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

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Abstract

This paper studies how changes in oil supply expectations affect the oil price and the macroeconomy. Using a novel identification design, exploiting institutional features of OPEC and high-frequency data, 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. This question is challenging because oil prices are endogenous and respond to global economic developments. To provide an answer, one has to account for the underlying drivers of the oil price. From a policy perspective, oil supply shocks are of particular interest because of their stagflationary effects. However, as oil prices are inherently forward-looking, not only current supply matters but also expectations about the future.

In this paper, I propose a novel approach to identify a shock to oil supply expectations, exploiting institutional features of the Organization of the Petroleum Exporting Countries (OPEC) and information contained in high-frequency data. The idea is to use 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, we 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 structural *oil supply news* shock.

Preview of results. 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 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. This evidence supports the notion that changes in expectations about future supply can have powerful effects even if current oil production does not move.

I also show that oil supply news contribute meaningfully to historical variations in the oil price. This finding illustrates that major episodes in oil markets, such as political events in the Middle East, impact the oil price not only through their effect on current supply but, crucially, also through changes in supply expectations.

Studying various propagation channels of oil supply news, I find that oil price and inflation expectations rise significantly while uncertainty indicators are hardly affected—consistent with the interpretation of a news shock. Interestingly, the rise in inflation expectations is stronger for households, in line with recent evidence by Coibion and Gorodnichenko (2015). Oil supply news also lead to a significant increase in consumer prices even after excluding energy prices, a persistent fall in consumption and investment expenditures, rising unemployment, and falling stock market indices. The U.S. dollar depreciates significantly, especially against the currencies of net oil exporting countries. Consistent with the exchange rate response, the terms of trade deteriorates substantially and the trade balance falls into 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 identification design, the estimation approach, as well as the model specification and sample period. In particular, the results are robust to accounting for background noise over the event window. An heteroskedasticity-based estimator produces consistent results, even though the responses are less precisely estimated. I also show that the results are robust to estimating the responses to the identified shock using local projections and controlling for OPEC's global demand forecasts in the construction of the instrument.

Related literature and contribution. This paper is related to a long literature studying the macroeconomic effects of oil price shocks. 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; 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, 2020).

A difficult problem in this context is the identification of the expectations-driven component. A number of studies have addressed this problem by augmenting the standard oil market model 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 as other proxies for oil shocks, including Hamilton's (2003) quantitative dummies or Kilian's (2008) production shortfall series, have been found to be weak instruments (Stock and Watson, 2012).

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*a*, among others). The idea is to isolate the impact of monetary policy news by measuring the change in asset prices in a tight window around policy announcements. To account for confounding news over the event window, Rigobon and Sack (2004) propose to exploit the heteroskedasticity in the data. Gertler and Karadi (2015) use these high-frequency surprises as an external instrument in a monetary SVAR to estimate the macroeconomic effects of monetary policy 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.[1]

My results indicate that news about future oil supply can have a meaningful impact on the oil price and macroeconomic aggregates even if current production does not move. 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,

[1]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, 2020).

Walker, and Yang, 2013). Only recently, there has been a growing interest in other kinds of news, such as news about future monetary policy or production possibilities (Nakamura and Steinsson, 2018*a*; Arezki, Ramey, and Sheng, 2017). Gambetti and Moretti (2017) also identify a news shock in the oil market but focus on the role of news versus noise shocks.

Outline. The paper proceeds 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 diagnostic tests. In Section 3, I cover the econometric approach. Section 4 presents the results. I start by analyzing the instrument strength before discussing the effects of oil supply news on the oil market and the macroeconomy, the contribution to historical episodes in the oil market, the wider effects and propagation channels as well as the quantitative importance. 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 observations. The oil market is dominated by a big player, OPEC, that makes regular announcements about its production plans. 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 oil market and OPEC. The global oil market 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 (based on data from the US Energy Information Administration EIA for 2016). It was founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. Since then, other countries joined the organization and currently, OPEC has a total of 13 member countries.[2]

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

According to the statutes, OPEC's 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 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 quotas for its members.[3] The conference ordinarily meets twice a year on pre-scheduled dates at its headquarters in Vienna but if necessary it can call for extraordinary meetings on 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'.[4]

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 and analysts 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

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

[4]This language is routinely used in the financial press, see e.g. `https://www.ft.com/content/1f84e444-9ceb-11e5-8ce1-f6219b685d74` [Online; accessed 17-Jan-2020].

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 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 liquid futures markets. The 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 for the following reasons. First, it is the relevant benchmark for pricing oil in the U.S., the country of primary interest in this paper. Second, the WTI crude futures have the longest available history as they were the first traded contracts on crude oil. They trade at the New York Mercantile Exchange (NYMEX) and were introduced in 1983. Finally, it 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. Oil futures prices are a natural, market-based proxy for oil price expectations and thus well suited to measure the impact of OPEC announcements. However, in principle, we could use any asset price that is sufficiently responsive.

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 global economic conditions can be plausibly ruled out because they are known and already priced by the market prior to the announcement and are unlikely to change within the tight window. Assuming that risk premia are constant over the window, 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 (see Appendix A.4 for some illustrative examples). It should also be noted that these problems are not specific to the oil market. As is by now well known monetary policy also transmits through an information channel that conflates high-frequency measures of monetary policy shocks (Nakamura and Steinsson, 2018*a*; Miranda-Agrippino and Ricco, 2018*b*; Jarociński and Karadi, 2020). 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 very political and does not respond as systematically to economic developments. However, to address this concern more rigorously, I construct an informationally robust surprise series by purging the original series from 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 surprise series, I collected OPEC press releases for the period 1983-2017. There were a total of 119 announcements made during this period. An overview of all announcement dates and 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 futures 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.

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 (see Pindyck, 2001). Assuming that the risk premium does not change within the daily window around the announcement, i.e. $RP^h_{t,d} = RP^h_{t,d-1}$, we 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.

A crucial choice in high-frequency identification concerns the size of the event window. There is a trade-off between capturing the entire response to the announcement and background noise, i.e. the threat of other news confounding the response.

Common window choices range from 30-minutes to multiple days. To balance this trade-off, I decided to use a daily window. I am not using a 30-minutes window as is common in the monetary policy literature because of the following reasons. First and foremost, OPEC does not communicate as clearly as a central bank and markets usually need some time to process what an announcement means. Second, there are also practical limitations. Official announcement times are unavailable and even if they were, often information about OPEC's decisions gets leaked before the official announcement. Furthermore, intraday data is only available for the later part of the sample. However, to mitigate concerns about background noise, I will also present results from a heteroskedasticity-based approach that allows for background noise in the surprise series.

Another important issue is the choice of the maturity of the futures contract, h. Given the implementation lag as well as the horizon of OPEC announcements, maturities ranging from one month to one year are the most natural candidates. These contracts are also available for a longer time period and are more liquid and less subject to risk premia (Baumeister and Kilian, 2017). To capture news about future supply at horizons relevant for OPEC announcements, I use a composite measure of oil supply surprises spanning the first year of the oil futures term structure. In particular, I use the first principal component of the surprises based on WTI crude futures contracts with maturities ranging from one month to one year.[5] However, oil futures prices are highly correlated across maturities and using different contracts yields very similar results, see Appendix A.4.

The daily surprises, $Surprise_{t,d}$, are aggregated to a monthly series, $Surprise_t$, as follows. When there is only one announcement in a given month, the monthly surprise is equal to the daily one. When there are multiple announcements, the monthly surprise is the sum of the daily surprises in the given month. When there is no announcement, the monthly surprise takes zero value.

2.3. Diagnostics of the surprise series

The monthly series of oil supply surprises is shown in Figure 1. In the following, I perform a number of diagnostic checks regarding the validity of the series, including a narrative assessment, a placebo exercise to gauge the extent of noise in the series, and tests concerning autocorrelation, forecastability and correlation with other shocks.

Narrative evidence. It turns out that the series accords quite well with the narrative account on some key historical episodes. Below, I discuss three specific

[5] Because OPEC announcements are about future supply, I do not include changes in the spot price or the front futures price. However, including them does not change the results materially.

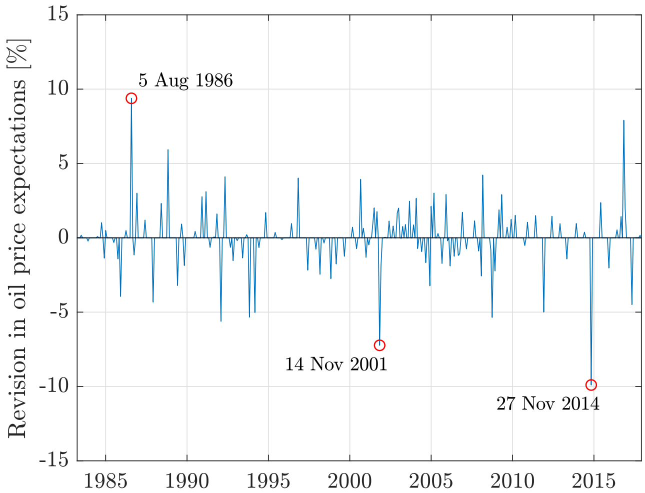


Figure 1: The oil supply surprise series

Notes: This figure shows the oil supply surprise series, constructed as the first principal component from changes in oil futures prices (using the 1-month to 12-month WTI crude contracts) around OPEC announcements, scaled to match the average volatility of the underlying price changes.

instances that are of particular interest as they were associated with substantial revisions in oil price expectations.

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 (Roberts, 2005). As we 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 had 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 (Al-Naimi, 2016). 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 (Lawler, Bakr, and Zhdannikov, 2014).

Background noise. As discussed above, a potential concern regarding the high-frequency approach is that other non-oil related news might affect the oil price during the event window. This concern is particularly relevant since we consider a one-day event window as opposed to a narrower intraday window.

To gauge the extent of background noise in the surprise series, I compare the daily changes in oil futures prices on OPEC announcement days to the price changes on a sample of control days that do not contain an OPEC announcement but are comparable on other dimensions (i.e. same weekday and week in the months prior a given announcement). For an overview of announcement and control dates, see Table B.1 in the Appendix.

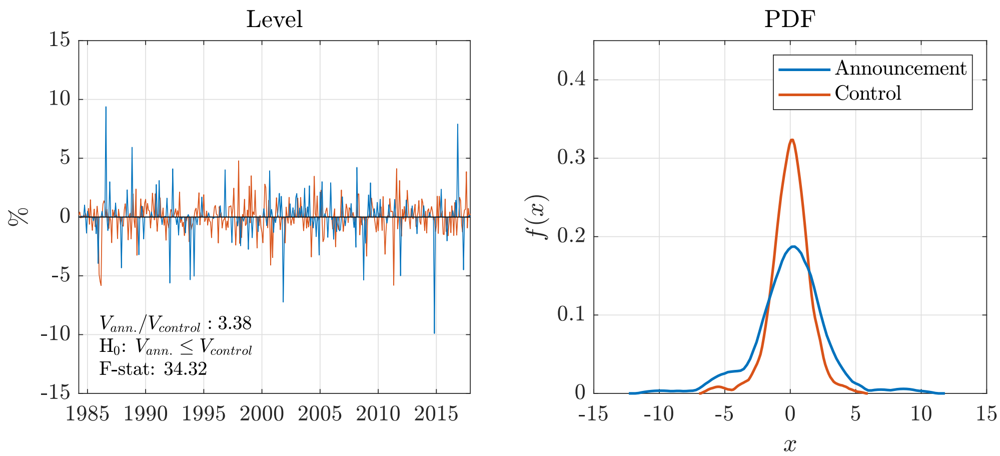


Figure 2: Announcement versus control days

Notes: The figure shows the daily price changes on OPEC announcement and control days. Left panel: Monthly time series. Right panel: Empirical pdf estimated using Epanechnikov kernel.

As shown in Figure 2, the price changes are significantly more volatile on announcement days and also feature some large spikes that are not present in the control sample. In fact, the variance on announcement days is over 3 times higher than on control dates, and a Brown–Forsythe test for the equality of group variances confirms that this difference is highly statistically significant. Another way to see this is by looking at the probability density function, which displays visibly more variance and fatter tails on announcement days. However, there still appears to be non-negligible background noise over the daily event window. This background noise could bias the results, since there is no way of knowing whether these other news are oil supply related or other news. In fact, Nakamura and Steinsson (2018*a*) show in the monetary policy context that background noise can lead to unreliable inference and overstate the statistical precision of the estimates—especially if longer event windows are used. In Section 4.2, I therefore check the sensitivity of the results when accounting for background noise.

Other diagnostic checks. I also perform a number of additional tests concerning the validity of the oil supply surprise series. Desirable properties are that it should not be autocorrelated, forecastable nor correlated with other structural shocks (Ramey, 2016).

Inspecting the autocorrelation function of the series, I find 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 study 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, uncertainty, financial, monetary, or fiscal policy shocks affecting the oil price. The corresponding figures and tables can be found in Appendix A.1. Overall, this evidence supports the validity of the oil supply surprise series.

3. Econometric approach

As illustrated above, the oil supply surprise series has many desirable properties. Nonetheless, it is only an imperfect shock measure because it does not capture all relevant instances of oil supply news and may be subject to measurement error.

Thus, I will not use it as a direct shock measure but as an *instrument*. More specifically, I use it as an external instrument in an otherwise standard oil market VAR model 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. To account for background noise, I alternatively employ an *heteroskedasticity-based* estimator that allows for confounding shocks during the event window (see Rigobon, 2003; Rigobon and Sack, 2004; Nakamura and Steinsson, 2018*a*). The idea is to clean out background noise in the surprise series by comparing movements in oil futures prices during event windows around OPEC announcements to other equally long and otherwise similar event windows that do not contain an OPEC announcement. Identification is then achieved by complementing the VAR residual covariance restrictions with the moment conditions for the external instrument/heteroskedasticity-based estimator.

An alternative approach would be to directly estimate the dynamic causal effects using local projections. However, as discussed in Nakamura and Steinsson (2018*a*), this can be difficult in the context of high-frequency identification because of a *power problem*. Intuitively, macroeconomic variables several periods out in the future are hit by a myriad of other shocks. At the same time, the oil price is an extremely volatile variable itself and the high-frequency surprises account only for a small part of the price fluctuations, rendering the signal-to-noise ratio low. This makes it challenging to directly estimate the macroeconomic effects of high-frequency oil supply surprises without imposing additional structure.[6]

3.1. Framework

Consider the following reduced-form 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 is the lag order, $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations 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.

We postulate that the reduced-form innovations are related to the structural shocks via a linear mapping

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \tag{5}$$

where $\mathbf{S}$ is a non-singular, $n \times n$ structural impact matrix and $\boldsymbol{\varepsilon}_t$ is a $n \times 1$ vector of structural shocks. 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 we have

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

Without loss of generality, let us denote the oil supply news shock as the first shock in the VAR, $\varepsilon_{1,t}$. Our aim is to identify the structural impact vector $\mathbf{s}_1$, which corresponds to the first column of $\mathbf{S}$.

External instruments approach. Under the assumption that the background noise in the surprise series is negligible, we can identify the structural impact vector using the external instruments approach. Identification with external instruments (or "proxies") works as follows. 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, we need

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

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

[6] In Appendix A.2, I show that the results based on local projections using the oil supply surprise series are, at least qualitatively, robust when controlling for enough lags. However, as expected, the estimates are more erratic and less precisely estimated.

where $\varepsilon_{1,t}$ is the oil supply news shock and $\boldsymbol{\varepsilon}_{2:n,t}$ 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. 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 structural impact vector is $\mathbf{s}_1 = (\mathrm{s}_{1,1},\ \ \tilde{\mathbf{s}}'_{2,1}\mathrm{s}_{1,1})'$. The scale $\mathrm{s}_{1,1}$ is then set by a normalization subject to $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$. One approach is to set $\boldsymbol{\Omega} = \mathbf{I}_n$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a one standard deviation positive effect on $\mathrm{y}_{1,t}$. Alternatively, we can set $\boldsymbol{\Omega} = \mathrm{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$ and $\mathrm{s}_{1,1} = x$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a positive effect of magnitude x on $\mathrm{y}_{1,t}$. To facilitate interpretation, I use the latter normalization such that the shock corresponds to a 10 percent increase in the price of oil. Having obtained the impact vector, it is straightforward to compute all objects of interest such as IRFs, FEVDs, the structural shock series and historical decompositions. For more information, see Appendix C.

Heteroskedasticity-based approach. We can also identify the structural impact vector under weaker assumptions, allowing for the presence of other shocks contaminating the instrument over the daily event window. Suppose that movements in the oil futures z_t we observe in the data are governed by both oil supply news and other shocks:

$$z_t = \varepsilon_{1,t} + \sum_{j\neq 1} \varepsilon_{j,t} + v_t,$$

where $\varepsilon_{j,t}$ are other shocks affecting oil futures and $v_t \sim iidN(0, \sigma^2_v)$ captures measurement error such as microstructure noise. Because z_t is also affected by other shocks, it is no longer a valid external instrument. However, we can still identify the structural impact vector by exploiting the heteroskedasticity in the data.

The identifying assumption is that the variance of oil supply news shocks increases at the time of OPEC announcements while the variance of all other shocks is unchanged. Define $R1$ as a sample of OPEC announcement dates and $R2$ as a sample of trading days that do not contain an OPEC announcement but are comparable on other dimensions. $R1$ can be thought of as the treatment and $R2$ as the control sample (see Section 2.3 for more information and some descriptive statistics of the instrument in the treatment and the control sample). The identifying assumptions can then be written as follows

$$\begin{aligned} \sigma^2_{\varepsilon_1,R1} &> \sigma^2_{\varepsilon_1,R2} \\ \sigma^2_{\varepsilon_j,R1} &= \sigma^2_{\varepsilon_j,R2}, \quad \text{for } j = 2,\dots,n. \\ \sigma^2_{v,R1} &= \sigma^2_{v,R2}. \end{aligned} \tag{10}$$

Under these assumptions, the structural impact vector is given by

$$\mathbf{s}_1 = \frac{\mathbb{E}_{R1}[z_t\mathbf{u}_t] - \mathbb{E}_{R2}[z_t\mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2] - \mathbb{E}_{R2}[z_t^2]}. \tag{11}$$

As shown by Rigobon and Sack (2004), we can also obtain this estimator through an IV approach, using $\tilde{\mathbf{z}} = (\mathbf{z}'_{R1},\ -\mathbf{z}'_{R2})'$ as an instrument in a regression of the reduced-form innovations on $\mathbf{z} = (\mathbf{z}'_{R1},\ \mathbf{z}'_{R2})'$. See Appendix D for more details. Reassuringly, the heteroskedasticity-based estimator produces similar results, supporting the validity of the external instruments approach (see Section 4.2).

Additional assumptions. Apart from the identifying restrictions discussed above, there are other important assumptions underlying the VAR approach (Nakamura and Steinsson, 2018*b*). A crucial assumption is invertibility, i.e. that the VAR contains all the relevant information to recover the structural shocks.[7] Non-invertibility is essentially an omitted variable bias problem. If the model does not span the relevant information, some endogenous variation may be falsely attributed to exogenous oil supply news shocks. In Section 5.1, I analyze how the results depend on the information contained in the VAR. I do not find any evidence that the model is informationally insufficient.

Computing impulse responses using the VAR involves additional assumptions. For the responses to be valid, the model has to be an adequate representation of the dynamics of all variables in the system. To analyze how restrictive the dynamic VAR structure is, I alternatively compute the impulse responses to the identified oil supply news shock using local projections à la Jordà (2005). This involves running the following set of regressions

$$y_{i,t+h} = \beta_0^i + \psi_h^i \text{Shock}_t + \boldsymbol{\beta}_h^{i\prime}\mathbf{x}_{t-1} + \xi_{i,t,h}, \tag{12}$$

where $y_{i,t+h}$ is the outcome variable of interest, $\text{Shock}_t = \hat{\varepsilon}_{1,t}$ is the oil supply news

[7]This is the assumption behind (5), which requires that the shocks can be recovered from current and lagged values of the observed data. Identification in VARs with external instruments requires weaker assumptions. In particular, only the shock of interest has to be invertible and the instrument has to satisfy a limited lead-lag exogeneity condition (Miranda-Agrippino and Ricco, 2018*a*).

shock identified from the external instruments VAR, $\mathbf{x}_{t-1}$ is a vector of controls and $\xi_{i,t,h}$ is a potentially serially correlated error term. ψ_h^i is the impulse response to the oil supply news shock of variable i at horizon h.[8] Using the shock identified from the VAR instead of the high-frequency oil supply surprises directly alleviates the challenges regarding statistical power discussed above, as the shock is consistently observed and spans the full sample going back to the 1970s. In Section 4.2, I compare the responses estimated from the VAR and the local projections approach and show that they produce comparable results.

3.2. Comparison to alternative strategies

Traditionally, *oil supply shocks* are thought of as sudden disruptions in the current availability of oil, causing an immediate fall in oil supply, an increase in the oil price and a depletion of inventories. A long literature identified such shocks using different techniques, ranging from the construction of narrative shock series (Hamilton, 2003; Kilian, 2008; Caldara, Cavallo, and Iacoviello, 2019) to SVAR models of the oil market (Kilian, 2009; Kilian and Murphy, 2012; Baumeister and Hamilton, 2019).

This paper proposes a novel focus: *oil supply news shocks*, i.e. expectational shocks about future oil supply. As is well known from the news literature, such shocks can have very different effects from surprise shocks (Beaudry and Portier, 2014). In particular, we 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 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 inventories and the oil price to increase in equilibrium. It is precisely the positive inventory response that makes it possible to disentangle inventory demand from other oil demand and supply shocks in sign-identified VARs.

[8] As controls, I use one lag of the outcome variables of interest to deal with non-stationarity in the data. To compute the confidence bands, I use a parametric bootstrap as in Stock and Watson (2018), accounting for the fact that the oil supply news shock is a generated regressor.

Such inventory demand shocks, however, are a composite of expectations-driven shocks without a clear attribution as to where the shift in expectations is coming from. They capture, among other things, news about future demand and supply, changes in uncertainty, or sentiments (Kilian and Murphy, 2014). With existing techniques, it has not been possible to disentangle the various expectations-driven components. Augmenting the model by oil futures prices would also not help in this respect, as the futures prices are inherently linked to inventories via an arbitrage condition (Hamilton, 2009; Alquist and Kilian, 2010). It is only the combination of the unique *institutional setting* of OPEC in combination with *high-frequency* data that allows me to isolate news about future oil supply.

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).[9] The first four variables are standard in oil market VAR models. I augment these core variables by the two U.S. variables to analyze the effects on the U.S. economy. The data is monthly and spans 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 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. I estimate the VAR in log levels. The lag order is set to 12 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 A.4.

4. Results

4.1. First stage

The main identifying assumption behind the external instruments approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. However, even if this holds, standard inference will not produce reliable results when the instrument and the shock are only weakly

[9] As the oil price indicator, I use the WTI spot price, deflated by U.S. CPI. For world industrial production, I use Baumeister and Hamilton's (2019) index for OECD countries and six other major economies. The results are robust if I use Kilian's (2009) global activity indicator. For world oil inventories, I use a measure based on OECD petroleum stocks, as proposed by Kilian and Murphy (2014). To get rid of the seasonal variation, I perform an adjustment using the Census X13 method.

correlated. 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 (see 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.

Table 1: Tests on instrument strength

	1M	2M	3M	6M	9M	12M	COMP
Coefficient	0.946	0.981	1.016	1.070	1.123	1.098	1.085
F-stat	24.37	24.25	24.33	22.90	22.35	13.58	22.67
F-stat (robust)	12.01	11.86	11.92	11.32	11.11	7.49	10.55
R^2	4.53	4.51	4.52	4.27	4.17	2.57	4.22
R^2 (adjusted)	4.34	4.32	4.33	4.08	3.98	2.38	4.04
Observations	516	516	516	516	516	516	516

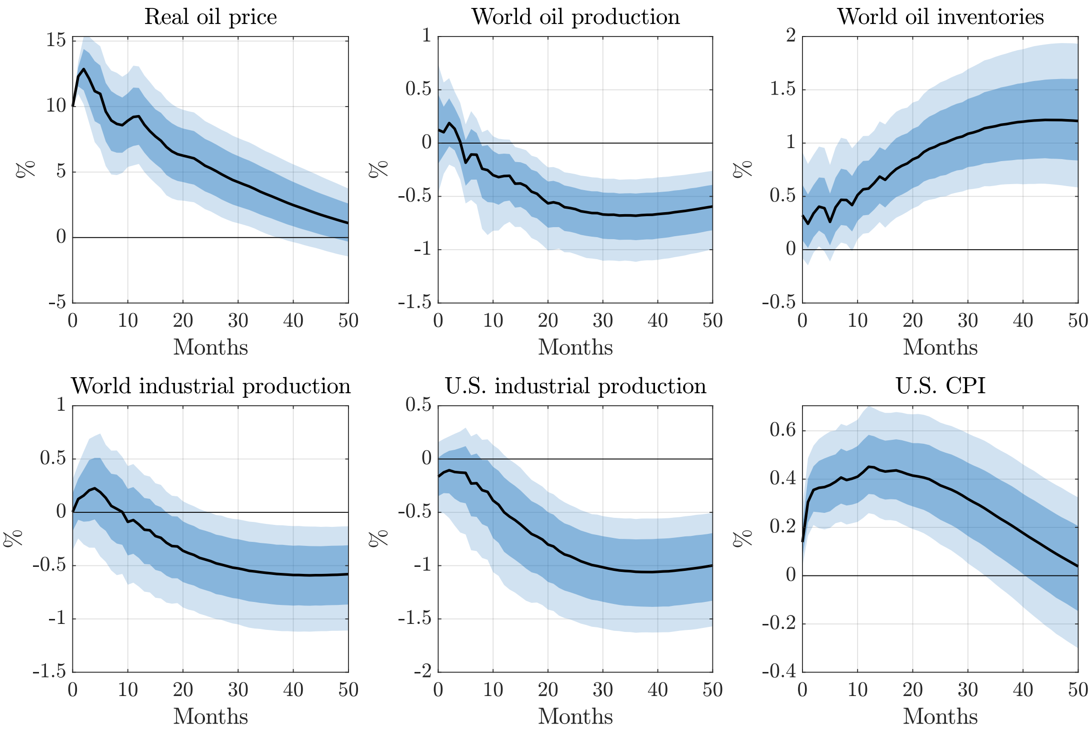
Notes: The table shows the results of the first-stage regressions of the oil price residual $\hat{u}_{1,t}$ on the proxies based on different futures contracts as well as the composite measure spanning the first year of the term structure. F-statistics above 10 indicate strong instruments. Robust F-statistics allow for heteroskedasticity.

