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The Effects of Disaggregate Oil Shocks on the Aggregate Expected Skewness of the United States

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Abstract: We examine the impact of the global economic activity, oil supply, oil-specific consumption demand, and oil inventory demand shocks on the expected aggregate skewness of the United States (US) economy, obtained based on a data-rich environment involving 211 macroeconomic and financial variables in the quarterly period of 1975:Q1 to 2022:Q2. We find that positive oil supply and global economic activity shocks increase the expected macroeconomic skewness in a statistically significant way, with the effects being relatively more pronounced in the lower regime of the aggregate skewness factor, i.e., when the US is witnessing downside risks. Interestingly, oil-specific consumption demand and oil inventory demand shocks contain no predictive ability for the overall expected skewness. With skewness being a metric for policymakers to communicate their beliefs about the path of future risks, our results have important implications for policy decisions.

Keywords: oil shocks; expected macroeconomic skewness; US economy; local projection model; impulse response functions

JEL Classification: C23; D81; Q41

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1. Introduction

Macroeconomic risks are not necessarily balanced around the baseline outlook, and hence skewness is a metric used by policymakers to communicate their beliefs about the evolution of future risks and analyse its potential impact on the economy (Jensen et al. 2020). Naturally, measuring aggregate macroeconomic skewness precisely is essential for the adoption of economic policies to mitigate it. In this regard, Iseringhausen et al. (2022) developed a data-rich measure of expected macroeconomic skewness in the United States (US) economy, which in turn was found to be strongly procyclical. Unlike the measures of financial market skewness, either computed at the market- or firm-level (Salgado et al. 2020; Dew-Becker 2022), Iseringhausen et al. (2022) relied on common movements of skewness from 211 quarterly time series. Thus, this skewness factor, as a measure of macro-level skewness, is distinct from micro-level and financial market measures of skewness, as well as Gross Domestic Product (GDP) growth skewness (Adrian et al. 2019), based on a single time series, as well as being immune to idiosyncratic noise in the measure of expected asymmetry for the individual variables.

While accurate estimates of expected skewness and its associated impact on the macroeconomy cannot be overemphasised enough, another equally important issue for policymakers is the identification of the underlying factor(s) that predict the expected skewness. In light of the widespread evidence of the role of oil price movements in historically driving a wide-array of macroeconomic and financial variables of the US economy (Fry-McKibbin and Zhu 2021; De et al. 2022)[1], we aim to evaluate the predictive link of oil price to the metric of expected aggregate skewness, obtained from a large database. In this regard, note that oil shocks affect real and financial variables through the channels involving supply (i.e., cost effects with oil being a direct raw material to the production process) and demand (via market allocation and income transfers), asset valuation, monetary and fiscal policies, and uncertainty (Degiannakis et al. 2018; Smyth and Narayan 2018; Bachmeier and Plante 2019; Zhang et al. 2022).

Realising that not all oil price changes originate from supply shocks (Kilian 2009), we also analyse the role of global demand (economic activity), precautionary (oil-specific consumption), and speculative (oil inventory) shocks, i.e., four disaggregated oil market innovations, on the expected skewness. Furthermore, there exists a long-standing argument that macroeconomic fluctuations are plagued by asymmetries, i.e., recessions tend to be relatively deeper and more pronounced than expansions (Hamilton 1989), coupled with the empirical evidence in favour of a nonlinear relationship between oil and macroeconomic variables in the US (Hamilton 2011; Rahman and Serletis 2011). In light of these two observations, we also account for the issue of whether the effects of the oil shocks are contingent on the US economy facing downside (negative values of expected aggregate skewness) or upside risks (positive values of expected aggregate skewness).

Econometrically, we estimate the impact of four structural oil market shocks on the expected aggregate skewness in the quarterly period of 1975:Q1 to 2022:Q2 by utilising the local projection (LP) method of Jordà (2005). Jordà (2005) developed the LP approach for calculating impulse response functions (IRF). The method does not impose restrictive assumptions on the specifications and estimations of the underlying multivariate system itself and has an advantage over the traditional approach of using the Vector Autoregression (VAR) method. In addition, the LP approach utilises the simple Ordinary Least Squares (OLS) regression estimation technique and accommodates models with flexible specifications, as used to obtain state-dependent IRFs for downside and upside risks.

