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Identifying oil supply news shocks and their effects on the global oil market

Zakaria Moussa & Arthur Thomas



Identifying oil supply news shocks and their effects on the global oil market*

ZAKARIA MOUSSA[†] ARTHUR THOMAS[‡]

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Abstract

This paper uses a Max-Share approach to identify oil supply news shocks within a noncausal VAR model of standard global oil market variables. News shocks are identified in a way that explain most of the movements in real oil price driven by global oil production over a long but finite time horizon. Our findings highlight the prominent role of expectations in propagating oil supply shocks. Negative oil supply news shocks cause a gradual and persistent decline in global oil production and global economic activity and a strong and immediate increase in the most forward-looking variables, namely real oil price and global oil stocks. Finally, news about future oil supply shortfalls has substantial consequences in macroeconomic variables leading to disruptions in both real and financial sectors.

JEL classification: C32, D84, E32, Q41, Q43

Keywords: Oil supply news shocks, Global oil market, Max-Share methodology, Non-fundamentalness, Structural Non-causal VAR

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[†]Nantes University, LEMNA, France, zakaria.moussa@univ-nantes.fr

[‡]Paris Dauphine University - PSL, UMR CNRS 8007, LEDa, France, arthur.thomas@dauphine.psl.eu

1 Introduction

The global oil market has undergone multiple turbulence, generating either demand or supply shocks, resulting in high oil price volatility. The recent US Energy Information Administration's (EIA) projections¹ of global oil supply matching demand through 2050 under multiple scenarios depending on the long-term availability of total recoverable resources, reflect the complexity of assessing future oil supply, as it is a multidimensional subject with multiple influencing factors. Future global oil supply is primarily impacted by the technical, economic and political viability of accessing oil resources and is also heavily influenced by geopolitical considerations. Moreover, and from a historical perspective, a new era for oil has begun, with geopolitical fractures on energy and climate becoming increasingly visible, adding to the uncertainties and risks surrounding the future global oil supply.

Oil production capacity investment decisions are faced with major environmental constraints both physically and in terms of energy-transition policy commitments that aim to develop and expand low-emissions energy instead. The first point relates to the fact that most of the new giant field discoveries were made in the middle of the last century and, despite steady improvements in exploration technology, new discoveries are fewer, smaller, and more difficult to find and exploit.² The second point is of particular concern as avoiding dangerous climate change is inconsistent with expanding the supply of both conventional and non-conventional crude oil. Investments in fossil fuels have already dropped sharply following the fall of the oil price in 2014-15 because of the poor returns that oil companies were generating. This reduced investment has persisted since 2014, but is now a result of decisions made by companies and financial organisations that have set goals and plans to scale it down. This implies that there are few new resources under development and a diminishing stock of discovered resources available for development. These factors, which tend to be persistent, are likely to change agents' expectations regarding future oil supply, thus impacting both the global oil market and global economic

¹For more details about different scenarios, see the International Energy Outlook 2022 (IEO2022).

²According to the EIA's International Energy Outlook 2022, "New oil resources discovered in 2021 were at their lowest level since the 1930s."

variables.

A large body of the business cycle literature establishes that the anticipated change in future productivity, that is, the news shock, constitutes an important driver of the business cycle (Beaudry and Portier, 2006; Barsky and Sims, 2011; Forni et al., 2014a; Beaudry and Portier, 2014; Kurmann and Sims, 2021, among others). Motivated by this literature, this paper aims to analyse the impact of policy decisions and company behaviour towards clean energy transitions, the agent's view of geopolitical (in)stability and also information about new field discoveries or lack thereof in the global oil supply and thereby the global energy market and the economy. More precisely, we refer to oil supply news shocks as exogenous changes that alter the information set on which agents base their expectations of the future global oil supply.

Only a few studies identify and measure the impact of oil supply news shocks.³ A related study by Arezki et al. (2017) focuses on capturing news shocks using a quasi-natural experiment approach by exploiting the natural timing lags between giant oil and gas discoveries and the subsequent output increase. The authors argue that, although policy decisions and oil prices may influence exploration decisions, the effective timing of discoveries remains exogenous given the uncertainty that characterizes oil and gas exploration. This important contribution sheds light on the important role of the anticipated component of the oil supply shock as a source of macroeconomic fluctuations.

This paper mainly differs from Arezki et al. (2017) in two perspectives. The first difference relies on the nature of the news shock. Instead of identifying oil supply news shocks at a country level concerning giant discoveries only, the focus of our study is on identifying the oil supply news shock at the global level thereby can capturing different expectations about the future oil supply. More precisely, using the four-variable VAR specification (Kilian and Murphy, 2014; Baumeister and Hamilton, 2019), we identify

³This "news shock" terminology is to be distinguished from the exogenous shock identified using the news component of either announcement of macroeconomic data releases (Andersen et al., 2003; Ramey, 2011; Kilian and Hicks, 2013, among others) or that used in the monetary policy literature exploiting central bank announcements to measure monetary policy shocks (Kuttner, 2001; Romer and Romer, 2004; Gürkaynak et al., 2005; Bernanke and Kuttner, 2005; Paul, 2020, among others), applied recently by Känzig (2021) on the OPEC announcements to identify an oil supply news shock.

the oil supply news shock as a shock that explains most of the movements in the real oil price driven by global oil production over a long but finite time horizon, which has an immediate effect on forward-looking variables. This identified oil supply news shock reflects, therefore, a wider range of information on oil supply. Examples include not only large oil discoveries (Arezki et al., 2017) and climate change policy decisions, but also new production technology which takes time to translate into oil production,⁴ the political stability of oil-producing countries, or a shock related to the Organization of Petroleum Exporting Countries (OPEC) announcements (Känzig, 2021; Degasperis et al., 2021). Second, and importantly, although the direct measure of Arezki et al. (2017)'s news shock is very relevant it does not allow us to assess the extent to which oil market and macroeconomic variable fluctuations can be attributed to the oil supply news shock, which is the precise aim of our work. We accordingly employ a different oil supply news identification strategy by exploiting the involvement of richer structures in a structural vector autoregression (SVAR) model.

In a recent contribution that is closely related to our work, Gambetti and Moretti (2017a) use a different VAR-based scheme to identify oil supply news shocks which are divided into "noise" and "true" components.⁵ Using the Kilian (2009)'s three-specification model as a benchmark, Gambetti and Moretti (2017a) show that identifying a news shock within a structural VAR model inevitably leads to a non-fundamentalness representation. The authors address the non-fundamentalness problem by using Blaschke matrices as in Forni et al. (2017b) and Forni et al. (2017a). However, this approach requires considerable restrictions which cannot be fully provided by economic theory.⁶ In this paper, we instead

⁴Global cumulative crude oil reserves are revised by either adding new discoveries or revisions of reserve estimates for existing fields, which is also called reserve growth. This latter component can be mainly due to new enhanced extraction technology or better geological understanding and is of major importance. As shown in Sorrell et al. (2009) using data spanning from 2000 and 2007, reserve growth accounts for about three-quarters of global cumulative reserve revisions, knowing that in addition the share of newly discovered fields is also expected to decrease in the future.

⁵Distinguishing between the "noise" and "true" components in the news shock is beyond the scope of this paper. With our identification technique, the captured news shock corresponds to the "true" news shock in Gambetti's terminology as it is identified by maximizing the share of the variance of the real oil price due to global oil production over a long horizon. Our shock is thus supposed to have an immediate and persistent effect on the two forward-looking variables and also on oil production with a certain time lag, whereas a "noise" shock has no impact on oil production and only a short-lived effect on the oil price.

⁶For more details on this point see also Kilian and Lütkepohl (2017), chapter 17 and Mertens and Ravn (2010).

use a noncausal SVAR (NC-SVAR) methodology (Lanne and Saikkonen, 2013; Lanne and Luoto, 2016; Gouriéroux and Jasiak, 2017, 2022; Davis and Song, 2020; Nelimarkka, 2017b,a) which has the advantage of allowing the identified shocks to be nonfundamental by construction. We show, thus, how the nonfundamental representation, due to the oil supply news shock identification, can be mapped in an NC-VAR and how impulse response functions can be derived within this model.

Moreover, as discussed in Barsky and Kilian (2004), there are a number of reasons for volatility changes in the oil market for the sample period starting in the 1970s and ending in the new millennium. In a recent work, using a sample data spanning January 1984 to December 2019 and employing a time-invariant VAR model, Bruns and Lütkepohl (2023) show that heteroskedasticity alters the transmission of oil market shocks. Thus, the NC-VAR model is appropriate for analyzing the transmission of the oil supply news shock when using the same sample period as it allows for heteroskedasticity. The non-causal process can not only feature heavy-tailed marginals and conditional heteroscedastic effects but it can also have been found convenient for modelling locally explosive phenomena such as speculative bubbles (Lanne and Saikkonen, 2013; Gouriéroux and Zakoïan, 2017; Gouriéroux and Jasiak, 2018; Cavaliere et al., 2020; Cubadda et al., 2023, among others). This allows us to include the COVID-19 pandemic event in our analysis. Such an event is particularly instructive as to the validity of our oil supply shock identification strategy. As the unprecedented sharp drop in oil prices at the onset of the COVID-19 pandemic in March-April 2020 was entirely due to an unexpectedly large drop in global oil demand⁷, an oil supply news shock should be positive without being able to explain the drop in oil prices.

Our analysis proceeds in two steps. First, once the oil supply news shock has been identified using the above method, we study its effect on oil market variables within what we call the baseline model, i.e. the NC-VAR model using the four standard variables in oil market structural models, namely global oil production, global economic activity, oil stocks and the real oil price. We detect a gradual and persistent diffusion of oil supply

⁷According to IEA 2020, the global oil demand was down 30% compared to a year ago. IEA Oil Market Report - April 2020, <https://www.iea.org/reports/oil-market-report-april-2020>

news shocks to global oil production and global real activity and a strong and immediate effects on the most forward-looking variables, namely the real oil price and global oil stocks. In particular, the global oil stock reaction, being consistent with a reaction to an anticipated oil supply shock, gives further support to our shock identification strategy. Moreover, relying on the historical decomposition exercise we take a fresh look at the overall importance of oil supply expectation shocks in driving real oil price fluctuations in recent decades, we provide, as in [Känzig \(2021\)](#)⁸, evidence that an oil supply news shock seems to contribute quite significantly to the real price at particular episodes. Interestingly, the cumulative effect of the news shocks to the real oil price around the COVID-19 pandemic not only confirms the prevailing view that the sharp fall in oil prices over this period is entirely due to exogenous demand shocks, but also further validates our oil supply news shock identification.

Second, we investigate the oil supply news shock effects on global and US economies. Our results suggest that oil supply news shocks have substantial consequences in macroeconomic variables, leading to disruptions in both real and financial sectors. In particular, news about future oil supply shortfalls can have simultaneously inflationary and recessionary effects, confirming the prominent role of the expectation channel.

