Disaggregated Oil Shocks and Stock-Market Tail Risks: Evidence from a Panel of 48 Economies[#]

Rangan Gupta[*], Xin Sheng[**], Christian Pierdzioch[***] and Qiang Ji[****]

Abstract

We analyse the impact of oil supply, global economic activity, oil-specific consumption demand, and oil-inventory demand shocks on equity-market tail risks of a panel of 48 developed and emerging economies over the monthly period from 1975:01 to 2017:12. We find that oil supply, global economic activity, and oil-inventory demand shocks reduce tail risks, but oil-specific consumption demand shock increases tail risks, with these effects stronger in oil-exporting economies. Our results have important implications for investors and policymakers.

Keywords: Oil shocks; Tail risks; International stock markets; Local projection model; Impulse response functions

JEL Codes: C23, G01, G11, G12, Q41

1. Introduction

Tail risk is the additional risk which, commonly observed, fat-tailed asset return distributions have relative to normal distributions (Li and Rose, 2009). Tail risks have been shown to predict not only stock-market returns but also real economic variables, such as employment, investment and output (Kelly and Jiang, 2014; Almeida et al., 2017; Hollstein et al., 2019). Naturally, determining which factors drive tail risks is an important question for both investors and policymakers. Given this, a couple of recent studies by Nicolò and Lucchetta (2017) and Gkillas et al., (2020) have estimated financial-market tail risks for the United States and Mexico and related them to a wide array of macroeconomic and financial variables.[1]

In this research, we aim to extend this line of research by relating stock-market tail risks of a panel of 48 developed and emerging economies, derived from the cross-section of stock returns in each of the stock markets, with oil-market shocks. The decision to relate oil-market shocks to stock-market tail risks is motivated by the large literature that exists (see Degiannakis et al., (2018), Smyth and Narayan (2018), and Shahzad et al., (2021) for detailed reviews) regarding the relationship between these two markets, due to the underlying multiple channels, namely,

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[1] Recently, quite a few recent studies have tried to determine the factors governing tail risks of macroeconomic variables (see for example, Adrian et al., (2019), Cook and Doh (2019), Loria et al., (2019), Carriero et al., (2020)).

stock valuation, monetary and fiscal policy, output, and uncertainty, through which the oil price can affect stock markets.[2] In other words, oil-market shocks by themselves tend to contain leading information for a gamut of macroeconomic and financial variables (Lombardi et al., 2012; Ji et al., 2020) that can drive stock-market tail risks. Further, realizing that not all oil price changes emanate from supply shocks, we also analyze the role of global demand (economic activity), precautionary (oil-specific consumption), and speculative (oil inventory) shocks on the tail risks, given the varied impact of the nature of oil-market shocks on stock markets (Kilian and Park, 2009).[3] Besides this, we also account for the issue of whether our results are contingent on the countries being exporters or importers of oil, tail risks of which in turn could likely be affected differently following these oil-market shocks, as often outlined for overall stock returns and other economic and financial variables (see Bouoiyour et al., (2017) and Shahzad et al., (2020) for a review of the relevant literature in this regard).

Econometrically, we estimate the impact of four structural oil-market shocks on tail risks over the monthly period from 1975:01 to 2017:12, using impulse response functions (IRF) generated from the local projection (LP) approach 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 exporters and importers. To the best of our knowledge, this is the first empirical study to analyse the impact of oil-market shocks on stock-market tail risks for a large panel of developed and developing oil-exporting and importing economies.

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. Data and Methodology

2.1. Data

The tail risks data are obtained from the work of Hollstein et al., (2019),[4] which is based on returns derived from stock indexes of all Morgan Stanley Capital International (MSCI) developed and emerging markets economies, which in turn involves the cross-sections of 48 different countries and regions.[5] The paper followed the estimation procedure of the tail risk

[2] In a related line of literature, Ji et al., (2018) also document evidence of volatility and information transmissions between oil and stock markets. Bouri et al., (2020) find that lagged volatility of the commodity and energy markets can help in predicting the volatility of sovereign risk in BRIC countries, i.e., Brazil, Russia, India, and China. This provides more channels through which oil price shocks can impact international stock markets

[3] Following Baumeister and Hamilton (2019), oil shocks are decomposed according to their origin into four different types, i.e., oil supply shocks (OSS) that are associated with shocks to oil supply, economic activity shocks (EAS) that are related to global aggregate demand, oil inventory demand shocks (OIDS) that can be described as speculative demand shocks, and oil-specific consumption demand shocks (OCDS) that capture shifts in precautionary demand for oil.

[4] We would like to thank Marcel Prokopczuk for kindly providing us with the data set on the tail risks.

[5] The economies included in the sample are: Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia,

(TR) measure introduced by Kelly and Jiang (2014). The tail risk is measured by the tail parameter of the tail distribution. The distribution of returns is assumed to obey a potentially time-varying power law and the tail parameter is estimated from the cross-section of stock returns. The tail probability distribution of an asset's return is given by: $P(r_{i,t+1} < R | r_{i,t+1} < u_t; \mathbb{F}_t = \left(\frac{R}{u_t}\right)^{-a_i/\lambda_t}$, where $r_{i,t+1}$ is the return of asset i on day $t+1$, $\mathbb{F}t$ is the information set at time t and u_t is the tail threshold, where $R< u_t<0$.[6] a_i/λ_t is the tail exponent which determines the shape of the tail, where a_i is a constant which determines the level of tail risk of a certain asset i and λ_t, which we use as a measure of tail risk ($TR_t = \lambda_t$), determines the common dynamics of the tail risk across assets. The TR_t is estimated by the power-law estimator of Hill (1975) using the cross-section of daily return observations for all stocks at time t, thus: $TR_t = \frac{1}{K_t}\sum_{i=1}^{K_t} log\left(r^*{}_{i,t}\right) - log(u_t)$, where K_t is the total number of daily returns falling below the threshold u_t for period t, with the threshold fixed to the 5% quantile of the cross-sectional return distribution using a month of daily return data (Kelly and Jiang, 2014). The TR can be interpreted as a rate of decay in the left tail since a higher λ_t results in a fatter left tail.

