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Abstract

Oil prices contain information on global shocks of key relevance for monetary policy decisions. We propose a novel approach to identify these shocks at the daily frequency in a Structural Vector Autoregression (SVAR). Our method is devised to be used in real-time to interpret the developments in the oil market and their implications for the macroeconomy, circumventing the problem of publication lags that plagues monthly data used in workhorse SVAR models. It proves particularly valuable for monetary policymakers at times when macroeconomic conditions evolve rapidly, like during the COVID-19 pandemic or the invasion of Ukraine by Russia.

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* Bank of Italy, Directorate General for Economics, Statistics and Research.

1 Introduction[1]

Policymakers constantly monitor financial markets and macroeconomic data releases to obtain cues about changes in the state of the global economy. Macroeconomic data are only available with a significant lag and are subject to non-negligible revisions (Aruoba and Diebold, 2010). Asset prices, on the other hand, are available in real-time but are only indirectly related to macroeconomic variables like output and inflation. The tension between using information that is timely, but potentially noisy, and information that is accurate, but lagging, is a key challenge for real-time decision making.

Our paper shows how to exploit information on oil market developments to resolve this tension. It proposes a credible structural identification strategy that connects the oil market, financial markets and the macroeconomy and that can be used to build a macroeconomic narrative that is timely and valuable for monetary policymakers.

When assessing the state of the global economy in real-time, the oil market plays a special role. First, the price of oil is closely related to economic activity (Alquist et al., 2020) and global inflation (Ciccarelli and Mojon, 2010). For this reason it is routinely monitored as a barometer of economic expansion or contraction and as a source of global inflation pressure. Second, oil prices can have a lasting impact on inflation expectations and therefore affect monetary policy decisions (Coibion and Gorodnichenko, 2015; Weber et al., 2022). Third, oil is traded in liquid financial markets and its price is available at high frequency.[2]

However, interpreting the sources of movement in oil prices is not straightforward. Their

[1]The views expressed in this paper belong to the authors and are not necessarily shared by the Banca d'Italia. We wish to thank Piergiorgio Alessandri, Ambrogio Cesa Bianchi, Juan Antolín-Díaz, Fabrizio Ferriani, Lutz Kilian, Ivan Petrella, Matteo Luciani, Juan Rubio-Ramirez, Robert Ready, Livio Stracca, Marco Taboga and seminar participants at the European Central Bank, the 3rd CEBRA Workshop on Commodities and Macroeconomics, the 2021 Barcelona Graduate School of Economics Forum for useful comments and suggestions. We thank Gabriele Cappadona for excellent research assistance. All remaining errors are our own.

[2]Among commodity markets, the oil market is the most globally integrated and the most liquid one. Other commodity prices, like those of metals, provide a weaker signal on the state of the global economy, since they are more sensitive to regional shocks and the financial contracts linked to these commodities are not as liquid.

relationship with inflation and output depends on the underlying structural drivers, which are typically identified with Structural Vector Autoregressions (SVAR) (Kilian, 2009; Kilian and Murphy, 2014; Caldara et al., 2019; Baumeister and Hamilton, 2019). Such models, however, are of little use for policymakers in real-time, as they rely on monthly data that are plagued by publication lags and ex-post revisions, like measures of economic activity and oil production. Hence, policymakers are left in the dark on the sources of the shocks precisely when this narrative would be valuable to inform their decisions.[3]

The main motivation of this paper, and its main contribution, is to fill this void. Our model is a daily SVAR that provides a real-time decomposition of the price of oil in three structural shocks. Two of these are related to, respectively, future and current global demand. We treat current and future demand separately since the price of oil, much like financial asset prices, is very sensitive to news about future economic prospects. The third is a shock to the supply of oil. We describe them briefly.

The first shock, which we label "forward-looking demand", embodies unexpected shifts in expectations and uncertainty about future global demand. From a financial markets perspective, it captures global investors' changes in risk appetite and, as such, in the premium required to hold risky assets. We identify forward-looking demand shocks via an external instrument, in the spirit of Stock and Watson (2012) and Mertens and Ravn (2013). These shocks capture the tight connection between oil and stock prices and, more generally, the bulk of the co-movement between oil prices and asset prices. They also have strong macroeconomic effects as they generate persistent movements in GDP, domestic demand and CPI.

The second shock, which we label "current demand", captures unexpected changes in the current demand for commodities, including crude oil. We identify it with sign and

[3] As emphasized by former ECB President Draghi (2016) "faced with adverse shocks, the pace at which monetary policy can bring inflation back to the objective depends on two factors: the *nature of the shock* itself, and the conditions in which monetary policy operates".

magnitude restrictions, by conjecturing that it induces a *positive* correlation between oil (both spot and futures) and stock prices, and that it affects spot more than futures prices. Current demand shocks raise output and inflation but their effect on asset prices is weaker than that of its forward-looking counterpart, corroborating our choice to treat them as separate disturbances. The distinction between forward-looking and current demand shocks is best clarified with an example. On the 9th of November 2020, Pfizer-BioNTech announced the successful development of a Covid-19 vaccine. In the weeks following the announcement, our model indicates that oil prices and stock returns rose due to positive forward-looking demand, driven by optimism about future global demand, despite containment measures still in place and curbing actual demand for oil.

The third is an "oil supply shock", conditional on which oil prices co-move *negatively* with stock prices. This shock has a stagflationary impact on the economy, i.e. it raises inflation, lowers economic activity and tightens financial conditions by raising interest rates and depressing stock prices.

The estimated shocks have a number of appealing properties. Their volatility is higher in days in which specific news hit the market: in particular, oil supply shocks tend to be large around OPEC announcements, while forward-looking and current demand shocks relate to macroeconomic data releases and/or announcements of the U.S. Federal Reserve Open Market Committee (FOMC). Moreover, the shocks from our model, identified based on economic reasoning, are also strikingly similar to those obtained from alternative identification procedures based on time-varying volatility (Lewis, 2021) or on non-gaussianity (Gourieroux et al., 2017). This confirms that we are effectively capturing the most relevant orthogonal sources of variation in oil prices.

We demonstrate the usefulness of our model in the context of real-time policy making.

Focusing on specific U.S. Federal Reserve meetings between 2011 and 2022, we show how FOMC members not only discussed oil price developments, but also aimed to disentangle the source of their movement.[4] Especially in December 2014 and in October 2018 the FOMC discussion on the relative importance of demand-supply factors underlying oil price movements displayed significant uncertainty. Our model could have dispelled those doubts by promptly quantifying the drivers of oil prices.

Outline of the paper. The paper is structured as follows. Section 2 describes the empirical model and the identification strategy. Section 3 briefly discusses the estimation algorithm, deferring most of the details to a technical Appendix. Section 4 presents estimates of the impact of our identified shocks on a wide range of macroeconomic variables. Section 5 illustrates the advantages of our model, vis-à-vis the existing ones, for real-time policy making. Section 6 discusses the validation of the shocks. Section 7 conducts robustness checks. Section 8 concludes.

2 Data, model and shocks identification

Our model is a daily three-variate Vector Autoregression (VAR) that includes the spot price of crude oil, global stock market prices and the 12-month crude oil futures price. Our measure of the spot price of oil is the log of Brent (1st futures delivery price). Futures prices are the log of the 12-month Brent crude oil futures. We measure global stock prices by extracting the first principal component from a large panel of stock returns.[5] This *global* equity factor adds

[4]We conducted a similar analysis for the European Central Bank (ECB) Governing Council meetings. However, besides official minutes, the ECB material remains mostly confidential.

[5]Stock market returns are taken from Bloomberg. The countries included are Mexico, Australia, Canada, Finland, Netherlands, Spain, France, United States, Hong Kong, Japan, United Kingdom, Argentina, India, Chile, Sri Lanka, Ireland, Italy, Pakistan, Malaysia, Austria, Mauritius, Philippines, Peru, Egypt, Bangladesh, Belgium, Slovak Republic, Republic Of Korea, Turkey, Czech Republic, Thailand, Iceland, China, Portugal, Venezuela, New Zealand, Switzerland, Croatia, Zambia, Hungary, Singapore, Israel, Europe, Ukraine, Luxembourg, Vietnam, Denmark, Colombia, Sweden, Brazil, Bulgaria, South Africa, Lebanon, Germany, Montenegro, Slovenia. We exclude large oil producers like for instance Iran, Venezuela, Indonesia, Kuwait, Russia, Norway

information about the global economy to the VAR and further contributes to the identification of global shocks. In contrast, more standard equity market indices, like the S&P500, are strongly affected by specific sectors, like Information Technology, marginally related to crude oil prices, and are not truly representative of global developments.[6] Our sample runs from the 1st of June 2007 to the 5th of April 2022.[7]

Collecting the n variables in the vector y_t, we can write the structural representation of the model, which allows for contemporaneous interaction of the variables:

$$A_0 y_t = A_+ x_t + e_t, \qquad e_t \sim \text{i.i.d. } N(0, I), \tag{1}$$

where $A_+ = [A_1, A_2, ..., A_p, c]$ and $x_t = [y'_{t-1}, y'_{t-2}, ..., y'_{t-p}, 1]'$. A_0 is an $n \times n$ matrix of contemporaneous interactions, the p matrices A_j ($j = 1, 2, ..., p$) of dimension $n \times n$ collect the autoregressive coefficients, c is an intercept term and e_t is an n dimensional vector of structural shocks. The reduced form model has a compact representation:

$$y_t = \Phi_+ x_t + u_t, \qquad u_t \sim \text{i.i.d. } N(0, \Sigma),$$

where $\Phi_+ = A_0{}^{-1} A_+$ and reduced form and structural shocks are related as follows:

$$u_t = A_0^{-1} e_t = B e_t, \tag{2}$$

$$\Sigma = (A_0' A_0)^{-1}. \tag{3}$$

The matrix B, the structural impact matrix, is the crucial object of interest in structural

and Saudi Arabia since for these countries an oil supply shock constitutes a source of additional revenues rather than a recessionary shock.

