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Tail risk, systemic risk and spillover risk of crude oil and precious metals

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A B S T R A C T

The relationship between oil prices and metal prices has been extensively investigated. However, the tail risk, systemic risk and spillover risk of oil prices have not been investigated via extreme value theory (EVT). We use this novel approach to determine the tail risk of oil, precious metals, how much risk they pose to the financial system and to what extent a shock in oil prices spill over to other precious metals as well as from the financial system. We use long time series of daily data from 1st January 1987 to 31st December 2021 as long time series is required for the EVT. The data is based on the total return index (RI) of four precious metals including gold, platinum, palladium and silver. Our results show that the tail risk of these metals is lower during the crisis period except the Covid-19 pandemic crisis. Most importantly, gold is a safer asset due to the lowest tail risk among four precious metals, indicating the claim that gold is a precious asset to mitigate the returns during market downturns and acts as a 'safe haven'. Moreover, we also find that extreme systemic risk (tail-β) for crude oil and selected precious metals reduces during crisis period. This is also recognising the fact that these commodities act as a prospective asset for portfolio diversification to hedge against financial assets' volatility. Finally, the spillover risk among crude oil and selected precious metals varies over time, especially during the crisis period and crude oil is an important stimulator of the spillover risk for precious metals. By using our findings, financial market investors can improve their investment planning to attain the maximum advantage of portfolio diversification. Financial managers can further apply these results in forecasting to estimate future global oil market trends for improving their hedging skills and portfolio performance.

1. Introduction

The link between oil and precious metals with major world economies has traditionally been associated to market confidence, with influential spillover impact arising when the uncertainty in the economy rises. For instance, the downfall of Lehman Brothers and the global financial crises indicated that risk spillovers built up when investors' confidence in the economy disintegrated (Stiglitz, 2016).

Rising oil prices usually cause inflationary burdens, increase growth issues and influence stock prices. This develops concerns for investors and they move to precious metals, such as gold, platinum, palladium and silver to hedge the true value of investments by controlling portfolio risk. Similarly, movement in oil price corrects the international reserve portfolio of oil exporting countries, which normally use gold and other precious metals to hedge their portfolio risk. Further, oil and precious metals are interdependent through hedging of currency exchange rates, for instance, the depreciation in the US dollar (USD) tend to diminish the value of oil and precious metals. Consequently, understanding of oil price fluctuations and underlying effects between oil and precious metal prices are key tools to hedge for portfolio managers, investors and policy legislators.

The association between oil prices and metal prices has been widely examined in the literature (for e.g. Batten et al., 2010; Ahmadi et al., 2016; Uddin et al., 2018 and Diebold et al., 2017 etc). However, the tail risk, systemic risk and spillover risk of oil prices have not been investigated via extreme value theory (EVT). The use of extreme value theory is important because of oil and metal prices have shown extreme movements and it is crucial to know how oil and metal prices behave in extreme market conditions. This is particularly relevant during crisis periods as commodity prices show extreme movements during crises.

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We observe several crisis periods during our sample period[1] and hence the use of EVT is crucial in our setting. EVT applies a semi parametric estimation method and measures marginal and joint probabilities of tail events without affecting the parametric measures. Moreover, it provides the benefit of concentrating on extreme events that happen with very low frequency and are long term in impact. Additionally, EVT also concentrates on the unconditional distribution of returns, for instance stochastic volatility models that develop time varying events of volatility and dependence with long term horizon. This is a well-established methodology and has been studied in a number of earlier research papers (See Hartmann et al., 2004; Straetmans et al., 2008; Straetmans and Chaudhry, 2015).

The current study contributes using this novel approach by first to determine the tail risk of oil and precious metals. The selected precious metals in this study including gold, platinum, palladium and silver because these precious metals are widely used to hedge the portfolio risk. Second, how much risk they pose to the economic system if there is any systemic shock. We innovate here by studying the impact of shock from crude oil and precious metals to major economies like G7 countries and China and to the global economy (CGG7). Furthermore, we also investigate the impact of crude oil and precious metals shock to the major consumer and major producer of respective crude oil and respective precious metals. Finally, we measure extent to which a shock in oil prices spills over to other precious metals as well as to and from the major economies and global economic system. We have used a long time series of daily data from 1987 to 2021 as a long time series is required for the EVT. In addition to that our paper provides inside interpretation of economic activities which influence global factors such as crude oil and precious metals generally use for hedging financial risk. We have also divided our extreme systemic risk and spillover risk results into three main parts such as pre-crisis (July 1st, 1987 to August 31st, 2008), crisis (September 1st, 2008 to June 30th, 2020) and another crisis (July 1st, 2015 to June 30th, 2020, another crisis started when oil prices moving down). Lastly, our paper has phenomenal implications for alternative investments and global financial regulators.

Our paper differs from Mensi et al. (2017a) and Tiwari et al. (2020) in the following ways. Mensi et al. (2017b) use simple value at risk (VaR), conditional VaR (CoVaR) and delta CoVaR of Adrian and Brunnermeier (2016) whereas Tiwari et al. (2020) use time-varying Markov-copula models, delta CoVaR of Adrian and Brunnermeier (2016) and marginal expected shortfall (MES) of Acharya et al. (2012). We estimate the tail risk of crude oil and precious metals, which both of these papers do not study. We use tail VaR (or tail quantile) and tail expected shortfall as proxies for tail risk, which are extreme measures of tail risk. Both of these papers use systemic risk and spillover risk measures that do not go beyond *p*-values of 1%. Our measure use EVT that evaluate systemic risk (tail-β) and spillover risk ($\widehat{E}$ *and* k) for p-values of 0.01% and 0.02%. Hence they capture the extreme systemic and spillover risk. These studies do not include China in their studies, however, we include China in our systemic and spillover risk analysis as it is the second biggest economy in the world. We also include global economy as to know how crude oil and precious metals shock impact the global economy. Furthermore, we also do analyses on major consumer and major producer of crude oil and precious metals in our systemic and spillover risk analysis.

The EVT approach reveals three major findings. Firstly, the tail risk of crude oil and precious metals (gold, platinum, palladium and silver) reduces during the 2008 global financial crisis and the 2015 oil price crisis period, except the Covid-19 pandemic crisis. It is worth noting that gold is a safer asset during the slump period of the market as it has the lowest tail risk among four precious metals. Secondly, the extreme systemic risk (tail-β) for these commodities clearly declines, especially during the 2015 oil price crisis. This means the risk in the portfolio and financial assets' volatility can be restricted by diversifying asset to crude oil and selected precious metals. Thirdly, crude oil and selected precious metals' spillover risk varies over time. Particularly, the co-crash probability of these commodities decreases during global financial crisis (2008–2009), European sovereign debt crisis (2010−2012) and Covid-19 pandemic crisis (2020−2021) which explained by multivariate spillover risk probability of these commodities obviously increases during these crises. Most notably, the result reports that crude oil seems to have both positive and negative spillover impacts on the selected precious metals. This result suggests that crude oil is a crucial stimulator of the spillover risk for precious metals.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on the impact of tail risk and systemic risk by using EVT and we have also examined the literature on impact of tail risk and systemic risk of finance firms on the financial system. Section 3 provides the data with the empirical models and explains the econometric methodology used in the empirical analysis. Section 4 reports the empirical findings as well as discussion. Section 5 provides the conclusion and policy implications.

2. Related literature

Extreme value theory (EVT) has been widely used across many subjects of application, for example insurance and engineering (Giesecke and Goldberg, 2005; Liu, 2013). Recently, it has also been applied to investigate extremes in financial markets regarding the instability in several financial markets experienced around the world. Among others, McNeil and Frey (2000), Danielsson and De Vries (2000), Neftci (2000), Hartmann et al. (2004), Gilli and Kellezi (2006), Straetmans et al. (2008) and Onour (2010) have been examined tails of financial data series. Zhao (2020) claims that extreme value theory is one of the most valuable approaches for analysing tail behaviour of financial markets.

Hartmann et al. (2004) examine the linkages within and between equity and bond markets in the G-5 industrial countries by using weekly stock and government bond returns over the period 1987 to 1999. An extreme-value analysis indicates small but non-negligible cross-asset market linkages in times of market turmoil. Extreme losses are generally much smaller for government bond indices than for stock indices. The flight-to-quality phenomenon is approximately as frequent as the cocrash of bond and stock markets. In addition, the finding reveals that national borders do not appear to limit the magnitude of flight to quality or contagion. Hence, the surveillance of financial market stability may consider across border, particularly, in the era of globalization and free capital flows.

