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The macroeconomic impact of oil earnings uncertainty: New evidence from analyst forecasts

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Abstract

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

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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 market 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 endogenously respond to the forces of energy demand and supply, which themselves include macroeconomic aggregates. Instead, we measure oil earnings uncertainty using forecasts and forecast errors from a large survey 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 when developing 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 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. We refer to our indices as measures of oil earnings uncertainty, or OEU.

To study the impact of OEU on macroeconomic aggregates and on oil markets, we estimate a series of structural vector auto-regressions (SVAR). We also provide further evidence on whether OEU is different from aggregate uncertainty, and in what way it is different. The VARs contain our baseline OEU measure and demand and supply factors for the oil market, as well as the oil price, in addition to representative macroeconomic and policy variables. Since the main channels through which aggregates and oil markets are affected are explicitly estimated...
in the procedure, any impact of OEU captures causality from uncertainty in the oil industry (or causality from shocks originating outside the oil industry through their impact on the oil industry)\(^\text{1}\) 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 OEU measure lowers US output and the US price level, as well as the federal funds rate. This suggests that OEU behaves like a negative aggregate demand shock. In the oil market, an increase in OEU lowers US oil production and the oil price. We reach the same conclusions when we include both OEU and aggregate uncertainty measures in the same VAR. This implies that our OEU measure contains information specific to energy markets that is absent from aggregate uncertainty measures. Finally, the stock market responds positively to changes in OEU when the estimation is conducted over the whole sample period (1982–2018). This is likely because an increase in oil earnings uncertainty lowers the oil price, which encourages economic activity in sectors that use energy.

Our OEU 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 earnings uncertainty could occasionally capture events that also drive aggregate uncertainty, they are nonetheless different concepts, which is validated by the lack of correlation between the identified OEU shocks and aggregate uncertainty shocks. In particular, when we exclude the post-Great Recession period from the sample, we find that OEU 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 OEU 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 OEU shocks. Again, the F-test statistics suggest that the association between our identified OEU 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.

In addition, 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 OEU, and weakly Granger-causes OEU. This suggests that our oil earnings uncertainty measure may at least partly reflect uncertainty stemming from advances in oil industry technology.

We develop several other measures of oil earnings uncertainty. One is the dispersion of forecasts 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 measures based on forecast errors. These dispersion measures are particularly useful for macroeconomic and oil industry forecasting, because they do not require data from after a given date \(t\) to compute these measures at any date \(t\). When estimated in the same VAR model as the baseline, we find generally similar behavior, indicating that our approach to measuring oil earnings uncertainty can be computed in real time as new forecasts are made and entered into the I/B/E/S database.

Alternative versions of our baseline oil earnings 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, which we call relative oil earnings uncertainty or relative OEU. This is a way of ensuring that any increases in our measure are due to innovations originating from the oil industry, disproportionately affecting the oil industry relative to other industries in the economy, or propagating in unique ways through the oil industry. We find that the behavior of this relative OEU measure is similar to our baseline measure. However, there is one difference: relative OEU has a clear positive impact on the stock market, similar to that obtained from the estimation with the baseline oil earnings uncertainty over the pre-2007 sample. This result reassures us that oil uncertainty has an independent impact on the macroeconomy that is distinct from aggregate uncertainty, and that it mainly reflects information specifically relevant for the oil industry.

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.\(^2\) 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 earnings uncertainty based on financial analyst stock forecast errors, and empirically investigating the dynamic impact of oil earnings 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 US real output; Kellogg (2014), which uses firms’ expected future oil price volatility 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 (2016), computed using oil futures prices. One possible concern 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), Elder and Serletis (2010), and Jo (2014) overcome this issue by estimating a fully specified Multivariate-GARCH-VAR model where oil price uncertainty is defined as the unanticipated component of oil price fluctuations conditional on the contemporaneous information set in the VAR. Our paper adopts an alternative approach by measuring oil uncertainty in a manner that uses neither oil prices nor oil production as an input, and estimating a VAR containing several important

\(^1\) For example, on April 20, 2020, May 2020 WTI futures closed at minus $37.63. The origin of this unprecedented event, was a combination of technological factors, political tensions and the spread of the coronavirus. However, the impact of these shocks on the aggregate economy will partly (although not entirely) be due to their impact on the oil industry, and the SVAR should capture that channel for the shocks’ impact.

