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An Empirical Study on the Impact of Investor Gambling Factors on Stock Cross-Sectional Returns

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Abstract: This study explores how investors' gambling preferences affect the cross-sectional returns of stocks in China's A-share market through behavioral finance factors. The portfolio ranking method and Fama-Macbeth regression analysis show how gambling behavior affects stock returns. On this basis, a multi-factor model (CHG model) incorporating gambling factor innovation was constructed to capture market dynamics more accurately. Research shows that going long on a low gaming index stock portfolio and short on a high gaming index stock portfolio can achieve significant average monthly returns. After adjustment by the Fama-French three-factor model, the returns of this long and short portfolio are significant at the 1% level. Significantly. In the CHG model, the coefficient of the gambling index Gamble is -0.0241, and the t-statistic is -6.1858, which is significant at the 1% level, further confirming the negative impact of gambling preferences on stock returns. In addition, the CHG model's ability to explain anomalies is also better than the CH-4 model. This study provides a new perspective on understanding behavioral finance factors in the Chinese stock market, and the results highlight the importance of considering behavioral finance factors in asset pricing and investment decisions in a highly irrational market environment. Future research can further explore the performance of behavioral financial factors in different market environments, as well as the differences and similarities of behavioral factors in different markets.

Keywords: Empirical asset pricing, cross-sectional stock returns, multi-factor model, gambling behavior.

1. Introduction

Since establishing Markowitz's modern portfolio theory, classical financial theory has been widely used in actual capital markets. However, with the development of the capital market, the market efficiency assumption and the rational person assumption are no longer fully applicable to the market. Shiller, Kahneman, and others relaxed the assumptions of rationality and efficient market, drew on psychology, sociology, and behavioral theories, starting from the psychological state and actual behavior of investors, and analyzed and established models to explain anomalies. Some scholars began to explore theories such as investor sentiment, herding effect, and anchoring effect, and constructed factors based on investor behavioral characteristics and incorporated them into factor investment models for application [1].

China's A-share market fluctuates frequently, and irrational trading behavior is obvious. Investors are often driven by news and policies and are easily affected by group behavior. This has prompted Chinese scholars to enter the field of behavioral finance and improve their explanation of China's capital market. Gambling factors are gradually receiving attention as an angle to study individual investor behavior. This natural preference for risk plays an important role in financial markets. Since individual investors lack professional investment knowledge, the information they obtain often lags, causing their investment behavior to deviate from rationality, and the market price of assets to deviate from the intrinsic value, which often creates an innate speculative atmosphere and affects market stability and efficiency to a certain extent.

On the other hand, since the CAPM model was proposed, empirical asset pricing has gradually formed a complete research system. In 1993, Fama and French added two factors, HML and SMB, which represent cheap stocks and small market capitalization effects, to the market factors of the CAPM model, and proposed the famous three-factor model, which became an empirical model in the stock markets of various countries around the world [2]. The first choice for asset pricing research. Based on the Fama-French three-factor model, academic circles have successively added momentum factors, profitability factors, investment factors, management and performance factors, etc., providing huge value in explaining cross-sectional return differences in stocks. Liu et al. added the abnormal turnover factor to the market, scale, and value factors, proving anomalies that cannot be explained by the Fama-French three-factor model.

From a behavioral finance perspective, an increasing number of studies focus on the relationship between these deviations and returns. However, in this research field, there are still gaps in theoretical and empirical research on the impact of investors' gambling behavior factors on stock cross-sectional returns. Therefore, this article introduces factors about investors' gambling behavior to explore how the behavior driven by investors' gambling psychology will affect the cross-sectional returns of stocks and compares it with the Chinese version of the four-factor model proposed by Liu et [3]. The purpose is to demonstrate the explanatory power and predictive ability of the model, further illustrate the prevalence of gambling behavior in China's A-share market, and have practical guiding significance for constructing investment strategies for excess returns and improving the performance of investment portfolios.

