The macroeconomic effects of oil supply news: Evidence from OPEC announcements*

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Abstract

This paper proposes a novel approach to study the macroeconomic effects of oil prices, exploiting institutional features of OPEC and high-frequency data. Using variation in futures prices around OPEC announcements as an instrument, I identify an oil supply news shock. These shocks have statistically and economically significant effects. Negative news leads to an immediate increase in oil prices, a gradual fall in oil production and an increase in inventories. This has consequences for the U.S. economy: activity falls, prices and inflation expectations rise, and the dollar depreciates – providing evidence for a strong channel operating through supply expectations.

JEL classification: C32, E31, E32, Q43

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1. Introduction

Recent turbulences in the oil market have sparked renewed interest in the long-standing question of how oil prices affect the macroeconomy. Answering this question is nontrivial because oil prices are endogenous and respond to global macroeconomic conditions – complicating the estimation of a causal effect. In the literature, many different approaches have been put forward to deal with this problem, ranging from non-linear transformations of the oil price to more structural approaches such as constructing narrative oil shock series or the identification of different shocks driving the oil price using structural vector autoregression (SVAR) models.[1]

In this paper, I propose a novel identification strategy exploiting institutional features of the Organization of the Petroleum Exporting Countries (OPEC) and information contained in high-frequency data. The idea is to utilize variation in oil futures prices around OPEC production announcements. OPEC accounts for about 44 percent of world oil production and thus, its announcements can have a significant impact on oil prices (Lin and Tamvakis, 2010; Loutia, Mellios, and Andriosopoulos, 2016). While OPEC is known to be heavily driven by political considerations, its decisions are likely not exogenous but also depend on the state of the global economy (Barsky and Kilian, 2004). However, by measuring the changes in oil futures prices in a tight window around the announcements, one can isolate the impact of news about future oil supply. Reverse causality of the global economic outlook can be plausibly ruled out because it is already priced in at the time of the announcement and is unlikely to change within the tight window. Using the resulting series as an external instrument in an oil market VAR model, I am able to identify a novel oil shock – a shock that is best thought of as a news shock about future oil supply.

Preview of results. I find that oil supply news shocks have statistically and economically significant effects. Negative news about future oil supply leads to a large, immediate increase in oil prices, a gradual but significant fall in world oil production and a significant increase in world oil inventories. Global economic activity, measured by world industrial production, does not change significantly on impact but then starts to fall persistently. This has consequences for the U.S. economy: industrial production falls and consumer prices rise significantly. I also show that the shock has significant effects on oil price expectations while uncertainty indicators are hardly affected – consistent with the interpretation of a news shock. This evidence supports the notion that changes in expectations about future oil supply may have powerful effects even if current oil production does not move (Kilian, 2008b).

[1] For two good complementary surveys on this literature see Hamilton (2008) and Kilian (2008a).

Looking at the wider effects of oil supply news shocks, I find that they lead to a significant rise in consumer prices even after excluding energy prices, a persistent fall in consumption and investment expenditures, rising unemployment, and falling stock market indices. Interestingly, they also cause a significant rise in inflation expectations, particularly for households, consistent with recent evidence by Coibion and Gorodnichenko (2015). Finally, they lead to a significant depreciation of the U.S. dollar, especially against the currencies of net oil exporting countries. This helps to reconcile the strong negative correlation between oil prices and the dollar. Consistent with the exchange rate response, the shock also leads to a substantial deterioration of the terms of trade and a significant trade deficit.

Oil supply news shocks also turn out to be an important driver of the economy as they explain a significant share of the variations in economic activity and prices. A comprehensive series of sensitivity checks indicate that the results are robust along a number of dimensions including the construction of the instrument, the specification of the model and the sample period. In particular, the results are robust to controlling for OPEC's global demand forecasts in the construction of the instrument, suggesting that there is no strong information channel confounding high-frequency measures of oil supply news.

Related literature and contribution. This paper is related to a long literature studying the macroeconomic effects of oil prices. A key insight in this literature is that oil price shocks do not occur ceteris paribus. Therefore, it is important to account for the fundamental drivers of oil price fluctuations (Kilian, 2009). These include oil supply, global demand and expectations about future oil market conditions. In the last years, the literature has made substantial progress in disentangling these drivers using SVAR models of the oil market, identified with the help of zero restrictions (Kilian, 2009), sign restrictions (Kilian and Murphy, 2012, 2014; Lippi and Nobili, 2012; Baumeister and Peersman, 2013; Baumeister and Hamilton, 2019), and narrative information (Antolín-Díaz and Rubio-Ramírez 2018; Caldara, Cavallo, and Iacoviello 2019; Zhou 2019).

A difficult problem in this context is the identification of the expectations-driven component. This is because in the presence of such a component, the VAR may no longer be fundamental. A number of studies have addressed this issue by augmenting the standard oil market VAR by global oil inventory data (Kilian and Murphy, 2014; Juvenal and Petrella, 2015). The idea is that expectational shifts in the oil market should be reflected in the demand for oil inventories (see also Hamilton, 2009; Alquist and Kilian, 2010). An important challenge is that these shifts in inventory demand capture many different things, including news about future demand and supply or higher uncertainty, that existing identification strategies cannot disentangle.

This paper contributes to this literature by proposing a new source of information and a novel identification strategy that can shed light on the role of oil supply expectations. Using high-frequency variation in oil prices around OPEC announcements, I identify a news shock about future oil supply. While I do not model the oil futures market explicitly, I show that oil futures prices contain valuable information for identification. High-frequency oil supply surprises turn out to be strong instruments for the price of oil. This is relevant against the backdrop that other proxies for oil shocks, e.g. Hamilton's (2003) quantitative dummies or Kilian's (2008b) production shortfall series, have been found to be weak instruments (Stock and Watson 2012; Montiel-Olea, Stock, and Watson 2016).

From a methodological viewpoint, my approach is closely related to the high-frequency identification of monetary policy shocks. In this literature, monetary policy surprises are identified using high-frequency asset price movements around monetary policy events, such as FOMC announcements (Kuttner, 2001; Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018, among others). The idea is to isolate the impact of news about monetary policy by measuring the change in asset prices in a sufficiently tight window around monetary policy announcements. Gertler and Karadi (2015) use these surprises as an external instrument in a monetary SVAR to identify a monetary policy shock. In this way, they are able to trace out the macroeconomic effects of these shocks. The key idea of this paper is to apply this approach to the oil market, exploiting institutional features of OPEC.

This paper is not the first to look at OPEC announcements. In fact, there is a large literature analyzing the effects of OPEC announcements on oil prices using event study techniques (Draper, 1984; Loderer, 1985; Demirer and Kutan, 2010, among others). To the best of my knowledge, however, this paper is the first to look at the macroeconomic effects of these announcements – combining the event study literature on OPEC meetings with the traditional oil market VAR analysis.[2]

My results indicate that even if current oil production does not move, news about future supply can have a meaningful impact on the price of oil and macroeconomic aggregates. In this sense, I also contribute to the literature on the role of news in the business cycle by providing evidence for a strong expectational channel in the oil market. Traditionally, this literature focuses on anticipated technology (Beaudry and Portier, 2006; Barsky and Sims, 2011) and fiscal shocks (Ramey, 2011; Leeper, Walker, and Yang, 2013). Only recently, there has been a growing interest in other

[2]There are a few papers that also exploited the financial market reaction to oil events for identification but in somewhat different contexts (Cavallo and Wu, 2012; Anzuini, Pagano, and Pisani, 2015; Branger, Flacke, and Gräber, 2018).

kinds of news, such as news about future monetary policy or production possibilities (see e.g. Gertler and Karadi, 2015; Arezki, Ramey, and Sheng, 2017). Gambetti and Moretti (2017) also identify a news shock in the oil market but use a different methodology. Furthermore, their focus is on the role of news versus noise shocks.

Outline of the paper. The remainder of this paper is structured as follows. In the next section, I discuss the identification design, providing background information on OPEC, details on the construction of the instrument and some instrument diagnostics. In section 3, I cover the proxy VAR approach, the relation to other identification strategies and the empirical specification. Section 4 presents the results. I start by analyzing the strength of the instrument before discussing the results of the baseline model, the role of news versus uncertainty, the wider effects as well as the quantitative importance of oil supply news shocks. In section 5, I perform a number of robustness checks. Section 6 concludes.

2. Identification

The identification strategy in this paper is motivated by the following two observations. First, the oil market is dominated by a big player, OPEC, that makes regular announcements about its production plans. Second, there exist very liquid futures markets for oil. OPEC is closely watched by markets and its announcements can lead to significant market reactions. This motivates the use of high-frequency identification techniques. The idea is to construct a series of high-frequency surprises around OPEC announcements that can be used to identify a structural oil supply news shock. Before discussing the construction of the surprise series, I provide some background information on OPEC and the global oil and oil futures markets.

2.1. Institutional background

The global oil market and OPEC. The global market for oil has a peculiar structure in that it is dominated by a few big players. The biggest and most important player is OPEC. OPEC is an intergovernmental organization of oil producing nations and accounts for around 44 percent of the world's crude oil production. It was founded in 1960 by five countries, namely Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. Since then, other countries have joined the organization and currently, OPEC has a total of 14 member countries.[3] According to the statutes, OPEC's

[3]The current member countries are Algeria, Angola, Congo, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, UAE, and Venezuela. For more information on the history of OPEC, see Yergin (2011).

mission is to stabilize global oil markets to secure an efficient, economic and regular supply of petroleum to consumers, a steady income to producers and a fair return on capital for those investing in the petroleum industry. Economists, however, often think of OPEC as a cartel that cooperates to reduce market competition.

The supreme authority of the organization is the OPEC conference, which consists of delegations headed by the oil ministers of the member countries. Several times a year, the OPEC conference meets in order to agree on oil production policies. Since 1982, this includes setting an overall oil production ceiling for the organization and individual production quotas for its members.[4] The conference ordinarily meets twice a year on pre-scheduled dates at its headquarters in Vienna but if necessary it can also call for extraordinary meetings with short notice. In making decisions, the conference generally operates on the principles of unanimity and 'one member, one vote'. However, since Saudi Arabia is by far the largest oil producer in OPEC, with enough capacity to function as a swing producer to balance the global market, it is often thought to be 'OPEC's de facto leader'.

The decisions of the conference are usually announced in a press communiqué shortly after the meeting concludes, followed by a press conference where members of the press can ask questions. A typical announcement starts with a review of the oil market outlook before communicating the decisions on production quotas, which normally become effective 30 days later. As an example, I include below an excerpt of an announcement made on December 14, 2006 after the 143rd meeting of the OPEC conference:

> *Having reviewed the oil market outlook, including the overall demand/ supply expectations for the year 2007, in particular the first and second quarters, as well as the outlook for the oil market in the medium term, the Conference observed that market fundamentals clearly indicate that there is more than ample crude supply, high stock levels and increasing spare capacity. [...]*
>
> *In view of the above, the Conference decided to reduce OPEC production by a further 500,000 b/d, with effect from 1 February 2007, in order to balance supply and demand.*

Despite the fact that OPEC sometimes has trouble agreeing and enforcing its production quotas, markets pay close attention to it and its announcements trigger significant price reactions (see e.g. Lin and Tamvakis, 2010; Loutia, Mellios, and

[4] The OPEC production quota system was established in 1982. Before, OPEC targeted oil prices instead of production quantities (OPEC Secretariat, 2003).

Andriosopoulos, 2016). In the above example, the announcement led to an oil price increase of about 2 percent.

Oil futures markets. Crude oil is an internationally traded commodity and there exist very liquid futures markets for crude oil. The two most widely traded contracts are the West Texas Intermediate (WTI) crude and Brent crude futures. WTI and Brent are grades of crude oil that are used as benchmarks in pricing oil internationally. I focus on WTI crude futures for the following reasons. First, WTI is the relevant benchmark for pricing oil in the U.S., the country of primary interest in this paper. Second, the quotes have the longest available history as these were the first traded futures on crude oil. WTI crude futures are traded at the New York Mercantile Exchange (NYMEX) and were introduced back in 1983, which constrains the start of the oil supply surprise series. Finally, the WTI crude futures market is the most liquid and largest market for crude oil, currently trading nearly 1.2 million contracts a day (CME Group, 2018).

2.2. Construction of oil supply surprises

To construct a time series of oil supply surprises, I look at how oil futures prices change around OPEC announcements. While OPEC is known to be driven a lot by political considerations, it also takes global economic conditions into account, as could be seen from the example announcement above. Thus, its decisions might be subject to endogeneity concerns. However, by measuring the price changes within a sufficiently tight window around the announcement, it is possible to isolate the impact of OPEC's decisions. Reverse causality of the global economic development can be plausibly ruled out because the global economic conditions are known and already priced in by the market and are unlikely to change within the tight window. Assuming that risk premia are constant over the window of interest, the resulting series will capture changes in oil price expectations caused by OPEC announcements.

To be able to interpret this as news about future oil supply, it is crucial that the announcements do not contain any new information about other factors such as oil demand, global economic activity or geopolitical developments. Even though it is hard to assess whether this is the case or not, looking at how OPEC announcements are received in the financial press is suggestive as the focus is usually on whether OPEC could agree on new production quotas or not. It should also be noted that these problems are not specific to the oil market. It is now well known that monetary policy also transmits through an information channel that likely conflates high-frequency measures of monetary policy shocks (Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2018b; Jarocinski and Karadi, 2018). I will argue that the information channel is if at all less of a problem in the oil market because the informational advantage is less obvious than in the case of a central bank. Furthermore, OPEC as an organization is much more political and does not respond as systematically to economic developments. However, to address this concern more rigorously, I will also construct an informationally robust surprise series by regressing the original series on revisions in OPEC's global demand forecasts, akin to the refinement of Romer and Romer (2004) in the monetary policy setting, and show that the results are robust (see section 5).

To construct the benchmark series, I collected OPEC press releases for the period 1983-2017. There were a total of 119 announcements made during this period. In a next step, I collected daily data on WTI crude oil futures prices. An overview of all announcement dates as well as the data sources can be found in appendix B. Based on this data, I construct a series of oil supply surprises by taking the (log) difference of the settlement price on the day of the OPEC announcement and the price on the last trading day before the announcement:

$$Surprise^h_{t,d} = F^h_{t,d} - F^h_{t,d-1}, \tag{1}$$

where d and t indicate the day and the month of the announcement, respectively, and $F^h_{t,d}$ is the (log) settlement price of the h-months ahead oil futures contract in month t on day d.[5]

Standard asset pricing implies that

$$F^h_{t,d} = \mathbb{E}_{t,d}[P_{t+h}] + RP^h_{t,d}, \tag{2}$$

where $\mathbb{E}_{t,d}[P_{t+h}]$ is the expected oil price conditional on the information on day d and $RP^h_{t,d}$ is a risk premium. Assuming that the risk premium does not change within the daily window around the announcement, i.e. $RP^h_{t,d} = RP^h_{t,d-1}$, one can interpret the surprise as a revision in oil price expectations

$$Surprise^h_{t,d} = \mathbb{E}_{t,d}[P_{t+h}] - \mathbb{E}_{t,d-1}[P_{t+h}] \tag{3}$$

caused by the respective OPEC announcement.

[5]In the monetary policy literature, sometimes an even tighter window is used to construct the surprises, e.g. a 30-minutes window around FOMC announcements. I decided to use a daily window because of the following reasons. First, OPEC is not as secretive as a central bank and often information about its decisions gets leaked before the official announcement. Second, OPEC does not communicate as clearly as a central bank and markets usually need longer to process what an announcement means. Third, the schedule of OPEC meetings is not as regular as for monetary policy events and thus daily surprises are less likely to be systematically biased by other news. Furthermore, some announcements were made on weekends or holidays when markets are closed.

These daily surprises, $Surprise^h_{t,d}$, are then aggregated to a monthly series, $Surprise^h_t$, as follows. When there was only one announcement in a given month, the monthly surprise is equal to the daily one. When there were multiple announcements, the monthly surprise is computed by summing the daily surprises in the given month. When there was no announcement, the monthly surprise is zero.

An important issue in this context is the choice of the maturity of the futures contract, h. Taking into account the horizon of OPEC announcements as well as implementation lags, maturities ranging from one month to one year seem to be the most natural choices. These contracts are also available for a longer time period as contracts with maturities of one year or more were only traded in the more recent past. Furthermore, they are more liquid and less subject to risk premia. Recent evidence suggests that up to a horizon of 6 months, risk premia are not big enough to contaminate price expectations (Baumeister and Kilian, 2017). This horizon also conforms well with the interpretation of a news shock about *future* oil supply and thus I use this contract as a benchmark, i.e. $z_t = Surprise^6_t$. However, oil futures prices are highly correlated across different maturities and the results using different contracts are very similar, see appendix C.2.

2.3. Diagnostics of the surprise series

The monthly series of oil supply surprises is shown in figure 1. To get a better understanding of the series, I discuss three specific historical episodes.

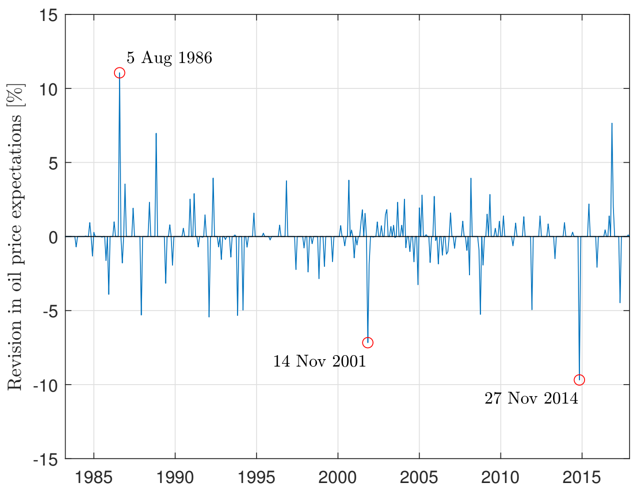


Figure 1: The oil supply surprise series constructed from changes in oil futures prices around OPEC announcements (based on the 6-month WTI crude futures contract).

On August 5, 1986, OPEC could finally agree on new production quotas after years of disagreement and lack of compliance. Just before, the oil price plummeted as Saudi Arabia flooded the markets with oil to make other OPEC members comply.

As one can see, the announcement came as a surprise and led to a big upward revision of oil price expectations. On November 14, 2001, amid a global economic slowdown that has been exacerbated by the September 11 terror attacks, OPEC pledged to cut production but only if other oil producers cut their production as well. Markets interpreted this announcement as a signal of a potential price war, which led to a significant downward revision of price expectations. Another major revision occurred on November 27, 2014 when OPEC announced that it was leaving oil production levels unchanged. Before, many market observers had expected OPEC to agree on a cut to oil production in a bid to boost prices. However, Saudi Arabia blocked calls from some of the poorer OPEC members for lower quotas, which led to a downward revision of oil price expectations by about 10 percent.

Even though it is impossible to directly test the exogeneity of the oil supply surprise series, one can perform a number of validity checks. In particular, a good shock series should not be autocorrelated nor forecastable by past macroeconomic variables. Furthermore, it should also not be correlated with other structural shocks (Ramey, 2016).

Looking at the autocorrelation function of the series, I find that there is no evidence for serial correlation. To check whether macroeconomic variables have any power in forecasting the series I run a series of Granger causality tests. I find no evidence that macroeconomic or financial variables have any forecasting power as all selected variables do not Granger cause the series at conventional significance levels. To analyze whether the surprise series is conflated by other structural shocks, I look at the correlation with a wide range of different shock measures from the literature. The results indicate that the oil supply surprise series is not mistakenly picking up global demand, productivity, monetary policy, uncertainty, financial, or fiscal policy shocks driving the oil price. The corresponding figures and tables can be found in appendix C. Overall, this evidence supports the validity of the oil supply surprise series.

3. Econometric framework

Following Gertler and Karadi (2015), I combine the high-frequency identification approach with the traditional SVAR analysis. The idea is to use the surprise series as an external instrument in an otherwise standard oil market VAR to identify a structural oil supply news shock, building on a methodology developed by Stock and Watson (2012) and Mertens and Ravn (2013). An external instrument is a variable that is correlated with the shock of interest but not with the other shocks, capturing some exogenous variation in the shock of interest (Stock and Watson, 2018). Identification is achieved by complementing the VAR residual covariance restrictions with the moment conditions for the external instrument.

3.1. Proxy VAR

Consider the following VAR(p) model

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{4}$$

where $p > 0$ is referred to as the order of the VAR, $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form shocks with covariance matrix $\text{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{b}$ is a $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices. Equation (4) is referred to as the reduced form of the VAR model. The parameters of the reduced form can be consistently estimated by OLS.

By postulating a linear mapping between reduced-form and structural shocks, $\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t$, one can write the structural form of the VAR model as

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1\mathbf{y}_{t-1} + \cdots + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{S}\boldsymbol{\varepsilon}_t, \tag{5}$$

where $\mathbf{S}$ is referred to as the $n \times n$ structural impact matrix and $\boldsymbol{\varepsilon}_t$ is a $n \times 1$ vector of structural shocks.[6] By definition, the structural shocks are mutually uncorrelated, i.e. $\text{Var}(\boldsymbol{\varepsilon}_t) = \mathbf{\Omega}$, is diagonal. From the linear mapping of the shocks it then follows that

$$\mathbf{\Sigma} = \mathbf{S}\mathbf{\Omega}\mathbf{S}'. \tag{6}$$

Identification is achieved as follows. Without loss of generality, one can order the variable that is instrumented as the first variable in the VAR. In the present case, this will be the price of oil, P_t. The aim is then to identify the structural impact vector $\mathbf{s}_1$, which corresponds to the first column of $\mathbf{S}$. Suppose there is an external instrument available, z_t. In the application at hand, z_t is the oil supply surprise series. For z_t to be a valid instrument, it has to be the case that

$$\mathbb{E}[z_t\varepsilon_{1,t}] = \alpha \neq 0 \tag{7}$$

$$\mathbb{E}[z_t\boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{8}$$

where $\varepsilon_{1,t}$ is the structural shock associated with the first variable in the VAR and

[6] Note that this amounts to assume fundamentalness, which implies that all the structural shocks can be accurately recovered from current and lagged values of the observed data included in the model (see e.g. Lippi and Reichlin, 1994). However, if one is only interested in a subset of shocks, identification can be achieved under much weaker conditions. In particular, for partial identification with external instruments it is only required that the VAR is partially invertible in combination with a limited lag exogeneity condition on the instrument (Miranda-Agrippino and Ricco, 2018a).

