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RESEARCH ARTICLE

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The influence from a demand perspective with real economic activity: China versus the United States in world oil markets

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Abstract

In this paper, we provide direct evidence on an increasingly critical role of China in the world oil markets. Specifically, our empirical results confirm that the influence of China's oil demand on the oil price of the world has increased over time and surpassed that of the United States. The contribution of demand perspective from China are formally quantified by three key variables of world oil market, which are world oil production, real economic activity and the real price of crude oil. The impact of oil demand from China is used to compared with those from other oil markets, including shocks from the United States. We also construct suitable proxies that reflect real economic activity from these economies, and identify them via a structural vector autoregressive model to disentangle the influence of oil demand from China, the United States and the rest of the world. Our results confirm the finding of recent research, which is the increasing demand for oil from developing countries has become a key driver of the price of oil.

KEYWORDS

China, oil demand, oil markets, real economic activity, US

1 | INTRODUCTION

Multiple scholars have recently claimed that the boom of the oil price in the mid-2000s was predominately driven by growth in emerging markets, including China.[1–3] Empirical evidence in support of this view has been provided by Aastveit et al.[4] Using a factor analysis with 33 countries, they found that approximately 40% of the 1–2 year variation in the oil price was explained by demand shocks from emerging markets (including China), while demand shocks from developed countries (including the United States) explained approximately 15%. Despite this result, direct evidence on the role of China specifically has not been clear. For instance, Liu et al. provided evidence that China-specific demand accounted for 51% of the variation between 2000 and 2014, however, others suggested that China's oil demand had little or zero impact on the global oil price.[5–9]

A key reason for this discrepancy is the lack of consistent real economic activity measures in China and the rest of the world (ROW). Such a metric is important because aggregate demand shocks are key drivers of the real prices of oil.[2] (Following Kilian real economic activity is not itself a measure of aggregate demand, however, the structural vector autoregreesive model (VAR) model introduced in Section 3 allows us to identify demand shifts associated with unexpected fluctuations in the global demand for all industrial commodities. Such shocks are referred as aggregate demand shocks.[2]) We have overcomed this problem by constructing consistent monthly indicators of real economic activity in China, the United States and the ROW. In the spirit of Baumeister and Hamilton,[10] this is done through the use of monthly industrial production in these economies.

Using an extended version of the structural VAR in Kilian, we find that the influence of China in world oil markets has increased over time as compared with that of the United States.[2] Particularly strong growth in the contributions has occurred since the turn of the century. Despite this fact, impulse response functions suggest that the price of oil is still sensitive to United States and ROW demand shocks. We find provided evidence that aggregate demand shocks from China have indeed been larger than those in the United States since 2003. However, despite this surge in demand, the shocks themselves are too small to cause the oil price boom in the 2003-2008. Instead, we provide evidence that the main contributor is specific oil demand shocks.

In the Section 5, we also utilize a new monthly indicator of global real economic activity based on world steel production provided by Ravazzolo and Vespignani[11] as an alternative measure. The rationale for this index as a proxy for real economic activity is that steel is an important input for many industries including construction, transportation, and manufacturing. Moreover, Kilian and Zhou showed that the index shared many of the same characteristics exhibited by the popular global real economic activity index of Kilian.[2,12] The primary advantage of the steel index over the one in Kilian, is that it's available on a country-specific level.[2] This is important for our research question because it allows for a clean decomposition of real economic activity within China, the United States and the rest of the world.

The remainder of the paper is organized as follow: First, Section 2 describes the method that we use to construct the index of country-specific real economic activity and presents the data that we use to model the oil market. Section 3 outlines the econometric methodology, including the model specification and estimation of the models. Identification strategy is also discussed in this section. Section 4 then presents our results and Section 5 reports the robustness check. Finally, Section 6 concludes the paper.

2 | DATA

To quantify the impact of demand shocks from the United States and China on international oil prices, we follow Kilian and use monthly data on three variables of interest: world oil production, real economic activity, and the real price of crude oil.[2] Consistent with existing research, world oil production is measured in thousands of barrels per day which is stated in the United States Energy Information Administration Monthly Energy Review. The real price of crude oil is taken to be the arithmetic average of three spot prices provided by the IMF: Dated Brant, West Texas Intermediate, and the Dubai Fateh. We use average prices to capture the possible influence of China's demand as one of the main traders in Asia. To get real prices, the nominal series are deflated by the US consumer price index, which is available from the FRED database. We note that existing literature also considers two other alternative measures of oil prices: the US refiners' acquisition cost (RAC) for imported crude oil and the West Texas Intermediate (WTI) price of crude oil. To address this concern, we also consider the RAC and WTI prices as a robustness check.

