
Xiaohan Ma* Roberto Samaniego†

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Abstract

We develop measures of oil industry uncertainty (OIU) using analyst forecasts drawn from a large firm-level dataset. OIU is related to future economic downturns, so some OIU measures may serve to forecast future downturns. An increase in OIU also has adverse effects on the US oil sector. The results are robust to conditioning on aggregate uncertainty. At the same time, OIU is related to increases in stock prices – unlike aggregate uncertainty, which has the opposite effect. OIU is thus an independent influence on both the oil industry and on economic aggregates.

Keywords: Oil industry uncertainty, business cycles, oil markets, analyst forecasts.

JEL Codes: D80 E32 E37 E47 E71 G17.

*Texas Tech University, Department of Economics, P.O. Box 41014, Lubbock, Texas 79409-1014 U.S.A. Email: xiaohan.ma@ttu.edu.
†Department of Economics, The George Washington University, 2115 G Street, NW Monroe Hall 340, Washington, DC 20052, U.S.A. Email: roberto@gwu.edu.
1 Introduction

The macroeconomic impact of events originating in or propagating through oil markets is a major research topic. An independent literature studies the impact of uncertainty shocks on business cycle dynamics. However, it remains an open question whether uncertainty in oil markets might have significant macroeconomic impact.

In this paper we develop several measures of oil industry uncertainty, and study their macroeconomic impact, at monthly frequency. Our measures are not based on traditional indicators such as oil prices, oil production, or oil price volatility. Oil prices and oil production are endogenously responding to forces of energy demand and supply, which themselves include macroeconomic aggregates. Instead, we measure oil industry uncertainty using forecasts and forecast errors from a large survey set of financial analysts regarding the financial variables of firms in the US oil and gas sector. The baseline measure is the median 12 month-ahead earnings-per-share (EPS) absolute forecast error, drawn from the Institutional Brokers’ Estimate System or I/B/E/S.

Our reasoning for measuring uncertainty in this manner is as follows. When analysts make a forecast regarding, for example, the EPS of a firm, they are using the best available information at the time that the forecast is made. Indeed, since their compensation and reputation are based on the usefulness of the forecasts they make, they have an incentive to incorporate and process as much information as is available in their forecasts. There will typically be a certain amount of background uncertainty in the environment which results in a non-zero forecast error one way or the other in normal times. However, when the absolute forecast errors are larger than normal, this indicates the impact of factors of uncertainty that were not adequately foreseen or processed at the time the forecasts were made.

To study the impact of our oil industry uncertainty (OIU) measure on macroeconomic aggregates and on oil markets, we estimate a series of structural vector auto-regressions (SVAR). We also provide further evidence on whether OIU is different from aggregate uncertainty, and in what way. The VARs contain our baseline OIU measure and demand and supply factors for the oil market, as well as the oil
price, in addition to some representative macroeconomic and policy variables. Since many of the channels through which aggregates and oil markets are affected are explicitly estimated in the procedure, any impact of OIU shocks are more likely to capture causality from uncertainty in the oil industry, as the impact from or through these other variables on business cycle fluctuations is controlled in the VAR model. This is a distinct advantage of our approach to measurement and estimation over, for example, using uncertainty indicators that are themselves based on oil prices and/or estimating a VAR with only oil market related variables, where endogeneity or omitted variables might otherwise present a challenge to estimation or to the interpretation of econometric relationships.

We find that our baseline OIU measure lowers US output and the US price level, as well as the federal funds rate. This suggests that OIU behaves like a negative aggregate demand shock. In the oil market, an increase in OIU lowers US oil production and the oil price. We reach the same conclusions when we include both OIU and aggregate uncertainty measures in the same VAR. This implies that our OIU measure contains information specific about energy markets that is absent from aggregate uncertainty measures. Finally, the stock market responds slightly positively to changes in OIU when the estimation is conducted over the whole sample period (1982 – 2018). This is likely because an increase in oil industry uncertainty lowers the oil price, which can serve as a positive signal for overall economic activity of sectors that use energy.

Our OIU appears to be distinct from overall macroeconomic uncertainty – identified using the Jurado et al (2015) measure of aggregate uncertainty. While there are periods of time when the two co-move, there are also periods when they do not. This suggests that, while oil industry uncertainty could occasionally capture events that also drive aggregate uncertainty, they are nonetheless different concepts, which is validated by the lack of contemporaneous and lagged correlation between the identified OIU shocks and aggregate uncertainty shocks. In particular, when we exclude the post-Great Recession period from the sample, we find that OIU leads to a significant and persistent increase in the stock market – unlike aggregate uncertainty, which does the opposite. Thus, the impact of oil uncertainty net of the impact of
aggregate uncertainty has distinct properties.

We also look at the correlation between our baseline OIU shocks and other oil shocks identified in the literature – namely oil supply shocks, economic activity shocks, oil specific demand shocks, and oil speculative demand shocks, which are external to our estimation – and examine whether oil shocks Granger cause OIU shocks. Again, the F-test statistics suggest that the association between our identified OIU shocks and both current and lagged values of those oil shocks is not significantly different from zero. Thus, the impact of oil uncertainty is not due to it functioning as a transmission channel for first-moment oil shocks.

However, we find that technical change specific to the oil industry, approximated by the stock of patents associated with the oil and gas industry, is significantly correlated with OIU, and weakly Granger-causes OIU. This suggests that our oil industry uncertainty measure may at least partly reflect uncertainty stemming from advances in oil industry technology.

We develop several other measures of oil industry uncertainty. One is the measures of forecast dispersion among financial analysts regarding firms in the oil and gas sector. When analyst forecasts about the same firm are more dispersed than normal, this indicates the insufficiency of information for arriving at a conclusion about the future, possibly reflecting uncertainty of a different form than a measure based on forecast errors. These dispersion measures are particularly useful for forecasting, because they do not require future data for their computation. When estimated in the same VAR model as the baseline, we find generally similar behavior, indicating that our approach to measuring oil industry uncertainty can be computed in real time as new forecasts are made and entered into the I/B/E/S database.

Other versions of our baseline oil industry uncertainty measure are median absolute forecast errors constructed using 3-month, 6-month and 9-month forecasts. Again, VAR exercises with these alternative quarter-based measures find that they generally behave similarly to our benchmark measure. The advantage of these measures is that they do not require waiting as long as the baseline measure in order to observe the realization of the EPS forecast.

Finally, we calculate the median absolute forecast error regarding oil producers
relative to the median absolute forecast error regarding firms outside the oil sector, or oil industry "relative" uncertainty. This is a way of ensuring that any increases in our measure are due to innovations originating from the oil industry or disproportionately affecting the oil industry relative to other industries in the economy. We find that the behavior of this relative OIU measure is similar to our baseline measure. However, there is one difference: relative OIU has a clear positive impact on the stock market, similar with that obtained from the estimation with the baseline oil industry uncertainty over the pre-2007 sample. This result reassures us that oil uncertainty can have an independent impact on the macroeconomy that is different from aggregate uncertainty and mainly reflects information specifically relevant for the oil industry, considering the fact that aggregate uncertainty rose dramatically before the Great Recession and had significantly negative impact on the stock market.\textsuperscript{1}

Our study is related to three strands of literature. First, it is widely documented that changes in economic uncertainty are an important driving force of business cycle fluctuations and oil market dynamics.\textsuperscript{2} However, even though the oil market is a major component of global markets, the literature has devoted relatively little attention to the question of how uncertainty in the oil industry accounts for macroeconomic and oil market fluctuations. Our paper contributes to the literature by developing measures of oil industry uncertainty based on millions of financial analyst stock forecast errors, and empirically investigating the dynamic impact of oil industry uncertainty – by itself, and conditional on the impact of aggregate uncertainty.

Second, while an extensive literature focuses on oil market uncertainty, almost all papers study the impact of oil price uncertainty. Examples include Elder and Serletis (2010), which assumes oil price shocks can lead to variations in oil price volatility and uses a GARCH model to estimate the impact of oil price volatility on the US real output; Kellogg (2014), which uses firms’ expected future oil price volatility con-

\textsuperscript{1}This is found in Bloom (2009), Jurado et al. (2015), Ma and Samaniego (2019), among others.

