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Shale oil revolution, the global oil market and the US economy

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Abstract

This study provides a novel perspective on the role of US oil production in the global oil market and the US economy. It employs a Bayesian Structural Vector Autoregression to identify distinct demand and supply oil market shocks. Although several studies have already used models that distinguish explicitly between US and non-US oil production, the present study does so by adopting a more flexible identification scheme as well as by allowing for time variation. In addition, a rolling-sample estimation approach is employed to investigate oil market shocks in a dynamic framework. The study finds considerable time variation in the effects of oil market shocks on the US economy. In particular, it identifies a sharp increase in the price elasticity of US oil supply after the shale oil revolution. This increased price responsiveness of US oil production is partly responsible for the resilience of the US economy to global oil market shocks in recent years. This conclusion remains robust regardless of whether the global oil market shocks originate from the demand or supply side.

Keywords Bayesian SVAR · Oil market shocks · US oil production · Shale oil · US economy · Time variation

Mathematics Subject Classification C32 · E32 · Q43

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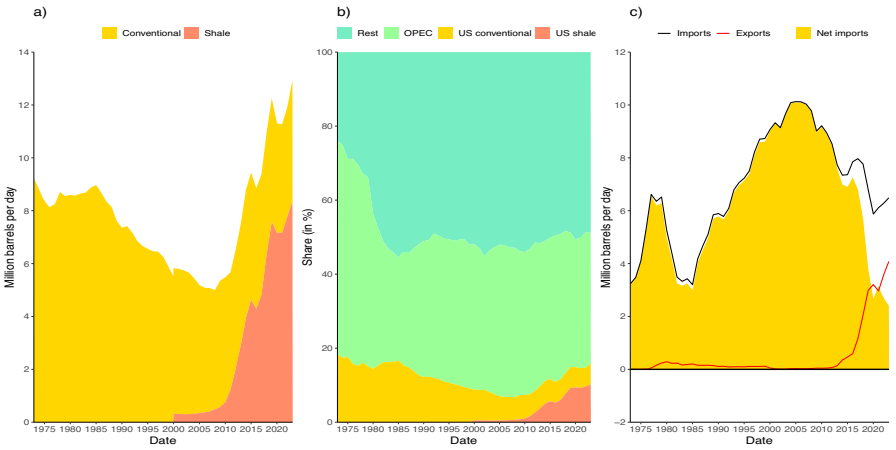

Fig. 1 Crude oil production and US crude oil trade balance. *Note*: **a** US conventional and shale oil production in million barrels per day (Source: EIA); **b** US conventional, US shale, OPEC and rest-of-the-world oil production shares (Source: EIA); **c** US imports and exports of crude oil and net position in the crude oil market (Source: EIA)

1 Introduction

During the last 15 years, the US oil market has undergone an important transformation. The reason is the so-called shale oil revolution, i.e., the sudden and sharp increase in US shale oil and gas production at the end of 2000s[1] (Fig. 1a). Until then, almost all US oil production came from conventional oil wells. This is because the relatively new extraction technologies for tight oil, namely horizontal drilling and hydraulic fracturing, were associated with significant costs that made them non-profitable. Therefore, for many years conventional oil production had the competitive advantage over unconventional oil extraction techniques. However, this changed in the mid-2000s, as persistent increases in the price of oil made the extraction of tight oil competitive, attracting in this way considerable investment. This shale oil boom drove total US oil production to historically high levels.

The new conditions in the US reinforced its role as an important player in the global oil market. After a period of 40 years, in 2013, the US regained its position as the top producer of oil, accounting now for approximately 16% of global oil production (Fig. 1b). In addition, the US significantly improved their trade balance in crude oil (Fig. 1c) and became a net oil exporter (when we also consider trade in petroleum products besides crude oil) for the first time in 2020 (see Figure C.1 in the online Appendix). These events have important consequences for both, the global oil market and the US economy. The ever decreasing reliance on oil imports enhances economic and political security in the US. Furthermore, amid increasing volatility in oil prices as well as growing doubts about OPEC's interest in stabilizing the market, the US could potentially play this role. This argument is reinforced by the significantly larger price responsiveness of tight compared to conventional oil production (Bjørnland et al. 2021;

[1] This paper uses the terms shale, tight and unconventional oil interchangeably.

Aastveit et al. 2022; Foroni and Stracca 2023), given also that tight oil accounts now for approximately 64% of total US oil production. As a consequence, understanding the role of US oil production for the global oil market and the domestic economy becomes of paramount importance.

Although there is a wide literature on the effects of oil market shocks on the US economy [see, among others, Hamilton (1983, 2011), Bjørnland (2000), Barsky and Kilian (2004), Kilian (2009), Herrera and Rangaraju (2020)], most articles ignore the role of US oil production. There are only few studies that explicitly account for the impact of the shale oil boom (Kang et al. 2016, 2017, Gundersen 2020, Bjørnland and Skretting 2024). However, these studies employ the recursive identification scheme of Kilian (2009), which is based on rather strong theoretical assumptions.[2] The most notable one concerns the shape of the US and non-US oil supply curves, which are both assumed to be vertical in the short term. However, recent studies suggest that the short-run elasticities of both shale and conventional oil production are nonzero (Caldara et al. 2019; Bjørnland et al. 2021; Aastveit et al. 2022). In addition, as the share of the more elastic shale oil production constantly grows in the domestic oil market (Fig. 1b), the assumption of non-reaction of US oil producers to oil price signals becomes increasingly problematic. Finally, existing studies in this particular strand of the literature focus mainly on the impact of US oil supply shocks on the domestic economy, while completely ignoring speculation, which cannot be explicitly identified in such models. Given the important role of speculation in the global oil market (Kilian and Murphy 2014; Juvenal and Petrella 2015), this is a considerable limitation of previous studies. This is because, besides analyzing the impact of US oil supply shocks on the domestic economy, it is equally important to examine the reaction of the domestic variables to the complete set of different shocks in the global oil market.

This paper, instead, relies on the Bayesian Structural Vector Autoregression (SVAR) model of Baumeister and Hamilton (2019), which uses prior information for all parameters of interest, including the elasticities of US and non-US oil supply, in a flexible and intuitive way. Furthermore, it employs a rolling-sample estimation approach to provide a dynamic perspective to the empirical analysis. This allows us to closely follow the impact of the shale oil revolution and examine the effects of oil market shocks on the US economy over time. Bjørnland and Skretting (2024), using a FAVAR-TVP model, also allow for time variation while distinguishing between US and non-US oil production, finding that the impact of oil market shocks on the US economy has changed after the shale oil boom.

This study prefers the rolling-sample approach instead of the popular time-varying parameter (TVP) VAR models (Primiceri 2005; Koop and Korobilis 2014; Bjørnland and Skretting 2024) for three reasons. First, current TVP-VAR models typically rely on sign or zero restrictions, but do not easily accommodate the informative priors for contemporaneous elasticities that are central to the Bayesian SVAR identification of Baumeister and Hamilton (2019). In contrast, the rolling-sample approach allows us to retain this identification strategy while still capturing structural change by estimating

[2] For a recent overview of the debate on oil market shock identification and its macroeconomic implications, see Herrera and Rangaraju (2020) and Arampatzidis and Panagiotidis (2023).

the model repeatedly over rolling samples of fixed length. Second, there is currently no TVP-VAR model that allows for time variation in both the autoregressive and the contemporaneous parameters. The latter is especially important for this study, since one of the research questions is to examine the impact of the shale oil revolution on the US oil supply elasticity. This can be approximated by the rolling-sample approach. Third, it is widely accepted in the oil market literature that we need up to two years of lagged observations due to slowly building and declining cycles in global commodity markets (Kilian 2009). However, estimating TVP-VAR models with monthly data and considering 12 or 24 lags is associated with considerable computational issues that in most cases render the estimation infeasible. Therefore, to overcome this issue researchers either consider fewer lags (e.g., 6) or data of quarterly frequency and employ 4 or 8 lags (Baumeister and Peersman 2013a, b). The first solution causes an underestimation of aggregate demand shocks (Kilian 2009). The second, in turn, deviates from the majority of studies that employ monthly data and it is associated with information loss due to temporal aggregation (Ghysels 2016). Nonetheless, there is an important trade-off, since rolling windows may exhibit discrete jumps when influential observations enter or leave the sample, whereas TVP models tend to yield smoother parameter paths. This is because TVP methods explicitly model parameter evolution as a gradual stochastic process rather than as stepwise changes.

