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Not all political relation shocks are alike: Assessing the impacts of US-China tensions on the oil market⋆

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Abstract

This paper aims at assessing the effects of US-China political tensions on the oil market. Relying on a quantitative measure of these relationships, we investigate how their dynamics impact oil demand, supply, and prices over various periods, starting from 1960 to 2019. To this end, we estimate a structural vector autoregressive model as well as local projections and show that trade tensions between the two countries pull down oil demand and supply, whereas prices tend to rise in the very short term. Overall, our findings show that conflicting relationships between these two major players in the oil market may have crucial impacts, such as the development of new strategic partnerships.

Keywords: China, Oil market, Political relations
JEL: Q4, F51, C32

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1. Introduction

China and the United States being the world's two largest oil consumers, and the US the largest producer, both countries are expected to play a key role in the oil market.[1] The recent trade war between the two nations provides a particularly appealing illustration. Trade tensions began in March 2018 when Donald Trump imposed an increase in tariffs of around $60 billion on imported Chinese goods to fight against the US trade deficit with China. In return, China announced a rise in tariffs on a list of several imported US products. These measures have provoked a decrease in Chinese production.[2] Given China's key role in the oil market, this reduction in production translated into a decline in Chinese consumption and demand for crude oil. Combined with an excess supply, this drop in oil demand has caused significant volatility in crude oil prices. This episode is far from being unique, and there are many other examples showing that the nature of the political relationships between the two countries is affecting the oil market significantly.

This paper tackles this issue by investigating the impact of US-China political relation shocks on the oil market. As stated above, the trade war between the US and China has spread over time since 2018, with a succession of multiple measures taking the form of threats and tariffs. Regarding the oil market, in August 2019, China announced that it would impose tariffs on US crude oil imports for the first time, leading to a severe drop in the prices. Such plunges in oil prices come from worries about a slowdown in world economic growth and, in turn, global oil demand. This uncertainty surrounding oil demand, fueled by the escalating trade tensions between the two countries, pulls prices down.

In addition to the threat of an economic downturn affecting the demand side, US-China political relations may also impact the oil market in various other ways. A typical illustration is provided by Iran, which faced severe dwindling demand—and, therefore, a decline in its oil exports—due to US sanctions since 2018. To defy US sanctions, China started to import Iranian oil, with a noticeable increase in 2020-2021. Since China is an important market for US oil exports, this move toward Iran obviously affects the US oil industry and, in turn, the global oil demand and supply.[3] Regarding the supply side, another mechanism could also be at play due to the nature of the oil industry. The latter is capital intensive, and a significant part of such capital equipment and raw materials necessary to produce it comes from China. As it is well known, pipelines are mainly composed of steel. Chinese steel being cheaper than the US one, if a pipeline company is forced to buy—more expensive—steel in the US, it will impact its capital budgets and result in fewer projects, thus affecting the oil supply. Finally, the escalating trade war between China and the US may also encourage oil demand for precautionary reasons.

The literature on the effects of US-China political tensions and trade war on the oil market is inexistent. As noticed by Bouoiyour et al. (2019), most studies dealing with political tensions and events concern their impact on stock returns and their volatility, not the oil market (see, e.g., Carlomagno and Albagli (2022) for a recent illustration). However, there are some rare papers (see Section 2) related to the oil market, but they mainly focus on the impact of tensions in the Middle

[1] According to BP Statistical Review of World Energy 2021, the US and the Chinese economies are the largest consumers of oil (around 20% and 16% of the world consumption, respectively).

[2] See, e.g., Chor and Li (2021).

[3] It is worth mentioning that the global oil demand is affected as Iran is under a sanctions regime by the US.

East (see, e.g., Alhajji and Huettner, 2000; Coleman, 2012; Chen et al., 2016). Thus, to the best of our knowledge, our paper is the first to assess the effects of political relation shocks between China and the US—two key actors in the oil market—on oil demand, supply, and prices.

More generally, investigating the impacts of geopolitical risks and political tensions on financial and macroeconomic variables has not been the subject of many empirical studies due to the lack of a relevant measure to proxy such phenomena. We fill this gap in the present paper by relying on a quantitative measure of political relations between China and the US, allowing us to have a detailed—quantitative—view of the evolution of the tensions between the two countries over time. We analyze the degree to which the dynamics of these relations impact the oil market by investigating the effects on demand, supply, and prices over various periods, starting from 1960 to 2019. Although the role of China as an international key player mainly starts in the 2000s, working on such a long horizon allows us to highlight China's growing influence on the international scene and, in particular, on the oil market. From a methodological viewpoint, we estimate a structural vector autoregressive (SVAR) specification, which we complement with several robustness checks—including the estimation of local projections.

Our main findings are that the threat of worsened relations impacts the oil market. Specifically, the climate of uncertainty created by these tensions between the two countries deteriorates oil demand and supply, whereas prices tend to rise in the very short term.[4] Since the Organization of the Petroleum Exporting Countries (OPEC) has no control over prices in that case, it is not inclined to reduce its production.

The rest of the paper is organized as follows. Section 2 reviews the literature related to the impact of political events on the oil market. Section 3 presents the methodology and data. Section 4 displays the SVAR estimation results. It also includes a detailed sub-period analysis and a counterfactual investigation. Section 5 provides several robustness checks, including the estimation of local projections. Finally, Section 6 concludes the paper.

2. Literature review

Baumeister and Kilian (2016) describe several historical episodes of major fluctuations in the real price of oil, and underline that the literature on their causes has largely evolved since the 1980s. Although exogenous political events and revolutions in OPEC member countries were initially considered the main drivers of fluctuations in oil prices (Hamilton, 2003, 2009), various studies further argue that they are only one possible explanatory factor (Bodenstein et al., 2012; Lippi and Nobili, 2012; Baumeister and Peersman, 2013; Kilian and Hicks, 2013; Kilian and Lee, 2014; Kilian and Murphy, 2014).

As an example, Hamilton (2003) argues that the 1973 oil price shock corresponds to a negative supply shock, as the supply fell and the prices soared, and results from a political conflict in the Middle East. In contrast, Kilian (2008) found empirical evidence that only 25 percent of the 1973 oil price increase is due to exogenous supply shocks; the other factors that play a key role being

[4]From a general viewpoint, it is worth recalling that a rise in oil prices constitutes an inflationary shock. For instance, Choi et al. (2018) empirically show that a 10% increase in oil prices leads to a rise in domestic inflation by 0.4 percentage points in the short run.

exogenous events in OPEC countries such as the Persian Gulf war or the Iranian revolution which may also include exogenous oil demand shocks.

More generally, at the global level, market forces and, especially, the demand for crude oil play a key role. As it is well known, when the global economy expands, the demand for raw materials (including crude oil) increases, inducing a rise in oil prices.

Disentangling the respective contributions of exogenous political events/tensions and market forces (demand, supply, inventories) in oil price fluctuations is a rather difficult task. Indeed, the causal structure and interactions between political tensions, oil demand, oil supply, oil inventories, and oil prices are not straightforward. It is worth mentioning that the evolution of oil prices could impact global supply, as OPEC members could find it interesting to produce more when prices are high. Besides, political tensions could affect the global cycle, lowering oil demand and, finally, oil prices.

With this general background in mind, we survey some recent studies that estimate the impact of exogenous political events, thanks to a quantitative measure of political tensions. Although the narrative—i.e., historical—approach is helpful to examine specific historical episodes, the quantitative approach is precious to discover more systematic evidence. Besides, we focus on studies that aim at (i) deciphering the complex structural interactions between political tensions, market forces, and oil price movements; and (ii) determining the relative contributions of political tensions and market forces to the oil price dynamics.

Chen et al. (2016) investigate the impact of OPEC's political risk on oil prices thanks to estimating an SVAR specification. They aim to shed light on two questions: how do international oil prices respond to shocks of political risk events? What is the relative contribution of those shocks in explaining changes in oil prices? To answer these questions, Chen et al. (2016) consider five variables in the SVAR, namely the political risk of OPEC countries, oil supply, oil demand, speculation, and crude oil prices. OPEC countries' political risk is measured by a transformation of the well-known International Country Risk Guide index (hereafter the ICRG index). Using monthly data from January 1998 to September 2014, they find that the two main contributors to oil price fluctuations are political risk shocks (for 34.6%), and demand shocks (for 17.6%). Specifically, OPEC's political risk shocks positively influence oil prices after 17 months; this positive effect lasting for 10 months, indicating delayed significant impacts over the examined period. Consistent with Kilian (2008, 2009) and Kilian and Murphy (2014), oil demand shocks positively impact oil prices for 20 months, whereas supply shocks do not exert a significant effect as they contribute only to 5.9% of the oil price fluctuations. Turning to financial speculation shocks, they positively affect oil prices, as in Morana (2013) and Dvir and Rogoff (2014).

Interestingly, through the impulse-response functions (IRF)' analysis, Chen et al. (2016) also find that political risk shocks in the Middle East positively affect oil prices, while political risk shocks in North Africa and South America have no significant effect.[5] Consequently, political tensions between strategic partners may impact the oil price dynamics, even if they do not find a significant effect of external conflicts for the studied sample and countries (OPEC).

Along with the empirical investigation of Chen et al. (2016), several papers aimed at estimating

[5]Political risk shocks in the Middle East have more impact due to the larger share of oil production and the higher occurrence of geopolitical events.

the quantitative impact of political risk on the oil price dynamics (Lee et al., 2017; Miao et al., 2017; Perifanis and Dagoumas, 2019; Abdel-Latif and El-Gamal, 2020; Qin et al., 2020; Caldara and Iacoviello, 2022). Alhajji and Huettner (2000) can be considered the first attempt to assess the quantitative impact of political risk shocks on oil price fluctuations, being the sole study that incorporates quantitative measures of political tensions—security cost per barrel (i.e., the increase of military spending for each OPEC country relative to Venezuela)—in a model of oil prices during the 2000s (Coleman, 2012).

In his work, Coleman (2012) aims at explaining crude oil prices with fundamental measures, including two variables for proxying political factors: the number of US troops deployed in the Middle East (expressed in logarithm), and the terrorist attacks with fatalities in the Middle East. According to him, these two variables provide a consistent measure of regional instability and the threat of war. Using monthly data over the 1984-2007 period, he confirms the traditional role played by market forces, and shows that fatal attacks in the Middle East and US troops deployed in the region have a positive impact on oil price fluctuations. A one-standard-deviation change in fatal attacks and in the log of US troops increases oil prices respectively by \$4 and \$1. Despite its interest, it is worth mentioning that this study does not control for reverse causality running from oil prices to the explanatory variables.