With regard to indicators capturing global real economic activity, several measures are proposed and commonly used in the oil market literature. The two most popular indexes are the *real economic activity* index proposed by Kilian and the OECD + 6 *industrial production* index computed by OECD and extended by Baumeister and Hamilton.[2,10,12] These indicators are designed to reflect cyclical variation in global real economic activity, however, to address our research question, we require a country-specific real economic activity measures for the United States, China, and the ROW. Since no such measures are directly available, we construct an individual proxy for each of these economic regions. To that end, we utilize (seasonally adjusted) industrial production from the World Bank's *Global Economic Monitor* database. Since each countries industrial production is measured in constant US dollar prices (based in 2010), we derive the values of industrial production for the ROW by simply subtracting the production of United States and China from the values of world production. The corresponding real economic activity index is then provided by changes in these values.

This straightforward method allows us to obtain a consistent proxy for real economic activity across the United States, China, and the ROW. It also avoids common concerns regarding the quantification an accurate weight for an individual economy in aggregating/dis-aggregating the ROW index. Another important issue we wish to avoid relates to Chinese New Year, which has been shown to have an important effect on monthly economic activity in China.[13,14] Specifically, since the Chinese New Year mostly falls in February, values of China's industrial production reported for this month are significantly lower than those for the other months of the year. We consequently treat the values of the series in February as outliers and replace them by the simple average value of the series for January and March.

Figure 1 depicts the annualized growth rate of industrial production index for the United States, China, and the ROW, along with the historical movements of world oil production and the real price of crude oil. Due to the availability of the time-series data of China's IP, the period of data spans from 1992M1 to 2017M12. As we can see from the figure, the growth rate of China's IP is significantly higher than those of the US and the ROW, especially for the period before Global Financial Crisis (GFC) 2008. Although the Chinese economy did not run in a deep recession as the US and the ROW did, but since GFC its economic activity has gradually been lowered and converged to the world level by the end of 2017.

3 | MODEL AND IDENTIFICATION

In this paper, we use a multivariate framework as it allows us to control for reverse causality from macro aggregates to oil prices. The structural VAR approach also allows us to decompose variation in the price of oil into those driven by distinct demand and supply shock. Structural VAR models of the global oil market have become the standard tool for understanding the evolution of the real price of oil over the past decade. A recent survey can be found in Kilian and Zhou.[15]

To quantify the United States and China factor, the global oil market is described in a 5-variable VAR model. Consider a vector of endogenous variables, y_t that includes monthly data on following five variables: the percent change in global crude oil production, prod_t, a measure of real economic activity for the US, $\text{rea}_{t,\text{US}}$, China, $\text{rea}_{t,\text{China}}$, and the ROW $\text{rea}_{t,\text{ROW}}$, and the percent change in the real price of oil, rpo_t. The reduced form model of interest is as follow:

$$y_t = c + \sum_{i=1}^{p} B_i y_{t-i} + e_t, e_t \sim N(0, \Sigma) \tag{1}$$

where c is a 5×1 vector of intercepts, B_i are 5×5 matrices of autoregressive coefficients, e_t is a vector of serially and mutually uncorrelated residuals and Σ is a 5×5 covariance matrix.

We highlight that this model modification is adapted from the one used in Kilian.[2] The exception is that real economic activity has been decomposed into three subsets using the methodology discussed in the previous section. To allow for potentially long delays in the effects of structural shocks, we set $p = 12$. The model is estimated using standard Bayesian methods which we outline in Appendix A.

After estimating the reduced form VAR in Equation 2, the structural VAR model is identified with a recursive identification strategy as in Kilian.[2] Kilian justifies this on the grounds that: (1) oil production is approximately perfectly inelastic at a monthly frequency, and (2) real oil price shocks without affecting global economic activity within a month due to market frictions for example, contracts.[2] Of course, such a recursive ordering is not easily justified for real economic activity

