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Book

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

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We analyse the impact of oil supply, global economic activity, oil-specific consumption demand, and oil inventory demand shocks on expected aggregate skewness of the United States (US) economy, obtained based on a data-rich environment involving 211 macroeconomic and financial variables over 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 manner, 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 Codes: 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) develop a data-rich measure of expected macroeconomic skewness in the United States (US) economy, which in turn is 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) relies on common movements of skewness of 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, besides 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 policy authorities is the identification of underlying factor(s) that predict the expected skewness. In light of the widespread evidence of the role of oil price movements in historically driving wide-array of macroeconomic and financial variables of the US economy (Fry-McKibbin and Zhu, 2021; De et al., 2022), our aim is 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 emanate 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 risk (negative values of expected aggregate skewness) or upside risk (positive values of expected aggregate skewness).

Econometrically, we estimate the impact of four structural oil-market shocks on the expected aggregate skewness over the quarterly period of 1975:Q1 to 2022:Q2, using impulse response functions (IRF) generated from the local projection (LP) method advocated by Jordà (2005). Jordà (2005) proposes the LP approach for calculating IRF, which does not require restrictive assumptions on the specification and estimation of the unknown true multivariate system itself and, thus, has a distinct advantage over the traditional Vector Autoregression (VAR) approach. Furthermore, the LP approach uses simple regression estimation techniques (such as the Ordinary Least Squares (OLS) method) and can easily accommodate 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 research is organised as follows: Section 2 discusses the data and methodology, while Section 3 presents the empirical results, with Section 4 concluding the paper.

2. Dataset and Methodology

2.1. Data

The expected macroeconomic skewness data are obtained from the study of Iseringhausen et al. (2022),[1] who use the quarterly version of the McCracken and Ng (2020) dataset (FRED-QD) that contains 248 time series starting from 1959 and categorised into 14 groups (national income and product accounts (NIPA); industrial production; employment and unemployment; housing; inventories, orders, and sales; prices; earnings and productivity; interest rates; money and credit; household balance sheets; non-household balance sheets; stock markets; exchange rates; and other). All variables are transformed to make them stationary by using the transformations suggested by the authors. Iseringhausen et al. (2022) remove those series that have missing observations over the sample period of 1960:Q1 to 2022:Q2, which then reduces the number of variables 211. Next, Iseringhausen et al. (2022) estimate each (de-meaned)

[1] The data is downloadable from: https://sites.google.com/site/konstantinostheodoridis/aggregate-skewness-index?authuser=0.

variable y_i and each quantile level $p = \{10\%,\ 50\%,\ 90\%\}$, following the autoregressive quantile regression as developed in Engle and Manganelli (2004):

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

where $i = 1, \dots, N$ and $t = 2, \dots, T$. Using the estimated model parameters from these quantile regressions, and assuming that agents use Equation (1) to form their expectations, Iseringhausen et al. (2022) compute for each variable the one-step-ahead expected, or predicted, Kelley skewness (Kelley, 1947) as follows:

$$\mathbb{E}_t[Skew(y_{i,t+1})] = \frac{\mathbb{E}_t[Q_{i,t+1}^{0.9}] + \mathbb{E}_t[Q_{i,t+1}^{0.1}] - 2\mathbb{E}_t[Q_{i,t+1}^{0.5}]}{\mathbb{E}_t[Q_{i,t+1}^{0.9}] - \mathbb{E}_t[Q_{i,t+1}^{0.1}]}. \qquad (2)$$

The overall measure of expected asymmetry is then constructed as the first principal component obtained from the set of series-specific expected skewness measures, where each measure is first standardised by subtracting the series-specific mean and dividing by its standard deviation. 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 obtained from the estimation of a structural vector autoregressive (SVAR) model following the work of Baumeister and Hamilton (2019), who formulate a less restrictive framework (than what has been traditionally used in the literature following Kilian (2009)), by incorporating uncertainty about the identifying assumptions of the SVAR. In other words, the obtained oil-market shocks can be considered to be relatively more accurately estimated. 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-specific consumption demand shock (OCDS), and the oil inventory demand shock (OIDS). The oil shocks are available at a monthly frequency from 1975:M2 to 2022:M6, and hence are averaged to quarterly values.[2] Based on the availability of the aggregate expected skewness and the four oil shocks, our common sample covers 1975:Q1 to 2022:Q2.