Table 1 presents the results on this test for a selection of instruments based on futures contracts with different maturities and the composite measure. In addition to the standard F-statistic, I also report a robust F-statistic allowing for heteroskedasticity. The instruments turn out to be strong with F-statistics safely above the threshold of 10. However, the strength of the instruments tends to decrease with the maturity of the futures contract. For my baseline, the composite measure spanning the first year of the term structure, the F-statistic is 22.7 and the instrument explains about 4.2 percent of the oil price residual. Overall, this evidence suggests that there is no weak instrument problem at hand.

4.2. Effects on the oil market and the macroeconomy

I present now the results from the baseline model, identified using the external instruments approach. Figure 3 shows the impulse responses to the identified oil supply news shock, normalized to increase the real oil price by 10 percent. As all variables are in logs, the responses can be interpreted as elasticities. The solid black lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands based on 10,000 bootstrap replications.[10]

[10] 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.



First stage regression: F: 22.67, robust F: 10.55, R^2: 4.22%, Adjusted R^2: 4.04%

Figure 3: Impulse responses to an oil supply news shock

Notes: Impulse responses to an oil supply news shock, normalized to increase the real price of oil by 10 percent on impact. The solid line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

A negative oil supply news 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 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.

The rise in inventories turns out to be somewhat more persistent than expected. As oil production starts falling, we may expect that some of the accumulated inventories get depleted. In contrast, inventories turn out to be elevated for an extended period. A potential explanation for this finding are speculative or precautionary motives. It is conceivable that negative oil supply news shocks are perceived as a signal for further negative news in the future, which would lead to an overaccumulation of inventories.[11]

Turning to the U.S. economy, we 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.

At the peak of the responses, an oil supply news shock raising the oil price by 10 percent today decreases future oil production by -0.7 percent, increases inventories by 1.2 percent, decreases world and U.S. industrial production by -0.6 and -1 percent, respectively, and increases U.S. consumer prices by 0.4 percent. Thus, oil supply news shocks have effects that are also economically significant.

Accounting for background noise. To analyze the role of background noise, I also present results from the heteroskedasticity-based approach. As shown in Section 2.3, the variance on OPEC announcement days is over 3 times higher than on other comparable trading days and this difference is highly statistically significant. It is exactly this shift in variance that can be exploited for identification, assuming that the shift is driven by the oil supply news shock.[12]

The results from the heteroskedasticity-based approach are shown in the top panel of Figure 4. The impulse responses turn out to be similar to the responses from the external instruments approach: the point estimates are very close to the baseline case, however, all responses turn out to be less precisely estimated. These results suggest that the bias induced by background noise is likely negligible in the present application. However, part of the statistical strength under the external instruments approach appears to come from the stronger identifying assumptions.

The finding that the external instruments and the heteroskedasticity-based approach lead to such similar conclusions may be a bit surprising given the non-trivial background noise documented in Figure 2. A potential explanation for this finding could be that the background noise may in fact largely reflect variation in market beliefs about future oil supply announcements. Alternatively, a large part of the

[11]Also note that a significant part of global oil inventories are strategic petroleum reserves. As such, their behavior does likely not reflect purely commercial motives as these strategic reserves are under government control.

[12]Because the change in variance appears to be large and significant enough, I rely on standard inference and compute the confidence bands using a moving block bootstrap as in the external instruments case. This is also confirmed by looking at the first-stage F-statistic which lies again safely above the threshold of 10.

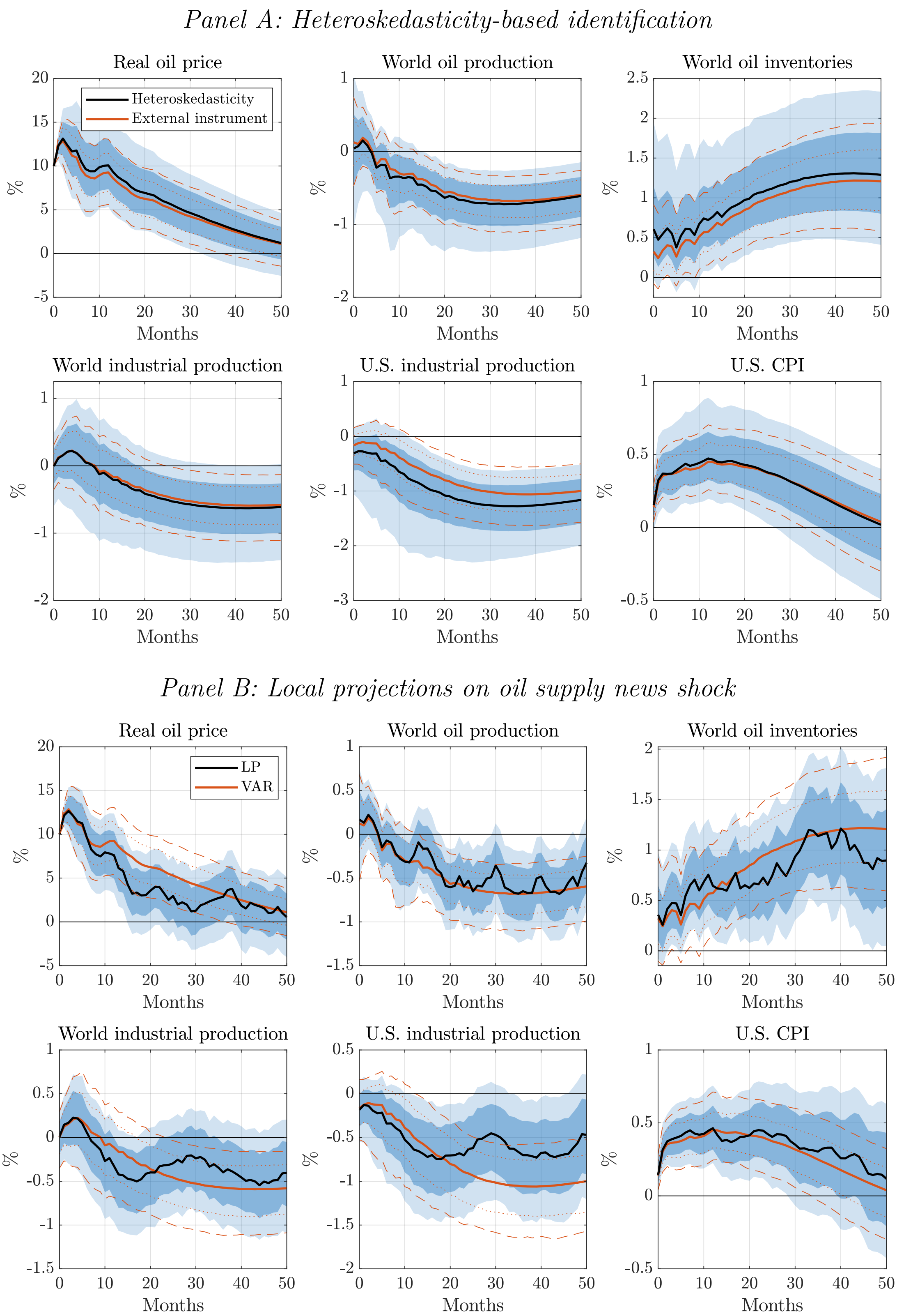


Figure 4: Background noise and dynamic VAR structure

Notes: Impulse responses to an oil supply news shock. Panel A: Identification based on heteroskedasticity (black) and external instruments (red). Panel B: Impulse responses estimated using local projections (black) and VAR (red). The shock is normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas (and dashed/dotted lines) are 68 and 90 percent confidence bands, respectively.

identification may be driven by large shocks and thus, the background noise, while significant in an average sense, turns out to be largely inconsequential. In Appendix A.2, I provide some suggestive evidence for these explanations.

Local projections. As discussed in Section 3, an important assumption behind the VAR approach is that the model is an adequate representation of the dynamic relationships governing the data. Because I am identifying a news shock, many of the impact responses are close to zero. Thus, a significant part of the longer-run dynamics may come from the underlying VAR structure (Nakamura and Steinsson, 2018*b*). To analyze to what extent the results are driven by this structure, I compute the responses to the identified oil supply news shock using local projections.

The results are presented in the bottom panel of Figure 4. Reassuringly, the two approaches to estimate the impulse responses yield comparable results. As expected, the responses based on local projections are more erratic as we do not impose any dynamic restrictions across impulse horizons. At shorter horizons, the responses are virtually identical. At longer horizons, the local projection responses are less persistent and less precisely estimated.

Discussion. The above findings illustrate that oil supply news shocks are quite different from the previously identified oil supply shocks (see e.g. Kilian and Murphy, 2012; 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 responses in any way.

The significant oil price response together with the positive inventory response conforms well with the literature on inventory demand shocks. Importantly, however, oil supply news shocks also lead to a gradual decrease of future oil production—consistent with the interpretation that these shocks capture expectations about future supply shortfalls. In contrast, the medium- to long-run oil production response to inventory demand shocks is unclear a priori, as these shocks are a composite of different expectational shocks, and the empirical evidence is mixed (Kilian and Murphy, 2014; Juvenal and Petrella, 2015; Baumeister and Hamilton, 2019).

4.3. Oil supply news as a driver of the real price of oil

As we have seen, oil supply news shocks can have powerful effects on the economy even if current oil production does not move. However, an equally interesting question is how important oil supply news are in explaining historical episodes in oil markets. To analyze this question, I perform a historical decomposition of the oil price.

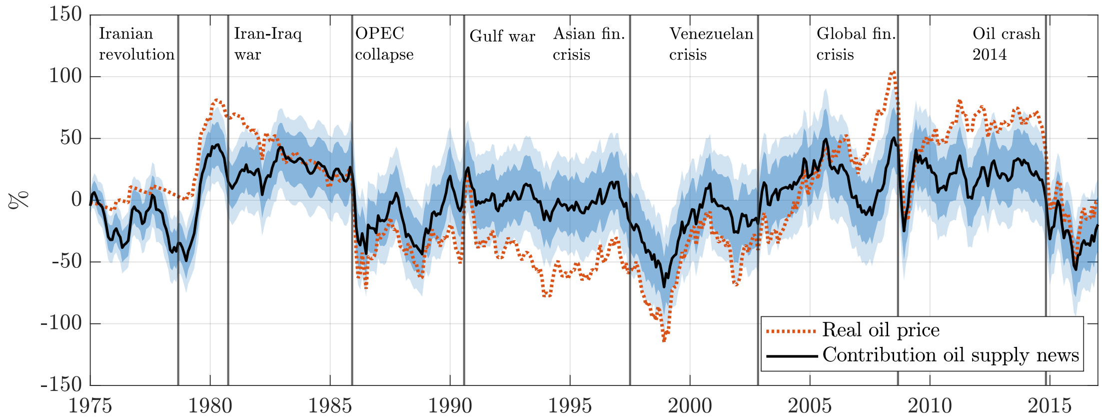


Figure 5: Historical decomposition of the real price of oil

Notes: The table shows the cumulative historical contribution of oil supply news shocks to the real price of oil and the 68 and 90 percent confidence bands together with the actual real price of oil (in percent deviations from mean). The vertical bars indicate major events in oil markets, notably the outbreak of the Iranian revolution in 1978M9, the start of the Iran–Iraq war in 1980M9, the collapse of OPEC in 1985M12, the outbreak of the Persian Gulf war in 1990M8, the Asian financial crisis of 1997M7, the Venezuelan crisis in 2002M11, the outbreak of the global financial crisis in 2008M9 and the recent collapse of the oil price starting in 2014M6.

Figure 5 shows the cumulative historical contribution of oil supply news shocks to the real price of oil together with the actual real price of oil for the period 1975-2017. It is important to stress in this context that the decomposition does not capture the contribution of all oil supply news on historical oil prices; it only captures the part that correlates with OPEC production announcements. Despite this caveat, we can immediately see from the figure that oil supply news shocks—in the sense of this paper—have contributed meaningfully to historical variations in the price of oil.

It is instructive to focus on specific episodes. For example, the rapid rise in the oil price in the late 1970s after the Iranian Revolution turns out to be strongly driven by lower oil supply expectations. Developments in the Middle East, such as Khomeini's arrival in Iran or the Iranian hostage crisis, fueled expectations of a war and the destruction of oil fields in the region. These expectational effects peaked prior to the outbreak of the Iran-Iraq war and then subsided in the early 1980s.

Similarly, the sharp drop in the oil price in late 1985 when OPEC essentially collapsed was mainly driven by higher supply expectations. This is also consistent with the notion that the OPEC breakdown was initially perceived irreversible. We can also see that OPEC's attempts to reunite in 1986-1987 lowered oil supply expectations, which in turn contributed to the partial reversal of the oil price. The spike in the real price of oil in 1990–1991 after the invasion of Kuwait can also at least partially be explained by negative oil supply news.

Subsequently, the contribution of supply expectations had been more muted up until the Asian crisis of 1997–1998, when the real price of oil fell to an all-time low. Oil supply expectations have contributed quite significantly to this fall and the subsequent reverse amid OPEC's efforts to coordinate production (see Yergin, 2011, for more information on these episodes).

In contrast, oil supply news did not contribute significantly to the surge in the real price of oil between 2003 and mid-2008, which has been mainly attributed to higher global demand (Kilian, 2009). However, oil supply news also played a role in more recent years. For instance, a significant part of the collapse in oil prices starting in June 2014 can be attributed to higher oil supply expectations, as Saudi Arabia announced its intention not to counter the increasing supply from other producers and OPEC subsequently decided to maintain their production ceiling in spite of the increasing glut (Arezki and Blanchard, 2015).

These results show that political events in the Middle East affect the real price of oil not only through changes in current supply but also, and perhaps more importantly, through changes in supply expectations. This finding is important as it speaks to the debate on the role of demand and supply shocks driving the price of oil.

4.4. Wider effects and propagation channels

To get a better understanding of how oil supply news shocks transmit to the macroeconomy, I analyze the effects on a wide range of macroeconomic and financial variables. To compute the impulse responses, I augment the baseline VAR by one variable at a time.[13] This also allows me to gauge the importance of various propagation channels.

[13] This is a flexible approach to estimate the effects on a wide range of variables without resorting to shrinkage techniques (Beaudry and Portier, 2014; Gertler and Karadi, 2015). If possible, the augmented VARs are estimated on the same sample as the baseline. If the series does not span the original sample, I adjust the sample accordingly. Some variables are only available at the quarterly frequency. To map out the responses of these variables, I use a quarterly version of the VAR (see also Section 5). Information on data sources and coverage can be found in Appendix B.2.

Expectations and uncertainty. Oil supply news are shocks to oil supply expectations. As such, we would expect that they strongly propagate through expectational variables such as oil price and inflation expectations. This turns out to be the case. The top panel of Figure 6 shows the responses of oil price and inflation expectations over the following year. Both measures increase significantly. The effects are particularly pronounced for oil price expectations but the effects on inflation expectations are also significant, in line with recent evidence by Wong (2015).

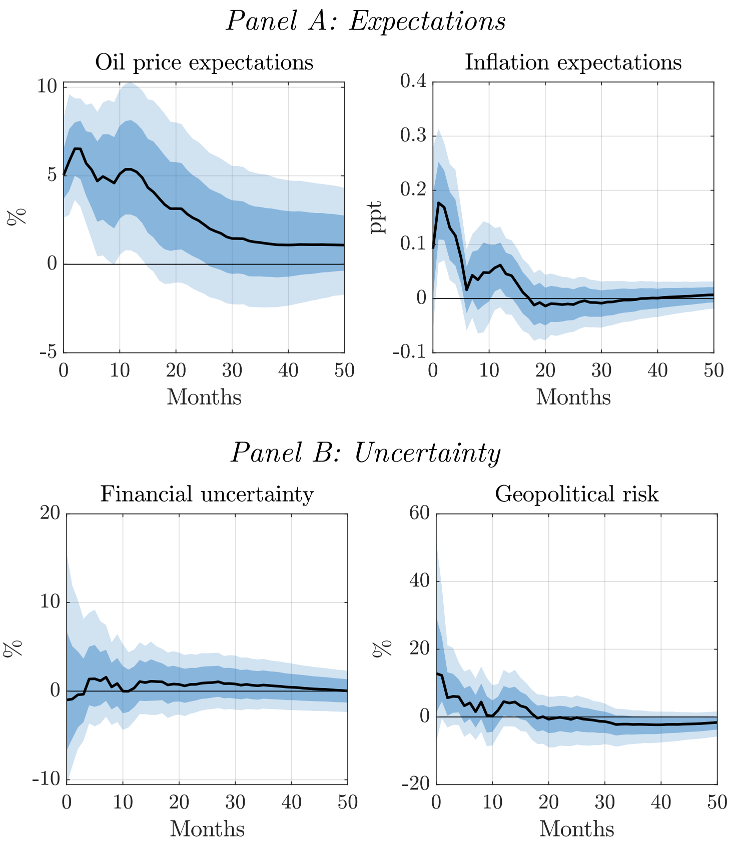


Figure 6: Expectations versus uncertainty

Notes: Responses of different measures of expectations (Panel A) and uncertainty (Panel B). The oil price expectations are from Baumeister and Kilian (2017) and the inflation expectations from the Michigan Surveys of Consumers (median). Both series capture expectations over the next 12 months. Financial uncertainty is measured by the VXO index from Bloom (2009) and the GPR index is from Caldara and Iacoviello (2018).

In the bottom panel of Figure 6, I show the responses of different measures of uncertainty, including financial uncertainty and geopolitical risk.[14] Interestingly, the uncertainty measures are not strongly affected: financial uncertainty does not respond at all while geopolitical risks increase slightly in the short run but the response is barely significant. The strong response of price expectations together

[14]The ideal variable would be a measure of oil price uncertainty. Unfortunately, such a measure is unavailable for a long enough sample and thus, I use the VXO and geopolitical risk as proxies.

with the muted effects on uncertainty is consistent with the interpretation of a news shock. In contrast, for uncertainty shocks, which can have similar effects to news shocks (see Alquist and Kilian, 2010), we would expect a stronger response of uncertainty indicators and no expected changes on future oil production.

The results on inflation expectations are of particular interest because of their central role for macroeconomic policy. However, measuring inflation expectations is challenging. An alternative to the Michigan survey is the Survey of Professional Forecasters (SPF), which captures expectations of professional forecasters as opposed to households. Analyzing potential differences between these measures is interesting. 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 from the augmented quarterly models.

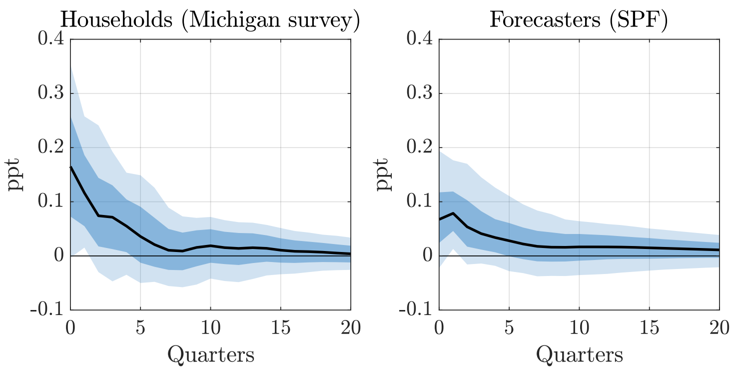


Figure 7: Inflation expectations

Figure 7 shows that the effects differ quite substantially 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. These findings are consistent with 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 oil prices. They also speak to 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).

Consumer prices. Oil supply news shocks lead to a significant and persistent increase in consumer prices. How much of this increase is driven by energy prices and how are other price categories affected? Figure 8 shows the responses of different components of the CPI, including the core, energy, non-durables, durables, and services components, together with the headline response from the baseline model. As expected, energy prices respond strongly. The response is front-loaded and mirrors the oil price response. In contrast, core consumer prices do not react significantly in the short run but then start to rise persistently as well.

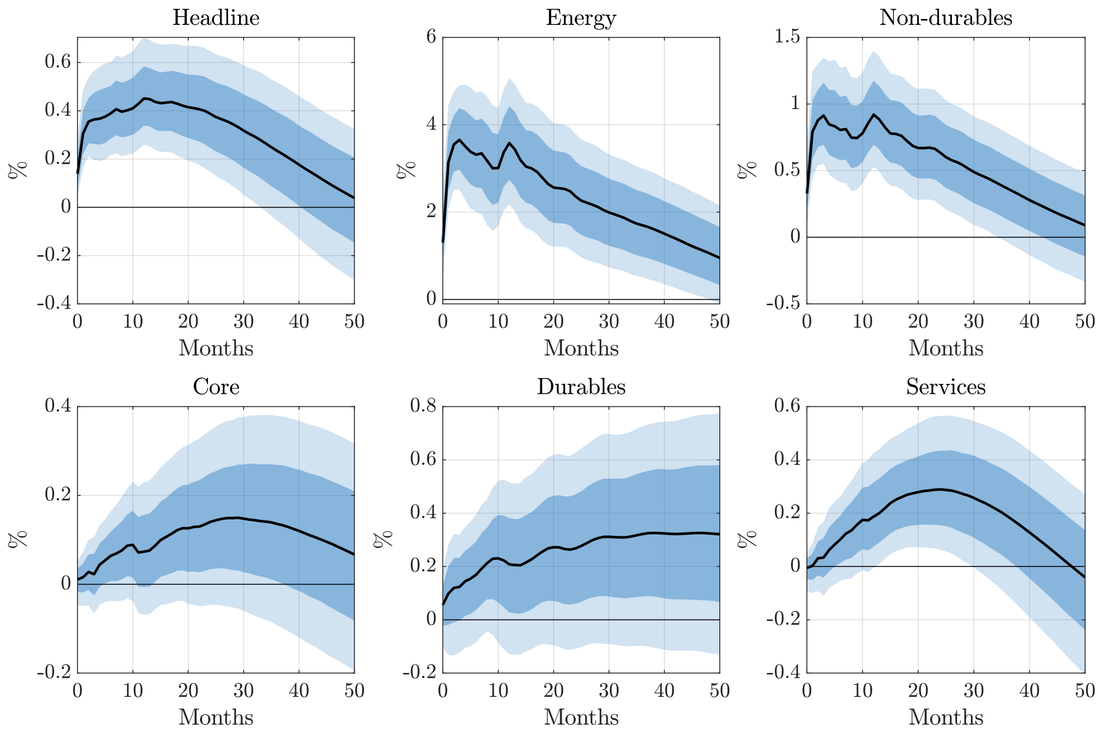


Figure 8: Consumer prices

While I find that all price categories increase significantly, the pass-through is relatively weak quantitatively for most categories. For headline CPI, the pass-through (measured at the peak) is about 4.5 percent, which is in line with previous findings in the literature (see e.g. Gao, Kim, and Saba, 2014). The pass-through is strongest for the energy component, standing at about 35 percent after one year, followed by non-durables (9 percent), durables (2 percent) and services (2 percent). The pass-through turns out to be very quick for energy prices and non-durables but takes longer to materialize for durables and services.

Economic activity. Oil supply news shocks also lead to a 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 9 shows the responses together with the response of industrial production from the baseline model.

Oil supply news shocks have significant effects on economic activity, broadly defined. From the monthly indicators, we can see that the unemployment rate rises

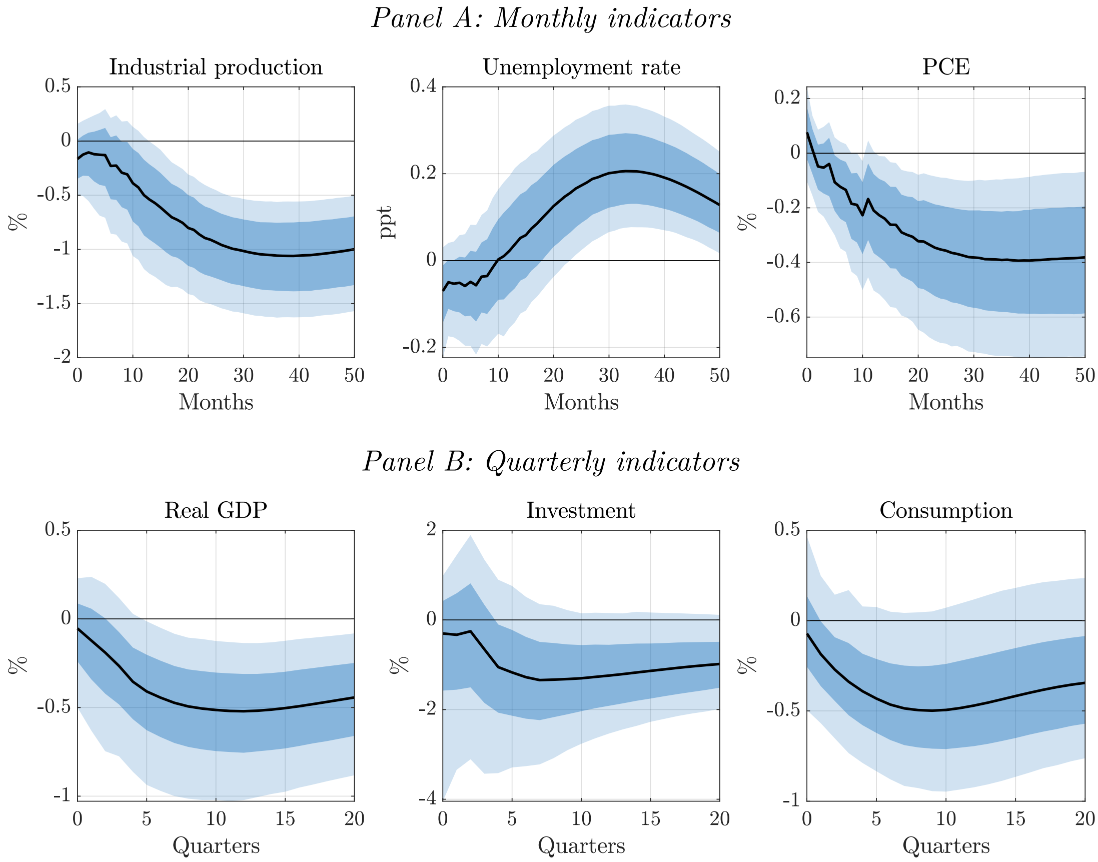


Figure 9: Economic activity

significantly and personal consumption expenditures fall persistently. These adverse economic effects are confirmed by looking at the quarterly measures. Real GDP, investment and consumption all fall, even though the quarterly responses are a bit less precisely estimated. Quantitatively, investment falls by more than consumption, consistent with consumption smoothing behavior on the part of the households.