Straetmans et al. (2008) apply multivariate extreme value estimators to measure the sectoral system risk in the US stock market and to assess the US sectoral index returns. The measurements classify into two types which one capturing extremal spill overs between economic sectors (sectoral co-exceedance probabilities) and another capturing the exposure of sectors to extreme systematic shocks (dubbed tail-βs). The cross-sectional homogeneity in tail index estimates indicates that the tail index alone cannot be a good measure of sectoral tail risk. The tail behaviour is conditional on structural change. In addition, the right tail reports more upward potential than downward risk for both the pre-9/11 and post-9/11. The bivariate results suggest that tail-βs often increase in a statistical and economic significance way, using 9/11 as the sample midpoint. Furthermore, Allen et al. (2013) apply univariate extreme value theory to study extreme market risk for the FTSE-100 UK Index and S&P-500 US indices as well as the CBOE-S&P-Vix and FTSE-100 Volatility indices. The finding exposes that EVT can be applied to model extreme market events, but the model did not fully function with the implied volatility indices.

Straetmans and Chaudhry (2015) estimate the likelihood of individual institutions' financial distress as well as individual banks'

[1] These crises include global financial crises, the fall of oil prices from July 2015 until 2019 and then the COVID-19 crisis.

exposure by applying statistical extreme value analysis. They find that both systemic risk and tail risk in the Eurozone are lower than in the US. This result is similar to earlier study by Hartmann et al. (2006), who examine contagion risk and systemic risk of banks in the US and the euro zone with multivariate extreme value theory. They find that banks spillover in the Eurozone seems to be significantly lower than in the US. This implies weak cross-border linkages in Europe. The increase of risk in the euro area seems to happen slowly from the integration of traditional banking firms. For the US, the largest financial institutions and the main clearing banks seem to have the strongest increases in extreme systematic risk. In addition, Gkillas and Katsiampa (2018) examine the tail behaviour of the returns of 5 major cryptocurrencies, which are Bitcoin, Ethereum, Ripple, Bitcoin Crash and Litecoin, by applying an extreme value theory to daily closing prices of each cryptocurrency. The finding reveals that Bitcoin Cash is the riskiest cryptocurrency because it has the highest potential loss and gain as well as the highest Expected Shortfall (ES) for both positive and negative returns, despite, it was launched latest in 2017. On the contrary, the results of Value-at-Risk (VaR) and ES of the extreme returns of Bitcoin in the right tail and of Litecoin in the left tail are the lowest ones which imply as the least risky among cryptocurrencies considered. Prior to this study, extreme value theory has been applied to cryptocurrencies by Osterrieder and Lorenz (2017) and Osterrieder et al. (2017).

Aforementioned existing studies show that extreme value theory (EVT) has been expansively applied to assess tail risk, systemic risk and spillover risk in financial markets. However, the tail risk, systemic risk and spillover risk of oil and precious metals have not been investigated via extreme value theory (EVT). This implies that the effect of oil and precious metals on financial stability have not received much attention. In contrast, the relationship between oil prices and metal prices has been extensively investigated. Previous literature on oil and precious metals employ a system generalized method of moments (GMM) and panel analysis. For instance, Alodayni (2016) evaluates the impact of the recent 2014–2015 oil prices slump on the financial stability in the Gulf Cooperation Council (GCC) region by applying a system generalized method of moments (GMM) and a panel fixed effect. The result reveals strong linkages between oil price variations and nonperforming loans (NPLs). This implies that decreases in oil prices increase NPLs. In addition, a panel VAR model indicates a negative feedback impacts from uncertainty in banking systems to the GCC macroeconomy. Recently, Lee and Lee (2019) use the generalized method of moments (GMM) techniques on dynamic panels to study the impacts of oil prices on bank performance in China by implementing CAMEL (Capital adequacy, Asset quality, Management, Earnings, and Liquidity) indicators as an assessment for the bank performance over the period of 2000 to 2014. The findings show that oil prices have a negative significant impact on banking performance. These imply that an increase in oil prices trigger a reduction in banking performance regarding capitalization, management efficiency, earning power, and liquidity. However, country stability, particularly political stability and economic stability, can mitigated these unfavourable effects.

In addition, other studies have explored the relationship between oil and precious metals via various approaches such as Reboredo and Ugolini (2016) use copulas to investigate the relationship between oil prices and precious metal prices and employ unconditional and conditional value-at-risk methods to quantify spillover effects of these variables for the period 2000 to 2015. The empirical evidence reveals that large downside and upside oil price movements have spillover effects on all metal markets and this effect is valid both before and after the global financial crisis. Similarly, Shahzad et al. (2019) study impact of oil price volatilities on five metal prices by using VAR for VAR and the cross-quantilogram methods, finding confirms that there is a spillover effect from oil prices to precious metal prices. Mokni (2018) applies fractional integrated exponential generalized autoregressive conditional heteroskedasticity (FIEGARCH)-copula framework and detects a positive significant and asymmetric relationship among oil and precious metals return, volatilities and market risk. Yıldırım et al. (2020) use causality-in-variance test to investigate linkages of a return and volatility spillover effect between oil price and precious metal prices over the period from 1990 to 2019. The empirical finding reports causality-in-mean relation running from the oil return series to precious metal return series. This implies that oil price is Granger cause of all precious metals. On the other hand, the causality-in-variance test reveals volatility spillover effect from the oil market to the precious metal market. Using quantile causality to test long-run dependence and causation between oil and precious metals, Shafiullah et al. (2020) find that causality running from oil to metal prices is quantile-dependent and differs regarding the metal, whilst downward and upward movements in metal prices have no causal influence on oil prices during 1990 to 2019.

3. Data and methodology

Our data is based on the daily resturns of four precious metals including gold, platinum, palladium and silver and crude oil to measure the tail risk of oil and precious metals. Further, it determines the financial risk if there is any systemic shock in oil prices spillover to four precious metals such as gold, platinum, palladium and silver. We have collected the long time series of daily data from 1st July 1987 to 31st December 2021. Our selection criteria are total return index (RI) based on precious metals from China, Global and G7 countries (CGG7). For measuring of tail-β, we have collected calculated indices for each respective country from DataStream. For extreme systemic risk, we select G7 countries because they are the biggest economies in the world and they are more likely to have an impact on oil and other precious metals. Although China is not in the G7 but we include it in our analysis as she is the second biggest economy in the world and also the biggest producer of gold and biggest consumer of gold and palladium.

3.1. Measurement of tail risk

We measure the tail risk because of decline in the equity indices of oil and precious metals. We follow univariate extreme value theory (EVT) to identify equity tail risk. The univariate EVT consist of Generalized Extreme Value (GEV) distribution and examine as limit law for maxima of stationary method. We use Peaks-over-Threshold (POT) technique to examine the factors of GEV distribution. We applied semi-parametric technique and compare the additional distributional losses over a high threshold that leads to Generalized Pareto Distribution (GPD).[2] For block maxima, we typically generate annual maxima series (AMS). Due to limited number of random events within a year, we may not be able to get generalized extreme value distribution (GEVD) from the observed AMS (Embrechts et al., 1997). Furthermore, the block maxima is not suited for financial time series because of volatility clustering, which means extreme events follow each other. Because the block maxima capture only the maximum return, several data points might get excluded. On the contrary, POT captures data more efficiently above a given threshold, it has become the method of choice in financial applications (Bhattacharyya and Ritolia, 2008).

For the point process, it is more associated with the variations in the excesses over the threshold (Boano-Danquah et al., 2020). Since we are not concerned about the variation in the excesses in our analysis, we chose POT method for our analysis.

We applied Haan et al. (1994) method of semi parametric estimator to examine the quantile x for extremely low values of $p = P\{X. x\}$ as follows:

[2] See for example Jansen and de Vries (1991), Danielsson and de Vries (1997) and Straetmans and Chaudhry (2015) among others for semi-parametric tail estimation approaches.

Table 1
Summary statistics.

Variable	Observations	Mean	Std. dev.	Min	Max
Crude Oil WTI Returns	9131	0.0001	0.0431	−3.0197	0.5309
Crude Oil Brent Returns	9131	0.0005	0.0266	−0.6143	0.7740
S&P GSCI Gold Returns	9131	0.0002	0.0099	−0.0934	0.0924
S&P GSCI Platinum Returns	9131	0.0003	0.0140	−0.1150	0.1184
Palladium Returns	9129	0.0004	0.0209	−0.6764	0.1848
S&P GSCI Silver Returns	9131	0.0003	0.0179	−0.1771	0.1328
US Stock Market Returns	9131	0.0005	0.0111	−0.1873	0.1120
China Stock Market Returns	9131	0.0005	0.0222	−0.8850	0.1703
Canada Stock Market Returns	9131	0.0006	0.0291	−0.6320	2.3354
France Stock Market Returns	9131	0.0006	0.0335	−0.7993	2.0471
Germany Stock Market Returns	8517	0.0004	0.0257	−0.9228	1.7593
Italy Stock Market Returns	7720	0.0008	0.0667	−0.9191	5.6710
Japan Stock Market Returns	7419	0.0002	0.0164	−0.9668	0.1309
UK Stock Market Returns	6243	0.0003	0.0112	−0.1046	0.0929
S&P GLOBAL 1200 Stock Market Returns	3036	0.0003	0.0144	−0.2738	0.1255
South Africa Stock Market Returns	9131	0.0008	0.0453	−0.7479	3.9238
Russia Stock Market Returns	9131	0.0008	0.0265	−0.9457	1.3089
Mexico Stock Market Returns	9131	0.0005	0.0139	−0.5470	0.1119

Notes: The returns of all variables are estimated by dalily returns with today's price minus yesterday's price divided by yesterday's price.

$$\widehat{x}_p = X_{n-m,n}\left(\frac{m}{np}\right)^{1/\alpha} \tag{1}$$

As $X_{n-m,\ n}$ is indication tail cut-off point of *(n-m)*th ascending order statistics from a sample size n such that $q > X_{n-m,\ n}$.

