A weekly structural VAR model of the US crude oil market

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Abstract: We present a weekly structural Vector Autoregressive model of the US crude oil market. Exploiting weekly data we can explain short-run crude oil price dynamics, including those related with the COVID-19 pandemic and with the Russia's invasion of Ukraine. The model is set identified with a Bayesian approach that allows to impose restrictions directly on structural parameters of interest, such as supply and demand elasticises. Our model incorporates both the futures-spot price spread to capture shocks to the real price of crude oil driven by changes in expectations and US inventories to describe price fluctuations due to unexpected of variations of above-ground stocks. Including the futures-spot price spread is key for accounting for feedback effects from the financial to the physical market for crude oil and for identifying a new structural shock that we label expectational shock. This shock plays a crucial role when describing the series of events that have led to the spike in the price of crude oil recorded in the aftermath of Russia's invasion of Ukraine.

Key Words: COVID-19; WTI price; futures-spot price spread; speculation; structural VAR; Bayesian VAR.

JEL Codes: C32; Q02; Q41; Q43.

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1 Introduction

Understanding and forecasting changes in the real price of crude oil is an important but challenging task. Oil price dynamics are closely tracked by authorities in charge of monetary and fiscal policies (Yellen, 2015; CEA - Council of Economic Advisers, 2019; Schnabel, 2020). Scholars have carefully scrutinized the functioning of crude oil markets and their relationship with the macroeconomy (Hamilton, 2019a; Baumeister and Kilian, 2016). Moreover, in recent years there has been growing interest in crude oil futures markets as an attractive venue for investors to benefit from portfolio diversification and inflation hedging (Erb and Campbell, 2006; Gorton et al., 2013a; Cheng and Xiong, 2014). Lastly, understanding the relationship between spot and futures oil prices is key for companies in the transportation and energy sectors whose assets and liabilities might be affected by oil price fluctuations (see e.g. Alizadeh et al., 2004; Chun et al., 2019).

We develop a weekly Structural Vector Autoregressive (SVAR) model of the US market for crude oil that can can be used to analyse short-run price fluctuations driven by shocks hitting the spot price of West Texas Intermediate (WTI). We exploit weekly data to disentangle the combination of structural shocks that have caused the price responses observed after the outbreak of the COVID-19 pandemic and in the aftermath of the Russia's invasion of the Ukraine. Our methodology for decomposing the WTI spot price into its structural drivers relies on the Bayesian approach due to Baumeister and Hamilton (2019). Bayesian inference incorporates uncertainty about the restrictions used to identify the structural shocks of our SVAR model.

Our work is related with different strands of the literature. First, we contribute to the literature on structural models of the crude oil market where the price of oil is endogenous with respect to macroeconomic aggregates (see e.g. Alquist et al., 2019; Baumeister and Hamilton, 2019; Bodenstein et al., 2012; Kilian, 2009; Kilian and Murphy, 2014). Moreover, our study can also be cast in the literature dealing with the relationship between the physical and financial markets for commodities (see e.g. Alquist and Kilian, 2010; Alquist and Gervais, 2013; Alquist et al., 2014; Juvenal and Petrella, 2015; Knittel and Pindyck, 2016; Pindyck, 2001; Singleton, 2014; Smith, 2009). Lastly, we contribute to the burgeoning literature on the economic impacts of the coronavirus pandemic (Lenza and Primiceri, 2022; Ng, 2021; Chudik et al., 2021; Sharif et al., 2020). This paper has three distinguishing features. Our structural model of the US crude oil market exploits data sampled at weekly frequency. On the contrary, most previous analyses relied on monthly or quarterly data. A notable recent exception is Venditti and Veronese (2020). Moreover, we draw on the theory of competitive storage to model the speculative component of the real price of oil with data on WTI futures prices. Specifically, in our model the interest-adjusted spread between the futures and spot prices of WTI crude oil proxies for the negative of the convenience yield of crude oil inventories. Thus, this variable reflects the perceived relative value of the amount of inventories that is available in the near future as conveyed by the oil futures market. Moreover, the sign of the interest-adjusted spread is highly informative about the slope of the term structure of the oil futures curve and represents valuable information for all traders participating to the futures oil market (Nikitopoulos et al., 2017). Lastly, we exploit the Bayesian approach of Baumeister and Hamilton (2015, 2019) to set-identify the structural shocks in our weekly SVAR model. The peculiarity of this approach is that it allows to summarize our beliefs about the value of key structural parameters – such as oil supply and oil demand elasticities – while incorporating uncertainty about such identifying assumptions.

The paper is structured as follows. Section 2 describes the data and the methodology underlying our weekly SVAR model. The identification assumptions are presented in Section 3. Estimation results are discussed in Section 4. Section 5 presents some robustness checks, while Section 6 concludes.

2 Data and Methods

2.1 Data

We describe the US market for crude oil with a SVAR model that includes $n = 5$ endogenous variables sampled at weekly frequency over the period spanning 1/1/1988 – 29/4/2022 for a total of $T = 1972$ observations. The vector of observable variables is $\mathbf{y}_t \equiv [\Delta q_t,\ y_t,\ s_t,\ \Delta i_t,\ \Delta p_t]'$. These variables are: (i) the growth rate of US crude oil production, Δq_t; (ii) a proxy for the global real economic activity, y_t; (iii) the interest-adjusted spread (IAS), s_t (iv) the change in US oil inventories, Δi_t; (v) the percent growth of the WTI real spot price, Δp_t.

Following Hamilton (2019b), we construct a proxy for the global business cycle based on the deflated value of the Baltic Dry Index (BDI), which represents the real shipping cost (RSC) index used in our study.[1] Our proxy of the global business cycle is then defined as $y_t \equiv \log\left(BDI_t/CPI_t\right) - log\left(BDI_{t-(2\times 52)}/CPI_{t-(2\times 52)}\right)$. Note that we consider a 2-year difference and hence we interpret y_t as the cyclical component of the RSC index.

The IAS is defined as: $s_t = 100 \times \log(F_t^{(3mo)}/P_t) - r_t^f$ where P_t is the WTI spot price, $F_t^{(3mo)}$ is the corresponding 3 month futures price and r_t^f is the 3-Month Treasury Bill rate. The construction of the IAS requires selecting the maturity of the underlying futures contracts. We choose a maturity of three-months because short-term contracts are more tightly linked to crude oil market fundamentals than long-term contracts (Lee and Zeng, 2011).[2] The IAS represents the negative of the convenience yield plus the cost of storage of crude oil inventories. In other words, it measures the benefit of holding stocks of crude oil above and below the ground.[3]

2.2 VAR representations and estimation

We write the structural form of the VAR model as:

$$\mathbf{A}\mathbf{y}_t = \mathbf{b_0} + \sum_{j=1}^{12} \mathbf{B}_j \mathbf{y}_{t-j} + \mathbf{v}_t \tag{1}$$

where $\mathbf{b}_0$ is a $n \times 1$ vector of intercepts, while $\mathbf{A}$ and $\mathbf{B}_j$ are $n \times n$ matrices of structural coefficients. The vector of structural shocks $\mathbf{v}_t \equiv \left[v_{1t}, v_{2t}, v_{3t}, v_{4t}, v_{5t}\right]'$ is assumed to be normally distributed with zero mean and diagonal variance-covariance matrix $\mathbf{D} \equiv E\left[\mathbf{v_t}\mathbf{v_t}'\right]$.

[1] We deflate the BDI using the interpolated value of U.S. Consumer Price Index (CPI_t).

[2] Notice that s_t is constructed subtracting the risk-free rate from the futures-spot price spread. This might seem at odd with the fact that the real price of oil is affected by changes in the US interest rates by means of the cost-and-carry equation (Frankel, 2014). However, in our model the potential exposure of the real price of oil to changes in the US interest rate is captured by shocks to the global business cycle, as discussed by Kilian and Zhou (2019) and Alquist et al. (2019).

[3] The theory of competitive storage postulates that the IAS is the the cost of storage minus the convenience yield. In the short-run the cost of storage is constant (Fama and French, 1987), while the convenience yield is a decreasing function of the level of inventories (Knittel and Pindyck, 2016).

The model includes 12 lagged values, that corresponds to three months which is the maturity of the futures contracts used to build the IAS.[4]

The reduced-form representation of the VAR is given by:

$$\mathbf{y}_t = \mathbf{c_0} + \sum_{j=1}^{12} \mathbf{\Phi}_j \mathbf{y}_{t-j} + \mathbf{u}_t \tag{2}$$

where $\mathbf{c}_0 = \mathbf{A}^{-1}\mathbf{b}_0$, $\mathbf{\Phi}_j = \mathbf{A}^{-1}\mathbf{B}_j$ and $\mathbf{u}_t = \mathbf{A}^{-1}\mathbf{v}_t$. Reduced-form errors, $\mathbf{u}_t$ are assumed to be normally distributed with zero mean and variance-covariance matrix $\mathbf{\Sigma}_u \equiv E\left[\mathbf{u}_t\mathbf{u}_t'\right]$. The reduced-form parameters can be consistently estimated by Ordinary Least Squares (OLS), however – absent any restrictions – the structural shocks are not point identified.

We follow the identification and estimation strategy proposed by Baumeister and Hamilton (2015) that delivers a set-identified SVAR model and is based on two main steps. The first step consists of a specification of informative prior beliefs about the structural parameters $\mathbf{A}$, $\mathbf{B}$, $\mathbf{D}$ and the determinant of $\mathbf{A}$. The second step relies on a random walk Metropolis-Hastings algorithm, which is designed to generate draws from the posterior distribution of the structural coefficients. Further details are provided in the on-line Appendix.

As for the matrix of contemporaneous correlations, we impose the following structure that allows to set-identify the structural shocks of interest:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & -a^s_{qs} & 0 & -a^s_{qp} \\ 0 & 1 & 0 & 0 & -a_{yp} \\ 0 & 0 & 1 & -a_{si} & -a_{sp} \\ -a_{iq} & 0 & -a_{is} & 1 & -a_{ip} \\ 1 & -a^d_{qy} & -a^d_{qs} & -1 & -a^d_{qp} \end{bmatrix} \tag{3}$$

[4]The choice of working with 12 lags is a compromise between smaller lag orders suggested by information criteria and larger lag orders typically used in the literature relying on monthly data. Results available from the authors upon request show that a SVAR model with 24 lags yields almost identical structural impulse response functions.

3 Identification

3.1 A SVAR model of the US crude oil market

To better illustrate our identification assumptions, we re-write the SVAR model as a system of five equations:

$$
\begin{cases}
\Delta q_t = a^s_{qs} s_t + a^s_{qp} \Delta p_t + \mathbf{b}_1' \mathbf{x}_{t-1} + v_{1t} & \text{(4a)} \\
y_t = a_{yp} \Delta p_t + \mathbf{b}_2' \mathbf{x}_{t-1} + v_{2t} & \text{(4b)} \\
s_t = a_{si} \Delta i_t + a_{sp} \Delta p_t + \mathbf{b}_3' \mathbf{x}_{t-1} + v_{3t} & \text{(4c)} \\
\Delta i_t = a_{iq} q_t + a_{is} s_t + a_{ip} \Delta p_t + \mathbf{b}_4' \mathbf{x}_{t-1} + v_{4t} & \text{(4d)} \\
\Delta q_t = a^d_{qy} y_t + a^d_{qs} s_t + \Delta i_t + a^d_{qp} \Delta p_t + \mathbf{b}_5' \mathbf{x}_{t-1} + v_{5t} & \text{(4e)}
\end{cases}
$$

where $\mathbf{x}_{t-1}$ is a $mn+1$ vector containing a constant and $m = 12$ lags of the variables, that is $\mathbf{x}'_{t-1} \equiv \left[\mathbf{y}'_{t-1},\ \mathbf{y}'_{t-2},\ \ldots,\ \mathbf{y}'_{t-m},\ 1\right]'$ and $\mathbf{b}'_i$ contains all structural coefficients on the lagged variables of the i^{th} equation and corresponds to the i^{th} row of $\mathbf{B} \equiv [\mathbf{B}_1, \ldots, \mathbf{B}_m,\ \mathbf{b}_0]$, a $[n \times (nm+1)]$ matrix. In this way, we include in each equation the lagged values of all the variables in the system.

Equation (4a) states that US oil supply is affected both by the IAS and the real price of oil, through the contemporaneous structural parameters a^s_{qs} and a^s_{qp}, respectively. The first parameter, a^s_{qs}, captures the feedback effects from the financial to the physical market for crude oil. The second parameter, a^s_{qp}, represents the short-run price elasticity of oil supply. Equation (4a) involves two exclusion restrictions, namely $a^s_{qy} = a^s_{qi} = 0$. These restrictions are consistent with the view that, within the same period, oil supply is not directly affected by changes in global business cycle and in above ground crude oil inventories. With these restrictions, the first structural shock, v_{1t}, corresponds to a “US oil supply shock”, triggered by any event that causes unexpected changes of the US production of crude oil (e.g. natural disasters, strikes, production decisions). A negative US supply shock shifts the contemporaneous oil supply curve to the left along the oil demand curve.

In equation (4b), global real economic activity is instantaneously affected only by the real price of oil, via a_{yp}. The second structural shock, v_{2t}, is then interpreted as a “global economic activity shock" that reflects unexpected changes in the demand for US crude oil driven by fluctuations in the global business cycle. A positive global economic activity shock captures any increase in the contemporaneous demand curve for US crude oil along the oil supply curve.[5]

Equation (4c) illustrates the determinants of the IAS, that is assumed to respond on impact to changes in US inventories and in the real price of crude oil. The parameter a_{si} captures the relationship between (the negative of) the convenience yield and the inventory level (see e.g. Working, 1949; Brennan, 1958; Fama and French, 1987). The relationship between changes in the spot price of crude oil and the IAS is captured by a_{sp}. This parameter is interpreted as a proxy for the slope of the term structure of the oil futures curve. The two exclusion restrictions – namely $a_{sq} = 0$ and $a_{sy} = 0$ – imply that on impact the IAS does not depend on oil production and global real economic activity.

One of the main contribution of our work is the identification of the third structural shock, v_{3t}, that we label "expectational shock". This shock captures unpredictable changes in financial markets expectations about the future path of crude oil spot prices. A positive expectational shock represents a shift to the left of the supply curve along the demand curve driven by changes in the market participants' expectations. Specifically, if futures prices are higher than spot prices, a positive IAS is interpreted as a signal of higher expected spot prices. Thus, in a contango market structure, oil producers with access to a flexible production process will reduce the production in the current period and bet on making more profits by increasing output in the near future.

Equation (4d) represents the oil inventory demand curve. Changes in the level of US oil production, the price of storage and the real price of oil result in an instantaneous shift of the oil inventory demand curve. Following Baumeister and Hamilton (2019), we assume that US crude oil stocks depend on economic activity, only through its effects on real price of crude oil. As a result, we impose an exclusion restriction on the structural coefficient a_{iy}. The fourth structural shock – labelled "US inventory demand shock" (v_{4t}) – also shifts

[5]We have also considered an alternative formulation of the SVAR model that includes IAS, in Equation (4b). The structural impulse response functions deriving from the alternative model are qualitatively similar to those arising from our main specification.

the demand curve for US crude oil. A positive shock to crude oil inventories – triggered by an increase in the demand for storage (i.e. above-ground oil inventories) – moves the contemporaneous demand curve to the right along the supply curve for US crude oil.

Lastly, equation (4e) represents the US oil consumption demand approximated by the difference between production Δq_t and inventories, Δi_i. The parameters a^d_{qy} and a^d_{qp} capture the effect of global real economic activity on US oil consumption demand and the short-run price elasticity of oil demand, respectively. The US consumption demand for oil is instantaneously related to the IAS, via a^d_{qs}, which is designed to capture the forward-looking component of oil consumption. Therefore we label the last shock as "US oil consumption demand shock" (v_{5t}). An unexpected increase of US oil consumption – driven by developments regarding the US economy – moves the contemporaneous demand curve for US crude oil to the right along the US oil supply curve.