In this context, this study seeks to answer the following research questions: (i) *What is the role of US oil production for the global oil market and the US economy?* and (ii) *what has changed with the shale oil boom?* The first question is addressed by modifying the Bayesian SVAR model of Baumeister and Hamilton (2019) to distinguish between US and non-US oil production. To answer the second question, a modified version of the standard rolling-sample estimation approach is used, which overcomes an important weakness that has been criticized in the literature (Antonakakis et al. 2020). The main finding is that the US economy appears increasingly resilient to oil market shocks, owing to a large extent to the shale oil boom. At the same time, it becomes more vulnerable to domestic oil supply disruptions.

This study contributes to three different strands of the literature. First, it provides new estimates of US and non-US oil supply elasticities, adding to the corresponding debate in the literature. Second, it adds to the limited strand of the literature that studies the effects of US oil supply shocks on the global oil market and the US economy by considering a more flexible identification scheme compared to earlier attempts. Third, the dynamic approach, necessary to identify the impact of the shale oil revolution, indirectly contributes to the literature that studies the effects of oil market shocks over time (Baumeister and Peersman 2013b; Foroni et al. 2017; Ewing et al. 2018).

The paper is organized as follows: Sect. 2 presents the data used in the empirical analysis. Section 3 describes the econometric methodology, and Sect. 4 presents the empirical results. Finally, Sect. 5 concludes.

2 Data

This study employs data for two sets of variables: (i) a set of variables for the global oil market, which encompasses US and non-US crude oil production, global real economic

activity, the global real price of crude oil and global oil inventories; (ii) another set that consists of variables related to the US economy, namely US industrial production and CPI. Observations for all variables are available at monthly frequency for the period 1960:01–2019:12. Figure C.2 and Table C.1 in the online Appendix depict the raw data of all variables and their main descriptive statistics, respectively.

To measure global oil supply (q_t^s), this study uses data on world crude oil production, measured in million barrels of oil pumped per day. US oil supply (q_t^{us}) is proxied by using the corresponding data for US crude oil production. Next, US crude oil production is subtracted from global crude oil production to get a measure of non-US oil supply (q_t^{ns}). Note that all oil production variables used in this study are composites of several petroleum and other liquid products, including crude oil, shale oil and NGPL. As a proxy for global real economic activity (y_t), the global industrial production index of Baumeister and Hamilton (2019) is used. This index is constructed using data on industrial production for OECD countries and six major non-member economies (namely Brazil, China, India, Indonesia, the Russian Federation and South Africa). For the global real crude oil price (p_t), this paper considers the West Texas Intermediate (WTI) spot price of crude oil, deflated by the seasonally adjusted US CPI. We prefer the WTI spot price over the widely used refiner's acquisition cost (RAC) of imported crude oil as a proxy for the global crude oil price since the former is available for the whole sample period, whereas the latter becomes available only after 1974.[3] Finally, to proxy global crude oil inventories, the method outlined by Kilian and Murphy (2014) and Baumeister and Hamilton (2019) is followed. This involves multiplying the US crude oil inventories by the ratio of OECD to US inventories of petroleum and petroleum products. The final proxy, namely the change in global crude oil inventories (ΔI_t), is calculated by determining the change in OECD oil inventories as a fraction of last period's oil production.

To analyze the impact of oil market shocks on the US economy, this study focuses on two key response variables: US industrial production ($indp_t$) and the US CPI (inf_t). The data for $indp_t$ are seasonally adjusted and represent the total US industrial production. Similarly, the data for inf_t are seasonally adjusted and concern the consumer price index for all items.[4]

3 Econometric methodology

To model global oil market shocks, this study employs a version of the Bayesian SVAR model proposed by Baumeister and Hamilton (2019). However, it differs from the original model as it dissects global oil production into US and non-US oil production. It also incorporates modifications suggested by Arampatzidis and Panagiotidis (2023).

The model can be written in compact form as:

[3] Following the approach suggested by Baumeister and Hamilton (2019), we tested the sensitivity of our results in the full sample by using a combination of the RAC and the WTI. The results are robust and available upon request.

[4] In the empirical analysis, all variables (except ΔI_t) are utilized in their first logarithmic differences. A list of data sources is given in the online Appendix.

$$\boldsymbol{A}z_t = \boldsymbol{B}x_t + u_t \tag{1}$$

where $z_t = (q_t^{ns}, q_t^{us}, y_t, p_t, \Delta I_t, US_t)$ is a $(n \times 1)$ vector of the observed variables, x_t is a $(k \times 1)$ vector of the lagged variables and a constant $(x_t^{'} = (z_{t-1}^{'}, ..., z_{t-m}^{'}, 1)^{'}, k = mn + 1, m = 12)$,[5] u_t is a $(n \times 1)$ vector of structural errors with variance–covariance matrix $(\boldsymbol{D})$ assumed to be diagonal, $\boldsymbol{A}$ is a $(n \times n)$ matrix of contemporaneous coefficients and $\boldsymbol{B}$ is a $(n \times k)$ matrix of autoregressive parameters. Finally, US_t refers to the domestic US variables, namely $indp_t$ for the first version and inf_t for the second version of the model.

3.1 Main equations of the model

Equations (2) and (3) are the non-US and US oil supply curves, respectively:

$$q_t^{ns} = \alpha_{nu} q_t^{us} + \alpha_{ny} y_t + \alpha_{np} p_t + b_1^{'} x_t + u_{1t} \tag{2}$$

$$q_t^{us} = \alpha_{un} q_t^{ns} + \alpha_{uy} y_t + \alpha_{up} p_t + b_2^{'} x_t + u_{2t} \tag{3}$$

where α_{nu} and α_{un} show the contemporaneous interaction between US and non-US oil production, and α_{ny} and α_{uy} capture the contemporaneous effect of economic activity on non-US and US oil production, respectively, whereas α_{np} and α_{up} are the two short-run price elasticities of oil supply.

The remaining equations in the oil market block refer to the demand side of the global oil market. Equation (4) aims to capture the determinants of aggregate global demand:

$$y_t = \alpha_{yn} q_t^{ns} + \alpha_{yu} q_t^{us} + \alpha_{yp} p_t + b_3^{'} x_t + u_{3t} \tag{4}$$

where α_{yn} and α_{yu} show the contemporaneous effects of oil production on economic activity, while α_{yp} captures the corresponding effect of the oil price.

To construct the oil demand curve, most studies assume that the quantities of oil produced (q_t^s) and consumed (q_t^d) at time t are identical $(q_t^s \equiv q_t^d \equiv q_t)$, resulting in an oil demand curve of the form: $q_t^d = \beta_{qy} y_t + \beta_{qp} p_t + b_4^{'} x_t + u_{4t}$. In contrast, this study formulates a modified version of the global oil demand curve (Eq. 5) by taking into account that: (i) global oil production is the sum of US and non-US oil production $(q_t^s = q_t^{ns} + q_t^{us})$; (ii) the observation by Kilian and Murphy (2014) that any potential difference in the amount of oil produced and consumed at time t is captured by changes in oil inventories $(q_t^s - q_t^d = \Delta I_t)$. This yields an augmented version of the oil demand curve:

[5] As a robustness exercise, we have also considered 24 lags, which is the standard in the literature (Kilian 2009; Kilian and Murphy 2014). The results, which are not presented here but are available upon request, remain qualitatively the same, indicating that our model is not sensitive to the choice of lags.

$$q_t^{ns} + q_t^{us} = \beta_{qy} y_t + \beta_{qp} p_t + \Delta I_t + b_4^{'} x_t + u_{4t} \tag{5}$$

where β_{qy} and β_{qp} are the income and price elasticities of oil demand, respectively.

