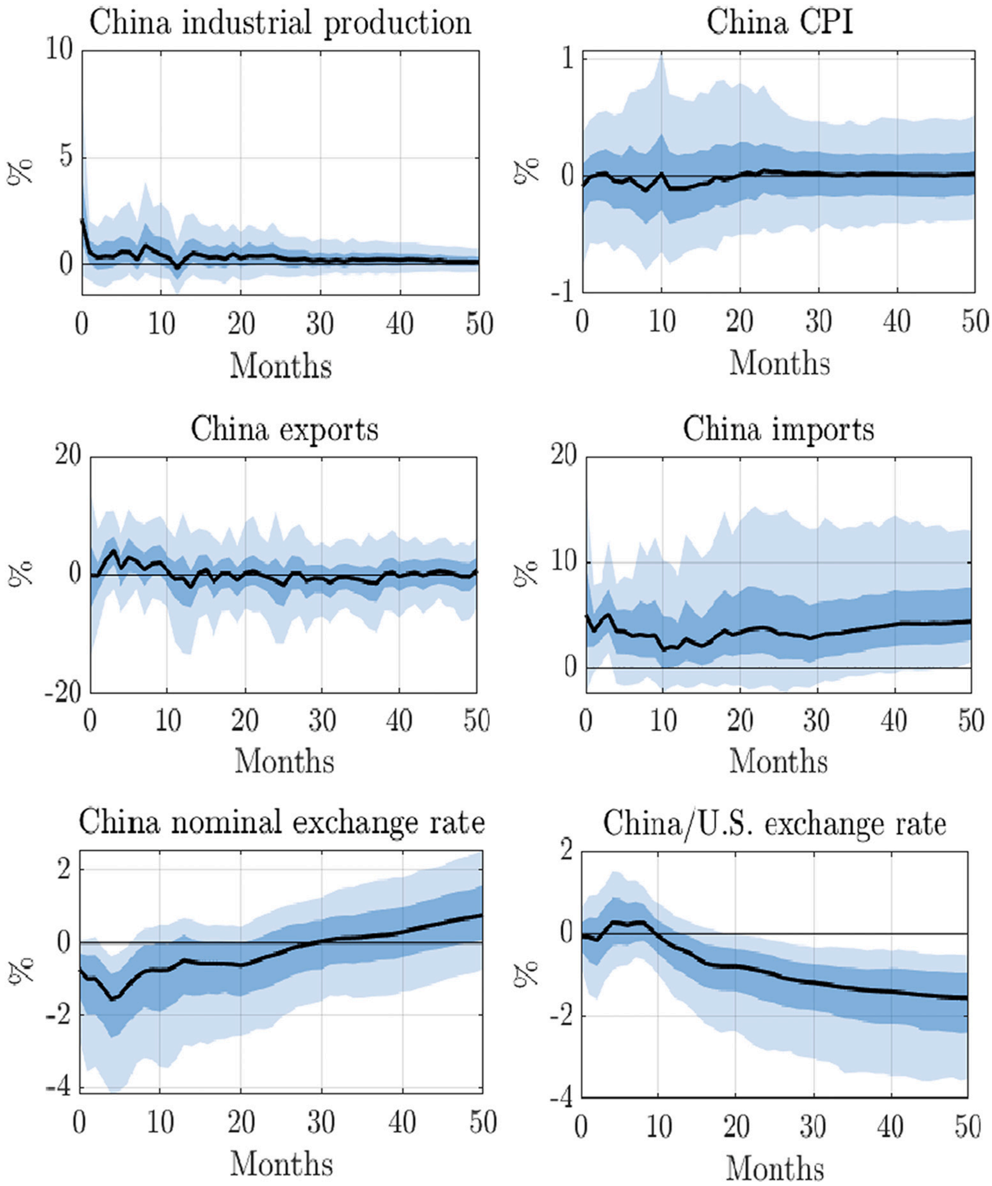

Fig. 5. Impulse Response Functions to an Oil Supply News Shock Excluding the COVID Period.

government's price control on retail fuel prices. China sets a $40 price floor for retail fuel prices on Jan 13, 2016. When world crude prices fall below $40 per barrel, retail gasoline and diesel prices in China are not adjusted downward. There are eight months (non-consecutive) when the world oil price fell below $40 after the price floor is set during the sample period. To make sure our results are unaffected by the price floor, we show the results with samples ending in 2015M12 before the implementation of the price floor in Fig. 6. There is also a $130 price ceiling. But during our whole sample period, there are only two months (2008M6 and 2008M7) when the world oil price was slightly higher than $130. We believe the effect of the price ceiling on our results is negligible. Finally, we explore alternative VAR specifications. Given our research interest is about the effects on the Chinese economy after an oil supply news shock, we specify the VAR variables as the four world oil market variables along with China industrial production and China CPI alternatively. We then augment the VAR with the international trade variables one at a time. The impulse response functions from this alternative specification are shown in Fig. 7. Figs. 5 to 7 show that our results are relatively robust to the alternative samples and VAR specifications. Both China's industrial production and CPI remain unaffected by the oil supply news shock, but China's imports increase significantly and persistently due to the appreciation of the Chinese yuan. China's exports either show no significant changes after the shock (Figs. 5 and 6) or some small drops (Fig. 7) due to the depreciation of the U.S. dollar against the Chinese yuan, which results in decreases in the trade balance.