\textsuperscript{2}See Bloom (2009), Bachmann et al. (2013), and Jurado et al (2015), inter alia, on the impact of aggregate uncertainty on the macroeconomy, and see Van Robays (2016), Joëts et al. (2017), and Bakas and Triantafyllou (2018) on oil market dynamics. The potential impact of industry-specific uncertainty is studied in Carriero et al. (2018) and Shin and Zhong (2018) for financial markets, and in a comprehensive breakdown of industries in Ma and Samaniego (2019).
constructed from NYMEX futures options prices as a proxy for oil market uncertainty; Maghyereh et al. (2016), which uses the crude oil implied volatility index as a measure of oil price uncertainty; and Yin and Feng (2019), which measures oil market uncertainty using the volatility risk premium as in Carr and Wu (2009), computed using oil futures prices. A drawback of using oil prices to measure uncertainty is that the oil price itself responds to changes in other macroeconomic aggregates, so that the direction of causality between oil prices and macroeconomic variables is unclear – as underlined by Kilian (2009). As well as measuring oil industry uncertainty in a manner that uses neither oil prices nor oil production as an input, we also estimate a VAR containing several macroeconomic and oil industry indicators to study how our oil uncertainty measures affect macroeconomic aggregates. In this sense, the causal relationship between oil industry uncertainty and macroeconomic variables is well-defined in our paper. In addition, volatility is at best a noisy proxy for uncertainty, as discussed in Jurado et al (2015). Our measures capture uncertainty in the form of an increase in the difficulty of analysts arriving at accurate or agreed forecasts, rather than volatility.

Given that we develop some of our oil uncertainty measures based on forecast errors, our work is perhaps most closely related to Jo (2014). Jo (2014) models oil price uncertainty as the time-varying standard deviation of the one-quarter-ahead oil price forecasting error, interpreted as an exogenous process that is independent from the level of oil price shocks, and examines how it affects the global economy. Aside from the potential issues related to measuring oil market uncertainty using statistics based on oil prices, a drawback of this measure is that, in the author’s own words, “predictable variation in a monthly or quarterly volatility measure is negligible at the horizons relevant to the cash flow of investment decisions, removing the theoretical rationale for a non-negligible contractionary effect on real activity.”

Our baseline forecast horizon is 12-months, which is likely to be a more relevant horizon for investment decisions, and therefore captures more accurately the effect

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3 Jo (2014) adds that “one of the interesting questions for future research will hence be the development of alternative specifications based on extraneous survey-based measures of oil price uncertainty.”
on real activity.

Finally, there is a large body of literature investigating the impact of oil shocks and uncertainty shocks on the oil market and macroeconomic aggregates. A common model used in these papers is the SVAR, with either macroeconomic variables or oil market variables. For example, Bloom (2009) uses an eight-variable VAR to estimate the macroeconomic impact of uncertainty. Kilian (2009) differentiates oil demand and oil supply shocks in a VAR with four variables related to the oil market to explain oil price variations. In contrast, our baseline model is a combination of both macroeconomic variables and oil market variables. In this way, the impact of oil industry uncertainty on the oil market is conditional on how it is affected by the shocks to important macroeconomic aggregates such as industrial production and the stock market, and policy variables such as the federal funds rate. At the same time, the model can also be used to study how oil industry uncertainty affects the macroeconomy, again conditional on the impact of various other shocks.

Our paper is structured as follows. Section 2 describes our measure of uncertainty. Section 3 describes in detail the data that we use, and some basic properties of the measure. Section 4 shows the impact of our measures of oil industry uncertainty on macroeconomic and oil market dynamics. Section 5 discusses possible sources of oil industry uncertainty. Section 6 concludes with a discussion of potential future work.

2 The Measure

The premise behind our measurement strategy is that changes in uncertainty, and thus the predictability of the economic environment – at the aggregate or at the industry level – will be reflected in that analyst forecasts are of lower accuracy than usual, or that analysts display excessive disagreement. We use this idea to develop a measure of uncertainty for energy markets. The approach to measurement is similar to that in Ma and Samaniego (2019), and our presentation of the methodology follows theirs.

Time is discrete and divided into days which are collected into months. Let $M \subset \mathbb{N}$ be the set of months, numbered consecutively, and let $t \in M$ be a
month. Then, define $D_t \subseteq [t, t+1)$ as the set of days in the month $t$, so that $d \in D_t$ represents a day in month $t$. Let $S_{i,d}$ be a statistic about a firm $i$ observed on day $d$, and let $F [S_{i,d^*} | I_{j,d}]$ be the forecast about the realization of statistic $S$ at firm $i$ on a future day $d^*$, using the information $I_{j,d}$ available to them on day $d < d^*$ to forecaster $j$. This means that $d^*$ minus $d$ is the forecast horizon. Note that $d^*$ will not be in the same month if the forecast horizon is longer than a month: this will be the case in general in our data. We define the firm-level forecast error as the difference between the forecast made on day $d$ about statistic $S$ at date $d^*$, and the actual realization of the statistic on day $d^*$:

$$FE_{i,d} = F [S_{i,d^*} | I_{j,d}] - S_{i,d^*}.$$  

In our benchmark measure, the forecast period is a year, but we also look at quarterly forecasts. If more than one analyst makes a forecast about firm $i$ on day $d$, we define $F [S_{i,d^*} | I_{j,d}]$ as the average forecast error made about firm $i$ on day $d$.

There are thousands of forecasts made every day about different firms. To measure uncertainty $U_t$ in month $t$, we will focus on the uncertainty experienced by a typical firm. In particular we look at the median absolute forecast error across all firms within the month. We focus on the median in order to avoid being swayed by individual outliers, which a large data set of forecasters will inevitably have.\footnote{Indeed, we found that uncertainty measured using the mean rather than the median was extremely volatile and had no meaningful properties.} In addition, we define uncertainty based on the median of the absolute value of the forecast error. This way uncertainty is measured as lack of accuracy – regardless of the direction. Not doing so would lead to a measure of relative optimism or pessimism compared to the realization, not uncertainty. As discussed below, we also try several other approaches for robustness. In practice, all our measures will be monthly, the highest frequency for which we have data on industrial production. Thus, on each date within month $t$, we compute the median value of $\|FE_{i,d}\|$ within the month, pooling all firm-day forecasts within the month, which gives our baseline uncertainty.
measure for month $t$:

$$OIU_t = \text{median} \{ \|FE_{i,d}\| : \forall d \in [t, t+1), i \in \mathcal{Y} \}.$$  

(2)

Notice that definition 2 restricts firms to be from some set $\mathcal{Y}$. We will define $\mathcal{Y}$ to be the set of firms in the oil and gas producing sector, i.e. firms reporting SIC codes between 1300 and 1389. We refer to this as oil industry uncertainty or just oil uncertainty (OIU for short). At times in the paper, however, we will refer to uncertainty measured outside the oil sector. In that case we will compute uncertainty for the set of firms that are not in the oil industry, i.e, $i \notin \mathcal{Y}$. We will refer to that measure as non-oil uncertainty.

The specific statistics that we look at are forecasts of the earnings-per-share ratios (EPS) of individual companies. We use EPS forecasts because they are the most widely available in our database, and also because EPS ratios are a basic indicator of the profitability of a share, and are thus widely understood and followed both by financial analysts and their clients.

A concern with the measure is that some variation in EPS ratios could be due to the fact that firms have different scales – or rather that the granularity of their share size may vary. As a result, we divide all of our forecast errors $FE_{i,d}$ by the price of the share of company $i$ on the day $d$ when the forecast was made. Conceptually, this measure has the interesting property that it can be interpreted as a forecast of inverse price-earnings ratios, a common statistic used for share valuations. To produce such a measure, we combine our forecasting data with data on share prices, which allows us to divide the EPS forecast error by the corresponding security prices.

