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DO INVESTOR SENTIMENTS DRIVE STOCK RETURNS?

EVIDENCE FROM CSI300 FUTURES

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Abstract

The impact of investor sentiment on stock prices has long been debated in financial economics, sparking discussions between traditional and behavioral finance. This study aims to analyze the effect of individual investors' emotions on stock market returns in Shanghai and Shenzhen, utilizing the DCC-GARCH model. By examining daily investment return series data for the joint index of both stock exchanges, the CSI300 futures return, during the period (2010-2020), the study provides insights into how investor sentiment shapes market trends. Additionally, a specialized index, constructed using the PCA method, is a key indicator for investors' emotions in China. The findings reveal a strong positive effect of investor sentiment on stock market performance, highlighting its role in driving price movements. Furthermore, the study identifies a significant positive dynamic conditional correlation between investor sentiment and stock returns for the CSI300 futures index. These results emphasize the importance of behavioral finance in understanding market dynamics, as emotional biases continue to influence stock volatility and long-term investment trends.

Keywords: *Behavioral finance, CSI300 futures index, Financial Markets, Investor Sentiment, Stock Return.*

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1 INTRODUCTION

Finance examines financial markets and their phenomena, including all of their developments, especially the effects resulting from human behavior. This process is influenced by many factors, with the investor's personality, tendencies, desires, and interests being primary, as they directly affect investment decisions. Numerous theories analyze the behavior of both individual and institutional investors, beginning with traditional finance, which describes how prices evolve and how to optimally allocate economic resources when financial options are neither time-bound nor inherently risky. Traditional finance posits that prices reflect all available information and assumes rational decision-making. However, a departure from ideal rationality introduces widespread risks to financial markets, such as the emergence of economic bubbles, which serve as key indicators of investors' failure to assess rationally and integrate information into their financial decisions. This gap led to the rise of behavioral finance as a branch of behavioral economics, focusing on the influence of psychology on the behavior of financial practitioners and its subsequent impact on markets. Behavioral finance is grounded in two key assumptions. The first assumption, proposed by Delong, Shleifer, Summers, and Waldman (1990), is that investors are influenced by emotions, specifically, beliefs about future cash flows and investment risks that are not supported by facts. The second assumption, confirmed by Vishny and Shleifer (1997), is that speculating against emotional investors is costly and risky. As a result, rational investors, often referred to as arbitrageurs, are less aggressive in pushing prices to align with the present value of cash flows, as outlined in the standard model. This concept is known in behavioral finance as the limits of arbitrage. (Baker & Wurgler, 2007, p. 130) Behavioral finance helps explain why and how markets may fail to be efficient.

This study aims to investigate the impact of investor sentiment on stock returns and the Chinese financial market, by conducting a standard analysis of the CSI300 Futures Index and the Investor Sentiment Index over 2010-2020.

2 LITERATURE REVIEW

Traditional finance generally revolves around the efficient market hypothesis (EMH) developed by Eugene Fama (1970), which asserts that investors make decisions rationally. The EMH also posits that asset prices reflect all available information, ensuring market efficiency (Kumar & Goyal, 2016). (Fama E. , 1970; 1976) introduced three forms of capital market efficiency, each based on the type of information reflected in prices. That is central to the definition of an efficient market: *"a market in which prices reflect all relevant information."* These forms include:

- *Weak efficiency:* No investor can earn excess returns by developing trading strategies based on historical price or return data.
- *Semi-strong efficiency:* No investor can earn excess returns from trading strategies based on publicly available information.
- *Strong efficiency:* No investor can earn excess returns by utilizing any information, whether publicly available or private.

In classical finance theory, rationality is understood as goal-directed action under certain constraints. Rationality is always tied to human action, which involves two key aspects:

1. The concept of preferences, where consistent decisions are made among different alternatives, and
2. The concept of expected utility, where the investor aims to maximize their expected utility (Schindler, 2007).

The expected utility theory in economics describes the process through which rational agents make decisions under uncertainty, considering not just expected outcomes, but also their variability (Sapra & Zak, 2008). While one might believe decisions are based solely on logic, in practice, emotions play a significant role in decision-making and often guide actions without restraint (Montier, 2009). This departure from the traditional models has led to behavioral finance, which integrates psychology and finance, exploring how psychological factors influence financial practitioners' behavior and the effects on markets.

