The macroeconomic effects of oil supply shocks: new evidence from OPEC announcements*

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Abstract

This paper proposes a novel approach to identify oil supply shocks exploiting institutional features of the OPEC and high-frequency data. Using variation in futures prices around OPEC announcements as an instrument in a SVAR, I identify an oil supply news shock. These shocks have statistically and economically significant effects. Negative news lead to an immediate increase in oil prices, a sluggish fall in oil production and an increase in inventories. This has consequences for the U.S. economy: industrial production falls, consumer 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

Many years after the oil crises of the 1970s, recent turbulences in the oil market have sparked renewed interest in the question of how oil prices affect the macroeconomy. Answering this question is nontrivial because oil prices are endogenous and respond to global macroeconomic conditions – complicating the estimation of a causal effect. In the literature, many different approaches have been put forward to deal with this problem, ranging from non-linear transformations of the oil price to more structural approaches such as constructing exogenous oil shock series or the identification of different shocks affecting oil prices based on structural vector autoregression (SVAR) models.¹

In this paper, I propose a novel identification strategy exploiting institutional features of the Organization of the Petroleum Exporting Countries (OPEC) and information contained in high-frequency data. The idea is to utilize variation in oil futures prices around OPEC announcements. The 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). Obviously, the OPEC’s decisions are not exogenous but depend rather directly on the state of the global economy (Barsky and Kilian, 2004). However, by measuring the changes in oil futures prices in a tight window around the announcements, one can credibly isolate the impact of news about future changes in 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 a SVAR, I am able to identify a novel oil supply shock. As I will argue, this shock is best thought of as a news shock about future oil supply.

Results preview. I find that oil supply news shocks have statistically and economically significant effects. A negative news shock about future oil supply leads to a large, immediate increase in oil prices, a sluggish but significant fall in world oil production and a significant increase in world oil inventories. Global economic activity, proxied by world industrial production, does not change significantly on impact but then starts to fall persistently. This has consequences for the U.S. economy: industrial production falls and consumer prices rise significantly. This evidence supports the notion that changes in expectations about future oil supply may have very powerful effects even if physical oil production does not move (Kilian, 2008b).

¹See Kilian (2008a) for a survey and Stock and Watson (2016) for a handbook chapter treatment of this literature.
Looking at the wider effects of oil supply news shocks, I find that they lead to a significant rise in consumer prices even after excluding energy prices, a persistent fall in personal consumption expenditures, rising unemployment, lower hours worked and falling stock market indices. Interestingly, they also cause a significant rise in inflation expectations, consistent with recent evidence on the determinants of inflation (Coibion and Gorodnichenko, 2015; Hasenzagl et al., 2017). Finally, they lead to a significant depreciation of the U.S. dollar, as measured by the nominal and real effective exchange rate. This helps to reconcile the strong negative correlation between oil prices and the dollar in recent years and corroborates recent empirical evidence by Kilian and Zhou (2018).

Oil supply news shocks also turn out to be an important driver of the economy as they explain a substantial share of the variations in economic activity and prices. A comprehensive series of sensitivity checks indicate that the results are robust along a number of dimensions including the construction of the instrument, the specification of the model and the sample period.

**Related literature and contribution.** This paper is related to a long literature studying the macroeconomic consequences of oil market shocks (see Kilian, 2008a, for a survey). Much of the recent work has relied on structural VAR models of the oil market. In a seminal paper, Kilian (2009) argued that the common approach of identifying a causal effect of oil prices is flawed because it does not account for the underlying shocks driving the price change. Based on a SVAR, he identified three different shocks driving the oil market – an oil supply, a global demand and an oil-specific demand shock – and showed that oil price increases indeed have very different effects depending on the underlying cause. Identification is achieved using exclusion restrictions that are interpretable in terms of the slopes of short-run demand and supply curves. In particular, it is assumed that the short-run price elasticity of oil supply is zero.

More recently, several studies aimed at relaxing these identifying assumptions with the help of sign restrictions (Baumeister and Peersman, 2013; Kilian and Murphy, 2012; Lippi and Nobili, 2012). To get a better understanding of oil-specific demand, some studies also augmented the standard oil market VAR by global oil inventory data (Kilian and Murphy, 2014; Juvenal and Petrella, 2015). However, as Kilian and Murphy (2012) show, sign restrictions alone are usually not enough to achieve credible identification. Further restrictions, such as assumptions on the price elasticities of oil demand and supply (Kilian and Murphy, 2012; Baumeister and Hamilton, forthcoming) or restrictions based on narrative information (Antolín-Díaz and Rubio-Ramírez, 2018), are needed to credibly identify the shocks of inter-
est. Depending on the exact specification of these additional restrictions, however, one can reach very different conclusions regarding the relative importance of demand and supply shocks (Caldara, Cavallo, and Iacoviello, 2018). The choice of the appropriate restrictions as well as their implementation are still subject to debate.

This paper contributes to this literature by proposing a novel identification strategy to enhance the credibility and realism of oil market VARs. Using a newly constructed instrument based on high-frequency data on oil futures prices, I am able to credibly identify an oil market shock that can be interpreted as a news shock about future oil supply. This is an important methodological advance because identifying the forward-looking component of the price of oil has proven to be challenging (Kilian and Murphy, 2014; Gambetti and Moretti, 2017). As in Kilian and Murphy (2014), I do not model the oil futures market explicitly. However, I show that oil futures prices contain valuable information for identification. In contrast to traditional oil market VARs, my approach does not rely on possibly controversial restrictions on demand and supply elasticities. Furthermore, the proxy VAR approach is potentially less vulnerable to the problem of non-fundamentalness (Miranda-Agrippino and Ricco, 2018a). This is particularly relevant against the backdrop that the small-scale oil market VARs have been found to be sensitive to the choice of the information set (Juvenal and Petrella, 2015).

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

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2Stock and Watson (2012) and Montiel-Olea, Stock, and Watson (2016) also use the external instruments approach to identify oil supply shocks. For identification, they use a number of exogenous supply shocks series based on political events in the middle east, including Hamilton’s (2003) quantitative dummies or Kilian’s (2008b) counterfactual based production shortfall series. However, they find that these series are only weak instruments.
at the macroeconomic effects of these announcements – combining the event study literature on OPEC meetings with the traditional oil market VAR analysis.

My results indicate that even if physical oil production does not move, news shocks about future supply can have a meaningful impact on the price of oil and macroeconomic aggregates. In this sense, I also contribute to the voluminous literature on the role of news in the business cycle (see Beaudry and Portier, 2014, for a survey) by providing evidence for a strong expectational channel in the oil market. The empirical literature on news shocks focuses on anticipated technology (Beaudry and Portier, 2006; Barsky and Sims, 2011) and fiscal shocks (Ramey, 2011; Leeper, Walker, and Yang, 2013). Only recently, there has been a growing interest in other kinds of news, such as news about future monetary policy or production possibilities (see e.g. Gertler, and Karadi, 2015; Arezki, Ramey, and Sheng, 2017). Gambetti and Moretti (2017) also identify a news shock in the oil market but use a completely different methodology. Furthermore, their shock seems to capture news about future demand, whereas the shock in this paper captures news about future supply.

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

2. Identification

An influential literature identifies monetary policy shocks exploiting the lumpy way in which monetary news is revealed and high-frequency data on interest rate futures.3 There are interesting similarities between the oil market and the monetary policy setting. First, the oil market is dominated by a big player, the OPEC, that reveals information about future supply in a lumpy way. Second, there are very liquid futures markets for oil. This motivates the use of high-frequency identification techniques to identify oil supply shocks. The idea is to construct an oil supply

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3This literature was pioneered by Rudebusch (1998), Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005) and notable contributions include, among others, Bernanke, and Kuttner (2005); Hamilton (2008); Campbell et al. (2012); Gertler, and Karadi (2015); Gilchrist, López-Salido, and Zakrajišek (2015); Rey (2016); Gerko, and Rey (2017); Nakamura, and Steinsson (2018); Caldara, and Herbst (2019).
surprise series that can be used as an external instrument to identify a structural oil supply shock. Before discussing the construction of the surprise series, I provide some background information on the OPEC and the global oil and oil futures markets.

2.1. Institutional background

The global oil market and the OPEC. The global market for oil has a peculiar structure in that it is dominated by a few big players. The biggest and most important player is the OPEC. The OPEC is an intergovernmental organization of oil producing nations and accounts for an estimated 44 percent of the world’s crude oil production.\(^4\) It was founded in 1960 by five countries, namely Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. Since then, other countries have joined the organization and currently, the OPEC has a total of 14 member countries (five in the Middle East, seven in Africa, and two in South America).\(^5\) According to the statutes, the 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 cite OPEC as a textbook example of a cartel that cooperates to reduce market competition.

The supreme authority of the organization is the OPEC conference, which consists of delegations headed by the oil ministers of the member countries. Several times a year, the OPEC conference meets in order to agree on oil production policies, based on its assessment of the global oil market. Since 1982, this includes setting an overall oil production ceiling for the organization and individual production quotas for its members.\(^6\) The conference ordinarily meets twice a year on pre-scheduled dates at its headquarters in Vienna but if necessary it can also call for extraordinary meetings with short notice. In making decisions, the conference generally operates on the principles of unanimity and ‘one member, one vote’. However, since Saudi Arabia is by far the largest and most profitable oil exporter in the world, 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’.\(^7\)

\(^4\)Estimated based on data for 2016 of the US Energy Information Agency (EIA).
\(^5\)For more information on the history of OPEC, see e.g. Yergin (2011).
\(^6\)The OPEC production quota system was established in 1982. Before, the OPEC targeted oil prices instead of production quantities (OPEC Secretariat, 2003).
The decisions of the conference are usually announced in a press communiqué shortly after the meeting concludes, followed by a press conference where members of the press can ask questions. A typical announcement starts with a review of the oil market outlook before communicating the decisions on production quotas, which normally become effective 30 days later. As an example, I include below an excerpt of an announcement made on December 14, 2006 after the 143rd meeting of the OPEC conference:

*Having reviewed the oil market outlook, including the overall demand/supply expectations for the year 2007, in particular the first and second quarters, as well as the outlook for the oil market in the medium term, the Conference observed that market fundamentals clearly indicate that there is more than ample crude supply, high stock levels and increasing spare capacity. The Conference noted that, although the global economy is forecast to continue to grow, economic growth is expected to slow down in 2007. Moreover, while world oil demand is estimated to increase by 1.3 mb/d in 2007, the Conference observed that this is likely to be more than offset by a projected increase of 1.8 mb/d in non-OPEC supply, its highest rise since 1984. [...]*

*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. The Conference further reiterated the Organization’s determination to take all measures deemed necessary to keep market stability through the maintenance of supply and demand in balance, for the benefit of producers and consumers alike.*

Since the OPEC accounts for a significant share of world oil production, these announcements are closely followed by markets and can have a significant impact on oil prices (Lin, and Tamvakis, 2010; Loutia, Mellios, and Andriosopoulos, 2016). However, it should also be noted that historically, the OPEC often had difficulties agreeing on policy decisions as well as enforcing them. This is only logical given the large differences in oil export capacities, production costs, reserves, geological features, population, economic development, budgetary situations, and political circumstances of its member countries. Nevertheless, the overall process closely resembles the monetary policy setting in which there is a monetary policy committee that meets on a regular basis to decide on policy measures and communicates the decisions to the markets via an announcement.
Oil futures markets. Crude oil is an internationally traded commodity and thus there exist very liquid futures markets for crude oil. The two most widely traded contracts are the West Texas Intermediate (WTI) crude and the Brent crude futures. WTI and Brent are grades of crude oil that are used as benchmarks in pricing oil internationally.

