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Quantile connectedness among gold, gold mining, silver, oil and energy sector uncertainty indexes

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ABSTRACT

This study examines the quantile relationships among silver, gold, gold mining, oil and energy sector uncertainty indexes. Using a quantile cross-spectral approach, results show that the uncertainty indexes have a time- and quantile-dependent structure. Moreover, the extent of dependence is higher at the long term than at the short- and medium-terms, irrespective of time horizons. Gold and silver show negative and positive short-term dependence during bearish and bull market conditions, respectively, at two-day trading. The dependence switches to positive beyond two trading days. We find asymmetric dependence between crude oil and energy sector uncertainty indexes at two-day trading. The dependence is positive at medium and long terms. Furthermore, the magnitude of dependence between metal (gold, gold mining and silver) and energy uncertainty indexes (crude oil and energy sectors) is sensitive to market conditions.

1. Introduction

Gold and oil are two important and strategic natural resources that are widely used in various activities (Bouri et al., 2017; Mensi et al., 2021a; Wei et al., 2020). The relationship between crude oil, gold and silver has attracted the attention of market participants and policymakers. The acceleration of industrialisation and urbanisation has intensified the instability and uncertainty in energy and metal markets. Moreover, the high oil price fluctuations have affected the metal manufacturing industries. Precious metals, especially gold, are commonly accepted as an investment alternative during periods of turmoil. Gold plays the role of a hedge and safe-haven asset in periods of turmoil of the crude oil market (Reboredo, 2013). Moreover, gold is a store value and an investment instrument. It serves as a safe haven asset against inflation. Gold reserves is a crucial for the financial policy adopted by the central banks. Gold and silver are widely employed by financial and commodity investors to hedge their position against risk exposure during episodes of financial and political uncertainties (Baur and McDermott, 2010; Hillier et al., 2006; Mensi et al., 2021b; Selmi et al., 2018). Crude oil is a vital commodity for the real economy. Oil is more sensitive to bad news whereas gold and silver are more dependent to good news (Chen and Qu, 2019). The prices of these commodities show large swings in recent years due to the financial and energy crises.

The literature has explained the transmission mechanism between oil and gold through two channels. First, the linkage may be explained via the inflation variable. Oil price rise increases production cost (Hanmoudeh and Yuan, 2008), resulting in the general price level of goods and services (Hooker, 2002; Hunt, 2006). This situation raises gold price to hedge against the inflation (Jaffe, 1989). Second, positive oil price shocks adversely impact financial asset prices, leading investors to switch to gold asset as a store of value. Zhang and Tu (2016) show that oil price changes influence production costs, resulting in metal price variations. Thus, metal and oil prices are interrelated, i.e., the high instability of oil prices increases the instability of metal markets.

The last decade has been marked by large fluctuations in energy prices due to China's economic growth as the world's second largest economy, the US–China trade war and the occurrence of geopolitical and economic events. Gao et al. (2018) argue that the rising uncertainty in oil predicts decrease in future real economic activities. Thus, the high instability and volatility of energy markets increases the difficulty in

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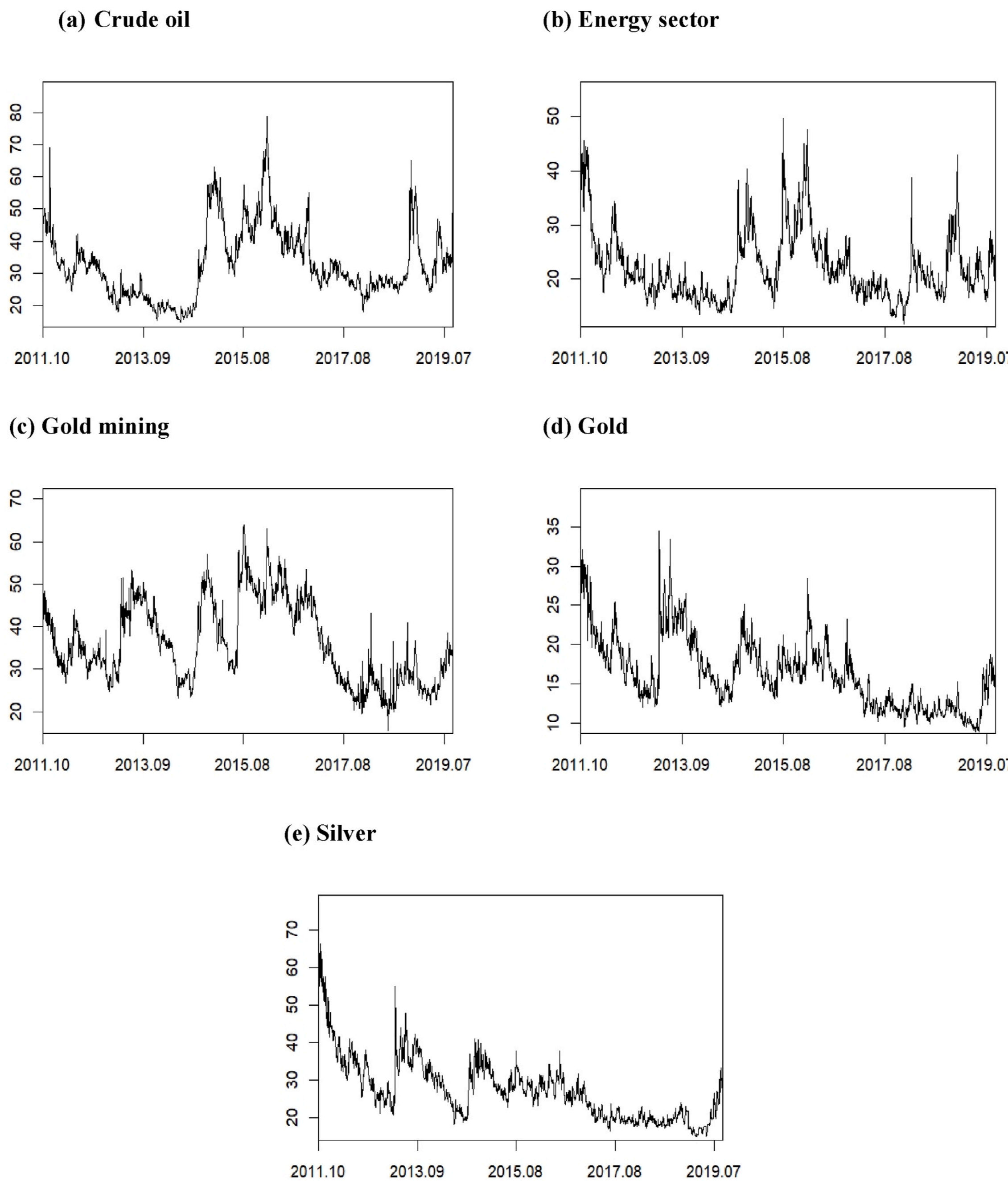

Fig. 1. Time variations of commodity uncertainty indexes.

management risk and imposes additional challenges on market participants.

The oil–precious metal price nexus has abundant empirical literature (Adewuyi et al., 2020; Al-Yahyee et al., 2019; Aourri et al., 2013; Baffes, 2007; Cagli et al., 2019; Le and Chang, 2012; Rehman et al., 2018; Sari et al., 2010; Zhand and Wei, 2010; Zhang et al., 2018; Zhu et al., 2015). However, only few studies have examined the interactions between oil and precious metals' uncertainty indexes. Using modified GARCH–jump models, Dutta (2017) examines the effects of crude oil volatility index (OVX) on precious metals and finds significant evidence of predictability of industrial metal returns using OVX. In addition, the author finds insignificant impacts of oil volatility shocks on the aggregate precious metal market. OVX and precious metals have an asymmetric relationship. Using the nonlinear autoregressive distributed lag (ARDL) model and nonlinear Granger causality test, Dutta et al. (2019) investigate the nonlinear linkages between oil, gold, silver and gold mining volatility indexes. The authors find nonlinear relationships between oil and precious metals in the long term. Moreover, oil and gold volatility indexes demonstrate bidirectional causality. Recently, Roh et al. (2020) show that the downside risk premiums in gold and oil markets may grasp significant market-specific information. Mensi et al. (2017) examine the average and tail dependence between the implied volatility indexes of corn, oil and wheat by combining copula and wavelet approaches. The results show asymmetric dependence between cereals and oil's uncertainty indexes at multiple time horizons.