Behavioral finance provides insights into why and how markets may be inefficient (Sewell, 2010). It has rapidly developed, demonstrating that internal and external behavioral factors shape investors' financial decisions (Shefrin, 2000; Shleifer, 2000;

Warner et al., 2001). The central premise of behavioral finance is that investor behavior often contradicts the assumptions of traditional finance, impacting financial markets. This field applies behavioral economics to economic decision-making, exploring how individuals make decisions and how these actions can be understood through established psychological theories. Shiller describes behavioral finance as "finance from a broader social scientific perspective, including psychology and sociology," which contrasts sharply with the efficient market theory. Barberis and Thaler define it as the analysis of how investors fail to rationally incorporate new information or make decisions inconsistent with maximizing expected utility (Raines & Leathers, 2011). Behavioral finance relies on two core concepts: cognitive psychology and the limits of arbitrage. Cognitive psychology studies how people think, perceive, and remember information, while the limits of arbitrage describe situations where arbitrage opportunities are limited due to irrational market behavior (Kumar, 2016).

3 PREVIOUS RESEARCH ON INVESTOR SENTIMENT AND STOCK RETURNS

Many previous studies have examined the topic of investors' emotional biases and their relationship to stock returns from multiple perspectives. Selden authored The Psychology of the Stock Market, asserting that price movements in financial markets are largely determined by investors' mindset and trading behavior in 1912. In 1956, Leon Festinger introduced the theory of cognitive dissonance, followed by Pratt in 1964 with contributions to utility theory and risk aversion. In 1968, Raiffa discussed the differences between human behavior and traditional economic assumptions, while in 1973, Tversky and Kahneman presented the concept of availability bias (Boda & Sunitha, 2018).

This study will review a selection of these works, highlighting their key aspects. It is worth noting that the examined studies encompass various countries and regions, reflecting both temporal and geographical diversity.

1. Wayne Y. Lee, Christine X. Jiang, and Daniel C. Indro (Stock Market Volatility, Excess Returns, and the Role of Investor Sentiment, 2002):

This study examines the effect of noise traders' risk on expected returns and their conditional volatility in three financial markets. It addresses the question: How do noise traders' sentiments affect the risk-return trade-off? The study used GARCH testing on a sample of three financial market indices: DJIA, S&P500, NASDAQ, and the Investors' Intelligence Index of New Rochelle to represent investor sentiment from January 5, 1973, to October 6, 1995. The results indicate:

- Sentiment is a significant factor in explaining stock returns and their volatility.
- Sentiment is a priced risk factor.
- Stock returns are positively correlated with changes in sentiment, and these changes significantly impact the volatility and expected returns.
- Upward (downward) changes in sentiment lead to lower (higher) volatility and are associated with higher (lower) excess returns.
- The importance of sentiment in explaining conditional volatility and expected returns is consistent across indices and periods (Lee, Jiang, & Indro, 2002).

2. Rahul Verma, Hasan Baklaci, and Gökçe Soydemir (The Impact of Rational and Irrational Sentiments of Individual and Institutional Investors on DJIA and S&P 500 Index Returns, 2008):

This study explores the relative effects of rational and irrational sentiments on stock returns in the DJIA and S&P 500 indices. The study uses investor sentiment data from the American Association of Individual Investors (AAII) and the Intelligence Individual Index. The sentiment index is divided into rational and irrational categories, with additional variables such as economic growth, interest rates, and inflation. Using monthly data from October 1988 to April 2004, the study applies the VAR regression model and finds:

- Rational sentiment has a greater impact on stock returns than irrational sentiment.
- Irrational sentiment leads to immediate positive market responses, followed by negative corrections in subsequent periods.
- Past stock returns have a significant impact on irrational sentiment, but not on rational sentiment.

- Irrational sentiment influences stock returns more quickly and dramatically than rational sentiment (Verma, Baklaci, & Soydemir, 2008).

