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Study of the Impact between Investor Sentiment and Return-Volatility: Evidence from Chinese Commodity Futures Market

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Abstract
There is no consensus on the relationship between investor sentiment and return-volatility in different financial markets. This study uses a machine learning approach to construct investor sentiment in Chinese commodity futures market, exploring the relationship of return-volatility and moderating effect of investor sentiment. We find that in Chinese commodity futures market, there is a negative correlation of return-volatility. Further analysis shows that under positive (negative) investor sentiment, the relationship of return-volatility is positive (negative). But regardless of the sentimental state, sentiment has a positive moderating effect, and different commodities have heterogeneity.

Keywords: Investor Sentiment; Return-Volatility; Commodity Futures Market
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1. Introduction

The return-volatility relationship of assets in financial markets has been one of the most important research topics, which Ghysels et al. (2005) referred as the "first fundamental law of finance". The relationship has been well discussed by early scholars, but no consistent conclusion has been reached, with positive correlations(Kinnunen, 2014; FRENCH et al., 1987) and negative(ANG et al., 2006; Nelson, 1991)correlations coexisting. And then scholars explored from the behavioral finance perspective, arguing that investors can't be fully rational and their trading behavior is susceptible to sentiment. Related studies based on stock markets in developed countries have also examined that investor sentiment is an important affecting factor to return-volatility (Jiang and Jin, 2021; Rupande et al., 2019).

The ongoing COVID-19 pandemic and the conflict between Russia and Ukraine had an impact on the international commodity futures market since 2019, pushing up some futures' price volatility and creating arbitrage space, also making investors' sentiment more sensitive. Especially for China, which insists on "dynamic clearing", the relationship between the two and the impact of sentiment are worth further exploration under the new challenges.

As an important industrial producer, Chinese commodity futures market accounts for 12% of the total global futures market volume, and its market is becoming increasingly financialized. In terms of account type, 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-based trading (CFA, 2022), and the contracts average holding period is less than four hours(Citi Group, 2016). This indicates that there is a high percentage of speculative investors in Chinese commodity futures market, which is significantly different from the investor structure in developed markets.

Due to the investor structure, the sentiment will have a stronger influence on the market under the COVID-19 pandemic(Ding et al., 2019). Thus, against this background, it has practical significance to explore the relationship of return-volatility and the impact of investor sentiment in Chinese commodity futures market. Investor sentiment is the judgment about the market based on information and investors' perceptions, which reflects their expectations of market trends(Baker and Wurgler, 2006; Wang and Sun, 2004). In China, investors mainly get market's information through mainstream financial media(CFA, 2022). Therefore, based on Chinese mainstream financial media, we use BiLSTM-Attention model to construct Chinese investor sentiment index through 89,636 market news for 439 trading days from 2019-2021, and then investigate the relationship of return-volatility and the moderating effect of investor sentiment in the Chinese futures market through overall and cross-sectional levels.

We find a negative correlation of return-volatility, indicating that on the whole, investors can't profit from volatility. Further study shows that when investor sentiment in positive(negative) sentiment periods, the relationship is positive(negative), but different investor sentiments both can positively enhance the relationship of return-volatility. Considering there are more individual investors in the Chinese futures market and their risk control ability is relatively weak, based on the "spiral of silence" and herd behavior theory, investors are driven by information and sentiment to blindly gamble, so it's difficult for them to seize the opportunity and profit from the risk.

We think make two contributions to the literature. Firstly, we extend the measurement method of investor sentiment. Based on data mining and text analysis, we use the BiLSTM-Attention model to measure investor sentiment, which has stronger timeliness than the BW method, and can measure intra-day period investor sentiment. The BiLSTM-Attention model also better solves the problem of contextual semantics compared with the dictionary method, so using it to measure investor sentiment is more accurate. Secondly, we incorporate investor sentiment into the analytical framework of the return-volatility relationship in the Chinese commodity futures market. Compared with previous studies analyzing the relationship between the two under different sentiments, we further explore the moderating effect of different sentiments and find that both sentiments positively affect the relationship between the two, and the negative sentiment effect is stronger.

