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The tail dependence structure between investor sentiment and commodity markets

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ABSTRACT
A growing body of literature considers investor sentiment as the partial driver of change in commodity prices. In contrast with previous studies that have almost exclusively focused on linear relationship, this empirical paper investigates the entire dynamic dependence of the quantile of investor sentiment and that of ten important commodities. To do so, we use the novel quantile cross-spectral dependence approach of Barunik and Kley (2019) and the nonparametric causality-in-quantiles test proposed by Balcilar et al. (2017a) over the period 1998–2018. Overall, the results show that the inter-dependence between sentiment and commodity differs according to return quantile and time frequency.

1. Introduction

In recent decade, there has been increasing interest in commodity markets as is evidenced by the significant increase in the number of commodity indices covering different ranges of commodities including Agriculture, Metal, Oil and Gas. The increase investment in commodities by financial investors (e.g. swap dealers and money managers) placed a greater importance on commodity futures exchanges as an asset class and led consequently to the financialization of commodity markets (among many others; see, Henderson et al. (2015); Adams and Glück, 2015; Gao and Suss, 2015; Charlot et al., 2016; Algieri and Leccadito, 2017; Nguyen et al., 2020a,b; Yang et al., 2020; Li et al., 2020).  

More recently, several studies investigated the effect of news media sentiment on return, volatility, and correlations on commodity markets. These studies are based on findings of past research showing how traded assets returns can be driven by behavioral factors rather than fundamentals due to investors’ psychological biases or attributional bias (e.g. Daniel et al., 1998; Barberis et al., 1998; Baker and Nofsinger, 2002). Based on these theories and given the vital role of commodities in investment and asset allocation, this study applies a comprehensive market-level emotion indices of commodities from Thomson Reuters MarketPsych Indices (TRMI), and ten commodities (Brent Crude Oil, Gold, Heating Oil, Natural Gas, Nickel, North Sea Oil, Palladium, Platinum, Silver, and Copper), to examine the interdependence between sentiment and these commodities at different quantiles and time-frequencies. It also examines the Granger causality in quantiles to detect causality in sentiment and the commodities at various sentiment states (i.e. bullish and bearish). Understanding of this dependence structure would provide useful information for investors’ risk management decisions, hedging strategies, and the predictability of commodity prices.

There are numerous studies that examine the sentiment effect on commodity return and volatility. Bahloul and Gupta (2018) studied the role of macroeconomic surprises in influencing returns and volatility for the West Texas Intermediate (WTI) and Brent Crude Oil futures markets. Bahloul and Bouri (2016) examined the effect of investor sentiment by traders' categories on the returns and volatilities in 13 commodity future markets, finding that non-money manager sentiment tends to increase price volatility in most of these markets. Using monthly, weekly, and daily data of investor sentiment and oil prices, Qadan and Nama (2018) showed that different proxies of sentiment have a significant effect in oil prices especially when oil-based financial products became a popular investment during and after the early 2000s. Even with the safe-haven commodities such as Smales (2015) found that the sentiment of

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newswire messages has a significant impact on the volatility of returns in the Gold market, whereby negative news has a greater impact on volatility than positive news. Using geopolitical risks and investor sentiment, Corbet et al. (2018) investigated the impact of terrorist events on European financial markets and found that acts of terrorism that take place within a particular country significantly influence that country’s stock market volatility, as well as other markets, indicating a volatility spill-over. Nooijen and Broda (2016) used different emotions derived from the Thomson Reuters Marketpsych Indices (TRMI) and documented greater effect of sentiment on conditional volatility than on expected returns. Using the TRMI, Shen et al. (2017) showed support of the short-term predictability of the sentiment emotions on the following five days of Thomson Reuters Core Commodity CRB Index, on Crude Oil and Gold returns. Shahzad et al. (2017) utilized nonparametric causality-in-quantiles and showed that investors’ sentiments (both bullish and bearish) have a causal impact on most of the return quantiles of six major commodities.

Although there are number of studies that examine how investor sentiments influence commodity prices, the concentration has on mean-to-mean dependence (linear relationship), neglecting the fact that interdependence patterns between variables could change during extreme market conditions of fear or stress (tails) and/or different time-horizons (frequencies). Since the financial time series exhibit chaotic nonlinear dynamics (Frenses and van Dijk, 2000) and tail dependence (Hartmann et al., 2004), one may reasonably expect that the relationship between investor sentiment and commodity returns vary across quantiles of the joint distribution. Han (2008) argues that the risk-neutral skewness of monthly index return is more (less) negative when investor sentiment becomes more bearish (bullish). Furthermore, Mollick and Assaf (2013), Shahzad et al. (2016) and Chau et al. (2016) point out that the financial markets behave differently in bear and bull markets and the relationship among variables may be subject to noticeable changes under different market states (i.e., across the different quantiles). Therefore, we examine whether the effects of investor sentiment under different market circumstances have important implications for investors in terms of portfolio construction, risk management, and the predictability of commodity prices.