I focus on WTI crude futures because of the following reasons. First, WTI is the relevant benchmark for pricing oil in the U.S., the country of primary interest in this paper. Second, the quotes have the longest available history as these were the first traded futures on crude oil. WTI crude futures are traded at the NYMEX and were introduced back in 1983, which effectively constrains the start of the oil supply surprise series. Finally, the WTI crude futures market is the most liquid and largest market for crude oil, currently trading nearly 1.2 million contracts a day (CME Group, 2018). The contract has the following characteristics. The contract size is 1,000 barrels, the futures is priced in U.S. dollars and cash settled against the prevailing market price for U.S. light sweet crude. Trading ends at the 3rd business day prior to the 25th calendar day of the month preceding the contract month. The contract series includes up to 108 consecutive months.

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. Just like in the monetary policy setting, the OPEC is reacting systematically to global economic conditions and therefore their decisions are endogenous. However, by measuring the changes within a sufficiently tight window around the announcement, one can hope to isolate the impact of news about changes in future oil supply.\(^8\) Reverse causality of the global economic development on OPEC decisions can be plausibly ruled out because the global economic conditions are known and priced by the market and unlikely to change within the tight window. Assuming that risk premia are constant over the window of interest, the resulting series will capture changes in oil price expectations caused by OPEC announcements.

To be able to interpret this as news about future oil supply, it is crucial that the announcements do not contain any new information about other factors such as oil demand, global economic activity or geopolitical developments. As the announcements often include projections about future oil demand, this also amounts to assume that the OPEC is not a better forecaster than other market participants. Even though it is hard to assess whether this is the case or not, looking at how

\(^8\)Given the implementation lag of OPEC decisions, I argue that the surprises mainly capture news about future supply, as opposed to current supply.
OPEC announcements are received in the financial press is suggestive as the focus is usually on whether the OPEC could agree on new production quotas or not. It should also be noted that these problems are not specific to the oil market. It is now well known that monetary policy also transmits through an information channel that likely conflates high-frequency measures of monetary policy shocks (Nakamura and Steinsson, 2018; Miranda-Agrippino and Ricco, 2018b; Jarocinski and Karadi, 2018). I will argue that the information channel is if at all less of a problem in the oil market because the informational advantage is less obvious than in the case of a central bank. To address this concern more rigorously, I will also construct an informationally robust surprise series by regressing the original series on revisions in OPEC’s global demand forecasts, akin to the refinement of Romer and Romer (2004) in the monetary policy setting, and show that the results are robust (see section 5).

To construct the benchmark series, I collected OPEC press releases for the period 1983-2015. There were a total of 113 announcements made during this period. An overview of all announcement dates can be found in appendix B.1. In a next step, I collected daily data on WTI crude oil futures prices. Based on this data, I construct a series of oil supply surprises by taking the (log) difference of the settlement price on the day of the OPEC announcement and the price on the last trading day before the announcement:

\[ \text{Surprise}_{t,d}^h = F_{t+h,d} - F_{t+h,d-1}, \]

where \(d\) and \(t\) indicate the day and the month of the announcement, respectively, and \(F_{t+h,d}\) is the (log) settlement price of the \(h\)-months ahead oil futures contract in month \(t\) on day \(d\). Any standard asset pricing framework implies that

\[ F_{t+h,d} = \mathbb{E}_d[P_{t+h}] + RP_{t+h,d}, \]

where \(\mathbb{E}_d[P_{t+h}]\) is the expected oil price conditional on the information at time \(d\) and \(RP_{t+h,d}\) is a risk premium. Assuming that the risk premium does not change within the daily window around the announcement, i.e. \(RP_{t+h,d} = RP_{t+h,d-1}\), one

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9 Other important contributions on this topic include Stavrakeva and Tang (2018) and Cieslak and Schrimpf (2018).

10 It should also be noted that even if one does not believe the interpretation of an oil supply news shock, one can still interpret the identified shock as an oil market news shock capturing expectational shifts driven by news about future oil demand and supply, akin to speculative demand shocks (Kilian and Murphy, 2014; Juvenal and Petrella, 2015).

11 The futures data comes from Datastream. In particular, I use the continuous synthetic series computed by Thomson Reuters. The relevant Mnemonic is NCLC.hh, where hh is the maturity (in months) of the contract.
can interpret the surprise as a revision in oil price expectations

\[ \text{Surprise}_{t,d}^h = E_d[P_{t+h}] - E_{d-1}[P_{t+h}] \]

that is caused by the respective OPEC announcement.\textsuperscript{12}

These daily surprises, \( \text{Surprise}_{t,d}^h \), are then aggregated to a monthly series, \( \text{Surprise}_{t}^h \), as follows. When there was only one announcement in a given month, the monthly surprise is equal to the daily surprise. When there were multiple announcements, the monthly surprise is computed by summing the different daily surprises in the given month. When there was no announcement, the monthly surprise takes zero value.\textsuperscript{13}

An important issue in this context is the choice of the maturity of the futures contract, \( h \). Recall, crude oil futures are traded at maturities up to 9 years, so in principle, these are all possible choices. Taking into account the horizon of OPEC announcements as well as implementation lags, maturities ranging from 1 month to one year seem to be the most natural choices. However, contracts with maturities several quarters out tend to be less liquid and have higher term and liquidity premia. Furthermore, these futures also have shorter coverage as they were only traded in the more recent past. The contract with the longest maturity that is still sufficiently liquid and has adequate coverage is the 6-month maturity contract. To sharpen the interpretation of a news shock about future oil supply, I use this contract as a benchmark, i.e. \( z_t = \text{Surprise}_t^6 \).

As Baumeister and Kilian (2014) show, risk premia at this horizon are not big enough to contaminate price expectations. Moreover, this choice conforms well with the speculative demand story that is captured in other papers by inventories (Kilian and Murphy, 2014; Juvenal and Petrella, 2015). If market players anticipate a production shortfall in the future, they will either accumulate inventories or buy a futures contract which they can take delivery of or cash settle at some time in the future. However, oil futures prices are highly correlated across different maturities and the results using different contracts are very similar, see section 5.

\textsuperscript{12}In the monetary policy literature, people sometimes use an even tighter window, e.g. a 30-minutes window around FOMC announcements. I decided to use a daily window because of the following reasons. First, OPEC is not as secretive as a central bank and often information about its decisions gets leaked before the official announcement, making it more difficult to use a 30-minutes window. Second, historical intraday or tick data is expensive to access and usually also quite noisy and requires a lot of cleaning. Furthermore, in the 1980s, the oil futures markets were not as liquid and efficient as today, meaning that news were not priced in within minutes after the announcement (see figure 9 in appendix C).

\textsuperscript{13}The monthly surprises are computed as an unweighted monthly aggregate of daily surprises because the weighting used in Kuttner (2001) and Gertler and Karadi (2015) is known to introduce autocorrelation (Miranda-Agrippino and Ricco, 2018b).
2.3. Diagnostics of the surprise series

The monthly oil supply surprise series is depicted in figure 1. To get a better understanding of the series, I discuss three specific episodes, namely the August 1986, the November 2001 and the November 2014 announcements, which are indicated in the figure by red dots.

On August 5, 1986, OPEC could finally agree on a new set of production quotas after years of disagreement and lack of compliance. Just before, the oil price plummeted as Saudi Arabia was flooding the markets with oil to make other OPEC members comply. As one can see, the announcement came as a surprise and led to a big upward revision of oil price expectations. On November 14, 2001, amid a global economic slowdown that has been exacerbated by the September 11 terror attacks, OPEC pledged to cut production but only if other oil producers cut their production as well. Markets interpreted this announcement as a signal of a potential price war, which led to a significant downward revision of price expectations. Another major revision occurred on the 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 members of the OPEC for lower quotas, which lead to a downward revision of oil price expectations by about 10 percent.

Looking at the time series properties of the surprise series, one can see that it is quite idiosyncratic and there is no visible autocorrelation. Even though it is impossible to test whether the series is exogenous, one can perform a number of validity checks. In particular, a good surprise series should not be autocorrelated nor fore-
castable by past macroeconomic variables (Miranda-Agrippino and Ricco, 2018b). Figure 10 in appendix C depicts the autocorrelation function of the series. One can see that there is no strong evidence for autocorrelation. To check whether macroeconomic variables have any power in forecasting the series I run a series of Granger causality tests. The p-values of these tests are shown in table 5 in the appendix. There is no evidence that macroeconomic variables have any forecasting power as all selected variables do not Granger cause the series at conventional significance levels and the joint test is also insignificant. Overall, this evidence supports the validity of the oil supply surprise series.

3. Econometric framework

Following Gertler and Karadi (2015), I combine the high-frequency identification approach with the traditional SVAR analysis. The idea is to use the oil supply surprise series as an external instrument in an oil market VAR, building on a methodology developed by Stock and Watson (2008) 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, thus capturing some exogenous variation in the shock of interest (Stock and Watson, 2018). Identification is achieved by complementing the VAR residual covariance restrictions with the moment conditions for the external instrument.

3.1. Proxy VAR

Point of departure is the generic VAR(p) model

\[ y_t = b + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t, \]  

(1)

where \( p > 0 \) is referred to as the order of the VAR, \( y_t \) is a \( n \times 1 \) vector of endogenous variables, \( u_t \) is a \( n \times 1 \) vector of reduced-form shocks with covariance matrix \( \text{Var}(u_t) = \Sigma \), \( b \) is a \( n \times 1 \) vector of constants, and \( B_1, \ldots, B_p \) are \( n \times n \) coefficient matrices. Equation (1) is referred to as the reduced form of the VAR model. The parameters of the reduced form can be consistently estimated by OLS.