2. Research Design

We use a sample of research, instant gist and other text listed on Sina Finance Futures section and the Jin10 Futures website from 2019.9 to 2021.7, total 439 trading days, including 89,636 text data to construct the investor sentiment indicator. Data on index returns, spot market prices, and other data are from the wind database.

Considering the supply and demand of the Chinese market, we choose the Composite Commodity Index, Shanghai Copper Commodity Index, Gold Commodity Index and Crude Oil Commodity Index as sample[1]. We winsorize all the continuous variables at the 1st and 99th percentile to alleviate the effect of potential outliers.

We construct the following model to investigate the relationship between investor sentiment and return-volatility.

$$Return_t = \beta_0 + \beta_1 Vol_t + \sum^{n} \beta_i Controls_t + \varepsilon_t$$

$$Return_t = \beta_0 + \beta_1 Vol_t \times Sen_t + \sum_{i=2}^{n} \beta_i Controls_t + \varepsilon_t$$

Return is the index return. Vol is the volatility of the index, calculated by GARCH (1,1) model. Controls are the control variables, including the corresponding industry stock market volatility, index trading volume and spot market price.

The primary variable of interest is investor sentiment index (Sen), which reflects the investors' attitudes towards the development of the futures market trends. The index construction process is as follows: First, we use Python to crawl and pre-process relevant texts from major Chinese financial websites, and then match them with a self-built commodity dictionary to determine the commodity type of each text. Second, we choose 9000 pieces data from the sample, 3000 of them were manually labeled to determine their sentiment and used as training data (some data labeling is shown in Table 1), and the other 6000 pieces were used as test data.

Finally, we use the Word2Vec model to vectorize the labeled data and train the Attention-BiLSTM model to classify the text sentiment, after that we use the model to classify the unlabeled data. After obtaining the sentiment classification probability of the corresponding text, we calculated the expectation as the sentiment value of each text (e.g., the probability of "crude oil production reduce" is {1:0.6, 0:0.1, -1:0.3}, and the sentiment value of this text is 0.3 after expectation), and then we calculated the daily sentiment values of each commodity category and the overall product using the equal-weighting method.

Before using our investor sentiment index to conduct empirical analysis, we first test the applicability of the index. Based on the method of Baker and Wurgler(2006) and considering the availability of commodity futures

[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; ②Crude oil 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 certain representativeness.

market data, we construct another investor sentiment index by using main contract positions, index trading volume, relative strength indicator and psychological line indicator, and then we test the suitability of the index we constructed from two perspectives: trend comparison and correlation test. The results show that the investor sentiment index constructed by Attention-BiLSTM model is significantly correlated with the sentiment index constructed by the BW method, and the former has a certain degree of forward-looking.

Table 1. 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 主力 LH2301 合 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 进口铁矿石跌破 金。
3	Cotton price operating pressure is still large.	棉价运行压力仍

We also control other variables that may affect commodity futures returns, such as commodity futures index volume (Deal), commodity corresponding stock market returns (Stock_Re, the stock of the company corresponding to the type of commodity futures), and futures corresponding spot price (Com_Price), we also control the fixed effects of the commodity when conducting robustness tests.

3. Results and Discussions

Table 2 presents the summary statistics of investor sentiment. In the sample period of this paper, the mean and median of the overall investment sentiment index is 0.03, indicating that investors are optimistic about the market developments. The mean and median of gold and copper are both bigger than 0, but the copper sentiment index is more volatile with a variance of 0.48. The mean and median for the crude oil commodity are -0.03 and -0.02, indicating the sentiment of the crude oil commodity is negative.

Table 3 presents the baseline result. We use ordinary least square (OLS) regression to test the relationship of return-volatility from both the overall and cross-sectional perspectives. Result shows that for both the overall and single commodity indices, there is a significant negative relationship of return-volatility, as volatility increases, the returns of the indices tend to decrease. For crude oil, the relationship between the two is significant at the 1% level with a coefficient of -0.027. But for gold, although the relationship is significant at the 5% level, the coefficient is up to -1.41. Returns in the futures market are also positively influenced by stock market returns and spot market prices.