These results support the notion that a primary transmission channel of oil price shocks is via a reduction in consumption and investment demand, i.e. by disrupting consumers' and firms' spending on goods and services other than energy (Hamilton, 2008; Edelstein and Kilian, 2009). This is confirmed by looking at the responses of different categories of consumption expenditures: 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 (see Figure A.7 in the Appendix). The rise in unemployment may also point to some reallocation frictions in the labor market, further amplifying the recessionary effects (Hamilton, 1988; Davis and Haltiwanger, 2001).

Monetary policy and financial markets. How does monetary policy respond to oil supply news given the significant effects on consumer prices and economic activity? Figure 10 shows the response of the federal funds rate. The monetary policy stance does not change significantly on impact and only starts tightening after about a year when core consumer prices start rising. However, the response is barely significant, reflecting the policy trade-off that the inflationary pressures paired with the economic downturn introduce. The sluggish, weakly positive response is consistent with the notion that the Fed follows a monetary reaction function placing a positive weight on inflation and a positive but smaller weight on output.

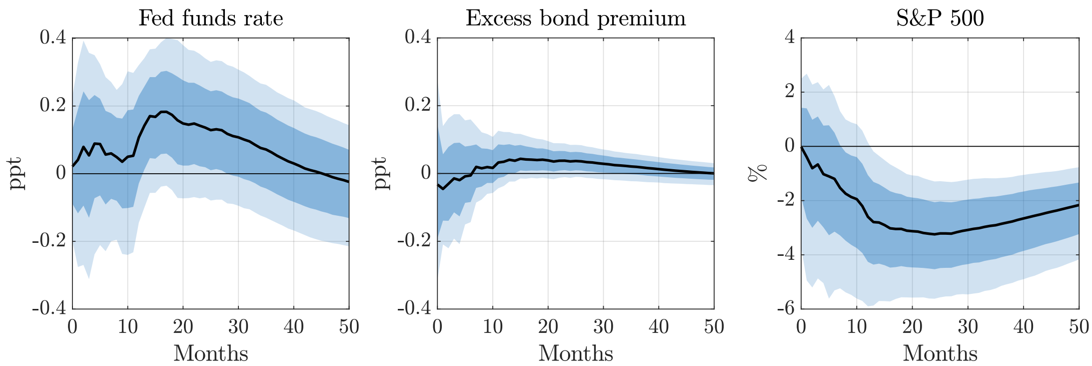


Figure 10: Monetary policy and financial markets

To analyze whether oil supply news also transmit through financial channels, I study the responses of stock and credit markets. The stock market takes a significant hit as the expected fall in demand decreases future cash flows. Interestingly, however, the S&P 500 index only falls gradually. To examine this further, I analyze the stock price response for a selection of different industries. At the industry level, I find more of an immediate response. There is also significant heterogeneity: while the utility sector booms in the short run, the automobile, retail and transportation industries fall immediately and persistently (see Figure A.8 in the Appendix). This underlying heterogeneity may explain the sluggish fall observed in the composite index. Credit markets, on the other hand, do not seem to be significantly affected. Credit conditions, as measured by Gilchrist and Zakrajšek's (2012) excess bond premium, remain broadly unchanged. Thus, oil supply news shocks do not seem to have further amplifying effects through a financial accelerator channel.

A potential concern in this context is that monetary policy may contaminate the baseline results, given how temporally correlated oil and monetary policy shocks are in certain periods of time (Hoover and Perez, 1994). Reassuringly, controlling for the federal funds rate does not affect the baseline responses materially. Moreover, the oil supply surprise series turns out to be uncorrelated with standard measures of monetary policy shocks (see Figure A.9 and Table A.3 in the Appendix). Thus, the high-frequency approach appears to be successful in disentangling such episodes.

Exchange rates and trade. 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 the two variables.

Figure 11 displays the responses for the narrow and broad U.S. nominal effective exchange rate together with a selection of bilateral exchange rates. 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.

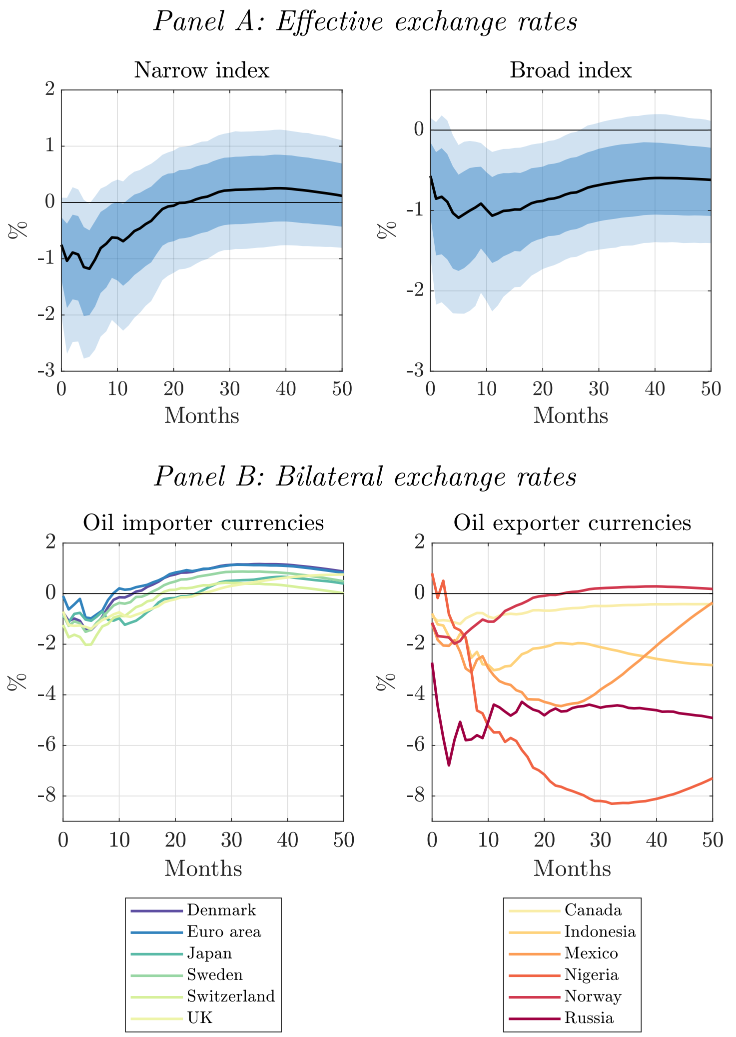


Figure 11: Nominal exchange rates

Notes: Responses of nominal effective (Panel A) and bilateral exchange rates (Panel B). All exchange rates are defined such that an increase corresponds to an appreciation 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.

An analysis of bilateral exchange rates reveals that 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. While the currencies of major oil importers, such as the Euro area or Japan, appreciate against the dollar in the short run but then tend to depreciate in the longer run, the currencies of major oil exporters, such as Russia, Mexico or Indonesia, appreciate persistently, in line with previous findings by Lizardo and Mollick (2010). Overall, these results help to reconcile the strong negative correlation between oil prices and the dollar (Klitgaard, Pesenti, and Wang, 2019).

Since the U.S. has historically been one of the major oil importers, we would also expect that the shock leads to a significant deterioration of the terms of trade. This intuition is confirmed. As shown in the left panel of Figure 12, the U.S. terms of trade deteriorates significantly and persistently. This result supports the notion that oil price shocks transmit as shocks to the terms of trade and also helps to reconcile the significant fall in consumption expenditures documented above (see also Baumeister, Kilian, and Zhou, 2018, for a discussion of this point).

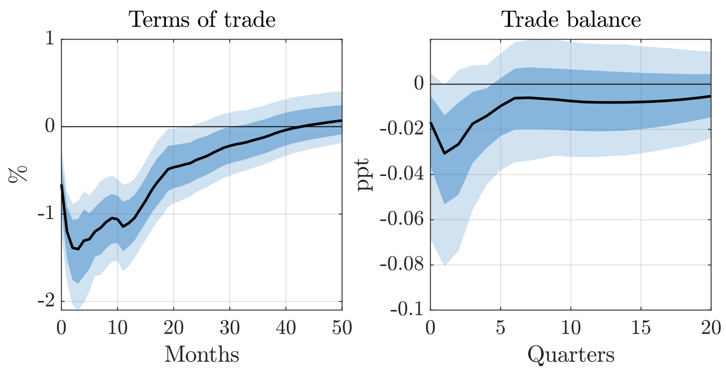


Figure 12: Trade

The significant depreciation together with the impaired terms of trade likely have an effect on the balance of trade. The right panel of Figure 12 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 supply news shocks affect demand. Quantitatively, however, this 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 important question is: how much of the historical variation in these variables can oil supply news account for? To analyze this, 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. We 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 and inventories at longer horizons. In contrast, the contribution to world industrial production turns out to be 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.

Table 2: Forecast error variance decomposition

Global variables and exchange rates:	Oil price	Oil production	Oil inventories	World IP	NEER
0	0.68	0.01	0.06	0.03	0.12
	[0.20, 0.88]	[0.00, 0.12]	[0.00, 0.28]	[0.00, 0.19]	[0.00, 0.43]
12	0.39	0.04	0.07	0.01	0.21
	[0.09, 0.63]	[0.01, 0.11]	[0.01, 0.29]	[0.00, 0.08]	[0.03, 0.51]
24	0.35	0.08	0.13	0.02	0.26
	[0.09, 0.60]	[0.02, 0.22]	[0.02, 0.41]	[0.00, 0.09]	[0.05, 0.54]
48	0.32	0.12	0.21	0.05	0.24
	[0.09, 0.58]	[0.04, 0.30]	[0.03, 0.53]	[0.01, 0.18]	[0.05, 0.52]
U.S. variables:	IP	CPI	FFR	VXO	TOT
0	0.07	0.08	0.00	0.00	0.15
	[0.00, 0.33]	[0.00, 0.38]	[0.00, 0.03]	[0.00, 0.01]	[0.01, 0.42]
12	0.05	0.17	0.00	0.00	0.41
	[0.00, 0.25]	[0.02, 0.46]	[0.00, 0.02]	[0.00, 0.02]	[0.12, 0.64]
24	0.07	0.15	0.04	0.02	0.36
	[0.01, 0.28]	[0.02, 0.45]	[0.01, 0.12]	[0.00, 0.06]	[0.12, 0.57]
48	0.19	0.11	0.03	0.02	0.33
	[0.04, 0.43]	[0.02, 0.38]	[0.01, 0.10]	[0.01, 0.05]	[0.12, 0.53]

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 90 percent confidence intervals are displayed in brackets.

Turning to the U.S. variables, I find that oil supply news shocks explain a meaningful portion of the variation in economic activity and prices. 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 the CPI. At the one year horizon, the contribution is close to 20 percent. They also explain a significant share of the effective exchange rate and the terms of trade. In contrast, the contributions to the fed funds rate and the VXO turn out to be negligible.

Taking stock. 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 can have significant effects on the macroeconomy and contribute meaningfully to historical variations in economic activity and prices.

5. Sensitivity analysis

In this section, I perform a comprehensive series of robustness checks. In particular, I perform some additional tests regarding the identification strategy and analyze the sensitivity with respect to the model specification and data choices. Some further checks and all corresponding tables and figures can be found in Appendix A.

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. To address this concern, I construct an informationally robust oil supply surprise series, following a strategy that has been previously employed in the monetary literature (Romer and Romer, 2004; Miranda-Agrippino and Ricco, 2018*b*). To this end, I collected global oil demand forecasts from OPEC monthly oil market reports.[15] 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:

$$Surprise_m = \alpha_0 + \sum_{j=-1}^{2} \theta_j F_m^{opec} y_{q+j} + \sum_{j=-1}^{2} \varphi_j [F_m^{opec} y_{q+j} - F_{m-1}^{opec} y_{q+j}] + IRS_m, \quad (13)$$

[15]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 A.4.

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}.[16] Note that because the monthly reports are only available from 2001, the informationally robust surprise series spans a shorter sample.

Figure A.11 in the Appendix depicts the results using the baseline and the informationally robust instrument. The responses are very similar apart from a few minor, statistically insignificant differences. These results suggest that there is no strong information channel confounding high-frequency oil supply surprises.

Another concern is that many of the OPEC conference meetings were extraordinary meetings scheduled in response to macroeconomic or geopolitical developments. This might induce 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. The responses, shown in Figure A.12, turn out to be very similar. However, the instrument turns out to be weaker as about 40 percent of the announcements had to be dropped, leaving less variation for identification.

News and surprise shocks. The crucial assumption behind the external instruments approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other shocks. This condition might be violated when the oil supply surprise series does not only correlate with the oil supply news shock but also with the unanticipated oil supply shock. To investigate this concern, I identify the oil supply news and the surprise shock jointly. To this end, I use Kilian's (2008) production shortfall series[17] and my oil supply surprise series as instruments. In the case with two shocks and two instruments, the instrument moment restrictions are not sufficient. To achieve identification, I have to impose one additional restriction. I assume that the oil supply news shock does not affect oil production within the first month.[18]

The results are shown in Figure A.13. The response to the news shock is very similar to the baseline, suggesting that we can identify the oil supply news shock without controlling for the surprise shock. The responses for the oil supply surprise 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.

[16] 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.

[17] More specifically, I use the extended version by Bastianin and Manera (2018).

[18] This can be justified with the 30 day implementation lag of OPEC announcements. Details on identification with two instruments and two shocks can be found in Appendix C.2.

However, the first stage turns out to be considerably weaker and thus the results should be interpreted with a grain of salt.

Invertibility. A necessary condition for identification is that the VAR spans all relevant information. As a robustness check, I analyze how the information contained in the VAR affects the results. In the context of news shocks, Ramey (2016) argues that using high-frequency surprises as instruments can be problematic without including them in the model. However, including the oil supply surprise series as the first variable in a recursive VAR, as proposed by Ramey (2011) and Plagborg-Møller and Wolf (2019), yields comparable results. Some responses are weaker and less precisely estimated but none of the differences are statistically significant (see Figure A.14). I also analyze how the baseline results are affected when including the additional variables in Section 4.4. As shown in Figure A.15, the results are robust to the inclusion of additional variables.

5.2. Specification and data choices

Model specification. An important issue in VAR models is the selection of appropriate indicators. Two crucial choices concern the global activity and the oil price indicator. In the baseline model, I use Baumeister and Hamilton's (2019) world industrial production index, because it is easily interpretable and directly comparable to its U.S. counterpart. An often used alternative is Kilian's (2009) global activity index. The results using this alternative activity indicator are very similar. As the oil price indicator, I use the WTI spot price, deflated by the U.S. CPI, to ensure maximum instrument strength. Another commonly used measure is the real refiner acquisition cost of imported crude. Using this alternative measure produces consistent results (see Figures A.18-A.19). In the Appendix A.4, I also analyze the robustness with respect to other specification choices including the lag order, variable transformations and deterministics. The responses turn out to be robust with respect to all of these choices.

Sample and data frequency. It is conceivable that over the relatively long sample period structural relationships have evolved over time. To examine this, I estimate the model for different subsamples. Figure A.27 presents the results based on a shorter estimation sample starting in 1982M4, which marks the start of the instrument and coincides with the beginning of the Great Moderation. The responses turn out to be less persistent and some responses are weaker. Qualitatively, however, the results are very similar. I also show that excluding the Great Recession or the shale oil revolution does not change the results materially (see Figures A.28-A.29).

The baseline VAR runs on monthly data. To analyze the effects on quarterly variables of interest, such as real GDP, I have to aggregate the VAR to the quarterly frequency. The baseline responses turn out to be very similar (see Figure A.31). As expected, however, the instrument is weaker reflecting the lower signal-to-noise ratio.

6. Conclusion

An important driver of oil prices are expectations about future oil market conditions. Identifying shocks to expectations, however, is a daunting task. This paper proposes a novel identification strategy to shed light on the role of oil supply expectations. Using variation in futures prices in a tight window around OPEC announcements, I identify an oil supply news shock. Oil supply news shocks have significant effects on the macroeconomy and contribute meaningfully to historical variations in economic activity and prices, pointing to a strong channel operating through supply expectations.

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Online Appendix

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

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Contents

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A. Charts, tables and additional sensitivity checks

In this Appendix, I present additional tables and figures, and sensitivity checks that are not featured in the main body of the paper. The subappendices refer to the corresponding sections in the main text.

A.1. Diagnostics of the surprise series

As discussed in the paper, I perform a number of additional validity checks on the surprise series. In the main text, I already discussed the role of background noise in detail. A related concern is that there may be other news confounding the surprise series in a systematic way. Even though this seems unlikely given the rather irregular schedule of OPEC conferences, I checked whether any of the major U.S. news releases systematically occur on OPEC dates. Table A.1 confirms that no release systematically overlaps with OPEC announcements. For all these releases, there are only a few, random overlaps. Excluding the overlapping dates in constructing the instrument does also not change the results materially.[1]

Table A.1: U.S. macroeconomic news announcements

Announcement	Observations	Source	Dates	Frequency	Overlaps
GDP	114	BEA	4/1987-12/2017	quarterly	2
Unemployment rate	466	BLS	1/1983-12/2017	monthly	5
Nonfarm payrolls	405	BLS	2/1985-12/2017	monthly	5
Retail sales	385	BC	12/1986-12/2017	monthly	3
Industrial production	385	FRB	12/1986-12/2017	monthly	6
Durable goods orders	464	BC	4/1983-12/2017	monthly	10
Trade balance	384	BEA	12/1986-12/2017	monthly	8
CPI	467	BLS	1/1983-12/2017	monthly	3
PPI	385	BLS	12/1986-12/2017	monthly	5
FOMC	305	FED	3/1983-12/2017	six-week	4

Notes: The table shows information on major U.S. macroeconomic news announcements on activity, prices and monetary policy together with the number of instances in which they coincide with OPEC announcement days. The U.S. news data are from Kilian and Vega (2011), extended for the most recent period using Bloomberg.

I also investigate the autocorrelation and forecastability of the surprise series as well as the relation to other shocks from the literature. Figure A.1 depicts the autocorrelation function. We can see that there is no evidence that the series is serially correlated. I also perform a number of Granger causality tests. Table A.2 shows that the series is not forecastable by past macroeconomic or financial vari-

[1] This is in line with the findings by Kilian and Vega (2011), who found that energy prices do not to respond instantaneously to U.S. macroeconomic news.

ables. 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 A.3). 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 supply. Finally, I find that the series is only weakly correlated with the previously identified unanticipated oil supply shocks.

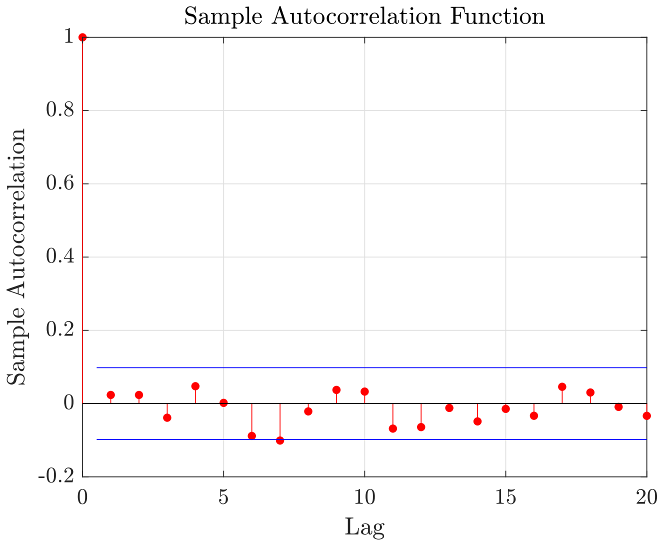


Figure A.1: The autocorrelation function of the oil supply surprise series

Table A.2: Granger causality tests

Variable	p-value
Instrument	0.3749
Oil price	0.4846
World oil production	0.7481
World oil inventories	0.6882
World industrial production	0.9502
US industrial production	0.9342
US CPI	0.7641
Fed funds rate	0.8849
S&P 500	0.1865
NEER	0.7282
Geopolitical risk	0.1526
Joint	0.7342

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 A.3: Correlation with other shock measures

Shock	Source	ρ	p-value	n	Sample
Panel A: Oil shocks					
Oil price	Hamilton (2003)	0.06	0.17	492	1977M01-2017M12
Oil supply	Kilian (2008)	-0.05	0.38	369	1974M01-2004M09
	Caldara, Cavallo, and Iacoviello (2019)	-0.02	0.74	372	1985M01-2015M12
	Baumeister and Hamilton (2019)	-0.08	0.09	515	1975M02-2017M12
	Kilian (2009)	0.08	0.09	395	1975M02-2007M12
Global demand	Kilian (2009)	0.03	0.51	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)	-0.04	0.66	152	1974Q1-2011Q4
	Smets and Wouters (2007)	-0.06	0.50	124	1974Q1-2004Q4
News	Barsky and Sims (2011)	-0.14	0.12	135	1974Q1-2007Q3
	Kurmann and Otrok (2013)	-0.03	0.76	126	1974Q1-2005Q2
	Beaudry and Portier (2014)	0.04	0.61	155	1974Q1-2012Q3
Monetary policy	Gertler and Karadi (2015)	0.07	0.20	324	1990M01-2016M12
	Romer and Romer (2004)	-0.00	0.99	276	1974M01-1996M12
	Smets and Wouters (2007)	0.04	0.64	124	1974Q1-2004Q4
Uncertainty	Bloom (2009)	0.01	0.87	522	1974M07-2017M12
	Baker, Bloom, and Davis (2016)	0.07	0.15	390	1985M07-2017M12
Financial	Gilchrist and Zakrajšek (2012)	0.02	0.70	498	1974M07-2015M12
	Bassett et al. (2014)	0.12	0.30	76	1992Q1-2010Q4
Fiscal policy	Romer and Romer (2010)	0.03	0.77	136	1974Q1-2007Q4
	Ramey (2011)	0.07	0.39	148	1974Q1-2010Q4
	Fisher and Peters (2010)	0.05	0.55	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, the p-value corresponds to the test whether the correlation is different from zero and 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.

A.2. Effects on the oil market and the macroeconomy

A.2.1. Accounting for background noise

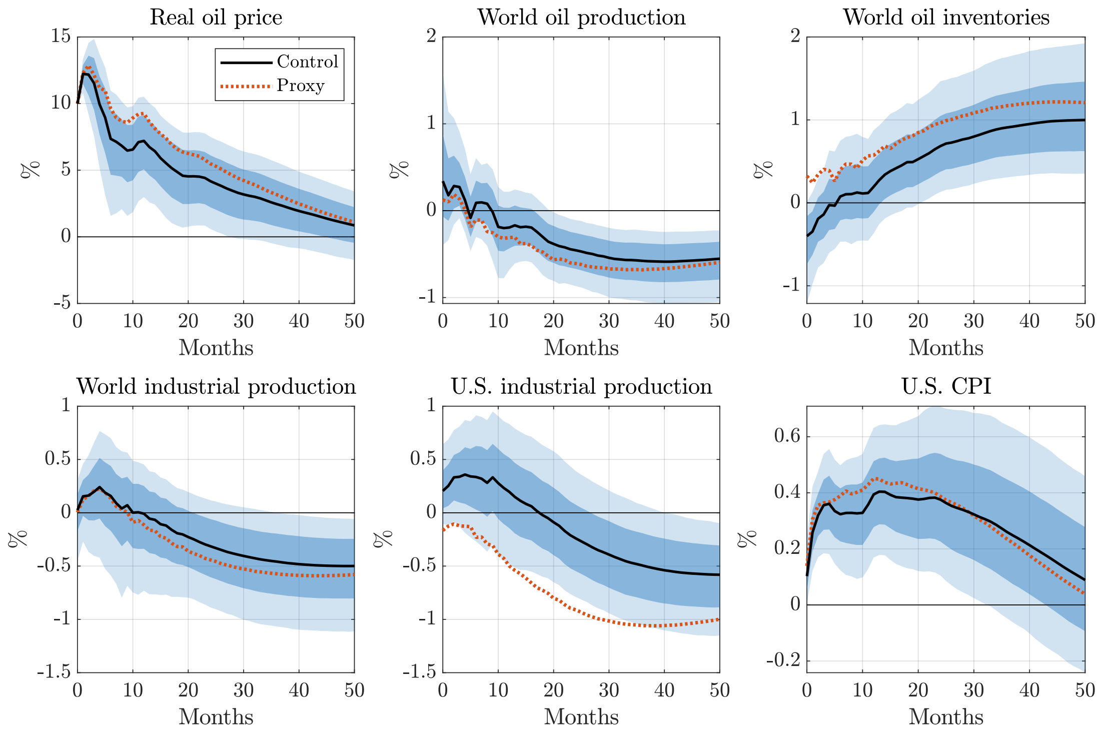
As discussed in the main text, background noise in the oil supply series may lead to unreliable inference and overstate the statistical precision of the estimates. Therefore, it is important to analyze the robustness of the results when accounting for background noise using the heteroskedasticity-based identification strategy.