Equation (6), in turn, represents the demand for oil inventories[6]:

$$\Delta I_t = \psi_1 q_t^{ns} + \psi_2 q_t^{us} + \psi_3 y_t + \psi_4 p_t + b_5^{'} x_t + u_{5t} \tag{6}$$

Finally, the last equation captures the impact of global oil market variables on the US economy:

$$US_t = \chi_1 q_t^{ns} + \chi_2 q_t^{us} + \chi_3 y_t + \chi_4 p_t + \chi_5 \Delta I_t + b_6^{'} x_t + u_{6t} \tag{7}$$

Note here that although the oil market variables are allowed to contemporaneously affect the US variables, it is assumed that the inverse does not hold. This is a standard assumption in the literature that takes global oil market variables as predetermined to the domestic variables (see, e.g., Gupta and Modise, 2013; Kang et al., 2015).

To identify the five structural oil market shocks,[7] namely a non-US oil supply shock (u_{1t}), an US oil supply shock (u_{2t}), an economic activity shock (u_{3t}), an oil-specific demand shock (u_{4t}) and an inventory demand shock (u_{5t}), we must make sure that the model satisfies the sign restrictions on the impact multiplier matrix[8]:

$$\boldsymbol{H} = \boldsymbol{A}^{-1} = (1/det(\boldsymbol{A})) \times \begin{bmatrix} + & - & + & + & + & 0 \\ - & + & + & + & + & 0 \\ + & + & + & - & - & 0 \\ - & - & + & + & + & 0 \\ ? & ? & ? & ? & + & 0 \\ ? & ? & ? & ? & ? & + \end{bmatrix} \tag{8}$$

While rotation uncertainty is a well-known concern in small sign-restricted VARs, the Bayesian SVAR of Baumeister and Hamilton (2019) already mitigates this problem by incorporating informative priors on key structural elasticities (see Sect. 3.2), which sharply reduce the space of admissible rotations. This approach goes beyond pure sign-restriction schemes and ensures that retained draws are consistent with both theoretical

[6] In contrast to Baumeister and Hamilton (2019), this study does not consider a measurement error equation for oil inventories. The reason is that this measurement error specification is time invariant. Therefore, it cannot resolve the main problem in the measurement of oil inventories, which is the rise in Chinese strategic oil inventories after 2010 (Kilian and Zhou 2018; Arampatzidis and Panagiotidis 2023). Thus, this paper follows the majority of earlier studies that do not model measurement errors in oil inventories.

[7] We are not interested in u_{6t}. This is because it is a residual shock which captures any other factor that affects the US variables besides the global oil market shocks.

[8] The question marks in Eq. (8) imply that this study remains agnostic regarding the signs of the corresponding parameters.

sign patterns and empirically plausible elasticity values. Alternative approaches, such as narrative anchors for historically identified supply shocks (Kilian 2008) or informative inventory priors (Caldara et al. 2019), could further restrict the rotation set, but at the cost of imposing additional episode-specific or storage-constraint assumptions. As our goal is to remain closely comparable to the existing literature using the Baumeister and Hamilton (2019) framework, we retain their identification strategy while acknowledging these alternatives as complementary avenues for future work.

The sign restrictions in Eq. (8) are based on economic theory.[9] More specifically, it is assumed that: a positive non-US oil supply shock raises non-US oil production and decreases US oil production, whereas it increases economic activity as it depresses the price of oil (1st column); a positive US oil supply shock has a negative impact on non-US oil production, a positive effect on US oil production, while it increases economic activity since it depresses the price of oil (2nd column); an increase in economic activity leads to higher non-US and US oil production, economic activity and oil prices (3rd column); and an oil-specific demand shock (4th column) and an inventory demand shock (5th column) have a positive impact on both non-US and US oil production, a negative effect on economic activity and a positive impact on the price of oil.

To make sure that the sign restrictions in Eq. (8) are satisfied, the following additional assumptions are necessary: (i) $\alpha_{nu} = \alpha_{un} = 0$, i.e., non-US (US) crude oil production affects US (non-US) crude oil production at time t only through the price of oil; (ii) $\alpha_{ny} = \alpha_{uy} = 0$, i.e., economic activity affects non-US/US oil production at time t only through the price of oil; and (iii) vice versa ($\alpha_{yn} = \alpha_{yu} = 0$); (iv) $\psi_3 = 0$.[10] Therefore, matrix $\boldsymbol{A}$ takes the form:

$$\boldsymbol{A} = \begin{bmatrix} 1 & 0 & 0 & -\alpha_{np} & 0 & 0 \\ 0 & 1 & 0 & -\alpha_{up} & 0 & 0 \\ 0 & 0 & 1 & -\alpha_{yp} & 0 & 0 \\ 1 & 1 & -\beta_{qy} & -\beta_{qp} & -1 & 0 \\ -\psi_1 & -\psi_2 & 0 & -\psi_4 & 1 & 0 \\ -\chi_1 & -\chi_2 & -\chi_3 & -\chi_4 & -\chi_5 & 1 \end{bmatrix} \tag{9}$$

The main advantage of this Bayesian SVAR model is that, besides the use of zero and sign restrictions, it allows to use further prior knowledge regarding the parameters of matrices $\boldsymbol{A}$, $\boldsymbol{B}$ and $\boldsymbol{D}$. The next subsection discusses the priors that are considered for those matrices.

[9] The only difference with the assumptions in Baumeister and Hamilton (2019) comes from the disaggregation of global oil supply. Consistent with the view that oil supply disruptions in one part of the world lead to higher production elsewhere (Kilian 2009), we assume that a decline (increase) in non-US oil supply raises (decreases) US oil production, and vice versa.

[10] Assumptions (ii), (iii) and (iv) are similar to Baumeister and Hamilton (2019). To ensure that the empirical analysis does not hinge on assumption (i), we considered two cases as a robustness exercise: a) We allowed for a contemporaneous impact of non-US oil supply on US oil production ($\alpha_{un} \neq 0$ in Eq. (3)); b) we allowed for a contemporaneous impact of US oil supply on non-US oil production ($\alpha_{nu} \neq 0$ in Eq. (2)). The results in both cases are qualitatively similar to those in Sect. 4 and are available upon request.

3.2 Prior and posterior distributions

Table 1 presents the prior distributions for all nonzero parameters of matrix $\boldsymbol{A}$. The most debated parameter in the literature is the price elasticity of oil supply. The traditional view is that this elasticity is zero, a standard assumption in recursive SVAR models (Kilian 2009). SVAR models identified with sign restrictions are more flexible since they allow the researcher to bound this elasticity between zero and an upper limit, usually defined at 0.0258 (Kilian and Murphy 2014). On the other hand, Baumeister and Hamilton (2019) employ a Bayesian SVAR model, which allows them to specify a whole prior distribution instead of a single value or an upper limit. In particular, they use a Student's t-distribution with mean equal to 0.1 and scale equal to 0.2.

