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The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements†

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This paper studies how changes in oil supply expectations affect the oil price and the macroeconomy. Using a novel identification design, exploiting institutional features of OPEC and high-frequency data, I identify an oil supply news shock. These shocks have statistically and economically significant effects. Negative news leads to an immediate increase in oil prices, a gradual fall in oil production, and an increase in inventories. This has consequences for the US economy: activity falls, prices and inflation expectations rise, and the dollar depreciates, providing evidence for a strong channel operating through supply expectations. (*JEL* E31, E32, F31, Q35, Q38, Q43)

Recent turbulences in the oil market have sparked renewed interest in the long-standing question of how oil prices affect the macroeconomy. This question is challenging because oil prices are endogenous and respond to global economic developments. To provide an answer, one has to account for the underlying drivers of the oil price. From a policy perspective, oil supply shocks are of particular interest because of their stagflationary effects. However, as oil prices are inherently forward-looking, not only current supply matters but also expectations about the future.

In this paper, I propose a novel approach to identify a shock to oil supply expectations, exploiting institutional features of the Organization of the Petroleum Exporting Countries (OPEC) and information contained in high-frequency data. The idea is to use variation in oil futures prices around OPEC production announcements. OPEC accounts for about 44 percent of world oil production and thus, its announcements

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can have a significant impact on oil prices (Lin and Tamvakis 2010; Loutia, Mellios, and Andriosopoulos 2016). While OPEC is known to be heavily driven by political considerations, its decisions are likely not exogenous but also depend on the state of the global economy (Barsky and Kilian 2004). However, by measuring the changes in oil futures prices in a tight window around the announcements, we can isolate the impact of news about future oil supply. Reverse causality of the global economic outlook can be plausibly ruled out because it is already priced in at the time of the announcement and is unlikely to change within the tight window. Using the resulting series as an external instrument in an oil market VAR model, I am able to identify a structural *oil supply news* shock.

Oil supply news shocks have statistically and economically significant effects. Negative news about future oil supply leads to a large, immediate increase in oil prices, a gradual but significant fall in world oil production, and a significant increase in world oil inventories. Global economic activity does not change significantly on impact but then starts to fall persistently. This has consequences for the US economy: industrial production falls and consumer prices rise significantly. This evidence supports the notion that changes in expectations about future supply can have powerful effects even if current oil production does not move.

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

Studying various propagation channels of oil supply news, I find that oil price and inflation expectations rise significantly while uncertainty indicators are hardly affected, consistent with the interpretation of a news shock. Interestingly, the rise in inflation expectations is stronger for households, in line with recent evidence by Coibion and Gorodnichenko (2015). Oil supply news also leads to a significant increase in consumer prices even after excluding energy prices, a persistent fall in consumption and investment expenditures, rising unemployment, and falling stock market indices. The US dollar depreciates significantly, especially against the currencies of net oil exporting countries. Consistent with the exchange rate response, the terms of trade deteriorates substantially and the trade balance falls into deficit. Oil supply news shocks also turn out to be an important driver of the economy as they explain a significant share of the variations in economic activity and prices.

A comprehensive series of sensitivity checks indicate that the results are robust along a number of dimensions including the identification design, the estimation approach, as well as the model specification and sample period. In particular, the results are robust to accounting for background noise over the event window. A heteroskedasticity-based estimator produces consistent results, even though the responses are less precisely estimated. I also show that the results are robust to estimating the responses to the identified shock using local projections and controlling for OPEC's global demand forecasts in the construction of the instrument.

This paper is related to a long literature studying the macroeconomic effects of oil price shocks. A key insight in this literature is that oil price shocks do not occur ceteris paribus. Therefore, it is important to account for the fundamental drivers of oil price fluctuations (Kilian 2009). These include oil supply, global demand,

and expectations about future oil market conditions. In the last years, the literature has made substantial progress in disentangling these drivers using SVAR models of the oil market, identified with the help of zero restrictions (Kilian 2009), sign restrictions (Kilian and Murphy 2012; Lippi and Nobili 2012; Baumeister and Peersman 2013; Baumeister and Hamilton 2019), and narrative information (Antolín-Díaz and Rubio-Ramírez 2018; Caldara, Cavallo, and Iacoviello 2019; Zhou 2020).

A difficult problem in this context is the identification of the expectations-driven component. A number of studies have addressed this problem by augmenting the standard oil market model by global oil inventory data (Kilian and Murphy 2014; Juvenal and Petrella 2015). The idea is that expectational shifts in the oil market should be reflected in the demand for oil inventories (see also Hamilton 2009; Alquist and Kilian 2010). An important challenge is that these shifts in inventory demand capture many different things, including news about future demand and supply or higher uncertainty, that existing identification strategies cannot disentangle.

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

From a methodological viewpoint, my approach is closely related to the high-frequency identification of monetary policy shocks. In this literature, monetary policy surprises are identified using high-frequency asset price movements around monetary policy events, such as FOMC announcements (Kuttner 2001; Gürkaynak, Sack, and Swanson 2005; Nakamura and Steinsson 2018a, among others). The idea is to isolate the impact of monetary policy news by measuring the change in asset prices in a tight window around policy announcements. To account for confounding news over the event window, Rigobon and Sack (2004) propose to exploit the heteroskedasticity in the data. Gertler and Karadi (2015) use these high-frequency surprises as an external instrument in a monetary SVAR to estimate the macroeconomic effects of monetary policy shocks. The key idea of this paper is to apply this approach to the oil market, exploiting institutional features of OPEC.

This paper is not the first to look at OPEC announcements. In fact, there is a large literature analyzing the effects of OPEC announcements on oil prices using event study techniques (Draper 1984; Loderer 1985; Demirer and Kutan 2010, among others). To the best of my knowledge, however, this paper is the first to look at the macroeconomic effects of these announcements, combining the event study literature on OPEC meetings with the traditional oil market VAR analysis.[1]

[1] There are a few papers that also exploited the financial market reaction to oil events for identification but in somewhat different contexts (Cavallo and Wu 2012; Anzuini, Pagano, and Pisani 2015; Branger, Flacke, and Gräber 2020).

My results indicate that news about future oil supply can have a meaningful impact on the oil price and macroeconomic aggregates even if current production does not move. In this sense, I also contribute to the literature on the role of news in the business cycle by providing evidence for a strong expectational channel in the oil market. Traditionally, this literature focuses on anticipated technology (Beaudry and Portier 2006; Barsky and Sims 2011) and fiscal shocks (Ramey 2011; Leeper, Walker, and Yang 2013). Only recently, there has been a growing interest in other kinds of news, such as news about future monetary policy or production possibilities (Nakamura and Steinsson 2018a; Arezki, Ramey, and Sheng 2017). Gambetti and Moretti (2017) also identify a news shock in the oil market but focus on the role of news versus noise shocks.

The paper proceeds as follows. In the next section, I discuss the identification design, providing background information on OPEC, details on the construction of the instrument, and some diagnostic tests. In Section II, I cover the econometric approach. Section III presents the results. I start by analyzing the instrument strength before discussing the effects of oil supply news on the oil market and the macroeconomy, the contribution to historical episodes in the oil market, the wider effects and propagation channels, as well as the quantitative importance. In Section IV, I perform a number of robustness checks. Section V concludes.