Although the existing studies have highlighted the relationship between investor sentiment and commodity prices, they often ignore the importance of the duration of such relationships. As a matter of fact, market participants’ trade with different investment horizons, thus it is important to know how investor’s sentiment influences commodity prices at various investment time horizons (time-frequency domain). Observing the linkages between investor sentiment and commodity prices over various investment horizons is important for market participants at least for two reasons. First, investors’ preference for risk is inversely related to time horizon and thus changing association across different time periods has important implications for asset allocation (Samuelson, 1989; Marshall, 1994). Second, the transmissions of shocks through market transactions varies according to timescale, due to investors’ heterogeneity (Harrison and Kreps, 1978; Morris, 1996; Reboredo and Rivera-Castro, 2013). These heterogeneities produce dissimilar responses to the information shocks and thereby creating various links at different investment horizons (Dacorogna et al., 2001; Tiwari et al., 2013; Chau et al., 2016).

This study uses a comprehensive market-level emotion indices of commodities (i.e. TRMI), and ten commodities (Brent Crude Oil, Gold, Heating Oil, Natural Gas, Nickel, North Sea Oil, Palladium, Platinum, Silver, and Copper), to examine the interdependence between sentiment and these commodities at different quantiles and time-frequencies. To measure the dependence structure between sentiment and commodities, this paper employs the novel quantile cross-spectral (QS) analysis pioneered by (Barunik and Kley, 2019). This novel technique allows to capture the interdependence patterns between time series over time frequencies and across quantiles. Specifically, this approach captures the existence of dependencies at various market states (e.g., bear, normal, and bull) across different investment horizons (e.g., high-frequency, i.e., short-term; medium frequency, i.e., medium-term; low-frequency, i.e., long-term). This is important to forecast the influence of sentiment on commodity markets at different time frequencies. Further, the results may explain additional premium brought by sentiment on commodity futures which is associated with investors’ risk tolerance in specific time horizons. To the best of our knowledge, this dependence in the tails as well as the dependence coherency across time-frequency domains analysis between investor sentiment and commodities is the first to be explored in the literature. To complete the picture, the study further employs a novel nonparametric causality-in-quantiles test, pioneered by Balcilar et al. (2017a), to examine the causality effects of sentiment under different market circumstances. This analytical and graphical design framework allows to test the nonlinearity across different quantiles (or market states) of the variables conditional distributions (i.e., low, medium and upper quantiles of the distribution). In addition to this, by combining quantile regression with non-parametric estimations, this approach is robust to misspecification errors as well as the well-known facts in financial time series such as heavy-tails, structural breaks and frequent outliers.

1.1. The findings of our paper are outlined below

Brent Oil and Gold dependence with sentiment is at the highest level for medium and low return quantiles during long-term frequency, indicating that low to normal return is correlated with bearish sentiments in the long term. The coherence of Heating Oil and sentiment medium return quantiles declines significantly from monthly to weekly frequency, suggesting that correlation between normal returns and normal sentiment (nor bullish nor bearish) occurs primarily at a monthly frequency. Natural Gas and sentiment medium return quintiles occur primarily at a frequency lower than weekly (i.e. monthly or annually). The coherence between Nickel and sentiment at low, medium, and high quantiles stays at a similar range across all time frequencies. In contrast, the high quantiles of North Sea Oil and sentiment coherence increases from annual to monthly frequency but declines from monthly to weekly frequency. The coherence between Palladium (or Platinum) and sentiment in high, medium, and low quantiles decreases sharply from annual to monthly frequencies; medium quantile coherence continues declining when the frequency becomes greater than weekly. Silver and sentiment quantiles show different patterns from annual to monthly frequency. With a higher frequency (from annually to monthly), the high return and bullish sentiment increases. Meanwhile, Copper and sentiment have generally low levels of coherence across all time frequencies and quantile distributions. Sentiment Granger-causes the returns of all

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2 Market frictions, transaction costs, investor herd behavior, investor heterogeneity, short selling and arbitrage limits create the nonlinear patterns in financial time series.

3 Barro (2006) demonstrated that some features commonly observed in financial markets, such as the high equity premium, low risk-free rate, and volatile stock returns can be explained by calibrated probability distribution of economic disasters (i.e. extreme negative events).

5 Investors exhibit different horizons due to the varying levels of their risk tolerance levels, investment objectives, different assimilation and absorption of information, and different institutional constraints (Chakrabarty et al., 2015; Baumohl and Shahzad, 2019; Magnyereh et al., 2018, 2020).