We applied Hill (1975) to estimate α in the mentioned tail quantile estimator in eq. (1), as follows:

$$\widehat{\alpha} = \left(\frac{1}{m}\sum_{j=0}^{m-1} ln\left(\frac{X_{n-j,n}}{X_{n-m,n}}\right)\right)^{-1} \tag{2}$$

Where parameter m indicates how many extreme returns are evaluated in estimation. We use sensitivity analysis by adjusting $m = 263$ for pre-crisis and $m = 137$ for crisis and $m = 67$ for another crisis. We examine m values by adopting Hill (1975) estimator. We find expected shortfall estimator by substituting the Hill (1975) eq. (2) and tail quantile estimator in eq. (1) as follows:

$$\widehat{E}\left(X - \widehat{x_p}\middle|X > \widehat{x}_p\right) = \frac{\widehat{x_p}}{\widehat{\alpha - 1}} \tag{3}$$

3.2. Measurement of systemic risk

In this study, we measure systemic risk estimate with semi-parametric estimation method because parametric probability distributions provide us incorrect distributional assumptions and due to many bias for systemic risk estimations leads to misspecification. For measuring the multivariate spillover risk, we apply the following equation:

$$\widehat{P}_{N|1} = \frac{\widehat{P}_q}{p} = \frac{m}{n}\left(C_{n-m,n}\right)^{\alpha} q^{1-\alpha}, \tag{4}$$

The equation is defined as finite $q = 1/p$. $N = 2$, this diminishes to the tail- β estimator. $C_{n-m,\ n}$ is the "tail cut-off" of $(n-m)^{th}$ ascending order statistic from the cross-sectional minimum series. m considers as nuisance parameter indicated by Hill as estimator, it measures how many extreme returns are required in estimation, n characterise as the total number of observations. While the new return vector shows tail independence ($\alpha > 1$), the systemic risk is a decreasing function of the threshold q and ultimately arrives zero if $q \to \infty$. Conversely, when $\alpha = 1$, as we highlighted in our examination, systemic risk is no longer influenced by changes in q.

We adopt additional systemic risk measure and employ the following equation to estimate that

$$\widehat{E}[\theta|\theta \geq 1] \approx \frac{N}{\frac{n}{k}\frac{1}{n}\sum_{i=1}^{n} U_{i=1}^{N} X_i > X_{i,n-k}} \tag{5}$$

The denominator in the equation shows an estimator of stable tail dependence function l(.).[3] Further $X_{i,\ n-k}$ estimates the quantile $Q_i\left(\frac{k}{n}\right)$ and l{.} is the indicator function. Nuisance parameter is k as m represent the hill estimator and n indicates the number of extremes in risk measures.

Hartmann et al. (2004) establishes a substitute spill over indicator through multivariate generalization of the two-dimensional "conditional expectation indicator". The conditional expectation is $E[k|\,k \geq 1]$ where Kstands for number of collective triggered into distress. It shows the expected number of distresses in the sector given at least one distressed. The "crash" k illustrate the sum of N indicator variables:

$$k = \sum_{i=1}^{N} 1\{X_i > Q_i(p)\} \tag{6}$$

As 1{.} equals is equal distressed and zero otherwise (for e.g. see detail in Straetmans and Chaudhry, 2015).

3.3. Summary statistics

Table 1 provides the summary statistics for the variables used in the study. The table shows that the average daily returns of crude oil and four of four precious metals including gold, platinum, palladium and silver volatiled between 0.01% and 0.05%. By comparing among four precious metals, the average daily returns of palladium were highest at 0.04%, while the average daily returns of gold were lowest at 0.02%. Moreover, the average daily returns of stock returns for CGG7 (China, Global and G7) fluctuated between 0.02% to 0.08%. By comparing among these stock markets, the average daily returns of stock market in Italy, South Africa and Russia had the highest returns at 0.08%. On the other hand, the average daily returns of stock market in Japan had the lowest returns at 0.02%. Interestingly, the maximum value of daily returns occured in the stock market of Italy at 567.1% but the minimum value of daily returns was crude oil WTI at −301.97%.

4. Empirical results

We first analyze the tail risk proxies of crude oil and four precious metals: gold, platinum, palladium and silver in Section 4.1. The

[3] For detail, see Straetmans and Chaudhry (2015).

indicators of extreme systemic risk (tail-βs) based on the different conditioning risk factors of CGG7 (China, Global and G7) are investigated in Section 4.2. Finally, the multivariate probability of spillover risk is considered in Section 4.3. Moreover, we also conduct the robustness test by adjusting the number of the nuisance parameter (m) for all selected commodities. However, our results are consistent.

4.1. Downside risk estimates of crude oil and four precious metals

Tables 2 (full samples) and 3A–3C (pre-crisis and crisis samples) report estimators of the tail index α and corresponding values of tail-VaR and expected shortfall for crude oil and four precious metals including gold, platinum, palladium and silver. Extreme quantiles are measured for p-values at 0.2% and 0.1%. Moreover, the corresponding tail-VaRs are expected to be violated every 500 days and every 1000 days, respectively. We also examine the expected shortfall estimates conditioned on both the p% tail-VaR and on crisis barriers $x = 25\%$ or 50%. Lastly, we define that the expected shortfalls with the condition of different threshold x are the more extreme expected shortfall calculator when the extreme quantile estimates $\hat{x}_p$ are nearly lower than x.

The tail indexes for crude oil, gold, platinum, palladium and silver volatile around 3, which is consistent with the evidence of prior literature including Jansen and De Vries (1991), Hartmann et al. (2006) and Straetmans and Chaudhry (2015) who investigated in the context of general stocks, bank stocks and US and Eurozone bank stocks, respectively. Table 2 (Panel I) shows that the tail index (α) for Crude Brent oil (2.3760), Crude WTI oil (2.5321), and Silver (2.6518) is lower, implying the fat tail. Conversely, Gold, Palladium and Platinum contain a thinner tail at 2.9124, 2.9771 and 3.2498, respectively. Moreover, the results remain broadly the same, although the number of the nuisance parameter is changed from 175 (Panel I) to 225 (Panel II) and 300 (Panel III). Comparing pre-crisis results with crisis results, we classify the period of crisis into two different crises; namely the 2008 global financial crisis from 1st September 2008 to 30th June 2020 and another crisis when 2015 oil prices started moving down from 1st July 2015 until 30th June 2020. Table 3A reveals the evidence that the majority of the returns for crude oil and selected precious metals seems to exhibit lower tail risk during both crises (higher values of the tail index and lower values of tail-VaR and expected shortfall). For calculation of pre-crisis and crisis tail risk measures, we adjust the nuisance paramter based on the number of observations used. Simultaneously, when the number of the nuisance parameter is adjusted for the pre-crisis, crisis and another crisis from 115, 60 and 29 in Table 3A to 148, 77 and 38 in Table 3B and 197,103 and 50 in Table 3C, respectively, the results are still confirmed. It is possible as crude oil, gold, platinum, palladium and silver are acknowledged as a safety asset from general investors, especially gold. Our findings are consistent with the claim of Baur and Lucey (2010) and Baur and McDermott (2010) that investors perceive that gold is an important instrument to mitigate cyclical returns during the periods of downturn market and act as a ‘safe haven’ to them. Also, our results of other precious metals including platinum, palladium and silver also support the findings of Hillier et al. (2006), Conover et al. (2009), Lucey and Li (2015) and Reboredo and Uddin (2016) that precious metals are able to be used as a potential asset for the diversification of risk in portfolio to hedge against financial assets’ volatility. Therefore, the tail risk of these metals is lower during the crisis period.