I. Identification

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

A. *Institutional Background*

The Oil Market and OPEC.—The global oil market has a peculiar structure in that it is dominated by a few big players. The biggest and most important player is OPEC. OPEC is an intergovernmental organization of oil-producing nations and accounts for around 44 percent of the world's crude oil production (based on data from the US Energy Information Administration (EIA) for 2016). It was founded in 1960 by Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela. Since then, other countries joined the organization and currently, OPEC has a total of 13 member countries.[2] According to the statutes, OPEC's mission is to stabilize global oil markets to secure an efficient, economic, and regular supply of petroleum to consumers, a

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

steady income to producers, and a fair return on capital for those investing in the petroleum industry. Economists, however, often think of OPEC as a cartel that cooperates to reduce market competition.

The supreme authority of the organization is the OPEC conference, which consists of delegations headed by the oil ministers of the member countries. Several times a year, the conference meets in order to agree on oil production policies. Since 1982, this includes setting an overall oil production ceiling for the organization and individual quotas for its members.[3] The conference ordinarily meets twice a year on pre-scheduled dates at its headquarters in Vienna but if necessary it can call for extraordinary meetings on short notice. In making decisions, the conference generally operates on the principles of unanimity and "one member, one vote." However, since Saudi Arabia is by far the largest oil producer in OPEC, with enough capacity to function as a swing producer to balance the global market, it is often thought to be "OPEC's de facto leader."[4]

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

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

Despite the fact that OPEC sometimes has trouble agreeing and enforcing its production quotas, markets pay close attention to it and its announcements trigger significant price reactions (see, e.g., Lin and Tamvakis 2010; Loutia, Mellios, and Andriosopoulos 2016). In the example above, the announcement led to an oil price increase of about 2 percent.

Oil Futures Markets.—Crude oil is an internationally traded commodity and there exist liquid futures markets. The most widely traded contracts are the West Texas Intermediate (WTI) crude and Brent crude futures. WTI and Brent are grades of crude oil that are used as benchmarks in pricing oil internationally. I focus on

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

[4] This language is routinely used in the financial press, see, e.g., "OPEC Discord Fuels Further Oil Price Drop," *Financial Times*, https://www.ft.com/content/1f84e444-9ceb-11e5-8ce1-f6219b685d74.

WTI for the following reasons. First, it is the relevant benchmark for pricing oil in the United States, the country of primary interest in this paper. Second, the WTI crude futures have the longest available history as they were the first traded contracts on crude oil. They trade at the New York Mercantile Exchange (NYMEX) and were introduced in 1983. Finally, it is the most liquid and largest market for crude oil, currently trading nearly 1.2 million contracts a day (CME Group 2018).

B. *Construction of Oil Supply Surprises*

To construct a time series of oil supply surprises, I look at how oil futures prices change around OPEC announcements. Oil futures prices are a natural, market-based proxy for oil price expectations and thus well suited to measure the impact of OPEC announcements. However, in principle, we could use any asset price that is sufficiently responsive.

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

To be able to interpret this as news about future oil supply, it is crucial that the announcements do not contain any new information about other factors such as oil demand, global economic activity, or geopolitical developments. Even though it is hard to assess whether this is the case, looking at how OPEC announcements are received in the financial press is suggestive as the focus is usually on whether OPEC could agree on new production quotas (see online Appendix Section A.4 for some illustrative examples). It should also be noted that these problems are not specific to the oil market. As is by now well known, monetary policy also transmits through an information channel that conflates high-frequency measures of monetary policy shocks (Nakamura and Steinsson 2018a; Jarociński and Karadi 2020; Miranda-Agrippino and Ricco forthcoming). I will argue that the information channel is, if at all, less of a problem in the oil market because the informational advantage is less obvious than in the case of a central bank. Furthermore, OPEC as an organization is very political and does not respond as systematically to economic developments. However, to address this concern more rigorously, I construct an informationally robust surprise series by purging the original series from revisions in OPEC's global demand forecasts, akin to the refinement of Romer and Romer (2004) in the monetary policy setting, and show that the results are robust (see Section IV).

To construct the benchmark surprise series, I collected OPEC press releases for the period 1983–2017. There were a total of 119 announcements made during this period. An overview of all announcement dates and data sources can be found in online Appendix Section B. Based on these data, I construct a series of oil supply surprises by taking the (log) difference of the futures price on the day of the OPEC announcement and the price on the last trading day before the announcement:

$$Surprise_{t,d}^{h} = F_{t,d}^{h} - F_{t,d-1}^{h}, \tag{1}$$

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

Standard asset pricing implies that

$$F_{t,d}^{h} = E_{t,d}[P_{t+h}] - RP_{t,d}^{h}, \tag{2}$$

where $E_{t,d}[P_{t+h}]$ is the expected oil price conditional on the information on day d and $RP_{t,d}^{h}$ is a risk premium (see Pindyck 2001). Assuming that the risk premium does not change within the daily window around the announcement, i.e., $RP_{t,d}^{h} = RP_{t,d-1}^{h}$, we can interpret the surprise as a revision in oil price expectations,

$$Surprise_{t,d}^{h} = E_{t,d}[P_{t+h}] - E_{t,d-1}[P_{t+h}], \tag{3}$$

caused by the respective OPEC announcement.

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

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

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

futures prices are highly correlated across maturities and using different contracts yields very similar results, see online Appendix Section A.4.

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

C. *Diagnostics of the Surprise Series*

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

Narrative Evidence.—It turns out that the series accords quite well with the narrative account on some key historical episodes. Below, I discuss three specific instances that are of particular interest as they were associated with substantial revisions in oil price expectations.

On August 5, 1986, OPEC could finally agree on new production quotas after years of disagreement and lack of compliance. Just before, the oil price plummeted as Saudi Arabia flooded the markets with oil to make other OPEC members comply (Roberts 2005). As we can see, the announcement came as a surprise and led to a big upward revision of oil price expectations. On November 14, 2001, amid a global economic slowdown that had been exacerbated by the September 11 terror attacks, OPEC pledged to cut production but only if other oil producers cut their production as well. Markets interpreted this announcement as a signal of a potential price war, which led to a significant downward revision of price expectations (Al-Naimi 2016). Another major revision occurred on November 27, 2014, when OPEC announced that it was leaving oil production levels unchanged. Before, many market observers had expected OPEC to agree on a cut to oil production in a bid to boost prices. However, Saudi Arabia blocked calls from some of the poorer OPEC members for lower quotas, which led to a downward revision of oil price expectations by about 10 percent.[6]

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

To gauge the extent of background noise in the surprise series, I compare the daily changes in oil futures prices on OPEC announcement days to the price changes on a sample of control days that do not contain an OPEC announcement but are

[6] See Alex Lawler, Amena Bakr, and Dmitry Zhdannikov, "Inside OPEC Room, Naimi Declares Price War on US Shale Oil." *Reuters Business News,* November 27, 2014, https://uk.reuters.com/article/uk-opec-meeting-idUK-KCN0JB0M420141128 (accessed January 17, 2020).