6 Moreover, our analysis is comprehensive in the sense that we consider ten different commodities rather than only a few or the general index for commodity performance, thereby providing a detailed understanding of the connection between sentiment and commodity market.
of previous studies, including Gao and Suss (2015), who document a return dependence with sentiment is generally at low levels for all time shorter frequency. In addition, Copper is a commodity that provides dependence at all quantiles with sentiment decreases sharply with quantiles decreases within a shorter time horizon and the latter’s return dependence with sentiment can provide diversification benefits for the portfolio of commodities can provide diversification benefits for specific investors the Thomson Reuters Datastream database; the daily commodity- investment portfolio to reduce their risk exposure to sentiment move study indicate that investors may include different commodities in their commodity is significant, particularly in the low and medium return results generally show that Granger causality from sentiment to com-

carried out with a constant and a time trend where the optimal lag length has been chosen using the Akaike information criterion. *** Significant at the 1% level.

\[
\text{Mean} \quad \text{Std. Dev.} \quad \text{Skewness} \quad \text{Kurtosis} \quad \text{Jarque-Bera} \quad \text{ADF Statistics}
\]

| Commodity          | Mean  | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | ADF Statistics |
|--------------------|-------|-----------|----------|----------|-------------|----------------|
| Brent Crude Oil    | 0.0003| 0.0235    | -0.0315  | 7.635    | 4747.123*** | -41.326***    |
| Gold               | -0.1067| 0.0788    | 1.4890   | 9.474    | 11221.130*** | -9.5290***    |
| Heating Oil        | 0.0003| 0.0230    | -0.2826  | 9.3878   | 9084.795*** | -41.714***    |
| Natural Gas        | -0.0341| 0.0830    | 0.0635   | 3.7564   | 129.983***  | -22.522***    |
| Nickel             | 0.0003| 0.2331    | 0.1333   | 7.1669   | 3852.164*** | -17.808***    |
| North Sea Oil      | -0.1358| 0.2331    | 0.1114   | 4.4438   | 466.248***  | -34.698***    |
| Palladium          | 2.20e-5| 0.0175    | 0.5389   | 9.5259   | 19960.310*** | -47.630***    |
| Platinum           | 0.0003| 0.0633    | 0.2035   | 2.7273   | 1178.700*** | -28.092***    |
| Silver             | 0.0001| 0.0997    | 0.0008   | 3.639    | 2878.000*** | -41.171***    |
| Copper             | 0.0001| 0.1611    | 0.2070   | 7.639    | 138.370***  | -24.034***    |
| Brent crude oil    | 0.0003| 0.0213    | -0.2210  | 9.1898   | 8507.179*** | -42.866***    |
| Gold               | -0.0729| 0.3026    | 0.0356   | 3.5401   | 66.994***   | -31.122***    |
| Heating Oil        | 0.0002| 0.0144    | -0.6917  | 11.9849  | 18257.180*** | -42.645***    |
| Natural Gas        | 0.0002| 0.2148    | -0.0478  | 3.9256   | 190.399***  | -32.971***    |
| Nickel             | 0.0002| 0.1143    | 0.1070   | 4.2348   | 346.921***  | -27.981***    |
| North Sea Oil      | 0.0002| 0.0183    | 0.5252   | 8.7593   | 7570.052*** | -41.926***    |
| Palladium          | 0.0002| 0.1143    | -0.7183  | 58.564   | 7.6476e-5*** | -27.762***    |
| Platinum           | -0.0314| 0.0068    | 0.1687   | 0.1378   | 28.883***   | -21.391***    |

Notes: The data for returns is daily and covers the period that extends from January 1, 1998 to July 30, 2018. Jarque-Bera statistic is testing for normality. The ADF stands for Augmented Dickey-Fuller test with the null hypothesis is defined as ‘the series has a unit root against the alternative of stationarity’. All unit root tests are carried out with a constant and a time trend where the optimal lag length has been chosen using the Akaike information criterion. *** Significant at the 1% level.

