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The quantile dependence of commodity futures markets on news sentiment

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Abstract
Focusing on energy commodities, industrial metals, and gold, this paper examines the degree to which commodity futures returns depend on news sentiment under various market conditions, and the structure of that dependence. We observe an asymmetric market reaction to positive and negative news sentiment, which changes in periods of financial turmoil. The quantile regression analysis shows that news sentiment's influence on the futures returns follows an upward trend at higher percentiles. This structure flattens for positive news during the global financial crisis, while the slope for the negative component steepens in backwardation periods.

KEYWORDS
backwardation, commodity markets, financial crisis., quantile regression, tail dependence

JEL CLASSIFICATION
C22, G10, G13, G14

1 | INTRODUCTION

In today's digital world, large information flows lead to consensus views on market impacts, known as market or news sentiment. Research has found that news sentiment is central to understanding short-term market fluctuations. A well-documented phenomenon is the asymmetric nature of short-term market responses to news, as negative news tends to have a stronger market reaction than positive news does (Gao & Süss, 2015; Smales, 2014b). This finding is an average result and raises questions concerning whether other parts of the return distribution are similarly affected and whether overall market direction influences these results. Using the quantile regression analysis Baur (2013) proposed, this study examines the degree and structure of the association between commodity market returns and the components of news sentiment. The analysis is conducted on major energy commodities, industrial metals, and gold.

A vast early literature has attempted to capture the market sentiment using macroeconomic announcements (e.g., Balduzzi, Elton, & Green, 2001; Barnhart, 1989; Boyd, Hu, & Jagannathan, 2005; Hess, Huang, & Niessen, 2008; Nowak, Andritzky, Jobst, & Tamirisa, 2011; Simpson & Ramchander, 2004; Simpson, Ramchander, & Chaudhry, 2005; Smales, 2013; Smales & Yang, 2015). As Baker and Wurgler (2006) pointed out, other studies have used market-based measures like the closed-end fund discount and the exchange turnover to construct a proxy for sentiment (e.g., Bahloul & Bouri, 2016; Gao & Süss, 2015; Zheng, 2015). In recent years, the development of news analytics has offered a more direct measure for capturing market sentiment. Analytics providers like Thomson Reuters have analyzed millions of macro- and microeconomic news articles and created sets of data containing information regarding to which financial assets (e.g., specific commodity and company) the news item is relevant and the tone of such news (i.e., positive or negative). An increasing number of recent academic studies have measured market sentiment using news analytics' aggregated data (e.g., Borovkova & Mahakena, 2015;

Borovkova, 2015; Groß-Klußmann & Hautsch, 2011; Maslyuk-Escobedo, Rotaru, & Dokumentov, 2017; Smales, 2014a, 2014b, 2014c).

News analytics sentiment measures have three major advantages. First, the overall market sentiment of the day can be disaggregated into positive and negative components to further demystify the role of sentiment. The literature has indicated that a fall (rise) in the price of financial securities is a result of the markets being dominated by a negative (positive) sentiment. However, these studies have not addressed four questions in sufficient detail: Is the degree/magnitude of this relationship influenced by the direction of market (i.e., falling or rising)? What does the structure of this relationship look like at various return levels? What is the role of the positive (negative) component of the sentiment under a bearish (bullish) market? How would the market environment/condition (i.e., a period of financial turmoil and the term structure of futures prices) affect this relationship? Answering these questions would help to clarify how commodity futures markets work. Second, as the sentiment is constructed from positive and negative news items on a specific day, it is simple to estimate, and the interpretation of the analysis results is intuitive. Third, the estimated news sentiment contains richer information than sentiment proxies that use only macroeconomic announcements.

Considering the basic association (i.e., a negative [positive] return is associated with negative [positive] sentiment), the absolute value of the positive (negative) sentiment component is expected to have an economically and statistically significant positive (negative) impact on the price when the market is rising (falling). By contrast, we expect the impact of positive (negative) component to be limited when the market is falling (rising). Thus, when it comes to the structure of dependence, an upward curve is expected when the quantile coefficients obtained for both sentiment components are plotted against the return quantiles. Nevertheless, for the negative (positive) component, we expect the association to be negative (around zero) in the lower percentiles and around zero (positive) in the higher percentiles.

Extending this basic hypothesis of the dependence structure, we argue that the steepness of the quantile coefficient curve is affected by the level of speculator participation and the mix of private and state-owned producers. Among the commodities selected for this study, industrial metals have the smallest proportion of speculators' trading positions.[1] Based on the rationale explained below, we expect the slope of the sentiment coefficients for these commodities to be moderate. On average, hedgers (speculators) take a net short (long) position (Moskowitz, Ooi, & Pedersen, 2012), and hedgers tend to underhedge their physical positions (Hirshleifer, 1991). Under these circumstances, when the price falls, the losses from the physical position surpass the gains realized from the hedged position. Thus, when the market sees negative news that may drag the price down substantially, rational hedgers strengthen their short positions to protect their future cash flow. By contrast, strong positive news may demotivate hedgers. In addition, speculators take net long positions because they anticipate the price will appreciate. Therefore, their reaction to the news should synchronize with that of hedgers, creating an upward curve of quantile coefficients. Nevertheless, as shown in Wang (2003), hedgers often trade against market sentiment, so they might respond adversely to what the rationale described above posits. Thus, these hedgers are likely to weaken the overall impact of the negative (positive) sentiment component at the lower (higher) tails of returns.

In addition, the production of energy commodities is dominated by state-owned enterprises (Bremmer, 2010b; Greene, 2010; Hori, 2017; Kowalski, Büge, Sztajerowska, & Egeland, 2013; Pirog, 2007) whose goals, such as a job creation, are often not driven by profit (Boardman & Vining, 1989; Bremmer, 2010a; Musacchio & Lazzarini, 2014; Vernon-Wortzel & Wortzel, 1989). These non-profit-driven producers can be less inclined to adjust their hedging positions swiftly as news arrives, which inflates the impact of the speculators' response and is likely to steepen the quantile coefficient curve of energy commodities.

A phenomenon that we saw in the last decade, the financialization of commodity markets is advancing,[2] so both speculators and hedgers are interested in how financial turmoil affects the potential asymmetric association. Smales (2014b) studied the gold market and showed that the news sentiment caused a stronger market reaction during the recession (2007Q4–2009Q2). In Smales' analysis, a strengthening in the response is statistically significant for the negative sentiment, but what has not been addressed is whether this strengthened dependence occurs with other major commodities as well and is unaffected by the magnitude and the signs of daily returns.

In addition, the commodity futures market is unique by its nature, particularly because of the presence of a physical market. The availability of a commodity, especially a nonagricultural product, can be adjusted relatively easily by

[1] Measured from the open-interest positions on futures exchanges.

[2] Evidenced, for example, by the paper barrel discussion in Yergin (2011), the safe-haven role of gold examined by Baur and McDermott (2010), and the strong growth in the market size of industrial metals documented in Dwyer, Gardner, and Wiliams (2011).

altering the production level, so the supply/demand environment of a physical commodity is determined by the proactive involvement of both suppliers and users. In the futures market, these parties' net trades are countered by other players, including speculators. At least partially driven by this mix of players, the market sees the prices of spot or futures contracts with short maturities surpass the prices of distant futures contracts. This phenomenon, known as "backwardation," occurs regularly, and various theories and hypotheses have attempted to explain it.

One of the explanations is based on the hedging pressure hypothesis that Cootner (1960), Hirshleifer (1990), and Basu and Miffre (2013), among others, explained. This hypothesis argues that backwardation is a result of hedgers' overall positions being overwhelmed by producers' short hedging. Then this net position of hedgers is countered by the net long position of speculators who expect the price to appreciate. Such speculators react more to negative news items to avoid losses than they do to positive news items. For this reason, backwardation strengthens the response to the negative component of sentiment and steepens the quantile coefficients.

By contrast, Borovkova (2015) showed that, during contango, negative sentiment receives a stronger reaction from the commodity market than positive sentiment does. Borovkova explained this view using the idea of a negative roll yield. When the market is in contango, investors who take long futures positions see losses if they simply roll the contracts (i.e., replace a nearly mature short contract with a distant contract). Borovkova asserted that this type of loss deepens when negative sentiment pushes the price farther down, amplifying the market reaction.

The market reaction Borovkova (2015) observed can also be rationalized by Kaldor's (1939) notion of convenience yield and associated theory of storage (see Brennan, 1958; Working, 1948, 1949). The theory of storage argues that the value of convenience from owning readily (or soon to be) available assets is awarded to futures contracts with short maturities. This relative value of convenience is a negative function of the inventory level, so backwardation is a result of scarce inventory. By contrast, the theory suggests that, in contango, a result of abundant inventory, the market reacts strongly to a negative news item that may ease the supply/demand environment, whereas a positive news item that may tighten the supply/demand environment may result in price appreciation.