3.2 The role of the interest-adjusted spread (IAS)

A distinguishing feature of our model is its reliance on both oil inventories and the IAS. This is a point of departure from several extant contributions, such as Kilian and Murphy (2014) and Baumeister and Hamilton (2020). These works build on standard arbitrage assumptions and argue that futures prices are redundant in SVAR models of the oil market, provided that the speculative component of prices is captured by data on above-ground crude oil inventories.[6]

The inclusion of the IAS in our model can be motivated as follows. First, the IAS captures the benefit of holding stocks of crude oil both above and below the ground (see Alquist et al. (2014)). Below-ground inventories play an important role for US shale oil producers that can easily adjust production in response to oil price expectations (Bjørnland, 2019; Newell and Prest, 2019).[7]

[6]For instance Kilian and Murphy (2014) perform the test developed by Giannone and Reichlin (2006) to show that that data on futures-spot spread do not contain extra-information relative to the proxy for global crude oil inventories.

[7]Newell and Prest (2019) state that: *"Using futures prices as a measure of spot price expectations is a shortcut to obtain price expectations. This is based on conversations with industry operators regarding how they generate their price expectations"*

The IAS based on WTI is also informative about the slope of the term structure of futures prices. In fact, the WTI market is exposed not only to US-specific shocks, but also to global oil price shocks.[8]

Lastly the IAS reflects the information set available to agents at the time they make their decisions in terms of production, consumption and investment strategies. Therefore, the IAS helps capturing the forward-looking component of the real price of crude oil through the feedback effect from the futures market to the spot market (see Singleton, 2014; Sockin and Xiong, 2015; Figuerola-Ferretti et al., 2020; van Huellen, 2020).

3.3 Prior information for the structural parameters

We rely on economic theory and empirical evidence from previous studies to specify a set of prior beliefs on the elements of $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{D}$. In this section we focus on the priors for the elements of the contemporaneous structural matrix $\mathbf{A}$, while priors for the remaining coefficients are discussed in the Appendix.

In this study we rely on a mixture of dogmatic (e.g. exclusion restrictions) and non-dogmatic identifying assumptions (in terms of Student t distributions on the contemporaneous structural parameters), as reported in Equation (3) and Table 1.[9]

Priors for parameters of the supply equation. Setting prior for the parameters of the supply equation is challenging due to the contemporaneous relationship between the price and the production of crude oil. Empirical analyses based on panel and time-series data provide mixed evidence on the magnitude of the short-run oil price supply elasticity (Kilian, 2022). Newell and Prest (2019) estimate the price elasticity of oil supply to be -0.022 for unconventional wells and 0.017 for conventional wells.[10]

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[8]According to Elder et al. (2014), WTI market has a dominant role in price discovery in comparison with Brent market, with an estimated information share larger than 80% over the period 2007-2012. Moreover, Kristoufek (2019) provides empirical evidence that WTI crude oil market is more efficient than Brent market.

[9]The Student t distribution is preferred to the Normal distribution in presence of outliers. This is particularly relevant with weekly data.

[10]Newell and Prest (2019) investigate the effects of price changes on drilling, completions and production in the five major oil-producing states of Texas, North Dakota, California, Oklahoma and Colorado. The authors provide empirical evidence of a positive response of drilling and completions to changes in futures prices, consistent with the view that price expectations play an important role in driving the first-two phases of well development. As opposed, for the production equation the futures prices are replaced with spot prices

Table 1: Specification of prior distributions for structural parameters $\mathbf{A}$

parameter	economic interpretation	Student t mode (c)	scale (σ)	dof (ν)	sign
a^s_{qs}	Effect of s_t on US oil supply	-0.10	0.10	3	?
a^s_{qp}	US oil price supply elasticity	0.15	0.05	3	+
a_{yp}	Effect of Δp_t on global economic activity	-0.05	0.1	3	?
a_{si}	Effect of Δi_t on IAS	0	0.2	3	?
a_{sp}	Effect of Δp_t on IAS	0	0.5	3	?
a_{iq}	Effect of q_t on US oil stocks	0	0.5	3	?
a_{is}	Effect of s_t on US oil stocks	0	0.2	3	?
a_{ip}	Effect of p_t on US oil stocks	0	1	3	?
a^d_{qy}	Effect y_t on US oil demand	0	0.5	3	+
a^d_{qs}	Effect of s_t US oil demand	0.2	0.2	3	?
a^d_{qp}	US oil price demand elasticity	-0.15	0.05	3	-

Notes: the location parameter is the mode of the t distribution, the scale parameter is its standard deviation, while "dof" denotes its degrees of freedom. "Sign" indicates whether a sign restriction has been enforced.

Other empirical studies find evidence of a large positive short-run supply elasticity, especially for unconventional crude oil producers. Bjørnland et al. (2021) report a monthly supply elasticity of shale oil in North Dakota in the range 0.3-0.9, depending on the technological characteristics of the wells.[11] Moreover, using a well-level dataset covering ten of the largest producing regions in the US, Aastveit et al. (2022) show that the response of shale firms to unexpected increase in the price of crude oil is 0.62. This figure is given by the sum of two components (i) the estimated price elasticity of oil supply (-0.06) and (ii) the estimated elasticity of oil supply with respect to the spot-futures price spread (0.68). For conventional oil producers, the oil supply elasticities with respect to spot price and spot-futures spread are -0.02 and -0.10, respectively. These results are in line with Anderson et al. (2018) who show that the responses of conventional oil producers to changes in the spot-futures spread and prices are close to zero.[12] Lastly, Rebelo et al. (2017) using a general equilibrium model

and the elasticity of oil supply for shale producers becomes negligible.

[11]Bjørnland et al. (2021) estimate the short-run price price elasticity of oil supply distinguishing conventional and shale oil producers with well level data. Moreover, each specification includes the spot price of crude oil and the spot-futures spread. Specifically, for conventional oil producers the response of production to changes in price and spot-futures spread are 0.03 and 0.07, respectively. Instead, the response of shale oil production to changes in the spot price is -0.015 and 0.76 to changes in the spread. Finally, the elasticities for unconventional and conventional oil supply are 0.1 and 0.71, respectively.

[12]Anderson et al. (2018) develop a theoretical model showing that crude oil production from existing wells in Texas does not respond to price incentives. The justification for this result is given by the high operational costs for conventional oil producers, as discussed in (Pindyck, 1994, 2001).

show that the use of hydraulic fracturing renders shale producers more price-sensitive than conventional producers.[13]

We use these studies to set the prior of a_{qp}^s and a_{qp}^s. As for the price elasticity of crude oil supply, we rely on a Student t distribution with support restricted on the positive domain and mode $c_{qp}^s = 0.15$. The prior for the mode is in the range of empirical estimates the price elasticity of oil supply that account for both conventional and unconventional crude oil production. We note that elasticities tend to (slightly) increase over time: monthly estimates reported in the literature can then be treated as an upper bound of the weekly US price elasticity of oil supply, a_{qp}^s.

For the elasticity of oil supply with respect to a change in the oil futures-spot spread we use a Student t distribution with a negative prior mode, but with support over the entire real line. The negative sign for the prior mode subsumes the idea that forward-looking shale oil producers have the option of leaving oil below the ground in anticipation of higher oil spot prices.

Priors for parameters of the global economic activity equation. The structural parameter a_{yp} measures the impact of a variation in the price of oil on real economic activity. For the structural coefficient a_{yp} we use a Student t distribution whose support is constrained to be negative. Since energy expenditure represents a small share of global GDP, an increase in the price of oil causes a small reduction in the proxy for global business cycle, we set $c_{yp} = -0.05$ (Hamilton, 2013).

Priors for parameters of the IAS equation. The structural coefficient a_{si} represents the effect of changes in the US crude oil inventories on the IAS. The sign of the relationship between s_t and Δi_t is not clear a priori, therefore we do not constraint the support of the Student t distribution.[14]. Similarly, we do not have reliable information to constraint the sign of a_{sp},

[13]Rebelo et al. (2017) relies on a novel data set compiled by Rystad Energy that contains detailed information (e.g. production, reserves, operational costs and investment) on 14.000 oil fields operated by 3.200 companies across 109 countries.

[14]For example, inventory accumulation can be associated with an increase in the IAS, mainly explained by a reduction in the convenience yield or, by an increase in the cost of storage. In this case, the built-up of US stocks would be driven by positive (or negative) shocks to supply (or demand), causing the spot price of crude oil to fall. On the other hand, speculators raise the demand for holding additional barrels of crude oil (also known as "precautionary demand for oil") driven by fears of production shortage or uncertainty in the

which represents the effect of an increase in the spot price of crude oil on the IAS. Therefore, we rely on relatively uninformative priors for both a_{si} and a_{sp} and set the mode of the priors distributions of these parameters to zero.

Priors for the inventory demand equation. For the inventory equation we follow Baumeister and Hamilton (2019) and assign relatively uninformative Student t prior for the structural coefficient a_{iq}, with mode at $c_{iq} = 0$. A recent work by Ederington et al. (2020) documents a positive relationship between crude oil inventories stored at Cushing, Oklahoma, and the futures-spot spread. In contrast, outside Cushing inventory changes are mainly explained by operational needs, consistent with the view that not all US storage locations are arbitrage hubs. For these reasons, we assign non-informative prior also for a_{is}. Also in the case of a_{ip} – the effect of a change in the spot price on US stocks – a tight prior cannot be set. In fact, if on the one hand a price increase might induce inventory accumulation, on the other hand, it might also cause inventories to be drawn down in an effort to smooth production (or consumption).

Priors for the consumption demand equation. The first structural coefficient of the US oil crude oil demand equation (4e) is a^d_{qy}, which represents the effect of global economic activity on the US oil consumption demand. We expect the global business cycle to exert only a mild effect on US consumption demand within the week. Thus, we use a relatively uninformative prior distribution with mode at $c^d_{qy} = 0$ and support constrained to be non-negative.

The structural coefficient a^d_{qs} represents the effect of changes in the IAS on the US oil demand. The sign of the relationship between the demand for crude oil and the IAS is not clear a priori. We then rely a relative uninformative prior distribution with mode $c^d_{qs} = 0.2$.

Lastly, the structural coefficient a^d_{qp} is the short-run price elasticity of US crude oil demand. Coglianese et al. (2017) estimate the short-run gasoline price demand elasticity to be approximately -0.37. Wadud et al. (2010) estimate US oil demand elasticity to be between -0.58 and -0.18. Similarly Levin et al. (2017) estimate the fuel demand elasticity to be between -0.36 and -0.30. Therefore, we set the mode of the prior distribution at

state of the economy. In this context, the structural parameter a_{sp} is expected to be negative (see Kilian, 2009; Alquist and Kilian, 2010; Anzuini et al., 2015)

$c^d_{qp} = -0.1$ and truncate the support of the distribution to be negative.

4 Results

4.1 Prior and posterior distributions of the structural parameters

The prior and posterior distributions of the structural parameters in $\mathbf{A}$ are compared in Figure 1 to assess whether the data have updated the prior distribution and to what extent our subsequent results are driven by the choice of the priors' parameters.

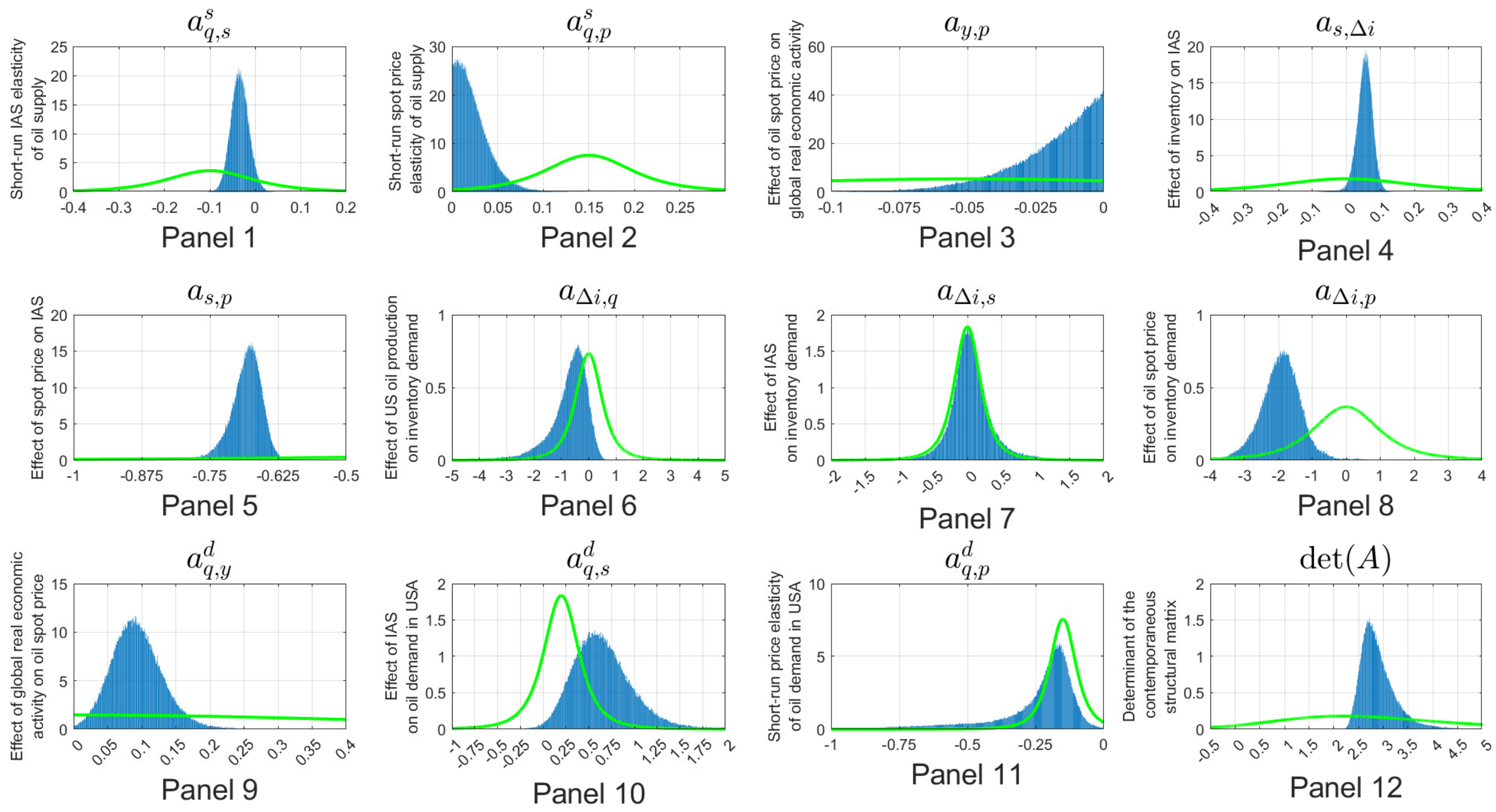
Posteriors for the oil supply equation. The posterior distribution of the elasticity of oil supply with respect to a change in the oil futures-spot spread, a^s_{qs}, is reported in Panel 1 of Figure 1. The posterior distribution of a^s_{qs} has smaller variance than its prior and is characterized by a posterior median equal to -0.035. In line with the results of Bjørnland et al. (2021), this result suggests that US producers – possibly driven by firms based on horizontal drilling technologies – respond to changes in market expectations by shifting the supply curve to the left and hence increasing oil spot prices within the week.[15]

Panel 2 of Figure 1 shows that the posterior median of the short-run price supply elasticity of oil supply, a^s_{qp}, is 0.02 and its distribution is skewed to the right. The posterior median is significantly smaller than the mode of the prior and is consistent with the empirical estimates available in the literature (see Anderson et al., 2018; Bjørnland, 2019; Kilian, 2022).

Two observations stand out from our results about oil supply elasticities. First, the posteriors median of elasticity of oil supply with respect to changes in the oil futures-spot spread is larger (in absolute value) than the posterior median of the price elasticity of oil supply. This suggests that the responsiveness of oil producers is mostly linked to changes in market expectations. This finding is not surprising, given that holding above-ground inventories is generally costlier than holding them below-ground. Second, our posterior

[15]It is worth noting that US crude oil production has increased significantly over the past ten years, driven mainly by the development of unconventional crude oil extractions. The US Energy Information Administration (EIA) reports that tight oil extraction accounted for around 63% of total crude oil production in the United States in 2019.

Figure 1: Priors VS posteriors for structural coefficients in model (1).



