

Does Investor Sentiment Affect Market Volatility? Evidence from China's Commodity Futures Market

Chenchen Ding[1,*], Yanxi Li[1], Yiyun Chen[2], Lijun Chen[1]

1. School of Economics and Management, Dalian University of Technology, Dalian China

2. School of Business, Monash University, Melbourne, Australia

E-mail of corresponding author: quiter_dcc@163.com

Abstract

More and more speculative capital is pouring into the commodity futures market, as a result, the investor sentiment become more susceptible to the market information, some investors may "chasing up and killing down", exacerbating market volatility. This paper uses text mining and Attention-BiLSTM model to analyze the information released by Chinese mainstream financial media, constructs an investor sentiment index of commodity futures markets, and analyses the relationship between investor sentiment and market volatility. We found that there is a U-shaped relationship between the two, meaning that the positive and negative investor sentiment will both exacerbate market volatility. Further research finds that investor sentiment can through investor behavior to affect market volatility. We suggest that regulatory authorities should strengthen monitoring of investor sentiment and establish the investor sentiment warning mechanism to ensure the smooth operation of the market.

Keywords: Investor Sentiment; Market Volatility; Commodity Futures Market; Investor Behavior

DOI: 10.7176/RJFA/16-3-01

Publication date: March 30th 2025

1. Introduction

Chinese futures market has developed for over 30 years since its establishment, and it has covered major areas of the national economy, such as agricultural products and energy. As an important industrial producing country, Chinese commodity futures market accounts for 12% of the total global futures market trading volume. In terms of account types, individual accounts up to more than 95%, while the data in the U.S. is less than 15% (Bhardwaj et al., 2016). Also, more than 85% of investors engage in trend trading (China Futures Industry Association, 2022), and the contracts average holding period is less than four hours (Group, 2016). These indicate that there is a high percentage of speculative investors in the Chinese commodity futures market, which is significantly different from the investor structure in developed markets.

Although traditional economics assumes that investors are "rational people", behavioral finance such as cognitive bias theory and prospect theory argue that it's difficult for investors to maintain rational affecting by the large amount of information (Dellavigna, 2009; Bernard, 1990; Hirshleifer, 2003). Especially in the internet age, investors' sentiment is complex and variable, it's difficult for them to make optimal decisions, some investors may overtrade, causing market volatility.

Some scholars have conducted research on the relationship between investor sentiment and market volatility, but mainly focused on the stock market (Bahloul and Bouri, 2016) or the stock index futures market (Dong, 2017), lacking research on the Chinese commodity futures market. Therefore, we use Attention-BiLSTM model to construct an investor sentiment index relying on Chinese mainstream financial media, and analysis the relationship between investor sentiment and market volatility.

The main contributions of this paper are as follows: Firstly, we use text mining and neural network methods to construct the investor sentiment index of the Chinese futures market relying on its mainstream financial media; Secondly, we use nonlinear model to verify the U-shaped function relationship between investor sentiment and market volatility; Finally, we explore the mechanism that how investor sentiment affects market volatility from the perspective of investor behavior. This paper provides a basis and theoretical support for regulatory authorities to establish investor sentiment monitoring platforms and warning mechanisms.

2. Research Hypothesis

Sentiment represents investors' belief in financial asset prices and biased expectations of future price trends. With the information transmission and mutual learning, investors' market cognition will gradually converge, forming a consistent social bias and potential energy for market price fluctuations. There are massive individual investors in Chinese market and they are more susceptible to become overly confident due to emotional influence, assign excessive weight to new information and engage in excessive trading. By chasing up or selling down, cognitive biases towards futures prices will be released and then cause market volatility.

We consider that when investor sentiment is positive, the market has the potential to rise. Some wait-and-see investors enter the market driven by others, pushing up contract prices and increasing market volatility; On the contrary, if sentiment is negative and investors are pessimistic about future market trends, they will sell off the contracts to "cut the flesh and leave the market", leading to a continuous prices decline and increase volatility. Therefore, we propose the first hypothesis:

Hypothesis 1: There is a U-shaped relationship between investor sentiment and market volatility. When investor sentiment shows a positive(negative) state, there is a positive(negative) correlation between the two.

