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Quantile Regression Study on the Impact of Investor Sentiment on Financial Credit from the Perspective of Behavioral Finance

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***Abstract*:** This study is based on the perspective of behavioral finance and systematically explores the impact mechanism of investor sentiment on financial credit through quantile regression models. The research background focuses on the practical needs of sustained growth in credit scale and structural optimization in the context of global financial market development, as well as the theoretical limitations of traditional finance in explaining market anomalies such as investor sentiment driven credit fluctuations; At the methodological level, principal component analysis was used to construct a composite indicator that includes direct (such as consumer confidence index) and indirect (such as closed-end fund discount rate and trading volume) emotional variables. Combined with macroeconomic control variables, a quantile regression model was used to characterize the heterogeneous impact characteristics of emotions on credit size, term structure (short-term/medium - to long-term loan ratio), and allocation structure (individual/institutional loan ratio) at different quantiles; Research has found that investor sentiment has a significant positive effect on credit scale (credit scale expands when sentiment is high), showing a dynamic feature of high sentiment driving up the proportion of medium - and long-term loans in credit term structure, and low sentiment increasing the proportion of short-term loans. On credit allocation structure, sentiment has a positive impact on personal loans and a negative impact on institutional loans, and quantile regression models have better explanatory power than traditional linear regression and VAR models because they can handle non normal distribution data and capture dynamic differences between variables; The research conclusion emphasizes that investor sentiment is a key link between direct and indirect financial markets, and quantile regression provides a new perspective on risk return balance for credit management. Future research can combine machine learning to optimize sentiment indicators and deepen the integration and application of quantile regression with other models.

1. Introduction

In terms of research background, the credit scale [1]continues to grow and there is a significant demand for structural optimization in the development of global financial markets. However, there is an imbalance in credit allocation between large enterprises and small and medium-sized enterprises, as well as between individuals and enterprises; Behavioral finance, as an interdisciplinary field, supplements traditional finance's explanation of market anomalies, such as how investor sentiment affects stock price volatility and market returns. Quantile regression models, due to their limited data distribution and strong robustness, have shown advantages in handling complex data and capturing potential relationships between variables in financial research. The previous literature challenges mainly reflected in the lack of a unified standard for measuring investor sentiment, and existing research mostly focuses on corporate financing efficiency and credit allocation, with less direct correlation between direct financial markets (such as investor sentiment) and indirect financial markets (such as financial credit); Financial credit research often analyzes from the perspectives of supply (policy, market risk) and demand (corporate investment), but there is insufficient research on the impact mechanism of investor sentiment on credit scale, term structure, and allocation structure; Although quantile regression models are widely used in fields such as economics and management, their ability to characterize financial data heterogeneity and their specific advantages in credit research need further validation. The motivation for this research is to fill the research gap mentioned above by integrating behavioral finance and quantile regression methods to construct a bridge between direct and indirect financial markets. The goal of this paper is to use quantile regression models to systematically analyze the impact of investor sentiment on the scale, maturity structure, and allocation structure of financial credit, verify the applicability and advantages of this model in financial data, and provide theoretical references for credit management. The core contributions include: demonstrating the comprehensiveness and effectiveness of quantile regression models in processing financial data at the theoretical level, and demonstrating the feasibility and importance of behavioral finance in explaining financial market behavior; On the practical level, it provides a new perspective for financial credit management, emphasizing the need to face up to the impact of investor sentiment on market unity, optimize credit risk control and development management from the perspective of risk and profit balance, and demonstrate the reliability and wide applicability of quantile regression models in financial modeling, providing methodological references for related research.

2. Correlation theory

2.1. Theoretical analysis of the impact of investor sentiment on financial credit

Investor sentiment[2], as a core concept in behavioral finance, originates from six cognitive biases (overconfidence, herd behavior, psychological accounts, loss aversion, regret aversion, and fuzzy aversion) and four research results (prospect theory, regret theory, overreaction theory, and overconfidence theory). Its essence is the expectation of the future market, reflecting the investment willingness of market participants. The field of financial credit involves four major risks of bank credit (credit risk, operational risk, market risk, liquidity risk), three major theories (commercial loan theory emphasizes the matching of short-term loans and deposit liquidity, convertible theory allows investment in convertible securities to ensure liquidity, expected income theory focuses on borrower repayment ability), and six major theories of risk management (enterprise lifecycle theory, information asymmetry theory, allocation theory, basket theory, game theory, data risk control theory). From the perspective of theoretical influence mechanisms, investor sentiment affects financial credit in three dimensions: from the investor's perspective, when sentiment is high, more funds are invested in the securities market, leading to a reduction in credit scale; When emotions are low, funds turn to bank deposits and credit sources increase. From the perspective of financiers, emotions affect the financing needs and capital allocation efficiency of enterprises. Different life cycle enterprises (such as initial stage inclined towards direct financing and mature stage mixed financing) have different financing methods. From the perspective of intermediary institutions, emotional fluctuations affect the efficiency of credit risk management and asset maturity structure. For example, when emotions are high, financial institutions may increase their medium and long-term loan scale, while when emotions are low, they prefer short-term loans to control risks. The above theoretical mechanism needs to be verified for its accuracy through empirical testing, providing theoretical support for credit management.