As shown in the paper, accounting for background noise does not materially change the point estimates but leads to larger sampling uncertainty. This may be a bit surprising, given the non-trivial background noise documented in Figure 2 in the paper. Here, I provide some suggestive evidence for the potential explanations discussed in the main text.

One explanation is that the background noise may in fact largely reflect variation in market beliefs about future oil supply announcements. Studying the impulse responses using the control series as an external instrument provides some suggestive evidence for this explanation. As shown in the top panel of Figure A.2, the responses to the control series display quite some similarity to the baseline responses, even though the responses for inventories and industrial production turn out to be somewhat different. Interestingly, these are also the variables for which we observe the relatively largest differences between the external instruments and the heteroskedasticity-based approach in Figure 4 in the paper. These results are in line with the interpretation that a large part of the background noise is in fact oil supply news related and also accord well with the finding that oil supply news shocks account for the bulk of the fluctuations in oil prices, especially in the short run.

I also explored the explanation that most of the identification could come from large shocks. To this end, I dropped very large surprises (i.e. surprises larger than 7 percent in absolute value) from the treatment sample. From the bottom panel of Figure A.2, we can see that point estimates of the heteroskedasticity-based and the external instruments estimator differ slightly more in this case. However, the most striking difference arises for the confidence bands, which are now substantially wider for the heteroskedasticity-based estimator, consistent with the lower variance ratio. Thus, the large shocks appear to be quite important for the statistical precision of the estimates.

Panel A: Responses to control series



Panel B: Censoring large oil supply surprises

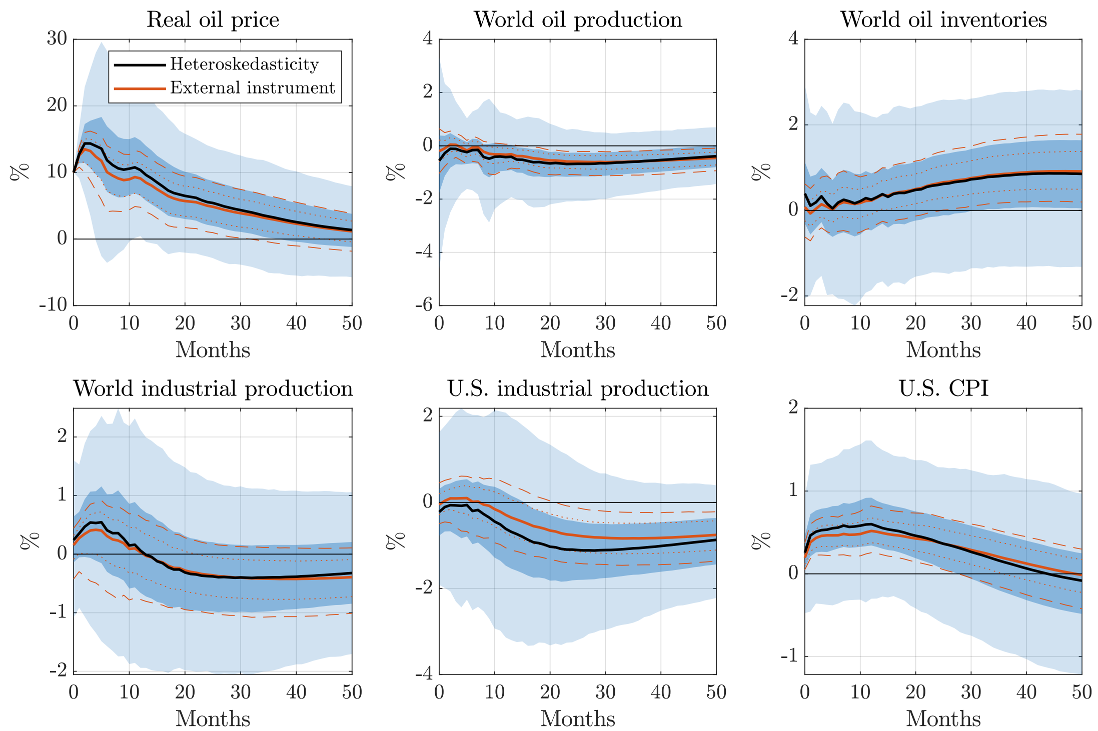


Figure A.2: Understanding heteroskedasticity-based identification

Notes: Investigating potential explanations for the similarity of the heteroskedasticity-based and the external instruments estimator. Panel A: Responses using the control series as an external instrument. Panel B: Responses from the two estimation approaches after censoring large values in the surprise series to zero. The shock is normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands, respectively.

To analyze the role of the dynamic VAR structure, I compute again the impulse responses to the identified shock from the heteroskedasticity-based VAR using local projections. The results are shown in Figure A.3. We can see that the VAR-based and the LP-based impulse responses are very similar but the LP responses are more erratic and less precisely estimated, in line with the findings for the external instruments approach.

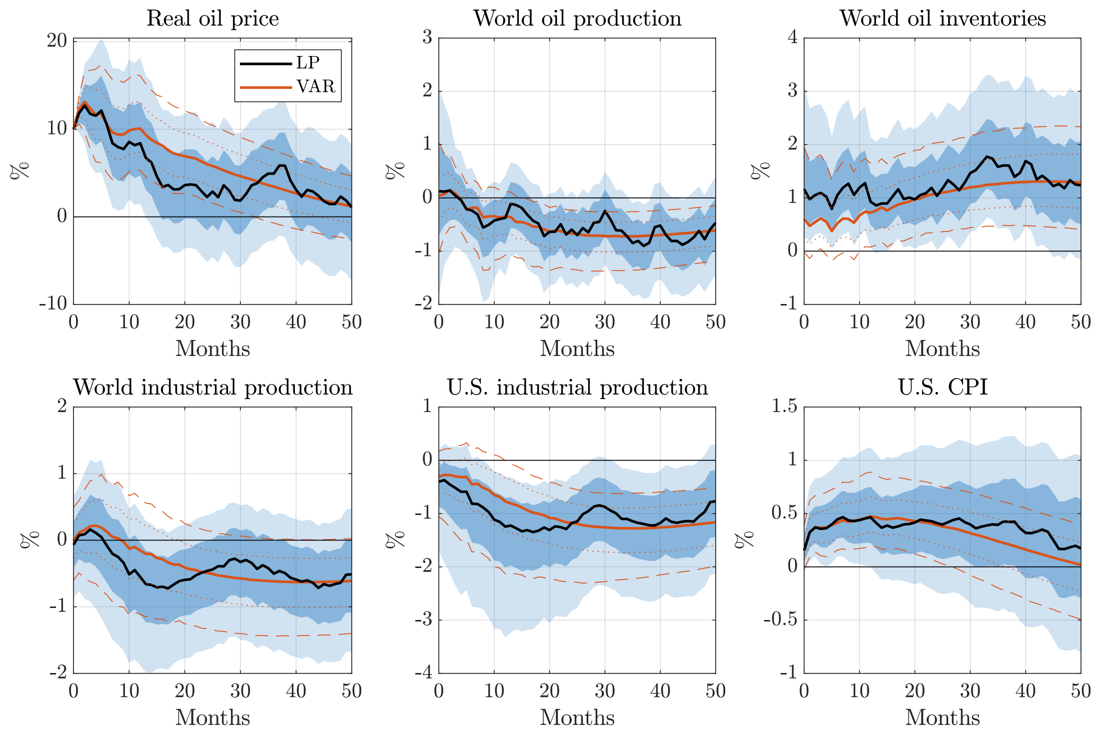


Figure A.3: Local projections on oil supply news shock (heteroskedasticity-based)

Notes: Impulse responses estimated from LPs on the oil supply news shock extracted from the heteroskedasticity-based VAR (black) together with VAR responses (red), normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

A.2.2. Local projections

An alternative approach would be to directly estimate the dynamic causal effects using local projections on the surprise series. However, directly estimating the *macroeconomic* effects of high-frequency surprises is challenging. As discussed in Nakamura and Steinsson (2018), the clean identification via the high-frequency approach often comes at the cost of lower statistical power. Intuitively, macroeconomic variables several months, quarters or even years out are hit by a myriad of shocks. At the same time, the oil price is an extremely volatile variable itself and the high-frequency surprises account only for a small part of the price fluctuations, rendering the signal-to-noise ratio low. This makes it challenging to directly estimate the macroeconomic effects of high-frequency oil supply surprises without imposing additional structure.

Furthermore, the high-frequency surprises are typically only available for a shorter sample than the outcome variables of interest, further reducing statistical power. The VAR approach allows one to estimate the reduced form over a longer sample even if the instrument is only available for a subperiod, improving efficiency at all horizons. By contrast, in the local projection framework there is less scope to improve efficiency (Stock and Watson, 2018).

Local projections-IV. Despite these challenges, I present here the results from a local projections-instrumental variable (LP-IV) approach. To fix ideas, the responses are estimated by running the following set of IV-regressions:

$$y_{i,t+h} = \beta_0^i + \psi_h^i p_t + \boldsymbol{\beta}_h^{i\prime} \mathbf{x}_{t-1} + \xi_{i,t,h}, \tag{1}$$

using the oil supply surprise series z_t as an instrument for the oil price, p_t, where $y_{i,t}$ is the outcome variable of interest and $\mathbf{x}_{t-1}$ is a vector of controls. ψ_h^i is the impulse response to the oil supply news shock of variable i at horizon h.[2]

An important choice in this context concerns the selection of control variables. According to Stock and Watson (2018), there are three reasons for adding control variables. First, and most importantly, the instrument may satisfy the exogeneity condition only after controlling for some observable factors. Second, control variables can help to increase the instrument strength in the first stage by filtering out the effects of past shocks and thus increasing the signal-to noise ratio. Third, and

[2] To increase efficiency, I follow Stock and Watson (2018) and estimate the controls on the full sample and then use the residuals in the local projections for the subsample for which the instrument is available. An alternative would be just to censor the missing values in the instrument to zero and run the local projections including the controls on the full sample (see also Noh, 2019). In practice, I found that these two approaches produce similar results. To compute the bands, I use HAC standard errors with a lag length of 1 plus the horizon in question.

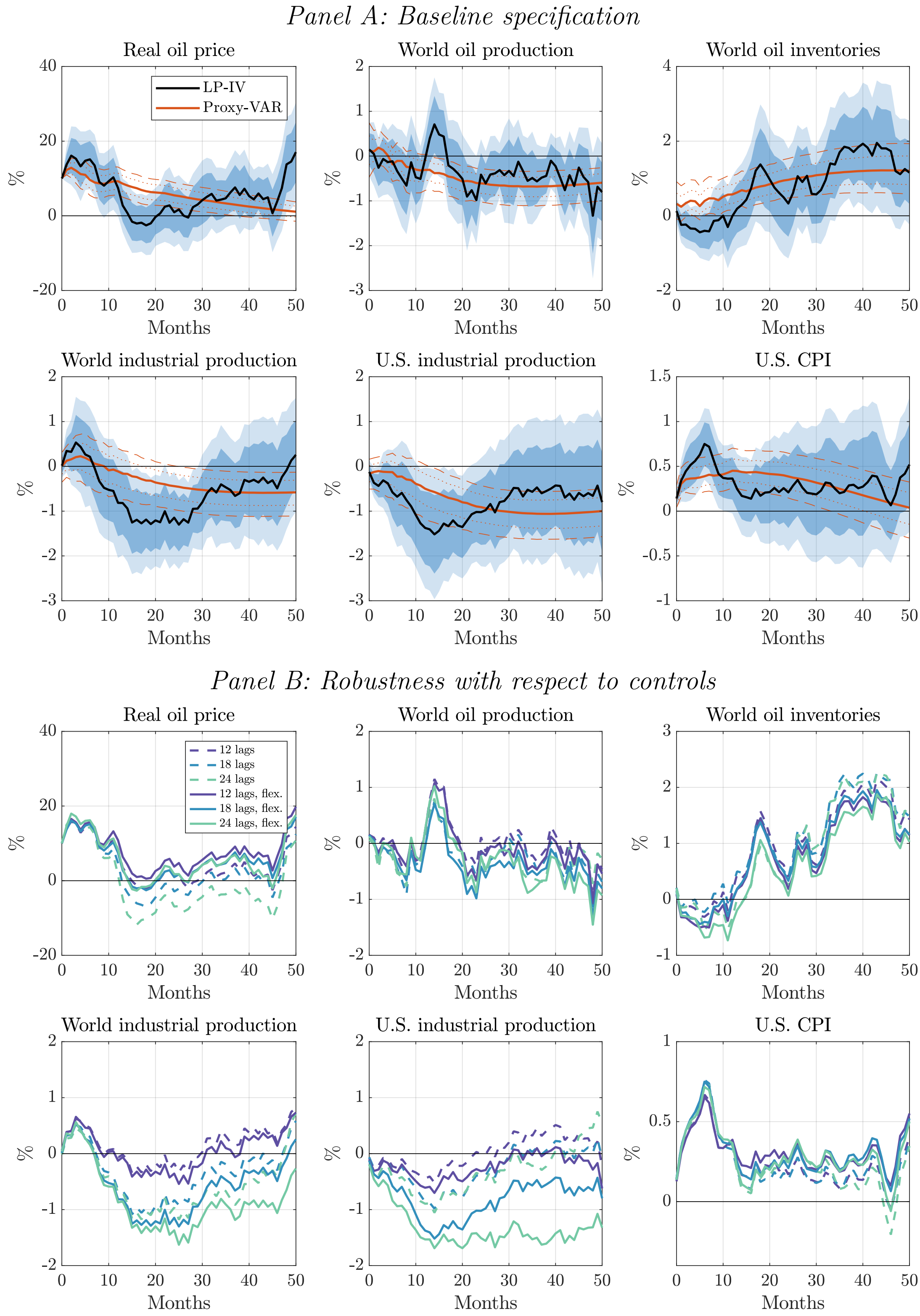


Figure A.4: Local projection-instrumental variable approach

Notes: Impulse responses to the oil supply news shock from LP-IVs. Panel A: Impulse responses from the baseline LP-IV (black) together with the responses from the external instruments VAR (red). The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively. Panel B: Robustness of LP-IV responses with respect to the selection of controls. I consider 12, 18, and 24 lags of all variables as well as the same number of lags in specifications with oil market and U.S. variable specific-controls.

relatedly, including control variables helps to reduce the sampling variance of the IV estimator by reducing the variance of the error term.

Because the oil market is known to feature persistent cycles (see e.g. Herrera and Hamilton, 2004), it is important to control for sufficient lags. However, when choosing the controls, there is always a trade-off between underfitting and overfitting. In light of this, I use a specification with 18 lags and oil market and U.S. variable specific controls as the baseline. For the oil market variables, I only use lags of the oil price, oil production, oil inventories and world industrial production. For the U.S. variables I also control for lags of industrial production and the CPI, respectively. This flexible specification allows to control for sufficient lags of the relevant variables while keeping the model degrees of freedom manageable.

The results are shown in the top panel of Figure A.4. The point estimates turn out to be reasonably similar to the VAR responses: the oil price rises significantly, world oil production tends to fall with a lag, oil inventories increase persistently, world and U.S. industrial production fall and the U.S. CPI increases significantly. However, compared to the VAR, all responses are much more erratic and the standard errors are substantially larger, especially at longer horizons. This had to expected to a certain extent as we impose less structure.

The bottom panel of Figure A.4 analyzes how the results depend on the controls used in the LP-IVs. In particular, I consider 12, 18, and 24 lags of all variables as well as the same number of lags in specifications with oil market and U.S. variable specific-controls. The main takeaway is that the results are not driven by one specific set of controls. Especially at shorter horizons, the responses are all very similar. At longer horizons there is more uncertainty, as is common in time series models. It should be noted, however, that given the relatively large standard errors, the differences across LP specifications are not statistically significant.

Heteroskedasticity-based local projections. We can also implement the heteroskedasticity-based identification strategy in the local projections framework. Define again a sample of treatment (R1) and control periods (R2) and compute the instrument z_t in both periods. As shown in Nakamura and Steinsson (2018), the heteroskedasticity-based estimator is then given by

$$\psi_h^i = \frac{\text{cov}_{R1}(y_{i,t+h}, z_t) - \text{cov}_{R2}(y_{i,t+h}, z_t)}{\text{var}_{R1}(z_t) - \text{var}_{R2}(z_t)}.$$

As in the LP-IVs, I first estimate the coefficients of the control variables on the full sample and then use the residuals $y_{i,t+h}^{\perp}$ in the heteroskedasticity-based estimator for the subsample for which z_t is available. As controls, I use the same set of variables as the baseline LP-IV specification. To compute the impulse responses, I use again the implementation through instrumental variables developed in Rigobon and Sack (2004).[3]

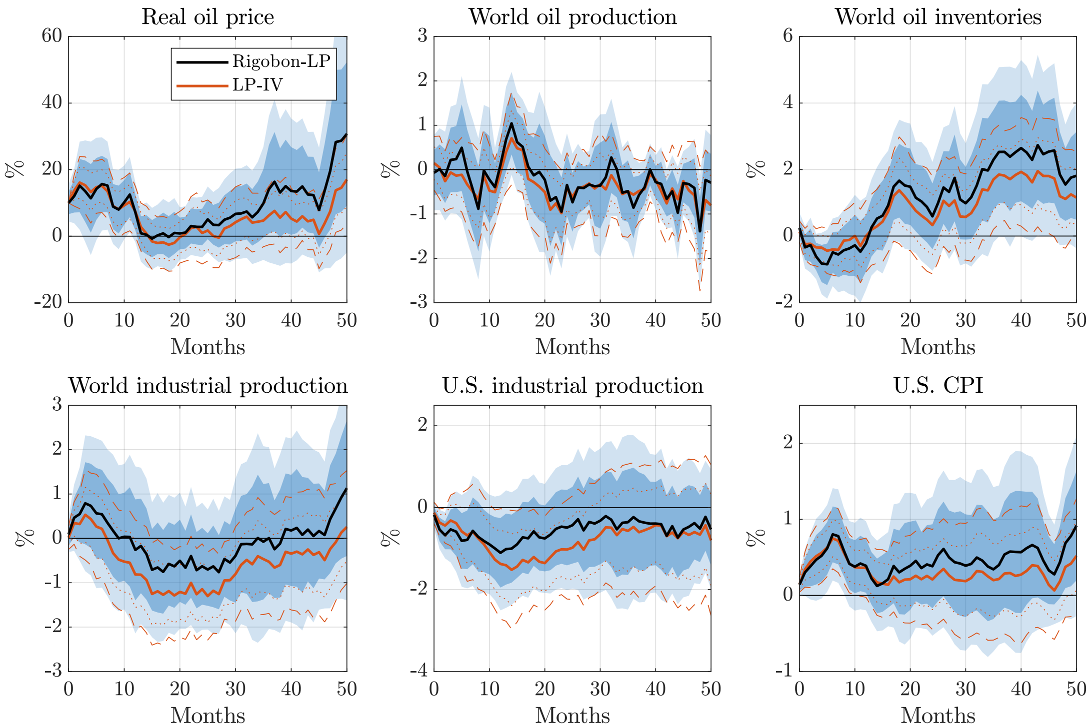


Figure A.5: Heteroskedasticity-based local projections

Notes: Impulse responses to the oil supply news shock from heteroskedasticity-based local projections (black) together with the LP-IV responses (red), normalized to increase the real price of oil by 10 percent on impact. The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.

The results are shown in Figure A.5. We can see that most responses are qualitatively similar to the baseline LP-IVs. However, some of the responses, in particular the world and U.S. industrial production responses, turn out to be a bit weaker. The responses are also less precisely estimated and somewhat more erratic. This probably had to be expected to a certain extent, as the problems regarding statistical power discussed above are likely more acute in this context because the sample has to be further split into a treatment and control sample.

These results illustrate again the challenges of directly estimating the economic effects of high-frequency surprises. An elegant solution to this problem is to focus on variables that move contemporaneously, such as financial variables and survey expectations, as proposed by Nakamura and Steinsson (2018). However, if we are interested in macroeconomic variables, estimating the dynamic causal effects turns

[3]Given that the first-stage F-statistic confirmed that the change in variance is significant enough, I use standard HAC errors to compute the bands, as in the LP-IV regressions.

out to be challenging without imposing additional structure, as illustrated above.

A.2.3. Model uncertainty

To study in more detail how the modeling choice affects the results, I perform a systematic evaluation of the role of model uncertainty. In particular, I consider the following models:

1. External instruments VAR
2. LP using shock from external instruments VAR
3. LP-IV using oil supply surprise series
4. Heteroskedasticity-based VAR
5. LP using shock from heteroskedasticity-based VAR
6. Heteroskedasticity-based LP
7. Heteroskedasticity-based VAR (implementation as in Wright 2012)

For each model, I further consider a specification with 12, 18, and 24 lags as controls.[4]

The results are presented in Figure A.6. Depicted is the minimum and the maximum of the point estimates of all the models and specifications considered, together with the baseline responses from the external instruments VAR. We can see that qualitatively, the conclusions of the paper turn out to be robust with respect to the modeling choice. For the large majority of models, an oil supply news shock leads to an immediate increase in the oil price, a gradual decrease in world oil production, an increase in world oil inventories, a fall in world and U.S. industrial production, and an increase in U.S. CPI.[5] Quantitatively, however, the effects can differ quite a bit across the different models: some models are associated with somewhat weaker effects while other models feature effects that are more pronounced. Importantly, the baseline responses appear to lie mostly somewhere in between.

[4]For the LP specifications, I use both general and variable-specific controls as discussed above.

[5]The only qualitative difference emerges for world and U.S. industrial production, which according to a few specifications that impose very little structure merely changes or even tends to increase slightly. However, in light of the power problems discussed above and the large uncertainty around these estimates, these results should be interpreted with a grain of salt.

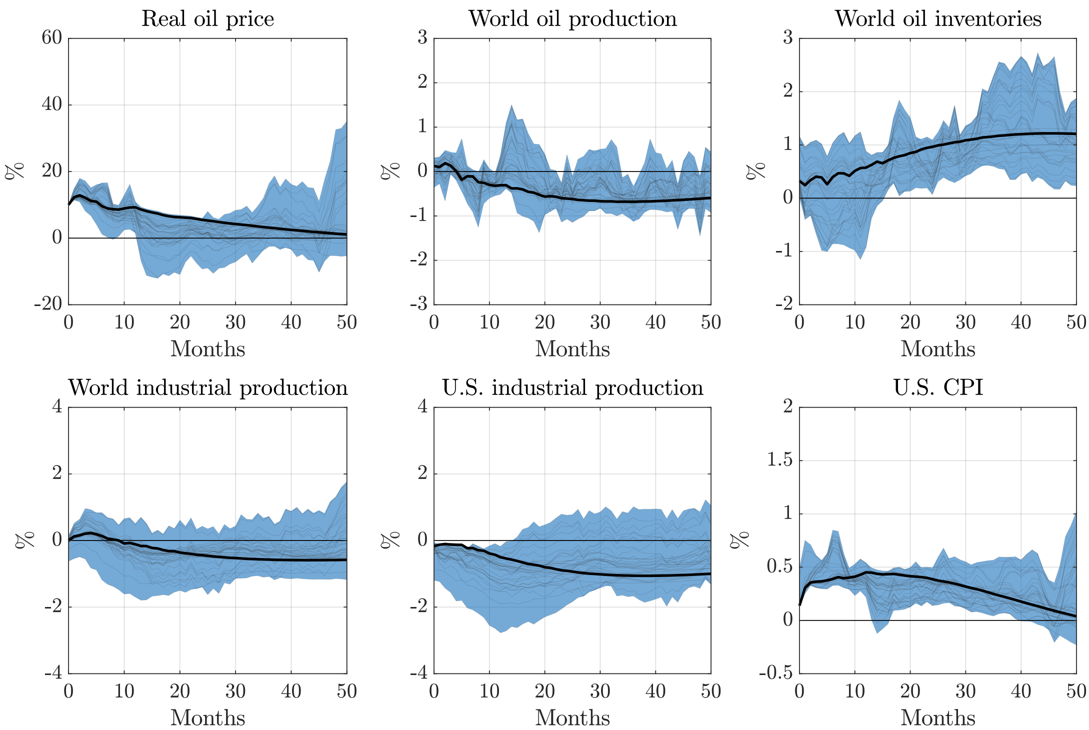


Figure A.6: The role of model uncertainty

Notes: The figure displays the model uncertainty for the results of oil supply news on the macroeconomy, as measured by the minimum and the maximum of the point estimates for a wide selection of different models and model specifications, including different specifications of the external instruments and heteroskedasticity-based VAR and LP models, together with the baseline responses (black line).

A.3. Wider effects and propagation channels

Below, I show the impulse responses of additional variables of interest, as discussed in the main text.