Note: Green lines and blue bars denote prior and posterior distributions, respectively.

median estimate of the price elasticity of oil supply is very much in line with those by Baumeister and Hamilton (2019) and Caldara et al. (2019). On this regard, the weekly elasticity of oil supply should not exceed the value of monthly elasticity estimates. However, if we follow Bjørnland et al. (2021) and we sum the absolute value of the posterior median of a^s_{qp} and a^s_{qs}, we get an even more elastic oil supply curve, with a median posterior estimate of 0.055.

Posteriors for the global economic activity equation. The prior distribution is flat compared with the posterior distributions for a_{yp}. However, we provide empirical evidence that most of the mass of the posterior distribution for a_{yp} is centered at -0.01. This implies that an increase in the real price of oil is associated with a very small reduction in the global real economic activity, within the week.

Posteriors for IAS equation. The posterior distribution of parameter capturing the effect of changes in US oil inventories on the IAS, a_{si}, has most of its mass on the positive support. This is in accordance with the theory of competitive storage and points to an inverse relationship between the quantity of crude oil held in inventories and the convenience yield. Panel 5 of Figure 1 shows that the prior distribution is flat when viewed on the scale adjusted for the posterior distribution for a_{sp}. Moreover, the empirical results show that most of the mass of the posterior distribution for a_{sp} is negative and centered at -0.60. This result is consistent with the fact that a high level of spot oil prices can lead to an increase in the convenience yield on inventories held to meet customer demand for spot delivery. Thus, a negative spread suggests that the ownership of the physical barrel of crude oil provides benefits that are not extended to the holders of oil futures contracts.

Posteriors for the inventory demand equation. The posterior distribution of a_{ip} – reported in panel 8 of Figure 1 – is narrower than the prior, suggesting that data are informative about the negative relationship between spot prices and inventories. This supports the idea that, in periods of high prices, crude oil stocks are drawn down to compensate for the adjustment in production and to deal with marketing and delivery costs (Pindyck, 2001; Knittel and Pindyck, 2016).

Posteriors for the oil consumption demand equation. The median of the posterior distribution of the short-run price elasticity of oil demand is close to its prior mode, with a posterior median of -0.2, as illustrated in panel 11 of Figure 1

The posterior distribution of a^d_{qs} reported in panel 10 of Figure 1 has median equal to 0.58 and mass concentrated on the positive support. This is reasonable, since periods during which the spread is positive are precisely those when oil stocks are high. Thus, the abundance of barrels of crude oil causes a reduction in the oil spot prices, which in turns stimulates the consumption of petroleum products.

Panel 9 of Figure 1 plots the posterior distribution for a^d_{qy}, which is centered at 0.08. This implies that the US crude oil demand for current consumption is positively affected by a global economic growth.

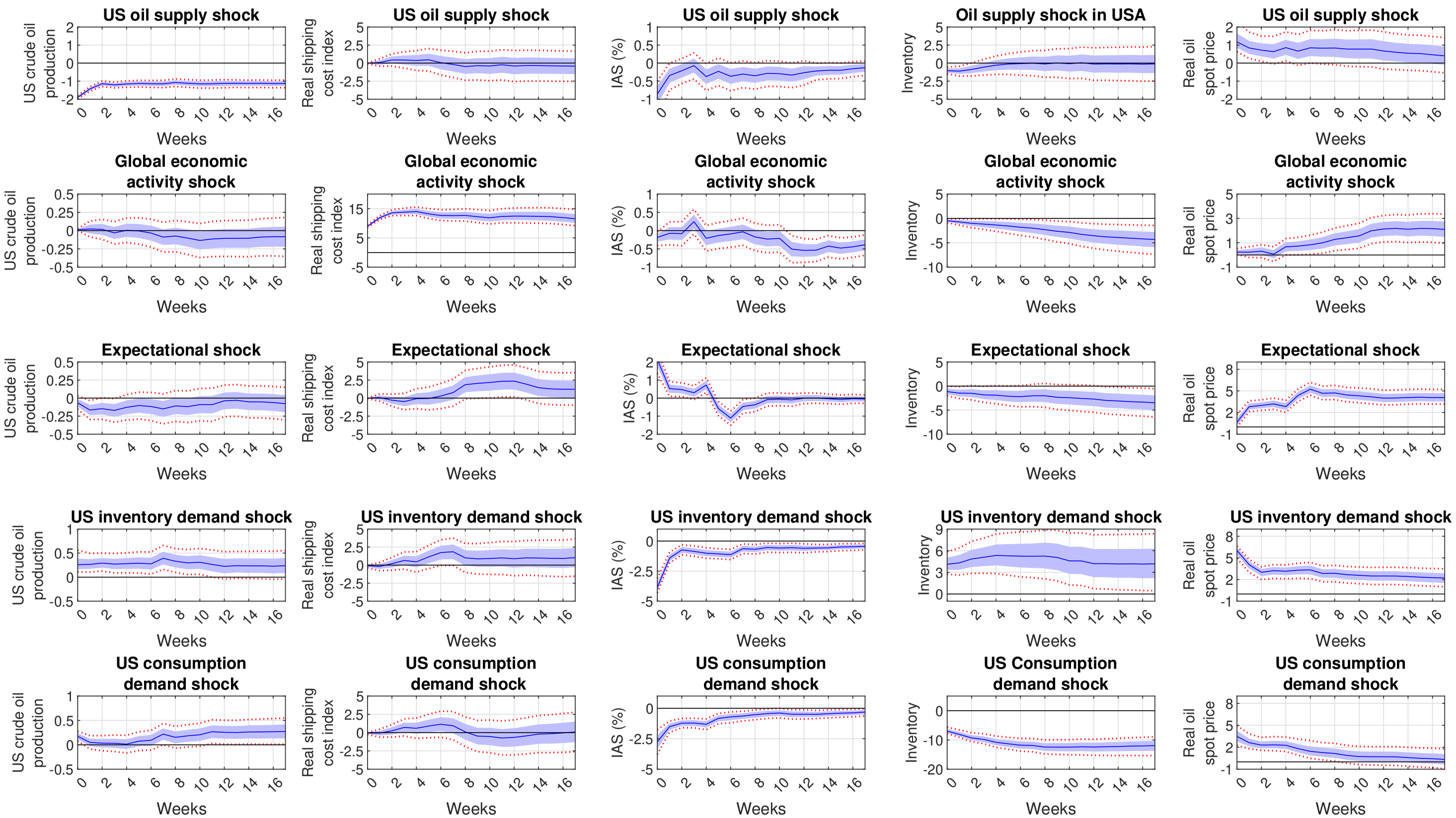
4.2 Impulse response functions

Figure 2 reproduces the impulse responses of the endogenous variables to one-unit change in each structural shock. Each graph reports the posterior median impulse responses, together with the highest posterior density at 68% and 95% credibility levels.

The structural impulse responses for the real price of crude oil are shown in the last column of Figure 2. As for supply shocks, we plot the responses to a disruption of US oil production. A negative shock to the US supply of crude oil immediately raises the spot price. The effect is however short-lived, in fact the highest posterior density region with credibility level 95% includes the value zero two weeks from the shock. A shock boosting global economic activity affects the real price of WTI only with a delay of four weeks and there is evidence of overshooting in the response. This contrasts with the immediate price increase that follows a US consumption demand shock. Both expectational and US inventory demand shocks induce a positive and long-lived price response.

The responses of the IAS are shown in the third columns of Figure 2. A disruption of US production causes a sharp but short-lived decrease of the IAS, as anticipated by the theory of competitive storage. A positive global economic activity shock induces a small reduction in the IAS on impact, however the 95% posterior credibility region is wide and

Figure 2: Impulse responses of the variables to the structural shocks of model 1



Note: The posterior median responses to a one-standard deviation shock are reported. Blue lines indicate the median impulse response estimates of model 1. Blue shaded bands and red dotted lines indicate the posterior credibility regions at 68% and 95%, respectively. The US supply shock has been normalized to imply an increase in the real price of oil.

includes zero. A positive expectational shock leads, on impact, to a temporary jump in the IAS. The subsequent reduction of the IAS is accompanied by a gradual increase in the real price of oil and a permanent reduction in US crude oil stocks, also triggered by the same underlining shock. An unexpected increase inventory demand shock is responsible for a large decline in the IAS on impact, that is partly absorbed in subsequent weeks. A positive US consumption demand shock also causes a large reduction in the IAS. The effect of the shock is also long-lived and takes about eight weeks for the 95% credible region to become negligible. The response of the IAS to each structural shock is coherent with the theory of competitive storage and it is highly informative about the interaction between the physical and futures markets. Specifically, an unexpected US oil supply disruption raises the value of future crude oil inventories for consumption smoothing and this is captured by a reduction in the IAS. Analogously, positive shocks to global economic activity and US crude oil consumption induce inventories to be drawn down in an effort to smooth production. Since the supply of storage takes time to respond to such shocks, the IAS – which is driven by a rise in the convenience yield – falls. Moreover, an upward shift of the demand for above-ground crude oil inventories causes a short-lived reduction of the IAS. The response of the IAS to each structural shock represents valuable information for all traders participating to the futures market for hedging and speculative purposes. If the spot price of oil is lower (higher) than it will be in later weeks, traders with access to physical oil and storage are encouraged to resell (hold) oil in the future (see e.g. Erb and Campbell, 2006; Valenti et al., 2020).

The responses of US crude oil inventories are reported in the fourth column of the Figure 2. While a shock to US crude oil consumption immediately reduces US inventories, a shock to global economic activity reduces the level of inventories only with a lag of few weeks.

The dynamics of the impulse responses is also useful to point out some features that distinguish the expectational shock from the inventory demand shock and the exogenous oil supply shock. A positive expectational shock is associated with a decline in US crude oil production because producers hold oil back from the spot market in anticipation of higher prices in the future. Producers have the option of leaving oil below the ground, rather than extracting it, causing the spot price of oil to overshoot (see Hotelling, 1931; Smith, 2009; Juvenal and Petrella, 2015). Conversely, a positive inventory demand shock is designed to capture an upward shift of the demand for oil storage, while exogenous supply shocks are related to oil supply outages.

4.3 Historical decomposition

Figures 3 and 4 present the historical decomposition of the real price of WTI crude oil during the first outbreak of the COVID-19 pandemic in early 2020 and at the time of the geopolitical tensions that culminated with Russia's invasion of Ukraine in February 2022.

COVID-19 pandemic. The COVID-19 pandemic represents a global crisis that has requested unprecedented policy responses. Quoting Chudik et al. (2021), the COVID-19 pandemic "has been a shock like no other", inducing both demand and supply disruptions worldwide. The US economy officially entered a recession in February 2020.[16]

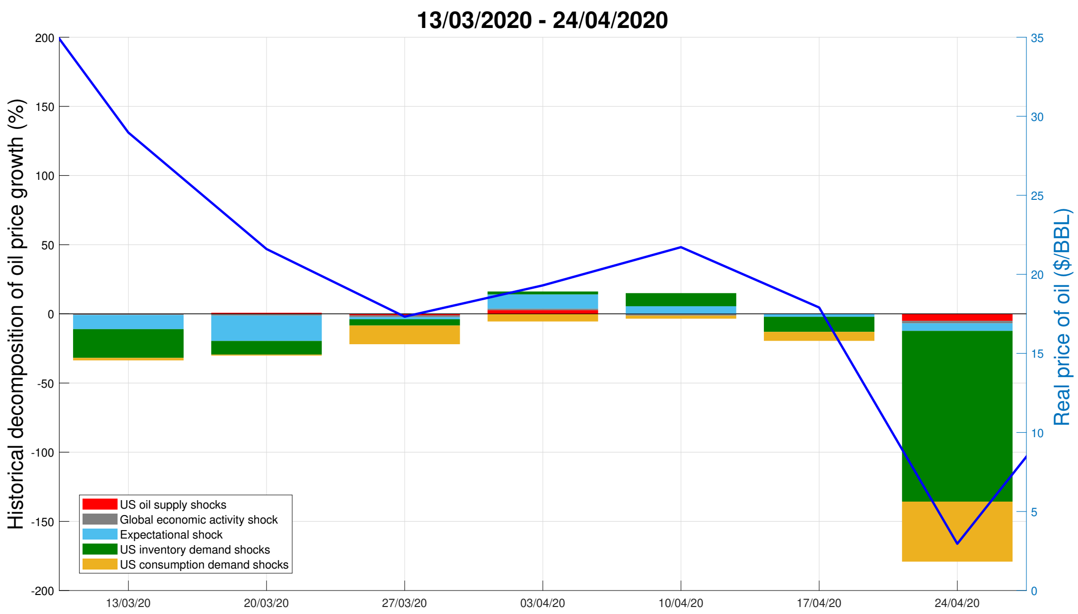
For the historical decomposition in Figure 3, we focus on the time period ranging from the week ending March 15 2020 to the week ending April 26 2020. The start of this time period was marked by a declaration of the World Health Organization stating that COVID-19 had to be considered a global health pandemic. Moreover, few days later – on March 13, 2020 – President Trump declared a national emergency concerning the COVID-19 pandemic. The subsequent weeks were characterized by stay-at-home orders and other restrictions. On the supply side these measures reduced dramatically labour supply and productivity. On the demand side the pandemic depressed households' consumption and firms' investments. Another effect of policy responses to the pandemic was a drop in fuel consumption due to reduced mobility. Over the time period under analysis the real price of WTI crude oil decreased from 29 to 3 dollars per barrel that represents a 228% reduction.[17]

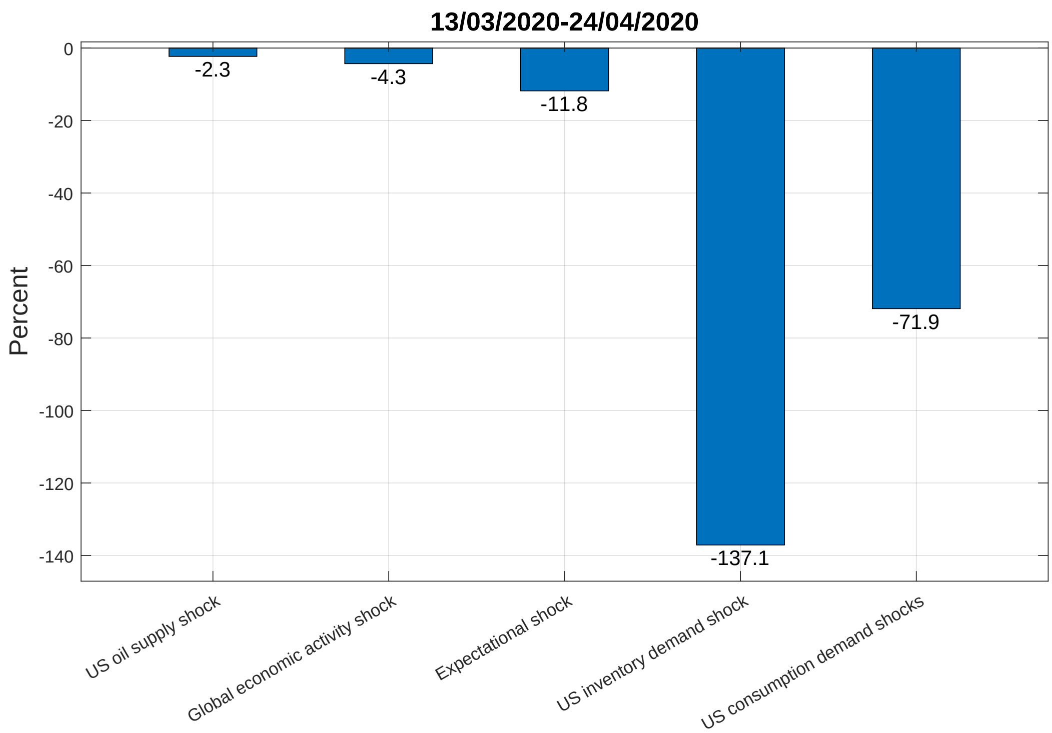
The top panel of Figure 3 shows the sequence of shocks that each week have contributed to the observed price decline. In the bottom panel of Figure 3 the bars represent the contribution of each structural shock to the total price reduction. Notice that the sum of such percentages yield a very close approximation of the observed -228% log-price change.

[16] The United States experienced two consecutive quarters of declines in GDP by 1.3% and 9.1%, respectively. To put this contraction into historical context, quarterly US GDP had never experienced a drop greater than 3%.