2.2. Theoretical basis and advantages analysis of quantile regression model

The quantile regression model[3]was proposed by Koenker and Bassett in 1978. As an extension of traditional linear regression, its core is to study the relationship between the independent variable and the dependent variable's conditional quantile, rather than just focusing on the conditional mean. This method minimizes the weighted absolute residual estimation parameters, without the need to satisfy homoscedastic or normal distribution assumptions, and has fewer restrictions on data distribution, especially suitable for heteroscedastic or non normal distribution data. Quantile regression has three key properties: robustness, which can provide reliable estimates even in the presence of outliers or spiky fat tailed distributions in the data; Monotonic homogeneity allows for monotonic transformations of variables without affecting the validity of estimation results; Asymptotic behavior, when the sample size is large enough, the quantile of the sample tends towards a normal distribution, improving estimation accuracy.Compared to traditional linear regression[4], quantile regression does not require classical assumptions such as homogeneity of variance and can more comprehensively characterize the distribution characteristics of the dependent variable. It captures the differential effects of independent variables on the distribution of the dependent variable through different quantiles. Compared with VAR models, quantile regression has more advantages in parameter estimation accuracy, especially when there are many variables or a small sample size, it can effectively avoid the problems of degree of freedom loss and insufficient explanatory power of parameters. In financial research, quantile regression demonstrates significant advantages: it can handle complex financial data and capture the heterogeneity of potential relationships between variables; In the analysis of credit scale, term structure, and allocation structure, the impact mechanism of investor sentiment on financial credit can be more accurately characterized. Its theoretical advantages and empirical applicability have been validated through the combination of behavioral finance and financial credit research, providing robust and comprehensive methodological support for financial modeling.

3. Research method

3.1. Construction and Empirical Preparation of Investor Sentiment Indicators

Before empirical modeling, it is necessary to construct investor sentiment indicators and analyze financial credit data. The quantification of investor sentiment is achieved through a combination of direct and indirect indicators: the direct indicator uses the Consumer Confidence Index [5] (reflecting the strength of market confidence), and the indirect indicators include the closed-end fund discount rate [6] (negatively correlated with sentiment), trading volume (positively correlated with sentiment), IPO quantity, and first day return rate (all positively correlated with sentiment). Innovatively incorporating macro control variables related to credit, such as consumer price index, producer price index, macroeconomic prosperity index, and total money supply, to strengthen the correlation between sentiment and financial credit.The data selected is monthly data from January 2000 to July 2022, involving 9 variables and their lagged terms. By using principal component analysis (PCA)[7] to reduce dimensionality, the correlation coefficient matrix is calculated after standardization. Six principal components (with a total variance contribution rate of 89.93%) are determined based on the principle that the eigenvalues are greater than 1 and the cumulative variance contribution rate exceeds 85%. The constructed Investor Sentiment Index (ISI) is significantly correlated with various variables, with a correlation coefficient of -0.55 with the lagged term of closed-end fund discount rate and a correlation coefficient of 0.69 with the number of IPOs, verifying the effectiveness of the indicators. The correlation coefficients between variables are concentrated between -0.55 and 0.71, and the cumulative variance contribution plot confirms the information utilization rate of the first six principal components. As shown in Table 1

Table 1 Principal Component Analysis Results

Variables/Principal Components	PC1	PC2	PC3	PC4	PC5	PC6
DCF(-1)	-0.41	0.12	-0.43	-0.10	0.37	0.08
TURN(-1)	-0.30	0.13	0.49	-0.41	-0.53	-0.19
IPON	0.41	0.15	-0.04	-0.21	0.24	0.82
IPOR(-1)	0.03	0.17	0.65	0.55	0.39	0.05
CCI(-1)	0.50	-0.20	0.11	-0.09	-0.09	-0.25
CPI	0.05	0.43	-0.33	0.58	-0.48	0.10
PPI	0.19	0.60	0.01	-0.17	-0.15 -	0.06
MECI(-1)	0.16	0.54	0.03	-0.31	0.31	-0.45
MS(-1)	0.52	-0.19	-0.14	0.00	-0.14	-0.09