2. Overview of Research Status

2.1. Existence of Investor Irrational Factors and Empirical Asset Pricing

Tversky proposed that people's perception of potential losses is greater than their perception of potential gains of the same size when making decisions, which is due to people's instinctive aversion to losses [3]. Shefrin and Odean discovered the disposition effect, in which individual investors tend to sell stocks whose value increases prematurely and hold on to stocks that lose money [4, 5]. Fama believes that individual investors, especially when facing market uncertainty or pressure, may show more risk-averse behavior [2]. This behavior may not be entirely based on actual changes in market fundamentals, but rather on the impact of perceived risk and other psychological factors. Wurgle proposed that investor sentiment significantly affects the cross-section of stock returns [6]. They argue that sentiment can lead to stock mispricing, particularly affecting younger, less profitable, and more volatile stocks. Wu analyzed the investment portfolio data of China's open-end funds and verified that China's open-end funds have significant herding behavior in the stock market [7].

Jegadeesh proposed the cross-sectional momentum anomaly, which was the most significant of many anomalies at the time [8]. Carhart therefore added the constructed cross-sectional momentum

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factor MOM to the Fama-French three-factor model and proposed the Carhart four-factor model [9]. Novy-Marx pointed out that profitability and expected return rate are closely related, and thus proposed a four-factor model including market factor, size factor, momentum factor, and profitability factor PMU [10]. Based on its three-factor model, Fama added profit and investment factors, improved the construction method of the scale factor, and proposed a new five-factor model [11]. Stambaugh-Yuan introduced management factors and performance factors based on market factors and scale factors, which was the first multi-factor model from behavioral finance [12]. Daniel et al. proposed two behavioral financial factors on both long and short-term scales, aiming to capture mispricing caused by overconfidence and limited attention [13]. Liu et al. specially designed a multi-factor model for China's A-share market. The model believes that individual investors dominate the Chinese stock market, holding 88% of the market's free-floating shares [3]. This heavy presence of individual investors makes Chinese stocks particularly vulnerable to investor sentiment. To capture this emotional effect, Liu added a fourth factor based on turnover rate to the model to evaluate changes in investor sentiment based on the overall market and the trading volume of individual stocks [3]. Research has proven that individual investor behavior and market sentiment play a very important role in the Chinese market.

2.2. Investor Gambling Behavior Literature

In 1988, Thale conducted a study on horse racing and lottery tickets and found that investors would still place bets and buy lottery tickets to obtain high returns when the expected return rate is known to be negative, that is, investors are willing to Choose to risk losing a small amount of money to obtain high returns [14]. This goes against the assumption of rational people because the expected rates of return on horse racing and lottery tickets are negative. Tverks explained investment gambling preferences based on cumulative prospect theory and confirmed a unique four-point model of risk attitude: risk aversion for high-probability gains and risk-seeking for high-probability losses; risk-seeking for low-probability gains and risk-seeking for low-probability gains. Risk aversion to low-probability losses means that investors are risk-averse on the one hand and seek risks in high-probability losses on the other [15].

Kummar conducted the first systematic empirical analysis of individual investors' gambling preferences and their preference for so-called "lottery stocks" (i.e., stocks with high potential returns but low probability, high risk, and high skewness) [16]. These stocks usually have low prices, high idiosyncratic volatility, and high idiosyncratic skewness, which is similar to the nature of buying lottery tickets in reality, that is, speculating on small gains and big gains. Kummar's research found that individual investors do tend to buy such lottery-type stocks, thus confirming the existence of significant gambling preferences in the market [16]. Furthermore, Kummar not only successfully identified lottery-type stocks by constructing a "stock betting index" that includes stock prices, idiosyncratic skewness, and characteristic volatility, but also revealed the correlation between the betting characteristics of these stocks and their returns [17]. Research shows that during bull markets, investors have stronger betting preferences for lottery stocks, further verifying the dynamic changes in betting preferences under different market environments. Kummar’s research deepens the understanding of the motivations of gambling behavior in the stock market and provides empirical support for how investors pursue high-risk, high-return investment opportunities in the market [17]. Research by Chen and others put forward the view that investors’ gambling behavior is significantly affected by profit and loss status and emotions [18]. By analyzing China's stock market data, it is found that when profits are in a state, investors are risk-averse and tend to avoid "gambling" stocks; while when investor sentiment is high, they prefer such stocks. This research not only reveals the existence of gambling behavior in the stock market but also points out the psychological motivations and market impacts behind it, providing a new perspective for understanding market anomalies.