Secondly, there is a lag in information transmission, and investors need some time to perceive and judge the market information before taking actions, so there may be a lag between sentiment and market fluctuations, that is, investor sentiment may have a predictive effect on market volatility. And scholars unanimously believe that investor sentiment is an important reason of market volatility (Tian and Tan, 2014), especially in the extreme state, the impact of sentiment is stronger(Shi et al., 2016). However, there is a dearth of research on whether extreme market volatility is more influenced by investor sentiment, such as the 2008 crash and 2015 surge, which cannot be explained by traditional theories of finance. So based on the overreaction theory of behavioral finance, we consider that the market's sudden rise and fall are more driven by investor sentiment, and we propose the following hypothesis:

Hypothesis 2: The impact of investor sentiment on market volatility is forward-looking.

Hypothesis 3: The high volatility of the market is more influenced by investor sentiment.

3. Research Design

3.1 Investor sentiment measurement

Investor sentiment is the investors' judgment based on market information and their own perception, reflecting their expectations of market trends (Wang and Sun, 2004; BAKER and J, 2006). In recent years, economists have found that the various financial assets market performance is related to the news (Gao and Süss, 2015), and investors' emotions can also be influenced by them (GARCÍA, 2013; Tetlock, 2011). Omura and Todorova (2019) found there's a correlation between commodity market returns and news by using quantile regression.

According to statistics from the China Futures Industry Association (CFA), investors in the Chinese futures market mainly obtain information through mainstream financial media and exchange announcements. Therefore, we conduct data mining and text analysis on relevant information from mainstream Chinese financial media like Sina Finance and Jinshi Futures websites, and then we use Word2Vec and Attention-BiLSTM model for text vectorization and sentiment classification, finally we get the sentiment score of the text.

Firstly, we use python's scrape web crawler framework to obtain the texts of commodity advisories, timely highlights, and variety studies from Sina Finance and Jinshi Futures websites from 2019.09-2021.07, totaling 90936 pieces of data, over 439 trading days. We further preprocess the data, construct the Chinese futures lexicon combine with the Wind database and distinguish futures categories for each text, finally we got 89636 valid data. The content classification and word cloud diagram are shown in table 1 and figure 1.

Tab. 1 Article Content distribution table

classification	information sources
News（55%）	Rolling news, instant news Expectation news, bond news, etc.
Research（23%）	Macro research Bond Research Variety research, etc.
Report（22%）	Metal information, metal reviews Agricultural and sideline product news Gold news, gold reviews, etc.

Then we vectorize the text by Word2Vec model, the model parameters are same as the study by Zhou (2016). Finally, we train Attention-BiLSTM model using manually labeled text (some annotations are shown in Table 2) to make the model has the ability to classify text. After training, the classification accuracy reached 78.17%. We input new text and get the corresponding sentiment classification probability, then use expected method to calculate the sentiment value for each text. For example, if the text "criticizing production reduction" classification probability is {1:0.6, 0:0.1, -1:0.3}, the sentiment value corresponding to the text is 0.3.

Therefore, we can get investor sentiment pool $S_{t,i} = \{S_1, S_2, S_3, \ldots, S_N\}$s futures category and t presents date. Then we use equal weight method to get the average emotional values $\overline{S_{t,i}}$, and f her average $\overline{S_{t,i}}$ to get overall investors sentiment Sen, as formula

$$Sen_t = \frac{1}{N}\sum_{i=1}^{N}\overline{S_{t,i}} \tag{1}$$

Tab. 2 Examples of artificial labeling of sentiment

Num.	English	Chinese
1	Live pig futures rose last week, the main contract LH2301 rose up to 995 RMB/Ton.	上周生猪期货出现上涨，主力 LH2301 合约单周上涨 995 元/吨。
2	Sichuan steel mills continued to stop production, and the price of imported iron ore fell below $100.	四川钢厂继续停产减产，进口铁矿石跌破 100 美金。
3	Cotton price operating pressure is still large.	棉价运行压力仍大。
4	Mysteel Interpretation: Guangxi pig market how to develop in the second	Mysteel 解读：广西市场生猪下半年如何发展？

Finally, referring to the BW method (Liang et al., 2020; BAKER and J, 2006; Renault, 2017), we construct another investor sentiment index to test the rationality of the investor sentiment index we calculated. The trend analysis and empirical analysis results showed that the investor sentiment index constructed in this article is rational and prospective.