By postulating a linear mapping between reduced-form and structural shocks, \( u_t = S \varepsilon_t \), one can write the structural form of the VAR model as

\[ y_t = b + B_1 y_{t-1} + \cdots + B_p y_{t-p} + S \varepsilon_t, \]  

(2)

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

\[
\Sigma = S\Omega S'.
\] (3)

Identification is achieved as follows. Without loss of generality, one can order the variable that is instrumented as the first variable in the VAR. In the present case, this will be the price of oil, \( P_t \). The aim is then to identify the structural impact vector \( s_1 \), which corresponds to the first column of \( S \). Suppose there is an external instrument available, \( z_t \). In the application at hand, \( z_t \) is the oil supply surprise series. For \( z_t \) to be a valid instrument, it has to be the case that

\[
E[z_t \varepsilon_{1,t}] = \alpha \neq 0
\]

(4)

\[
E[z_t \varepsilon_{2:n,t}] = 0,
\]

(5)

where \( \varepsilon_{1,t} \) is the structural shock associated with the first variable in the VAR and \( \varepsilon_{2:n,t} \) is a \((n - 1) \times 1\) vector consisting of the other structural shocks. Assumption (4) is the relevance requirement and assumption (5) is the exogeneity condition for the instrument at hand. Under assumptions (4)-(5), \( s_1 \) is identified up to sign and scale:

\[
\tilde{s}_{2:n,1} \equiv s_{2:n,1} / s_{1,1} = E[z_t u_{2:n,t}] / E[z_t u_{1,t}],
\]

(6)

provided that \( E[z_t u_{1,t}] \neq 0 \). Note that \( \tilde{s}_{2:n,1} \) can be thought of the population analogue of the IV estimator of \( u_{2:n,t} \) on \( u_{1,t} \) using \( z_t \) as an instrument. The scale of \( s_1 \) is then set by a normalization subject to \( \Sigma = S\Omega S' \). One approach is to impose that \( \Omega = I_n \). This implies that a unit positive value of \( \varepsilon_{1,t} \) has a one standard deviation positive effect on \( y_{1,t} \). Alternatively, one can set \( \Omega = \text{diag}(\sigma_{\varepsilon_1}^2, \ldots, \sigma_{\varepsilon_n}^2) \) and \( s_{1,1} = 1 \), which implies that a unit positive value of \( \varepsilon_{1,t} \) has a unit positive effect on \( y_{1,t} \). I will use the former normalization such that the size of the shock is one standard deviation. The structural impact vector is then given by \( \tilde{s}_1' = (s_{1,1} \tilde{s}_{2:n,1}) \).

After having obtained the impact vector, it is straightforward to compute all objects of interest such as IRFs, FEVDs as well as the structural shock series. For a detailed derivation of the structural impact vector, see appendix A.

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14Note that this amounts to assume fundamentalness, which implies that all the structural shocks can be accurately recovered from current and lagged values of the observed data included in the model (see e.g. Lippi and Reichlin, 1994). However, if one is only interested in a subset of shocks, identification can be achieved under much weaker conditions. In particular, for partial identification with external instruments it is only required that the VAR is partially invertible in combination with a limited lag exogeneity condition on the instrument (Miranda-Agrippino and Ricco, 2018a).
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 (1) to get estimates of the reduced-form shocks \( \hat{u}_t \). In a second step, estimate (6) by regressing \( \hat{u}_{2,n,t} \) on \( \hat{u}_{1,t} \) 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 \( \hat{s}_1 \).\(^{15}\)

### 3.2. Comparison to alternative strategies

Traditionally, oil supply shocks are thought of as sudden disruptions in the current physical availability of oil, causing a contemporaneous fall in oil supply, an increase in the price of oil and a decrease in oil inventories. In the following, I will refer to such shocks as *conventional oil supply shocks*. There are many different approaches to identify such shocks, ranging from the construction of exogenous supply shocks series based on political events such as wars in the middle east (Hamilton, 2003; Kilian, 2008b) to SVAR models based on zero or sign restrictions (Kilian, 2009; Kilian and Murphy, 2012; Baumeister and Hamilton, forthcoming).

The identification strategy in this paper is quite different from the existing literature as it exploits variation in the price of oil that is driven by *news* about future oil supply. This motivates the interpretation of a news shock about future oil supply, henceforth referred to as an *oil supply news shock*. It is well known from the news literature that news shocks can have effects that are very different from unanticipated shocks (Beaudry and Portier, 2014). This suggests that oil supply news shocks are potentially very different from the previously identified conventional supply shocks. In particular, one would expect that a negative oil supply news shock has a positive effect on the oil price while oil production does not respond significantly on impact but only decreases with a substantial lag. Most importantly, the shock should lead to an increase in oil inventories. This is the key distinguishing feature between news and conventional supply 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 *speculative demand* for oil (Kilian and Murphy, 2014; Juvenal

\(^{15}\)An alternative approach would be to treat the instrument as a direct measure of the structural shock and to include it directly as a variable in the VAR. However, because the instrument is likely only an imperfect measure of the shock, this may bias the inference due to measurement errors. The proxy VAR approach in contrast is robust to many forms of these measurement problems (Mertens and Ravn, 2013).
The key idea behind these studies is that otherwise unobservable shifts in expectations about future oil market conditions must be reflected in the demand for oil inventories. A positive speculative demand shock will shift the demand for oil inventories, causing the level of inventories and the oil price to increase in equilibrium. It is precisely the positive inventory response that allows one to disentangle the speculative demand from other oil demand and supply shocks in sign-identified oil market VARs. In contrast, my approach exploits high-frequency data from oil futures markets, which is another margin market players can use to react to news about future oil market conditions.

It is also worth noting that an unexpected rise in uncertainty about future supply can have very similar effects as well. This has been formally demonstrated in a general equilibrium model by Alquist and Kilian (2010). The main difference is that such uncertainty shocks would not be associated with expected changes in future oil production. To distinguish news from uncertainty shocks, one can thus look at the response of oil production. After a contractionary news shock, oil production should decrease significantly with some lag. By contrast, the response of oil production after an uncertainty shock should be insignificant because it only affects the uncertainty around expected supply but not the mean.\(^{16}\)

### 3.3. Empirical specification

The baseline specification includes six variables: The price of WTI crude oil, world oil production, world oil inventories, world industrial production, U.S. industrial production and U.S. CPI. The first four variables are standard in any oil market VAR. I augment these core variables by the two U.S. variables to be able to analyze the effects on the U.S. economy. For world industrial production, I use Baumeister and Hamilton’s (forthcoming) industrial production index for Organization for Economic Co-operation and Development (OECD) countries and six major non-member economies as a proxy.\(^{17}\) For world oil inventories, I use a proxy based on OECD petroleum inventories, as proposed by Kilian and Murphy (2014).\(^{18}\) A de-

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\(^{16}\)Such mean-preserving shocks are inherently difficult to identify. Anzuini, Pagano, and Pisani (2015) use a two-stage identification procedure to identify shocks to the precautionary demand for oil. In a first step, they use daily changes in the futures spot price spread to proxy for such shocks and map out the response of oil prices. This information is then used to restrict the oil price response in a oil market VAR. The problem with this approach is that it is not possible to rule out that the proxy captures other factors such as speculation due to news about future supply and demand. My approach might suffer from similar shortcomings. However, as I will argue, my results suggest that I am mainly capturing news about future supply.

\(^{17}\)The results are robust if I use Kilian’s (2009) global activity indicator instead, which is another widely used proxy for global real economic activity, see section 5.

\(^{18}\)For details on the construction of this series, see Kilian and Murphy (2014). To get rid of the seasonal variation, I perform a seasonal adjustment using the Census X13 method.
etailed overview on the data and its sources can be found in appendix B.2. The data are all monthly and span the period 1974M1 to 2015M12. The beginning of the sample is motivated by the argument that oil prices only became endogenous after 1973 (Hamilton, 1983, 1985). Following Gertler and Karadi (2015), I use a shorter sample for identification, namely 1983M4 to 2015M12. This is because the futures data that is used to construct the instrument is only available for this period. The motivation for using a longer sample for estimation is to get more precise estimates of the reduced-form coefficients.

Small-scale VARs like the one in this paper are prone to suffer from problems of non-fundamentalness, which occur when the VAR does not convey all the relevant information. To mitigate such concerns, it is crucial to include variables that contain information about the future such as oil inventories. As an additional robustness check, I will later augment the baseline model with additional variables and check the sensitivity of the results.

The VAR is estimated in levels because taking first differences can be associated with a substantial loss of information and for the purpose of this paper it is not necessary to have a stationary VAR (see Sims, Stock, and Watson, 1990). All variables enter the VAR in logs. To be able to interpret changes in the IRFs as percentages, the logged variables are multiplied by 100. The transformed series are depicted in figure 11 in the appendix. The lag order is set to 13 and in terms of deterministics only a constant term is included.  

4. Results

4.1. First stage

As discussed above, the main identifying assumptions behind the proxy VAR approach are that the instrument is correlated with the structural shock of interest and uncorrelated with all other structural shocks. However, even if these assumptions hold, problems arise when the instrument is only weakly correlated with the

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19The argument is that before 1973, U.S. oil producing states had commissions that actively regulated the quantity of oil that could be produced by each field, the most important of which was the Texas Railroad Commission (TRC). Whenever demand went up, the TRC would increase the amount of production it allowed, and when demand went down, the TRC would decrease the amount of production – thus preventing demand changes from causing any change in price. The only events that did change the price were exogenous disruptions in supply (Hamilton, 2003). However, the exact timing of the break point is subject to debate. In particular, it is not clear whether the Yom Kippur War of October 1973, which was followed by the Arab oil embargo from October 1973 to March 1974, should be treated as exogenous or not (see Barsky and Kilian, 2002; Hamilton, 2003, for further discussion). To be on the safe side, I thus start the sample in 1974.

20As shown in section 5 the results turn out the be robust with respect to all of these choices.
structural shock of interest. In this case, the proxy VAR estimator is inconsistent and standard inference will not deliver reliable results. In a first step, it is thus important to test the strength of the instrument. This can be done using an F-test in the first-stage regression of the oil price residual from the VAR on the instrument, as proposed by Montiel-Olea, Stock, and Watson (2016). To be confident that a weak instrument problem is not present, Stock, Wright, and Yogo (2002) recommend a threshold value of 10 for the corresponding F-statistic.