Table 2

| Commodity          | Nonlinear Granger causality test (Diks and Panchenko test). |
|--------------------|-------------------------------------------------------------|
| Brent crude oil vs| H0: Sentiment Does Not Cause Brent crude oil               |
| Sentiment          | 2.616*** ([0.0049])                                         |
| Gold vs Sentiment  | H0: Sentiment Does Not Cause Gold                           |
| 3.027*** ([0.0012])|                                                             |
| Heating Oil vs Sentiment | H0: Sentiment Does Not Cause Heating Oil                  |
| 2.415*** ([0.0033])|                                                             |
| Natural Gas vs Sentiment | H0: Sentiment Does Not Cause Natural Gas                |
| 2.846*** ([0.0022])|                                                             |
| Nickel vs Sentiment| H0: Sentiment Does Not Cause Nickel                        |
| 1.678*** ([0.0302])|                                                             |
| North Sea oil vs Sentiment | H0: Sentiment Does Not Cause North Sea oil                |
| 2.070*** ([0.0192])|                                                             |
| Palladium vs Sentiment | H0: Sentiment Does Not Cause Palladium                    |
| 2.748*** ([0.0097])|                                                             |
| Platinum vs Sentiment | H0: Sentiment Does Not Cause Platinum                     |
| 1.846*** ([0.0493])|                                                             |
| Silver vs Sentiment | H0: Sentiment Does Not Cause Silver                        |
| 3.488*** ([0.0007])|                                                             |
| Copper vs Sentiment | H0: Sentiment Does Not Cause Copper                        |
| 3.654*** ([0.0098])|                                                             |

Notes: The table reports the nonparametric t statistic of nonlinear Granger causality test proposed by Diks and Panchenko (2006) with bandwidth b = 0.2768. The p-values are in brackets. ***, **, or * denote that the null hypothesis is rejected at the 1%, 5%, or 10% significance levels, respectively.

Fig. 1. Q-Q plot of the data.

commodities except for those of Copper and Platinum. In addition, the results generally show that Granger causality from sentiment to commodity is significant, particularly in the low and medium return quantiles.

Given that the interdependence between sentiment and commodity differs across commodities and quantile distributions, findings from our study indicate that investors may include different commodities in their investment portfolio to reduce their risk exposure to sentiment movements. For example, adding Gold or Brent Oil and Palladium or Platinum to the portfolio of commodities can provide diversification benefits for short-term investors as the former’s dependence with sentiment in low quantiles decreases within a shorter time horizon and the latter’s return dependence at all quantiles with sentiment decreases sharply with shorter frequency. In addition, Copper is a commodity that provides diversification potential for investors with different time horizons as its return dependence with sentiment is generally at low levels for all time frequencies and quantile distributions. Finally, our findings extend those of previous studies, including Gao and Suss (2015), who document a predictive power of investor sentiment for commodity futures returns at a daily frequency level, by showing that the causality of sentiment on commodity takes place primarily in medium return quantiles.

2. Data

The data set used in this study includes the daily closing prices for ten commodities (Brent Crude Oil, Gold, Heating Oil, Natural Gas, Nickel, North Sea Oil, Palladium, Platinum, Silver, and Copper), obtained from the Thomson Reuters Datastream database; the daily commodity-specific investors’ sentiment indices are provided to us free of charge from Thomson Reuters, for which we are grateful.

The TRMI’s sentiment indices are word-count indices that are developed by Thomson Reuters in collaboration with MarketPsych LLC.
It is derived from textual data taken from news wires, financial news, and social media. The data contributing to it includes more than two million daily news articles and posts that reflects the investors’ psychology regarding a particular commodity. The information used to build the indices come from investor groups, analysts, journalists, and economists. The granularity of the data is at the minute level but the daily index reflects an average of information that is collected over 24 h. More specifically, the TRMI measures provide a 24-h rolling average

**Fig. 2.** Quantile coherency estimates for the $0.05/0.05$, $0.5/0.5$, and $0.95/0.95$ of the joint distribution across the different frequencies.
score of all news and social media references. As compared to market-based indices, TRMI is available in real time and thus users avoid delays (Ammann et al., 2014). A further advantage of TRMI is that it provides marginal information that cannot be confused with common macroeconomic and financial predictors as it is independent. Market-Psych’s indices are not bipolar positive or negative sentiment but are normalized to make their values range from −1 to 0 indicating negative (bearish) sentiment and from 0 to 1 indicating positive (bullish).
The daily series covered the period from January 1, 1998 (a start date determined by data availability for the MarketPsych’s sentiment indices) to July 30, 2018, comprising 5363 observations. Descriptive statistics for commodities return, calculated as the log-difference of daily closing prices, and MarketPsych’s sentiment can be found in Table 1. As shown in the table, the average daily returns over the sample period are positive for all commodities except for Copper, while the mean sentiment values are negative for all commodities. The kurtosis statistic is above three for all series (except for the sentiment indices of Natural Gas, North Sea Oil, and Copper), showing that these series have fatter tails compared with the normal distribution, with values being concentrated around the mean and the thicker tails. The Jarque-Bera statistic rejects the null hypothesis of normality for all series. The results of the unit root tests indicate that the data is covariance stationary over the sample period.

At the start of our analysis, we assess nonlinear causality between investor sentiment and returns of our ten commodities using a nonlinear Granger causality test of Bekiros and Diks (2008). The test results are presented in Table 2. The test results provide evidence that we can reject the null hypothesis that sentiment does not Granger-cause any of the commodity return, while we cannot reject the null hypothesis that commodity return does not cause sentiment. Overall, the estimated results show a significant one-way nonlinear Granger causality from investor sentiment to the return series of commodities.