Overall, these views pose a challenge to hypothesizing how the term structure affects the quantile vector of futures price reactions against the given sentiment. Following Delatte and Lopez (2013), we do not hypothesize a specific dependence structure but let the data speak for itself. As a result, we show that the estimation of regressors' average effects on dependent variables in an OLS regression can lead to underestimating or overestimating the effects at individual parts of the return distribution.

The current study makes three primary contributions. First, the market reaction to disaggregated market sentiment (i.e., both positive and negative components) is examined in light of market conditions at different return quantiles. The extant literature tests nonuniform reactions only, as they either divide the sample by the overall daily sentiment (e.g., Borovkova, 2015; Gao & Süss, 2015), or relate to the signs of futures returns and macroeconomic states like periods of expansion and contraction, without considering the direction of the pricing vector (e.g., Boyd et al., 2005; Elder, Miao, & Ramchander, 2012; Smales, 2014b; Zheng, 2015).

Second, related to the first contribution, this study is the first to show how commodity futures markets are related to news sentiment during contango and backwardation periods. The effect of the term structure can differ depending on which rationale we follow. The large majority of studies have focused on explaining the characteristics of the basis or convenience yield itself (e.g., Casassus, Liu, & Tang, 2013; Milonas & Paratsiokas, 2017; Omura, Todorova, Li, & Chung, 2015; Sévi, 2015) and how these yields are related to business cycles (e.g., Fernandez, 2016).

Third, our study contributes to extending the applicability of Baur's (2013) approach, which Mensi, Hammoudeh, Reboredo, and Nguyen (2014) and Zhu, Guo, You, and Xu (2016) have also used. This powerful and flexible technique employs a quantile regression approach to capture the degree to which a variable depends on another factor based on market conditions, and the structure of that dependence.

The results of this study broadly confirm the economic and statistical significance of the market sentiment. In addition, similar to the findings of Gao and Süss (2015) and Smales (2014b), the study finds an asymmetric nature of the market reaction against positive and negative sentiments; more specifically, the market is more strongly associated with the negative news component than it is with the positive news component. The incremental explanatory power of adding the sentiment factor is also supported. (The value of the adjusted R^2 improves by as much as 10%.) This result is consistent with Smales (2014b), who showed that the explanatory power for gold's futures returns improves by more than 10% when the news sentiment is factored in. In relation to the structure of dependence, the quantile regressions show that sentiment's influence on futures' returns follows an upward trend toward higher percentiles. In addition, a statistically significant dependence between the negative component of sentiment and daily returns is generally observed at lower percentiles.

As for the impact of financial conditions on this relationship, our findings are consistent with those of Smales (2015) for both gold and crude oil. To be more specific, we find that the asymmetric nature of the market response strengthens for these commodities during periods of financial turmoil, which indicates that the level of financialization may be an important driving factor of the dependence we observe. We also find that the market response to positive sentiment during financial turmoil is statistically flatter. In other words, the dependence is less asymmetric across return quantiles than it is in quieter periods. By contrast, we find that the slope of the quantile coefficients is steeper for the negative sentiment during backwardation than it is for the positive sentiment. Our results for the backwardation period support the hypothesized relationship rationalized by the hedging pressure theory; in particular, the commodities considered in this study may be influenced more by the reaction of speculators when the market is backwarded.

The remainder of the paper is structured as follows. Section 2 introduces the data, Section 3 explains the methodology, Section 4 presents and discusses the results, and the last section concludes.

2 | Data

2.1 | Futures returns

A range of daily data for the period from January 2003 to June 2014 is used to synchronize with the news data obtained from the Thomson Reuters News Analytics (TRNA) database. The present study's focus is on examining the degree and structure of commodity markets' dependence on the news sentiment, represented by the daily changes in futures prices, using five major commodities: aluminum, copper, crude oil, natural gas, and gold. The data are obtained from the Thomson Reuters Tick History database, which is available in the Securities Industries Research Centre of the Asia Pacific.

We estimate the daily returns of the selected commodities using the log-transformed closing prices. The 3-month contract prices at the London Metal Exchange (LME) are used for aluminum and copper, as they are the most actively traded contracts (Geman & Smith, 2013).[3] For crude oil and natural gas, the study uses the futures prices of the crude sweet oil Western Texas Intermediate (WTI) and the Henry Hub Natural Gas, respectively, traded at the New York Mercantile Exchange (NYMEX). The futures contracts traded at the Commodity Exchange (COMEX) are used for gold. For these five commodities, we identify the most frequently traded of the three nearest contracts for each trading day to ensure that a highly liquid contract is used in these commodities.

2.2 | News sentiment

The study uses readily available, preprocessed news data from the TRNA database to estimate a day's news sentiment. The text of news items reported over the Thomson Reuters network is analyzed using linguistic pattern-recognition algorithms established by Thomson Reuters. The sentiment for each news item is coded +1, 0, or −1 for positive, natural, and negative tones, respectively, and the topic code, the product code, and the stock Reuters identification codes (RICs) are allocated to each news item to identify to which commodity the news item is relevant.[4] Each article is also assigned a relevance score between 0 and 1 to indicate the prominence of the commodity in the news. As in Riordan, Storkenmaier, Wagener, and Sarah Zhang (2013), news items with relevance scores below 0.5 are disregarded. We also use a novelty identifier to avoid allowing previously reported news to influence the results. These steps reduced the sample by 70–80%.

We employ several methods to capture news that is relevant to each of the five commodities under consideration. We use the topic and stock RIC codes that are allocated to crude oil, natural gas, and gold (CRU, NGS, and GOL, respectively) to extract news that is relevant to these three commodities. Since there is no individual topic or product code allocated to aluminum or copper, we first extract the news items that are relevant to these metals using the topic code MET and the product code MTL[5] to ensure that the selected news articles refer to metals. Then, to isolate the news items that refer to a particular metal, we disregard news articles that contain

[3]Data are for the exchange-operated electronic trading platform, LMEselect, and the open-outcry trading pit.

[4]Refer to the product guide of Thomson Reuters for additional details; http://share.thomsonreuters.com/assets/elektron/news-analytics-flyer.pdf.

[5]These codes cover the news items for lead, zinc, tin, nickel, iron, bismuth, cadmium, chrome, cobalt, gallium, germanium, indium, magnesium, manganese, mercury, molybdenum, ruthenium, selenium, silicon, tantalite, titanium, tungsten, vanadium, wolfram, batteries, and steel.

the name of any metal other than the metal in focus.[6] The final number of news items for each commodity is between 53,142 and 280,213.

Following Dzielinski (2011) and Smales (2015), we estimate the news sentiment on a certain day by taking the weighted average of the prevailing sentiment for that day. The mathematical representation of this method is shown in the following equation:

$$\text{Sent} = \frac{\sum 1.prob_{\text{positive}} + \sum -1.prob_{\text{negative}}}{\eta_{\text{positive}} + \eta_{\text{neutral}} + \eta_{\text{negative}}} \in [-1,\ 1], \tag{1}$$

where *prob* is the sentiment probability, positive (negative) is the proportion of a certain news article that is taken favorably (unfavorably) by the market and η is the number of news items during a day.

2.3 | Market conditions

To examine the impact of the market environment/condition, we use the interaction terms constructed by multiplying the environment/condition dummy by the market sentiment proxy. We use an interest-adjusted basis to determine whether the market is in contango or backwardation, and the London Interbank Offered Rate (LIBOR) to determine the time value of money. We record the basis for each commodity using the prices found at the open-outcry trading pits of the exchange[7] and compute the interest-adjusted basis for aluminum and copper by subtracting the cash price from the 3-month futures price, after considering the time value of money. For crude oil, natural gas, and gold, the front-month contract price is subtracted from the third-month contract price, after considering the time value of money. The estimated interest-adjusted basis variables are converted into dummy variables, which take the value of one when the market is in backwardation (when the interest-adjusted basis is negative), and zero otherwise.

This study also examines the impact of the recent global financial crisis (GFC) on the relationship between the futures returns and the news sentiment during our sample period. By combining the views of Baur (2013) and Souček and Todorova (2013), we set the period between August 2007 and December 2009 as the crisis period. The GFC dummy takes the value of one during the GFC period, and zero otherwise.

2.4 | Other control variables

We incorporate three control variables to examine the relationships among the variables under consideration: To separate the effects of the overall equity and commodity markets, we use the S&P 500 and the Thomson Reuters CRB indices, and use the VIX to isolate the financial market's overall sentiment. Since the study addresses five of the CRB index's 19 commodities, the information contained in the dependent variable (the return of a commodity futures) and that in the CRB index variable overlaps. To control for effects that may arise from this issue, we orthogonalize the CRB index variable by regressing the CRB on the return series of a commodity and then employ the residual series as a proxy for the overall commodity market.