[17] This is computed as $100 \times \log(P_t/P_{t-h})$ to be consistent with the data used in the SVAR model. P_t (P_{t-h}) denotes the price in the last (first) week considered in the historical decomposition.

Figure 3: Historical decomposition of the real price of WTI crude oil: COVID-19





Note: The figure shows the (posterior median) historical decomposition derived from model (1). The bars illustrate the contribution of each structural shock to the price chance during the period 15/03/2020-26/04/2020, where the day denotes the last day of the week included in the sample.

The bottom panel of Figure 3 shows that -137% of the total decline was driven by shocks to US inventory demand. Policy responses to the pandemic have induced large reductions of consumption of crude oil and oil products worldwide. Such decreases, combined with the fact that crude oil production cannot be reduced much in the short-run, implied an accumulation of inventories. The high level of oil inventories led market participants to lease tankers for floating storage.

As anticipated a second a very important driver of the observed price reduction is related with lower demand. The combined effect of shocks to global economic activity and US consumption accounts for -76.2% of the total -228% log-price change.

This series of events led to the well known "negative price episode" with the WTI crude oil front-month futures price falling below zero dollars per barrel on April 20, 2020. A negative futures prices suggested that oil traders were willing to pay money in order to avoid delivery. These extreme price developments were induced by several factors, including the scarcity of oil storage and the difficulties to sell futures contracts. Moreover, the temporary failure to reach a production agreement among OPEC and other large oil producers raised uncertainty regarding the oil markets conditions, especially during the last three weeks of March 2020. This is captured by negative expectational and US inventory demand shocks.

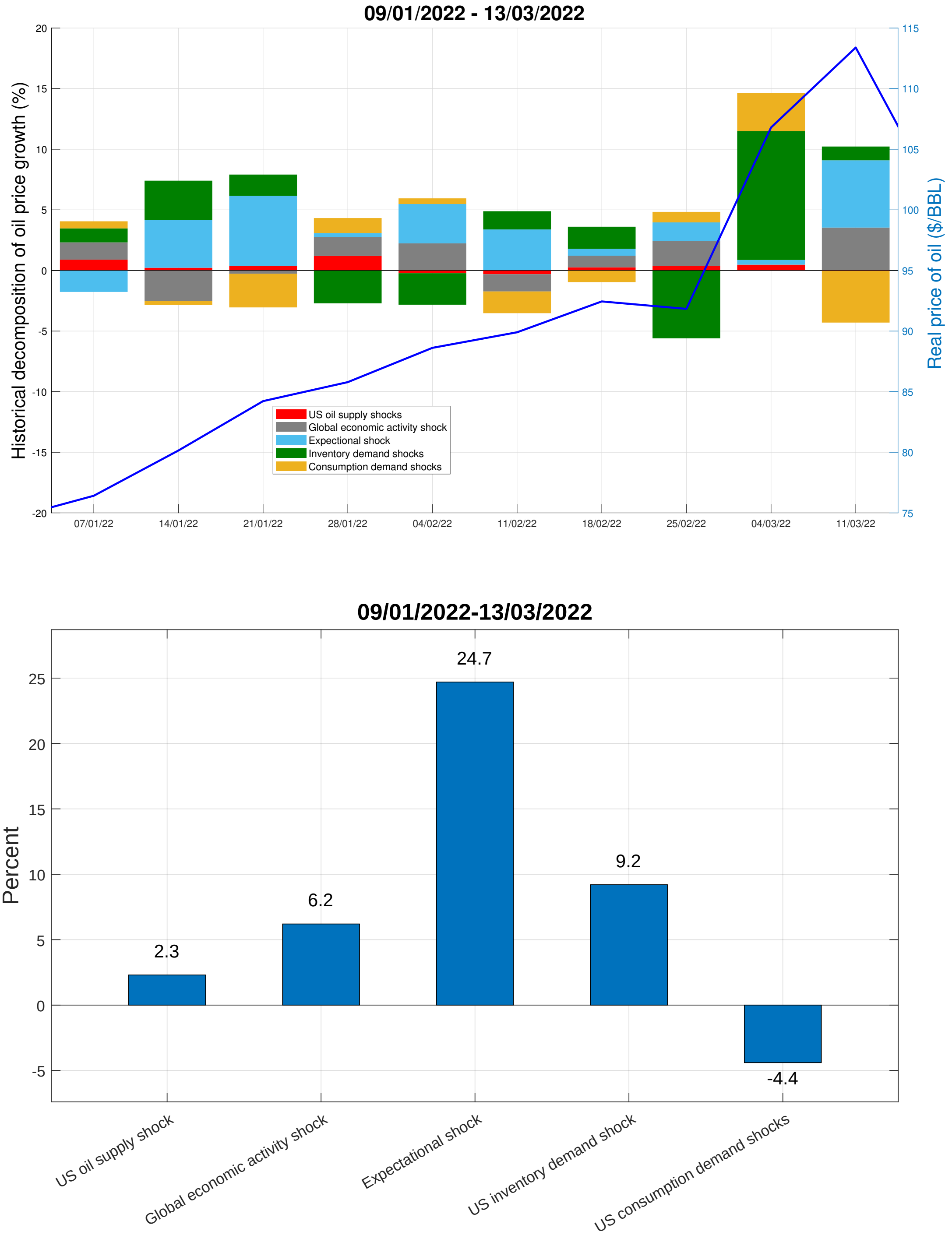
Russia's invasion of Ukraine. We now analyse the price rally culminated with the real price WTI reaching 113.4 dollars per barrel on the week ending March 13, 2022. The historical decomposition of the price starts from the week ending January 9, 2022 when the real WTI price was 76.4 dollars per barrel. The percent log-price increase over the time span considered in this exercise equals 39.5%. This price increase has happened at a time when the global market for crude oil was characterized by low inventories.

As reported by EIA in the Short-Term Energy Outlook of February 2022 "*global oil consumption has exceeded global oil supply since mid-2020, leading to six consecutive quarters of global oil inventory draws.*"[18]

The top panel of Figure 4 illustrates that a combination of different shocks have contributed to the price increase observed during the first monts of 2022. The bottom panel

[18]See `https://www.eia.gov/outlooks/steo/archives/Feb22.pdf` (last accessed May 20, 2022).

Figure 4: Historical decomposition of the real price of WTI crude oil: Russia's invasion of Ukraine



Note: The figure shows the (posterior median) historical decomposition derived from model (1). The bars illustrate the contribution of each structural shock to the price chance during the period 09/01/2022-13/03/2022, where the day denotes the last day of the week included in the sample. The figure in the bottom panel shows the percent contribution of each shock (i.e. the sum equals the total percent log-price change).

of Figure 4 shows that the contribution of expectational shocks is the largest and equals 24.7%. These shocks have been mainly driven by concerns about the future of oil supply disruptions due to geopolitical tensions, notably regarding the Russia-Ukraine war started on February 24, 2022. The large expectational shock characterizing the last week of the sample also reflects the fact that sanctions levied by the US and the EU against Russia further contribute to uncertainty regarding the future supply shortages due to the cut of Russian crude oil exports from the market. US inventory demand shocks have also had a large impact on the price increase we are analysing. As we can see from the bottom panel of Figure 4, the contribution of these shocks is 9.2%. Lastly, we can see that shocks to global economic activity have also contributed to the price increase observed at the beginning of 2022. Decreasing COVID-19 cases worldwide have likely contributed to price pressure coming from the demand-side.

5 Robustness checks

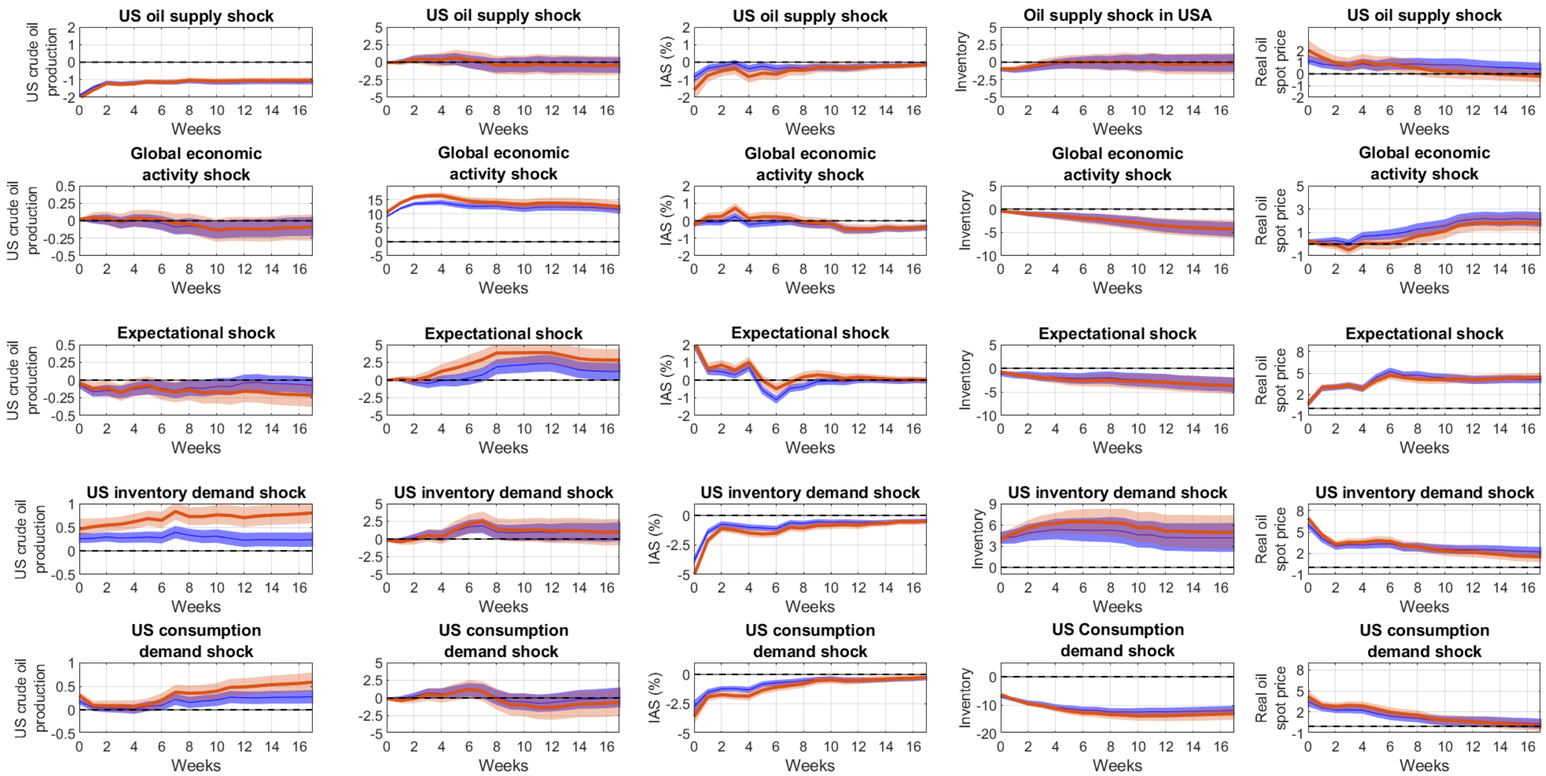
5.1 An alternative proxy for oil market expectations

Since the interest-adjusted spread might be a biased measure of oil price expectations if the crude oil risk-premium is not zero, in this section we estimate model (1) by including an alternative proxy of the IAS. More precisely, we replace the observed futures prices with futures prices adjusted for the time-varying risk-premium (see Baumeister, 2022).[19]

We define the risk-premium as the difference between the expected spot price $E_t(P_{t+h})$ – proxied by the price of the futures contract with one-month maturity F^1_{t+h-1} – and the oil futures price F^h_t, with h-months maturity ($h = 3$ months in our case). Following Fama and

[19] Baumeister (2022) presents two main methods to retrieve the oil price expectations. The first method relies on a return regression approach. The second method exploits the affine-term structure model proposed by Hamilton and Wu (2014). We opt for the first method, since it is easier to implement and according to Table 2 in Baumeister (2022) and Table 1 in Valenti et al. (2020), the corresponding risk-adjusted oil futures price yields the largest reduction of the Mean Square Prediction Error ratio. Clearly, since we are working with weekly data, the set of regressors available is smaller than when considering monthly data as in Baumeister (2022).

Figure 5: Impulse response functions of the endogenous variables to each structural shock - An alternative proxy of IAS



Note: The Bayesian posterior median responses to one-standard deviation structural shocks are represented as continuous lines. Blue area and lines denote posterior median and the 68% posterior credible region for the main specification. Red area and lines denote posterior median and the 68% posterior credible region using risk-premium adjusted futures prices for the construction of the IAS.

French (1987), we construct a regression-based measure of oil risk-premium as follows:

$$\frac{F^1_{t+h-1} - F^h_t}{F^h_t} = \beta' \mathbf{z}_t + \varepsilon_{t+h} \tag{5}$$

where the $\frac{F^1_{t+h-1} - F^h_t}{F^h_t}$ represents the final percentage payoff of a crude oil futures investment of $h = 3$ months and ε_{t+h} is the error term of the regression. In our example we select the following regressors $\mathbf{z}_t = [y_t, ted_t, vix_t, ewi_t, fer^{5y}_t]$ as proxies of risk factors, where y_t is the index of global real economic activity; ted_t is the TED spread, that is a measure of credit-risk (Matvos et al., 2018)[20]; vix_t is a proxy of stock market volatility and ewi_t is a measure of US economic uncertainty, designed to estimate the recession probabilities in each US state (Baumeister et al., 2022). We also account for expected inflation, fer^{5y}_t, which is positively correlated with the oil risk premium, since investors use futures contracts to hedge against inflation risks (Gorton and Rouwenhorst, 2006; Gorton et al., 2013b).

Solving equation (5) for F^1_{t+h-1} under the hypothesis of $E_t[\varepsilon_{t+h}] = 0$, a risk-adjusted futures price is obtained, which is then used to build the IAS. Due to data constraints, we estimate the model with this new definition of the IAS over a shorter time period, running from the third week of January 2003 through the last week of October 2021.[21] Figure 5 shows the structural impulse response estimates obtained using the IAS measure and its alternative, which are qualitatively similar.

5.2 Alternative measure of real economic activity

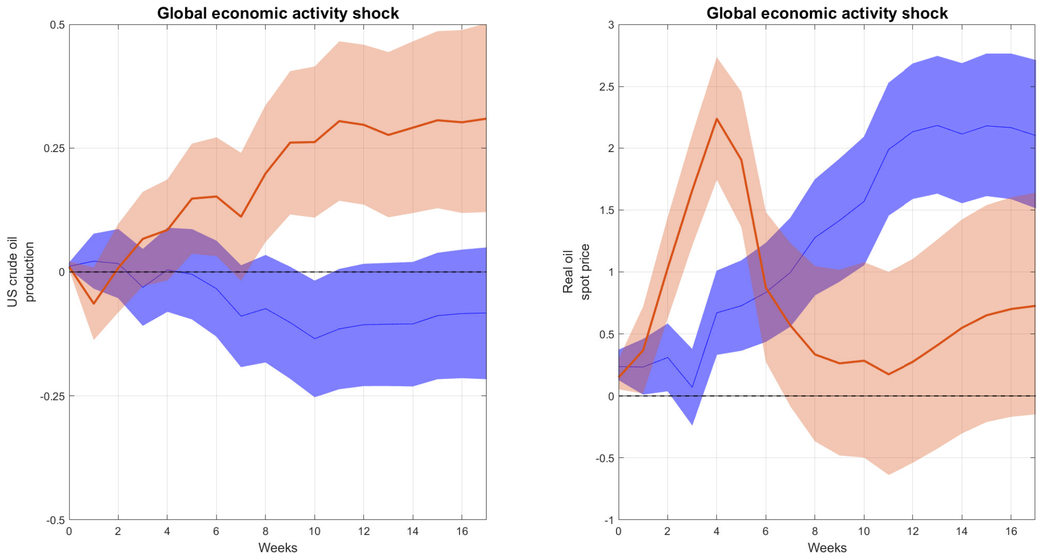
The use of a proxy for global economic activity derived from shipping costs has been largely debated in the literature (e.g. Baumeister et al., 2020; Hamilton, 2019b; Kilian and Zhou, 2018). Alternative measures of business cycle fluctuations at weekly sampling frequency do exist (e.g. Aruoba et al., 2009; Baumeister et al., 2022; Lewis et al., 2021). Although these indices are mostly representative of the US economy, nevertheless they could be used to

[20]The TED spread is defined as the difference between the 3-month LIBOR rate and the rate on 3-month Treasury bills.