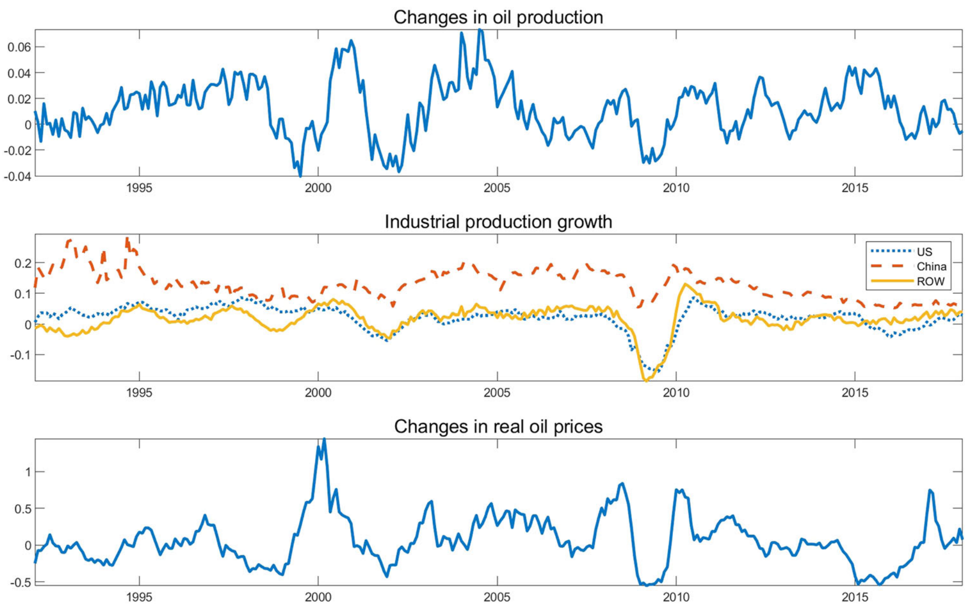


FIGURE 1 Historical evolution of the series

among China, the US and the ROW. For this reason, we provide a battery of robustness checks by computing the main results for all six possible orderings (There are $3! = 3 \times 2 \times 1$ ways of arranging the three measures of real economic activity.). Since the results are robust, we present the set of results associated with the ordering in Equation 1 in the main analysis (Section 4) and defer the rest to Section 5 where we report robustness checks.

4 | RESULTS

In the following, we first present the responses of oil price to demand shocks from the United States, China, and the ROW. Next, we compare the relative contributions of all shocks by examining variance decompositions for the real price of oil. Finally, we explore what drives the historical oil prices with specifically emphasizing the United States and China factors.

4.1 | Oil price responsing to demand shocks from the United States, China, and the ROW

The main objective of this paper is to quantify the United States and China factors in driving the price of crude oil. For this purpose, Figure 2 reported the posterior responses of the price to a positive demand shock from the United States, China, and the ROW. We normalize all the shocks by increasing 1% to compare the effects of these shocks. Consistent with a large number of studies, positive shocks to demand increase the real oil price significantly. Our estimated results further reveal that a shock to economic activity from the ROW has the strongest effect on the oil price, which immediately increases the price by about 2% after impact. Interestingly, we observe that a shock from China produces a relatively smaller impact on the oil price as compared with the same shock arriving from the United States. Indeed, after 1 year, the response of the oil price to the shock from China almost dies out, while the corresponding response to the shock from the United States turns to negative.

4.2 | Forecast error variance decompositions of the oil price

Figure 3 displays the variation of the 2-year-ahead forecast error variance in the real price of oil, which allows us to compare the relative contributions of the five structural shocks in the oil market. Overall, at all horizons, the oil specific demand shock is found to be more important than the other shocks in explaining the fluctuations in the oil price. This finding is consistent with recent empirical results found in Baumeister and Peersman and Aastveit et al.[3,4] This is, as we can see from the figure, approximately 40%–50% of the variation of the oil price is explained by the oil specific demand shock. The figure also confirms our results above. We find that after 6 months, demand shocks from the ROW account for about 15% of the fluctuations in oil price. With the same horizon, the contributions of demand disturbances that originate from the United States and China are about 10% and 5% for the variation of oil prices, respectively. Furthermore, according to the model, the contribution of the demand shocks from the United States is smaller than that of the demand shocks from the ROW in explaining the variation in the oil price in the short run forecast horizon. However, in the longer horizons, the shocks from the United States turn out to be larger as compared with the other demand shocks arriving from the ROW and China. These results suggest