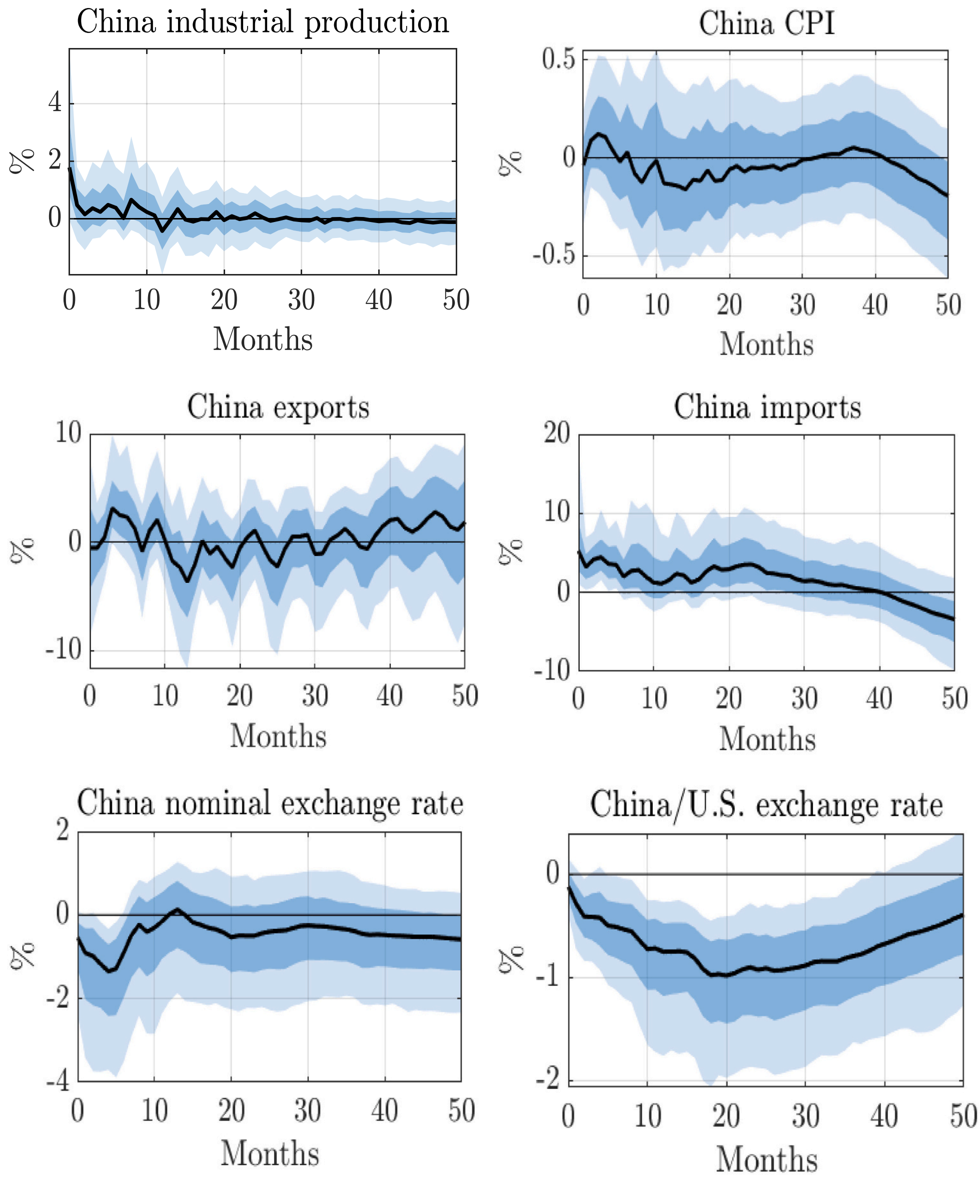

Fig. 6. Impulse Response Functions to an Oil Supply News Shock Excluding the Price Floor Period.