[21]Our model yields a Mean Squared Prediction Error (MSPE) lower than a random walk specification. However, the MSPE differential is not distinguishable from zero, according to the Diebold-Mariano test of equal predictive ability.

proxy the global business cycle.

Figure 6: Weekly Economic Index as a proxy of real economic activity



Note: The Bayesian posterior median responses to one-standard deviation structural shocks are represented as continuous lines. Blue area and lines denote posterior median and the 68% posterior credible region for the main specification. Red area and lines denote posterior median and the 68% posterior credible region using the WEI as a proxy of real economic activity.

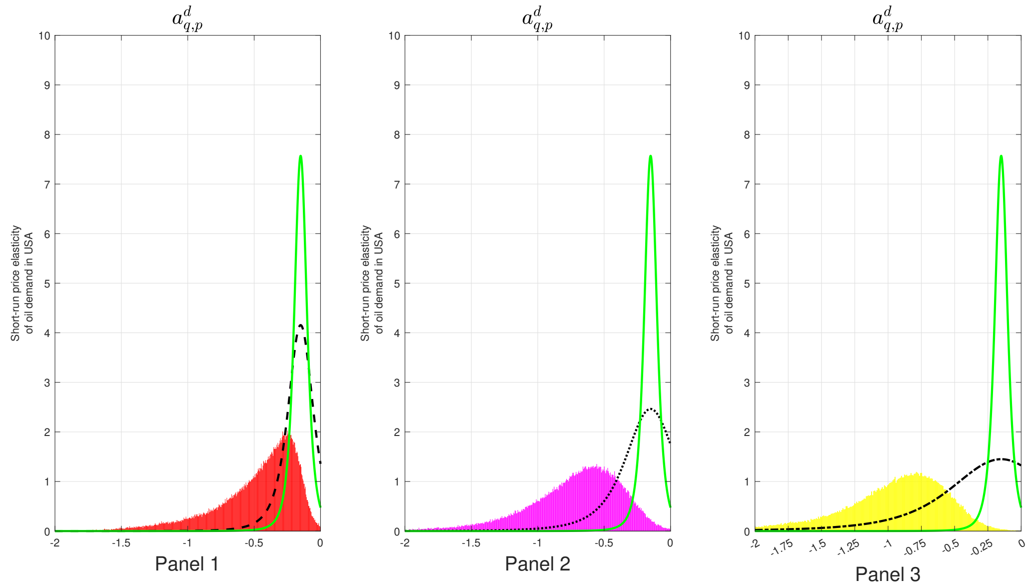
As a robustness check, we replace the global economic activity represented by the RSC index with the Weekly Economic Index (WEI) of Lewis et al. (2021). The WEI, available from 2008 onwards, relies on a factor model to extract a composite of ten weekly time series for the US economy. Given that the WEI captures economic developments of the US economy, rather than directly tracking global economic conditions, its correlation with the RSC is positive, although not very large (0.38).

Figure 6 displays the responses of US crude oil production and the real price of oil to real economic activity shocks based on the WEI. When using the WEI, a positive shock to economic activity induces a large and persistent increase in US crude oil production. This suggests that US oil producers react more to US economic activity shocks than to global economic activity shocks. If we consider the RSC index, the response of the real price of oil to a global economic activity shock is positive and persistent. Conversely, the specification including the WEI yields a positive, but very short lived, response, which is at odd with much of the literature (see e.g. Kilian and Murphy, 2014; Juvenal and Petrella, 2015; Caldara et al., 2019).

5.3 Sensitivity analysis

We consider an in-depth sensitivity analysis on the role of priors in shaping the posterior distributions of three key structural parameters, namely $a^d_{p,q}$, $a_{\Delta i,q}$ and $a_{\Delta i,q}$. For each of these parameters, we investigate the effect of considering less informative priors. We do so by increasing the scale parameter of the original prior distribution shown in Table 1 by a factor of 2, 4, and 8.

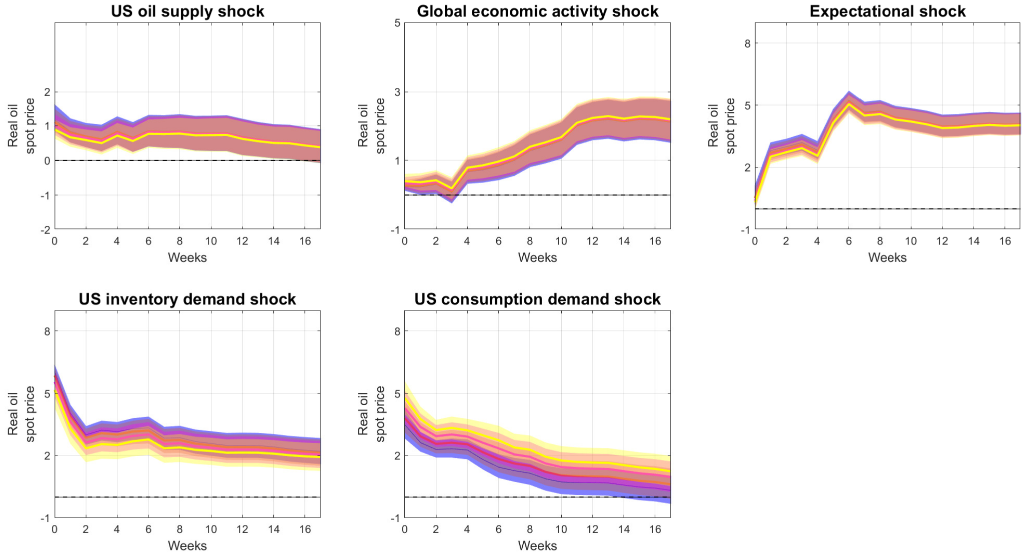
Figure 7: Sensitivity analysis for $a^d_{p,q}$: Priors VS posteriors distributions



Notes: Green solid lines denotes prior distributions used in model 1. Dashed and dotted lines indicate prior distributions with scale parameters $\sigma_{a_q p^d} = 0.05 \times 2 = 0.1$. and $\sigma_{a_q p^d} = 0.05 \times 4 = 0.2$, respectively. Orange and pink bars are the corresponding posterior distributions. Dash-dotted lines denote prior distributions with scale parameter $\sigma_{a_q p^d} = 0.05 \times 8 = 0.4$. The associated posterior distributions are represented by yellow bars.

For the sake of brevity, in this section we focus on the price elasticity of oil demand, $a^d_{p,q}$ and report the other results in the on-line Appendix. The baseline prior for $a^d_{p,q}$ is a Student t distribution constrained to have nonpositive support, mode -0.15, scale parameter 0.05 and 3 degrees of freedom. This implies a 97% probability that the weekly price elasticity of oil demand falls in the interval [-0.3, 0]. The prior with the largest scale parameter is almost flat when compared to the prior used in the baseline model (see Figure 5.3). Moreover, note that in this case it assigns a 10% probability to a price demand elasticity greater than 1 in absolute value. The posteriors medians of for $a^d_{p,q}$ are -0.40 (scale = 0.1), -0.70 (scale = 0.2) and -0.90 (scale = 0.4). These values are significantly larger than the baseline posterior median, equal to -0.20 and are difficult to reconcile with the weekly elasticity of oil demand

Figure 8: Sensitivity analysis for $a^{d}_{p,q}$: impulse responses of the real price of oil to each structural shock



Notes: The posterior median responses to a one-standard deviation shock are reported. Solid lines indicate the median impulse response estimates. Shaded bands indicate the posterior credibility regions at 68%. Blue lines (bands) are estimated from priors for a^{d}_{qp}, with scale parameter $\sigma_{a_q p^d} = 0.05$, as reported in Table 1. Orange and pink lines (bands) imply scale parameters $\sigma_{a_q p^d} = 0.05 \times 2 = 0.1$ and $\sigma_{a_q p^d} = 0.05 \times 4 = 0.2$, respectively. Finally, yellow lines (bands) use scale parameters $\sigma_{a_q p^d} = 0.05 \times 8 = 0.4$.

in US. Figure 8 shows that the structural impulse responses of the real price of crude oil are only marginally affected by the prior choice.

6 Conclusions

In this paper we develop a SVAR model suitable for explaining short-run crude oil price fluctuations in the US – including those related with the COVID-19 pandemic and with the Russia's invasion of Ukraine.

Reliance on weekly data allows to obtain analyses of the most recent developments of the oil market in a timely fashion.

The paper provides empirical evidence that the IAS plays an important role in proxying the convenience yield of crude oil inventories (above- and below-ground) and in capturing the market's expectations of all traders. This measure allows to identify a new structural shocks, that we label expectational shock. This represents the expected component of the real price of oil that is transmitted from futures to spot markets (Sockin and Xiong, 2015).

Our results shows that a positive expectational shock is associated with a decline in

US crude oil production and US inventories, while contemporaneously inducing an increase of the IAS and of the real price of crude oil. The role of this shock is fundamental when describing the series of events that have caused the spike in the price of crude oil observed in the aftermath of Russia's invasion of Ukraine.

The use of financial data as a proxy of market expectations is key when working with data sampled daily or weekly. Most survey measures of market expectations are in fact usually available only at monthly or quarterly horizon. The inclusion of forward-looking variables has the potential of making our model well-suited for forecasting the price of crude oil at short horizons and building forecast scenarios (see e.g. Antolin-Diaz et al., 2021; Baumeister and Kilian, 2014).

However, one problem with data sampled weekly is that, while they are informative of short-run market developments, they might also be noisy. A possible solution – allowing to benefit from high-frequency data while reducing the impact of noise – would be to rely on ad-hoc estimation procedures such as those developed Carriero et al. (2022), Lenza and Primiceri (2022) and Ng (2021). We leave these extensions as topics for future research.

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A weekly structural VAR model of the US crude oil market

On-line Appendix

June 7, 2023

Contents

A Identification algorithm

This section synthetically describes the identification algorithm of Baumeister and Hamilton (2015) to estimate the SVAR model (1). The identification is mainly based on two steps. In the first step we assign priors for the structural parameters **A**, **B** and **D**. The second step relies on a random walk Metropolis-Hastings algorithm, which is designed to generate draws from the posterior distribution of the structural coefficients. The SVAR model can be written in a compact form as:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{v}_t \tag{1}$$

where:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & -a^s_{qs} & 0 & -a^s_{qp} \\ 0 & 1 & 0 & 0 & -a_{yp} \\ 0 & 0 & 1 & -a_{si} & -a_{sp} \\ -a_{iq} & 0 & -a_{is} & 1 & -a_{ip} \\ 1 & -a^d_{qy} & -a^d_{qs} & -1 & -a^d_{qp} \end{bmatrix}$$

$$\mathbf{y}_t \equiv [\Delta q_t, y_t, s_t, \Delta i_t, \Delta p_t]'$$

$$\mathbf{B} \equiv [\mathbf{B}_1, \ldots, \mathbf{B}_m,\ \mathbf{b}_0]$$

$$\mathbf{x}'_{t-1} \equiv \left[\mathbf{y}'_{t-1},\ \mathbf{y}'_{t-2},\ \ldots,\ \mathbf{y}'_{t-m}\ 1\right]'$$

$$\mathbf{v}_t \equiv [v_{1t}, v_{2t}, v_{3t}, v_{4t}, v_{5t}]'$$

Priors for **A**. Let α be the vector collecting the priors for the elements of matrix **A** and $h_1 = det(\mathbf{A})$. We follow Baumeister and Hamilton (2018) and impose a prior asymmetric t distribution to assign probability of observing $h_1 > 0$, where h_1 is defined as follows:[22]

$$\begin{aligned} h_1 = a^s_{qp} - a^d_{qp} - a_{ip} - a_{is}a_{sp} - a_{sp}a^d_{qs} - a_{yp}a^d_{qy} - a_{iq}a^s_{qp} - a_{sp}a^s_{qs} - \\ a_{ip}a_{si}a^d_{qs} + a_{is}a_{si}a^d_{qp} + a_{ip}a_{si}a^s_{qs} - a_{is}a_{si}a^d_{qp} + a_{ip}a_{si}a^s_{qs} - \\ a_{is}a_{si}a^s_{qp} - a_{iq}a_{sp}a^s_{qs} + a_{is}a_{si}a^s_{qp} - a_{iq}a_{sp}a^s_{qs} + a_{is}a_{si}a_{yp}a^d_{qy} + \\ a_{iq}a_{si}a^d_{qp}a^s_{qs} - a_{iq}a_{si}a^d_{qs}a^s_{qp} + a_{iq}a_{si}a_{yp}a^d_{qy}a^s_{qs} \end{aligned}$$

Consequently, $\mu_1 = 0.79$, $\sigma_1 = 27.5$, $\lambda_1 = 2$ and $\nu_1 = 3$ indicate priors aimed to assign 95% probability to $h_1 > 0$ and are selected from $50,000$ draws from the prior distribution of the unknown elements of **A**. Therefore, assuming independence across the contemporaneous structural parameters, the joint prior distribution of **A**, denoted by $p(\mathbf{A})$, is:

$$p(\mathbf{A}) = p(a^s_{qs})p(a^s_{qp})p(a_{yp})p(a_{si})p(a_{sp})p(a_{iq})p(a_{is})p(a_{ip})p(a^d_{qy})p(a^d_{qs})p(a^d_{qp})p(h_1) \quad (2)$$

The priors for the unknown elements of matrix **A** are Student t distributions, with mode, scale parameters and degrees of freedom as reported in Table 1 of our paper. It is worth noting that, in our model we do not use any priors information on the equilibrium impacts of the structural shocks. On this respect, priors on **A** and h_1 ensure the sign-structure on

[22]The asymmetric t distribution introduced by Baumeister and Hamilton (2018) is

$$p(h_1) = \sigma_1^{-1}\tilde{\phi}_{\nu_1}\left(\left(h_1 - \mu_1\right)/\sigma_1\right)\Phi\left(\lambda_1 h_1/\sigma_1\right)$$

where $\tilde{\phi}_{\nu_1}(w)$ denotes the probability density function of a standard Student t variable with ν_1 degrees of freedom evaluated at the point w. Moreover, $\Phi(w)$ denotes the cumulative distribution function for a standard Normal distribution. The parameter λ_1 measures the skewness of h_1. Specifically, if $\lambda_1 = 0$, the asymmetric t distribution becomes symmetric and if λ_1 tends to $-\infty$ the symmetric t distribution will converge to a Student t distribution truncated to be negative.