3. Methodology

In this paper, our interest lies primarily in measuring the extent of the dependence between sentiment and returns of ten different commodities focusing on the lowest and highest percentiles of the joint distribution (the periods of large negative or positive values) in the frequency domain. To achieve this, we utilize the quantile cross-spectral approach (QS) recently developed by Barunik and Kley (2019). The QS is valuable in that it relies on cross-quantiles of variables thereby capturing the extreme co-movements of the variables under consideration and is not dependent on the second moment (conditional variances) of the distribution to draw the interdependence between variables at different quantiles. From this model, it is also possible to detect the dependence structure between variables at different frequencies (i.e., in the short- and the long-run). This methodology, therefore, is a novel measure to examine the dynamic interdependence under varying market conditions.

To see how the results may change using another methodology, we estimate a novel nonparametric causality-in-quantiles test proposed by Nishiyama et al. (2011) and Jeong et al. (2012) and extended by Balcilar et al. (2017a). This approach can be used to test for causality that exists in the tails of the joint distribution of the variables.

We provide a brief overview of the two methods below.
Fig. 3. The dependence between the 0.05|0.95 quantiles of joint distribution.
3.1. Quantile cross-spectral (coherency) approach (QS)

Let a set of \((R_t)_{t \in \mathbb{Z}}\) variables, which are two strictly stationary processes, with components \(R_t = (R_{t1}, R_{t2})\). Following Barunik and Kley (2019), the quantile coherency between these two processes \(\widehat{m}_{\mu, \lambda}\) can be written as\(^9\)

\(^9\) The discussion and notation contained in this section followed Barunik and Kley (2019); Baumohl and Shahzad (2019); and Balcilar et al. (2016).
where $-\pi < \omega < \pi$ and $(\tau_1, \tau_2) \in [0, 1]$. $f_{\theta; \tau_1, \tau_2}$ and $f_{\theta; \tau_1, \tau_2}$ are the quantile cross-spectral density and the quantile spectral densities of processes $R_{\theta, 1}$ and $R_{\theta, 2}$ respectively obtained from the Fourier transform of the matrix of quantile cross-covariance kernels $I(\tau_1, \tau_2) := (f(\omega; \tau_1, \tau_2))_{\theta, \theta}$, where

\[
\text{Where}
\]

\[
\begin{align*}
R_{\theta; \tau_1, \tau_2} & = \frac{\mathcal{L}\{-I(\omega; \tau_1, \tau_2)\}}{\mathcal{L}\{-I(\omega; \tau_1, \tau_2)\}} \\
\end{align*}
\]

As detailed by Barunik and Kley (2019), quantile coherency is estimated by the smoothed quantile cross-periodograms as follows

\[
\tilde{G}_{\theta; \tau_1, \tau_2} = \frac{2\pi}{n} \sum_{k=\omega}^{n-1} W_k (\omega - \frac{2\pi k}{n}) f_{\theta; \tau_1, \tau_2} (\frac{2\pi k}{n}, \tau_1, \tau_2)
\]

where $\tilde{G}_{\theta; \tau_1, \tau_2}$ is the rank-based copula cross-periodograms matrix (CCR-periodograms) and $W_k$ is a sequence of weight functions. Then, the estimators for the quantile coherency can be given by

\[
\tilde{\gamma}_{\theta; \tau_1, \tau_2} = \frac{\tilde{G}_{\theta; \tau_1, \tau_2}}{G_{\theta; \tau_1, \tau_2} G_{\theta; \tau_1, \tau_2}}
\]

In this paper, we estimate the coherency matrices for three quantiles (0.05, 0.5, 0.95) that correspond to lower, medium, and upper quantiles respectively and their combinations of quantile levels of the joint distribution (0.05/0.05, 0.5/0.5, 0.95/0.95) that correspond to the left tail, the middle, and the right tail of the distributions respectively. In addition, we present the coherency (co-dependence) for three time frequencies; short run (one week), the medium run (one month) and the long run (one year) that correspond to $\omega \in \{0.1, 1.22, 1.25\}$.