This study aims to analyse the quantile relationships between five important commodity implied volatility indexes, namely CBOE Gold Volatility Index (GVZ), CBOE Gold Mining ETF Volatility Index (VXGDX), CBOE Silver ETF Volatility Index (VXSLV), CBOE Crude Oil Volatility Index (OVX) and CBOE Energy Sector ETF Volatility Index

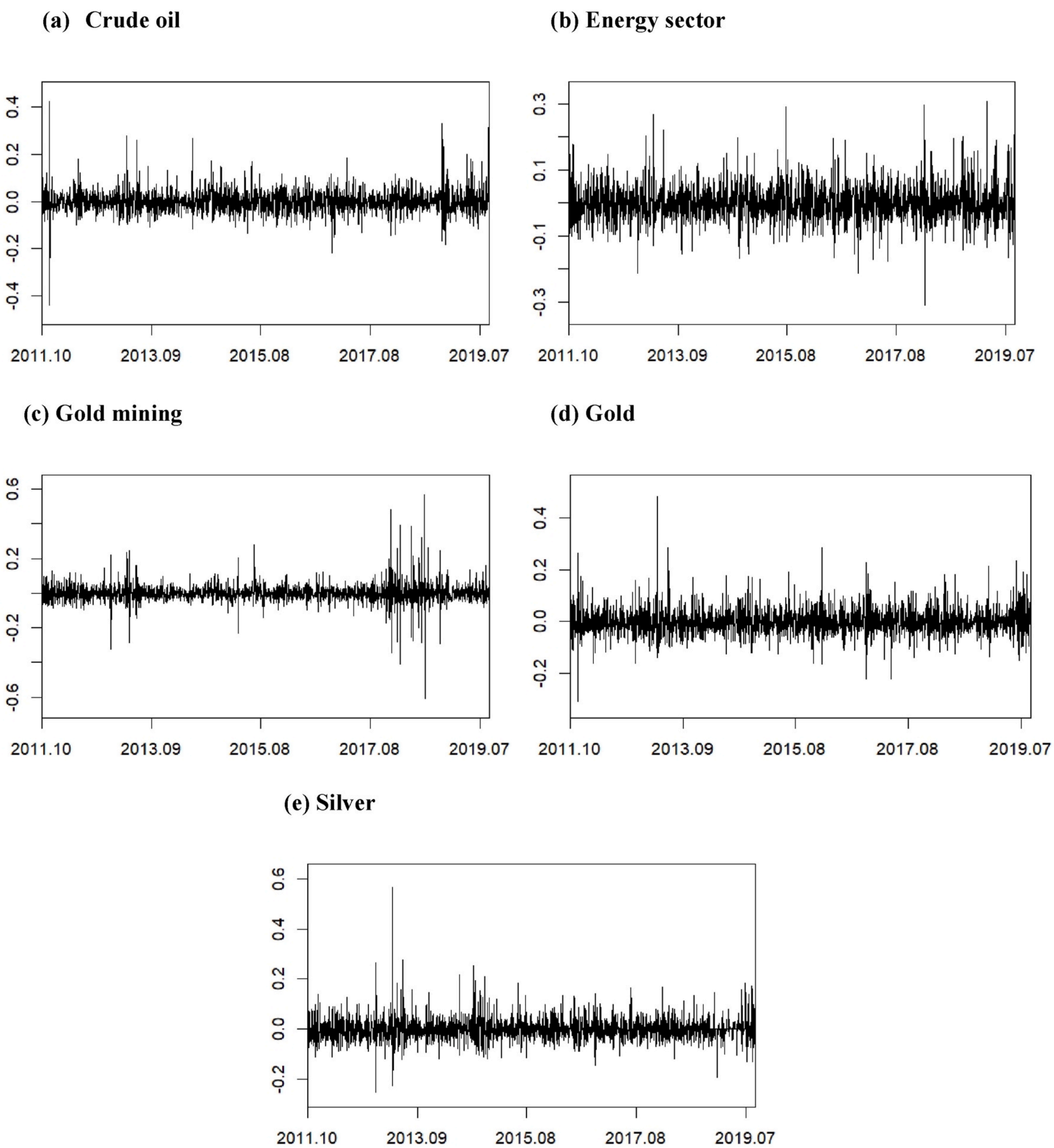

Fig. 2. Time evolution of return changes of commodity uncertainty indexes.

Table 1
Preliminary statistics of returns (%).

	Crude oil		Energy sector		Gold mining		Gold		Silver	
Mean	−0.005		−0.033		−0.019		−0.040		−0.041	
Std.	4.861		5.610		5.510		5.328		4.672	
Min	−43.991		−31.032		−60.788		−30.692		−25.126	
Max	42.497		30.876		57.074		48.073		56.610	
Skewness	0.798		0.531		0.392		0.964		1.616	
Kurtosis	10.402		2.745		24.578		6.531		14.407	
Jarque Bera test	10.402	***	2.745	***	24.578	***	6.531	***	14.407	***
ADF	−47.449	***	−45.898	***	−61.831	***	−49.317	***	−48.404	***
PP	−46.342	***	−46.343	***	−48.026	***	−46.352	***	−48.020	***

Note: *** stands for significance at 1% level.

(VXXLE). The analysis is performed under different markets conditions and time horizons for a detailed explanation.

The market value of global gold mining market is expected to soar from $214.1 billion in 2021 to $249.6 billion by (annual growth by 3.1% from 2021 to 2026).[1] Gold mining volatility index enables investors to

[1] https://www.businesswire.com/.

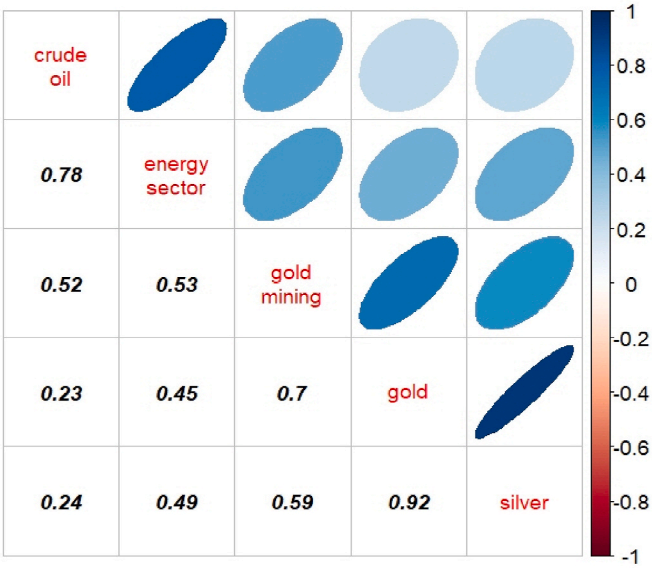

Fig. 3. Visualization of the Pearson correlation matrix.

identify the opportunity to track the attractive growth companies operating in the areas of gold mining, especially during crisis and inflation periods. This allows investors to hedge their exposure. This fear index is affected by debt, and macroeconomic policies, extraction costs and reserves, and company management strategy. If the zero index value indicates a stable gold mining market whereas a value close 100 indicates unstable gold mining market.