[6] As in Miranda-Agrippino and Rey (2020) we cumulate the common stock returns factor. A model in which the global stock market factor is replaced by the World MSCI stock market index gives similar results. Results are reported in the Supplementary Material.

[7] The beginning of the sample is constrained by the availability of the OVX (option-implied volatility related to oil contracts) that is employed to identify the forward-looking demand shock. Appendix C contains more details on the data.

identification. To estimate this matrix we place several types of restrictions, to which we now turn.

2.1 Identification restrictions on daily data

Forward-looking demand shock. The first structural shock that we analyze captures a change in expectations and uncertainty about future global demand. This shock is quickly reflected in changes in the willingness of market participants to bear risk. The importance of investors' sentiment in driving the high-frequency correlation between stock and oil prices appears often in market commentaries and is also used by policymakers to rationalize, in real-time, the nature of the shocks that hit the economy. Bernanke (2016), for instance, explicitly makes this point: *"[...] recent market moves have been accompanied by elevated volatility. If investors retreat from commodities as well as stocks during periods of high uncertainty and risk aversion, then shocks to volatility may be another reason for the observed tendency of stocks and oil prices to move together."* In formal asset pricing models this shock captures flight to safety dynamics that lead investors to flee from risky to safe assets (i.e. government bonds) in times of heightened risk aversion (Cieslak and Pang, 2021). This shock could capture news about the future state of the economy (Beaudry and Portier, 2006; Barsky and Sims, 2011), exogenous shifts in confidence (Angeletos et al., 2018), a rise in economic uncertainty (Bloom, 2014; Alessandri and Mumtaz, 2019), or arise from increased risk aversion in a model with consumption habits (Campbell et al., 2020). Disentangling the exact source would require a larger model and additional restrictions. We do not pursue this road, as the literature has documented that, at business cycle frequencies, those shocks produce broadly similar macroeconomic effects, moving inflation and output in the same direction and would, therefore, call for a similar monetary policy response.

The forward-looking demand shock is identified with an external instrument, in the spirit of Mertens and Ravn (2013). The construction of the instrument proceeds in two steps. First, we select, through a statistical procedure, days in which we observe a large increase (decrease) of volatility in equity and oil markets[8] and in the price of gold, and a large decrease (increase) in the price of oil.[9] By 'large' we mean that they fall, respectively, either below their 10th percentile or above their 90th percentile. These are days when, in response to negative news on the global economy, market participants run to safety, volatility in oil and stock markets spikes, gold prices rise, while oil prices plunge (alternatively, these are days in which positive news about global growth raise oil prices and reduce volatility in financial markets). In the second step, we trace back the origin of such shocks to specific events scanning the main market commentaries.[10] This cross-check reveals that these days were indeed characterized by important revisions of global demand prospects, associated with a shift in global risk appetite. Operationally, we define our external instrument as a variable equal to the actual change in the VIX in these days, and zero on all other days in the sample.

We are left with 16 days (see Table 1).[11] The selected episodes include, among others, the unfolding of the global financial crisis, the reduction of the U.S. credit rating by Standard & Poor's in 2011, the eruption of the euro area crisis, the Brexit referendum, mounting trade tensions between the United States and China and the pandemic crisis.

Current demand shock. Our second shock of interest is an unexpected change in the current state of the business cycle and, as a consequence, in the demand for oil. We identify this shock through sign and magnitude restrictions. We assume that an increase in the

[8]Volatility in equity markets is measured by the VIX, that is the CBOE Volatility Index. Implied volatility in oil markets is captured by the OVX, which measures the market's expectation of 30-day volatility of crude oil prices by applying the same methodology used for the VIX to options on crude oil futures.

[9]Changes in the price of gold have been used to isolate shocks to uncertainty (Piffer and Podstawski, 2018) and can be used as an indicator of risk on/off mood in financial markets.

[10]Bloomberg, private sector newsletters and the IMF daily Global Markets Monitor.

[11]In Appendix A we report a descriptive account, sourced from these market commentaries, of the key events that, in each of these days, triggered a change in global risk appetite.

Table 1: **Episodes used to define the external instrument**

event date	*key headline*	OVX	VIX	Gold	Oil
30-Sep-2008	Rescue package hopes	-4.7	-7.3	-2.3	4.4
06-Oct-2008	Global growth fears	8.6	6.9	2.7	-7.6
17-Feb-2009	Global growth fears	10.1	5.7	2.8	-5.3
20-Apr-2009	Global growth fears	4.7	5.2	1.8	-6.8
01-Jun-2010	Global growth fears	5.6	3.5	2.0	-2.6
08-Aug-2011	U.S. sovereign downgrade	13.8	16.0	2.5	-5.3
18-Aug-2011	Euro sovereign	14.8	11.1	2.2	-3.3
07-Sep-2011	Global growth rebound	-2.5	-3.6	-4.3	2.6
01-Jun-2012	Global growth fears	6.8	2.6	2.9	-3.4
24-Jun-2016	Brexit	3.2	8.5	3.9	-5.0
02-Apr-2018	Trade tensions	2.5	3.7	1.2	-3.8
23-May-2019	Trade tensions	5.6	2.2	0.9	-4.7
31-May-2019	Trade tensions	7.3	1.4	0.9	-3.6
14-Aug-2019	Global growth fears	2.6	4.6	1.1	-3.0
24-Feb-2020	Corona virus shock	3.7	8.0	1.9	-3.8
11-Jun-2020	Corona virus shock	6.9	13.2	1.4	-7.9

Notes: *event date* reports the specific date from our statistical and narrative selection criteria; *key headline* reports the main driver identified from daily market commentaries; OVX, VIX, Gold and Oil, report the daily change for the variable indicated (log percentage change for Gold and Oil).

demand for oil induces a *positive* correlation between oil (both spot and futures) and stock prices, and that it affects spot prices more than future prices.[12] The underlying assumption is that, everything else equal, a current demand shock changes the market balance relatively more in the present than in the future, so that the spot price of crude oil has to adjust more than futures prices to clear the market.

Oil supply shock. The third structural shock is a supply-driven tightening of the oil market. This can occur because of an exogenous disruption in oil production, due for instance to a natural disaster or to a decision by oil producers to cut production independently from demand conditions. These are not rare events: Caldara et al. (2019), for instance, identify 29 such episodes between 1985 and 2011. But a tightening of the oil market can also stem

[12]This translates into an identifying assumption on the slope of the futures curve, which we expect to shift relatively more in "backwardation" (i.e. sloping downwards) following a positive demand shock and more in "contango" (i.e. sloping upwards) following a negative demand shock.

from higher precautionary demand for inventories (Kilian and Murphy, 2014; Anzuini et al., 2015). In this case, crude extraction actually increases, but oil ends up being stored rather than reaching consumers and producers.[13] In both cases oil is scarcer and more expensive, leading to lower economic activity and to higher inflation. This poses a trade-off for central banks between stabilizing output and tolerating higher inflation. Since what matters for policymakers is this trade-off, regardless of whether it arises from lower supply or higher desire for inventories, we do not try to distinguish between these two cases.[14] We identify an oil supply shock, by assuming that it induces a negative correlation between oil prices and equity prices. This assumption is supported by the theoretical model in Ready (2017).

Narrative restrictions. We further sharpen the structural identification with two additional narrative restrictions, in the spirit of Antolín-Díaz and Rubio-Ramírez (2018). On the 14^{th} of September 2019, a drone attack hit the state-owned Saudi Aramco oil processing facilities in Saudi Arabia. The damage to the production facility led to a substantial, albeit temporary, cut of Saudi Arabia's oil production, amounting to about 5% of global oil output. As a result, as markets opened the following Monday (the 16^{th} of September) oil prices jumped by 13 percent, from 60 to 68 USD per barrel. We use this episode to place two identifying narrative restrictions.