Lee et al. (2017) expand Chen et al. (2016)'s investigation and estimate an SVAR model including the following variables: world oil production, real global economic activity index (Kilian, 2009), oil prices (Brent), and country risk rating for each G7 member (ICRG index). Using monthly data over the 1994-mid-2015 period for the G7 countries, they highlight different results between oil-exporting (the UK and Canada) and oil-importing (Germany, France, Italy, Japan, and the US) countries.[6] For instance, in Canada, unanticipated shocks to the country's risk could lead to a short-lived increase in oil prices, in line with Chen et al. (2016). In the United States, those shocks may have a different impact on the world economy than for other oil-importing countries, given the size of the US economy and the place of the US dollar in the international monetary system.

The remaining recent studies on the impact of political tensions on oil price fluctuations can be split according to the type of variables used to measure political risks, threats, and tensions. On the one hand, some empirical studies (Miao et al., 2017; Perifanis and Dagoumas, 2019) rely on the number of terrorist attacks coming from the Global Terrorism Database, following the approach of Coleman (2012). On the other hand, some more recent empirical investigations (Abdel-Latif and El-Gamal, 2020; Qin et al., 2020; Caldara and Iacoviello, 2022) use the Geopolitical Risk index (hereafter GPR) introduced in the literature by Caldara and Iacoviello (2022).[7]

Using a sample of daily data spanning from January 04, 2002 to September 25, 2015, Miao et al. (2017) aim at forecasting WTI crude oil prices with several types of variables (supply factors, demand factors, financial factors, commodity market factors, speculative factors, and political factors). The authors find that geopolitical risk factors, captured by the number of terrorist attacks

[6] Thanks to an open-economy dynamic stochastic general equilibrium model for Norway, Bergholt et al. (2019) provide theoretical evidence that helps in understanding the different transmission mechanisms at play for oil-exporting and oil-importing countries. They highlight that the commodity industry supply chain has a key role.

[7] The index is available since 2018.

in the Middle East and North Africa, are one of the most important determinants of oil prices.

Aiming at quantifying the impact of the fundamental drivers of oil prices over the 2007-2018 period using monthly data, Perifanis and Dagoumas (2019) consider various variables: (i) traditional variables for market forces, (ii) US shale oil production for supply factors, and (iii) number of terrorist attacks in oil-producing countries for the geopolitical factor. Relying on cointegration analysis, they find that the geopolitical factor does not significantly influence oil prices in the long run.

As stressed above, Caldara and Iacoviello (2018, 2022) introduce the geopolitical risk (GPR) index, a monthly index obtained by running automated text searches on the electronic archives of 11 newspapers, available since 1985.[8] They distinguish between geopolitical threats—which tend to increase uncertainty—and geopolitical acts. Their measure has the advantage to be largely independent of business cycle fluctuations, although the authors acknowledge that their index can be viewed as: "as a measure of risks that are mostly relevant from a North-American and British perspective." In their empirical investigation, they rely on a Bayesian VAR analysis over the 1985-2016 period, and consider several macroeconomic variables (GPR index, EPU index, consumer sentiment, US production, US trade balance, S&P 500 index, oil prices (WTI), and yield on two-year US treasuries). Their results show that an increase in the GPR index leads to a short-lived decrease in oil prices of around 7% after 3 months.

Abdel-Latif and El-Gamal (2020) use the GPR index to assess the dynamic interactions between oil prices, financial liquidity, and geopolitical risks over the period spanning from 1979 to mid-2017. To this end, they consider a Global VAR (GVAR) model as they argue that financial liquidity and geopolitical risks are probably endogenous to the US. They find that a one-standard-deviation shock to the geopolitical risk index induces a persistent and significant increase in oil prices (around 4%).

Qin et al. (2020) use quantile regressions to investigate the asymmetric effects of geopolitical risks on energy returns (including crude oil). Their sample period spans from June 28, 1990 to October 31, 2018, and they use four dummies that correspond to the four spikes in the GPR index: the Gulf War, the 2003 Iraq invasion, the 2014 Russia-Ukraine crisis, and the 2015 Paris terrorist attacks. They find that the GPR index has a negative impact on crude oil returns at the lower quantiles, and a positive effect at the higher quantiles. Besides, geopolitical threats have a higher impact than geopolitical acts in absolute value.

To our best knowledge, our study is the first to use a quantitative index of bilateral political relationships between the US and China to quantify the effect of political shocks on the oil market. This lack in the literature is quite surprising since, given the weight of these two economies in terms of GDP, oil consumption, and oil production, the dynamic of their political relations is likely to play a key role in the oil market. Our structural analyses aim at (i) deciphering the complex structural interactions between political relations, market forces, and oil price movements; and (ii) determining the respective contributions of these factors to the oil price dynamics.

[8] The historical index is available since 1900, but only based on 3 newspapers.

3. Methodology and Data

3.1. *The SVAR specification*

The widely used method to investigate the impacts of macroeconomic shocks is structural vector autoregression (SVAR) models.[9] Obtaining structural shocks are crucial to impulse response analysis, forecast error variance decomposition, historical decomposition, and VAR-based counterfactual analysis. Let us recall that the SVAR specification is given by:

$$\mathbf{A}_0 y_t = \mathbf{c} + \mathbf{A}_1 y_{t-1} + \mathbf{A}_2 y_{t-2} + \cdots + \mathbf{A}_p y_{t-p} + \mathbf{B} u_t \tag{1}$$

where y_t is the vector of endogenous variables, $\mathbf{c}$ is a constant term, $\mathbf{A}_0$, $\mathbf{A}_1$, $\cdots$, $\mathbf{A}_p$ denote the structural coefficients, and u_t are the orthonormal unobserved structural innovations with $\mathbf{E}(u_t u_t^{'}) = \mathbf{I}_k$; $\mathbf{I}$ being the identity matrix. Assuming that $\mathbf{A}_0$ is invertible, we rewrite (1) as follows:

$$y_t = \alpha + \mathbf{Q}_1 y_{t-1} + \mathbf{Q}_2 y_{t-2} + \cdots + \mathbf{Q}_p y_{t-p} + \mathbf{S} u_t \tag{2}$$

where $\alpha = \mathbf{A}_0^{-1}\mathbf{c}$, $\mathbf{Q}_1 = \mathbf{A}_0^{-1}\mathbf{A}_1$, $\mathbf{Q}_2 = \mathbf{A}_0^{-1}\mathbf{A}_2$, $\cdots$, $\mathbf{Q}_p = \mathbf{A}_0^{-1}\mathbf{A}_p$, and $\mathbf{S} = \mathbf{A}_0^{-1}\mathbf{B}$. Also, the reduced-form error structural can be expressed by:

$$\varepsilon_t = \mathbf{A}_0^{-1}\mathbf{B} u_t = \mathbf{S} u_t \tag{3}$$

$$\mathbf{E}(\varepsilon_t \varepsilon_t^{'}) = \Sigma_\varepsilon = \mathbf{A}_0^{-1}\mathbf{B}\mathbf{B}^{'}\mathbf{A}_0^{-1'} = \mathbf{S}\mathbf{S}' \tag{4}$$

To recover $\mathbf{S}$, we rely on the recursive identification scheme by using Cholesky decomposition to obtain a lower-triangular matrix. The benchmark-SVAR model is specified as $y_t = [pri_t, pro_t, dem_t, rpo_t]'$, where pri_t, pro_t, dem_t and rpo_t denote US-China political relations, oil supply, oil demand, and oil prices at time t, respectively. According to our ordering, the identified shocks of US-China political relations contemporaneously impact oil-related variables, but the reverse effects of other oil shocks take time.[10] It is worth mentioning that since we are only interested in the responses of oil market variables to US-China political relation shocks, only the first column of $\mathbf{S}$ needs to be identified. We use the moving block bootstrapping method proposed by Brüggemann et al. (2016) to generate confidence intervals at 68% and 90% significance levels.

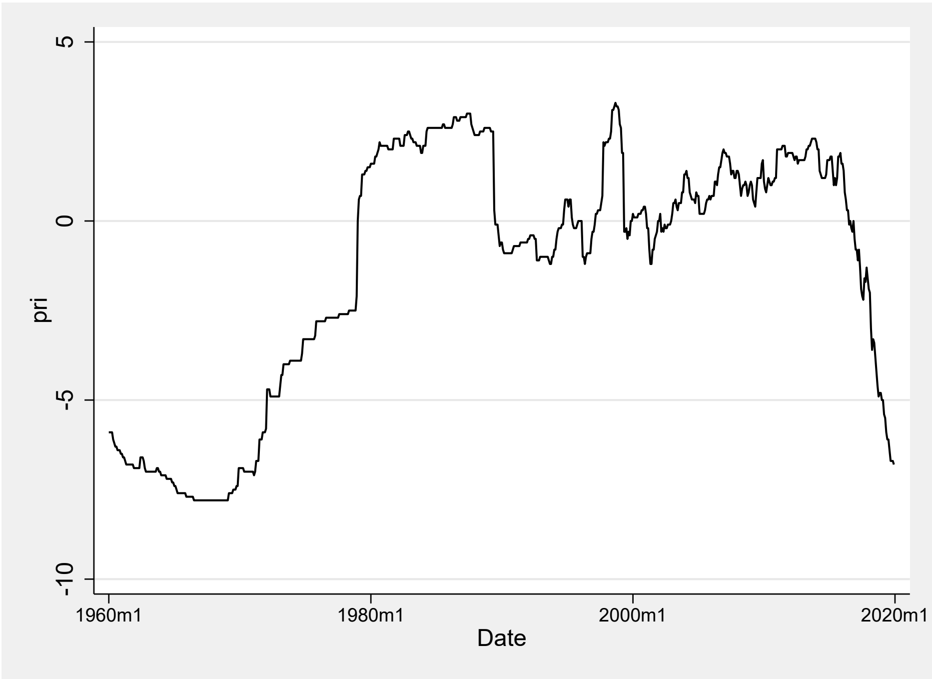
3.2. *Data*

We use monthly data over the period spanning from January 1960 to December 2019. We chose to work over a long time period, although the role of China as an international key player has been effective since the beginning of the 2000s. Relying on an extended period allows us (i) to highlight the growing influence of the Chinese economy on the international scene, and (ii) to have a complete picture of the evolution of the political relationships between China and the US

[9] As an example, Herwartz and Plödt (2016) estimate an SVAR model to analyze the dynamics in the global crude oil market. They find a strong impact of aggregate demand and oil-specific demand shocks on oil prices, but a small effect of both shocks on oil production.