2.5 | Descriptive statistics

Table 1 presents the descriptive statistics of the variables used in this study. The mean value of the daily price changes of the selected commodities and the indices are close to zero, as expected. In terms of variability, the returns of all of the selected commodity futures except gold fluctuate more than the commodity and stock market indices do. Most volatile are the futures contracts on natural gas, as is largely acknowledged in the literature. Except for gold, the commodities under consideration exhibit positive average daily news sentiments. Finally, the means of the disaggregated sentiment components are found to take similar absolute values.

The next section presents the methodology used to shed light on the impact of the news flow on how the futures' returns are distributed.

[6]The limitation of this method is that the selected news articles may not relate exclusively to aluminum or copper. However, as Omura, Chung, Todorova, and Li (2016) showed that the consumption and production of metals are closely related to each other, so this method ensures that the selected news items are relevant to aluminum or copper.

[7]The trading activities of the second or third most frequently traded contracts on the electronic trading platform are not sufficiently frequent to estimate the daily interest-adjusted basis.

TABLE 1 Descriptive statistics (daily)

	Return	Sentiment	$Sent^+$	$\lvert Sent^-\rvert$
Al				
Mean	0.000	0.042	0.388	0.363
SD	0.014	0.151	0.077	0.060
Minimum	−0.086	−0.542	0.132	0.160
Maximum	0.075	0.645	0.645	0.639
Cu				
Mean	0.001	0.029	0.391	0.372
SD	0.019	0.155	0.072	0.063
Minimum	−0.148	−0.599	0.172	0.155
Maximum	0.114	0.701	0.701	0.664
WTI				
Mean	0.000	0.052	0.394	0.357
SD	0.022	0.104	0.049	0.036
Minimum	−0.129	−0.309	0.249	0.255
Maximum	0.146	0.331	0.527	0.509
Natgas				
Mean	0.000	0.051	0.383	0.345
SD	0.033	0.102	0.047	0.042
Minimum	−0.279	−0.312	0.178	0.145
Maximum	0.235	0.775	0.775	0.527
Gold				
Mean	0.000	−0.007	0.377	0.381
SD	0.012	0.146	0.059	0.057
Minimum	−0.088	−0.486	0.199	0.219
Maximum	0.073	0.523	0.640	0.593
Control variables				
	SP500	CRB	VIX	
Mean	0.000	0.000	19.918	
SD	0.011	0.012	9.421	
Minimum	−0.072	−0.100	9.890	
Maximum	0.057	0.110	80.860	

Note. Al: aluminum; CRB: Thomson Reuters CRB index; Cu: copper; Natgas: natural gas; SP500: S&P 500 index; VIX: CBOE volatility index; WTI: Western Texas Intermediate.

3 | METHODOLOGY

This study follows Baur (2013) in using the quantile regression method that Koenker and Bassett (1978) introduced to examine the degree to which one economic factor depends on another and to examine the structure of that dependence. Quantile regression is an extension of standard regression, but quantile regression assumes that the residual term that is conditional on the regressors in the τth quantile is zero. The basic conditional quantile model is shown in the following equation:

$$Q_{y_i}(\tau|\boldsymbol{X}) = \alpha_{(\tau)} + \boldsymbol{X}_i'\beta_{\tau,i}, \tag{2}$$

where τ is the quantile with $0 < \tau < 1$, $Q_{y_i}(\tau|X_i,\alpha)$ is the τth conditional quantile of y_i, $\beta(\tau)$ is the estimated parameter in the equation, α is the unobserved effect, and the regressor matrix $\boldsymbol{X}$ includes the variables that are assumed to influence the dependent variable's conditional quantile. The coefficients of the conditional quantile regression are estimated as shown in the following equation:

$$\hat{Q}_y(\tau) = \text{argmin}_a\left\{\sum_{i:y_i \geq a} \tau|y_i - a| + \sum_{i:y_i < a} (1-\tau)|y_i - a|\right\} = \text{argmin}_a \sum_i \rho_\tau(y_i - a), \tag{3a}$$

with the check function $\rho_\tau(z) = \begin{cases} \tau z: & z \geq 0, \\ (\tau - 1)z: & z < 0, \end{cases}$

so the quantile regression coefficients are obtained by solving

$$\hat{\beta}(\tau) = \text{argmin}_{\beta(\tau)\in\mathbb{R}^k}\left\{\sum_{i:y_i \geq x'\beta(\tau)} \tau|y_i - x_i'\beta(\tau)| + \sum_{i:y_i < x'\beta(\tau)} (1-\tau)|y_i - x_i'\beta(\tau)|\right\} = \text{argmin}_{\beta(\tau)}\sum_i \rho_\tau(y_i - x_i'\beta(\tau)), \tag{3b}$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the check function with an indicator function $I(.)$.

Based on Baur (2013), the basic quantile model is transformed to two specifications:

$$Q_{r_i}(\tau|\boldsymbol{X}) = \alpha_i(\tau) + \beta_i(\tau)Sent_i + \gamma_i(\tau)Sent_iD_{j,i} + \sum_{m=1}^{3}\delta_m(\tau)x_m \tag{4a}$$

and

$$Q_{r_i}(\tau|\boldsymbol{X}) = \alpha_i(\tau) + \beta_i^+(\tau)Sent_i^+ + \gamma_i^+(\tau)Sent_i^+D_{j,i} + \beta_i^-(\tau)Sent_i^- + \gamma_i^-(\tau)Sent_i^-D_{j,i} + \sum_{m=1}^{3}\delta_m(\tau)x_m, \tag{4b}$$

where r_i is the daily log return of commodity i; $Sent_i$ is the daily news sentiment (as per Equation (1)); $Sent_i^+$ and $Sent_i^-$ are the disaggregated sentiments consisting of the positive and negative components of news items, respectively (the negative sentiment variable in an absolute value form); D_j is the dummy variable j for commodity i, which takes the value of one if the market is in a certain state (backwardation or GFC), and zero otherwise; and x_m is the control variable m ($m = 1, 2, 3$: CRB index, S&P 500 index, and VIX). The interaction term between the news sentiment and the dummy captures the marginal effect of changes in the degree of dependence in the subsample period for each quantile τ.[8]

Whether there are changes in the degree to which futures' returns are associated with the news sentiment in different market conditions—and the structure of that dependence—can be tested by analyzing the coefficients of γ_i in Equation (4). Following Baur (2013), we set the average *degree* of dependence to remain unchanged if the estimates of γ_i across quantiles are zero. A change in the *structure* of dependence is given when the coefficients γ_i differ across quantiles.

To examine basic relationships between the futures' returns of selected commodities and news sentiment, we also conduct a standard regression analysis using

$$r_{i,t} = \alpha_i + \beta_i Sent_{i,t} + \gamma_i Sent_i D_{j,i} + \sum_{m=1}^{3}\delta_m x_{m,t} + \varepsilon_t \tag{5a}$$

and

$$r_{i,t} = \alpha_i + \beta_i^+ Sent_i^+ + \gamma_i^+ Sent_i^+ D_{j,i} + \beta_i^- Sent_i^- + \gamma_i^- Sent_i^- D_{j,i} + \sum_{m=1}^{3}\delta_m x_{m,t} + \varepsilon_t. \tag{5b}$$

The regressions are estimated with Newey–West standard errors with a lag of 4 to overcome possible heteroscedasticity and serial-correlation issues.

4 | RESULTS

4.1 | Dependence of returns on news sentiment

Table 2 presents the results of the simple regression analysis using Equation (5a) without an interaction term. For the sake of brevity, Table 2 reports only the coefficients obtained for the sentiment variable and the values of adjusted R^2 with and without the sentiment variable. Analysis confirms the economic and statistical significance of the market sentiment constructed with news analytics and the evident incremental explanatory power of adding the sentiment factor. The value of the adjusted R^2 improves by as much as 10% over that of the model without the news sentiment.

[8]For additional details regarding the quantile regression framework used, see Baur (2013).

TABLE 2 Full-sample regression analysis

	Al	Cu	WTI	Natgas	Gold
Sent	0.013*	0.028*	0.024*	0.030*	0.024*
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	0.113	0.184	0.129	0.013	0.084
Adjusted R^2 without Sent	0.097	0.136	0.117	0.005	0.002

Note. The results of full-sample regression analysis without interaction terms are presented. For the sake of brevity, only the results obtained for the sentiment variable (Sent) are shown. The coefficients are obtained from the contemporaneous regression model having the daily futures return of the indicated commodity as the explained variable, and the CRB, S&P500, and VIX indices as the control variables. "Adjusted R^2 without Sent" means the regression analysis is conducted without the sentiment variable, the main explanatory variable in this study. The p values based on Newey–West standard errors with a lag of 4 are in parentheses.

Al: aluminum; CRB: Thomson Reuters CRB index; Cu: copper; Natgas: natural gas; SP500: S&P 500 index; VIX: CBOE volatility index; WTI: Western Texas Intermediate.

*Significant at the 1% level.

This result is consistent with Smales (2014b), who showed that the explanatory power of gold futures' returns improves by more than 10% when the news sentiment is factored in.