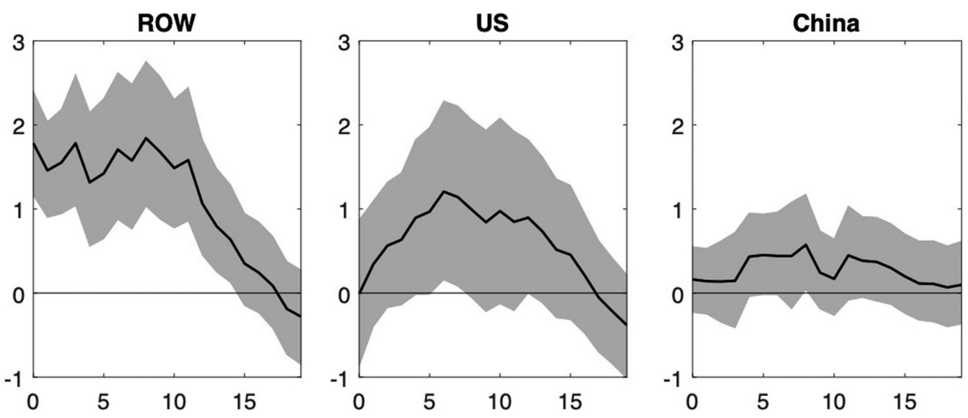


FIGURE 2 Posterior impulse responses of the real price of crude oil to 1% demand shocks from the United States, China, and the ROW. ROW, rest of the world.

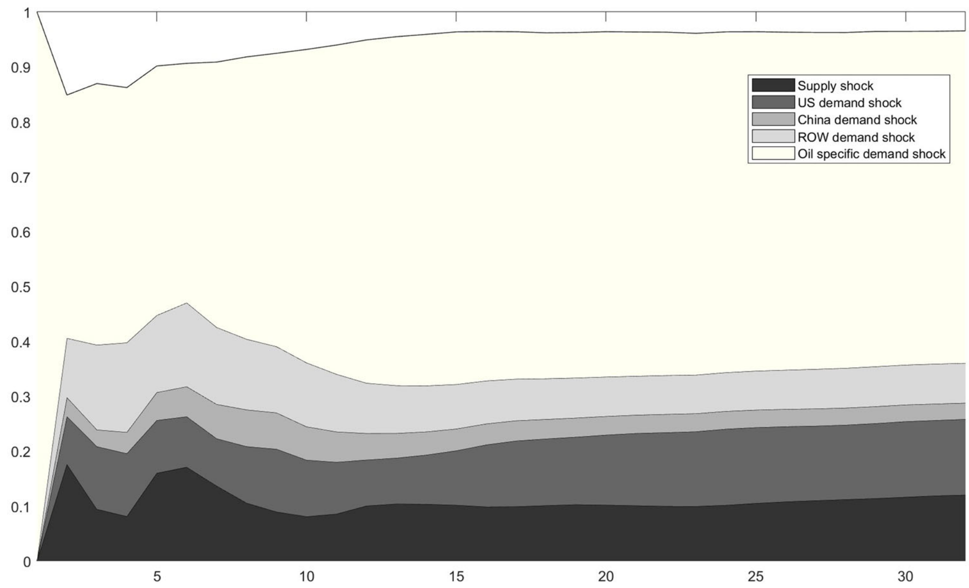


FIGURE 3 Forecast error variance decompositions for the real price of oil

that oil demand from the United States fundamentally plays a crucial role in the oil market. More interestingly, turning to the China factor, we observe that demand shocks from the country account for a smaller share of the variance decomposition of the oil price than the other structural shocks. Despite this fact, the contribution is pronounced and sizable on average. In this way, our findings are consistent with those of Liu et al. and Yu and Zhang, and confirm the popular perception that the role of China in the world oil market is important.[5,16]

4.3 | Historical counterfactual analysis of the oil price

So far we have focused on the responses of the oil price to demand shocks and how these shocks, on average, contribute to the fluctuations of the price. We now turn to investigate the main source driving the oil price in greater detail over the sample period. To this end, we calculate the historical decomposition of the oil price, which specially focuses on the shocks from the United States and China as our main interest. As highlighted in Kilian and a range of subsequent papers, supply shocks played a little role in explaining the historical movements of the price of oil.[2] In our sample period, we find that the oil supply shocks have a heterogeneous effect, which is reported upon request. Further investigation of the oil supply shock can be found in Gundersen, Herrera and Rangaraju, and Baumeister and Hamilton.[10,17,18] The historical counterfactuals of the real oil price to the four identified demand shocks are reported in Figure 4. The solid (blue) lines display the mean of the real price of oil and the dashed (red) lines display the oil price would have been if we exclude one of the structural shocks. The bars (shaded areas) show the difference between the solid lines and the dashed lines and thus a positive value indicates that the structural shock contributed to an increase in the real price of oil.