To the best of our knowledge, this is the first empirical study to analyse the impact of oil market shocks on the overall expected macroeconomic skewness of the US and its associated states involving negative and positive skewness. The remainder of the paper is organised as follows: Section 2 presents the data and methodology, Section 3 discusses the empirical results, and Section 4 concludes the paper.

2. Dataset and Methodology

2.1. Data

The expected macroeconomic skewness data are at the quarterly frequency and obtained from the study by Iseringhausen et al. (2022)[2], who use the FRED-QD dataset of McCracken and Ng (2020) that consists of 248 macroeconomic time series (for example, interest rates, exchange rates, employment rates, etc.). Iseringhausen et al. (2022) removed the series that have missing observations over the sample period of 1960:Q1 to 2022:Q2, which then reduced the number of variables to 211. Next, Iseringhausen et al. (2022) estimated each (de-meaned) variable y_i and each quantile level $p = \{10\%, 50\%, 90\%\}$, following the autoregressive quantile regression developed by Engle and Manganelli (2004):

$$Q^p(y_{i,t}) = \beta_0^p + \beta_1^p(y_{i,t-1}) + \beta_2^p y_{i,t-1}\Pi(y_{i,t-1} > 0) + \beta_3^p y_{i,t-1}\Pi(y_{i,t-1} < 0), \quad (1)$$

where $i = 1, \ldots, N$ and $t = 2, \ldots, T$. Utilising the parameters estimated from the autoregressive quantile regressions and assuming that agents formulate their expectations according to Equation (1), Iseringhausen et al. (2022) computed the one-step-ahead expected Kelley skewness (Kelley 1947) for each variable as follows:

$$\mathbb{E}_t[Skew(y_{i,t+1})] = \frac{\mathbb{E}_t\left[Q^{0.9}_{i,t+1}\right] + \mathbb{E}_t\left[Q^{0.1}_{i,t+1}\right] - 2\mathbb{E}_t\left[Q^{0.5}_{i,t+1}\right]}{\mathbb{E}_t\left[Q^{0.9}_{i,t+1}\right] - \mathbb{E}_t\left[Q^{0.1}_{i,t+1}\right]}. \quad (2)$$

The expected macroeconomic skewness is computed as the first principal component calculated from the set of standardised series-specific predicted skewness measures. Since the skewness factor is based on Principal Component Analysis (PCA), its sign is not identified, which in turn is achieved by assuming a positive correlation between the skewness factor and the skewness of GDP growth.

Our data for oil shocks are from the estimation of a structural vector autoregressive (SVAR) model following the method of Baumeister and Hamilton (2019). By including uncertainty about the identifying assumptions of the SVAR, the method formulates a less restrictive framework than the traditional approach of Kilian (2009), and thus the obtained oil shocks can be relatively estimated more accurately. The oil shocks are disentangled according to their origins into four components, i.e., the economic activity shock (EAS), the oil supply shock (OSS), the oil inventory demand shock (OIDS), and the oil-specific consumption demand shock (OCDS). The oil shocks are available at a monthly frequency from 1975:M2 to 2022:M6, and hence are averaged to quarterly values[3]. Based on the availability of the aggregate expected skewness and the four oil shocks, our common sample covers 1975:Q1 to 2022:Q2. We present the summary of the data statistics in Table 1.

Table 1. Summary statistics.

	EAS	OSS	OCDS	OIDS	SF
Mean	−0.01	−0.05	−0.10	0.01	−0.98
Median	0.03	−0.06	0.08	−0.01	0.38
Maximum	1.37	3.14	8.02	1.67	5.73
Minimum	−1.70	−3.64	−9.17	−1.68	−18.49
Std. Dev.	0.34	0.93	2.42	0.66	5.05
Skewness	−0.60	0.05	−0.26	−0.02	−1.25
Kurtosis	7.98	4.66	4.41	3.17	4.33
Observations	189.00	189.00	189.00	189.00	189.00

2.2. Econometric Models

The standard model for calculating impulse response functions (IRFs) using the local projections (LPs) method of Jordà (2005) can be defined as follows:

$$SF_{t+s} = \alpha_s + \beta_s Oil\ Shock_t + \epsilon_{t+s}, \quad \text{for } s = 0, 1, 2, \ldots H \tag{3}$$

where SF_{t+s}, is the expected macroeconomic skewness factor of the US at time t+s. β_s captures the response of the skewness factor at time t+s to an observed oil shock ($Oil\ Shock_t$) at time t. The LP-IRFs are derived from a series of β_s which are estimated separately by the ordinary least squares (OLS) method at each horizon (s)[4].