3. Maik Schmeling (Investor sentiment and stock returns: Some international evidence, 2009):

This study investigates whether consumer sentiment (as a proxy for individual investor sentiment) influences expected stock returns in 18 industrialized countries. It tests whether sentiment effects are more pronounced in countries with less developed institutions or those prone to herd behavior. Using data from January 1985 to December 2005 across 18 countries, the study finds:

- Sentiment negatively predicts future stock market returns.
- When sentiment rises, stock returns tend to decrease, and vice versa. This relationship holds across different stock categories (growth, value, small-cap).

The effect of sentiment on returns is stronger in countries with underdeveloped institutions and cultures prone to herd behavior (Schmeling, 2009).

4. Usman Bashir et al. (Investor Sentiment and Stock Price Crash Risk: The Mediating Role of Analyst Herding, 2024).

This study analyzes the impact of investor sentiment on firm's stock price crash risk by using Chinese A-Share firms' data this study assesses the potency and existence of a relationship between crash risk and investor sentiment in the Chinese stock market and introduces analyst herding as a mediating variable for explaining the relationship between crash risk and investor sentiment. By utilizing a large data set of A-share listed firms on Chinese stock exchanges, comprising 19,371 firm-year observations for the period of 2004–2019, an investor sentiment index is constructed. Results point towards a positive, significant relation between stock price crash risk and investor sentiment. Furthermore, the stock price crash exhibits a positive relationship with analyst herding, i.e., it significantly mediates between the stock price crash risk and investor sentiment. By measuring the relationship between crash risk, investor sentiment, and analyst herding, this study provides systematic support for the mediating role of analyst herding in deepening the market sentiment, which results in crash risk. These findings are robust when tested using alternative proxies and after controlling for firm-specific variables, economy-wide shocks, time trends, and year fixed effects.

5. Cheema and Fianto (Investor Sentiment and Stock Market Anomalies: Evidence from Islamic Countries, 2024):

Studies of the Ramadan effect argue that higher stock returns in Muslim countries during Ramadan relate to higher investor sentiment. However, Islamic countries rank low on the Hofstede Individualism Index, a proxy for investor overconfidence. Therefore, this study examines the impact of investor sentiment on stock market anomalies in two advanced Islamic finance jurisdictions: Malaysia and Indonesia. It hypothesizes that stock market anomalies are stronger following high sentiment if investors in Malaysia and Indonesia are overconfident. The results show that the long and short legs of the stock market anomalies earn relatively low returns following high investor sentiment, indicating overpricing during high sentiment. Moreover, the short leg earns relatively lower returns than the long leg following high sentiment because the short leg is more overpriced than the long leg when sentiment is high. Therefore, consistent with the hypothesis, the long-short returns of anomalies are stronger following high investor sentiment because of the relatively lower returns of the short leg than the long leg.

6. Maurya, Bansal, and Mishra (Investor Sentiment and Its Implication on Global Financial Markets: A Systematic Review of Literature, 2025):

This study aims to systematically review the literature on how various factors influence investor sentiment and affect financial markets. This study also sought to present an overview of explored contexts and research foci, identifying gaps in the literature and setting an agenda for future research. The systematic literature investigation yielded 555 journal articles, with a few other exceptional inclusions. The data were extracted from two databases, namely Scopus and Web of Science. VOSviewer and Biblioshiny by R have been used for bibliometric analysis. The period of investigation is from 1985 to July 2023. This systematic literature review helped us identify factors influencing investor sentiment and financial markets. This study broadly classified these factors into two categories, rational and irrational. Rational factors include economics and monetary policy, exchange rates, interest rates, inflation, government mandatory regulations, earnings announcements, stock splits, dividend decisions, audit quality, environmental, social, and governance aspects, and ratings. Irrational factors include behavioural and psychological influences, as well as discussions on social media and online platforms. News and entertainment also shape sentiment, geopolitical tensions, war events, and calendar anomalies. Environmental factors, natural disasters, religious events, and festivals contribute to market fluctuations. Irrationality can be caused by government or supervisory body regulations and corporate events. Using these factors, this study has developed an investor sentiment model. In addition, this review identified research trends, methodology, data, and techniques used by researchers.