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:

$$SF_{t+s} = \alpha_s + \beta_s Oil\ Shock_t + \epsilon_{t+s},\ \text{ for } s = 0,1,2, \dots H \qquad (3)$$

[2] The data can be downloaded from: https://sites.google.com/site/cjsbaumeister/datasets?authuser=0.

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).[3]

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:

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

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

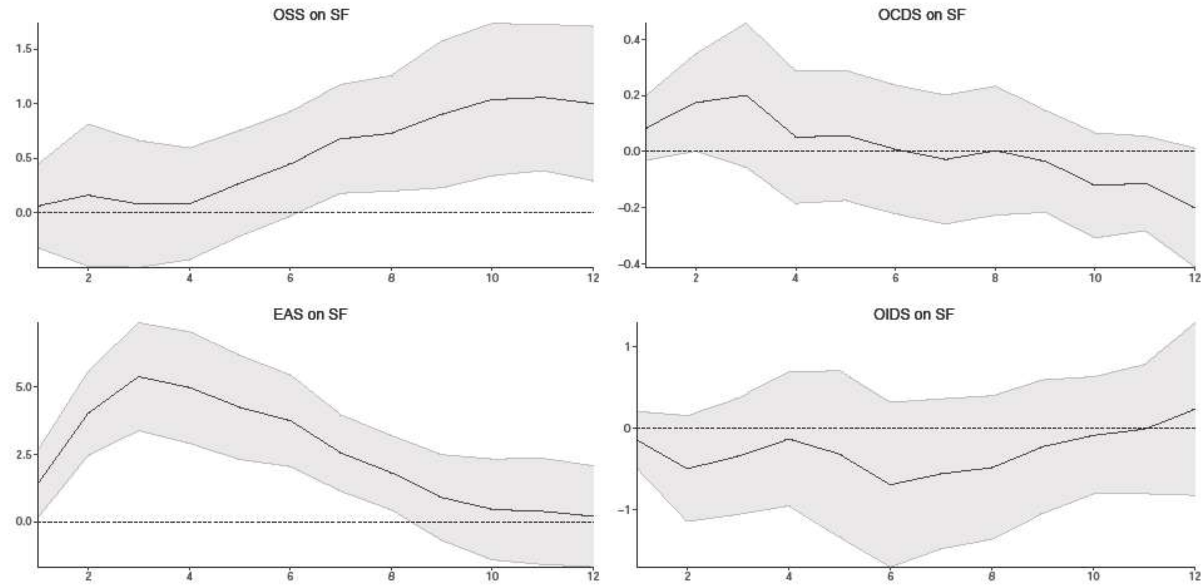
In Figure 1, the linear LP IRFs show how the quarterly macroeconomic expected skewness factor responds to a one-unit increase in the disaggregated oil shocks over the 12-period forecast horizon.

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 6 quarters of impact. As far as the economic activity shock (EAS) is concerned, the positive effect is statistically significant around 8-quarters-ahead on the aggregate expected skewness factor. 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.[4]

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

[4] Iseringhausen et al. (2022) also computes 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 as well over the period of 1975:M2-2022:M6. As observed from 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 of the one-year-ahead horizon. The only

Figure 1: Linear Effects of Disaggregated Oil Shocks on the Quarterly Macroeconomic Expected Skewness Factor (1975:Q1-2022:Q2)