As far as the four structural oil-shocks, i.e., oil supply shock (OSS), global economic activity shock (EAS), oil-specific consumption demand shock (OCDS), and oil-inventory demand shock (OIDS), are concerned, these are obtained from the structural vector autoregressive (SVAR) model of Baumeister and Hamilton (2019),[7] 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.

Our effective (unbalanced) panel dataset at monthly frequency ranges from 1975:01 to 2017:12, as determined by the availability of the tail-risks data.

2.2. Methodology

The linear model for calculating IRFs using the LP method of Jordà (2005) can be defined as follows:

$$TR_{i,t+s} = \alpha_{i,s} + \beta_s OilShock_t + \epsilon_{i,t+s}, for s = 0,1,2, \dots H \quad (1)$$

where $TR_{i,t}$ is the tail risks of country i at time t, s is the length of forecast horizons up to the maximum forecast horizon H,[8] $\alpha_{i,s}$ measures the fixed effect for the panel dataset, and β_s captures the responses of tail risks at time $t + s$ to an identified oil-market shock at time t. The LP-IRFs are calculated as a series of β_s which are estimated separately at each horizon (s).[9]

Ireland, Israel, Italy, Japan, Malaysia, Mexico, New Zealand, The Netherlands, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Kingdom (UK), the United Arab Emirates (UAE), and the United States (US).

[6] $r_{i,t} = (P_{i,t}/ P_{i,t-1}-1)$, where $P_{i,t}$ is the total return price index of asset i on day t.

[7] The data is available for download from the research segment of the website of Professor Christiane Baumeister at: https://sites.google.com/site/cjsbaumeister/research.

[8] Following Kang et al., (2014), we investigate the impact of oil price shocks over 24 months. The maximum length of forecast horizons is set to 24, corresponding to a 2-year forecast horizon.

[9] See Jordà (2005) for detailed discussions about the LP method.

We also test whether the impacts of oil-market shocks on tail risks are contingent on whether a specific country is an oil exporter or importer. Equation (1) can then be rewritten into a state-dependent model where IRFs depend differently on the oil-market profile of each country (Ahmed and Cassou, 2016). A dummy variable that distinguishes oil importers from exporters can be included in the following nonlinear model specified as follows:

$$TR_{i,t+s} = (1-D)\left[\alpha_{i,s}^{exp} + \beta_s^{exp} OilShock_t\right] + D\left[\alpha_{i,s}^{imp} + \beta_s^{imp} OilShock_t\right] + \epsilon_{t+s}, for s = 0,1,2, \dots H \quad (2)$$

where D is a dummy variable that takes a value of 1 if country i is an oil importer, and 0 otherwise. Superscripts exp and imp represent oil-exporting and importing economies, respectively.[10] The model distinguishes the responses to oil-market shocks of stock-market tail risks of oil importers from that of exporters.

3. Empirical Results

3.1. Main Analyses

In Figure 1, we present the impact of the four structural oil-market shocks on the tail risks. The figure tracks the responses calculated by local linear projections to a 1-unit increase of the disaggregated oil shocks on the future path of tail risks associated with the returns of the panel of 48 economies for 1 to 24-month-ahead, along with the 95% confidence bands. The first observation that we can draw is that all the oil-market shocks have a statistically significant impact over the 2-year horizon (barring the first 3 months and at the 7th month following the EAS shock). Next, we turn to the sign of the effect. We find that tail risks fall following a positive shock to oil production, i.e., oil supply, with this effect staying negative over the entire forecast horizon of two years. A positive global economic activity shock causes tail risks to be reduced over the entire forecasting horizon. When we look at the oil-specific consumption-demand shock, the effect is consistently positive for the entirety of the two-year-ahead forecast horizon. Finally, the impact of the oil-inventory-demand shock is consistently negative for a period of two years ahead following the shock. More importantly, the effects of the four oil-market shocks seem to be in line with intuition. A decline in oil price due to increase in oil production, and expansion of global economic activity that causes an oil-price increase, are perceived to be a positive news shock, and hence lead to a decline in tail risks, primarily due to output increases (Hollstein et al., 2019). In contrast, a precautionary oil-specific consumption demand shock tends to increase oil prices and increase tail risks, since this shock is generally regarded as negative news that adversely influences output and also raises uncertainty (Kang and Ratti, 2013).[11] The consistent and positive effect of an oil-specific consumption demand shock on tail risks is also in line with the finding from Ji et al. (2020) who highlight the importance of this type of oil shock in affecting the extreme risk in stock markets. When we look at the negative tail risks impact of the speculative oil-inventory-demand shock, which also tends to increase oil prices and is considered as negative news, our results seem to be defying intuition. But as recently shown by Sheng et al., (2020), such shocks

