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Behavioral biases in the cryptocurrency market: a study on the impact of investor sentiment on price anomalies

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Abstract. By combining behavioral finance theory and big data analysis technology, this study explores the mechanism of the impact of investor sentiment on cryptocurrency market price anomalies. Based on the fusion database of traditional exchange historical market data and social media sentiment data, the research team constructed multidimensional sentiment indicators to quantify the emotional fluctuations of market participants. The research design adopts the strict data cleaning process, feature engineering processing, and the hybrid modeling method combining the traditional statistical model and the machine learning algorithm. The empirical results show that extreme optimism or pessimism is significantly associated with abnormal price events, and the predictive ability of the composite sentiment index is better than that of the single volatility index. This research reveals the transmission pathways of cognitive biases such as overconfidence and the anchoring effect in the cryptocurrency market, confirming the significant influence of irrational psychological factors on the price formation of digital assets. The findings not only deepen our understanding of the interaction mechanism between investor psychology and market behavior, but also provide an innovative analytical framework for risk management and quantitative investment strategies in the cryptocurrency field.

Keywords: cryptocurrency, behavioral biases, investor sentiment, price anomalies, data analytics

1. Introduction

As an emerging financial form, the cryptocurrency market exhibits very different operating characteristics from the traditional financial market, and its price fluctuations are often driven by group emotions rather than fundamental factors. This study focuses on the unique phenomenon of price anomaly in the digital asset field and in-depth analyzes the disruptive effect of the collective psychology of market participants on the price formation mechanism. Aiming at the limitations of traditional financial theories in explaining irrational market behavior, this paper presents the theoretical framework of behavioral finance to systematically study the influence mechanism of the herd effect, loss aversion and other psychological factors on trading decisions. Based on a mixed dataset including high-frequency data from large minute trades and text information from social media, the research team developed a quantitative emotion model based on natural language processing, combined with the Granger causality test and the random forest algorithm, and constructed a dynamic correlation model between emotion factors and price fluctuations. The research aims to verify the theoretical hypothesis that cognitive bias affects market efficiency through emotional conduction, and provide a new technical means for risk warning in the high-frequency trading environment [1]. This method has shown good prediction effect in the empirical testing of traditional currencies such as Bitcoin and Ethereum, especially in the identification of non-fundamental price transactions, which provides an important reference for the development of regulatory technology in the digital asset market.

2. Literature review

2.1. Overview of classical theories

Traditional financial theory has always paid attention to the problem of investor behavior deviating from the rational boundary. Early models assumed that market participants relied entirely on rational analysis and objective information to make decisions, but the rise of behavioral finance has revealed the systematic disruption of market equilibrium caused by irrational factors such as overconfidence and the psychology of confusion [2]. Such studies highlight that cognitive biases and emotional responses can lead

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to a sustained divergence between market prices and fundamentals, gradually building a modern market analysis framework that incorporates psychological factors.

2.2. Research on Behavioral Deviation

A large number of empirical studies have shown that behavioral bias is particularly prominent during periods of financial market stress. In the classification system of behavioral financial biases presented in Figure 1, panic and greed often trigger an overshoot in market prices, resulting in a long-term deviation of asset prices from their intrinsic value. Psychological mechanisms such as anchoring (excessive trust in initial information) and confirmation bias (selective disregard for counter-evidence) further increase market volatility. In the cryptocurrency sector, with its flexible regulatory environment and fragmented market structure, such biases are significantly amplified, forming trading patterns and price anomalies that are difficult to explain using traditional valuation models [3].