Before quantifying the influence of the United States and China factors in the oil market to address our focal research question, it is interesting to examine the demand factor in general. Not surprisingly, the results reveal that demand shocks from the ROW and oil-specific demand shocks have been the prominent drivers of the oil price. This confirms findings in Kilian and Aastveit et al.[2,4] Interestingly, our results indicate that these shocks have influenced the price in opposite directions, as can be seen from Figure 4c,d. In particular, before 2000, demand shocks from the ROW influenced the oil prices positively but the oil-specific demand shocks contributed to pushing the oil prices down. In contrast, since 2000 the demand for oil from the ROW has contributed negatively to the oil price while oil-specific demand has contributed to driving up the price. Especially, when we zoom in on the episode after the global financial crisis, the large slump in the real oil price was partly explained by the decline in the demand from the ROW. The decomposition also reveals that the real price of oil would have been extremely lower than the actual price if oil-specific demand was not strong. Indeed, the oil-specific demand shocks, which would

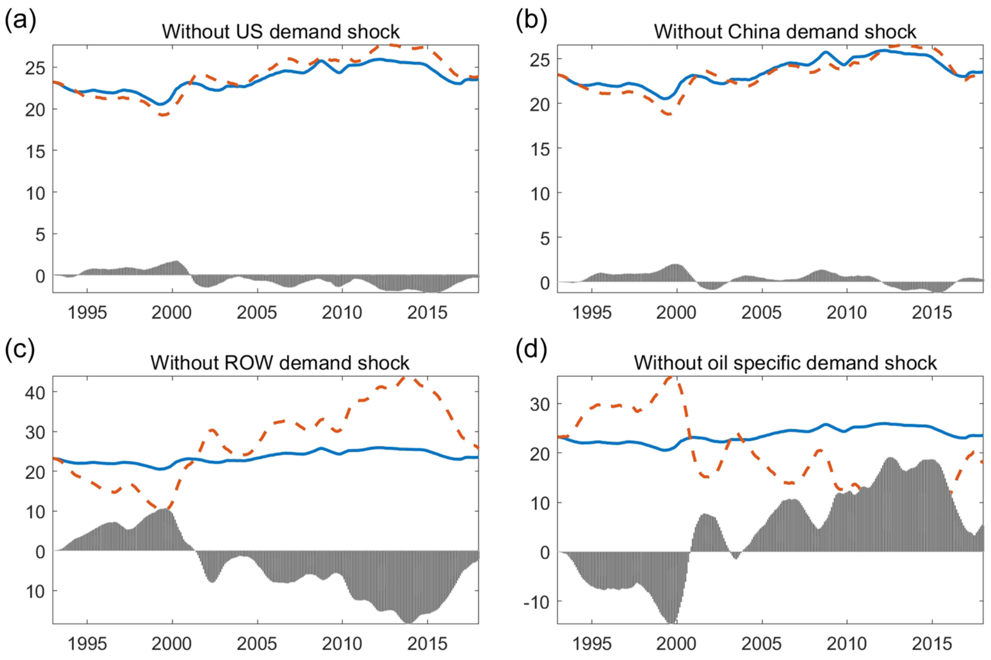


FIGURE 4 Historical counterfactuals of oil prices

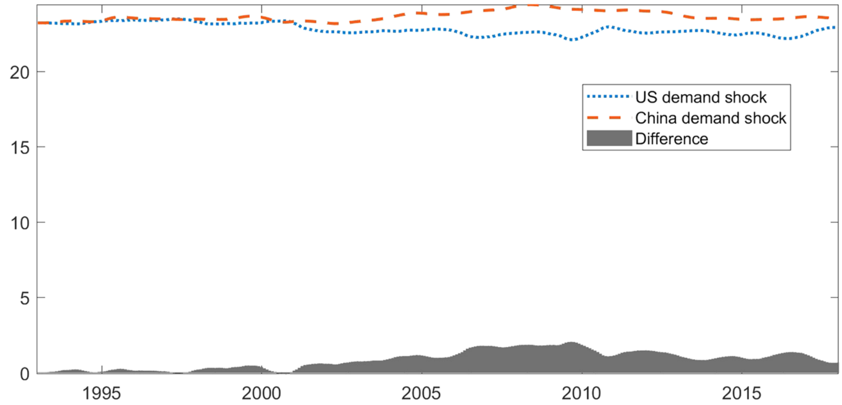
be associated with speculation in the oil market, induced upward pressure on oil prices, accounting for about half of the increase.