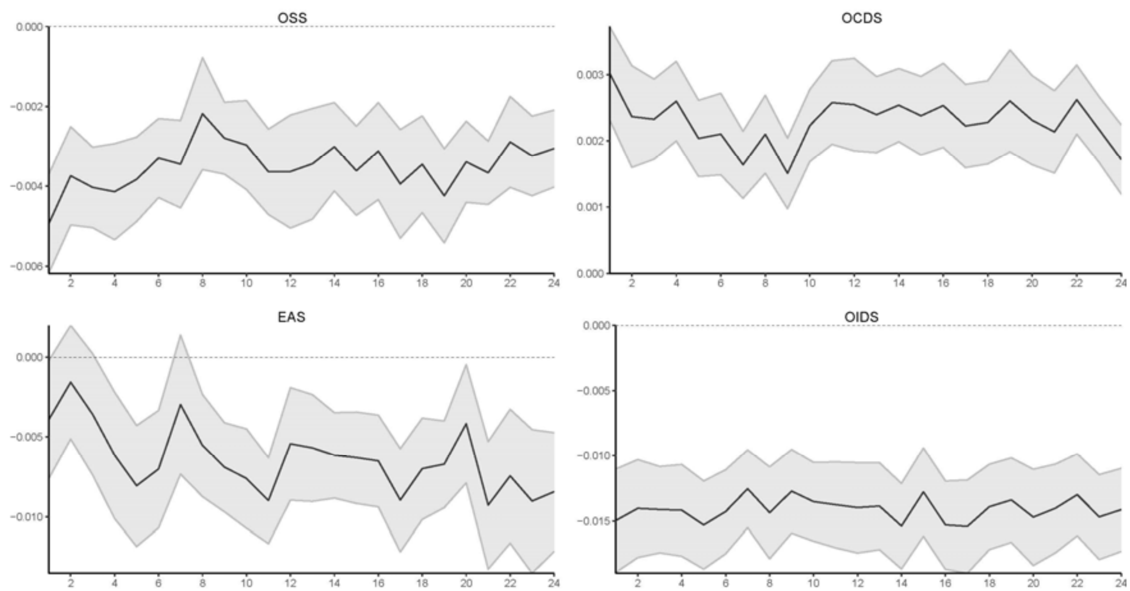
[10] Oil exporters in our dataset are based on the crude oil balance of trade derived from Enerdata, Energy Statistical Yearbook, 2019, and include Algeria, Argentina, Brazil, Canada, Colombia, Egypt, Iran, Kazakhstan, Kuwait, Malaysia, Mexico, Nigeria, Norway, Russia, Saudi Arabia, the UAE, and Venezuela. Understandably, the remaining 31 countries are characterized as oil importers.

[11] Kang et al. (2014) also find evidence that global economic activity shocks resulted from innovations in global demand for all industrial commodities can have persistent and statistically significant influences on real economic activity. Kilian and Park (2009) report evidence that unexpected increases in global aggregate demand are related to rises of real stock returns.

actually reduce global uncertainty (based on a panel of 45 countries) and do not necessarily reduce global economic activity (Baumeister and Hamilton, 2019), which, in turn, is possibly causing the observed decline in the tail risks. Moreover, as shown by Demirer et al., (2021), speculative risks from the oil market do not necessarily enhance the same for stock markets.

Finally, with all the shocks being of the same magnitude, i.e., 1-unit, we find that the strongest initial impact results from the oil-inventory-demand shock, followed by the oil-specific supply shock, and then due to the economic-activity shock and the oil-specific demand shocks.

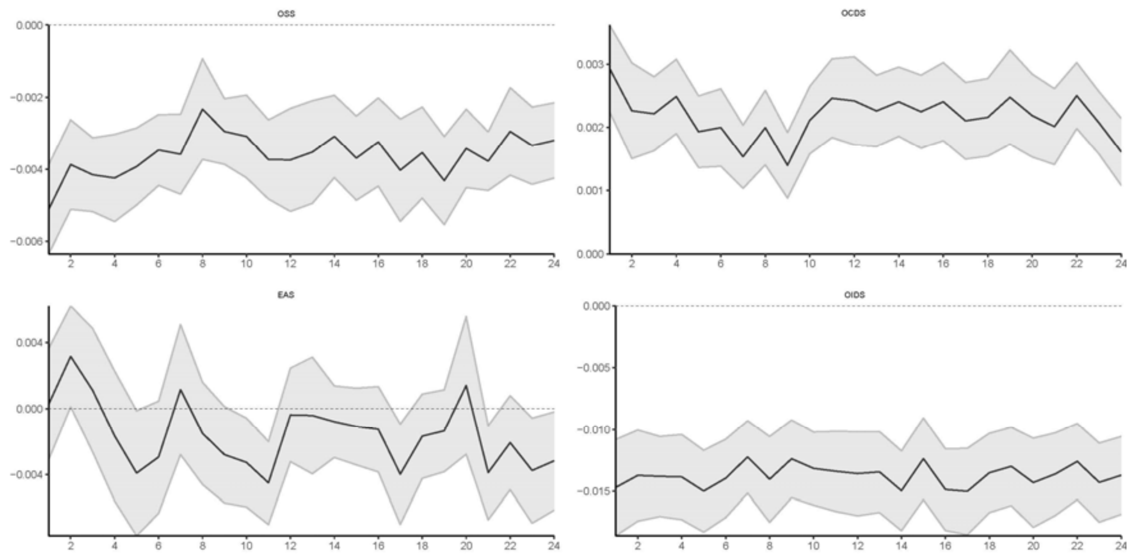
Figure 1. Responses of Tail Risks of 48 Developed and Emerging Countries to the Four Structural Oil Shocks



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 tail risks (*TR*) to a one unit increase in a specific disaggregated oil shock. The shaded areas represent the 95% confidence bands.