$\mathbf{H}$ to be consistent with the theory of competitive storage, that is:

$$\mathbf{H} = \begin{pmatrix} \underbrace{h_{\Delta q_t,v_{1t}}}_{(93\%)} & \underbrace{h_{\Delta q_t,v_{2t}}}_{(80\%)} & \underbrace{h_{\Delta q_t,v_{3t}}}_{(38\%)} & \underbrace{h_{\Delta q_t,v_{4t}}}_{(81\%)} & \underbrace{h_{\Delta q_t,v_{5t}}}_{(80\%)} \\ \underbrace{h_{y_t,v_{1t}}}_{(80\%)} & \underbrace{h_{y_t,v_{2t}}}_{(98\%)} & \underbrace{h_{y_t,v_{3t}}}_{(31\%)} & \underbrace{h_{y_t,v_{4t}}}_{(15\%)} & \underbrace{h_{y_t,v_{5t}}}_{(15\%)} \\ \underbrace{h_{s_t,v_{1t}}}_{(54\%)} & \underbrace{h_{s_t,v_{2t}}}_{(46\%)} & \underbrace{h_{s_t,v_{3t}}}_{(93\%)} & \underbrace{h_{s_t,v_{4t}}}_{(46\%)} & \underbrace{h_{s_t,v_{5t}}}_{(46\%)} \\ \underbrace{h_{\Delta i_t,v_{1t}}}_{(81\%)} & \underbrace{h_{\Delta i_t,v_{2t}}}_{(18\%)} & \underbrace{h_{\Delta i_t,v_{3t}}}_{(30\%)} & \underbrace{h_{\Delta i_t,v_{4t}}}_{(82\%)} & \underbrace{h_{\Delta i_t,v_{5t}}}_{(18\%)} \\ \underbrace{h_{\Delta p_t,v_{1t}}}_{(20\%)} & \underbrace{h_{\Delta p_t,v_{2t}}}_{(85\%)} & \underbrace{h_{\Delta p_t,v_{3t}}}_{(69\%)} & \underbrace{h_{\Delta p_t,v_{4t}}}_{(85\%)} & \underbrace{h_{\Delta p_t,v_{5t}}}_{(85\%)} \end{pmatrix} \tag{3}$$

The values in parenthesis of matrix (3) denote the prior probabilities implied by model (1) that the equilibrium impact of each structural shock on any given variable is positive. In particular, the impact responses to US oil supply shocks are:

- $h_{\Delta q_t,v_{1t}} \equiv \frac{h^*_{\Delta q_t,v_{1t}}}{h_1} = \frac{(a_{is}a_{si}a^d_{qp}-a^d_{qp}-a_{is}a_{sp}-a_{sp}a^d_{qs}-a_{yp}a^d_{qy}-a_{ip}a_{si}a^d_{qs}-a_{isp}+a_{is}a_{si}a_{yp}a^d_{qy})}{h_1}$
- $h_{\Delta y_t,v_{1t}} \equiv \frac{h^*_{y_t,v_{1t}}}{h_1} = \frac{(a_{yp}(a_{iq}+a_{is}a_{si}+a_{iq}a_{si}a^d_{qs}-1))}{h_1}$
- $h_{s_t,v_{1t}} \equiv \frac{h^*_{s_t,v_{1t}}}{h_1} = \frac{(a_{iq}a_{sp}-a_{ip}a_{si}-a_{sp}-a_{iq}a_{si}a^d_{qp}-a_{iq}a_{si}a_{yp}a^d_{qy})}{h_1}$
- $h_{\Delta i_t,v_{1t}} \equiv \frac{h^*_{\Delta i_t,v_{1t}}}{h_1} = \frac{(-a_{ip}-a_{is}a_{sp}-a_{iq}a^d_{qp}-a_{iq}a_{sp}a^d_{qs}-a_{iq}a_{yp}a^d_{qy})}{h_1}$
- $h_{\Delta p_t,v_{1t}} \equiv \frac{h^*_{\Delta p_t,v_{1t}}}{h_1} = \frac{(a_{iq}+a_{is}a_{si}+a_{iq}a_{si}a^d_{qs}-1)}{h_1}$

Thus, a positive unexpected oil supply shock causes an increase in the US crude oil production with probability of 93%, in the economic activity measured by the BDI with probability of 80%, in the inventory changes with probability of 81% and a reduction in the spot price of oil with probability of 80%.

The impact responses to global economic activity shocks are:

- $h_{\Delta q_t,v_{2t}} \equiv \frac{h^*_{\Delta q_t,v_{2t}}}{h_1} = \frac{(a^d_{qy}(a^s_{qp}+a_{sp}a^s_{qs}+a_{ip}a_{si}a^s_{qs}-a_{is}a_{si}a^s_{qp}))}{h_1}$
- $h_{y_t,v_{2t}} \equiv \frac{h^*_{y_t,v_{2t}}}{h_1} = (a^s_{qp}-a^d_{qp}-a_{ip}-a_{is}a_{sp}-a_{sp}a^d_{qs}-a_{iq}a^d_{qp}+a_{sp}a^s_{qs}-a_{ip}a_{si}a^d_{qs}+a_{is}a_{si}a^d_{qp}+$ $a_{ip}a_{si}a^s_{qs}-a_{is}a_{si}a^s_{qp}-a_{iq}a_{sp}a^s_{qs}+a_{iq}a_{si}a^d_{qp}a^s_{qs}-a_{iq}a_{si}a^d_{qs}a^s_{qp})/h_1$

- $h_{s_t,v_{2t}} \equiv \frac{h^*_{s_t,v_{2t}}}{h_1} = \frac{a^d_{qy}(a_{sp}+a_{ip}a_{si}+a_{iq}a_{si}a^s_{qp})}{h_1}$
- $h_{\Delta i_t,v_{2t}} \equiv \frac{h^*_{\Delta i_t,v_{2t}}}{h_1} = \frac{a^d_{qy}(a_{ip}+a_{is}a_{sp}+a_{iq}a^s_{qp}a_{iq}a_{sp}a^s_{qs})}{h_1}$
- $h_{\Delta p_t,v_{2t}} \equiv \frac{h^*_{\Delta p_t,v_{2t}}}{h_1} = \frac{-a^d_{qy}(a_{is}a_{si}+a_{iq}a_{si}a^s_{qs}-1)}{h_1}$

Thus, an unanticipated positive global economic activity shock yields an instantaneous increase in the BDI with probability 98%, in the US oil production with probability of 80% and in the spot price of oil with probability of 85%. This shock also causes a contemporaneous decline in the inventory changes with probability of 82%.

The impact responses to expectional shocks are:

- $h_{\Delta q_t,v_{3t}} \equiv \frac{h^*_{\Delta q_t,v_{3t}}}{h_1} = \frac{a_{is}a^s_{qp}-a_{ip}a^s_{qs}-a^d_{qp}a^s_{qs}+a^d_{qs}a^s_{qp}-a_{yp}a^d_{qy}a^s_{qs}}{h_1}$
- $h_{y_t,v_{3t}} \equiv \frac{h^*_{y_t,v_{3t}}}{h_1} = \frac{(a_{yp}(a_{is}+a_{qs}d-a^s_{qs}+a_{iq}a^s_{qs}))}{h_1}$
- $h_{s_t,v_{3t}} \equiv \frac{h^*_{s_t,v_{3t}}}{h_1} = \frac{(a^s_{qp}-a^d_{qp}-a_{ip}-a_{yp}a^d_{qy}-a_{iq}a^s_{qp})}{h_1}$
- $h_{\Delta i_t,v_{3t}} \equiv \frac{h^*_{\Delta i_t,v_{3t}}}{h_1} = \frac{(a_{ip}a^d_{qs}-a_{is}a^d_{qp}-a_{ip}a_{qs})^s+a_{is}a^s_{qp}-a_{is}a_{yp}a^d_{qy}-a_{iq}a^d_{qp}a^s_{qs}+a_{iq}a^d_{qs}a^s_{qp}-a_{iq}a_{yp}a^d_{qy}a^s_{qs})}{h_1}$
- $h_{\Delta p_t,v_{3t}} \equiv \frac{h^*_{\Delta p_t,v_{3t}}}{h_1} = \frac{a_{is}+a^d_{qs}-a^s_{qs}+a_{iq}a^s_{qs}}{h_1}$

Thus, a positive expectational shock induces a contemporaneous increase in the IAS and in the spot price of oil with probabilities of 93% and 69%, respectively. This shock is also responsible of a reduction in the global economic avtivity with probability 69%. In contrast, a positive expectational shock is associated with a simultaneous reduction in US crude oil inventories and production with probability of 70% and 62%, respectively.

The impact responses to US oil inventory demand shocks are:

- $h_{\Delta q_t,v_{4t}} \equiv \frac{h^*_{y_t,v_{4t}}}{h_1} = \frac{(a^s_{qp}a_{sp}a^s_{qs}-a_{si}a^d_{qp}a^s_{qs}+a_{si}a^d_{qs}a^s_{qp}-a_{si}a_{yp}a^d_{qy}a^s_{qs})}{h_1}$
- $h_{y_t,v_{4t}} \equiv \frac{(a_{yp}(a_{si}a^d_{qs}-a_{si}a^s_{qs}+1))}{h_1}$
- $h_{s_t,v_{4t}} \equiv \frac{h^*_{s_t,v_{4t}}}{h_1} = \frac{(a_{sp}-a_{si}a^d_{qp}+a_{si}a^s_{qp}-a_{si}a_{yp}a^d_{qy})}{h_1}$
- $h_{\Delta i_t,v_{4t}} \equiv \frac{h^*_{\Delta i_t,v_{4t}}}{h_1} = \frac{(a^s_{qp}-a^d_{qp}-a_{sp}a^d_{qs}-a_{yp}a^d_{qy}+a_{sp}a^s_{qs})}{h_1}$
- $h_{\Delta p_t,v_{4t}} \equiv \frac{h^*_{\Delta p_t,v_{4t}}}{h_1} = \frac{(a_{si}a^d_{qs}-a_{si}a^s_{qs}+1)}{h_1}$

Thus, a positive US oil inventory demand shock causes an increase in the US crude oil stocks with probability of 82% , in the US crude oil production and spot price of oil with probabilities of 81% and 85%, respectively. The increase in the spot price of oil is also associated with a contemporaneous reduction in the economic activity with probability of 85%. Finally, the impact responses to US oil consumption demand shocks are:

- $h_{\Delta q_t,v_{5t}} \equiv \frac{h^*_{\Delta q_t,v_{5t}}}{h_1} = \frac{(a^s_{qp}+a_{sp}a^s_{qs}+a_{ip}a_{si}a^s_{qs}-a_{is}a_{si}a^s_{qp})}{h_1}$
- $h_{y_t,v_{5t}} \equiv \frac{h^*_{y_t,v_{5t}}}{h_1} = \frac{(-a_{yt}(a_{is}a_{si}+a_{iq}a_{si}a^s_{qs}-1))}{h_1}$
- $h_{s_t,v_{5t}} \equiv \frac{h^*_{s_t,v_{5t}}}{h_1} = \frac{(a_{sp}+a_{ip}a_{si}+a_{iq}a_{si}a^s_{qp})}{h_1}$
- $h_{\Delta i_t,v_{5t}} \equiv \frac{h^*_{\Delta i_t,v_{5t}}}{h_1} = \frac{(a_{ip}+a_{is}a_{sp}a_{iq}a^s_{qp}+a_{iq}a_{sp}a^s_{qs})}{h_1}$
- $h_{\Delta p_t,v_{5t}} \equiv \frac{h^*_{\Delta p_t,v_{5t}}}{h_1} = \frac{(1-a_{iq}a_{si}a^s_{qs}-a_{is}a_{si})}{h_1}$

Thus, a positive US oil consumption demand shock causes a simultaneous increase in the spot price of oil and in the US crude oil production with probabilities of 85% and 80%, respectively. As opposed, global economic activity and US crude oil stocks are negatively affected by a positive US oil consumption demand shock, with probabilities of 85% and 82%, respectively. It is worth noting that the probability signs of the impact response of the IAS to each structural shock (except for the expectional shock) is ambiguous. This is consistent with the idea of which effect dominated is unclear ex ante, typically of the forward-looking variable.

Priors for $\mathbf{D}|\mathbf{A}$. The priors for d_{ii}^{-1} (where d^{-1} denotes the i^{th} element on the diagonal of $\mathbf{D}$ - the variance-covariance matrix of the structural errors -) conditional on $\mathbf{A}$ are given by a Gamma distribution, $\Gamma(\kappa, \tau_i)$, as follow:

$$p(\mathbf{D}|\mathbf{A}) = \prod_{i=1}^{n} p(d_{ii}|\mathbf{A}) \tag{4}$$

where κ/τ_i and κ/τ_i^2 represent the first and second moments of d_{ii}^{-1}, respectively.
Following Baumeister and Hamilton (2015), we set the prior mean for d_{ii}^{-1} equals to the reciprocal of the diagonal element of matrix $\mathbf{A\Omega A'}$, where $\mathbf{\Omega}$ represents the sample variance-covariance matrix of the residuals from the univariate autoregressive models (of order 12)

estimated on each endogenous variable. Moreover, we set $\kappa = 2$, which implies that the prior carries as much weight as four observations.

Priors for $\mathbf{B}$*,* $\mathbf{D}$ *and* $\mathbf{A}$*.* We assume that $\mathbf{b}_i'$ conditional on $\mathbf{A}$ and $\mathbf{D}$ is a row vector of random structural parameters following a multivariate Normal distribution, $\mathbf{b}_i|\mathbf{A},\mathbf{D} \sim \mathcal{N}(\mathbf{m}_i,\, d_{ii}\mathbf{M}_i)$, where $\mathbf{m}_i$ is the best guess about $\mathbf{b}_i$ before looking at the data and $\mathbf{M}_i$ represents the covariance matrix about the prior.
Thus, the prior for the lagged structural coefficients is:

$$p(\mathbf{B}|\mathbf{D},\mathbf{A}) = \prod_{i=1}^{n} p(\mathbf{b}'|\mathbf{A},\mathbf{D}) \tag{5}$$

where for most parameters $\mathbf{m}_i = \mathbf{0}$ for $i = 1, 2, \cdots, 5$. The only exceptions are for the lagged coefficients of the supply and the consumption demand equations. Indeed, we set the third and fifth elements of $\mathbf{m}_1$ to -0.10 and 0.15 and of $\mathbf{m}_5$ to -0.15 and 0.2, respectively. The prior information about the lagged parameters help to better distinguish consumption shocks from supply shocks. For the prior variance $\mathbf{M}_i$, we set a standard Minnesota prior that assigns large confidence that coefficients related to higher lags are zero (see Doan et al. (1984)). Following Baumeister and Hamilton (2015), three values for the hyper-parameters of the prior for $\mathbf{B}$ are chosen. First, a parameter controlling the overall tightness of the prior, which is set to 0.5. Second, a parameter governing how quickly the prior of the past coefficients tightens to zero as the lags increase, which is set to 1. Third, a parameter governing the tightness of the prior for the constant term, which is set to 100. This makes the prior on the constant term is not relevant.

The prior distribution for $\mathbf{A},\mathbf{D},\mathbf{B}$. The joint probability distribution of the prior information about the plausible values of matrices $\mathbf{A},\mathbf{D},\mathbf{B}$ is:

$$p(\mathbf{A},\mathbf{D},\mathbf{B}) = p(\mathbf{A})p(\mathbf{D}|\mathbf{A})p(\mathbf{B}|\mathbf{A},\mathbf{D}) \tag{6}$$

The last step is designed to construct the joint posterior distribution of the parameters, $p(\mathbf{A},\mathbf{D},\mathbf{B}|\mathbf{Y_T})$, where $\mathbf{Y_T}$ represents the data sample. According to Baumeister and Hamilton (2015), we proceed as follow.

Generating draws from $p(\mathbf{A}|\mathbf{Y_T})$. We use the Metropolis-Hasting algorithm to generate draws from the posterior distribution of $\mathbf{A}$. The iteration starts from setting $\alpha^{\mathbf{1}} = \hat{\alpha}$ and, for a generic step $l+1$ we generate a candidate $\tilde{\alpha}^{(l+1)}$ as follows:

$$\tilde{\alpha}^{(l+1)} = \alpha^l + \xi(\hat{P}_\Lambda)'\mathbf{v}_{l+1}$$

where $\mathbf{v}_{l+1}$ is a 5×1 vector of independent standard Student t variables with 2 degrees of freedom, ξ is a scalar tuning parameter for 30% acceptance ratio and $\hat{P}_\Lambda$ is the Cholesky factorization of the matrix capturing the curvature of the posterior distribution of the vector of unknowns parameters α. Then, we compare the value of the target function, $q(\cdot)$, evaluated in $\tilde{\alpha}^{(l+1)}$ and $\alpha^{(l)}$. If $q(\tilde{\alpha}^{(l+1)}) < q(\alpha^{(l)})$, we set $\alpha^{(l+1)} = \alpha^{(l)}$ with probability $1-exp[q(\tilde{\alpha}^{(l+1)} - q(\alpha^{(l+1)})]$; otherwise we set $\alpha^{(l+1)} = \tilde{\alpha}^{(l+1)}$. The value l indicates the number of iterations, including the first M burn-in draws.