- *Narrative Restriction #1: sign of the shock.* On the 14^{th} of September 2019 the supply shock gave a positive contribution to the increase in oil prices.
- *Narrative Restriction #2: contribution of the shock.* On the 14^{th} of September 2019 the supply shock accounted for most of the change in oil prices.[15]

[13] As pointed out by Känzig (2021), these shifts in inventory demand capture different factors, including for instance higher uncertainty on the future balance of the oil market as well as unexpected news on future oil supply.

[14] Moreover, identifying a separate shock to inventories would be challenging, as we do not have good data for global oil storage. Inventories are measured with significant uncertainty and once measurement error is accounted for, shocks to inventories turn out to have a negligible impact on oil prices (Baumeister and Hamilton, 2019).

[15] In the following days, worries about oil supply quickly retreated, as Saudi Arabia's energy minister pledged

2.2 Restrictions on monthly variables and elasticity bounds

So far, we have sought to identify primitive shocks to oil prices by using information exclusively from daily financial market data. One may reasonably doubt, however, whether the shocks delivered by this identification scheme have sensible implications for macroeconomic variables as well as for the physical oil market. For instance, both demand shocks should induce a positive correlation between oil prices, global economic activity and oil production; we have also motivated our identification of supply shocks by arguing that they should move oil prices and global economic activity in opposite directions.

To address this issue, we add a set of identifying assumptions on the response of oil production and global economic activity to demand and oil supply shocks. We require both oil production as well as global industrial production to co-move positively with oil prices, conditional on demand shocks.[16] This restriction is imposed by projecting oil production and global industrial production on the monthly shocks, and discarding candidate structural models (i.e. candidate A_0 matrices obtained in the daily model) that are inconsistent with this identifying restriction on monthly data. In a similar vein, in response to a supply shock, we require global industrial production and U.S. unemployment rate to co-move, respectively, negatively and positively with oil prices.[17] We also place an upper bound at 0.05 on the monthly elasticity of oil supply to limit the range of acceptable daily structural models. This value strikes a balance between the very low bound of 0.0258 set by Kilian and Murphy (2014) and the evidence presented by Caldara et al. (2019) that this elasticity might be as high as

the use of strategic reserves to stabilise oil exports. Since we use daily data this does not represent a problem for our identification strategy.

[16]We measure oil production as the world production of crude taken from the International Energy Agency. As a proxy for global economic activity we use the industrial production based measure developed by Baumeister and Hamilton (2019).

[17]We do not impose a restriction on the response of oil production because, as explained above, this disturbance also includes uncertainty about future supply shocks. While this shock is stagflationary (like a standard negative supply shock) its effect on oil production is ambiguous. Conditional on this shock, production could actually increase to satisfy higher demand for storage.

0.08.

To the best of our knowledge, disciplining the set-identification in a mixed frequency framework is a novel procedure that constitute a further contribution of this paper to the structural VAR literature.

A summary of the identification restrictions is presented in Table 2. We have populated the first column of this table, which relates to the impact of the forward-looking demand shock on the high and low frequency variables, with the word '*Proxy*', to clarify that the response of both the daily and monthly variables to this shock is determined by the external instrument.

Table 2: **Summary of the Identifying Restrictions**

	forward look. demand	current demand	supply
	Daily Model		
Oil Price	*Proxy*	+	+
Equity Prices	*Proxy*	+	-
Oil futures price (12m)	*Proxy*	+	
	Monthly Model		
Oil Production	*Proxy*	+	
Global IP	*Proxy*	+	-
US unemployment rate	*Proxy*		+

Additional Restrictions

- Magnitude: demand shocks affect spot more than futures oil prices
- Narrative on the supply shock (14^{th} of September)
- Upper bound (0.05) on the elasticity of oil supply

3 Model Estimation

The model is estimated using Bayesian methods, setting p, the number of lags, to 12.[18] Here we briefly explain the main estimation steps and refer the reader to Appendix B for all the

[18]According to traditional lag length criteria, even a single lag would be sufficient to take care of residuals' auto-correlation.

technical details.

Shocks identification requires the estimation of the reduced form parameters Φ_+ and Σ and of the columns of the structural impact matrix $B = [b_1, b_2, b_3]$. The estimation of these parameters is conceptually split in three steps. The first step consists of estimating the reduced form parameters and the column b_1 using the external instrument described in Section 2.1. We draw on the literature on Proxy-SVARs to estimate these parameters, and in particular on the method developed by Caldara and Herbst (2019). In the second step we use sign restrictions to set-identify b_2 and b_3 conditional on the estimate for b_1 obtained in the first step. Methods that tackle this problem have been developed by Braun and Brüggemann (2022) and Arias et al. (2021). In this step we also implement narrative sign restrictions on the supply shock, rejecting all the candidate structural models in which supply shocks are not the predominant contributors to the spike in crude oil prices on the 14^{th} of September 2019, see Appendix B for details. The final step consists of adding identification restrictions on lower frequency variables. These are implemented by estimating the effects of the shocks (identified on daily data and then averaged at the monthly frequency) on two monthly variables, namely global oil production and global industrial production, and by discarding the candidate structural shocks that do not satisfy either the sign restrictions on the monthly variables or the elasticity bounds. Intuitively, this final step requires nothing more than a local projection of the monthly variables on the identified shocks.[19]

Crucially, this last step does not hinder the real-time nature of the structural decomposition, as the information sets in the daily and in the monthly data do not need to be aligned. To give a concrete example, take a real-time update of the model in a given day, say on Monday

[19] In practice, this is implemented in a Proxy-SVAR framework, along the lines of Jarociński and Karadi (2020) and Paul (2020) by using the averaged shock as an internal instrument in a monthly VAR.[20] Alessandri et al. (2023) show that as long as the data-generating process is a VAR, averaging the high-frequency proxy to a lower frequency delivers consistent estimates of the responses in a broad range of empirical setups and model specifications.

the 12th of March 2018. On that day, data on global industrial production was available only up to December 2017. An update would consist of these steps: (1) run the daily model to obtain a range of candidate structural shocks up to the 12th of March 2018; (ii) for each of these candidate shocks run the (monthly) local projections with data up to December 2017; (iii) out of the daily candidate shocks, keep those for which the (monthly) models satisfy the sign restrictions and the elasticity bounds. In other words, monthly information is only used to select, among the daily candidate shocks, those that have macroeconomic implications that are consistent with our identifying restrictions.

Data issues due to the Covid-19 shock. Since our estimation sample includes the Covid-19 shock, when implementing the monthly restrictions, we need to deal with the potential structural breaks induced by this shock on the correlation structure of macroeconomic data. We resort to the ad-hoc strategy of dropping problematic observations, as suggested by Lenza and Primiceri (2022).

Alternative mixed frequency methods. In this paper we employ daily data to identify structural shocks in real-time but also use lower frequency data to sharpen the identified set of acceptable draws and to analyze the macroeconomic effects of the shocks. Daily and monthly/quarterly data could be employed jointly through a mixed frequency VAR, typically modelled using a state-space representation (Schorfheide and Song, 2015) or a stacked VAR approach (Ghysels, 2016).[21] Our approach builds on the results by Alessandri et al. (2023), who show that the average of the high frequency shocks can be used as internal or external

[21]In state-space models low-frequency variables are treated as high-frequency variables with missing observations and recovered with the Kalman filter. While this approach is, in principle, optimal conditional on employing the right model specification, its performance depends in practice on the model's accuracy in reconstructing the high-frequency dynamics of the low-frequency variables. In the stacked VAR approach, a high-frequency variable is decomposed into several low-frequency variables and directly employed in the VAR. This prevents the implementation of more sophisticated identification restrictions, forcing researchers to use recursive identification strategies that are not generally suited to capturing macro-financial interactions. Moreover, there is no trivial way to obtain a unique measure of the impact of a high-frequency shock on low-frequency variables (Ghysels, 2016).

instrument to consistently estimate the IRFs in linear models.[22]

4 Impact of the shocks on the macro-economy

4.1 Daily variables

Figure 1 shows the response of the endogenous variables included in the daily VAR to our structural shocks. All impulse response functions are normalized to generate on impact a 1 percent increase in the oil price.

Forward-looking demand shock. Since the IRFs are normalized so as to generate a rise in oil prices, the first column of Figure 1 shows the effects of a *positive* forward-looking demand shock, i.e. an exogenous rise in global risk appetite. It is worth remarking that these are estimated through an external instrument, so that neither the sign nor the magnitude of these responses are constrained. A striking result is that a 1 percent increase in the spot oil price is associated with a close to 1 percent increase also in oil futures prices. This implies that, in response to a forward-looking demand shock, the slope of the futures curve barely changes. At the same time the shock leads to a marked increase of global stocks.[23]

Current demand shock. The second source of positive correlation between oil and stock prices comes from the demand shock. However, the increase in stock prices following a demand shock is three times smaller than the one observed after a forward-looking demand shock and the effect is hump shaped. This shock has also a much stronger impact on spot

[22] Alessandri et al. (2023) discuss in detail advantages of each of the methods and compare their performances in Monte Carlo experiments, finding that when using daily with monthly/quarterly data, averaging the structural shocks proves to be a valid alternative to mixed frequency VARs. For our purposes, averaging the high-frequency shocks constitutes the best option for two reasons. First, it can be easily used in combination with sophisticated identification schemes. Second, it is particularly well-suited to setups with a daily-monthly frequency mismatch typical of macro-financial applications, which would make the use of alternative methods overly cumbersome.