Then we reconducted the simple regression analysis using the decomposed market sentiments and Equation (5b). The results are reported in Panel A of Table 3. Similar to Gao and Süss (2015) and Smales (2014b), we observe an asymmetric nature of the market reaction against positive and negative sentiments, as the market is more strongly associated with the negative component of news sentiment than the positive. To examine this outcome further, we conduct a statistical test that compares the coefficients obtained for the positive and negative components (Table 3, Panel B) and find statistical support for the difference in the degree of dependence. The model's explanatory power of model improves, especially for gold when the sentiment measure is disentangled into positive and negative components.

Next, we examine the structure of dependence using quantile regression analysis (Figure 1) in the general case (i.e., without considering the interaction terms). Figure 1 shows that, in some areas, only the negative component is statistically significant at the 10% level, in others only the positive component is statistically significant, and in still others both coefficients are significant.

As initially expected, the coefficients follow an upward trend toward higher percentiles. A statistically significant dependence between the negative component of sentiment and the daily returns is generally observed at lower percentiles, while at higher percentiles there is a statistically significant dependence between the positive component of sentiment and the daily returns. The difference in the quantile dependence is statistically supported by the equality tests (presented in Table 4) conducted among the coefficients obtained at the 5th, 50th, and 95th percentiles for both the

TABLE 3 Full-sample regression analysis with decomposed sentiment

	Al	Cu	WTI	Natgas	Gold
Panel A					
Sent^+	0.017***	0.034***	–0.001	0.029*	0.023***
(p-value)	(0.00)	(0.00)	(0.90)	(0.10)	(0.00)
$\lvert\text{Sent}^-\rvert$	–0.016***	–0.041***	–0.081***	–0.057***	–0.047***
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Adjusted R^2	0.114	0.186	0.134	0.015	0.101
Panel B					
p-Value	0.000	0.000	0.000	0.000	0.000

Note. The outcomes of full-sample regression analysis are presented. Panel A presents the regression analysis result and Panel B presents the coefficients equality test (F test) results for the sentiment variables. For the sake of brevity, the table only shows the results obtained for the sentiment variables. Sent^+ is the positive component of the daily sentiment and Sent^- is the negative component. The coefficients are obtained from the contemporaneous regression model having the daily futures return of the indicated commodity as the explained variable, and the CRB, S&P500, and VIX indices as the controlling variables. The p values based on Newey–West standard errors with a lag of 4 are in parentheses.

Al: aluminum; CRB: Thomson Reuters CRB index; Cu: copper; Natgas: natural gas; SP500: S&P 500 index; VIX: CBOE volatility index; WTI: Western Texas Intermediate.

***, *Significant at the 1%, and 10% levels, respectively.

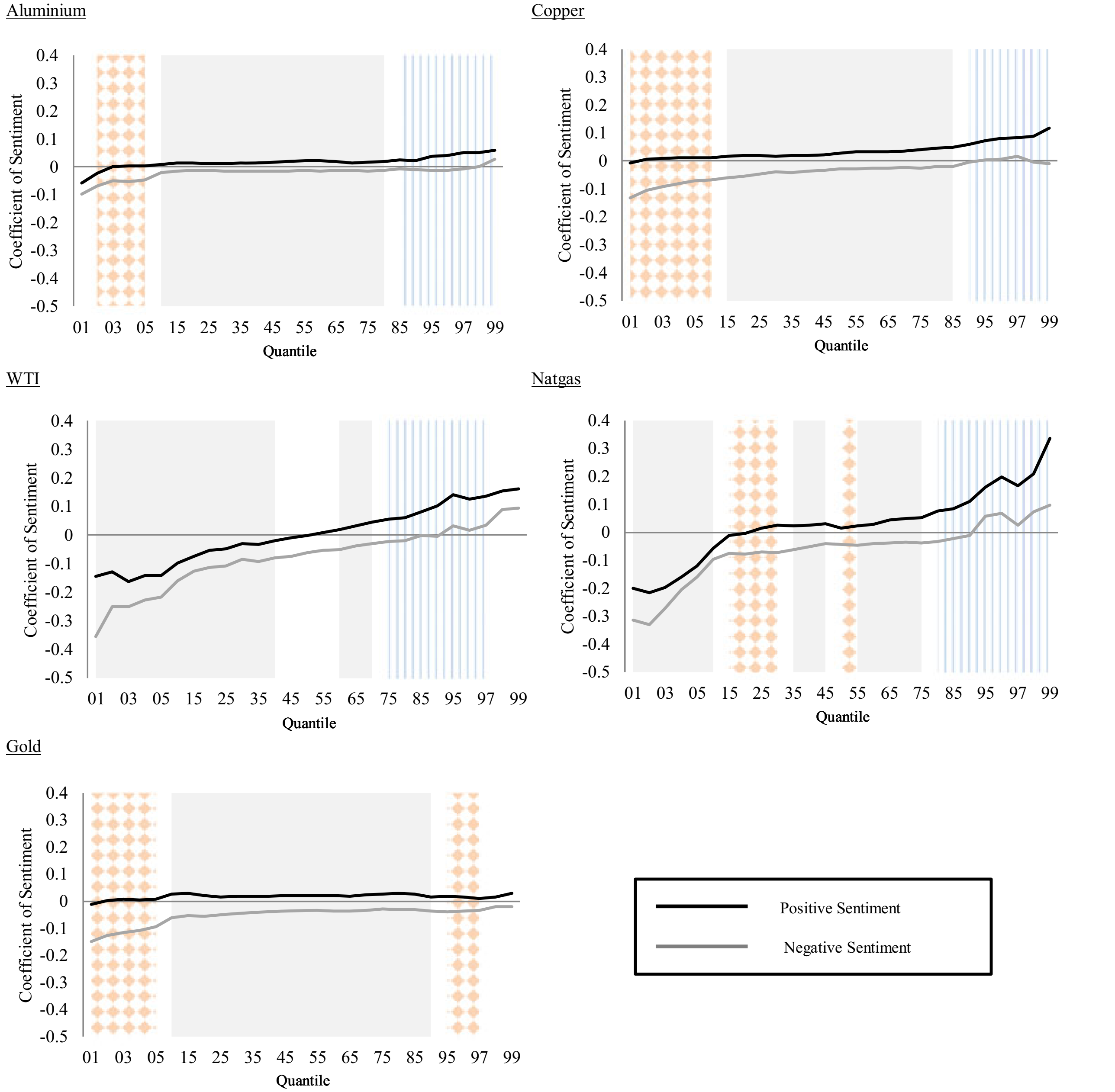

FIGURE 1 Quantile regression estimates for news sentiment with decomposed sentiment. It is noted that the graphs present the dependence of the daily futures returns on the new sentiment for a specified commodity. The regression analyses are conducted following Equation (4a). The standard errors of the original quantile regression analysis are estimated by bootstrapping with 1,000 simulations. The gray shaded areas in the figures indicate that the coefficients for both negative and positive sentiments are statistically significant at the 10% level, the dot shaded areas in the figure indicate only the negative sentiment is significant, and the vertical lines indicate only the positive sentiment is significant. WTI: Western Texas Intermediate [Color figure can be viewed at wileyonlinelibrary.com]

positive and the negative components. The shape of the dependence structure indicates that, in a downturn (upturn) market, speculators and hedgers pay less attention to positive (negative) news items.

Also regarding the asymmetric response, the analysis shows that the absolute magnitude of the shock that negative news brings to the market at lower percentiles is larger than that of the positive component at higher percentiles, indicating again that the market reacts more strongly to negative news than it does to positive news. This asymmetry is statistically supported by the results presented in Table 5, where the equality of positive and negative sentiments is tested at the 5th, 50th, and 95th percentiles. As for the dependence structure of the commodities, the energy commodities exhibit steeper curves than the nonenergy commodities do for both the negative and the positive components, as expected.

TABLE 4 Equality tests of percentile sentiment coefficients (p values)

	Al	Cu	WTI	Natgas	Gold
Positive sentiment component					
Q5 vs. 95	0.002	0.000	0.000	0.000	0.573
Q95 vs. 50	0.010	0.000	0.000	0.006	0.870
Q5 vs. 50	0.072	0.112	0.000	0.001	0.276
Negative sentiment component					
Q5 vs. 95	0.020	0.000	0.000	0.003	0.016
Q95 vs. 50	0.730	0.001	0.001	0.054	0.715
Q5 vs. 50	0.005	0.001	0.000	0.019	0.002

Note. It presents the results of F tests examining whether the difference between the given percentile coefficients is indifferent from zero. For example, Q5 versus 95 in the positive sentiment component panel shows that the coefficients for 5th and 95th percentiles are tested. The tests are conducted on the results shown in Figure 1. The standard errors of the original regression analysis are estimated by bootstrapping with 1,000 simulations.
Al: aluminum; Cu: copper; Natgas: natural gas; WTI: Western Texas Intermediate.