We conduct different robustness tests. First, we transform the time series data into panel data and test the relationship between them using a fixed effects model. Second, we construct a PVAR model to test the lagged effects of returns and use the GMM approach to overcome the endogeneity problem of the model. The results all prove the accuracy of the benchmark test.

We classify the sample according to investor sentiment and then investigate the relationship of return-volatility under different sentiment states. Panel A of Table 4 shows the empirical results, we find the relationship of return-volatility is positive(negative) when the investor sentiment is positive(negative).

And then we investigate the moderating effect of sentiment, Panel B of Table 4 shows the result. Regardless of the state of investor sentiment, the relationship of return-volatility is positively moderated, when investor sentiment is in a positive(negative) period, sentiment can enhance the positive(negative) relationship of return-volatility. It means that positive investor sentiment can strengthen the positive relationship of return-volatility, and negative investor sentiment can deteriorate the negative relationship of return-volatility. But for both copper and crude oil commodities, the moderating effect of negative sentiment is significantly higher than positive sentiment. As for gold commodities, the moderating effect of positive sentiment is stronger.

We also use fixed effects model, GMM model and replacing investor sentiment calculated by BW method as robustness testing, the results confirm the previous findings.

Table 2. Descriptive statistics of investor sentiment

Variables	N	Mean	SD	Min	P5	P25
Sentiment_All	439	0.03	0.15	-0.46	-.0.23	-0.06
Sentiment_Au	439	0.01	0.24	-0.63	-0.39	-0.17
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

The table reports descriptive statistics for the investor sentiment index constructed in this paper. The sample period is from 2019.9 to 2021.7, total 439 trading days.

Table 3. Relationship of return-volatility

	(1) Wind_Re	(2) Nanhua_Re	(3) Cu_Re
Vol	-0.131**	-0.119**	-0.057*
	(-2.50)	(-2.23)	(-1.94)
Stock_Re	0.300***	0.370***	0.371***
	(8.26)	(10.95)	(10.64)
Tra_Num	-0.412*	-0.371**	0.421***
	(-1.96)	(-2.10)	(2.65)
Spot_Price	1.531***	1.175**	-0.003
	[illegible]	[illegible]	[illegible]

The table reports the results of the benchmark regressions in this paper. It shows the relationship of return-volatility from different perspectives, and the corresponding t-statistics are reported in parentheses.

Table 4. Investor sentiment's effect on return-volatility

Panel A: Relationship between return—volatility under different Sentiment						
	Positive Sentiment					
	(1)	(2)	(3)	(4)	(5)	(6)
	Wind_Re	Nanhua_Re	Cu_Re	Oil_Re	Gold_Re	Wind_Re
Vol	0.146**	0.150**	0.073*	0.086**	0.264***	-0.214***
	(2.10)	(2.10)	(1.68)	(2.15)	(3.01)	(-3.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	259	259	187	178	206	179
Adj.R-Square	0.08	0.11	0.29	0.19	0.17	0.21
Panel B: Moderating effect of sentiment on relationship of return—volatility						
	Positive Sentiment					
	(1)	(2)	(3)	(4)	(5)	(6)

Table 4 examines the relationship of returns-volatility under different investor sentiments and further explores the moderating effect of different investor sentiments. All regressions include control variables, and the t-statistics are reported in parentheses.

4. Conclusion

This paper evaluates the relationship of return-volatility in the Chinese futures market. Unlike the market in developed countries, the relationship of return-volatility is negatively correlated in the Chinese market. To further investigate the impact of investor sentiment on the relationship, we construct an investor sentiment index through a machine learning approach. It is found that the relationship of return-volatility is positive (negative) when investor sentiment is positive (negative), and both sentiments positively moderate the relationship of return-volatility in different sentimental states. These findings allow us to re-examine the relationship between market return and volatility from the perspective of investor sentiment, and to incorporate investor sentiment into the analytical framework of asset pricing theory, providing a new perspective to analyze the problem.

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