[23] The stock market factor is normalized to have zero mean and standard deviation of 100.

than on futures oil prices: as the spot oil price rises on impact by 1%, oil price futures only rise by around 0.1 percent, and thus the slope of the futures curve declines significantly.

Supply shock. Conditional on a supply shock, a 1 percent increase in the oil price is associated with a very mild fall in global stock prices. Futures prices respond strongly to this shock, although their increase (0.8 percent) is milder than that of spot prices.

Other financial variables We also look at the effect of our shocks on a range of other financial variables, namely two stock indices (S&P 500 and the MSCI index for emerging markets), the VIX, the nominal effective U.S. dollar exchange rate, inflation compensations derived from inflation swaps (5 year, 5 years forward) and 10-year U.S. bond yields.[24] Four results emerge. First, EMEs stock prices are very sensitive to forward-looking demand shocks, indicating that this shock induces a strong shift in risk appetite also within this asset class. Second, the U.S. dollar depreciates significantly conditional on positive forward-looking and current demand shocks, as investors move to higher return currencies in periods of global expansion, and responds only weakly to supply shocks.[25] Third, forward-looking demand shocks are the main source of the positive co-movement observed in the data between the price of oil, bond yields and market-based inflation expectations. Fourth, supply shocks induce a tightening of financial conditions, i.e. a fall in stock returns as well as a rise in bond yields.

4.2 Macroeconomic aggregates

We now turn to analyzing the effects of the identified shocks on key U.S. macroeconomic aggregates both at the monthly and at quarterly frequency. The monthly (quarterly) average of the daily shocks is taken as a proxy for the monthly (quarterly) VAR as described in

[24]The results hereby presented are based on a two step local projection model, taking into account all sources of uncertainty, see Appendix E for details on the methodology.

[25]Within our sample the unconditional correlation between the U.S. dollar and the oil price is -0.78.

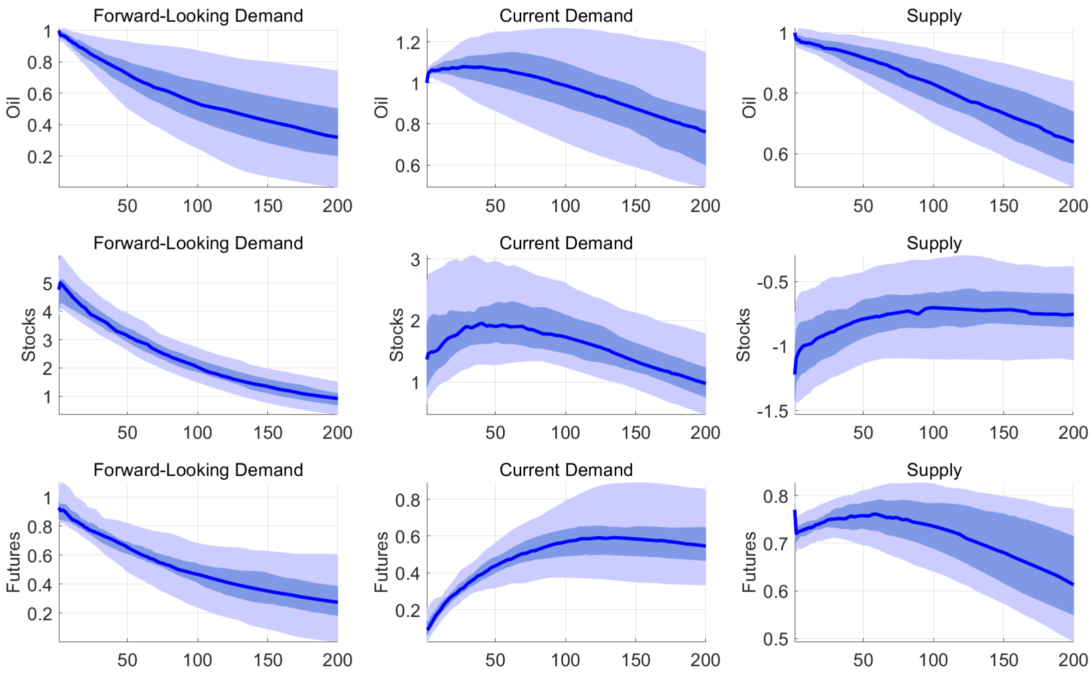


Figure 1: Impulse Response Functions for the daily VAR

Note. The solid blue line represents the median estimate. The blue and grey shaded areas correspond to 68 and 90 percent credible sets that reflect both parameter and identification uncertainty. The responses are standardized so as to lead to a 1 percent increase in the oil price. The horizontal axis shows days after the shock.

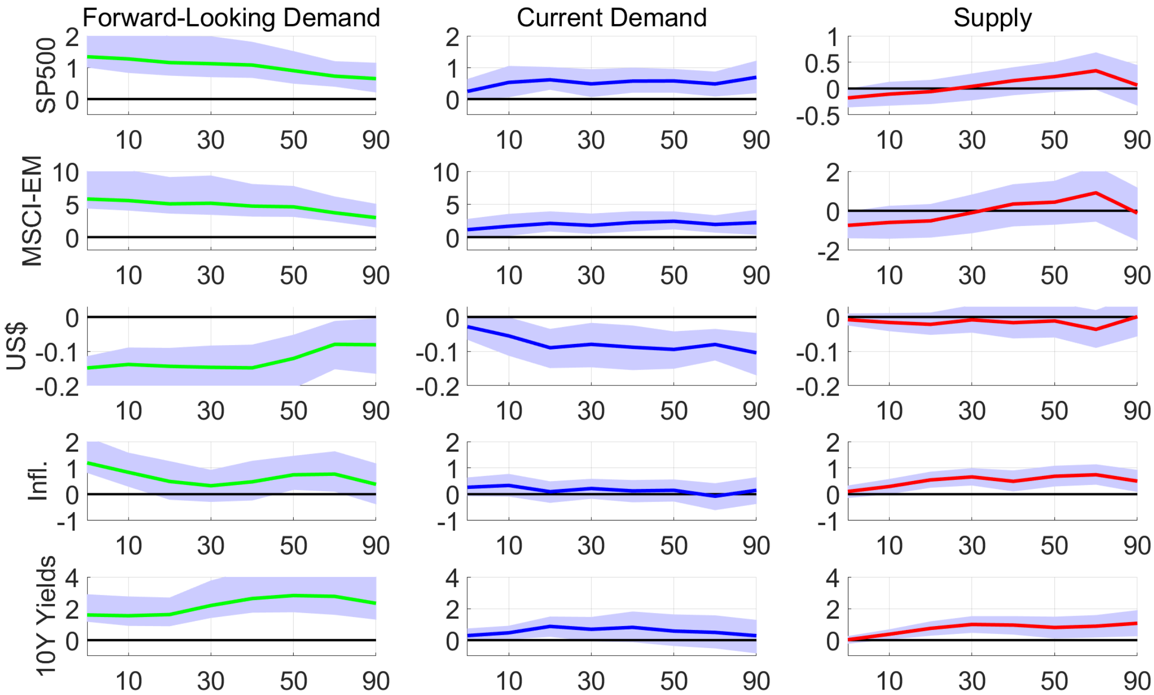


Figure 2: Impulse Response Functions of other financial variables

Note. Impulse Response Functions are estimated using local projections, see Appendix E. Error bands are 90 percent confidence intervals obtained by simulation techniques taking into account both uncertainty on the estimation of the shock as well as uncertainty on the parameters of the local projections. They are adjusted to account for autocorrelation of the residuals via a Newey-West correction. The horizontal axis measures days after the shock.

Alessandri et al. (2023) and used as an internal instrument (Wolf and Plagborg-Moller, 2021).[26] Our baseline monthly VAR includes the unemployment rate, core CPI, headline CPI, and one year ahead households inflation expectations from the Michigan Survey of Consumers.[27] The quarterly model includes real GDP, real consumption, and real private non-residential investment.[28] The results are shown in Figure 3 where the effects of the three shocks are organized in columns.

Forward-looking and current demand shocks. Expansionary forward-looking and current demand shocks lead to a gradual yet persistent increase in headline inflation and to a fall in the unemployment rate. In the case of current demand shocks, part of the inflationary effect also comes from a rise in core prices. Household inflation expectations rise significantly with some delay after the two demand shock.[29] This confirms both that expectations are an integral part of the transmission mechanism of our identified shocks as well as that short-term households expectations are very sensitive to changes in prices of products they purchase frequently, like gasoline (Weber et al., 2022). At the quarterly frequency, forward-looking and current demand shocks elicit a positive response of GDP, investment and consumption. The response of domestic demand and of overall economic activity is more front-loaded in the case of the forward-looking demand shock.