Focusing on the individual commodities, Table 3A reports that the magnitude of tail risk for Crude Brent oil is the lowest value during two crises. For example, the tail index (α) of Crude Brent oil increased from 2.7770 to 4.1795 and to 6.0661, indicating that the probability mass in the tails in dramatically dropped approximately 50.51% and 118.45% during 2008 global financial crisis and 2015 oil price crisis, respectively. Conversely, the extreme quantiles and expected shortfall measures for Crude Brent oil have plummeted during crisis period as compared to pre-crisis period. Crude Brent oil 0.1% tail-VaR has definitely fallen from 0.1401 to 0.0976 for 2008 global financial crisis and to 0.0782 for 2015 oil price crisis or decreased approximately 30.33% and 44.16%, respectively. The 2008 global financial crisis $p = 0.1\%$ VaR of 0.1401

Table 2
Full samples of tail risk indicators for crude oil and other metals.

Commodity	α	x(p)		ES (X > s)		ES (x(p))	
		p = 0.2%	p = 0.1%	s = 25%	s = 50%	p = 0.2%	p = 0.1%
Panel I: *m* = *175*							
Crude WTI	2.5321	0.1337	0.1757	0.1631	0.3261	0.0871	0.1145
Crude Brent	2.3760	0.1294	0.1732	0.1817	0.3634	0.0940	0.1259
Gold	2.9124	0.0501	0.0636	0.1307	0.2615	0.0262	0.0333
Platinum	3.2498	0.0661	0.0818	0.1111	0.2222	0.0294	0.0364
Palladium	2.9771	0.0963	0.1216	0.1264	0.2529	0.0487	0.0615
Silver	2.6518	0.0996	0.1294	0.1513	0.3027	0.0603	0.0783
Average	2.7832	0.0959	0.1242	0.1441	0.2881	0.0576	0.0750
Panel II: *m* = *225*							
Crude WTI	2.4343	0.1364	0.1813	0.1742	0.3485	0.1263	0.0950
Crude Brent	2.3995	0.1288	0.1720	0.1786	0.3573	0.1229	0.0920
Gold	2.9023	0.0502	0.0638	0.1314	0.2628	0.0335	0.0264
Platinum	3.1603	0.0671	0.0835	0.1157	0.2314	0.0387	0.0310
Palladium	2.9283	0.0970	0.1229	0.1296	0.2593	0.0638	0.0503
Silver	2.7400	0.0981	0.1263	0.1437	0.2874	0.0726	0.0564
Average	2.7608	0.0963	0.1250	0.1456	0.2911	0.0763	0.0585
Panel III: *m* = *300*							
Crude WTI	2.4707	0.1350	0.1788	0.1699	0.3399	0.0918	0.1215
Crude Brent	2.5469	0.1237	0.1624	0.1616	0.3232	0.0800	0.1050
Gold	2.6748	0.0527	0.0683	0.1493	0.2985	0.0315	0.0408
Platinum	2.8032	0.0718	0.0919	0.1386	0.2773	0.0398	0.0510
Palladium	2.6756	0.1024	0.1327	0.1492	0.2984	0.0611	0.0792
Silver	2.5102	0.1038	0.1368	0.1655	0.3311	0.0687	0.0906
Average	2.6136	0.0982	0.1285	0.1557	0.3114	0.0621	0.0813

Notes: Estimators for tail index, α, the tail quantile x(p) and the expected shortfall ES are given in Eqs. (2), (1) and (3), respectively with full samples from 1st January 1987 to 31st December 2021. The nuisance parameter m denoting the number of extreme results used in estimation equals 175 (Panel I), 225 (Panel II) and 300 (Panel III), respectively for crude oil and other metals.

Table 3A
Tail risk indicators for selected commodities: pre-crisis and crisis estimators.

Commodity	α	x(p)		ES (X > s)		ES (x(p))	
		p = 0.2%	p = 0.1%	s = 25%	s = 50%	p = 0.2%	p = 0.1%
Panel I: Pre-crisis estimates (m = 115)							
Crude WTI	2.6881	0.1153	0.1492	0.1481	0.2962	0.0683	0.0884
Crude Brent	2.7770	0.1091	0.1401	0.1407	0.2814	0.0614	0.0788
Gold	3.1175	0.0443	0.0553	0.1181	0.2361	0.0209	0.0261
Platinum	3.5486	0.0581	0.0707	0.0981	0.1962	0.0228	0.0277
Palladium	2.9938	0.0946	0.1192	0.1254	0.2508	0.0474	0.0598
Silver	2.9636	0.0828	0.1046	0.1273	0.2546	0.0422	0.0533
Panel II: Crisis estimates (m = 60)							
Crude WTI	3.6545	0.1049	0.1268	0.0942	0.1884	0.0395	0.0478
Crude Brent	4.1795	0.0827	0.0976	0.0786	0.1573	0.0260	0.0307
Gold	3.3891	0.0490	0.0601	0.1046	0.2093	0.0205	0.0252
Platinum	3.3525	0.0637	0.0783	0.1063	0.2125	0.0271	0.0333
Palladium	3.2610	0.0884	0.1094	0.1106	0.2211	0.0391	0.0484
Silver	3.1699	0.0983	0.1223	0.1152	0.2304	0.0453	0.0564
Panel III: Another crisis estimates (m = 29)							
Crude WTI	4.9249	0.0850	0.0978	0.0637	0.1274	0.0216	0.0249
Crude Brent	6.0661	0.0698	0.0782	0.0493	0.0987	0.0138	0.0154
Gold	4.8412	0.0294	0.0339	0.0651	0.1302	0.0076	0.0088
Platinum	3.7807	0.0489	0.0587	0.0899	0.1798	0.0176	0.0211
Palladium	3.2702	0.0696	0.0861	0.1101	0.2202	0.0307	0.0379
Silver	3.6911	0.0635	0.0766	0.0929	0.1858	0.0236	0.0285

Notes: Estimators for tail index, α, the tail quantile x(p) and the expected shortfall ES are given in Eqs. (2), (1) and (3), respectively. The table distinguishes pre-crisis from 1st July 1987 to 31st August 2008, crisis from 1st September 2008 to 20th June 2020 and another crisis when oil prices started moving down from 1st July 2015 until 30th June 2020. The nuisance parameter *m* equal to 115, 60 and 29 for the pre-crisis, crisis and another crisis, respectively.

Table 3B
Tail risk indicators for selected commodities: pre-crisis and crisis estimators.

Commodity	α	x(p)		ES (X > s)		ES (x(p))	
		p = 0.2%	p = 0.1%	s = 25%	s = 50%	p = 0.2%	p = 0.1%
Panel I: Pre-crisis estimates (m = 148)							
Crude WTI	2.7262	0.1144	0.1475	0.1448	0.2897	0.0663	0.0854
Crude Brent	2.7564	0.1094	0.1407	0.1423	0.2847	0.0623	0.0801
Gold	2.7582	0.0470	0.0605	0.1422	0.2844	0.0268	0.0344
Platinum	3.1305	0.0615	0.0767	0.1173	0.2347	0.0289	0.0360
Palladium	2.9439	0.0954	0.1207	0.1286	0.2572	0.0491	0.0621
Silver	2.7213	0.0866	0.1117	0.1452	0.2905	0.0503	0.0649
Panel II: Crisis estimates (m = 77)							
Crude WTI	3.3596	0.1088	0.1337	0.1059	0.2119	0.0461	0.0567
Crude Brent	3.8449	0.0853	0.1021	0.0879	0.1758	0.0300	0.0359
Gold	3.2219	0.0501	0.0621	0.1125	0.2250	0.0225	0.0279
Platinum	3.3769	0.0636	0.0781	0.1052	0.2104	0.0268	0.0329
Palladium	2.9986	0.0918	0.1157	0.1251	0.2502	0.0459	0.0579
Silver	2.9238	0.1022	0.1296	0.1300	0.2599	0.0531	0.0673
Panel III: Another crisis estimates (m = 38)							
Crude WTI	4.6449	0.0865	0.1004	0.0686	0.1372	0.0237	0.0276
Crude Brent	5.7296	0.0710	0.0801	0.0529	0.1057	0.0150	0.0169
Gold	4.5083	0.0301	0.0351	0.0713	0.1425	0.0086	0.0100
Platinum	3.4717	0.0507	0.0619	0.1011	0.2023	0.0205	0.0250
Palladium	3.3005	0.0693	0.0855	0.1087	0.2173	0.0301	0.0372
Silver	3.3800	0.0659	0.0809	0.1050	0.2101	0.0277	0.0340

Notes: Estimators for tail index, α, the tail quantile x(p) and the expected shortfall ES are given in Eqs. (2), (1) and (3), respectively. The table distinguishes pre-crisis from 1st July 1987 to 31st August 2008, crisis from 1st September 2008 to 20th June 2020 and another crisis when oil prices started moving down from 1st July 2015 30th June 2020. The nuisance parameter *m* equal to 148, 77 and 38 for the pre-crisis, crisis and another crisis, respectively.

implies that a daily erosion of Crude Brent oil returns with 0.1401 or more is expected happen once every 1000 days = 1000/260 ≈ 3.8 years. The corresponding (p = 0.1%) expected shortfall of 0.0788 implies that once the tail-VaR of 0.1401 is exceeded, the expected loss given this exceedance equals an additional 0.0788. All these numbers are much lower during both two crises. In addition, the results of Crude WTI oil is in line with Crude Brent oil but the magnitude of movement is less than Crude Brent oil. However, the tail risk of Crude WTI oil is lower than selected precious metals, especially in 2015 oil price crisis. Comparing the tail risk among selected precious metals, one observes that gold returns seems to demonstrate lower tail risk during both crises which is not surprising (higher values of tail index and lower values of tail-VaR and expected shortfall). This indicates that gold is a safer asset during the downturn of markets as compared to platinum, palladium and silver.