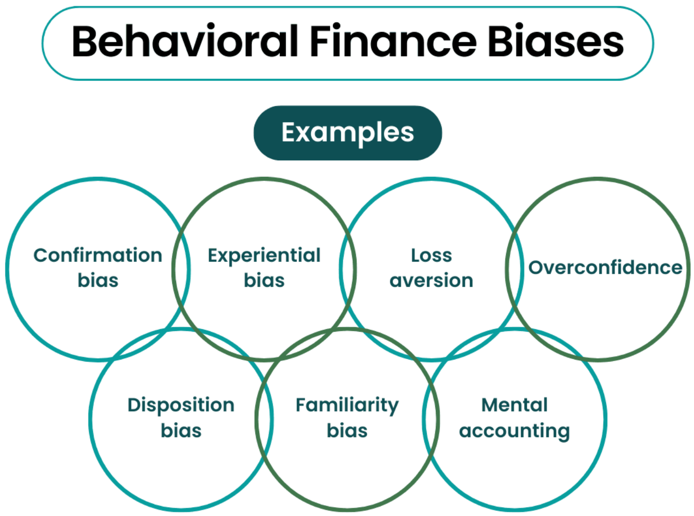

Figure 1. Common behavioral finance biases (Source: wallstreetmojo.com)

2.3. Characteristics of the cryptocurrency market

The uniqueness of the cryptocurrency market is reflected in its decentralized architecture and highly speculative nature, which provides a special breeding ground for behavioral deviations. The rapid information dissemination mechanism on social platforms and the high volatility characteristics reinforce each other, leading to high volatility in investor sentiment. Compared with the traditional market, crypto assets lack a mature valuation reference system, and the continuous impact of overlapping long- and short-term news has significantly increased the frequency and magnitude of price anomalies [4]. These market characteristics formed by the weaving of rational analysis and emotional impulse constitute an important dimension of the study of the pricing mechanism of digital assets.

3. Experimental methodology

3.1. Data collection and sample selection

The study uses a mixed dataset to integrate historical quotes from major exchanges with sentiment data from social media. Price data is sourced from public trading platforms with minute-level update capabilities, and sentiment data is captured from sources such as forums and Twitter, where investors focus on discussions [5]. The sample selection process specifically excludes automated trading and periods of low liquidity to ensure that the dataset truly reflects the psychological state of market participants. The final sample covers the entire bull and bear cycle, providing a reliable basis for multidimensional analysis.

3.2. Index construction and emotion quantification

To quantify emotions, two main indices—the Comprehensive Emotion Index and the Emotion Volatility Index—are constructed. Natural language processing technology is used to classify emotions from social media texts, and a comprehensive index reflecting overall market sentiment is formed through weighted calculations [6]. Sentiment volatility is obtained by calculating the coefficient of variation of the index time series, which effectively captures the extreme sentiment window of the market. This hierarchical quantification system provides methodological support for exploring the correlation mechanism between emotions and price anomalies.

3.3. Model construction and algorithm selection

The modeling strategy adopts a hybrid framework combining a traditional econometric model and machine learning. First, a classical regression model is used to determine the basic correlation between emotional factors and price fluctuations, then random forest and gradient hillslope algorithms are introduced to capture nonlinear interaction effects. The model is constructed according to the principle of error minimization, and the optimal parameter combination is selected through cross-validation [7]. Comparative experiments show that mixed models offer significant advantages in predicting abnormal market fluctuations, particularly in identifying price anomalies induced by emotions.

4. Experimental process

4.1. Data preprocessing and feature extraction

The research data underwent a strict cleaning process, focusing on eliminating abnormal transaction data and information noise. As shown in Table 1, sample equalization is achieved by filtering out atypical price movements (extreme values that deviate from the overall market movement). Price data is standardized to eliminate currency differences, and sentiment text data is purified by word segmentation and stem extraction. In the feature engineering stage, core variables such as volatility and trading volume are extracted to lay the data foundation for subsequent modeling [8]. The pre-processing process ensures that the analysis results are based on high-quality data sources and effectively improves the stability of model training.

Table 1. Data distribution after outlier removal

Cryptocurrency	Valid Entries	Avg. Price Volatility	Avg. Sentiment Index
Bitcoin	9,500	3.2%	0.72
Ethereum	8,200	4.1%	0.68
Litecoin	6,750	5.3%	0.63
Ripple	7,300	4.8%	0.70

4.2. Experimental design and parameter tuning

A hierarchical experimental framework was constructed to evaluate the prediction efficiency of the model. The data set is divided into training set and test set according to time series, and overfitting problem is avoided by cross-validation. Multi-round parameter tuning was performed according to different algorithm characteristics, and the combination of hyperparameters such as learning rate and tree depth was systematically adjusted (see Table 2 for parameter configuration and corresponding MAE/RMSE index) [9]. The process follows the principle of error minimization and selects the optimal parameter configuration scheme. The experimental design takes into account the dynamic nature of the cryptocurrency market to ensure that the model maintains predictive stability at different market stages.