Given that tail risks could be affected by a large number of other factors (Nicolò and Lucchetta, 2017), we re-estimated Equation (1) by including a control variable, namely the global economic conditions (GECON) index, recently developed by Baumeister et al., (2020). This index is derived by applying the expectation-maximization (EM) algorithm to 16 indicators, including commodity (excluding energy and precious metals) prices, economic activity, financial indicators, transportation, uncertainty and expectation measures, weather and energy-related indicators, and hence, encapsulates the various measures of economic conditions in the overall world economy. The new set of results for the four oil shocks on *TR* is presented in Figure 2. Barring the case of the muted effect of the EAS shock, our results for the other three structural oil shocks are qualitatively (and to some extent even quantitatively) similar. This is probably not surprising, given that the GECON index also tends to capture the global demand for oil, just like the shock to the economic activity variable, which corresponds to the world industrial production index of Baumeister and Hamilton (2019).

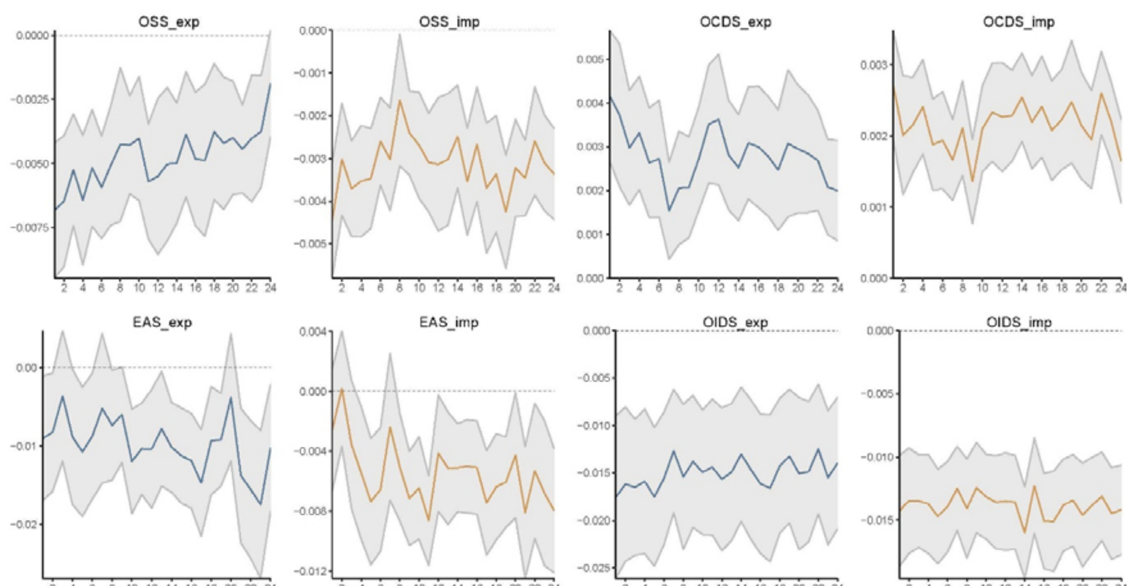
Figure 2. Responses of Tail Risks of 48 Developed and Emerging Countries to the Four Structural Oil Shocks with Global Economic Conditions (GECON) Index as a Control Variable



Note: See Notes to Figure 1.

Next in Figure 3, we present the results for the impact of the four oil shocks on tail risks of exporters and importers of oil, as obtained from Equation (2). Again, our basic results of Figure 1 continue to hold in terms of statistical significance and sign, but now the impacts on the *TR* of the oil exporters are relatively stronger than that observed for the importers. This result is not surprising given that oil-market movements are likely to be more strongly related to the stock markets of the exporters, given the high reliance of these economies on oil revenues.

Figure 3. Responses of Tail Risks of 48 Developed and Emerging Countries Categorized as Oil-Exporters and Importers to the Four Structural Oil Shocks



Note: See Notes to Figure 1; _exp and _imp denote exporters and importers respectively.

3.2. Additional Analyses

Note that, Hollstein et al., (2019) aggregated the tail risk of individual countries to a World Fear Index as a proxy for global tail risk, whereby the World Fear Index was obtained as the market capitalisation weighted average of the individual tail risk estimates of each country. Interestingly, as shown in Figure A1 in the Appendix of the paper, the impact of the four structural oil shocks (obtained from the time series version of the LP method) was in general statistically insignificant (and at times counter-intuitive). As a robustness check, using the stock returns derived from the MSCI World, Developed, and Emerging Countries indexes, we estimated an alternative measure of tail risks along the lines described by Adrian et al., (2019). Specifically, we estimated an AR(1) model for one-month-ahead annualized continuously compounded stock returns utilizing a quantile regression, and then fitted a quantile regression including only a constant to model the unconditional distribution of stock returns. Next, we computed the downside entropy of the unconditional distribution relative to the conditional distribution of stock returns. A high realization of downside entropy indicates that the probability of downside tail returns is higher than under the unconditional distribution. Finally, we calculated IRFs due to the oil shocks for downside entropy using the LP method. The data coverage was 1976:03-2020:12 for the World MSCI index, and 1988:01-2020:12 for the Developed and Emerging Countries indexes, derived from Datastream of Thompson Reuters. Consistent with the World Fear Index findings, results are hardly significant as shown in Figure A2 in the Appendix. In a similar vein, we used as an alternative measure of tail risk at the 5% quantiles implied by the AR(1) quantile regressions, giving again largely insignificant results reported in Figure A3 in the Appendix. These largely insignificant results possibly highlight the importance of using the panel data-based LP approach, which allows us to control for the heterogeneity across the economies, as well as the cross-sectional dependence of the tail risks (as depicted by Hollstein et al., (2019)), and hence assist in deducing correct inferences.