As detailed by Barunik and Kley (2019), the quantile cross-spectral density kernels $\{f_{\theta; \tau_1, \tau_2}\}$ in Eq. (3) can be decomposed into real and imaginary parts. The real part of the quantities represents the cross-spectrum of the processes (I$\{R_{\theta, 1} \leq q_{\theta, 1}(t_1)\} \cap \{R_{\theta, 2} \leq q_{\theta, 2}(t_2)\}$) and the imaginary part represents the quadrature spectrum that eliminates various sources of noise coherence. For readability and better presentation, we follow Barunik and Kley (2019) and display only the real parts of the quantile coherency estimates.\(^\text{10}\)

3.2. Granger causality test in quantiles

The Balcilar et al. (2017a) procedure to measure nonlinear causality relies on obtaining the causality that may exist in the tails of the joint distribution of the variables. In particular, following Jeong et al. (2012), to test that sentiment related commodity $x(t)$ does not cause corresponding commodity returns $y(t)$ in the $\theta$ quantile for the lag vector of

\^\text{10}\ We also estimate the imaginary parts of the quantile coherency (to save on space, the results are not reported but available from the authors upon request) and find similar results in most cases between the real and the imaginary one especially at short-term (one week) and medium-term (one month) frequencies. We find considerable difference between them only at lower time frequency (one year). In this case, we find that the real coherency ranges between -0.6 and 0.3, whereas the imaginary coherency is close to zero.
Fig. 4. The dependence between the 0.95|0.05 quantiles of joint distribution.
Fig. 4. (continued).
\{y_{t-1}, \ldots, y_{t-p}; x_{t-1}, \ldots, x_{t-p}\} \quad \text{if} \quad Q_{\theta} \{y_{t-1}, \ldots, y_{t-p}; x_{t-1}, \ldots, x_{t-p}\} = Q_{\theta} \{y_{t-1}, \ldots, y_{t-p}\} \quad (6)

and further, \(x(t)\) does cause \(y(t)\) in the \(\theta\)th quantile with regards to \(\{y_{t-1}, \ldots, y_{t-p}; x_{t-1}, \ldots, x_{t-p}\}\) if

\[Q_{\theta} \{y_{t-1}, \ldots, y_{t-p}; x_{t-1}, \ldots, x_{t-p}\} \neq Q_{\theta} \{y_{t-1}, \ldots, y_{t-p}\}\] \quad (7)

where \(Q_{\theta} \{y_t\}\) is the \(\theta\)th quantile of \(y(t)\). The conditional quantiles of \(Q_{\theta} \{y_t\}\) dependent on \(t\) and range between zero and one, i.e. \(0 < \theta < 1\).

Let’s define the vectors \(Y_{t-1} = \{y_{t-1}, \ldots, y_{t-p}\}\), \(X_{t-1} = \{x_{t-1}, \ldots, x_{t-p}\}\) and \(Z_{t}(X_{t}, Y_{t})\). The functions \(F_{y \mid Z_{t-1}}(Y_{t} \mid Z_{t-1})\) and \(F_{y \mid Y_{t-1}}(Y_{t} \mid Y_{t-1})\) are the conditional distribution functions of \(Y_{t}\) given \(Z_{t-1}\) and \(Y_{t-1}\), respectively. Assuming that \(Q_{\theta_{l}}(Z_{t-1}) \equiv Q_{\theta}(y_{t} \mid Z_{t-1})\) and \(Q_{\theta}(Y_{t-1}) \equiv Q_{\theta}(y_{t} \mid Y_{t-1})\), we will have \(F_{y \mid Y_{t-1}}(Q_{\theta}(Z_{t-1} \mid Z_{t-1})) = \theta\) with probability one. Therefore, the causality in quantile hypothesis based on Eqs. (6) and (7) can be presented as:

\[H_0 : P\{F_{Y \mid Z_{t-1}}(Q_{\theta}(Z_{t-1})) = \theta\} = 1 \quad (8)\]
\[H_1 : P\{F_{Y \mid Z_{t-1}}(Q_{\theta}(Z_{t-1})) = \theta\} < 1 \quad (9)\]

Jeong et al. (2012) used the following distance measure \(J = (\epsilon E(Z_{t-1})f_{Z_{t-1}})\) to get the practical implementation of the formal causality in quantile tests, where \(f_{Z_{t-1}}\) represents the marginal density function of \(Z_{t-1}\) and \(\epsilon \) is the regression error which is estimated as:

\[\hat{\epsilon} = 1\{y_t \leq \hat{Q}_{\theta}(Y_{t-1})\} - \theta \quad (10)\]

where \(\hat{Q}_{\theta}(Y_{t-1})\) represents the quantile estimator of \(y_t\) given \(Y_{t-1}\), which can be estimated by using the non-parametric kernel method as:

\[\hat{Q}_{\theta}(Y_{t-1}) = \tilde{F}^{-1}_{Y_{t-1}}(\theta) \quad (11)\]

where \(\tilde{F}^{-1}_{Y_{t-1}}(\theta)\) describes the Nadarya-Watson kernel estimator calculated by:

\[\tilde{F}^{-1}_{Y_{t-1}}(\theta) = \frac{\sum_{t=1}^{T} \omega(L^{\frac{\max(y_t)}{h}})}{\sum_{t=1}^{T} \omega(L^{\frac{\max(y_t)}{h}})} 1\{y_t \leq \theta\} \quad (12)\]

where \(\omega(\cdot)\) is the kernel function and \(h\) is the bandwidth.