3.2 Market volatility measurement

Volatility is the measure of asset returns uncertainty, reflecting assets' risk level, higher volatility represents the stronger uncertainty in asset returns. In recent decades, scholars have conducted extensive research on volatility and constructed different volatility measurement models to calculate volatility, such as historical volatility models, implicit volatility models, and realized volatility models. Referring to previous research (Brailsford and Faff, 1995), we use the GARCH (1,1) model to calculate market volatility.

3.3 Modeling

Based on the previous theoretical analysis, we consider that there is a U-shaped relationship between investor sentiment and market volatility, meaning that volatility will increase when investor sentiment tends to be positive or negative. Therefore, we construct a quadratic term model (Formula 2) to test the relationship between the two.

$$Vol_t = \beta_0 + \beta_1 Sentiment_{t-i}{}^2 + \sum_{i=2}^{n} \beta_i Controls_t + \varepsilon_t, \quad i = 0,1,2 \tag{2}$$

Vol_t the volatility of the futures market, $Sentiment_{t}$ are term of investor sentiment with a lag of i period , is the contro $Control$ is the error term. ε_t

3.4 Research samples and data sources

We used Attention-BiLSTM model to calculate investor sentiment, including 439 trading days from September 2019 to July 2021. The calculation samples are from Sina Finance and Jinshi Futures websites, including instant news, research reports, and other forms of text, we finally get 89636 pieces of data after processing. The market volatility data is obtained through the Wind database and calculated using the GARCH(1,1) model; The trading volume of commodity futures index, corresponding stock market volatility and spot prices are all from Wind database, spot prices are uniformly as futures contracts. In order to reduce the impact of extreme values, we conduct 1% and 99% quantile truncation on all continuous variables. The variable definition table is shown in Table 3.

In order to explore the relationship between investor sentiment and market volatility from the perspectives of overall and cross-sectional effects, we select the overall market commodity index and the three single commodity indices of copper, gold, and oil[1].

[1].We choose these commodity reasons are as follows: ①Gold is not a necessity for production and life, it is more equipped as a speculative or inflationary risk hedging tool, with a certain degree of speculation; ②Oil as the "blood" of industry, China has a high degree of dependence on foreign countries commodities, reaching 70%, so it can better represent imported bulk commodities. ③Copper commodity is known as "Dr. Copper", it is an important raw material for China's industry with

Tab. 3 Variable Definition Table

Variable type	Variable Name	Variable Symbol	Variable De
Explained Variable	Market Volatility	Vol	Calculated using GARCH a respectively.
Explanatory variable	Sentiment	Sentiment	Constructed by relevant m construction process is as s
	Trading Volume of Commodity Futures Index	Deal	The weighted trading volu corresponding product in t
Control Aariable	Commodity Corresponding Stock Market Volatility	Stock_Vol	Referring to Ma(2016), it v GARCH model.

4. Analysis of empirical results

4.1 Descriptive statistics

We select the overall commodity sentiment index, gold, copper, and oil sentiment. Due to space limitations, we only conduct descriptive statistics on investor sentiment (Table 4). Other results are available on request. In terms of overall commodity futures, the average and median sentiment are both 0.03, indicating that overall sentiment is in a positive state, and investors are more optimistic about the development of the market.

Similarly, the mean and median sentiment indices of gold and copper commodities are both greater than 0, the sentiment indices of copper commodity fluctuates greatly, with a maximum value of 1 and a minimum value of -1, and a variance of 0.48, indicating that investors have significant sentiment fluctuations in copper commodity. The average and median values of the crude oil index are -0.03 and -0.02, indicating that the investor sentiment index is relatively negative for oil commodity.

Tab. 4 Descriptive statistics of the sentiment index

Variables	N	Mean	SD	Min
Overall sentiment Index	439	0.03	0.15	-0.46
Gold sentiment index	439	0.01	0.24	-0.63
Copper sentiment index	439	0.10	0.48	-1.00

4.2 Regression results of quadratic function

Table 5 shows the quadratic function empirical results of overall commodity, and Table 6 shows the empirical results of copper, gold, and oil commodities. Table 5 indicates that there is a significant positive correlation between market volatility and the quadratic term of investor sentiment, as well as its lagged term. By comparing the coefficients of current investor sentiment with its lagged term, we find that the coefficient of the current sentiment on volatility is 2.1, but the coefficient of lagged sentiment is around 3 and 4, which is much higher than the current coefficient. This indicates that investor sentiment has a certain lag effect on the volatility of the commodity futures market, which verifies hypothesis 2.