Table 3C
Tail risk indicators for selected commodities: pre-crisis and crisis estimators.

Commodity	α	x(p)		ES (X > s)		ES (x(p))	
		p = 0.2%	p = 0.1%	s = 25%	s = 50%	p = 0.2%	p = 0.1%
Panel I: Pre-crisis estimates (m = 197)							
Crude WTI	2.7736	0.1131	0.1452	0.1410	0.2819	0.0638	0.0819
Crude Brent	2.7655	0.1093	0.1404	0.1416	0.2832	0.0619	0.0795
Gold	2.7268	0.0475	0.0612	0.1448	0.2896	0.0275	0.0354
Platinum	3.0170	0.0628	0.0790	0.1239	0.2479	0.0311	0.0392
Palladium	2.6275	0.1025	0.1334	0.1536	0.3072	0.0630	0.0820
Silver	2.6777	0.0876	0.1135	0.1490	0.2980	0.0522	0.0676
Panel II: Crisis estimates (m = 103)							
Crude WTI	2.9416	0.1173	0.1484	0.1288	0.2575	0.0604	0.0764
Crude Brent	4.0024	0.0838	0.0996	0.0833	0.1665	0.0279	0.0332
Gold	2.9667	0.0525	0.0664	0.1271	0.2542	0.0267	0.0338
Platinum	2.9336	0.0688	0.0871	0.1293	0.2586	0.0356	0.0451
Palladium	2.7719	0.0963	0.1236	0.1411	0.2822	0.0543	0.0698
Silver	2.6881	0.1078	0.1394	0.1481	0.2962	0.0638	0.0826
Panel III: Another crisis estimates (m = 50)							
Crude WTI	4.4712	0.0880	0.1028	0.0720	0.1440	0.0254	0.0296
Crude Brent	5.4811	0.0720	0.0817	0.0558	0.1116	0.0161	0.0182
Gold	3.9710	0.0318	0.0378	0.0841	0.1683	0.0107	0.0127
Platinum	3.8006	0.0486	0.0583	0.0893	0.1785	0.0174	0.0208
Palladium	3.2952	0.0696	0.0859	0.1089	0.2178	0.0303	0.0374
Silver	3.0660	0.0696	0.0872	0.1210	0.2420	0.0337	0.0422

Notes: Estimators for tail index, α, the tail quantile x(p) and the expected shortfall ES are given in Eqs. (2), (1) and (3), respectively. The table distinguishes pre-crisis from 1st July 1987 to 31st August 2008, crisis from 1st September 2008 to 20th June 2020 and another crisis when oil prices started moving down from 1st July 2015 30th June 2020. The nuisance parameter m equal to 197, 103 and 50 for the pre-crisis, crisis and another crisis, respectively.

Looking at comparing the change of pre-crisis and crisis values for tail risk of crude oil and selected precious metals between 2008 global financial crisis and 2015 oil price crisis, the point estimates for α, x_p and E(X - x_p/X > x_p) change more considerably indeed during 2015 oil price crisis than during 2008 global financial crisis. Table 3A exhibits that the tail index (α) of Crude Brent oil shifts approximately 118.45% for 2015 oil price crisis, while the change is only 50.51% for 2008 global financial crisis. Furthermore, the tail quantiles (x_p) and corresponding (p = 0.1%) expected shortfall of Crude Brent oil reduced approximately 36.07% and 77.58% during 2015 oil price crisis, whereas the reduction is only 22.24% and 57.66% during 2008 global financial crisis, respectively. In addition, the change proportions of Crude WTI oil, gold, platinum, palladium and silver are also higher during 2015 oil price crisis than during 2008 global financial crisis, although the number of the nuisance parameter is adjusted in Tables 3B and C. This indicates that the tail risk of crude oil and precious metals is lesser in the 2015 oil price crisis than 2008 global financial crisis.

The truly time varying tail risk metrics are also estimated by conditioning on five year rolling samples as a supplement for our subsample estimation and testing findings. Fig. 1 presents the evolution of (average) rolling Hill estimates, (average) tail quantile rolling estimates and (average) expected shortfalls for crude WTI oil, crude Brent oil, gold, platinum, palladium and silver. The figure demonstrates that tail risk metrics have been strongly time varying, even during the pre-crisis period. However, it is quite clear that upward trend in the tail index (reduced tail risk) for crude oil and four precious metals occurs during 2008 global financial crisis and 2015 oil price crisis as seen in the left top raw of the graph. This also documents the decrease in the tail quantile estimates on the right top raw of graph and the expected shortfall metrics on the bottom raw of graph for crude oil and four precious metals during both crises. On the other hand, there are downward trend in the tail index (increase tail risk) and an increase in the tail quantile estimates and the expected shortfall metrics for crude oil and four precious metals during 2020–2021 Covid-19 pandemic crisis. However, the movement levels of both tail quantile and expected shortfall metrics of crude oil substantially higher than four precious metals during this crisis. This indicates that the tail risks for crude oil and four precious metals reduce during 2008 global financial crisis and 2015 oil price crisis but increase during Covid-19 pandemic crisis, especially for crude oil. Within precious metals, the tail risk for gold is dominated by platinum, palladium and silver even crude oil during 2008 global financial crisis, 2015 oil price crisis until Covid-19 pandemic crisis. This may result from the fact that investors avoid a risky asset and they perceive that gold can be an instrument to prevent from return's loss or to diversify the risk of their portfolio. This is consistent with the findings of Hammoudeh et al. (2013) gold is the most appropriate asset to be included in the portfolio in order to hedge the downward risk during high volatility period such as the 2007/2009 Great Recession compared to silver, platinum, palladium, oil and S&P 500 index.

Overall, the tail risk of crude oil and four precious metals declines during the crises comparing to the pre-crisis except Covid-19 pandemic crisis. Interestingly, the proportion of reduction for tail risk is higher during the 2015 oil price crisis than 2008 global financial crisis. Moreover, gold seems to be a safer asset compared to platinum, palladium and silver due to the lowest tail risk. Importantly, even if the tail risk of gold increases during Covid-19 pandemic crisis as well as crude oil and other precious metals, the level of increased tail risk for gold is lower than others. This insists that gold can be used as a safe haven asset.

4.2. Extreme systematic risk of crude oil and four precious metals

The exposure of the returns of crude oil, gold, platinum, palladium and silver to enormous adverse movements in "aggregate" shocks is estimated in this subsection. We define the term "aggregate" in this context as a macroeconomic or non-diversifiable shock. Our indicator of "extreme systemic risk" (tail-β) is measured by different candidate-risk factors. The conditional factors are employed including China, global and G7 (US, Canada, France, Germany, Italy, Japan and UK: CGG7) stock indexes. In addition, we also condition the tail-β on an equally weighted portfolio of the respective producer countries' return indices and respective consumer countries' return indices.

Evaluations of tail-β are summarized in Table 4 (crude oil and four precious metals: full samples) and Table 5 (crude oil and four precious metals: pre-crisis, crisis and another crisis subsamples).