Table 1: Tests on the strength of the instrument

<table>
<thead>
<tr>
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<th>Front</th>
<th>1M</th>
<th>2M</th>
<th>3M</th>
<th>4M</th>
<th>5M</th>
<th>6M</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTI crude spot price Coefficient</td>
<td>0.986</td>
<td>1.018</td>
<td>1.077</td>
<td>1.120</td>
<td>1.144</td>
<td>1.159</td>
<td>1.178</td>
</tr>
<tr>
<td>F-stat (robust)</td>
<td>16.55</td>
<td>14.85</td>
<td>15.64</td>
<td>16.03</td>
<td>15.78</td>
<td>15.31</td>
<td>15.11</td>
</tr>
<tr>
<td>$R^2$</td>
<td>5.21</td>
<td>4.86</td>
<td>4.97</td>
<td>5.01</td>
<td>4.90</td>
<td>4.77</td>
<td>4.71</td>
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<tr>
<td>$R^2$ (adjusted)</td>
<td>5.02</td>
<td>4.66</td>
<td>4.77</td>
<td>4.81</td>
<td>4.70</td>
<td>4.57</td>
<td>4.52</td>
</tr>
<tr>
<td>Observations</td>
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<td>491</td>
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<td>491</td>
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<td>491</td>
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<th>4M</th>
<th>5M</th>
<th>6M</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real WTI crude spot price Coefficient</td>
<td>0.975</td>
<td>1.005</td>
<td>1.063</td>
<td>1.104</td>
<td>1.128</td>
<td>1.142</td>
<td>1.160</td>
</tr>
<tr>
<td>F-stat (robust)</td>
<td>16.47</td>
<td>14.73</td>
<td>15.50</td>
<td>15.86</td>
<td>15.59</td>
<td>15.10</td>
<td>14.88</td>
</tr>
<tr>
<td>$R^2$</td>
<td>5.21</td>
<td>4.84</td>
<td>4.94</td>
<td>4.97</td>
<td>4.86</td>
<td>4.73</td>
<td>4.67</td>
</tr>
<tr>
<td>$R^2$ (adjusted)</td>
<td>5.02</td>
<td>4.64</td>
<td>4.75</td>
<td>4.78</td>
<td>4.67</td>
<td>4.53</td>
<td>4.47</td>
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<tr>
<td>Observations</td>
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<td>491</td>
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<td>491</td>
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<td>491</td>
</tr>
</tbody>
</table>

Notes: The table shows the results of the first-stage regressions of the residual $\hat{u}_{1,t}$ from the baseline VAR on the proxies constructed from the front to the 6-month ahead futures contract. F-statistics above 10 indicate strong instruments. Robust F-statistics allow for heteroskedasticity. I also provide results for a VAR using the real price of oil (deflated by U.S. CPI) as the oil price indicator.

Table 1 presents the results on this test for a selection of different instruments and using both the nominal as well as the real price of oil as the relevant oil price indicator in the VAR. In addition to the standard F-statistic, I also report a robust F-statistic which allows for heteroskedasticity. The instruments turn out to be very strong both for the real and the nominal price of oil as all F-statistics are safely above the threshold of 10. Furthermore, the instruments seem to contain valuable information as they explain around 5 percent of the oil price residual. For my baseline, the instrument based on the 6-month ahead futures, the F-statistic is 24.2 and the instrument explains 4.7 percent of the oil price residual. Overall, this evidence is suggestive that there is no weak instrument problem at hand.

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21 I also perform the test for a weak proxy proposed by Lunsford (2016). The corresponding
4.2. Baseline model

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

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

The shock leads to a significant, immediate increase in the price of oil. World oil production does not change significantly on impact but then starts to fall sluggishly and persistently. World oil inventories increase significantly and persistently. The large positive response of the oil price together with the sluggish decrease of oil production and the strong positive inventory response are consistent with the interpretation of a news shock about future oil supply. World industrial production does not change much over the first year after the shock but then starts to...

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F-statistic is 4.8 and thus large enough to reject the null of a weak proxy for an asymptotic bias of 20% and a significance level of 10%.

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To compute the confidence bands, I use a moving block bootstrap, as proposed by Jentsch and Lunsford (forthcoming). This method produces asymptotically valid confidence bands under fairly mild \( \alpha \)-mixing conditions. The block size is set to 24 and to deal with the difference in the estimation and identification samples, I censor the missing values in the proxy to zero as in Mertens and Ravn (2018). I do not use a recursive wild bootstrap as is common in the literature because this was shown to be invalid, producing confidence intervals that are too narrow (Jentsch and Lunsford, forthcoming).
fall significantly and persistently. This is in line with the notion that oil exporting countries might benefit in the short-run from higher oil prices before the adverse general equilibrium effects kick in.

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

Table 2: Forecast error variance decomposition

<table>
<thead>
<tr>
<th>Oil price</th>
<th>Oil production</th>
<th>Oil inventories</th>
<th>World IP</th>
<th>US IP</th>
<th>US CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.83</td>
<td>0.01</td>
<td>0.04</td>
<td>0.00</td>
<td>0.03</td>
</tr>
<tr>
<td>12</td>
<td>0.72</td>
<td>0.03</td>
<td>0.15</td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>24</td>
<td>0.33, 0.88</td>
<td>0.01, 0.09</td>
<td>0.03, 0.38</td>
<td>0.00, 0.08</td>
<td>0.01, 0.23</td>
</tr>
<tr>
<td>36</td>
<td>0.36, 0.87</td>
<td>0.05, 0.31</td>
<td>0.11, 0.61</td>
<td>0.02, 0.29</td>
<td>0.04, 0.43</td>
</tr>
<tr>
<td></td>
<td>0.34, 0.85</td>
<td>0.10, 0.49</td>
<td>0.18, 0.74</td>
<td>0.03, 0.43</td>
<td>0.10, 0.58</td>
</tr>
</tbody>
</table>

Notes: The table shows the forecast error variance explained by oil supply news shocks at horizons 0, 12, 24, and 36 months together with the pointwise 90% confidence intervals.

Table 2 presents the fraction of forecast error variance decomposition.\(^\text{23}\) One can see that oil supply news shocks account for the bulk of the variance in oil prices, especially in the short run.\(^\text{24}\) Furthermore, they explain a non-negligible portion of the variation in world oil production at longer horizons and a significant part of the variation in world oil inventories. In contrast, the contribution to world industrial production turns out to be much smaller, especially in the short run. One reason for this could be that the positive effects on oil exporting countries and the negative effects on oil importing countries offset each other to a certain extent. Turning to the U.S. variables, I find that oil supply news shocks explain a meaningful portion of the variance of industrial production and the CPI. While the shocks account for

\(^{23}\)Note that because the VAR is not stationary, the MSFE does not converge as the forecast horizon goes to infinity. Thus, the variance decomposition at longer horizons is not very reliable and should be interpreted with a grain of salt. This is also reflected in the large uncertainty around the variance decomposition at longer horizons.

\(^{24}\)At the one year horizon, the contribution is about 70 percent, which seems a bit high. However, as can be seen from the confidence intervals, the contribution is estimated rather imprecisely and could lie anywhere in between 33 and 88 percent.
Overall, these findings suggest that oil supply news shocks appear to have effects that are quite different from conventional oil supply shocks (Kilian, 2009; Kilian and Murphy, 2012, 2014; Baumeister and Hamilton, forthcoming). 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 conventional oil supply shocks. It is important to note that this result emerges naturally as my identification strategy does not restrict the signs of the impulse responses in any way.

Interestingly, oil supply news shocks have effects that are, at least qualitatively, similar to speculative demand shocks identified by the literature (Kilian and Murphy, 2014; Kilian and Lee, 2014; Juvenal and Petrella, 2015). This does not come entirely as a surprise. Speculative demand shocks capture, among other things, news about future oil supply and demand. Other sources include uncertainty about future oil supply, changes in oil traders’ perception of what other traders think or changes in beliefs unrelated to fundamentals (Kilian and Murphy, 2014). With my approach, however, I am able to isolate the component of speculative demand that is driven by news about future supply. Furthermore, my approach yields responses that are point-identified whereas speculative demand shocks are usually only set-identified. This is also reflected in the relatively narrow confidence bands, allowing for sharper predictions. My findings suggest that oil supply news shocks are an important driver of the price of oil and macroeconomic aggregates – providing evidence for a strong channel operating through expectations about future oil supply conditions.

4.3. Wider effects of oil supply news shocks

In this section, I analyze the wider consequences of oil supply news shocks by augmenting the baseline VAR by one variable at a time.\footnote{If possible, the augmented VAR is estimated on the same sample as the baseline VAR. If the additional series does not span the original sample, I adjust the sample accordingly. Information on the sources of the data can be found in appendix B.2.} This approach, which was put forward by Beaudry and Portier (2014) and Gertler and Karadi (2015), is par-
particularly flexible as it allows one to characterize the dynamic effects of structural shocks on a wide range of variables without resorting to shrinkage techniques or a panel or factor structure to address the curse of dimensionality. Furthermore, it constitutes an important robustness check on how the information contained in the VAR affects the results.

**Consumer prices.** A key implication of the baseline model is that oil supply news shocks lead to a significant and persistent increase in consumer prices. However, the rise in consumer prices, as measured by headline CPI, might be primarily driven by higher energy prices. To check this, I augment the baseline VAR by the core and energy components of the CPI, respectively.

Figure 3: Impulse response functions of different consumer price indices to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.

Figure 3 shows the IRFs of the augmented models together with the CPI response from the baseline model. The results are quite intuitive. Core consumer prices do not react on impact but then tend to rise persistently. However, the response is not estimated very precisely as is reflected in the relatively wide confidence bands. In contrast, the response of the energy component is more front-loaded and mirrors the response of the price of oil. Thus, in the short run, the response of headline CPI seems to be mainly driven by energy prices whereas a lot of its persistence comes from the underlying rise in core consumer prices.
To get a better understanding on how the shock is transmitted, I further decompose the consumer price response into the non-durables, durables and services components. The prices of non-durables rise immediately and the response turns out to be quite persistent as well. The response of durables is more pronounced on impact but turns out to be less persistent. Interestingly, the response is quite similar to energy prices. One explanation for this could be that some durables are energy intensive to produce and their prices are heavily affected by changes in energy prices. The prices of services do not change significantly on impact. After a couple of months, however, they start to rise significantly as well. Quantitatively, energy prices rise the most, followed by the prices of durables, non-durables and services.

**Consumption expenditures.** Increases in consumer prices due to higher oil prices do likely have an impact on consumption expenditures. Possible channels are discretionary income, substitution and precautionary savings effects. In figure 4, I present the IRFs based on models augmented by data on real personal consumption expenditures. In particular, I include total expenditures as well as expenditures on energy, non-durables, durables, and services.

![Figure 4: Impulse response functions of real consumption expenditures to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.](image)

Overall, consumption expenditures do not change significantly on impact but start to fall only after a couple of months. Looking at the responses of the different
components, one can see that the expenditures on energy and durable goods respond the most, especially in the short to medium run. The stark short-run response of durables is consistent with the fact that consumers may have to postpone expensive durable purchases because of the decrease in disposable income caused by higher energy prices. The expenditures on non-durables fall by less quantitatively, however, the response turns out to be a bit more persistent. Expenditures on services also fall significantly and the response features a similar pattern as non-durable expenditures.