Later in the paper we will study the behavior of relative oil uncertainty. This is because our baseline measure could potentially be affected by changes in aggregate uncertainty: a relative measure, in contrast, should be more focused on uncertainty specific to the oil sector. If we define $\mathcal{Y}$ as the set of firms reporting SIC codes


[6] Later on we also use different moments of these forecasts. In particular, in Section ?? we study several measures based on the extent of forecast dispersion.
between 1300 and 1389, relative oil uncertainty is defined simply as:

\[ OIU_t = \frac{\text{median} \{ \|FE_{i,d}\| : \forall d \in [t, t + 1), i \in \Upsilon \}}{\text{median} \{ \|FE_{i,d}\| : \forall d \in [t, t + 1), i \not\in \Upsilon \}}. \]  

(3)

These measures are useful for measuring uncertainty as we can see whether or not forecasts made at a particular date were less accurate than usual, in an absolute or a relative sense. However, a drawback is that they require future information for their computation – i.e. the econometrician must observe the realization of the forecasted variable \( S_{i,d} \). As a result, we will also use measures of uncertainty based on forecast dispersion, i.e. based on the extent of disagreement among forecasters. These measures can be computed month-to-month in real time, as soon as the forecasts are reported. For each firm \( i \) and within each month \( t \), we compute

\[ D_{it} = \text{Disp} \{ F [S_{i,d} | I_{j,d}] : \forall d \in [t, t + 1) \} \]

where "Disp" indicates a measure of dispersion. Then, we measure uncertainty in the subset of firms \( i \in \Upsilon \) (e.g. firms in the oil industry) using the formula:

\[ OIU_t = \text{median} \{ D_{it} : i \in \Upsilon \}. \]  

(4)

3 Data

Our forecasts are drawn from the Institutional Brokers’ Estimate System or I/B/E/S, available through a WRDS subscription and managed by Thomson Reuters. It contains analyst forecasts of several measures of interest to investors and researchers, the most widely-available being earnings per share (EPS) forecasts. I/B/E/S also reports realizations of the forecast data, collected from a variety of public data sources. Companies are included in the database as long as at least one analyst provides a forecast for that company. Forecasts are not included unless they are confirmed
Forecasts are collected each day as they are released by analysts. We focus on US firms. This yields about 4.7 million forecasts issued by about 1,500 different brokers, who make forecasts about many firms over time. For each firm on each day we compute the average forecast error. We take the absolute value of this average forecast error, and divide it by the share price of the forecasted firm on the day that the forecast was taken. Share price data are available from CRSP. The absolute forecast error normalized using share prices in this manner will be our empirical counterpart of the term $\|FE_{i,d}\|$ in equation 2. Our measure of uncertainty is the median absolute value of these forecast errors across all firms within each month, starting in March 1982. Thus it is the median forecast error by firm-day pair.

As well as share price information, CRSP reports NAICS and SIC codes of these firms. This allows us to compute our uncertainty measure for subsets of the firms inside or outside the oil/gas industries, based on industry classification. We use SIC codes for these purposes because NAICS codes did not exist early in our sample. Based on this information we narrow our sample down to about 4 million observations, of which about a third of a million are analyst forecasts about oil and gas firms.

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8 Later we also look at EPS forecasts made over different horizons. No forecasts for different horizons are made about the same firm on the same day by the same analysts. However, all analysts that make an annual forecast make a quarterly forecast about a given firm sometime that month. About 46 percent of forecasters who make an annual forecast make a given firm make a 2-quarter ahead forecast the same month, and about 39 percent for 3-quarter ahead forecasts.

9 86 percent of them are single forecasts about a firm on a given day. The rest have 2 forecasters making forecasts about a firm on the same day, except for 0.29 percent of the sample which has 3 – 5 forecasts. Averaging when there are multiple forecasters yields about 3 million day-firm observations.

10 This is the first month after which continuous series may be computed for oil industry uncertainty. The date is based on the month and year of the variable annodats.

11 We find that some of our measures appear to have seasonal effects. In particular, our measure tends to decline from October to January, possibly due to the forecasters being better informed about firms’ financial conditions as annual statements are compiled and delivered towards the end of the year. As a result we remove the mean value for each month from the data to remove any such seasonal effects.
Figure 1 displays the series for oil industry uncertainty. Several observations stand out. First, the series appears to have a more or less stable level of uncertainty, punctuated by sharp spikes. This is consistent with the notion that there is a background level of oil industry uncertainty which is subject to occasional shocks. Second, while some of these spikes coincide with recessions, many do not, including the largest spikes. Given that the literature suggests that aggregate uncertainty is related to recessions, this suggests that oil industry uncertainty is different from overall uncertainty, and thus a factor of uncertainty that could potentially have distinct effects on the oil industry and on aggregates\(^\text{12}\).

To verify this conjecture, Figure 2 compares our oil industry uncertainty measure (OIU) to the aggregate uncertainty measure of Jurado et al (2015).\(^\text{13}\) There are times when OIU co-moves with aggregate uncertainty, and in fact the correlation between the two series is 0.41 and significant. On the other hand, it is also clear that spikes in one series do not always coincide with spikes on the other. This suggests that, while there is a relationship between OIU and aggregate uncertainty, they are distinct forms of uncertainty, the economic impact of which an appropriate econometric specification should be able to tease apart.

\(^{12}\)In Appendix E, we compare the time series of OIU with other oil market uncertainty measures proposed in the literature.

\(^{13}\)As discussed in Ma and Samaniego (2019), other popular measures of aggregate uncertainty behave similarly.
Figure 1 – Oil industry uncertainty and the business cycle, 1981-2018. Bands represent NBER recession dates. The measure is the median absolute value of the forecast error from I/B/E/S by month. The forecast error is the difference between the 12-month EPS forecast and the realized EPS, deflated by share price, for firms reporting SIC codes between 1300 and 1389.
Figure 2 – Comparison of different uncertainty measures. The dashed line is our oil industry uncertainty measure and the thick line is the measure of Jurado et al (2015). The sample period is 1982m3-2015m4.

4 Impact of Oil Industry Uncertainty

To investigate the role of OIU in characterizing the dynamics of macroeconomic aggregates and oil market, we use vector-autoregression (VAR) method to estimate the responses of key macro and oil market variables to innovations in OIU, which we refer as to oil uncertainty shocks.
The specification of the baseline VAR includes representative macroeconomic and oil market variables, where the macroeconomic elements are similar to that studied in Bloom (2009) and Samaniego and Ma (2019), and the oil market elements are similar to that studied in Kilian (2009), as to what variables to include and how to order them in the VAR. Following Bloom (2009), we include log S&P 500 index, federal funds rate, log CPI, and log US real economic activity approximated by US industrial production. Following Kilian (2009), we use log US crude oil production, log World crude oil production, World real economic activity approximated by Kilian Index introduced by Kilian (2009), and log real oil price, which is the nominal WTI crude oil prices deflator by CPI. We use 12 lags of monthly data of these variables between 1982m3 and 2018m12:

\[
\begin{bmatrix}
\text{log (S&P 500 Index)} \\
\text{oil uncertainty} \\
\text{federal funds rate} \\
\text{log (CPI)} \\
\text{log (US oil production)} \\
\text{log (US real activity)} \\
\text{log (World oil production)} \\
\text{World real activity} \\
\text{log (real oil price)}
\end{bmatrix}
\]

Unlike Bloom (2009) and Kilian (2009), we use all the variables in levels in the estimation as Jurado et al. (2015). One exception is the World real activity index, as it is measured as a percentage deviation from trend. As suggested by Sims (1980), Sims et al. (1990) and others, stationarity of the variables is not necessary if the results of interest are dynamic impulse responses, and keeping the levels of variables can shed light on long-run relations between variables. In addition, as discussed in Toda and Yamamoto (1995), including more lags (and in our case, 12 lags) in the VAR can generate consistent estimates even when we use variables in levels. For robustness, we re-estimate the baseline VAR with more lags (13 lags and 24 lags), as well as with stationary variables obtained from HP-filtering and log-differencing.
The results shown Appendix A suggest that qualitatively, oil uncertainty shocks have similar impact.