Since the early days of behavioral finance theory, there has been debate and discussion regarding the impact of investors' emotional biases on stock returns and the overall performance of financial markets. Numerous previous studies have explored this topic, yielding varying results on the direction of sentiment effects on stock returns. Some studies have confirmed a negative relationship between stock returns and investors' emotional biases, while others have identified a positive correlation. Meanwhile, some studies—aligned with the efficient market hypothesis—have denied the existence of any relationship.

Previous literature has debated the varying impact of investors' emotional biases on stock returns. Most studies have found that stocks with more objective valuations and greater arbitrage difficulty are disproportionately affected by investor sentiment. It is generally stated that small-cap stocks are more influenced by emotions than large-cap stocks.

Additionally, previous studies focusing on the relationship between stock returns and behavioral indicators have employed various econometric methods, including ARCH and GARCH models, Johansen's cointegration test, and VAR models. These methods assume linear relationships between independent and dependent variables and examine specific characteristics such as long-term and short-term causality (cointegration models), volatility (ARCH and GARCH), and error correction (VECM).

Reviewing the points of agreement and divergence among previous studies, we note that the current study aligns with prior research in its main subject and overall objective. However, it differs in several aspects, representing the scientific gap that this study aims to address:

- The study integrates the research problem with investors' emotional biases and stock returns
- Rather than relying on the commonly used questionnaire method in behavioral studies, this study aimed to construct a dedicated index to measure investors' emotional biases. Following the Baker-Wurgler methodology, an empirical analysis was then conducted to assess the impact of these biases on stock returns. Unlike previous studies that limited their analysis to the first principal component, this study employed the first and second components derived from Principal Component Analysis (PCA). Additionally, to more precisely capture the influence of emotional biases on investor behavior, a daily time frame was adopted, rather than monthly or yearly intervals.

4 DATA AND METHODOLOGY

In recent years, China has experienced significant economic growth, becoming the largest economy in Asia and the second-largest economy globally. It is considered the primary driver of regional and global economic growth, especially after the global financial crisis.

The CSI300 index futures contract was introduced on April 16, 2010, at the China Financial Futures Exchange (CFFEX) to support China's financial markets. China Financial Futures Exchange Co., Ltd was established with the approval of the State Council of the People's Republic of China and the China Securities Regulatory Commission (CSRC). It is an integrated exchange that offers trading and clearing services for financial futures, options, and various derivatives.

On September 8, 2006, CFFEX was founded in Shanghai by the Shanghai Futures Exchange, Zhengzhou Commodity Exchange, Dalian Commodity Exchange, Shanghai Stock Exchange, and Shenzhen Stock Exchange. The establishment of CFFEX and the development of China's financial futures market hold significant strategic importance in deepening financial market reforms, strengthening the financial system, facilitating the robust performance of financial markets, and adapting to the new normal of economic development.

The company is committed to serving the real economy and supporting China's capital market by offering secure, efficient, and well-performing financial derivative products and services. CFFEX facilitates the proper transfer and allocation of financial risks, enhances financial market efficiency, and promotes social and economic prosperity.

CFFEX is responsible for organizing and managing the trading, clearing, and settlement of financial futures contracts and various derivatives. It formulates relevant regulations and ensures self-regulation within the market. The exchange also publishes market data and related information. Additionally, it provides technologies, venues, and facilities to support trading operations. Finally, CFFEX performs additional functions approved by the CSRC.

By adhering to high standards and focusing on market stability, CFFEX strives to expand its offerings of financial derivative products, improve its product lines in equities, interest rates, and foreign exchange, and meet the diverse risk management needs of market participants. (Cffex, 2025)

This study uses daily stock return data from the China Stock Exchange (Shanghai Shenzhen 300) futures contracts, spanning January 2010 to December 2020. The data, sourced from the Eastmoney and CFFEX databases, includes 2555 observations.

4.1 Futures Market Sentiment Index

Using principal component analysis based on Baker and Wurgler (2007), we create a composite sentiment index for the futures market using the following proxies:

- Open Futures OI
- Relative Strength Index (RSI)
- Psychological Line Index (PSY)
- Trading Volume (VOL)

The following section defines each variable separately.

