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Empirical Evidence on Mispricing, Trading Volume, and Expected Stock Returns

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Abstract. This study investigates the impact of stock mispricing (MISP) on expected returns in China's A-share market, using monthly data from March 2008 to March 2025. The analysis further examines the moderating effect of trading volume, measured by turnover. Empirical results show that mispricing exhibits strong predictive power for future returns: undervalued stocks generate higher subsequent returns, while overvalued stocks yield lower returns. Moreover, trading volume plays an amplifying role—high volume accelerates price correction, making the relationship between mispricing and returns more pronounced.

Keywords: Mispricing (MISP); Expected returns; Trading volume; Amplification effect.

1. Introduction

Asset pricing has long been a central topic in financial research, aiming to identify the systematic factors that influence asset prices and expected returns. Since Sharpe (1964) proposed the Capital Asset Pricing Model (CAPM), Fama and French (1993) significantly improved its explanatory power by introducing the size and book-to-market factors [1]. However, subsequent studies revealed the persistence of anomalies such as momentum, investment, and profitability, suggesting that stock prices systematically deviate from their intrinsic values—commonly referred to as mispricing.

Stambaugh and Yuan (2017) developed a comprehensive mispricing measure (MISP) that effectively captures such deviations and demonstrated its predictive power for future returns across international markets [2]. Meanwhile, trading volume—an important indicator of market activity and information diffusion—may play a critical role in the price correction process. Han et al. (2022) further documented that trading volume can amplify the relationship between mispricing and future returns [3].

Building on these insights, this study examines China's A-share market to construct a localized MISP measure, evaluate its predictive ability for future returns, and analyze the amplifying roles of trading volume and idiosyncratic volatility. The findings provide new empirical evidence on market pricing efficiency in an emerging market context.

2. Literature Review

2.1. Research on Mispricing

Fama (1970) proposed the Efficient Market Hypothesis (EMH), which posits that asset prices fully and instantaneously reflect all available information. However, as numerous market anomalies such as the value effect and momentum effect have been identified, the universality of the traditional EMH has been increasingly challenged. Behavioral finance suggests that investor irrationality, information asymmetry, and limits to arbitrage may cause stock prices to deviate from their intrinsic values, thereby generating systematic mispricing.

There are three main approaches to measuring mispricing. The first is the relative valuation method, which assesses the degree of price deviation using indicators such as the price–earnings ratio (PE), price–book ratio (PB), or book-to-market ratio (BM). The second is the residual income model (Feltham & Ohlson, 1995), which estimates a firm's intrinsic value based on accounting information and compares it with the market price [4]. The third approach is the statistical method based on regression decomposition or abnormal returns, which captures risk-adjusted pricing deviations through model residuals or alpha values (Han et al., 2022) [3].

In recent years, Stambaugh et al. (2015, 2017) proposed a composite mispricing index (MISP) that integrates multiple anomaly signals to systematically capture stock price deviations [2,5]. This approach overcomes the limitations of single-indicator measures and has become a mainstream method for assessing mispricing, with strong empirical validation across different markets.

2.2. Mispricing and Stock Returns

Existing studies on the relationship between mispricing and stock returns can be broadly divided into three perspectives. First, based on the limits-to-arbitrage theory, Stambaugh, Yu, and Yuan (2015) argue that due to short-sale constraints and transaction costs, the price correction of overvalued stocks is slower than that of undervalued stocks, leading to a significant negative relationship between mispricing and subsequent returns [2].Second, from the perspective of investor sentiment, Baker and Wurgler (2006) find that during periods of high optimism, overvalued stocks tend to earn lower future returns, whereas undervalued stocks often generate excess returns when sentiment declines, suggesting that investor sentiment is an important driver of mispricing [6].

In the Chinese stock market, empirical evidence generally confirms a significant relationship between market anomalies and returns, though the persistence and explanatory power of these anomalies are weaker than those observed in mature markets (Liu & Pi, 2007; Lu, 2012) [7,8]. In recent years, some scholars have applied composite mispricing indices to evaluate China's pricing efficiency and found that mispricing can indeed predict future returns. However, the mechanisms amplifying this relationship have not yet been fully explored.

2.3. Trading Volume and Stock Returns

Trading volume is a key indicator of market liquidity and information responsiveness, exerting a crucial influence on price formation. Blume et al. (1994) argue that trading volume contains information not fully reflected in prices and can help investors improve their expectations [9]. In the Chinese market, Wu et al. (2002) find a bidirectional causal relationship between returns and trading volume, suggesting that volume partially captures the flow of new information [10].

More recently, Han et al. (2022) proposes the "volume amplification effect", which indicates that for undervalued stocks, high trading volume is associated with higher future returns, whereas for overvalued stocks, it corresponds to lower returns. This finding implies that trading volume may amplify the relationship between mispricing and returns [3]. Overall, trading volume not only reflects market activity but may also serve as an important channel linking investor behavior to price correction.