[10] We will further investigate the robustness of our findings to the ordering of the variables (Section 5).

Figure 1: US-China political relation index



Source: http://www.tuiir.tsinghua.edu.cn/ (Tsinghua University).

through time. To assess the effect of US-China political tensions on the oil market, we rely on the US-China political relation index (PRI). The latter is developed by the Center for US-China Relations at Tsinghua University,[11] and mainly describes the political relations between China and its twelve major trading partners.[12] It is divided into six sections, ranging from -9 to 9, which classify the political relations as confrontation (-9), rival, disharmonious, common, harmonious, and friendly (9).[13]

Figure 1 displays the evolution of PRI over the 1960-2019 period. As shown, the index maintains around -7.5 before Kissinger's secret trip to China in 1971, and sharply increases due to Nixon's China visit in 1972. The PRI index peaked in 1979 after US and China formally established diplomatic relations. The stability of the index at around 2 from 1980 to 1989 is disturbed by the Tiananmen Square events that led the US government to suspend military sales to China, freezing political relations between the two countries. These sudden changes were quickly fixed after Washington and Beijing agreed to exchange officials anew. The Belgrade Embassy bombing again shook the bilateral relation, which cooled down in 1999. In October 2000, President Clinton signed the US-China Relations Act, granting Beijing permanent normal trade relations with the US and paving the way for China to join the World Trade Organization (WTO) in 2001. After that, US and

[11] PRI is available at http://www.tuiir.tsinghua.edu.cn/

[12] Du et al. (2017) provide a description of the PRI index and its impact on bilateral trade for twelve major trading partners of China.

[13] The minimum unit of the index is 0.1.

China experienced a long-term slow recovery in their political relations. Since Donald Trump came to power in 2017, PRI has significantly dropped because of the trade war—the US labeling China a currency manipulator—Hong Kong's judicial independence, and intellectual property issues.

Regarding the variables related to the oil market, we consider global oil supply, global oil demand, and the price of oil.[14] Specifically, oil supply, demand, and prices are respectively represented by the level of oil production, world industrial production, and the real price of oil. All variables are expressed in logarithmic terms. The world industrial production index is measured by Hamilton (2021) by considering 23 OECD countries and six other emerging economies (Brazil, China, India, Indonesia, the Russian Federation, and South Africa). As a robustness check, we will also consider the world economic activity index introduced by Kilian (2009) to proxy the demand for oil.

4. Baseline results

As stressed above, we rely on the recursive identification strategy to obtain desired US-China political relation shocks, and use the Cholesky decomposition to recover the contemporaneous impact matrix. We order US-China political relations at first, and follow Kilian (2008) regarding the ordering of the rest of the variables: oil supply, oil demand, and oil prices. As previously mentioned, this variable ordering indicates that US-China political relation shocks contemporaneously impact oil market variables, but the reverse effects take time.[15]

We include 24 lags into the model,[16] and implement the moving block bootstrapping method that Peersman (2022) suggested to generate one and two standard error bands.

4.1. Baseline impulse-responses functions

Figure A.1 in Appendix plots the identified US-China political relation shocks based on the estimation of our SVAR model. As the two leading economies in the world, the worsening bilateral political relations could create worries about potential conflicts and geopolitical risks, and affect the oil market. To interpret the impact of US-China deteriorating relations on the world oil market, let us first report the impulse-response functions' (IRF) analysis results.

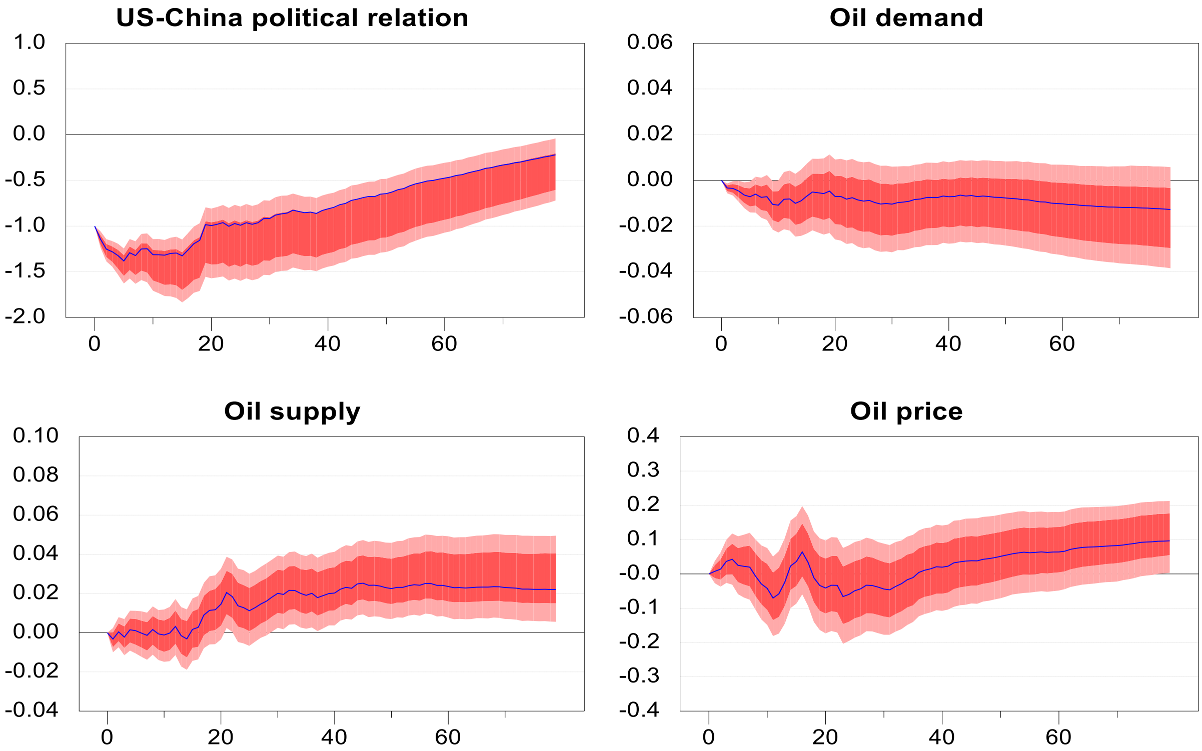
As shown in Figure 2, an unanticipated decrease in US-China political relations raises oil production, shortly pulls down oil demand, and drives up oil prices. More in detail, oil production persistently increases, with a maximum impact (0.02%) 4,2 years after an immediate shock. In contrast, oil demand—represented by world industrial production growth—continually decreases following the shock, although the significance is quite weak. Finally, after a brief increase in the very short run, oil prices exhibit a rising tendency at long horizons.

[14] All these series are extracted from Christiane Baumeister's personal website: https://sites.google.com/site/cjsbaumeister/.

[15] See Section 5 for a robustness analysis to the ordering of the variables.

[16] We select this lag number as political relations is a persistent series that is only changed by some political or geopolitical events occasionally. For the sake of completeness, note that we have investigated the sensitivity of our findings to the lag number. The results, available upon request to the authors, are robust to the choice of the lag number.

Figure 2: Baseline impulse responses



Note: The baseline SVAR model is estimated over the period from 1960M1 to 2019M12. It is specified as $y_t = [pri_t, pro_t, dem_t, rpo_t]'$ (variables expressed in logarithmic terms) and includes 24 lags. Impulse-response horizons: 80 months. The shock is explained by a 1% decrease in $\log(pri_t + \sqrt{1 + pri_t^2})$. One and two standard error bands are displayed in red.

It is worth noticing that the decrease in demand is not accompanied by a decline in oil prices due to the nature of the considered shock. Indeed, while an oil price increase is expected to follow a positive demand shock, our results show that oil prices are affected by other factors than market forces, such as geopolitical and political events. Although these findings may be nuanced due to the apparent low significance, this can be explained by the fact that we rely on a long time span, including the period before the 2000s during which China's international role is out of all proportion to nowadays. This illustrates the relevance of sub-sample analyses (see Section 4.3).

Overall, deteriorating political relations between China and the US harm world economic growth and, in turn, the demand for oil. In that case, OPEC has no control over prices, and does not reduce its production as member countries could gain extra benefits from rising oil prices. The latter vary following such a sudden decrease due to unanticipated worries about future political relations between the two countries.

4.2. Counterfactual evolution and impulse responses

An interesting question is to assess what the evolutions are when the impacts of US-China political relation shocks are excluded from the SVAR model. To address this issue, we report the results of both historical decomposition and counterfactual evolutions of variables in the absence of US-China political relation shocks (Figure 3).

As shown, the identified shocks negatively contribute to the variations in US-China political relations before 1980, in several months from 1990 to 1995, and after 2016. These results are not surprising because of the historical events between US and China during these periods. Before 1980, the international role of China was negligible, and US and China political relations were still fragile and easily disturbed by sudden changes. During the first mid-1990s, excluding the identified political relation shocks shows that PRI is above the actual evolution. The identified shocks negatively impacted US-China political relations due to the Tiananmen Square events.

The most interesting result concerns the period starting in the 2000s, during which the influence of China on the international scene has continued to grow. As shown, until 2016, counterfactual PRI evolves below its actual dynamics. This comes from the fact that the US and China tried to maintain a good relationship through diplomatic methods, although some sudden events affected it. Since the end of the 1990s and the beginning of the 2000s, US companies have been increasingly trading with this growing China, which appears to be a land of economic opportunity. However, in 2005, George W. Bush described the Sino-American relationship as mixed and urged China to democratize. Under Barack Obama's presidency, some concerns emerge in the face of the rise in China's international power. This led the US to develop contracts with other countries in Southern Asia, including Vietnam.

Finally, during Trump's administration, US-China political relations reached the freezing point due to multiple economic and political events, including the trade war, Hong Kong's judicial independence, intellectual property issues, and the international status of Taiwan. As shown, since Trump's election, the shocks negatively contribute to the variations in US-China political relations.