Finally, the sign of $\mathbf{H}$, denoted as sign($\mathbf{H}$), is:

$$\text{sign}(\mathbf{H}) = \begin{pmatrix} \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{-}_{(91\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} \\ \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{-}_{(97\%)} & \underbrace{-}_{(100\%)} & \underbrace{-}_{(100\%)} \\ \underbrace{+}_{(100\%)} & \underbrace{-}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{-}_{(100\%)} & \underbrace{-}_{(100\%)} \\ \underbrace{+}_{(100\%)} & \underbrace{-}_{(100\%)} & \underbrace{+}_{(98\%)} & \underbrace{+}_{(100\%)} & \underbrace{-}_{(100\%)} \\ \underbrace{-}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(97\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} \end{pmatrix} \tag{7}$$

where $+$ and $-$ denote a positive and negative impact sign of the endogenous variables to each structural shock and their posterior probabilities indicated in parenthesis. We provide evidence of a strong reduction in the uncertainty around the probability signs of the response of the endogenous variables to each structural shock.

Generating draws from $p(\mathbf{D}|\mathbf{A}, \mathbf{Y_T})$. Starting with $l = M+1$, for each α^l we generate $\delta_{ii}^l \sim \Gamma(k_i^*, \tau_i^*(\mathbf{A}(\alpha^l)))$, $i = 1, 2, 3, 4$, and take $\mathbf{D}^l$ to be a diagonal matrix whose elements are

$d^l_{ii} = 1/\delta^l_{ii}$.

Generating draws from $p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y_T})$. From the posterior distribution of the variance-covariance matrix of the structural shocks we can further generate $\mathbf{b}^l_i \sim \mathcal{N}(\mathbf{m}^*_i,\, d^l_{ii}\mathbf{M}^*_i)$, $i = 1, 2, 3, 4, 5$.

The joint posterior distribution of size N is :

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}|\mathbf{Y_T}) = p(\mathbf{A}|\mathbf{Y_T})p(\mathbf{D}|\mathbf{A}, \mathbf{Y_T})p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y_T})) \tag{8}$$

with the first M burn-in draws equal to $2.5e^6$ and $N = 1e^6$. Finally, following Baumeister and Hamilton (2019), we split the estimation sample in two parts $\mathbf{Y_T} = \{\mathbf{Y^1}, \mathbf{Y^2}\}$, where $\mathbf{Y^1}$ spans from 1/01/1988 to 19/03/2010 and $\mathbf{Y^2}$ covers the remaining period, that is, 26/02/2010-29/04/2022. Then. we put a prior which treats observations in the first sample as half informative as those in the second sample.

B Data: further details

Let Q_t be the U.S. field production of crude oil in thousands barrels (mnemonic: WCRFPUS2), then $\Delta q_t = 100 \times \log(Q_t/Q_{t-1})$. Notice that EIA provides production data in thousands barrels per day, therefore we multiply by 7 to obtain the value in thousands barrels per week.

In constructing y_t we follow Hamilton (2019b) and rely on the daily value of Baltic Dry Index (BDI_t) sourced from Bloomberg (mnemonic: BDIY). To deflate the index we use the U.S. Consumer Price Index sourced from FRED (mnemonic: CPIAUCSL) that is linearly interpolated to obtain daily values. Both variables are then converted to weekly sampling frequency by averaging daily data. Lastly, we define $y_t = \log(BDI_t/CPI_t) - log(BDI_{t-(2\times 52)}/CPI_{t-(2\times 52)})$. Notice that taking a 2 years difference we interpret y_t a cyclical indicator.

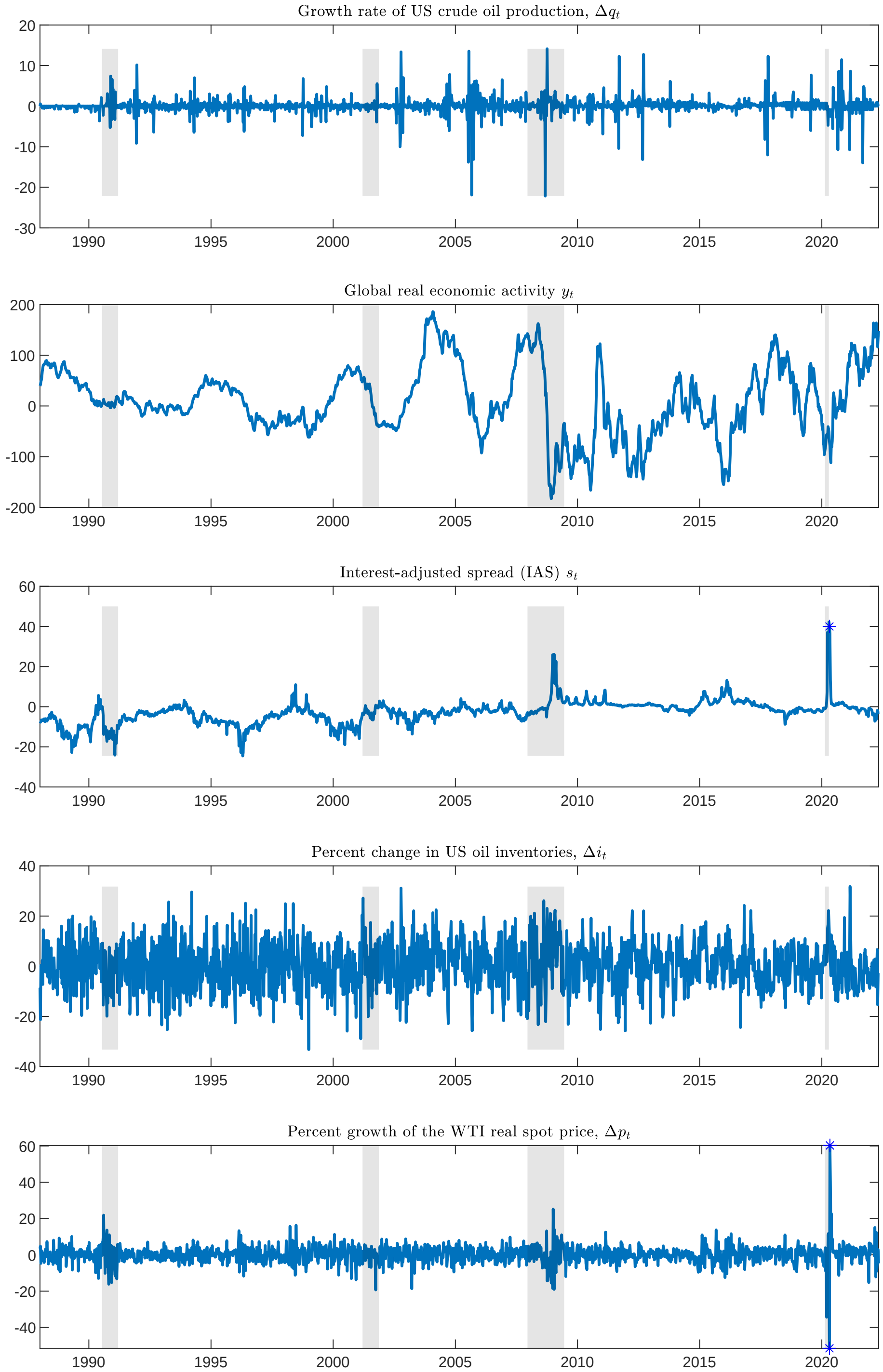
The interest-adjusted spread (IAS) is defined as: $s_t = 100 \times \log(F^{(3mo)/P_t}_t) - r^f_t$ where P_t is the WTI spot price (mnemonic: RWTC), $F^{(3mo)}_t$ is the 3 month futures price (mnemonic:

RCLC3) and r_t^f is the 3-Month Treasury Bill rate (mnemonic: WTB3MS). Prices are sourced from EIA, while r_t^f from FRED.

Let I_t be the U.S. ending stocks of crude oil in thousands barrels (mnemonic: WCRSTUS1), then $\Delta i_t = 100 \times [(I_t - I_{t-1})/Q_{t-1}]$, where Q_t is U.S. field production of crude oil in thousands barrels.

Figure A1 plots the variables analyzed in the weekly SVAR model, namely: growth rate of US crude oil production, global real economic activity, interest-adjusted spread, percentage change in US crude oil inventories and percentage growth of WTI real spot price. Variables are represented over the period 01/01/1988 - 29/04/2022.

Figure A1: Data for the weekly structural VAR: 01/01/1988 – 29/04/2022 ($T = 1792$)



Notes: for s_t and Δrpo_t we have capped extreme observations to improve the readability of figure. These caps are denoted with an asterisk in the plots. Importantly, these caps have not been imposed in our empirical analyses. As for s_t, the largest observation, equal to 194.79 and recorded on 24 April 2020, we set a cap equal to 40 (second plot from the top). For Δrpo_t we set a cap on the smallest as well as on the largest observations, recorded on 24 April 2020 and 01 May 2020 respectively. This cap is equal to $1.5 \times \max(|\Delta rpo_t|)$, where the maximum is taken on the sample that excludes the two capped observations.

C Robustness checks

C.1 Sensitivity analysis

In this section we provide a sensitivity analysis on the structural parameters a_{iq}, a_{is} and a^d_{pq}. This can be motivated by the fact that the data cause modest revisions in our priors about these coefficients. In particular, we investigate the impacts of considering less informative priors. We do so by increasing the variance of the prior distribution. We rely on a Student t density with the same location parameter and degrees of freedom identical as those in the original specification but increase the scale parameter. Specifically, we increase the scale parameter by a factor of 2, 4, and 8 to assess the consequences of using less informative priors on the parameters of interest.

C.1.1 The price elasticity of oil demand

Our baseline prior for a^d_{qp} is Student t, with mode -0.15, scale parameter 0.05 and 3 degrees of freedom. Moreover, we consider a truncated distribution constrained to have negative support. This implies a 97% probability that the weekly price elasticity of oil demand falls in the interval [-0.3, 0], as shown in panel A of Table C1.

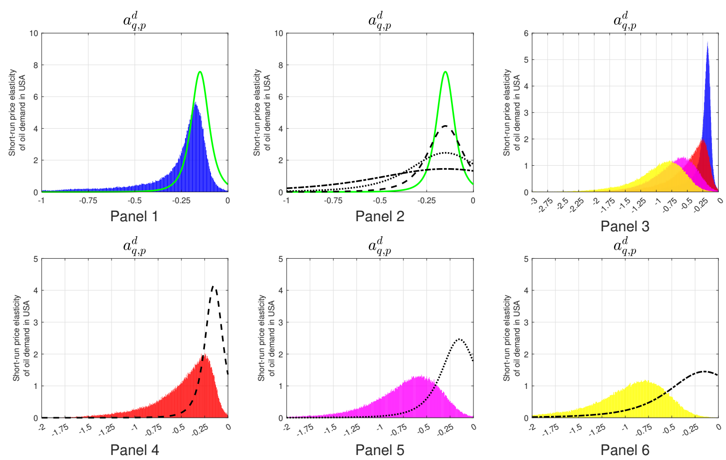
Table C1: Implied probabilities for a^d_{qp}

	Prior distributions for a^d_{qp}		
Panel A	Prob($-0.3 \leq a^d_{qp} \leq 0$)	Prob($a^d_{qp} \leq -0.5$)	Prob($a^d_{qp} \leq -1$)
$\sigma_{a^d_{qp}} = 0.05$	97%	0%	0%
$\sigma_{a^d_{qp}} = 0.1$	78%	2%	0
$\sigma_{a^d_{qp}} = 0.2$	57%	12%	2%
$\sigma_{a^d_{qp}} = 0.4$	36%	35%	10%
	Posterior distributions for a^d_{qp}		
Panel B	Prob($-0.3 \leq a^d_{qp} \leq 0$)	Prob($a^d_{qp} \leq -0.5$)	Prob($a^d_{qp} \leq -1$)
$\sigma_{a^d_{qp}} = 0.05$	74%	12%	1%
$\sigma_{a^d_{qp}} = 0.1$	34%	36%	0%
$\sigma_{a^d_{qp}} = 0.2$	8%	71%	2%
$\sigma_{a^d_{qp}} = 0.4$	2%	91%	10%

Notes: $\sigma_{a^d_{qp}}$ represents the scale parameter, that is the standard deviation for both prior and posterior distributions.

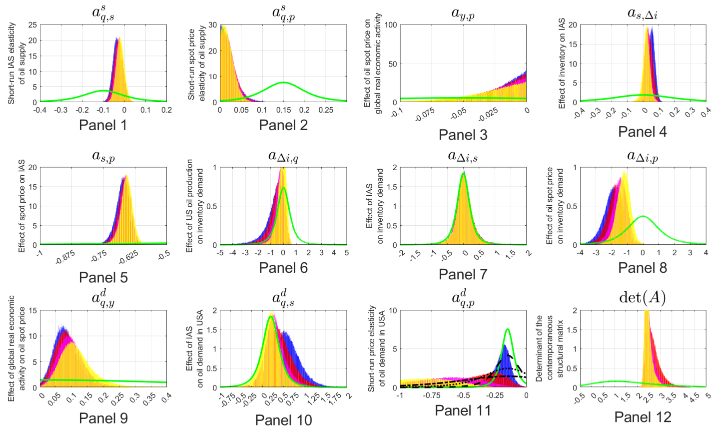
Based on the characteristics of the US crude oil market and the sampling frequency of the data in our analysis, we believe that the original prior for a^d_{qp} is reasonable. On the contrary, the prior with a greater scale parameter ($\sigma_{a^d_{qp}} = 0.05 \times 8 = 0.4$) is highly uninformative and assigns a 10% probability to a price demand elasticity greater than 1, in absolute value. Panel 2 of Figure A2 plots the priors distributions for the parameters under scrutiny. The green solid line indicates the baseline prior, with a scale parameter equal to 0.05, while dashed, dotted and dash-dotted lines represent less informative priors with increasing scale parameters equal to $0.05 \times 2 = 0.1$, $0.05 \times 4 = 0.2$ and $0.05 \times 8 = 0.4$, respectively. The prior with the largest scale parameter is almost flat when compared to the prior used in the baseline model. Panel 3 of Figure A2 shows the posterior distributions of the weekly price elasticity of oil demand implied by the prior distributions discussed above. Specifically, the posteriors medians of a^d_{qp} are -0.9 (for scale parameter equals 0.4), -0.67 (for scale parameter equals 0.2) and -0.39 (for scale parameter equals 0.1). These values are significantly larger than -0.20 and are difficult to reconcile with the *weekly* elasticity of oil demand in US. The implications of these changes for the other structural parameters of the model are reported in Figure A3. If we had limited prior information about the oil demand elasticity, the model would tend to slightly revise the posterior distribution of the remaining parameters. Figures A4 shows that the impulse response estimates to each structural shock are robust to changes in the prior of the weekly elasticity of crude oil demand.

Figure A2: Priors and posteriors distributions for the structural coefficient a^d_{qp}



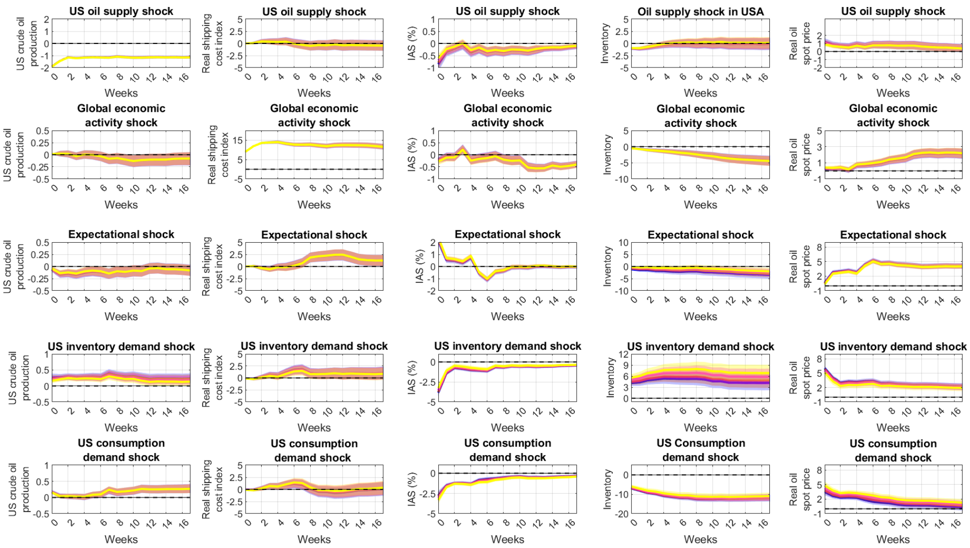
Notes: Green solid lines and blue bars denote prior distributions used in model 1. Blue bar is the corresponding posterior distribution. Dashed and dotted lines indicate prior distributions with scale parameters two and three times larger than those reported in Table 1 of the paper. Orange and pink bars are the corresponding posterior distributions. Dash-dotted lines denote prior distributions with scale parameters four times larger than the original value. The associated posterior distributions are represented by yellow bars.