4.1 Results

We estimate the VAR model with the baseline OIU measure using recursive ordering identification. In Appendix A and B, we report robustness check results estimated from alternative VAR specifications, ordering and variables, including a VAR with a different identification scheme, VARs with different numbers of lags, VARs with stationary variables, a VAR with the World production index constructed by Baumeister and Hamilton (2019) as an indicator of World real activity, VARs with dispersion-based measures of OIU, VARs with OIU measures constructed from shorter horizon forecasts, a VAR based on the sample excluding post-2007 periods, and a VAR with oil inventories.

Figure 3 displays our baseline results, where solid lines display the impulse responses of macroeconomic aggregates and oil market to a one-standard deviation shock to OIU. The shaded area represents +/- one standard error confidence bands. As shown, macroeconomic aggregates respond negatively to an increase in OIU, with a maximum decline in real activity of 0.4 percent and in the price level of 0.13 percent. The monetary authority responds to the declines by lowering the federal funds rate. The stock market, however, hardly responds to OIU innovations in the baseline VAR. As we shall see later, however, this is due to the influence of the Great Recession, a period when aggregate uncertainty spills over into oil industry uncertainty. When we measure oil industry uncertainty relative to uncertainty in the rest of the economy, as we do later, or when we exclude the Great Recession, we find that the stock market rises after OIU shocks.
Figure 3 – Impulse response of the federal funds rate, the price level, the stock index, US and World real economic activity, US and World oil production, and real oil price to oil uncertainty shock. The results are estimated from VAR with the baseline oil industry uncertainty. The shock is one standard deviation, and the shared areas represent +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m3-2018m12.

In addition, the increase in OIU negatively affects the US and World oil markets. On impact, US oil production decreases immediately, with a peak effect of 4 percent
that occurs around 7 months after initial impact. Interestingly, World real activity and oil production also react to the increase in US oil uncertainty. Specifically, World real activity significantly decreases for almost 10 months. This could be due to the possibility that OIU reflects to some extent an increase in aggregate uncertainty, which is shown to have an adverse impact on the Worldwide economic activity as in Mumtaz and Theodoridies (2015), among others. World oil production slightly increases, and then returns to the long run trend. As a result, it is not surprising that the real oil price declines, as World oil demand decreases as reflected by lower World real activity, and World oil supply increases (or remains unchanged).

Figure 4 provides evidence on the overall role of OIU in explaining the dynamics of the oil market, by showing the historical contribution of the identified oil uncertainty shocks in the baseline VAR to variation in US oil production and oil prices. It is clear that oil uncertainty shocks play an important role in accounting for variations in US oil production. For oil price dynamics, we find that OIU shocks are important in explaining the oil price decline in 1986, and the oil price increase during First Persian Gulf War, whereas the role of oil supply shocks is minimal. This is consistent with Kilian (2009) but different from Baumeister and Hamilton (2019), who finds that oil supply disturbances are an important source of oil price increases during 1990-1991. We also find that the 2007 – 2008 oil price rise and the 2014 – 2016 oil price collapse are mainly accounted for by oil demand shocks over those periods, consistent with the analysis in Kilian and Murphy (2014) – not by OIU shocks.
Figure 4: Historical Decomposition of US Oil Production and Oil Price.
In Appendix B we provide some further results. First, our baseline OIU measure requires information realized after date $t$ to compute uncertainty at date $t$, making it unsuitable for forecasting at horizons shorter than a year. As a result, we introduce alternative measures of OIU based on dispersion, as described earlier. The behavior of these alternative measures is similar to the baseline measure: see Appendix B.

Second, I/B/E/S contains forecasts at horizons shorter than a year, which again could be more suitable for forecasting. We find that OIU measured with longer horizons has a stronger and more persistent negative impact on the macroeconomy than the short-horizon OIU, possibly as longer-horizon uncertainty may matter more for economic agents’ decisions at business-cycle frequency.

Third, we repeat the analysis excluding data for 2007 onwards, to eliminate the possible influence of a large uncertainty spike - the Great Recession. These results are important: we find that when we exclude the Great Recession there is a marked increase in the stock market when OIP rises. This suggests that the Great Recession masks the positive impact that OIP on its own has on the stock market, through lower oil prices.

Finally we also run a VAR with inventories, to proxy for a possible "speculative depand shock" identified in the literature. Results are robust to including this shock in the VAR.

### 4.2 Oil and Non-Oil Uncertainty

To investigate the difference in the specific information conveyed by uncertainty in the oil sector versus uncertainty in the rest of the economy, we construct a measure that is also based on financial analysts forecasts, but using firms in all the sectors excluding the oil and gas industries. We call this non-oil uncertainty.

First, we estimate the same VAR system as in the benchmark, except that oil uncertainty is replaced by non-oil uncertainty, to see how this measure behaves on its own. Figure 5 shows that non-oil uncertainty has more significant impact on US and World real activity and the stock market than oil uncertainty, in a negative direction. This is not surprising, as non-oil uncertainty captures uncertainty that originates in
or is transmitted through non-oil sectors, and therefore it is likely to have more impact on macroeconomic variables, especially if other types of uncertainty shocks occur more often than oil uncertainty shocks during the sample period. On the other hand, non-oil uncertainty does not affect World oil production as significantly. Finally, it has a delayed and smaller impact on US oil production and on the real oil price, suggesting that oil uncertainty contributes more to the dynamics of US oil production and oil prices.

Figure 5 – Impulse response of macroeconomic variables and oil sector variables from estimation of benchmark VAR with non-oil uncertainty.

We also estimate a VAR that simultaneously includes both oil and non-oil uncertainty measures. We order non-oil uncertainty before oil uncertainty, which allows us
to examine whether uncertainty from the oil sector still matters for macroeconomic and oil sector dynamics *conditional* on the impact of uncertainty in the rest of the economy.

Figure 6 shows the impulse responses to oil and non-oil uncertainty shocks. As before, we find that the macroeconomic impact of non-oil uncertainty is greater than that of oil uncertainty, as shown by the more persistent decrease in US real economic activity. Interestingly, World real activity reacts similarly to oil uncertainty and to non-oil uncertainty in the *short run* (within 6 months), but *more* significantly to non-oil uncertainty in the medium and long run. In addition, World oil production reacts more to oil uncertainty relative to non-oil uncertainty, though the effects quickly become insignificant within one year. Finally, oil uncertainty has more significant impact on US oil production and on the real oil price at almost all horizons. Note that, as oil uncertainty is placed after non-oil uncertainty, the effects of oil uncertainty are measured *after* we have accounted for all the variation in oil uncertainty attributable to shocks to non-oil uncertainty. The finding that US oil production and the oil price still significantly fall due to oil uncertainty shocks reinforces the conclusion that our oil uncertainty measure contains unique information that has important implications for the oil sector, whereas non-oil uncertainty contains more information about macroeconomic activity.\textsuperscript{14}

Similar findings are suggested by the results of variance error decomposition over horizons of 3, 12, 36, and 60 months for macroeconomic and oil market variables due to oil and non-oil uncertainty. Table 1 shows that the baseline OIU measure explains more variation in US and World oil production in almost all horizons compared to non-oil uncertainty, whereas the non-oil uncertainty has stronger impact on US real economic activity relative to OIU. OIU has a similar effect on World activity in the short run, but less significant effect in the long run. Finally, the impact of OIU on oil prices is more significant than that due to non-oil uncertainty in all horizons.