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3. 3. Methodology

3.1. Portfolio Ranking Method

The purpose of the portfolio ranking test is to test the factor's expected return. Let $\{\lambda_t\}(t = 1,2,\ldots,T)$ represent the factor return time series, then the estimate, standard error and t value of the factor expected return are:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\lambda_t \tag{1}$$

$$\mathrm{s.e.}\left(\hat{\lambda}\right) = \frac{\mathrm{std}(\lambda_t)}{\sqrt{T}} \tag{2}$$

$$\mathrm{t-statistic} = \frac{\hat{\lambda}}{\mathrm{s.e.}\left(\hat{\lambda}\right)} \tag{3}$$

Among them, the estimate of factor expected return $\hat{\lambda}$ is the average return λ_t in period T. The standard error of expected return $\mathrm{s.e.}\left(\hat{\lambda}\right)$ is the standard deviation of λ_t divided by $\sqrt{T}$. The t value is the ratio of the estimate of the factor's expected return to its standard error.

Double sorting is to sort by two variables and build a factor simulation portfolio. Consider two sorting variables X_1 and X_2, divide the stocks into L_1 and L_2 groups from small to large according to these two variables, and obtain a total of $L_1 \times L_2$ combinations P_{ij}. Drawing on Fama's processing, two variables are often divided into quintiles [2]. If you go long on stocks that rank high on this variable and short on stocks that rank low on this variable, and meet fund neutrality, then the rate of return of factor X_1 in period t is:

$$\lambda_{X_1 t} = \frac{1}{L_2}\sum_{i=1}^{L_2} R_{L_1 i,t} - \frac{1}{L_2}\sum_{i=1}^{L_2} R_{1i,t} \tag{4}$$

Among them, $R_{L_1 i}$ and R_{1i} respectively represent the return rate of the group with the largest and smallest sorting variable X_1.

In the same way, the return rate of factor X_2 in period t is:

$$\lambda_{X_2 t} = \frac{1}{L_1}\sum_{i=1}^{L_1} R_{iL_2,t} - \frac{1}{L_1}\sum_{i=1}^{L_1} R_{i1,t} \tag{5}$$

Among them, R_{iL_2} and R_{i1} respectively represent the return rate of the group with the largest and smallest ranking variable X_2.

3.2. Fama-MacBeth Returns

Fama-MacBeth regression is a cross-sectional regression. Assuming there are N assets, it first obtains the exposure $\hat{\beta_i}$ of the asset to all factors through time series regression N times, and then performs OLS estimation on R and $\hat{\beta_i}$ respectively in each t period of each asset i (total T periods), and we get The estimate $\hat{\lambda}$ of the factor return in period t and the estimate $\hat{\alpha_i}$ of the residual. Finally, averaging them in time series is the factor expected return $\hat{\lambda}$ and the residual mean $\hat{\alpha_i}$. Its advantage is that it can eliminate the influence of the cross-sectional correlation of $\hat{\alpha_{it}}$ on the standard error.

3.3. α Test

The α test treats the residual α_i of each asset i independently and tests whether it is zero. After obtaining the test results of all α_i, they are averaged and used to evaluate the multi-factor model. For each asset used to test the multi-factor model, use its excess return as the explained variable, use the multi-factor model to be tested as the explanatory variable, perform time series regression, and estimate the standard error of its pricing error (usually when calculating the standard error using Newey–West adjustment). With $\hat{\alpha_i}$ and its standard error, calculate the t value. Under the null hypothesis, the multi-factor model can explain these assets, so $\alpha_i = 0$. The two evaluation indicators that the α test focuses on are $\hat{\alpha_i}$ and the mean of the absolute value of the t value. The lower these two indicators are, the better a multi-factor model can explain these assets and is therefore a "better" model.

3.4. Calculation of Gambling Index

To better reflect the irrational psychological behavior of investors when investing, especially those who are greedy for high risks and like to "take small to gain big", this article draws on Kumar's definition of gambling stocks and the proposed calculation method to construct the gambling index Gamble [14, 16].