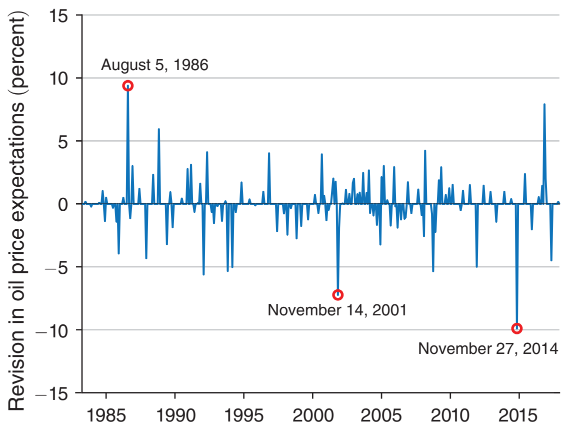

Figure 1. The Oil Supply Surprise Series

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

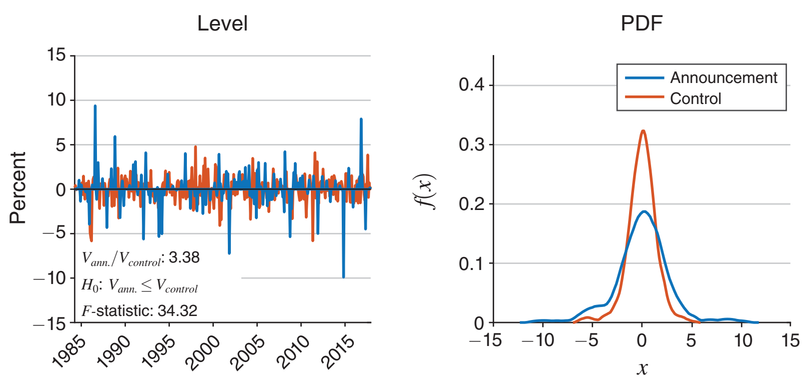

Figure 2. Announcement versus Control Days

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

comparable on other dimensions (i.e., same weekday and week in the months prior to a given announcement). For an overview of announcement and control dates, see online Appendix Table B.1.

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

Other Diagnostic Checks.—I also perform a number of additional tests concerning the validity of the oil supply surprise series. Desirable properties are that it should not be autocorrelated, forecastable, or correlated with other structural shocks (Ramey 2016).

Inspecting the autocorrelation function of the series, I find no evidence for serial correlation. To check whether macroeconomic variables have any power in forecasting the series I run a series of Granger causality tests. I find no evidence that macroeconomic or financial variables have any forecasting power as all selected variables do not Granger cause the series at conventional significance levels. To analyze whether the surprise series is conflated by other structural shocks, I study the correlation with a wide range of different shock measures from the literature. The results indicate that the oil supply surprise series is not mistakenly picking up global demand, productivity, uncertainty, financial, monetary, or fiscal policy shocks affecting the oil price. The corresponding figures and tables can be found in online Appendix Section A.1. Overall, this evidence supports the validity of the oil supply surprise series.

II. Econometric Approach

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

Thus, I will not use it as a direct shock measure but as an *instrument*. More specifically, I use it as an external instrument in an otherwise standard oil market VAR model to identify a structural oil supply news shock, building on a methodology developed by Stock and Watson (2012) and Mertens and Ravn (2013). An external instrument is a variable that is correlated with the shock of interest but not with the other shocks. To account for background noise, I alternatively employ an *heteroskedasticity-based* estimator that allows for confounding shocks during the event window (see Rigobon 2003; Rigobon and Sack 2004; Nakamura and Steinsson 2018a). The idea is to clean out background noise in the surprise series by comparing movements in oil futures prices during event windows around OPEC announcements to other equally long and otherwise similar event windows that do not contain an OPEC announcement. Identification is then achieved by complementing the VAR residual covariance restrictions with the moment conditions for the external instrument/heteroskedasticity-based estimator.

An alternative approach would be to directly estimate the dynamic causal effects using local projections. However, as discussed in Nakamura and Steinsson (2018a), this can be difficult in the context of high-frequency identification because of a power problem. Intuitively, macroeconomic variables several periods out in the future are hit by a myriad of other shocks. At the same time, the oil price is an extremely volatile variable itself and the high-frequency surprises account only for a small part of the price fluctuations, rendering the signal-to-noise ratio low. This makes it challenging to directly estimate the macroeconomic effects of high-frequency oil supply surprises without imposing additional structure.[7]

A. *Framework*

Consider the following reduced-form VAR(p) model:

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

where p is the lag order, $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is an $n \times 1$ vector of reduced-form innovations with covariance matrix $\mathrm{var}(\mathbf{u}_t) = \boldsymbol{\Sigma}$, $\mathbf{b}$ is an $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices.

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

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

where $\mathbf{S}$ is a nonsingular, $n \times n$ structural impact matrix and $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of structural shocks. By definition, the structural shocks are mutually uncorrelated, i.e., $\mathrm{var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ is diagonal. From the linear mapping of the shocks we have

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

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

External Instruments Approach.—Under the assumption that the background noise in the surprise series is negligible, we can identify the structural impact vector using the external instruments approach. Identification with external instruments (or "proxies") works as follows. Suppose there is an external instrument available, z_t. In the application at hand, z_t is the oil supply surprise series. For z_t to be a valid instrument, we need

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

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

where $\varepsilon_{1,t}$ is the oil supply news shock and $\boldsymbol{\varepsilon}_{2:n,t}$ is an $(n-1) \times 1$ vector consisting of the other structural shocks. Assumption (7) is the relevance requirement and

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

assumption (8) is the exogeneity condition. Under assumptions (7)–(8), $\mathbf{s}_1$ is identified up to sign and scale:

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

provided that $E[z_t u_{1,t}] \neq 0$. Note that $\tilde{\mathbf{s}}_{2:n,1}$ can be thought of as the population analogue of the IV estimator of $\mathbf{u}_{2:n,t}$ on $u_{1,t}$ using z_t as an instrument. The structural impact vector is $\mathbf{s}_1 = (s_{1,1}, \tilde{\mathbf{s}}'_{2,1} s_{1,1})'$. The scale $s_{1,1}$ is then set by a normalization, subject to $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$. One approach is to set $\boldsymbol{\Omega} = \mathbf{I}_n$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a one standard deviation positive effect on $y_{1,t}$. Alternatively, we can set $\boldsymbol{\Omega} = \text{diag}(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$ and $s_{1,1} = x$, which implies that a unit positive value of $\varepsilon_{1,t}$ has a positive effect of magnitude x on $y_{1,t}$. To facilitate interpretation, I use the latter normalization such that the shock corresponds to a 10 percent increase in the price of oil. Having obtained the impact vector, it is straightforward to compute all objects of interest such as IRFs, FEVDs, the structural shock series, and historical decompositions. For more information, see online Appendix Section C.

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

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

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

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

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

Under these assumptions, the structural impact vector is given by

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

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

Additional Assumptions.—Apart from the identifying restrictions discussed above, there are other important assumptions underlying the VAR approach (Nakamura and Steinsson 2018b). A crucial assumption is invertibility, i.e., that the VAR contains all the relevant information to recover the structural shocks.[8] Non-invertibility is essentially an omitted variable bias problem. If the model does not span the relevant information, some endogenous variation may be falsely attributed to exogenous oil supply news shocks. In Section IVA, I analyze how the results depend on the information contained in the VAR. I do not find any evidence that the model is informationally insufficient.

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

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

where $y_{i,t+h}$ is the outcome variable of interest, $Shock_t = \hat{\varepsilon}_{1,t}$ is the oil supply news shock identified from the external instruments VAR, $\mathbf{x}_{t-1}$ is a vector of controls, and $\xi_{i,t,h}$ is a potentially serially correlated error term. The term ψ_h^i is the impulse response to the oil supply news shock of variable i at horizon h.[9] Using the shock identified from the VAR instead of the high-frequency oil supply surprises directly alleviates the challenges regarding statistical power discussed above, as the shock is consistently observed and spans the full sample going back to the 1970s. In Section IIIB, I compare the responses estimated from the VAR and the local projections approach and show that they produce comparable results.