\textsuperscript{14}We obtain a similar conclusion if we change the ordering of oil and non-oil uncertainty. The results are shown in Appendix C.
Figure 6 – Impulse responses from estimation of VAR with Oil uncertainty and Non-Oil uncertainty. The responses are estimated from the VAR including both forms of uncertainty, with non-oil uncertainty ordered first. The gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to long run trend.
Table 1 – Macroeconomic Variables and Oil Market Variables Forecast
Variance Due to Oil Uncertainty and Non-Oil Uncertainty (in percent)

| Horizon | US oil prod Oil | World oil prod Oil | US activity Oil | World Activity Oil | Oil Price Oil | Non-Oil Oil | Non-Oil Oil | Non-Oil Oil
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>h = 3</td>
<td>10.98</td>
<td>0.10</td>
<td>0.09</td>
<td>0.45</td>
<td>3.91</td>
<td>5.68</td>
<td>0.44</td>
<td>1.34</td>
</tr>
<tr>
<td>h = 12</td>
<td>31.96</td>
<td>0.44</td>
<td>1.77</td>
<td>0.57</td>
<td>3.21</td>
<td>13.34</td>
<td>2.71</td>
<td>4.95</td>
</tr>
<tr>
<td>h = 36</td>
<td>20.25</td>
<td>3.30</td>
<td>2.70</td>
<td>0.97</td>
<td>2.32</td>
<td>13.42</td>
<td>2.61</td>
<td>6.33</td>
</tr>
<tr>
<td>h = 60</td>
<td>17.86</td>
<td>3.02</td>
<td>2.48</td>
<td>1.14</td>
<td>2.12</td>
<td>12.42</td>
<td>2.01</td>
<td>6.33</td>
</tr>
</tbody>
</table>

4.3 Oil Uncertainty and Aggregate Uncertainty

The previous exercises show that our oil uncertainty measure can contain information exclusive to the oil sector that has an impact on oil markets. To further shed light on whether OIU originates from the oil sector or instead reflects the transmission of aggregate uncertainty to the oil market, we conduct additional exercises in this section with aggregate uncertainty and oil uncertainty.

First, we re-estimate the same VAR system as in the benchmark, but replace OIU with aggregate uncertainty. The aggregate uncertainty measure is the macroeconomic uncertainty measure created in Jurado et al. (2015). As shown in Appendix D, we find that aggregate uncertainty lowers economic activity. It also lowers US oil production, World oil production, World economic activity, and oil prices. The impact of aggregate uncertainty on oil markets is consistent with the findings of Joëts et al (2017) about commodity markets in general.

To investigate whether the impact of OIU is still significant conditional on aggregate uncertainty, or equivalently, whether OIU contains independent information compared to aggregate uncertainty, we estimate an alternative VAR system by including both OIU and aggregate uncertainty measures while keeping other variables the same. Figure 7 displays the impulse responses of macroeconomic variables and oil sector variables to a one-standard deviation innovation in OIU and in aggregate
uncertainty. As before, macroeconomic variables, such as US and World real activity, still decline following higher oil uncertainty, even though the impact of aggregate uncertainty is already accounted for. The magnitude of the impact is smaller, though. The stock market response to oil uncertainty is similar to that estimated from sample up to 2006, suggesting that, generally, uncertainty specific to the oil industry has a positive influence on the stock market. This becomes visible once we account for the potential influence of aggregate uncertainty both on macroeconomic aggregates and through OIU itself.

Turning to the oil market, OIU has more significant impact on US oil production than does aggregate uncertainty, generating a 1 percent greater variation at the peak level. Interestingly, for World oil production, OIU tends to raise it, whereas aggregate uncertainty lowers it. Finally, OIU lowers oil prices immediately, as before. Relative to aggregate uncertainty, the magnitude of the effect of OIU is larger in the short run, but smaller in the medium and long run. These results imply that, at least to some extent, uncertainty originating from the oil sector alone can serve as a driving force of macroeconomic and oil sector dynamics, as the effects of uncertainty spreading from the aggregate economy to oil sector have already been captured by the inclusion of aggregate uncertainty in the VAR. This conclusion can also be inferred from a Granger causality test, which is performed on the previously described VAR system. The p-value for the statistical test that all coefficients of lags of the aggregate uncertainty in the oil uncertainty equation are zero is 0.38. Thus, we fail to reject the null hypothesis that lags of aggregate uncertainty do not affect oil uncertainty, or equivalently, we can conclude that aggregate uncertainty does not Granger-cause oil uncertainty.\footnote{In fact, for all the variables in the VAR, the null hypothesis that they Granger-cause oil uncertainty can be rejected.}

It is worth underlining that, in Figure 7, the magnitude of the impact of OIU on US oil production is similar to that in Figure 3, when aggregate uncertainty is not in the VAR. Thus, while aggregate uncertainty does impact on US oil production, the impact of OIU on the domestic oil market is independent, and is preserved when we condition on aggregate uncertainty. On the other hand, regarding the oil price, OIU
becomes less impactful when conditioning on the impact of aggregate uncertainty. This suggests that OIU contains some of the same the information as aggregate uncertainty in accounting for the World oil market dynamics.

Figure 7 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with oil uncertainty and aggregate uncertainty.

We also calculate the VAR forecast error variance decomposition for OIU and aggregate uncertainty: see Table 2. Similar to our previous analysis, OIU explains more variation in US oil production and in the oil price (in the short run), whereas aggregate uncertainty explains more variation in US and World real economic activity, and in the oil price (in the medium and long run). The two aggregate measures explain similar variation in World oil production. These results show that OIU has
important implications for the oil market, and is therefore especially informative for studying the behavior of variables closely linked with the US oil sector.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>US oil prod</th>
<th>World oil prod</th>
<th>US activity</th>
<th>World Activity</th>
<th>Oil Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>h = 3</td>
<td>10.44</td>
<td>0.14</td>
<td>0.08</td>
<td>0.12</td>
<td>3.11</td>
</tr>
<tr>
<td></td>
<td>0.22</td>
<td>2.80</td>
<td>9.16</td>
<td>0.22</td>
<td>6.35</td>
</tr>
<tr>
<td>h = 12</td>
<td>26.59</td>
<td>8.89</td>
<td>1.87</td>
<td>4.63</td>
<td>5.11</td>
</tr>
<tr>
<td></td>
<td>1.35</td>
<td>12.87</td>
<td>40.87</td>
<td>1.35</td>
<td>6.34</td>
</tr>
<tr>
<td>h = 36</td>
<td>18.22</td>
<td>16.00</td>
<td>2.69</td>
<td>3.47</td>
<td>2.32</td>
</tr>
<tr>
<td></td>
<td>1.36</td>
<td>10.79</td>
<td>25.94</td>
<td>1.36</td>
<td>5.48</td>
</tr>
<tr>
<td>h = 60</td>
<td>15.48</td>
<td>15.17</td>
<td>2.44</td>
<td>3.08</td>
<td>3.43</td>
</tr>
<tr>
<td></td>
<td>1.21</td>
<td>9.99</td>
<td>19.33</td>
<td>1.21</td>
<td>4.77</td>
</tr>
</tbody>
</table>

Table 2 – Macroeconomic Variables and Oil Sector Variables

Forecast Variance Due to Oil Uncertainty and Aggregate Uncertainty
(in percent)

We also conclude that OIU contains exclusive information from an alternative exercise, an estimation of a VAR with both non-oil uncertainty and aggregate uncertainty, as well as other same macroeconomic and oil market variables. The impulse responses are displayed in Figure 8. The results reassure us that information contained in our oil uncertainty measures is not contained in non-oil sector uncertainty measures, as US oil production and the oil price barely respond to non-oil uncertainty shocks once we condition on aggregate uncertainty.

4.4 Relative Oil Uncertainty

An alternative way to capture uncertainty emanating from the oil sector is to explore the impact of uncertainty when oil sector experiences relatively higher uncertainty than the non-oil sector. To see this, we construct a relative OIU measure, which is the ratio of oil uncertainty to non-oil uncertainty, capturing periods of uncertainty that are particularly large for the oil sector. The time series of this relative uncertainty measure is shown in Figure 9. Notably, oil relative uncertainty coincides with baseline uncertainty most of the time – whereas during some crises that are known not to
originate from the oil sector, such as the Great Recession, oil relative uncertainty is lower than the baseline oil uncertainty measure.