Turning to oil supply, the identified US-China political relation shocks positively contributed to oil production for several months from 1965 to 1985, and after 2017. The shocks negatively contribute to variations in oil demand before 2003. A few years after China entered into WTO, the impacts were positive and significantly increased in the following years. This result was expected as

China's rapid economic growth started from entering into WTO, and the country has gained much of benefits from trading with external partners. In Trump's administration, China is even labeled as a strategic competitor of the US. In other words, the political shocks make positive contributions to world oil demand and economic activities. Regarding oil prices, the shocks positively contribute before 1990, and negatively after 2000. Finally, it is worth mentioning that after excluding the identified shocks, the US-China political relation is much improved after 2016.

The IRFs based on those counterfactual variables are reported in Figure 4. As shown, the patterns significantly differ compared to those displayed in Figure 2. Specifically, the IRF of oil production is significant between around a 20 to 40 months horizon, the oil demand IRF is significantly negative in the very short run, and the oil price IRF is non-significant. Overall, the identified US-China political relation shocks substantially differ between baseline IRFs and counterfactual IRFs, corroborating the significant impact of tensions between the two countries on the oil market.

4.3. Sub-sample estimates

Since US-China political relations and the oil market are both easily disturbed by unanticipated changes in international political affairs, the baseline results may differ depending on the considered sub-sample period. Moreover, since the whole period includes different regimes of political relationships and because the international influence of China has considerably evolved through time, working on the full sample may mask—by averaging those diverse regimes—important facts regarding the impact of US-China political relationships during some specific sub-periods. According to Figure 1, four main periods can be distinguished: repaired relation, fluctuating relation, common relation, and deteriorating relation. The most interesting periods are the last two because they correspond to the growing international influence of China. For the sake of completeness, we also report the results for the two first sub-periods, although China was not a key international player during those times.

4.3.1. Distinguishing four sub-sample periods

Repaired relation (1971M1-1988M12). The first period describes a repaired relationship between the two countries since Kissinger's secret trip to China in 1971. This period lasted for nearly 20 years, and included many important events such as Ping-Pong diplomacy, Kissinger's secret trip, Nixon's visit to China, Formal Ties and One China Policy, and Reagan's visit to China. During this period, PRI quickly raised and described a common relation between US and China. As stated above, the international role of China was negligible during those decades, in line with the absence of a noticeable impact of its political relation with the US on oil market variables (see Figure A.2 in Appendix).

Fluctuating relation (1989M1-1999M12). Some particular events suddenly disrupted the previous improving political relation. Specifically, the Tiananmen Square events and the Belgrade Bombing shortly iced the warming relation in 1989 and 1999, respectively. As shown in Figure A.3 in Appendix, an unanticipated decrease in PRI momentarily increases oil variables, but has negative impacts in the medium and long run.

Common relation (2000M1-2010M12). PRI falls into a common relation period and has maintained for nearly 10 years until China became the second-largest economy in the world.

Figure 3: Counterfactual analyses

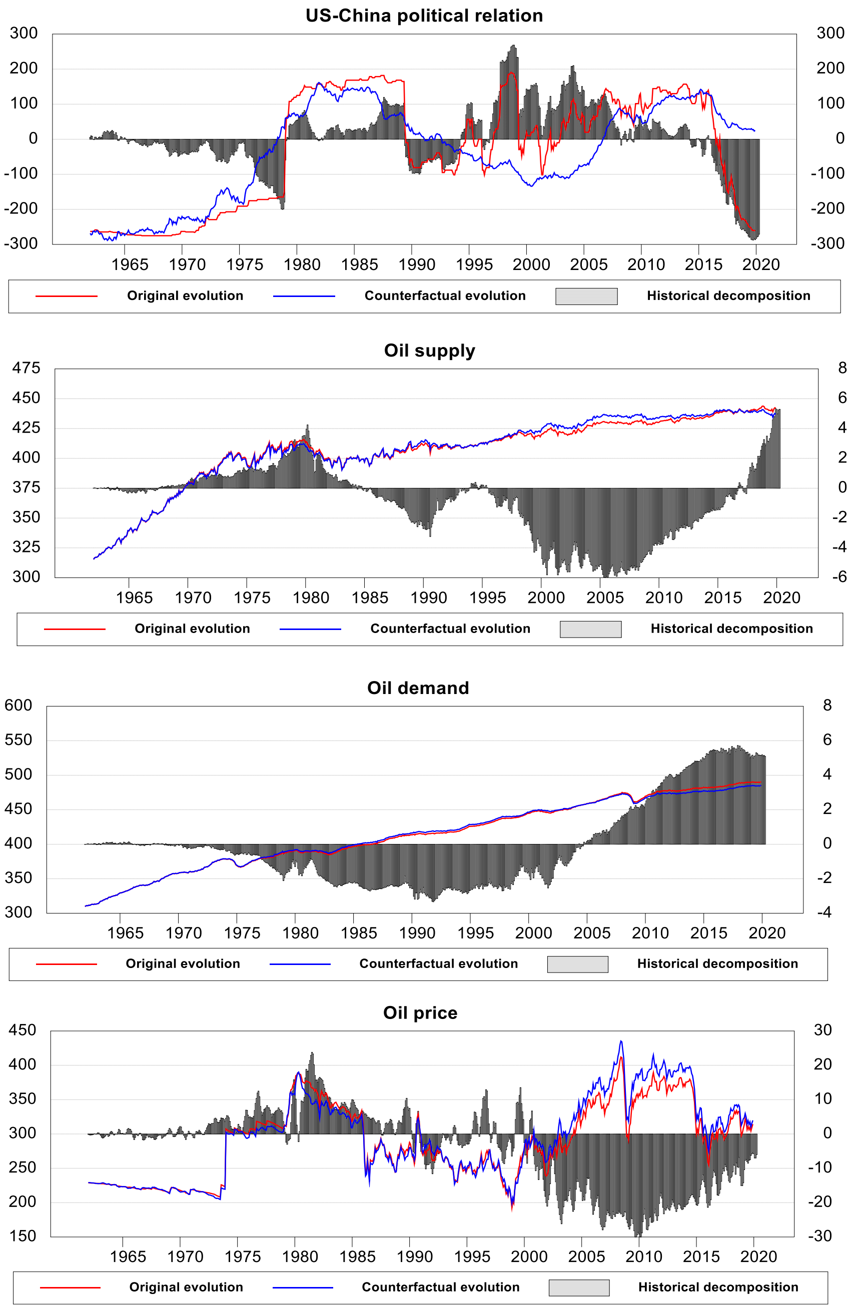
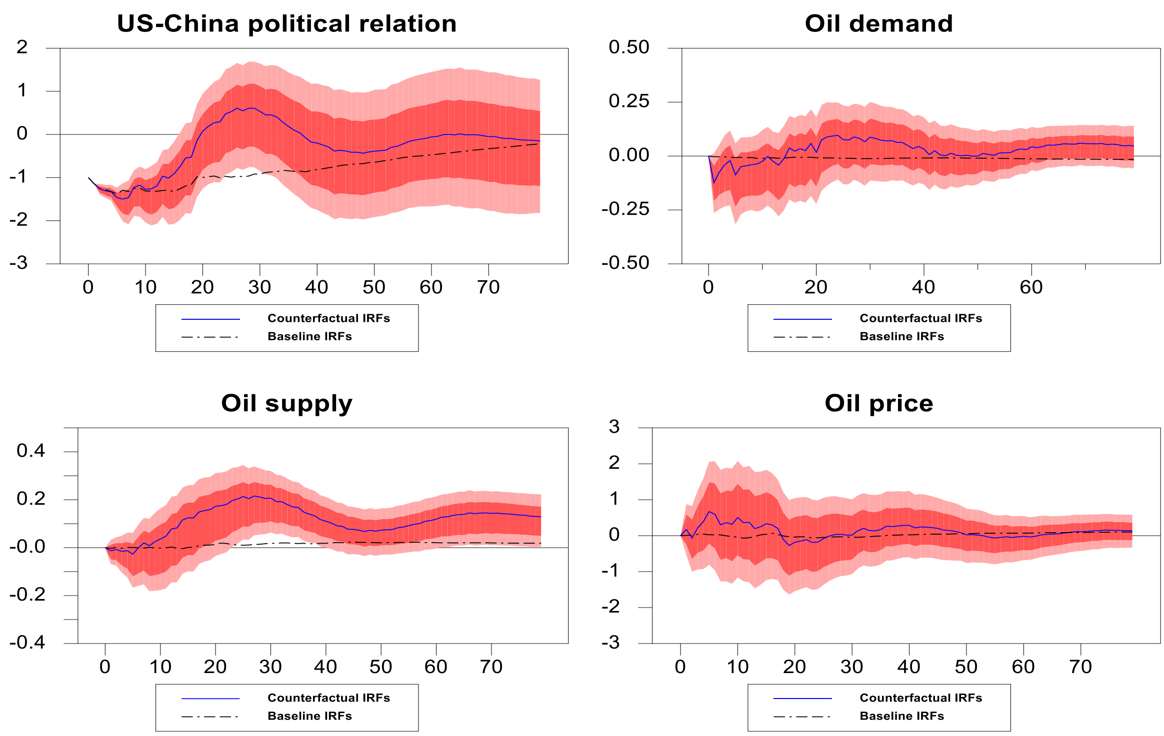


Figure 4: Counterfactual impulse responses



Note: The counterfactual SVAR model is estimated over the period from 1960M1 to 2019M12, and corresponding IRFs are obtained by using counterfactual variables. The SVAR model is specified as $y_t = [pri_t, pro_t, dem_t, rpo_t]'$ (variables expressed in logarithmic terms) and includes 24 lags. Impulse-response horizons: 80 months. The shock is explained by a 1% decrease in $\log(pri_t + \sqrt{1 + pri_t^2})$. One and two standard error bands are displayed in red.