3. Research Design

3.1. Research Hypotheses

In asset pricing research, mispricing (MISP) reflects the deviation of stock prices from their intrinsic values and serves as a key indicator of market irrationality. Although the Efficient Market Hypothesis (EMH) suggests that prices fully incorporate all available information, factors such as bounded rationality, information asymmetry, and short-sale constraints often lead to predictable deviations from fundamentals.

Stambaugh and Yuan (2017) find that overvalued stocks tend to generate lower future returns, while undervalued stocks yield higher returns, indicating that MISP has significant predictive power for future returns [2]. Accordingly, this study proposes the following hypothesis:

H1: The greater the degree of mispricing, the lower the stock's future return.

Moreover, market liquidity may affect the speed of price correction. High trading volume reflects stronger investor attention and faster information dissemination, facilitating quicker price adjustment. Han et al. (2022) show that higher trading volume amplifies the return differences between undervalued and overvalued stocks [3]. Based on this, the second hypothesis is proposed:

H2: Trading volume amplifies the relationship between mispricing and future returns.

3.2. Variable Construction

3.2.1. Dependent Variable — Logarithmic Monthly Stock Return

In this study, the dependent variable is the logarithmic monthly return of individual stocks, which is calculated as follows:

$$R_{i,t}=\ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Where $R_{i,t}$ denotes the logarithmic return of stock i in month t, and P_t and P_{t-1} represent the closing prices at the end of months t and t–1, respectively.

3.2.2. Independent Variable — Mispricing Index (MISP)

To measure the degree of overvaluation or undervaluation of stocks, this study follows the approach of Stambaugh et al. (2017) and constructs a composite mispricing index (MISP) based on anomaly rankings, adjusted to fit the characteristics of the Chinese A-share market. Seven representative market anomalies are selected: Return on Assets (ROA), Gross Profitability (GPP), Investment-to-Assets Ratio (INA), Return on Equity (ROE), Composite Equity Issuance (CEIA), Momentum (MOM), and Short-term Reversal (REV).

For each stock, the overall mispricing score is calculated as the arithmetic mean of its decile rankings across the selected anomalies. Stocks with higher composite rankings are considered overvalued, while those with lower rankings are regarded as undervalued. The calculation formula is expressed as follows:

$$MISP_{i,t}=\frac{\sum_{x=1}^{k}Rank_{i,t,x}}{n} \tag{2}$$

Where $Misp_{i,t}$ represents the mispricing score of stock i in month t; $Rank_{i,t,x}$ denotes the decile rank of stock i on anomaly x in month t; and n is the total number of anomalies, which equals 7 in this study.

3.2.3. Moderating Variables — Trading Volume

Trading volume is an important variable that reflects market liquidity and investor behavior. Following Lo and Wang (2006, 2010) and Han et al. (2022) [11,12,3], turnover ratio is widely regarded as one of the most effective measures of trading activity. In this study, the natural logarithm of the average turnover ratio over the past three months is used as the proxy for trading volume, calculated as follows:

$$TO_{i,t}=\frac{SharesTraded_{i,t}}{SharesOutstanding_{i,t}} \tag{3}$$

$$\text{Volume}_{i,t} = \ln\left(\frac{1}{3}\sum_{k=0}^{2} \text{TO}_{i,t-k}\right) \tag{4}$$

Where $\text{SharesTraded}_{i,t}$ denotes the number of shares traded for stock i in month t, and $\text{SharesOutstanding}_{i,t}$ represents the total tradable shares of stock i at the end of month t.

3.2.4. Control Variables

Firm Size (Size): measured by the natural logarithm of the firm's market capitalization of tradable shares.

Book-to-Market Ratio (BM): the ratio of book value to market value, used to control for the value effect.

Beta: for each stock, the beta is estimated using monthly returns over the past 24 months based on the Fama and French (1993) three-factor model. The time-series regression is specified as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{smb,i}\text{SMB}_t + \beta_{hml,i}\text{HML}_t + \varepsilon_{i,t} \tag{5}$$

Where $R_{i,t}$ is the monthly return of stock i, $R_{f,t}$ is the risk-free rate, $R_{m,t}$ is the market return, and SMB_t and HML_t represent the size and book-to-market factors, respectively.

Price Range (RP): the difference between the highest and lowest prices of a stock within a given period, capturing return volatility.

Amihud Illiquidity (Amihud): a proxy for liquidity, defined as

$$\text{Amihud}_{i,t} = \frac{1}{D_{i,t}}\sum_{t=1}^{D_{i,t}} \frac{\left|R_{i,t,d}\right|}{\text{TradeValue}_{i,t,d}} \times 10^6 \tag{6}$$

Where $R_{i,t}$ is the daily return, $\text{TradeValue}_{i,t,d}$ is the daily trading value (in RMB), and $D_{i,t}$ is the number of valid trading days in month *t*.