As outlined in the introduction, we also test whether the impacts of the oil market shocks on the expected macroeconomic skewness are contingent on whether the economy is subjected to a negative or positive state of skewness. Equation (3) can then be rewritten into a state-dependent model where IRFs depend differently and are contingent on downside or upside risks (Ahmed and Cassou 2016). A dummy variable that distinguishes positive and negative values of the expected aggregate skewness factor can be included in the following nonlinear model specified as follows:

$$\begin{aligned} SF_{t+s} = (1 - D_t)\left[\alpha_s^{positive} + \beta_s^{positive} Oil\ Shock_t\right] + D_t\Big[\alpha_s^{negative} + \\ \beta_s^{negative} Oil\ Shock_t\Big] + \epsilon_{t+s}, \quad \text{for } s = 0, 1, 2, \ldots h, \end{aligned} \tag{4}$$

where D_t is a dummy variable measuring the regimes of the expected macroeconomic skewness factor. D_t takes a value of 1 if the skewness factor is negative, and 0 otherwise. Superscripts *positive* and *negative* represent the regimes of the skewness factor, i.e., its positive and negative values, respectively.

3. Empirical Results

In Figure 1, the linear LP IRFs show how the quarterly macroeconomic expected skewness factor responds to a one-unit increase in the disaggregated oil shocks over the 12-month forecast horizon.