B. *Comparison to Alternative Strategies*

Traditionally, oil supply shocks are thought of as sudden disruptions in the current availability of oil, causing an immediate fall in oil supply, an increase in the oil price, and a depletion of inventories. A long literature identified such shocks

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

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

using different techniques, ranging from the construction of narrative shock series (Hamilton 2003; Kilian 2008; Caldara, Cavallo, and Iacoviello 2019) to SVAR models of the oil market (Kilian 2009; Kilian and Murphy 2012; Baumeister and Hamilton 2019).

This paper proposes a novel focus: *oil supply news shocks*, i.e., expectational shocks about future oil supply. As is well known from the news literature, such shocks can have very different effects from surprise shocks (Beaudry and Portier 2014). In particular, we would expect that a negative oil supply news shock has a positive effect on the oil price while oil production does not respond significantly on impact but only decreases with a lag. Most importantly, the shock should lead to an increase in oil inventories. This is the key distinguishing feature between oil supply news and surprise shocks. If a shortfall in production happens today, market players will immediately draw down inventories to make up for the shortage in supply. In contrast, if market players expect a shortfall in the future, they will build up inventories today to make sure that they have oil when the shortfall occurs.

The positive inventory response conforms well with a literature that aims at identifying shocks to the inventory demand for oil (Kilian and Murphy 2014; Juvenal and Petrella 2015). The idea behind these studies is that otherwise unobservable shifts in expectations about future oil market conditions must be reflected in the demand for oil inventories. A positive inventory demand shock will shift the demand for oil inventories, causing inventories and the oil price to increase in equilibrium. It is precisely the positive inventory response that makes it possible to disentangle inventory demand from other oil demand and supply shocks in sign-identified VARs.

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

C. *Empirical Specification*

The baseline specification includes six variables: the real price of oil, world oil production, world oil inventories, world industrial production, US industrial production, and the US consumer price index (CPI).[10] The first four variables are standard in oil market VAR models. I augment these core variables by the two US variables to analyze the effects on the US economy. The data are monthly and span the period 1974:1 to 2017:12. A detailed overview on the data and their sources can be found in

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

online Appendix Section B.2. Following Gertler and Karadi (2015), I use a shorter sample for identification, namely 1983:4 to 2017:12. This is because the futures data used to construct the instrument are only available for this period. The motivation for using a longer sample for estimation is to get more precise estimates of the reduced-form coefficients. I estimate the VAR in log levels. The lag order is set to 12 and in terms of deterministics only a constant term is included. However, the results turn out the be robust with respect to all of these choices, see online Appendix Section A.4.

III. Results

A. *First Stage*

The main identifying assumption behind the external instruments approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other structural shocks. However, even if this holds, standard inference will not produce reliable results when the instrument and the shock are only weakly correlated. In a first step, it is thus important to test the strength of the instrument. This can be done using an F-test in the first-stage regression of the oil price residual from the VAR on the instrument (see Montiel-Olea, Stock, and Watson forthcoming). To be confident that a weak instrument problem is not present, they recommend a threshold value of 10 for the corresponding F-statistic.

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

B. *Effects on the Oil Market and the Macroeconomy*

I present now the results from the baseline model, identified using the external instruments approach. Figure 3 shows the impulse responses to the identified oil supply news shock, normalized to increase the real oil price by 10 percent. As all variables are in logs, the responses can be interpreted as elasticities. The solid black lines are the point estimates and the shaded areas are 68 and 90 percent confidence bands based on 10,000 bootstrap replications.[11]

A negative oil supply news shock leads to a significant, immediate increase in the price of oil. World oil production does not change significantly on impact but

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

TABLE 1—TESTS ON INSTRUMENT STRENGTH

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

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

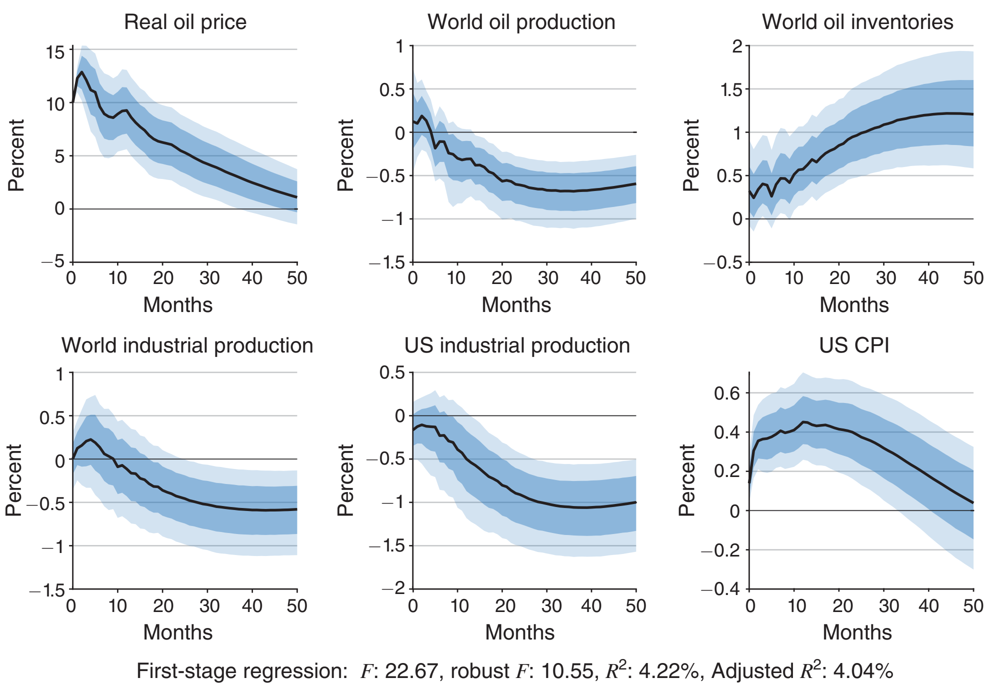

FIGURE 3. IMPULSE RESPONSES TO AN OIL SUPPLY NEWS SHOCK

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

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

The rise in inventories turns out to be somewhat more persistent than expected. As oil production starts falling, we may expect that some of the accumulated inventories get depleted. In contrast, inventories turn out to be elevated for an extended period. A potential explanation for this finding are speculative or precautionary motives. It is conceivable that negative oil supply news shocks are perceived as a signal for further negative news in the future, which would lead to an over-accumulation of inventories.[12]

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

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

Accounting for Background Noise.—To analyze the role of background noise, I also present results from the heteroskedasticity-based approach. As shown in Section IC, the variance on OPEC announcement days is over 3 times higher than on other comparable trading days and this difference is highly statistically significant. It is exactly this shift in variance that can be exploited for identification, assuming that the shift is driven by the oil supply news shock.[13]

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

The finding that the external instruments and the heteroskedasticity-based approach lead to such similar conclusions may be a bit surprising given the nontrivial background noise documented in Figure 2. A potential explanation for this finding could be that the background noise may in fact largely reflect variation in market beliefs about future oil supply announcements. Alternatively, a large part of the identification may be driven by large shocks and thus, the background noise, while significant in an average sense, turns out to be largely inconsequential. In online Appendix Section A.2, I provide some suggestive evidence for these explanations.