The rest of the paper is structured as follows. In the next section, we provide a simple stylised model to illustrate how nonfundamentalness arises in the presence of lagged shock effects of oil supply on observables. This provides a theoretical background to the empirical investigations that follow. Section 3 describes the noncausal VAR model and outlines its estimation. Section 4 presents the estimation results. Finally, section 5 concludes and discusses avenues for future research.

⁸It is worth noting that it is somewhat difficult to interpret the results of [Känzig \(2021\)](#) due to the fact that his (OPEC) oil supply news shock could be tangled by a demand component, as explained in [Degasperi et al. \(2021\)](#), and due to the problems associated with constructing of the monthly proxy variable from a daily surprise series as demonstrated in [Kilian \(2023\)](#)

2 Stylised model of the oil market with news shocks

In this section, we consider a stylized model of rational expectations for the global oil market that explains oil price movements driven by the expected future oil supply. We show then how nonfundamentalness arises out of the presence of lagged shock effects of oil supply on the oil price.

Assuming that the dynamic of global oil production evolves as an AR(1) as follows:

$$q_t = \alpha q_{t-1} + \epsilon_t^u + \epsilon_{t-l}^a \quad (1)$$

where $|\alpha| < 1$, ϵ_{t-l}^a is an anticipated shock that affects oil production with a l -period lag. For the rest, let us take $l = 2$ as an example.⁹ While ϵ_t^u is an unanticipated or "surprise" shock, with the two types of shocks evolving a strong white noise process. This rational expectation model à la [Gambetti and Moretti \(2017a\)](#) based on the three-variable specification model of [Kilian \(2009\)](#) considers the price as the only forward-looking variable containing information that agents receive about possible changes in future oil production.¹⁰ Suppose then that the oil price p_t , is determined by:

$$p_t = \beta \mathbb{E}_t(p_{t+1}) + q_t \quad (2)$$

where $\mathbb{E}_t[\cdot]$ denotes the conditional expectation with respect to the information set containing the history of $\{q_t, p_t, \epsilon_t^a, \epsilon_t^u\}$. We assume that the news shock is orthogonal to the surprise shock in all leads and lags ($\forall h, h', \mathbb{E}_t(\epsilon_{t+h}^u | \epsilon_{t+h'}^a) = 0$), reflecting the fact that agents have already adapted their behaviour at time t by anticipating the future effects of ϵ_{t-2}^a on oil supply. In other words, ϵ_{t-2}^a comes into the information set on which agents form their expectations for q_{t+2} , while the econometrician is only able to see the impact

⁹We use $l = 2$ here for simplicity, but l must be greater than or equal to 1 for non-fundamentalness to be treated within the NC-VAR framework. If l is equal to zero, solutions exist to treat nonfundamentalness in the NC-VARMA framework where non-causality is located in the MA part and not in the AR part ([Gouriéroux et al., 2020](#)).

¹⁰As explained earlier in the introduction, unlike [Gambetti and Moretti \(2017a\)](#), we regard the signal received by the agent is being composed only of "true" news and not tainted by noise. This is because our identification strategy allows us to isolate the news shock without having to distinguish between the "noise" and "true" components of the signal. This point will be discussed in detail in the next section.

of it two periods later.

We assume p_t as a forward-looking solution which is the sum of the expected oil supply q_t

$$p_t = \sum_{j=0}^{\infty} \beta^j \mathbb{E}_t(q_{t+j}), \quad \beta < 1 \quad (3)$$

Substituting the expression for $\mathbb{E}_t(q_{t+j})$ into (1) and using $\mathbb{E}_t(\epsilon_{t+j}^u) = 0, \forall j \geq 0$ and $\mathbb{E}_t(\epsilon_t^u | \epsilon_t^a) = 0$ leads to:

$$p_t = \frac{1}{1 - \alpha\beta}(q_{t-1} + \epsilon_{t-2}^a) + \frac{\beta}{1 - \alpha\beta} [\beta\epsilon_t^a + \epsilon_{t-1}^a] \quad (4)$$

The structural moving average representation of $(q_t, p_t)'$ is:

$$\begin{bmatrix} q_t \\ p_t \end{bmatrix} = \begin{bmatrix} \alpha & 0 \\ \frac{\alpha}{1-\alpha\beta} & 0 \end{bmatrix} \begin{bmatrix} q_{t-1} \\ p_{t-1} \end{bmatrix} + \underbrace{\begin{bmatrix} 1 & L^2 \\ 0 & \frac{\beta^2}{1-\alpha\beta} + \frac{1}{1-\alpha\beta}\beta L + \frac{1}{1-\alpha\beta}L^2 \end{bmatrix}}_{=A(L)} \begin{bmatrix} \epsilon_t^u \\ \epsilon_t^a \end{bmatrix} \quad (5)$$

where $(q_t, p_t)'$ -fundamental process requires that $|A(L)| \neq 0$. $|A(z)| = \frac{1}{1-\alpha\beta}(\beta^2 + \beta z + z^2)$ this polynomials as two roots, $z_{+,-} = \beta \left(\frac{1 \pm \sqrt{3}i}{2} \right)$, with the modulus of z_- below one and that of z_+ greater than one. Therefore, the process still has a nonfundamental MA representation due to roots in the unit circle. In other words, once the news shock contributes to q_t , the observables suffer from nonfundamentalness and thus no causal VAR representation of $(q_t, p_t)'$ exists for structural shocks (Gambetti and Moretti, 2017a; Kilian and Lütkepohl, 2017; Gouriéroux et al., 2020; Nelimarkka, 2017a, among others).

In order to address the nonfundamentalness issue, equation (4) can be rewritten by substituting ϵ_t^a with its value from equation (1):

$$p_t = \alpha q_{t-1} + \beta q_{t+1} + \frac{\beta}{1 - \alpha\beta} \beta q_{t+2} + \epsilon_{t-2}^a \quad (6)$$

Then, the dynamics of (q_t, p_t) can be mapped into a noncausal VAR(1,2) using (1) and

(6):

$$\underbrace{\left(I_2 - \begin{bmatrix} \alpha & 0 \\ \alpha & 0 \end{bmatrix} L \right)}_{\Pi(L)} \underbrace{\left(I_2 - \begin{bmatrix} 0 & 0 \\ \beta & 0 \end{bmatrix} L^{-1} + \begin{bmatrix} 0 & 0 \\ \frac{\beta^2}{1-\alpha\beta} & 0 \end{bmatrix} L^{-2} \right)}_{\Phi(L)} \begin{bmatrix} q_t \\ p_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^u \\ \epsilon_{t-2}^a \end{bmatrix} \quad (7)$$

where $\Pi(L)$ and $\Phi(L)$ correspond to the causal, with one lag, and the noncausal, with two leads, polynomials, respectively. Importantly, as these latter matrices are invertible, p_t has a two-sided MA representation. Then, and as shown by [Nelmarkka \(2017a\)](#) who uses roughly the same equation (6), impulse response coefficients generated from the noncausal representation (7) perfectly match that generated from the theoretical model (1)-(2) to the structural shocks ϵ_t^u and ϵ_{t-2}^a .

3 Non-Causal VAR

Consider the following Bayesian NC-VAR(r,s) model developed by [Lanne and Luoto \(2016\)](#), where y_t is generated by:

$$\Pi(L) \Phi(L^{-1}) y_t = \epsilon_t \quad (8)$$

where the causal polynomial $\Pi(L) = I_n - \Pi_1 L - \dots - \Pi_r L^r$, the non-causal polynomial $\Phi(L^{-1}) = I_n - \Phi_1 L^{-1} - \dots - \Phi_s L^{-s}$ and ϵ_t is a sequence of independent, identically distributed (continuous) random vectors with zero mean and a finite positive definite covariance matrix. L is a backward shift operator. The stationarity of the process and the existence of a two-sided MA representation are guaranteed by the assumption that the matrix polynomials $\Pi(L)$ and $\Phi(z)$, $\forall z \in \mathbf{C}$ have their zeroes outside the unit disc, i.e. $\det \Pi(z) \neq 0$ for $|z| \leq 1$ and $\det \Phi(z) \neq 0$ for $|z| \leq 1$.¹¹

¹¹It is assumed that y_t can be written in such a way that its past and future parts can be separated. This makes the model a particular case within the general framework of [Gouriéroux et al. \(2020\)](#).

We can then write the process $\Phi(L^{-1})y_t$ as a one-sided MA representation:

$$\Phi(L^{-1})y_t = \Pi(L)^{-1}\epsilon_t = M(L)\epsilon_t = \sum_{j=0}^{\infty} M_j \epsilon_{t-j} \quad (9)$$

It is easier to highlight the future-dependant component by rewriting equation (9):

$$y_t = \phi_1 y_{t+1} + \dots + \phi_s y_{t+s} + \sum_{j=0}^{\infty} M_j \epsilon_{t-j} \quad (10)$$

where lead terms ϕ_i are different from zero, indicating that y_t is nonfundamental, as lags are insufficient to recover the structural shocks.

Finally, a two-sided MA representation of equation (9) can be written as follows:

$$y_t = \sum_{-\infty}^{\infty} \Psi_j \epsilon_{t-j}, \quad \forall z, \quad \Psi(z) = \Phi(z^{-1})^{-1} \Pi(z)^{-1} \quad (11)$$

It is important to emphasize that the error term of the model ϵ_t is necessarily non-Gaussian, otherwise estimating NC-VAR(r,s) becomes equivalent to estimating a causal VAR($r+s$). This hypothesis is also crucial because it allows us to identify structural shocks.¹² More precisely, a multivariate t -distribution is assigned to ϵ_t as follows:

$$\epsilon_t = \omega_t^{-\frac{1}{2}} \eta_t, \quad (12)$$

where $\eta_t \sim N(0, \Sigma)$ and $\lambda \omega_t$ is χ_λ^2 -distributed, and $\omega_t^{-\frac{1}{2}}$ is the scalar volatility factor with λ degree-of-freedom. Consequently, variables in y_t are characterised by fat tails for a smaller λ or tend towards normality when λ is substantially high.