All responses feature a considerable amount of inertia and the impact response can even be positive. This is indicative of the fact that consumers take some time to adjust their expenditures. At the one-year horizon, the results are qualitatively in line with the elasticities reported in Edelstein and Kilian (2009). Quantitatively, however, the elasticities are much smaller. This is not surprising as Edelstein and Kilian (2009) estimate elasticities with respect to changes in retail energy prices, whereas the elasticities here are with respect to crude oil prices and it is likely that changes in crude oil prices do not pass through completely to retail energy prices.

**Economic activity and labor market.** To get a better picture of how the shock affects economic activity, I study the responses of a number of activity and labor market indicators, including industrial production for the manufacturing sector, the
unemployment rate, nonfarm payrolls, real compensation of employees and average weekly hours in manufacturing. Figure 5 presents the IRFs together the response of industrial production from the baseline model.

Oil supply news shocks have significant effects on a wide range of economic activity and labor market indicators. Industrial production of the manufacturing sector decreases significantly and the fall appears to be more pronounced than for total industrial production, consistent with the fact that manufacturing is a particularly energy intensive sector. Looking at the labor market, I find that the unemployment rate rises persistently and the number of employed workers, measured by nonfarm payrolls, falls significantly as do average weekly hours. Finally, overall compensation of employees falls significantly and persistently in real terms.

Financial variables. An important advantage of the high-frequency approach adopted in this paper is that it allows one to analyze the responses of financial variables. Traditional oil market VARs identified using short-run zero restrictions are not well suited for this because the timing restrictions become problematic once financial variables are present in the VAR. The problem is simultaneity: shifts in oil prices do not only affect financial variables, they may be also responding to them. The high-frequency identification approach addresses the simultaneity issue by exploiting variation at a sufficiently high frequency (Gertler and Karadi, 2015).

Figure 6: Impulse response functions of a selection of financial variables and variables relevant to monetary policy to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.
In figure 6, I present the IRFs for a selection of financial variables and variables relevant for monetary policy. In response to an oil supply news shock, the federal funds rate increases, even though only with some lag, before converging back to normal. The large part of the response, however, is insignificant – consistent with the notion that monetary policy regularly looks through inflationary pressures stemming from oil price fluctuations. Credit supply conditions, as measured by the excess bond premium of Gilchrist and Zakrajšek (2012), do not change significantly on impact but then tend to deteriorate. However, the response is very imprecisely estimated. Stock prices, measured by the S&P 500 index, do also not change on impact but then quickly start to fall significantly and persistently – in line with previous findings of Kilian and Park (2009). Interestingly, as one can see from the response of the VIX, the shock has no significant effects on financial uncertainty. However, the VIX does not measure uncertainty about oil supply. To proxy for uncertainty about oil supply, I use Caldara and Iacoviello’s (2018) geopolitical risk index. It turns out that the shock is associated with a temporary increase in geopolitical risks. However, the response is barely significant. This finding strengthens the interpretation that the identified shock is a news shock operating through changes in expectations about future supply as opposed to changes in uncertainty.

**Inflation expectations.** A key variable in the context of this paper are inflation expectations. From figure 6, one can see that oil supply news shocks cause a significant increase in inflation expectations, as measured by median expected price change over the next 12 months from the University of Michigan Surveys of Consumers. This finding is in line with recent empirical evidence by Wong (2015).

![Figure 7: Impulse response functions of inflation expectations to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.](image)

Inflation expectations are, however, generally hard to measure. An alternative to the Michigan Survey is the Survey of Professional Forecasters (SPF), which captures inflation expectations based on the predictions of professional forecasters as
opposed to households. An interesting exercise is then to analyze potential differences between the two measures of inflation expectations. Unfortunately, the SPF data is only available at the quarterly frequency. To study the potential differences, I therefore aggregate the VAR to the quarterly frequency, as discussed in section 5. The IRFs are depicted in figure 7.

The effects differ greatly among the two measures. In line with the monthly evidence, household inflation expectations increase significantly and persistently. In contrast, the response of the SPF inflation expectations turns out to be much weaker. This is consistent with the findings of Coibion and Gorodnichenko (2015) who show that a large part of the historical differences in inflation forecasts between households and professionals can be attributed to the level of oil prices. It is also in line with a recent literature ascribing an important role to oil prices in explaining inflation dynamics via their effects on inflation expectations (Coibion, Gorodnichenko, and Kamdar, 2017; Hasenzagl et al., 2017; Gerko, 2018).

**Exchange rates.** Another important variable is the exchange rate. Because the U.S. dollar is the world’s reserve currency, most of the crude oil is priced and traded in dollars. Thus, it is only natural to suspect a tight link between oil prices and the dollar. Figure 8 displays the IRFs for three different U.S. nominal and real effective exchange rate indices: an index against the major currencies, an index against other important trading partners and a broad index including all the countries.26

Oil supply news shocks lead to a significant depreciation of the dollar. Looking at the broad effective exchange rates, one can see that the short-run responses turn out to be quite similar in nominal and real terms, consistent with the observation that real and nominal exchange rates co-move closely at shorter horizons (Mussa, 1984). However, the responses at longer horizons turn out to be quite different. While the nominal depreciation of the dollar is quite persistent, the dollar tends to appreciate in real terms after about two years. This in line with a literature on the long-run relationship between the U.S. real exchange rates and the real price of oil which finds that the two variables are cointegrated and exhibit a positive long-run equilibrium relationship (Amano and Van Norden, 1998a,b).

These differences appear to be driven by the currencies of other important trading partners, which include some of the major oil producing countries. In contrast, the responses of the nominal and real effective exchange rates for the major curren-

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26Note that the effective exchange rate is defined such that an increase (decrease) in the index corresponds to an appreciation (depreciation) of the U.S. dollar. The major currencies index includes Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. The other important trading partners index includes Mexico, China, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Thailand, Philippines, Indonesia, India, Israel, Saudi Arabia, Russia, Argentina, Venezuela, Chile and Colombia.
cies, which mainly include oil importers, are almost identical. This points to some interesting heterogeneities in the responses of oil exporting and importing countries.

The significant effects on U.S. exchange rates help to reconcile the strong negative correlation between oil prices and the dollar in recent years (Klitgaard, Pesenti, and Wang, 2019) and complement recent empirical evidence by Kilian and Zhou (2018). Likely, there are also important implications for global trade as an overwhelming share of world trade is invoiced in dollars. In a recent study, Plagborg-Moller, Gopinath, and Boz (2017) document that the U.S. dollar exchange rate drives global trade prices and volumes, providing evidence in favor of the dominant currency paradigm as opposed to the traditional Mundell-Fleming paradigms. They show that the dollar exchange rate quantitatively dominates the bilateral exchange rate in price pass-through and trade elasticity regressions and that U.S. monetary policy

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Figure 8: Impulse response functions of effective exchange rate indices to a one standard deviation oil supply news shock. The dashed lines are pointwise 90% confidence bands.
induced dollar fluctuations have high pass-through into bilateral import prices. It would be interesting to see how oil price induced exchange rate fluctuations affect import and export prices and quantities but this goes beyond the scope of this paper.

Overall, the evidence presented in this section supports the notion that the identified shock is a news shock operating through expectational channels as it significantly affects both financial variables as well as inflation expectations and the exchange rate. The inclusion of a wide range of macroeconomic and financial variables in the VAR also serves as an important robustness check on how the results are affected by the information contained in the VAR. As can be seen from figure 12 in the appendix, the responses of the baseline variables appear to be robust as the IRFs from the augmented VARs are very similar. In particular, the impact responses turn out to be quite stable, supporting the validity of the baseline proxy VAR.  

5. Sensitivity analysis

In this section, I perform a comprehensive series of robustness checks. In particular, I check the robustness with respect to the identification strategy, the model specification, the estimation and instrument sample as well as the data frequency. The results are discussed in turn. All tables and figures can be found in appendix C.

5.1. Identification

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

To address this concern more rigorously, I construct an informationally robust series, following a strategy that has been previously applied to monetary policy shocks (Romer and Romer, 2004; Miranda-Agrippino and Ricco, 2018b). To this end, I collected global oil demand forecasts from the OPEC monthly oil market reports. The idea is to purge the oil supply surprise series from potential contamination stemming from OPEC’s informational advantage on the global oil demand outlook.

As Miranda-Agrippino and Ricco (2018a) show, unstable impact responses are an indication that the instrument is contaminated by other past structural shocks that are not filtered out by the VAR model.

These reports are available online https://www.opec.org/opec_web/en/publications/338.htm and contain among other things OPEC’s global oil demand forecasts and forecast revisions.
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:

\[
Surprise_m = \alpha_0 + \sum_{j=-1}^{2} \theta_j F^{OPEC}_m y_{q+j} + \sum_{j=-1}^{2} \varphi_j [F^{OPEC}_m y_{q+j} - F^{OPEC}_{m-1} y_{q+j}] + IRS_m,
\]

where \( m \) is the month of the meeting, \( q \) denotes the corresponding quarter, \( y_q \) is global oil demand growth in quarter \( q \) and \( F^{OPEC}_m y_{q+j} \) is the OPEC forecast for quarter \( q+j \) made in month \( m \). \( F^{OPEC}_m y_{q+j} - F^{OPEC}_{m-1} y_{q+j} \) is the revised forecast for \( y_{q+j} \). Note that because the monthly reports are only available from 2001, the informationally robust surprise series also only spans a shorter sample.

Figure 13 in the appendix depicts the results based on the baseline and the informationally robust instrument. The responses from the two models are very similar apart from a few minor, statistically insignificant differences. This supports the validity of the OPEC surprise series as a proxy for an oil supply news shock.

Another concern regarding the announcements is that many of the OPEC conference meetings are extraordinary meetings, scheduled in response to macroeconomic or geopolitical news. This might give rise to an endogeneity problem. However, if the window around the announcement is tight enough, concerns about endogeneity can be plausibly ruled out because the macroeconomic and geopolitical outlook is already priced in prior to the announcement and does not change over the tight window. To address this concern more rigorously, I only use the announcements from ordinary meetings to construct the instrument as a robustness check. The IRFs are depicted in figure 14. One can see that the results are robust as the IRFs are very similar to the baseline responses. However, it should be noted that the instrument turns out a bit weaker. This was to be expected as about 40 percent of the announcements had to be dropped, leaving less variation for identification.

Futures contracts. As discussed in section 2.2, a crucial issue in the context of the high-frequency proxy VAR is the choice of the futures contract used to construct the instrument. As a benchmark, I use the 6-month contract because it accords well with the interpretation of a news shock. Even though risk premia at this horizon are likely not big enough to contaminate price expectations (Baumeister and Kilian, 2014), it is interesting to analyze how the results change if one uses contracts with shorter maturities to construct the instrument. It would also be interesting to look at longer maturities, however, the fact that these contracts are less liquid and have

\[Note that the baseline results are different from section 4 because of the shorter identification sample.\]
a shorter coverage makes this comparison infeasible. Figure 15 presents the IRFs from the baseline VAR as well as the confidence bands together with the IRFs from proxy VARs that use instruments constructed from the front to the 5-month contract, where contracts with shorter maturity are depicted in lighter color. The results turn out to be quite robust with respect to the choice of the futures contract, consistent with the fact that the prices of the different contracts are quite highly correlated. Interestingly, the responses of world oil production, world oil inventories as well as U.S. industrial production and the CPI tend to be more pronounced the longer the maturity of the futures contract – supporting the interpretation of an oil supply news shock.