\(^2\) 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), Jaříček 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, 2020 for financial markets, and in a comprehensive breakdown of industries in Ma and Samaniego (2019).
macroeconomic and oil industry indicators. In this way, the causal relationship between oil earnings uncertainty and the macroeconomy is also 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. Measures of uncertainty at shorter horizons, such as in Jo (2014), can be very adequate for studying fluctuations of some variables, such as movements in the labor market, as well as for forecasting future volatility. On the other hand, uncertainty at longer horizons is also of interest, as it is likely to be more relevant for other economic activities such as firms’ investment decisions. Characterizing oil uncertainty at long horizons is generally challenging: for example, implied volatility from option markets is not as reliable beyond 12–18 months. Our paper contributes to this literature by constructing oil uncertainty at a one-year-horizon, i.e., 12-month-ahead forecast errors on firms’ earnings in the US oil and gas industry.

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 aggregate 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 earnings 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 earnings 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 earnings uncertainty on macroeconomic and oil market dynamics. Section 5 discusses possible sources of oil earnings uncertainty. Section 6 concludes with a discussion of potential future work.

2. Defining OEU

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 $M \subset N$ be the set of months, numbered consecutively, and let $t \in M$ be a month. Then, define $D_t \subset \{t, t + 1\}$ 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 $F[S_{i,d} - I_{i,j,d}]$ be the forecast about the realization of statistic $S$ at firm $i$ on a future day $d^*$, using the information $I_{i,j,d}$ 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 $d^*$:

$$F_{E_{i,d}} = F[S_{i,d} | I_{i,j,d}] - S_{i,d}. \tag{1}$$

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 $F[S_{i,d} | I_{i,j,d}]$ 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 $U_i$ 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. 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 $\|F_{E_{i,d}}\|$ within the month, pooling all firm-day forecasts within the month, which gives our baseline uncertainty measure for month $t$:

$$OEU_t = \text{median}\{\|F_{E_{i,d}}\| : \forall d \in D_t, t + 1, i \in \mathcal{T}\}. \tag{2}$$

Notice that the definition in Eq. (2) restricts firms to be from some set $\mathcal{T}$. We will define $\mathcal{T}$ 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 $oil$ earnings uncertainty or just $oil$ uncertainty (OEU 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., $i \notin \mathcal{T}$. 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 $F_{E_{i,d}}$ 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 $\mathcal{T}$ as the set of firms reporting SIC codes between 1300 and 1389, relative oil uncertainty is defined simply as:

\[ RF_{E_{i,d}} = \frac{F_{E_{i,d}}}{\text{Price}_{i,d}}, \]
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 whether or not forecasts made at a particular date were less accurate. The econometrician must observe the realization of the forecasted variable Si. As a result we remove the mean value for each month, as soon as the forecasts are reported. For each firm i and within each month t, we compute

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

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

\[OEU_i = \text{median}(D_{it} : i \in T).\]  

(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 within 6 months.7 Forecasts are collected each day as they are released by analysts.8

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.2 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 \(|F_{tand}\) in Eq. (2). Our measure of uncertainty is the median absolute value of these forecast errors across all firms within each month, starting in March 1982.11 Thus it is the median forecast error by firm-day pair.11

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.

Fig. 1 displays the series for oil earnings 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 earnings 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 earnings 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.12

To verify this conjecture, Fig. 2 compares our oil earnings uncertainty measure (OEU) to the aggregate uncertainty measure of Jurado et al. (2018).13 There are times when OEU 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 OEU and aggregate uncertainty, they are distinct forms of uncertainty, the economic impact of which an appropriate econometric specification should be able to tease apart.