Oil supply shock. Oil supply shocks have a stagflationary effect on the U.S. economy, bar some peculiarities due to the fact that, over our sample, the U.S. has become a major oil

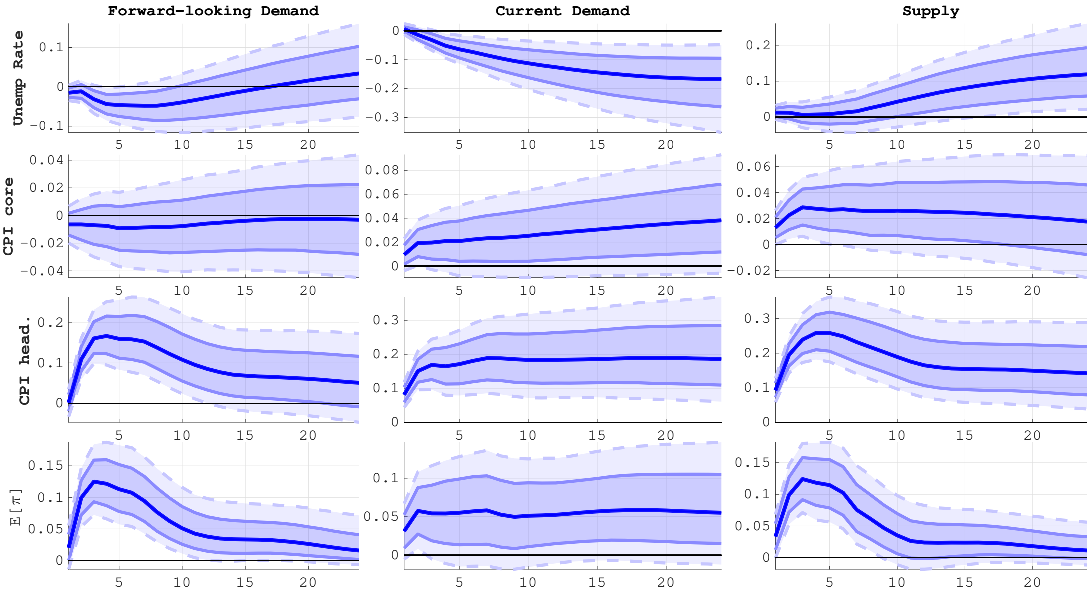
[26] A formal explanation of the procedure is provided in Appendix B.

[27] Alternative specifications of the monthly model based on industrial production, total non-farm payroll employment, consumer durables, and house prices paint a very similar picture and are available upon request. The CPIs are in log-levels, while the unemployment rate and inflation expectations are in year-on-year percentage changes. The VAR is estimated with Bayesian methods under a standard Minnesota prior with 12 lags over the sample January 2007 to December 2019. We focus on the pre-Covid period for simplicity in order to avoid the issues documented in Lenza and Primiceri (2022). The monthly and quarterly aggregates of the shocks are orthogonalized with respect to one another.

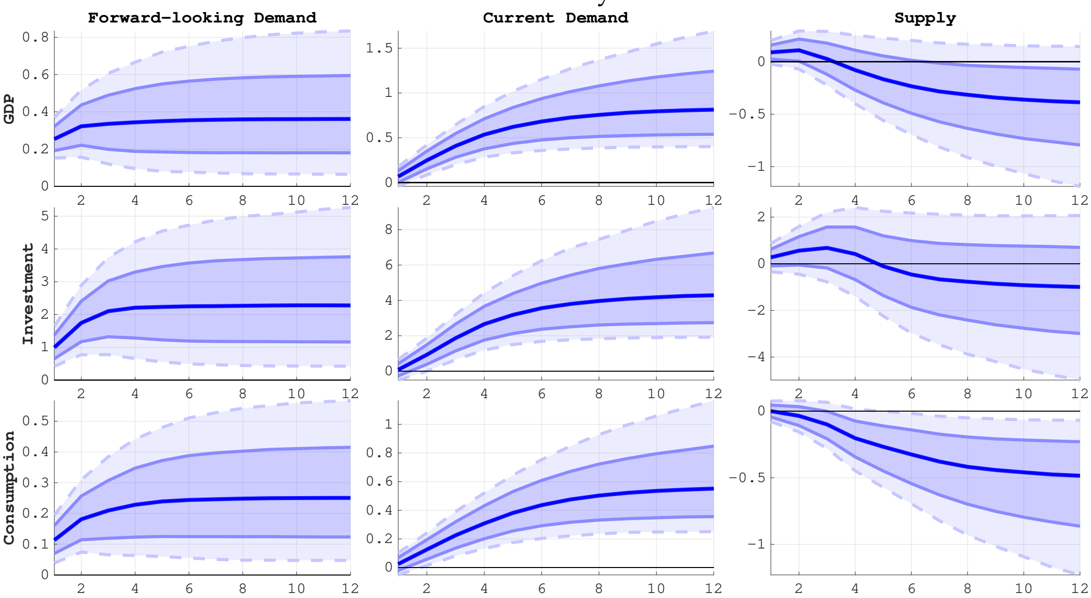
[28] The quarterly VAR is estimated with 4 lags on the sample 2007:Q1 to 2019:Q4 by Bayesian methods under a standard Minnesota prior. Variables are in log-levels.

[29] Notice that households inflation expectations are measured in year-on-year terms, while CPI and core CPI enter the model in log-levels. This explains the different shape of the impulse response functions.

Figure 3: Impulse response functions of macroeconomic variables



Panel A: Monthly model.



Panel B: Quarterly model.

Note. In both panels the solid blue line represents the median estimate. The blue and grey shaded areas correspond to 68 and 90 percent credible sets that reflect both parameter and identification uncertainty. The horizontal axis shows months (top panel), quarters (bottom panel) after the shock.

producer and the main oil exporter worldwide. First, as expected, following an oil supply shock headline inflation, core inflation and households inflation expectations rise significantly and persistently. Unemployment also rises, albeit with some delay. Second, consumption falls sharply, as consumers are strongly hit by higher prices and tighter financial conditions (lower stocks and higher rates, as shown in Figures 1 and 2). Investment, instead, does not respond significantly. As we show in Appendix D, this muted response reflects the combination of the boost from higher oil prices to investment in the energy sector, possibly with some spillovers on non-energy investment in the short-term, and the overall negative response of investment in the non-energy sectors, which becomes more pronounced in the longer term. The overall effect on economic activity is negative, as GDP contracts some quarters after the shock.

In Appendix D we describe the effects of the structural shocks on monthly world industrial production and world oil production. Also at the global level, forward-looking and demand shocks have broadly similar macroeconomic consequences, i.e. they raise persistently both industrial production and oil production, but the effects are more heterogeneous than in the US. This difference between the global economy and the US could arise from the relatively high degree of financial development in the US and from the central role played by financial markets in firms' financing in the US, implying a faster transmission from financial markets to the macroeconomy. Supply shocks, on the other hand, have a significant recessionary impact and reduce oil production.

5 How a daily narrative would have helped the FOMC

This section illustrates the advantages of our daily VAR for policymakers, compared to monthly VAR models of the oil market. To this end, we consider how FOMC decisions would have benefited from the insights provided by our daily model, compared to those from the state-of-the-art monthly VAR model proposed by Baumeister and Hamilton (2019) (BH). BH's model includes the price of oil, a measure of global industrial production, global oil production and a measure of oil inventories. The first advantage of our approach is that it offers a structural decomposition of the price of oil in real-time at the daily frequency. As the publication delays in the variables employed in monthly VARs are substantial, the timeliness of the oil price narrative that these models make available to FOMC members is limited. Since the measure of global industrial production used in the BH model is published with a three-months delay, a decomposition of the price of oil becomes available two to three months after an FOMC meeting.[30] Additionally, monthly models cannot provide intra-monthly information, which is problematic since meetings can take place in the middle of the month. Second, monthly models in which shocks are often identified with sign restrictions (like in BH) are severely affected by data revisions, as shown by Croushore and Stark (2003) and Croushore and Evans (2006). In contrast, in our model monthly variables are used only to discipline the identification of the daily model through a projection on candidate structural shocks. As long as revision errors are uncorrelated with the structural shocks (a plausible assumption), they do not impact shock identification in our daily model.[31] The comparison with BH that we display below does not take into account this issue. As we do not have access to all the vintage data to run the exercise in real-time, we have to rely on the current data vintage, where the data has already been revised. As a result, the exercise is conducted in pseudo-real time, leading to an underestimation of the advantages of our method.

Next, we explore how our model could have provided valuable insights to the FOMC. To contain the exposition, we delve into six FOMC meetings which occurred at time of major gyrations in oil prices (April 2011, December 2014, December 2018, April 2020, March 2021 and March 2022; see Table A3, in Appendix F for more details). In these meetings FOMC members explicitly discussed the oil price movements, to gauge their effect on economic activity, inflation and inflation expectations. Mentions of U.S. and global economic activity

[30] This limitation is not specific to the BH model. Even using Kilian and Murphy (2014) model would not solve this issue. At the time of writing (end of July 2023), the global index of real economic activity index (IGREA), a crucial ingredient of this model, was only available up to May 2022. See `https://fred.stlouisfed.org/series/IGREA` consulted on the 25th of July 2023.