This study follows Baumeister and Hamilton (2019) and employs their proposed Student's t-distribution for both oil supply elasticities (α_{np} and α_{up}). On the one hand, one might argue that a big share (approximately 62% in 2021, see IEA, 2022) of US crude oil production since 2011 comes from shale oil wells, which are known to have a much larger elasticity compared to conventional wells due to differences in the extraction technology (Bjørnland et al. 2021; Aastveit et al. 2022; Foroni and Stracca 2023). This is not the case for crude oil production in the rest of the world, since tight oil production still accounts only for a very small fraction (approximately 0.8% in 2021, see IEA, 2022) of total crude oil production. Such arguments would lead one to expect a priori α_{up} to be larger than α_{np}. On the other hand, the more elastic tight oil production surged in the US only after 2011, which accounts only for the more recent years in our 60-year sample. Furthermore, as OPEC oil production accounts for a big share of non-US oil production (approximately 48% on average in our sample, see Fig. 1b), one might argue that the non-US oil supply elasticity is expected to be larger than the corresponding US elasticity, as it is known that OPEC can adjust its production relatively faster (Caldara et al. 2019; Foroni and Stracca 2023). Overall, since a priori it is difficult to tell which oil supply elasticity is larger over a period of 60 years, this paper specifies the same prior distribution for both elasticities, letting the data indicate any potential differences.[11]

For the remaining parameters in $\boldsymbol{A}$ as well as for matrices $\boldsymbol{D}$ and $\boldsymbol{B}$, this study follows Baumeister and Hamilton (2015, 2019) and the modifications proposed by Arampatzidis and Panagiotidis (2023) without further changes.[12] Finally, following Baumeister and Hamilton (2019), the sample period 1960:01–1972:12 is used to further inform the priors. The reason for using this period as prior information and not as part of the full sample is the considerable structural break in the oil market in 1973. Consequently, most studies consider 1973:01 as the starting point in their analysis and argue against using pre-1973 data (Kilian and Zhou 2020). Nonetheless, Baumeister and Hamilton (2019) recommend using pre-1973 data rather as prior information than

[11] To ensure that our results do not hinge on the selection of the exact same prior distribution for both elasticities, we consider the following cases as a robustness exercise: i) α_{np} (mean = 0.10, scale = 0.20), α_{up} (mean = 0.07, scale = 0.20); ii) α_{np} (mean = 0.10, scale = 0.20), α_{up} (mean = 0.13, scale = 0.20); iii) α_{np} (mean = 0.07, scale = 0.20), α_{up} (mean = 0.10, scale = 0.20); and iv) α_{np} (mean = 0.13, scale = 0.20), α_{up} (mean = 0.10, scale = 0.20). The results are robust and available upon request.

[12] For a detailed description of the prior and posterior distributions, the reader is referred to the online Appendix.

Table 1 Prior distributions for parameters of the model

Parameter	Meaning	Location	Scale	Degrees of freedom	Skew	Sign restriction
Student's t-distribution						
α_{np}	Non-US price elasticity of oil supply	0.1	0.2	3	–	Positive
α_{up}	US price elasticity of oil supply	0.1	0.2	3	–	Positive
α_{yp}	Effect of p on economic activity	−0.05	0.1	3	–	Negative
β_{qy}	Income elasticity of oil demand	0.3	0.15	3	–	Positive
β_{qp}	Price elasticity of oil demand	−0.1	0.1	3	–	Negative
ψ_1	Effect of q^{ns} on oil inventories	0	0.5	3	–	None
ψ_2	Effect of q^{us} on oil inventories	0	0.5	3	–	None
ψ_4	Effect of p on oil inventories	0	0.5	3	–	None
χ_1	Effect of q^{ns} on US variables	0	0.5	3	–	None
χ_2	Effect of q^{us} on US variables	0	0.5	3	–	None
χ_3	Effect of y on US variables	0	0.5	3	–	None
χ_4	Effect of p on US variables	0	0.5	3	–	None
χ_5	Effect of ΔI_t on US variables	0	0.5	3	–	None
h_3	Effect of economic activity shock on y	0.8	0.2	3	–	None
Asymmetric t-distribution						
h_1	Determinant of $\boldsymbol{A}$	0.7	1.03	3	2	None
Gamma distribution						
d_{ii}^{-1}	Reciprocal of variance	$1/(a_i^{'}\hat{\boldsymbol{S}}a_i)$	$1/(\sqrt{2}a_i^{'}\hat{\boldsymbol{S}}a_i)$	–	–	Positive
Normal distribution						
$b_{i,j}$	Lagged autoregressive coefficients	0	M_i	–	–	None
$b_{1,4}$	Response of non-US oil supply to oil price after 1 month	0.1	M_i	–	–	None
$b_{2,4}$	Response of US oil supply to oil price after 1 month	0.1	M_i	–	–	None
$b_{4,4}$	Response of oil demand to oil price after 1 month	−0.1	M_i	–	–	None

completely disregard it. In this case, there is also the option to assign a lower weight to this initial sub-sample, based on the quality of the data. The parameter μ controls the weight given to the first sub-sample, with values ranging from 0 to 1, where larger values imply a higher weight on the first sub-sample. Note that this additional feature of the Bayesian SVAR is particularly useful for the time-varying approach, which will be discussed in Sect. 3.3.

3.3 The rolling Bayesian SVAR

The main goal of this study is to closely monitor the impact of the shale oil boom on the global oil market and the US economy over time. To achieve this, the model in Eq. (1) is estimated using rolling samples of fixed size. This is not new in the literature, since previous studies considered a similar approach to assess the dynamic impact of oil market shocks on commodity (Rehman et al. 2018) and financial markets (Arampatzidis et al. 2021). However, the approach of this study has two novelties compared to previous attempts. First, besides the evolution of the impulse response functions (IRFs) over time, the Bayesian SVAR model allows us to assess also the evolution of key posterior oil demand and supply elasticities. Recall that monitoring the evolution of US price elasticity of oil supply (α_{up}) is one of the main research questions. This would not be possible with a standard recursive SVAR model. Second, the option of using earlier data as prior information for the main sample is an appealing feature of this Bayesian SVAR model. This helps us overcome the information loss associated with the rolling-sample technique, which is often the main critique against this approach (Antonakakis et al. 2020).

More specifically, the rolling-sample approach follows a combination of expanding windows for the sample period used as prior information and windows of fixed size (180 observations, i.e., 15 years) for the main sample.[13] The step size is set to 3 months instead of the usual step of 1 month in order to reduce the considerable computation time. For instance, we start by using the period 1960:01–1972:12 as prior information for the sample period 1973:01–1987:12. Next, the model is estimated for the sample period 1973:04–1988:03, using as prior information the period 1960:01–1973:03. This procedure is repeated (in total, the model is estimated in 128 rolling samples) until the end of the full-sample period, namely December 2019, when the period 1960:01–2004:12 is used as prior information for the sample period 2005:01–2019:12.

In this way, this study overcomes the issue of information loss, since the observations that are used in each estimated sample are not disregarded. Instead, they are used as prior information for the next rolling sample.[14] At the same time, the size of the main sample remains fixed in order to have the same number of observations in all

[13] To ensure that the empirical analysis is not sensitive to the choice of the rolling-window size, 10-year and 20-year rolling windows were also considered. The results in both cases are qualitatively similar to those with 15-year rolling windows and are available upon request.

[14] Note here that, as discussed at the end of Sect. 3.2, we have the option of down-weighting the importance of the observations used as prior information. More specifically, μ starts with a value of 0.2 for the first rolling sample and it gradually increases until it reaches the value of 0.5 for the final rolling sample. The intuition is that as we keep adding more recent data in the sample used as prior, this sample gradually becomes more reliable. This is reflected in the gradual increase in its importance through μ.

rolling samples. For each window, the IRFs to different oil market shocks as well as the posterior oil supply and demand elasticities are derived and plotted over time.

Note though that the rolling-sample estimation approach is known for generating jumps in the results, since it is influenced by the addition or removal of observations with a big impact on the model. Such jumps are usually not present in TVP-VAR models, since the transition is usually smoother by construction. Despite this known limitation of the rolling SVAR compared to TVP-VAR models, we prefer the former for the reasons discussed in Sect. 1. However, note that our novel rolling-sample approach helps us alleviate the impact of the observations that in the standard rolling-sample approach would have been dropped from the rolling sample as we keep rolling. Nonetheless, jumps can still occur, but they are less pronounced compared to the standard rolling-sample approach (Fig. 5 vs Figure C.4 in the online Appendix). With this potential caveat in mind, the discussion of our results focuses mostly on the observed structural change instead of identifying its exact timing.

4 Empirical results

Section 4.1 presents some indicative results from the full sample (1960:01–2019:12). For the reasons already explained, the first 13 years are used as prior information, down-weighted with a factor of $\mu = 0.4$. Section 4.2, in turn, discusses the insights that we draw based on the rolling-sample approach.