Finally, the correlation coefficients between ISI indicators and 9 variables are shown in Table 2

Table 2 Correlation coefficients between investor sentiment (ISI) and various variables

variable	DCF(1)	TURN(1)	IPON	IPOR (-1)	CCI(-1)	CPI	PPI	MECI(-1)	MS(-1)
correlation coefficient	0.55	0.31	0.69	0.47	0.49	0.31	0.64	0.57	0.47

Further confirming its strong correlation lays the foundation for subsequent quantile regression model analysis of the impact of investor sentiment on financial credit scale, term structure, and allocation structure.

3.2. Credit data analysis and impact assumptions

This section is based on 271 monthly observations from the CSMAR database from January 2000 to July 2022, conducting a systematic analysis of credit scale, term structure, and allocation structure. In terms of credit scale, the average total loan amount is 68288.84 billion yuan, with a standard deviation of 56615.12 billion yuan, showing a peak to right skewed distribution (kurtosis -0.47, skewness 0.85), indicating that the loan increment has been below 0.5 trillion yuan annually since before 2008, and has exceeded 1 trillion yuan since 2015. The 2008 financial crisis led to the bottoming out of the increment, confirming the strong correlation between macroeconomics and credit markets; In terms of term structure, the average value of short-term loans (STL) is 232.151 billion yuan, with a variance of 2.27E+10, while the average value of medium - and long-term loans (LTL) is 4066.35 billion yuan, with a variance of 1.44E+11, both showing a sharp right skewed distribution, indicating that the proportion of STL continues to decline while the proportion of LTL steadily increases. After a brief adjustment from 2008 to 2015, the original trend continues. Analysis of the use of short-term loans shows that industrial loans have the largest proportion and are steadily increasing, while the proportion of commercial loans has been decreasing year by year, and the proportion of agricultural loans continues to rise, reflecting the policy's support orientation towards industry and agriculture; In terms of allocation structure, data from January 2015 to July 2022 shows that personal loans range from 23.57-73.86 trillion yuan, while institutional loans range from 59.43-132.99 trillion yuan, both exhibiting a peak to right skewed distribution (kurtosis -1.28 and -1.00). This indicates that the ratio of personal to institutional loans (PI) fluctuates and increases, but remains below 0.6, reflecting the advantage of institutional loans. The internal structure of personal loans shows that consumer loans account for over 60% of the total. The e-commerce trend drove their proportion to rise from 2015 to 2020, but gradually declined after 2020 with the adjustment of the economic situation. Based on theoretical mechanisms and empirical observations, three core hypotheses are proposed: H1- Investor sentiment has a positive effect on credit scale, with the scale expanding when sentiment is high and contracting when sentiment is low; H2- Investor sentiment has a negative impact on short-term credit and a positive impact on medium - to long-term credit. When sentiment is high, the proportion of short-term loans decreases and the proportion of medium - to long-term loans increases; H3- Investor sentiment has a negative impact on institutional loans and a positive impact on personal credit. When sentiment is high, the ratio of personal to institutional loans increases. The fourth chapter will empirically verify the above hypothesis through quantile regression models.

3.3. Construction method and empirical analysis of investor sentiment indicators

This study constructs a composite indicator of investor sentiment using principal component analysis, integrating direct and indirect indicator data to quantify sentiment fluctuations. The direct indicator is the Consumer Confidence Index, which reflects the subjective expectations of market entities towards the economic outlook; Indirect indicators include closed-end fund discount rates, trading volumes, IPO first day issuance volumes, and returns, capturing emotional signals in market behavior. To enhance the timeliness of indicators, macroeconomic control variables such as consumer price index, producer price index, macroeconomic prosperity index, and money supply are included to form a multidimensional dataset. After standardizing the data, the correlation between variables was analyzed through a correlation coefficient matrix, and a total of 9 original indicators were selected, including lagged variables and highly correlated variables for the current period. Principal component analysis showed that the cumulative variance contribution rate of the first six components reached 89.93%, meeting the requirements for information retention. The final investor sentiment index (ISI) is synthesized by weighting the contribution rates of each principal component, and the correlation test with the original variable confirms its effective capture of emotional characteristics. This indicator provides a core explanatory variable for the dynamic impact analysis of investor sentiment on financial credit scale, term structure, and allocation structure in subsequent quantile regression models.