[31] We thank an anonymous referee for pointing this out to us.

were often made in relation to oil demand, while specific events in the oil market, such as oil supply disruptions, OPEC policies, or drilling activity by U.S. oil producers, were frequently singled out as supply-side drivers. Most interestingly, on certain occasions, some participants also expressed their stance or doubts regarding the relative balance of these factors. For example, during the April 2011 meeting, after Libya's oil production came to a halt as a result of the country's unrest, Chair Bernanke stated "We know some very explicit reasons why oil prices have gone up, why demand has increased and supply has fallen".[32]

Our model provides a price decomposition up to the day before the FOMC meeting, a clear timeliness advantage of our daily model over the monthly one. Nevertheless, a legitimate question arises: whether the decomposition provided by our model is, in hindsight, reasonable and consistent with the one obtained from the BH monthly model, despite the three-month time lag (and after accounting for biases arising from data revisions). The results in Figure 6 dispel this doubt. The charts show the cumulative change in the price of crude over the indicated range, as well as the relative contribution of the structural shocks. To facilitate the comparison between the two models, we sum together the two demand shocks in the BH model (economic activity and consumer demand shocks) and disregard the inventory shock, that has virtually zero effects on oil prices, as we show in Figure A11 in Appendix I. The models convey broadly similar messages.

In Sections 5.1 and 5.2 we discuss in detail two FOMC meetings where our model could have been crucial to inform the policy discussion. The remaining FOMC meetings are discussed in Appendix F.[33]

[32] Bernanke also referred to the possible incidence of a specific "Hamilton shock'', referring to the papers by James Hamilton, see for instance Hamilton (2003), in assessing how the ongoing price increases could be damaging for the economy. Appendix F reports the text snippets regarding oil prices from the respective FOMC meetings.

[33] Appendix F reports the narrative description, the historical decompositions of oil prices before each FOMC meeting and the related FOMC communication.

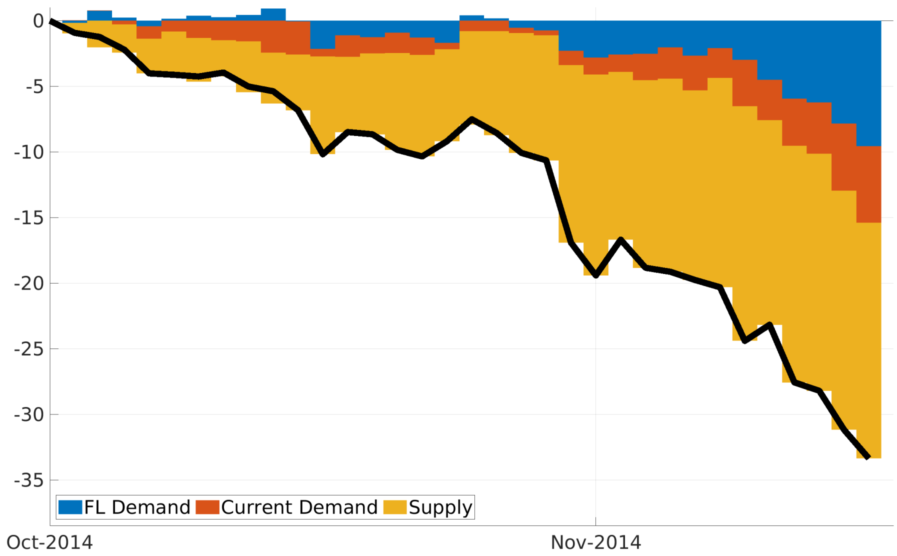
5.1 FOMC in December 2014

During 2014, as oil prices slid due to an oversupplied market, some OPEC members, such as Venezuela and Algeria, called for production cuts. However, Saudi Arabia halted the initiative, being aware that persistently low oil prices would harm significant competitors, including Iran and U.S. shale oil producers. Consequently, oil prices plunged to a four-year low. At the December 2014 press-conference, the Fed Chair Yellen declared that "The very substantial decline we have seen in oil prices is one of the most important developments shaping the global outlook". The minutes for the meeting show that Chair Yellen wrapped up the discussion as follows *"I think the judgment of the Committee is that, from the standpoint of the United States and the U.S. outlook, the decline we have seen in oil prices is likely to be, on net, a positive. [...] It's something that's certainly good for families, for households. [...] Having to spend less on gas and energy, and so, in that sense, it's like a tax cut that boosts their spending power."*

The issue is also analyzed in the FOMC Tealbook, in a dedicated box "The Global Macroeconomic Effects of the Recent Decline in Oil Prices" that reports the following analysis: *"Since late June, the price of crude oil has fallen sharply, with the spot price of Brent [...] dropping about 40 percent and the price of the December 2017 futures contract [...] declining almost 20 percent.* **Much of the decline is likely due to favorable supply factors, including the rapid growth of U.S. oil production**. **A substantial portion, however, is a reaction to a downgrade in expectations for global growth since June, which complicates the assessment of the macroeconomic effects of the lower prices."**

Our model would have allowed FOMC members to incorporate in their information set the structural decomposition of oil prices up to the previous day (Figure 4). The results of the model suggest that both demand and supply factors played an important role in driving down oil prices between October and December 2014 and that, quantitatively, in the last observations their share is equally distributed. In light of these results, Chair Yellen's conclusions appear somewhat optimistic, as the slump in oil prices was also the symptom of an incipient slowdown in global demand, shown in the contribution of our forward-looking component, with adverse consequences for the US macroeconomy.[34]

Figure 4: Cumulative oil price change before the December 2014 FOMC meeting



Note. The solid line shows the cumulative change in the price of Brent between the 29th of October and the 15th of December 2014. The areas represent the contribution of the forward-looking demand shock (blue) of the current demand shock (red) and of the supply shock (yellow).

5.2 FOMC in December 2018

In 2018, as the Federal Reserve progressed with its policy normalization, the escalating U.S.-China trade war came into the limelight, posing a threat to global growth prospects. In the last three months of the year, evidence of a slowdown in economic activity became noticeable.[35] At the same time, news from the oil market indicated that supply was larger than expected, with Saudi Arabia pledging to add 1.3 millions of barrels of oil, while robust U.S.

[34]See Appendix F for further details.

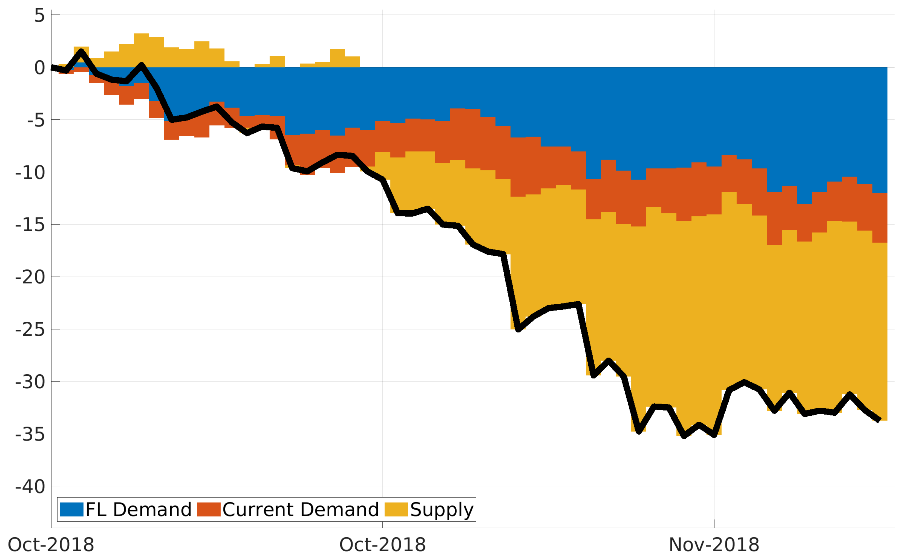
[35]China's Caixin Manufacturing PMI continued to decrease, and other demand indicators disappointed, on top of an already deteriorated market sentiment.

drilling activity boosted production. During the December 2018 meeting, FOMC members' views on the reasons for the oil price decline appear to be divided, with some attributing it to weakening global demand and others noting that the recent decline could also be associated with increasing oil supply. The minutes point to substantial heterogeneity, and even polarization, among FOMC members on the underlying drivers of oil prices and, consequently, on the future comovement between output and inflation*: "A sizable decline in oil prices was cited as an important factor contributing to the drop in measures of inflation compensation. [...] A couple of participants commented that the recent decline in oil prices could be a sign of a weakening in global demand that could weigh on capital spending by oil production companies and affect companies providing services to the oil industry. However, a couple of participants noted that the recent oil price decline could also be associated with increasing oil supply rather than softening global demand."*[36]

Our daily model highlights contributions from both forward-looking and current demand shocks, as well as a sizeable role of supply shocks in driving the price fall between October and mid-December 2018. Accordingly, our decomposition could have better informed the FOMC discussion on the underlying drivers of the oil price movements over the intermeeting period, including the singling out a sizeable contribution from the forward looking demand component. The latter was only qualitatively suggested in the FOMC *Staff Review of the Financial Situation* which illustrated how asset price movements were a sign of "Investors' perceptions of downside risks to the domestic and global outlook" having increased.