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

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

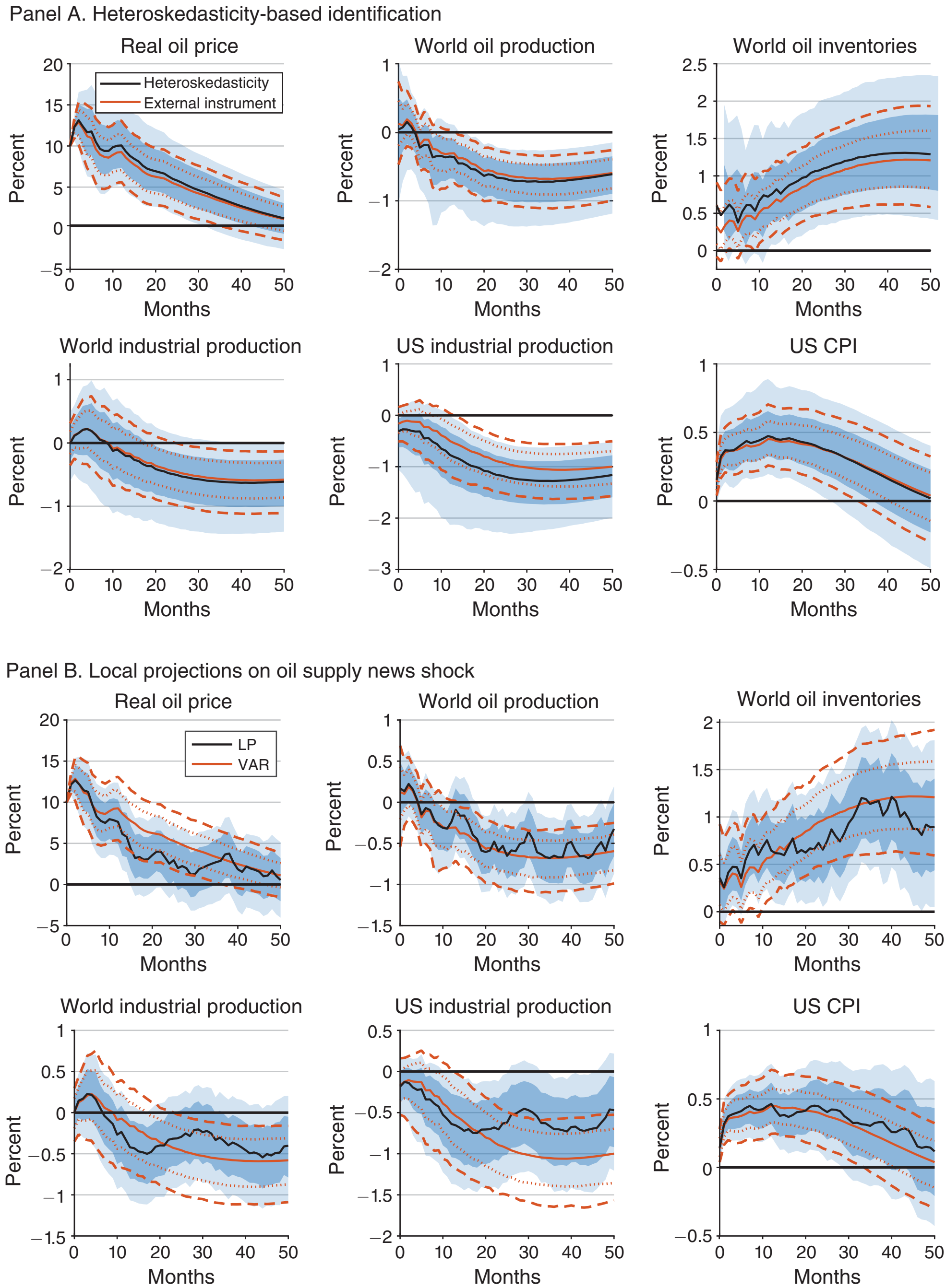

Figure 4. Background Noise and Dynamic VAR Structure

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

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

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

Discussion.—The findings illustrate that oil supply news shocks are quite different from the previously identified oil supply shocks (see, e.g., Kilian and Murphy 2012; Baumeister and Hamilton 2019). In particular, oil supply news shocks lead to a significant and persistent increase in inventories and a sluggish but significant fall in oil production. This stands in stark contrast to the negative response of inventories and the strong, immediate fall in oil production that is observed after unanticipated oil supply shocks. It is important to note that this result emerges naturally as my identification strategy does not restrict the signs of the responses in any way.

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

C. *Oil Supply News as a Driver of the Real Price of Oil*

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

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

It is instructive to focus on specific episodes. For example, the rapid rise in the oil price in the late 1970s after the Iranian Revolution turns out to be strongly driven by

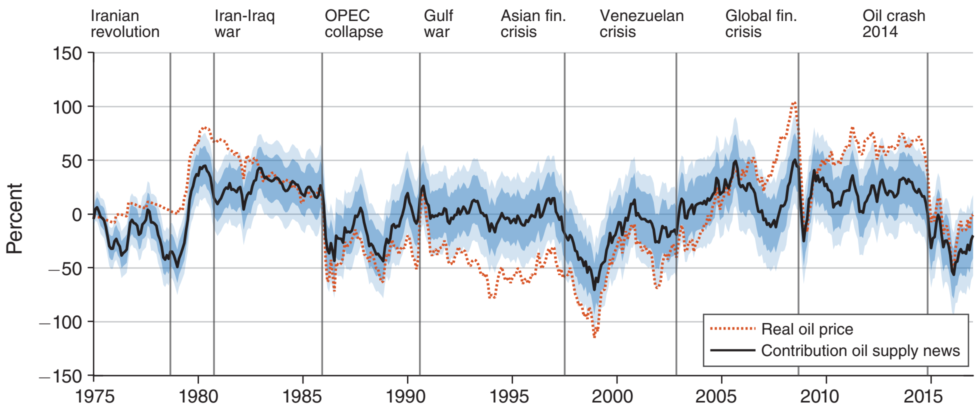

Figure 5. Historical Decomposition of the Real Price of Oil

Notes: The figure shows the cumulative historical contribution of oil supply news shocks to the real price of oil and the 68 and 90 percent confidence bands together with the actual real price of oil (in percent deviations from mean). The vertical bars indicate major events in oil markets, notably the outbreak of the Iranian revolution in 1978:9, the start of the Iran-Iraq war in 1980:9, the collapse of OPEC in 1985:12, the outbreak of the Persian Gulf war in 1990:8, the Asian financial crisis of 1997:7, the Venezuelan crisis in 2002:11, the outbreak of the global financial crisis in 2008:9, and the recent collapse of the oil price starting in 2014:6.

lower oil supply expectations. Developments in the Middle East, such as Khomeini's arrival in Iran or the Iranian hostage crisis, fueled expectations of a war and the destruction of oil fields in the region. These expectational effects peaked prior to the outbreak of the Iran-Iraq war and then subsided in the early 1980s.

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

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

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

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

D. *Wider Effects and Propagation Channels*

To get a better understanding of how oil supply news shocks transmit to the macroeconomy, I analyze the effects on a wide range of macroeconomic and financial variables. To compute the impulse responses, I augment the baseline VAR by one variable at a time.[14] This also allows me to gauge the importance of various propagation channels.