3.1 Oil supply news shock identification

To implement our identification strategy, the reduced-form NC-VAR specification described in the previous section consists of four endogenous variables that are standard in the oil market empirical literature, in this order: global oil production, global real

¹²Structural shocks have recently been shown to be identifiable under the assumption of strong white noise in the error terms (See e.g. [Gouriéroux et al., 2020](#); [Gourieroux and Jasiak, 2022](#)).

economic activity, real oil price, and global oil inventories (see [Baumeister and Hamilton, 2019](#)). We build on the extensive econometric literature on the identification of news shocks based on the Max-Share methodology ([Beaudry and Portier, 2006](#); [Barsky and Sims, 2011](#); [Forni et al., 2014a](#); [Beaudry and Portier, 2014](#); [Kurmman and Sims, 2021](#), among others). More precisely, we use the identification procedure of [Barsky and Sims \(2011\)](#) maximizing the share of variance of real oil price at a finite horizon that captures new information about global oil production instantaneously and anticipates variations in oil production that will take place. This strategy has two principal advantages. First, it allows us to isolate the forward-looking component of the real oil price which is captured solely by global oil production from that captured by future oil demand and changes in global oil inventories. Second, this strategy also makes it possible to isolate a "true" news shock from a "noise" shock, according to the terminology of [Gambetti and Moretti \(2017b\)](#), in the sense that it induces persistent change in real oil prices.

To identify the oil supply news shock, i.e. the anticipated structural ϵ_t^u from (1) some restrictions are needed. First, we assume the production to be backward-looking to its own dynamics by restricting its leads to zero ($\forall j > 0, k > 0 \Phi_k(1, j) = 0$ in equation (8)). Second, global oil production is ordered first in the NC-VAR system, being also backward-looking with respect to the other variables in the system, particularly to oil price and global oil inventories, which are the most forward-looking variables. Finally, standard identification restrictions on the reduced-form error terms from the NC-VAR implied by equation (12) are imposed:

$$\epsilon_t = \omega_t^{-\frac{1}{2}} \eta_t = \bar{B} \bar{u}_t \quad (13)$$

where the t -distributed structural shock vector, $\bar{u}_t = \omega_t^{-\frac{1}{2}} u_t^* = [\bar{u}_{1,t} \cdots \bar{u}_{k,t}]' \sim t_\lambda(I_k)$ is a product of two latent factors, a k -dimensional vector of Gaussian shocks $u_t^* \sim N(0, I_k)$ and the volatility term $\omega_t^{-\frac{1}{2}}$. Denote by W in equation (13) an orthogonal ($k \times k$) matrix with w_i on its i th column, and \tilde{A} a Cholesky factor such that $\Sigma = \tilde{A} \tilde{A}'$. The rotation matrix \bar{B} is thus now given by $\bar{B} = \tilde{A} W$. By using the impulse function response to a

unit shock of the two-sided MA representation of the NC-VAR model from (11), we define the share of the forecast error variance of variable i attributable to structural shock j over a finite time horizon $[H_1, H_2]$ as follows:

$$\Omega_{i,j}^{[H_1, H_2]} = \frac{\mathbb{E} \left[\sum_{\tau=H_1}^{H_2} e_i' \Psi_\tau \tilde{A} w_j \bar{u}_{j,t-\tau} \bar{u}_{j,t-\tau}' w_j' \tilde{A}' \Psi_\tau' e_i \right]}{\mathbb{E} \left[\sum_{\tau=H_1}^{H_2} e_i' \Psi_\tau \Sigma \Psi_\tau' e_i \right]} = \frac{\sum_{\tau=H_1}^{H_2} e_i' \Psi_\tau \tilde{A} w_j w_j' \tilde{A}' \Psi_\tau' e_i}{\sum_{\tau=-\infty}^{\infty} e_i' \Psi_\tau \Sigma \Psi_\tau' e_i} \quad (14)$$

with the vector $e_i = [0 \cdots 1 \cdots 0]'$ having one in its i th element.

We assume, as in Barsky and Sims (2011), that the share of the variance in global oil production due to its innovations ($\Omega_{1,1}$) is invariant at all h . In a multivariate VAR setting, it is unreasonable to expect this restriction to apply for all horizons, we therefore choose the impact matrix that satisfies this restriction over a finite truncation horizon between H_1 and H_2 . We discuss in the next section our choice of the finite truncation horizons H_1 and H_2 . This medium-run identification strategy is essentially the same as the *Max-Share* identification proposed by Uhlig (2004) and Francis et al. (2014) to measure news shocks and consists of solving for the second column of the impact matrix w_1 such that $\gamma_1 = \tilde{A} w_1$.

$$\gamma_1 = \operatorname{argmax}_{\tau=H_1}^{H_2} \Omega_{3,1}(\tau) \quad (15)$$

with the following constraints (a) $\gamma_1' \gamma_1 = 1$, (b) $\gamma_1(1, 1) = 0$ and (c) $\tilde{A}(1, j) \forall j > 1$. This optimisation problem differs from the Barsky and Sims (2011) identification procedure as we maximize the share of the forecast error variance of the real oil price attributable to global oil production, which has a prime position in the system. Constraint (a) ensures that γ_1 is orthogonal to ϵ_t the reduce-form error term and also that $\mathbb{E}[\omega_1 | \epsilon_t] = 0$ as in (1). The (b) and (c) ensure a no-contemporaneous impact on the level of global oil production.

3.2 Data and estimation

Estimation data span the period between January 1974 and November 2022.¹³ We estimate a monthly NC-VAR model using the above standard global oil market endogenous variables (our baseline model) :

$$y_t = [\Delta prod_t, \Delta wip_t, rpo_t, \Delta inv_t],$$

where $\Delta prod_t$ denotes the percentage change in global oil production, obtained from the US Energy Information Administration’s Monthly Energy Review, wip_t is the growth rate of the world industrial production proxied by the OECD+6 industrial production proposed by [Baumeister and Hamilton \(2019\)](#),¹⁴ rpo_t denotes the real oil price, expressed in logarithm) measured by the refiner acquisition cost (RAC) for imported crude oil and deflated by the US consumer price index and Δinv_t is the proxy for the percentage change in global oil stocks as constructed in [Kilian and Murphy \(2014\)](#).¹⁵ It should be noted that this variable is very useful for our analysis not only because it solves the informational deficit of the VAR system as already explained in [Kilian and Murphy \(2014\)](#), but also because it helps judge the validity of our oil news shock. When agents anticipate, for example, a future oil shortfall, they increase their oil stock level, whereas an unanticipated oil supply shortage has an opposite effect on the stock as agents who did not anticipate this drop in oil supply will have to draw on their reserves.

The NC-VAR(r,s) models are estimated by employing a lag and lead length of 12 to capture the full dynamic of observables. As clearly explained in [Nelmarkka \(2017a\)](#), this choice enables observables to fully capture oil supply news innovations when the NC-VAR(r,s) reduces to a standard autoregressive VAR in the absence of any non-fundamentalness issues. Moreover, the noncausal part will have a rich structure if a

¹³More details about the data and their sources can be found in Table A in Appendix ??

¹⁴The choice between different measures of global real economic activity is a subject of extensive debate. See [Funashima \(2020\)](#) and [Baumeister and Guérin \(2021\)](#) among other recent papers on this point.

¹⁵Our baseline regression uses a similar specification as in [Baumeister and Hamilton \(2019\)](#) and [Kilian and Murphy \(2014\)](#), except for the global oil stocks variable which is expressed in logarithms before differentiating it. This is for ease of comparison with related empirical studies, particularly with [Känzig \(2021\)](#) and [Degasperi et al. \(2021\)](#).

nonfundamentalness problem arises.

Moreover, the NC-VAR is estimated with Bayesian methods as described in [Lanne and Luoto \(2016\)](#).¹⁶ To define priors for the NC-VAR dynamic parameters, we follow [Nelmarkka \(2017a\)](#) and impose a standard Minnesota prior. Specifically, hyperparameters that control the tightness of the priors on leads and lags are chosen so that variable dynamics are driven primarily by lag coefficients, as lead coefficients are shrunk more heavily towards zero.¹⁷ This helps to attain the unimodality when posterior distributions are more likely to be multimodal when estimating the NC-VAR model ([Lanne and Luoto, 2016](#)). Then, a numerical Bayesian approach (Gibbs sampling) is used to estimate NC-VAR models. Results are based on 10,000 posterior draws obtained after a burn-in length of 50,000 draws.

4 Empirical Results

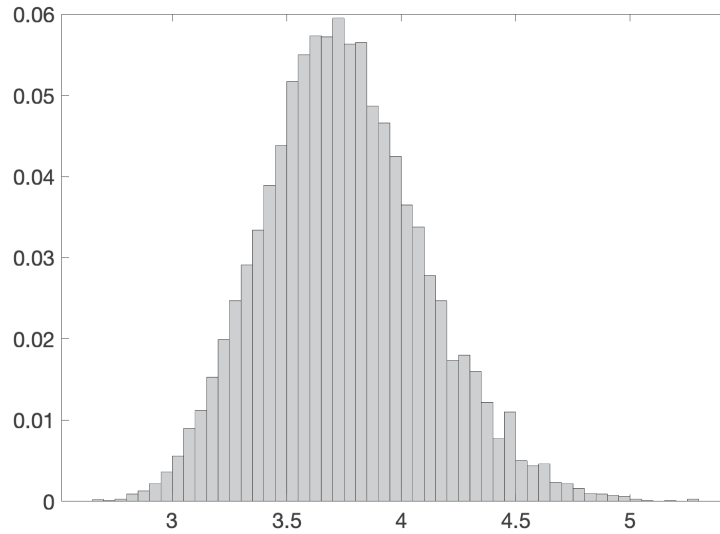
In this section, we present the results of the impulse response function analysis of the oil supply news shock. Recall that in this particular case, the key advantage of the NC-VAR model lies in providing an attractive solution to the underlying problem of nonfundamentalness.

Our first step is to check whether a nonfundamental representation is supported by the data. As pointed out by [Lanne and Saikkonen \(2013\)](#), [Gourieroux and Jasiak \(2017\)](#) and [Davis and Song \(2020\)](#), the non-Gaussian assumption of the error term is a necessary and sufficient condition for uniqueness and it is thus required in the NC-VAR estimation. [Figure 1](#) plots the estimated marginal posterior density of the degrees of freedom (DOF) λ . The histogram indicates strong evidence in favour of fat tails as the posterior density

¹⁶Alternative approaches estimating the NC-VAR include either the ML method as in [Lanne and Saikkonen \(2013\)](#) or the semi-parametric method as in [Gourieroux and Jasiak \(2017\)](#). However, the Bayesian approach has the advantage of allowing the coefficient estimates to be shrunk towards zero. In addition, this is particularly useful for avoiding the multimodality problem, as discussed further below.

¹⁷When estimating the baseline model, we set overall tightness of prior values to 0.5 and decay parameter prior values to 1. For the tightness parameters for the lag coefficients, we choose 0.2, and for the lead coefficient 0.15. For more details about prior information, refer to Appendix pages 28-29 in [Nelmarkka \(2017a\)](#).

Figure 1: Posterior density of DOF parameter λ



Notes: grey bars represent the frequency distribution of the DOF parameters from the 4-variable NC-VAR(12,12).