4. Conclusion

In this research, we have analysed the impact of disaggregated oil (supply, global economic activity, oil-specific consumption demand and oil-inventory-demand) shocks on stock-market tail risks of a panel of 48 developed and emerging economies over the monthly period from 1975:01 to 2017:12. We have found that oil supply, economic activity, and oil-inventory demand shocks reduce tail risks, and that oil-specific consumption-demand shocks are associated with an increase in tail risks. In addition, we have found that distinguishing the economies into oil-exporters and importers does not change the nature of the impact of the four oil-market shocks on tail risks, but the size of the effects is relatively stronger for oil-exporting economies.

The research has important implications for investors and policymakers. Given the increasing interconnectedness between international oil on stock markets, a good understanding of the underlying linkage between oil price shocks and stock-market tail risks can be beneficial for both investors and policymakers.

Our findings suggest that investors must be aware that the nature of oil-market shocks matters in driving tail risks, and, hence, the corresponding impact on the equity premium is shock-dependent. Specifically, with the oil-specific supply, economic activity, and oil -inventory-demand shock reducing tail risks, excess stock returns are expected to go down, while the same are likely to increase following an oil-specific consumption-demand shock. In other words, investors would need to design their portfolios contingent on the nature of the oil-market shock affecting oil prices. From a policy perspective, our results imply that policymakers would need to undertake expansionary policies in the wake of the speculative oil-specific consumption demand shock which increases tail risks and negatively impacts economic activity, with stronger policies required for oil exporters.

As part of future research, it is interesting to extend our analysis to a forecasting exercise of stock-market market tail risks due to oil shocks, given that in-sample predictability does not guarantee the same over an out-of-sample (as pointed out by Rapach and Zhou (2013) for stock returns).

References

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. American Economic Review, 109(4), 1263–89.
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.
Almeida, C., Ardison, K., Garcia, R., and Vicente, J. (2017). Nonparametric tail risk, stock returns, and the macroeconomy. Journal of Financial Econometrics, 15(3), 333-376.
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.
Baumeister, C., Korobilis, D., and Lee, T.K. (2020). Energy markets and global economic conditions. The Review of Economics and Statistics, 1-45.
Bouri, E., Jalkh, N., and Roubaud, D. (2019). Commodity volatility shocks and BRIC sovereign risk: A GARCH-quantile approach. Resources Policy, 61, 385-392.
Bouoiyour, J., Selmi, R., Shahzad, S.J.H., and Shahbaz, M. (2017). Response of Stock Returns to Oil Price Shocks: Evidence from Oil Importing and Exporting Countries. Journal of Economic Integration, 32(4), 913-936.
Carriero, A., Clark, T.E., and Marcellino, M. (2020). Capturing Macroeconomic Tail Risks with Bayesian Vector Autoregressions. Working Papers 202002R, Federal Reserve Bank of Cleveland.
Cook, T.R., and Doh, T. (2019). Assessing Macroeconomic Tail Risks in a Data-Rich Environment. Federal Reserve Bank of Kansas City Working Paper RWP 19-12.
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), Article No. 4.
Demirer, R., Gabauer, D., Gupta, R., and Ji, Q. (2021). Monetary Policy and Speculative Spillovers in Financial Markets. Research in International Business and Finance, 56, 101373.
Gkillas, K., Konstantatos, C., Tsagkanos, A., and Siriopoulos, C. (2021). Do economic news releases affect tail risk? Evidence from an emerging market. Finance Research Letters, 40, 101727.
Hill, B.M. (1975). A simple general approach to inference about the tail of a distribution. Annals of Statistics, 3(5), 1163–1174.
Hollstein, F., Nguyen, D.B.B., Prokopczuk, M., and Wese Simen, C. (2019). International Tail Risk and World Fear. Journal of International Money and Finance, 93, 244-259.
Jordà, Ò. (2005). Estimation and Inference of Impulse Responses by Local Projections. American Economic Review, 95(1), 161–182.
Ji, Q., Bouri, E., and Roubaud, D. (2018). Dynamic network of implied volatility transmission among US equities, strategic commodities, and BRICS equities. International Review of Financial Analysis, 57, 1-12.

Ji, Q., Liu, B.Y., Zhao, W.L., and Fan, Y. (2020). Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. International Review of Financial Analysis, 68, 101238.

Ji, Q., Shahzad, S.J.H., Bouri, E., and Suleman, M.T. (2020). Dynamic structural impacts of oil shocks on exchange rates: lessons to learn. Journal of Economic Structures, 9(1), 1-19.

Kang, W., and Ratti, R.A. (2013). Structural oil price shocks and policy uncertainty. Economic Modelling, 35(C), 314-319.

Kang, W., Ratti, R. A., and Yoon, K. H. (2014). The impact of oil price shocks on US bond market returns. Energy Economics, 44, 248-258.

Kelly, B., and Jiang, H. (2014). Tail risk and asset prices. Review of Financial Studies, 27(10), 2841–2871.

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 Park, C. (2009). The Impact of Oil Price Shocks on the U.S. Stock Market. International Economic Review, 50(4), 1267-1287.

Li, X-M., and Rose, L.C. (2009). The tail risk of emerging stock markets. Emerging Markets Review, 10, 242–256.