TABLE 5 Equality tests of positive and negative sentiment components (p values)

	Al	Cu	WTI	Natgas	Gold
Q5	0.000	0.000	0.018	0.350	0.000
Q95	0.000	0.000	0.000	0.064	0.000
Q50	0.000	0.000	0.000	0.000	0.000

Note. It presents the results of F test examining whether the difference between the coefficients obtained for positive and negative sentiment components at the given percentile is statistically different from zero. For example, Q5 indicates the test is conducted using the coefficients obtained for the 5th percentile. The tests use the results shown in Figure 1. The standard errors of the original regression analysis are estimated by bootstrapping with 1,000 simulations.
Al: aluminum; Cu: copper; Natgas: natural gas; WTI: Western Texas Intermediate

TABLE 6 Full-sample regression with GFC dummy

	Al	Cu	WTI	Natgas	Gold
Panel A					
Constant	0.001	0.003	0.030***	0.010	0.010**
(p-value)	(0.55)	(0.45)	(0.00)	(0.33)	(0.02)
$Sent^+$	0.015***	0.031***	−0.004	0.023	0.020***
(p-value)	(0.00)	(0.00)	(0.72)	(0.23)	(0.00)
$\lvert Sent^- \rvert$	−0.015***	−0.038***	−0.075***	−0.051***	−0.044***
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$GFC \times Sent^+$	0.009	0.012	0.041**	0.031	0.015**
(p-value)	(0.15)	(0.14)	(0.02)	(0.11)	(0.01)
$GFC \times \lvert Sent^- \rvert$	−0.007	−0.012	−0.056**	−0.030	−0.014**
(p-value)	(0.32)	(0.18)	(0.01)	(0.17)	(0.03)
Adjusted R^2	0.115	0.187	0.137	0.015	0.104
Panel B					
GFC (p-value)	0.000	0.000	0.000	0.000	0.000
Non-GFC (p-value)	0.000	0.000	0.000	0.000	0.000

Note. The outcomes of full-sample regression analysis with an GFC interaction term are presented. Panel A presents the regression analysis result and Panel B presents the coefficients equality test (F test) results for the sentiment variable at different financial market environments (GFC and non-GFC). For the sake of brevity, it only shows the results obtained for the sentiment variables. However, the regression analyses are conducted based on Equation (5b) with control variables. For Panel A, adjusted R^2 is the value of the adjusted R^2. $Sent^+$ is the positive component of sentiment while $Sent^-$ is the negative component. The p values based on Newey–West standard errors with a lag of 4 are in parentheses. For Panel B, the F test examines whether the coefficients of positive and negative components obtained in the regression analysis are statistically indifferent or not. GFC indicates that the tests are conducted using the sum of coefficients obtained for β and γ in the equation.
Al: aluminum; Cu: copper; GFC: global financial crisis; Natgas: natural gas; WTI: Western Texas Intermediate.
***, **Significant at the 1% and 5%, levels, respectively.

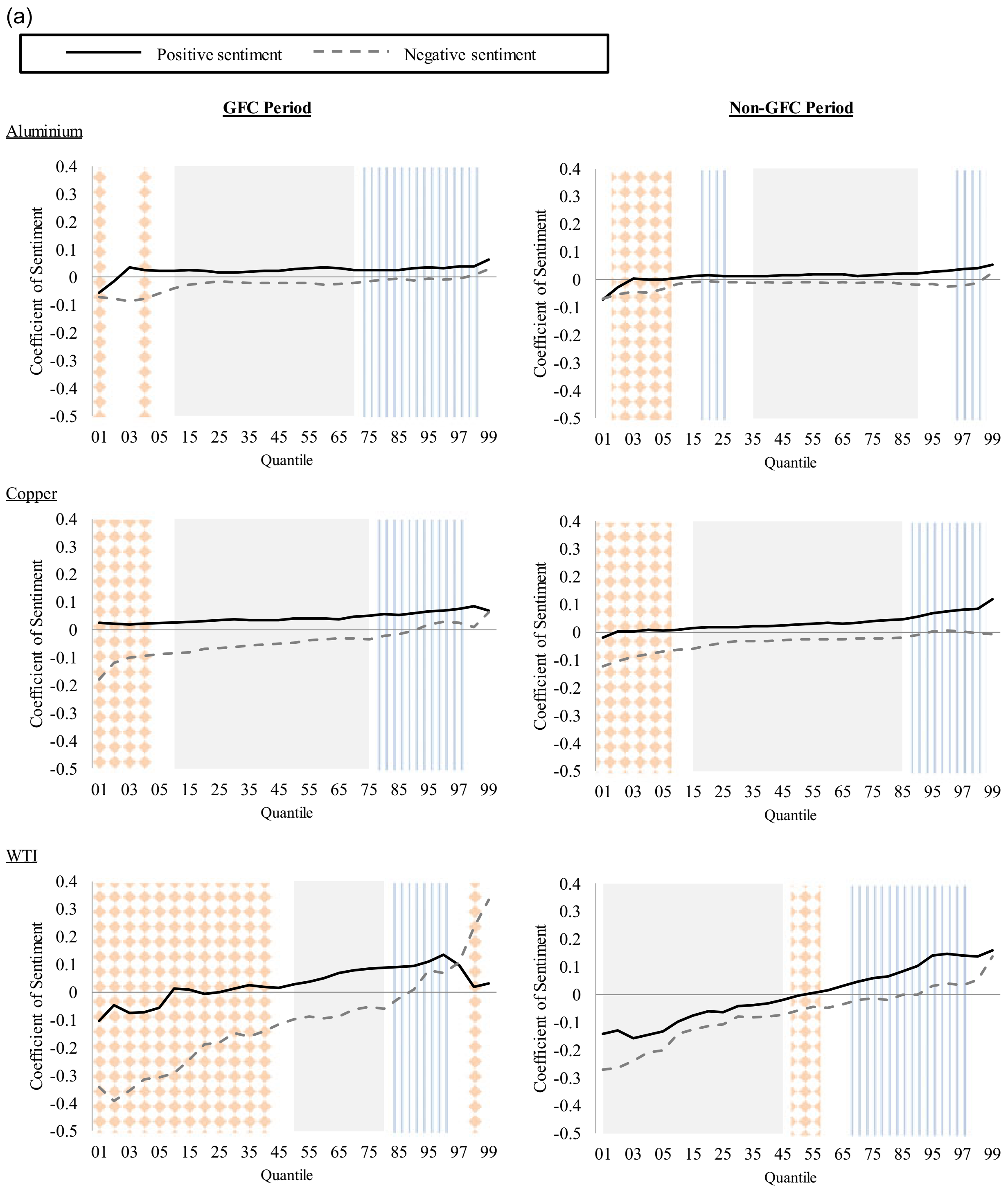

FIGURE 2 (a,b) Quantile regression estimates, GFC and non-GFC. It is noted that the figures present the dependence of the dailyfutures return on the new sentiment for a specified commodity. The regression analyses are conducted following Equation (4b). In theanalysis, the GFC dummy is used. For the GFC period, the sum of coefficients obtained for β and γ in the equation is given and the F test isconducted on the aggregated coefficients. The standard errors of the original quantile regression analysis are estimated by bootstrappingwith 1,000 simulations. The gray shade in the figures indicates that the coefficients for both negative and positive sentiments are statisticallysignificant at the 10% level, the dot shade in the figure indicates only the negative sentiment is significant, and the vertical line shadeindicates only the positive sentiment is significant. GFC: global financial crisis; WTI: Western Texas Intermediate. [Color figure can be viewed at wileyonlinelibrary.com]