The Energy Sector Index provides a benchmark representation of the energy sector of the S&P 500 index. This sector embodies oil, gas and consumable fuels firms; and energy equipment and services. OVX is measure of crude oil uncertainty by estimating the expected 30-day volatility of crude oil as priced by the US oil fund. The reason behind selecting both OVX and VXXLE is to observe whether oil represents the main driver of the energy sectors during bearish, normal, and bullish market scenarios as well under various time horizons. This allows one to gather the valuable information on the dependencies among these indexes and their impacts on the investors' expectations on future volatility. Shaikh (2021) shows that the implied volatility index of crude oil, energy, and silver reach the highest level during the 2008 global financial crisis (GFC). The author also finds that COVID-19 cases intensify the volatility uncertainty of commodities. Thus, examining the interactions among different commodity volatility indexes provides new insights into portfolio optimization, risk management, hedging, price discovery, and risk-diversification benefits.

To the best of our knowledge, this is the first study to combine frequency and time horizon factors to analyse the dependence structure between precious metal (gold, gold mining and silver) and energy (crude oil and energy sector) uncertainty indexes. All possible market scenarios and different time horizons are considered to achieve our objective.

This study contributes to the existing literature in three fronts. First, it examines the quantile relationships between five important commodity uncertainty indexes (gold, gold mining, silver, crude oil and energy sector) using daily data from 2011 to 2019. This sample period is turbulent and includes several economic and political events. We observe that gold, oil and silver are the main commodities in the real economy, in addition to crude oil. The Crude oil and energy sector are characterised by high instability during the last three decades. Specifically, the price of Brent reached $145 per barrel in summer of 2008 and declined to less than $60 per barrel in 2014. According to The Washington Post, the crash of oil started in mid-2014, when oil prices fall approximately 40%.

Second, commodity markets experience periods of upside and downside trends. The interaction among markets is asymmetric to market trends (Richards et al., 2012). Thus, this study examines the relationship during bear, normal and bull markets. Energy investors are questioning the predictive power of commodity uncertainty indexes particularly during financial stress episodes.

Third, we apply the quantile cross-spectral approach mainly due to its ability to determine the average and tail dependence between two markets across quantiles. Studying the dependency between market networks is more crucial during the lowest percentiles (large downside price movements or bear market status) than during the highest percentiles of the joint distribution (sustained upside price movements or bull market status). The quantile cross-spectral analysis can flexibly examine the nonlinear dependence structure between markets as it considers asymmetric market relationship and covers all market statuses. Nine market scenarios are accounted for, namely bear–bear, bear–normal, bear–bull, normal–bear, normal–normal, normal–bull, bull–bear, bull–normal and bull–bull. This method provides a detailed examination of the interconnectedness of market networks, thus helping investors to define positions they should hold in the markets.

We plot the dependency structure matrix under different markets horizons to consider the heterogeneous market hypothesis. We analyse the dependence structure at two days, one week, two weeks, one month, three months, six months and one year of trading. Barunik and Kley (2015, 2019) document that uncorrelated variables may exhibit dependence in different parts of the joint distribution and/or at different frequencies. This finding indicates that the dependence between markets remains hidden when classical methods based on linear correlation and traditional cross-spectral analysis are applied (Croux et al., 2001; Fan and Patton, 2014). Our method can flexibly capture any type of dependence structure that may arise between markets under investigations.

Our results show evidence of dynamic and quantile relationships between uncertainty indexes. The dependence level is higher in the long term compared with those in the short and medium term, irrespective of time horizons. Moreover, gold and silver show negative and positive short-term dependence during bearish and bull market conditions, respectively, at two-day trading. In addition, the dependence switches to positive beyond two trading days. We find asymmetric dependence between crude oil and energy sector uncertainty indexes at two days of trading. Finally, the dependence is positive at medium and long terms. Furthermore, the magnitude of dependence between precious metal (silver, gold, and gold mining) and energy uncertainty indexes (crude oil and energy sector) is sensitive to market conditions.

The rest of this paper is organised as follows. Section 2 outlines the methodology. Section 3 presents the data and descriptive statistics. Section 4 discusses the results. Last section concludes the paper.

2. Quantile coherency method

Barunik and Kley (2015) and Baumöhl (2019) introduced quantile coherency as a measure of the general dependence structures between two stationary processes. In this paper, $(X_t)_{t\in\mathbb{Z}}$ denotes strictly stationary process, with components $X_{t,j}$, $j = 1, \cdots, d$, i.e., $X_t = (X_{t,1}, \cdots, X_{t,d})'$. Considering the two processes of (X_{t,j_1}) and (X_{t,j_2}), the quantile coherency is defined as follows:

$$\mathfrak{R}^{j_1,j_2}(\omega;\tau_1,\tau_2) = \frac{f^{j_1,j_2}(\omega;\tau_1,\tau_2)}{\left(f^{j_1,j_1}(\omega;\tau_1,\tau_1)f^{j_2,j_2}(\omega;\tau_2,\tau_2)\right)^{1/2}},$$
$$j \in \{1,\cdots,d\}, \tau = [0,1],$$

where f^{j_1,j_1}, f^{j_2,j_2} and f^{j_1,j_2} are quantile spectral densities and quantile cross-spectral density of processes X_{t,j_1} and X_{t,j_2}, respectively. The quantile cross-spectral density X_{t,j_1} and X_{t,j_2} are obtained from the Fourier transform of the matrix of quantile cross-covariance kernels $\Gamma_k(\tau_1,\tau_2) := (\gamma_k^{j_1,j_2}(\tau_1,\tau_2))_{j_1,j_2=1,\ldots,d}$:

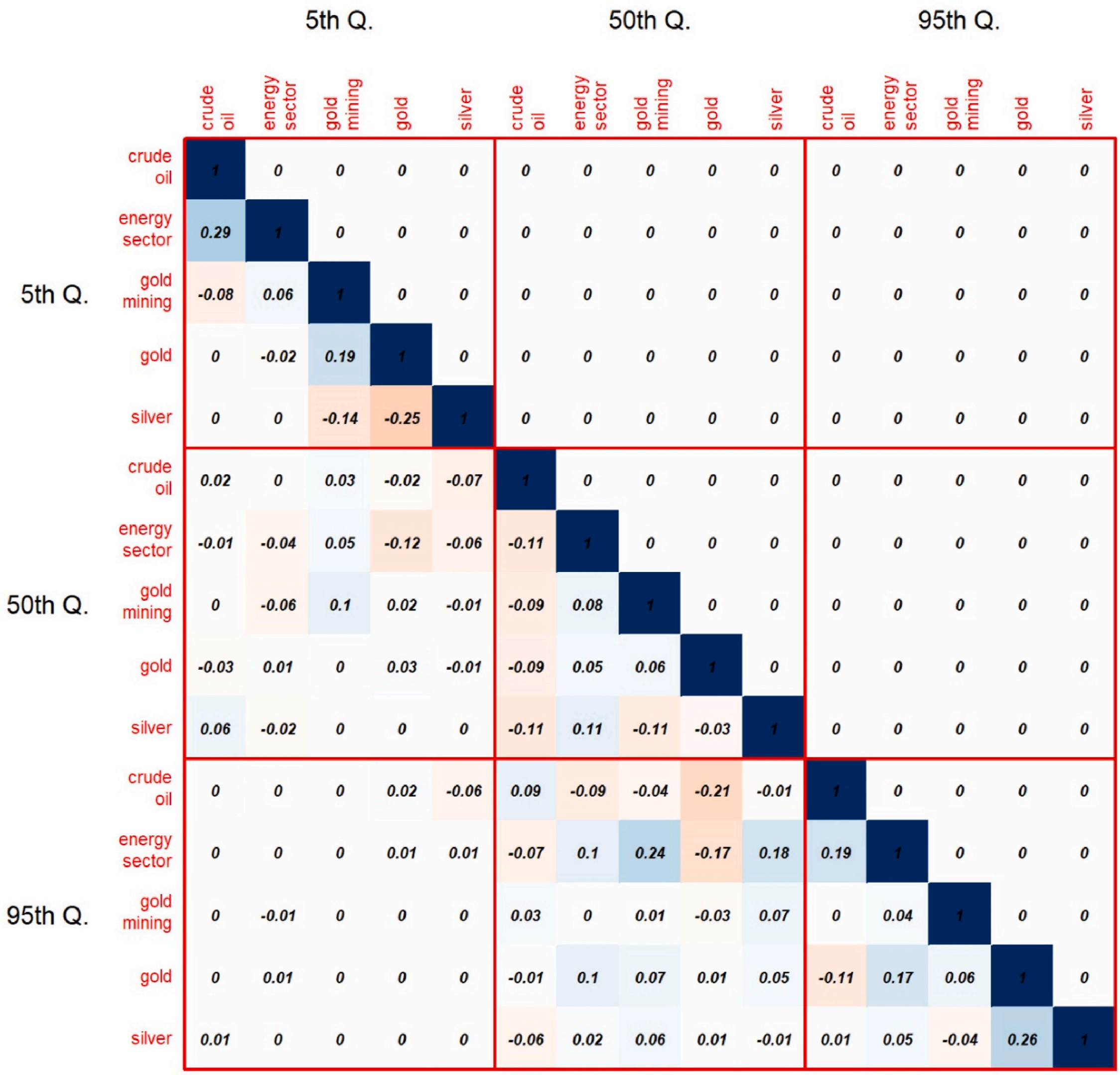

Fig. 4. Two-day quantile coherency matrix.
Note: We set 0 for insignificant coherences.