4.1 Full sample

4.1.1 Posterior elasticities

Figure 2 presents the prior and posterior distributions for the non-US (α_{np}) and US (α_{up}) price elasticities of oil supply. We observe a relatively small difference between the two elasticities. The US oil production appears more elastic as the posterior median oil supply elasticity is 0.079, whereas the corresponding median non-US elasticity is 0.059. This is somewhat surprising at first glance, since OPEC, which accounts for the biggest share of non-US oil production, is known to have a larger oil supply elasticity compared to other oil producers (Caldara et al. 2019). The dynamic approach in Sect. 4.2.1 helps us explain this unexpected finding. Overall, in both cases, the estimates are closer to Baumeister and Hamilton (2019), Caldara et al. (2019) and Foroni and Stracca (2023) and 2–3 times larger than the upper bound in Kilian and Murphy (2014).

4.1.2 Impulse response functions

Figure 3 presents the effects of different oil supply and demand shocks on the real price of oil, which is the main transmission channel of oil market shocks to the US economy. Starting with the side of oil supply, we do not observe important differences in the reaction of the oil price to non-US and US oil supply disruptions. In both

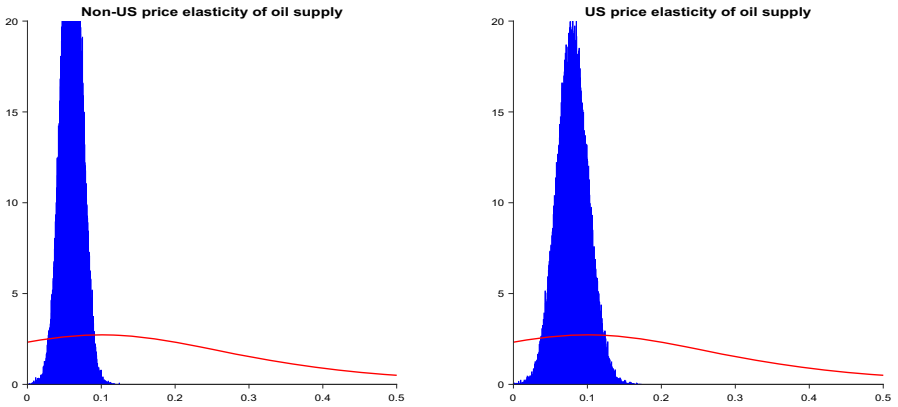

Fig. 2 Prior and posterior non-US and US price elasticities of oil supply. *Note*: Left plot: prior (red line) and posterior (blue histogram) distributions of non-US price elasticity of oil supply (α_{np}); Right plot: prior (red line) and posterior (blue histogram) distributions of US price elasticity of oil supply (α_{up})

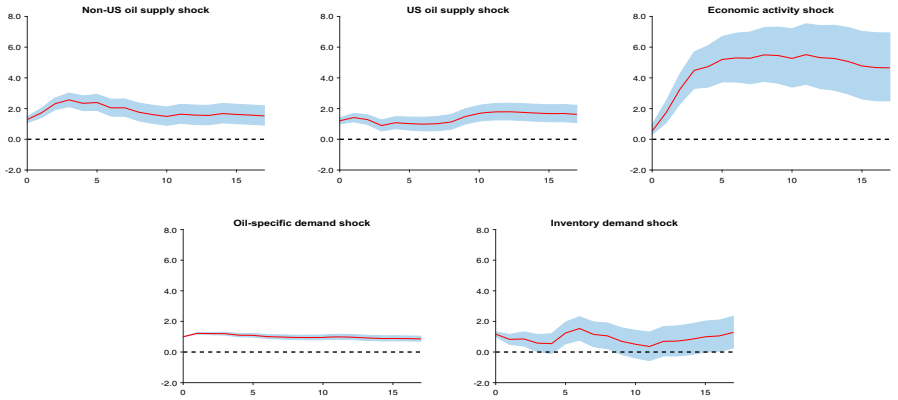

Fig. 3 Cumulative IRFs of oil price to oil market shocks. *Note*: (i) Red lines: posterior medians; Light blue shaded areas: 68% posterior credible sets; (ii) All shocks have a magnitude of 1% and are normalized such that to imply an increase in the price of oil

cases, the effect is positive and persistent, which is in line with the recent studies of Baumeister and Hamilton (2019) and Herrera and Rangaraju (2020). However, this comes in contrast with earlier studies that employ different identification schemes, concluding that oil supply shocks do not have a statistically significant impact on the price of oil (Kilian 2009; Kilian and Murphy 2014). For the case of US oil supply in particular, the persistent effect is in line with the finding in Ewing et al. (2018), but it comes in contrast to the zero or short-lived impact in Kang et al. (2017) and Gundersen (2020), respectively. On the demand side, all shocks have a positive and statistically significant impact on the oil price, but the effect of inventory demand shocks is less persistent and the impact of economic activity shocks is of higher magnitude compared to the rest. Overall, this full-sample analysis confirms the importance of demand-side shocks for the global oil market, but it also reinforces the role of oil supply.

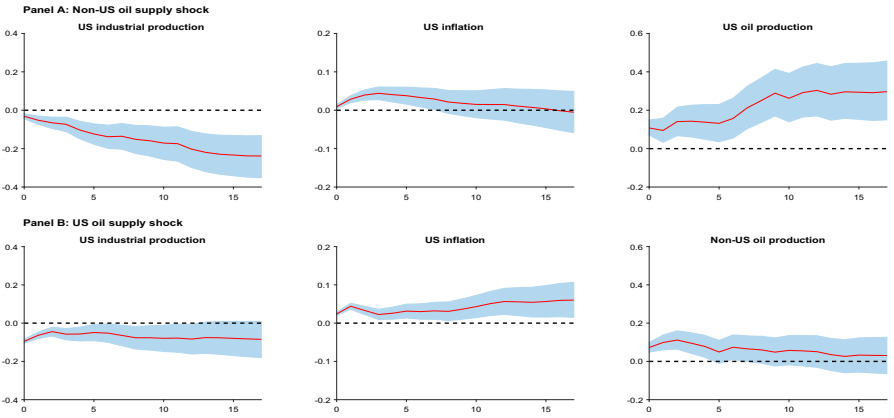

Fig. 4 Cumulative IRFs to non-US and US oil supply shocks. *Note*: (i) Red lines: posterior medians; Light blue shaded areas: 68% posterior credible sets; (ii) Both are negative shocks and have a magnitude of 1%

Figure 4 shows the reaction of US oil production, industrial production and inflation to 1% non-US and US oil supply disruptions.[15] Starting with Panel A, we observe a negative and long-term impact on US industrial production, which can be attributed to the increase in the price of oil (see Fig. 3). Note also that a negative US oil supply shock has on impact a larger effect on US industrial production compared to a non-US oil supply shock, but the overall effect is less persistent. Both shocks contribute also to US inflation, with US oil supply disruptions having longer-lasting effects. A possible explanation for the different effects of US and non-US oil supply disruptions could be related to the Fed's stance in each case. As both shocks put inflationary pressure on the US economy since they increase the price of oil and, thus, transportation and production costs, the Fed is expected to follow a contractionary monetary policy.[16] It seems that the reaction is stronger when oil supply disruptions originate from the rest of the world, since the effect on inflation is smaller, while the negative impact on industrial production is stronger compared to disruptions in the domestic oil market. Those distinct effects on the domestic economy highlight the need of distinguishing between US and non-US oil production.

Finally, we observe a strong reaction of US oil production to a negative non-US oil supply shock. The positive effect is expected, since a non-US oil supply disruption raises the price of oil, which motivates US oil producers to increase domestic oil production.[17] What is somewhat unexpected is the magnitude and persistence of the response, since it is larger and lasts longer compared to the corresponding effect of US

[15] Since there is a large difference in the volume of US and non-US oil production, considering shocks of 1% magnitude for both might be somewhat misleading. Following Baumeister and Peersman (2013a), the US and non-US oil supply shocks are also normalized such that they both lead to a 10% increase in the price of oil. The results remain qualitatively similar and are available upon request.