First, do a Fama-French three-factor regression on the daily data of individual stocks in period t:

$$r_{i,d} - r_{f,d} = \alpha_{i,d} + \beta_{MKT,d}MKT_d + \beta_{SMB,d}SMB_d + \beta_{HML,d}HML_d + \varepsilon_{i,d} \tag{6}$$

The left side of equation (6) represents the expected excess return of individual stock i. $\mathrm{MKT_d}$,$\mathrm{SMB_d}$ and $\mathrm{HML_d}$ are daily market factors, size factors and value factors respectively.$\varepsilon_{i,d}$ is the daily regression residual of stock i.

Then based on $\varepsilon_{i,d}$, calculate the idiosyncratic volatility and idiosyncratic skewness of individual stocks in period t:

$$IVol_{i,t} = \left(\frac{1}{N_i(t)} \sum_{d \in S_i(t)} \varepsilon_{i,d}^2\right)^{\frac{1}{2}} \tag{7}$$

$$\mathrm{ISKew_{i,t}} = \frac{1}{\mathrm{N_i(t)}} \cdot \frac{\sum_{\mathrm{d \in S_i(t)}} \varepsilon_{\mathrm{i,d}}^3}{\mathrm{IVol_{i,t}^3}} \tag{8}$$

Among them, $S_i(t)$ represents the set of trading days for individual stock i in period t, and $N_i(t)$ represents the number of trading days for individual stock i in period t.

Finally, construct the gambling index Gamble:

$$Gamble_{i,t} = \left(\frac{IVol\_Rank_{i.t}}{N} + \frac{ISkew\_Rank_{i.t}}{N} + \frac{Price\_Rank_{i.t}}{N}\right)/3 \tag{9}$$

Among them, $IVol\_Rank_{i,t}$ is the ranking of stock i's idiosyncratic volatility in period t from small to large. $ISkew\_Rank_{i,t}$ is the ranking of the idiosyncratic skewness of stock i in month t from small to large. $Price\_Rank_{i,t}$ is the ranking of the average price of stock i in month t from large to small. This indicator ranges between 0 and 1. The closer it is to 1, the stronger the impact of investors' gambling behavior.

4. Empirical Results

This paper uses the data of China's A-share market from 2010 to 2022 as samples, and the sources are Guotai's database and the Reisi database. According to Liu's method of data processing, stocks with a market value of less than 30% and those with ST and PT were excluded in this paper, and necessary tailing processing was carried out after data consolidation [3].

4.1. Sorting Results

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Num	Mean	Sd	Min	Median	Max
Ret	1900	0.0076	0.0970	-0.1987	-0.0055	0.3660
Gamble	1900	0.5202	0.1616	0.1791	0.5137	0.8885
Beta	1900	1.0589	0.3157	0.3307	1.0406	2.0066
MV	1900	4.0122	0.8858	2.5074	3.8555	6.9351
BM	1900	0.5059	0.3353	0.0420	0.4299	1.8804
Moment	1900	0.0933	0.3440	-0.4427	0.0200	1.4908

Table 1 shows descriptive statistics of yield, betting index, Beta, market cap, book-to-market ratio, and momentum. The maximum value of the Gamble index is 0.8885, indicating that there are a large number of betting stocks in the sample range.

Table 2: Average monthly return rate of univariate ranking

Panel A: Equal weight					
Low	2	3	4	High	Low-High
Ret1	Ret2	Ret3	Ret4	Ret5	Ret(1-5)
0.0109*	0.0095	0.0082	0.0068	0.0023	0.0086***
(1.8713)	(1.6513)	(1.3926)	(1.1284)	(0.3650)	(4.4120)
Panel B: Market capitalization weighting					
Low	2	3	4	High	Low-High
Ret1	Ret2	Ret3	Ret4	Ret5	Ret(1-5)
0.0078	0.0048	0.0035	0.0037	0.0001	0.0077**
(1.4769)	(0.9039)	(0.6276)	(0.6322)	(0.0215)	(2.1432)

The t values adjusted by Newey-West are shown in parentheses.

Table 2 shows the results of the ranking test with betting index as a variable. Regardless of equal weight or market value weighting, it is found that there is a "low gambling effect", and the return rate of the portfolio decreases with the increase of the gambling factor. The average monthly return of the long-short combination constructed by long low betting index and short high betting index is very significant.