3.3. Regression Model Specification

(1) To examine the impact of the mispricing index on expected returns, the following regression model is employed:

$$R_{i,t} = \beta_0 + \beta_{1,t-1}\text{MISP}_{i,t-1} + \epsilon_{i,t} \tag{7}$$

(2) To test whether trading volume amplifies the relationship between mispricing and stock returns, trading volume (Volume) and its interaction term are introduced:

$$R_{i,t} = \beta_0 + \beta_{1,t-1}\text{MISP}_{i,t-1} + \beta_{2,t-1}\text{Control}_{i,t-1} + \epsilon_{i,t} \tag{8}$$

(3) Based on the above specification, control variables are further incorporated:

$$\begin{aligned} R_{i,t} = {} & \beta_0 + \beta_{1,t-1}\text{MISP}_{i,t-1} + \beta_{2,t-1}\text{Volume}_{i,t-1} \\ & + \beta_{3,t-1}(\text{Volume}_{i,t-1} \times \text{MISP}_{i,t-1}) + \beta_{4,t-1}\text{Control}_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{9}$$

All variables are defined in Section 3.2.

3.4. Sample Selection and Data Sources

This study uses all A-share listed companies on the Shanghai and Shenzhen stock exchanges as the research sample. The sample period spans from March 2008 to March 2025, covering 204 monthly observations. The data are obtained from the RESSET database, including monthly stock returns, turnover rates, market capitalization, and relevant financial indicators.

To ensure data reliability, firms with missing return or financial information, those under special treatment (ST or *ST), and financial institutions are excluded. In addition, firms listed for less than one year are removed to mitigate the impact of abnormal fluctuations.

4. Empirical Results

4.1. Descriptive Statistics

To provide a comprehensive understanding of the sample characteristics, this study conducts descriptive statistical analysis on the main variables. The sample period spans from March 2008 to March 2025, with monthly frequency. Table 1 reports the mean, standard deviation, percentiles, and extreme values for each variable.

Table 1. Descriptive Statistics of the Sample

Variable	Mean	SD	p25	p50	p75	Min	Max
$R_{i,t}$	0.001	0.134	-0.071	-0.001	0.072	-1.618	2.621
MISP5	2.975	0.655	2.500	3.000	3.500	0.625	5.000
Size	17.605	1.083	16.850	17.422	18.180	12.933	22.656
RP	0.215	0.092	0.148	0.207	0.273	0.000	0.850
Amihud	0.061	0.207	0.009	0.022	0.045	0.000	3.139
BM	0.519	0.761	0.245	0.402	0.641	0.001	4.920
Volume	-1.254	0.945	-1.877	-1.257	-0.607	-3.539	0.695
Beta	1.034	0.293	0.838	1.013	1.303	-0.897	6.301

The results show that the average logarithmic monthly return ($R_{i,t}$) is 0.001 with a standard deviation of 0.134, indicating substantial variation in stock returns across China’s A-share market. The mean value of the core variable, MISP5, is 2.975—close to the quintile midpoint—suggesting that the mispricing index is relatively balanced across the sample. Other variables also fall within reasonable ranges, confirming that the dataset is well-behaved and suitable for subsequent empirical analysis.

4.2. Univariate Portfolio Analysis

To examine the predictive ability of the mispricing index (MISP5), stocks are sorted into five portfolios based on their MISP5 values. The results show a clear downward trend in portfolio returns as MISP5 increases: the most undervalued group exhibits the highest average return, while the most overvalued group yields the lowest. The High−Low portfolio return is −3.5% (t = −4.61), significant at the 1% level, indicating that higher mispricing is associated with lower future returns.

Table 2. Value-Weighted Portfolio Returns and Significance Tests Based on MISP5 Grouping

Group	Low	2	3	4	High	High-Low
Ri (%)	0.027	0.015	0.017	0.007	-0.008	-0.035
t value	4.52	2.67	3.01	1.32	-1.25	-4.61

Note: The values in parentheses represent t-statistics.

4.3. Bivariate Portfolio Analysis

Stocks are independently sorted into quintiles based on the mispricing index (MISP) and trading volume (Volume), forming 25 value-weighted portfolios. The results show that in the undervalued group, portfolio returns increase significantly with higher trading volume, with a High−Low return of 0.040 ($t = 5.41$). In contrast, returns in the overvalued group decrease as trading volume rises. Moreover, the return spread between undervalued and overvalued portfolios (U−O) increases from 0.019 to 0.071 across volume quintiles, indicating that higher trading volume amplifies the relationship between mispricing and future returns.