$\boldsymbol{\varepsilon}_{2:n,t}$ is a $(n-1)\times 1$ vector consisting of the other structural shocks. Assumption (7) is the relevance requirement and assumption (8) is the exogeneity condition for the instrument at hand. Under assumptions (7)-(8), $\mathbf{s}_1$ is identified up to sign and scale:

$$\tilde{\mathbf{s}}_{2:n,1} \equiv \mathbf{s}_{2:n,1}/\mathrm{s}_{1,1} = \mathbb{E}[z_t \mathbf{u}_{2:n,t}]/\,\mathbb{E}[z_t \mathrm{u}_{1,t}], \tag{9}$$

provided that $E[z_t \mathrm{u}_{1,t}] \neq 0$. Note that $\tilde{\mathbf{s}}_{2:n,1}$ can be thought of as the population analogue of the IV estimator of $\mathbf{u}_{2:n,t}$ on $\mathrm{u}_{1,t}$ using z_t as an instrument. The scale of $\mathbf{s}_1$ is then set by a normalization subject to $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$. One approach is to impose that $\boldsymbol{\Omega} = \mathbf{I}_n$. This implies that a unit positive value of $\varepsilon_{1,t}$ has a one standard deviation positive effect on $\mathrm{y}_{1,t}$. Alternatively, one can set $\boldsymbol{\Omega} = \mathrm{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$ and $\mathrm{s}_{1,1} = 1$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a unit positive effect on $\mathrm{y}_{1,t}$. I will use the former normalization such that the size of the shock is one standard deviation. The structural impact vector is then given by $\mathbf{s}_1' = (\mathrm{s}_{1,1},\ \ \tilde{\mathbf{s}}_{2,1}'\mathrm{s}_{1,1})$. After having obtained the impact vector, it is straightforward to compute all objects of interest such as IRFs, FEVDs as well as the structural shock series. For a detailed derivation of the structural impact vector, see appendix A.

The above illustration of the identification strategy holds in population. In practice, identification is achieved as follows. Assume that there is a sample of size $n \times T$ available. In a first step, estimate the reduced form (4) to get estimates of the reduced-form shocks $\hat{\mathbf{u}}_t$. In a second step, estimate (9) by regressing $\hat{\mathbf{u}}_{2:n,t}$ on $\hat{\mathrm{u}}_{1,t}$ using z_t as an instrument. Finally, using the estimated residual covariance matrix from step 1 and the IV estimates from step 2, impose the desired normalization to obtain an estimate of the structural impact vector $\hat{\mathbf{s}}_1$.

I rely on the proxy VAR approach because it is robust to many forms of measurement error in the instrument (Mertens and Ravn, 2013) and can easily accommodate instruments that are only available for a shorter sample than the other variables in the system (Gertler and Karadi, 2015). However, the results are robust to including the proxy directly in the VAR (see section 5).

3.2. Comparison to alternative strategies

Traditionally, *oil supply shocks* are thought of as sudden disruptions in the current physical availability of oil, causing a contemporaneous fall in oil supply, an increase in the price of oil and a depletion of oil inventories. A long literature has identified such shocks using different techniques, including the construction of narrative supply shock series (Hamilton, 1985, 2003; Kilian, 2008b; Caldara, Cavallo, and Iacoviello,

2019) and SVAR models of the oil market (Kilian, 2009; Kilian and Murphy, 2012, 2014; Baumeister and Hamilton, 2019).

The identification strategy in this paper is quite different from the existing literature as it exploits variation in the price of oil that is driven by *news* about future oil supply. This motivates the interpretation of an *oil supply news shock*. It is well known that news shocks can have effects that are very different from unanticipated shocks (Beaudry and Portier, 2014). This suggests that oil supply news shocks are potentially very different from the previously identified oil supply shocks. In particular, one would expect that a negative oil supply news shock has a positive effect on the oil price while oil production does not respond significantly on impact but only decreases with a lag. Most importantly, the shock should lead to an increase in oil inventories. This is the key distinguishing feature between oil supply news and surprise shocks. If a shortfall in production happens today, market players will immediately draw down inventories to make up for the shortage in supply. In contrast, if market players expect a shortfall in the future, they will build up inventories today to make sure that they have oil when the shortfall occurs.

The positive inventory response conforms well with a literature that aims at identifying shocks to the *inventory demand* for oil (Kilian and Murphy, 2014; Juvenal and Petrella, 2015). The key idea behind these studies is that otherwise unobservable shifts in expectations about future oil market conditions must be reflected in the demand for oil inventories. A positive inventory demand shock will shift the demand for oil inventories, causing the level of inventories and the oil price to increase in equilibrium. It is precisely the positive inventory response that allows one to disentangle inventory demand from other oil demand and supply shocks in sign-identified oil market VARs. In contrast, my approach exploits high-frequency data from oil futures markets, which is another margin market players can use to react to news about future oil market conditions. An advantage of using futures prices is that they are directly observed while oil inventories are difficult to measure.

It is also worth noting that an unexpected rise in *uncertainty about future supply* can have very similar effects. This has been formally demonstrated in a general equilibrium model by Alquist and Kilian (2010). The main difference is that such uncertainty shocks would not be associated with expected changes in future oil production. Looking at the response of oil production can thus help to distinguish news from uncertainty shocks. To further sharpen the interpretation of the shock, I will also look at the responses of different expectational variables and measures of uncertainty.

3.3. Empirical specification

The baseline specification includes six variables: The real price of oil, world oil production, world oil inventories, world industrial production, U.S. industrial production and the U.S. consumer price index (CPI). The first four variables are standard in oil market VAR models.[7] I augment these core variables by the two U.S. variables to analyze the effects on the U.S. economy. The data are all monthly and span the period 1974M1 to 2017M12. A detailed overview on the data and its sources can be found in appendix B.2. Following Gertler and Karadi (2015), I use a shorter sample for identification, namely 1983M4 to 2017M12. This is because the futures data that is used to construct the instrument is only available for this period. The motivation for using a longer sample for estimation is to get more precise estimates of the reduced-form coefficients.

The VAR is estimated in log levels. To be able to interpret the IRFs in percentages, the logged variables are multiplied by 100. The lag order is set to 13 and in terms of deterministics only a constant term is included. However, the results turn out the be robust with respect to all of these choices, see appendix C.2.

4. Results

4.1. First stage

As discussed above, the main identifying assumptions behind the proxy VAR approach are that the instrument is correlated with the structural shock of interest and uncorrelated with all other structural shocks. However, even if these assumptions hold, problems arise when the instrument is only weakly correlated with the structural shock of interest. In this case, the proxy VAR estimator is inconsistent and standard inference will not deliver reliable results. In a first step, it is thus important to test the strength of the instrument. This can be done using an F-test in the first-stage regression of the oil price residual from the VAR on the instrument, as proposed by Montiel-Olea, Stock, and Watson (2016). To be confident that a weak instrument problem is not present, they recommend a threshold value of 10 for the corresponding F-statistic.

[7]As the oil price indicator, I use the spot price of WTI crude, deflated by U.S. CPI, to ensure maximum instrument strength. However, the results are robust to using Brent or the refiner acquisition cost. For world industrial production, I use Baumeister and Hamilton's (2019) industrial production index for Organization for Economic Co-operation and Development (OECD) countries and six other major economies. The results are robust if I use Kilian's (2009) global activity indicator instead. For world oil inventories, I construct a measure based on OECD petroleum inventories, as proposed by Kilian and Murphy (2014). To get rid of the seasonal variation, I perform a seasonal adjustment using the Census X13 method.

Table 1: Tests on the strength of the instrument

	Front	1M	2M	3M	6M	9M	12M
Coefficient	0.923	0.950	0.998	1.035	1.093	1.128	1.134
F-stat	26.81	25.05	25.49	25.61	24.24	24.06	15.55
F-stat (robust)	13.21	11.87	12.06	12.14	11.57	11.64	8.68
R^2	4.97	4.66	4.73	4.76	4.51	4.48	2.94
R^2 (adjusted)	4.78	4.47	4.55	4.57	4.33	4.29	2.75
Observations	515	515	515	515	515	515	515

Notes: The table shows the results of the first-stage regressions of the residual $\hat{u}_{1,t}$ from the baseline VAR on the proxies constructed from the front, 1-month, 2-month, 3-month, 6-month, 9-month, and 12-month ahead futures contracts. F-statistics above 10 indicate strong instruments. Robust F-statistics allow for heteroskedasticity.

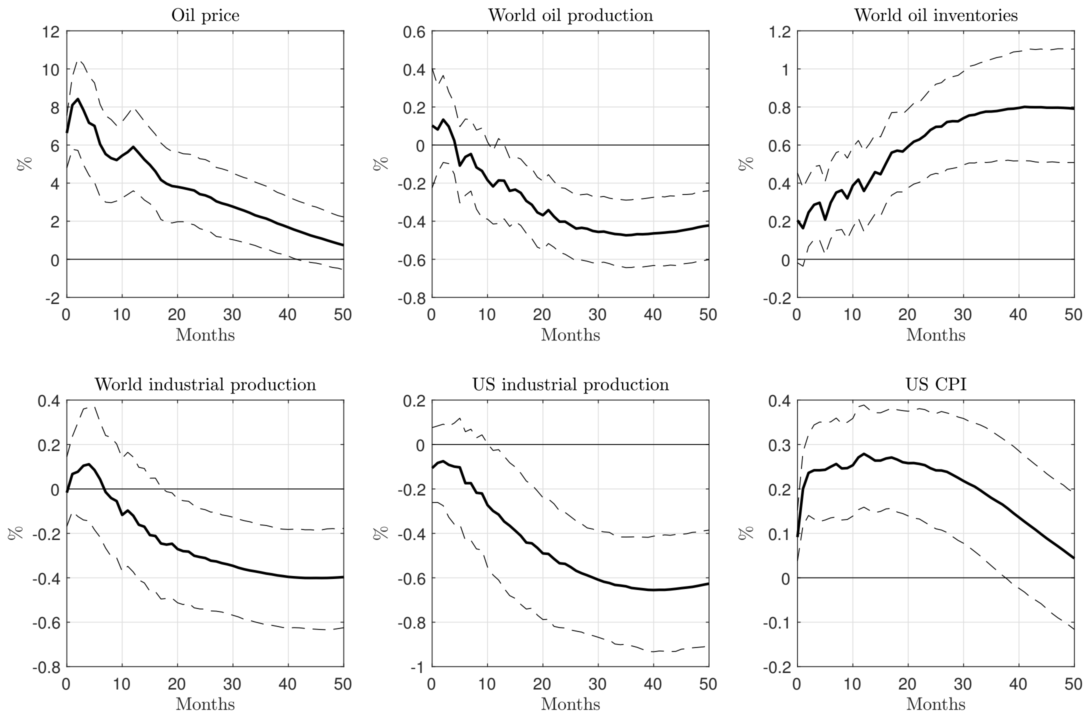
Table 1 presents the results on this test for a selection of instruments based on futures contracts with different maturities. In addition to the standard F-statistic, I also report a robust F-statistic which allows for heteroskedasticity. The instruments turn out to be very strong as all F-statistics are safely above the threshold of 10. Furthermore, the instruments seem to contain valuable information as they explain 4-5 percent of the oil price residual. However, the strength of the instruments tends to decrease with the maturity of the futures contract. For my baseline, the instrument based on the 6-month ahead futures, the F-statistic is 24.2 and the instrument explains 4.5 percent of the oil price residual.[8] Overall, this evidence suggests that there is no weak instrument problem at hand.

4.2. Baseline model

In the following, I present the results from the baseline VAR. Figure 2 shows the IRFs to the identified oil supply news shock. The size of the shock is one standard deviation and because all variables are in logs (multiplied by 100), the IRFs can be interpreted in percentages. The thick black lines represent the point estimates and the dashed lines are pointwise 90% confidence bands based on 1000 bootstrap replications.[9]

[8]I also the perform the test for a weak proxy proposed by Lunsford (2016). The corresponding F-statistic is 4.8 and thus large enough to reject the null of a weak proxy for an asymptotic bias of 20% and a significance level of 10%.

[9]To compute the confidence bands, I use a moving block bootstrap, as proposed by Jentsch and Lunsford (2019). This method produces asymptotically valid confidence bands under fairly mild α-mixing conditions. The block size is set to 24 and to deal with the difference in the estimation and identification samples, I censor the missing values in the proxy to zero as in Mertens and Ravn (2019).



First stage regression: F: 24.24, robust F: 11.57, R^2: 4.51%, Adjusted R^2: 4.33%

Figure 2: Impulse response functions to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

The shock leads to a significant, immediate increase in the price of oil. World oil production does not change significantly on impact but then starts to fall sluggishly and persistently. World oil inventories increase significantly and persistently. The large positive response of the oil price together with the gradual decrease of oil production and the strong positive inventory response are consistent with the interpretation of a news shock about future oil supply. World industrial production does not change much over the first year after the shock but then starts to fall significantly and persistently. This is in line with the notion that oil exporting countries might benefit in the short run from higher oil prices before the adverse general equilibrium effects kick in.

Turning to the U.S. economy, one can see that the shock leads to a fall in industrial production that is deeper and seems to materialize more quickly compared to the world benchmark. This is in line with the fact that the U.S. has historically been one of the biggest net oil importers and thus particularly vulnerable to higher oil prices. Finally, U.S. consumer prices increase significantly on impact and continue to rise for about one year before converging back to normal. The response is highly statistically significant and features a considerable degree of persistence.

These findings suggest that oil supply news shocks have effects that are quite different from the previously identified oil supply shocks (see e.g. Kilian 2009; Kilian and Murphy 2012; Caldara, Cavallo, and Iacoviello 2019; Baumeister and Hamilton

2019). In particular, oil supply news shocks lead to a significant and persistent increase in inventories and a sluggish but significant fall in oil production. This stands in stark contrast to the negative response of inventories and the strong, immediate fall in oil production that is observed after unanticipated oil supply shocks. It is important to note that this result emerges naturally as my identification strategy does not restrict the signs of the impulse responses in any way.

Interestingly, oil supply news shocks have effects that are, at least qualitatively, similar to inventory demand shocks (Kilian and Murphy, 2014; Juvenal and Petrella, 2015). This does not come entirely as a surprise. Inventory demand shocks capture, among other things, news about future oil supply and demand. Other sources include uncertainty about future oil supply, changes in oil traders' perception of what other traders think or changes in beliefs unrelated to fundamentals (Kilian and Murphy, 2014). With my approach, however, I am able to isolate the component of inventory demand that is driven by news about future supply. Furthermore, my approach yields responses that are point-identified whereas inventory demand shocks are usually only set-identified. This is also reflected in the relatively narrow confidence bands, allowing for sharper predictions.

4.3. News versus uncertainty

As discussed above, changes in uncertainty can in principle have very similar effects to news about future supply. Even though the sluggish but significant response of oil production is suggestive that the shock is mainly capturing news, it might still propagate through changes in uncertainty as well. To further sharpen the interpretation of the shock, I study the responses of different expectational variables and measures of uncertainty. In particular, I look at oil price expectations, inflation expectations, financial uncertainty and geopolitical risk.[10]

To compute the responses, I augment the baseline VAR by one variable at a time. This approach, which was put forward by Beaudry and Portier (2014) and Gertler and Karadi (2015), is particularly flexible as it allows one to characterize the dynamic effects of structural shocks on a wide range of variables without resorting to shrinkage techniques or a panel or factor structure to address the curse of dimensionality.[11]

[10] For oil price expectations, I use the measure of Baumeister and Kilian (2017), extended using oil futures data for the early part of the sample. For inflation expectations, I use the median expected price change over the next 12 months from the University of Michigan Surveys of Consumers. As an indicator of financial uncertainty, I use the extended VXO index from Bloom (2009). To proxy for geopolitical risk, I use the geopolitical risk index from Caldara and Iacoviello (2018).

[11] If possible, the augmented VARs are estimated on the same sample as the baseline VAR. If the additional series does not span the original sample, I adjust the sample accordingly. Information on the sources of the data as well as the coverage can be found in appendix B.2.

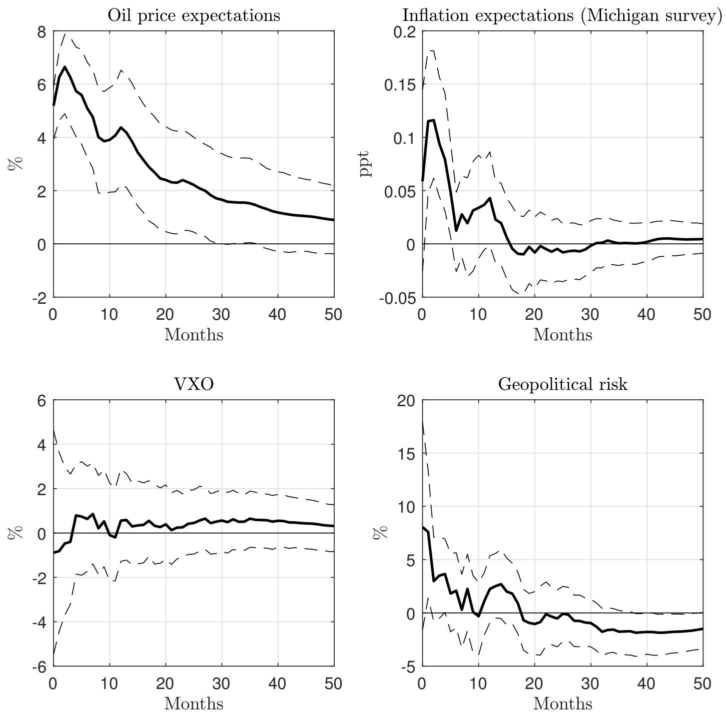


Figure 3: Impulse response functions of different expectations and uncertainty indicators to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

Figure 3 presents the results. One can see that the shock leads to a significant increase in oil price and inflation expectations. The significant effects on inflation expectations are in line with recent empirical evidence by Wong (2015). Interestingly, the shock appears to have no significant effects on uncertainty. Financial uncertainty, as measured by the VXO index, does not seem to respond at all. However, the VXO is probably not the best measure of uncertainty in the oil market. A better proxy for uncertainty about oil supply is geopolitical risk. As one can see, the shock leads to a slight, temporary increase in geopolitical risks. However, the response is barely significant. Overall, these findings strengthen the interpretation that the identified shock is a news shock operating through changes in expectations about future supply as opposed to changes in uncertainty.

4.4. Wider effects

Having further established the interpretation of an oil supply news shock, I now analyze the wider consequences of these shocks. As above, I do so by augmenting the baseline VAR by one variable at a time.[12] This will help to get a better understanding of how the shock transmits to the macroeconomy.

[12]Some of the variables of interest are only available at the quarterly frequency. To map out the responses of these variables, I aggregate the VAR to the quarterly frequency, as discussed in section 5, and augment the quarterly VAR by the variable of interest.

Prices and inflation expectations. A key implication of the baseline model is that oil supply news shocks lead to a significant and persistent increase in consumer prices. However, the rise in consumer prices, as measured by headline CPI, might primarily be driven by higher energy prices. To analyze this, I augment the baseline VAR by the core and energy components of the CPI, respectively. To get an even better picture, I also include the durables, non-durables, and services components.

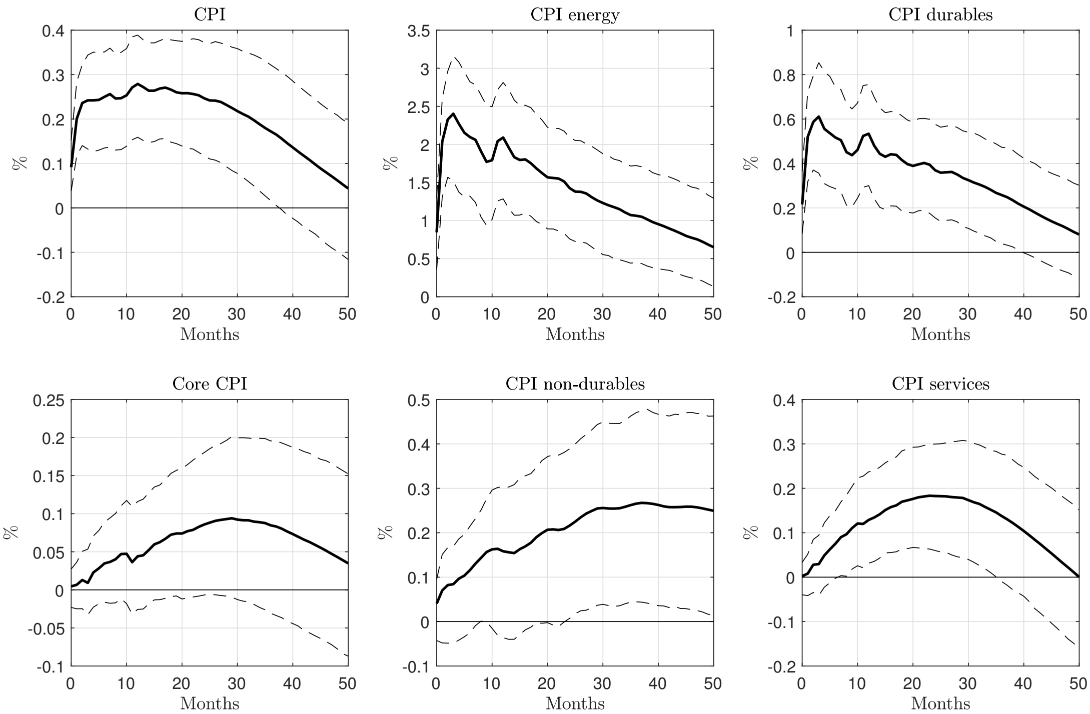


Figure 4: Impulse response functions of different consumer price indices to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

Figure 4 shows the IRFs of the augmented models together with the CPI response from the baseline model. The results are quite intuitive. Core consumer prices do not react significantly on impact but then tend to rise persistently. However, the response is not estimated very precisely as is reflected in the relatively wide confidence bands. In contrast, the response of the energy component is more front-loaded and mirrors the oil price response. Thus, in the short run, the response of headline CPI seems to be mainly driven by energy prices whereas a lot of its persistence comes from the underlying rise in core consumer prices. Turning to the different components, one can see that the prices of durables rise quickly and significantly and the response turns out to be quite similar to energy prices. One explanation for this could be that some durables, e.g. cars, are energy intensive to produce and their prices are heavily affected by changes in energy prices. The response of non-durables is less pronounced on impact but turns out to be more persistent. Similarly, the prices of services do not change significantly on impact but after a couple of months, they rise significantly as well. Quantitatively, energy prices rise the most, followed by the prices of durables, non-durables and services.

As shown in the previous subsection, the shock does not only affect consumer prices but also leads to a significant increase in inflation expectations, measured by the University of Michigan Survey of Consumers. Inflation expectations are, however, generally hard to measure. An alternative to the Michigan survey is the Survey of Professional Forecasters (SPF), which captures inflation expectations of professional forecasters as opposed to households. An interesting exercise is then to analyze potential differences between the two measures of inflation expectations. Unfortunately, the SPF data is only available at the quarterly frequency. To allow for better comparison, I also aggregate the monthly expectations from the Michigan survey and compute the responses based on the expectations-augmented quarterly VAR models.