Figure 8 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with non-oil uncertainty and aggregate uncertainty.
Figure 9 – Comparison of different uncertainty measures. The thick line is our baseline oil industry uncertainty measure and the dashed line is the relative measure i.e. oil industry uncertainty divided by uncertainty outside the oil market. The sample period is 1982m3-2018m12.

Intuitively, this measure should have similar impact compared to OIU, and especially capture the information contained in the oil sector but not in the non-oil sectors. This intuition is verified by the results shown in Figure 10, which show that an increase in relative OIU lowers US oil production, raises World oil production, lowers US and World economic activity, and lowers oil prices. Again, notably, relative OIU has a positive impact on the stock market. These findings are consistent
with our previous analysis using absolute (rather than relative) OIU.

Figure 10 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with oil relative uncertainty.

5 Discussion

Unlike oil-related uncertainty indices in the literature, our baseline oil industry uncertainty is constructed as the absolute forecast error of earnings per share for oil and gas corporations, made by financial analysts. Still, an important question is whether our oil uncertainty shocks simply reflect other first moment oil shocks or aggregate uncertainty shocks, rather than isolating uncertainty in the oil market. In our earlier VAR exercises, we include oil market variables, such as World oil production,
World economic activity, oil price, and oil inventories to identify the main oil shocks that are discussed in the literature: oil supply shocks, economic activity (aggregate demand) shocks, oil specific demand shocks, and oil speculative demand shocks. We also included aggregate uncertainty in some VARs. Since the VARs are estimated using recursive identification, our oil uncertainty shocks are orthogonal to those oil shocks and to aggregate uncertainty shocks that are estimated in the VARs.

To assess whether the same orthogonality is evident when our oil uncertainty shocks confront oil shocks and aggregate uncertainty shocks in the literature, we calculate the correlations of our oil uncertainty shocks and oil shocks estimated by Baumeister and Hamilton (2019), and the correlation with aggregate uncertainty shocks estimated by Basu and Bundick (2017). Following Caldara et al. (2016), we regress our oil uncertainty shocks estimated from the baseline VAR on the selected oil shocks and aggregate uncertainty shocks. The results in Table 3 suggest that our oil uncertainty shocks are not significantly correlated with those shocks. Therefore our oil uncertainty shocks seem to capture waves of uncertainty exclusively associated with the oil industry, rather than first moment innovations in the oil market, or second moment innovations in the aggregate economy.

<table>
<thead>
<tr>
<th>Oil shock and Uncertainty Shock</th>
<th>Oil Uncertainty Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>oil supply</td>
<td>0.031 (0.030)</td>
</tr>
<tr>
<td>economic activity</td>
<td>-0.138 (0.080)</td>
</tr>
<tr>
<td>oil specific demand</td>
<td>-0.033 (0.021)</td>
</tr>
<tr>
<td>oil speculative demand</td>
<td>-0.165 (0.160)</td>
</tr>
<tr>
<td>aggregate uncertainty</td>
<td>-0.008 (0.043)</td>
</tr>
</tbody>
</table>

Table 3. Correlations of Oil Uncertainty Shock with Other Shocks

Note. The column shows the estimated correlations between our OIU shocks and other oil shocks and aggregate uncertainty shock. The values in parentheses provide robust t-statistics of the coefficients.

To shed further light on whether OIU variation serves as a transmission channel of
other oil shocks and/or aggregate uncertainty, we conduct several Granger causality
tests. We show earlier that none of the variables in the baseline VAR Granger-cause
OIU, suggesting that it plays an independent role in contributing to business cycle
and oil market dynamics. Like in the first exercise, we also confront our uncer-
tainty measures with known oil shocks in the literature based on an autoregressive
distributive lag (ADL) model with robust errors:

\[ y_t = \alpha + \sum_{j=1}^{m} \beta_j y_{t-j} + \sum_{j=1}^{k} \gamma_j x_{t-j} + \eta_t, \]

(5)

where \( y \) is either the baseline oil uncertainty measure or non-oil uncertainty, and \( x \)
represents oil shocks or aggregate uncertainty. The aggregate uncertainty index is
that constructed by Jurado et al. (2015). We use the Akaike information criterion
(AIC and BIC) to select lag lengths \( m \) and \( k \) for each specification.

Test results are summarized in Table 4. For the baseline OIU measure, we fail
to reject the hypothesis at the 5 percent significance level that oil shocks do not
Granger cause OIU, indicating that variation in OIU is not predicted by these oil
shocks. However, we can reject the hypothesis at the 10 percent significance level for
the case of aggregate uncertainty. In contrast, non-oil uncertainty mainly captures
aggregate uncertainty, as we strongly reject that aggregate uncertainty does not
Granger cause OIU.
### Table 4. p-Values of the Granger causality test. The entries show p-Values from a F-test with the null hypothesis that the coefficients of the lags of each oil shocks as well as aggregate uncertainty are jointly zero. The number of lags are 3 based on the AIC and BIC criteria.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Oil Unc</th>
<th>Non-Oil Unc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil supply</td>
<td>0.34</td>
<td>0.06</td>
</tr>
<tr>
<td>Economic activity</td>
<td>0.16</td>
<td>0.53</td>
</tr>
<tr>
<td>Oil specific demand</td>
<td>0.16</td>
<td>0.75</td>
</tr>
<tr>
<td>Oil speculative demand</td>
<td>0.27</td>
<td>0.44</td>
</tr>
<tr>
<td>Aggregate uncertainty</td>
<td>0.06</td>
<td>0.00</td>
</tr>
</tbody>
</table>

If OIU is not exclusively caused by any one of these shocks, what does our oil uncertainty pick up? As shown in Figure 3, an increase in OIU lowers real economic activity and the price level. This behavior seems on par with a negative aggregate demand shock. On the other hand, OIU also displays some characteristics usually associated with positive oil supply shocks, since it increases World oil supply, lowers the oil price, and raises the stock market index. Finally, as Figure 7 shows, even conditioning on aggregate uncertainty, US oil production is still negatively affected by increases in OIU, implying that it captures uncertainty specific to the US oil industry that can slow its development.

The previous evidence suggests that the behavior of our oil uncertainty that is similar with negative demand shock could occasionally capture similar events that also drive the aggregate uncertainty. At the same time, OIU behaves partly like a positive supply shock. An extensive literature relates the business cycle fluctuations to innovations in technology, building on Kydland and Prescott (1982). This suggests

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16For example, the generated dynamics are similar to those in Figure D1 due to aggregate uncertainty shock, which represents a negative aggregate demand shock as discussed in Basu and Bundick (2017).
that it is worth exploring whether our measure is related to measures of technical change in the oil industry. An improvement in technology could increase World oil production, but might affect the US oil industry negatively if it facilitates entry, if it is introduced by entrants, or if it tends to benefit oil producers in other countries. For example, the US oil industry is dominated by fracking, so innovations that are related to more traditional oil extraction methods, or innovations that favor fracking techniques related to the types of deposits in other countries, or innovations that entail the entry of new oil/gas producers that compete against current ones (e.g. by enabling fracking in new regions).

To explore this possibility, we measure technical progress using the stock of patents related to the oil industry. We use the perpetual inventory method, so that if the stock of patents in month $t$ is $P_t$ and $a_t$ is the number of patent applications in month $t$ then:

$$P_{t+1} = a_t + P_t (1 - \delta)$$

where $\delta \in (0, 1)$ is the rate at which ideas depreciate.

Monthly data on patent applications are compiled by Marco et al (2015). These data are available for the industry classification system developed by Hall et al (2001). We focus on patents developed in Sector 13, which are related to oil and gas. These correspond to Patent Classes 48, 55, 95 and 96. They include innovations related to power generation using oil and gas, and also innovations in fluid separation. The survey in Samaniego (2007) finds values of $\delta$ in the literature in the range $[0.12, 0.26]$. We examine several values in this range, finding similar results: as a baseline we assume $\delta = 0.26$ as in Pakes and Schankerman (1984).

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17 See Griliches (1990), Porter and Stern (2000) and Samaniego (2007), for example, as papers that use patent counts to measure technical progress.