A- The Relative Strength Index (RSI):

It is a widely used market indicator that reflects whether a market is overbought or oversold. It is considered one of the proxies for market sentiment and is calculated as follows:

$$RSI_t = 100 * \frac{RS_t}{1 + RS_t}$$

$$RS_t = \frac{\sum_{t=1}^{6} \max(P_t - P_{t-1}, 0)}{\sum_{t=1}^{6} \max(P_{t-1} - P_t, 0)}$$

P_t - The closing price of the stock *i* at the moment *t*.

When $RSI < 50$, the stock's losses exceed its gains. Conversely, when $RSI > 50$, it means that gains outweigh losses.

The market is considered overbought when $RSI = 80$, and it is oversold when $RSI = 20$. (Yao & Li, 2020)

B- Psychological Line (PSY) Indicator:

Yang and Gao (2014) proposed a sentiment indicator to measure market psychology in the Chinese stock market.. It is calculated as follows:

$$PSY_t = \frac{T^U}{T} * 100$$

Where:

- T^U represents the days in which the closing price of stock i at time t is higher than its closing price at time t-1.
- T is the trading period.

The market is considered overbought when $PSY = 75$ and oversold when $PSY = 25$. (Gao, Liang, Xu, & Xie, 2020)

C- Open Interest (OI):

OI is considered a forward-looking sentiment indicator, as highlighted by Wang (2000). Instead of focusing on net positions or long/short positions, OI was selected to study its predictive potential for returns in futures markets.

It is regarded as an indicator that provides a clearer interpretation of traders' actions. Due to its nature, OI is similar to other market sentiment indicators and is widely accepted among futures market participants. (Gao,2020)

D- Trading volume:

Wurgler and Baker (2006) stated that trading volume serves as an indicator of investor sentiment. Similarly, Baker and Stein (2004) suggested that when irrational investors are optimistic, they trade more actively, increasing market liquidity. (Jaziri & Abdelhedi, 2018)

Table 1. Results of the principal component analysis method for the composite sentiment index of the futures market

Component	Standard deviation	Variance (%)	Cumulative Proportion (%)
1	1.2121	36.73	36.73
2	1.0993	30.21	66.94
3	0.8202	16.82	83.76
4	0.8059	16.24	100

Source: Prepared by the researchers

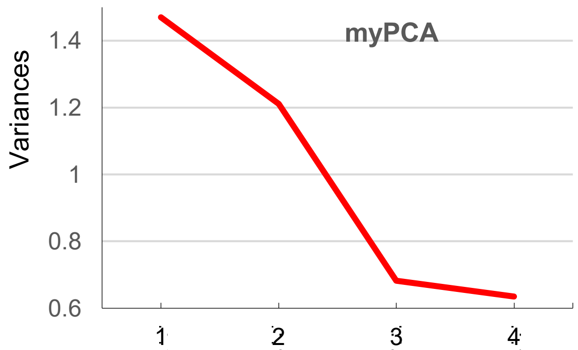

Fig. 1: Variation of the main components representing the composite sentiment index for the futures market

Source: Authors' analysis

From Table 1 and Figure 1, we notice that after standardizing each of the four components using the PCA method, the first and second main components have the highest explanatory power compared to the rest of the components, and they represent the best linear combination of the variables used according to the weighting coefficient, as they explain 66.94% of the standard sample variance, and the first and second eigenvalues are much higher than 1.00, so we conclude that two factors capture the common variance, and therefore the composite index of investor sentiment depends on the first and second main components. Given the weak short-term impact of macroeconomic variables, we exclude them from the analysis. Thus, we have the equation of investors' future emotional biases as follows:

$$SENTf_t = 0.658PSY_t - 0.201OI_t + 0.544RSI_t - 0.479VOL_t$$

4.2 Testing the suitability of the ordinary least squares method to estimate the model

Table 2 shows the results of estimating the relationship between the sentiment index and the returns of the CSI300 index, which shows a positive and statistically significant relationship between them, as the degree of influence was estimated at 0.0892, which means that any change of one unit in the sentiment index leads to a positive change in the returns of the CSI300 index by 0.0892 units.