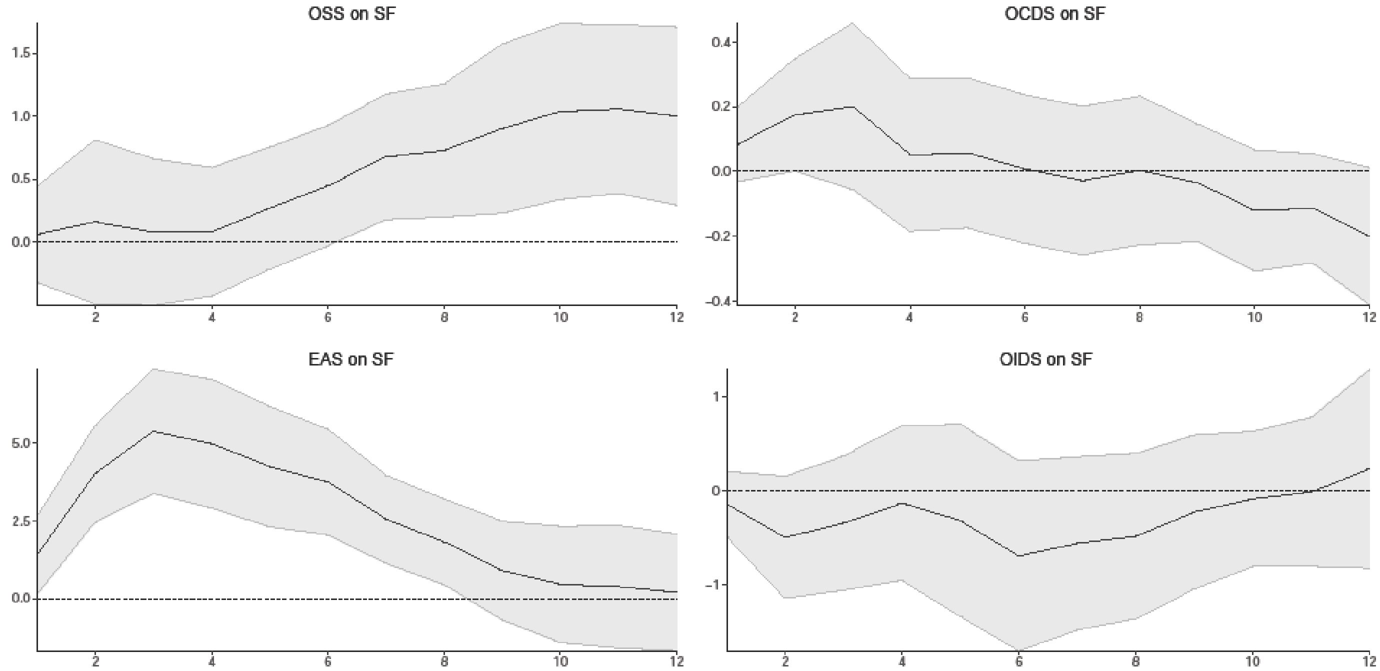

Figure 1. Linear effects of disaggregated oil shocks on the quarterly macroeconomic expected skewness factor (1975:Q1–2022:Q2). Note: OSS, EAS, OCDS, and OIDS represent the oil supply, global economic activity, oil-specific consumption demand and OIDS shocks, respectively. The figures show the impulse response of the expected skewness factor (*SF*) to a one-unit increase in a specific disaggregated oil shock. The shaded areas are the 90% confidence bands.

Our results also show that the positive effect of the oil supply shock (OSS) on the aggregate expected skewness factor is statistically insignificant in the short term but becomes statistically significant after six quarters of impact. As far as the economic activity shock (EAS) is concerned, the positive effect is statistically significant eight quarters ahead on the aggregate expected skewness factor, before it becomes statistically insignificant from the ninth quarter. We find statistically insignificant effects of the oil-specific consumption demand shock (OCDS) and the oil inventory demand shock (OIDS) on the macroeconomic expected skewness factors over the entire forecast horizon[5].

More importantly, the effects of the disaggregated oil shocks on the macroeconomic skewness factor align with economic intuition, in light of the findings of Iseringhausen et al. (2022), reporting that the expected macroeconomic skewness is strongly procyclical. The extant literature suggests that the EAS leads to an increase in economic activity, while the OSS, associated with a rise in oil production and lowers oil prices, is also expansionary in terms of economic activity. In contrast, the OIDS, which is often referred to as a speculative demand shock, is found to have a negative effect on economic activity, while the OCDS—a precautionary demand shock—is known to have no effect on subsequent economic activity (Baumeister and Hamilton 2019); however, both these shocks raise oil prices. Given the above, it is not surprising to see a positive and statistically significant effect of OSS and EAS, and a negative (though statistically insignificant) impact due to OIDS on the aggregate expected skewness of the US economy.[6]

Next in Figure 2, we present the results for the impact of the four oil shocks on the expected macroeconomic skewness, but now conditional on its state, i.e., positive or negative values. As before, the delayed positive effect of the OSS for upside risks is only significant beyond 10 quarters ahead, while, for downside risks, significance holds between 5 and 10 quarters ahead following the shock. Interestingly, EAS has a statistically significant positive impact when only the expected macroeconomic skewness is negative, i.e., under a recessionary regime. As with the results for the expected aggregate skewness under the linear model, OIDS and OCDS continue to have an insignificant predictive impact under the nonlinear framework. In essence, the nonlinear framework highlights the fact that the overall results are primarily driven by the downside risk state of the expected aggregate skewness. In other words, OSS and EAS are likely to have a positive predictive impact on the expected aggregate skewness in a recessionary macroeconomic state. Given the procyclical nature of the aggregate expected skewness factor, our observations are vindicated by the empirical evidence that oil price movements tend to better predict recessions than recoveries (Engemann et al. 2011; Kilian and Vigfusson 2017).