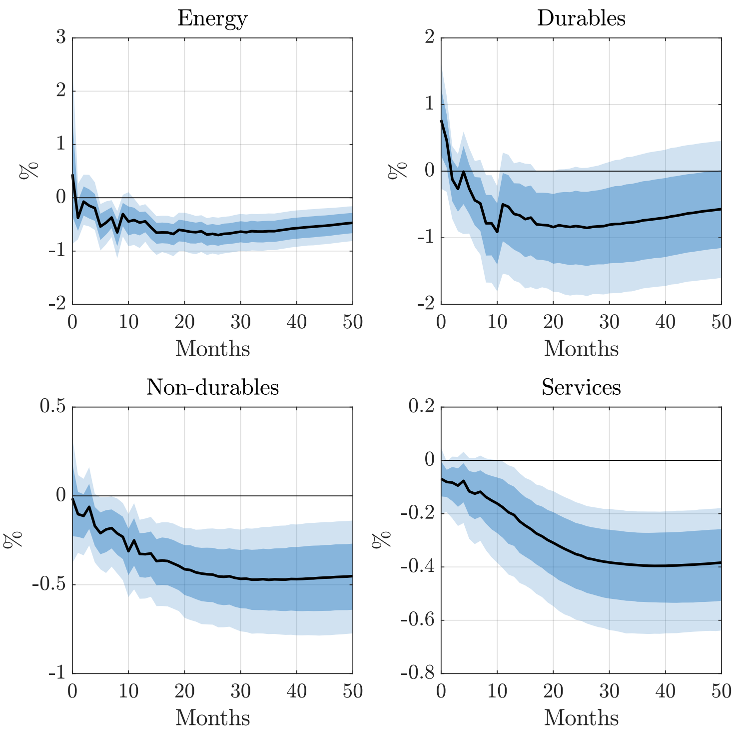


Figure A.7: Personal consumption expenditures

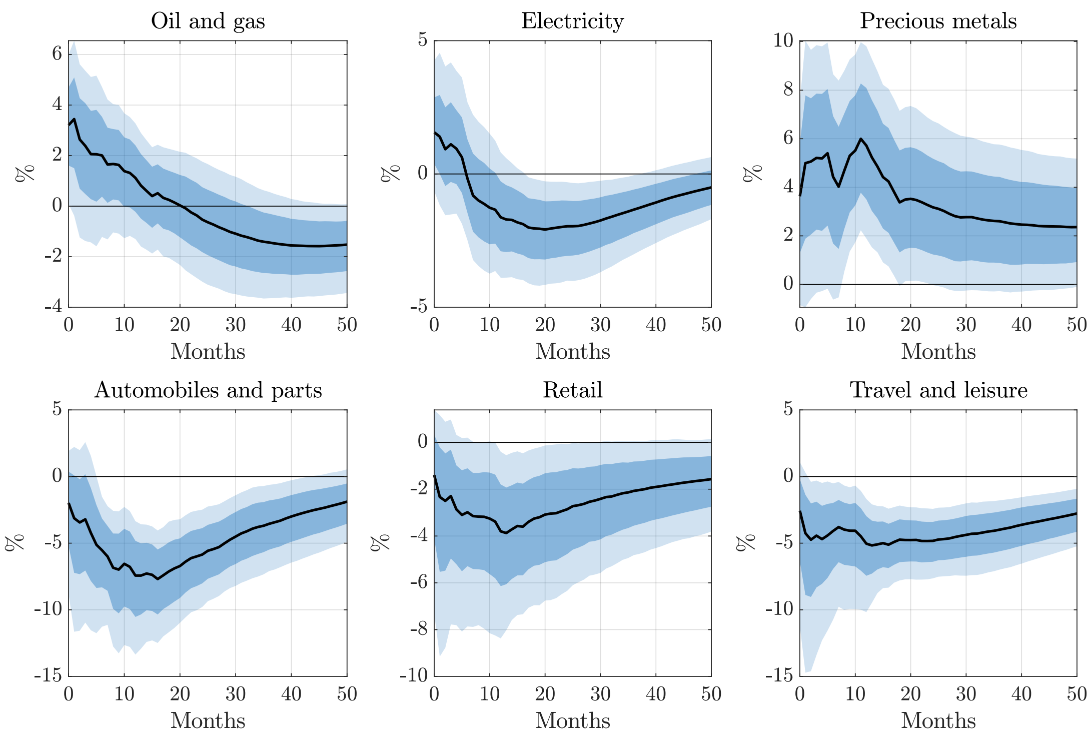
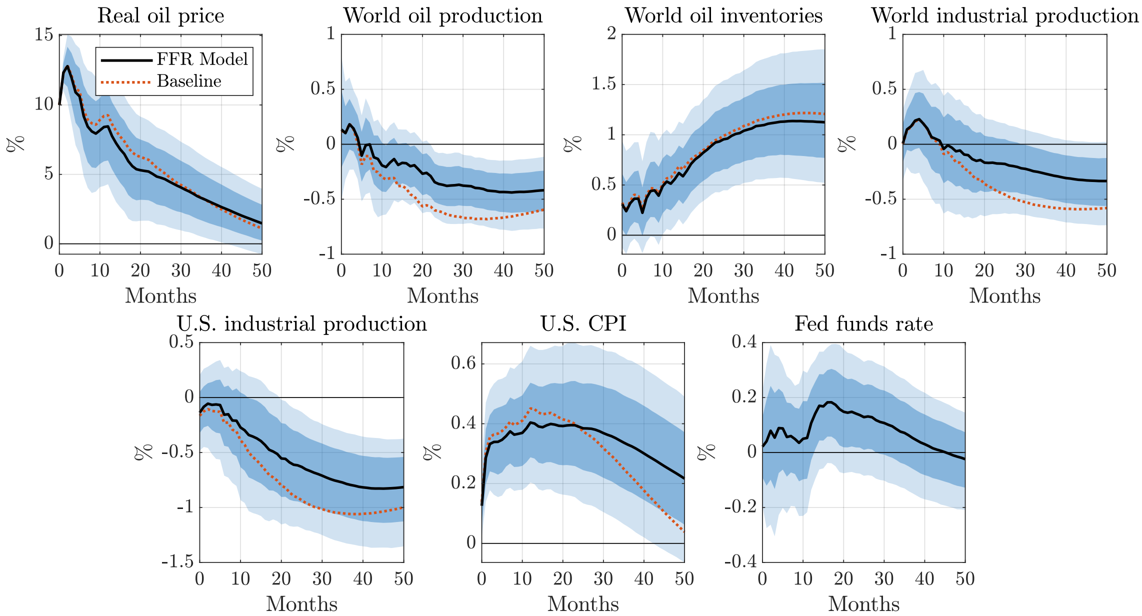


Figure A.8: Stock indices for different industries

To address the potential concern that monetary policy may contaminate the baseline results, I also study how the results are affected when controlling for the policy rate. Figure A.9 presents the responses from the model augmented by the federal funds rate together with the baseline responses. We can see that controlling for the federal funds rate does not affect the results materially.



First stage regression: F: 22.21, robust F: 10.23, R^2: 4.14%, Adjusted R^2: 3.96%

Figure A.9: Model with federal funds rate

Notes: Impulse responses from the model augmented with the federal funds rate. The shaded areas are 68 and 90 percent confidence bands, respectively. The red dotted lines are the responses from the baseline proxy VAR.

A.4. Sensitivity analysis

A.4.1. Identification

Announcements. The news coverage of OPEC meetings in the financial press is suggestive that there is no strong information channel confounding high-frequency oil supply surprises, as the focus is typically on whether OPEC could agree on production quotas or not. This is illustrated in Table A.4, which shows the headlines and main paragraphs of a selection of articles by the Financial Times on OPEC meetings.

Table A.4: News coverage on OPEC meetings by the Financial Times

Date	Headline	Main paragraph
Dec 4, 2019	OPEC and Russia agree deeper production cuts to prop up oil prices	The so-called OPEC+ alliance, which also includes Russia, agreed curbs of 500,000 barrels per day on Friday after two days of fraught meetings in Vienna, with Saudi Arabia pledging additional voluntary cuts of a further 400,000 b/d.
Dec 4, 2015	OPEC meeting ends in acrimony	OPEC will stick with its policy of not constraining output and has all but abandoned its official production target at its semi-annual meeting, risking a further drop in oil prices that are currently close to six-year lows.
Mar 17, 2010	OPEC keeps oil quota unchanged	The OPEC oil cartel on Wednesday kept its production quotas unchanged, as ministers flipped from worrying about oil prices falling too far to becoming wary of them rising too high.
Mar 16, 2005	OPEC agrees to raise oil production quotas	OPEC producers agreed a 2 per cent increase in oil supplies on Wednesday, raising production limits by 500,000 barrels a day to 27.5m b/d, the highest level since the quota system was introduced in 1987.

To address this concern more formally, I construct an informationally robust oil supply surprise series. 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 A.10 shows an excerpt of the oil market report from December 2006.

Table 10: World oil demand forecast for 2007, mb/d								
							Change 2007/06	
	2006	1Q07	2Q07	3Q07	4Q07	2007	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 A.10: 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 the reports are 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. In addition, I also analyze whether only using ordinary announcements in the construction of the instrument changes the results.

The results are displayed in Figures A.11-A.12. We can see that the responses 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 of the paper because of the shorter identification sample. Likewise, using only ordinary announcements to construct the instrument yields very similar results to the baseline case.

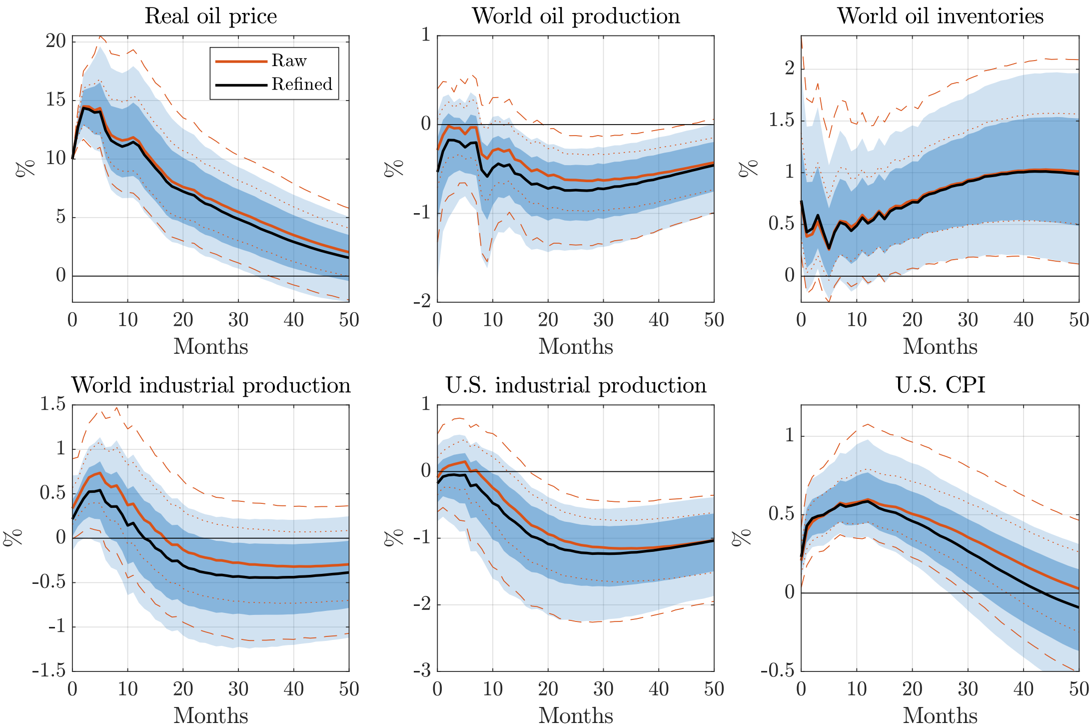
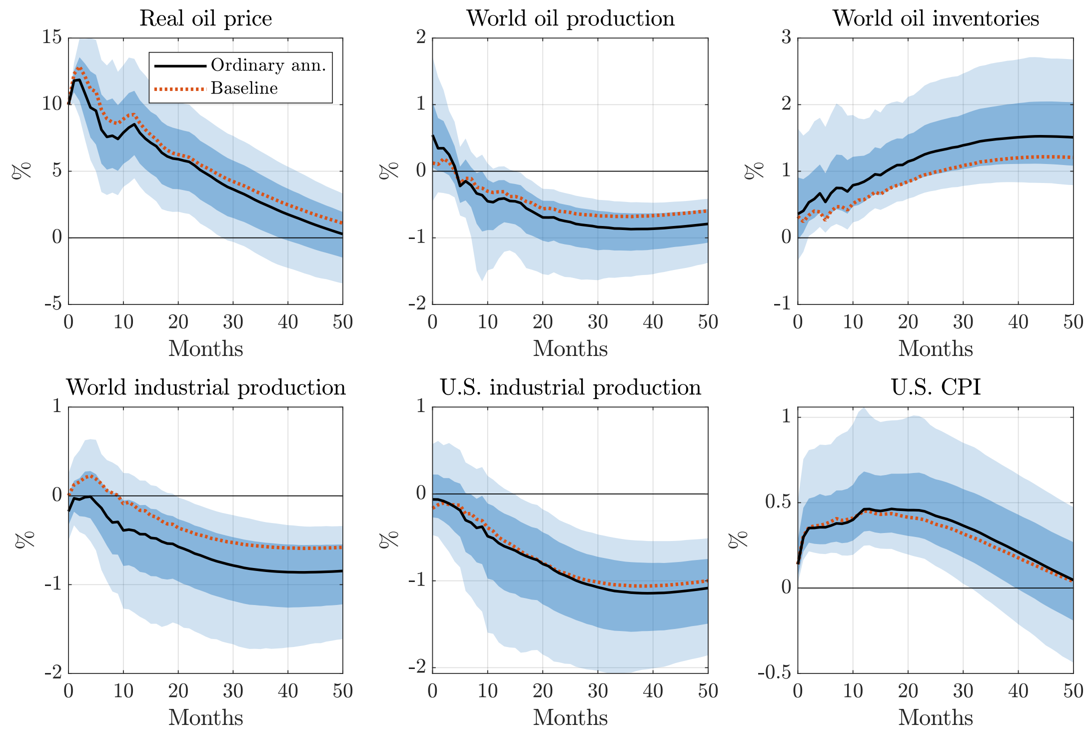


Figure A.11: Raw versus refined instrument

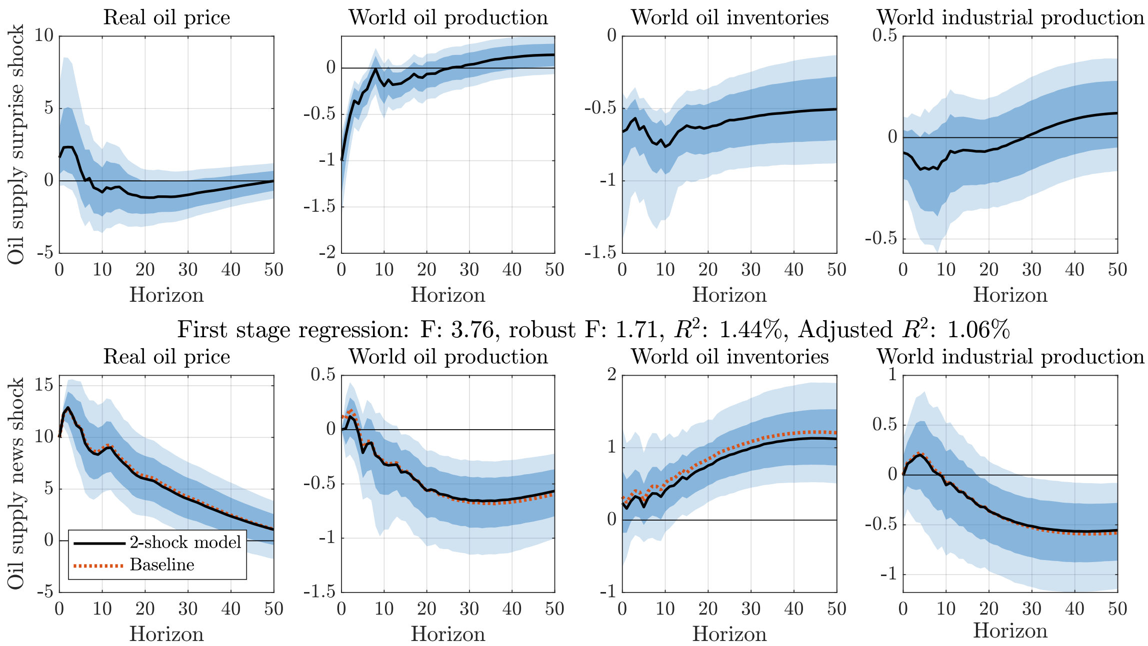
Notes: Impulse responses using the refined (black) and the raw oil supply surprise series (red). The solid lines are the point estimates and the shaded areas and dashed/dotted lines are 68 and 90 percent confidence bands, respectively.



First stage regression: F: 9.75, robust F: 4.46, R^2: 1.86%, Adjusted R^2: 1.67%

Figure A.12: Using ordinary announcements only

News and surprise shocks. Figure A.13 presents the IRFs from the two-shock proxy VAR introduced in the main text. The results suggest that we can identify the oil supply news shock without controlling for the oil supply surprise shock.



First stage regression: F: 12.05, robust F: 5.66, R^2: 4.49%, Adjusted R^2: 4.11%

Figure A.13: Two-shock proxy VAR

Notes: The top panel is the oil supply surprise shock and the bottom panel is the oil supply news shock. The shocks are identified using Kilian's (2008) production shortfall series, extended by Bastianin and Manera (2018), and the oil supply surprise series as instruments. The surprise shock is normalized to decrease oil production by 1 percent and the news shock to increase the oil price by 10 percent on impact.

Invertibility. To be able to identify the shock of interest, the VAR has to span all relevant information. As a robustness check, I analyze how the information contained in the VAR affects the results. In the context of news shocks, Ramey (2016) argues that using high-frequency surprises as instruments can be problematic without including them in the VAR. Thus, as an alternative to the external instruments approach, I include the oil supply surprise series as the first variable in a recursive VAR. This is the so-called internal instruments approach (Ramey, 2011; Plagborg-Møller and Wolf, 2019).[6] The results are shown in Figure A.14. Overall, the responses are less precisely estimated. Furthermore, the responses of the industrial production indicators turn out to be less pronounced. However, none of these differences are statistically significant.

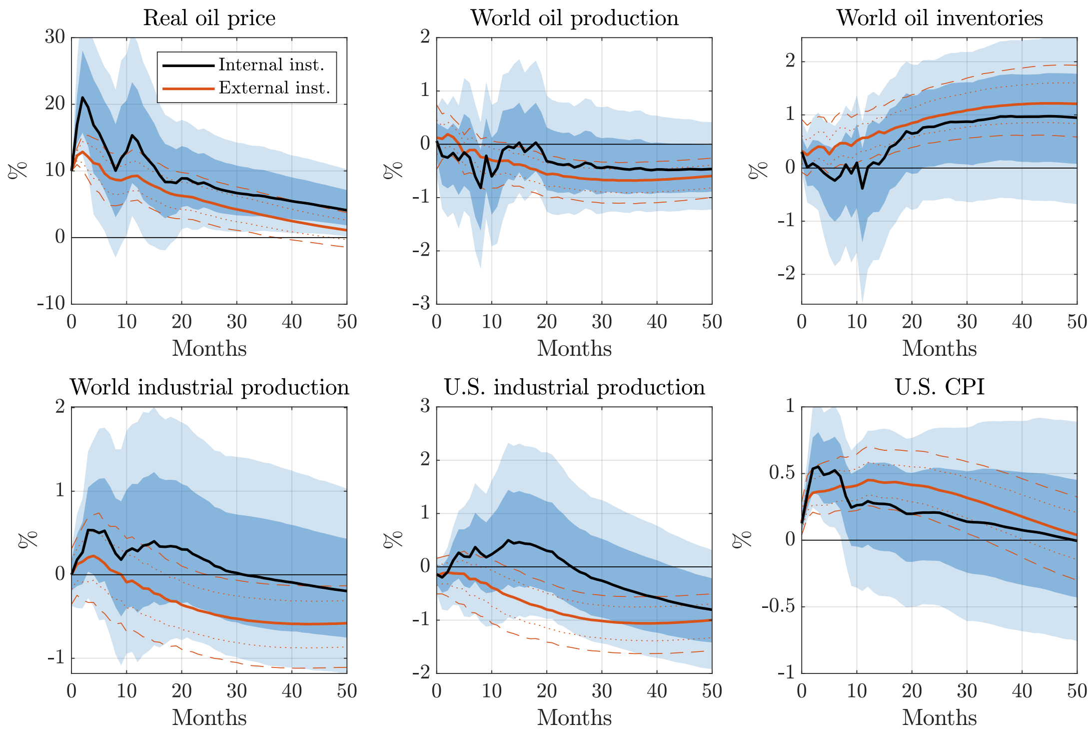


Figure A.14: Internal versus external instruments approach

I also analyze how the inclusion of additional variables in Section 4.4 in the paper affects the baseline results. Figure A.15 shows the impulse responses of the baseline variables from all the augmented VAR models. 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 im-

[6] A disadvantage of this approach is that we cannot easily accommodate instruments that are only available for a shorter sample than the variables in the VAR, which is relevant for the application at hand. Following Noh (2019), I censor the missing values to zero.

pact responses are an indication that the instrument is contaminated by other past structural shocks that are not filtered out by the VAR model. I also augmented 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.

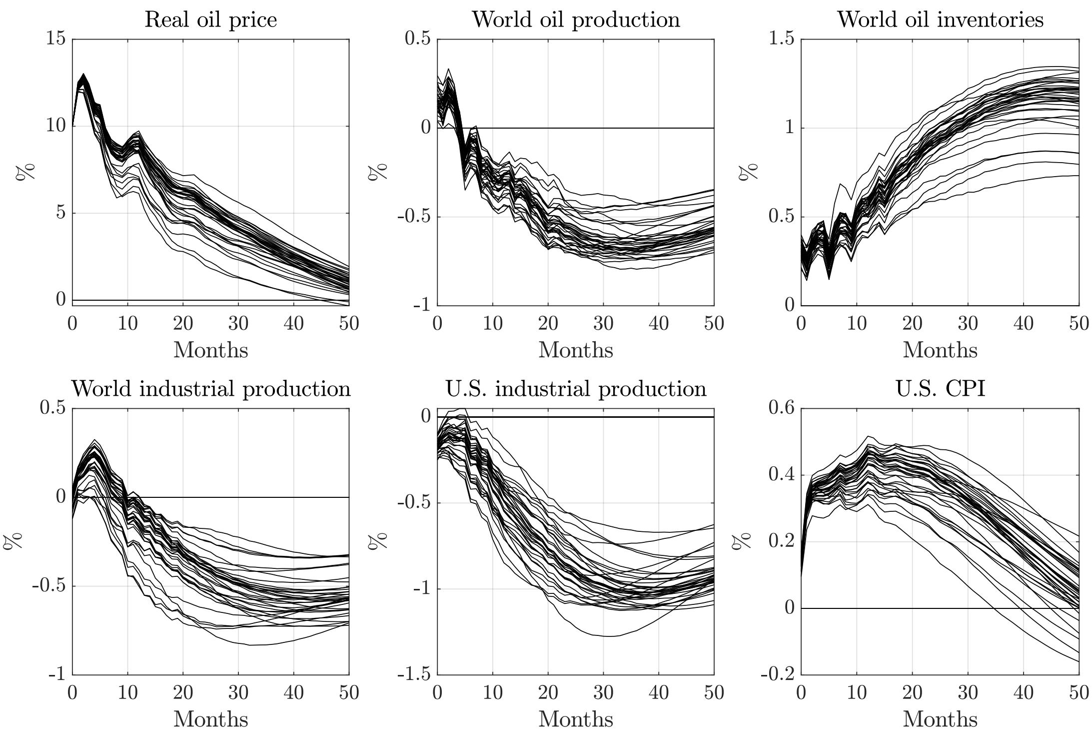


Figure A.15: Responses from the extended models in Section 4.4

Additional robustness checks:

Constructing the instrument. To construct a time series of oil supply surprises, I look at how oil futures prices change around OPEC announcements. In particular, I use a composite measure, spanning the first year of the term structure. However, in principle, we can use any asset price that is sufficiently responsive, such as single futures contracts or the spot price. Figure A.16 presents responses based on instruments constructed using the 1-month, 3-month, 9-month, and 12-month futures and an extended composite measure (COMP+), which also includes the spot price and the front contract, together with the response using the baseline composite measure. The results do not change materially, illustrating that the crucial feature of my identification strategy is OPEC's institutional framework and not the specific asset used to measure the impact of OPEC announcements. The fact that the responses do not differ much using different maturities also suggests that the results are not severely affected by changes in risk premia.