At the same time, there is a significant linkage between stock market and futures market, volatility will be transmitted between the two. Changes in spot market prices will also impact the futures market volatility. Table 6 shows the empirical results between the sentiment and market volatility in the single commodity futures market. We find that investor sentiment also has a significant impact on the three single commodity futures, the coefficient of the oil is relatively large in the current and lag periods, but copper and gold are smaller compared to the oil.

certain representativeness.

Tab. 5 Empirical results of the quadratic term of investor sentiment in the overall market and the lag effect of market volatility

	(1) volatility	(2) volatility
Sentiment^2	2.148**	
	(2.35)	
Lag_1 Sentiment^2		2.978***
		(3.18)
Lag_2 Sentiment^2		
Index trading volume	-0.329**	-0.326**
	(-2.48)	(-2.47)
Stock market volatility	0.376***	0.370***
	(13.65)	(13.40)
Corresponding spot price	2.627***	2.516***
	(7.03)	(6.71)
[illegible]	[illegible]	[illegible]

Tab. 6 Empirical analysis results of the relationship between single commodity sentiment index and market volatility

	(1) Oil volatility	(2) Oil volatility	(3) Oil volatility	(4) Copp volatil
Sentiment^2	9.567***			0.739
	(3.19)			(2.1
Lag_1 Sentiment^2		11.360***		
		(3.85)		
Lag_2 Sentiment^2			13.832***	
			(4.77)	
Index trading volume	1.466***	1.407***	1.248***	1.634
	(3.82)	(3.72)	(3.34)	(4.5
Stock market volatility	0.010**	0.011***	0.011***	0.003
	(2.43)	(2.73)	(2.75)	(2.21
Corresponding spot price	-0.198***	-0.198***	-0.198***	0.09
	(-12.24)	(-12.36)	(-12.52)	(0.11
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Continued Tab. 6 Empirical analysis results of the relationship between single commodity sentiment index and market volatility

	(6) Copper volatility	(7) Gold volatility	(8) Gold volatility
$Sentiment^2$		1.202***	
		(2.72)	
Lag_1 $Sentiment^2$			1.597**
			(3.50)
Lag_2 $Sentiment^2$	1.193***		
	(3.36)		
Index trading volume	1.648***	-0.062	-0.075
	(4.66)	(-0.86)	(-1.04)
Stock market volatility	0.003**	-0.001	-0.002
	(2.21)	(-0.31)	(-0.58)
Corresponding spot price	-0.220	-0.447	-0.465
	(-0.27)	(-0.93)	(-0.97)

5. Further research

5.1 Research on threshold effect

We construct a threshold regression model(Formula 3) and refer to Baker and Wurgler's(2006) research to set 0 as the threshold parameter, which means that when investor sentiment is bigger than 0, it's the positive state; when it is smaller than 0, it's the negative state, as shown in equations 3 and 4.

$$\begin{cases} Vol_t = \beta_0 + \beta_1 Sentiment_{t-i} + \sum_{i=2}^{n} \beta_i Controls_t + \varepsilon_t, \quad Sentiment \\ Vol_t = \beta_0 + \beta_1 Sentiment_{t-i} + \sum_{i=2}^{n} \beta_i Controls_t + \varepsilon_t, \quad Sentiment \end{cases} \tag{3}$$

$$Vol_t = \beta_0 + \beta_1 Sentiment_{t-i} * I(Sentiment_{t-i} > 0) + \beta_2 S \ldots I(Sentiment_{t-i} < 0) + \sum_{i=2}^{n} \beta_i Controls_t + \varepsilon_t \quad i=0 \tag{4}$$

$Sentiment_{t-i}$ is the threshold criterion, and we set the threshold variable to 0. $I(Sentiment_{t-i} > 0)$ cteristic function of this article. If the judgment result in parentheses is true, the value is 1, otherwise the value is 0. By the characteristic function, we can divide positive and negative sentiment. Other variables are the same as before.

Table 7 and 8 show the empirical results of the threshold regression models for the overall commodity index and the single commodity index.