[36]See Appendix F for further details.

Figure 5: Cumulative oil price change before the December 2018 FOMC meeting



Note. The solid line shows the cumulative change in the price of Brent between the 1st of October and the 17th of December 2018. The areas represent the contribution of the forward-looking demand shock (blue) of the current demand shock (red) and of the supply shock (yellow).

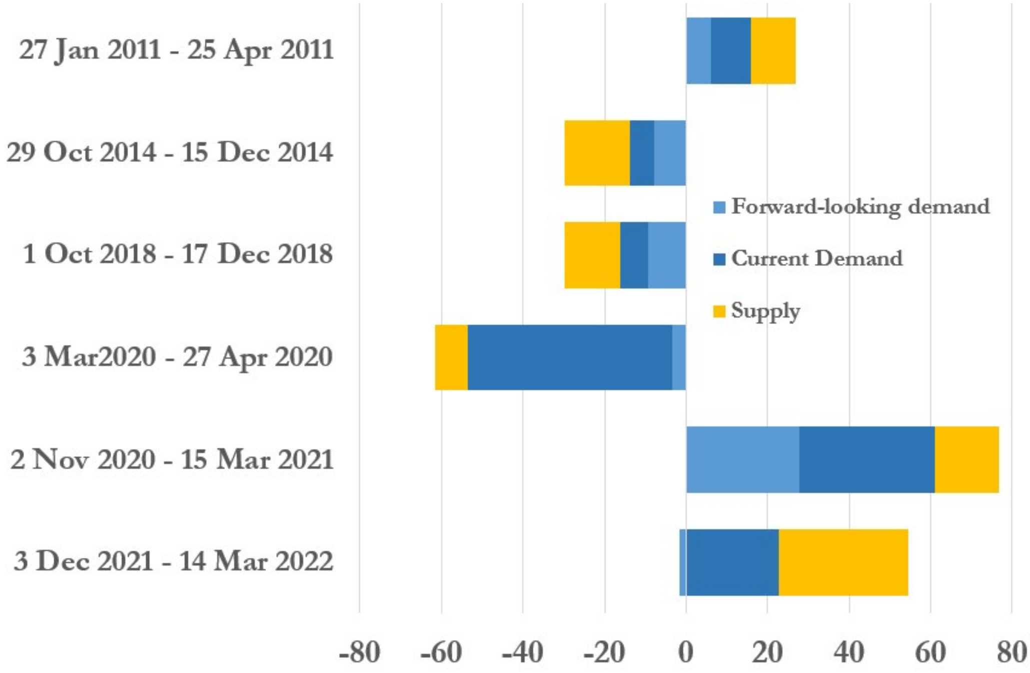
6 Shocks validation

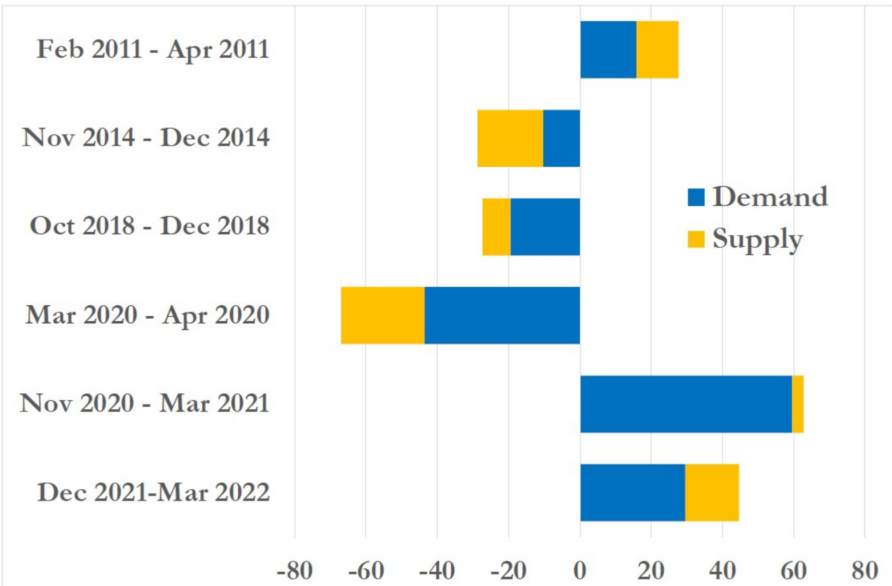
The shocks from our identification strategy have some compelling properties. Namely: i) they are highly correlated with shocks identified with state-of-the-art statistical methods; ii) their role is magnified on the day of particular macroeconomic releases, FOMC meetings or OPEC announcements.

6.1 Validation via statistical identification procedures

As a validation tool of our baseline identification, we contrast our structural shocks to those extracted from state-of-the-art statistical identification strategies, which leverage on the time-varying volatility and non-gaussianity of daily data. Given a VAR including n endogenous variables, the second-moments of the reduced-form residuals provide only $(n+1)/2$ moments due to the symmetry of the variance-covariance matrix such that the system is short of $n(n-1)/2$ identifying restrictions. Typically, timing, economic or narrative

Figure 6: Oil price decomposition in daily (top) and Baumeister and Hamilton's monthly (bottom) models





Note: Details on data and estimation of the BH model are provided in Appendix I. The original BH model contains 4 shocks, namely a supply, an economic activity, a consumer demand and an inventory shock. We show only two because (i) the inventory shock gave in the decompositions a negligible contribution, see Figure A11 in Appendix I (ii) we sum the economic activity and consumer demand shock so as to separate more neatly demand-side from supply-side shocks.

restrictions are employed to identify the system. In case of statistical identification, higher-order moments provide additional restrictions that can pinpoint the parameters of the system. Specifically, we explore two identification strategies: i) via time-varying volatility (TVV) as in Lewis (2021), a generalization of the popular identification through heteroskedasticity by Rigobon (2003); ii) via the higher-order moments (non-gaussianity) of the data, through independent component analysis (ICA); see (Gourieroux et al., 2017, 2018). Both methods identify three shocks that are highly correlated with the (median) shocks obtained from our baseline strategy. In particular, ICA (TVV) pinpoint three shocks that correlate respectively 0.94 (0.93) with our forward-looking demand shock, 0.97 (0.96) with our current demand shock, and 0.95 (0.90) with our supply shocks. Not surprisingly, given the high correlation of the shocks, the IRFs computed via ICA and TVV are strikingly similar to our baseline IRFs (see Figures A19 and A10 in the Appendix G). We report below further details on TVV while more details on the results based on ICA are in Appendix G.

6.1.1 Identification via time varying volatility

The identification via TVV proposed by Lewis (2021) is essentially a generalization of the popular identification via heteroskedasticity of Rigobon (2003), which exploits the change in the variance of the structural shocks over time for identification but requires parametric assumptions. Lewis (2021) generalizes the method and proposes to employ the lagged variance of the residuals as an instrument for the current variance of the structural shocks (the intuition is that the variance is persistent although changing over time).[37] Condition for identification via TVV is the full-rank condition of the structural variance process. We apply the test for the rank of the reduced form residuals' variance that, according to the

[37]We employ the formulation of the TVV identification the models the variance of the innovations as AR(1) stochastic volatility process (Lewis, 2021, shows that it works better than the GMM estimator in finite samples).