$$\gamma_k^{j_1,j_2}(\tau_1,\tau_2)e^{-ik\omega} := Cov\left(I\left\{X_{t+k,j_1} \le q_{j_1}(\tau_1)\right\}, I\left\{X_{t+k,j_2} \le q_{j_2}(\tau_2)\right\}\right),$$

where $j_1, j_2 \in \{1, \cdots, d\}, \omega \in \mathbb{R}, \tau_1, \tau_2 \in [0,1]$ and $I\{A\}$ is the indicator function of event A. Thus, we can gain information about the serial and cross-sectional dependence by letting k vary and choosing $j_1 \neq j_2$, respectively. As a result, the matrix of quantile cross-spectral density kernels in the frequency domain is as follows:

$$f(\omega;\tau_1,\tau_2) := \left(f^{j_1,j_2}(\omega;\tau_1,\tau_2)\right)_{j_1,j_2=1,\cdots,d},$$

$$f^{j_1,j_2}(\omega;\tau_1,\tau_2) := (2\pi)^{-1}\sum_{k=-\infty}^{\infty}\gamma_k^{j_1,j_2}(\tau_1,\tau_2)e^{-ik\omega}.$$

3. Data and preliminary analysis

We use the daily data of commodity implied volatility indexes (GVZ, VXGDX, VXSLV, COVX and VXXLE). The information content in the implied volatility index of commodities are more informative and reflective to the investor sentiment and market uncertainty than the traditional commodity prices (Liu et al., 2013). GVZ explores the investor sentiment by estimating the expected 30-day volatility of returns on the S&P's Depositary Receipts gold shares. The SPDR gold shares exchange-traded fund is the spot price of gold less fund expenses. It is a benchmark of gold price movements. Luo et al. (2016) document that GVZ is a predictor for future volatility of the gold futures contracts. Similarly, VXSLV determines the uncertainty degree in the silver market as it assesses the market's expectation of 30-day volatility of silver. By using VIX methodology to oil option, OVX has a power predictability of oil spot volatility (Chen et al., 2018). Haugom et al. (2014) show that considering OVX-based implied volatility in realized volatility models can provide an accurate volatility forecasting of crude oil futures returns. We extend existing papers because of three motivations. VXXLE measures the expected 30-day volatility of the price of the Energy Sector ETF. The sample period ranges from October 6, 2011 to September 17, 2019. The data are extracted from http://www.cboe.com/.

Fig. 1 shows an evolution of the commodity uncertainty indexes. The crude oil and energy sector uncertainty indexes show a similar pattern. Both uncertainty indexes experience a downside trend from 2011 to 2014. The two series show an upside trend during this period, which correspond to the great oil bust. The gold and gold mining uncertainty indexes exhibit different patterns. The silver uncertainty index demonstrates a downside trend from 2014 to late 2018, followed by an increase in the first three quarters of 2019.

Fig. 2 depicts the time variations of return changes of the five

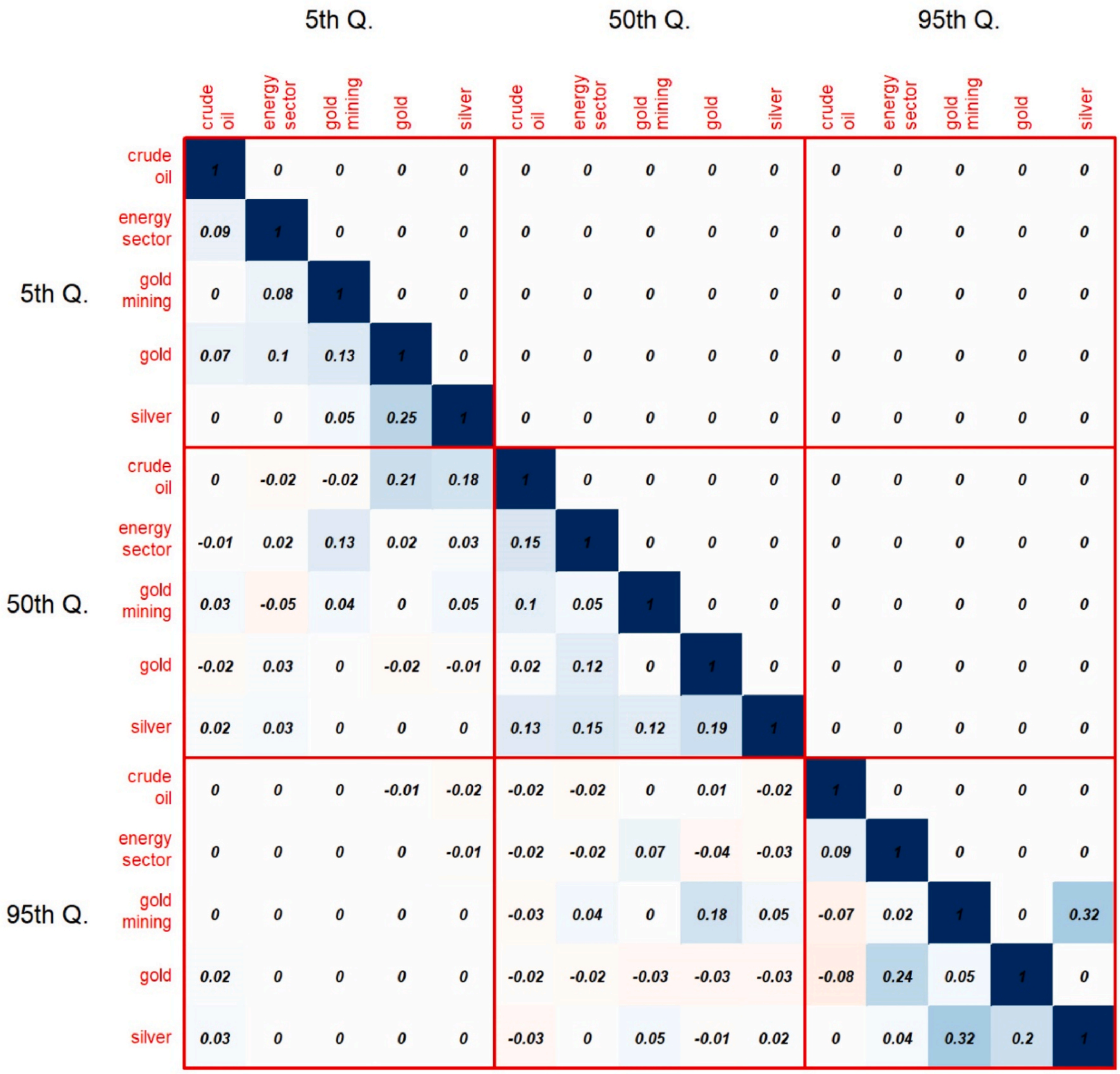

Fig. 5. One-week quantile coherency matrix
Note: We set 0 for insignificant coherences.

commodity uncertainty indexes. An examination of this figure shows volatility clustering, indicating a nonlinear behaviour of return series. This result motivates us to apply nonlinear models.