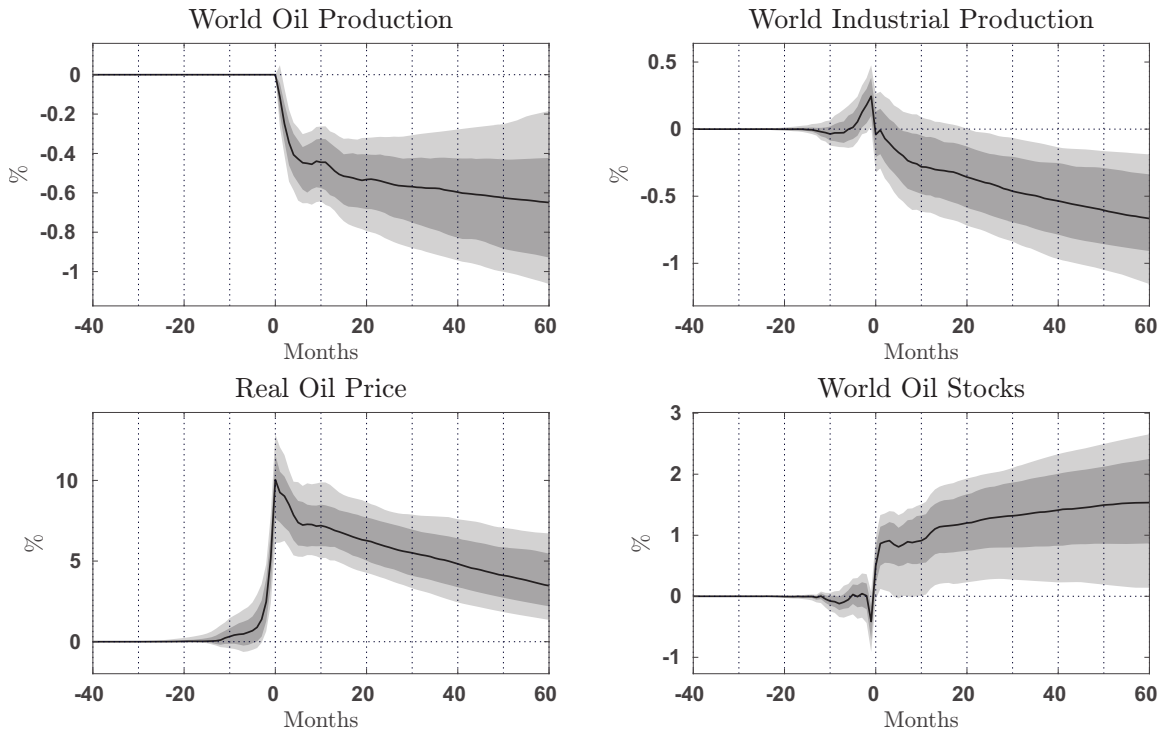
is centred around 3.75 degrees of freedom; with the probability of λ being greater than 6 at almost nil.¹⁸ Similarly, distributions of the residuals estimated by causal BVAR and densities of the observed variables, shown in Figure 6 in Appendix B, point to non-normality. This suggests that the normality assumption is inappropriate, confirming the choice of multivariate t -distribution for the error term, which makes it possible to identify a unique NC-VAR(r,s) specification. This therefore indicates that capturing the non-causal component is crucial for the data studied here.

4.1 How does the oil supply news shock diffuse to the oil market variables?

Figure 2 shows the cumulative impulse responses to an oil supply news shock which is normalized to represent an oil supply shortfall that leads to a 10% increase in the real oil price on impact. Light and dark shaded bands represent 90 and 68% posterior credible sets, respectively. In the noncausal model context, the left side of the x-axis is added to represent responses related to the lead terms of the MA representation. The news shock is

¹⁸As in Nelimarkka (2017a), we set the prior mean of λ to 10. With a very low posterior mean of λ (less than 5), data dominate the assumed prior mean of λ .

Figure 2: Impulse-response functions to the oil supply news shock



Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model from [Baumeister and Hamilton \(2019\)](#). The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

measured with a truncation horizon of $[H_1 = -20, H_2 = 20]$ but similar results, reported in [Appendix C](#), are obtained with shorter and longer truncation horizons.

Whereas the lack of reaction of global oil production at its leads and on impact is by construction due to our news shock identification, the reaction of global real economic activity remains insignificant for the same period. But relevant to our analysis, there is clear evidence from the estimated impulse responses that a substantial proportion of the oil supply reduction triggered by the news shock can be anticipated before the drop materialises. The median response estimates from the noncausal model suggest large and significant responses of noncausal components for the most forward-looking variables, namely the real oil price.

As for the causal part, we detect an expected zero impact of global oil production and a gradual but persistent significant decrease of about 0.4% after five months before reaching a maximum of around 0.6% after roughly two-and-a-half years. The dynamic

of the response is consistent with the idea of a progressive diffusion of oil supply news shocks to global oil production. However, it is noteworthy that the speed of the dynamics is more consistent with a news shock effect linked to geopolitical events and/or OPEC announcements (Känzig, 2021), than events linked to the discovery of new oilfields or the development of new exploration technologies, whose effect on oil production takes longer to materialize (Arezki et al., 2017). Global real activity also contracts permanently but with a longer delay, reaching a trough of about -0.6% after two-and-a-half years from impact. It should be noted that the slow diffusion of the recessionary effect of the future oil supply shortfall can be explained by the fact that this shock has a different impact on net oil importing and exporting countries at different periods. A similar result was reached by Käuzig (2021), although it is somewhat more difficult to interpret the results in his exercise due to the fact that his (OPEC) oil supply news shock could be tangled by a demand component, as explained in Degasperis et al. (2021) and due to problems related to the construction of the monthly proxy variable from a daily surprise series as shown in Kilian (2023).

Our estimates show a persistent positive effect of the oil supply news shock on both real oil prices and global oil stocks. The real oil price remains above the baseline, at around 5%, in a quite persistent way and global oil stocks jump up on impact peaking at 1% and persistently continues to increase. As they are the most forward-looking, real oil prices and global oil stocks respond instantaneously to news shocks, peaking much earlier than global oil production and the global real activity. Very importantly, as the direction of the global stock reaction is crucial to our analysis, our estimates provide further proof of the relevance of our oil supply news shock identification scheme. The global oil stock reaction is in line with conventional wisdom: namely when market players expect a future oil shortfall, they increase their current demand so as to build up stocks as a precautionary measure.

Overall, findings generalize and corroborate the results in Arezki et al. (2017) and Käuzig (2021) that also detect a gradual diffusion of oil supply news shocks to global oil production and global real activity and a strong and immediate effect on the most

forward-looking variables, like real oil prices and global oil stocks.

Sensitivity checks: A number of checks are performed to test the robustness of the main results. First, as already mentioned, we show that our results are robust to different truncation windows and to different H_1 and H_2 , values used to identify news shocks in the baseline model (see Figures in Appendix C). Also, Figure 12 in Appendix C shows that our results are also robust to closely-related alternative shock identifications suggested by Forni et al. (2014b) when the news shock maximally explains changes in the real oil price in the long run at a particular horizon (60-months horizon).¹⁹ Second, figures 13 and 14 in Appendix E provide evidence that using shorter estimation samples produces results that are very similar to the benchmark case in that a negative shock to oil supply expectations leads to a gradual and persistent decrease in oil production and real activity and a sharp increase in the oil price and global oil stocks. However, it is noteworthy that, while global real activity reacts significantly when the estimation sample period is February 1974 to December 1989 (Figures 13), its reaction becomes less significant when considering the sample spanning the period January 1990 to November 2022 (Figures 14). This result could be explained by the declining oil consumption as a share of gross domestic output over time (see for example Blanchard and Gali, 2007). Our estimates therefore show that our results are robust to sample size and do not lead to puzzles, a problem pointed out by Degasperi et al. (2021) when estimating the effects of the oil supply news shock of Känzig (2021) for shorter samples. Finally, as we show in the next section, our results are robust to the inclusion of additional macroeconomic and financial variables in the system.

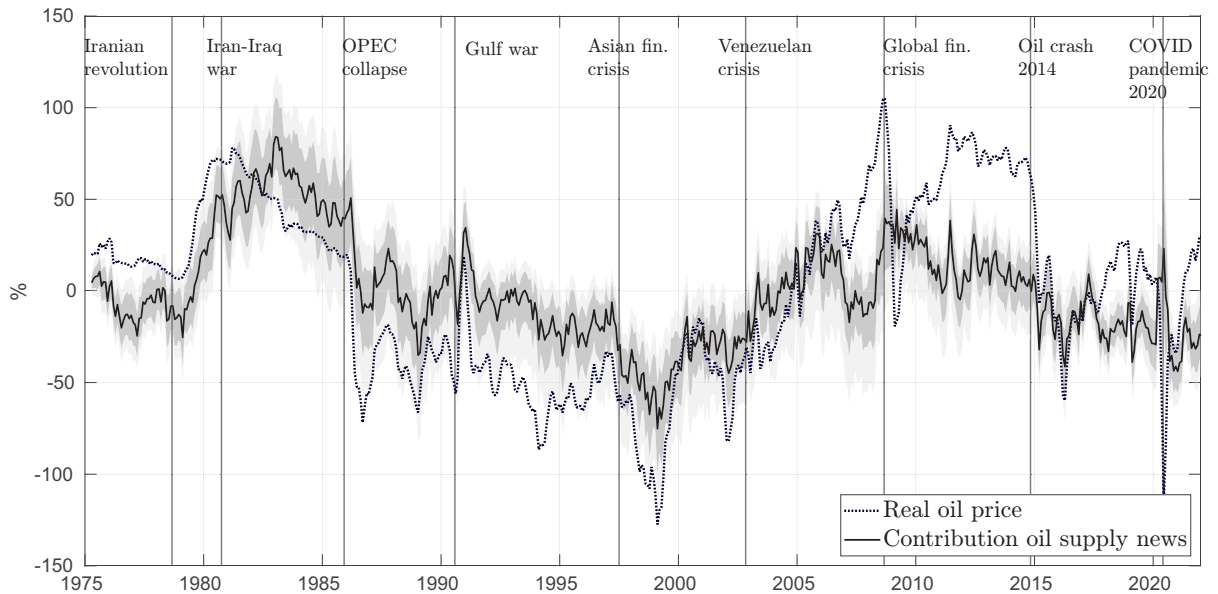
4.2 How much the oil supply news shock explains real oil price fluctuations in different historical episodes?

The question of the origin of oil price fluctuations remains central to the global oil market analysis (Kilian, 2009; Juvenal and Petrella, 2015; Baumeister and Kilian, 2016; Baumeister and Hamilton, 2019; Caldara et al., 2019; Känzig, 2021, among others). In this section

¹⁹We retain five years as the horizon at which the news shock has a maximal effect, but results are roughly the same when setting the horizon to 2 and 3 years. Results are available upon request.

we rely on the historical decomposition exercise to get a sense of the overall importance of oil supply expectation shocks in driving real oil price fluctuations over the last few decades, and particularly for specific historical episodes. Details on the historical decomposition calculation in the case of an NC-VAR are presented in Appendix D.