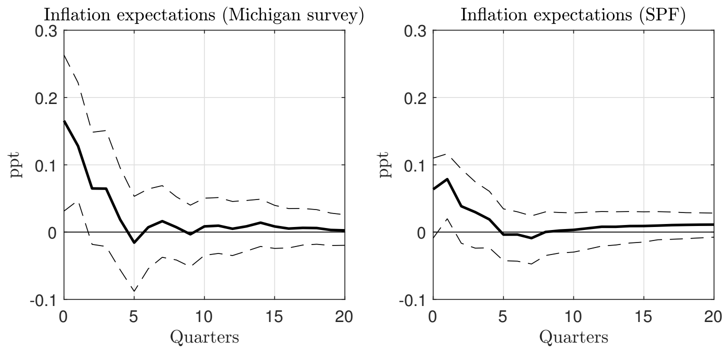
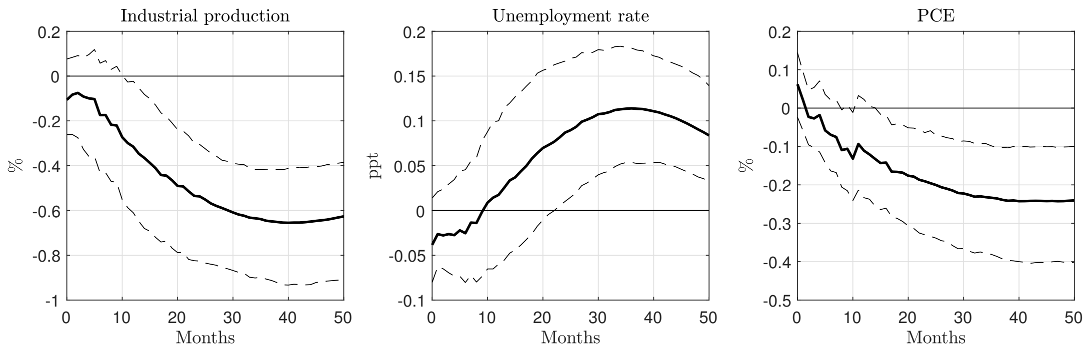


Figure 5: Impulse response functions of inflation expectations to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

As can be seen from figure 5, the effects differ greatly among the two measures. In line with the monthly evidence, household inflation expectations increase significantly. In contrast, the response of inflation expectation of professional forecasters turns out to be much weaker. This is consistent with the findings of Coibion and Gorodnichenko (2015) who show that a large part of the historical differences in inflation forecasts between households and professionals can be attributed to the level of oil prices. It is also in line with a recent literature ascribing an important role to oil prices in explaining inflation dynamics via their effects on inflation expectations (Coibion, Gorodnichenko, and Kamdar, 2018; Hasenzagl et al., 2018).

Economic activity. Another important result is that the shock leads to significant fall in industrial production. However, industrial production is but one measure of economic activity. To get a broader picture of how the shock affects the economy, I study the responses of a number of monthly and quarterly activity indicators, including the unemployment rate, personal consumption expenditures (PCE), as well as real GDP, investment and consumption. Figure 6 shows the responses together with the response of industrial production from the baseline model.

Panel A: Monthly indicators



Panel B: Quarterly indicators

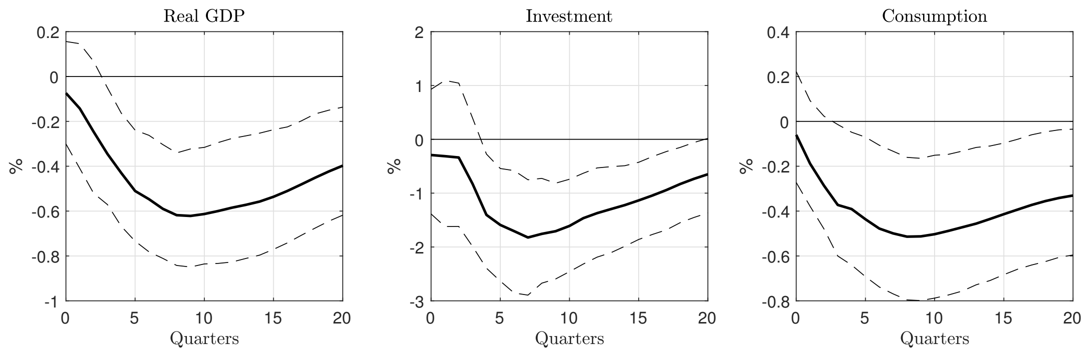


Figure 6: Impulse response functions of different economic activity indicators to a one standard deviation oil supply news shock. Panel A shows monthly and Panel B quarterly indicators. The dashed lines are pointwise 90% confidence bands.

Oil supply news shocks turn out to have significant effects on economic activity, broadly defined. Looking at the monthly indicators, one can see that the shock leads to a significant rise in the unemployment rate and a persistent fall in personal consumption expenditures. These significant adverse economic effects are confirmed by looking at the quarterly measures. Real GDP, investment and consumption all fall significantly. These results are consistent with the notion that a primary transmission channel of oil price shocks is via a reduction in consumption and investment demand, i.e. through a disruption in consumers' and firms' spending on goods and services other than energy (Hamilton, 2008; Edelstein and Kilian, 2009).

Indeed, by looking at the responses of different categories of consumption expenditures one can see that consumers significantly cut expenditures on goods and services other than energy as well, likely because of the decrease in discretionary income caused by higher energy prices. Figure 7 shows the responses of energy, non-

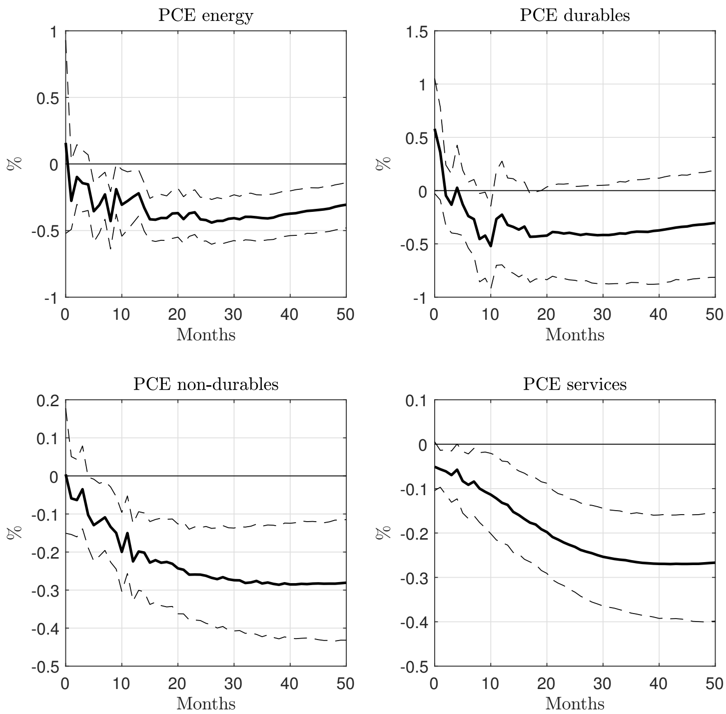


Figure 7: Impulse response functions of different categories of consumption expenditures to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

durables, durables, and services expenditures. Expenditures on energy and durable goods respond the most, especially in the short to medium run. However, expenditures on non-durables and services also fall significantly and the responses turn out to be even a bit more persistent.

Financial variables. As shown above, the shock has significant effects on prices and economic activity. But does it also transmit through financial variables? Being able to analyze this question is another important advantage of the high-frequency approach proposed in this paper. Traditional oil market VARs identified using short-run zero restrictions are not well suited for this because the timing restrictions become problematic in the context of financial variables. The problem is simultaneity: shifts in oil prices do not only affect financial variables, they may be also responding to them. The high-frequency identification approach addresses the simultaneity problem by exploiting variation at a sufficiently high frequency (Gertler and Karadi, 2015).

In figure 8, I present the IRFs for a selection of financial variables and variables relevant for monetary policy. In response to an oil supply news shock, the federal funds rate increases, even though only with some lag, before converging back to normal. The large part of the response, however, is insignificant – consistent with the

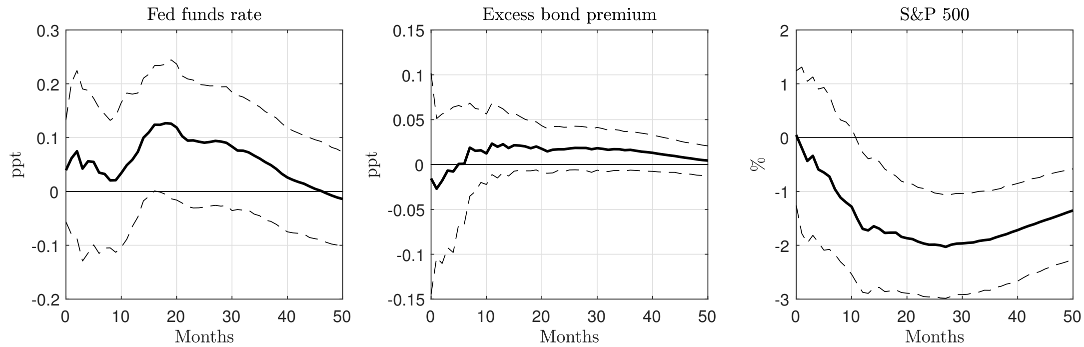


Figure 8: Impulse response functions of a selection of financial variables to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

notion that monetary policy regularly looks through inflationary pressures stemming from oil price fluctuations. Credit supply conditions, as measured by the excess bond premium of Gilchrist and Zakrajšek (2012), do not change significantly on impact but then tend to deteriorate. However, the response is rather imprecisely estimated. Stock prices, measured by the S&P 500 index, do also not change significantly on impact but then start to fall persistently. The muted impact response might reflect the fact that certain industries, e.g. utilities, benefit in the short run from higher energy prices.

Exchange rates and trade. Another key variable is the exchange rate. Because the U.S. dollar is the world's reserve currency, most of the crude oil is priced and traded in dollars. Thus, it is only natural to suspect a tight link between oil prices and the dollar. Figure 9 displays the IRFs for the narrow and broad U.S. nominal effective exchange rate as well as a number of bilateral exchange rates.[13]

Oil supply news shocks lead to a significant depreciation of the dollar. While the depreciation of the narrow effective exchange rate appears to be temporary and tends to reverse after about one and a half years, the broad effective exchange rate depreciates persistently. These differences are likely driven by heterogeneities between the currencies of net oil importing and exporting countries as the broad index includes some of the major oil producing nations. This is confirmed by looking at the responses of a selection of bilateral U.S. dollar exchange rates, grouped into currencies of net oil importing and exporting countries. Indeed, the currencies of major oil importers, such as the euro area or Japan, appreciate against the dollar

[13] All exchange rates are defined such that an increase (decrease) in the index corresponds to an appreciation (depreciation) of the U.S. dollar. The narrow index includes Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. The broad index also includes Mexico, China, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Thailand, Philippines, Indonesia, India, Israel, Saudi Arabia, Russia, Argentina, Venezuela, Chile and Colombia.

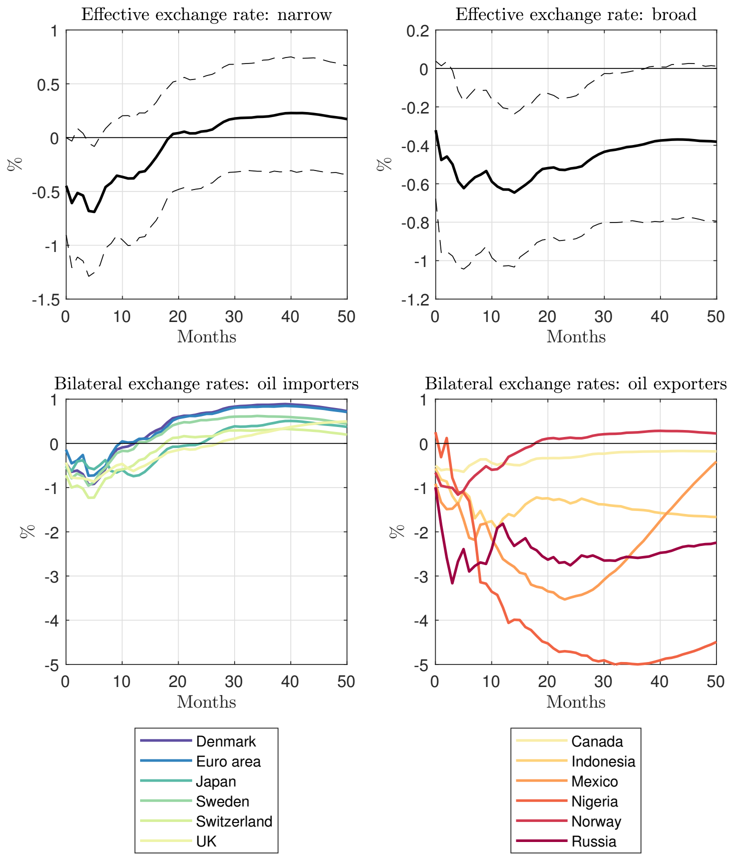


Figure 9: Impulse response functions of nominal effective and bilateral exchange rates to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

in the short run but then tend to depreciate in the longer run. In contrast, the currencies of major oil exporters, such as Russia, Mexico or Indonesia, appreciate persistently. This is in line with previous findings by Lizardo and Mollick (2010) and complements recent evidence by Kilian and Zhou (2018).

The significant depreciation of U.S. exchange rates helps to reconcile the strong negative correlation between oil prices and the dollar (Klitgaard, Pesenti, and Wang, 2019) and further underpins the notion of a news shock as precautionary demand shocks have been found to appreciate the dollar, likely because of safe haven flows (Anzuini, Pagano, and Pisani, 2015).

Since the U.S. has historically been one of the major oil importers, one would expect that the shock also leads to a significant deterioration of the terms of trade – an effect that might even be exacerbated by the depreciation of the dollar. This is exactly what I find. As can be seen from the left panel of figure 10, the U.S. terms of trade deteriorates significantly and persistently. This supports the notion that oil shocks transmit as shocks to the terms of trade and also helps to reconcile the significant fall in consumption expenditures documented above.

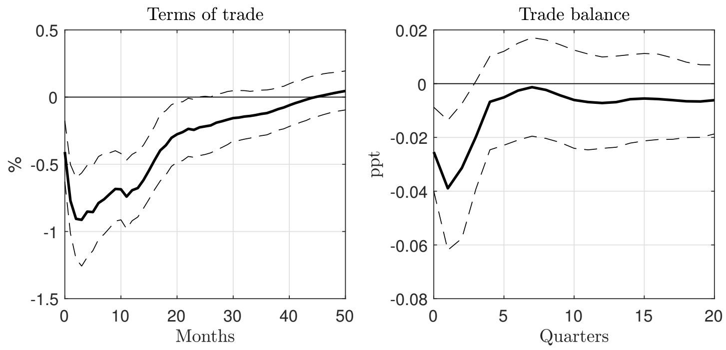


Figure 10: Impulse response functions of the U.S. terms of trade as well as the merchandise trade balance as a share of nominal GDP to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

The significant depreciation together with the impaired terms of trade have likely also an effect on the balance of trade. The right panel of figure 10 depicts the merchandise trade balance as a share of nominal GDP. As expected, the shock leads to a significant trade deficit for about a year. This is an additional channel through which oil shocks can affect demand. Quantitatively, however, the channel appears to be less important than the decrease in consumption and investment.

4.5. Quantitative importance

As shown above, oil supply news shocks have significant effects on economic activity and prices. Another interesting question is how much of the historical variation in these variables can oil supply news account for. To analyze this question, I augment the baseline VAR by a selection of key U.S. variables, i.e. the broad nominal effective exchange rate, the federal funds rate, the VXO, and the terms of trade and perform a forecast error variance decomposition.

Table 2 presents the results. One can see that oil supply news shocks account for a large part of the variance in oil prices, especially in the short run. Furthermore, they explain a non-negligible portion of the variation in world oil production at longer horizons and a significant part of the variation in world oil inventories. In contrast, the contribution to world industrial production turns out to be much smaller. One reason for this could be that the positive effects on oil exporting countries and the negative effects on oil importing countries offset each other to a certain extent.

Turning to the U.S. variables, I find that oil supply news shocks explain a meaningful portion of the variation in industrial production, CPI, terms of trade, and exchange rates. While the shocks account for a rather low share of the variation in industrial production in the short run, they explain a non-negligible share at longer horizons. They also explain a significant portion of the variance in CPI. At the one year horizon, they account for about 21 percent of the variation, which is substantial. Furthermore, they explain a significant share in the broad effective exchange rate and the terms of trade, especially at medium to longer horizons. In contrast, the contributions to the fed funds rate and the VXO turn out to be negligible.

Table 2: Forecast error variance decomposition

Global variables and exchange rates:	Oil price	Oil production	Oil inventories	World IP	NEER
0	0.73	0.00	0.04	0.05	0.11
	[0.23, 0.90]	[0.00, 0.03]	[0.00, 0.23]	[0.00, 0.26]	[0.00, 0.43]
12	0.43	0.04	0.07	0.02	0.20
	[0.12, 0.66]	[0.01, 0.11]	[0.01, 0.28]	[0.00, 0.12]	[0.02, 0.51]
24	0.39	0.09	0.14	0.02	0.25
	[0.12, 0.63]	[0.03, 0.24]	[0.02, 0.40]	[0.00, 0.12]	[0.05, 0.56]
48	0.37	0.14	0.24	0.06	0.22
	[0.12, 0.62]	[0.05, 0.30]	[0.04, 0.56]	[0.01, 0.20]	[0.05, 0.49]
U.S. variables:	IP	CPI	FFR	VXO	TOT
0	0.07	0.11	0.01	0.00	0.13
	[0.00, 0.33]	[0.00, 0.48]	[0.00, 0.05]	[0.00, 0.02]	[0.00, 0.39]
12	0.07	0.21	0.00	0.01	0.40
	[0.01, 0.27]	[0.03, 0.55]	[0.00, 0.01]	[0.00, 0.04]	[0.12, 0.64]
24	0.08	0.18	0.04	0.03	0.35
	[0.01, 0.29]	[0.03, 0.53]	[0.01, 0.12]	[0.01, 0.10]	[0.12, 0.56]
48	0.20	0.14	0.04	0.03	0.33
	[0.05, 0.42]	[0.03, 0.43]	[0.01, 0.10]	[0.01, 0.08]	[0.12, 0.54]

Notes: The table shows the forecast error variance of the key global and U.S. variables explained by oil supply news shocks at horizons 0, 12, 24, and 48 months. The pointwise 90% confidence intervals are displayed in brackets.

Taking stock. Overall, the evidence presented in this section points to a strong expectational channel in the oil market. Even if big suppliers such as OPEC cannot simply set the price as a cartel in the traditional sense, they can exert significant influence over oil prices by affecting expectations about future supply. These expectational shocks in turn have significant effects on the macroeconomy and appear to transmit through both real and financial channels. Furthermore, they contribute meaningfully to historical variations in macroeconomic and financial variables.

5. Sensitivity analysis

In this section, I perform a comprehensive series of robustness checks. In particular, I test the robustness with respect to the identification strategy as well as the model specification and data choices. Some further checks and all corresponding tables and figures can be found in appendix C.

5.1. Identification

Announcements. To be able to interpret the identified shock as a news shock about future *supply*, it is crucial that the announcements do not contain any new information about other factors and global demand in particular. Looking at the announcements and how they are received in the financial press is suggestive that there is no strong information channel confounding high-frequency measures of oil supply news shocks.

To address this concern more rigorously, I construct an informationally robust oil supply surprise series, following a strategy that has been previously applied to monetary policy shocks (Romer and Romer, 2004; Miranda-Agrippino and Ricco, 2018b). To this end, I collected global oil demand forecasts from OPEC monthly oil market reports.[14] The idea is to purge the raw oil supply surprise series from potential contamination stemming from OPEC's informational advantage on the global oil demand outlook using revisions in OPEC's global oil demand forecasts around conference meetings. More precisely, the informationally robust surprise series, IRS_t, is constructed based on the residual of the following regression:

$$Surprise_m = \alpha_0 + \sum_{j=-1}^{2} \theta_j F_m^{opec} y_{q+j} + \sum_{j=-1}^{2} \varphi_j [F_m^{opec} y_{q+j} - F_{m-1}^{opec} y_{q+j}] + IRS_m, \quad (10)$$

where m is the month of the meeting, q denotes the corresponding quarter, y_q is global oil demand growth in quarter q and $F_m^{opec} y_{q+j}$ is the OPEC forecast for quarter $q+j$ made in month m. $F_m^{opec} y_{q+j} - F_{m-1}^{opec} y_{q+j}$ is the revised forecast for y_{q+j}.[15] Note that because the monthly reports are only available from 2001, the informationally robust surprise series only spans a shorter sample.

Figure C.3 in the appendix depicts the results based on the baseline and the informationally robust instrument. The responses from the two models are very

[14] These reports are available online in pdf format (https://www.opec.org/opec_web/en/publications/338.htm) and contain among other things OPEC's global oil demand forecasts and forecast revisions. For more information, see appendix C.2.

[15] In computing the forecast revisions, the forecast horizons for meetings m and $m-1$ are adjusted so that the forecasts refer to the same quarter.

similar apart from a few minor, statistically insignificant differences. This supports the validity of the OPEC surprise series as a proxy for an oil supply news shock.

Another concern regarding the announcements is that many of the OPEC conference meetings are extraordinary meetings scheduled in response to macroeconomic or geopolitical news on relatively short notice. This might give rise to an endogeneity problem if markets do not have enough time to form expectations about the oil market outlook prior to the announcements. To address this concern, I only use the announcements from ordinary meetings scheduled well in advance to construct the instrument. The IRFs, shown in figure C.4, are very similar to the baseline responses. However, the instrument turns out to be a bit weaker as about 40 percent of the announcements had to be dropped, leaving less variation for identification.

To illustrate that my identification approach is not picking up some spurious correlation, I perform a placebo exercise. In particular, I compute a set of artificial proxies by computing the changes in futures prices on a set of "fake announcements", i.e. a sample of random trading days. For better comparison, I keep the number of trading days used constant at 119, the number of announcements used to construct the oil supply surprise series. Figure C.5 presents the results based on a set of 1000 artificial proxies. The dashed lines are the 90% bands from all responses using the placebos and the solid line is the baseline response. Reassuringly, the placebos do not have systematic effects on the oil market and the macroeconomy.

News and surprise shocks. The crucial assumption behind the proxy VAR approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. This condition might be violated when the oil supply surprise series is not only correlated with the oil supply news shock but also with the unanticipated oil supply shock. The differential effects of oil supply news and surprise shocks are suggestive that the exogeneity restriction is likely satisfied. However, to address this concern more carefully, I jointly identify an unanticipated oil supply shock and an oil supply news shock in a proxy VAR using Kilian's (2008b) production shortfall series and my OPEC surprise series as instruments.[16] Note that in the case with two shocks and two instruments, the instrument moment restrictions are not sufficient for identification. To achieve identification, one has to impose one additional restriction. Thus, I assume that the oil supply news shock does not affect oil production within the first month.[17] This can be justified with the 30 day implementation lag of OPEC announcements.

[16] I use the extended version by extended by Bastianin and Manera (2018). Alternatively, I also used Kilian's (2008b) original shock series as well as the instrument of Caldara, Cavallo, and Iacoviello (2019). The results turned out to be very similar.

[17] Details on identification with two instruments and two shocks can be found in appendix A.2.