Table 1 reports the preliminary analysis of our return series. All volatility indexes have negative average returns. The standard deviation values are similar, i.e., that of silver and energy sector are the lowest (4.672) and the highest (5.610), respectively. Additionally, the Jarque–Bera (JB) test results for each return series reject the null hypothesis of normality at 1% significance level. This result indicates that the return distribution differs from the normal distribution. We use the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test as unit root tests to validate the stationarity of our return series and shows that all return series are stationary.

Fig. 3 below illustrates the Pearson correlation matrix showing high correlations among the uncertainty indexes under investigation. Among all pairs, the correlation coefficient is positive, indicating that all uncertainty indexes move in the same direction. The correlation level ranges from 0.24 for silver–crude oil pair to 0.92 for gold–silver pair. Moreover, the correlation within the same sector is higher than those between sectors. The linear correlations between crude oil and energy sector and between silver and gold mining are 0.78 and 0.59, respectively.

4. Empirical results

Figs. 4–10 below depict the quantile relationships between commodity volatility uncertainty indexes under two days, one week, two weeks, one month, three months, six months, and one year, respectively.

4.1. Short-term quantile cross-spectral results

Fig. 4 shows a negative dependence between silver–gold (−0.25) and silver–gold mining (−0.14) pairs under bear market conditions at two-day trading. This result indicates that both pairs move in an inverse direction during bearish market conditions. This result also reveals that when the implied volatility in the silver market goes up, the implied volatility of both gold and gold mining falls. This result also reveals that gold and gold mining serve as safe-haven assets during silver price crash. Risk-averse investors reallocate their investments from silver to gold during times of high uncertainty. Silver is independent of crude oil and energy sector during bear market scenarios. This results have significant implications in terms of portfolio risk management. This result is in line with the findings of Yildirim et al. (2020) who find evidence of significant bidirectional causality-in-variance running from silver to oil. This result is also consistent with Sari et al. (2010) and Zhang and Wei (2010). This relationship is expected because silver is heavily used in the

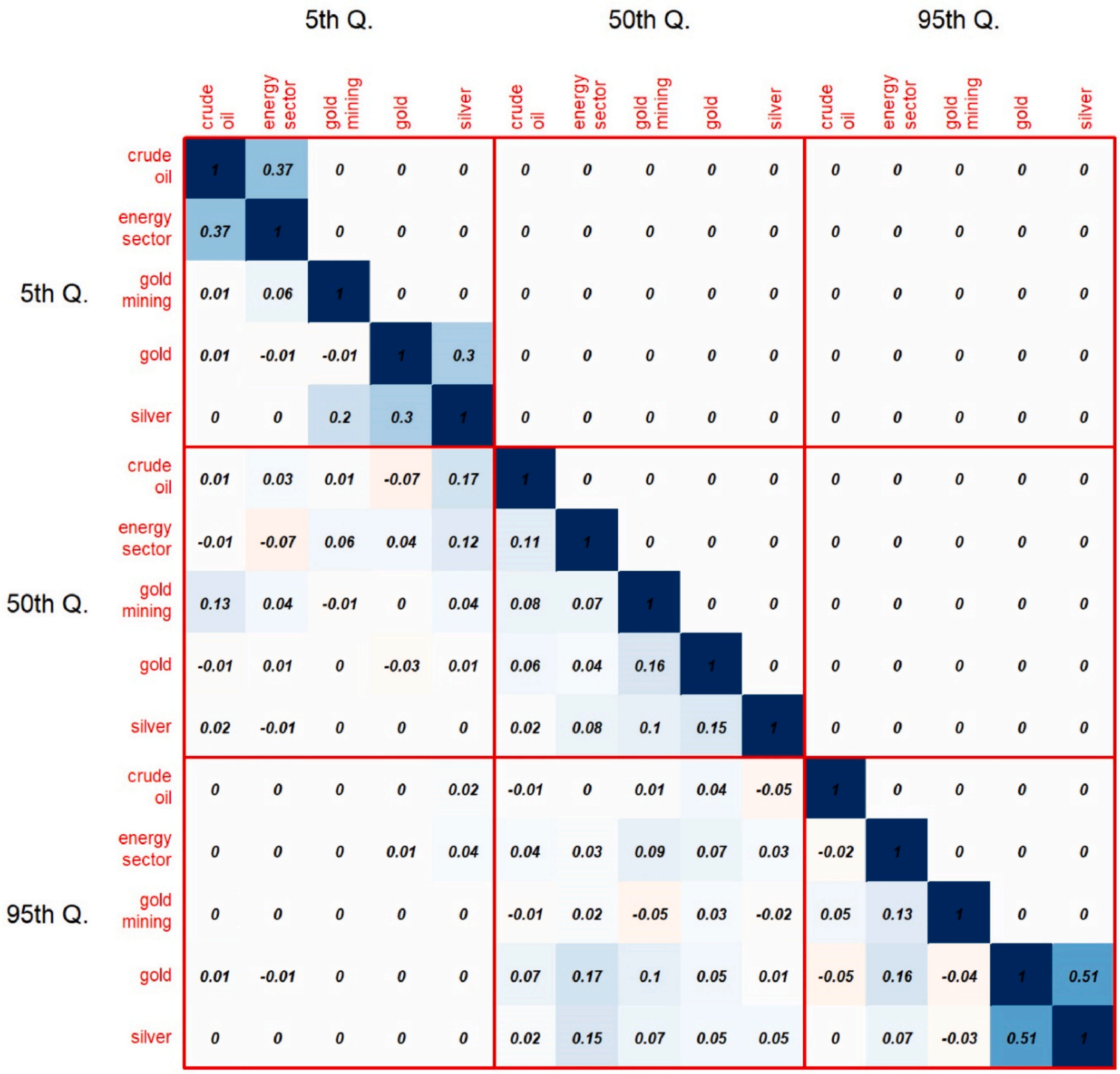

Fig. 6. Two-week quantile coherency matrix
Note: We set 0 for insignificant coherences.

industrial production process. The use of silver in vehicles has increased in the recent years which has implication on oil consumption and as a result oil prices. Gold uncertainty index is negatively dependent on energy sector (−0.02) and independent of crude oil. Gold mining uncertainty index is negatively dependent on crude oil and weakly dependent on energy sector uncertainty index. This result shows that gold is a refuge asset for oil traders and speculators. This result corroborates the findings of Selmi et al. (2018) who find that both gold and Bitcoin play the role of hedge and safe haven against oil price fall. Antonakakis et al. (2020) find low correlations between oil volatility index and gold volatility index, Euro/dollar currency volatility index (EVZ) and energy sector volatility index (VXXLE). Crude oil and energy sector are positively dependent on each other (0.29) during bear market conditions, indicating that they crash simultaneously. This result indicates a significant price transmission effect from oil to energy sector. It also indicates a clear contagion effects between crude oil and energy volatility indexes. Thus, oil prices can be a predictor indicator for energy sector. We find insignificant dependence between the uncertainty indexes under normal–bear (0.5–0.05 quantiles) and bull–bear (0.95–0.05) scenarios. A similar result is found for bull–normal scenario.

We find that silver is negatively dependent on all other uncertainty indexes under bear–normal scenario. This result shows that silver uncertainty index has a predictive power for all uncertainty indexes. Moreover, gold and gold mining are positively and weakly dependent on each other, indicating that both series move in the same direction. This result negates the presence of dive. Gold is negatively dependent on crude oil and energy sector uncertainty indexes, whereas gold mining uncertainty index is positively dependent on crude oil and energy sector. We find a negative dependence of silver on gold mining, gold and crude oil under normal–normal market state, whereas silver shows a positive dependence on energy sector. Crude oil uncertainty index is negatively dependent on gold and gold mining. Under bull–bull market state, a positive dependence exists between different indexes, except for the silver–gold mining and gold–crude oil pairs. Overall, the dependence structure is dependent on market states and pronounced during bear–bear, bull–bull, bear–normal and normal–bull market states.