4. Impact of oil earnings uncertainty

To investigate the role of OEU 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 OEU, 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 Ma and Samaniego (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 1982 m3 and 2018 m12:

\[
\begin{align*}
\text{log (SP500Index)} \\
\text{oil uncertainty} \\
\text{federal funds rate} \\
\text{log (CPI)} \\
\text{log (USoil production)} \\
\text{log (USreal activity)} \\
\text{log (World oil production)} \\
\text{World real activity} \\
\text{log (real oil price)} \\
\end{align*}
\]

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, in Appendix E, we compare the time series of OEU with other oil market uncertainty measures proposed in the literature.

12 As discussed in Ma and Samaniego (2019), other popular measures of aggregate uncertainty behave similarly.

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7 For further details, see https://wrdsweb.wharton.upenn.edu/wrds/support/Data/\_001Manuals%20and%20Overviews/\_0031-B-E-S-Release%20Notes/, last checked 3/20/2018.

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% of forecasters who make an annual forecast about a given firm make a 2-quarter ahead forecast the same month, and about 39% for 3-quarter ahead forecasts.

9 68% 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’s origin.

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.

12 In Appendix E, we compare the time series of OEU 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.
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.

Fig. 1. Oil earnings 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.

Fig. 2. Comparison of different uncertainty measures. The dashed line is our oil earnings uncertainty measure and the thick line is the measure of Jurado et al. (2015). The sample period is 1982 m3–2015 m4.
creases for almost 10 months. World oil production slightly increases, in US oil uncertainty. Specifically, World real activity and oil production also react to the increase peak effect of 4% that occurs around 7 months after initial impact. Inter-

oil markets. On impact, US oil production decreases immediately, with a 

standard error con- fidence bands. The unit in the vertical axis is proportional deviation relative to their respective long run trends. The sample period is 1982 m3–2018 m12.

4.1. Results

We estimate the VAR model with the baseline OEU 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 OEU, VARs with OEU measures constructed from shorter horizon forecasts, a VAR based on the sample excluding post-2007 periods, and a VAR with oil inventories.

Fig. 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 OEU. The shaded area represents $+/−$ one standard error confidence bands. As shown, macroeconomic aggregates respond negatively to an increase in OEU, 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 OEU 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 earnings uncertainty. When we measure oil earnings 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 OEU shocks.

In addition, the increase in OEU negatively affects the US and World oil markets. On impact, US oil production decreases immediately, with a peak effect of 4% 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. 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).

The negative impact on industrial production, the price level, and the federal funds rate suggest that our OEU measure behaves like a negative aggregate demand shock. For example, the generated dynamics are similar to those due to aggregate uncertainty shock – see Fig. C1 in Appendix C, which represents a negative aggregate demand shock as discussed in Leduc and Liu (2016), and Basu and Bundick (2017). The response of those macroeconomic variables in the baseline VAR imply that OEU could capture to some extent events that increase aggregate uncertainty, such as the failure of Lehman Brothers in September 2008. This could also explain the decline of world real activity in response to an increase in OEU, as OEU could reflect aggregate uncertainty that is shown to have an adverse impact on the worldwide economic activity as in Mumtaz and Theodorides (2015), among others. These results on macroeconomic variables are similar with Elder and Serletis (2010) and Jo (2014), who find that an innovation in oil uncertainty lowers US real economic activity and world economic activity, respecti
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Secondly, the impulse responses show how oil markets are affected by OEU. For the US oil industry, an increase in OEU lowers oil production. This implies that OEU is also likely to capture non-economic events that have negative impact specifically on the US oil and gas sector (relative to other sectors), such as the historical period of 1986 when OPEC abandoned attempts to oil prices, or economic events, such as the 1998 Asian financial crisis. For the global oil market, however, OEU increases world oil supply and lowers the oil price. This reaction of global oil market is in contrast to the findings in Jo (2014), where an increase in oil
price volatility slightly lowers world oil production and raises oil prices. Thus, our OEU measure displays some characteristics usually associated with positive oil supply shocks. This suggests that our OEU could capture events that positively affect the global oil industry and/or production. A candidate of such event is discussed in Section 5, where we show that OEU seems to be positively related to technological innovations in the oil and gas industry. An improvement in such 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), would increase oil production globally while impacting the US oil industry negatively.