Tab. 7 Empirical analysis results of threshold regression (overall commodity)

Positive emotions		
	(1) volatility	(2) volatility
Sentiment	0.610	
	(1.53)	
Lag_1 Sentiment		0.844**
		(2.14)
Lag_2 Sentiment		
N	259	258
_cons	Yes	Yes
Controls	Yes	Yes
Adj.R-Square	0.23	0.23
Negative emotions		
Sentiment	-1.334**	
	(-2.21)	
Lag_1 Sentiment		-2.326***
		(-3.91)
Lag_2 Sentiment		

Tab. 8 Empirical analysis results of threshold regression (single commodity)

	(1) Oil volatility	(2) Oil volatility	(3) Oil volatility	(Co vola
Positive sentiment				
Sentiment	0.717			0.8
	(0.33)			(2.
Lag_1 Sentiment		4.373**		
		(2.23)		
Lag_2 Sentiment			3.252*	
			(1.70)	
_cons	4.595*	4.068**	2.292	13.
	(1.90)	(2.05)	(1.20)	(1.
N	187	186	185	1
Adj.R-Square	0.28	0.25	0.26	0.
Negative sentiment				
Sentiment	-5.891**			-2.0
	(-2.30)			(-2
Lag_1 Sentiment		-6.687***		
		(-2.69)		
Lag_2 Sentiment			-8.475***	

Continued Tab. 8 Empirical analysis results of threshold regression(single commodity)

	(6) Copper volatility	(7) Gold volatility	(8) Gold volatili
Positive sentiment			
Sentiment		0.792**	
		(2.39)	
Lag_1 Sentiment			1.152*
			(3.44
Lag_2 Sentiment	0.375		
	(1.13)		
_cons	-0.927	-1.791	-0.97
	(-0.13)	(-0.51)	(-0.27
N	190	206	205
Adj.R-Square	0.22	0.18	0.14
Negative sentiment			
Sentiment		-0.795**	
		(-2.18)	
Lag_1 Sentiment			-1.306*
			(-3.54
Lag_2 Sentiment	-1.528		

5.2 Quantile effect test

In order to further explore the impact of extreme market volatility on investor sentiment, we construct a quantile regression model(Formula 5) to explore the extent of investor sentiment's influence at different quantile points.

$$Quant_n(Vol|Controls) = \beta_0^p + \beta_1^p Sen + \sum_{i=2}^{n} \beta_i^p Cc \quad (5)$$

$Quant$ presents different quantile levels of the dependent variable , Vo is β_0^p、β_1^p、β ssion coefficient of the corresponding variable at different points, and other variables are consistent with the previous. We have verified a U-shaped relationship between market volatility and investor sentiment, so we divide investor sentiment before quantile regression firstly, and then conduct quantile empirical testing under different investor sentiment. The empirical results are shown in Table 9.

Tab. 9 Table of market volatility quantile regression results

	Negative emotions			Positive e	
	(1) 0.2 quantile	(2) 0.5 quantile	(3) 0.8 quantile	(4) 0.2 quantile	(5 0. quan
Overall	-0.843**	-2.405**	-3.520**	0.533**	0.6
	(-2.52)	(-2.30)	(-2.21)	(2.29)	(1.3
Gold	0.146	-0.555**	-1.801***	0.322	0.2
	(1.46)	(-2.09)	(-2.71)	(1.21)	(1.3
Copper	-0.047	-0.645	-2.891**	0.064	0.0
	(-0.76)	(-1.26)	(-2.31)	(1.22)	(0.1
Oil	-1.052	-4.959**	-12.730**	0.266	1.3
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

From the regression results in Table 9, we find that when investor sentiment is in the negative period, all the futures index are stronger influenced by investor sentiment in high market volatility states, especially for oil commodities, the impact of investor sentiment is significantly greater than other commodities, confirming hypothesis 3.

5.3 The intermediary effect of investor behavior

Investor sentiment and behavior are two key research areas in behavioral finance. Psychology suggests that investor sentiment can represent investors' real thoughts, and investor behavior is an external manifestation of investor sentiment.

Forgas(1995) believes that people make decisions based on their own sentiment. When investors make decisions based on sentiment, they will take corresponding actions to achieve it(Loewenstein et al., 2001). When sentiment is high or low, investors often can't make the optimal decision, some of them even "buying high and selling low", exacerbating market volatility.