Figure 3: Contribution of oil supply news shocks to real oil price fluctuations



Notes: The solid black line is the average contribution of the oil supply news shock to the real crude oil price from the NC-VAR(12,12). Light grey shaded regions are the 90% credible sets.

Figure 3 illustrates the cumulative effect of the oil supply news shocks together with actual the real oil price for the period 1975-2022. Two key findings emerge from Figure 3. First, results clearly show that oil supply news shocks have consistent overall contribution to historical variations in the real oil price, with the exception of a few episodes where shocks are muted. Second, it is noteworthy that, despite the notable difference in the shock identification strategies adopted, our results are fairly close to that of Känzig (2021) whose oil news shocks are exclusively linked to OPEC announcements. This underscores the dominant position of the coalition and its significant influence on the crude oil supply in the global market and its capacity to exert control over the price of oil. Having said that, as in our study agents' expectations can be based on multiple information from outside OPEC announcements, periods of large contribution of our oil supply news shocks may also reflect geopolitical, oil discoveries and exploration information, but fewer energy-transition policy commitment considerations, at least for the period considered.

More precisely and taking particular historical episodes, while the contribution of oil supply news shocks to the sharp increase in the oil price following the Iranian revolution in the late 1970s has been relatively modest, the collapse on the real price of oil in late 1986 is largely attributed to higher oil supply expectations. During the period 1980-1985, the non-OPEC production increased by about 15% (Gately, 1986). These increases were made by a large number of relatively small producers whose exploration and development activities had been stimulated by the price rises of the 1970s, and who had grown sufficiently in size and incurred sufficient fixed costs not to be discouraged by the price declines of the early 1980s. Thus, the contribution of expectations of an increase in the oil supply due to new discoveries is at least as important as the expectation of OPEC's collapse, when Saudi Arabia abandoned production constraints (Känzig, 2021).

Thereafter, oil supply news shocks seem to contribute quite significantly to the real price variations for the period 1986-1990. Despite its modest contribution to the spike in real prices around the Gulf War in 1991 and the absence of its contribution for the subsequent period until 1994, news shocks seem to be better able to explain the trend reversal initiated in late 1994 and ending with the onset of the Asian financial crisis. Following Iraq's invasion, higher level of Core-OPEC's²⁰ output were expected to offset most of the loss in crude oil supply (see Verleger (1990) for more information about the 1990 oil crisis). Then, abrupt price decreases following the Asian crisis and its recovery since then until 2001 were largely attributed to the oil supply news shocks.

As found in Käuzig (2021), oil supply news shocks have not been able to explain the surge of the real oil price between 2003 and mid-2008, however, their contribution to explaining the subsequent recovery until 2011 is not negligible. That is, in the wake of the global financial crisis, OPEC member countries announced an oil production cut of the equivalent of 5% of daily world demand to counter the fall in prices and demand.

What happened in the global oil market at the onset of the COVID-19 pandemic in March and April 2020 is a key milestone in the sense that the unprecedented sharp

²⁰Core OPEC consisted at this period of Saudi Arabia and its immediate neighbors, namely Kuwait, the United Arab Emirates, and Qatar.

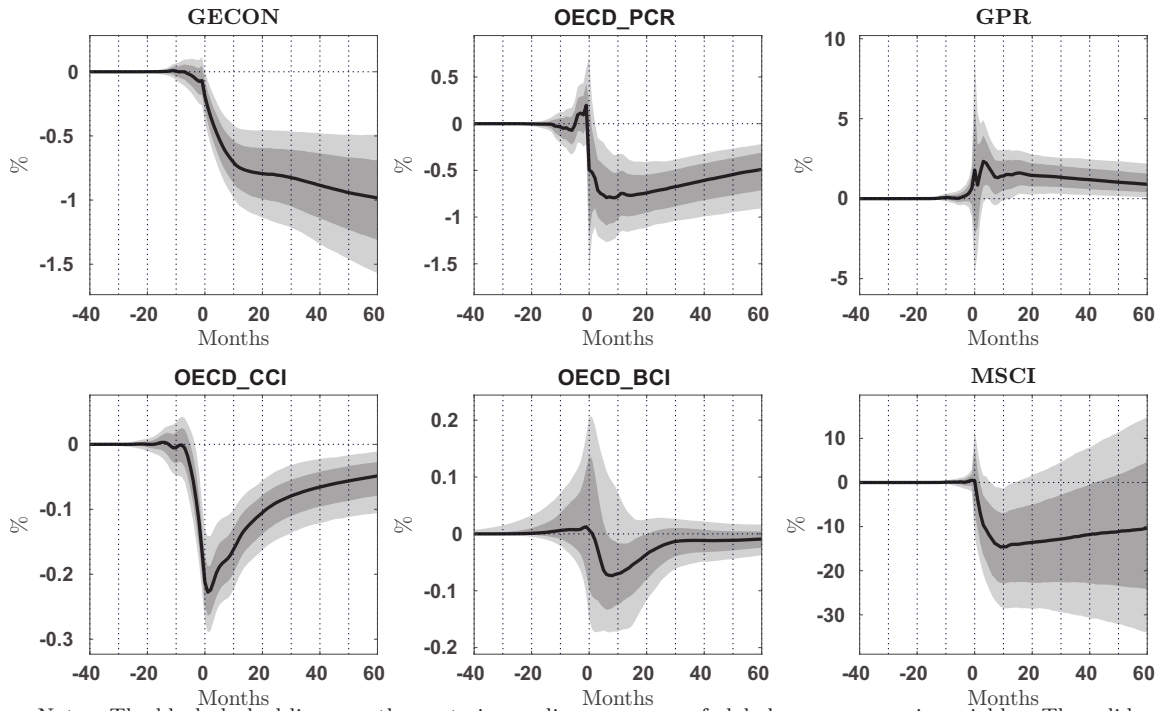
decline in the price of oil was entirely due to an unexpectedly significant drop in global oil demand. This event allows us to check the validity of our shock identification in that oil supply news shocks should be positive, without accounting for the fall in oil prices. Historical decompositions confirm not only the prevailing view that the sharp fall in oil prices over this period is entirely due to exogenous demand shocks, but also the positive expected sign of an oil supply news shock. Despite its increase, the oil supply news shock turns out not to be able to explain the fall that occurred during this period. Finally, the contribution of oil supply news shocks proves, however, to be meaningful to explain the oil price recovery since the pandemic when oil producer countries were expected to cut their production in response to the demand decline.

4.3 What impact does a news shock have on global and US macroeconomic variables?

The macroeconomic consequences of a negative exogenous oil supply shock have been extensively debated, both theoretically and empirically, particularly in the context of the debate on the role of oil shocks in generating stagflation ([Hamilton, 1983, 2009](#); [Gisser and Goodwin, 1986](#); [Barsky and Kilian, 2002, 2004](#), among others). However, there are fewer studies on the effect of oil supply expectation shocks on macroeconomic variables ([Arezki et al., 2017](#); [Känzig, 2021](#); [Degasperi et al., 2021](#)). The evidence provided in Section 3.1 indicates that oil supply expectation shocks significantly affect oil market variables, especially the real price of oil. In this section, we first examine how this shock affects the global economy more broadly, before looking at the US variables.

Figure 4 displays the response of the global macroeconomic variables, namely the Global Economic Conditions (GECON) indicator of [Baumeister et al. \(2022\)](#), the geopolitical risk index (GPR) developed by [Caldara and Iacoviello \(2022\)](#), the OECD consumer confidence index (OECD_CCI), the OECD business confidence index (OECD_BCI), the OECD passenger car registrations (OECD_PCR), and as a financial index, the world stock price index (MSCI). The additional variables are included in the system, one vari-

Figure 4: Reactions of macroeconomic variables to a news shock

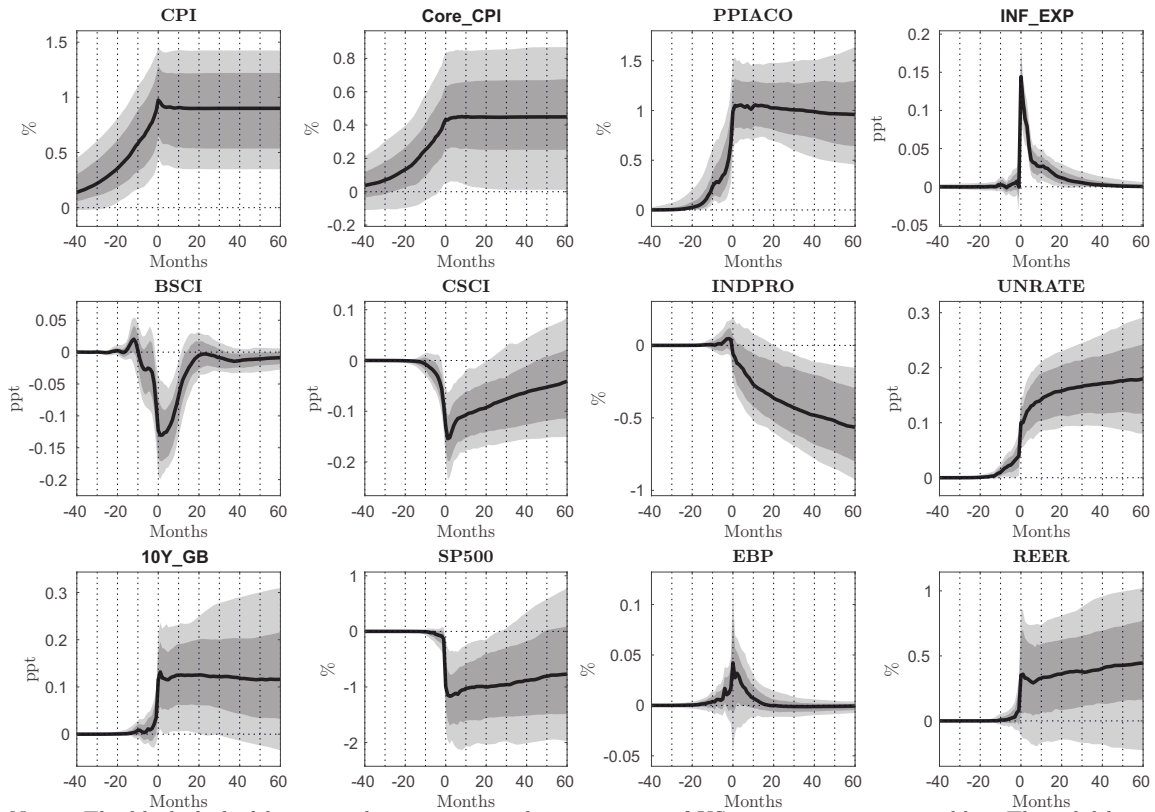


Notes: The black dashed lines are the posterior median responses of global macroeconomic variables. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 and 68 % credible sets of the NC-VAR(12,12). Because of non-causality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

able at a time in order to avoid estimating a large model.