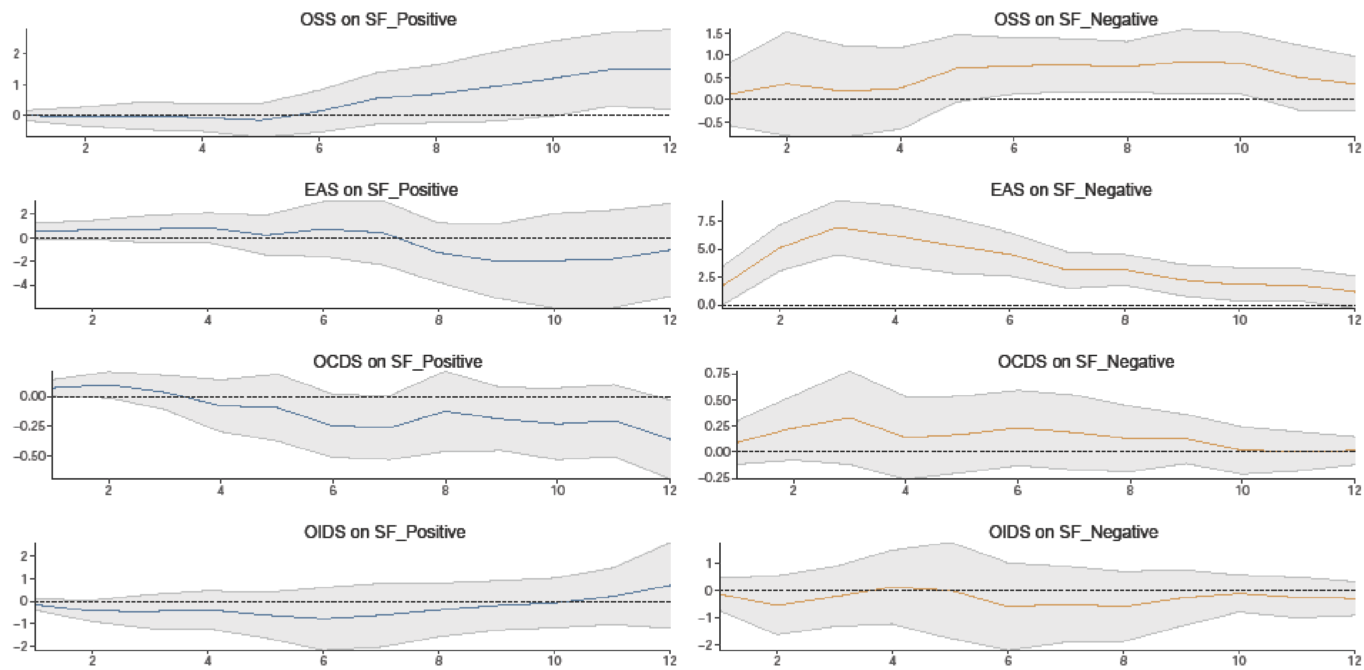

Figure 2. Nonlinear effects of disaggregated oil shocks on the quarterly macroeconomic expected skewness factor (1975:Q1–2022:Q2). Note: OSS, EAS, OCDS, and OIDS represent the oil supply, global economic activity, oil-specific consumption demand and OIDS shocks, respectively. The figures show the impulse response of the positive (SF_Positive) and negative (SF_Negative) expected skewness factor (SF) to a one-unit increase in a specific disaggregated oil shock. The shaded areas are the 90% confidence bands.

4. Discussion

From a policy perspective, our results imply that policymakers must, first, be aware that it is very important to identify the source of an oil price change, i.e., what shock is driving the oil market, since price increases through oil inventory demand and oil-specific consumption demand shocks will have no impact on the expected macroeconomic skewness, while upside risk will occur following a positive global demand shock. At the same time, a decline (rise) in oil price due to a positive (negative) oil supply shock involving an increase (reduction) in oil production will predict a downside risk in the medium to long term. Second, policy authorities must also recognise that the effects of the oil supply and global economic activity shocks carry relatively stronger predictive ability for the expected macroeconomic skewness when the latter is in its lower regime (negative values), i.e., when the economy is witnessing downside risks. With oil shocks now impacting the aggregate economy and financial markets via the expected macroeconomic skewness as an additional route over and above the channels discussed in the introduction (namely, supply, demand, asset valuation, policies, and uncertainty), oil price movements are now likely to have a more persistent effect on the US economy, which the policymakers should also keep in mind. Against this backdrop, comparatively stronger expansionary policies need to be undertaken if the US is hit by negative oil supply and economic activity shocks, especially if the economy is already facing downside risks and an associated recession.

5. Conclusions

In this paper, we analysed the impact of disaggregated oil (supply, global economic activity, oil-specific consumption demand and oil-inventory-demand) shocks on the expected macroeconomic skewness of the US economy, based on a data-rich environment, over the quarterly period of 1975:Q1 to 2020:Q2.

To the best of our knowledge, this paper is the first empirical study to investigate the effects of disaggregated oil shocks on the overall expected macroeconomic skewness in the US and its associated states involving negative and positive skewness. With skewness being an important metric for policymakers to communicate their beliefs about the evolution of future risks, our results have important implications for policy decisions.