A related issue is the choice of the underlying of the futures contract. As a benchmark, I relied on WTI futures. This might be problematic in the most recent part of the sample because as Baumeister and Kilian (2016) argue, WTI has become less representative for the global price of oil since the shale oil boom in 2011. A viable alternative would be to use Brent futures. However, these futures only started trading in the late 1980s and were less liquid, especially at the beginning of the sample. The contract with the longest maturity and adequate coverage is the 4-month contract. Figure 16 presents the IRFs based on the instrument constructed from this contract. As one can see, the results turn out to be robust.

Exogeneity. The crucial assumption behind the proxy VAR approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. This condition might be violated when only identifying an oil supply news shock. The reason is that the instrument might not only be correlated with the oil supply news shock but also with the conventional, unanticipated oil supply shock. The differential effects of oil supply news shocks and conventional oil supply shocks are suggestive that the exogeneity restriction is likely satisfied. However, to address this concern more carefully, I jointly identify an unanticipated oil supply shock and an oil supply news shock in a proxy VAR using Caldara, Cavallo, and Iacoviello’s (2018) exogenous supply shock series based on wars and geopolitical events and my OPEC surprise series as instruments. Note that in the case with two structural shocks and two instruments, the instrument moment restrictions are not sufficient to achieve identification (see e.g. Mertens and Ravn, 2013). To achieve identification, one has to impose one additional restriction. Thus, I assume that the oil supply news shock does not affect oil production within the first month.30 This can be justified with the 30 day implementation lag of OPEC announcements.

30 More details on the identification strategy with two instruments and two shocks can be found in appendix A.2.
The results from the two shock proxy VAR are depicted in figure 17. Looking at the first stage, both instruments turn out to be strong enough to credibly rule out weak instrument problems. From the IRFs, one can see that the identified news shock from the two shock proxy VAR is very similar to the shock from the baseline VAR. This suggests that it is possible to agnostically identify the oil supply news shock in a simple proxy VAR without violating the exogeneity condition. The responses for the unanticipated oil supply shock look quite reasonable as well: it leads to a temporary increase in the oil price, a significant and immediate fall in oil production and a persistent decrease in inventories.  

5.2. Model specification

An important issue in small-scale VARs is the selection of appropriate indicators for the variables in the VAR. A sensitive choice is the global economic activity indicator. Measuring global real economic activity is challenging, especially at the monthly frequency. In the baseline model, I use Baumeister and Hamilton’s (forthcoming) proxy for world industrial production. An alternative measure that has often been used in the literature is Kilian’s (2009) global activity indicator constructed from dry cargo single voyage freight rates. An advantage of this index is that it provides a direct measure of global economic activity which does not involve exchange rate weighting and the associated complexities. A potential drawback, however, is that it might be affected by ship-building and scrapping cycles that confound the link between freight rates and economic activity. This concern is particularly relevant since the Great Recession and the collapse in iron ore shipments. Figure 18 depicts the IRFs using Kilian’s (2009) (corrected) global activity indicator. Overall, the results appear to be robust to the choice of the activity indicator. The main difference is that global economic activity as measured by Kilian’s (2009) index tends to increase in the short run and only turns negative after about 2 years.

Another important choice is the oil price indicator. To ensure that the instrument has maximum strength, I use the WTI spot price as a benchmark. An alternative that has often been used in the literature is the refiner acquisition cost of imported crude oil provided by the U.S. Department of Energy. Figure 19 depicts the IRFs using this measure for the price of oil in the VAR. The results are very similar to the baseline case.

As an alternative, I also tried Kilian’s (2008b) exogenous production shortfall series as an instrument for the unanticipated shock. The results are very similar but the first stage turns out to be much weaker. This is likely because the sample for identification is much shorter as the production shortfall measure is only available until 2004M9.

I use the corrected version of the index because there are some problems with the original index due to a coding mistake as discussed in Hamilton (2018) and Kilian (2018).
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 and include a linear trend in the VAR. 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 20-24, one can see that the results are robust with respect to all these choices. As an additional check, I analyze the robustness of the results when I rely on the exact same specification as in Kilian and Murphy (2014) and Baumeister and Hamilton (forthcoming), respectively.\textsuperscript{33} The results turn out to be robust.

5.3. Subsample analysis

Another concern might be that the results are sensitive with respect to the choice of the sample. This is relevant against the backdrop that the sample period considered is quite long and includes different policy regimes and potential structural breaks. Thus, I perform a number of robustness checks based on different subsamples.

Figure 27 presents the results based on an estimation sample that starts in 1982M3, which coincides with the start of the instrument sample (corrected for the observations lost because of the lags) and roughly marks the beginning of the Great Moderation period. The results are very similar to the baseline VAR. The main differences lie in the responses of world oil production and inventories, which turn out to be much weaker. Furthermore, all responses tend to feature a bit less persistence. To analyze whether the results are driven by more recent events such as the Great Recession or the shale oil revolution, I estimate VARs that end in 2007 and 2010, respectively. As one can see from figures 28-29, the results turn out to be robust.

Lastly, I check the robustness with respect to the instrument sample. In particular, I test whether the results are robust if I exclude the first years of the instrument in which the volumes traded in the futures market were relatively low. Figure 30 depicts the IRFs using an instrument that starts in 1990M1. Again, the results turn out to be robust.

\textsuperscript{33}Kilian and Murphy (2014) use a VAR(24) in real refiner acquisition cost, world oil production growth, change in world oil inventories and global activity. Baumeister and Hamilton (forthcoming) rely on a VAR(24) in the change of real refiner acquisition cost, world oil production growth, change in world oil inventories as a percent of the previous month’s oil production and world industrial production growth.
5.4. Data frequency

The baseline VAR runs on monthly data. It is interesting to see whether the results go through when the model is estimated at the quarterly frequency, aggregating the data and the instrument accordingly. This has the advantage that one can analyze the effects on variables that are only observed at the quarterly frequency such as real GDP. To aggregate the instrument to the quarterly frequency, I sum it over the respective months. From figure 31, one can see that the results turn out to be consistent with the monthly VAR. However, it should be noted that the instrument is weaker at the quarterly frequency and thus, the results should be interpreted with a bit of caution.

Overall, I conclude that the results are very robust along a number of dimensions and are not driven by a particular model specification or a specific sample choice.

6. Conclusion

A recurring question in the academic discourse as well as in policy work concerns the effects of oil prices on the macroeconomy. Answering this question is nontrivial because oil prices are endogenous and respond to global macroeconomic conditions. A large literature has tried to identify exogenous oil market shocks to establish a causal link. However, some of the identifying assumptions commonly used in the literature are quite restrictive and can be questioned.

In this paper, I propose a novel approach to identify oil supply shocks exploiting institutional features of the OPEC and variation in high-frequency data. The idea is to use variation in oil futures prices in a tight window around OPEC announcements as an instrument in a SVAR to identify an oil supply news shock. I show that these news shocks have statistically and economically significant effects, providing evidence for a strong expectational channel in the oil market. A negative news shock about future oil supply leads to an immediate increase in oil prices, a sluggish but significant fall in world oil production and a significant increase in world oil inventories. This has consequences for the world and U.S. economy as industrial production falls and consumer prices rise significantly. Interestingly, the shocks also cause a significant rise in inflation expectations and a sharp depreciation of the dollar. Getting a better understanding of the relation between oil prices and inflation dynamics and the link between oil prices, exchange rates and trade are interesting avenues for future research.
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A. Derivations – For online publication

A.1. Derivation of the structural impact vector

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

\[ E[z_t \varepsilon_{1,t}] = \alpha \neq 0 \]
\[ E[z_t \varepsilon_{2:n,t}] = 0. \]

Under these assumptions, \( s_1 \) is identified up to sign and scale. To see this, note that

\[ E[z_t u_t] = S E[z_t \varepsilon_t] = \begin{pmatrix} s_1 & S_{2:n} \end{pmatrix} \begin{pmatrix} E[z_t \varepsilon_{1,t}] \\ E[z_t \varepsilon_{2:n,t}] \end{pmatrix} = s_1 \alpha. \]

By partitioning this equation, one can write

\[ E[z_t u_t] = \begin{pmatrix} E[z_t u_{1,t}] \\ E[z_t u_{2:n,t}] \end{pmatrix} = \begin{pmatrix} s_{1,1} \alpha \\ s_{2:n,1} \alpha \end{pmatrix}. \]

Combining the two equations yields

\[ \tilde{s}_{2:n,1} \equiv s_{2:n,1}/s_{1,1} = E[z_t u_{2:n,t}]/E[z_t u_{1,t}], \]

provided that \( E[z_t u_{1,t}] \neq 0 \). This condition is satisfied iff \( \alpha \neq 0 \) and \( s_{1,1} \neq 0 \). Thus, \( s_1 \) is identified up to scale, provided that these conditions hold.