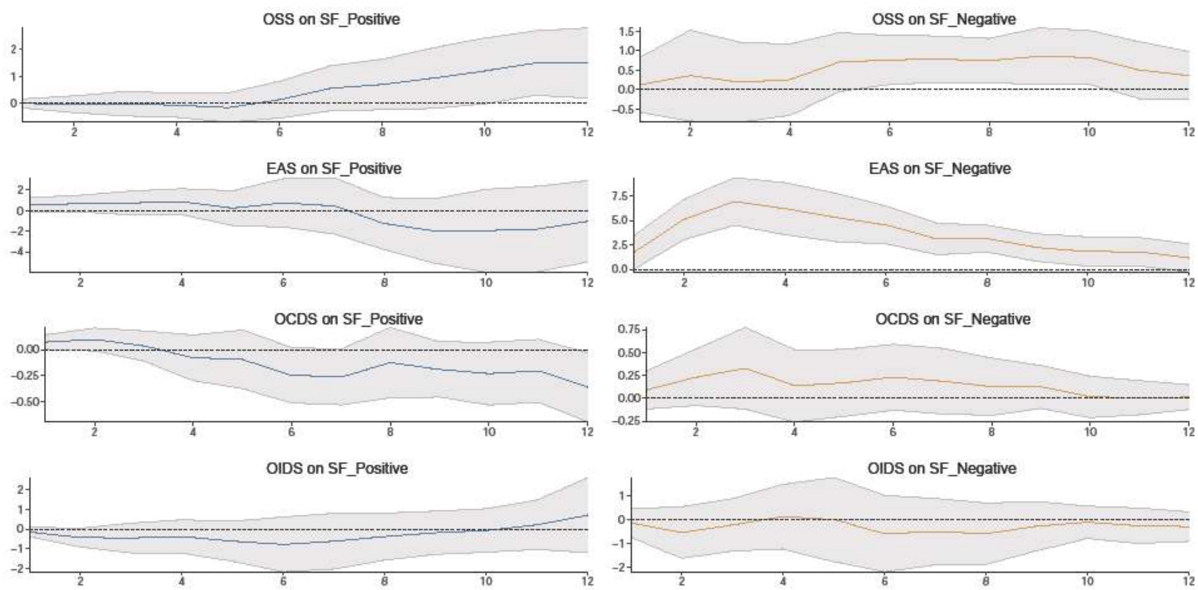
Note: OSS represents oil supply shock; EAS represents global economic activity shock; OCDS represents oil-specific consumption demand shock; OIDS represents oil inventory demand shock. The figures show the impulse response of the Expected Skewness Factor (*SF*) to a one-unit increase in a specific disaggregated oil shock. The shaded areas represent the 90% confidence bands.

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), who report 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), though 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.[5]

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.

[5] In our analysis of the predictive role of oil shocks, we also utilize 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/), as well as firm- (value-weighted average across firms), market-level (for the S&P500), and idiosyncratic option-implied expected skewness of Dew-Becker (2022), available at:

Figure 2: Nonlinear Effects of Disaggregated Oil Shocks on the Quarterly Macroeconomic Expected Skewness Factor (1975:Q1-2022:Q2)



Note: OSS represents oil supply shock; EAS represents global economic activity shock; OCDS represents oil-specific consumption demand shock; OIDS represents oil inventory demand shock. 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 represent the 90% confidence bands.

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 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 only when the expected macroeconomic skewness is in its negative, i.e., under the 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 too. In essence, the nonlinear framework highlights the fact that the overall results are primarily

http://www.dew-becker.org/. In general, just like the aggregate measure of expected skewness, we primarily detect 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 show that negative tail risks can go down following oil price rises associated with the OIDS shock, due to declines in uncertainty, which causes increases in skewness. Complete details of these results are available upon request from the authors.

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 predict recessions better than recoveries (Engemann et al., 2011; Kilian and Vigfusson, 2017).

4. Conclusion

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

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 result 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 recognize 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 policy needs 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 associated recession.