The results from the two shock proxy VAR are shown in figure C.6. One can see that the response to the news shock is very similar to the baseline VAR. This suggests that it is possible to agnostically identify the oil supply news shock without violating the exogeneity condition. The responses for the unanticipated oil supply shock look quite reasonable as well: it leads to a temporary increase in the oil price, a significant, immediate fall in oil production and a persistent decrease in inventories. However, the first stage turns out to be considerably weaker and thus the results should be interpreted with a grain of salt.

Fundamentalness. To identify the shock of interest, it is crucial that the VAR spans all relevant information. In the context of news shocks, Ramey (2016) argues that it can be problematic to use high-frequency surprises as instruments without including them directly in the VAR. As a robustness check, I thus include the oil supply surprise series as the first variable in a recursive VAR, as proposed by Ramey (2011) and Plagborg-Møller and Wolf (2019). The results turn out to be qualitatively in line with the proxy VAR, however, some responses are a bit weaker and less precisely estimated (see figure C.7). A complementary test is to check how the results are affected by the inclusion of additional variables. Figure C.8 presents the responses of the baseline variables form the augmented VARs in sections 4.3-4.4. The results appear to be robust to the inclusion of additional variables.

5.2. Specification and data choices

Model specification. An important issue in small-scale VARs is the selection of appropriate indicators for the variables in the VAR. A crucial choice is the global activity indicator. Measuring global activity is challenging, especially at the monthly frequency. In the baseline model, I rely on Baumeister and Hamilton's (2019) index for world industrial production. I use this index because it is easily interpretable and directly comparable to its U.S. counterpart. An alternative measure that has often been used in the literature is Kilian's (2009) index constructed from dry cargo freight rates. As can be seen from figure C.11, the results based on this alternative indicator are very similar. The main difference is that global activity tends to increase in the short run and only turns negative after about 2 years.

Another important choice is the oil price indicator. To ensure that the instrument has maximum strength, I use the WTI spot price, deflated by the U.S. CPI, as a benchmark. Another commonly used measure is the real refiner acquisition cost of imported crude oil. From figure C.12, it can be seen that the results using this alternative oil price indicator are very similar.

As a final check, I analyze the robustness of the results when I rely on the exact same specification as in Kilian and Murphy (2014) and Baumeister and Hamilton (2019), respectively.[18] The results turn out to be robust, see figures C.19-C.20.

Sample and data frequency. It is conceivable that over such a long sample period structural relationships have evolved over time. To examine this possibility I estimate the model for different subsamples. Figure C.21 presents the results based on an estimation sample that starts in 1982M3, which marks the beginning of the Great Moderation period and coincides with the start of the instrument (adjusted for the lags). Overall, the results are very similar. The main differences lie in the responses of world oil production and inventories, which turn out to be weaker. Furthermore, all responses tend to feature a bit less persistence. To analyze whether the results are affected by more recent events such as the Great Recession or the shale oil revolution, I estimate VARs that stop in 2007 and 2010, respectively. As one can see from figures C.22-C.23, the results are robust.

The baseline VAR runs on monthly data. It is interesting to see whether the results go through when the model is estimated at the quarterly frequency, aggregating the data and the instrument accordingly. This also has the advantage that one can analyze the effects on variables that are only observed at the quarterly frequency, such as real GDP. The results turn out to be consistent with the monthly VAR. However, it should be noted that the instrument is a bit weaker.

6. Conclusion

A recurring question in the academic discourse as well as in policy work concerns the effects of oil prices on the macroeconomy. Answering this question is challenging because oil prices are endogenous. To understand how oil prices affect the macroeconomy, one has to account for the fundamental sources of oil price fluctuations. An important driver of oil prices are expectations about future oil market conditions.

This paper proposes a novel identification strategy and a new source of information that can shed light on the role of oil supply expectations. Using variation in futures prices in a tight window around OPEC announcements as an instrument in a SVAR, I identify an oil supply news shock. I show that these news shocks have statistically and economically significant effects, providing evidence for a strong

[18] Kilian and Murphy (2014) use a VAR(24) in real refiner acquisition cost, world oil production growth, change in world oil inventories and global activity. Baumeister and Hamilton (2019) rely on a VAR(12) in the percent change of real refiner acquisition cost, world oil production growth, change in world oil inventories as a percent of the previous month's oil production and world industrial production growth.

channel in the oil market operating through supply expectations. Negative news leads to an immediate increase in oil prices, a gradual fall in world oil production and an increase in world oil inventories. This has consequences for the world and U.S. economy as activity falls and prices increase significantly. Interestingly, the shocks also cause a significant rise in inflation expectations and a sharp depreciation of the dollar but do not appear to have significant effects on measures of uncertainty. Getting a better understanding of the relation between oil prices, inflation expectations and actual inflation as well as the link between oil prices and exchange rates are interesting avenues for future research.

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The macroeconomic effects of oil supply news: Evidence from OPEC announcements

Appendix – For online publication

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Contents

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A. Identification using external instruments

This appendix shows how to identify the structural impact vector using external instruments for the simple case with one instrument and one shock as well as the general case with k instruments and k shocks.

A.1. Structural impact vector in the simple proxy VAR

In this section, I derive the structural impact vector for the simple proxy VAR. Recall, the moment conditions for the external instrument were given by

$$\begin{aligned}\mathbb{E}[z_t\varepsilon_{1,t}] &= \alpha \neq 0\\ \mathbb{E}[z_t\boldsymbol{\varepsilon}_{2:n,t}] &= \mathbf{0}.\end{aligned}$$

Under these assumptions, $\mathbf{s}_1$ is identified up to sign and scale. To see this, note that

$$\mathbb{E}[z_t\mathbf{u}_t] = \mathbf{S}\,\mathbb{E}[z_t\boldsymbol{\varepsilon}_t] = \begin{pmatrix}\mathbf{s}_1 & \mathbf{S}_{2:n}\end{pmatrix}\begin{pmatrix}\mathbb{E}[z_t\varepsilon_{1,t}]\\ \mathbb{E}[z_t\boldsymbol{\varepsilon}_{2:n,t}]\end{pmatrix} = \mathbf{s}_1\alpha.$$

By partitioning this equation, one can write

$$\mathbb{E}[z_t\mathbf{u}_t] = \begin{pmatrix}\mathbb{E}[z_t\mathrm{u}_{1,t}]\\ \mathbb{E}[z_t\mathbf{u}_{2:n,t}]\end{pmatrix} = \begin{pmatrix}\mathrm{s}_{1,1}\alpha\\ \mathbf{s}_{2:n,1}\alpha\end{pmatrix}$$

Combining the two equations yields

$$\tilde{\mathbf{s}}_{2:n,1} \equiv \mathbf{s}_{2:n,1}/\mathrm{s}_{1,1} = \mathbb{E}[z_t\mathbf{u}_{2:n,t}]/\,\mathbb{E}[z_t\mathrm{u}_{1,t}],$$

provided that $E[z_t\mathrm{u}_{1,t}] \neq 0$. This condition is satisfied iff $\alpha \neq 0$ and $\mathrm{s}_{1,1} \neq 0$. Thus, $\mathbf{s}_1$ is identified up to scale, provided that these conditions hold.

The scale of $\mathbf{s}_1$ is then set by a normalization subject to

$$\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'.$$

One approach is to impose that $\boldsymbol{\Omega} = \mathbf{I}_n$. This implies that a unit positive value of $\varepsilon_{1,t}$ has a one standard deviation positive effect on $\mathrm{y}_{1,t}$. $\mathrm{s}_{1,1}$ can then be recovered as follows. In a first step, partition $\boldsymbol{\Sigma}$ and $\mathbf{S}$ as

$$\boldsymbol{\Sigma} = \begin{pmatrix}\sigma_{1,1} & \boldsymbol{\sigma}_{1,2}\\ \boldsymbol{\sigma}_{2,1} & \boldsymbol{\Sigma}_{2,2}\end{pmatrix}, \text{ and } \qquad \mathbf{S} = \begin{pmatrix}\mathrm{s}_{1,1} & \mathbf{s}_{1,2}\\ \mathbf{s}_{2,1} & \mathbf{S}_{2,2}\end{pmatrix}.$$

To economize on notation, parameters pertaining to the variables $i \in \{2, \ldots, n\}$ are indexed by 2 instead of $2{:}n$.

From the covariance restrictions $\boldsymbol{\Sigma} = \mathbf{S}\mathbf{S}'$, we then have

$$\begin{pmatrix} \mathrm{s}_{1,1} & \mathbf{s}_{1,2} \\ \mathbf{s}_{2,1} & \mathbf{S}_{2,2} \end{pmatrix} \begin{pmatrix} \mathrm{s}_{1,1} & \mathbf{s}'_{2,1} \\ \mathbf{s}'_{1,2} & \mathbf{S}'_{2,2} \end{pmatrix} = \begin{pmatrix} \mathrm{s}^2_{1,1} + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} & \mathrm{s}_{1,1}\mathbf{s}'_{2,1} + \mathbf{s}_{1,2}\mathbf{S}'_{2,2} \\ \mathbf{s}_{2,1}\mathrm{s}_{1,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} & \mathbf{s}_{2,1}\mathbf{s}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} \end{pmatrix} = \begin{pmatrix} \sigma_{1,1} & \boldsymbol{\sigma}_{1,2} \\ \boldsymbol{\sigma}_{2,1} & \boldsymbol{\Sigma}_{2,2} \end{pmatrix}.$$

Note that $\boldsymbol{\Sigma}$ is a covariance matrix and thus symmetric, i.e. $\boldsymbol{\sigma}'_{1,2} = \boldsymbol{\sigma}_{2,1}$. Thus, this system yields three equations (one is redundant):

$$\begin{aligned} \mathrm{s}^2_{1,1} + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= \sigma_{1,1} \\ \mathrm{s}_{1,1}\mathbf{s}_{2,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} \\ \mathbf{s}_{2,1}\mathbf{s}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} &= \boldsymbol{\Sigma}_{2,2}. \end{aligned}$$

By substituting out $\mathbf{s}_{2,1} = \tilde{\mathbf{s}}_{2,1}\mathrm{s}_{1,1}$, one can obtain

$$\begin{aligned} \mathrm{s}^2_{1,1} + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= \sigma_{1,1} && (1) \\ \mathrm{s}^2_{1,1}\tilde{\mathbf{s}}_{2,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} && (2) \\ \mathrm{s}^2_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} &= \boldsymbol{\Sigma}_{2,2}. && (3) \end{aligned}$$

From equation (1), it follows that $\mathrm{s}_{1,1} = \pm\sqrt{\sigma_{1,1} - \mathbf{s}_{1,2}\mathbf{s}'_{1,2}}$. Thus, it remains to solve for $\mathbf{s}_{1,2}\mathbf{s}'_{1,2}$. By substracting (1) multiplied by $\tilde{\mathbf{s}}_{2,1}$ from (2), one can write

$$\begin{aligned} \mathbf{S}_{2,2}\mathbf{s}'_{1,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1} \\ (\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1} \\ \Rightarrow \mathbf{s}'_{1,2} &= (\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}). \end{aligned}$$

Thus,

$$\begin{aligned} \mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= (\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1})'(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})'^{-1}(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}) \\ &= (\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1})'[\underbrace{(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})(\mathbf{S}_{2,2} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2})'}_{=\boldsymbol{\Gamma}}]^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}). \end{aligned}$$

Now, note that

$$\boldsymbol{\Gamma} = \mathbf{S}_{2,2}\mathbf{S}'_{2,2} - \mathbf{S}_{2,2}\mathbf{s}'_{1,2}\tilde{\mathbf{s}}'_{2,1} - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{S}'_{2,2} + \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}'_{1,2}\tilde{\mathbf{s}}'_{2,1}$$

By subtracting (2) multiplied by $\tilde{\mathbf{s}}_{2,1}'$ from (3), one can write

$$\begin{aligned}\mathbf{S}_{2,2}\mathbf{S}_{2,2}' - \mathbf{S}_{2,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}' &= \boldsymbol{\Sigma}_{2,2} - \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}' \\ \Rightarrow \mathbf{S}_{2,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}' &= \mathbf{S}_{2,2}\mathbf{S}_{2,2}' - (\boldsymbol{\Sigma}_{2,2} - \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}').\end{aligned}$$

Substituting this and its transpose into the above equation yields

$$\boldsymbol{\Gamma} = -(\mathbf{S}_{2,2}\mathbf{S}_{2,2}' - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}') + 2\boldsymbol{\Sigma}_{2,2} - \tilde{\mathbf{s}}_{2,1}\boldsymbol{\sigma}_{1,2} - \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}'.$$

Similarly, by subtracting (1) pre-multiplied by $\tilde{\mathbf{s}}_{2,1}$ and post-multiplied by $\tilde{\mathbf{s}}_{2,1}'$ from (3), one can write

$$\mathbf{S}_{2,2}\mathbf{S}_{2,2}' - \tilde{\mathbf{s}}_{2,1}\mathbf{s}_{1,2}\mathbf{s}_{1,2}'\tilde{\mathbf{s}}_{2,1}' = \boldsymbol{\Sigma}_{2,2} - \sigma_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}_{2,1}'.$$

Using this in the equation above gives

$$\boldsymbol{\Gamma} = \boldsymbol{\Sigma}_{2,2} - (\tilde{\mathbf{s}}_{2,1}\boldsymbol{\sigma}_{1,2} + \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}') + \sigma_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}_{2,1}'.$$

Thus,

$$\mathbf{s}_{1,2}\mathbf{s}_{1,2}' = (\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1})'[\boldsymbol{\Sigma}_{2,2} - (\tilde{\mathbf{s}}_{2,1}\boldsymbol{\sigma}_{1,2} + \boldsymbol{\sigma}_{2,1}\tilde{\mathbf{s}}_{2,1}') + \sigma_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}_{2,1}']^{-1}(\boldsymbol{\sigma}_{2,1} - \tilde{\mathbf{s}}_{2,1}\sigma_{1,1}),$$

which completely characterizes the structural impact vector as a function of known quantities. Note that by choosing the positive root $\mathrm{s}_{1,1} = \sqrt{\sigma_{1,1} - \mathbf{s}_{1,2}\mathbf{s}_{1,2}'}$, one can interpret $\mathrm{s}_{1,1}$ as the standard deviation of $\varepsilon_{1,t}$, i.e. $\mathrm{s}_{1,1} = \sigma_{\varepsilon_1}$. The structural impact vector is then given by

$$\mathbf{s}_1 = \begin{pmatrix} \mathrm{s}_{1,1} \\ \tilde{\mathbf{s}}_{2,1}\mathrm{s}_{1,1} \end{pmatrix}.$$

Alternatively, one can set $\boldsymbol{\Omega} = \mathrm{diag}(\sigma_{\varepsilon_1}^2, \ldots, \sigma_{\varepsilon_n}^2)$ and $\mathrm{s}_{1,1} = 1$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a unit positive effect on $\mathrm{y}_{1,t}$. The structural impact vector is then given by

$$\mathbf{s}_1 = \begin{pmatrix} 1 \\ \tilde{\mathbf{s}}_{2,1} \end{pmatrix} = \begin{pmatrix} 1 \\ \mathbf{s}_{2,1} \end{pmatrix}.$$

After having obtained the structural impact vector $\mathbf{s}_1$, it is straightforward to compute all objects of interest such as IRFs, FEVDs and the structural shock series (see e.g. Montiel-Olea, Stock, and Watson, 2016).

A.2. General case for k shocks and k instruments

In this appendix, I provide more details on the identification strategy for the case with k shocks and k instruments.

To begin, partition the structural shocks into $\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}'_{1,t},\ \boldsymbol{\varepsilon}'_{2,t}]'$, where $\boldsymbol{\varepsilon}_{1,t}$ is the $k \times 1$ vector of structural shocks to be identified and $\boldsymbol{\varepsilon}_{2,t}$ is a $(n-k) \times 1$ vector containing all other shocks. The identifying restrictions are given by the moment restrictions for the instrument

$$
\begin{aligned}
\mathbb{E}[\mathbf{z}_t \boldsymbol{\varepsilon}'_{1,t}] &= \boldsymbol{\alpha} \\
\mathbb{E}[\mathbf{z}_t \boldsymbol{\varepsilon}'_{2,t}] &= \mathbf{0}_{k\times(n-k)},
\end{aligned}
$$

where $\boldsymbol{\alpha}$ is a $k \times k$ matrix (of full rank) and the covariance restrictions

$$\mathbf{S}\mathbf{S}' = \boldsymbol{\Sigma}.$$

In a next step, partition $\mathbf{S}$ as

$$\mathbf{S} = (\mathbf{S}_1,\ \mathbf{S}_2) = \begin{pmatrix} \mathbf{S}_{11} & \mathbf{S}_{12} \\ \mathbf{S}_{21} & \mathbf{S}_{22} \end{pmatrix},$$

where $\mathbf{S}_1$ is of dimension $n \times k$, $\mathbf{S}_2$ is of dimension $n \times (n-k)$. $\mathbf{S}_{11}$ is of dimension $k \times k$, $\mathbf{S}_{21}$ and $\mathbf{S}_{12}$ are of dimension $(n-k) \times k$ and $k \times (n-k)$, respectively, and $\mathbf{S}_{22}$ is $(n-k) \times (n-k)$.

The instrument moment conditions together with $\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t$ imply

$$\boldsymbol{\Sigma}_{\mathbf{zu}'} = \mathbb{E}[\mathbf{z}_t \mathbf{u}'_t] = \mathbb{E}[\mathbf{z}_t \boldsymbol{\varepsilon}'_t]\mathbf{S}' = \mathbb{E}[\mathbf{z}_t(\boldsymbol{\varepsilon}'_{1,t},\ \boldsymbol{\varepsilon}'_{2,t})] \begin{pmatrix} \mathbf{S}'_1 \\ \mathbf{S}'_2 \end{pmatrix} = (\boldsymbol{\alpha},\ \mathbf{0}) \begin{pmatrix} \mathbf{S}'_1 \\ \mathbf{S}'_2 \end{pmatrix} = \boldsymbol{\alpha}\mathbf{S}'_1$$

Now, partition $\boldsymbol{\Sigma}_{\mathbf{zu}'} = (\boldsymbol{\Sigma}_{\mathbf{zu}'_1},\ \boldsymbol{\Sigma}_{\mathbf{zu}'_2})$. The above restrictions can then be expressed as

$$\boldsymbol{\alpha}(\mathbf{S}'_{11},\ \mathbf{S}'_{21}) = (\boldsymbol{\Sigma}_{\mathbf{zu}'_1},\ \boldsymbol{\Sigma}_{\mathbf{zu}'_2}),$$

or equivalently

$$
\begin{aligned}
\boldsymbol{\alpha}\mathbf{S}'_{11} &= \boldsymbol{\Sigma}_{\mathbf{zu}'_1} \\
\boldsymbol{\alpha}\mathbf{S}'_{21} &= \boldsymbol{\Sigma}_{\mathbf{zu}'_2}.
\end{aligned}
$$

Combining the two yields

$$\mathbf{S}_{21}\mathbf{S}_{11}^{-1} = (\boldsymbol{\Sigma}_{\mathbf{zu}_1'}^{-1}\boldsymbol{\Sigma}_{\mathbf{zu}_2'})',$$

which can be estimated from the data. In particular, $\boldsymbol{\Sigma}_{\mathbf{zu}_1'}^{-1}\boldsymbol{\Sigma}_{\mathbf{zu}_2'}$ corresponds to the 2SLS estimator in a regression of $\mathbf{u}_{2,t}$ on $\mathbf{u}_{1,t}$ using $\mathbf{z}_t$ as an instrument for $\mathbf{u}_{1,t}$.

The covariance restrictions then yield

$$\mathbf{S}\mathbf{S}' = \boldsymbol{\Sigma}$$

$$\begin{pmatrix}\mathbf{S}_{11} & \mathbf{S}_{12}\\ \mathbf{S}_{21} & \mathbf{S}_{22}\end{pmatrix}\begin{pmatrix}\mathbf{S}_{11}' & \mathbf{S}_{21}'\\ \mathbf{S}_{12}' & \mathbf{S}_{22}'\end{pmatrix} = \begin{pmatrix}\mathbf{S}_{11}\mathbf{S}_{11}' + \mathbf{S}_{12}\mathbf{S}_{12}' & \mathbf{S}_{11}\mathbf{S}_{21}' + \mathbf{S}_{12}\mathbf{S}_{22}'\\ \mathbf{S}_{21}\mathbf{S}_{11} + \mathbf{S}_{22}\mathbf{S}_{12}' & \mathbf{S}_{21}\mathbf{S}_{21}' + \mathbf{S}_{22}\mathbf{S}_{22}'\end{pmatrix} = \begin{pmatrix}\boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12}\\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22}\end{pmatrix}.$$

Note that $\boldsymbol{\Sigma}$ is a covariance matrix and thus symmetric, i.e. $\boldsymbol{\Sigma}_{12}' = \boldsymbol{\Sigma}_{21}$. Thus, this system yields three matrix equations (one is redundant):

$$\begin{aligned}\mathbf{S}_{11}\mathbf{S}_{11}' + \mathbf{S}_{12}\mathbf{S}_{12}' &= \boldsymbol{\Sigma}_{11}\\ \mathbf{S}_{11}\mathbf{S}_{21}' + \mathbf{S}_{12}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{12}\\ \mathbf{S}_{21}\mathbf{S}_{21}' + \mathbf{S}_{22}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{22}.\end{aligned}$$

Note, to identify $\mathbf{S}$ up to a rotation, it is sufficient to find $\mathbf{S}_{11}\mathbf{S}_{11}'$, $\mathbf{S}_{22}\mathbf{S}_{22}'$, $\mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ and $\mathbf{S}_{12}\mathbf{S}_{22}^{-1}$. This is because one can write

$$\mathbf{S} = \begin{pmatrix}\mathbf{L}_1 & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{L}_2\\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1 & \mathbf{L}_2\end{pmatrix},$$

where $\mathbf{L}_1 = \text{chol}(\mathbf{S}_{11}\mathbf{S}_{11}')$ and $\mathbf{L}_2 = \text{chol}(\mathbf{S}_{22}\mathbf{S}_{22}')$. This still satisfies $\mathbf{S}\mathbf{S}' = \boldsymbol{\Sigma}$. Thus, it proves useful to rewrite these equations in terms of $\mathbf{S}_{11}\mathbf{S}_{11}'$, $\mathbf{S}_{22}\mathbf{S}_{22}'$, $\mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ and $\mathbf{S}_{12}\mathbf{S}_{22}^{-1}$

$$\begin{aligned}\mathbf{S}_{11}\mathbf{S}_{11}' + \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{S}_{22}')^{-1}\mathbf{S}_{12}' &= \boldsymbol{\Sigma}_{11}\\ \mathbf{S}_{11}\mathbf{S}_{11}'\mathbf{S}_{11}^{-1}\mathbf{S}_{21}' + \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{S}_{12}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{1,2}\\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{S}_{21}\mathbf{S}_{21}'\mathbf{S}_{11}^{-1}\mathbf{S}_{21}' + \mathbf{S}_{22}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{2,2}.\end{aligned}$$