Table 2. Results of estimating the model using the OLS method

Dependent Variable: FUTUR_RETURN
Method: Least Squares
Date: 08/24/21 Time: 21:27
Sample (adjusted): 4/16/2010 9/30/2020
Included observations: 2514 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.023475	0.013516	1.736747	0.0826
SENTF	0.089226	0.011002	8.109800	0.0000

R-squared	0.025514	Mean dependent var	0.004919
Adjusted R-squared	0.025126	S.D. dependent var	0.676483
S.E. of regression	0.667931	Akaike info criterion	2.031531
Sum squared resid	1120.682	Schwarz criterion	2.036169
Log likelihood	-2551.634	Hannan-Quinn criter.	2.033214
F-statistic	65.76886	Durbin-Watson stat	1.915632
Prob(F-statistic)	0.000000		

Source: Authors' calculations

The estimation results of the relationship between the sentiment index and the CSI 300 Index returns, as presented in Table 2, show a statistically significant correlation between the two variables. The estimated coefficient is 0.0892, indicating that a one-unit change in the sentiment index leads to a change of 0.0892 units in the index returns.

To examine the presence of multicollinearity among the independent variables, the Variance

Inflation Factor (VIF) test was applied. A VIF value equal to 1 indicates that the variable is not correlated with any other explanatory variable, implying no multicollinearity within the regression model. In general, VIF values below 5 are considered acceptable, while values exceeding 10 may indicate serious multicollinearity issues. The results of the VIF test in Table 3 show that all variables have VIF values close to 1, confirming the absence of multicollinearity and supporting the robustness of the regression estimates.

Table 3. Results of the Variance Inflation Factor (VIF) Test

Variance Inflation Factors
Date: 05/05/25 Time: 10:47
Sample: 1 2614
Included observations: 2556

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	9.50E-08	1.030418	NA
FUTURE_SENT	6.29E-08	1.030418	1.000000

Source: Authors‘ analysis

4.3 ARCH Effect Test

As observed in Table 4, the probability of the Chi-Square test is below 5%, leading us to reject the assumption of constant conditional variance. This confirms the presence of the ARCH effect in the residuals, indicating time-varying volatility. Given these findings, the GARCH model should be applied to account for this variability.

Table 4. Results of the ARCH effect test for the residuals of the model estimation using the OLS method

Heteroskedasticity Test: ARCH

F-statistic	264.6490	Prob. F(1.2553)	0.0000
Obs *R-squared	239.9796	Prob. Chi-Square(1)	0.0000

Source: Authors' analysis

Table 5. Results of estimating the GARCH(1,1) model

Dependent Variable: FUTURE_RETURN
Method: ML ARCH - Generalized error distribution (GED)
Date: 01/06/21 Time: 20:32
Sample (adjusted): 1 2556
Included observations: 2556 after adjustments
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
GED parameter fixed at 1.5
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009024	0.009369	0.963213	0.3354
FUTURE_SENT	0.055914	0.007408	7.547931	0.0000
Variance Equation				
C	0.003445	0.000738	4.670457	0.0000
RESID(-1)^2	0.058558	0.005207	11.24592	0.0000
GARCH(-1)	0.929072	0.005462	170.0861	0.0000

R-squared	0.022117	Mean dependent var	0.005289
Adjusted R-squared	0.021734	S.D. dependent var	0.675425
S.E. of regression	0.668045	Akaike info criterion	1.634956
Sum squared resid	1139.809	Schwarz criterion	1.646392
Log likelihood	-2084.473	Hannan-Quinn criter.	1.639103
Durbin-Watson stat	1.911715		

Source: Authors' analysis

4.4 Estimating the GARCH Model

We will estimate the GARCH(1,1) model below, considering that the time series of returns and indicators of emotional biases do not follow a normal distribution and that fluctuations are present in the graphs of each variable.

Based on Table 5, it is clear that the GARCH coefficients are significant and statistically significant at 5%, and there is a positive effect of the emotional biases included in the average equation on stock returns; that is, the more positive the investors' feelings are and the more optimistic they are about improving future economic conditions, the more their purchase rate of securities increases, which pushes prices up as a result of increased trading on them.