Lombardi, M., Osbat, C., and Schnatz, B. (2012). Global commodity cycles and linkages: a FAVAR approach. Empirical Economics, 43(2), 651-670.

Loria, F., Matthes, C., and Zhang, D. (2019). Assessing Macroeconomic Tail. FRB Richmond Working Paper No. 19-10.

Nicolò, G.D., and Lucchetta, M. (2016). Forecasting Tail Risks. Journal of Applied Econometrics, 32(1), 159-170.

Rapach, D.E., and Zhou, G. (2013). Forecasting stock returns. Handbook of Economic Forecasting, 2 (Part A), Graham Elliott and Allan Timmermann (Eds.), Amsterdam: Elsevier, 328−383.

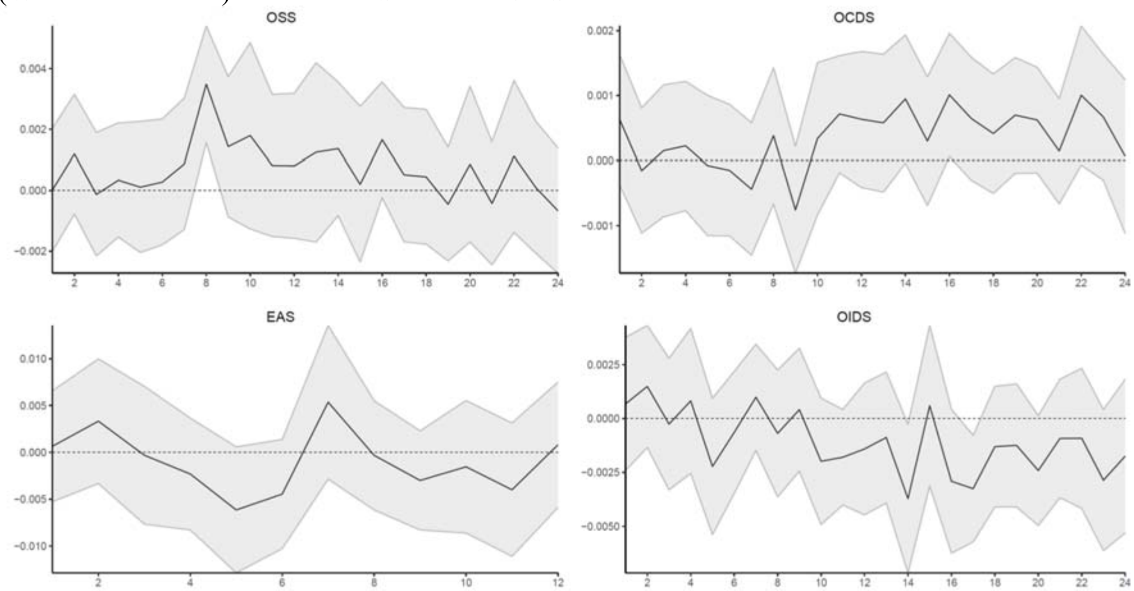
Shahzad, S.J.H., Bouri, E., Rehman, M.U., Naeem, M.A., and Saeed, T. (2021). Oil price risk exposure of BRIC stock markets and hedging effectiveness. Annals of Operations Research, 1-26.

Sheng, X., Gupta, R., and Ji, Q. (2020). The impacts of structural oil shocks on macroeconomic uncertainty: Evidence from a large panel of 45 countries. Energy Economics, 91, 104940.

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.

APPENDIX:

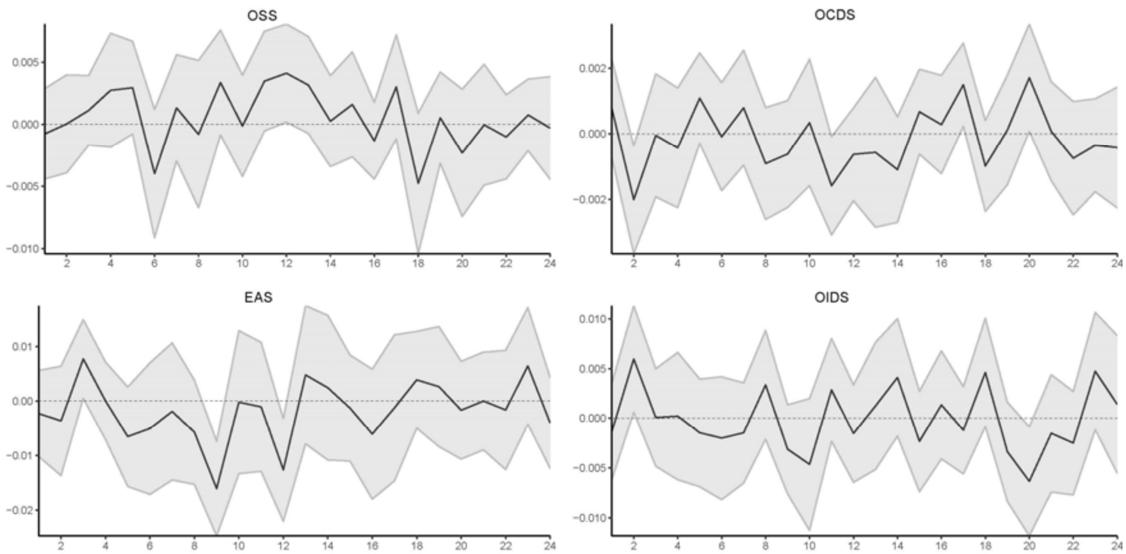
Figure A1. Responses of Aggregated Tail Risks of 48 Developed and Emerging Countries (World Fear Index) to the Four Structural Oil Shocks