As part of future research, 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 impacting adversely economic activity and financial markets (Salisu et al., 2022; 2023). In this regard, one can rely on the VAR-Generalized Autoregressive Conditional Heteroskedasticity in Mean (VAR-GARCH-M) econometric specification popularized by Elder and Serletis (2010) when dealing with oil uncertainty and its impact.[6]

[6] We firstly fitted GARCH model fitted 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 was 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 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 oil volatility reduces economic activity more in recessions than in expansions. Further details of these results are available upon request from the authors.

References

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. American Economic Review, 109(4), 1263-1289.

Ahmed, M.I., and Cassou, S.P. (2016). Does consumer confidence affect durable goods spending during bad and good economic times equally? Journal of Macroeconomics, 50, 86-97.

Bachmeier, L.J., and Plante, M.D. (2019). Oil prices and the macroeconomy. Handbook of Energy Economics, Edited by U. Soytaş and R. Sari, 1st Edition, Routledge, Chapter 3, 45-65.

Baumeister, C., and Hamilton, J.D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. American Economic Review, 109(5), 1873-1910.

De, K., Compton, R.A., and Giedeman D.C. (2022). Oil Shocks and the U.S. Economy in a Data-rich Model. Economic Modelling, 108, 105755.

Degiannakis, S.A., Filis, G., and Arora, V. (2018). Oil Prices and Stock Markets: A Review of the Theory and Empirical Evidence. The Energy Journal, 39(5), 85-130.

Dew-Becker, I. (2022). Real-time forward-looking skewness over the business cycle. Mimeo, Northwestern University.

Engle, R.F., and Manganelli, S. (2004). CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles. Journal of Business & Economic Statistics, 22(4), 367–381.

Elder, J., and Serletis, A. (2010). Oil Price Uncertainty. Journal of Money, Credit and Banking, 42(6), 1137-1159.

Engemann, K.E., Kliesen, K.L., and Owyang, M.T. (2011). Do Oil Shocks Drive Business Cycles? Some U.S. and International Evidence. Macroeconomic Dynamics, 15(Supplement S3: Oil Price Shocks), 498-517.

Fry-McKibbin, R., and Zhu, B. (2021). How do oil shocks transmit through the US economy? Evidence from a large BVAR model with stochastic volatility. CAMA Working Papers 2021-13, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.

Gupta, R., Sheng, X., Pierdzioch, C., and Ji, Q. (2021). Disaggregated oil shocks and stock-market tail risks: Evidence from a panel of 48 economics. Research in International Business and Finance, 58, 101515.

Hamilton, J.D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57(2), 357-384.

Hamilton, J.D. (2011). Nonlinearities and the Macroeconomic Effects of Oil Prices. Macroeconomic Dynamics, 15(Supplement S3: Oil Price Shocks), 364-378.

Iseringhausen, M., Petrella, I., and Konstantinos, T. (2022). Aggregate skewness and the business cycle. European Stability Mechanism, Working Paper Series, No. 53-2022.

Jensen, H., Petrella, I., Ravn, S.H., and Santoro, E. (2020). Leverage and deepening business-cycle skewness. American Economic Journal: Macroeconomics, 12(1), 245-81.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. American economic review, 95(1), 161-182.

Kelley, T.L. (1947). Fundamentals of Statistics. Harvard University Press.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99, 1053-1069.

Kilian, L., and Vigfusson, R.J. (2017). The Role of Oil Price Shocks in Causing U.S. Recessions. Journal of Money, Credit and Banking, 49(8), 1747-1776.

Koenker, R., and Bassett, G. (1978). Regression Quantiles. Econometrica, 46(1), 33-50.

McCracken, M.W., and Ng, S. (2016). FRED-MD: A Monthly Database for Macroeconomic Research. Journal of Business and Economic Statistics, 34(4), 574-589.

McCracken, M.W., and Ng, S. (2020). FRED-QD: A Quarterly Database for Macroeconomic Research, Federal Reserve Bank of St. Louis Working Paper 2020-005.