During this period, President Clinton signed the US-China Relations Act in October 2000, granting Beijing permanent normal trade relations with the United States, and paving the way for China to join the World Trade Organization in 2001—which was crucial for China's economic growth. In addition, Deputy Secretary of State Robert B. Zoellick initiated a strategic dialogue with China. Recognizing Beijing as an emerging power, he called on China to serve as a "responsible stakeholder", and used his influence to draw nations such as Sudan, North Korea, and Iran into the international system in 2005. During this "golden age" period for Chinese growth, US and China experienced a relatively stable relation. As displayed in Figure A.4 (Appendix), the results are highly significant. Specifically, the identified US-China political relation shock decreases the three oil-related variables, except a temporary increase in oil prices in the very short run. As shown by the counterfactual analysis, although this period was relatively calm in terms of US-China tensions, some concerns appear due to the growing international role of China, which could potentially threaten the worldwide dominant position of the US. This threat created a climate of uncertainty, especially for firms, that is reflected in the oil market.

Deteriorating relation (2011M1-2019M12). The last period corresponds to deteriorating political relations. "US 'Pivots' Toward Asia" was viewed as a most important signal to illustrate that the opinions of the US towards China were completely changed. In 2012, trade deficit tensions raised. In Trump's administration, the conflicts between US and China are becoming more explicit. The political relation significantly dropped down and nearly touched the bottom since US and China established Diplomacy because of a series of events such as the trade war, disputes regarding China's human rights, Chinese currency manipulator accusation, and Hong Kong's judicial independence. As displayed in Figure A.5 in Appendix, the short-run IRFs of oil demand are not significant, the oil supply IRFs are negative in most of the horizons, and oil prices positively respond to such a sudden decrease. Compared to the previous sub-period, the significance of the effects of US-China political relation is lower. This result is not surprising as deteriorated relationships between the two countries are already at play. Indeed, the trade war has begun, and uncertainty is thus lower for firms compared to the previous period. Put it differently, a further degradation of the US-China relation produces lower effects in a worsened environment than in a calm context. This finding is in line with Caldara and Iacoviello (2022) who underline different impacts between (i) threat of war that generates uncertainty for firms, and (ii) war that reduces uncertainty due to the habituation of firms to a troubling context.

Overall, our sub-period analysis shows that there are no supply-side tensions during calm episodes because global growth prospects are not affected by a possible crisis between the two countries. When the relations become strained, supply and demand tend to decrease, accompanied by a short-term rise in oil prices, which diminishes at longer horizons. The main effect is found during the period in which China's spectacular growth and increasing weight on the international scene threatened the dominant position of the US.

4.3.2. China entering to WTO

Given the importance for China of WTO accession, it is relevant to assess the impacts of US-China political relation shocks before and after 2001. As shown in Figure A.6 in Appendix, the patterns of oil market variables before 2001 are considerably similar to the baseline SVAR model (Figure 2). However, such results significantly changed after 2001 (Figure A.7 in Appendix). First, the identified shocks have significant impacts on oil demand in the short run, but, in the long run, the IRFs of oil supply are insignificant. In addition, oil supply significantly increases after the immediate shocks. Finally, oil prices go down given the unanticipated decrease in the political relation index. To sum up, the long-run impacts on oil-related variables disappear after 2001, and only short-run effects are significant.

5. Robustness analyses

To assess the robustness of our results, we implement several sensitivity analyses. First, we check the validity of our conclusions regarding the ordering of the variables in the Cholesky decomposition. Then, we evaluate the sensitivity of our findings to the choice of the proxy used for oil demand. Finally, we check that our conclusions remain unchanged if we use the local projection method as an alternative to the SVAR specification.

5.1. Variable ordering

As it is well known, IRFs depend upon the variable ordering used in the Cholesky decomposition. To assess the robustness of our results, we locate PRI at other positions. We report in Figure A.8 in Appendix the results when PRI is ordered at last, which indicates that all variables contemporaneously affect it. As shown, the patterns are similar to those reported in Figure 2, illustrating the robustness of our findings to different variable ordering.

5.2. Proxy for oil demand

Our previous findings are obtained using the world industrial production index measured by Hamilton (2021). An alternative proxy for oil demand has been suggested by Kilian (2009), who proposed a world real economic activity index. The IRFs obtained when replacing the world industrial production with the world real economic activity index are shown in Figure A.9 in Appendix. The dynamics are globally similar to those displayed in Figure 2, although the decrease in oil demand is more pronounced.

5.3. Local projections

As an alternative to SVAR IRFs, Jordà (2005) proposes to estimate local projections, allowing to compute IRFs without specifying and estimating the underlying multivariate dynamic system. Comparing local projections and SVAR approaches, Montiel Olea and Plagborg-Møller (2021) and Plagborg-Møller and Wolf (2021) show that the former is more robust than the latter, especially when the dataset is highly persistent. In addition, Montiel Olea and Plagborg-Møller (2021) argue that the local projection method could deliver more accurate inference than standard autoregressive inference no matter whether datasets are or not stationary. As shown by Plagborg-Møller and Wolf (2021), local projection and VAR methods lead to the same impulse responses in the short and medium run, but disagree substantially in longer horizons. To assess the sensitivity of our results to the choice of methodology, we complement our SVAR analysis with the implementation of the local projection method.

As shown in Figure A.10, the SVAR impulse response patterns are highly consistent with local projections in the first 20 horizons. There are slight differences in the IRFs of oil demand

and supply in longer horizons, in line with the remarks formulated by Plagborg-Møller and Wolf (2021). Regarding the patterns of local projections, impulse responses in longer horizons more quickly recover to zero than typical SVAR models. Indeed, based on the SVAR results, the impacts of US-China political relation shocks are more persistent in longer horizons and do not disappear after 80 horizons. Put differently, local projection impulse responses describe more dynamics in the long run. Overall, our main conclusions are not altered when considering Jorda's procedure as we find similar impulse response patterns.[17]

6. Conclusion

This paper examines the effects of US-China political relation shocks on the oil market. Relying on a quantitative measure of these relationships, we investigate how their dynamics impact demand, supply, and prices in the oil market over the 1960-2019 period and various sub-samples.

The estimation of a structural VAR specification shows that trade tensions between China and the US pull down oil demand and supply, whereas prices tend to rise only in the very short term. The most significant effects are observed during the 2000 decade, corresponding to the "golden age" of Chinese growth. The potential threat *vis-à-vis* the dominant position of the US caused by the increasing international role of China feeds a climate of uncertainty reflected in the oil market. Overall, our findings show that other factors than market forces impact the oil market, as illustrated by the tensions between US and China.

We complement our analysis with a counterfactual investigation aiming at assessing what are the evolutions when the impacts of US-China political relations shocks are excluded. Our findings corroborate the significant effect of trade tensions between the countries on the oil market, as shown by the distinct profile of the impulse-response functions.

From a policy viewpoint, our findings show that trade tensions between these two major players in the oil market may have crucial impacts, especially during the last two decades, when China's role in the international scene has grown considerably. In particular, this leads to the development of new strategic partnerships. Whereas Iran had seen its oil exports drop considerably following the US sanctions in 2018, the path towards a recovery seems to be well confirmed. Indeed, Chinese oil imports from Iran have dramatically increased again, and this trend is expected to continue. This may reinforce the tensions between the US and China. The Biden administration could see this rapprochement as a dangerous geostrategic alliance, especially if it becomes too great a hindrance to the defense of Washington's interests in its trade war with Beijing.

[17] Ramey (2016) suggests that Jorda's procedure imposes fewer restrictions on the impulse responses and does not estimate IRF based on nonlinear functions of the reduced-form parameters. However, both local projections and VAR still impose the recursiveness assumptions to identify the desired structural shocks. Therefore, it is natural to find similar impulse response patterns.

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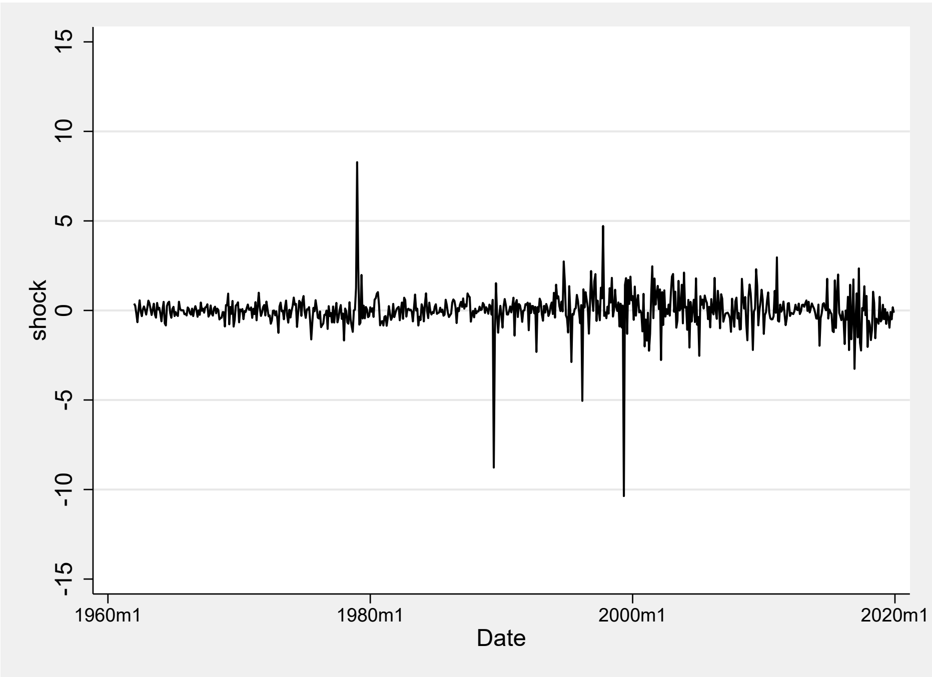
Appendix A. Supplementary materials

This section presents the details of supplementary materials about sub-sample estimates, robustness checks, VAR diagnostic statistics and data descriptions.

Sub-sample estimates

In Figure A.1, we first plot the evolution of the identified US-China political relation shock based on the SVAR model. Since our interest is US-China political relation shocks, there are no necessities to show the evolution of other shocks.