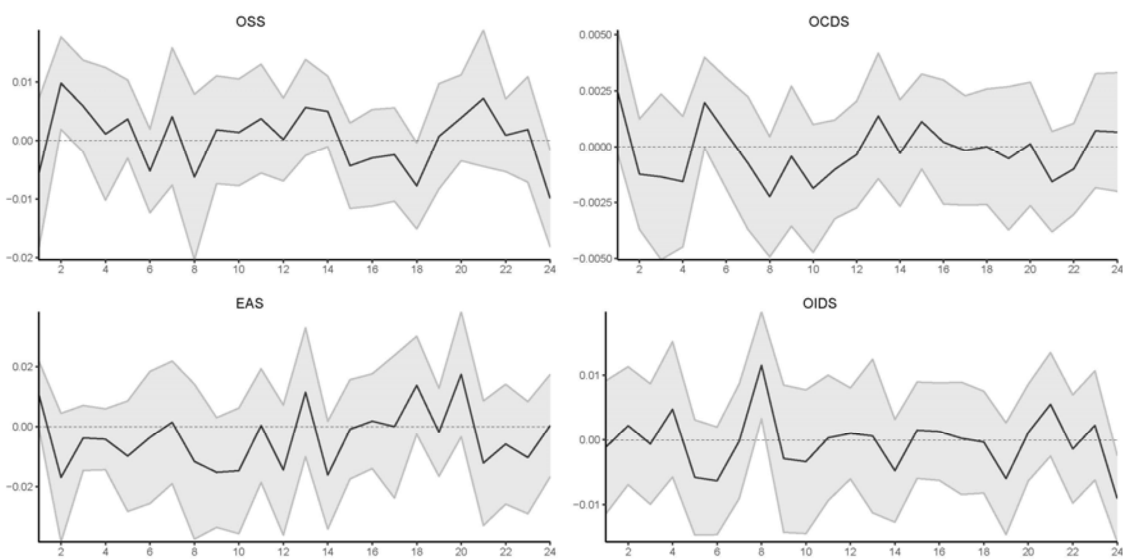
Note: See Notes to Figure 1.

Figure A2. Responses of Tail Risks of World, Developed and Emerging Countries Derived Using an Alternative Approach (Adrian et al., 2019) to the Four Structural Oil Shocks