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

In panel B of Figure 6, I show the responses of different measures of uncertainty, including financial uncertainty and geopolitical risk.[15] Interestingly, the uncertainty measures are not strongly affected: financial uncertainty does not respond at all while geopolitical risks increase slightly in the short run but the response is barely significant. The strong response of price expectations together with the muted effects on uncertainty is consistent with the interpretation of a news shock. In contrast, for uncertainty shocks, which can have similar effects to news shocks (see Alquist and Kilian 2010), we would expect a stronger response of uncertainty indicators and no expected changes on future oil production.

The results on inflation expectations are of particular interest because of their central role for macroeconomic policy. However, measuring inflation expectations is challenging. An alternative to the Michigan survey is the Survey of Professional Forecasters (SPF), which captures expectations of professional forecasters as opposed to households. Analyzing potential differences between these measures is interesting. Unfortunately, the SPF data are only available at the quarterly frequency. To allow for better comparison, I also aggregate the monthly expectations from the Michigan survey and compute the responses from the augmented quarterly models.

Figure 7 shows that the effects differ quite substantially among the two measures. In line with the monthly evidence, household inflation expectations increase significantly. In contrast, the response of inflation expectation of professional forecasters turns out to be much weaker. These findings are consistent with Coibion

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

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

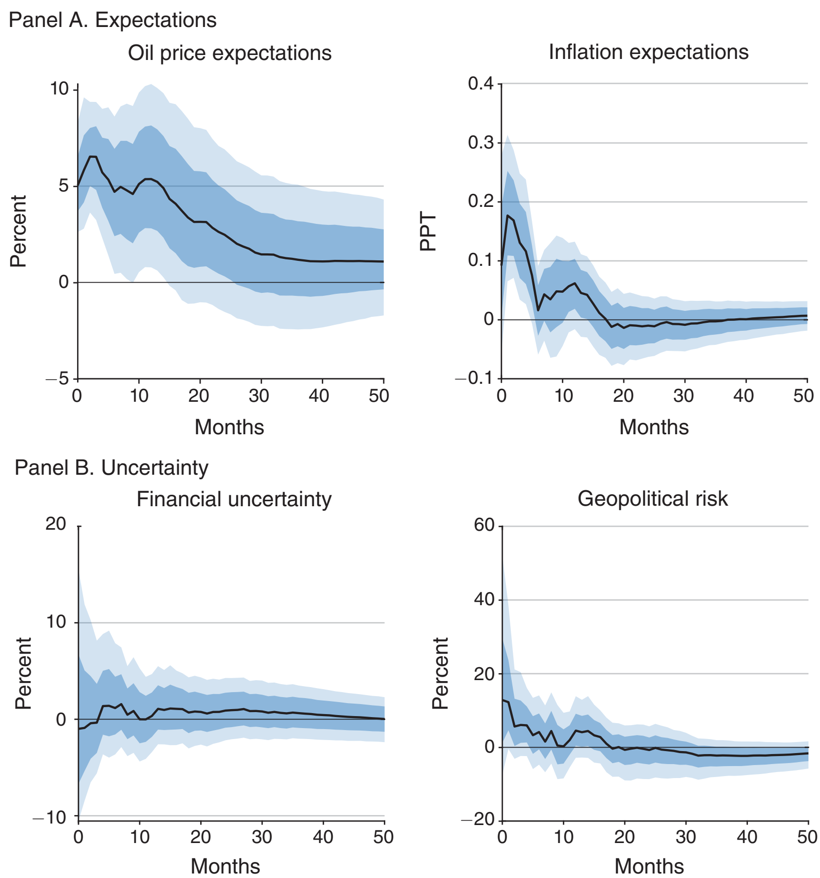

Figure 6. Expectations versus Uncertainty

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

and Gorodnichenko (2015), who show that a large part of the historical differences in inflation forecasts between households and professionals can be attributed to oil prices. They also speak to a recent literature ascribing an important role to oil prices in explaining inflation dynamics via their effects on inflation expectations (Coibion, Gorodnichenko, and Kamdar 2018; Hasenzagl et al. forthcoming).