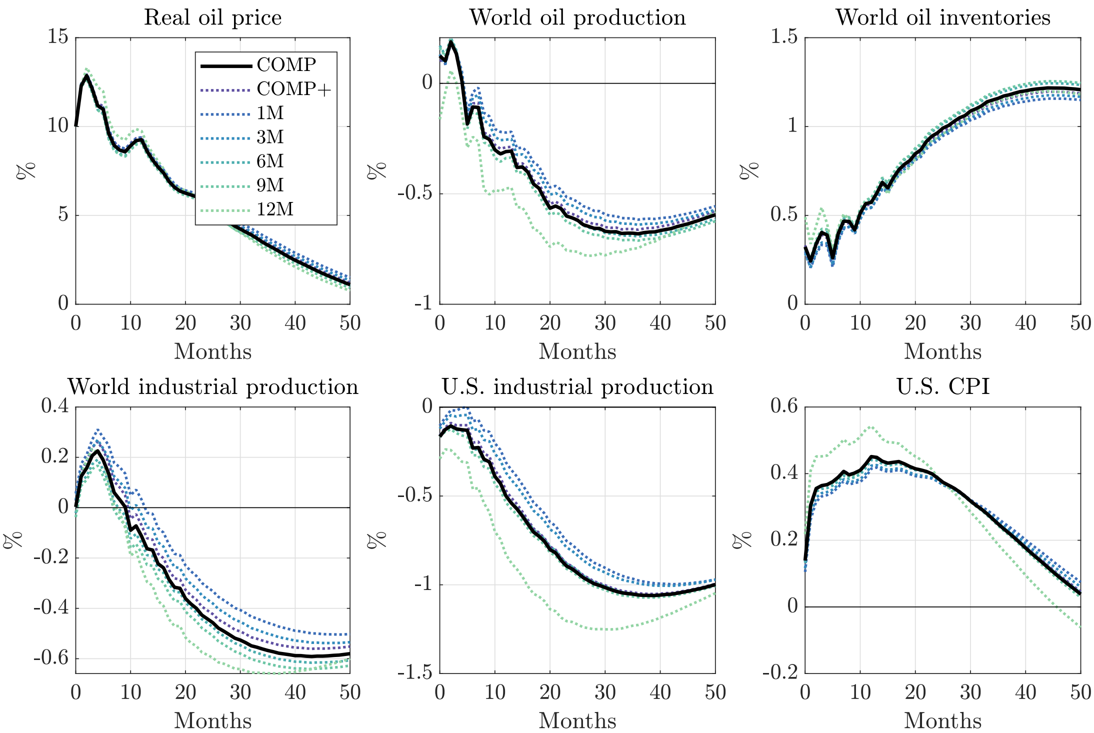
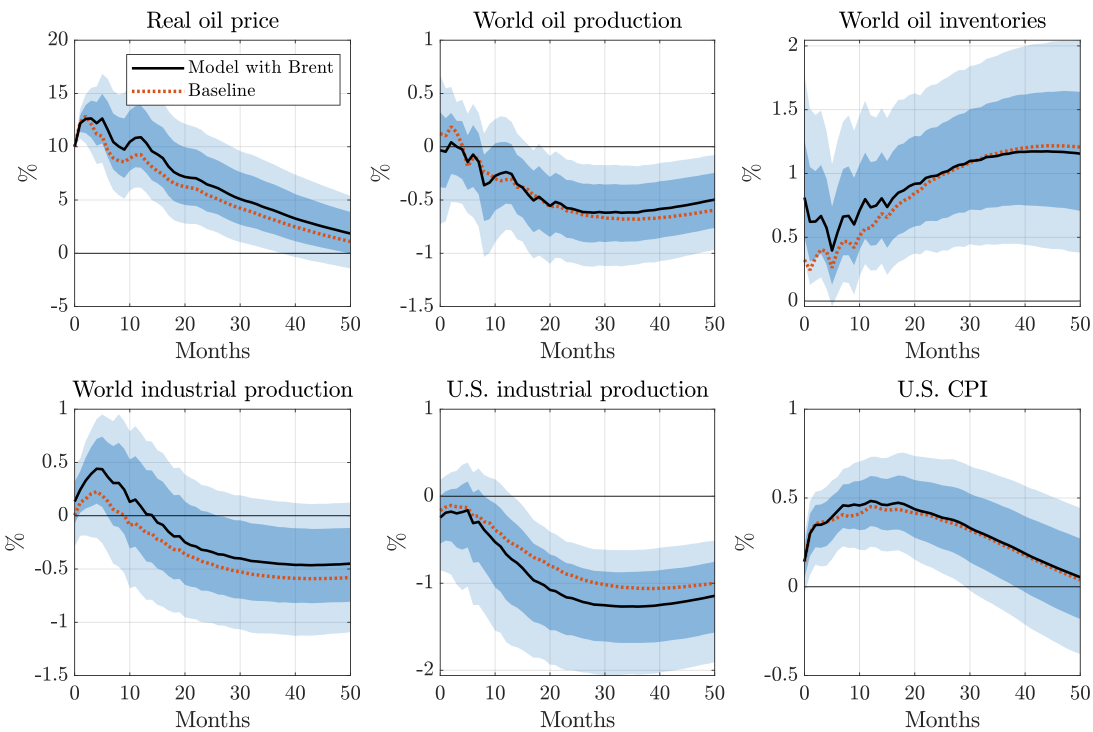


Figure A.16: Instruments based on different futures contracts



First stage regression: F: 10.27, robust F: 5.56, R^2: 1.96%, Adjusted R^2: 1.77%

Figure A.17: Using Brent as oil price indicator and to construct instrument

A related issue is the choice of the relevant oil price measure. As a benchmark, I rely on WTI. However, in the most recent part of the sample, WTI has become less representative for the global price of oil because of the shale oil boom (Baumeister and Kilian, 2016). For this period, Brent is probably the better measure. However, Brent futures only started trading in the late 1980s and were less liquid at the beginning, making the instrument sample even shorter. Figure A.17 presents the IRFs using a composite instrument spanning the first year of the Brent futures term structure and using the Brent spot price as the oil price indicator in the VAR. The results turn out to be robust.

A.4.2. Specification and data choices

Model specification. Figures A.18-A.19 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 are robust to using these alternative indicators.

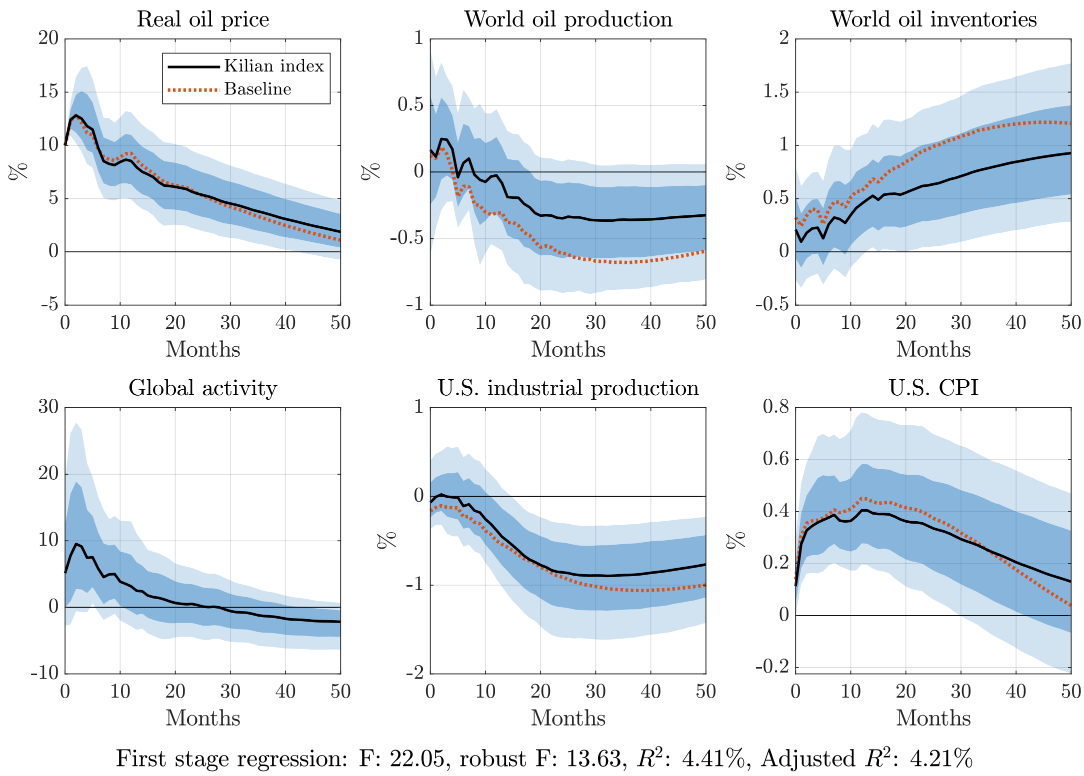
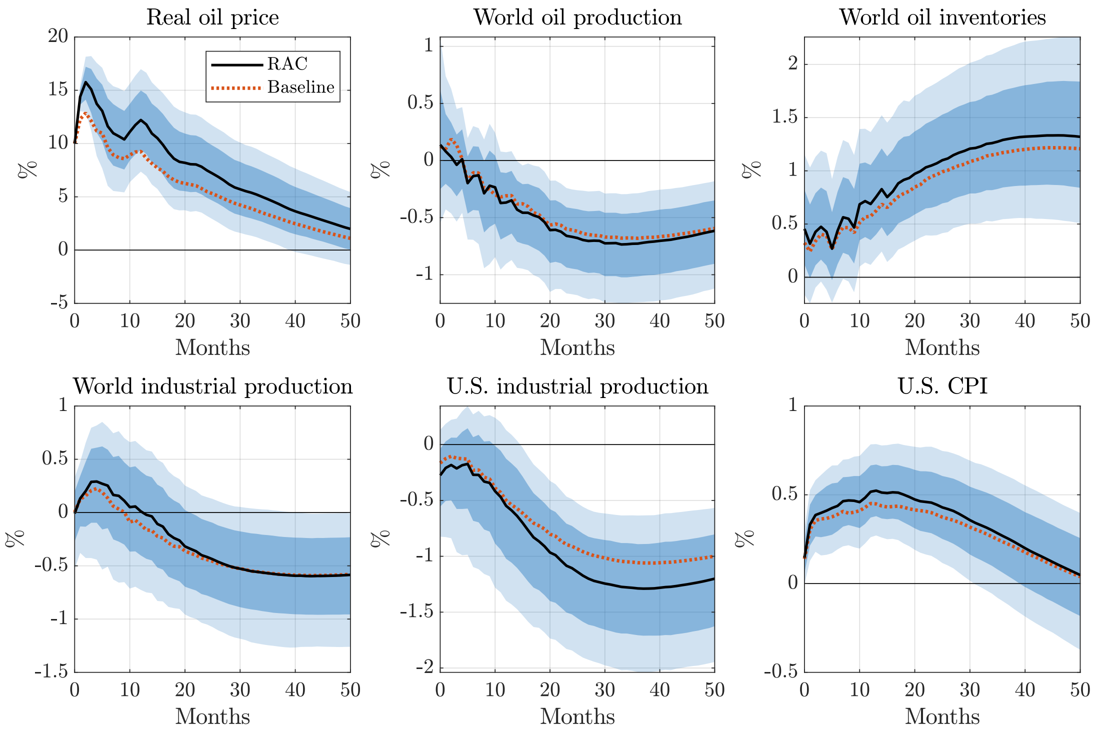


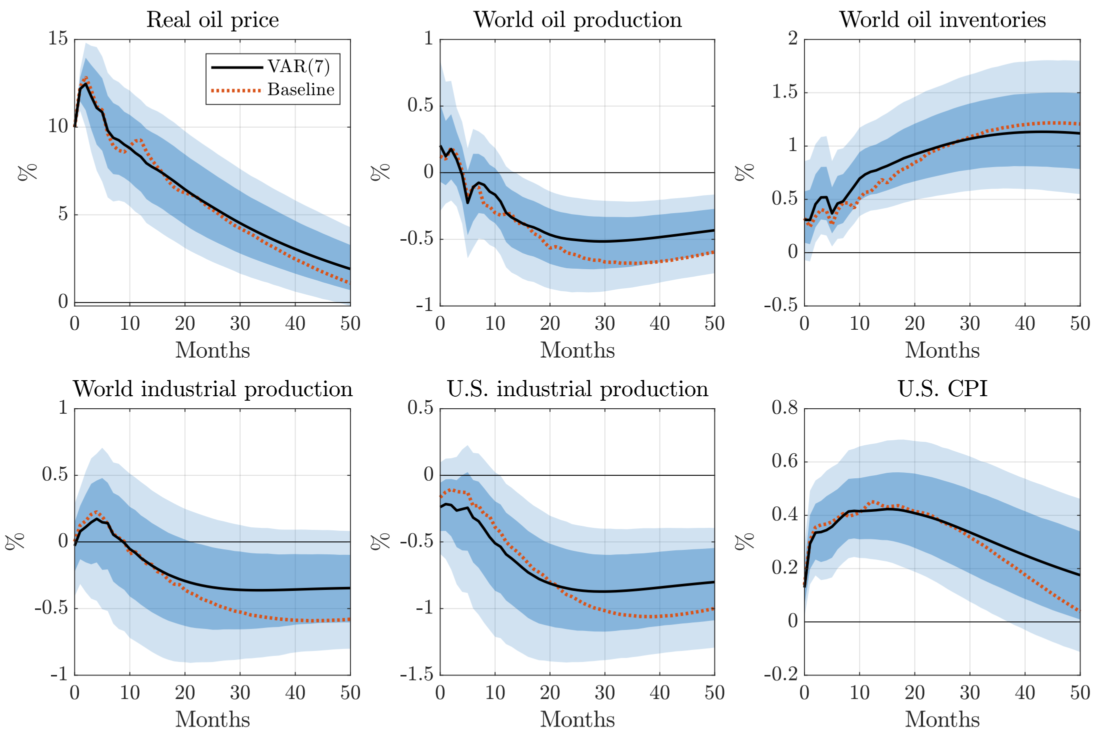
Figure A.18: Model with Kilian's (2009) global activity indicator



First stage regression: F: 15.19, robust F: 9.55, R^2: 2.87%, Adjusted R^2: 2.68%

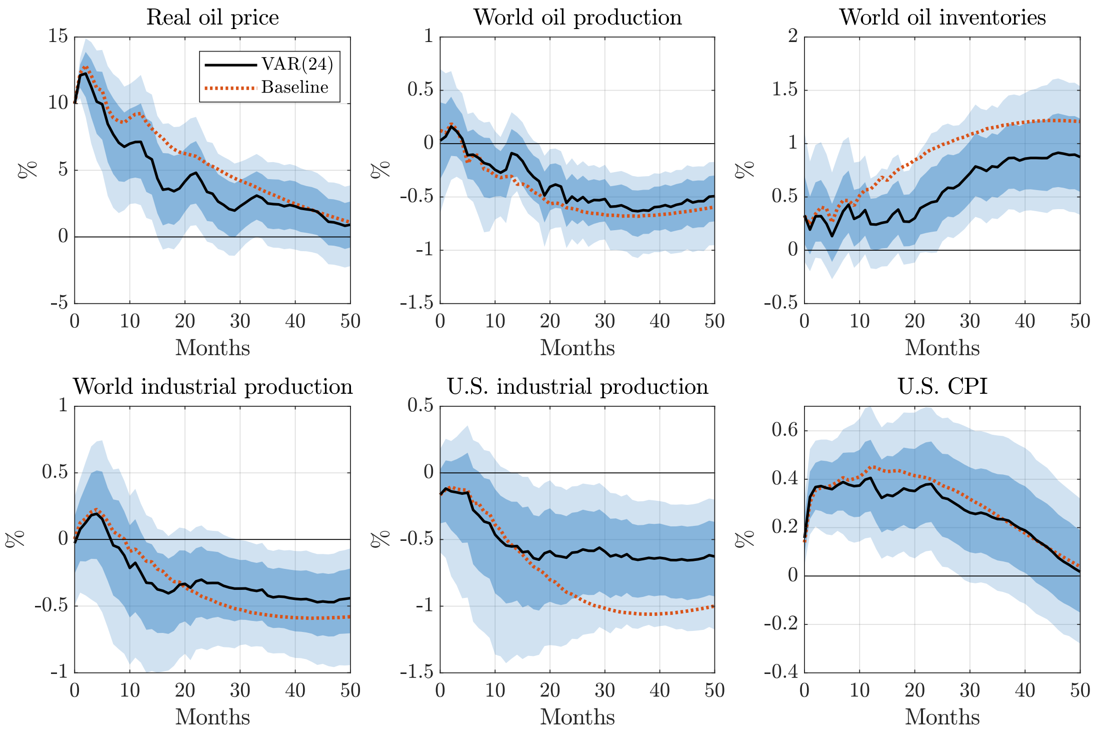
Figure A.19: Model with real refiner acquisition cost as oil price indicator

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 A.20-A.24, we can see that the results are robust with respect to all these choices. Finally, in Figures A.25-A.26, 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.



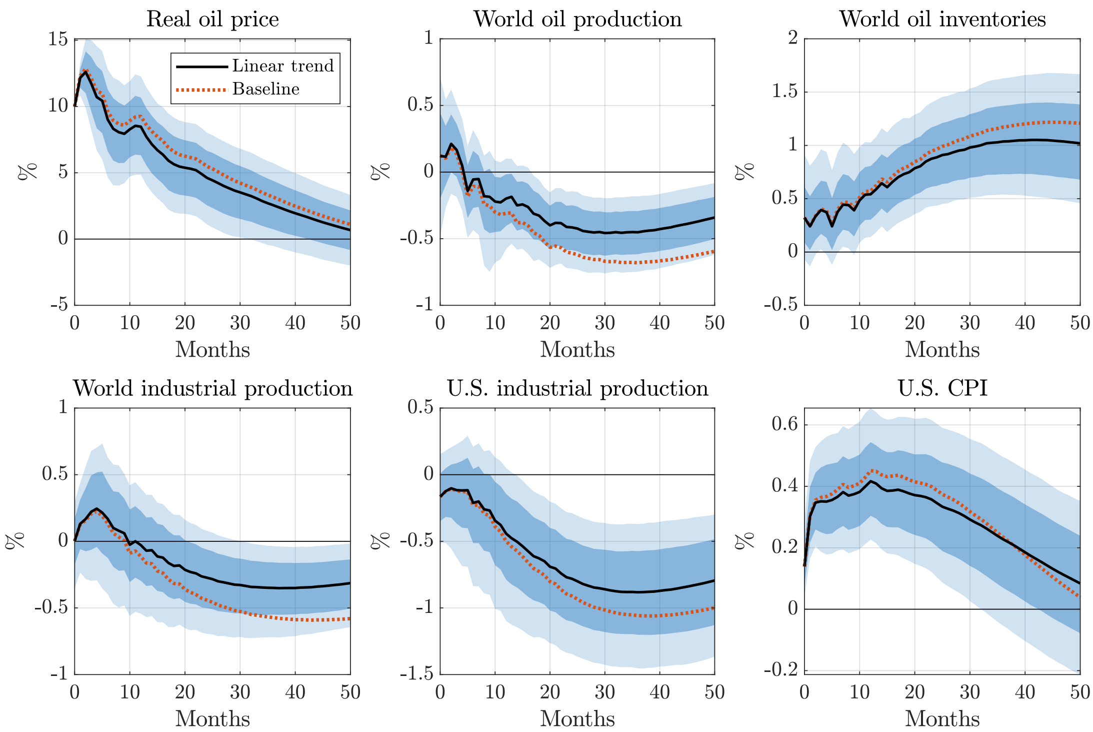
First stage regression: F: 20.75, robust F: 9.06, R^2: 3.84%, Adjusted R^2: 3.66%

Figure A.20: Results from a VAR(7), selected by AIC



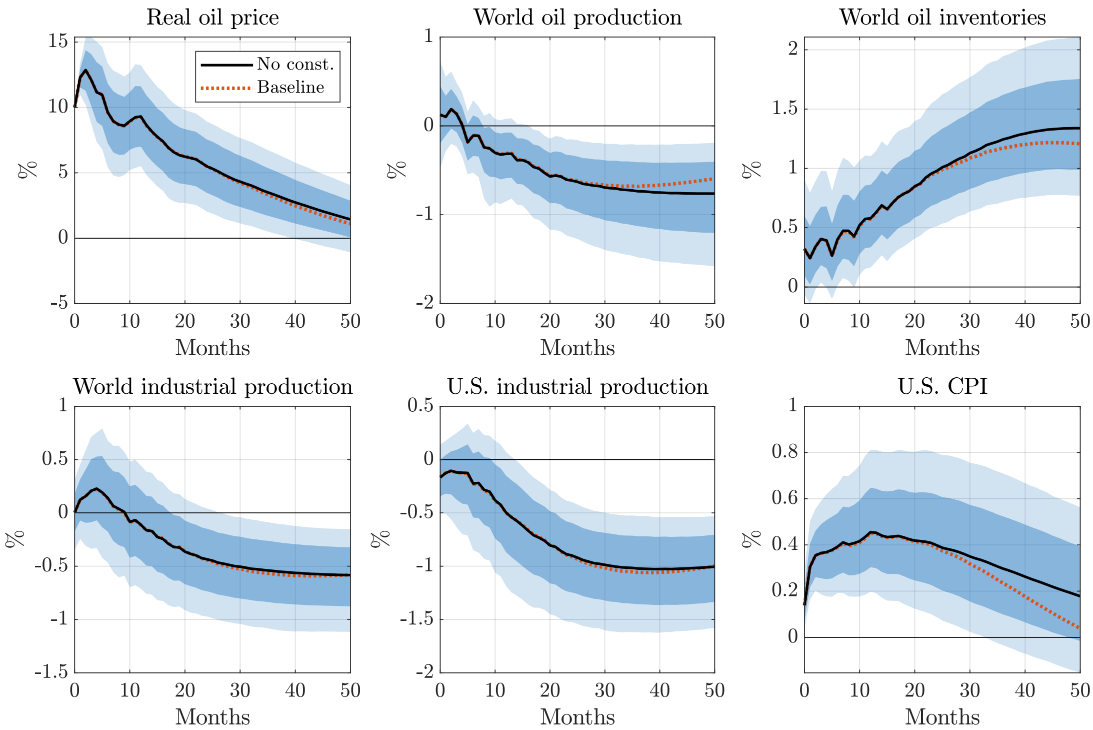
First stage regression: F: 20.98, robust F: 11.17, R^2: 4.01%, Adjusted R^2: 3.82%

Figure A.21: Results from VAR(24)



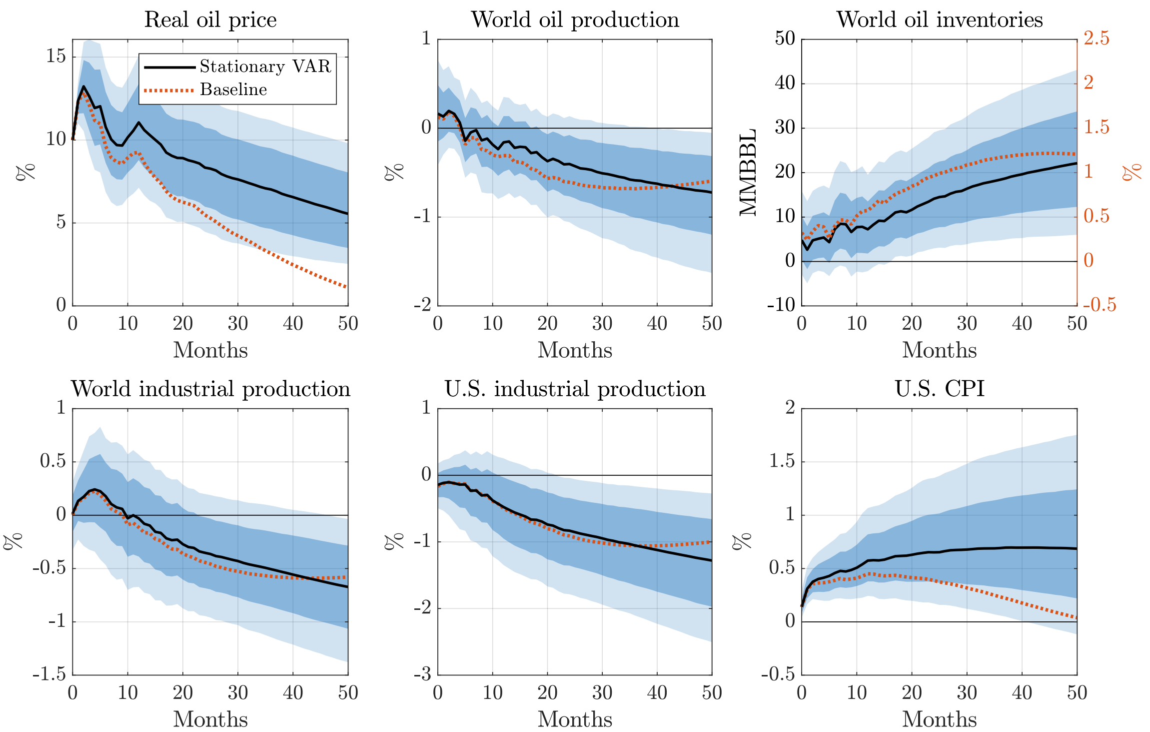
First stage regression: F: 23.08, robust F: 11.11, R^2: 4.30%, Adjusted R^2: 4.11%

Figure A.22: VAR with linear trend



First stage regression: F: 22.67, robust F: 10.54, R^2: 4.22%, Adjusted R^2: 4.04%

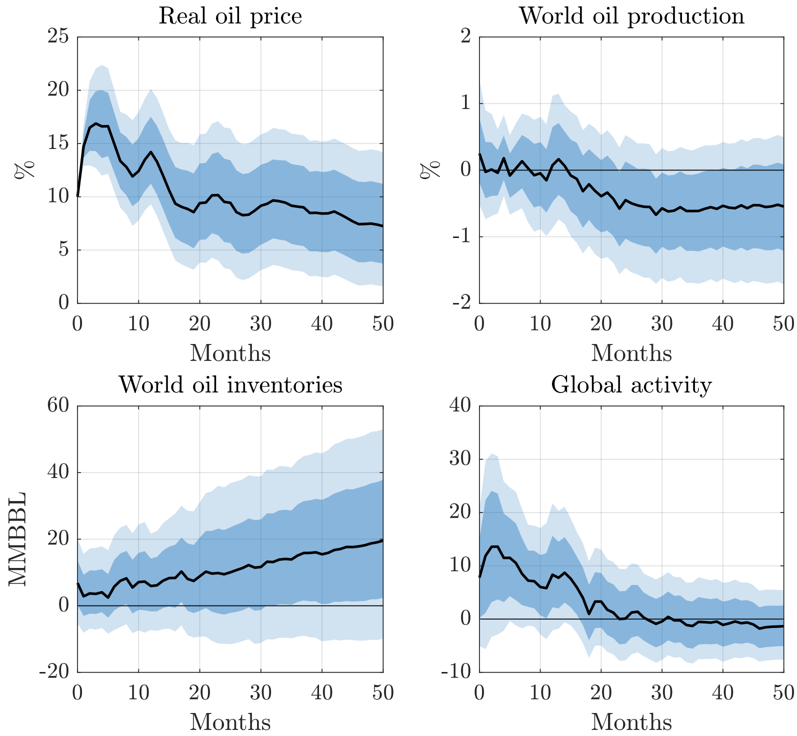
Figure A.23: VAR without a constant



First stage regression: F: 22.89, robust F: 11.60, R^2: 4.26%, Adjusted R^2: 4.08%

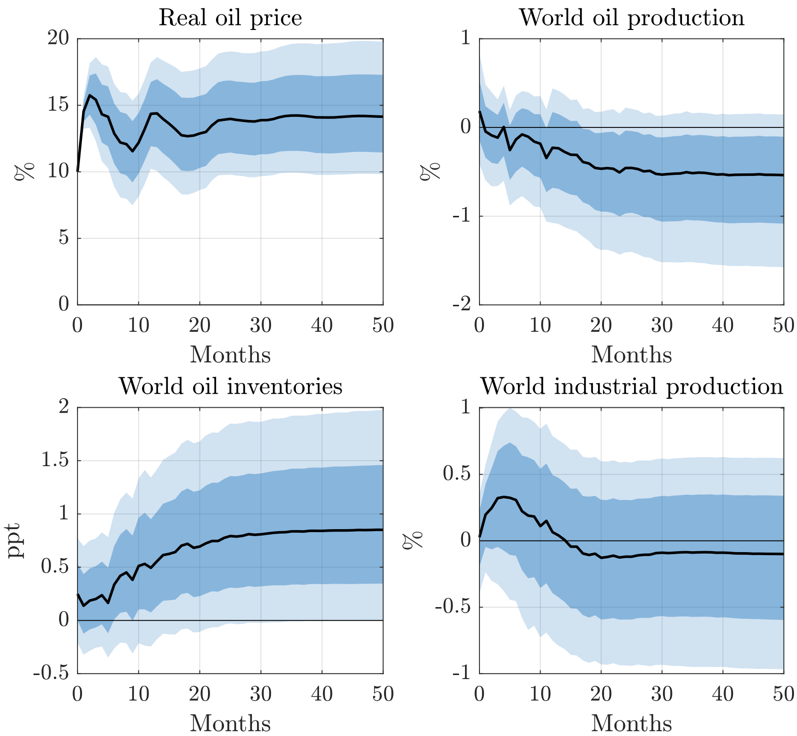
Figure A.24: Stationary VAR

Notes: (Cumulative) responses from stationary VAR in real oil price, world oil production growth, change in world oil inventories, world IP growth, U.S. IP growth, and U.S. CPI inflation.