4. Results and discussion

4.1. Hypothesis analysis of the impact of credit data characteristics and investor sentiment

This section is based on credit data from January 2000 to July 2022 for analysis. In terms of credit scale, the loan increment during the sample period showed an increasing trend, with a growth rate of less than 0.5 trillion yuan before 2008 and exceeding 1 trillion yuan after 2015; Descriptive statistics show that the distribution of credit scale is skewed to the right, with a median smaller than the mean, reflecting market volatility characteristics. At the level of term structure, both short-term loans and medium - to long-term loans exhibit a peak to right skewed distribution. The proportion of short-term loans gradually decreases over time, while the proportion of medium - to long-term loans continues to rise. After undergoing structural adjustments from 2008 to 2015, the original trend was restored. The analysis of short-term loan usage shows that the proportion of industrial loans is the highest and steadily increasing, while the proportion of agricultural loans has been increasing year by year, and the proportion of commercial loans continues to decline. In terms of allocation structure, data from January 2015 to July 2022 shows that both personal loans and institutional loans exhibit a peak to the right skewed distribution. The scale of personal loans is smaller than that of institutional loans, but the ratio of the two fluctuates and rises (always below 0.6), reflecting the accelerated development of personal credit; The proportion of consumer loans in personal loans exceeds 60%. From 2015 to 2020, the ratio of consumer loans to business loans increased, but gradually declined with changes in the economic situation. Based on theoretical mechanisms, three impact hypotheses are proposed: Hypothesis 1 suggests that investor sentiment has a positive effect on credit scale; Assumption 2 states that when emotions are high, the proportion of short-term loans decreases while the proportion of medium - to long-term loans increases; Assumption 3 indicates that emotions have a positive impact on personal credit and a negative impact on institutional loans. The next chapter will verify the above hypothesis through quantile regression models.

4.2. Model experiment

This article studies the impact of investor sentiment on the size, maturity structure, and allocation structure of financial credit through quantile regression models. Nine quantiles within the range of 0.05 to 0.95 are selected and modeled using Python software. The data is preprocessed (such as taking the logarithm of credit size and the first-order difference) to construct a three-dimensional analysis framework. The credit scale analysis takes investor sentiment (ISI) as the independent variable and credit scale increment[8] (OLI) as the dependent variable. The results show that all quantile regression coefficients are positive (gradually increasing from 0.1341 to 0.4413), indicating that investor sentiment has a positive impact on credit scale and the degree of influence increases with scale growth. The test results are significant ($P<0.05$), verifying the robustness of the model (as shown in Table 3)

Table 3 Inspection Results of Credit Scale

Quantile (r)	Coefficient estimation value	T-value (P0)	P-value (30)	Coefficient standard error	P-value (Pi)
0.05	0.0626	2.653	0.008	0.1341	0.000
0.15	0.1620	5.441	0.000	0.1987	0.000
0.25	0.2975	9.524	0.000	0.3830	0.000
0.35	0.3883	10.931	0.000	0.3285	0.000
0.50	0.5629	13.517	0.000	0.3305	0.000
0.65	0.8217	16.352	0.000	0.3614	0.000
0.75	0.9965	19.634	0.000	0.3169	0.001
0.85	1.2300	17.742	0.000	0.3821	0.007
0.95	2.1556	4.989	0.000	0.4413	0.009

In the analysis of credit term structure, the Short Term Loan Ratio (STL) [9] model shows that investor sentiment below the 0.95 percentile has a negative impact, and the negative effect increases with the increase of the percentile; Above the 0.95 percentile, there is a positive impact, and an increase in the absolute value of the regression coefficient reflects a gradual increase in the negative emotional influence on short-term credit development. The Long Term Loan Ratio (LTL) model[10] shows that below the 0.05 percentile, there is a negative impact, which then turns into a positive impact and the positive effect first strengthens and then weakens, reflecting the dynamic influence of emotions on the development of the medium and long-term loan market. The analysis of credit allocation structure takes the ratio of personal to institutional loans (PI) as the dependent variable, and the regression coefficients are all positive. The impact is the greatest at the 0.35 percentile, and then gradually weakens. The test results are significant (P<0.05), indicating that investor sentiment has a positive effect on the proportion of personal to institutional loans, and the impact shows asymmetry with quantile changes (as shown in Table 4)