[16] Note though that this only reflects the author's intuition and it is not derived from the empirical analysis. This is because the model used in this study does not contain a monetary policy variable, and thus, it cannot be used to answer such questions.

[17] Note though that previous studies (Kang et al. 2017; Gundersen 2020) find a zero effect, most likely due to their recursive identification scheme.

oil supply shocks on non-US oil production. It is intuitive that the shale oil revolution plays an important role for this result. This is because it enables US oil producers to increase tight oil production much faster and in larger volumes than conventional oil production. This intuition motivates the dynamic approach in the next section.

4.2 Rolling samples

4.2.1 Posterior elasticities

The conclusion based on Fig. 2 was that the US oil supply elasticity is slightly larger than the corresponding non-US elasticity. However, as Fig. 5 shows,[18] this is only a recent phenomenon. Starting with the top-left plot, we observe a gradual decrease in the non-US oil supply elasticity, which starts at approximately 0.27 and stabilizes around 0.035 in the more recent years. Baumeister and Peersman (2013a), Economou and Fattouh (2021), Foroni and Stracca (2023) and Baumeister and Hamilton (2023), using models that allow parameters to vary over time, also find evidence of a sharp decline in global oil supply elasticity since the late 80 s.

Three factors are mainly responsible for this development. First, Baumeister and Peersman (2013a) argue that the development of oil futures markets in the 80 s makes oil producers less responsive to oil price changes, since it gives them the opportunity to hedge against declines in oil prices by selling oil futures contracts. Second, OPEC's oil production was for years known for its larger price responsiveness compared to other oil producers (Caldara et al. 2019; Foroni and Stracca 2023). However, as Fig. 1b shows, OPEC's share in non-US oil production decreased sharply in the 70 s and early 80 s, from 70% to 40%, and it remains constant at this level ever since. This implies that the importance of OPEC in this non-homogeneous group of oil producers decreases over time and so does the non-US oil supply elasticity. Third, OPEC's own ability to timely react to changes in the price of oil seems to decline over time as well, mainly due to the gradual decrease in its spare capacity, which started in the 90 s and continues until the end of our sample period (see Figure C.2 in the online Appendix). In a counterfactual analysis, Economou and Fattouh (2021) show that in the extreme case of zero OPEC spare capacity, the average global oil supply elasticity is even lower, approximately half compared to the actual. Foroni and Stracca (2023) find a gradual decrease in the price responsiveness of OPEC oil production in recent years as well, driven mainly by a considerable decline in Saudi Arabia's oil supply elasticity.

Turning now to the US oil supply elasticity, we observe opposite dynamics. For many years, the posterior median of this elasticity remains constant at around 0.035. But starting in 2006, it increased considerably, reaching a maximum value of 0.2 toward the end of the sample[19]. The reason for this sharp increase is the shale oil boom. This is because the ever increasing share of tight oil production in the US

[18] For all remaining figures, the x-axis shows the end date of each rolling window. For instance, the first posterior distribution is taken from the window 1973:02–1988:01.

[19] The increase is even sharper if we consider a standard rolling-sample approach, i.e., if we do not use an expanding window as prior information. This is shown in Figure C.3 in the online Appendix.

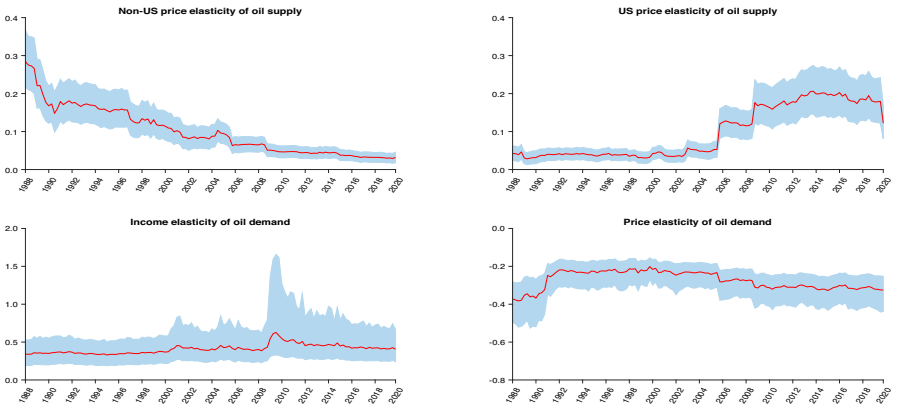

Fig. 5 Time-varying posterior oil supply and demand elasticities. *Note*: Red lines: posterior medians; Light blue shaded areas: 68% posterior credible sets

in the more recent years is associated with an increase in the price responsiveness of total US oil production, since shale oil is more elastic than conventional oil production (Bjørnland et al. 2021; Aastveit et al. 2022). This explanation is in line with the findings in Baumeister and Hamilton (2023) and Foroni and Stracca (2023), who document a substantial increase in tight oil supply elasticity in the US after the shale oil revolution. Note though that this significant jump in the US oil supply elasticity, besides a change in the composition of total US oil production (i.e., a shift from conventional to shale oil production), could also reflect favorable policy changes in the US oil market, such as the 2015 export-ban repeal. Overall, the analysis so far highlights the considerable structural change that took place in the global oil market, which is masked when we follow a time-invariant approach. On the other hand, we observe no considerable time variation in the income and price elasticities of oil demand.

4.2.2 Impulse response functions

Figures 6,7, 8, 9 and 10 show the effects of each oil market shock on different US and non-US response variables over time. In all figures, a three-dimensional coordinate system is employed to display the magnitude (left, vertical axis) of the IRFs over time (bottom, horizontal axis) and across different forecast horizons (bottom, right axis). Red and yellow colors indicate negative responses, whereas light and dark blue colors correspond to positive effects. Finally, the two-dimensional contour area at the bottom of each plot denotes statistical significance based on the 68% confidence interval, with blue and red colors indicating statistical significance for positive and negative responses, respectively, while white color indicates non-statistical significance.

Figure 6 displays the time-varying effects of non-US oil supply disruptions on the real price of oil and the three US variables considered in this study. Starting with the price of oil, we observe a statistically significant impact in all time periods and up to one year after the shock. This result is in line with previous studies that also assume a nonzero oil supply elasticity (Baumeister and Hamilton 2019; Herrera and Rangaraju

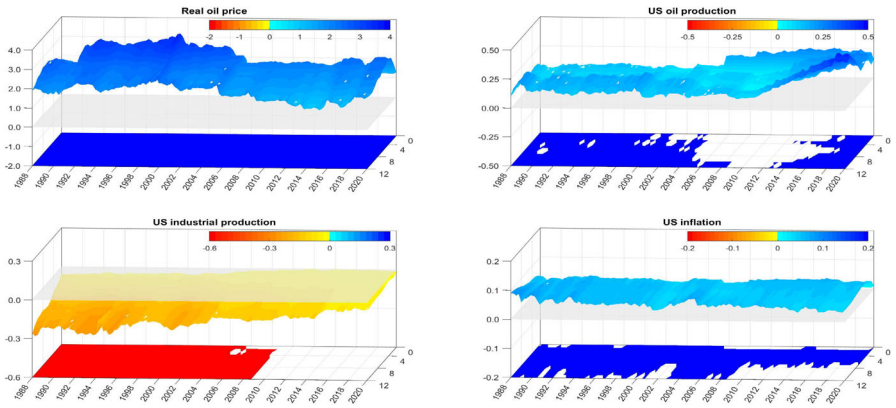

Fig. 6 Time-varying cumulative IRFs to non-US oil supply shocks. *Note*: (i) The shock is normalized to 1% decrease in non-US oil production; (ii) The three-dimensional areas show the posterior median IRFs, while the two-dimensional areas at the bottom show statistical significance for positive (blue) and negative (red) responses based on the 68% confidence level. (Color figure online)

2020). Note though that the magnitude of the responses declines in the more recent years. This increase in the price of oil triggers, in turn, oil production in the US. The reaction of US oil production is statistically significant across all forecast horizons in the first half as well as toward the end of the sample period. Besides time variation in statistical significance, we also observe an increase in the magnitude of the IRFs toward the end of the sample period. This change in the magnitude can be attributed to the increased capacity and price responsiveness of US oil production after the shale oil boom. Using a TVP-VAR model, Ewing et al. (2018) find similar results. Note though that other studies, which employ recursive identification schemes and time-invariant models, do not find a strong and statistically significant reaction of US oil production (Kang et al. 2017; Gundersen 2020).