4. Conclusion

In this paper, we study the effects of the oil supply news shock on the Chinese economy using a structural VAR model. Following Känzig (2021), we use the changes of WTI oil futures prices around OPEC meeting announcements as a high-frequency instrument. We find that the shock does not have a significant effect on China's industrial production and CPI, two important macroeconomic indicators. The results are in contrast to the findings on the U.S. economy in Känzig (2021). The oil supply news shock leads to a significant increase in U.S. CPI and a decrease in U.S. industrial production. This could be mainly due to China's energy mix which depends primarily on coal. Another factor could be the Chinese government's strategic initiative to diversify the oil import sources and the declining share of Chinese crude oil imports from OPEC countries. Meanwhile, we find that the shock has led to a significant and persistent increase in China's imports, but there is no significant effect on the exports. Our results are robust to excluding the COVID-19 period or the period with the oil price floor in China from our sample, and to alternative VAR specifications. We hope that this study can shed light on the role of oil supply news shock and OPEC on China's economy and offer useful insights for policymakers.

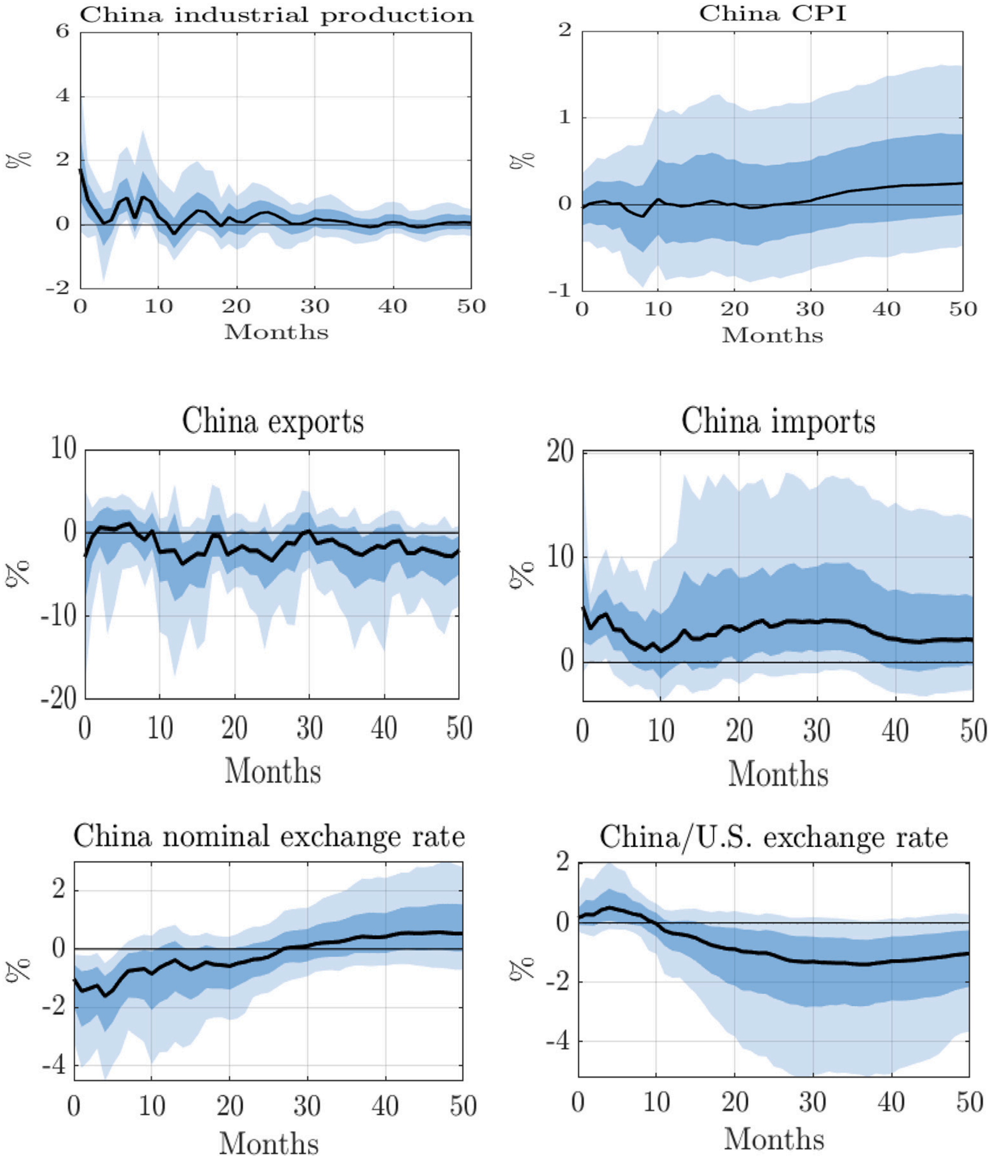

Fig. 7. China VAR Macroeconomic Indicators Impulse Response Functions to an Oil Supply News Shock.

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