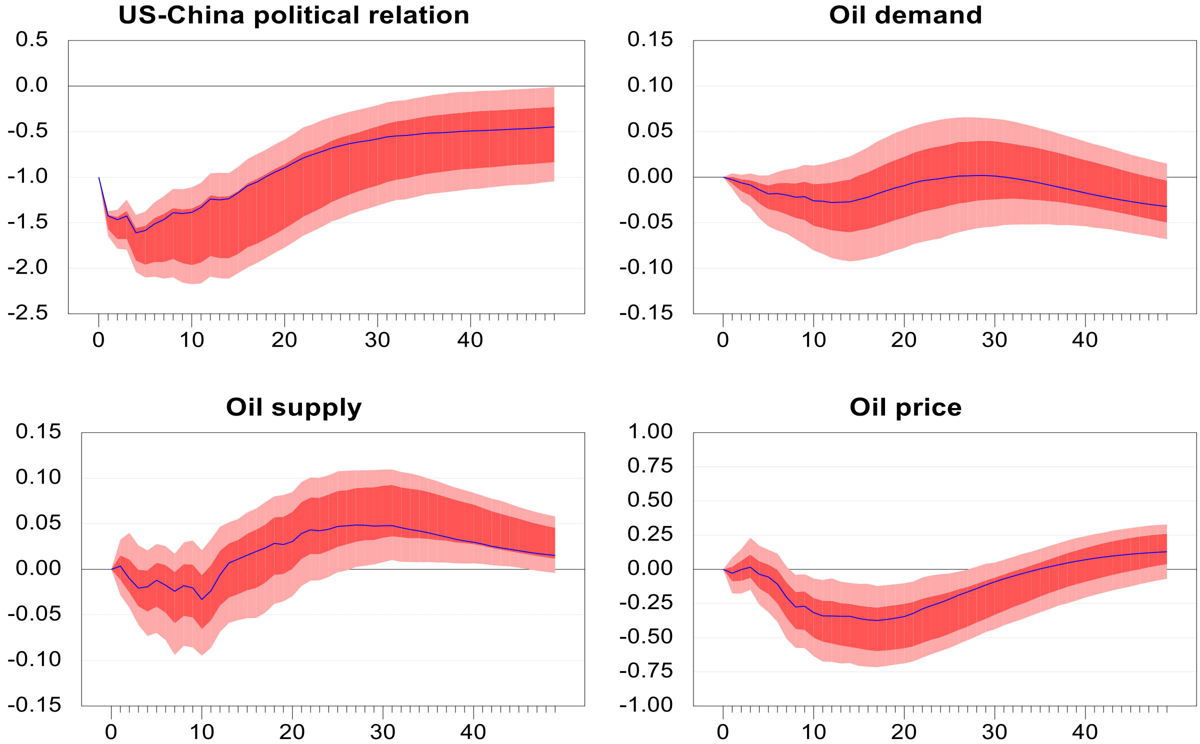
Figure A.1: Identified US-China political relation shocks



Note: The baseline SVAR model is specified as $y_t = [pri_t, pro_t, dem_t, rpo_t]'$ (variables expressed in logarithmic terms). It is estimated over the 1960M1-2019M12 period and includes 24 lags.

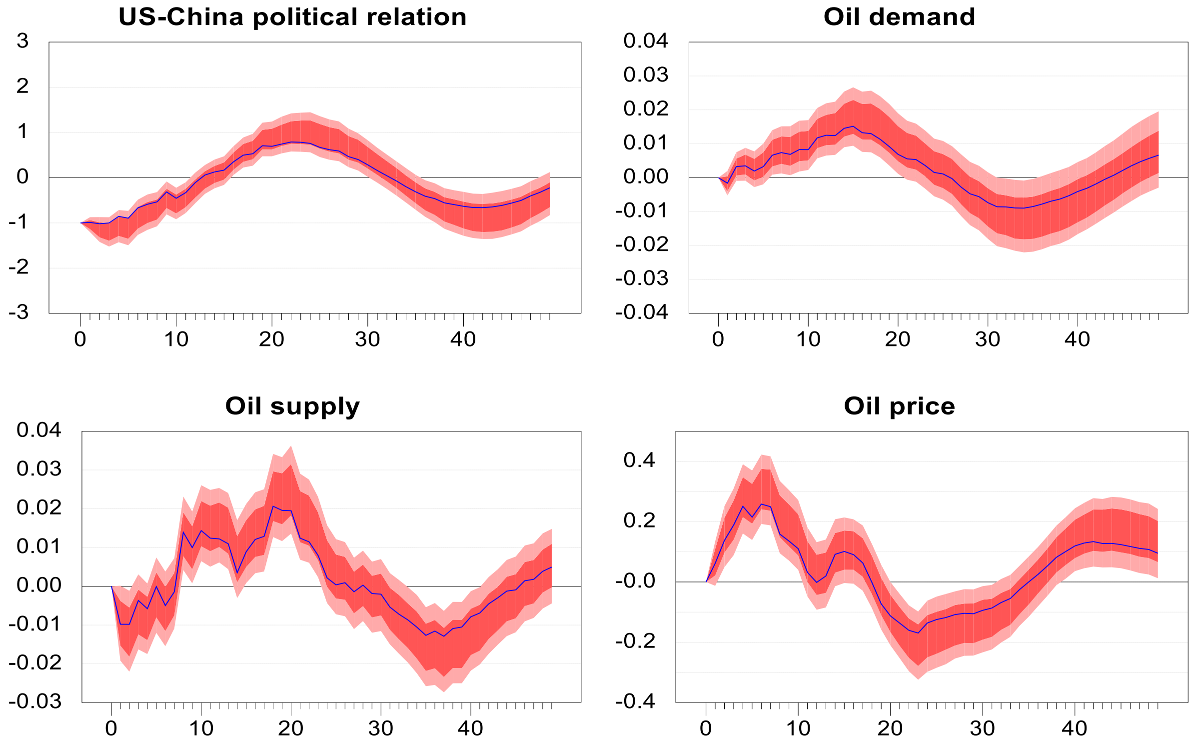
According to the results shown in the main text, we divide the whole sample into four sub-periods: recovery relationship period (1971M1-1988M12), fluctuating relationship period (1989M1-1999M12), common relationship period (2000M1-2010M12), and deteriorating relation period (2011M1 to 2019M12). The results are obtained under the same recursive identification scheme used in the baseline model. Due to limited number of observations, we change the lags order to 12, other than 24 lags used in the benchmark model. Since entering into WTO is milestone event in China's development, we further separate the whole sample before and after 2001. The impulse response horizons are determined to 50 accordingly. The results are available at Figures A.2, A.3, A.4, A.5, A.6 and A.7, respectively.

Figure A.2: Impulse responses in recovery relation



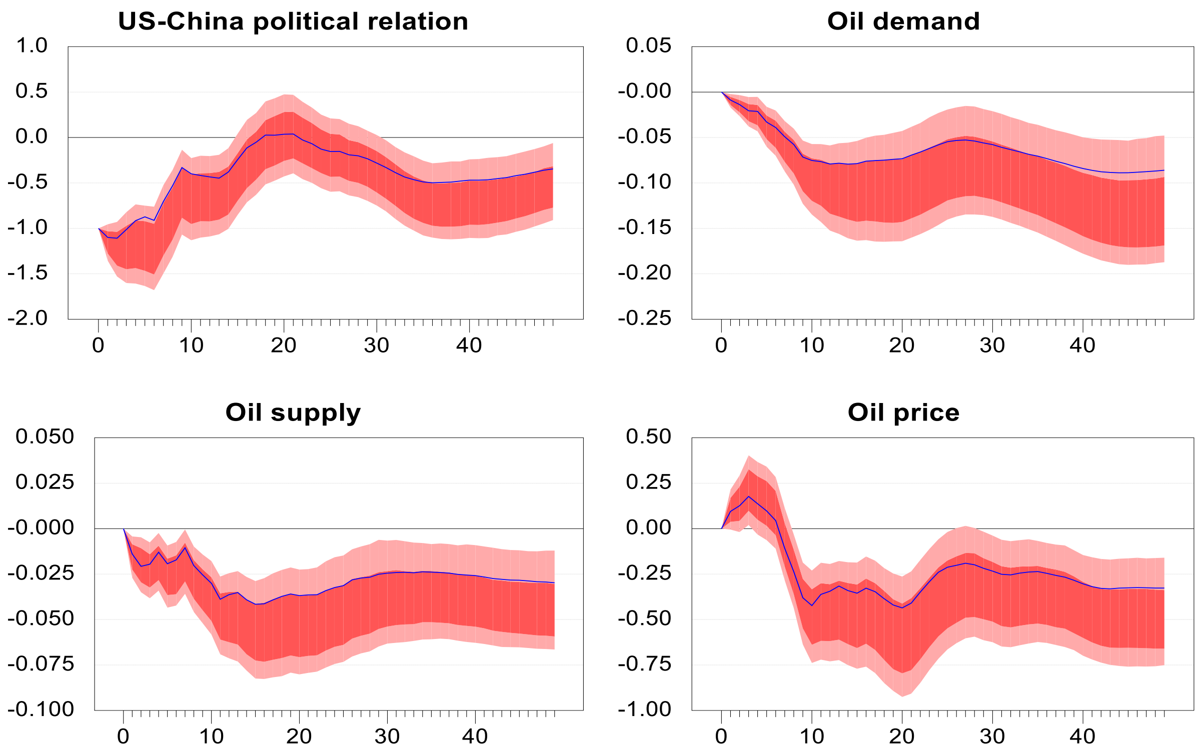
Note: The baseline SVAR model is estimated over the 1971M1-1988M12 period (variables expressed in logarithmic terms) and includes 12 lags. Impulse response horizons: 50 months. One and two standard error bands are displayed in red.