The scale of \( s_1 \) is then set by a normalization subject to

\[ \Sigma = S \Omega S'. \]

One approach is to impose that \( \Omega = I_n \). This implies that a unit positive value of \( \varepsilon_{1,t} \) has a one standard deviation positive effect on \( y_{1,t} \). \( s_{1,1} \) can then be recovered as follows. In a first step, partition \( \Sigma \) and \( S \) as

\[ \Sigma = \begin{pmatrix} \sigma_{1,1} & \sigma_{1,2} \\ \sigma_{2,1} & \Sigma_{2,2} \end{pmatrix}, \text{ and } S = \begin{pmatrix} s_{1,1} & s_{1,2} \\ s_{2,1} & s_{2,2} \end{pmatrix}. \]

\[ ^{34} \text{To economize on notation, parameters pertaining to the variables } i \in \{2, \ldots, n\} \text{ are indexed by } 2 \text{ instead of } 2:n. \]
From the covariance restrictions $\Sigma = SS'$, we then have

$$
\begin{pmatrix}
  s_{1,1} & s_{1,2} \\
  s_{2,1} & s_{2,2}
\end{pmatrix}
\begin{pmatrix}
  s_{1,1} & s_{2,1}' \\
  s_{1,2}' & s_{2,2}'
\end{pmatrix}
= 
\begin{pmatrix}
  s_{1,1}' + s_{1,2}s_{1,2}' & s_{1,1}s_{2,1}' + s_{1,2}s_{2,2}' \\
  s_{2,1}s_{1,1}' + s_{2,2}s_{1,2}' & s_{2,1}s_{2,1}' + s_{2,2}s_{2,2}'
\end{pmatrix}
= 
\begin{pmatrix}
  \sigma_{1,1} & \sigma_{1,2} \\
  \sigma_{2,1} & \Sigma_{2,2}
\end{pmatrix}.
\]

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

$$
\begin{align}
  s_{1,1}' + s_{1,2}s_{1,2}' &= \sigma_{1,1} \\
  s_{1,1}s_{2,1} + s_{2,2}s_{1,2}' &= \sigma_{2,1} \\
  s_{2,1}s_{2,1}' + s_{2,2}s_{2,2}' &= \Sigma_{2,2}.
\end{align}
$$

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

$$
\begin{align}
  \tilde{s}_{1,1}' + s_{1,2}s_{1,2}' &= \sigma_{1,1} \\
  \tilde{s}_{1,1}s_{2,1} + s_{2,2}s_{1,2}' &= \sigma_{2,1} \\
  s_{2,1}s_{2,1}' + s_{2,2}s_{2,2}' &= \Sigma_{2,2}.
\end{align}
$$

From equation (7), it follows that $s_{1,1} = \pm \sqrt{\sigma_{1,1} - s_{1,2}s_{1,2}'}$. Thus, it remains to solve for $s_{1,2}s_{1,2}'$. By substituting (7) multiplied by $\tilde{s}_{2,1}$ from (8), one can write

$$
S_{2,2}s_{1,2}' - \tilde{s}_{2,1}s_{1,2}s_{1,2}' = \sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1} \\
(S_{2,2} - \tilde{s}_{2,1}s_{1,2})s_{1,2}' = \sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1} \\
\Rightarrow s_{1,2}' = (S_{2,2} - \tilde{s}_{2,1}s_{1,2})^{-1}(\sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1}).
$$

Thus,

$$
s_{1,2}s_{1,2}' = (\sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1})' (S_{2,2} - \tilde{s}_{2,1}s_{1,2})^{-1}(S_{2,2} - \tilde{s}_{2,1}s_{1,2})^{-1}(\sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1})
$$

$$
= (\sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1})' [ (S_{2,2} - \tilde{s}_{2,1}s_{1,2})(S_{2,2} - \tilde{s}_{2,1}s_{1,2}) ]^{-1} (\sigma_{2,1} - \tilde{s}_{2,1}\sigma_{1,1})
$$

Now, note that

$$
\Gamma = S_{2,2}s_{2,2}' - S_{2,2}s_{1,2}'\tilde{s}_{2,1}' - \tilde{s}_{2,1}s_{1,2}s_{2,2}' + \tilde{s}_{2,1}s_{1,2}s_{1,2}'\tilde{s}_{2,1}
$$

By subtracting (8) multiplied by $\tilde{s}_{2,1}'$ from (9), one can write

$$
S_{2,2}s_{2,2}' - S_{2,2}s_{1,2}'\tilde{s}_{2,1}' = \Sigma_{2,2} - \sigma_{2,1}\tilde{s}_{2,1}'
\Rightarrow S_{2,2}s_{1,2}'\tilde{s}_{2,1}' = S_{2,2}s_{2,2}' - (\Sigma_{2,2} - \sigma_{2,1}\tilde{s}_{2,1}')
$$
Substituting this and its transpose into the above equation yields

$$\Gamma = -(S_{2,2}S'_{2,2} - \bar{s}_{2,1}s_{1,2}s'_{1,2} \bar{s}'_{2,1}) + 2\Sigma_{2,2} - \bar{s}_{2,1}\sigma_{1,2} - \sigma_{2,1}\bar{s}'_{2,1}.$$ 

Similarly, by subtracting (7) pre-multiplied by $\bar{s}_{2,1}$ and post-multiplied by $\bar{s}'_{2,1}$ from (9), one can write

$$S_{2,2}S'_{2,2} - \bar{s}_{2,1}s_{1,2}s'_{1,2} \bar{s}'_{2,1} = \Sigma_{2,2} - \sigma_{1,1}\bar{s}_{2,1}\bar{s}'_{2,1}.$$ 

Using this in the equation above gives

$$\Gamma = \Sigma_{2,2} - (\bar{s}_{2,1}\sigma_{1,2} + \sigma_{2,1}\bar{s}'_{2,1}) + \sigma_{1,1}\bar{s}_{2,1}\bar{s}'_{2,1}.$$ 

Thus,

$$s_{1,2}s'_{1,2} = (\sigma_{2,1} - \bar{s}_{2,1}\sigma_{1,1})'(\Sigma_{2,2} - (\bar{s}_{2,1}\sigma_{1,2} + \sigma_{2,1}\bar{s}'_{2,1}) + \sigma_{1,1}\bar{s}_{2,1}\bar{s}'_{2,1})^{-1}(\sigma_{2,1} - \bar{s}_{2,1}\sigma_{1,1}),$$

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

$$s_1 = \begin{pmatrix} s_{1,1} \\ s_{2,1}s_{1,1} \end{pmatrix}.$$

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

$$s_1 = \begin{pmatrix} 1 \\ \bar{s}_{2,1} \end{pmatrix} = \begin{pmatrix} 1 \\ s_{2,1} \end{pmatrix}.$$

After having obtained the structural impact vector $s_1$, it is straightforward to compute all objects of interest such as IRFS, FEVDs and the structural shock series (see e.g. Montiel-Olea, Stock, and Watson, 2016).

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

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

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

\[
\mathbb{E}[z_t \varepsilon'_{1,t}] = \alpha \\
\mathbb{E}[z_t \varepsilon'_{2,t}] = 0_{k \times (n-k)},
\]

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

\[
SS' = \Sigma.
\]

In a next step, partition $S$ as

\[
S = (S_1, S_2) = \begin{pmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{pmatrix},
\]

where $S_1$ is of dimension $n \times k$, $S_2$ is of dimension $n \times (n - k)$. $S_{11}$ is of dimension $k \times k$, $S_{21}$ and $S_{12}$ are of dimension $(n - k) \times k$ and $k \times (n - k)$, respectively, and $S_{22}$ is $(n - k) \times (n - k)$.

The instrument moment conditions together with $u_t = S \varepsilon_t$ imply

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

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

\[
\alpha (S'_{11}, S'_{21}) = (\Sigma_{zu'_1}, \Sigma_{zu'_2}),
\]

or equivalently

\[
\alpha S'_{11} = \Sigma_{zu'_1} \\
\alpha S'_{21} = \Sigma_{zu'_2}.
\]

Combining the two yields

\[
S_{21} S^{-1}_{11} = (\Sigma_{zu'_1}^{-1} \Sigma_{zu'_2})',
\]

which can be estimated from the data. In particular, $\Sigma_{zu'_1}^{-1} \Sigma_{zu'_2}$ corresponds to the 2SLS estimator in a regression of $u_{2,t}$ on $u_{1,t}$ using $z_t$ as an instrument for $u_{1,t}$.
The covariance restrictions then yield

\[
\begin{bmatrix}
S_{11} & S_{12} \\
S'_{11} & S'_{21}
\end{bmatrix}
\begin{bmatrix}
S'_{11} & S'_{12} \\
S'_{21} & S'_{22}
\end{bmatrix} =
\begin{bmatrix}
S_{11}S'_{11} + S_{12}S'_{12} & S_{11}S'_{21} + S_{12}S'_{22} \\
S_{21}S'_{11} + S_{22}S'_{12} & S_{21}S'_{21} + S_{22}S'_{22}
\end{bmatrix} =
\begin{bmatrix}
\Sigma_{11} & \Sigma_{12} \\
\Sigma_{21} & \Sigma_{22}
\end{bmatrix}.
\]

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

\[
\begin{align*}
S_{11}S'_{11} + S_{12}S'_{12} &= \Sigma_{11} \\
S_{11}S'_{21} + S_{12}S'_{22} &= \Sigma_{12} \\
S_{21}S'_{21} + S_{22}S'_{22} &= \Sigma_{22}.
\end{align*}
\]

Note, to identify \(S\) up to a rotation, it is sufficient to find \(S_{11}S'_{11}, S_{22}S'_{22}, S_{21}S'_{11}\) and \(S_{12}S'_{22}\). This is because one can write

\[
S = \begin{bmatrix}
L_1 & S_{12}S'_{22}L_2 \\
S_{21}S'_{11}L_1 & L_2
\end{bmatrix},
\]

where \(L_1 = \text{chol}(S_{11}S'_{11})\) and \(L_2 = \text{chol}(S_{22}S'_{22})\). This still satisfies \(SS' = \Sigma\). Thus, it proves useful to rewrite these equations in terms of \(S_{11}S'_{11}, S_{22}S'_{22}, S_{21}S'_{11}\) and \(S_{12}S'_{22}\):

\[
\begin{align*}
S_{11}S'_{11} + S_{12}S_{22}^{-1}S_{22}S'_{22}(S'_{22})^{-1}S_{12}' &= \Sigma_{11} \\
S_{11}S_{11}^{-1}S_{11}'_{21} + S_{12}S_{22}^{-1}S_{12}S_{22}' &= \Sigma_{12} \\
S_{21}S_{21}^{-1}S_{21}'_{21}S_{11}^{-1}S_{21}S_{22}' + S_{22}S_{22}' &= \Sigma_{22}.
\end{align*}
\]

Recall that \(S_{21}S'_{11}\) is identified by the instrument conditions. Thus, this is a system of 3 matrix equations in 3 unknown matrices. The solutions are given by

\[
\begin{align*}
S_{12}S'_{12} &= (\Sigma_{21} - S_{21}S_{11}^{-1}\Sigma_{11})\Gamma^{-1}(\Sigma_{21} - S_{21}S_{11}^{-1}\Sigma_{11}) \\
\Gamma &= (\Sigma_{22} + S_{21}S_{11}^{-1}\Sigma_{11}(S'_{21})^{-1}S_{21}' - S_{21}S_{11}^{-1}\Sigma_{12} - \Sigma_{21}(S'_{11})^{-1}S_{21}') \\
S_{11}S'_{11} &= \Sigma_{11} - S_{12}S'_{12} \\
S_{22}S'_{22} &= \Sigma_{22} - S_{21}S_{11}^{-1}\Sigma_{11}S_{11}'(S_{11}')^{-1}S_{21}' \\
S_{12}S_{22}^{-1} &= (\Sigma_{12} - S_{11}S_{11}'(S_{11}')^{-1}S_{21}')(S_{22}S'_{22})^{-1}.
\end{align*}
\]
To show this, define \( a = S_{21}S_{11}^{-1} \) and \( b = S_{12}S_{22}^{-1} \). Then note that

\[
\Sigma_{12} - \Sigma_{11}a' = bS_{22}S_{22}'(I - b'a') \\
\Sigma_{22} + a\Sigma_{11}a' - a\Sigma_{12} - \Sigma_{21}a' = (I - ab)S_{22}S_{22}'(I - b'a').
\]