The results at one week change presented in Fig. 5 are compared with those at two days of trading for few cases. For example, the dependence between silver and gold mining switches to positive under bear market state. The same result is obtained between silver and gold and between gold and energy sector. The dependence level between gold and gold mining decreases from 0.19 for 2 days of trading to 0.13 for 1 week of trading. The dependence between silver and the remaining uncertainty indexes becomes positive under normal market states. The same result is obtained for gold and gold mining on crude oil uncertainty index. Alternatively, under normal–bull state, the effects of own-shocks

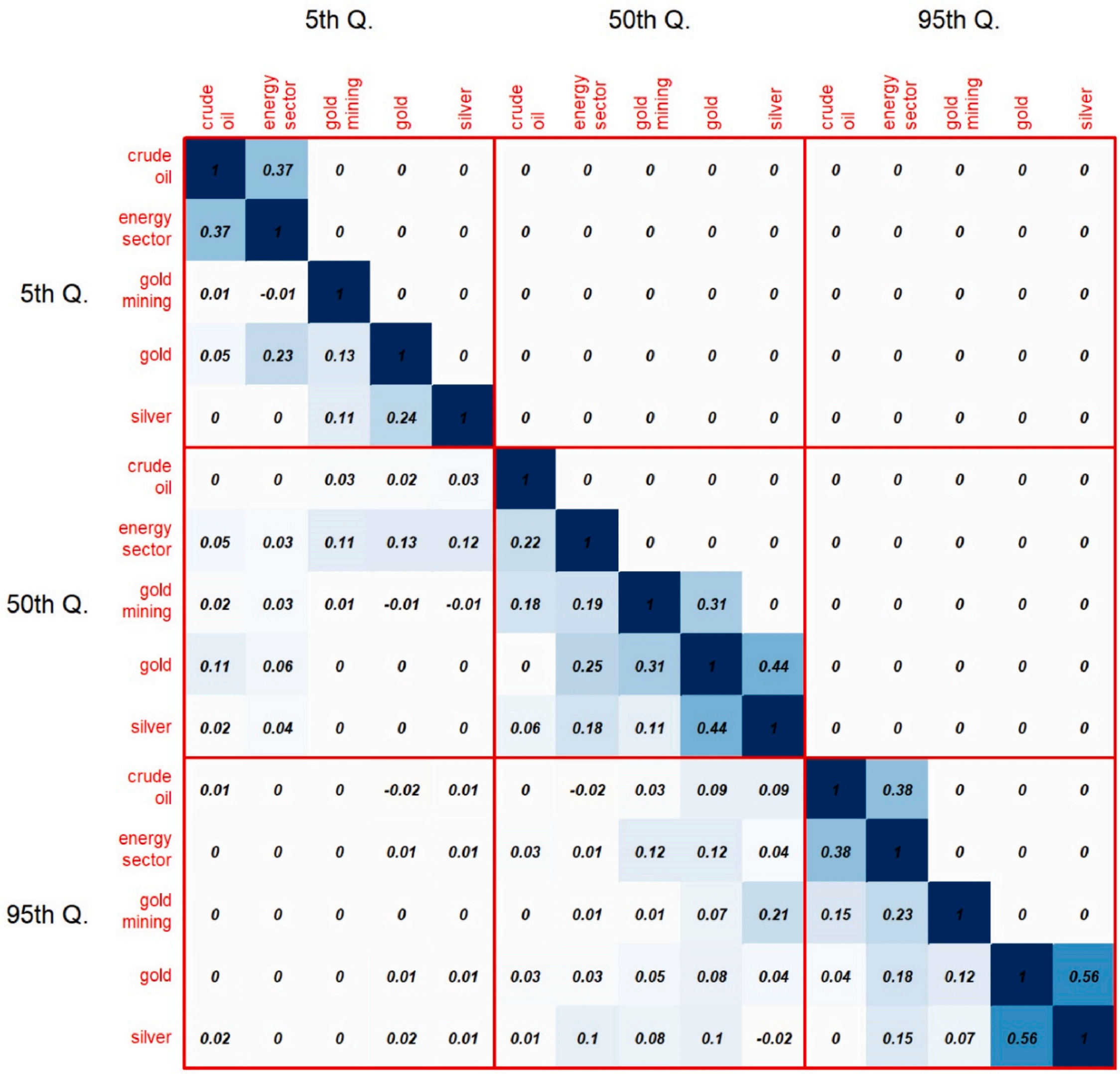

Fig. 7. One-month quantile coherency matrix
Note: We set 0 for insignificant coherences.

influence negatively the uncertainty indexes, except for silver and gold mining. Under the bull–bull market scenario, the dependence structure between silver and gold mining and between gold mining and crude oil change to positive and negative, respectively. The dependence between energy sector on the other indexes decreases, except on gold uncertainty index. The highest dependence is observed between silver and gold mining under bull–bull state (0.32), with only 0.05 and 0.12 under bear–bear and normal market conditions.

4.2. Medium-term quantile cross-spectral results

Figs. 6 and 7 depict the medium dependence between the uncertainty indexes. We find that the medium dependence level during bear–bear market status increases for the majority of pairs compared with those of the short term. The dependence of silver on gold and gold mining indexes increases relative to those at 1 week of trading. The result is similar to those of gold and crude oil and energy sector and crude oil. In contrast, the dependence structure switches to negative for gold–gold mining and gold–energy sector pairs. These findings indicate that time factor is a key driver of the dependence structure between metal and energy uncertainty indexes. The dependence of silver on crude oil and energy sector is positive under bear–bull state. In addition, the dependence between crude oil and gold between and gold and energy sector is similar (0.01). The dependence between silver and gold at one month is positive and higher compared with that at the short term. Gold mining is positively dependent on energy sector and crude oil. However, gold is negatively dependent on crude oil but positively dependent on energy sector under bear–normal market state. The coherence values between gold mining and other indexes are all zero for bear–bull market state. Overall, silver–gold mining, silver–energy sector, gold–crude oil, gold–energy sector and crude oil–energy sector pairs have asymmetric dependence.

We compare the dependence structure between a month of trading and two weeks of trading. We find that gold–gold mining and gold–energy sector pairs have positive dependence, whereas gold mining–energy sector pair has negative dependence under bear–bear state. Overall, we find that the majority of cases (bear–normal, normal–bull and bull–bull) have positive dependence. This finding indicates that the integration between the uncertainty indexes increases over time. The medium-term dependence between gold and silver, gold and gold mining and crude oil and energy sector is positive, irrespective of market conditions.