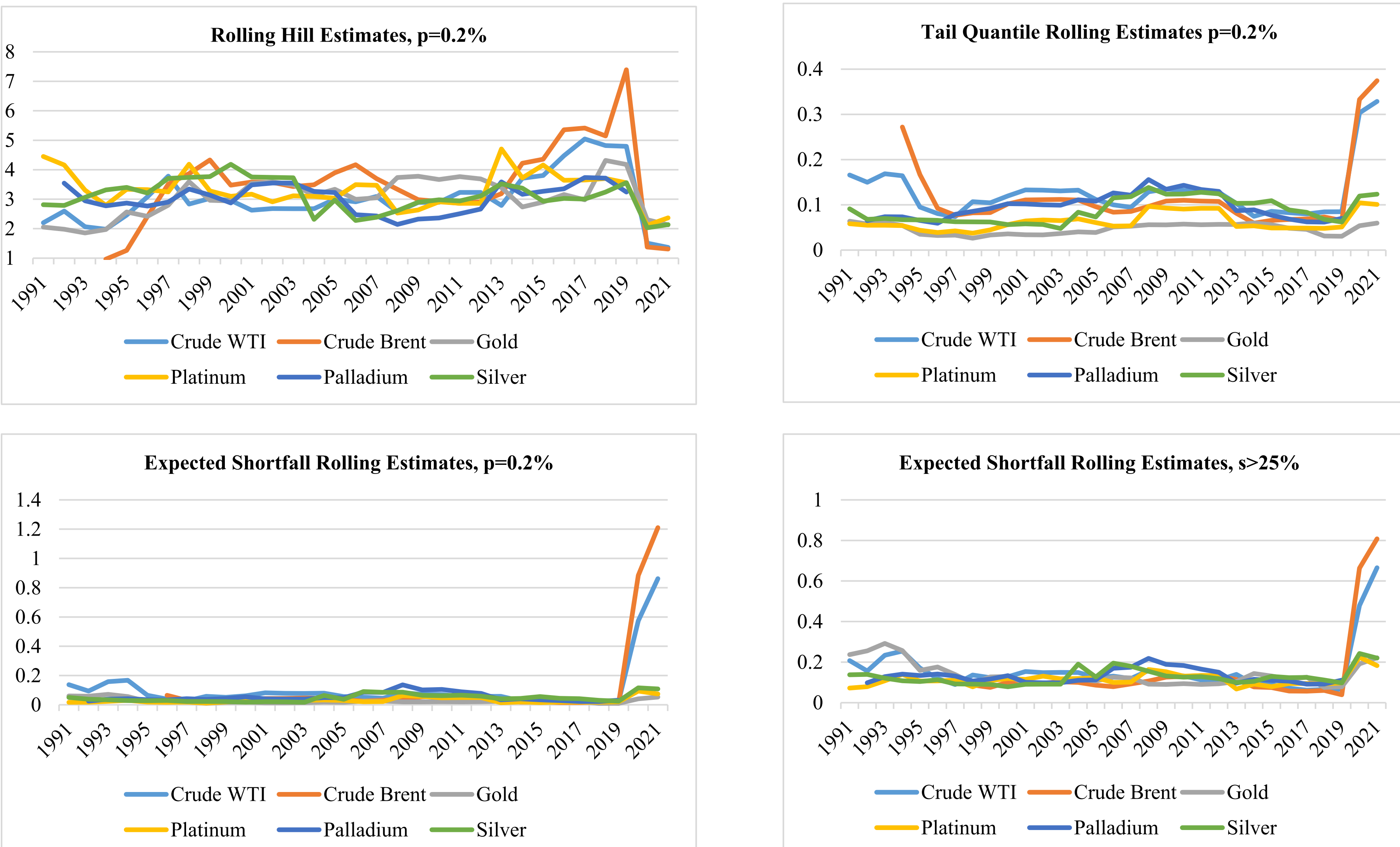

Fig. 1. The rolling tail risk of crude oil and other metals.

Table 4
Extreme systemic risk (tail-βs) for selected commodities: full sample results.

Commodity	Aggregate risk factor (index)												
	US	China	Canada	France	Germany	Italy	Japan	UK	Global	Respective producer country	Respective consumer country	Respective producer country	Respective consumer country
Crude WTI	0.2620	0.2341	0.2835	0.2508	0.2496	0.2545	0.2298	0.2635	0.2222	0.2620	0.2620	US	US
Crude Brent	0.2516	0.2492	0.2734	0.2703	0.2699	0.2884	0.2584	0.2957	0.2420	0.2516	0.2516	US	US
Gold	0.2129	0.2236	0.2448	0.2165	0.2132	0.2181	0.2272	0.2394	0.2059	0.2236	0.2236	China	China
Platinum	0.2391	0.2482	0.2701	0.2442	0.2312	0.2500	0.2349	0.2620	0.2359	0.2888	0.2482	South Africa	China
Palladium	0.2293	0.2603	0.2357	0.2338	0.2306	0.2397	0.2529	0.2551	0.2315	0.2507	0.2603	Russia	China
Silver	0.2265	0.2345	0.2671	0.2388	0.2338	0.2397	0.2303	0.2578	0.2215	0.2427	0.2265	Mexico	US

Note: The tail-βs is given by Eq. (4) with full samples from 1st January 1987 to 31st December 2021. The table reports results conditional on different aggregate risk factors. The nuisance parameter m denotes the number of extreme results used in estimation equals 400 for crude oil, gold, platinum, palladium and silver.

Table 5
Extreme systemic risk (tail-βs) for selected commodities: pre-crisis vs. crisis vs. another crisis results.

Commodity	Aggregate risk factor (index)										
	US	China	Canada	France	Germany	Italy	Japan	UK	Global	Respective producer country	Respective consumer country
Panel I: Pre-crisis estimates											
Crude WTI	0.2227	0.2176	0.2203	0.2218	0.2212	0.2139	0.2181	0.2216	0.2218	0.2735	0.2735
Crude Brent	0.2262	0.2599	0.2299	0.2262	0.2268	0.2132	0.2212	0.2244	0.2671	0.2788	0.2788
Gold	0.2196	0.2212	0.2160	0.2036	0.2142	0.2093	0.2196	0.2098	0.2133	0.2651	0.2707
Platinum	0.2254	0.2224	0.2246	0.2179	0.2287	0.2256	0.2199	0.2178	0.2130	0.2256	0.2752
Palladium	0.2252	0.2376	0.2252	0.2160	0.2225	0.2179	0.2187	0.2144	0.2328	0.2316	0.2735
Silver	0.2149	0.2378	0.2135	0.2073	0.2126	0.2142	0.2111	0.2073	0.2121	0.2066	0.2665
Panel II: Crisis estimates											
Crude WTI	0.2089	0.2138	0.2115	0.2158	0.2115	0.2115	0.2083	0.2073	0.2099	0.2089	0.2089
Crude Brent	0.2186	0.2261	0.2243	0.2339	0.2243	0.2288	0.2135	0.2335	0.2218	0.2186	0.2186
Gold	0.2179	0.2108	0.2247	0.2196	0.2175	0.2265	0.2193	0.2141	0.2102	0.2108	0.2179
Platinum	0.2203	0.2070	0.2052	0.2058	0.2045	0.2064	0.2128	0.2012	0.2080	0.2092	0.2203
Palladium	0.2115	0.2138	0.2141	0.2182	0.2214	0.2221	0.2118	0.2182	0.2158	0.2228	0.2115
Silver	0.2141	0.2070	0.2232	0.2186	0.2225	0.2228	0.2179	0.2108	0.2089	0.2175	0.2141
Panel III: Another crisis estimates											
Crude WTI	0.1581	0.1737	0.1592	0.1836	0.1750	0.1651	0.1615	0.1714	0.1693	0.1581	0.1581
Crude Brent	0.1667	0.1852	0.1821	0.1899	0.1773	0.1831	0.1663	0.1852	0.1741	0.1667	0.1667
Gold	0.1826	0.1728	0.1888	0.1783	0.1792	0.1932	0.1842	0.1755	0.1759	0.1728	0.1826
Platinum	0.1737	0.1651	0.1759	0.1714	0.1706	0.1680	0.1764	0.1732	0.1746	0.1778	0.1737
Palladium	0.1750	0.1769	0.1750	0.1826	0.1755	0.1759	0.1741	0.1773	0.1807	0.1862	0.1750
Silver	0.1701	0.1706	0.1842	0.1831	0.1842	0.1857	0.1723	0.1706	0.1676	0.1836	0.1701

Note: The tail-βs is given by Eq. (4). The table reports results conditional on different aggregate risk factors. The table distinguishes pre-crisis estimates from crisis estimates (sample mid-point equals September 1st, 2008) and another crisis estimates (sample mid-point equals July 1st, 2015). The nuisance parameter m equals 263, 137 and 67 for the pre-crisis, the crisis and another crisis samples.

The reported tail-βs in Tables 4 and 5 have a straightforward economic interpretation. For instance, the pre-crisis value 0.2196 in the row "Gold" and column "US" in panel I of Table 5 implies that a very gigantic downturn in the US stock index during the pre-crisis period is related to a 0.2196 (21.96%) propensity that gold faces a daily price decrease of comparable magnitude. In other words, even before the systemic 2008 global financial crisis struck, a daily sharp drop in the US stock index is expected to coincide with a comparably huge decline in gold returns 21.96%. Furthermore, gold's probability toward co-crashing with the US stock index has approximately dropped 0.77% to 0.2179 during the 2008 global financial crisis period (panel II of Table 5) and declined 16.85% to 0.1826 during the 2015 oil price crisis period (panel III of Table 5).