Finally, the positive response of the stock market to an increase in OEU is likely because an increase in oil earnings uncertainty lowers the oil price, which can serve as a positive signal for economic activity in sectors that use energy. This also suggests that OEU contains information specific to energy markets that is absent from aggregate uncertainty measures, as aggregate uncertainty negatively affects the stock market as in Fig. C1.

Fig. 4 provides evidence on the overall role of OEU 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 OEU 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 OEU shocks.

In Appendix B we provide some further results. First, our baseline OEU 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 OEU 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 OEU measured with longer horizons has a stronger and more persistent negative impact on the macroeconomy than the short-horizon OEU, 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 OEU rises. This suggests that the Great Recession masks the positive impact that OEU 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 demand shock” identified in the literature. Results are robust to including this variable in the VAR.

4.2. Oil uncertainty and aggregate uncertainty

These exercises suggest that our oil uncertainty measure contains information exclusive to the oil sector that has an impact on oil markets. To further shed light on whether (a) OEU is specific to the oil sector or captures shocks whose impact on aggregates transmits through the oil sector, or (b) simply reflects the transmission of aggregate uncertainty to the oil market, with no independent effect on aggregates via the oil sector, 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 OEU with aggregate uncertainty. The aggregate uncertainty measure is the macroeconomic uncertainty measure created in Jurado et al. (2015). As shown in Appendix C, 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 OEU is still significant conditional on aggregate uncertainty, or equivalently, whether OEU contains independent information compared to aggregate uncertainty, we estimate an alternative VAR system by including both OEU and aggregate uncertainty measures while keeping other variables the same. Fig. 5 displays the impulse responses of macroeconomic variables and oil sector variables to a one-standard deviation innovation in OEU 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 OEU itself.

Turning to the oil market, OEU has more significant impact on US oil production than does aggregate uncertainty, generating a 1% greater variation at the peak level. Interestingly, for World oil production, OEU tends to raise it, whereas aggregate uncertainty lowers it. Finally, OEU lowers oil prices immediately, as before. Relative to aggregate uncertainty, the magnitude of the effect of OEU 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 (or transmitting through) 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.14

It is worth underlining that, in Fig. 5, the magnitude of the impact of OEU on US oil production is similar to that in Fig. 3, when aggregate uncertainty is not in the VAR. Thus, while aggregate uncertainty does impart on US oil production, the impact of OEU on the domestic oil market is independent, and is preserved when we condition on aggregate uncertainty. On the other hand, regarding the oil price, OEU becomes less impactful when conditioning on aggregate uncertainty. This suggests that OEU contains some of the same the information as aggregate uncertainty in accounting for the World oil market dynamics, but also contains independent information that affects aggregates and oil markets.

We also calculate the VAR forecast error variance decomposition for OEU and aggregate uncertainty: see Table 1. Similar to our previous analysis, OEU 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

14 In fact, for all the variables in the VAR, the null hypothesis that they Granger-cause oil uncertainty can be rejected.
explain similar variation in World oil production. These results show that OEU 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.

Another way to explore whether OEU contains exclusive information is discussed in Appendix D, where we develop an additional measure: earnings uncertainty measured in firms outside the oil industry. For brevity we call this “non-oil uncertainty”. First, we replace aggregate uncertainty with non-oil uncertainty in the VAR in this section. We find again that oil and non-oil uncertainty have distinct effects, broadly similar to the contrast between oil and aggregate uncertainty. Second, we estimate a VAR with non-oil uncertainty and aggregate uncertainty.
uncertainty, as well as the macroeconomic and oil market variables in the above VAR. We find that the impact of non-oil uncertainty is both different and less important both for oil markets and for aggregate behavior than the impact of oil uncertainty in Fig. 5. These 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.