To calculate the nonparametric test statistics, following Balcilar et al. (2017a) we use the least squares cross-validation method to choose \(h\) (bandwidth)\(^{12}\) and Gaussian kernels to select \(L(\cdot)\). Further, a lag order (of one) has been used based on the Schwarz information criterion (SIC).

4. Empirical results

4.1. Quantile coherency results

The quantile coherency estimates obtained from the quantile cross-spectral are reported in Fig. 2. All the plots report the real imaginary part of the quantile coherency estimates for the lower, middle, and upper quantiles \(0.05/0.05, 0.5/0.5, \) and \(0.95/0.95\) of the joint distribution across the different frequencies. The daily cycles over the interval

\(^{12}\) Note that this test is sensitive for the choice of the smoothing parameter (bandwidth). Hence, some simulation studies (i.e., Chen et al., 2019) showed that the leave-one-out cross-validation estimators of Racine and Li (2004) and Li and Racine (2007) is asymptotical optimal and consistent.
s [0, 0.5] are shown on the horizontal axis, while the vertical axis measures the co-dependence of two time series. The frequencies cycles in the upper label of the horizontal axis show how yearly (Y), monthly (M), and weekly (W) are connected across quantiles of the joint distribution. For example, if the sample frequency is 0.2 that means there is 0.2 cycles per day translating to a 5 days period.

Brent crude oil medium and low return quantiles are at the highest level (between 0.4 and 0.6 coherency) during long term frequency and they witness a significant reduction if the frequency changes from annually to monthly while the high return quantile stays in the same range of coherency (between 0 and 0.2) across all time frequencies. These findings suggest that sentiment correlates more (less) strongly with Brent Oil at low (high) return in the long term. This pattern does not exist with all other commodities. This offers advantage to investors who search for commodities with significantly lower correlated downside risk with sentiments. The Gold-sentiment coherency decreases consistently at all quantiles when the time frequency increases. In addition, there is a greater gap between the medium and low or high return quantiles at long term (i.e. yearly) frequency than other commodities. The coherence of Heating Oil and sentiment medium return quantiles declines significantly from monthly to weekly frequency suggesting that correlation between sentiment and Heating Oil normal return occurs mostly at monthly frequency. Natural Gas and sentiment medium return quintiles occurs the most during at a frequency lower than weekly (for example, annually and monthly).

Nickel and sentiment coherence at low, medium, and high return quantiles stay within a similar range (0–0.2) across all time frequencies. The high quantiles of North Sea Oil and sentiment increases from yearly to monthly frequency but declines from monthly to weekly frequency. The low quintiles decrease the most from yearly to weekly frequency.
while the medium quintiles frequency decreases from the yearly to a frequency greater than weekly (very short-term horizons). Palladium and sentiment high, medium, and low quantiles coherence decreases sharply from annually to monthly frequencies and medium quantile coherence continues to decline when the frequency becomes greater than weekly. Platinum-sentiment coherence shows a similar pattern to that of Palladium-sentiment, but the former has a lower overall coherence across all quantiles compared to the latter. Silver and sentiment quantiles show different patterns from annual to monthly frequency. In particular, high quantiles increase, and medium quantiles stay at the same level, while low return quantiles decrease when the time frequency increases from annually to monthly. Copper and sentiment have generally low levels of coherence across all time frequencies and quantile distributions.

Overall, the above findings are consistent with long memory of financial returns (Crato, 1994; Lobato and Savin, 1998; Sadique and Silvapulle, 2001; Boubaker and Sghaier, 2013) in which the dependence between commodity return and sentiment is generally higher during long-term horizons. In addition, the highest quantiles of sentiment and commodity has the lowest dependence compared to medium and low quantiles, especially for Gold and Silver. This finding is consistent with the role of precious metals in hedging against bearish sentiment levels (low quantile), explaining why the bullish sentiment is less correlated with higher returns of commodity. For example, during bearish sentiments, investors may flight for quality to precious metals such as gold, thereby raising the demand for the metals and thus lowering the dependence between sentiments and commodity returns in high quantiles. 14