We now turn to the role of the United States and China factors. Figure 4a,b demonstrate the role of demand shocks from the two countries in the way that they have driven the fluctuations of the real price of oil. Surprisingly, these shocks have played a much smaller role in price fluctuations than the shocks from the ROW and oil-specific demand shocks. However, it reveals that the demand shocks from the United States share similar features with the shocks from the ROW while the impact of China's demand is different. This is, we find that the demand shocks from the United States have pushed the oil price down, especially in recent years. In other words, the oil price would have been slightly higher if demand shocks from the United States had not occurred.

With regard to the impact of the demand shocks from China, we find that it varies across episodes. To illustrate this point, we shift our focus on some important episodes that involve large swings in oil prices. The first important period in our sample is 1997–1999, the aftermath of the Asian Financial Crisis. We observe that during this time China's demand had a positive influence on the oil price. However, the impact of China's demand on the oil price played a little role in explaining the 2003–2008 oil price runup. This finding is somewhat different from the view speculating that the sharp spike in the real price of oil during this period was due to the increasing demand for oil in China. In our model, the oil specific demand shock, which involved speculative or precautionary motives, was the major determinant of the surge in the oil price in this episode. This is consistent with Hamilton and Juvenal and Petrella who found similar results for the 2004–2006 period but do not identify individually demand shocks from the United States and China.[1,19] The latest event in the oil market in our sample is the 2014–2015 oil price slump. We observe that the decline in the demand for oil from China, along with demand from the United States and the ROW, induced downward pressure on oil prices. The oil specific demand was the main driver to push the oil price up.

Figure 5 parses out the role of the United States and China demand shocks in determining the fluctuations in the mean-real price of oil. The bars (shaded areas) in the figure display the relationship between the historical contributions of United States demand shock and China demand shock in the fluctuation of the oil price over the sample period. The positive value suggests that the China factor quantitatively has a larger impact on the oil price than the US factor. This presentation provides us with a clear picture that China's demand for oil has gradually played a more important role than the US demand in explaining oil price fluctuations. This is a new finding in the literature.

FIGURE 5 China versus the United States in driving the oil price



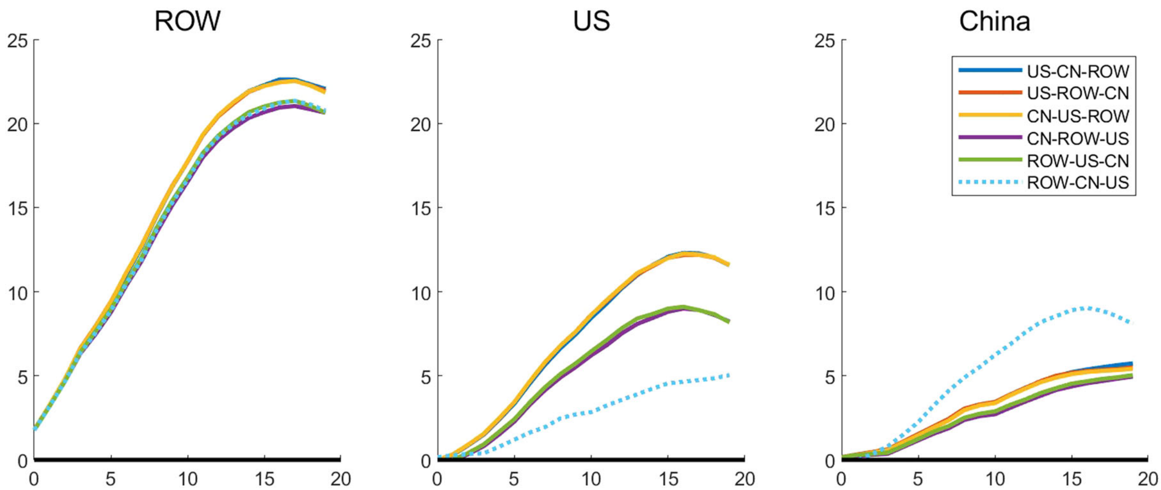


FIGURE 6 Median responses of the price of crude oil to demand shocks under six orderings of recursive identifications