Figure A.3: Impulse responses in fluctuating relation



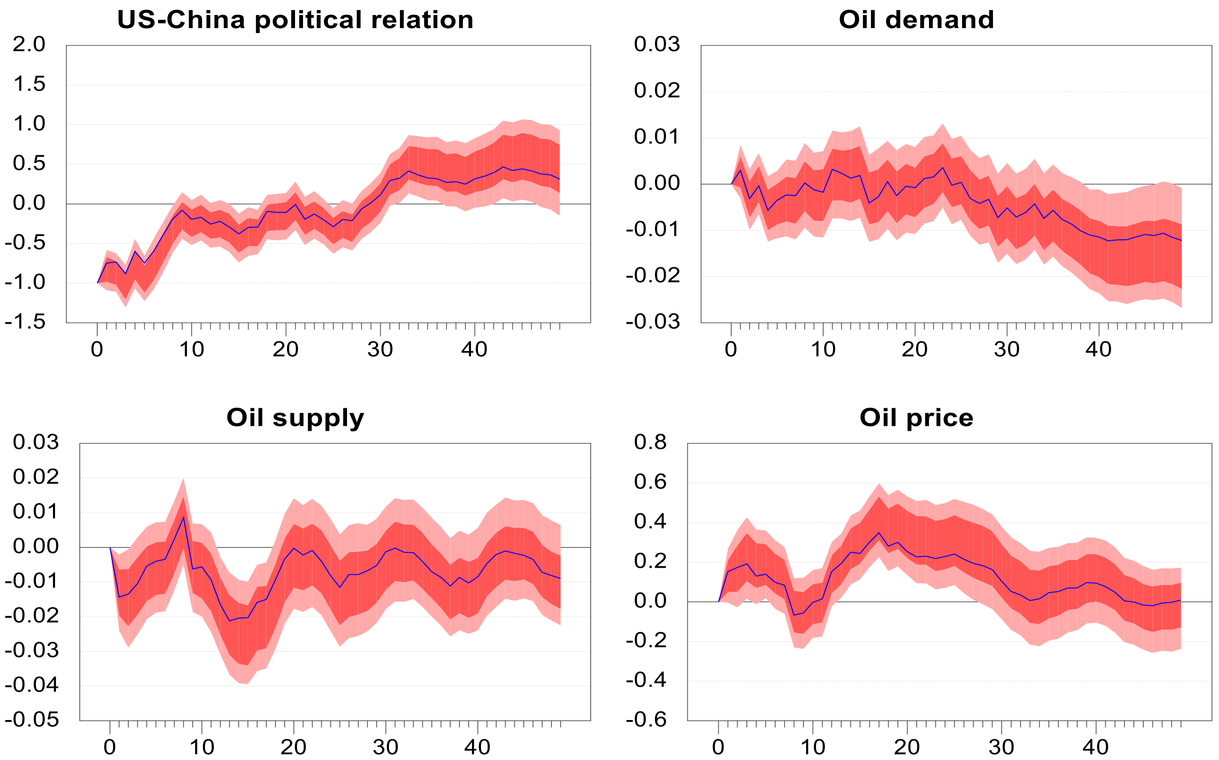
Note: The baseline SVAR model is estimated over the 1989M1-1999M12 period (variables expressed in logarithmic terms) and includes 12 lags. Impulse response horizons: 50 months. One and two standard error bands are displayed in red.

Figure A.4: Impulse responses in common relation



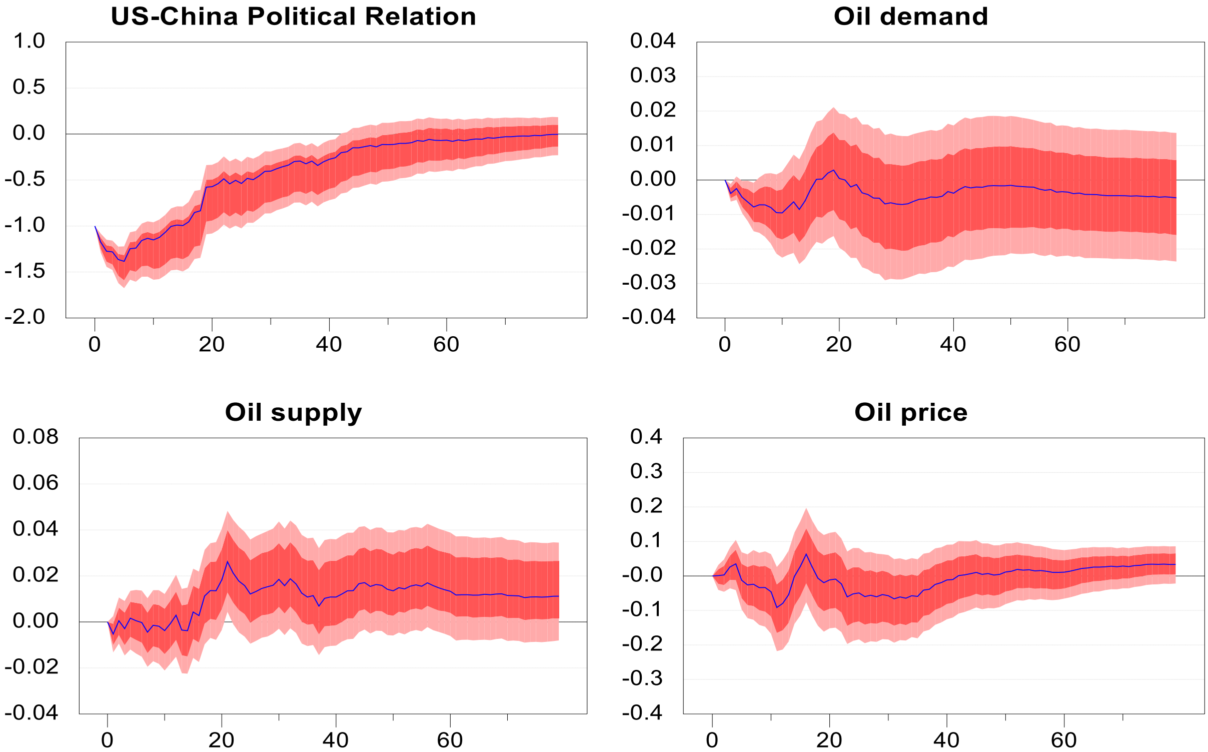
Note: The baseline SVAR model is estimated over the 2000M1-2010M12 period (variables expressed in logarithmic terms) and includes 12 lags. Impulse response horizons: 50 months. One and two standard error bands are displayed in red.

Figure A.5: Impulse responses in deteriorating relation



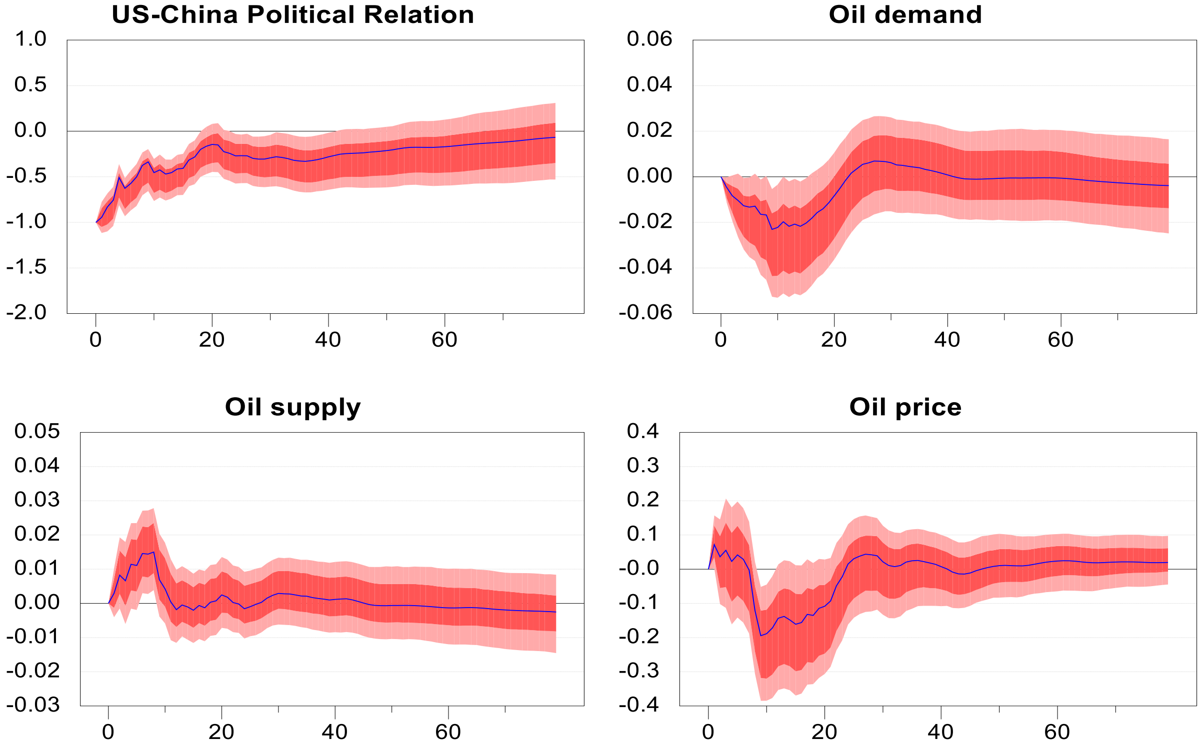
Note: The baseline SVAR model is estimated over the 2011M1-2019M12 period (variables expressed in logarithmic terms) and includes 12 lags. Impulse response horizons: 50 months. One and two standard error bands are displayed in red.

Figure A.6: Impulse responses before China entered into WTO



Note: The baseline SVAR model is estimated over the 1960M1-2001M12 period (variables expressed in logarithmic terms) and includes 12 lags. Impulse response horizons: 80 months. One and two standard error bands are displayed in red.