4.3. 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 OEU 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 Fig. 6. 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.

Intuitively, this measure should have similar impact compared to OEU, 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 Fig. 7, which show that an increase in relative OEU lowers US oil production, raises World oil production, lowers US and World economic activity, and lowers oil prices. Again, notably, relative OEU has a positive impact on the stock market. These findings are consistent with our previous analysis using absolute (rather than relative) OEU.

5. Discussion

5.1. OEU and other oil industry shocks

Unlike oil-related uncertainty indices in the literature, our baseline oil earnings 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 identifying uncertainty in the oil market. In our

Fig. 5. Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with oil uncertainty and aggregate uncertainty.

| Horizon | Oil prod | World prod | US activity | World activity | Oil price |
|---------|----------|------------|-------------|----------------|-----------|
| $h=3$   | 0.08     | 3.11       | 0.12        | 9.16           | 0.22      | 2.80      | 6.35      | 1.10      |
| $h=12$  | 2.69     | 1.87       | 4.63        | 5.11           | 40.87     | 1.35      | 12.87     | 6.34      | 11.94     |
| $h=36$  | 2.09     | 3.47       | 2.32        | 25.94          | 1.36      | 10.79     | 5.48      | 12.17     |
| $h=60$  | 1.54     | 3.08       | 3.43        | 19.33          | 1.21      | 9.99      | 4.77      | 10.18     |
Fig. 6. Comparison of different uncertainty measures. The thick line is our baseline oil earnings uncertainty measure and the dashed line is the relative measure i.e. oil earnings uncertainty divided by uncertainty outside the oil market. The sample period is 1982m3–2018m12.

Fig. 7. Impulse response of macroeconomic variables and oil sector variables from estimation of VAR with oil relative uncertainty.
earlier VAR exercises, we include oil market variables, such as World oil production, World economic activity, oil prices, 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 included in the VAR estimation.

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 Basu and Bundick (2017), 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 2 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.

To shed further light on whether OEU 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 OEU, suggesting that it plays an independent role in contributing to business cycle and oil market dynamics. As in the first exercise, we also confront our uncertainty measures with known oil shocks from the literature based on an autoregressive distributive lag (ADL) model with robust errors:

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

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 3. For the baseline OEU measure, we fail to reject the hypothesis at the 5\% significance level that oil shocks do not Granger cause OEU, indicating that variation in OEU is not predicted by these oil shocks. However, we can reject the hypothesis at the 10\% 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 OEU.

5.2. OEU and technical progress

If OEU is not exclusively caused by any one of these shocks, what does our oil uncertainty pick up? The previous evidence suggests that the behavior of our oil uncertainty measure is similar to that of negative demand shock, so it could sometimes capture events that also drive the aggregate uncertainty. At the same time, OEU also behaves partly like a positive supply shock. An extensive literature relates business cycle fluctuations to supply side factors, particularly innovations in technology, building on Rydland and Prescott (1982). This suggests that it is worth exploring whether our measure is related to measures of technical change in the oil industry.

To explore this possibility, we measure technical progress using the stock of patents related to the oil industry.\(^\text{15}\) 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.\(^\text{16}\)

Monthly data on patent applications are compiled by Marco et al. (2015).\(^\text{17}\) 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.\(^\text{18}\) 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 that \( \delta = 0.26 \) as in Pakes and Schankerman (1984).\(^\text{19}\) We take natural logarithms 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 OEU.

First, as shown in Fig. 8, we find that the series of OEU and stock of oil patents have a correlation of 0.20, significant at the 1\% level. The highest correlation turns out to be 0.24 between the technology series and OEU measured 7 months later. In contrast, the cross-correlation between OEU and the 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 to OEU, but rather innovations specifically related to the oil and gas industry.