First stage regression: F: 15.78, robust F: 15.19, R^2: 3.28%, Adjusted R^2: 3.07%

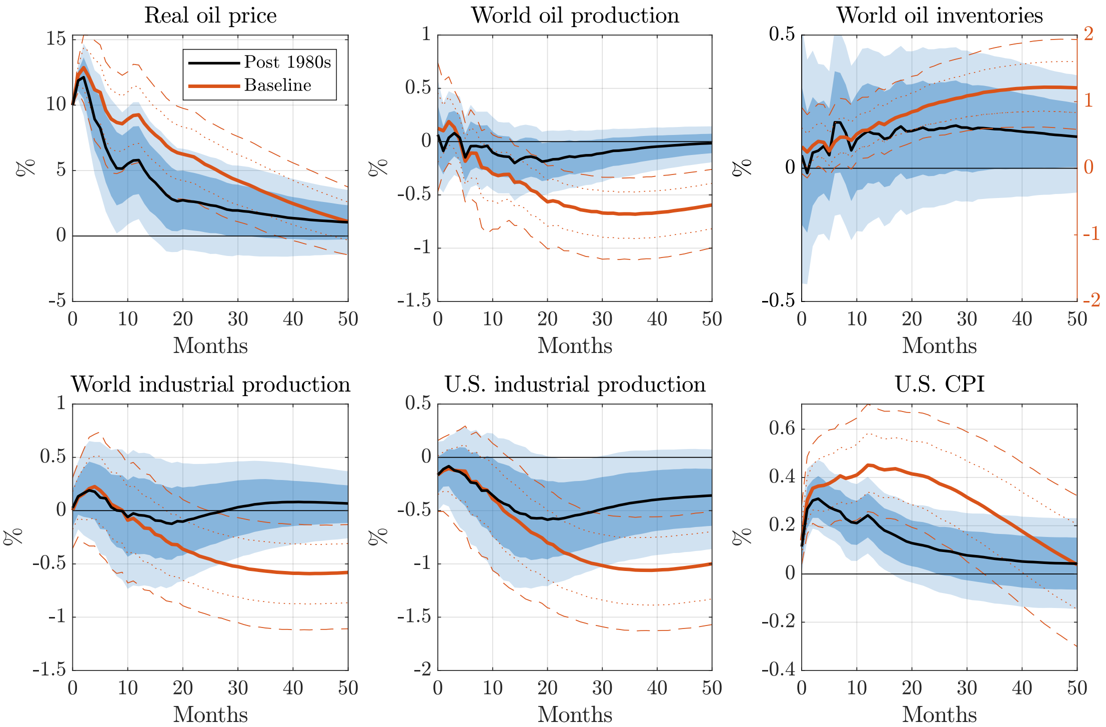
Figure A.25: Kilian and Murphy's (2014) model specification



First stage regression: F: 15.33, robust F: 11.18, R^2: 3.04%, Adjusted R^2: 2.84%

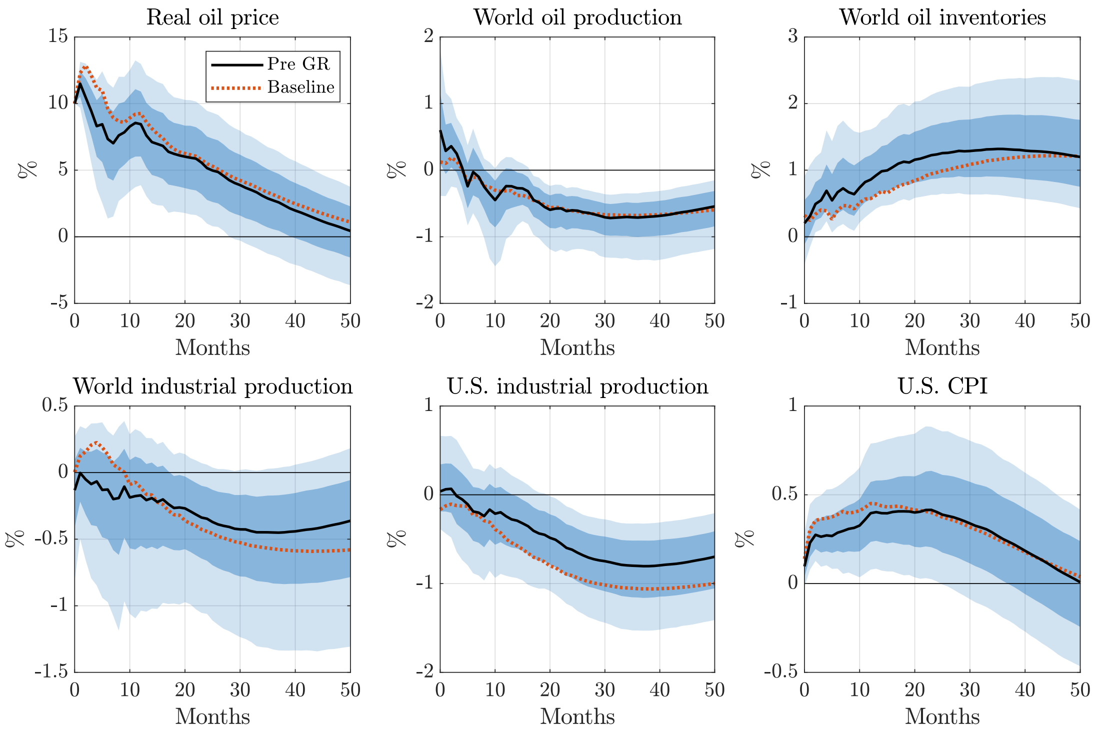
Figure A.26: Baumeister and Hamilton's (2019) model specification

Sample and data frequency. Figures A.27-A.29 present the results from the subsample analyses. It turns out that the results do not seem to be driven by a specific sample choice.



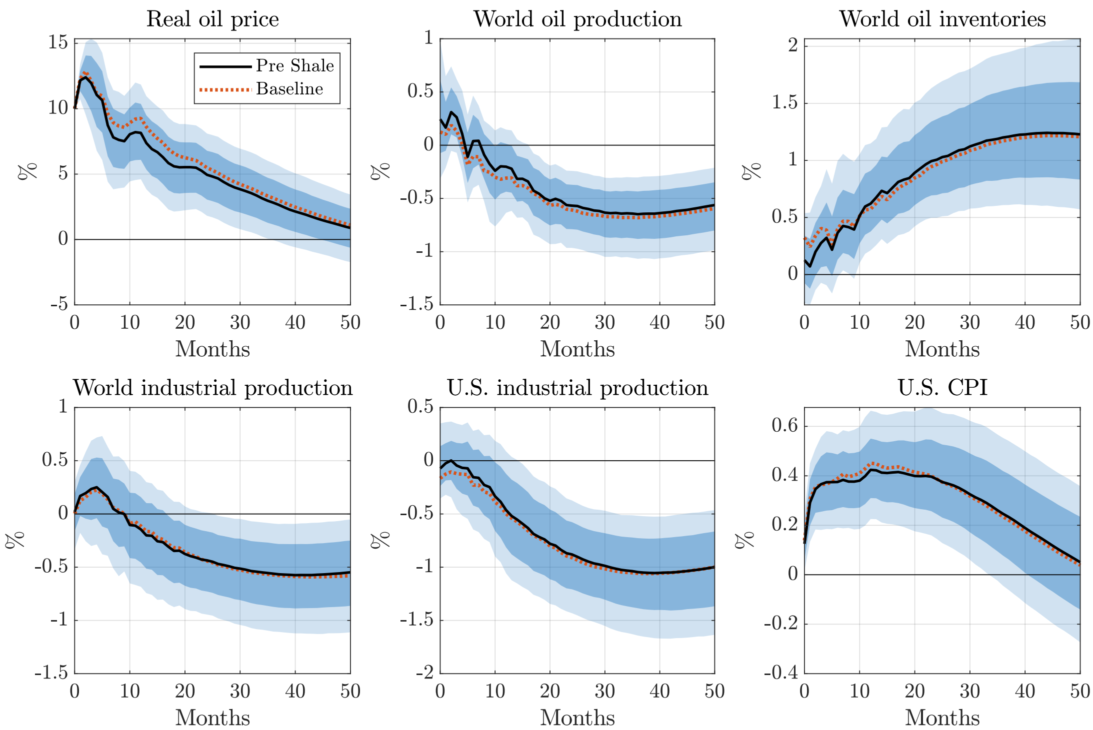
First stage regression: F: 19.78, robust F: 11.51, R^2: 4.55%, Adjusted R^2: 4.32%

Figure A.27: Shorter estimation sample: 1982M4-2017M12.



First stage regression: F: 15.79, robust F: 8.66, R^2: 3.85%, Adjusted R^2: 3.61%

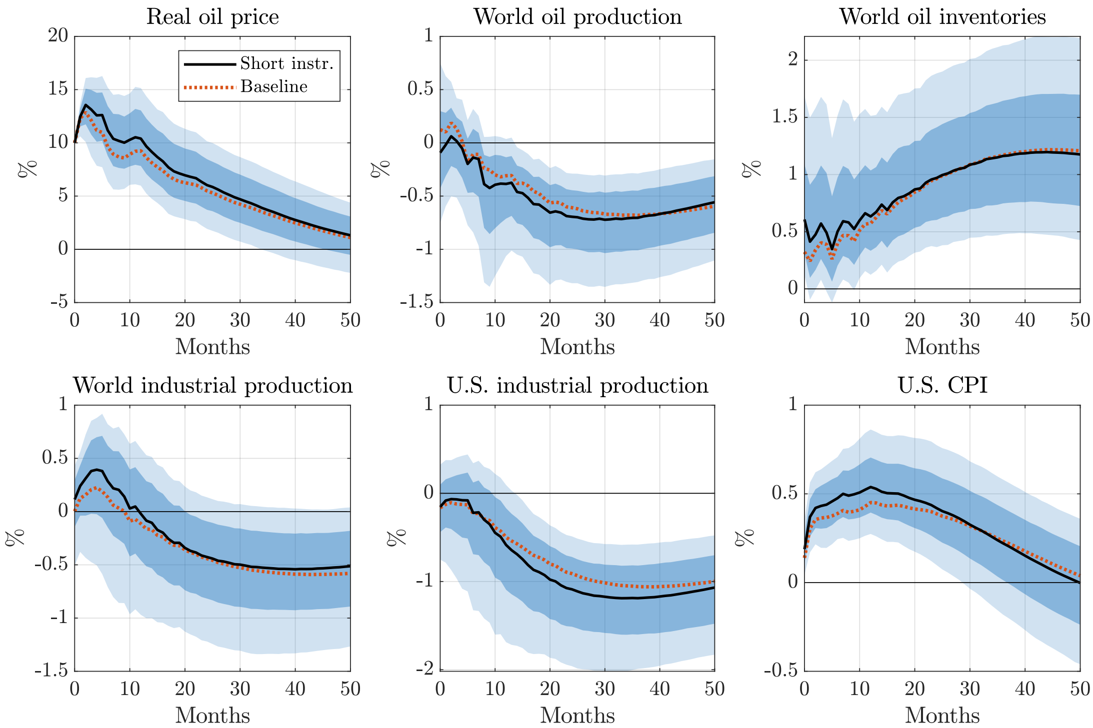
Figure A.28: Pre Great Recession: 1974M1-2007M12.



First stage regression: F: 29.13, robust F: 18.65, R^2: 6.35%, Adjusted R^2: 6.13%

Figure A.29: Pre shale oil revolution: 1974M1-2010M12.

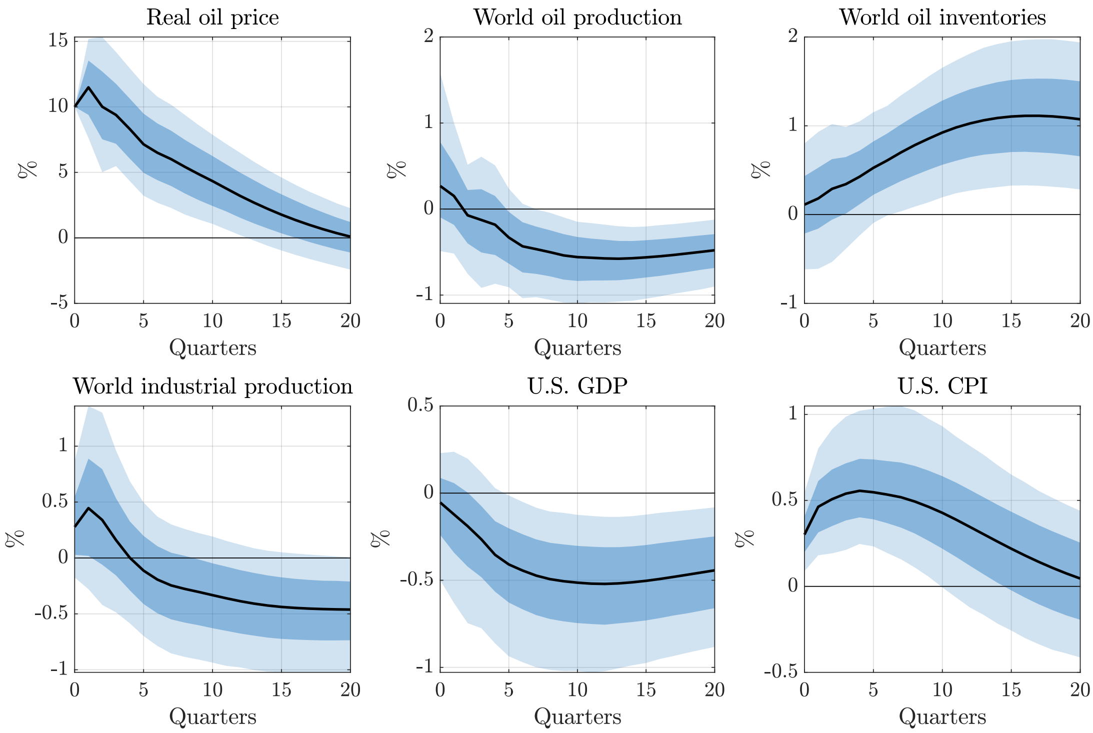
I also check the sensitivity with respect to the instrument sample. In particular, I test whether the results are robust if I exclude the first years of the instrument when the futures markets were not as liquid. Figure A.30 depicts the IRFs using an instrument that starts in 1990. Again, the results are robust.



First stage regression: F: 12.93, robust F: 6.68, R^2: 2.45%, Adjusted R^2: 2.26%

Figure A.30: Shorter instrument sample: 1990M1-2017M12.

Finally, I check the robustness with respect to the data frequency. Figure A.31 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: 10.92, robust F: 6.96, R^2: 6.03%, Adjusted R^2: 5.48%

Figure A.31: Quarterly VAR

B. Data

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

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.[7] 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 used to compute the surprise. The table also includes the trading days in the control sample used for the heteroskedasticity-based identification.

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

Month	Announcement date	Control date	Additional information
1983M04		19/04/1983	
1983M05		17/05/1983	
1983M06		21/06/1983	
1983M07	19/07/1983		68th meeting of the OPEC conference
1983M08		12/08/1983	
1983M09		09/09/1983	
1983M10		07/10/1983	
1983M11		11/11/1983	
1983M12	09/12/1983		69th meeting of the OPEC conference
1984M01		11/01/1984	
1984M02		08/02/1984	
1984M03		14/03/1984	
1984M04		11/04/1984	
1984M05		09/05/1984	
1984M06		13/06/1984	
1984M07	11/07/1984		70th meeting of the OPEC conference
1984M08		29/08/1984	
1984M09		26/09/1984	
1984M10	31/10/1984		71st (extraordinary) meeting of the OPEC conference
1984M11		28/11/1984	
1984M12	29/12/1984		72nd meeting of the OPEC conference
1985M01	30/01/1985		73rd meeting of the OPEC conference
1985M02		11/02/1985	
1985M03		11/03/1985	
1985M04		08/04/1985	
1985M05		06/05/1985	
1985M06		10/06/1985	
1985M07	07/07/1985, 25/07/1985		Consultative meeting of the OPEC conference, 74th meeting of the OPEC conference
1985M08		02/08/1985	
1985M09		06/09/1985	
1985M10	04/10/1985		75th (extraordinary) meeting of the OPEC conference
1985M11		11/11/1985	
1985M12	09/12/1985		76th meeting of the OPEC conference
1986M01		20/01/1986	
1986M02		18/02/1986	
1986M03		24/03/1986	
1986M04	21/04/1986		77th meeting of the OPEC conference
1986M05		06/05/1986	
1986M06		03/06/1986	

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

Month	Announcement date	Control date	Additional information
1986M07		08/07/1986	
1986M08	05/08/1986		78th meeting of the OPEC conference
1986M09		24/09/1986	
1986M10	22/10/1986		79th meeting of the OPEC conference
1986M11		24/11/1986	
1986M12	20/12/1986		80th meeting of the OPEC conference
1987M01		26/01/1987	
1987M02		23/02/1987	
1987M03		30/03/1987	
1987M04		27/04/1987	
1987M05		26/05/1987	
1987M06	27/06/1987		81st meeting of the OPEC conference
1987M07		13/07/1987	
1987M08		17/08/1987	
1987M09		14/09/1987	
1987M10		12/10/1987	
1987M11		16/11/1987	
1987M12	14/12/1987		82nd meeting of the OPEC conference
1988M01		12/01/1988	
1988M02		16/02/1988	
1988M03		15/03/1988	
1988M04		12/04/1988	
1988M05		17/05/1988	
1988M06	14/06/1988		83rd meeting of the OPEC conference
1988M07		25/07/1988	
1988M08		29/08/1988	
1988M09		26/09/1988	
1988M10		31/10/1988	
1988M11	28/11/1988		84th meeting of the OPEC conference
1988M12		07/12/1988	
1989M01		04/01/1989	
1989M02		08/02/1989	
1989M03		08/03/1989	
1989M04		05/04/1989	
1989M05		10/05/1989	
1989M06	07/06/1989		85th meeting of the OPEC conference
1989M07		26/07/1989	
1989M08		30/08/1989	
1989M09	27/09/1989		3rd meeting of the 8 ministerial monitoring committee
1989M10		31/10/1989	
1989M11	28/11/1989		86th meeting of the OPEC conference
1989M12		29/12/1989	
1990M01		26/01/1990	
1990M02		23/02/1990	
1990M03		30/03/1990	
1990M04		27/04/1990	
1990M05		25/05/1990	
1990M06		29/06/1990	
1990M07	27/07/1990		87th meeting of the OPEC conference
1990M08		16/08/1990	
1990M09		13/09/1990	
1990M10		18/10/1990	
1990M11		15/11/1990	
1990M12	13/12/1990		88th meeting of the OPEC conference
1991M01		15/01/1991	
1991M02		12/02/1991	
1991M03	12/03/1991		3rd meeting
1991M04		02/04/1991	
1991M05		07/05/1991	
1991M06	04/06/1991		89th meeting of the OPEC conference
1991M07		24/07/1991	
1991M08		28/08/1991	
1991M09	25/09/1991		4th meeting of the ministerial monitoring committee
1991M10		23/10/1991	
1991M11	27/11/1991		90th meeting of the OPEC conference
1991M12		17/12/1991	
1992M01		21/01/1992	
1992M02	15/02/1992		6th meeting of the ministerial monitoring committee
1992M03		24/03/1992	
1992M04		28/04/1992	
1992M05	22/05/1992		91st meeting of the OPEC conference
1992M06		18/06/1992	
1992M07		16/07/1992	
1992M08		20/08/1992	
1992M09	17/09/1992		9th meeting of the ministerial monitoring committee
1992M10		26/10/1992	
1992M11	27/11/1992		92nd meeting of the OPEC conference

Month	Announcement date	Control date	Additional information
1992M12		16/12/1992	
1993M01		20/01/1993	
1993M02	16/02/1993		10th meeting of the ministerial monitoring committee
1993M03		11/03/1993	
1993M04		08/04/1993	
1993M05		13/05/1993	
1993M06	10/06/1993		93rd meeting of the OPEC conference
1993M07		29/07/1993	
1993M08		26/08/1993	
1993M09	29/09/1993		94th (extraordinary) meeting of the OPEC conference
1993M10		25/10/1993	
1993M11	24/11/1993		95th meeting of the OPEC conference
1993M12		27/12/1993	
1994M01		31/01/1994	
1994M02		28/02/1994	
1994M03	26/03/1994		12th meeting of the ministerial monitoring committee
1994M04		14/04/1994	
1994M05		19/05/1994	
1994M06	16/06/1994		96th meeting of the OPEC conference
1994M07		19/07/1994	
1994M08		23/08/1994	
1994M09		20/09/1994	
1994M10		25/10/1994	
1994M11	22/11/1994		97th meeting of the OPEC conference
1994M12		20/12/1994	
1995M01		17/01/1995	
1995M02		21/02/1995	
1995M03		21/03/1995	
1995M04		18/04/1995	
1995M05		23/05/1995	
1995M06	20/06/1995		98th meeting of the OPEC conference
1995M07		19/07/1995	
1995M08		23/08/1995	
1995M09		20/09/1995	
1995M10		25/10/1995	
1995M11	22/11/1995		99th meeting of the OPEC conference
1995M12		08/12/1995	
1996M01		05/01/1996	
1996M02		09/02/1996	
1996M03		08/03/1996	
1996M04		12/04/1996	
1996M05		10/05/1996	
1996M06	07/06/1996		100th meeting of the OPEC conference
1996M07		29/07/1996	
1996M08		26/08/1996	
1996M09		30/09/1996	
1996M10		28/10/1996	
1996M11	28/11/1996		101st meeting of the OPEC conference
1996M12		26/12/1996	
1997M01		23/01/1997	
1997M02		27/02/1997	
1997M03		27/03/1997	
1997M04		24/04/1997	
1997M05		29/05/1997	
1997M06	26/06/1997		102nd meeting of the OPEC conference
1997M07		07/07/1997	
1997M08		04/08/1997	
1997M09		08/09/1997	
1997M10		06/10/1997	
1997M11		03/11/1997	
1997M12	01/12/1997		103rd meeting of the OPEC conference
1998M01		26/01/1998	
1998M02		23/02/1998	
1998M03	30/03/1998		104th (extraordinary) meeting of the OPEC conference
1998M04		22/04/1998	
1998M05		27/05/1998	
1998M06	24/06/1998		105th meeting of the OPEC conference
1998M07		27/07/1998	
1998M08		31/08/1998	
1998M09		28/09/1998	
1998M10		26/10/1998	
1998M11	26/11/1998		106th meeting of the OPEC conference
1998M12		22/12/1998	
1999M01		19/01/1999	
1999M02		23/02/1999	
1999M03	23/03/1999		107th meeting of the OPEC conference
1999M04		21/04/1999	