4.3. Long-term quantile cross-spectral results

Figs. 8–10 display the dependence structure between the uncertainty

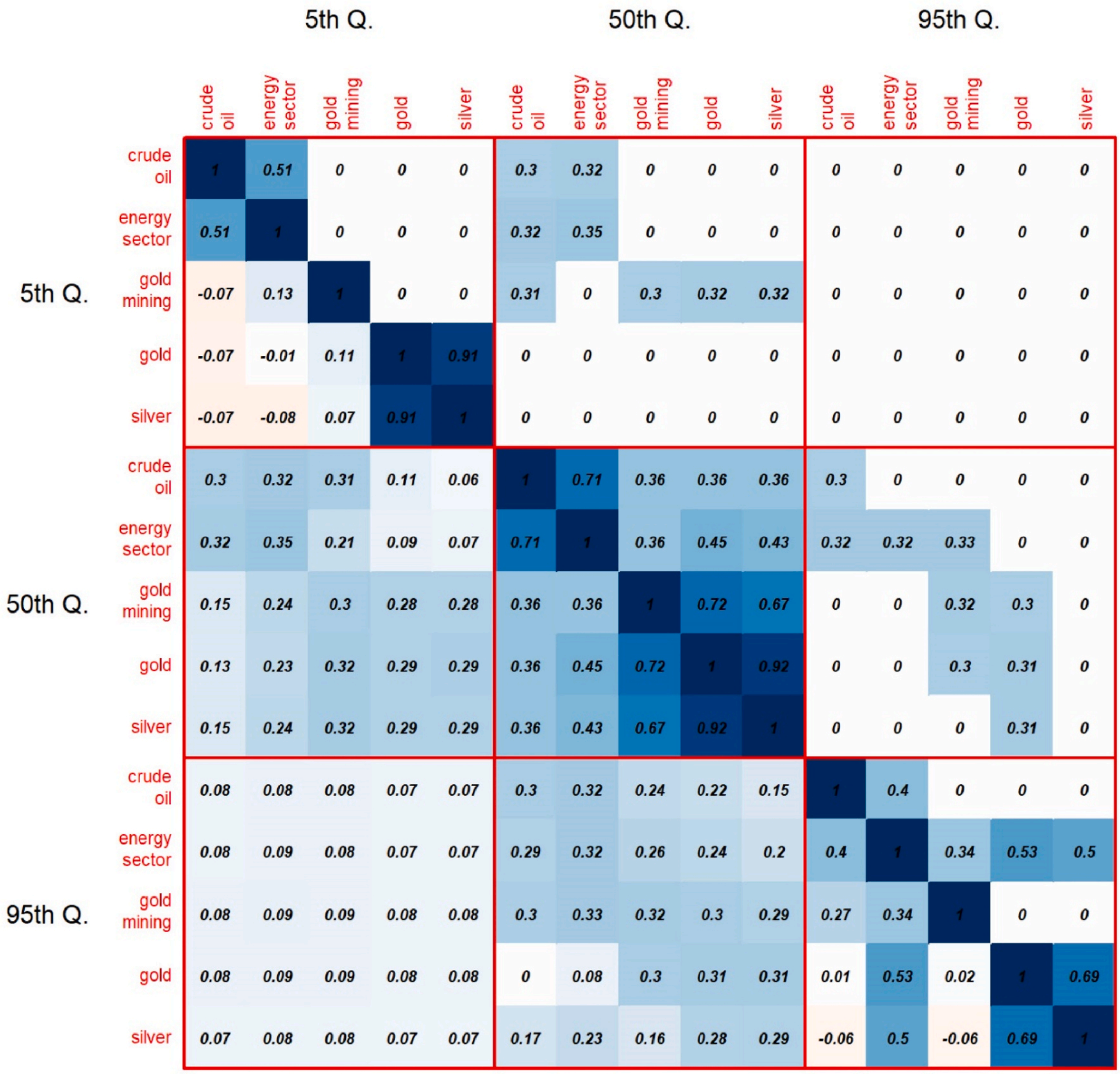

Fig. 8. Three-month quantile coherency matrix
Note: We set 0 for insignificant coherences.

indexes for three months, six months and one year, respectively. The dependence structure between the uncertainty indexes for the three horizons is similar. We observe a positive long-term dependence between silver and gold during all market conditions. Additionally, we show independence between silver and gold mining during bear–bear and bull–bull market conditions. Conversely, the dependence between silver and gold and between crude oil and energy sector is higher in the long term compared with that in the short and medium terms, irrespective of market conditions. Crude oil is negatively dependent on metal uncertainty indexes (silver, gold and gold mining) but positively dependent on energy sector uncertainty index in the long-term during bear–bear market states. The result is similar for energy sector, which is negatively dependent on gold and silver but positively dependent on gold mining. It is noteworthy that we find a positive dependence of gold mining on silver, gold and crude oil under normal–bear market condition. A similar result is found for crude oil and energy sector uncertainty indexes. Under bear–normal market state, the dependence is positive for all cases, ranging from 0.06 for silver–crude oil pair to 0.32 for crude oil–energy sector pair. Under normal–normal market state, the dependence has intensified for all cases. The dependence level is 0.92 for gold–silver pair and 0.71 for crude oil–energy sector pair, supporting the recoupling hypothesis. An examination of the bull–normal case shows a different result from those obtained in the short and medium terms. We find positive and significant dependence among metal indexes and between crude oil and energy sector. In addition, the dependence is positive for gold mining and energy sector.

Under bear–bull and normal–bull market states, the long-term dependence is positive and significant among all uncertainty pairs. In addition, the long-term dependence among uncertainty indexes is higher under normal–bull market state than under bear–bull. Under bull–bull market state, we find that the dependence is mixed. Silver is negatively dependent on gold mining and crude oil but positively dependent on gold and energy sector. However, gold mining are positively dependent on gold, crude oil and energy sector. This dependence is highest on energy sector. Gold is also positively dependent on the remaining uncertainty indexes.

5. Conclusion

In this paper, we examine the dependence structure between gold, gold mining, silver, oil and energy sector uncertainty indexes. We apply a quantile cross-spectral approach to account for different market conditions and time investment horizons. The results show evidence of negative short-term dependence between silver–gold and silver–gold mining pairs under bear market conditions. Furthermore, gold uncertainty index is negatively dependent on energy sector but independent

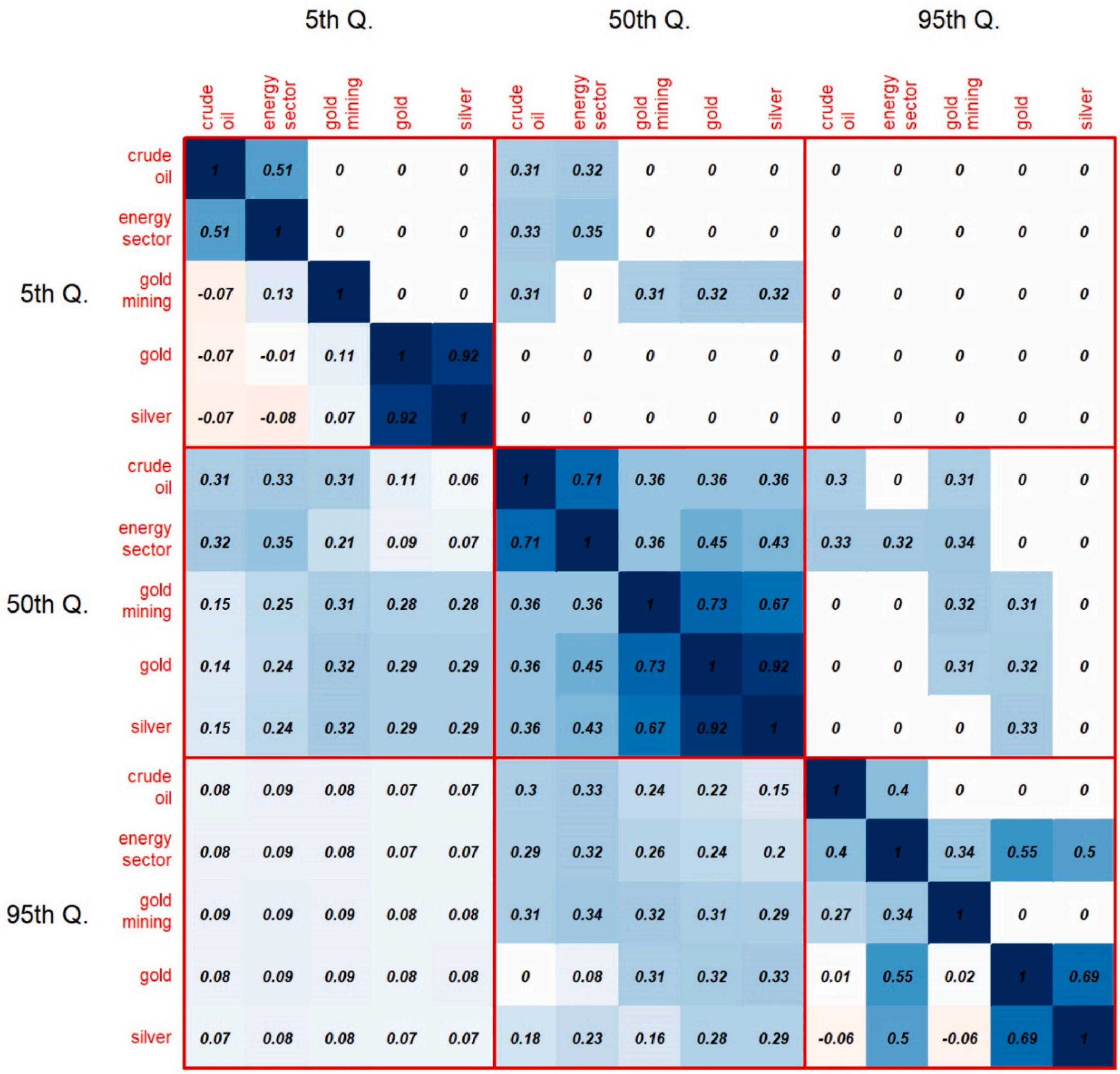

Fig. 9. Six-month quantile coherency matrix
Note: We set 0 for insignificant coherences.