It is interesting to note that all global variables, except for the OECD business confidence index react significantly to the negative oil supply news shock. The GECON does not respond to the shock on impact but it gradually falls, reaching its peak of -0.6% after about three years and the estimated effect is highly persistent. We observe virtually the same reaction from the passenger car registration highlighting the automobile industry sector's exposure to oil supply news shocks. The geopolitical risk index increases significantly on impact by about 2% and stabilizes persistently at roughly the same level. This results shows the bi-directional causality between the geopolitical risk and oil supply expectations. A sharp decline is observed in the consumer confidence index which starts from the leads terms, reaches around -0.2% on impact to steadily stabilizes at -0.05%. The reaction of business confidence is negative but remains statistically non-significant. The stock price index (MSCI) does not react on impact but falls sharply by 10 percentage point and the effects of the shock veers to be insignificant within 15 months.

Figure 5: Reactions of US macroeconomic variables to a news shock



Notes: The black dashed lines are the posterior median responses of US macroeconomics variables. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

As for the effect of the oil supply news shock on the US economy, Figure 5 shows the reactions of US macroeconomic variables²¹ belonging to different categories spanning multiple dimensions of the US economy. It shows that all price variables increase sharply on impact. More precisely, the consumer price index for all urban consumers and all items (CPI) reacts significantly from its leads and reaches its pick of around 1% on impact and and persistently stabilizes at this level. The consumer price index excluding food and energy (Core CPI), however, does not react significantly from its leads and increases at a lesser magnitude of 0.4% to stabilize persistently. The producer price index starts to react at its leads and sharply increases reaching its peak of 1% on impact with the estimated effect displaying high persistence. Inflation expectation also increases significantly on impact, but with a short-lived effect. The US industrial production (INDPRO) and

²¹All variables come from the FRED database, except for the excess bond premium which is an updated version of the measure of Gilchrist and Zakrajšek (2012) available from the Fed website: <https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html>

the unemployment rate (UNRATE) do not react during the anticipatory lags. While industrial production reacts significantly to the shock with about twenty months lags, with a pattern similar to that of global economic activity, the unemployment rate increases significantly on impact with a persistent effect reaching 0.2 percentage point. It is noteworthy that these findings, which are in line with those of [Känzig \(2021\)](#), show that news about future oil supply shortfalls, which is associated with an increase in the oil price, can simultaneously have inflationary and recessionary effects, generating negative co-movement between CPI and the real activity, leading to stagflation. This shock, therefore, presents serious challenges for central bankers, due to the negative inflation-output trade-off.

Not surprisingly, the deterioration in business and consumer confidence goes in tandem with the ensuing deterioration in economic activity. Business and consumer confidence indices decrease on impact, falling by around 0.15 point respectively, starting to recover and return to their initial values after about ten and twenty months respectively. The long-term interest rate (10Y GB) does not react during the anticipatory lags and but peaks on impact with persistence at a maximum of about 0.12 basis points. The stock price index (SP500) exhibits a sharp reduction that reach maxima of around 1%. It is interesting to note that stock prices react differently to anticipated and unanticipated oil supply shocks. While, as shown in [Kilian and Park \(2009\)](#), in the context of a linear VAR model,²² unanticipated oil supply shocks have a negligible effect on stock prices, our results indicate that when shocks are anticipated stock prices do react significantly. This result is in line with those in [Känzig \(2021\)](#) and [Degasperi et al. \(2021\)](#). Finally, the excess bond premium (EBP) and the real effective exchange rate (REER) do not respond significantly to the oil supply news shock. However, the sign of the exchange rate reaction, indicating the appreciation of the dollar, is in contrast to [Känzig \(2021\)](#)'s findings and most of the empirical studies on the relationship between oil shocks and the exchange rate, but in line with [Degasperi et al. \(2021\)](#) which shows that all domestic currencies

²²It is worth noting that, according to [Mumtaz et al. \(2018\)](#), there is evidence of nonlinear stock price dynamics in response to unanticipated oil supply shocks. [Mumtaz et al. \(2018\)](#) show that the stock price reaction can be significant during the regime, characterised by low oil inflation.

depreciate against the dollar as a response to an oil supply news shock. As a net importer, the United States should see its currency depreciate following a supply shock that raises oil prices, but this effect may be distorted by the fact that oil is essentially traded in US dollars.

In summary, these results suggest oil supply news shocks have substantial consequences in macroeconomic variables leading to disruptions in both real and financial sectors. In particular, news about future oil supply shortfalls can simultaneously have inflationary and recessionary effects.

5 Conclusion

We used a new empirical strategy to identify oil supply news shocks in order to analyse their effects on both oil market variables and macroeconomic variables. For this purpose, we employed a model that takes into account forward-looking behaviour, to avoid the nonfundamentalness problem that can arise when using a VAR model. Up to now, the nonfundamentalness issue regarding the global oil market has been addressed either by augmenting small-scale VAR models with additional variables or latent factors, or by using external instruments or proxies to provide a more credible identification scheme. We dealt with this issue by employing noncausal VAR (NC-VAR) to model a standard global oil market including global oil production, global economic activity, global oil stock and the real oil price plus global and US macroeconomic variables, so as to analyse the oil supply news shock effects.

Our oil supply news shock is identified by maximizing the share of oil price variance explained by global oil production. We showed, then, that nonfundamental representation is supported by the data, thus confirming noncausal VAR as an option to deal with information deficiency when identifying expectation shocks within the global oil market. We further showed that our identified oil supply news shock is anticipated by forward-looking variables before it materialises, highlighting the prominent role of expectations in propagating the shock. A negative oil supply news shock results in a gradual but significantly

persistent decrease of global oil production, and global economic activity. However, the two most forward-looking variables, namely the real oil price and global oil stocks increase instantaneously and peak much earlier than the other variables. Importantly, the positive reaction of the global oil stock provides further proof of the validity of our identification strategy, as stocks should increase following an anticipated negative oil supply news shock.

Moreover, using global and US macroeconomic variables, there is evidence that a news shock regarding oil supply shortfalls has macroeconomic consequences in both real and financial sectors. Notably, oil supply shortfall expectations have both inflationary and recessionary effects.

A first promising extension of our empirical evidence is to build and estimate a DSGE model for the global oil market à la [Bornstein et al. \(2017\)](#). The use of a DSGE model would improve our understanding of the transmission of the oil supply news shock to global oil variables and the macroeconomy. Secondly, while NC-VAR proves promising in dealing with the nonfundamentalness problem, the issue of identifying structural shocks within it remains challenging. The lack of development of structural NC-VAR is unfortunate, preventing analysis of the effect of further interesting shocks using a credible identification scheme. Future research could usefully explore the impact of an oil demand shock on the global oil market and macroeconomic variables.

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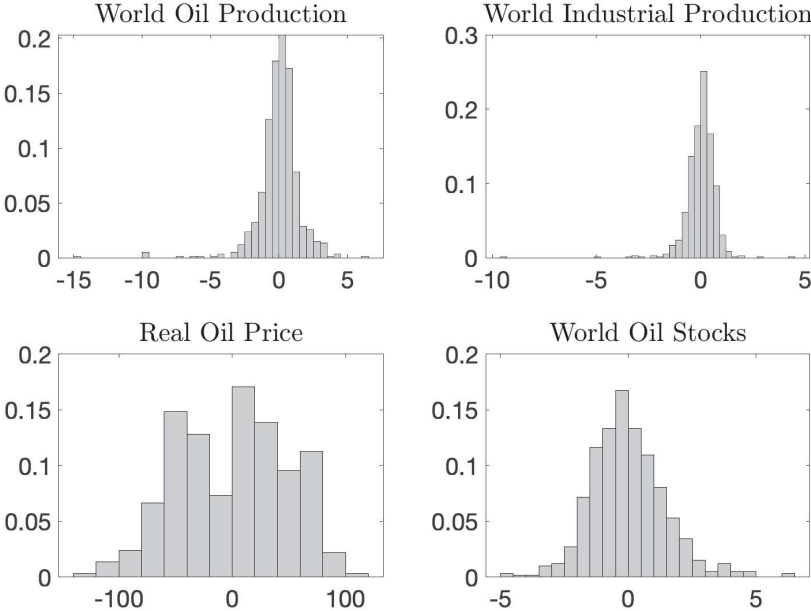
Table 1: Variables used, sources and transformations

Data category	Variable	Code	Period	Data source	Transformation
Global oil markets	World oil production	prod	1974:01-2022:11	US Energy Information Administration's Monthly Energy Review	First log difference
	World industrial production	wip	1974:01-2022:11	Industrial production of OECD, Brazil, China, India, Indonesia, the Russian Federation and South Africa aggregated as described in Baumeister and Hamilton (2019)	First log difference
	Refiner acquisition cost	RAC	1974:01-2022:11	US Energy Information Administration's Monthly Energy Review	Log Level
	World oil stocks	inv	1974:01-2022:11	US Energy Information Administration's Monthly Energy Review	First log difference
Global economic variable	Global Economic Conditions indicators	GECON	1974:01-2022:11	Christiane Baumeister website	Level
	Geopolitical Risk Index	GPR	1974:01-2022:11	Caldara et al. (2019)	Level
	OECD consumer confidence index	OECD_CCI	1974:01-2022:11	Datastream	Level
	OECD business confidence index	OECD_BCI	1974:01-2022:11	Datatsream	Level
	OECD passenger car registrations	OECD_PCR	1974:01-2019:1	Bloomberg	Level
	World stock price index	MSCI	1974:01-2022:11	Datastream	First log difference
US macroeconomic variables	Consumer price index for all urban consumers and all items	CPI	1974:01-2022:11	FRED Database	First log difference
	Consumer price index excluding food and energy	Core CPI	1974:01-2022:11	FRED Database	First log difference
	Producer Price Index	PPIACO	1974:01-2022:11	FRED Database	First log difference
	US Industrial production	INDPROD	1974:01-2022:11	FRED Database	First log difference
	US Unemployment rate	UNRATE	1974:01-2022:11	FRED Database	Level
	University of Michigan Index of Consumer Expectations	INF_EXP	1978:01-2022:02	Michigan Survey	Level
	Business Tendency Surveys for Manufacturing	BSCI	1974:01-2022:11	FRED Database	Level
	Consumer Opinion Surveys: Confidence Indicators	CSCI	1974:01-2022:11	FRED Database	Level
	Long-term interest rate	10Y GB	1974:01-2022:11	FRED Database	Level
	Stock price index	SP500	1974:01-2022:11	Bloomberg	First log difference
	Excess bond premium	EBP	1974:01-2022:11	FRED Database, updated version of Gilchrist and Zakrajšek (2012) measure	Level
	Nominal effective exchange rate	NEER	1974:01-2022:11	FRED Database	First log difference