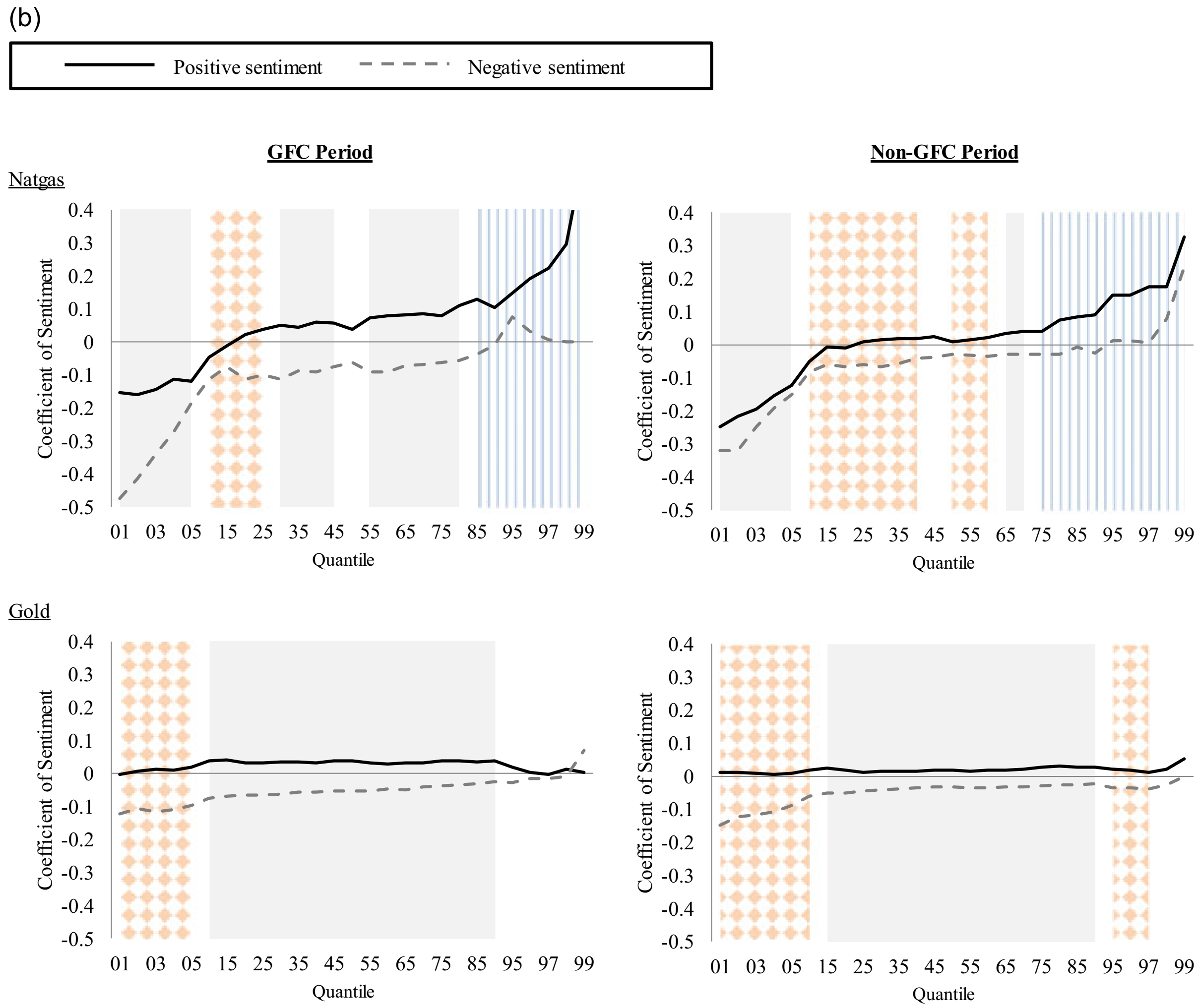

FIGURE 2 Continued

What differs from our expectation is that, for energy commodities, the market response even towards positive sentiment is significantly negative at lower percentiles. Perhaps the proportion of days that are dominated by the positive sentiment affects this result, as when we sort the sample by the daily returns, 60–80% of the days that nonenergy commodities are in the 5th percentile or lower are dominated by negative sentiment, while the positive sentiment is dominant for around 70% of the days that these commodities are in 95th percentile or higher. By contrast, for energy commodities, while the situation at higher percentiles is similar to that of nonenergy commodities, close to 70% of days, even those in the bottom five percentiles, are dominated by positive sentiment. This dominance structure can directly affect our result. Next, we extend the analysis by taking market conditions into consideration.

4.2 | Commodity returns, news sentiment, and the financial crisis

We use the recent GFC period to analyze the degree to which futures' returns depend on the news sentiment, and the structure of that dependence. Table 6 (Panel A) presents the results of a simple regression analysis using Equation (5b). Smales (2015) focused on gold only and showed that the association between disaggregated market sentiment (constructed from news analytics) and the daily return strengthens during the most recent recession in the United States, which largely overlapped with the GFC. Smales also found that the asymmetric nature of the response to different components of the sentiment measure amplifies under such market conditions. The present analysis obtains results that are consistent with those of Smales (2015) for both gold and crude oil, two of the most financialized commodities. As for the remaining commodities, while the signs of the interaction terms' coefficients are consistent with our basic hypothesis, they are not

TABLE 7 Full-sample regression with the term structure dummy

	Al	Cu	WTI	Natgas	Gold
Panel A					
Constant	0.000	0.001	0.033***	0.011	0.010**
(p-value)	(0.87)	(0.74)	(0.00)	(0.27)	(0.02)
Sent^+	0.016***	0.036***	−0.010	0.020	0.023***
(p-value)	(0.00)	(0.00)	(0.37)	(0.18)	(0.00)
$\lvert\text{Sent}^-\rvert$	−0.014***	−0.035***	−0.077***	−0.052***	−0.048***
(p-value)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$\text{Back} \times \text{Sent}^+$	0.005	0.002	0.021**	0.043	0.005
(p-value)	(0.28)	(0.71)	(0.03)	(0.30)	(0.56)
$\text{Back} \times \lvert\text{Sent}^-\rvert$	−0.007	−0.008	−0.016	−0.040	0.001
(p-value)	(0.26)	(0.26)	(0.12)	(0.37)	(0.86)
Observations	2,841	2,852	2,955	2,954	2,955
Adjusted R^2	0.114	0.188	0.136	0.016	0.103
Panel B					
Backwardation	0.000	0.000	0.000	0.000	0.000
Contango	0.000	0.000	0.000	0.000	0.000

Note. It presents the outcomes of full-sample regression analysis with the backwardation interaction term. Panel A presents the regression analysis result and Panel B presents the coefficients equality test (F test) results for the sentiment variables at different term-structure status (backwardation and contango). For the sake of brevity, it only shows the results obtained for the sentiment variables. However, the regression analyses are conducted based on Equation (5b) with control variables. For Panel A, adjusted R^2 is the value of the adjusted R^2. Sent^+ is the positive component of sentiment while Sent^- is the negative component. The p values based on Newey–West standard errors with a lag of 4 are in parentheses. For Panel B, the F test examines whether the coefficients of positive and negative components obtained in the regression analysis are statistically indifferent or not. Backwardation indicates that the tests are conducted using the sum of coefficients obtained for β and γ in the equation.
Al: aluminum; Cu: copper; Natgas: natural gas; WTI: Western Texas Intermediate.
***,**Significant at the 1% and 5% levels, respectively.

statistically significant, suggesting that the level of financialization and, thus, investors' participation may be a key factor in the magnitude of the observed dependence. On the full-sample regression analysis using the GFC dummy, the results in Table 6 (Panel B) confirm that the market responds asymmetrically to positive and negative news.

The quantile coefficient trend in Figure 2 indicates no substantial change in the structure of dependence during the GFC period, but the statistical tests reveal that the structure of the market reaction to positive sentiment during the GFC was statistically flatter than in comparatively less volatile market periods (see Table A1). In other words, the dependence was less asymmetric across all levels of return. Turning to the asymmetric nature of the response to the positive and negative components of the sentiment, it appears that, in the higher quantiles, the reaction was statistically indifferent during the GFC.[9] This phenomenon is generally consistent at even higher percentiles (i.e., the 96th, 97th, 98th, and 99th percentiles; results not tabulated). Figure 2 shows that the coefficients of the positive and negative components at the higher percentiles are widely divergent, indicating that investors' response in the upturn market was dispersed.

4.3 | News sentiment and term structure

Next, we examine how the term structure that is uniquely observed in the commodity market affects the degree of investors' dependence on the news sentiment. As explained above, the hypothesized impact of term structure may vary based on which basic notion one follows.[10] The basic regression analysis displayed in Table 7 (Panel A) shows an insignificant impact of term structure on the degree of dependence, as neither of the positive and negative backwardation interaction terms has a significant coefficient. Consistent with the results of the basic regression, the

[9]Results are provided in Table A2.

[10]Following the hedging pressure theory, as backwardation is a result of hedgers' overall position's being overwhelmed by producers' short hedging, speculators who take net long positions would react more to negative news items to avoid losses. By contrast, based on the idea of a negative roll yield, negative news is likely to have a stronger impact when the market is in contango because, during contango periods, investors who take long positions take losses when they simply roll the contracts, and those losses deepen when negative sentiment pushes the price farther down.