Table 4 Quantile Regression Parameters of Short term Credit Test Results

Quantile (r)	Coefficient Estimate	T-value (P0)	P-value (30)	Coeff. Std. Error	T-value (βi)	P-value (Pi)
0.05	0.2992	63.413	0.000	-0.0540	-6.365	0.000
0.15	0.3245	72.618	0.000	-0.0557	-6.145	0.000
0.25	0.3482	76.367	0.000	-0.0627	-7.205	0.000
0.35	0.3574	69.259	0.000	-0.0590	-6.161	0.000
0.50	0.3732	63.478	0.000	-0.0527	-5.374	0.000
0.65	0.4151	48.250	0.000	-0.0835	-6.433	0.000
0.75	0.4841	39.337	0.000	-0.1145	-6.372	0.000
0.85	0.5290	43.324	0.000	0.1203	-6.689	0.000
0.95	0.6313	51.314	0.000	+0.0490	+5.233	0.000

In summary, the quantile regression model comprehensively reveals the dynamic impact mechanism of investor sentiment on various dimensions of financial credit through detailed characterization of different quantiles, and is superior to traditional linear regression and VAR models in terms of robustness, comprehensiveness, and simplicity.

4.3. Effect analysis

Empirical analysis shows that the impact of investor sentiment on financial credit has been validated in multiple dimensions. In terms of credit scale, the quantile regression model shows that the regression coefficients of investor sentiment are all positive, confirming the hypothesis of its positive impact on credit scale (H1). Specifically, there are differences in the impact coefficients at different percentiles: the 0.95 percentile (the TOP5 level with the highest credit scale growth) has the greatest impact, while the 0.05 percentile has the smallest impact (coefficient 0.1341), reflecting that the market was initially disturbed by multiple factors, and as the market matured, the influence of investor sentiment on credit scale gradually increased. For the credit term structure, quantile regression verified the negative impact of investor sentiment on the proportion of short-term loans and the positive impact on the proportion of medium - and long-term loans (H2). When the proportion of short-term loans is at or below the 0.85 percentile, the negative impact of increased investor sentiment is more significant (especially reaching its maximum at the 0.85 percentile); When the proportion of medium and long-term loans is below the 0.05 percentile, high investor sentiment will suppress its proportion, while above the 0.05 percentile, it will promote growth, and the 0.25 percentile has the greatest impact. The overall impact effect is weak, but it exhibits asymmetric characteristics at different quantiles. In terms of credit allocation structure, the quantile regression coefficients are all positive, supporting the hypothesis that investor sentiment has a positive impact on the ratio of personal to institutional loans (H3). Specifically, below the 0.35 percentile, the positive effect of increased investor sentiment gradually increases, reaching its maximum at the 0.35 percentile, and then showing a downward trend thereafter. The advantages of quantile regression models are reflected in three aspects: robustness (different quantile coefficients have the same direction and pass significance tests, which is better than the instability of general linear regression), comprehensiveness (can describe the direction, size, and dynamic process of the influence of different quantiles, discover asymmetry, and compensate for the limitation of general linear regression that only reflects mean changes, and is better than VAR models' fuzzy characterization of time ranges), simplicity (less restrictive conditions, not affected by outliers, stable number of variables and equation forms, better than general regression models' sensitivity to outliers and VAR models' dependence on stationarity and lag order). Overall, quantile regression outperforms general linear regression and VAR models in terms of robustness, comprehensiveness, and simplicity, making it more suitable for empirical analysis of complex financial data.

5. Conclusion

This article uses quantile regression to study the impact of investor sentiment on financial credit. The empirical results are summarized as follows: from the perspective of impact direction, investor sentiment has a positive effect on credit scale, and credit scale increases when sentiment is high; In terms of credit term structure, high emotions promote an increase in the proportion of medium and long-term credit, while low emotions promote an increase in the scale of short-term credit; Regarding the credit allocation structure, personal loans are positively influenced by emotions, while institutional loans are negatively influenced. From the perspective of impact effect, emotions have a significant impact on credit scale, while their impact on term structure and allocation structure is relatively weak. The impact is effective in the short term and gradually weakens in the long term, indicating that the lag of emotional influence is not significant. In terms of model application, quantile regression has significant advantages over traditional linear regression and VAR models: it has fewer data limitations, is suitable for complex financial data with non normal distribution and outliers, can more comprehensively characterize data distribution, and reflects the differential influence of independent variables on dependent variables through different quantiles, resulting in better explanatory effects. The limitations of the research are reflected in the completeness of constructing investor sentiment indicators (requiring higher frequency data and more variables) and the depth of applying quantile regression theory (requiring optimization of parameter estimation in conjunction with other models). Future research can combine machine learning and text mining techniques to construct more appropriate indicators of investor sentiment, and further improve quantile regression models to enhance parameter estimation robustness and deepen their application analysis in various fields.

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