As for the variance equation, we note that the squared error coefficient is significant, which confirms the existence of the ARCH effect. The β value of 0.92 indicates that the variance resulting from a high volatility value will be followed by another high variance. The GARCH model coefficients (1,1) are positive and their sum is less than 1, which fulfills the model's stability condition, as:

$$\alpha+\beta = 0.058558+0.929072 = 0.98763 < 1$$

This indicates the continuity of the impact of previous fluctuations, shocks, and variations in the current volatility. Consequently, investor sentiment captures the persistence of market volatility and accumulates it in capital markets. In other words, previous emotional biases of investors lead to stock market fluctuations and continue over the long term.

4.5 Estimation of the GARCH(1,1) Model with Sentiment Index

From the results of Table 6, the GARCH(1,1) coefficients and the bias index in the mean and variance equation are significant, and the emotional bias index included in the variance equation hurts the conditional variance. This means that in the event of an increase or rise in the emotional bias index, the CSI300 index will record low volatility and vice versa. That can be explained by the fact that investors' pessimism about the economic and financial conditions will push them to sell securities due to loss aversion and their belief that stock prices will decline in the future, which will lead to a decrease in trading in them, causing instability in the financial market.

4.6 Estimation of the DCC-GARCH Model

Table 7 shows the results of estimating the DCC-GARCH model according to Engel's methodology using the t-student distribution. We notice that the coefficients of the DCC-GARCH model are positive, and their sum is less than one, where $\theta_1+\theta_2=0.024763+0.611714=0.636477<1$, but they are not significant, which means that the fluctuations are unstable. We also notice that the dynamic conditional correlation coefficient is substantial and positive. This indicates a positive dynamic conditional correlation between investors' emotional biases and stock returns, meaning that the CSI300 futures returns are sensitive to any change in investors' emotional biases over time.

Table 6. Estimation results of the GARCH(1,1) model with the inclusion of the sentiment index in the mean equation and the conditional variance equation

Dependent Variable: FUTURE_RETURN
Method: ML ARCH - Generalized error distribution (GED)
Date: 01/06/21 Time: 20:36
Sample (adjusted): 1 2556
Included observations: 2556 after adjustments
Convergence achieved after 19 iterations
Presample variance: backcast (parameter = 0.7)
GED parameter fixed at 1.5
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)
*FUTURE_SENT

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.010452	0.009350	1.117880	0.2636
FUTURE_SENT	0.055396	0.007420	7.465421	0.0000
Variance Equation				
C	0.004650	0.000863	5.389921	0.0000
RESID(-1)^2	0.060118	0.005273	11.40131	0.0000
GARCH(-1)	0.923028	0.005865	157.3814	0.0000
FUTURE_SENT	-0.001429	0.000452	-3.162515	0.0016

R-squared	0.022052	Mean dependent var	0.005289
Adjusted R-squared	0.021669	S.D. dependent var	0.675425
S.E. of regression	0.668067	Akaike info criterion	1.633182
Sum squared resid	1139.884	Schwarz criterion	1.646906
Log likelihood	-2081.207	Hannan-Quinn criter.	1.638159
Durbin-Watson stat	1.911868		

Source: Authors' analysis

Table 7. Estimation results of the DCC-GARCH model

```
  ********************
 **  SECOND STEP   **
*******************


  *************
 ** SERIES  **
*************
#1: futur_return
#2: futur_sent

The dataset is: C:\Users\HP\Desktop\new03.in7
The estimation sample is:  1 - 2557

 *******************************
 ** MG@RCH(1) SPECIFICATIONS **
 *******************************
Conditional Variance : Dynamic Correlation Model (Engle)
Multivariate Student distribution, with 13.7821 degrees of freedom.

Strong convergence using numerical derivatives
Log-likelihood = -5671.81
Please wait : Computing the Std Errors ...

 Robust Standard Errors (Sandwich formula)
                  Coefficient  Std.Error  t-value  t-prob
rho_21               0.062517   0.020498    3.050  0.0023
alpha                0.024763   0.017386    1.424  0.1545
beta                 0.611714    0.14759    4.145  0.0000
df                  13.782082     2.2373    6.160  0.0000
No. Observations :       2557  No. Parameters  :       12
No. Series       :          2  Log Likelihood  : -5671.814
Elapsed Time : 0.422 seconds (or 0.00703333 minutes).
```