Second, we conduct Granger causality tests based on the ADL model specified by Eq. (5), with our baseline OEU as the dependent variable, lags of OEU 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 4. We can reject the hypothesis that stock of oil patents does not Granger cause oil uncertainty at 10\% significance level, but cannot reject that for non-oil patents. While by no means definitive, this

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\(^{15}\) See Griliches (1990), Porter and Stern (2000) and Samaniego (2007), for examples of papers that use patent counts to measure technical progress.

\(^{16}\) 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.

\(^{17}\) See https://www.uspto.gov/learning-and-resources/electronic-data-products/historical-patent-data-files, last checked 10/02/2019.

\(^{18}\) Details may be found at http://www.biblio.org/patents/classes.html, last checked 10/02/2019.

\(^{19}\) Data are available starting in 1981 m1. We set the initial condition \( P_0 = \frac{1}{\delta} \) where \( g \) is the growth rate of patent applications over the period. This approach is common for measuring capital stocks and essentially assumes that at date zero the stock was on its long run growth path. See Caselli (2005).
again suggests that one factor of OEU could be technical change specific to the oil industry.  

5.3. Policy implications of OEU

According to the previous empirical exercises, an increase in OEU lowers real economic activity (both domestic and global) and price level, but slightly increases the stock index. In the oil market, it lowers oil price and domestic oil production, but raises worldwide oil production. These results are robust across different measure specifications and estimation techniques. We find supporting evidence that our OEU can reflect episodes of increased aggregate uncertainty (such as the Great Recession), uncertainty specific to the oil industry (such as OPEC decisions on oil production or technological change in energy industry), or events originating outside the oil industry but affecting the economy through their impact on the oil industry (such as the 1998 Asian Crisis).

There are several policy implications based on the results of this paper. Since OEU behaves like a negative demand shock, it is an important macroeconomic factor that can lower real activity, or an important macroeconomic transmission channel through which real activity is negatively affected. Monetary policy-makers, after observing increased uncertainty in the oil industry, could use expansionary policy instruments to offset the potential negative impact due to higher OEU. Such expansionary policies are still appropriate even during the episodes when OEU is driven by technogical change in energy sector because, even though improvements in technology are generally thought of as a positive supply shock, we show above that OEU has a negative influence on both US energy markets and US aggregate activity.

Fiscal policy can coordinate with monetary policy to stimulate the economy in response to an increase in OEU. For example, to the extent that OEU reflects technical progress in energy, government policies can use tax rebates or other funding initiatives to promote innovations of technology in alternative energy products (such as renewable or clean energy). In this context, promoting clean energy sources might have threefold benefits. First, as shown by the empirical evidence, the stock market index responds positively to technological progress in the energy sector, which indicates an increase in productive capacity in the long run. Second, OEU can increase due to international geopolitical events and economic events affecting the global oil market, which are beyond the influence by national energy policies. As a result, usage of alternative energy sources could help to reduce the negative impact of OEU in the long run, possibly reducing the volatility of US economic activity in the long run. This is because oil and gas would then become less important as an energy input in firms’ production functions. Third, of course, policies to promote alternative energy products can also benefit the environment and reduce pollution in the long run.

6. Concluding remarks

We construct several measures of oil earnings uncertainty (OEU) 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 OEU, particularly during the Great Recession, OEU 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, OEU 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 earnings uncertainty shocks, it would be interesting in the future to develop a structural quantitative model where some uncertainty shocks originate in or propagate through 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.

CRediT authorship contribution statement

Xiaohan Ma: Conceptualization, Methodology, Software, Formal analysis, Investigation, Validation, Writing - original draft, Writing - review & editing. Roberto Samaniego: Conceptualization, Methodology, Software, Formal analysis, Investigation, Validation, Writing - original draft, Writing - review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2020.104832.

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