Therefore, we believe that in the commodity futures market, investors' trading behavior plays a mediating role in the relationship between investor sentiment and market volatility. When sentiment is high, investors tend to buy contracts, and when sentiment is negative, investors tend to sell contracts. Overbuying and selling will lead to an increase in market volatility.

Based on LSV model and the algorithm of Lee and Ready(1991), we divide intraday market trading data into minute level, and then construct a model (Formula 6) and intermediary effect model (Formula 7-9) to calculate investors' behavior and explore the intermediary effect of it. Data from Chinese futures exchanges, calculated using daily data for the main contract

$$BSI_{i,t} = \frac{BI_{i,t}-SI_{i,t}}{BI_{i,t}+SI_{i,t}} \quad (6)$$

$$Vol_{i,t} = \beta_0 + \beta_1 Sentiment_{i,t}^2 + \sum_{i=2}^{n} \beta_i Cont \quad (7)$$

$$BSI_{i,t} = \beta_0 + \beta_1 Sentiment_{i,t} + \sum_{i=2}^{n} \beta_i Con\imath \quad (8)$$

$$Vol_{i,t} = \beta_0 + \beta_1 Sentiment_{i,t}^2 + \beta_2 BSI_{i,t}^2 + \sum_{i=3}^{n} \beta_i Controls_t + \varepsilon_{i,t} \quad (9)$$

BI_i represents the main buying volume of the commodity, i is main contract, $SI_{i,t}$represents the main selling volume of the commodity, represe $BSI_{i,t}$ the investors behavior. If BSI is greater than 0, it indicates that investors tend to buy, if BSI is less than 0, it indicates that investors tend to sell. Other variables are consistent with the previous.

Table 10 and Table 11 are the test results of the mediating effect. Since the results of investor sentiment and market volatility have been given previously, they will not be repeated here.

From the results, we can see that both for the overall commodity futures market and the single commodity futures market, investor sentiment has a significant positive impact on behavior. Table 11 shows that there is also a U-shaped relationship between investor behavior and market volatility, that is, as investor behavior tends to buy or sell, market volatility shows an increasing trend. This validates the mediating effect of investor behavior.

Tab. 10 Empirical results of the impact of investor sentiment on investor behavior

	(1) Investor behavior_All	(2) Investor behavior_Copper	(3) Investor behavior_Oil
Investor Sentiment	0.048***	0.017*	0.171***
	(4.10)	(1.85)	(7.14)
Index trading volume	0.013***	0.039***	0.089***
	(9.58)	(2.95)	(10.31)
Stock market volatility	0.005	0.010***	0.006
	(0.63)	(3.43)	(0.98)
Corresponding spot price	0.016	-0.006	0.001
	(0.86)	(-0.19)	(1.65)
_cons	-0.294	-0.060	-0.277***

Tab. 11 Empirical results of investor sentiment, behavior and market volatility

	(1) Investor behavior_All	(2) Investor behavior_Copper	(3) Investor behavior_Oil
$Sentiment^2$	2.483**	0.552**	8.893***
	(2.59)	(2.28)	(2.97)
$Behavior^2$	20.467***	14.175***	7.132**
	(3.22)	(8.17)	(2.40)
Index trading volume	0.288***	0.003***	0.010**
	(10.12)	(3.86)	(2.37)
Stock market volatility	0.351**	1.811***	2.137***
	(2.25)	(7.23)	(4.52)
Corresponding spot price	2.671***	-1.873***	-0.189***
	(6.49)	(-3.31)	(-11.45)
cons	-39.907***	15.933***	9.999***

5.4 Robust Test

In order to verify the robustness of previous conclusion, we use fixed effects model and replace the dependent variable to perform robustness tests.

Firstly, we transform the time series data of investor sentiment and market volatility into panel data and construct a fixed effects model for testing. The results indicate a U-shaped relationship between investor sentiment and market volatility regardless of whether individual fixed effects are controlled.

Secondly, we use the EGARCH(1,1) model to calculate market volatility as a substitute variable for the dependent variable. The Spearman correlation test shows that the volatility calculated by the two methods has a significant correlation, and the conclusion remains robust after replacing the dependent variable.

6. Research Conclusions and Applications

6.1 Research conclusion

In this paper, we use text mining, data analysis methods and Attention-BiLSTM model to construct the investor sentiment index of Chinese futures market based on Chinese mainstream financial media. Then we further explore the relationship between investor sentiment and market volatility and the action path. The paper's conclusions are as follows:

(1) There is a U-shaped relationship between investor sentiment and market volatility. As investor sentiment tends to be positive or negative, market volatility will increase, and the correlation between the two is even higher for species with strong speculative attributes.