Table 3. Value-Weighted Portfolio Returns from Independent Sorting by MISP and Turnover

misp_group	Low volume	2	3	4	High volume	High - Low
Underpriced	0.016	0.028	0.033	0.046	0.056	0.040 (5.41)
MISP2	0.006	0.011	0.023	0.032	0.046	0.040 (4.87)
MISP3	0.000	0.007	0.017	0.021	0.028	0.028 (3.62)
MISP4	−0.007	−0.001	0.008	0.015	0.021	0.028 (1.71)
Overpriced	−0.003	−0.004	−0.011	−0.013	−0.015	−0.012 (−1.53)
U-O	0.019 (1.34)	0.032 (4.68)	0.044 (3.88)	0.059 (3.48)	0.071 (4.63)	0.052 (2.68)

Note: The values in parentheses represent t-statistics.

4.4. Fama–MacBeth Regression

To examine the predictive power of mispricing (MISP) on future returns and the amplification effect of trading volume, this study employs the two-step Fama–MacBeth (1973) cross-sectional regression.The results, shown in Table 4, indicate that the coefficients of MISP, Volume, and their interaction term MISP×Volume are all negative and statistically significant at the 1% level.This suggests that mispricing has a strong negative predictive effect on future returns. Moreover, higher trading volume intensifies this negative relationship by accelerating price corrections, reflecting a clear amplification effect.After controlling for firm characteristics, the results remain robust.

Table 4. Fama–MacBeth Regression Results

Variables	(1)	(2)	(3)
MISP	-0.0086 (-6.38)	-0.0067 (-4.52)	-0.0053 (-4.10)
Volume		-0.0073 (-4.89)	-0.0048 (-2.36)
MISP×Volume		-0.0064 (-4.59)	-0.0049 (-4.37)
Size			-0.0103 (-2.30)
BM			0.0035 (3.47)
Beta			-0.0028 (-1.93)
RP			0.0065 (1.94)
Amihud			-0.0068 (-1.37)

Note: The values in parentheses represent t-statistics.

5. Robustness Tests

5.1. Fama–MacBeth Regression

To verify the robustness of the results, this study replaces the baseline mispricing indicator (MISP5) with a decile-based mispricing measure (MISP10) and re-estimates the regression model. As shown in Table 5, the coefficient of MISP10 is −0.0085 (t = −4.92), significantly negative at the 1% level, confirming Hypothesis 1 (H1) that higher mispricing leads to lower future returns. Meanwhile, the interaction term MISP×Volume is −0.0029 (t = −4.41), also significantly negative, indicating that higher trading volume strengthens the negative relationship between mispricing and future returns, thereby supporting the presence of a robust amplification effect (H2).

Table 5. Fama–MacBeth Regression Using an Alternative Mispricing Measure (MISP10)

Variables	(1)	(2)	(3)
MISP10	-0.0085 (-4.92)	-0.0060 (-3.66)	-0.0045 (-3.40)
Volume		-0.0056 (-4.09)	-0.0037 (-2.05)
MISP×Volume		-0.0029 (-4.41)	-0.0024 (-4.12)
Size			-0.0101 (-2.18)
BM			0.0035 (3.52)
Beta			-0.0027 (-1.90)
RP			0.0063 (1.83)
Amihud			-0.0068 (-1.37)

Note: The values in parentheses represent t-statistics.

5.2. Robustness Test with an Alternative Moderator

To ensure the robustness of the findings, this study replaces the baseline trading volume measure (Volume) with the natural logarithm of the monthly turnover of tradable shares (Volume-d) and re-estimates the regression. As shown in Table 7, the coefficient of MISP5 is −0.0068 (t = −4.35), significantly negative, indicating that higher mispricing leads to lower future returns. The interaction term MISP×Volume-d is −0.0083 (t = −4.16), and remains significantly negative after adding control variables. This suggests that higher trading volume strengthens the negative relationship between mispricing and future returns, confirming a stable amplification effect.

Table 6. Fama–MacBeth Regression Results Using Volume-d as an Alternative Moderator

Variables	(1)	(2)
MISP5	-0.0068 (-4.35)	-0.0064 (-4.13)
Volume-d	-0.0056 (-3.03)	-0.0059 (-2.53)
MISP×Volume-d	-0.0083 (-4.16)	-0.0059 (-3.47)
Size		-0.0149 (-2.57)
BM		0.0018 (2.80)
Beta		-0.0062 (-2.17)
RP		0.0071 (1.84)
Amihud		-0.0080 (-1.53)

Note: The values in parentheses represent t-statistics.

6. Conclusion

Using a sample of Chinese A-share listed companies, this study examines the impact of mispricing (MISP) on expected stock returns. The results indicate that higher levels of mispricing are associated with lower future returns, confirming a significant negative predictive effect. Moreover, higher trading volume amplifies this relationship by accelerating price correction. Overall, the findings are robust, suggesting that market activity plays an important role in influencing the return effects of mispricing in the Chinese stock market.

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