Table 3: Risk-adjusted returns for univariate ranking

	Low	2	3	4	High	Low-High
FREE	0.0089	0.0075	0.0063	0.0049	0.0003	0.0067***
	(1.5353)	(1.3053)	(1.0701)	(0.8040)	(0.0533)	(3.4373)
CAPM	0.0036	0.0021	0.0008	-0.0007	-0.0054*	0.0070***
	(1.2408)	(0.7649)	(0.2859)	(-0.2542)	(-1.7895)	(3.7560)
FF-3	0.0016	-0.0006	-0.0022**	-0.0041***	-0.0093***	0.0089***
	(1.2578)	(-0.6130)	(-2.4963)	(-4.2134)	(-8.7673)	(5.7170)
FFC-4	0.0017	-0.0005	-0.0022**	-0.0041***	-0.0092***	0.0089***
	(1.4342)	(-0.5939)	(-2.5524)	(-4.2343)	(-8.9995)	(5.6367)

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

FF-3 is a Fama-French three-factor model, and FFC-4 is a Carhart four-factor model.

Table 3 reports α returns for each of the five asset portfolios and their portfolio differences. Taking the Fama-French three-factor adjustment as an example, after adjusting risk, almost all T-values are greater than 2 in absolute value, and the adjusted return of the long-short combination is significant in all cases. This indicates that the relationship between the Gamble index and the expected stock return is of great economic and statistical significance.

Table 4: Returns adjusted for the FFC model of control scale

	Low	2	3	4	High	Low-High
L-MV	0.0101***	0.0067***	0.0063***	0.0033**	-0.0031*	0.0112***
	(5.1023)	(4.6728)	(4.2918)	(2.1739)	(-1.7293)	(5.6094)
2	0.0026*	0.0004	-0.0017	-0.0043***	-0.0097***	0.0104***
	(1.7503)	(0.3663)	(-1.2723)	(-3.8807)	(-7.2805)	(6.1088)
3	0.0018	-0.0041***	-0.0043***	-0.0089***	-0.0127***	0.0126***
	(1.1011)	(-3.4328)	(-3.0704)	(-7.5655)	(-8.5865)	(5.1117)
4	-0.0020	-0.0042***	-0.0062***	-0.0066***	-0.0117***	0.0077***
	(-1.3872)	(-3.1938)	(-4.4304)	(-4.6448)	(-6.9348)	(3.2867)
H-MV	-0.0008	-0.0034***	-0.0054***	-0.0063***	-0.0075***	0.0048**
	(-0.5065)	(-2.9949)	(-3.9043)	(-4.9775)	(-4.5612)	(2.0328)

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

Table 4 shows that after controlling the scale, the stock portfolio with a lower gambling index has a higher average monthly return, while the stock portfolio with higher gambling index has a lower average monthly return. A significant gain at the significance level of 1% can be achieved when taking a portfolio of stocks with a low betting index and shorting a portfolio of stocks with a high betting index.

Table 5: Fama-MacBeth regression results

	(1)	(2)	(3)	(4)	(5)
	FRFet	FRFet	FRFet	FRFet	FRFet
Gamble	-0.0184***	-0.0180***	-0.0197***	-0.0242***	-0.0241***
	(-4.4148)	(-4.3445)	(-4.9864)	(-6.1316)	(-6.1858)
Beta		-0.0038	-0.0031	-0.0026	-0.0030
		(-1.5424)	(-1.2776)	(-1.1483)	(-1.3182)
BM			0.0075**	0.0059*	0.0057*
			(2.3123)	(1.8350)	(1.9191)
Size				-0.0056***	-0.0057***
				(-3.0052)	(-3.1818)
Moment					0.0000
					(0.0042)
_cons	0.0152***	0.0188***	0.0163***	0.0411***	0.0417***
	(2.6317)	(3.4510)	(2.7478)	(3.5265)	(3.5874)
r2	0.0097	0.0197	0.0342	0.0575	0.0688
N	291241	291241	291241	291241	291241

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

When no control variables are added, the betting index is negatively correlated with the expected return of stocks, with a coefficient of -0.0184, which is significant at 1% level. When the control variables are gradually added, the size and significance of the coefficients are almost unchanged. Column (5) of Table 5 shows that when all control variables are added, the coefficient of the betting index is -0.0241 and the T-value is -6.1858, which is significant at the 1% level. The results in Table 5 show that when we control other factors, the betting index is negatively correlated with the expected return of stocks.