Source: Prepared by researchers

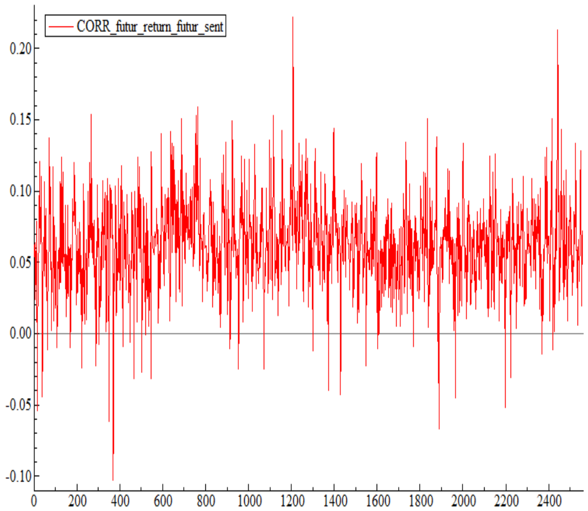

Fig. 2 Dynamic conditional correlation between CSI300 futures stock returns and investors' emotional biases in the futures market
Source: Prepared by the Authors

From Figure 2, we notice that the dynamic conditional correlation between the futures returns series and investors' emotional biases has changed over time, sometimes rising and sometimes falling. We also found a significant increase of more than 30% during the crisis that hit the Chinese financial market in 2015.

5 CONCLUSIONS

Through this paper, we tried to measure and analyze the impact of investors' sentiments on stock returns across 2010-2020 in China. This was done by addressing the most important theoretical beliefs that govern this relationship, after which we tried to project what was stated in the theoretical aspect onto the reality of the Chinese economy by relying on the DCC-GARCH model. We presented the economic variables used in estimating this model according to what economic theory dictated to us and what was used in previous studies that addressed the subject, and according to the nature of the Chinese economy, using the RSI, PSY, OI, and VOL variables. The study found that investor sentiment positively influences the stock returns of the CSI300 index. Furthermore, there is a strong dynamic conditional correlation between the two, indicating that fluctuations in investor sentiment significantly impact the index's performance over time. This relationship suggests that the returns of the CSI300 index are highly responsive to changes in investor sentiment, making them particularly susceptible to market mood shifts.

The findings of this study underscore the significant influence of investors' emotional biases on stock returns in the futures market. This highlights that investment decisions are not always rational or objective, often leading to mispriced assets and unwarranted fluctuations in financial markets. Such sentiment-driven distortions weaken market efficiency, as shifts in supply and demand may not accurately reflect the intrinsic value of assets.

Furthermore, excessive market volatility fueled by investor sentiment can profoundly affect the real economy. Sharp price swings—whether upward or downward—can disrupt investment and consumption patterns, creating instability. Recognizing the critical role of sentiment, governments and central banks implement monetary and fiscal policies aimed to restore confidence, such as interest rate reductions or increased government spending. Historical examples include the 2008 global financial crisis, where investor panic triggered market collapses, and the post-COVID-19 economic recovery, where renewed trust drove economic revitalization.

Additionally, the study's findings support the integration of psychological and emotional factors into economic policymaking. The sentiment index developed in this research could be a valuable tool for financial and monetary authorities, enabling them to identify early signs of market volatility or financial bubbles and implement preventive measures to mitigate risks. A deeper understanding of sentiment's impact on the economy enhances the ability to analyze economic trends and make more informed financial and business decisions.

Finally, this study reinforces the relevance of behavioral economic models, which incorporate psychological factors to explain market dynamics and macroeconomic behavior. By integrating sentiment indicators into these models, economists can better anticipate irrational market movements, allowing policymakers to craft more sustainable and effective economic strategies that account for investor psychology.

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