Recall that $\mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ is identified by the instrument conditions. Thus, this is a system of 3 matrix equations in 3 unknown matrices. The solutions are given by

$$\begin{aligned}
\mathbf{S}_{12}\mathbf{S}_{12}' &= (\boldsymbol{\Sigma}_{21} - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\boldsymbol{\Sigma}_{11})'\boldsymbol{\Gamma}^{-1}(\boldsymbol{\Sigma}_{21} - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\boldsymbol{\Sigma}_{11}) \\
\boldsymbol{\Gamma} &= (\boldsymbol{\Sigma}_{22} + \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\boldsymbol{\Sigma}_{11}(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}' - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\boldsymbol{\Sigma}_{12} - \boldsymbol{\Sigma}_{21}(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}') \\
\mathbf{S}_{11}\mathbf{S}_{11}' &= \boldsymbol{\Sigma}_{11} - \mathbf{S}_{12}\mathbf{S}_{12}' \\
\mathbf{S}_{22}\mathbf{S}_{22}' &= \boldsymbol{\Sigma}_{22} - \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{S}_{11}\mathbf{S}_{11}'(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}' \\
\mathbf{S}_{12}\mathbf{S}_{22}^{-1} &= (\boldsymbol{\Sigma}_{12} - \mathbf{S}_{11}\mathbf{S}_{11}(\mathbf{S}_{11}')^{-1}\mathbf{S}_{21}')(\mathbf{S}_{22}\mathbf{S}_{22}')^{-1}.
\end{aligned}$$

To show this, define $\mathbf{a} = \mathbf{S}_{21}\mathbf{S}_{11}^{-1}$ and $\mathbf{b} = \mathbf{S}_{12}\mathbf{S}_{22}^{-1}$. Then note that

$$\begin{aligned}
\boldsymbol{\Sigma}_{12} - \boldsymbol{\Sigma}_{11}\mathbf{a}' =& \mathbf{b}\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{I} - \mathbf{b}'\mathbf{a}') \\
\boldsymbol{\Sigma}_{22} + \mathbf{a}\boldsymbol{\Sigma}_{11}\mathbf{a}' - \mathbf{a}\boldsymbol{\Sigma}_{12} - \boldsymbol{\Sigma}_{21}\mathbf{a}' =& (\mathbf{I} - \mathbf{ab})\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{I} - \mathbf{b}'\mathbf{a}').
\end{aligned}$$

Thus,

$$\begin{aligned}
&(\boldsymbol{\Sigma}_{12} - \boldsymbol{\Sigma}_{11}\mathbf{a}')(\boldsymbol{\Sigma}_{22} + \mathbf{a}\boldsymbol{\Sigma}_{11}\mathbf{a}' - \mathbf{a}\boldsymbol{\Sigma}_{12} - \boldsymbol{\Sigma}_{21}\mathbf{a}')^{-1}(\boldsymbol{\Sigma}_{21} - \mathbf{a}\boldsymbol{\Sigma}_{11}) \\
&= \mathbf{b}\mathbf{S}_{22}\mathbf{S}_{22}'(\mathbf{I} - \mathbf{b}'\mathbf{a}')(\mathbf{I} - \mathbf{b}'\mathbf{a}')^{-1}(\mathbf{S}_{22}\mathbf{S}_{22}')^{-1}(\mathbf{I} - \mathbf{ab})^{-1}(\mathbf{I} - \mathbf{ab})\mathbf{S}_{22}\mathbf{S}_{22}'\mathbf{b}' \\
&= \mathbf{b}\mathbf{S}_{22}\mathbf{S}_{22}'\mathbf{b}' = \mathbf{S}_{12}\mathbf{S}_{12}'.
\end{aligned}$$

The rest of the solutions then follows immediately from the original system of matrix equations.

We have now all the ingredients to evaluate

$$\mathbf{S} = \begin{pmatrix} \mathbf{L}_1 & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}L_2 \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1 & \mathbf{L}_2 \end{pmatrix}.$$

Recall, however, that this does only identify $\mathbf{S}$ up to a rotation. The parameter space of the proxy VAR can be characterized by

$$\mathbf{SR} = \begin{pmatrix} \mathbf{L}_1 & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}\mathbf{L}_2 \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1 & \mathbf{L}_2 \end{pmatrix} \begin{pmatrix} \mathbf{R}_k & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{n+k} \end{pmatrix} = \begin{pmatrix} \mathbf{L}_1\mathbf{R}_k & \mathbf{S}_{12}\mathbf{S}_{22}^{-1}L_2\mathbf{R}_{n+k} \\ \mathbf{S}_{21}\mathbf{S}_{11}^{-1}\mathbf{L}_1\mathbf{R}_k & \mathbf{L}_2\mathbf{R}_{n+k} \end{pmatrix},$$

where $\mathbf{R}$ is an orthonormal rotation matrix. As I am only interested in identifying the first k shocks, identification of $\mathbf{S}_1$ amounts to choose an appropriate rotation submatrix $\mathbf{R}_k$. In the application at hand, $\mathbf{R}_k = \mathbf{I}$ is a reasonable choice provided that world oil production is ordered first and the real price of oil is ordered second in the VAR. Because $\mathbf{L}_1$ is a lower triangular matrix, this amounts to assume that the oil supply news shock does not affect world oil production on impact. This additional assumption identifies the two structural shocks.

B. Data

This appendix gives more details on the historical OPEC announcements used to construct the instruments as well as an overview of the sources of the data used in the VAR models.

B.1. OPEC announcements

Table B.1 lists all OPEC announcements over the period 1983-2017. Starting from 2002, the press releases are available in the archive on the official OPEC webpage.[1] Before that, I used OPEC resolutions (OPEC, 1990) and Bloomberg news to collect the announcement dates. Note that some conferences ended on a weekend or a holiday. Similarly, some conferences ended after the market close of the NYMEX. For these conferences, the date of the next trading day is taken as the announcement date.

Table B.1: OPEC announcement dates over the period 1983–2017

Release date	Release type
19.07.1983	68th meeting of the OPEC conference
09.12.1983	69th meeting of the OPEC conference
11.07.1984	70th meeting of the OPEC conference
31.10.1984	71st (extraordinary) meeting of the OPEC conference
31.12.1984	72nd meeting of the OPEC conference
30.01.1985	73rd meeting of the OPEC conference
08.07.1985	Consultative meeting of the OPEC conference
25.07.1985	74th meeting of the OPEC conference
04.10.1985	75th (extraordinary) meeting of the OPEC conference
09.12.1985	76th meeting of the OPEC conference
21.04.1986	77th meeting of the OPEC conference
05.08.1986	78th meeting of the OPEC conference
22.10.1986	79th meeting of the OPEC conference
22.12.1986	80th meeting of the OPEC conference
29.06.1987	81st meeting of the OPEC conference
14.12.1987	82nd meeting of the OPEC conference
14.06.1988	83rd meeting of the OPEC conference
28.11.1988	84th meeting of the OPEC conference
07.06.1989	85th meeting of the OPEC conference
27.09.1989	3rd meeting of the 8 ministerial monitoring committee
28.11.1989	86th meeting of the OPEC conference
27.07.1990	87th meeting of the OPEC conference
13.12.1990	88th meeting of the OPEC conference
12.03.1991	3rd meeting of the ministerial monitoring committee
04.06.1991	89th meeting of the OPEC conference
25.09.1991	4th meeting of the ministerial monitoring committee
27.11.1991	90th meeting of the OPEC conference
17.02.1992	6th meeting of the ministerial monitoring committee
22.05.1992	91st meeting of the OPEC conference

[1] See http://www.opec.org/opec_web/en/press_room/28.htm

Release date	Release type
17.09.1992	9th meeting of the ministerial monitoring committee
27.11.1992	92nd meeting of the OPEC conference
16.02.1993	10th meeting of the ministerial monitoring committee
10.06.1993	93rd meeting of the OPEC conference
29.09.1993	94th (extraordinary) meeting of the OPEC conference
24.11.1993	95th meeting of the OPEC conference
28.03.1994	12th meeting of the ministerial monitoring committee
16.06.1994	96th meeting of the OPEC conference
22.11.1994	97th meeting of the OPEC conference
20.06.1995	98th meeting of the OPEC conference
22.11.1995	99th meeting of the OPEC conference
07.06.1996	100th meeting of the OPEC conference
29.11.1996	101st meeting of the OPEC conference
26.06.1997	102nd meeting of the OPEC conference
01.12.1997	103rd meeting of the OPEC conference
30.03.1998	104th (extraordinary) meeting of the OPEC conference
24.06.1998	105th meeting of the OPEC conference
26.11.1998	106th meeting of the OPEC conference
23.03.1999	107th meeting of the OPEC conference
22.09.1999	108th meeting of the OPEC conference
29.03.2000	109th meeting of the OPEC conference
21.06.2000	110th (extraordinary) meeting of the OPEC conference
11.09.2000	111th meeting of the OPEC conference
13.11.2000	112th (extraordinary) meeting of the OPEC conference
17.01.2001	113th (extraordinary) meeting of the OPEC conference
19.03.2001	114th meeting of the OPEC conference
05.06.2001	115th (extraordinary) meeting of the OPEC conference
03.07.2001	116th (extraordinary) meeting of the OPEC conference
25.07.2001	Agreement of the OPEC conference
27.09.2001	117th meeting of the OPEC conference
14.11.2001	118th (extraordinary) meeting of the OPEC conference
28.12.2001	Consultative meeting of the OPEC conference
15.03.2002	119th meeting of the OPEC conference
26.06.2002	120th (extraordinary) meeting of the OPEC conference
19.09.2002	121st meeting of the OPEC conference
12.12.2002	122nd (extraordinary) meeting of the OPEC conference
13.01.2003	123rd (extraordinary) meeting of the OPEC conference
11.03.2003	124th meeting of the OPEC conference
24.04.2003	Consultative meeting of the OPEC conference
11.06.2003	125th (extraordinary) meeting of the OPEC conference
31.07.2003	126th (extraordinary) meeting of the OPEC conference
24.09.2003	127th meeting of the OPEC conference
04.12.2003	128th (extraordinary) meeting of the OPEC conference
10.02.2004	129th (extraordinary) meeting of the OPEC conference
31.03.2004	130th meeting of the OPEC conference
03.06.2004	131st (extraordinary) meeting of the OPEC conference
15.09.2004	132nd meeting of the OPEC conference
10.12.2004	133rd (extraordinary) meeting of the OPEC conference
31.01.2005	134th (extraordinary) meeting of the OPEC conference
16.03.2005	135th meeting of the OPEC conference
15.06.2005	136th meeting of the OPEC conference
20.09.2005	137th meeting of the OPEC conference
12.12.2005	138th (extraordinary) meeting of the OPEC conference
31.01.2006	139th (extraordinary) meeting of the OPEC conference
08.03.2006	140th meeting of the OPEC conference
01.06.2006	141st (extraordinary) meeting of the OPEC conference

Release date	Release type
11.09.2006	142nd meeting of the OPEC conference
20.10.2006	Consultative meeting of the OPEC conference
14.12.2006	143rd (extraordinary) meeting of the OPEC conference
15.03.2007	144th meeting of the OPEC conference
11.09.2007	145th meeting of the OPEC conference
05.12.2007	146th (extraordinary) meeting of the OPEC conference
01.02.2008	147th (extraordinary) meeting of the OPEC conference
05.03.2008	148th meeting of the OPEC conference
10.09.2008	149th meeting of the OPEC conference
24.10.2008	150th (extraordinary) meeting of the OPEC conference
17.12.2008	151st (extraordinary) meeting of the OPEC conference
16.03.2009	152nd meeting of the OPEC conference
28.05.2009	153rd (extraordinary) meeting of the OPEC conference
10.09.2009	154th meeting of the OPEC conference
22.12.2009	155th (extraordinary) meeting of the OPEC conference
17.03.2010	156th meeting of the OPEC conference
14.10.2010	157th meeting of the OPEC conference
13.12.2010	158th (extraordinary) meeting of the OPEC conference
08.06.2011	159th meeting of the OPEC conference
14.12.2011	160th meeting of the OPEC conference
14.06.2012	161st meeting of the OPEC conference
12.12.2012	162nd meeting of the OPEC conference
31.05.2013	163rd meeting of the OPEC conference
04.12.2013	164th meeting of the OPEC conference
11.06.2014	165th meeting of the OPEC conference
27.11.2014	166th meeting of the OPEC conference
05.06.2015	167th meeting of the OPEC conference
04.12.2015	168th meeting of the OPEC conference
02.06.2016	169th meeting of the OPEC conference
28.09.2016	170th (extraordinary) meeting of the OPEC conference
30.11.2016	171st meeting of the OPEC conference
12.12.2016	OPEC and non-OPEC ministerial meeting
25.05.2017	172nd meeting of the OPEC conference
30.11.2017	173rd meeting of the OPEC conference

B.2. Data sources

Table B.2 gives details on the data used in the paper, including information on the coverage and data sources.

Table B.2: Data description, sources, and coverage

Variable	Description	Source	Sample
Instrument			
NCLC.hh (PS)	WTI crude oil futures *hh*-month contract (settlement price)	Datastream	1983M4-2017M12
Baseline variables			
OILPRICE	WTI spot crude oil price (WTISPLC) deflated by U.S. CPI (CPIAUCSL)	FRED	1974M1-2017M12
EIA1955	World oil production	Datastream	1974M1-2017M12
OECD+6IP	Industrial production of OECD + 6 (Brazil, China, India, Indonesia, Russia and South Africa) from Baumeister and Hamilton (2019)	Baumeister's webpage	1974M1-2017M12
OECDSTOCKS	OECD crude oil inventories, calculated based on OECD petroleum stocks (EIA1976) and U.S. crude oil and petroleum stocks (EIA1933, EIA1941), as in Kilian and Murphy (2014)	Datastream/own calculations	1974M1-2017M12
INDPRO	U.S. industrial production index	FRED	1974M1-2017M12
CPIAUCSL	U.S. CPI for all urban consumers: all items	FRED	1974M1-2017M12
Additional variables			
Expectations and uncertainty			
BKEXP6M	Oil price expectations (6-month) from Baumeister and Kilian (2017), extended using futures prices	Baumeister's webpage/ own calculations	1983M4-2017M12
MICH	University of Michigan: inflation expectation	FRED	1978M1-2017M12
CPI6	SPF median inflation expectations (1 year horizon)	Philadelphia FED	1981Q3-2017Q4
VXOCLS	CBOE S&P 100 volatility index: VXO, extended as in Bloom (2009)	FRED/own calculations	1974M1-2017M12
GPR	Geopolitical risk index from Caldara and Iacoviello (2018)	Iacoviello's webpage	1985M1-2017M12
Prices			
CPILFESL	U.S. CPI for all urban consumers: all items less food and energy	FRED	1974M1-2017M12
CPIENGSL	U.S. CPI for all urban consumers: energy	FRED	1974M1-2017M12
CUSR0000SAN	U.S. CPI for all urban consumers: nondurables	FRED	1974M1-2017M12
CUSR0000SAD	U.S. CPI for all urban consumers: durables	FRED	1974M1-2017M12
CUSR0000SAS	U.S. CPI for all urban consumers: services	FRED	1974M1-2017M12
WPSFD49207	U.S. PPI: Finished Goods	FRED	1974M1-2017M12
WPSFD4131	U.S. PPI: Finished Goods Less Foods and Energy	FRED	1974M1-2017M12
Activity			
UNRATE	Civilian unemployment rate	FRED	1974M1-2017M12
RPCE	U.S. personal consumption expenditures (PCE), deflated by chain-type price index (PCEPI)	FRED	1974M1-2017M12
RDNRGRC1M027SBEA	U.S. PCE energy goods and services, deflated by DNRGRG3M086SBEA	FRED	1974M1-2017M12
RPCEND	U.S. PCE nondurable goods, deflated by DNDGRG3M086SBEA	FRED	1974M1-2017M12
RPCEDG	U.S. PCE durable goods, deflated by DDURRG3M086SBEA	FRED	1974M1-2017M12
RPCES	U.S. PCE services, deflated by DSERRG3M086SBEA	FRED	1974M1-2017M12
GDPC1	U.S. Real Gross Domestic Product	FRED	1974Q1-2017Q4
GPDIC1	U.S. Real Gross Private Domestic Investment	FRED	1974Q1-2017Q4
PCECC96	U.S. Real Personal Consumption Expenditures	FRED	1974Q1-2017Q4
Financial variables			
FF	Effective federal funds rate	FRED	1974M1-2017M12
EBP	Excess bond premium from Gilchrist and Zakrajšek (2012)	Gilchrist's webpage	1974M1-2017M12
SPCOMP	S&P 500 composite price index	Datastream	1974M1-2017M12
Exchange rates and trade			
TWEXBMTH	Trade Weighted U.S. Dollar Index: Broad	FRED	1974M1-2017M12
TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies	FRED	1974M1-2017M12
–	Bilateral exchange rates, domestic currency per U.S. dollar	IFS, Datastream	1974M1-2017M12 RUS starts 1995M6
USTOTPRCF	U.S. terms of trade	Datastream	1974M1-2017M12
USBALGDSB	U.S. merchandise trade balance, as a share of nominal GDP (GDP from FRED)	Datastream/FRED	1974Q1-2017Q4
Misc			
GLOBALACT	Kilian's (2009) index of global real economic activity	Kilian's webpage	1974M1-2015M12
USCOCOIMA	U.S. refiners acquisition cost of imported crude oil	Datastream	1974M1-2017M12

Figure B.1 shows the series included in the baseline VAR over the sample period 1974-2015. All the variables are depicted in logs.

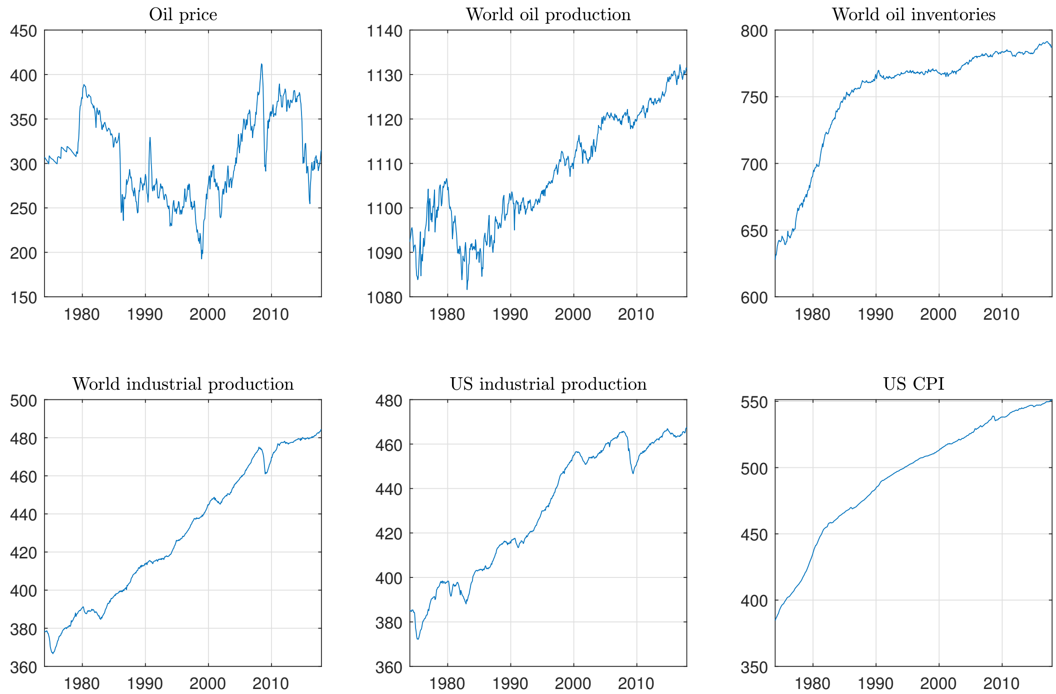


Figure B.1: Series included in the baseline VAR over the sample period 1974-2017

C. Charts, tables and additional sensitivity checks

In this appendix, I present additional tables and figures that are not shown in the main body of the paper. The subsections refer to the corresponding sections in the main text. Furthermore, I perform a number of additional robustness checks that are not discussed in the paper.

C.1. Diagnostics of the surprise series

As discussed in the paper, I perform a number of validity checks on the surprise series. Figure C.1 depicts the autocorrelation function. One can see that there is no evidence that the series is serially correlated. I also perform a number of Granger causality tests. From table C.1, it can be seen that the series is not forecastable by past macroeconomic or financial variables. Finally, I look how the series correlates with other shock series from the literature and find that it is not correlated with other shocks such as global demand or uncertainty shocks (see table C.2). Not surprisingly, I find that the series is significantly correlated with oil-specific demand shocks. This is consistent with the fact that oil-specific demand shocks capture among other things news about future demand and supply. Finally, I find that the series is only weakly correlated with the previously identified unanticipated oil supply shocks.

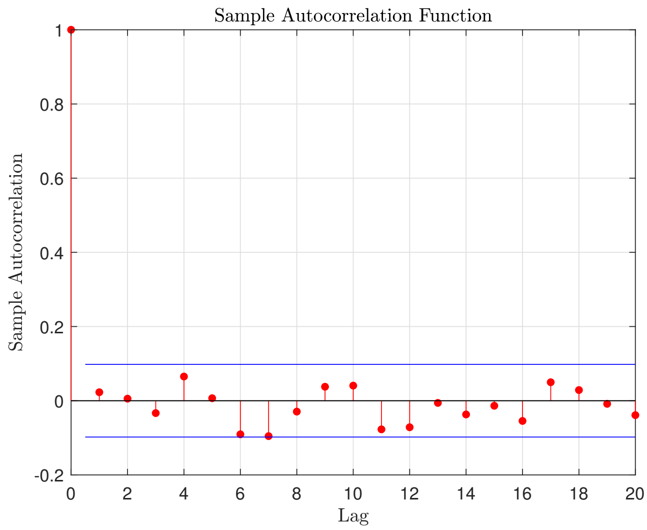


Figure C.1: The autocorrelation function of the oil supply surprise series

Table C.1: Granger causality tests

Variable	p-value
Instrument	0.3974
Oil price	0.4835
World oil production	0.6901
World oil inventories	0.6664
World industrial production	0.9491
US industrial production	0.9329
US CPI	0.7658
Fed funds rate	0.8916
S&P 500	0.2004
NEER	0.6270
Geopolitical risk	0.1461
Joint	0.6344

Notes: The table shows the p-values of a series of Granger causality tests of the oil supply surprise series using a selection of macroeconomic and financial variables. To be able to conduct standard inference, the series are made stationary by taking first differences where necessary. The lag order is set to 12 and in terms of deterministics, only a constant term is included.