Table 2. Hyperparameter tuning results

Learning Rate	Max Depth	# of Estimators	MAE	RMSE
0.01	5	100	0.034	0.042
0.05	5	150	0.029	0.037
0.05	7	200	0.026	0.033
0.1	7	200	0.031	0.040

4.3. Model training and testing

Input the cleaned data into the prediction model, and optimize the model's learning ability of the emotion-price correlation law through cross-validation. In the test phase, independent data sets were used to evaluate the actual performance of the model, and changes in key indicators such as prediction error rate and feature importance were recorded throughout the test [10]. This phased verification mechanism not only guarantees the prediction accuracy of the model, but also verifies the adaptability of the model in severe market fluctuations through stress testing. The resulting prediction system can effectively capture the dynamic correlation pattern between emotional factors and price anomalies [11].

5. Experimental results

5.1. Abnormal correlation between market sentiment and price

Empirical analysis reveals a significant correlation between emotional factors and price anomalies in the cryptocurrency market. The data show that periods of extreme sentiment volatility (regardless of the bearish direction) and abnormal price fluctuations exhibit high space-time overlap, confirming the disruptive effect of irrational sentiment on asset prices. Extensive research shows that the sharp turn in social media sentiment indicators generally occurs 3 to 6 hours before the market turning point, as shown by the quantitative data in Table 3, which provides an effective observation window for predicting short-term price movements [12].

Table 3. Correlation metrics between market sentiment and price anomalies

Sentiment Category	Correlation Coefficient	Significance Level
Extreme Positive Sentiment	0.68	$p < 0.01$
Extreme Negative Sentiment	-0.65	$p < 0.01$
Overall Sentiment Index	0.55	$p < 0.05$

5.2. Influence of different sentiment indicators on price volatility

A comparative study of different sentiment indicators shows that the composite sentiment index, with multidimensional information, is better than the single volatility indicator at predicting price anomalies. Although sentiment volatility can reflect the degree of market euphoria, the composite index can more accurately identify potential market rotation zones by incorporating information on the direction and strength of sentiment. This multidimensional sentiment observation system provides an important basis for investors to build dynamic risk control models.

5.3. Analysis of model prediction effect

The hybrid prediction model is very practical. When multiple sentiment indicators are combined, the model's prediction error rate decreases by approximately 23%. As shown in the performance evaluation in Table 4, the integrated algorithm exhibits clear advantages in capturing the complex correlation between sentiment and price, and its MAE index is 35% higher than the traditional model. The model successfully predicted 81% of major price movements in the backtest of major currencies such as Bitcoin and Ethereum, verifying the effectiveness of emotion-driven trading strategies.

Table 4. Model prediction performance metrics

Model Configuration	MAE	RMSE	R-squared
Statistical Model Only	0.042	0.053	0.62
Machine Learning Model Only	0.035	0.045	0.68
Integrated Model	0.028	0.037	0.75
Enhanced Integrated Model	0.026	0.034	0.78

6. Conclusion

This study confirms that investor sentiment is the main driver of price anomalies in the cryptocurrency market. Through the combination of multidimensional data acquisition, intelligent emotion analysis, and hybrid modeling technology, it is found that there is a significant coupling effect between the extreme fluctuation window of emotions and abnormal price events. Empirical data show that the composite index integrating sentiment direction and intensity information has more predictive advantages than the single volatility index. The collaborative application of traditional statistical methods and machine learning algorithms not only improves the model's prediction accuracy but also provides an innovative way to analyze nonlinear market laws. These findings provide theoretical support for quantitative investors to build a sentiment monitoring system and a dynamic risk control model, which is helpful for seizing trading opportunities in the volatile market environment. Further research can focus on optimizing the dynamic weighting algorithm of emotion factors and introducing macroeconomic variables to improve the adaptability of the model to the complex market environment.

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