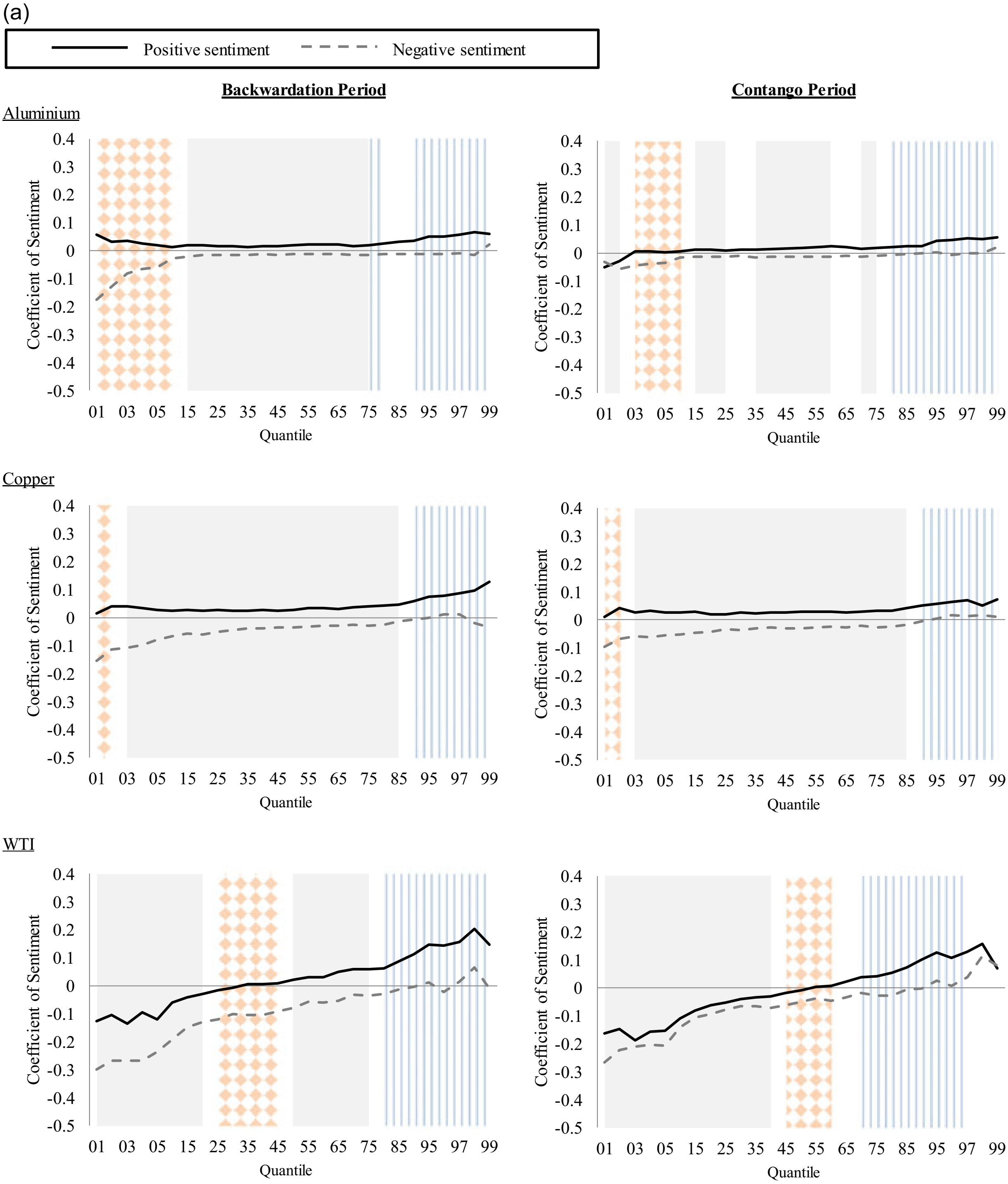

FIGURE 3 (a,b) Quantile regression estimates, contango and backwardation. It is noted that the figures present the dependence of thedaily futures return on the new sentiment for a specified commodity. The regression analyses are conducted following Equation (4b). In theanalysis, the backwardation dummy is used. For the backwardation period, the sum of coefficients obtained for β and γ in the equation isgiven and the F test is conducted on the aggregated coefficients. The standard errors of the original quantile regression analysis are estimatedby bootstrapping with 1,000 simulations. The gray shade in the figures indicates that the coefficients for both negative and positivesentiments are statistically significant at the 10% level, the dot shade in the figure indicates only the negative sentiment is significant, and thevertical line shade indicates only the positive sentiment is significant. WTI: Western Texas Intermediate. [Color figure can be viewed at wileyonlinelibrary.com]

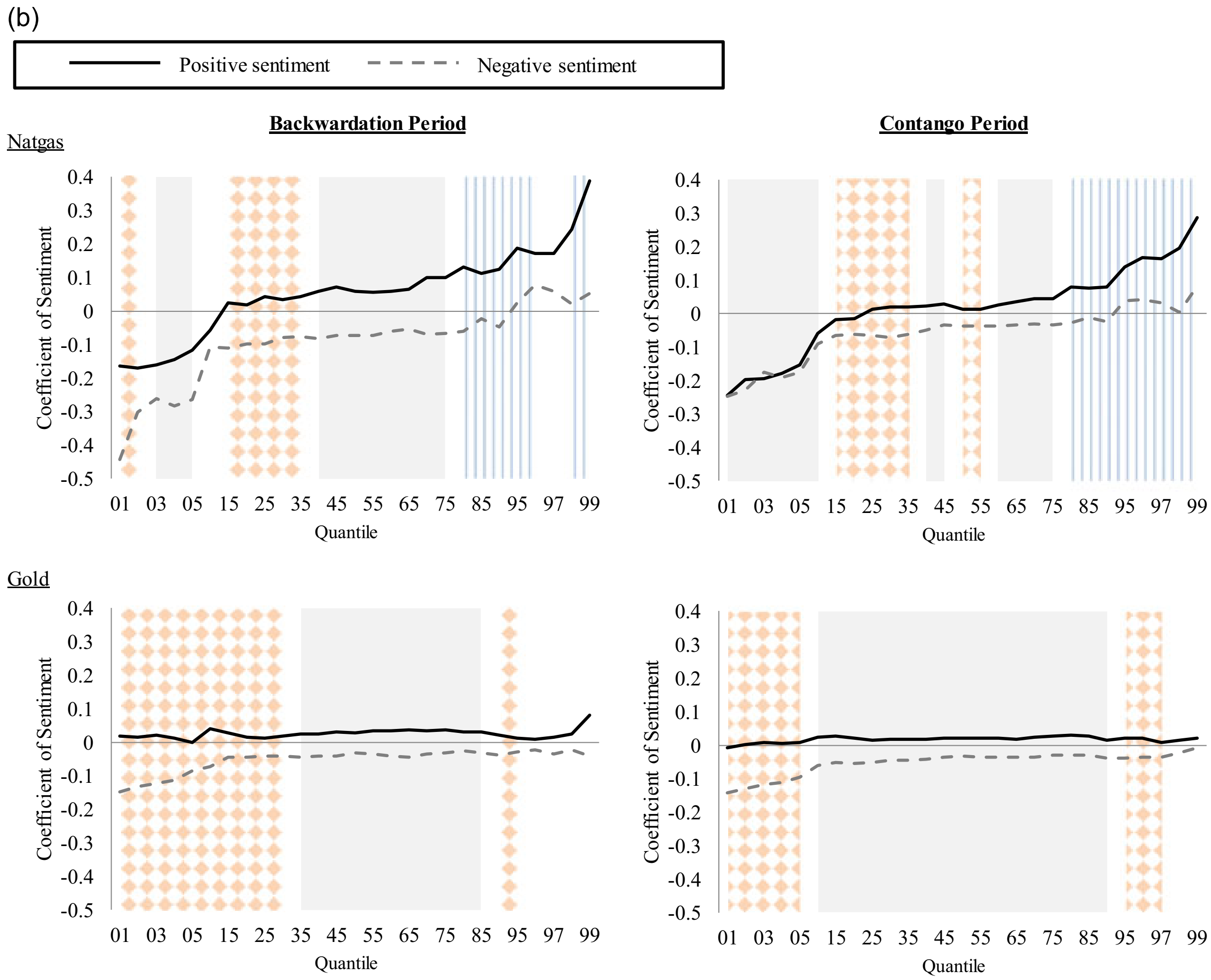

FIGURE 3 Continued

coefficients of the negative and positive components are statistically different from each other (Table 7, Panel B). In addition, just as in the case of GFC (Section 4.2), we conduct equality tests on the coefficients obtained in the quantile regressions,[11] but we observe no unique influence of the term structure. These results may indicate that the mixed reactions of various categories of market players weaken the impact of one another's strategic decisions. Nevertheless, we extend the examination by plotting the percentile coefficients, as was done in previous subsections.

Figure 3 shows that, at the lower percentiles, the degree of dependence on the negative sentiment component increases during backwardation periods, while at the higher percentiles, the absolute magnitude of dependence on the positive component also increases. For example, for aluminum, the average value of the negative sentiment coefficients obtained for the bottom five percentiles (i.e., the 1st, 2nd, 3rd, 4th, and 5th percentiles) are −0.102 in backwardation and −0.042 in contango. For the top five percentiles, the values for positive sentiment in backwardation and contango are 0.056 and 0.049, respectively.

In addition, the slope of the coefficients obtained for the negative component appears to be steeper in backwardation than it is in contango, which becomes clearer when trend lines are drawn using the percentile coefficients. For example, for aluminum, the value of the slope (i.e., the beta of the trend line) is twice as steep in backwardation as it is in contango. As explained above, this strengthening of dependence during the backwardation period is hypothesized as a reaction of speculators and rationalized using the hedging pressure hypothesis. That is, backwardation is a result of hedgers' overall positions being overwhelmed by producers' short hedging but is countered by speculators' long positions. These speculators appear more likely to react new information that may shrink risk premiums.