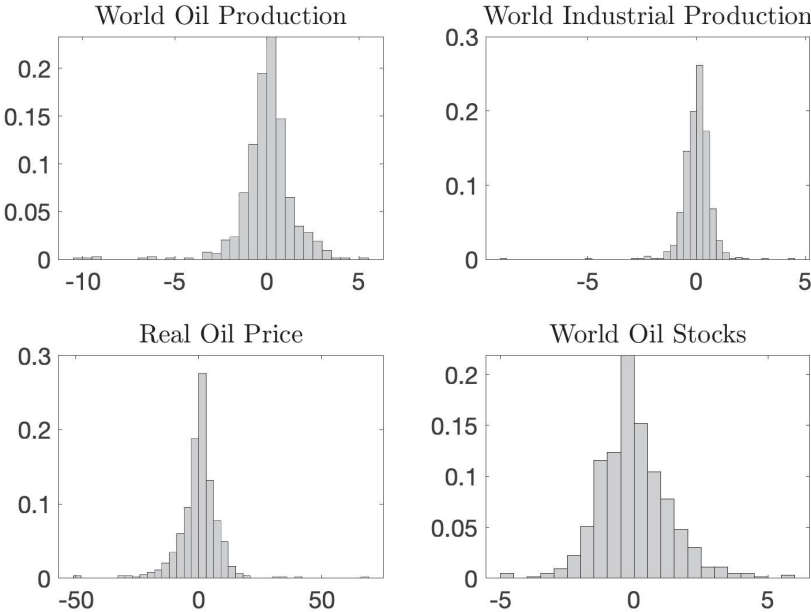
B Non-normality

Figure 6: Histograms of the baseline 4-variable model and the associated residuals from causal VAR(12) estimation

(a) Variables

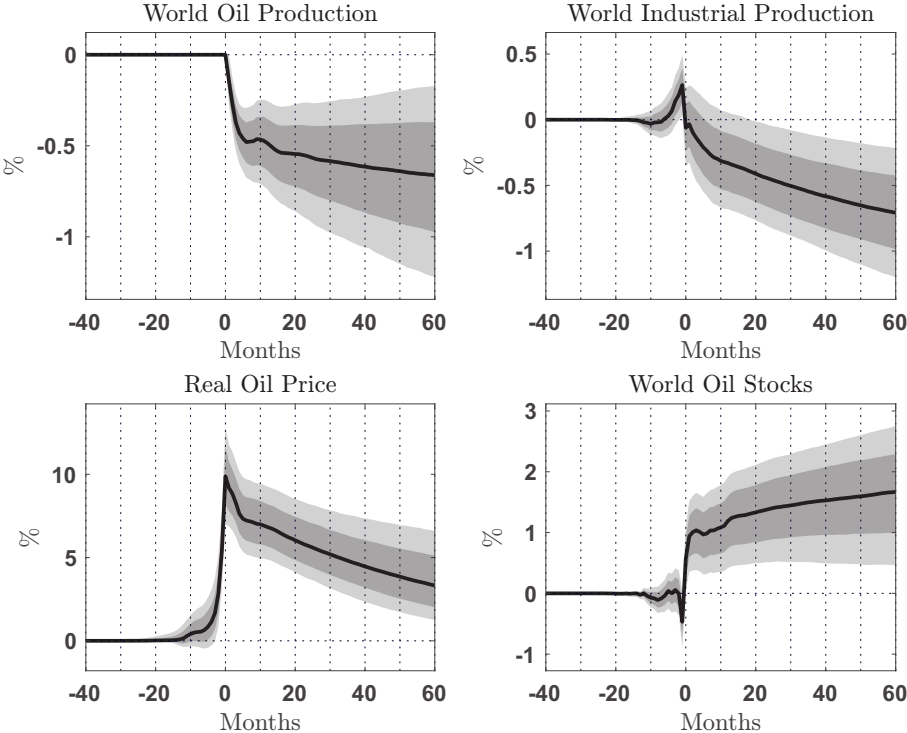


(b) VAR(12) residuals



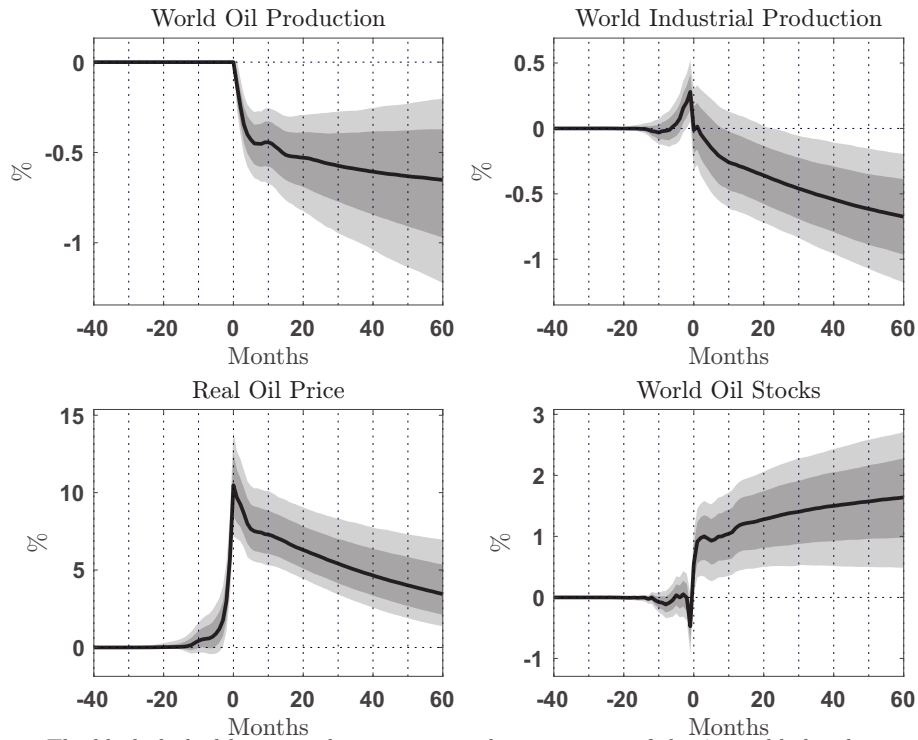
C News shock identification with different truncation windows ($H_1; H_2$)

Figure 7: Impulse-response functions to news shock: $H_1=-6$ and $H_2=6$



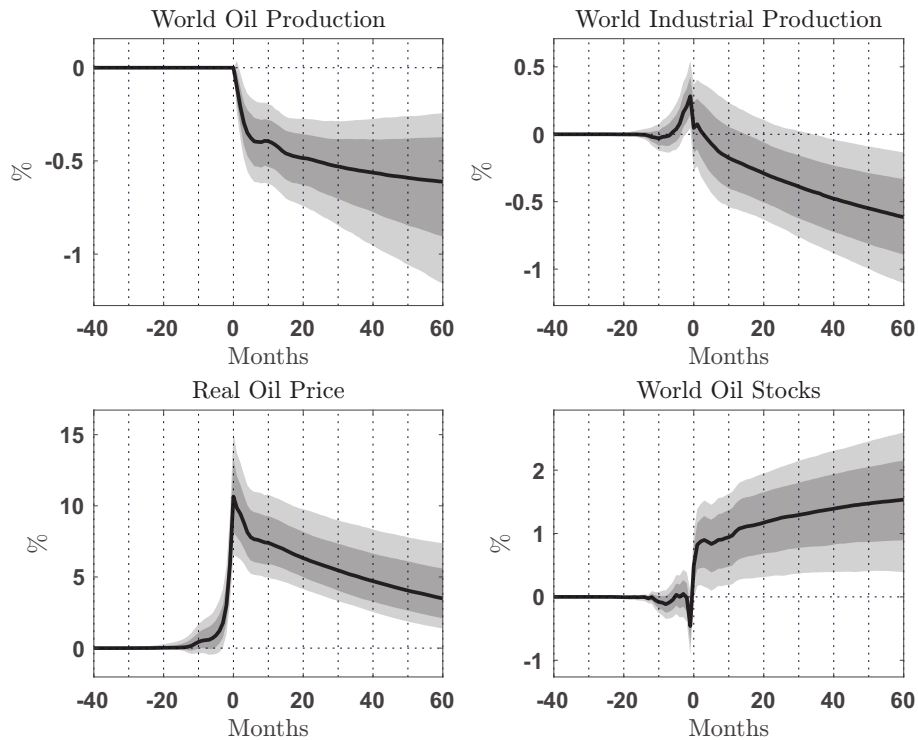
Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(6,6). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

Figure 8: Impulse-response functions to news shock: $H_1=-6$ and $H_2=20$



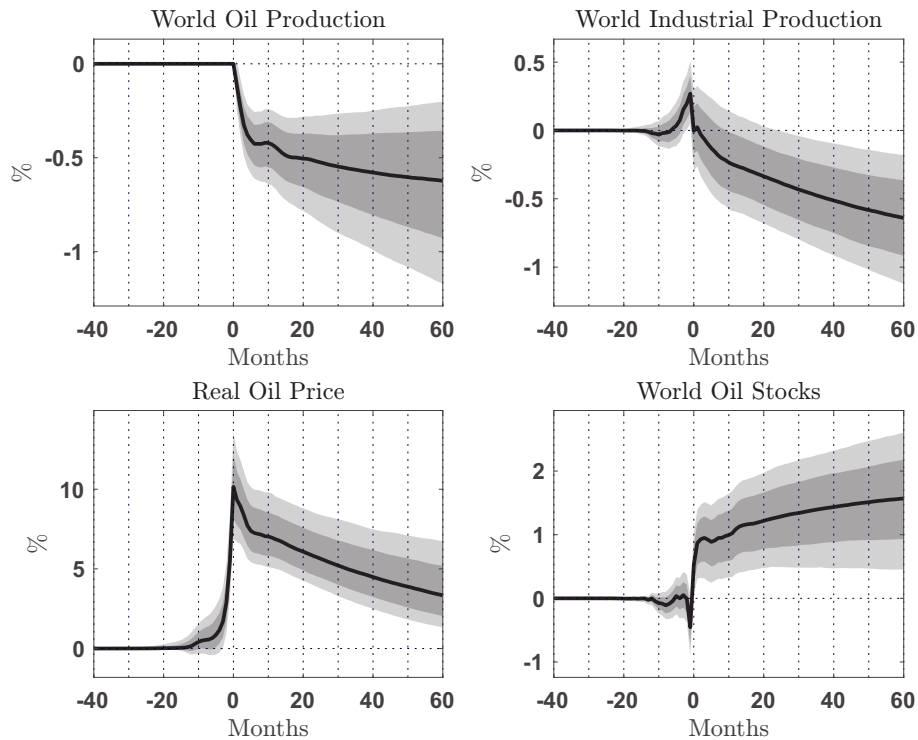
Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(6,6). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