Focusing now on the US economy, we see that the importance of oil supply disruptions in the rest of the world declines over time. Starting with the reaction of US industrial production, we observe a gradual shift from negative, persistent and statistically significant responses to close to zero and statistically insignificant effects. The responses of US inflation, in turn, do not show any considerable variation in magnitude over time. However, in the more recent years the effects become less persistent. Both results point to a more resilient US economy to non-US oil supply disruptions, which is consistent with previous findings (Blanchard and Gali 2007; Herrera and Pesavento 2009; Kang et al. 2015). Note though that if we also consider the positive and timely reaction of US oil production to non-US oil supply disruptions, here we offer an additional explanation for this development, besides the traditional ones (i.e., improved monetary policy, declining share of oil in production, etc.). This is because the increased US oil production, as a response to a negative non-US oil supply shock, helps stabilizing the price of oil in the global oil market and at the same time it boosts domestic income.

We now turn to the corresponding effects of negative US oil supply shocks, which are displayed in Fig. 7. Starting with the impact on the price of oil, we observe a

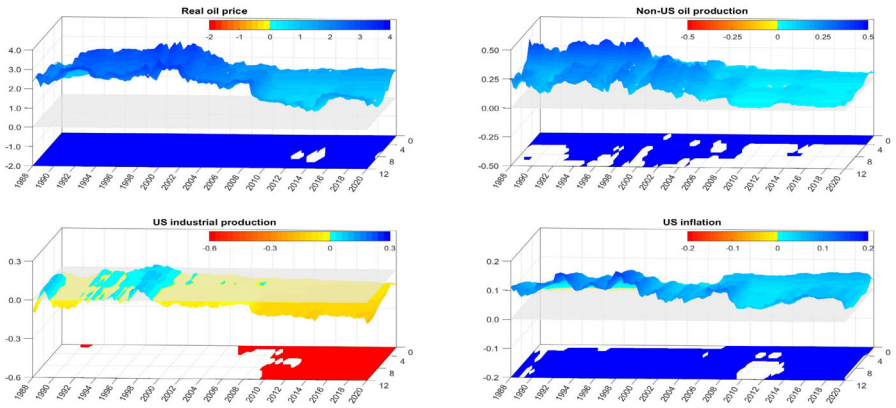

Fig. 7 Time-varying cumulative IRFs to US oil supply shocks. *Note*: (i) The shock is normalized to 1% decrease in US oil production; (ii) The three-dimensional areas show the posterior median IRFs, while the two-dimensional areas at the bottom show statistical significance for positive (blue) and negative (red) responses based on the 68% confidence level. (Color figure online)

similar pattern as in the case of non-US oil supply shocks. The reaction of non-US oil production to the increased price of oil shows also considerable time variation. In particular, in the first half of the sample, the responses are of higher magnitude and more persistent, whereas they gradually decline in magnitude over time. Ewing et al. (2018) reach the same conclusion. This pattern follows the evolution of the non-US oil supply elasticity discussed earlier, highlighting the considerable decline in the ability of non-US oil producers to react to oil supply disruptions in the US. Overall, Figs. 5, 6 and 7 provide evidence in support of the argument that US oil producers can takeover Saudi Arabia's role as swing producer in the oil market after the shale oil boom (Aastveit et al. 2022).

Regarding the impact on the US economy, Fig. 7 shows a gradually increasing, negative impact on industrial production, which becomes statistically significant in the last decade of the sample. A potential explanation is related to the increased reliance of US industrial production on oil produced domestically. As Fig. 1c shows, after the shale oil revolution there is a persistent decrease in oil imports and a corresponding sharp increase in oil exports. This implies that the US economy becomes gradually more dependent on domestic than foreign oil production, which makes it more vulnerable to sudden domestic oil supply disruptions. Nonetheless, the IRFs of US inflation do not show considerable time variation.

The remaining three figures display the effects of demand-side shocks. Figure 8 shows the impact of an 1% increase in global economic activity. Although global economic activity has always been an important driver of oil prices, since the early 2000s its effects become more persistent and of larger magnitude, mainly due to increased demand in emerging economies. It is reassuring that our dynamic approach captures this well-established development in the oil market (Baumeister and Peersman 2013a; Kilian and Murphy 2014). The responses of non-US and US oil production follow the pattern discussed in the previous two figures. More specifically, the positive influence of aggregate demand shocks on non-US oil production steadily declines

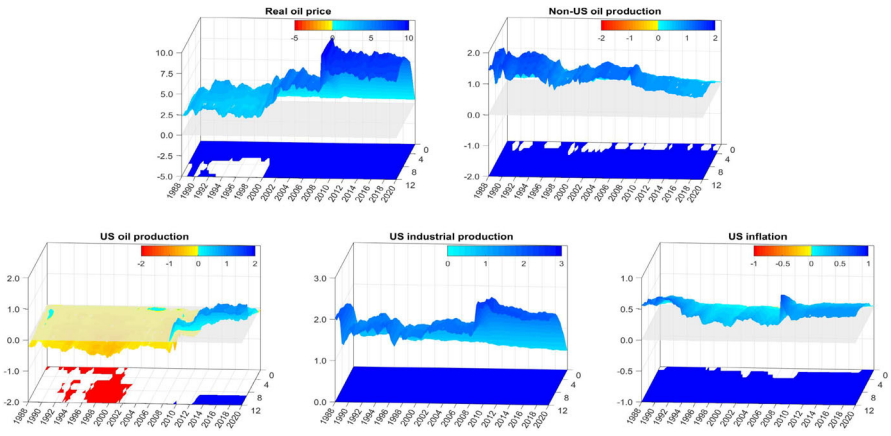

Fig. 8 Time-varying cumulative IRFs to economic activity shocks. *Note*: (i) The shock is normalized to 1% increase in global economic activity; (ii) The three-dimensional areas show the posterior median IRFs, while the two-dimensional areas at the bottom show statistical significance for positive (blue) and negative (red) responses based on the 68% confidence level. (Color figure online)

over time, which is consistent with the diminishing price responsiveness of non-US oil producers in the more recent years. This finding is also in line with Baumeister and Peersman (2013a). US oil producers, instead, can benefit from aggregate demand shocks only in recent years, owing to the increased capacity and larger oil supply elasticity after the shale oil boom.

To discuss the impact of economic activity shocks on the US economy, we should first outline the underlying mechanism. A positive global economic activity shock stimulates the US economy, since the demand for US products is expected to rise. At the same time though, increased aggregate demand boosts the demand for oil. This leads to an increase in the price of oil, which in turn has a negative impact on the economy. Whether the positive or negative effect dominates in the long run depends on many factors, such as the dependence of domestic production on oil and the response of oil production to the increased demand for oil. In the case of US industrial production, the positive effect dominates across all examined forecast horizons in all rolling samples. This is also the case in the more recent years, when despite the sharp increases in the price of oil, the IRFs of US industrial production remain positive and statistically significant, owing to some extent to the increased domestic oil production.