18 Old ideas may be superseded by new ones, or some research directions may be depleted so that further advances are no longer important for the production of new knowledge or products. See Pakes and Schankerman (1984), Griliches (1990) and Nadiri and Prucha (1996) among others.


20 Details may be found at http://www.ibiblio.org/patents/classes.html, last checked 10/02/2019.

21 Data are available starting in 1981m1. We set the initial condition $P_0 = q_0$ where $g$ is the growth rate of patent applications over the period. This approach is common for measuring capital
of the series $P_t$, and detrend the log series using the Hodrick Prescott filter to make it stationary. We then compare this series to the series for OIU.

First, as shown in Figure 11, we find that the series of OIU and stock of oil patents have a correlation of 0.20, significant at the 1 percent level. The highest correlation turns out to be 0.24 between the technology series and OIU 7 months later. In contrast, the cross correlation between OIU and stock of non-oil patents is insignificant at all leads and lags. This indicates that it is not technical change in general that is related with OIU, but rather innovations specifically related to the oil and gas industry.

Second, we conduct Granger causality tests based on the ADL model specified by (5), with our baseline OIU as the dependent variable, lags of OIU and lags of the stationary series of stock of oil and non-oil patents as explanatory variables. The p-values of the test results are shown in Table 5. We can reject the hypothesis that stock of oil patents does not Granger cause oil uncertainty at 10 percent significance level, but cannot reject that for non-oil patents. While by no means definitive, this again suggests that one factor of OIU could be technical change specific to the oil industry.

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22 stocks and essentially assumes that at date zero the stock was on its long run growth path. See Caselli (2005).

22 We also run VARs with the stock of patents associated with the oil industry to replace our baseline oil uncertainty. The results show that a positive innovation in the stock of patents lead to higher world oil production and stock market index, but lower US oil production and oil price. This is similar with the impact of the baseline oil uncertainty, suggesting that the positive-supply feature of oil uncertainty could capture innovations in the technology of the oil industry. Results are available on request.
Figure 11 – Cross correlations between OIU and lags of detrended Oil and Non-Oil patent stocks.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Oil patents</th>
<th>Non-Oil patents</th>
</tr>
</thead>
<tbody>
<tr>
<td>p-value</td>
<td>0.07</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Table 5. p-Values of the Granger causality test. The entries show p-Values from a F-test with the null hypothesis that the coefficients of the lags of stock of oil and non-oil patents are jointly zero. The number of lags is 7.
6 Concluding Remarks

We construct several measures of oil industry uncertainty (OIU) based on a large number of financial analysts forecasts. The measure we develop turns out to have unique implications for oil market dynamics and for macroeconomic aggregates – implications that are distinct from those of aggregate uncertainty. While aggregate uncertainty has an influence on OIU, particularly during the Great Recession, OIU is an independent factor of uncertainty, especially when uncertainty in the oil sector is measured relative to uncertainty outside the oil sector. In particular, while aggregate uncertainty shocks behave like negative aggregate demand shocks, depressing both the macroeconomy and the oil market, OIU shocks are related to aggregate contractions in the US as well as a contraction in the US oil market, but with an expansion of the stock market and of the global oil market. While our baseline measure is based on forecast errors, some of our measures are based on forecast dispersion, meaning that they can be computed contemporaneously, making them suitable for forecasting purposes.

Given the empirical findings in this paper that underline the importance of oil uncertainty shocks, it would be interesting in the future to develop a structural quantitative model where uncertainty originates in the oil industry and spreads to the rest of the economy in the ways we uncover. This could be especially useful for policy analysis if incorporated in a monetary DSGE framework.

7 References


Basu, Susanto, and Brent Bundick. 2017. Uncertainty Shocks in a Model of


Appendix A: Robustness for baseline VAR results

We explore the robustness of the baseline results through additional VAR estimations.

First, in the benchmark, oil uncertainty is placed as the second variable, assuming that innovations in oil uncertainty have contemporaneous effects on all the macroeconomic variables and oil market variables in the VAR, except for the stock market index. To investigate whether the baseline results are driven by this ordering, we re-estimate a VAR with the same variables, but place oil uncertainty as the last variable. In this way, it is assumed that oil uncertainty shock does not affect other variables in the VAR in the same period. The estimation results are shown in Figure A1. Compared with Figure 3, a difference is that oil uncertainty shock does not affect US oil production and oil price on impact. This is not surprising by the assumption of the timing of the shock. However, the main results that higher oil uncertainty depresses macroeconomic and oil market activity remain with this new ordering.
Figure A1 – Impulse response of the federal funds rate, the price level, the stock index, US and World real economic activity, US and World oil production, and real oil price to oil uncertainty shock. The results are obtained from estimation of benchmark VAR, with oil uncertainty measured using the 12-month forecast error and placed last in the VAR. The shock is one standard deviation, and the gray areas are +/- one standard error confidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982m3 to 2018m12.

Second, we use more lags in the VAR to capture the possibility that oil shocks may take long before having significant impact on the economy. Figure 2A and 3A show
the results when we implement the baseline VAR with 13 and 24 lags respectively. The main results still hold for 13-lag specification. For 24-lag specification, however, the impact is qualitatively similar but quantitatively smaller.

Figure A2 – Impulse response of macroeconomic variables and oil sector variables from estimation of benchmark VAR, with 13 lags of the variables in the VAR.
Figure A3 – Impulse response of macroeconomic variables and oil sector variables from estimation of benchmark VAR, with 24 lags of the variables in the VAR.

Third, we use the log of some variables in the baseline VAR for estimation to not exclude possible medium and long run dynamics between variables. To see whether the results are robust to stationarity of variables, we convert whichever variable that is not stationary to stationary before estimating the VAR with the same variables. In particular, we use two method for stationarity purpose: i) HP-filter as in Bloom (2009) and ii) log-differencing as in Kilian (2009). The estimation results with the new variables are shown in Figure 4A and 5A respectively. Qualitatively, the results are very similar with the benchmark results.
Figure A4 – Impulse response of macroeconomic variables and oil sector variables from estimation of benchmark VAR, with oil uncertainty measured using the 12-month forecast error and HP-filtered variables in the VAR.
Figure A5 – Impulse response of macroeconomic variables and oil sector variables from estimation of benchmark VAR, with oil uncertainty measured using the 12-month forecast error and log-differenced variables in the VAR.

Finally, an alternative index is used to represent World real activity. In the baseline, we use the index constructed by Kilian (2009), while we use the World production index constructed by Baumeister and Hamilton (2019) for robustness check. The estimation results are shown in Figure A6. It is clear that oil uncertainty still has similar impact on the endogenous variables included in the exercise.
Appendix B: Alternative measures of oil industry uncertainty

Measures constructed from dispersions

Our baseline OIU measure is built on ex-post absolute forecast errors, which is the absolute difference between the EPS forecast and the realized EPS 12 months later. Therefore, we are not able to use it to forecast the near future (within 12 months), as the EPS realization is not yet known. Alternatively, if an oil industry measure is constructed from information that does not rely on future EPS realizations, it
can potentially be used as a leading indicator of the dynamic impact of OIU on macroeconomic aggregates and oil markets. To this end, we use I/B/E/S forecast data to construct two measures based on forecast dispersion that may also capture uncertainty prevailing in oil industry but which do not depend on forecast errors using equation (4). These are the median interquartile range and the median standard deviation of analyst forecasts about a particular oil/gas firm in a month. These uncertainty indices measure the extent of disagreement among forecasters rather than the extent to which forecasts are correct. Consequently, they may serve as forecasting tools in future work. Figures B1 and B2 plot the impulse responses estimated from VARs with these alternative uncertainty measures replacing the baseline measure. The impact of dispersion-based measures of OIU on macroeconomic and oil sector dynamics is qualitatively similar compared to the baseline.
Figure B1 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with interquartile uncertainty measure.
Figure B2 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with standard deviation uncertainty measures.