4.2. CHG four-factor model

The Chinese version of the four-factor model (hereinafter referred to as CH-4 model) proposed by Liu is as follows:

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{VMG}VMG_t + \beta_{PMO}PMO_t + \varepsilon_t \tag{10}$$

According to the research on gambling index in section 3.4, this paper proposes a four-factor model based on gambling index (hereinafter referred to as CHG model) :

$$R_t = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{VMG}VMG_t + \beta_{RMW}RMW_t + \varepsilon_t \tag{11}$$

Among them, RMW represents the gambling factor, and its structure is as follows:
W: Solid, Gamble's top 30% stock.
R: It's a risky Gamble. It's a stock in the bottom 30%.
M: Gamble is in the middle 40%.
Distinguish 2 groups according to market value, and then distinguish W, R and M groups within each group, a total of 2*3=6 groups, gambling factor RMW calculation formula is as follows:

$$RMW = \frac{1}{2}(SR + BR) - \frac{1}{2}(SW + BW) \tag{12}$$

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The correlation among the four factors of CHG model, namely R2, is statistically as follows:

Table 6: R-square-CHG model

Variable	Obs	Mean	Std. dev.	Min	Max
R2_MKT	294,344	.3852443	.2151377	2.64e-10	1
R2_MKT_SMB	290,144	.4946449	.2104541	8.98e-07	1
R2_MKT_VMG	290,144	.4876834	.2057607	.0000223	1
R2_MKT_RMW	290,144	.440165	.2089332	.0000165	1
R2_MKT_SMB_VMG	285,983	.539094	.1980376	.0013594	1
R2_MKT_SMB_VMG_RMW	281,884	.5656501	.1906807	.0060932	1

It can be seen from Table 6 that with the addition of factors, the mean value of $\boldsymbol{R^2}$ gradually increases, the minimum value gradually increases, and the standard deviation gradually decreases, indicating that the fitting effect is gradually getting better.

Table 7: Correlation among factors -CHG model

	MKT	SMB	VMG	RMW
MKT	1.0000			
SMB	0.1274	1.0000		
VMG	-0.2673	-0.5707	1.0000	
RMW	0.3795	0.2931	-0.5500	1.0000

As can be seen from Table 7, there is no significant correlation between the four factors, so the problem caused by factor collinearity can be ignored.

4.3. Comparison Between the CHG Model and the CH-4 Model

Table 8: Comparison of models for α test

	Alphas concerning	
Factors	CHG	CH-4
PMO	0.0008	-
	(0.4301)	-
RMW	-	0.0042***
	-	(-2.4627)

The t values adjusted by Newey-West are shown in parentheses.

As can be seen from Table 8, after α test, the T-value of CH-4 model explained by CHG model is not significant, and $\hat{\alpha}_i$is small. This means that we do not reject the null hypothesis, that is, we do not reject alpha =0. CHG can explain CH-4. On the contrary, when CH-4 is used to explain the factors in CHG, the T-value is significant at the 1% significance level, and the null hypothesis should be rejected, that is, α is significant not 0, that is, CH-4 is difficult to fully explain CHG.

In this paper, the anomaly constructed in Liu et al. 's original paper is selected and α test adjusted by White statistic is performed on the two models respectively, comparing the mean of the two models $\hat{\alpha}_i$, the results are as Table 9.