Figure A.7: Impulse responses after China entered into WTO

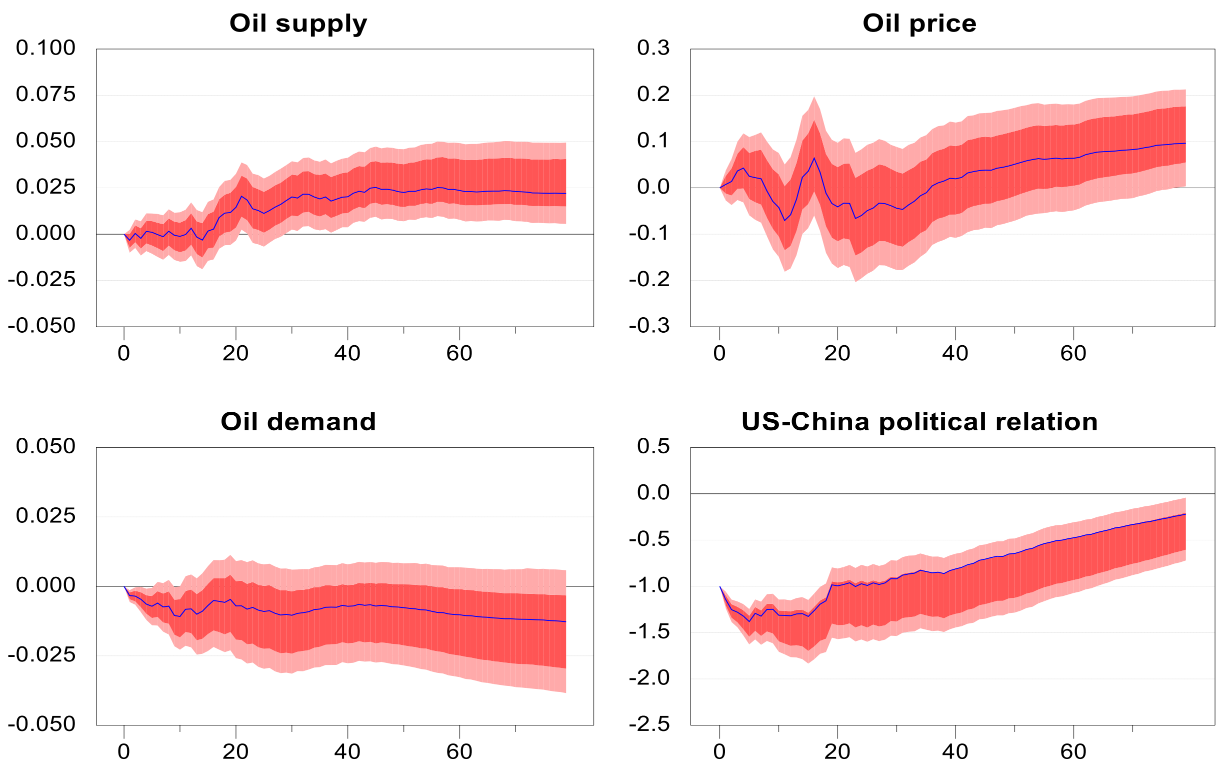


Note: The baseline SVAR model is estimated over the 2002M1-2019M12 period (variables expressed in logarithmic terms) and includes 12 lags. Impulse response horizons: 80 months. One and two standard error bands are displayed in red.

Robustness Checks

As it is well-known, the baseline results of the VAR are sensitive to variable ordering under a recursive identification scheme. Locating US-China PRI first indicates that it may immediately impact oil market variables, whereas the reverse effects take time. Some may argue that US-China political relations are at least affected by oil demand measured by world industrial production. Indeed, according to the constructing method proposed by Hamilton (2021), the industrial production of US and China has a large weight, which can significantly affect the evolution of the world industrial production index. Therefore, as a robustness check, we consider an alternative ordering by locating US-China political relation index at last. The results are displayed in Figure A.8.

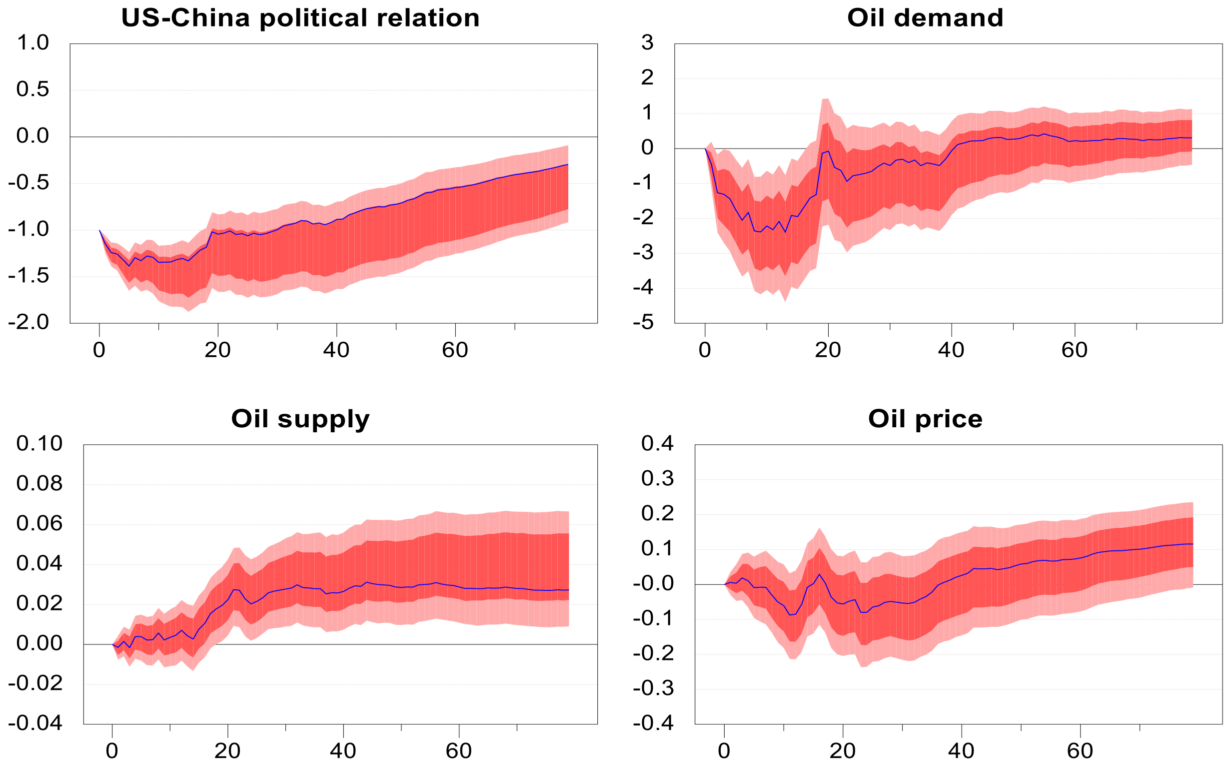
Figure A.8: Robustness against variable ordering



Note: The baseline SVAR model is estimated over the 1960M1-2019M12 period. It is specified as $y_t = [pro_t, dem_t, rpo_t, pri_t]'$ (variables expressed in logarithmic terms) and includes 24 lags. Impulse response horizons: 80 months. The shock is explained by a 1% decrease in $\log(pri_t + \sqrt{1 + pri_t^2})$. One and two standard error bands are displayed in red.

Another factor that potentially affects the robustness of the benchmark model is the choice of variables. Based on existing literature, there are two indices to describe world economic activity. Excluding the world industrial production (hereafter WIP) index of Hamilton (2021), Kilian (2009) proposed a world real economic activity (hereafter REA) index which is also widely

Figure A.9: Robustness against the proxy for world economic activity

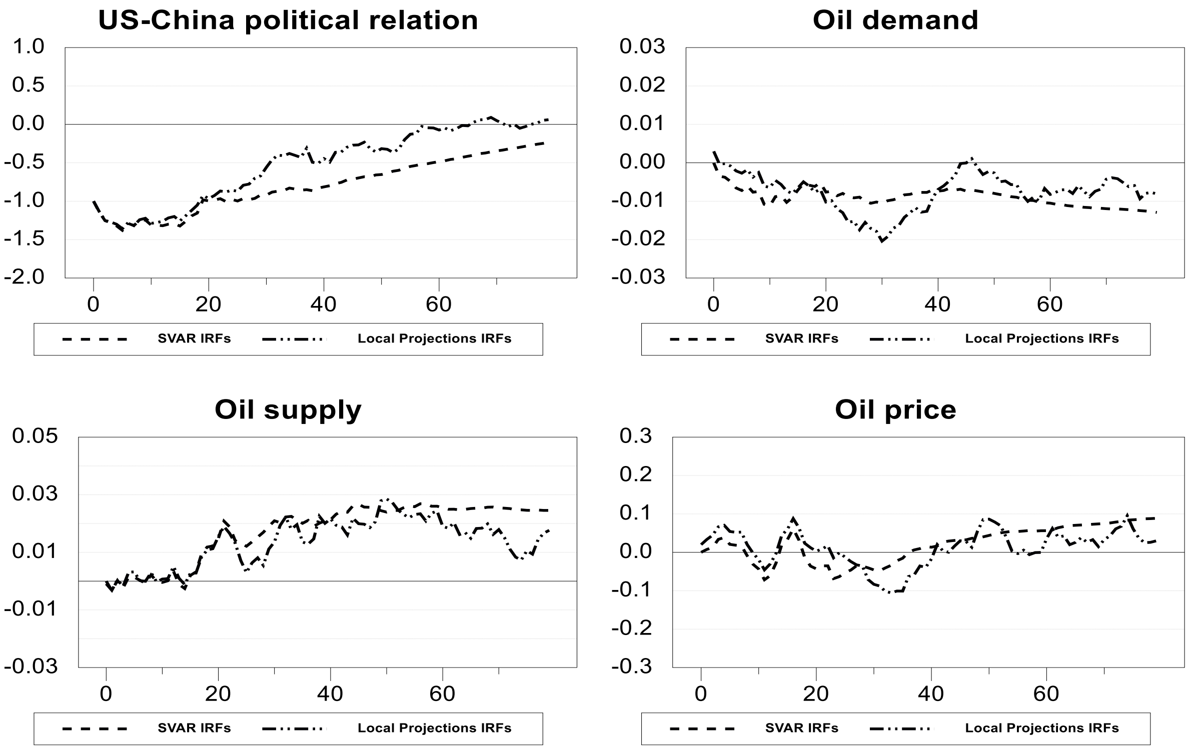


Note: The baseline SVAR model is estimated over the period from 1968M1 to 2019M12. It is specified as $y_t = [pro_t, dem_t, rpo_t, pri_t]'$ (variables expressed in logarithmic terms) and includes 24 lags. The world oil demand is represented by the world real economic activity index proposed by Kilian (2009). Impulse response horizons: 80 months. The shock is explained by a 1% decrease in $\log(pri_t + \sqrt{1 + pri_t^2})$. One and two standard error bands are displayed in red.

used. Therefore, we replace the WIP to REA for robustness checks. The results are shown in Figure A.9.

Last, Jordà (2005) first developed a local projection-based impulse response function. As suggested by Ramey (2016), the VAR-based impulse responses are more likely to be estimated under an iterated forecasting method, however the local projections are similar to direct forecasting. Plagborg-Møller and Wolf (2021) note that local projections and VAR should estimate the same impulse responses though observable differences are occurred in longer horizons. Based on recursive identification scheme, the IRFs of VAR and local projections are reported in Figure A.10.

Figure A.10: Local projections impulse responses



Note: The estimated model covers the period from 1960M1 to 2019M12, and includes 24 lags. Impulse response horizon: 80 months. The shock is explained by a 1% decrease in $\log(pri_t + \sqrt{1 + pri_t^2})$.