**Measures with various forecast horizons**

As the I/B/E/S dataset also provides forecasts with shorter horizons, another way of constructing oil industry uncertainty measures that does not require realized EPS values 12 months later is to use shorter-horizon forecasts. Specifically, we construct three alternative oil uncertainty measures, where the uncertainty about the current month’s oil industry is respectively measured as the absolute difference between the forecasted EPS and the realized EPS of oil and gas firms 1 quarter, 2 quarters, and 3 quarters later, leading to 1-, 2-, and 3-quarter ahead oil industry uncertainty measures. The advantage of these measures is that they can be measured earlier,
providing earlier insight into future macroeconomic and oil market events.

Figures B3, B4 and B5 show the impulse responses to innovations in these uncertainty measures. Increases in oil uncertainty based on one quarter-ahead absolute forecast errors have a different impact on the federal funds rate, US real activity, and the stock market, which suggests that short-run and long-run oil industry uncertainty may contain different information that in turn has different impact on the macroeconomy. In particular, as the forecast horizon based on which our oil industry uncertainty is constructed increases from 1 quarter to 4 quarters (baseline), the impact of oil uncertainty on US real activity and the price level becomes increasingly significantly negative, as does the impact on the federal funds rate. This suggests that OIU regarding longer horizons has a stronger and more persistent negative impact on the macroeconomy, as longer-horizon uncertainty may matter more for economic agents’ decisions, at least at business-cycle frequency. On the other hand, all the measures generally lead to significant decreases in US oil production and oil prices. This implies that these measures can also serve as forecasting tools, just as the uncertainty measures based on dispersion.

23Jurado et al. (2015) have similar findings for aggregate uncertainty. They show that uncertainty based on shorter forecasting horizon (1 and 3 months) generally explains less variation in real economic activity compared to that based on longer forecasting horizon (12 months).

24Using quarter-ahead measures as forecasting tools allow us to incorporate more recent information. For example, suppose we are in 2019m8, if we want to forecast the oil production in 2019m9, the last available data point of the year-ahead oil uncertainty measure would be 2018m8 given the definition of our uncertainty measure (the uncertainty in 2018m8 equals to the absolute difference between the forecasted EPS made in 2018m8 for 2019m8 and the realized EPS in 2019m8), whereas the last available data point of the two-quarter-ahead oil uncertainty measure is 2019m2 (the uncertainty in 2019m2 equals to the absolute difference between the forecasted EPS made in 2019m2 for 2019m8 and the realized EPS in 2019m8).
Figure B3 – Impulse responses of macroeconomic variables and oil sector variables from estimation of VAR with 1-quarter ahead oil uncertainty measure.
Figure B4 – Impulse responses of macroeconomic variables and oil sector variables from estimation of VAR with 2-quarter ahead oil uncertainty measures.
Figure B5 – Impulse responses of macroeconomic variables and oil sector variables from estimation of VAR with 3-quarter ahead oil uncertainty measure.

**Before the Great Recession**

The 2007 financial crisis may contribute to some of the impact of OIU shocks, as it is a major demand-driven event in our sample period. To see whether our results are dominated or affected by that event, we re-estimate the VAR system with data spanning between 1982m3 and 2006m12. Figure B6 shows that OIU still has an adverse impact on US real activity, US oil production and the real oil price. An interesting difference, though, is that the stock market index rises more significantly relative to the baseline estimation when we remove the Great Recession. It is likely
that, during the historical periods before the Great Recession, an increase in oil uncertainty drives up the stock market on average, as it can lower the oil price and therefore lower production costs in the economy at large. We will see later that there is other evidence indicating that OIU shocks lead to an increase in the stock market index, which implies that OIU shocks are not merely a refinement of broader uncertainty shocks or a conduit for uncertainty shocks.

Figure B6 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with sample 1982m3 to 2006m12.

VAR with oil inventories

There is another type of oil shock that has been discussed in the literature: the "speculative oil demand shock". This shock is identified using oil inventories, and is
thought to reflect changes in expectations about future changes in oil supply and/or oil demand. To investigate whether our OIU shocks capture similar movements in the oil market as speculative oil demand shocks, we estimate a new VAR with oil inventories as an explicit endogenous variable and explore the impact of OIU shocks conditioning on oil inventories. Following Kilian and Murphy (2014), we use OECD crude oil inventories as an approximation for the World oil inventories. The data for OECD crude oil inventories is calculated by using US crude oil inventories, scaled by the ratio of OECD petroleum stocks over US petroleum stocks. We add oil inventories to the benchmark VAR, and order it after oil supply and before oil demand in the model. This ordering assumes that speculative oil demand shocks contribute to contemporaneous changes in oil demand but not in oil supply, as in Kilian and Murphy (2014). Figure B7 shows the results. As in the baseline, an increase in oil industry uncertainty leads to lower US real activity and general price level, but raises the stock market index. It has adverse impact on World real activity, but slightly positive impact on World oil production. As a result, the oil price falls. US oil production also declines in response to the increase in oil industry uncertainty. These results are obtained after accounting for the variations in oil industry uncertainty that might be accounted for by changes in speculative oil demand shocks. The fact that the main findings still hold suggests that OIU reflects movement in the oil market that is not captured by shifts in oil inventories.\(^{25}\)

\(^{25}\)The impulse responses are similar when we order oil uncertainty as the last variable in the VAR. Results are available on request.
Appendix C: Robustness for VAR results with Oil and Non-Oil Uncertainty

In the main text, we estimate the VAR with both oil and non-oil uncertainty by ordering non-oil uncertainty before oil uncertainty, and find that oil uncertainty contributes more to the fluctuations in US oil production and oil price. In this robustness check, we explore whether the conclusion is related to the ordering of the oil and non-oil uncertainty by estimating an alternative VAR that orders non-oil uncertainty after oil uncertainty. This implies that the effects of non-oil uncertainty...
on macroeconomic variables and oil market variables are measured after we have removed all the variation in non-oil uncertainty that is attributable to shocks to oil uncertainty.

The impulse responses are shown in Figure C1. As before, increases in oil uncertainty and non-oil uncertainty still generate significant impact on US real activity. The ordering is also irrelevant when analyzing the contribution of these two uncertainty measures to the dynamics of oil market.

Figure C1 – Impulse responses from estimation of VAR with Oil uncertainty and Non-Oil uncertainty. The solid lines show the responses estimated from the VAR using the baseline data sample and including both forms of uncertainty, with oil uncertainty ordered first.
Appendix D: The Impact of Aggregate Uncertainty

Figure D1 shows the impulse responses of macroeconomic aggregates and oil market variables to a one standard deviation increase in aggregate uncertainty. All the variables in the estimation are the same as in the baseline VAR model, except that we replace OIU with aggregate uncertainty. The aggregate uncertainty measure is the macroeconomic uncertainty measure based on 12-month ahead forecast errors, which is created in Jurado et al. (2015).

Figure D1 – Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with aggregate uncertainty.

Appendix E: Comparison with Other Oil Uncertainty Measures
Figure E1 – Comparison of different oil uncertainty measures. The black line is our oil industry uncertainty measure. The blue lines in the top figure are the measure of Kellogg (2014) for the periods between 1993m1 and 2003m12, and the measure of OVX between 2007m5 and 2018m12. The blue line in the bottom figure is the measure of Yin and Feng (2019). See text for detailed explanation of the measures.

Figure E1 compares our baseline OIU with three oil uncertainty measures in the literature: the measure of Kellogg (2014), which is constructed as 18-month future oil
price volatilities; the measure of OVX, such as in Maghyereh et al. (2016), which is the Cboe Crude Oil ETP Volatility Index that measures the market’s expectation of 30-day volatility of crude oil prices; and the measure of Yin and Feng (2019), named oil volatility risk premium, which is the difference between the realized volatility and implied volatility of the oil market. It turns out that our measure spans the longest horizon, and is significantly positively correlated with Kellogg (2014) and OVX, at 0.50 and 0.22, respectively, but significantly negatively correlated with Yin and Feng (2019), at —0.26.