(2) High market volatility is more influenced by investor sentiment. The quantile test proves that investor sentiment plays a greater role when the market is in a period of high volatility.

(3) Investor sentiment affects market volatility by influencing investor behavior. Through intermediary effect model, we find that when investor sentiment tends to be positive or negative, investors will buy or sell contracts, or even "chase the bulls" and "kill the losers", and this will exacerbate market volatility.

6.2 Research Applications

(1) Regulatory authorities can rely on big data platforms to build investor sentiment indices for the commodity futures market, realize accurate monitoring of investor sentiment, and set up investor sentiment monitoring platforms, so that the investor sentiment can be included in the supervision.

(2) Based on investor sentiment monitoring platform, regulatory authorities can identify the extreme sentiment range of each commodity through neural network model, establish the extreme sentiment threshold and warning mechanism for each commodity.

References

Bahloul W., Bouri A. (2016). The impacts of investor sentiment on returns and conditional volatility of U.S. futures markets[J]. *Journal of Multicultural Financial Management*,36:89-102.

Baker M, J W. (2006). Investor Sentiment and the Cross-Section of Stock Returns[J]. T*HE JOURNAL OF FINANCE*;LXI:1645-80.

Bernard VL. (1990).Evidence that stock prices do not fully reflect the implications of current earnings for future earnings[J]. *Journal of Accounting and Economics*,305-40.

Bhardwaj G, Gorton GB. (2016). Rouwenhorst KG. Investor Interest and the Returns to Commodity Investing[J]. *Portf Manage*,42:44-55.

Brailsford TJ, Faff RW. (1995). An evaluation of volatility forecasting techniques[J]. *Bank Financ*,20:419-38.

Dellavigna S, M PJ. (2009). Investor Inattention and Friday Earnings Announcements[J]. *The Journal of finance*,64:709-49.

Forgas JP. (1995). Mood and judgment: the affect infusion model (AIM) [J]. *Psychol Bull*,117:39-66.

Gao L, Suss S. (2015). Market sentiment in commodity futures returns[J]. *J Empir Finance*,33:84-103.

Garcia D. (2013).Sentiment during Recessions[J]. *The Journal of Finance*,68:1267-300.

Group C. (2016). *China Commodities*.

Hirshleifer D, Teoh SH. (2003). Limited attention, information disclosure, and financial reporting[J]. *Journal of Accounting and Economics*,36:337-86.

Liang C, Tang L, Li Y, Wei Y. (2020).Which sentiment index is more informative to forecast stock market volatility? Evidence from China[J]. *Int Rev Financ Anal*,71:101552.

Loewenstein GF, Weber EU, Hsee CK, Welch N. (2001). Risk as feelings[J]. *Psychol Bull*,127:267-86.

M CLC, J RM. (1991). Inferring Trade Direction from Intraday Data[J]. *The Journal of finance*,46:733-46.

Omura A, Todorova N. (2019). The quantile dependence of commodity futures markets on news sentiment[J]. *J Futures Mark*,39:818-37.

Renault T. (2017).Intraday online investor sentiment and return patterns in the U.S. stock market[J]. *J Bank Financ*,84:25-40.

Tetlock PC. (2011). All the News That's Fit to Reprint: Do Investors React to Stale Information? [J]. *Rev Financ Stud*,24:1481-512.

Dong, X. W. (2017). A Study on the Impact of Investor Sentiment on China's Stock Market[D]. *Shanxi University*.

Shi, G.P., Liu, X.X., Wei, Y.S. (2016). Investor Sentiment, Market Liquidity and Stock Market Bubbles——Based on TVP－SV－SVAR model[J]. *Research in Financial Economics*,31:107-17.

Tian, L.H., Tan, D.K. (2014). The Financialization and Americanization of Commodity Spot Pricing——A Study of the Relationship between Stock Indices and Commodity Spot[J]. *China's industrial economy*,72-84.

Wang, M.J., Sun, J.J. (2004). Chinese Stock Market Returns, Return Volatility and Investor Sentiment[J]. *Economic research*,75-83.

China Futures Association. (2022). Survey on the status of traders in the national futures market.