Thus,

\[
(S_{12} - \Sigma_{11}a')(\Sigma_{22} + a\Sigma_{11}a' - a\Sigma_{12} - \Sigma_{21}a')^{-1}(\Sigma_{21} - a\Sigma_{11}) = bS_{22}S_{22}'(I - b'a')(I - b'a')^{-1}(S_{22}S_{22}')^{-1}(I - ab)^{-1}(I - ab)S_{22}S_{22}'b' \\
= bS_{22}S_{22}'b' = S_{12}S_{12}'.
\]

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

I have now all the ingredients to evaluate

\[
S = \begin{pmatrix} \text{L}_1 & S_{12}S_{22}^{-1}\text{L}_2 \\ S_{21}S_{11}^{-1}\text{L}_1 & \text{L}_2 \end{pmatrix}.
\]

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

\[
SB = \begin{pmatrix} \text{L}_1 & S_{12}S_{22}^{-1}\text{L}_2 \\ S_{21}S_{11}^{-1}\text{L}_1 & \text{L}_2 \end{pmatrix} \begin{pmatrix} \text{R}_k & 0 \\ 0 & \text{R}_{n+k} \end{pmatrix} = \begin{pmatrix} \text{L}_1\text{R}_k & S_{12}S_{22}^{-1}\text{L}_2\text{R}_{n+k} \\ S_{21}S_{11}^{-1}\text{L}_1\text{R}_k & \text{L}_2\text{R}_{n+k} \end{pmatrix},
\]

where \( R \) is an orthonormal rotation matrix. As I am only interested in identifying the first \( k \) shocks, identification of \( S_1 \) amounts to choose an appropriate rotation submatrix \( R_k \). In the application at hand, \( R_k = I \) 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 \( L_1 \) is a lower triangular matrix, this amounts to assume that the oil supply news shock does not affect world oil production on impact. This additional assumption identifies the two structural shocks.
B. Data – For online publication

B.1. OPEC announcements

Table 3 lists all OPEC announcements over the period 1983-2017. The press releases are available in the archive on the official OPEC webpage.\footnote{See http://www.opec.org/opec_web/en/press_room/28.htm} Note that some conferences ended on a weekend day. For these conferences, the date of the next trading day is taken as the end date.

Table 3: OPEC announcement dates over the period 1983–2015

<table>
<thead>
<tr>
<th>Release date</th>
<th>Release type</th>
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<tbody>
<tr>
<td>19.07.1983</td>
<td>68th meeting of the OPEC conference</td>
</tr>
<tr>
<td>09.12.1983</td>
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**B.2. Data sources**

Table 4 lists detailed descriptions and the sources of the data used in the paper.
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<tr>
<th>Identifier</th>
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<th>Source</th>
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<tr>
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<tr>
<td>NCLC.hh (PS)</td>
<td>WTI crude oil futures hh-month contract (settlement price)</td>
<td>Datastream</td>
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<td>NCLC.hh (VM)</td>
<td>WTI crude oil futures hh-month contract (traded volume)</td>
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<td>TWEXMMTH</td>
<td>Trade Weighted U.S. Dollar Index: Major Currencies</td>
<td>FRED</td>
</tr>
<tr>
<td>TWEXMPA</td>
<td>Real Trade Weighted U.S. Dollar Index: Major Currencies</td>
<td>FRED</td>
</tr>
<tr>
<td>TWEXOMTH</td>
<td>Trade Weighted U.S. Dollar Index: Other Important Trading Partners</td>
<td>FRED</td>
</tr>
<tr>
<td>TWEXOPA</td>
<td>Real Trade Weighted U.S. Dollar Index: Other Important Trading Partners</td>
<td>FRED</td>
</tr>
<tr>
<td>Misc</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GLOBALACT</td>
<td>Killian’s (2009) index of global real economic activity</td>
<td>Killian’s webpage</td>
</tr>
<tr>
<td>USCOCOIMA</td>
<td>U.S. refiners acquisition cost of imported crude oil</td>
<td>Datastream</td>
</tr>
</tbody>
</table>

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C. Additional charts and tables – For online publication

In this appendix, I present additional tables and figures that are not shown in the main body of the paper. The subsections indicate the reference to the corresponding sections in the main text.

C.1. Construction of oil supply surprises

Figure 9: Monthly volumes of the WTI crude oil futures.

C.2. Diagnostics of the surprise series

Figure 10: The autocorrelation function of the external instrument
Table 5: Granger causality tests (p-values)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Instrument</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instrument</td>
<td>0.6709</td>
</tr>
<tr>
<td>Oil price</td>
<td>0.1148</td>
</tr>
<tr>
<td>World oil production</td>
<td>0.3216</td>
</tr>
<tr>
<td>World oil inventories</td>
<td>0.6642</td>
</tr>
<tr>
<td>World industrial production</td>
<td>0.5561</td>
</tr>
<tr>
<td>US industrial production</td>
<td>0.4273</td>
</tr>
<tr>
<td>US CPI</td>
<td>0.9461</td>
</tr>
<tr>
<td>Joint</td>
<td>0.5733</td>
</tr>
</tbody>
</table>

Notes: The table shows the p-values of a series of Granger causality tests based on a VAR including the series of the baseline specification. 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.

C.3. Empirical specification

Figure 11: Series included in the baseline VAR over the sample period 1974-2015
C.4. Baseline model

Table 6: Forecast error variance decomposition of CPI components

<table>
<thead>
<tr>
<th></th>
<th>Core CPI</th>
<th>CPI energy</th>
<th>CPI non-durables</th>
<th>CPI durables</th>
<th>CPI services</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.00</td>
<td>0.21</td>
<td>0.13</td>
<td>0.19</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>0.00, 0.01</td>
<td>0.03, 0.52</td>
<td>0.00, 0.43</td>
<td>0.01, 0.51</td>
<td>0.00, 0.01</td>
</tr>
<tr>
<td>12</td>
<td>0.03</td>
<td>0.57</td>
<td>0.19</td>
<td>0.49</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>0.00, 0.18</td>
<td>0.21, 0.80</td>
<td>0.01, 0.55</td>
<td>0.15, 0.74</td>
<td>0.01, 0.37</td>
</tr>
<tr>
<td>24</td>
<td>0.04</td>
<td>0.58</td>
<td>0.19</td>
<td>0.45</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>0.00, 0.22</td>
<td>0.21, 0.80</td>
<td>0.02, 0.59</td>
<td>0.15, 0.70</td>
<td>0.02, 0.50</td>
</tr>
<tr>
<td>36</td>
<td>0.04</td>
<td>0.54</td>
<td>0.19</td>
<td>0.37</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>0.00, 0.22</td>
<td>0.20, 0.78</td>
<td>0.02, 0.57</td>
<td>0.12, 0.61</td>
<td>0.02, 0.49</td>
</tr>
</tbody>
</table>

Notes: The table shows the forecast error variance decomposition at horizons 0, 12, 24, and 36 months together with the pointwise 90% confidence intervals.

C.5. Wider effects of oil supply news shocks

Figure 12: IRFs for the baseline variables from the augmented VARs in section 4.3.
C.6. Sensitivity analysis

C.6.1. Identification

Figure 13: Comparison of the results using the raw and the refined, informationally robust oil supply surprise series as an instrument.
Figure 14: Sensitivity with respect to the announcement type: IRFs from VAR using instrument constructed only from announcements from ordinary meetings.

Figure 15: Sensitivity with respect to the futures contract: IRFs from VAR using instruments constructed from the front to the 5-month futures contracts together with the baseline responses. Contracts with shorter maturity are depicted in lighter color.
Figure 16: Sensitivity with respect to the underlying of the futures: IRFs from VAR using instrument constructed from Brent futures prices (4-month contract).

Figure 17: Two shock proxy VAR: The top row is the oil supply surprise shock and the bottom row is the oil supply news shock identified using Caldara, Cavallo, and Iacoviello's (2018) exogenous supply shock series and the OPEC surprise series as instruments.
C.6.2. Model specification

![Graphs showing sensitivity with respect to the model specification.](image)

Figure 18: Sensitivity with respect to the model specification: VAR with Kilian’s (2009) (corrected) global activity series as global economic activity indicator.

First stage regression: F: 21.41, robust F: 12.89, $R^2$: 4.19%, Adjusted $R^2$: 4.00%
Figure 19: Sensitivity with respect to the model specification: VAR with refiner acquisition cost of imported crude oil as oil price measure.

First stage regression: F: 14.61, robust F: 12.50, $R^2$: 2.90%, Adjusted $R^2$: 2.70%

Figure 20: Sensitivity with respect the model specification: IRFs based on VAR(7), which is the lag length selected by the AIC.

First stage regression: F: 21.14, robust F: 12.38, $R^2$: 4.14%, Adjusted $R^2$: 3.95%
Figure 21: Sensitivity with respect the model specification: IRFs based on VAR(24).

Figure 22: Sensitivity with respect to the model specification: IRFs based on VAR(12).
Figure 23: Sensitivity with respect to the model specification: VAR with linear trend.

First stage regression: F: 24.07, robust F: 14.55, $R^2$: 4.69%, Adjusted $R^2$: 4.50%

Figure 24: Sensitivity with respect to the model specification: stationary VAR (real oil price, world oil production growth, change in world oil inventories, world industrial production growth, U.S. industrial production growth, U.S. CPI inflation)

Figure 25: IRFs based on Kilian and Murphy’s (2014) model specification. The dashed lines are pointwise 68% confidence bands.

First stage regression: F: 11.71, robust F: 13.01, \( R^2 \): 2.40%, Adjusted \( R^2 \): 2.19%

Figure 26: IRFs based on Baumeister and Hamilton’s (forthcoming) model specification. The dashed lines are pointwise 68% confidence bands.

First stage regression: F: 13.15, robust F: 15.19, \( R^2 \): 2.68%, Adjusted \( R^2 \): 2.48%
C.6.3. Subsample analysis

Figure 27: Sensitivity with respect to the estimation sample: 1982M3-2015M12.

Figure 28: Sensitivity with respect to the estimation sample: 1974M1-2007M12.
Figure 29: Sensitivity with respect to the estimation sample: 1974M1-2010M12.

First stage regression: F: 25.78, robust F: 16.14, $R^2$: 5.67%, Adjusted $R^2$: 5.45%

Figure 30: Sensitivity with respect to the instrument sample: 1990M1-2015M12.

First stage regression: F: 13.60, robust F: 8.73, $R^2$: 2.70%, Adjusted $R^2$: 2.51%
C.6.4. Data frequency

Figure 31: Baseline VAR based on quarterly data.