Figure A3: Priors and posteriors distributions for the structural coefficients



Note: See figure A2.

Figure A4: Impulse responses of the variables to the structural shocks

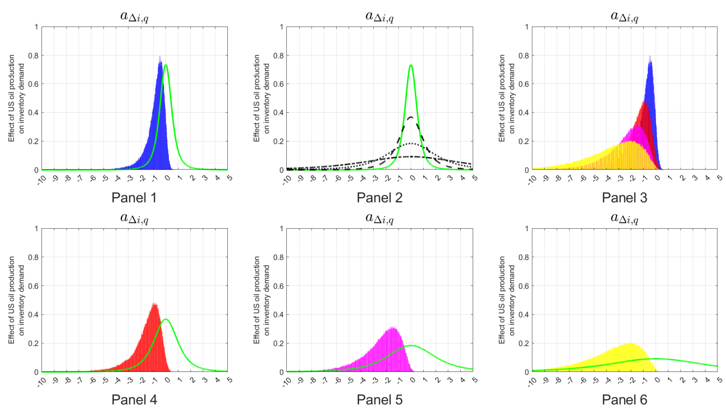


Note: The posterior median responses to a one-standard deviation shock are reported. Solid lines indicate the median impulse response estimates of model 1. Shaded bands indicate the posterior credibility regions at 68. The US supply shock has been normalized to imply an increase in the real price of oil.

C.1.2 The effect of US crude oil production on US crude oil inventories

Following Baumeister and Hamilton (2019), we use a relatively uninformative prior for a_{iq}, that is, a Student t distribution with mode 0, scale parameter 0.5 and 3 degrees of freedom. Panel 2 of Figure A5 plots the priors distributions for the parameters under scrutiny. When

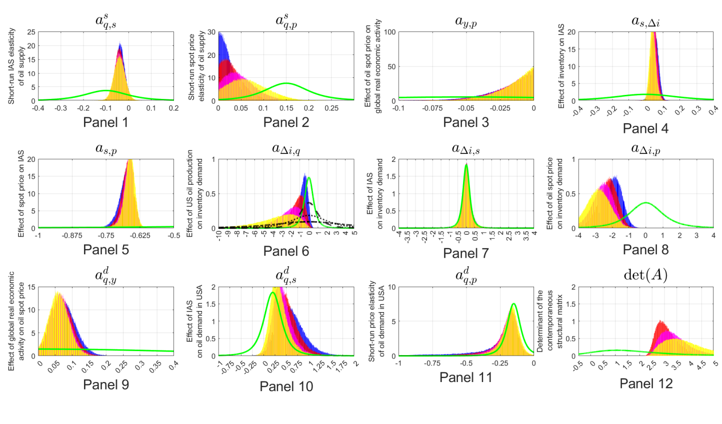
Figure A5: Priors and posteriors distributions for the structural coefficient a_{iq}



Note: see Figure A5.

we consider a scale parameter 8 times larger than the baseline specification, a flat prior distribution (dash-dotted line) is obtained, compared to the original prior. The implications of these changes for the structural parameters of the model are reported in Figure A6.

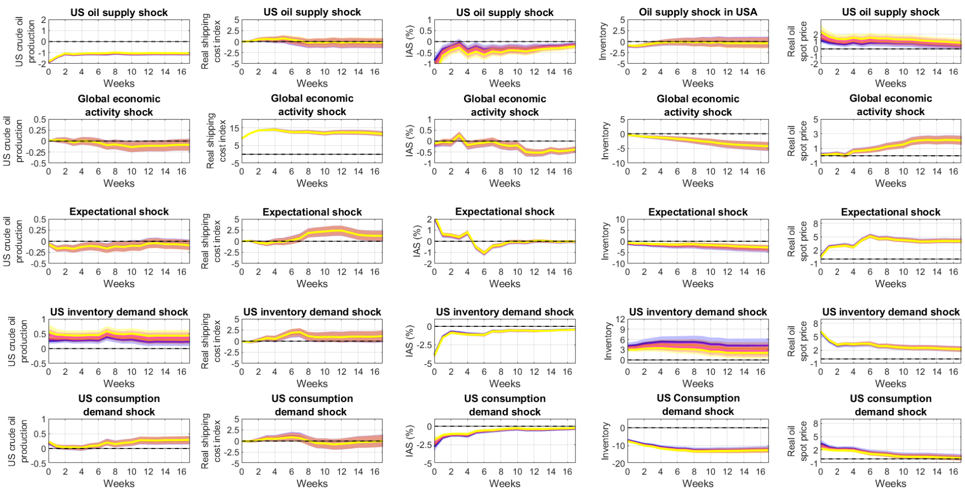
Figure A6: Priors and posteriors distributions for the structural coefficients



Note: See figure A2.

If we had fully uninformative prior information about the effect of inventory changes on crude oil production, the model would produce an upward revision of a^s_{qp} as shown in panel 2 of Figure A6. This revision would be more consistent with the empirical estimates of the

Figure A7: Impulse responses of the variables to the structural shocks



Note: see Figure A4.

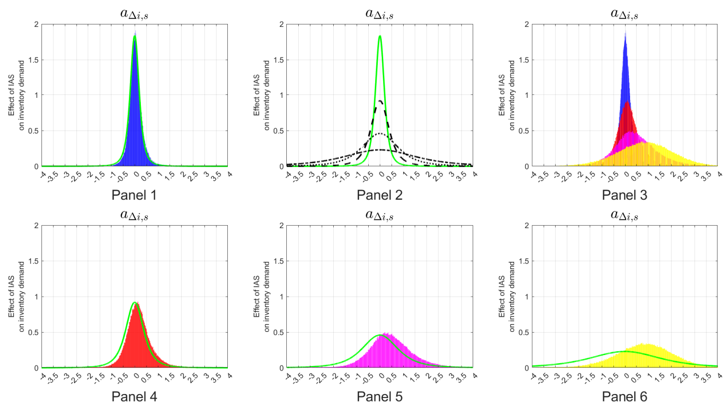
monthly price elasticity of oil supply that are available in the literature, rather than *weekly* response of oil producers to oil price changes.

Finally, Figure A7 shows that the impulse response estimates to each structural shock are robust to changes in the prior of the effect of crude oil production on inventory changes.

C.1.3 The effect of IAS on US crude oil inventories

For a_{is} we opt for a Student t prior distribution with mode at 0, scale parameter equal 0.2 and 3 degrees of freedom. Panel 2 of A8 plots the priors distributions for the parameters

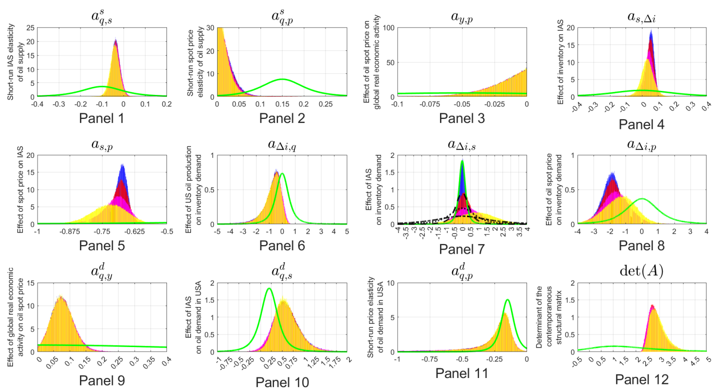
Figure A8: Priors and posteriors distributions for the structural coefficient a_{is}



Note: see Figure A5.

under scrutiny when changing the scale parameter. The implications of these changes for

Figure A9: Priors and posteriors distributions for the structural coefficients

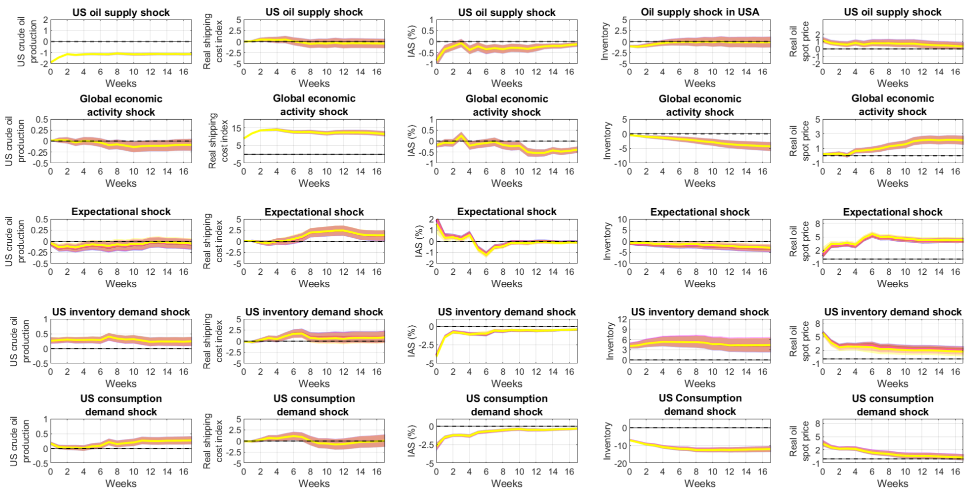


Note: See figure A2.

the structural parameters of the model are reported in Figure A9. It is worth noting that the distribution of the short-run price demand (a^d_{qp}) and supply (a^s_{qp}) elasticities are robust to changes in the prior for a_{is}.

Moreover, Figure A10 shows that the impulse response estimates to each structural shock are robust to changes in the prior of the coefficient governing the effect of IAS on inventory changes.

Figure A10: Impulse responses of the variables to the structural shocks

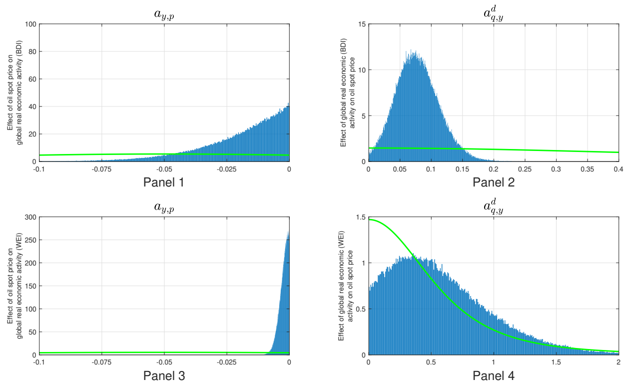


Note: see Figure A4.

C.2 WEI as an alternative proxy for global real economic activity

As a robustness check, we replace the proxy of global economic activity based on the RSC/BDI index with the Weekly Economic Index (WEI) of Lewis et al. (2021). The WEI, available from year 2008 onwards, relies on a factor model to extract a composite of ten weekly time series. Thus we re-estimate the SVAR model by replacing RSC with WEI. Panels 1 and 2 of Figure A11 plot the prior and posterior distributions for the coefficients a_{yp} and a^d_{qy} (in Eq. 4b and 4e, respectively) when using the RSC index, while Panels 3 and 4 of Figure A11 are based on the WEI. Two important features emerge. First, the RSC is likely to be more affected by changes in the real price of oil than the WEI. Second, as shown in panel 4 of Figure A11, the median of the posterior distribution of coefficient capturing the effect of WEI on US oil consumption demand, a^d_{qy}, is approximately 0.5, and it is larger than that reported in panel 2 which is based on the RSC. This is consistent with the idea that the WEI represents a good proxy for the US economic activity and, therefore the structural coefficient a^d_{qy} can be interpreted as the income elasticity of crude oil US demand (see, among others Gately and Huntington (2002) and Csereklyei et al. (2016).)

Figure A11: Priors and posteriors distributions for the structural coefficient a_{yp} and a^d_{qy}

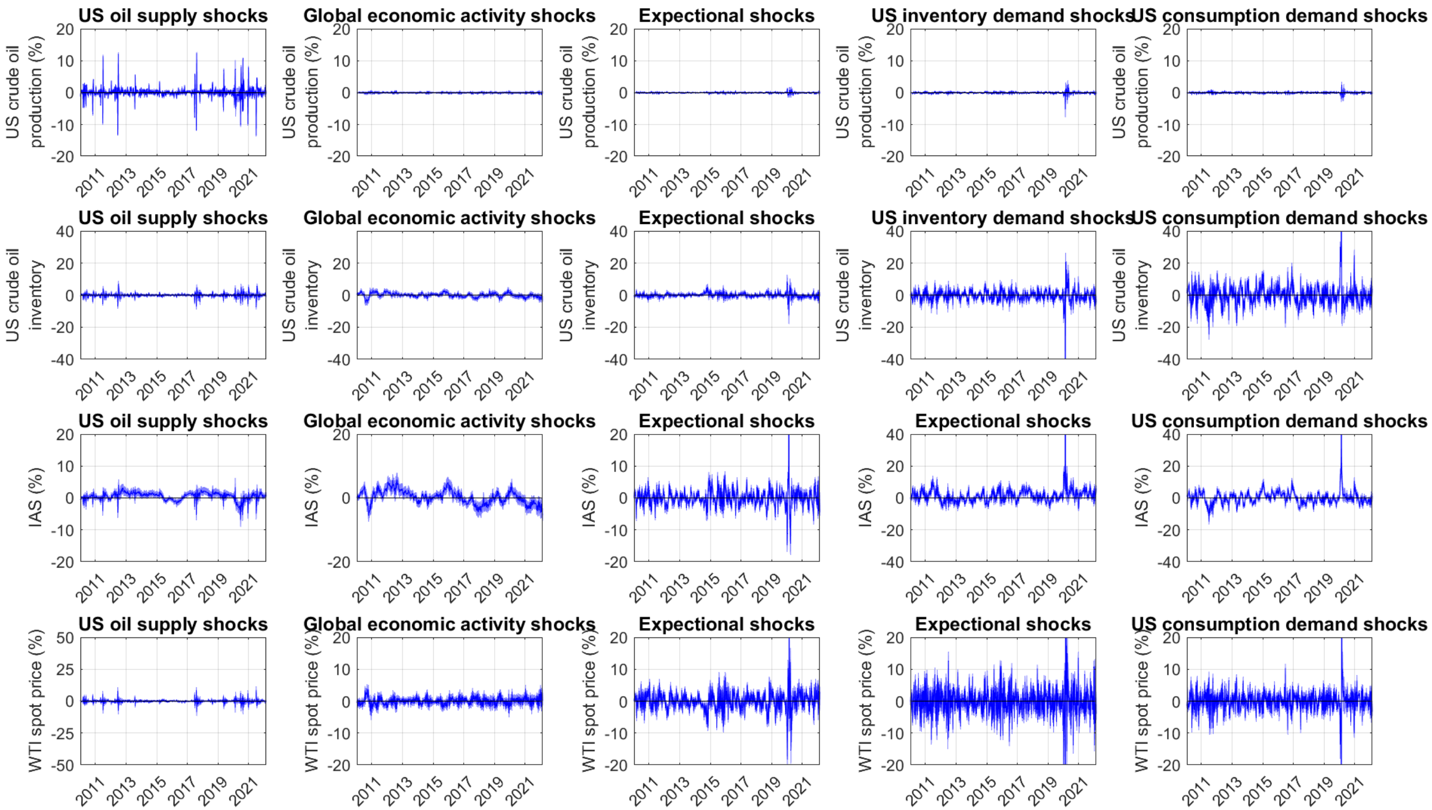


Notes: Green line and blue bars denote prior and posterior distributions, respectively.

D Historical decompositions

In Figure A12 we present the historical decompositions of the following variables: growth rate of US crude oil production, changes in US crude oil inventories, IAS and the percentage growth of the WTI real spot price.

Figure A12: Cumulative effect of each structural shock on the oil-market specific variables



Note: The posterior median responses to a one-standard deviation shock are reported. Blue lines indicate the median impulse response estimates of model 1. Blue shaded bands indicate the posterior credibility regions at 68%.