Figures 9 and 10 are of secondary importance, in the sense that their influence on the global oil market and the US economy is weaker compared to oil supply and aggregate demand shocks. However, some results deserve a short discussion. First, both shocks are important drivers of oil prices over time, despite their lower impact. Second, in contrast to other oil market shocks, inventory demand shocks cause only a short-lived, positive reaction in both non-US and US oil production, which is in line with earlier findings (Kilian and Murphy 2014; Baumeister and Hamilton 2019). On the other hand, the IRFs of non-US and US oil production to oil-specific demand shocks evolve in opposite ways, as in the case of oil supply shocks. Third, inventory demand shocks do not have a considerable impact on the US economy, as their effects

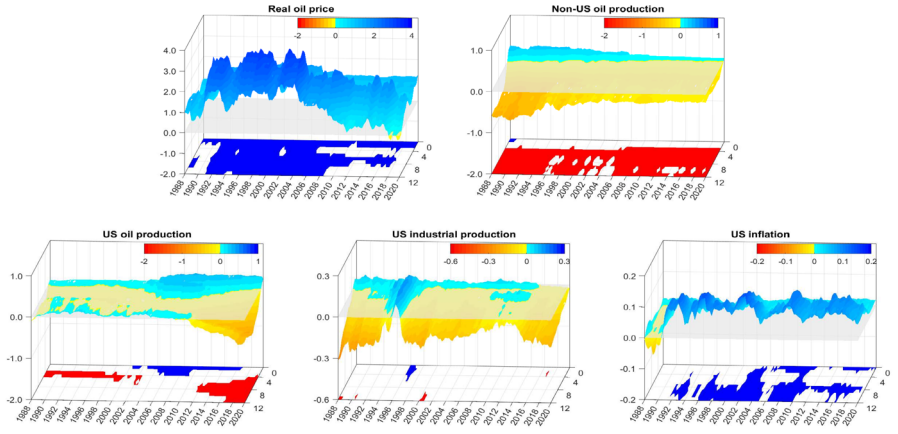

Fig. 9 Time-varying cumulative IRFs to inventory demand shocks. *Note*: (i) The shock is normalized to 1% increase in inventory demand; (ii) The three-dimensional areas show the posterior median IRFs, while the two-dimensional areas at the bottom show statistical significance for positive (blue) and negative (red) responses based on the 68% confidence level. (Color figure online)

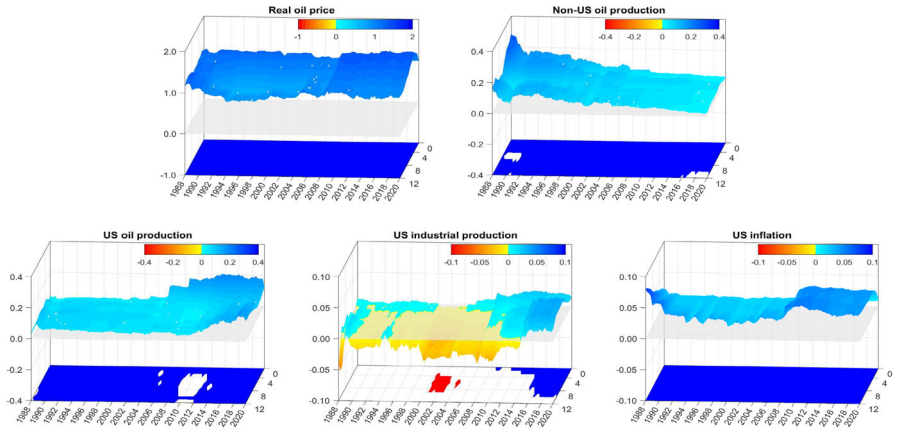

Fig. 10 Time-varying cumulative IRFs to oil-specific demand shocks. *Note*: (i) The shock is normalized to 1% increase in oil-specific demand; (ii) The three-dimensional areas show the posterior median IRFs, while the two-dimensional areas at the bottom show statistical significance for positive (blue) and negative (red) responses based on the 68% confidence level. (Color figure online)

on US industrial production and inflation are negligible and sporadic, respectively. Finally, whereas oil-specific demand shocks historically contribute to US inflation, their impact on US economic activity is minimal. In addition, the shift of the IRFs from negative to positive in the more recent years is consistent with earlier studies (Kang et al. 2015; Foroni et al. 2017; Arampatzidis et al. 2021).

Overall, the time-varying analysis of this section yields three main findings: (i) The non-US oil supply elasticity decreases over time, which results in a gradually lower price responsiveness of non-US oil production to favorable oil supply and demand shocks over time; (ii) in contrast, the US oil supply elasticity follows the opposite

route after the shale oil boom, which enables domestic oil production to timely react to oil price changes, no matter whether they originate from the supply or demand side; and (iii) the US economy appears increasingly resilient to oil market shocks that originate from the rest of the world. As the robustness exercise in Section C.2 of the online Appendix shows, these conclusions are not only robust, but even reinforced once we consider the conventional rolling-sample estimation approach.

5 Conclusion

The main purpose of this study is to assess the impact of the shale oil revolution on the global oil market and the US economy. To this end, the Bayesian SVAR model of Baumeister and Hamilton (2019) is modified by separating global oil production into US and non-US components and employing a rolling-sample technique to track time variation. This approach enables close monitoring of the timing and dynamic effects of the shale oil boom.

The empirical results highlight three main findings. First, the price responsiveness of non-US oil production has declined over time, likely reflecting a decrease in OPEC's oil supply elasticity, consistent with Baumeister and Peersman (2013a), Economou and Fattouh (2021) and Foroni and Stracca (2023). Second, the shale oil boom has sharply increased the total US oil supply elasticity, as the share of the more elastic tight oil production has risen. Third, this study offers an additional reason for the mild effects of oil market shocks on the US economic activity in the more recent years, reinforcing the conclusions of Bjørnland and Skretting (2024).[20] In particular, this resilience can be partly explained by the enhanced role of US oil production and the reduced importance of oil imports.

This greater resilience appears to reflect changes in the underlying macroeconomic transmission channels as well. Several mechanisms likely contribute to this structural shift. First, the long-run decline in the oil intensity of US GDP, driven by efficiency improvements, a transition toward less energy-intensive sectors and the growing share of services, reduces the direct cost-push impact of oil price increases (Hamilton 2009, Herrera et al. 2011). Second, lower energy-cost pass-through to consumer prices dampens the indirect drag on real incomes, while improved monetary policy credibility helps contain inflation expectations, mitigating confidence effects. Third, the expansion of domestic shale oil production reduces dependence on imports, limiting the adverse trade balance and income effects of foreign supply shocks. These channels are consistent with the evidence in Bjørnland and Skretting (2024), who also document muted US macroeconomic responses in the post-shale era, alongside differentiated effects for shale versus conventional oil supply shocks. Together, these findings suggest that structural changes in both the energy sector and the broader US economy have materially weakened the macroeconomic propagation of global oil market shocks.

These developments have important implications. The declining non-US oil supply elasticity suggests reduced OPEC responsiveness to oil price changes, while the grow-

[20] Note though that our sample period excludes the dramatic demand collapse in 2020 due to COVID-19, the OPEC+ production war and the 2022–24 energy price spikes. Therefore, our results and conclusions should be interpreted with caution in the post-2019 period.

ing share of tight oil production enhances US capacity to stabilize the market. This is consistent with Bornstein et al. (2022), who employ a world equilibrium model, showing that the expansion of fracking weakens OPEC's market power and reduces long-run oil price volatility, as shale oil producers can rapidly adjust output to oil demand changes. The fracking boom has also reduced US exposure to foreign oil price shocks, complementing factors such as improved monetary policy and more flexible labor markets (Blanchard and Gali 2007). However, greater reliance on domestic production increases vulnerability to domestic supply disruptions and higher petroleum exports make the US more exposed to declines in oil prices.

Finally, this study contributes to the oil market literature by showing that models which assume a zero (Kilian 2009) or close to zero (Kilian and Murphy 2014) oil supply elasticity might not be realistic anymore. Instead, more flexible identification schemes, like in the Bayesian SVAR model of Baumeister and Hamilton (2019), ought to be preferred. Ideally, future research should focus on developing models that allow for time variation in the priors for the contemporaneous coefficients, which would add even more flexibility to the identification scheme.

Overall, the shale oil revolution has altered both the origin and nature of US exposure to oil market risks. Policymakers should consider diversifying energy sources and investing in renewables to mitigate these risks, while global oil market models should account for the substantial post-shale changes in US oil supply elasticity.

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Declarations

Conflict of interest The authors have no conflict of interest to declare that is relevant to the content of this article.

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