[11]Results are presented in Tables A3 and A4.

Finally, we reconduct all of these analyses using the sentiment variable constructed with uncleaned news data and find results that are similar to those discussed above. However, it appears that the structure of quantile dependence between sentiment and commodity returns weakens when duplicated and repeated news items are not removed from the sample, flattening the quantile dependence. The association we observe may be directly affected by the change in the absolute level of estimated sentiment and its variation. When data are not cleaned, the absolute mean values of the positive and negative sentiments still inflate, but they become less volatile, perhaps strengthening the apparent association with the stock returns when two variables are regressed against each other, amplifying the apparent associations are amplified throughout the quantiles, and flattening the quantile dependence structure. These results underscore the effectiveness of the data-cleaning procedure used in the extant literature.

5 | CONCLUSIONS

This study examines the degree to which the returns of commodities' futures depend on market sentiment, and how such an association is influenced by the level of futures' returns and market conditions. As documented in the existing literature, markets for commodity derivatives are influenced by the news flow, so determining how the markets are related to the sentiment inherent in incoming news under various market conditions can have significant value. This study addresses in detail four questions related to this issue that the extant literature has not: Is the degree/magnitude of this relationship influenced by the overall tone (positive or negative) of the sentiment? What does the structure of this relationship look like at different levels of return? What is the role of the positive (negative) component of the sentiment in bearish (bullish) markets? How does the market environment/condition affect this relationship? To address this study gap, the present study focuses on five major energy and metal commodities: aluminum, copper, crude oil, gold, and natural gas.

The study's analyses broadly support an asymmetric nature of the dependence of the commodities' returns on positive and negative news sentiment and find that the market is more strongly associated with the negative component than the positive component. The incremental explanatory power of adding a sentiment factor is also supported, as the value of the adjusted R^2 improves by as much as 10%. As for the structure of dependence, the simple quantile regressions conducted here show that sentiment's influence on futures' returns follows an upward trend toward higher percentiles, while a statistically significant dependence between the negative component of sentiment and daily returns is observed at lower percentiles.

Our analyses also show that the positive sentiment has a flatter quantile regression coefficient slope during the GFC, indicating that the dependence becomes less asymmetric over all return levels during times of financial turmoil. Contrarily, the slope of the quantile coefficients is steeper for the negative sentiment during backwardation than in contango. The results for backwardation periods support the relationship hypothesized by the hedging pressure theory, particularly that the market may be under stronger influence of speculators during backwardation.

The study's findings contribute to enriching the literature on the markets' responses to the flow of information. It also extends the applicability of the quantile regression technique that Baur (2013) proposed to capture the degree to which futures depend on news sentiment under various market conditions, and to capture the structure of that dependence. In addition, the study highlights how market conditions affect investors' reactions to news sentiment. Our work is of practical relevance not only to hedgers, but also to all participants in the commodity derivatives markets.

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APPENDIX

TABLE A1 Equality test of percentile sentiment coefficients: GFC and non-GFC (p values)

	Al	Cu	WTI	Natgas	Gold
Non-GFC Sent^{+}					
Q5 vs. 95	0.019	0.000	0.000	0.000	0.597
Q95 vs. 50	0.229	0.000	0.000	0.006	0.925
Q5 vs. 50	0.032	0.033	0.000	0.001	0.442
GFC Sent^{+}					
Q5 vs. 95	0.545	0.060	0.019	0.934	0.978
Q95 vs. 50	0.608	0.186	0.070	0.581	0.300
Q5 vs. 50	0.751	0.281	0.115	0.545	0.351
Non-GFC Sent^{-}					
Q5 vs. 95	0.283	0.000	0.000	0.020	0.052
Q95 vs. 50	0.675	0.005	0.002	0.418	0.724
Q5 vs. 50	0.058	0.001	0.000	0.017	0.007
GFC Sent^{-}					
Q5 vs. 95	0.037	0.000	0.000	0.253	0.018
Q95 vs. 50	0.388	0.001	0.007	0.143	0.282
Q5 vs. 50	0.034	0.039	0.001	0.980	0.025

Note. The results of F tests examining whether the difference between the coefficients obtained for indicated sentiment variable at given percentiles are indifferent from zero are presented. GFC indicates that the tests are conducted using the sum of coefficients obtained for β and γ in the equation. Sent^{+} indicates the positive sentiment component is used, while Sent^{-} indicates the use of the negative component. Furthermore, a row with the heading of Q5 versus 95 shows the test results examining the coefficients for 5th and 95th percentiles. The tests are conducted on the results shown in Figure 2. The standard errors of the original regression analysis are estimated by bootstrapping with 1,000 simulations.

Al: aluminum; Cu: copper; GFC: global financial crisis; Natgas: natural gas; WTI: Western Texas Intermediate.

TABLE A2 Coefficients quality test of positive and negative components (GFC/non-GFC)

	Al	Cu	WTI	Natgas	Gold
GFC					
Q5	0.003	0.001	0.016	0.469	0.000
Q95	0.166	0.158	0.757	0.514	0.058
Q50	0.000	0.000	0.000	0.027	0.000
Non-GFC					
Q5	0.022	0.000	0.046	0.568	0.000
Q95	0.000	0.000	0.000	0.013	0.000
Q50	0.000	0.000	0.000	0.028	0.000

Note. It presents the results of F tests examining whether the difference between the coefficients obtained for positive and negative components is indifferent from zero. Q5, 50, and 95 indicate which percentile result is used in the analysis. GFC indicates that the tests are conducted using the sum of coefficients obtained for β and γ in the equation. The tests are conducted on the results shown in Figure 2. The standard errors of the original regression analysis are estimated by bootstrapping with 1,000 simulations. The presented values are p values.

Al: aluminum; Cu: copper; GFC: global financial crisis; Natgas: natural gas; WTI: Western Texas Intermediate.

TABLE A3 Equality test of percentile sentiment coefficients: backwardation and contango

	Al	Cu	WTI	Natgas	Gold
Contango Sent+					
Q5 vs. 95	0.001	0.076	0.000	0.000	0.569
Q95 vs. 50	0.006	0.035	0.006	0.010	0.908
Q5 vs. 50	0.069	0.862	0.001	0.000	0.308
Backwardation Sent$^+$					
Q5 vs. 95	0.089	0.005	0.002	0.001	0.730
Q95 vs. 50	0.005	0.000	0.120	0.055	0.490
Q5 vs. 50	0.866	0.905	0.005	0.011	0.336
Contango Sent$^-$					
Q5 vs. 95	0.039	0.001	0.020	0.001	0.022
Q95 vs. 50	0.200	0.002	0.418	0.140	0.746
Q5 vs. 50	0.105	0.076	0.017	0.002	0.002
Backwardation Sent$^-$					
Q5 vs. 95	0.021	0.000	0.007	0.013	0.137
Q95 vs. 50	0.900	0.011	0.062	0.260	0.896
Q5 vs. 50	0.009	0.004	0.062	0.012	0.084

Note. It presents the results of F tests examining whether the difference between the coefficients obtained for indicated sentiment variable at given percentiles are indifferent from zero. The presented values are the p values. Backwardation indicates that the tests are conducted using the sum of coefficients obtained for β and γ in the equation. Sent$^+$ indicates the positive sentiment component is used, while Sent$^-$ indicates the use of the negative component. Furthermore, a row with the heading of Q5 versus 95 shows the test results examining the coefficients for 5th and 95th percentiles. The tests are conducted on the results shown in Figure 3. The standard errors of the original regression analysis are estimated by bootstrapping with 1,000 simulations.
Al: aluminum; Cu: copper; Natgas: natural gas; WTI: Western Texas Intermediate.

TABLE A4 Coefficients equality test of positive and negative components (backwardation/contango)

	Al	Cu	WTI	Natgas	Gold
Backwardation					
Q5	0.003	0.000	0.035	0.226	0.112
Q95	0.000	0.000	0.001	0.236	0.247
Q50	0.005	0.000	0.000	0.021	0.005
Contango					
Q5	0.008	0.000	0.242	0.644	0.000
Q95	0.007	0.002	0.000	0.065	0.000
Q50	0.000	0.000	0.000	0.001	0.000

Note. It presents the results of F tests examining whether the difference between the coefficients obtained for positive and negative components is indifferent from zero. Q5, 50, and 95 indicate which percentile result is used in the analysis. Backwardation indicates that the tests are conducted using the sum of coefficients obtained for β and γ in the equation. The tests are conducted on the results shown in Figure 3. The standard errors of the original regression analysis are estimated by bootstrapping with 1,000 simulations. The presented values are p values.
Al: aluminum; Cu: copper; Natgas: natural gas; WTI: Western Texas Intermediate.