Our results show that oil supply and economic activity shocks increase the expected aggregate skewness factor in a statistically significant fashion, while the oil inventory demand and oil-specific consumption demand shocks have no predictive capacity. In addition, we have found that distinguishing the state of the expected aggregate skewness into its positive and negative values to capture upside and downside risks, respectively, points to the fact that the predictive impact of the oil supply and economic activity shocks primarily originate in a negative regime.

It is noteworthy that in this study we limit our focus to the predictive link of oil shocks to the metric of expected aggregate skewness in the US economy. A comparison study across countries could be a promising area to pursue for future research. In addition, given existing studies indicate closer relationships between oil price movements and macroeconomic and financial variables during the global financial crisis and the COVID-19 pandemic, further studies could be carried out to examine the dynamic responses of skewness to oil shocks during these crisis periods. In addition, it would be interesting to analyse the effects of oil price volatility, i.e., second moment impacts on the aggregate expected uncertainty of the US, in light of the evidence of oil market uncertainty adversely impacting economic activity and the financial markets. In this regard, one can rely on the VAR-Generalised Autoregressive Conditional Heteroskedasticity in Mean (VAR-GARCH-M) econometric specification when dealing with oil uncertainty and its impact[7].

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

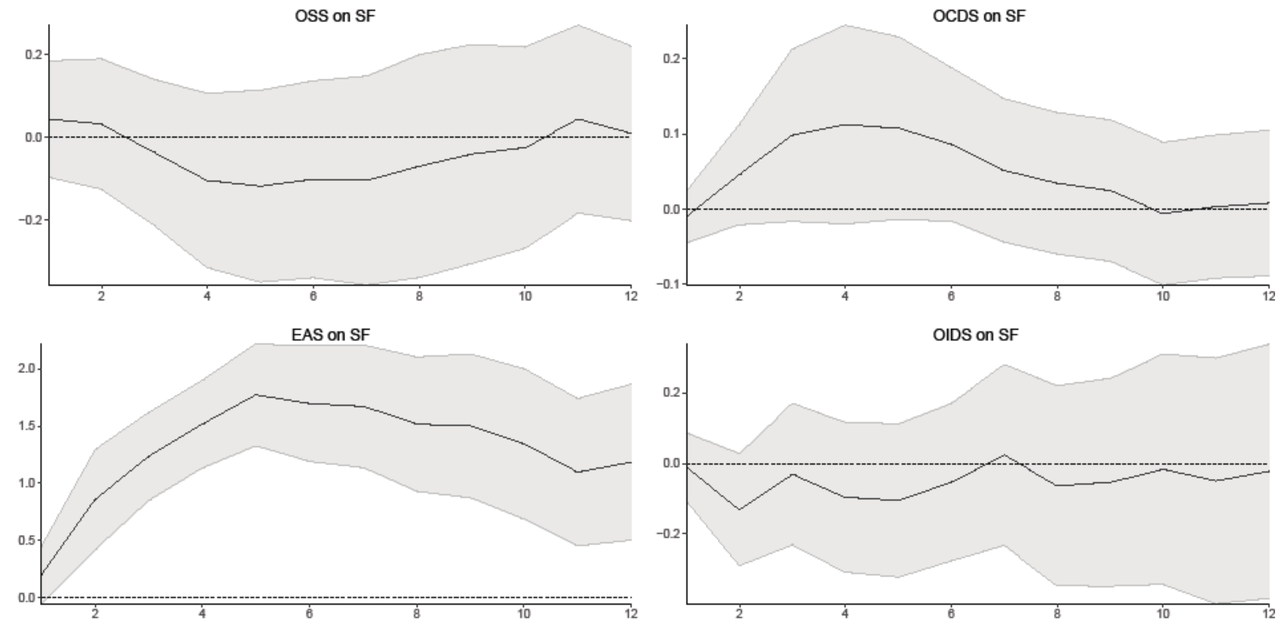

Figure A1. Linear effects of disaggregated oil shocks on the monthly macroeconomic expected skewness factor (1975:M2–2022:M6). Note: OSS, EAS, OCDS, and OIDS represent the oil supply, global economic activity, oil-specific consumption demand and OIDS shocks, respectively. The figures show the impulse response of the expected skewness factor (*SF*) to a one-unit increase in a specific disaggregated oil shock. The shaded areas are the 90% confidence bands.