on crude oil. Similarly, gold mining uncertainty index is negatively dependent on crude oil and weakly dependent on energy sector uncertainty index. Crude oil and energy sector show positive short-term dependence during bear market conditions. Evidence of insignificant short-term dependence between uncertainty indexes is also observed during bull–normal scenario. In contrast, the results show significant negative dependence between silver and all other uncertainty indexes under bear–normal scenario. Gold and gold mining uncertainty indexes are negatively and positively dependent, respectively, on crude oil and energy sector uncertainty indexes. Silver has negative short-term dependence on gold mining, gold and crude oil under normal–normal market state. Conversely, silver shows a positive short-term dependence on energy sector. Crude oil uncertainty index is negatively dependent on gold and gold mining. Under bull–bull market state, a positive dependence exists between different uncertainty indexes, except for silver–gold mining and gold–crude oil pairs. Overall, the dependence structure is dependent on market states and pronounced during bear–bear, bull–bull, bear–normal and normal–bull market states. At the medium term, the results show the dependence of silver on gold and gold mining indexes increases relative to that at short term. The dependence structure is negative for gold–gold mining and gold–energy sector pairs. In addition, the medium-term dependence of silver on crude oil and energy sector is positive under bear–bull market state. Gold mining is positively dependent on energy sector and crude oil. In contrast, gold is negatively dependent on crude oil but positively dependent on energy sector.

The long-term dependence structure among uncertainty indexes is positive most cases. The dependence between silver and gold mining is higher at the medium term than at the long term. We also observe that the dependence between silver and gold and between crude oil and energy sector is higher at the long term compared with that at the short and medium terms, regardless of market conditions. However, crude oil is negatively dependent on metal uncertainty indexes (silver, gold and gold mining) at the long term and during bear–bear states. Moreover, energy sector is also negatively dependent on gold and silver. Gold mining show positive dependence on silver, gold and crude oil under normal–bear market state. Under bull–bull market state, silver is negatively dependent on gold mining and crude oil but positively dependent to gold and energy sector. However, gold mining is positively dependent on gold, crude oil and energy sector. This dependence is highest on energy sector. Gold is also positively dependent on the remaining uncertainty indexes.

Our findings have valuable implications for decision-makers and portfolio managers in risk management. Portfolio managers should gain awareness of the dependence between uncertainty indexes, i.e., frequency-sensitive and higher at the long term compared with that in

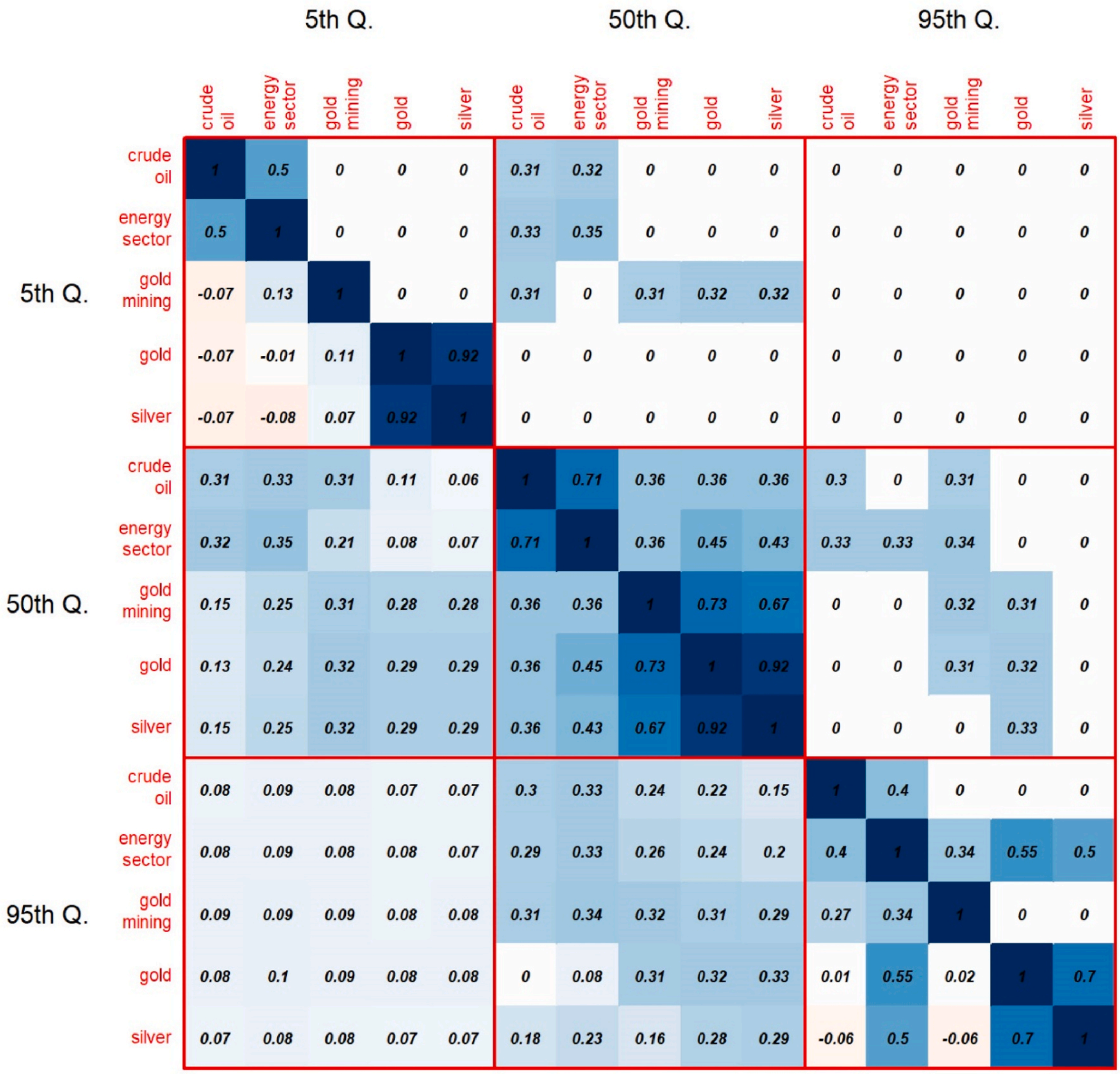

Fig. 10. One-year quantile coherency matrix
Note: We set 0 for insignificant coherences.

the short term. This finding reflects investors' fear in metal and energy markets. The uncertainty measures may cause instability in precious metals and energy commodity prices. This condition may lead to expensive hedging in the long term compared with that in the short and medium terms. Thus, portfolio manager behaviour changes according to different market conditions and time investment horizons. Market environmental changes can significantly alter the market structure. Thus, policymakers should pay particular attention to real-time and frequency dependence among uncertainty indexes under investigation. Policymakers should identify the sources of the increase in the dependence structure (frequencies and time horizons) between uncertainty indexes to enhance the stability of precious metal and energy markets and cut-price volatilities.

Author statement

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Appendix A. Supplementary data

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