Based on the QS measurements, we can also measure the dependence between 0.05|0.95 quantiles of the joint distribution as shown in Fig. 3. In particular, the dependence between a negative return (0.05 quantile) of sentiment and a high positive return (0.95 quantile) of commodity can be examined. Fig. 3 shows the results. As can be seen, there is generally weak dependence between low (0.05 quantiles) of sentiment and large positive returns (0.95 quantiles) of each of the commodities. It is also shown that Brent Oil, Heating Oil, Nickel, North Sea Oil, Palladium and Silver-sentiment extreme quantiles (0.05 for sentiment |0.95 for commodity) dependence increases when the time frequency increases from annually to monthly where it reaches the highest level at monthly frequency. However, (0.05 |0.95) quantile dependence between Gold, Natural Gas, Platinum, and sentiment decrease from annual to monthly frequency. These findings suggest investing in at least one of these commodities (Brent Oil, Heating Oil, Nickel, North-sea Oil, Palladium and Silver) along with Gold, Natural Gas or Platinum if the investment horizon is between annually and monthly in order to diversify the risk from sentiment effects, as the two groups of commodities are oppositely related to extreme movements in sentiment levels.

Fig. 4 presents the coherence (or co-movement) analysis between bullish sentiment and low or negative returns of commodities (0.95 for sentiment |0.05 for commodity). Overall, the coherence between extreme values of sentiments and commodity is close to zero. However, in some time frequencies, the coherence fluctuates and in only in one commodity it shows a trend. Specifically, the coherence between sentiment and Silver increases modestly over longer time horizon. The findings are in contrast to the bearish sentiment and bullish commodity return (0.05 for sentiment |0.95 for commodity) reported earlier. For example, in Fig. 3, the coherence between sentiment and medium quantile sentiments suggest that no commodity can be considered a consistent haven for commodity returns. We expect our findings to resonate with portfolio investment implications for several reasons. First, identifying a high-return dependence between sentiment and commodities in the long term suggests that more diversification benefits against sentiment should take place during short-term investments rather than long-term investments. Further diversification benefits can be obtained by including Copper in the commodity’s portfolio, as the former has a weak dependence with sentiments. Second, the fact that unidirectional causality exists from sentiment to commodity provides hedges with an opportunity to decide whether they should avoid going long or short on commodity investment during swings in market sentiment. Finally, to avoid biased forecasting, the findings advocate an understanding of the link between sentiments and the commodity markets at different return distributions, swings in sentiment conditions, and time frequencies.

The spread of COVID-19 has led to a global health pandemic causing human and economic suffering worldwide. A lot of people are panicking because of this fast-spreading infectious disease which can change investor’s sentiments by bad mood and anxiety. This sudden change in investor’s sentiments suggest that investment decisions and the subsequent returns on traded commodities can be affected by the COVID-19. Our research findings can be extended by examining the influence of the COVID-19 on return connectedness between sentiment and commodities returns. We leave that to a future research.

14 For example, Gold is widely known for its role as safe heaven against uncertainty in financial markets (Baur and Lucey, 2010; Baur and McDermott, 2010).
There is no conflict of interest to declare. This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal’s policies, and we believe that neither the manuscript nor the study violates any of these.

With regard to authors roles in this manuscript, the first author (Aktham) handled the Conceptualization, Methodology, Software functions and the second author (Hussein) handled the Validation, Formal analysis and writing the original draft. Both authors handled the Review & Editing function.

Appendix A. Supplementary data

Supplementary data to this article can be found online at [https://doi.org/10.1016/j.resoupo.2020.101789](https://doi.org/10.1016/j.resoupo.2020.101789).

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Ali, A., Bouri, E., Czudaj, R.L., Shahzad, S.J.H., 2020. Revisiting the valuable roles of investor sentiment to commodities returns. y-axis shows the non-parametric quantile causality test statistics whereas x-axis quantiles from investor sentiment to commodities returns. y-axis shows 0.95 quantile (large positive returns) of one variable and 0.05 quantile (large positive returns) of another variable together with 95% confidence intervals. W, M, and Y denotes weekly, monthly, and yearly periods.

Notes: Plot of the real parts of the quantile coherency estimates of Barunik and Kley (2019) for the sentiment and commodity returns for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denotes weekly, monthly, and yearly periods.

Notes: Plot of the real parts of the quantile coherency estimates for the 0.05 quantile (large negative returns) of one variable and 0.95 quantile (large positive returns) of another variable returns together with 95% confidence intervals. W, M, and Y denotes weekly, monthly, and yearly periods.

Notes: Plot of the real parts of the quantile coherency estimates for the 0.05 quantile (large negative returns) of one variable and 0.05 quantile (large negative returns) of another variable returns together with 95% confidence intervals. W, M, and Y denotes weekly, monthly, and yearly periods.

Notes: The figure reports the nonparametric causality tests at various quantiles from investor sentiment to commodities returns. y-axis shows the non-parametric quantile causality test statistics whereas x-axis highlights quantiles. The red line represents the causality statistics whereas two dashed black and green lines represent critical values (CV) at 5% and 10%, respectively.

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