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

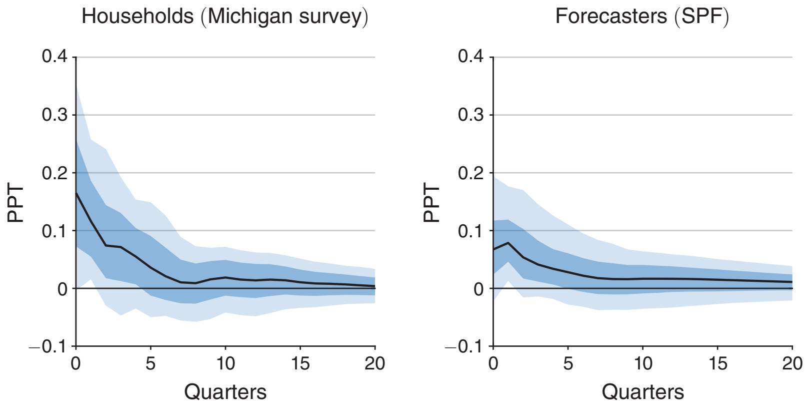

Figure 7. Inflation Expectations

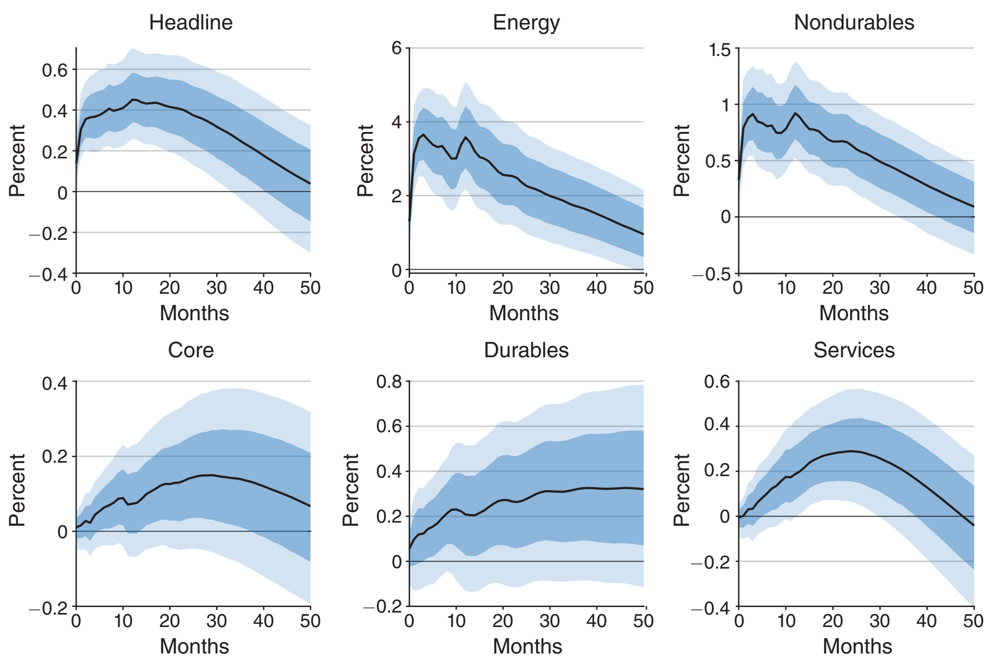

Figure 8. Consumer Prices

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

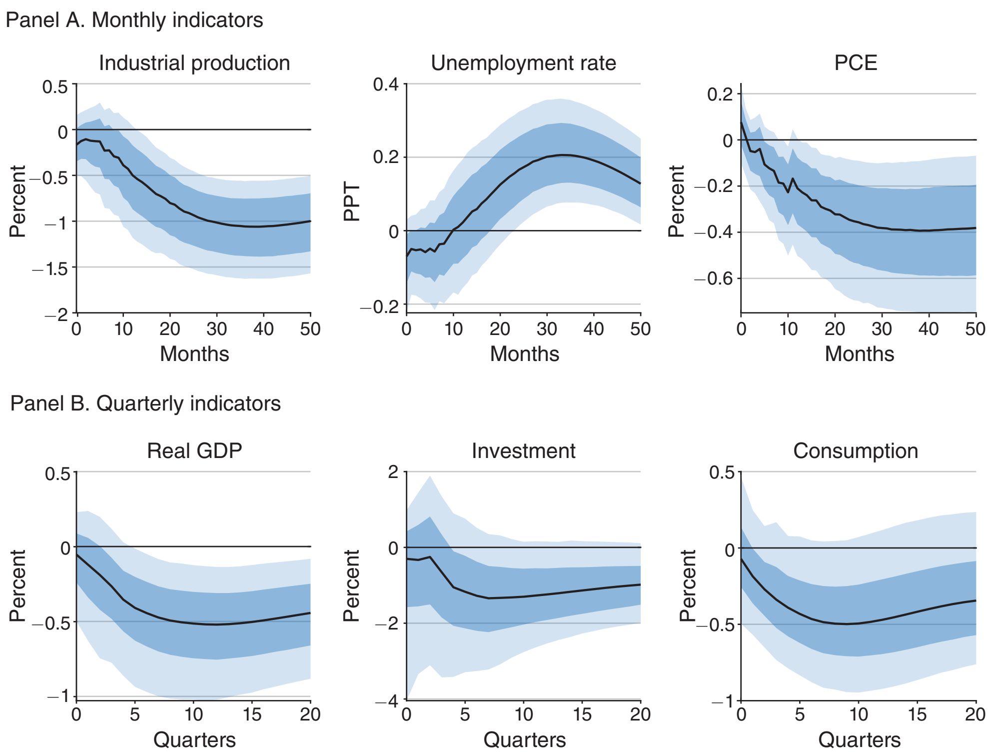

FIGURE 9. ECONOMIC ACTIVITY

Economic Activity.—Oil supply news shocks also lead to a significant fall in industrial production. However, industrial production is but one measure of economic activity. To get a broader picture of how the shock affects the economy, I study the responses of a number of monthly and quarterly activity indicators, including the unemployment rate, personal consumption expenditures (PCE), as well as real GDP, investment, and consumption. Figure 9 shows the responses together with the response of industrial production from the baseline model.

Oil supply news shocks have significant effects on economic activity, broadly defined. From the monthly indicators, we can see that the unemployment rate rises significantly and personal consumption expenditures fall persistently. These adverse economic effects are confirmed by looking at the quarterly measures. Real GDP, investment, and consumption all fall, even though the quarterly responses are a bit less precisely estimated. Quantitatively, investment falls by more than consumption, consistent with consumption smoothing behavior on the part of the households.

These results support the notion that a primary transmission channel of oil price shocks is via a reduction in consumption and investment demand, i.e., by disrupting consumers' and firms' spending on goods and services other than energy (Hamilton 2008; Edelstein and Kilian 2009). This is confirmed by looking at the responses of different categories of consumption expenditures: consumers significantly cut expenditures on goods and services other than energy as well, likely because of the decrease in discretionary income caused by higher energy prices (see online

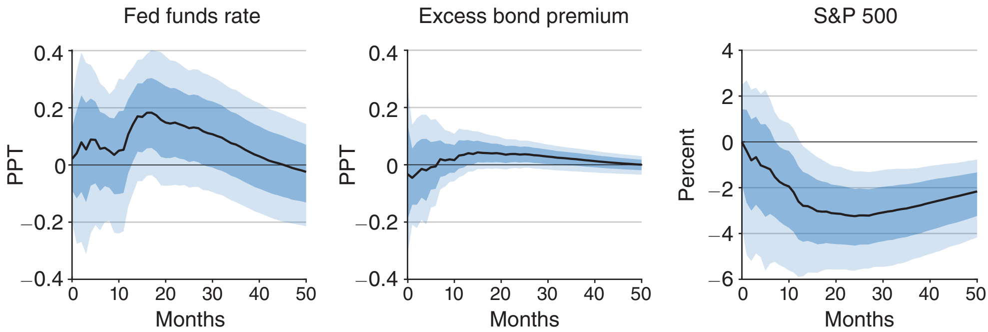

Figure 10. Monetary Policy and Financial Markets

Appendix Figure A.7). The rise in unemployment may also point to some reallocation frictions in the labor market, further amplifying the recessionary effects (Hamilton 1988; Davis and Haltiwanger 2001).

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

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

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

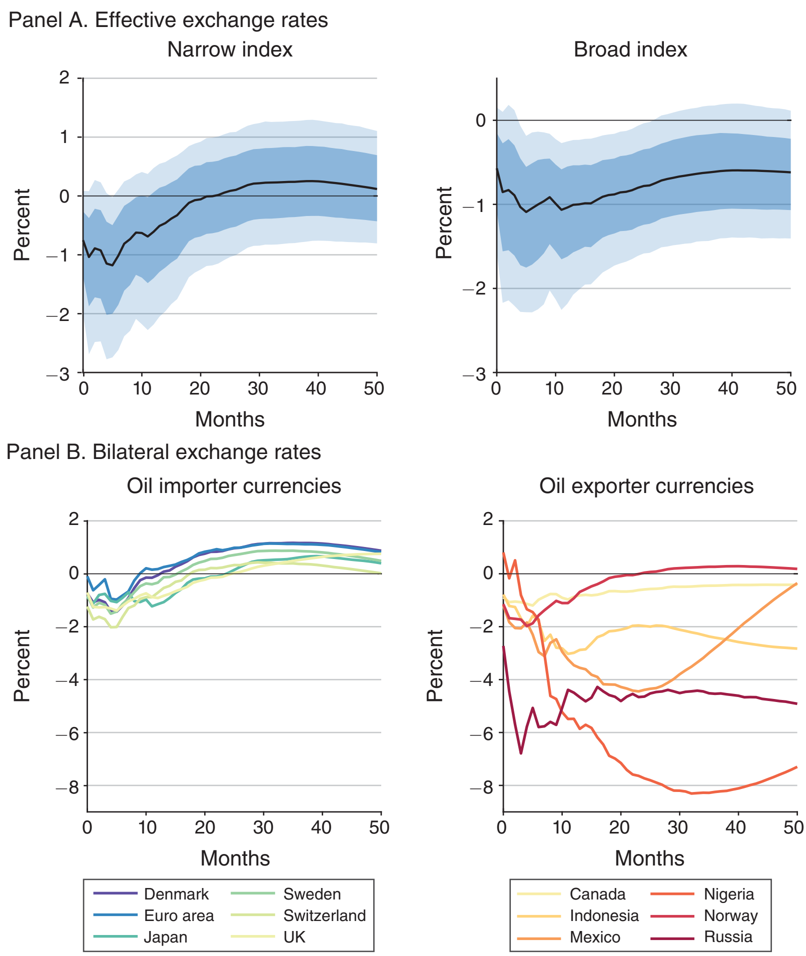

Figure 11. Nominal Exchange Rates

Notes: Responses of nominal effective (panel A) and bilateral exchange rates (panel B). All exchange rates are defined such that an increase corresponds to an appreciation of the US dollar. The narrow index includes Euro area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. The broad index also includes Mexico, China, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Thailand, Philippines, Indonesia, India, Israel, Saudi Arabia, Russia, Argentina, Venezuela, Chile, and Colombia.