Table C.2: Correlation with other shock measures

Shock	Source	ρ	p-value	n	Sample
Panel A: Oil shocks					
Oil price	Hamilton (2003)	0.06	0.18	492	1977M01-2017M12
Oil supply	Kilian (2008)	-0.05	0.36	369	1974M01-2004M09
	Caldara, Cavallo, and Iacoviello (2019)	-0.02	0.77	372	1985M01-2015M12
	Baumeister and Hamilton (2019)	-0.07	0.10	515	1975M02-2017M12
	Kilian (2009)	0.09	0.08	395	1975M02-2007M12
Global demand	Kilian (2009)	0.03	0.53	395	1975M02-2007M12
Oil-specific demand	Kilian (2009)	0.17	0.00	395	1975M02-2007M12
Panel B: Other shocks					
Productivity	Basu, Fernald, and Kimball (2006)	-0.03	0.74	152	1974Q1-2011Q4
	Smets and Wouters (2007)	-0.06	0.50	124	1974Q1-2004Q4
News	Barsky and Sims (2011)	-0.13	0.14	135	1974Q1-2007Q3
	Kurmann and Otrok (2013)	-0.03	0.76	126	1974Q1-2005Q2
	Beaudry and Portier (2014)	0.05	0.53	155	1974Q1-2012Q3
Monetary policy	Gertler and Karadi (2015)	0.07	0.23	324	1990M01-2016M12
	Romer and Romer (2004)	-0.00	0.94	276	1974M01-1996M12
	Smets and Wouters (2007)	0.03	0.71	124	1974Q1-2004Q4
Uncertainty	Bloom (2009)	0.01	0.89	522	1974M07-2017M12
	Baker, Bloom, and Davis (2016)	0.07	0.19	390	1985M07-2017M12
Financial	Gilchrist and Zakrajšek (2012)	0.02	0.66	498	1974M07-2015M12
	Bassett et al. (2014)	0.12	0.28	76	1992Q1-2010Q4
Fiscal policy	Romer and Romer (2010)	0.02	0.81	136	1974Q1-2007Q4
	Ramey (2011)	0.06	0.45	148	1974Q1-2010Q4
	Fisher and Peters (2010)	0.05	0.59	140	1974Q1-2008Q4

Notes: The table shows the correlation of the oil supply surprise series with a wide range of different shock measures from the literature. Panel A depicts the relationship with other oil shocks. Panel B shows the relationship to other types of shocks. For these shock measures, I draw on the shocks studied in Stock and Watson (2012) and Piffer and Podstawski (2017). ρ is the Pearson correlation coefficient, n is the sample size. When the shock measure is only available at the quarterly frequency, the oil supply surprise series is aggregated by summing across months.

C.2. Sensitivity analysis

C.2.1. Identification

Announcements. Since 2001, OPEC publishes monthly oil market reports, including information about world oil demand, supply as well as stock movements. Importantly the report also includes OPEC's global demand forecasts and forecast revisions. Figure C.2 shows an excerpt of the oil market report from December 2006.

Table 10: World oil demand forecast for 2007, mb/d

	2006	1Q07	2Q07	3Q07	4Q07	2007	Change 2007/06 Volume	%
North America	25.45	25.52	25.21	25.65	26.27	25.66	0.21	0.83
Western Europe	15.49	15.62	15.13	15.47	15.82	15.51	0.02	0.13
OECD Pacific	8.45	9.40	7.77	7.91	8.76	8.46	0.01	0.09
Total OECD	**49.40**	**50.54**	**48.12**	**49.04**	**50.85**	**49.64**	**0.24**	**0.48**
Other Asia	8.76	8.81	9.07	8.80	8.98	8.91	0.15	1.77
Latin America	5.16	5.12	5.23	5.36	5.28	5.25	0.09	1.75
Middle East	6.16	6.33	6.35	6.67	6.47	6.46	0.30	4.88
Africa	2.95	3.01	3.00	2.95	3.05	3.00	0.05	1.75
Total DCs	**23.03**	**23.26**	**23.65**	**23.79**	**23.78**	**23.62**	**0.60**	**2.59**
FSU	3.78	3.78	3.50	3.76	4.13	3.79	0.01	0.32
Other Europe	0.91	1.01	0.88	0.90	0.95	0.93	0.03	3.19
China	7.16	7.44	7.85	7.72	7.41	7.61	0.45	6.26
Total "Other Regions"	**11.84**	**12.23**	**12.23**	**12.39**	**12.49**	**12.33**	**0.49**	**4.13**
Total world	**84.27**	**86.04**	**84.00**	**85.21**	**87.12**	**85.59**	**1.33**	**1.57**
Previous estimate	84.26	85.99	84.01	85.20	87.13	85.58	1.33	1.57
Revision	0.01	0.05	-0.01	0.02	-0.01	0.01	0.00	0.00

Figure C.2: OPEC's world oil demand forecast for 2007. Source: OPEC Monthly Oil Market Report, December 2006

I collected all world oil demand forecasts as well as forecast revisions from the reports for 2001-2017. This data is then used to construct a refined version of the oil supply surprise series, purged from potential confounding factors coming from global demand. A delicate issue here is the timing, i.e. when are the reports released for publication. For a large part of the OPEC announcements, these reports were published shortly after the OPEC meetings. For some meetings, in particular extraordinary ones taking place towards the end of a given month, the report is already available before the announcement. In these cases, the refinement should have no effect as this information is already known to markets. In this sense, the refinement does not control for all potential confounding demand factors but for a large part. Furthermore, I also show that only using ordinary announcements in the construction of the instrument leads to very similar conclusions.

The results are displayed in figures C.3-C.4. One can see that the IRFs based on the refined, informationally robust instrument are consistent with the responses using the raw instrument. Apart from a few minor, statistically insignificant differences, the responses are very similar. Note that the results based on the raw instrument are slightly different from the baseline in section 4 in the paper because of the shorter identification sample. Likewise, using only ordinary announcements to construct the instrument also leads to responses that are very similar to the baseline case.

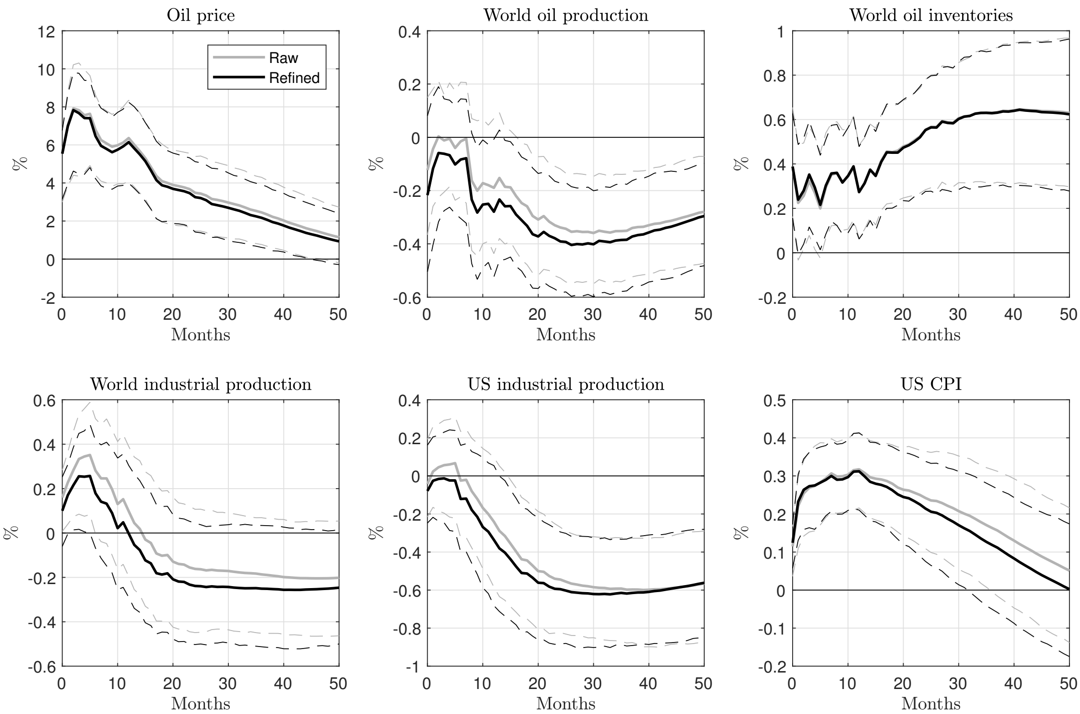
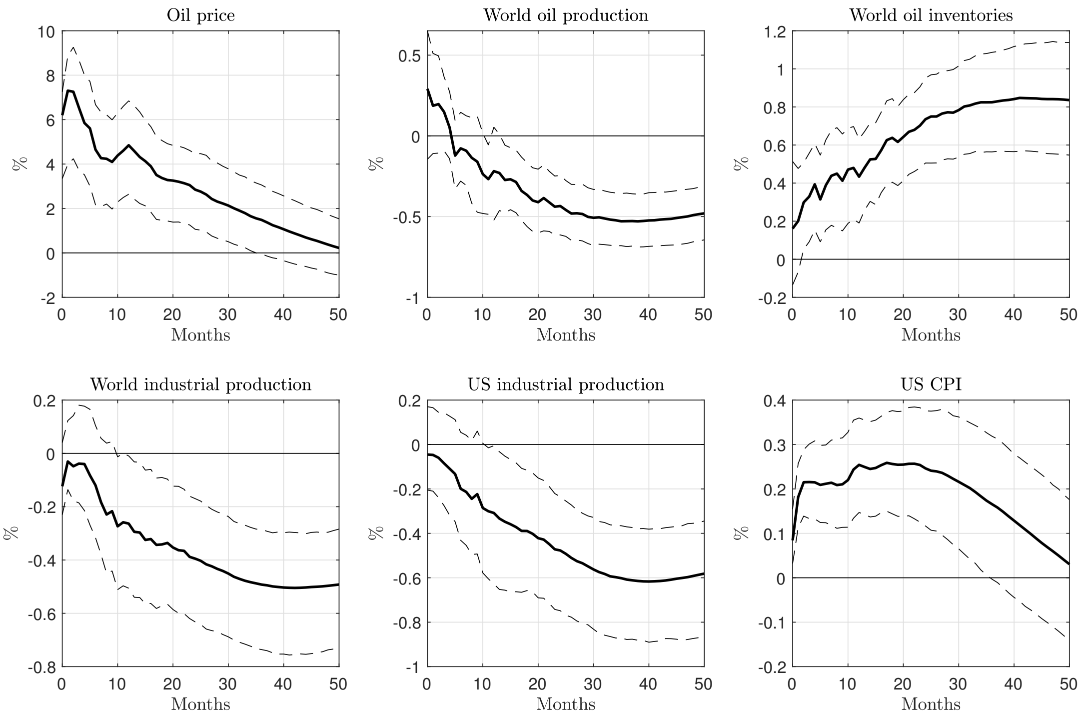


Figure C.3: Comparison of the results using the raw and the refined, informationally robust oil supply surprise series as an instrument.



First stage regression: F: 11.56, robust F: 5.33, R^2: 2.20%, Adjusted R^2: 2.01%

Figure C.4: Sensitivity with respect to the announcement type: IRFs from VAR using instrument constructed only from announcements from ordinary meetings.

To illustrate that the high-frequency proxy VAR is not picking up some spurious correlation, I perform a placebo test. Figure C.5 shows the IRFs. It turns out that the placebos do not have systematic effects on the oil market and the macroeconomy, which supports the validity of the identification approach.

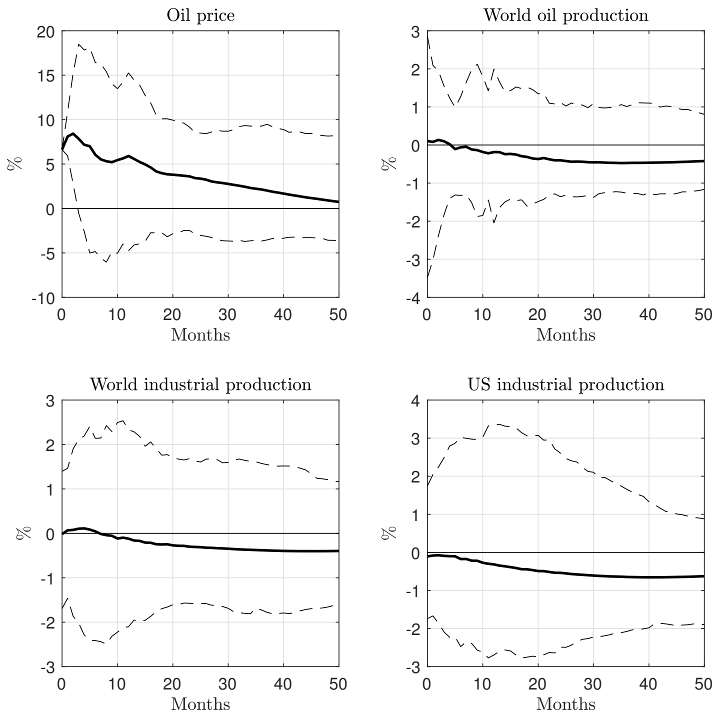


Figure C.5: Placebo test: The figure depicts the 90% percentiles of the responses obtained using a set of 1000 artificially generated proxies together with the baseline response. All impulse responses have been standardized such that the impact response of the oil price has the same magnitude as the baseline impact response.

News and surprise shocks. Figure C.6 presents the IRFs from the two shock proxy VAR. The results suggest that one can agnostically identify the oil supply news shock without violating the exogeneity assumption.

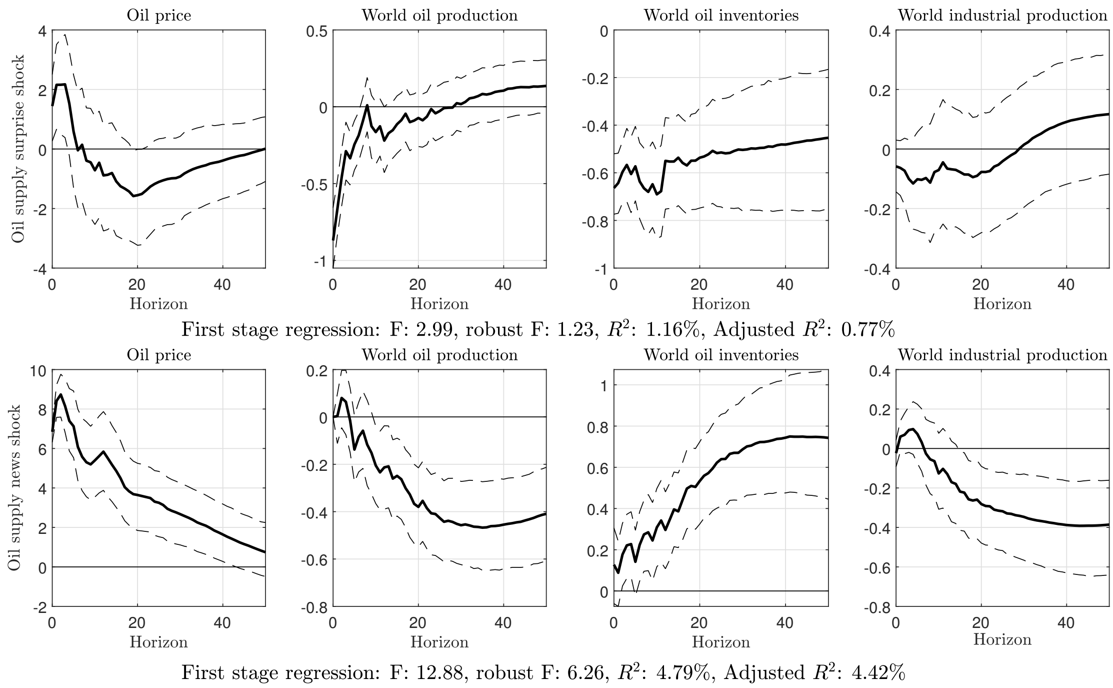


Figure C.6: Two shock proxy VAR: The top row is the oil supply surprise shock and the bottom row is the oil supply news shock identified using Kilian's (2008) exogenous supply shock series, extended by Bastianin and Manera (2018), and the OPEC surprise series as instruments.

Fundamentalness. As an alternative to the proxy VAR, I include my oil supply surprise series as the first variable in a recursive VAR. This approach tends to be more robust to problems of non-fundamentalness (Ramey, 2016; Plagborg-Møller and Wolf, 2019). One disadvantage is that one cannot easily accommodate instruments that are only available for a shorter sample than the other variables, which is relevant for the application at hand. The responses based on this approach are depicted in figure C.7. The results turn out to be qualitatively in line with the baseline VAR. However, in particular the responses of oil production and the activity indicators turn out to be weaker and less precisely estimated. Overall, the responses turn out to be more similar to the proxy VAR that only uses a shorter estimation sample, see figure C.21.

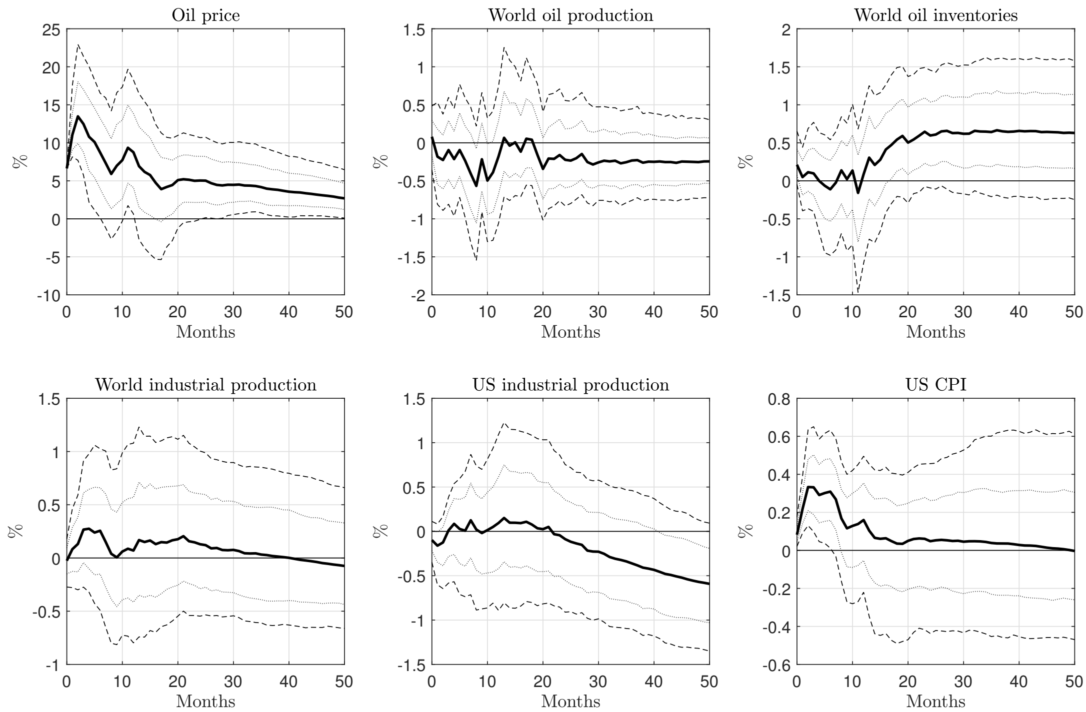


Figure C.7: IRFs computed from recursive VAR including the oil supply surprise series ordered first. Dotted lines are 68% and dashed lines are 90% confidence bands.

The inclusion of additional variables also serves as an important robustness check on how the results are affected by the information contained in the VAR. Figure C.8 shows the impulse responses of the baseline variables from the augmented VAR models in sections 4.3-4.4 in the paper. As can be seen from figure C.8, the responses of the baseline variables appear to be robust to the inclusion of additional variables. In particular, the impact responses turn out to be quite stable, supporting the validity of the baseline proxy VAR. As Miranda-Agrippino and Ricco (2018) show, unstable impact responses are an indication that the instrument is contaminated by other past structural shocks that are not filtered out by the VAR model. I have also tried to augment the VAR by factors estimated from the FRED-MD database. The results turn out to be robust, indicating that there is no problem of informational insufficiency. These results are available upon request.

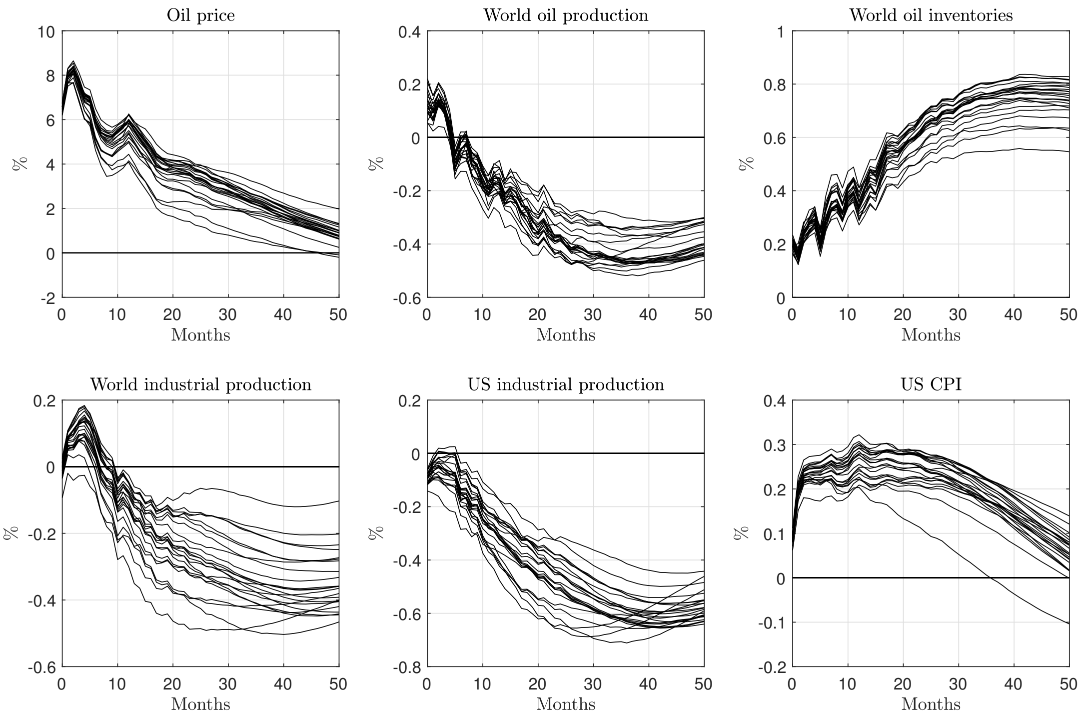


Figure C.8: IRFs for the baseline variables from the augmented VARs in section 4.4.

Futures contracts. As discussed in section 2.2 in the paper, a crucial issue in the context of the high-frequency proxy VAR is the choice of the futures contract used to construct the instrument. As a benchmark, I use the 6-month contract because it has good coverage and accords well with the interpretation of a news shock. However, it is interesting to see how the results change using different maturities. Figure C.9 presents the IRFs from the baseline VAR as well as the confidence bands together with the IRFs from proxy VARs that use instruments constructed from the front, 1-month, 2-month, 3-month, 9-month, and 12-month contracts. The results turn out to be very robust with respect to the choice of the futures contract, especially at maturities ranging from one to nine months. This is suggestive that the results are not severely affected by changes in risk premia.