Notes

1 We first fitted the GARCH model to real West Texas Intermediate (WTI) oil returns to deduce its uncertainty over the quarterly and monthly periods of 1960:Q1 to 2022:Q2 and 1960:M1 to 2022:M8, respectively, with the WTI oil price obtained from the FRED database of the Federal Reserve Bank of St. Louis. Secondly, when the corresponding measures of aggregate expected skewness of the US were regressed on oil price uncertainty at monthly and quarterly frequencies, in line with intuition, we found that the estimated OLS coefficients are −8.14 and −60.61, respectively, with both being statistically significant at the highest level. In addition, using a quantile regression approach (Koenker and Bassett 1978), we found a statistically significant impact of quarterly (monthly) oil uncertainty at the quantiles of 0.10, 0.50 and 0.90 equal to −20.77, −12.47, and −3.19 (−176.65, −72.61, and −40.93), respectively. This implies that oil uncertainty affects downside risks more than upside values of the same, in line with the evidence found by Rahman and Serletis (2010) that suggests that oil volatility reduces economic activity more in recessions than in expansions. Further details of these results are available upon request from the authors.

2 The data is downloadable from: https://sites.google.com/site/konstantinostheodoridis/aggregate-skewness-index?authuser=0, accessed on 1 October 2022.

3 The data can be downloaded from: https://sites.google.com/site/cjsbaumeister/datasets?authuser=0, accessed on 1 October 2022.

4 See Jordà (2005) for detailed discussions about the technical details of the LP method.

5 Iseringhausen et al. (2022) also computed a monthly version of the aggregate expected skewness measure based on 132 variables derived from the FRED-MD database of McCracken and Ng (2016). We repeated the LP-IRFs analysis of the oil shocks on the monthly version of the factor over the period of 1975:M2–2022:M6. As observed from Appendix A Figure A1, as with the quarterly data, OCDS and OIDS continue to have insignificant impacts, while the EAS has a positive and significant effect over the entire one-year-ahead horizon. The only difference is that the effect of OSS is no longer significant, which could possibly be a result of the narrower information content of the underlying database, particularly associated with the real side of the economy.

6 In our analysis of the predictive role of oil shocks, we also utilised the alternative quarterly and annual expected skewness measures of the growth rates of employment, sales, and productivity derived by Salgado et al. (2020) based on firm-level panel data from the US Census Bureau and almost fifty other countries (downloadable from: https://sergiosalgado.net/home/data/, accessed on 1 October 2022), as well as firm-level (value-weighted average across firms), market-level (for the S&P500), and idiosyncratic option-implied expected skewness of Dew-Becker (2022), available at: http://www.dew-becker.org/ (accessed on 1 October 2022). In general, just like the aggregate measure of expected skewness, we primarily detected the positive significant

predictive effect of OSS and EAS shocks, with some evidence of the precautionary OCDS shock significantly reducing these financial market-oriented metrics of skewness. Interestingly, the speculative OIDS shock at times is found to increase in a statistically significant manner, rather than decrease skewness. This finding is in line with Gupta et al. (2021), who showed that negative tail risks can decrease following oil price rises associated with the OIDS shock due to declines in uncertainty, which causes increases in skewness. The complete details of these results are available upon request from the authors.

7 We first fitted the GARCH model to real West Texas Intermediate (WTI) oil returns to deduce its uncertainty over the quarterly and monthly periods of 1960:Q1 to 2022:Q2 and 1960:M1 to 2022:M8, respectively, with the WTI oil price obtained from the FRED database of the Federal Reserve Bank of St. Louis. Secondly, when the corresponding measures of the aggregate expected skewness of the US were regressed on oil price uncertainty at monthly and quarterly frequencies, in line with intuition, we found that the estimated OLS coefficients are −8.14 and −60.61, respectively, with both being statistically significant at the highest level. In addition, using a quantile regression approach (Koenker and Bassett 1978), we found a statistically significant impact of quarterly (monthly) oil uncertainty at the quantiles of 0.10, 0.50 and 0.90 equal to −20.77, −12.47, and −3.19 (−176.65, −72.61, and −40.93), respectively. This implies that oil uncertainty affects downside risks more than upside values of the same, in line with the evidence found by Rahman and Serletis (2010) that suggests that oil volatility reduces economic activity more in recessions than in expansions. Further details of these results are available upon request from the authors.

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