5 | ROBUSTNESS

We began this paper by questioning whether an increasing demand for oil from China could be the major source of fluctuations in the price of oil. Our results confirm the common perception that China factors have gradually played a larger role in the oil market. However, the oil price appears to be more sensitive to shocks originating from the United States than China. As is common in SVAR studies, the primary concern with the findings is whether or not they are robust to the exclusion restrictions used in our identification strategy. Following Kilian, the structural shocks were identified with a recursive scheme, implying that the dynamics of the structural shocks on endogenous variables may result in adverse order effects.[2] As we discussed in Section 3, by placing world oil production as the first variable in the model, we rest on the assumption that an unanticipated change in world production would have a contemporaneous effect on the price of oil and world economic activity. The variation of oil price is ordered last in our specification, implying that shocks to the price of oil, or oil-specific demand shocks, only have an impact on world economic activity and oil production after a month. While these restrictions are implied by economic theory, restrictions on the impact of oil demand shocks across the US, China, and the ROW and thus orderings of the corresponding proxies for oil demand of these regions are likely not easy to justify. To test whether the main results are sensitive to alternative orderings, we re-estimate the model with a set of possible identifications stemming from six possible orderings of the three proxies for oil demand. Figure 6 reports the median responses of the price of oil to the demand shocks. It shows that, for five of six orderings, a one unit shock from the United States produces consistently a larger impact on the oil price than that from China. Interestingly, it also reveals that, when we place China above the United States, suggesting that economic activity in China has a contemporaneous

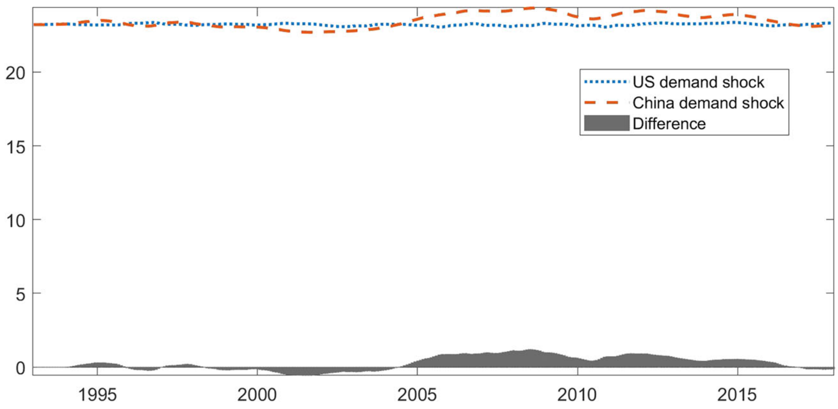


FIGURE 7 China versus the United States in driving the oil price (using the country's steel production as a proxy for oil demand)

effect on the US economy, we find that the impact of China demand shocks becomes larger. This could be interpreted as the overestimate the role of China. Having said that, allowing for China has contemporaneous on the US economy is likely not a reasonable identification. Hence, the result of this exercise is that our main conclusions remain unchanged.

Aside from evaluating alternative identifications to confirm the robustness of our results, we also replace the average oil prices with the two alternative merits of oil prices that are also commonly used in the literature: WTI and the US RAC. We do not report the results obtained from this exercise as they are extremely similar to the main results discussed in this paper.

Finally, we checked the sensitivity of the main results by using an alternative measure of global economic activity as proposed in Ravazzolo and Vespignani, which has been shown to share many of the same characteristics exhibited by the popular global real economic activity index of Kilian.[2,11,12] To that end, we consider annualized growth of steel production in the United States, China, and the ROW, in place of our original proxies for real economic activity measured by industrial production. The data was obtained from the *World Steel Association* website. Figure 7 presents the equivalent counterfactual displayed in Figure 5 using steel production. In line with our benchmark results, we find that the contribution of the China factors has been relatively stronger than that of the US factors, however, the evidence is slightly weaker than that in the main analysis. This result may be due to the fact that the measure fails to reflect the actual position of the United States and China in international oil markets. This is because both steel production and consumption in China are about 10 times larger than those in the United States. This confounding factor suggests that the use of each country's steel production as a proxy for oil demand, especially for China, may significantly understate the influence of China in the oil market.

6 | CONCLUSION

In this paper, we provided formal evidence for the claim that rapidly increasing demand for oil from China is one of the prominent factors driving oil price fluctuations in recent years. We constructed the country's specific proxies for real economic activity from China, the United States, and the ROW. Using an extended structural VAR model of the oil market, our results confirmed that the influence from a demand perspective of China has increased over time and surpassed that of the United States in the world oil market. In particular, the changes of oil demand from China have a growing impact on the fluctuation of the oil price of the world. Furthermore, this influence from China has exceeded that from the United States and becomes a main contributor to the volatility of the oil market. Our results contribute the findings to other scholars that the influence from a demand perspective of the emerging markets is critical and cannot be ignored.

Our main results are also found to be robust to various sensitivity checks, including different orders of three oil market key variables (world oil production, real economic activity and the real price of crude oil) in the VAR models, alternative merits of oil prices (West Texas Intermediate and the US RAC), and an alternative measure of global economic activity (the country's steel production). The robustness test results also suggest that the influence of China to the world oil markets keeps growing. The impact from China has already exceeded that of the United States from the turn of the century up to recent years.