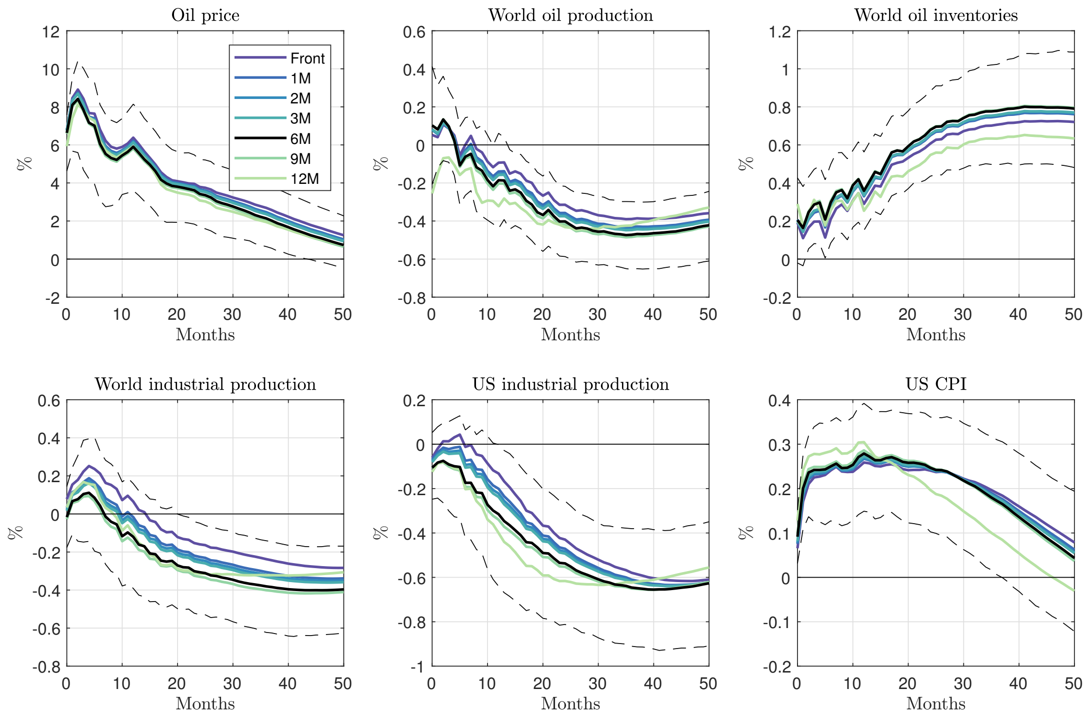
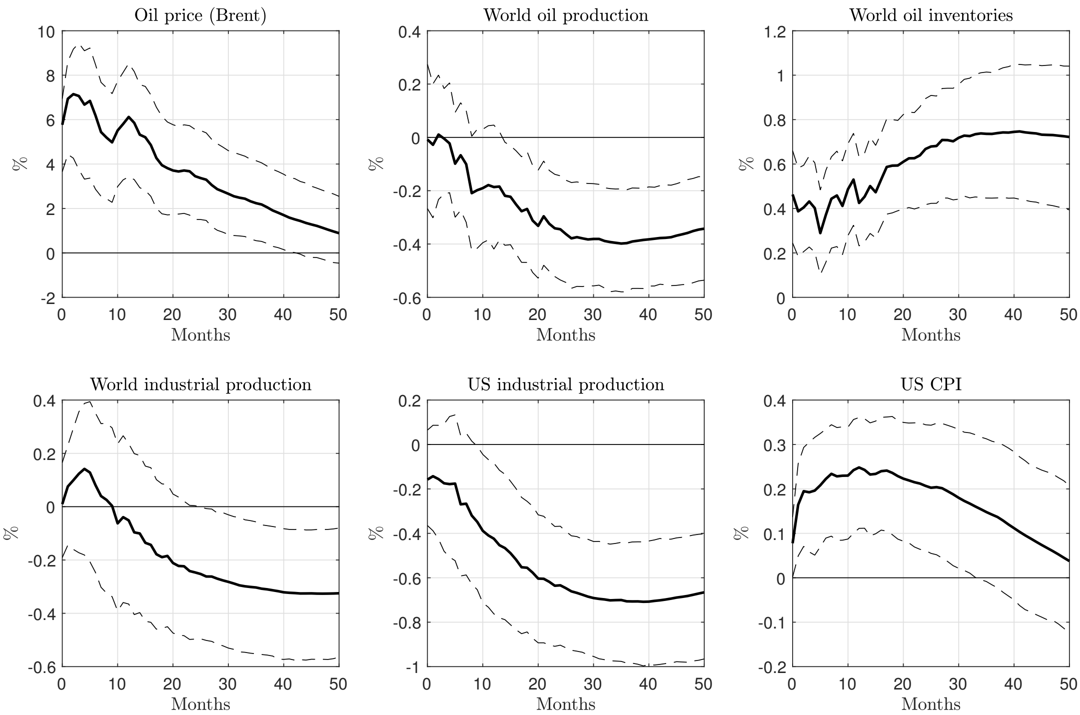


Figure C.9: Sensitivity with respect to the futures contract: IRFs from VAR using instruments constructed from different futures contracts together with the baseline responses.

A related issue is the choice of the underlying of the futures contract. As a benchmark, I relied on WTI futures. This might be problematic in the most recent part of the sample because as Baumeister and Kilian (2016) argue, WTI has become less representative for the global price of oil since the shale oil boom in 2011. A viable alternative would be to use Brent futures. However, these futures only started trading in the late 1980s and were less liquid, especially at the beginning of the sample. The contract with the longest maturity and adequate coverage is the 3-month contract. Figure C.10 presents the IRFs based on the instrument constructed from this contract and using the Brent spot price as the oil price indicator in the VAR. As one can see, the results turn out to be robust.

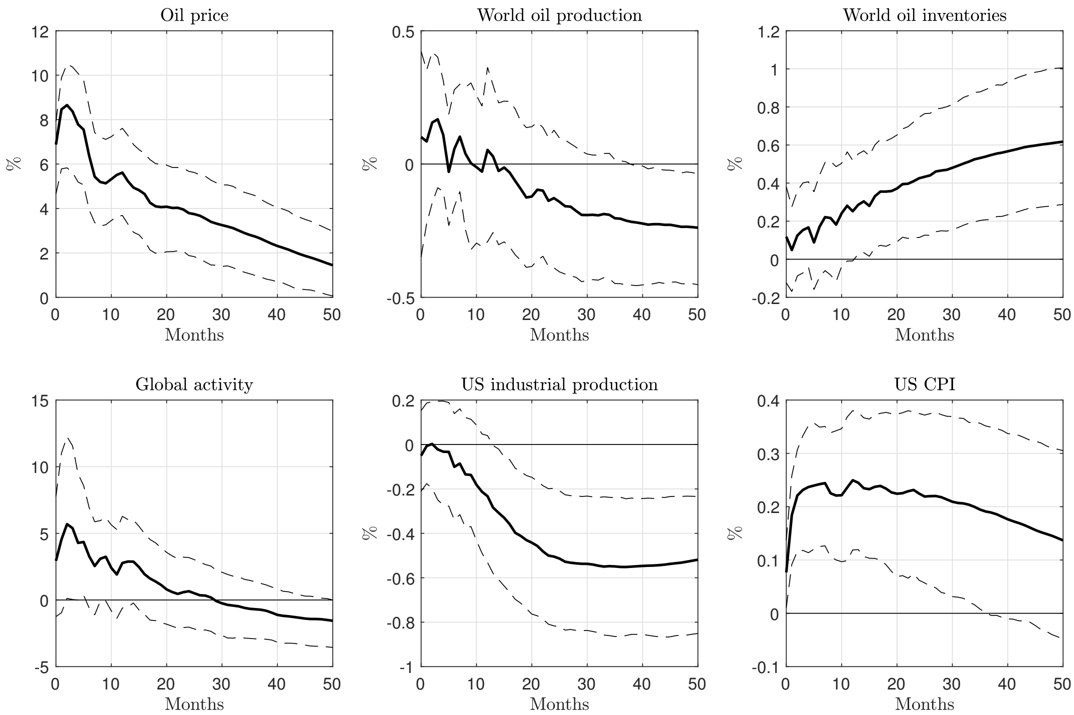


First stage regression: F: 11.47, robust F: 7.22, R^2: 2.19%, Adjusted R^2: 2.00%

Figure C.10: Sensitivity with respect to the underlying of the futures: IRFs from VAR using instrument constructed from Brent futures prices.

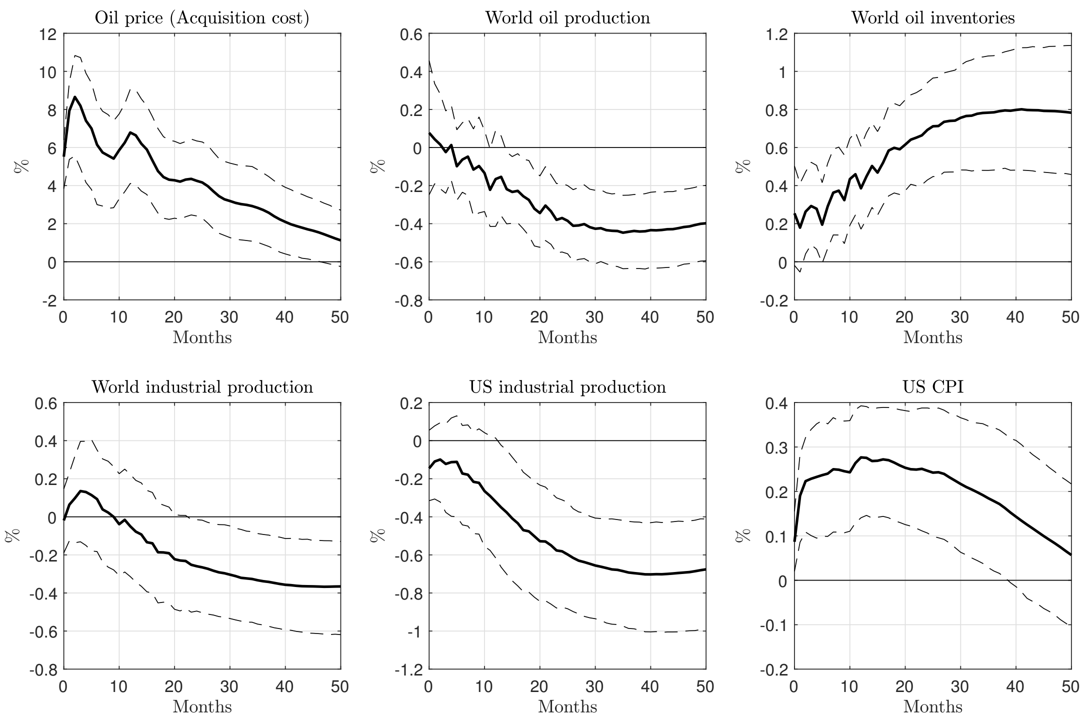
C.2.2. Specification and data choices

Model specification. Figures C.11-C.12 show the responses using Kilian's (2009) index as the global economic activity indicator and the responses using the real refiner acquisition cost as the oil price indicator. The results turn out to be robust.



First stage regression: F: 23.30, robust F: 14.86, R^2: 4.66%, Adjusted R^2: 4.46%

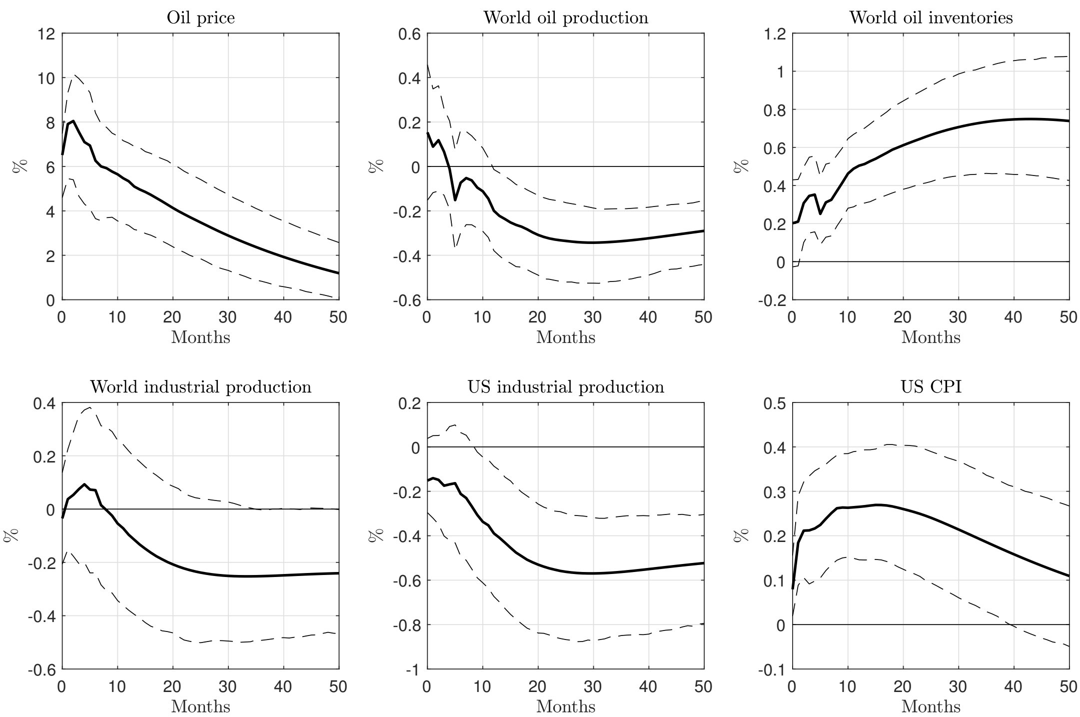
Figure C.11: Sensitivity with respect to the model specification: VAR with Kilian's (2009) corrected global activity series as global economic activity indicator.



First stage regression: F: 15.11, robust F: 9.94, R^2: 2.86%, Adjusted R^2: 2.67%

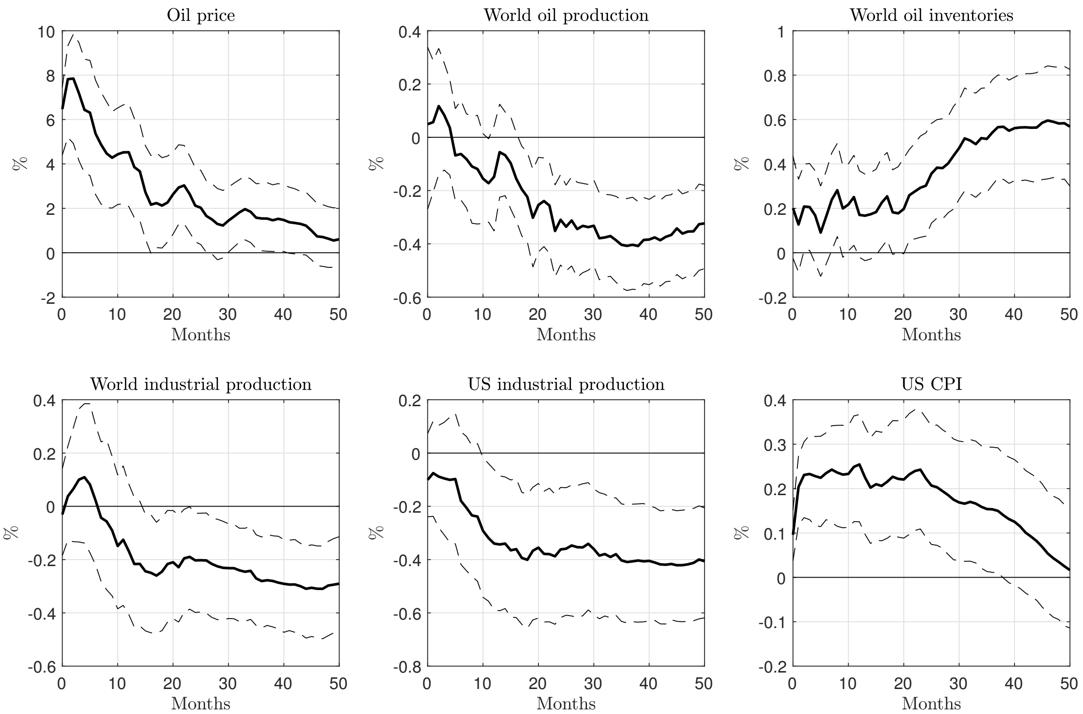
Figure C.12: Sensitivity with respect to the model specification: VAR with real refiner acquisition cost of imported crude oil as oil price measure.

I also perform a number of robustness checks with respect to the lag order, the deterministics included in the model as well as the treatment of non-stationary variables. In particular, I vary the lag order according to information criteria and other popular choices in the literature, estimate a VAR without a constant as well as VAR with a constant and a linear trend. Furthermore, I estimate a stationary VAR in the real price of oil, world oil production growth, the change in world oil inventories, world industrial production growth, U.S. industrial production growth and U.S. CPI inflation. From figures C.13-C.18, one can see that the results are robust with respect to all these choices. Finally, in figures C.19-C.20, I rely on the exact same specification as in Kilian and Murphy (2014) and Baumeister and Hamilton (2019), respectively. Again, the results turn out to be robust.



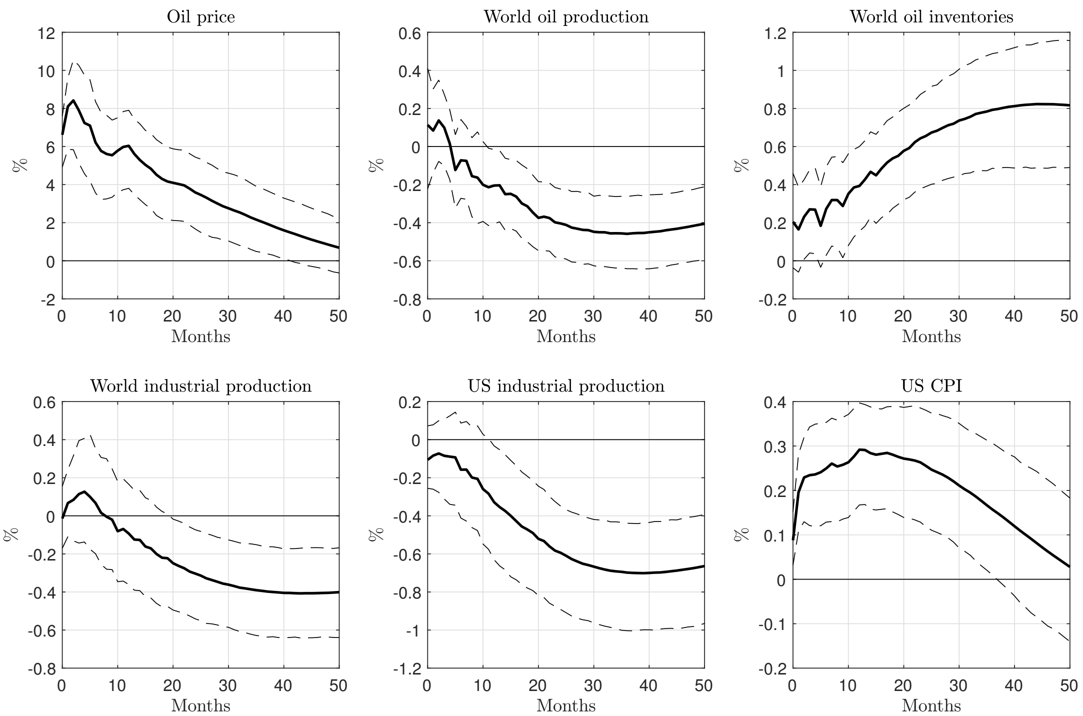
First stage regression: F: 21.17, robust F: 9.69, R^2: 3.96%, Adjusted R^2: 3.78%

Figure C.13: Sensitivity with respect the model specification: IRFs based on VAR(7), which is the lag length selected by the AIC.



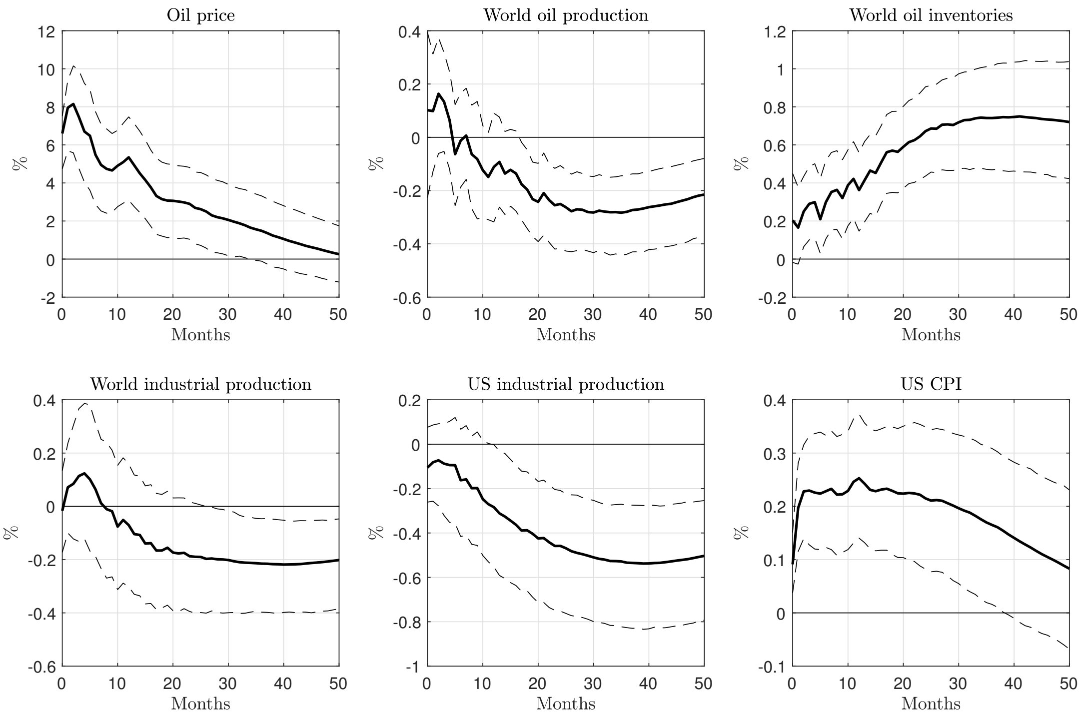
First stage regression: F: 21.01, robust F: 12.09, R^2: 4.02%, Adjusted R^2: 3.83%

Figure C.14: Sensitivity with respect the model specification: IRFs based on VAR(24).