Moving on to more detail of tail-β for crude oil, gold, platinum, palladium and silver, a number of interesting findings can be observed. First, all tail-βs of vary around 0.2 for full samples even before the crisis and 2008 global financial crisis periods. Whereas, all tail-βs decline to approximately 0.1 during the 2015 oil price crisis. Second, the vast majority of tail-βs spectacularly decreases during both 2008 global financial crisis and 2015 oil price crisis periods. Third, the magnitudes of tail-β reduction are considerably stronger in 2015 oil price crisis period than the 2008 global financial crisis period. Fourth, tail-βs differ quite dramatically across commodities, continents (CGG7) and respective producer and consumer countries. Fifth, tail-βs of crude oil and four precious metals for respective consumer countries in the crises have a higher proportion of decrease compared to CGG7 stock indexes. Finally, tail-βs of only crude oil producer country where US is the biggest producer and gold respective producer county where China is the biggest producerhave a stronger proportion of reduction than CGG7 stock indexes. Our result for crude oil is consistent with the finding of Tasi (2015) that some energy-intensive manufacturing industries in US earns more positive equity results to respond oil price shocks.

We also consider the tail-βs of CGG7 stock indexes conditioning on a crash in each selected commodity over different time periods. Fig. 2

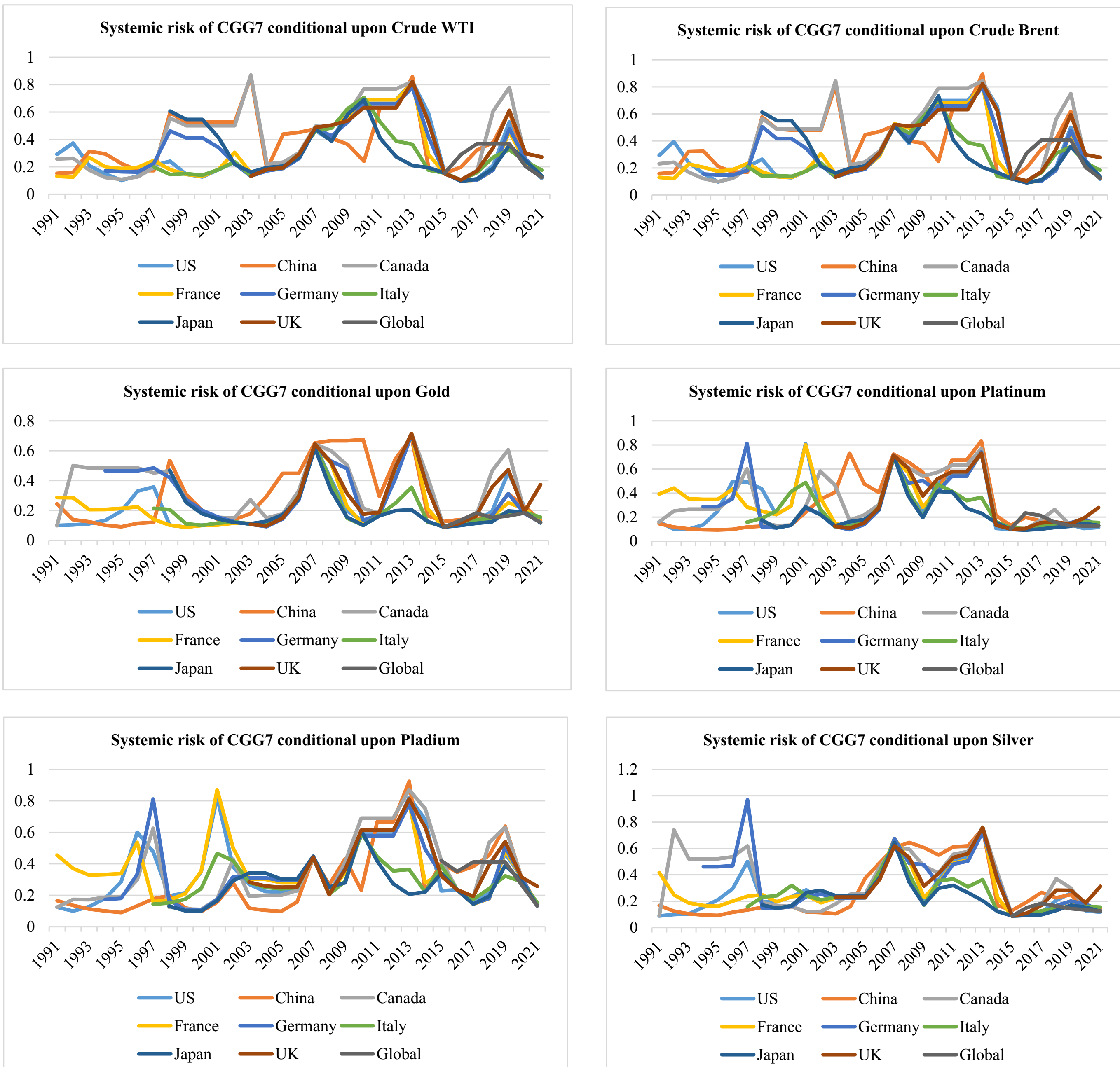

Fig. 2. Systemic risk (tail-βs) of CGG7 (China, Global and G7) conditional upon crude oil and precious metals.

shows that the systemic risk (tail-β) of all CGG7 stock indexes fluctuates over time. One observes that tail-βs of all CGG7 stock indexes considerably decrease during both the 2008 global financial crisis, the 2015 oil price crisis and the Covid-19 pandemic crisis periods conditioning with all selected commodities. This implies that if the investors invest in the crude oil and precious metals which seems to contain with lower risk, this supports to reduce the systemic risks from a shap fall in the stock markets of CGG7 countries during the crisis periods.

4.3. Spillover risk of crude oil and four precious metals

The multivariate contagion probability indicator ($P_{N/1}$) is analyzed in this subsection. We attempt to deal with two issues: (i) does spillover risk increase over time? (ii) how does crude oil and precious metals spillover risk?

The economic interpretation of the point estimates $P_{N/1}$ is straightforward. For example, Fig. 3 demonstrates multivariate metric $P_{N/1}$ of crude oil and precious metals values peaks at 0.1444 in 2011 on the top graph. This probability implies that if one of six selected commodities is triggered into distress, there is a 0.1444 (14.44%) chance that all six selected commodities undergo the same fate. This meltdown probability equals 0.1163 (11.63%) for the 2008 global financial crisis period and 0.1269 (12.69%) for the 2015 oil price crisis period.

To address how multivariate spillover risk evolves over time. Fig. 3 shows five year rolling sample estimates of the multivariate spillover risk indicators (crude oil, gold, platinum, palladium and silver). The top figure presents the rolling multivariate contagion probability ($P_{N/1}$) for crude oil and all selected precious metals. The two bottom figures exhibit the rolling multivariate contagion probability ($P_{N/1}$) of joint crashes for Crude WTI oil and selected precious metals on the left figure, while for Crude Brent oil and selected precious metals on the right figure. We observe an increase over time for the multivariate contagion probability regardless of the crude oil and selected precious metals considered until 2011. However, the multivariate contagion probability of these commodities decreases over time after 2011 until 2019. Interestingly, it has a slightly increase during in 2020 Covid-19 pandemic crisis and then it has a slightly decrease in 2021 as seen in the top figure. Also, the movement of the multivariate spillover risk probability of joint crashes for Crude WTI oil and selected precious metals (the bottom left figure) is nearly the same except for Crude WTI oil and gold during Covid-19 pandemic crisis which there is a decrease in $P_{N/1}$ in 2020 but a slightly increase in 2021.Whereas, the multivariate contagion probability for Crude Brent oil and selected precious metals (the bottom right figure) nearly similarly moves to above two figures; however, there is an increase of this indicator in 2018–2019 but it has a decrease during Covid-19 pandemic crisis in 2020–2021. Interestingly, the multivariate spillover risk probability for crude oil and platinum dominates other precious metals from 2009 to 2021, roughly. This may be resulted from the reduction of raw price for platinum during this period, while the raw prices of gold, palladium and silver go up at that time. Hence, this reflects a higher level of spillover risk for platinum than other selected metals at that time. Overall, our results show that the spillover risk of crude oil and selected precious metals do not increase over time but varies over time, especially the definitely increase of spillover risk for theses commodities during global financial crisis (2008–2009), European sovereign debt crisis (2010–2012) and Covid-19 pandemic crisis (2020–2021). This is consistent with the findings of Kang et al. (2017) that there is a considerably spillover risk of these commodities during both global financial crisis and European sovereign debt crisis. Moreover, Mensi et al. (2017a) claim that a source of volatility spillover risk of selected precious metals is the fluctuation of stock market returns.