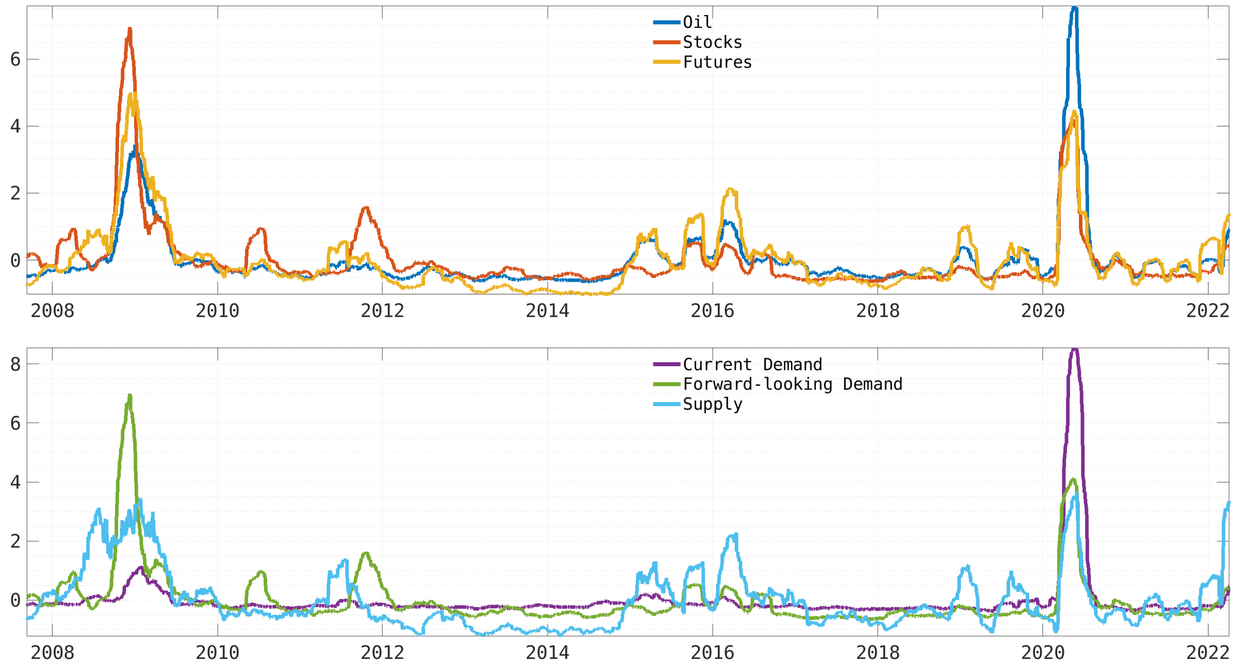


Figure 7: Time varying volatility

Note. The plot reports the standardized 3 month moving average of the volatility of the VAR reduced form residuals (upper panel) and structural shocks (lower panel).

Cragg-Donald statistic (Table A4), corroborates the identifiability of the VAR via TVV.

Figure 7 display the 3-months moving averages of the variance of the VAR reduced-form residuals and of the structural shocks. Notably, the variance of the forward-looking demand shocks spikes during the global financial crisis as the fall in demand was anticipated due to the financial nature of the shock. Conversely, during the outburst of the Covid pandemic the volatility of all the shocks surged, but demand was the most affected structural disturbance as the limitations to mobility and international travels immediately affected oil demand. Finally, supply shocks' volatility spike during 2008 due to uncertainty on future supply, during Covid due to disagreement within the OPEC+, and with the Russian invasion of Ukraine. Overall, the data provides variations in volatility that are sound from an economic perspective and consistent with our baseline identification scheme.

6.2 Narrative validation

To further corroborate our identification strategy we conduct two additional exercises. First, we look at the volatility of the structural shocks during major macroeconomic data-release days. Second, we build an economic narrative for the most sizable structural shocks at the daily frequency based on news databases. Both exercises lend support to our interpretation of the shocks that we identify in the econometric model.

6.2.1 Volatility during data-release days

Our structural shocks are correlated with innovations to financial investors' information set. Therefore, an additional test of the plausibility of our identification strategy consists of checking whether in days when OPEC decisions, major scheduled macroeconomic releases and FOMC decisions surprise investors, the volatility of our shocks is boosted compared to the rest of the sample.

On the days of OPEC meetings, the volatility of crude oil prices is markedly higher than in the rest of the sample, by almost one third for both spot and futures, while that of stock prices is not amplified (see Table 3, first row of Panel A). On these days, all our shocks display a large and significant increase in volatility (Table 3, first row of the Panel B), indicating that OPEC meetings convey news not only on mere production decisions, but also on OPEC deviations from the "endogenous response" to global demand conditions.

Next, we consider U.S. non-farm payroll (NFP) announcements, undoubtedly the most closely followed U.S. scheduled macroeconomic release. We construct NFP surprises (actual minus expected) using market participants' expectations surveyed from Bloomberg. In general neither the VAR variables, nor the structural shocks, move significantly in days when NFP are released, resonating with the results of Kilian and Vega (2011). However, oil

Table 3: **Volatility ratios on selected event days**

Panel A

		VAR variables		
event	N(days)	oil price	stocks	oil futures
OPEC	49	1.26***	1.04	1.31***
NFP	169	0.96	0.99	0.96
NFP surpr. $> 1\sigma$	63	1.26***	1.17**	1.10
FOMC	136	1.09**	1.42***	1.08*
China PMI	169	1.14***	1.03	1.10**

Panel B

		VAR shocks		
event	N(days)	forw. looking demand	current demand	supply
OPEC	49	1.20**	1.28***	1.27***
NFP	169	1.00	1.22	0.99
NFP surpr. $> 1\sigma$	63	1.22***	1.52***	0.98
FOMC	136	1.33***	1.22***	0.99
China PMI	169	1.08*	1.33***	1.08*

The table reports volatility ratios of the variable indicated in the column header, i.e. the ratio of between the variable standard deviation on specific event days and the one in all remaining days. Panel A reports the results for the log change in the VAR variables and Panel B for the structural shocks. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.
Notes: events correspond to days with OPEC meetings; FOMC announcements days; Non Farm Payroll release dates (NFP); NFP release dates with particularly large surprises (respectively larger than 1 standard deviation over the sample). China PMI refer to the first business days immediately following the release day of China's Caixin Purchasing Managers Index.

and stock prices react significantly in days in which NFP surprises are abnormally large. Moreover, in all NFP announcement days volatility is dominated by current demand and forward-looking demand shocks. Oil supply shocks are unrelated to NFP announcements.

Coming to FOMC dates, we find that stocks respond very strongly, whereas oil prices more weakly.[38] Supply shocks play no role at all on FOMC dates consistently with our prior, while the volatility of forward-looking and current demand shocks is relatively large, a sign that the information and the risk-premium channel of monetary policy are at play in these days, see also Cieslak and Pang (2021) and Kroencke et al. (2021).

Finally, we consider the effect of news on the Chinese economy on the volatility of VAR variables and shocks. Given the global nature of oil markets it is not surprising to find that China's macroeconomic releases have an impact on oil prices. Considering the Caixin Manufacturing PMI's, China's most timely macroeconomic release, we find that current demand shocks' volatility is significantly boosted on days of its release, whereas risk and supply volatilities are largely unaffected.[39] This further confirms that the labeling of our shocks conforms to reasonable economic narratives.

6.2.2 Narrative for the largest structural shocks

In this additional exercise, upon those days when our model identifies the largest structural shocks, we scan which where the most relevant news hitting the market. Nearly all those days are associated with some relevant piece of news, that aligns well with our economic interpretation of the identified shocks.[40] Table A6 in Appendix H reports a detailed description

[38]The response of oil price to FOMC announcement has been shown in Rosa (2014).

[39]The Caixin Manufacturing PMI is released on the last day of each month providing timely information on economic activity in the same month. If the last day falls on a weekend we consider the first business day following the release.

[40]The most sizable shocks are staggered in some specific periods, consistently with the results from the time-varying volatility identification in Section 6.1 (Figure 7): forward-looking demand shocks are most volatile during the global financial crisis, current demand shocks during the Covid, and supply shocks spike during 2008 due to geopolitical tensions, during Covid due to disagreement within the OPEC+, and during the Russian

of the largest shocks and associated news.

7 Robustness checks

The results presented in the paper hold through a series of robustness checks. Specifically, very similar results are obtained when (i) replacing the global stock market factor with a standard MSCI World index (ii) adding variables (long-term yields and the OVX) to the system (iii) estimating the model with daily data up to the end of 2019 (i.e. excluding the Covid crisis). We also explored the sensitivity of our results with respect to the statistical criteria used to select the dates in which we define our external instrument (which were described in Section 2.1). A full set of results obtained with each of these robustness checks is available upon request.

8 Conclusion

The oil price provides timely information on global shocks, of key relevance for monetary policy decisions. Identifying these shocks is crucial to understand the relationship between oil prices, inflation and output, and it is the object of a large body of research in the VAR literature. Workhorse monthly models of the oil market are, however, of limited use for monetary policy in real-time, as they rely on data that are released with considerable delay.

In this paper we propose a novel approach to identify shocks to the price of oil at the daily frequency and in real-time through a combination of narrative and sign restrictions. We focus on forward-looking demand shocks related to changes in global demand prospects and uncertainty, on shocks to the current demand for oil, capturing surprises to the state

invasion of Ukraine.

of the global business cycle, and on supply shocks, that represent an exogenous shift in the availability of oil. These shocks have intuitive and significant effects on the U.S. macroeconomy and on global financial markets.

State-of-the-art statistical identification procedures confirm that our identification strategy separates the most relevant orthogonal sources of variation of the price of oil. Moreover, the volatility of our shocks is significantly higher in days in which the narrative emerging from macroeconomic news and data releases coincides with that offered by our model.

The paper practically illustrates how the model, unlike existing monthly VARs, could have informed the FOMC decisions in a timely fashion, precisely at times of substantial uncertainty on the drivers of oil prices such as in December 2014 and December 2018 and during periods of abrupt turmoil, like during the COVID-19 pandemic or the invasion of Ukraine by Russia.

The paper also makes a broader methodological contribution. Our strategy to circumvent publication lags, by identifying shocks on daily data and using their lower frequency average as instruments in lower frequency models to validate them based on their macroeconomic impact, is in fact generally applicable to other settings.

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