Table 9: CHG's interpretation of the vision

Category	Anomaly	α	t(α)
Panel A: Unconditional sorts			
Size	Market cap	-0.0013	-1.22
Value	EP	-0.004	-0.51
Value	BM	0.0023	0.49
Value	CP	-0.0002	-0.09
Profitability	*[1] ROE*	-0.0085	-1.08
Volatility	1-Month vol.	-0.0072	-1.29
Volatility	MAX	0.0065	0.48
Reversal	1-Month return	0.0022	0.44
Turnover	12-Month turn.	-0.0115	-1.16
Turnover	1-Mo. abn. turn.	-0.0008	-0.24
Panel B: Size-neutral sorts			
Value	EP	0.0004	0.29
Value	BM	-0.0016	-0.47
Value	CP	-0.0015	-1.11
Profitability	ROE	-0.0024	-1.1
Volatility	1-Month vol.	-0.0028	-1.17
Volatility	MAX	-0.0033	-1.37
Reversal	1-Month return	0.0033	0.87
Turnover	12-Month turn.	0.0071	1.13
Turnover	1-Mo. abn. turn.	-0.0122	-0.24
Average absolute value of α and t(α)		0.004163	0.7763

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

Table 10: CH-4 Explanation of the vision

Category	Anomaly	α	t(α)
Panel A: Unconditional sorts			
Size	Market cap	-0.001	-0.91
Value	EP	-0.0041	-0.61
Value	BM	0.0036	0.74
Value	CP	-0.0014	-0.61
Profitability	ROE	-0.0098	-3.33
Volatility	1-Month vol.	-0.0057	-1.39
Volatility	MAX	0.0052	0.77
Reversal	1-Month return	-0.0016	-0.34
Turnover	12-Month turn.	-0.0129	-0.53
Turnover	1-Mo. abn. turn.	-0.0026	-1.35
Panel B: Size-neutral sorts			
Value	EP	0.0006	-0.48
Value	BM	-0.0026	-0.75
Value	CP	-0.0006	-0.47
Profitability	ROE	0.0033	-1.39
Volatility	1-Month vol.	-0.0038	-1.54

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Table 10: (continued).

Volatility	MAX	-0.0041	-1.98
Reversal	1-Month return	0.0065	1.86
Turnover	12-Month turn.	-0.0077	-0.41
Turnover	1-Mo. abn. turn.	-0.0103	-0.74
The average absolute value of α and t(α)		0.0046	1.0631

Adjustments are made in parentheses for Newey-West's (1987) four-stage hysteresis.

Table 9 and Table 10 show the results of the interpretation ability of the CHG model and CH-4 model for all 19 anomalies, and the absolute average value of residual and mean residual respectively. It can be seen that the CHG model can explain all the anomalies that can be explained by CH-4, and the average value of the absolute residual error under the CHG model is about 0.0042, which is less than 0.0046 under the CH-4 model. The average value of the absolute T-value under the CHG model is about 0.78, which is smaller than 1.0631 under the CH-4 model. The explanatory power of the CHG model is higher than that of the Liu CH-4 model.

5. Conclusion

Through systematic discussion and empirical analysis, this paper deeply understands how investors' gambling psychology affects stock cross-sectional returns, especially the performance in China's A-share market. By constructing A four-factor model based on gambling behavior (CHG model), this study not only demonstrates the existence of speculative gambling behavior in China's A-stock market, but also reveals the significant role of gambling factors in asset pricing, and provides a new perspective to explain irrational behavior in the market and its impact on stock prices.

In comparison with the traditional CH-4 model, the CHG model in this paper shows higher explanatory power. This difference is mainly reflected in the fact that CHG model can more accurately capture those investment behaviors driven by gambling psychology, and effectively explain how these behaviors affect the cross-sectional returns of stocks through the market mechanism. This finding is of great significance to investors, which can help them understand the volatility of stock prices in highly irrational market environment, and serve as a reminder and warning to investors' irrational behavior.

In summary, the empirical research results of CHG model in China's A-share market emphasize the importance of considering behavioral finance factors in asset pricing and investment decisions. This provides important strategic and theoretical guidance for the future theory and practice of asset pricing, especially in the emerging market environment of developing countries. Future research could focus on the performance of behavioral finance factors in different market environments. For example, during periods of high market volatility or different types of market cycles, the behavior of investors may be significantly different, and the effects of the corresponding behavioral financial factors may also be different. This understanding of dynamic change helps to better leverage these behavioral factors when building more flexible and adaptable investment strategies. On the other hand, considering the connectivity of global financial markets, studying the differences and similarities of behavioral factors in markets in different countries and regions is also an area worth exploring. Comparing the effectiveness of behavioral finance factors across different markets can reveal how factors such as culture, market structure, and the regulatory environment affect investor behavior and asset pricing.

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Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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