Exchange Rates and Trade.—Because the US dollar is the world's reserve currency, most of the crude oil is priced and traded in dollars. Thus, it is only natural to suspect a tight link between the two variables.

Figure 11 displays the responses for the narrow and broad US nominal effective exchange rate together with a selection of bilateral exchange rates. Oil supply news shocks lead to a significant depreciation of the dollar. While the depreciation of the narrow effective exchange rate appears to be temporary and tends to reverse after about one-and-a-half years, the broad effective exchange rate depreciates persistently.

An analysis of bilateral exchange rates reveals that these differences are likely driven by heterogeneities between the currencies of net oil importing and exporting countries, as the broad index includes some of the major oil-producing nations.

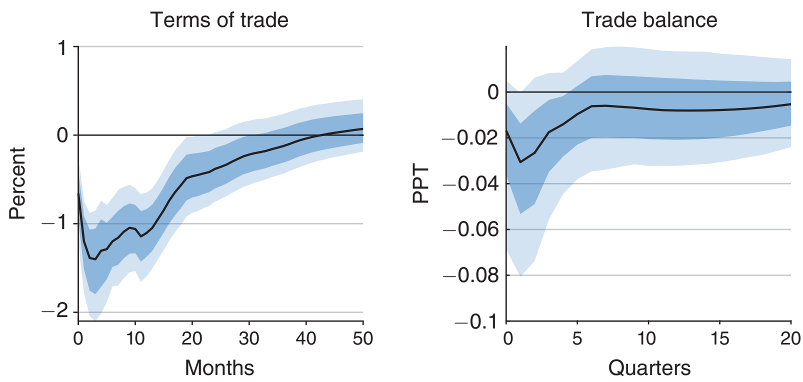

Figure 12. Trade

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

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

The significant depreciation together with the impaired terms of trade likely have an effect on the balance of trade. The right panel of Figure 12 depicts the merchandise trade balance as a share of nominal GDP. As expected, the shock leads to a significant trade deficit for about a year. This is an additional channel through which oil supply news shocks affect demand. Quantitatively, however, this channel appears to be less important than the decrease in consumption and investment.

E. *Quantitative Importance*

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

Table 2 presents the results. We can see that oil supply news shocks account for a large part of the variance in oil prices, especially in the short run. Furthermore, they explain a nonnegligible portion of the variation in world oil production and inventories at longer horizons. In contrast, the contribution to world industrial production turns out to be smaller. One reason for this could be that the positive effects on oil

Table 2—Forecast Error Variance Decomposition

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

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

exporting countries and the negative effects on oil importing countries offset each other to a certain extent.

Turning to the US variables, I find that oil supply news shocks explain a meaningful portion of the variation in economic activity and prices. While the shocks account for a rather low share of the variation in industrial production in the short run, they explain a nonnegligible share at longer horizons. They also explain a significant portion of the variance in the CPI. At the one-year horizon, the contribution is close to 20 percent. They also explain a significant share of the effective exchange rate and the terms of trade. In contrast, the contributions to the fed funds rate and the VXO turn out to be negligible.

Taking Stock.—The evidence presented in this section points to a strong expectational channel in the oil market. Even if big suppliers such as OPEC cannot simply set the price as a cartel in the traditional sense, they can exert significant influence over oil prices by affecting expectations about future supply. These expectational shocks in turn can have significant effects on the macroeconomy and contribute meaningfully to historical variations in economic activity and prices.

IV. Sensitivity Analysis

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

A. *Identification*

Announcements.—To be able to interpret the identified shock as a news shock about future supply, it is crucial that the announcements do not contain any new information about other factors and global demand in particular. To address this concern, I construct an informationally robust oil supply surprise series, following a strategy that has been previously employed in the monetary literature (Romer and Romer 2004; Miranda-Agrippino and Ricco forthcoming). To this end, I collected global oil demand forecasts from OPEC monthly oil market reports.[16] The idea is to purge the raw oil supply surprise series from potential contamination stemming from OPEC's informational advantage on the global oil demand outlook using revisions in OPEC's global oil demand forecasts around conference meetings. More precisely, the informationally robust surprise series, IRS_t, is constructed based on the residual of the following regression:

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

where m is the month of the meeting, q denotes the corresponding quarter, y_q is global oil demand growth in quarter q, and $F_m^{opec} y_{q+j}$ is the OPEC forecast for quarter $q+j$ made in month m. The expression $F_m^{opec} y_{q+j} - F_{m-1}^{opec} y_{q+j}$ is the revised forecast for y_{q+j}.[17] Note that because the monthly reports are only available from 2001, the informationally robust surprise series spans a shorter sample.

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

Another concern is that many of the OPEC conference meetings were extraordinary meetings scheduled in response to macroeconomic or geopolitical developments. This might induce an endogeneity problem if markets do not have enough time to form expectations about the oil market outlook prior to the announcements. To address this concern, I only use the announcements from ordinary meetings scheduled well in advance. The responses, shown in online Appendix Figure A.12, turn out to be very similar. However, the instrument turns out to be weaker as about 40 percent of the announcements had to be dropped, leaving less variation for identification.

News and Surprise Shocks.—The crucial assumption behind the external instruments approach is that the instrument is correlated with the structural shock of interest but uncorrelated with all other shocks. This condition might be violated when the

[16] These reports are available online in .pdf format (https://www.opec.org/opec_web/en/publications/338.htm) and contain among other things OPEC's global oil demand forecasts and forecast revisions. For more information, see online Appendix Section A.4.

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

oil supply surprise series does not only correlate with the oil supply news shock but also with the unanticipated oil supply shock. To investigate this concern, I identify the oil supply news and the surprise shock jointly. To this end, I use Kilian's (2008) production shortfall series[18] and my oil supply surprise series as instruments. In the case with two shocks and two instruments, the instrument moment restrictions are not sufficient. To achieve identification, I have to impose one additional restriction. I assume that the oil supply news shock does not affect oil production within the first month.[19]

The results are shown in online Appendix Figure A.13. The response to the news shock is very similar to the baseline, suggesting that we can identify the oil supply news shock without controlling for the surprise shock. The responses for the oil supply surprise shock look quite reasonable as well: it leads to a temporary increase in the oil price, a significant, immediate fall in oil production, and a persistent decrease in inventories. However, the first stage turns out to be considerably weaker and thus the results should be interpreted with a grain of salt.

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

B. *Specification and Data Choices*

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

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

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

Sample and Data Frequency.—It is conceivable that over the relatively long sample period structural relationships have evolved over time. To examine this, I estimate the model for different subsamples. Online Appendix Figure A.27 presents the results based on a shorter estimation sample starting in 1982:4, which marks the start of the instrument and coincides with the beginning of the Great Moderation. The responses turn out to be less persistent and some responses are weaker. Qualitatively, however, the results are very similar. I also show that excluding the Great Recession or the shale oil revolution does not change the results materially (see online Appendix Figures A.28–A.29).

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

V. Conclusion

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

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