A2(a). World MSCI Index



A2(b). MSCI Developed Countries Index



A2(c). MSCI Emerging Countries Index

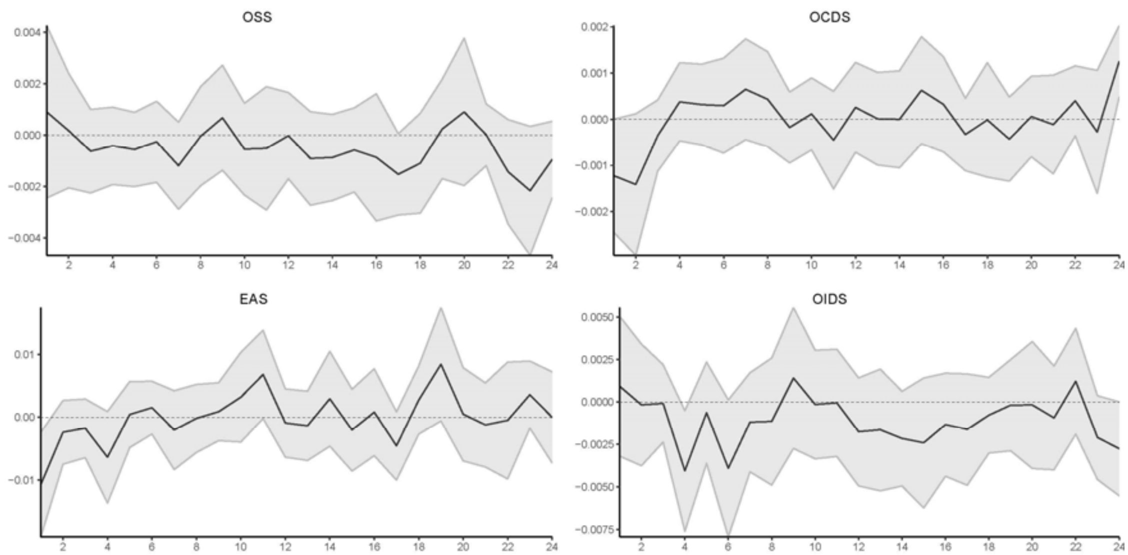
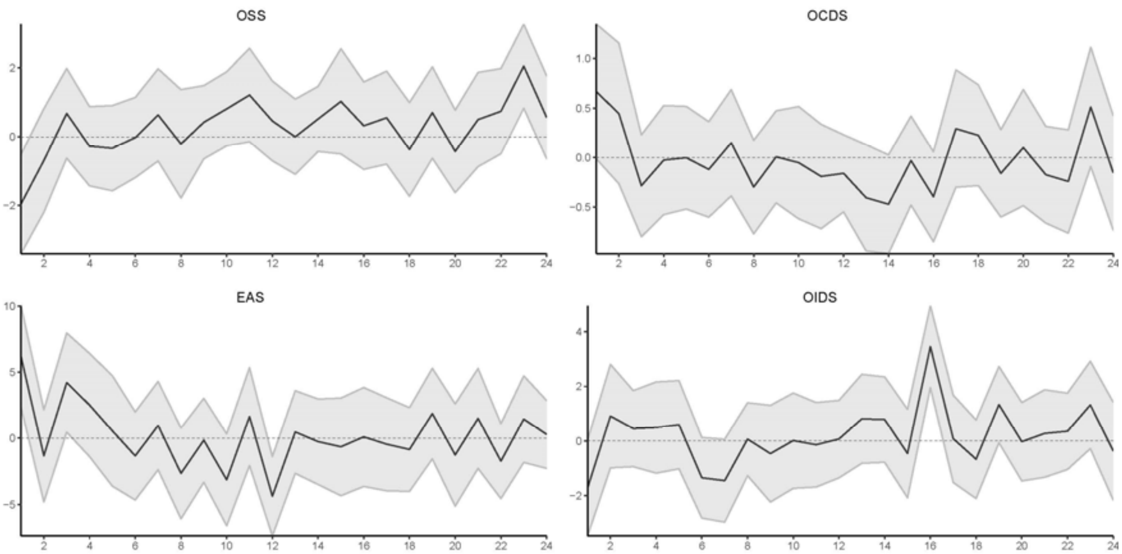
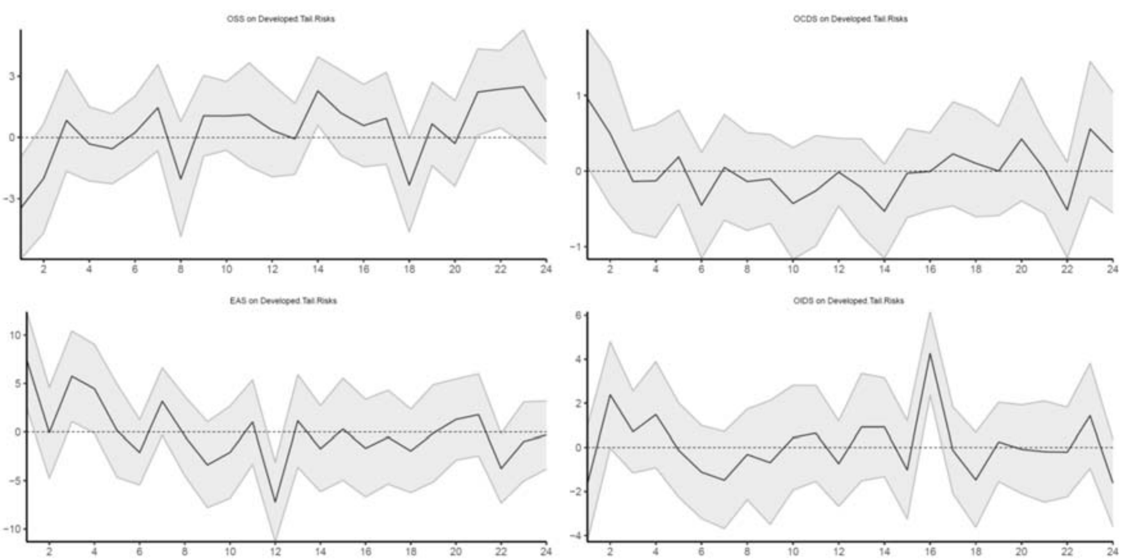


Figure A3. Responses of Tail Risks of World, Developed and Emerging Countries Derived Using a Quantile Regression-Based Approach to the Four Structural Oil Shocks

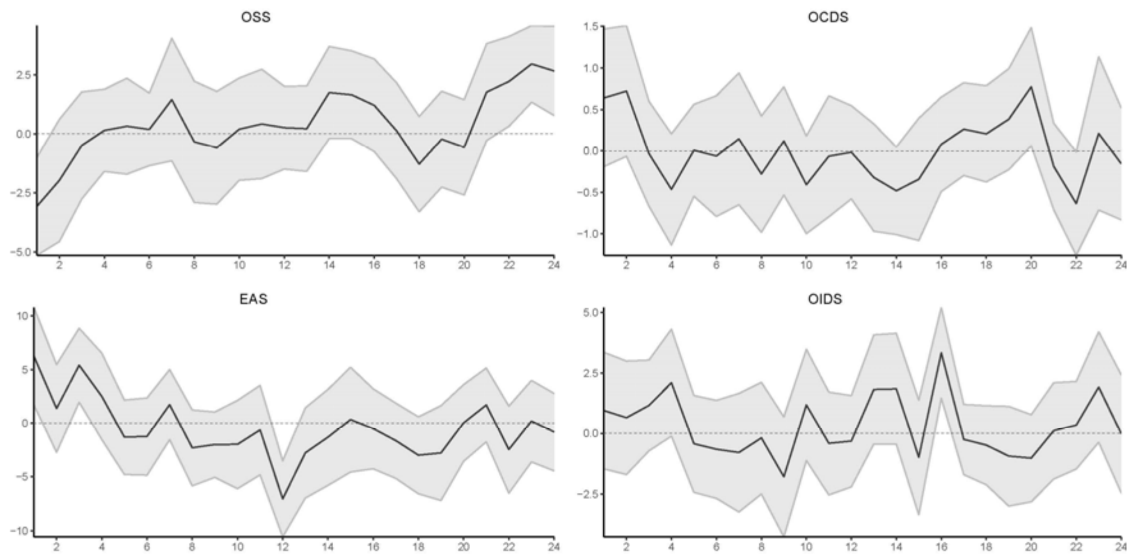
A3(a). World MSCI Index



A3(b). MSCI Developed Countries Index



A3(c). MSCI Emerging Countries Index



Note: See Notes to Figure 1.