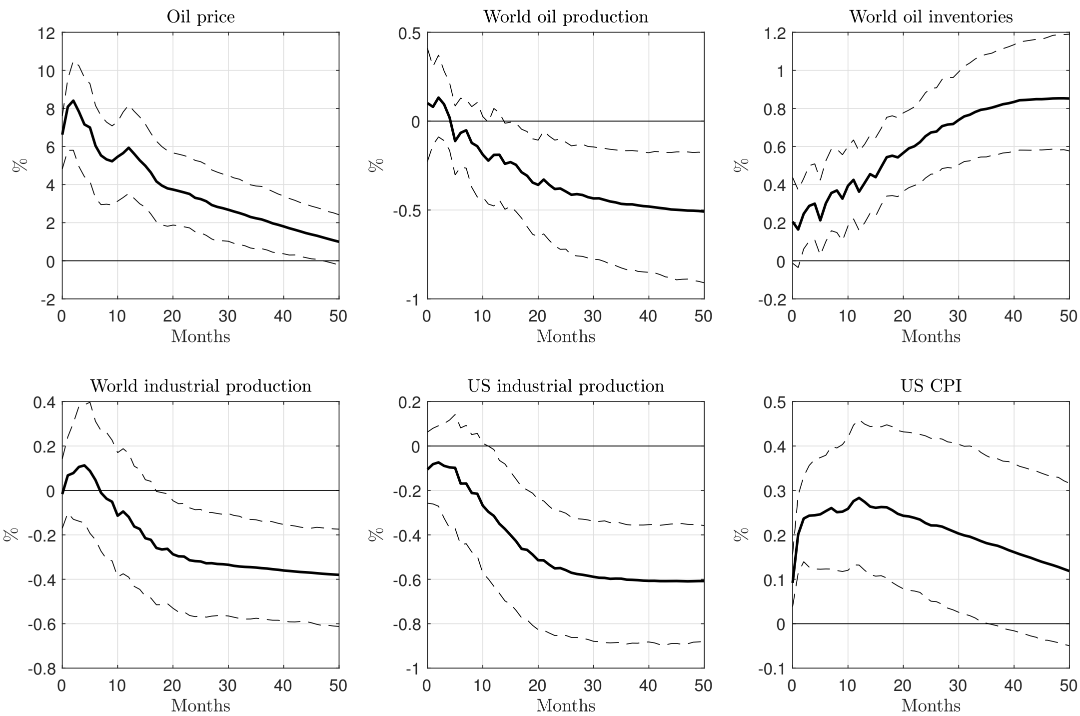
First stage regression: F: 22.86, robust F: 11.32, R^2: 4.27%, Adjusted R^2: 4.08%

Figure C.15: Sensitivity with respect to the model specification: IRFs based on VAR(12).



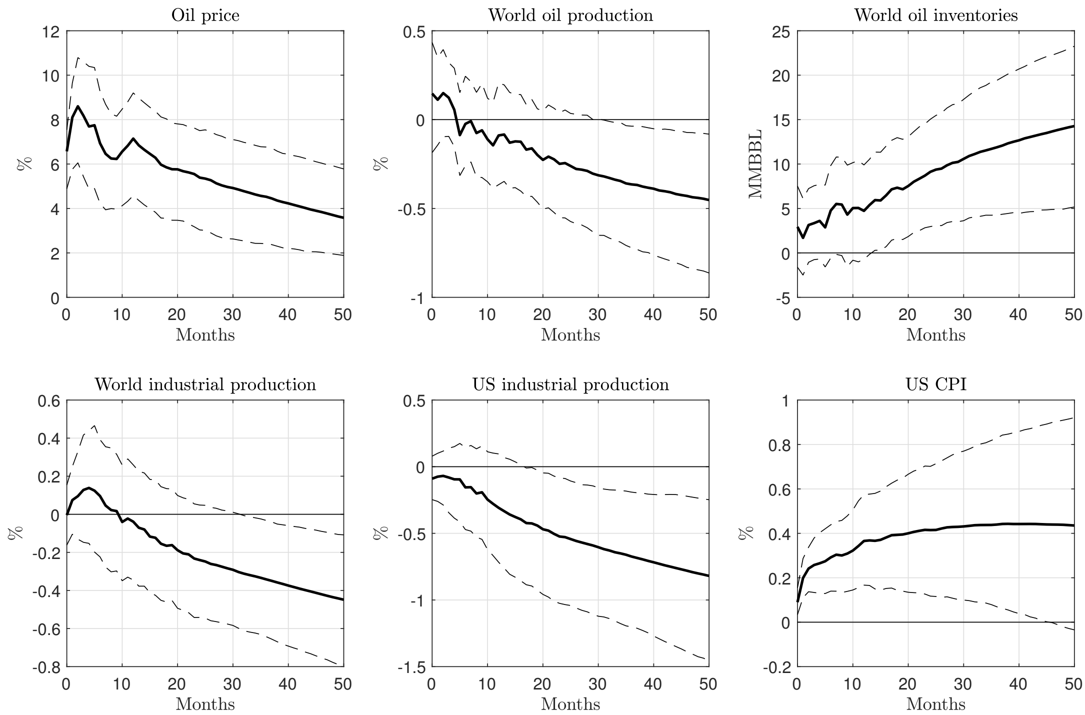
First stage regression: F: 24.66, robust F: 12.21, R^2: 4.59%, Adjusted R^2: 4.40%

Figure C.16: Sensitivity with respect to the model specification: VAR with linear trend.



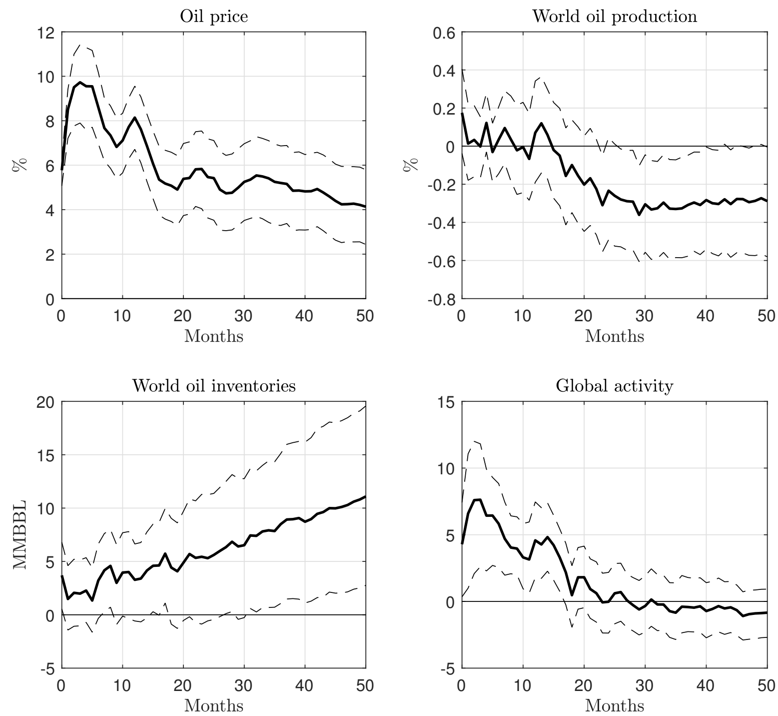
First stage regression: F: 24.22, robust F: 11.55, R^2: 4.51%, Adjusted R^2: 4.32%

Figure C.17: Sensitivity with respect to the model specification: VAR without a constant.



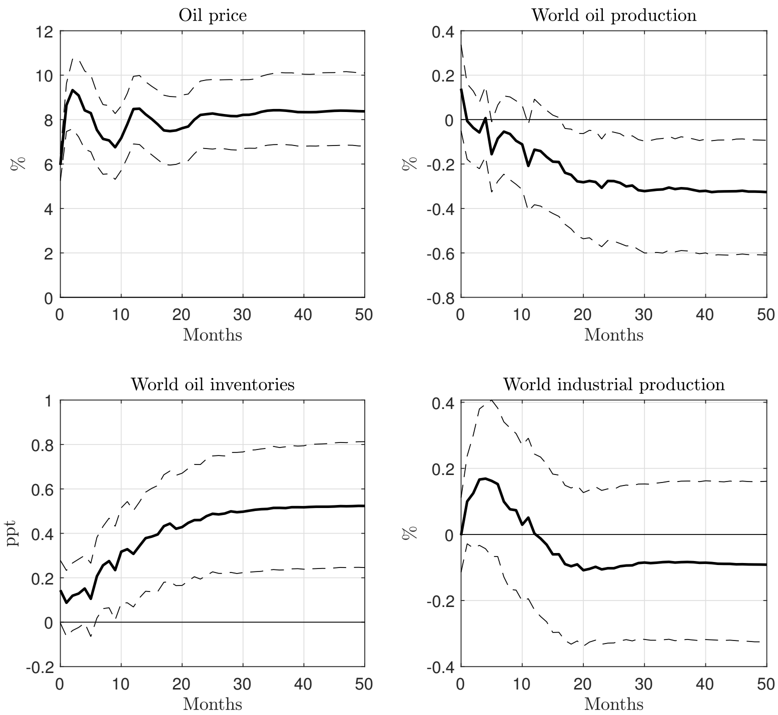
First stage regression: F: 22.91, robust F: 12.29, R^2: 4.27%, Adjusted R^2: 4.09%

Figure C.18: Sensitivity with respect to the model specification: stationary VAR (real oil price, world oil production growth, change in world oil inventories, world industrial production growth, U.S. industrial production growth, U.S. CPI inflation).



First stage regression: F: 14.85, robust F: 15.59, R^2: 3.10%, Adjusted R^2: 2.89%

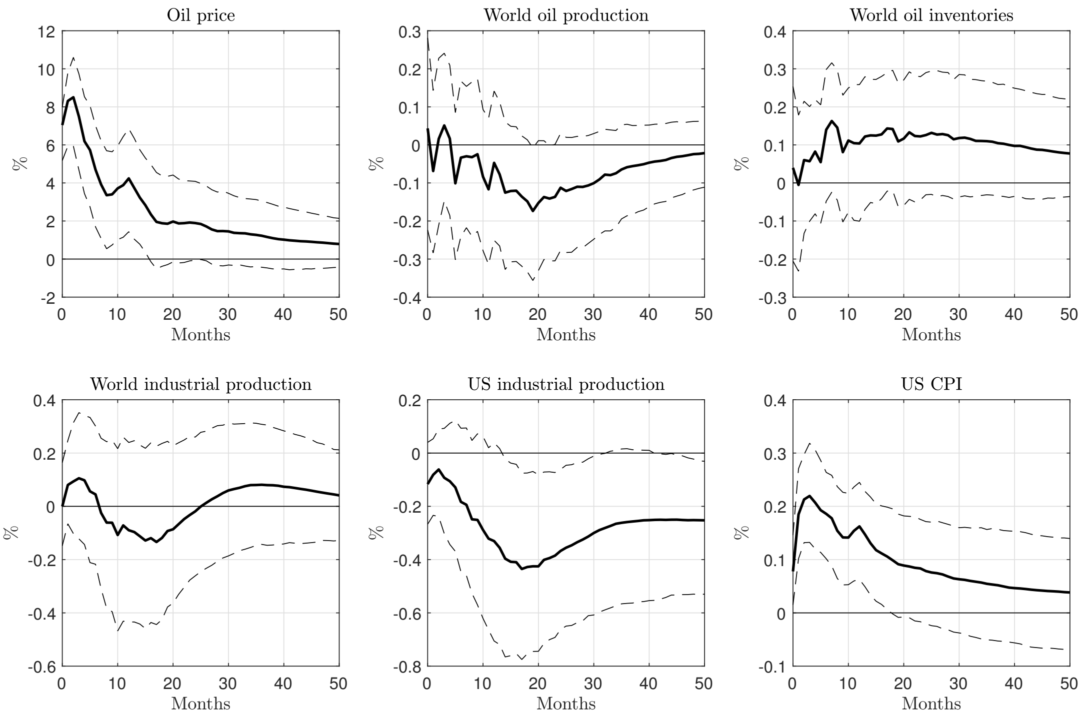
Figure C.19: IRFs based on Kilian and Murphy's (2014) model specification. The dashed lines are pointwise 68% confidence bands.



First stage regression: F: 14.51, robust F: 11.71, R^2: 2.88%, Adjusted R^2: 2.68%

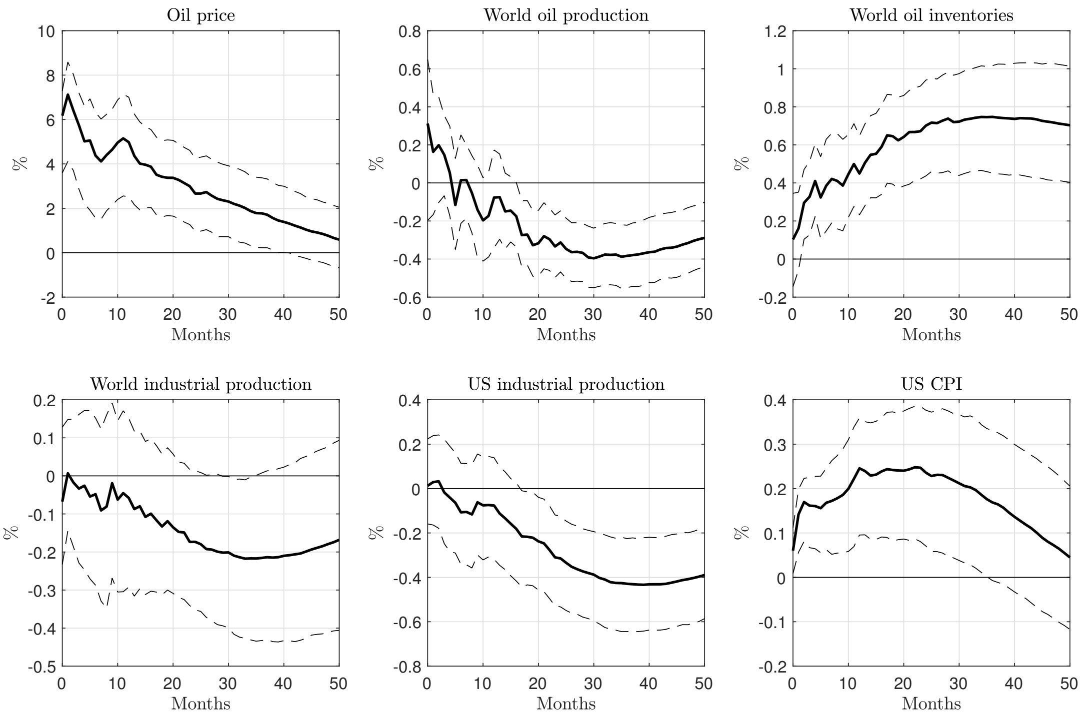
Figure C.20: IRFs based on Baumeister and Hamilton's (2019) model specification. The dashed lines are pointwise 68% confidence bands.

Sample and data frequency. Figures C.21-C.23 present the results from the subsample analyses. It turns out that the results do not seem to be driven by a specific sample choice.



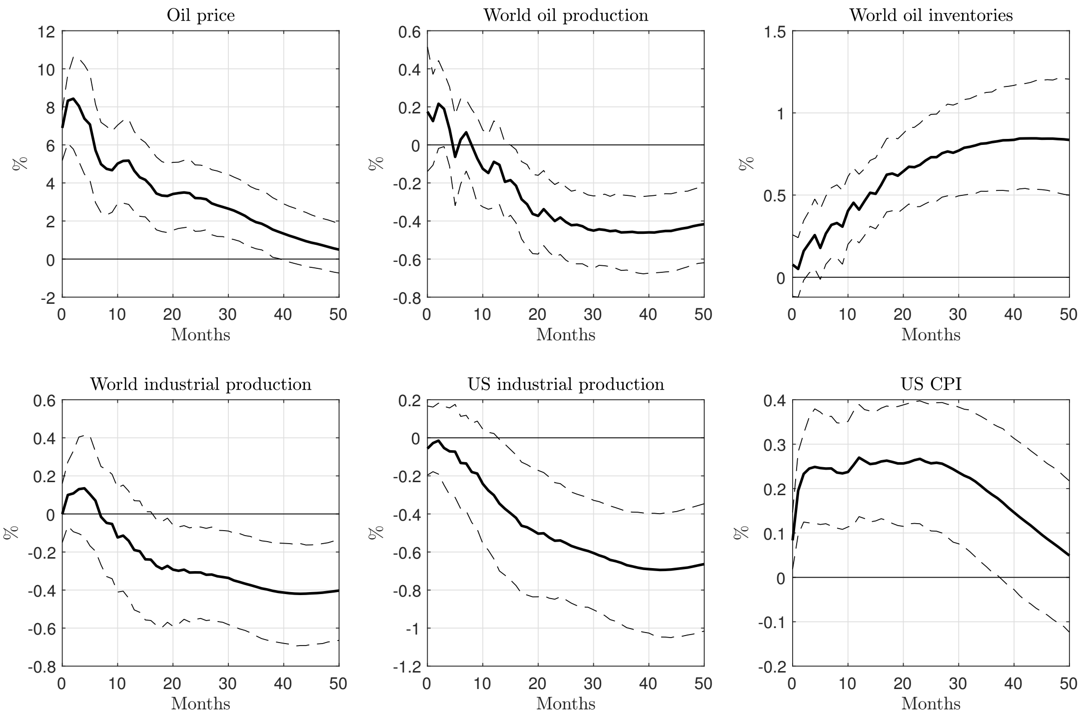
First stage regression: F: 19.90, robust F: 11.59, R^2: 4.58%, Adjusted R^2: 4.35%

Figure C.21: Sensitivity with respect to the estimation sample: 1982M3-2017M12.



First stage regression: F: 17.52, robust F: 9.74, R^2: 4.27%, Adjusted R^2: 4.02%

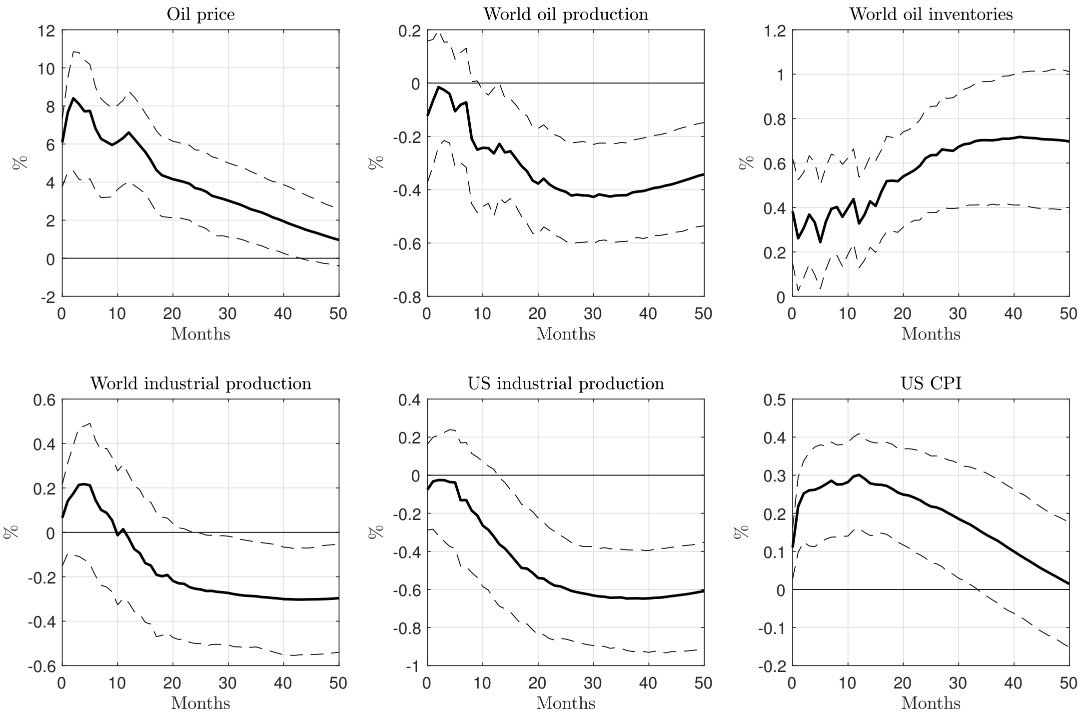
Figure C.22: Sensitivity with respect to the estimation sample: 1974M1-2007M12.



First stage regression: F: 28.93, robust F: 19.35, R^2: 6.32%, Adjusted R^2: 6.10%

Figure C.23: Sensitivity with respect to the estimation sample: 1974M1-2010M12.

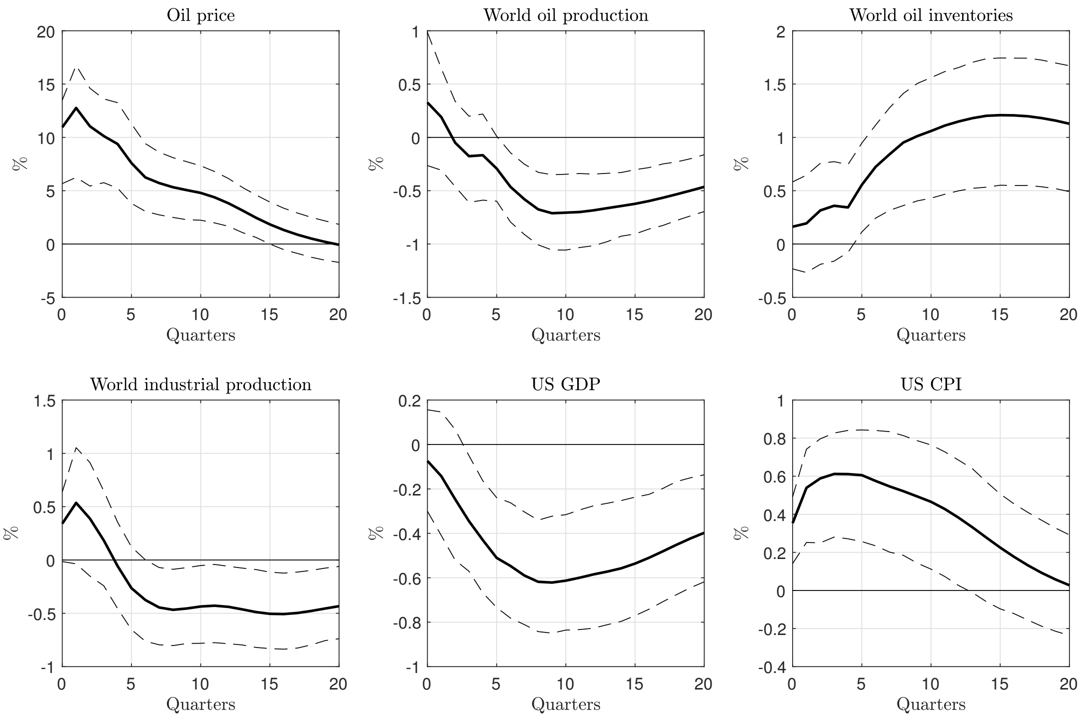
I also check the sensitivity with respect to the instrument sample. In particular, I test whether the results are robust if I exclude the first years of the instrument when the futures markets were not as liquid. Figure C.24 depicts the IRFs using an instrument that starts in 1990. Again, the results are robust.



First stage regression: F: 13.27, robust F: 6.77, R^2: 2.52%, Adjusted R^2: 2.33%

Figure C.24: Sensitivity with respect to the instrument sample: 1990M1-2015M12.

Finally, I check the robustness with respect to the data frequency. Figure C.25 presents the results based on the quarterly VAR. To aggregate the instrument to the quarterly frequency, I sum it over the respective months. The results are very similar to the monthly evidence.



First stage regression: F: 9.16, robust F: 5.98, R^2: 5.14%, Adjusted R^2: 4.58%

Figure C.25: Baseline VAR based on quarterly data.

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