Figure 9: Impulse-response functions to news shock: $H_1=-6$ and $H_2=60$



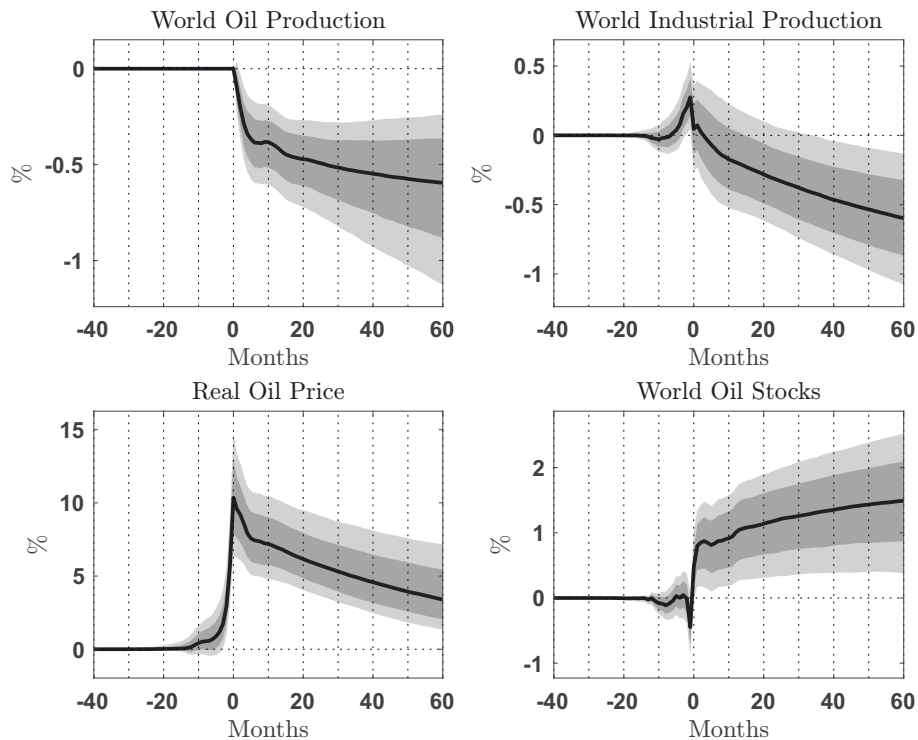
Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(6,6). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

Figure 10: Impulse-response functions to news shock: $H_1=-12$ and $H_2=24$



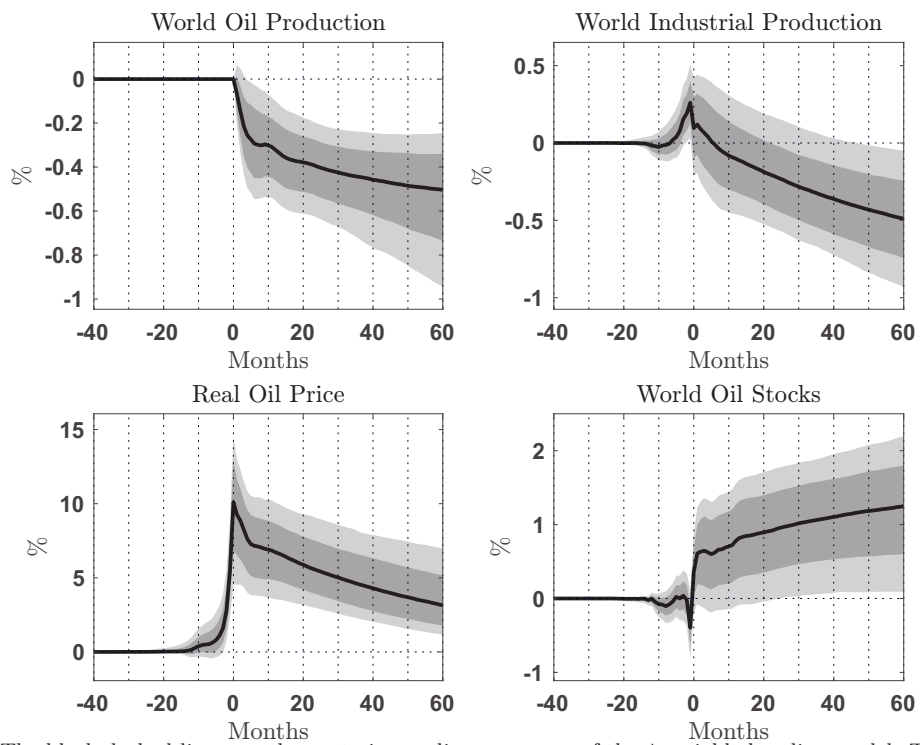
Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

Figure 11: Impulse-response functions to news shock: $H_1=-12$ and $H_2=60$



Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

Figure 12: Impulse-response functions to news shock: $H1 = H2 = 60$



Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

D Details on historical decomposition

The structural two-sided MA form of the NC-VAR [Lanne and Luoto \(2016\)](#) can be written as follows:

$$y_t = \sum_{i=-\infty}^{\infty} \Theta_i \omega_{t-i} = \sum_{i=-\infty}^{-t} \Theta_i^- \omega_{t-i} + \sum_{i=-t+1}^{-1} \Theta_i^- \omega_{t-i} + \Theta_0 \omega_0 + \sum_{i=1}^{t-1} \Theta_i^+ \omega_{t-i} + \sum_{i=t}^{+\infty} \Theta_i^+ \omega_{t-i} \quad (16)$$

where ω_t is the oil supply news shock identified as in section 3.1, and Θ_j^- (or Θ_j^+) are the corresponding structural impulse response matrices to the past (or future). Due to the stationary conditions from equation (8) of the NC-VAR, the Θ_j coefficients decrease exponentially as we move further into the past or future. Thus, the first and last term of (16), corresponding to the pre-sample period / post-sample period, will have a gradually decreasing effect on y_t as t increases or decreases. We can approximate (16) by

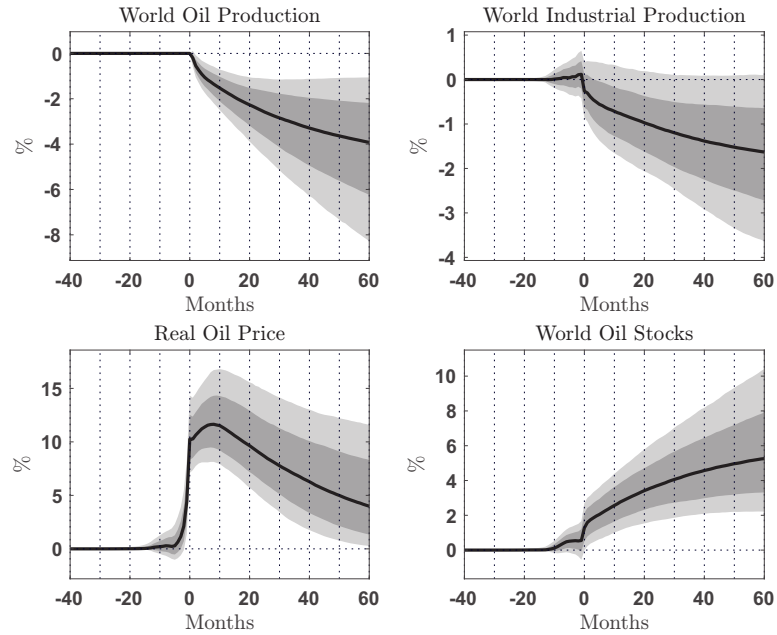
$$\hat{y}_t = \sum_{i=-t+1}^{t-1} \Theta_i \omega_{t-i}$$

Then, by assuming that data are observed from 1 to T , the estimation of the historical decomposition is in three steps:

1. compute the structural MA coefficient matrices $\Theta_{T-s}^-, \dots, \Theta_0, \dots, \Theta_{T-r}^-$.
2. compute structural shocks $w_t = \tilde{A}^{-1} \epsilon_t$, $t = 1, \dots, T$.
3. and compute $\hat{y}_{k,t} = \sum_{j=1}^K \sum_{i=-t+1}^{t-1} \theta_{k,j} \omega_{j,t-i}$

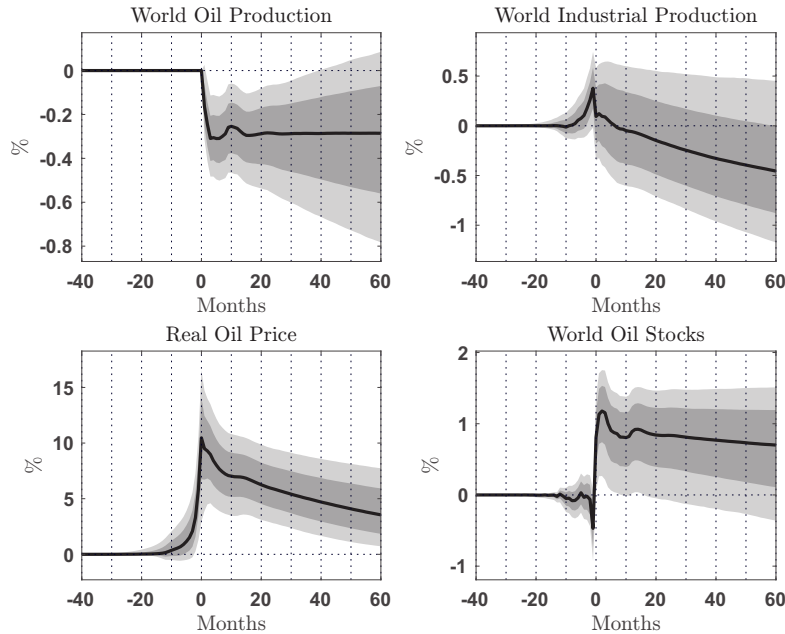
E Time backtest

Figure 13: Impulse-response functions to news shock: 1974:2-1989:12



Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.

Figure 14: Impulse-response functions to news shock: 1990:2022:11



Notes: The black dashed lines are the posterior median responses of the 4-variable baseline model. The solid lines are the posterior median cumulated impulse responses of the NC-VAR(12,12). Light and dark grey shaded regions are the 90 % and 68 % credible sets of the NC-VAR(12,12). Because of noncausality, the impulse responses are located on both sides of zero. The negative side corresponds to the lead terms of the MA representation of NC-VAR.