Rahman, S., and Serletis, A. (2010). The asymmetric effects of oil price and monetary policy shocks: A nonlinear VAR approach. Energy Economics, 32(6), 1460-1466.

Rahman, S., and Serletis, A. (2011). The Asymmetric E§ects of Oil Price Shocks. Macroeconomic Dynamics, 15(Supplement S3: Oil Price Shocks), 437-471.

Salgado, S., Guvenen, F., and Bloom, N. (2020). Skewed business cycles. National Bureau of Economic Research (NBER) Working Papers, No. 26565.

Salisu, A.A., Gupta, R., and Demirer, R. (2022). Oil Price Uncertainty Shocks and Global Equity Markets: Evidence from a GVAR Model. Journal of Risk and Financial Management,15(8), 355.

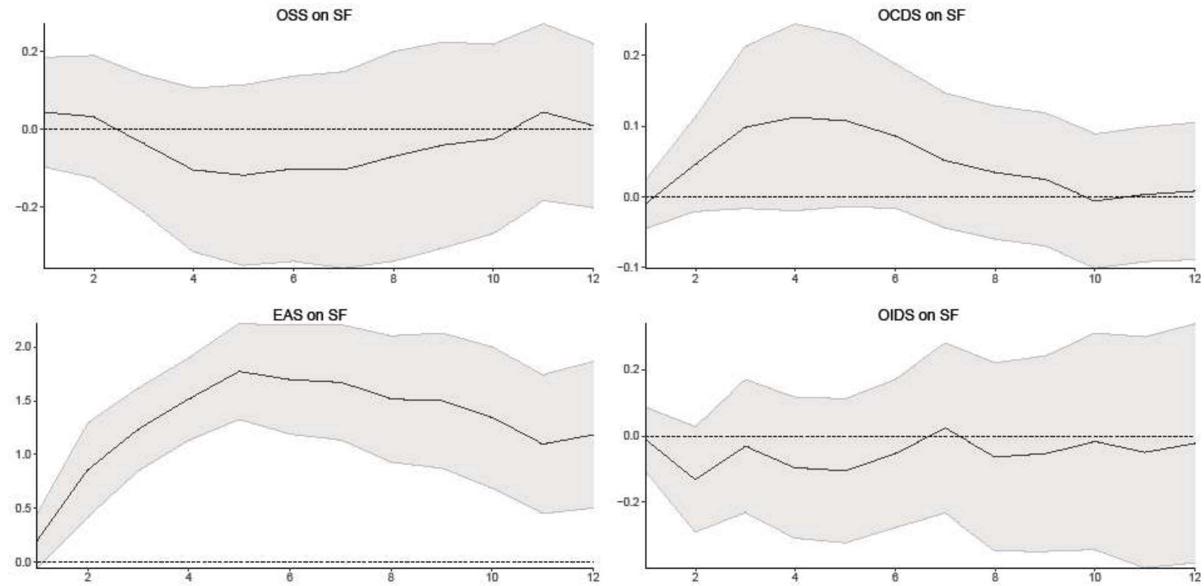
Salisu, A.A., Gupta, R., and Olaniran, A. (2023). The effect of oil uncertainty shock on real GDP of 33 countries: A global VAR approach. Applied Economics Letters, 30(3), 269-274.

Smyth, R., and Narayan, P.K. (2018). What do we know about oil prices and stock returns? International Review of Financial Analysis, 57, 148-156.

Zhang, B., Ai, X., Fang, X., and Chen, S. (2022). The Transmission Mechanisms and Impacts of Oil Price Fluctuations: Evidence from DSGE Model. Energies, 15, 6038.

Appendix

Figure A1: Linear Effects of Disaggregated Oil Shocks on the Monthly Macroeconomic Expected Skewness Factor (1975:M2-2022:M6)



Note: OSS represents oil supply shock; EAS represents global economic activity shock; OCDS represents oil-specific consumption demand shock; OIDS represents oil inventory demand shock. 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 represent the 90% confidence bands.