AUTHOR CONTRIBUTIONS

Each author has an equal contribution to this paper.

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None.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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APPENDIX: BVAR

The model is estimated with Bayesian methods using a standard Minnesota prior. This prior was originally developed by Litterman, modified by Kadiyala and Karlsson, Sims and Zha, and recently popularized by Bańbura et al.[20–23] To be explicit, note that Equation 1 can be stacked over all dates t to give

$$y = \mathrm{XB} + e, \tag{2}$$

where $y = (y_1, \ldots, y_T)'$, $X = (X_1, \ldots, X_T)'$ with $X_t = (y'_{t-1}, \ldots, y'_{t-p}, 1)'$, $B = (B_1, \ldots, B_p, c)'$ and $e = (e_1, \ldots, e_T)'$.

The prior beliefs are imposed on Equation 2 by setting the following Normal-inverse-Wishart prior

$$\mathrm{vec}(B)|\sum \sim N\left(\mathrm{vec}(B_0), \sum\otimes\sum\nolimits_0\right) \tag{3}$$

$$\sum \sim iW\left(S_0, \upsilon_0\right), \tag{4}$$

where the hyperparameters: B_0, $\sum_0$, S_0 and υ_0 are chosen such that the prior expectations and variance of the autoregressive coefficient matrices are given by

$$\mathbb{E}\left[(B_k)_{ij}\right] = 0 \tag{5}$$

$$\mathrm{Var}\left[(B_k)_{ij}\right] = \begin{cases} \dfrac{\lambda^2}{k^2}\ i = j \\ \dfrac{\lambda^2}{k^2}\dfrac{\sigma_i^2}{\sigma_j^2}\ i \neq j \end{cases} \tag{6}$$

and the expectation of the reduced form covariance matrix is equal to $\sum = \mathrm{diag}\left(\sigma_1^2, \ldots, \sigma_n^2\right)$, in which σ_i^2 are scale parameters.

Following Bańbura, we implement this prior by adding dummy observations and an additional prior on the sum of the reduced form coefficients.[23] The dummy observations are given by

$$\begin{aligned} Y_d &= \begin{bmatrix} \mathrm{diag}(\delta_1\sigma_1, \ldots, \delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ \cdots \\ \mathrm{diag}(\sigma_1, \ldots, \sigma_n) \\ \cdots \\ 0_{1\times n} \end{bmatrix} X_d \\ &= \begin{bmatrix} J_p\otimes\mathrm{diag}(\sigma_1, \ldots, \sigma_n)/\lambda\ 0_{\mathrm{np}\times 1} \\ \cdots \\ 0_{n\times \mathrm{np}}\ \ 0_{\mathrm{np}\times 1} \\ \cdots \\ 0_{n\times \mathrm{np}}\ \epsilon \end{bmatrix} \end{aligned} \tag{7}$$

where $J_p = \mathrm{diag}(1,2, \ldots, p)$, $n = 5$ and $p = 24$. The first block imposes prior beliefs on the autoregressive coefficients, the second block implements the prior for the covariance matrix and the third block reflects the uninformative prior for the intercept via ϵ. It can be shown that adding T_d such dummy observations to Equation 2 is equivalent to imposing the Normal-inverse-Wishart prior with $B_0 = (X_d'X_d)^{-1}(X_d'Y_d)$, $\Sigma_0 = (X_d'X_d)^{-1}$, $S_0 = (Y_d - X_dB_0)^{-1}(Y_d - X_dB_0)$ and $\nu_0 = T_d - k$; we refer the interested reader to Bańbura for more details.[23] Finally, to allow for a prior on the sum of the VAR coefficients, we add the following dummy observations:

$$Y_d = \frac{\mathrm{diag}(\delta_1\mu_1, \ldots, \delta_n\mu_n)}{\tau}, X_d = (\iota_p \bigotimes Y_d \; 0_{n\times 1}), \tag{8}$$

where ι_p is a $1 \times p$ unit vector, μ_i captures the average level of variable y_{it} and τ controls for the degree of shrinkage. In our application we follow Bańbura and set the scale parameters σ_i^2 equation equal to the residual variance from a univariate autoregressive model of order p for the variables y_{it}, choose a diffuse prior variance of $\epsilon = 1000$, set μ_i equal to the sample average of y_{it}, $\lambda = 0.1$ and $\tau = 10\,\lambda$.