Going to analyze deep detail on the multivariate contagion probability of joint crashes between crude oil and precious metals, the bottom left graph of Fig. 3 exhibits that this indicator between crude WTI and palladium is the lowest level compared to other precious metals in the 2008 global financial crisis and in the 2015 oil price crisis periods. While, if Crude Brent oil is stimulated into distress, the lowest probability of palladium also undergone into trouble only in the 2008 global financial crisis. This implies that palladium may be a diversify asset for the portfolio containing with Crude oil during the 2008 global financial crisis period. However, the multivariate contagion probability of joint crashes between crude oil and gold is lowest level among four precious metals during the 2020–2021 Covid-19 pandemic crisis period. This indicates that gold may be a safe haven asset for the portfolio consisting of Crude oil during the 2020–2021 Covid-19 pandemic crisis period. In addition, our findings are consistent with Salisu et al. (2021) that gold is a better safe haven asset during the Covid-19 pandemic crisis conpated to other precious metals such as silver, palladium and platinum. When we compare the two bottom figures, the movements of spillover risk between crude oil and precious metals are closely similar each other. This indicates that crude oil seems to spillover their effects both positive and negative impacts on the selected precious metals. This is consistent with the findings of Reboredo and Ugolini (2016) and Shahzad et al. (2019) that there is linkage between oil price volatilities and precious metals. This implies that crude oil is a stimulator of the price of precious metals.

Furthermore, Table 6 reports the multivariate spillover risk indicator $P_{N/1}$ of crude oil and precious metals (full samples). The results show that the multivariate measure $P_{N/1}$ of crude oil and precious metals values is around 0.2. This indicates that if crude oil price falls, the probability that precious metal also crashes equal to 0.2 (20%). Moreover, the probability of joint crashes between silver and crude WTI oil is the highest value at 0.2407 (24.07%). This implies that there is a chance of 1 out of 4 that both crude WTI and silver will collapse if one systemic commodity collapses. On the other hand, the result seems to exhibit that multivariate probability indicator between crude WTI and palladium is the lowest value at 0.2079 (20.79%). This means that if crude oil is dived into trouble, the co-crash chance of palladium is also lowest compared to gold, platinum and silver. Therefore, this implies that if crude oil is during the downward market period, a palladium can serve as a good diversifier risk for portfolio than gold, platinum and silver.

5. Conclusion and policy recommendations

This study opens the debate of tail risk proxies of crude oil and four precious metals: gold, platinum, palladium and silver. In this paper, we examine extreme systemic risk (tail-βs) relies on the different conditioning risk factors of CGG7 (China, Global and G7). Futher, we also measure spillover risk along with sensitivity analysis by adjusting the number of the nuisance parameter (m) for all selected commodities. The influence of oil price on precious metals is examined through novel approach of extreme value theory (EVT). Our approach facilitates to encircle the safe haven potentials of precious metals against the oil price shocks during the pre-crisis, crisis and another crisis periods. We identify that crude oil, gold, platinum, palladium and silver are considered as a safe asset for common investors, specifically gold. Our results indicate the claim that gold, platinum, palladium and silver are precious asset to mitigate the decline of returns during the falling periods of market and perform as 'safe haven'.

We find three novel findings. *First,* the tail risk of crude oil and precious metals (gold, platinum, palladium and silver) reduces during the 2008 global financial crisis and the 2015 oil price crisis periods except the Covid-19 pandemic crisis. Interestingly, gold is the lowest tail risk among four precious metals, indicating that gold is as a safer asset during the downturn market period. *Second,* our results also show that extreme systemic risk (tail-β) for these commodities clearly declines during above crises, especially the 2015 oil price crisis. This implies that crude oil and selected precious metals can be used as a diversified asset to hedge the risk in the portfolio against financial assets' volatility. *Third*, the spillover risk of crude oil and selected precious metals varies over time. Specially, the multivariate spillover risk probability of these commodities obviously decreases during global financial crisis (2008–2009) and European sovereign debt crisis (2010–2012) and the Covid-19 pandemic crisis (2020–2021), indicating that the co-crash probability of these commodities declines during these crises. Most importantly, we find that crude oil seems to spillover their effects both positive and negative impacts on the selected precious metals. This indicates that crude oil is an important stimulator of the spillover risk for precious metals.

Our findings also provide meaningful implication for portfolio risk management practices for single investors as well as financial institutional investors working in the commodity markets, oil and precious metal markets specifically. The illustration of unpredictable transmission between crude oil and precious metal markets carry valuable

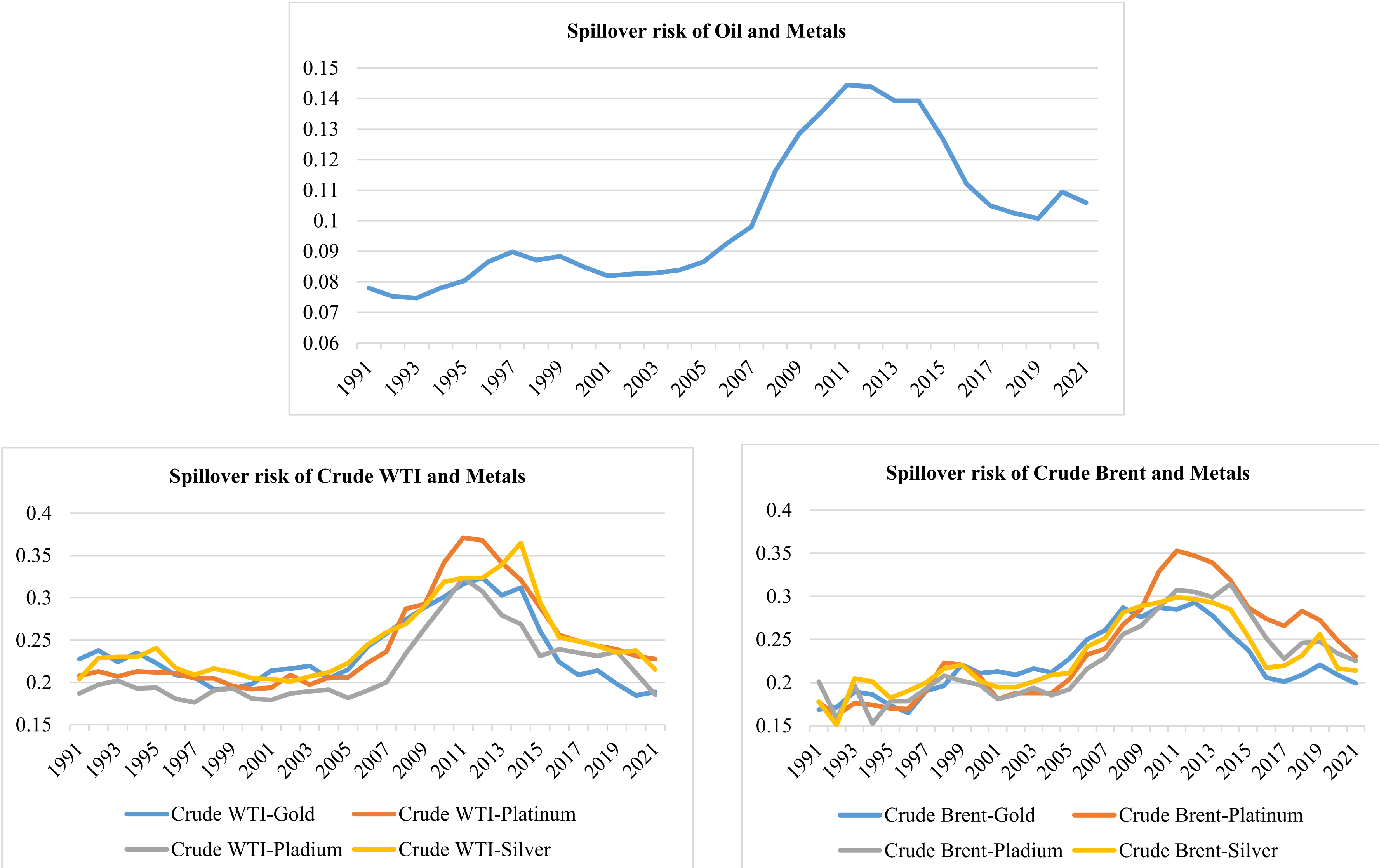

Fig. 3. The rolling spillover risk of crude oil and precious metals.

Table 6
Full sample risk of oil and metals.

	Crude WTI	Crude Brent
Gold	0.2350	0.2329
Platinum	0.2354	0.2336
Palladium	0.2079	0.2293
Silver	0.2407	0.2275

insights for estimating the accurate extreme systemic risk (tail-βs). Our findings can also be significant and helpful for financial market investors in making proper investment planning to attain the maximum advantage of portfolio diversification. Financial managers can further apply these results in forecasting to estimate future global oil market trends for refining their hedging skills and portfolio performance.

CRediT authorship contribution statement

Rizwan Ahmed: Conceptualization, Resources, Data curation. **Sajid M. Chaudhry:** Resources, Data curation, Supervision, Writing – original draft, Writing – review & editing, Visualization. **Chamaiporn Kumpamool:** Formal analysis - summary statistics and analysing empirical results, Investigation, Resources - collected data, Writing original draft, Writing – review & editing. **Chonlakan Benjasak:** Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

There is no conflict of interest among the Authors.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106063.

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