Month	Announcement date	Control date	Additional information
1999M05		26/05/1999	
1999M06		23/06/1999	
1999M07		21/07/1999	
1999M08		25/08/1999	
1999M09	22/09/1999		108th meeting of the OPEC conference
1999M10		27/10/1999	
1999M11		24/11/1999	
1999M12		29/12/1999	
2000M01		26/01/2000	
2000M02		23/02/2000	
2000M03	29/03/2000		109th meeting of the OPEC conference
2000M04		19/04/2000	
2000M05		24/05/2000	
2000M06	21/06/2000		110th (extraordinary) meeting of the OPEC conference
2000M07		10/07/2000	
2000M08		14/08/2000	
2000M09	11/09/2000		111th meeting of the OPEC conference
2000M10		16/10/2000	
2000M11	13/11/2000		112th (extraordinary) meeting of the OPEC conference
2000M12		13/12/2000	
2001M01	17/01/2001		113th (extraordinary) meeting of the OPEC conference
2001M02		20/02/2001	
2001M03	17/03/2001		114th meeting of the OPEC conference
2001M04		03/04/2001	
2001M05		08/05/2001	
2001M06	05/06/2001		115th (extraordinary) meeting of the OPEC conference
2001M07	03/07/2001, 25/07/2001		116th (extraordinary) meeting of the OPEC conference
2001M08		30/08/2001	
2001M09	27/09/2001		117th meeting of the OPEC conference
2001M10		17/10/2001	
2001M11	14/11/2001		118th (extraordinary) meeting of the OPEC conference
2001M12	28/12/2001		Consultative meeting of the OPEC conference
2002M01		11/01/2002	
2002M02		15/02/2002	
2002M03	15/03/2002		119th meeting of the OPEC conference
2002M04		24/04/2002	
2002M05		29/05/2002	
2002M06	26/06/2002		120th (extraordinary) meeting of the OPEC conference
2002M07		18/07/2002	
2002M08		22/08/2002	
2002M09	19/09/2002		121st meeting of the OPEC conference
2002M10		10/10/2002	
2002M11		14/11/2002	
2002M12	12/12/2002		122nd (extraordinary) meeting of the OPEC conference
2003M01	12/01/2003		123rd (extraordinary) meeting of the OPEC conference
2003M02		11/02/2003	
2003M03	11/03/2003		124th meeting of the OPEC conference
2003M04	24/04/2003		Consultative meeting of the OPEC conference
2003M05		14/05/2003	
2003M06	11/06/2003		125th (extraordinary) meeting of the OPEC conference
2003M07	31/07/2003		126th (extraordinary) meeting of the OPEC conference
2003M08		27/08/2003	
2003M09	24/09/2003		127th meeting of the OPEC conference
2003M10		02/10/2003	
2003M11		06/11/2003	
2003M12	04/12/2003		128th (extraordinary) meeting of the OPEC conference
2004M01		13/01/2004	
2004M02	10/02/2004		129th (extraordinary) meeting of the OPEC conference
2004M03	31/03/2004		130th meeting of the OPEC conference
2004M04		01/04/2004	
2004M05		06/05/2004	
2004M06	03/06/2004		131st (extraordinary) meeting of the OPEC conference
2004M07		14/07/2004	
2004M08		18/08/2004	
2004M09	15/09/2004		132nd meeting of the OPEC conference
2004M10		08/10/2004	
2004M11		12/11/2004	
2004M12	10/12/2004		133rd (extraordinary) meeting of the OPEC conference
2005M01	30/01/2005		134th (extraordinary) meeting of the OPEC conference
2005M02		16/02/2005	
2005M03	16/03/2005		135th meeting of the OPEC conference
2005M04		13/04/2005	
2005M05		18/05/2005	
2005M06	15/06/2005		136th meeting of the OPEC conference
2005M07		19/07/2005	
2005M08		23/08/2005	

Month	Announcement date	Control date	Additional information
2005M09	20/09/2005		137th meeting of the OPEC conference
2005M10		10/10/2005	
2005M11		14/11/2005	
2005M12	12/12/2005		138th (extraordinary) meeting of the OPEC conference
2006M01	31/01/2006		139th (extraordinary) meeting of the OPEC conference
2006M02		08/02/2006	
2006M03	08/03/2006		140th meeting of the OPEC conference
2006M04		06/04/2006	
2006M05		04/05/2006	
2006M06	01/06/2006		141st (extraordinary) meeting of the OPEC conference
2006M07		10/07/2006	
2006M08		14/08/2006	
2006M09	11/09/2006		142nd meeting of the OPEC conference
2006M10	20/10/2006		Consultative meeting of the OPEC conference
2006M11		09/11/2006	
2006M12	14/12/2006		143rd (extraordinary) meeting of the OPEC conference
2007M01		18/01/2007	
2007M02		15/02/2007	
2007M03	15/03/2007		144th meeting of the OPEC conference
2007M04		10/04/2007	
2007M05		08/05/2007	
2007M06		12/06/2007	
2007M07		10/07/2007	
2007M08		14/08/2007	
2007M09	11/09/2007		145th meeting of the OPEC conference
2007M10		03/10/2007	
2007M11		07/11/2007	
2007M12	05/12/2007		146th (extraordinary) meeting of the OPEC conference
2008M01		04/01/2008	
2008M02	01/02/2008		147th (extraordinary) meeting of the OPEC conference
2008M03	05/03/2008		148th meeting of the OPEC conference
2008M04		09/04/2008	
2008M05		07/05/2008	
2008M06		04/06/2008	
2008M07		09/07/2008	
2008M08		06/08/2008	
2008M09	10/09/2008		149th meeting of the OPEC conference
2008M10	24/10/2008		150th (extraordinary) meeting of the OPEC conference
2008M11		19/11/2008	
2008M12	17/12/2008		151st (extraordinary) meeting of the OPEC conference
2009M01		12/01/2009	
2009M02		09/02/2009	
2009M03	15/03/2009		152nd meeting of the OPEC conference
2009M04		30/04/2009	
2009M05	28/05/2009		153rd (extraordinary) meeting of the OPEC conference
2009M06		11/06/2009	
2009M07		09/07/2009	
2009M08		13/08/2009	
2009M09	10/09/2009		154th meeting of the OPEC conference
2009M10		20/10/2009	
2009M11		24/11/2009	
2009M12	22/12/2009		155th (extraordinary) meeting of the OPEC conference
2010M01		13/01/2010	
2010M02		17/02/2010	
2010M03	17/03/2010		156th meeting of the OPEC conference
2010M04		15/04/2010	
2010M05		13/05/2010	
2010M06		10/06/2010	
2010M07		15/07/2010	
2010M08		12/08/2010	
2010M09		16/09/2010	
2010M10	14/10/2010		157th meeting of the OPEC conference
2010M11		15/11/2010	
2010M12	11/12/2010		158th (extraordinary) meeting of the OPEC conference
2011M01		05/01/2011	
2011M02		09/02/2011	
2011M03		09/03/2011	
2011M04		06/04/2011	
2011M05		11/05/2011	
2011M06	08/06/2011		159th meeting of the OPEC conference
2011M07		13/07/2011	
2011M08		10/08/2011	
2011M09		14/09/2011	
2011M10		12/10/2011	
2011M11		16/11/2011	
2011M12	14/12/2011		160th meeting of the OPEC conference
2012M01		12/01/2012	

Month	Announcement date	Control date	Additional information
2012M02		16/02/2012	
2012M03		15/03/2012	
2012M04		12/04/2012	
2012M05		17/05/2012	
2012M06	14/06/2012		161st meeting of the OPEC conference
2012M07		11/07/2012	
2012M08		15/08/2012	
2012M09		12/09/2012	
2012M10		10/10/2012	
2012M11		14/11/2012	
2012M12	12/12/2012		162nd meeting of the OPEC conference
2013M01		25/01/2013	
2013M02		22/02/2013	
2013M03		22/03/2013	
2013M04		26/04/2013	
2013M05	31/05/2013		163rd meeting of the OPEC conference
2013M06		05/06/2013	
2013M07		03/07/2013	
2013M08		07/08/2013	
2013M09		04/09/2013	
2013M10		02/10/2013	
2013M11		06/11/2013	
2013M12	04/12/2013		164th meeting of the OPEC conference
2014M01		08/01/2014	
2014M02		12/02/2014	
2014M03		12/03/2014	
2014M04		09/04/2014	
2014M05		14/05/2014	
2014M06	11/06/2014		165th meeting of the OPEC conference
2014M07		25/07/2014	
2014M08		29/08/2014	
2014M09		26/09/2014	
2014M10		31/10/2014	
2014M11	27/11/2014		166th meeting of the OPEC conference
2014M12		05/12/2014	
2015M01		02/01/2015	
2015M02		06/02/2015	
2015M03		06/03/2015	
2015M04		10/04/2015	
2015M05		08/05/2015	
2015M06	05/06/2015		167th meeting of the OPEC conference
2015M07		10/07/2015	
2015M08		07/08/2015	
2015M09		04/09/2015	
2015M10		02/10/2015	
2015M11		06/11/2015	
2015M12	04/12/2015		168th meeting of the OPEC conference
2016M01		07/01/2016	
2016M02		04/02/2016	
2016M03		03/03/2016	
2016M04		07/04/2016	
2016M05		05/05/2016	
2016M06	02/06/2016		169th meeting of the OPEC conference
2016M07		28/07/2016	
2016M08		25/08/2016	
2016M09	28/09/2016		170th (extraordinary) meeting of the OPEC conference
2016M10		26/10/2016	
2016M11	30/11/2016		171st meeting of the OPEC conference
2016M12	10/12/2016		OPEC and non-OPEC ministerial meeting
2017M01		26/01/2017	
2017M02		23/02/2017	
2017M03		23/03/2017	
2017M04		27/04/2017	
2017M05	25/05/2017		172nd meeting of the OPEC conference
2017M06		29/06/2017	
2017M07		27/07/2017	
2017M08		31/08/2017	
2017M09		28/09/2017	
2017M10		26/10/2017	
2017M11	30/11/2017		173rd meeting of the OPEC conference
2017M12		28/12/2017	

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	Trans.
Instrument				
NCLC.hh (PS)	WTI crude oil futures *hh*-month contract (settlement price)	Datastream	30/03/1983-31/12/2017	100*Δlog
Baseline variables				
OILPRICE	WTI spot crude oil price (WTISPLC) deflated by U.S. CPI (CPIAUCSL)	FRED	1974M1-2017M12	100*log
EIA1955	World oil production	Datastream	1974M1-2017M12	100*log
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	100*log
OECDSTOCKS	OECD crude oil inventories, calculated based on OECD petroleum stocks (EIA1976) and U.S. crude oil and petroleum stocks (EIA1533, EIA1541), as in Kilian and Murphy (2014)	Datastream/own calculations	1974M1-2017M12	100*log
INDPRO	U.S. industrial production index	FRED	1974M1-2017M12	100*log
CPIAUCSL	U.S. CPI for all urban consumers: all items	FRED	1974M1-2017M12	100*log
Additional variables				
Expectations and uncertainty				
BKEXP12M	Oil price expectations (12-month) from Baumeister and Kilian (2017), extended using futures prices	Baumeister's webpage/ own calculations	1983M4-2017M12	100*log
MICH	University of Michigan: inflation expectation	FRED	1981M7-2017M12	Level
CPI6	SPF median inflation expectations (1 year horizon)	Philadelphia FED	1981Q3-2017Q4	Level
VXOCLS	CBOE S&P 100 volatility index: VXO, extended as in Bloom (2009)	FRED/own calculations	1974M1-2017M12	100*log
GPR	Geopolitical risk index from Caldara and Iacoviello (2018)	Iacoviello's webpage	1985M1-2017M12	100*log
Prices				
CPILFESL	U.S. CPI for all urban consumers: all items less food and energy	FRED	1974M1-2017M12	100*log
CPIENGSL	U.S. CPI for all urban consumers: energy	FRED	1974M1-2017M12	100*log
CUSR0000SAN	U.S. CPI for all urban consumers: nondurables	FRED	1974M1-2017M12	100*log
CUSR0000SAD	U.S. CPI for all urban consumers: durables	FRED	1974M1-2017M12	100*log
CUSR0000SAS	U.S. CPI for all urban consumers: services	FRED	1974M1-2017M12	100*log
Activity				
UNRATE	Civilian unemployment rate	FRED	1974M1-2017M12	Level
RPCE	U.S. personal consumption expenditures (PCE), deflated by chain-type price index (PCEPI)	FRED	1974M1-2017M12	100*log
GDPC1	U.S. Real Gross Domestic Product	FRED	1974Q1-2017Q4	100*log
GPDIC1	U.S. Real Gross Private Domestic Investment	FRED	1974Q1-2017Q4	100*log
PCECC96	U.S. Real Personal Consumption Expenditures	FRED	1974Q1-2017Q4	100*log
Financial variables				
FF	Effective federal funds rate	FRED	1974M1-2017M12	Level
EBP	Excess bond premium from Gilchrist and Zakrajšek (2012)	Gilchrist's webpage	1974M1-2017M12	Level
SPCOMP	S&P 500 composite price index (monthly average)	Datastream/ own calculations	1974M1-2017M12	100*log
Exchange rates and trade				
TWEXBMTH	Trade Weighted U.S. Dollar Index: Broad	FRED	1974M1-2017M12	100*log
TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies	FRED	1974M1-2017M12	100*log
–	Bilateral exchange rates, domestic currency per U.S. dollar	IFS	1974M1-2017M12 RUS starts 1995M6	100*log
USTOTPRCF	U.S. terms of trade	Datastream	1974M1-2017M12	100*log
USBALGDSB	U.S. merchandise trade balance, as a share of nominal GDP (GDP from FRED)	Datastream/FRED	1974Q1-2017Q4	Level

Table B.3: Description of data in online appendix

Variable	Description	Source	Sample	Trans.
Wider effects				
RDNRGRC1M027SBEA	U.S. PCE energy goods and services (DNRGRC1M027SBEA), deflated by DNRGRG3M086SBEA	FRED	1974M1-2017M12	100*log
RPCEND	U.S. PCE nondurable goods (PCEND), deflated by DNDGRG3M086SBEA	FRED	1974M1-2017M12	100*log
RPCEDG	U.S. PCE durable goods (PCEDG), deflated by DDURRG3M086SBEA	FRED	1974M1-2017M12	100*log
RPCES	U.S. PCE services (PCES), deflated by DSERRG3M086SBEA	FRED	1974M1-2017M12	100*log
OILGSUS	Oil & Gas stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
ELECTUS	Electricity stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
MNINGUS	Mining stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
AUTOSUS	Automobiles stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
RTAILUS	Retail stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
TRLESUS	Travel & Leisure stock price index (monthly average)	Datastream/own calculations	1974M1-2017M12	100*log
Sensitivity				
LLCC.hh (PS)	Brent crude oil futures *hh*-month contract (settlement price)	Datastream	24/06/1983-31/12/2017	100*Δlog
BRENTP	Brent spot crude oil price (DCOILBRENTEU, extended using POILBREUSDM and WTISPLC) deflated by U.S. CPI (CPIAUCSL)	FRED/own calculations	1974M1-2017M12	100*log
REFINERCOST	U.S. refiners acquisition cost of imported crude oil (USCOCOIMA) deflated by U.S. CPI (CPIAUCSL)	Datastream	1974M1-2017M12	100*log
GLOBALACT	Kilian's (2009) index of global real economic activity	Kilian's webpage	1974M1-2015M12	Level

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

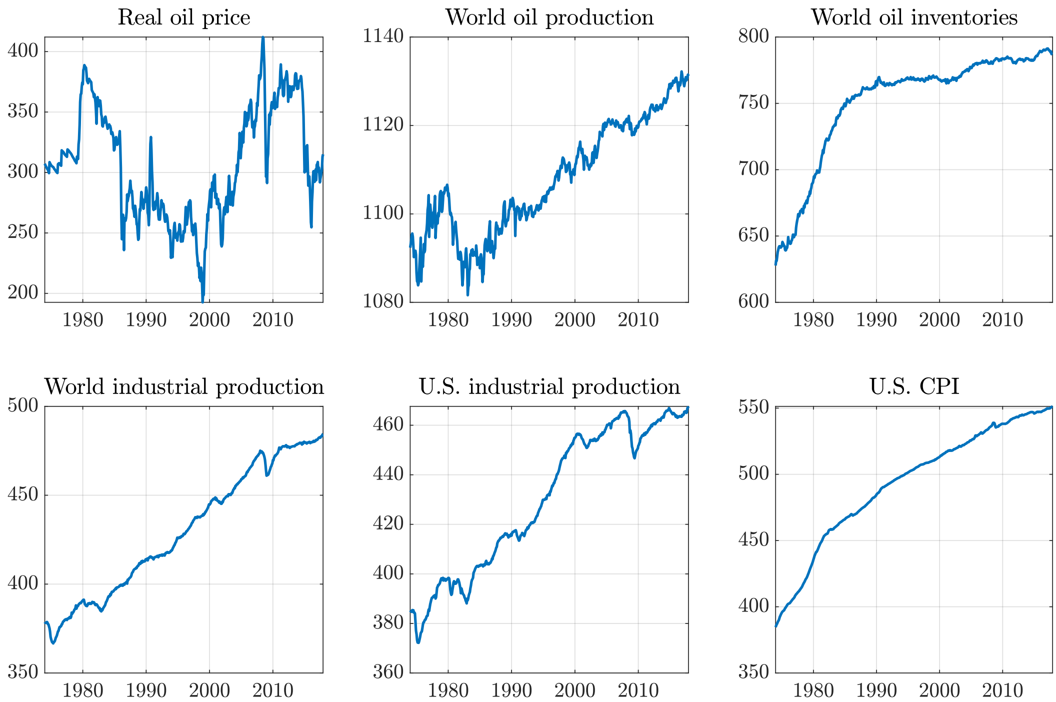


Figure B.1: Transformed data series in the baseline VAR

C. 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.

C.1. Simple case with one shock and one instrument

In the following, I derive the structural impact vector for the simple case with one instrument and one shock. Recall, the moment conditions for the external instrument were given by

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

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

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

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 $i \in \{2, \dots, n\}$ are indexed by 2 instead of $2{:}n$.

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

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

Note that $\mathbf{\Sigma}$ 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):

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

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

$$\begin{aligned} \mathrm{s}^2_{1,1} + \mathbf{s}_{1,2}\mathbf{s}'_{1,2} &= \sigma_{1,1} && (3) \\ \mathrm{s}^2_{1,1}\tilde{\mathbf{s}}_{2,1} + \mathbf{S}_{2,2}\mathbf{s}'_{1,2} &= \boldsymbol{\sigma}_{2,1} && (4) \\ \mathrm{s}^2_{1,1}\tilde{\mathbf{s}}_{2,1}\tilde{\mathbf{s}}'_{2,1} + \mathbf{S}_{2,2}\mathbf{S}'_{2,2} &= \mathbf{\Sigma}_{2,2}. && (5) \end{aligned}$$

From equation (3), 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 (3) multiplied by $\tilde{\mathbf{s}}_{2,1}$ from (4), 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,

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

Now, note that

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

By subtracting (4) multiplied by $\tilde{\mathbf{s}}'_{2,1}$ from (5), 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 (3) pre-multiplied by $\tilde{\mathbf{s}}_{2,1}$ and post-multiplied by $\tilde{\mathbf{s}}'_{2,1}$ from (5), 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 $\boldsymbol{\Omega} = \mathrm{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$ and $\mathrm{s}_{1,1} = x$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a positive effect of magnitude x on $\mathrm{y}_{1,t}$. The structural impact vector is then given by

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

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

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 to get estimates of the reduced-form innovations $\hat{\mathbf{u}}_t$. In a second step, estimate (2) 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 $\hat{\mathbf{s}}_1$.

Having obtained the impact vector, it is straightforward to compute all objects of interest such as IRFs, FEVDs, and historical decompositions. In particular, as shown in Stock and Watson (2018), it is also possible to compute the structural shock series, $\varepsilon_{1,t}$. It is given by

$$\begin{aligned}
\mathbf{s}_1'\boldsymbol{\Sigma}^{-1}\mathbf{u}_t &= \mathbf{s}_1'(\mathbf{S}\mathbf{S}')^{-1}\mathbf{u}_t && \text{(assuming that } \boldsymbol{\Sigma} = \mathbf{S}\mathbf{S}'\text{)} \\
&= \mathbf{s}_1'\mathbf{S}'^{-1}\mathbf{S}^{-1}\mathbf{S}\boldsymbol{\varepsilon}_t \\
&= \mathbf{e}_1'\boldsymbol{\varepsilon}_t && \text{(because } \mathbf{S}^{-1}\mathbf{s}_1 = \mathbf{e}_1\text{)} \\
&= \varepsilon_{1,t},
\end{aligned}$$

where $\mathbf{e}_1$ is the first standard basis vector.

C.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 $\mathbf{S}\mathbf{S}' = \mathbf{\Sigma}$. 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 $\mathbf{S}_{12}\mathbf{S}_{22}^{-1}$:

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

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

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

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

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

Thus,

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

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.

D. Identification via heteroskedasticity

This Appendix provides more detail on the heteroskedasticity-based identification strategy. In the following, I derive the formula for the structural impact vector.

As discussed in the main text, we assume that movements in the oil futures z_t we observe in the data are governed by both oil supply news and other shocks:

$$z_t = \varepsilon_{1,t} + \sum_{j \neq 1} \varepsilon_{j,t} + v_t,$$

where $\varepsilon_{j,t}$ are other shocks affecting oil futures and v_t captures measurement error such as microstructure noise, satisfying $v_t \sim iidN(0, \sigma_v^2)$.

Recall, the identifying assumption is that the variance of oil supply news shocks increases at the time of OPEC announcements while the variance of all other shocks is unchanged. We can write the identifying assumptions as

$$\begin{aligned} \sigma^2_{\varepsilon_1,R1} &> \sigma^2_{\varepsilon_1,R2} \\ \sigma^2_{\varepsilon_j,R1} &= \sigma^2_{\varepsilon_j,R2}, \quad \text{for } j = 2, \dots, n. \\ \sigma^2_{v,R1} &= \sigma^2_{v,R2}, \end{aligned}$$

where $R1$ is the treatment sample of OPEC announcements and $R2$ is the control sample.

Under these assumptions, the structural impact vector obtains as

$$\mathbf{s}_1 = \frac{\mathbb{E}_{R1}[z_t\mathbf{u}_t] - \mathbb{E}_{R2}[z_t\mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2] - \mathbb{E}_{R2}[z_t^2]}.$$

To see why this is the case, note that

$$\frac{\mathbb{E}_{R1}[z_t\mathbf{u}_t]-\mathbb{E}_{R2}[z_t\mathbf{u}_t]}{\mathbb{E}_{R1}[z_t^2]-\mathbb{E}_{R2}[z_t^2]}=\frac{\mathbf{S}\,\mathbb{E}_{R1}[z_t\boldsymbol{\varepsilon}_t]-\mathbf{S}\,\mathbb{E}_{R2}[z_t\boldsymbol{\varepsilon}_t]}{\mathbb{E}_{R1}[z_t^2]-\mathbb{E}_{R2}[z_t^2]}=\frac{\mathbf{s}_1(\sigma^2_{\varepsilon_1,R1}-\sigma^2_{\varepsilon_1,R2})}{\sigma^2_{\varepsilon_1,R1}-\sigma^2_{\varepsilon_1,R2}}=\mathbf{s}_1,$$

where the first equality uses $\mathbf{u}_t=\mathbf{S}\boldsymbol{\varepsilon}_t$ and the second equality follows directly from $\sigma^2_{\varepsilon_j,R1}=\sigma^2_{\varepsilon_j,R2}$ and $\sigma^2_{v,R1}=\sigma^2_{v,R2}$, and the fact that the structural shocks are mutually uncorrelated.

As shown by Rigobon and Sack (2004), we can also obtain this estimator through an IV approach, using $\tilde{\mathbf{z}}=(\mathbf{z}'_{R1},\ -\mathbf{z}'_{R2})'$ as an instrument for $\mathbf{z}=(\mathbf{z}'_{R1},\ \mathbf{z}'_{R2})'$ in a regression of $\mathbf{U}=(\mathbf{U}'_{R1},\ \mathbf{U}'_{R2})'$ on $\mathbf{z}$, where $\mathbf{z}$ is an $T\times 1$ vector containing the daily changes in futures prices in the treatment and the control regime and $\mathbf{U}$ is a $T\times n$ matrix containing the reduced-form residuals in the treatment and the control regime. To see why this is the case, substitute these expressions in the IV estimator $\mathbb{E}[\tilde{\mathbf{z}}'\mathbf{z}]^{-1}\,\mathbb{E}[\tilde{\mathbf{z}}'\mathbf{U}]$, and the above estimator obtains.

Based on $\mathbf{s}_1$, it is then straightforward to compute the impulse responses to the oil supply news shock and all other objects of interest. As in the external instruments case, we can also obtain an estimate of the structural shock. From the covariance restrictions, we have that

$$\begin{aligned}\boldsymbol{\Sigma}_{R1}&=\mathbf{S}\boldsymbol{\Omega}_{R1}\mathbf{S}'\\ \boldsymbol{\Sigma}_{R2}&=\mathbf{S}\boldsymbol{\Omega}_{R2}\mathbf{S}'.\end{aligned}$$

We can then obtain the structural shock as

$$\varepsilon_{1,t}=\mathbf{s}_1'\boldsymbol{\Sigma}_{R1}^{-1}\mathbf{u}_t(\mathbf{s}_1'\boldsymbol{\Sigma}_{R1}^{-1}\mathbf{s}_1)^{-1}.$$

To see why this is the case, note that

$$\begin{aligned}\mathbf{s}_1'\boldsymbol{\Sigma}_{R1}^{-1}\mathbf{u}_t&=\mathbf{s}_1'(\mathbf{S}\boldsymbol{\Omega}_{R1}\mathbf{S}')^{-1}\mathbf{S}\boldsymbol{\varepsilon}_t\\ &=\mathbf{e}_1'\boldsymbol{\Omega}_{R1}^{-1}\boldsymbol{\varepsilon}_t\\ &=\frac{\varepsilon_{1,t}}{\sigma^2_{\varepsilon_1,R1}},\end{aligned}$$

and $(\mathbf{s}_1'\boldsymbol{\Sigma}_{R1}^{-1}\mathbf{s}_1)^{-1}=\sigma^2_{\varepsilon_1,R1}$.[8]

[8]Note that we can also estimate the shock based on the covariance matrix of the second regime. In population, the two should be the same. In my sample, the two were almost identical (correlation stands at over 99 percent).

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