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Research on the Amplification Effect of Trading Volume on Mispricing in the Chinese A-share Market

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Abstract: With the continuous growth of the economy, the residents' demand for preserving and appreciating family wealth has gradually become prominent. The stock market has become the primary choice for investors pursuing asset appreciation. Investors expect to achieve higher returns through scientific methods, and factor models, as well as mispricing, have become the focus of attention, aiming to obtain excess returns through market anomalies. However, with technological advances, the complexity of the market is increasing, making it increasingly difficult to find excess returns through pricing models. As trading volume is the most fundamental indicator in the market, containing many effective market insights and capturing investor disagreements, it is necessary to delve into the role of trading volume in the impact of mispricing on expected returns. This research selects all A-share stocks from 2000 to 2022, excluding the Sci-Tech Innovation Board, measuring mispricing through the anomaly in pricing models. Then, by independently double-sorting mispricing and trading volume into 5x5 portfolios, constructing market-weighted investment portfolios, and holding for one month, we observe the predictive ability of mispricing for future returns at different levels of trading volume. The results reveal that in stocks with high trading volume, the predictive ability of mispricing is stronger. Specifically, in stocks with high trading volume, the difference in future returns between the undervalued stock portfolio and the overvalued stock portfolio is greater than the difference in returns in low trading volume stocks. In other words, trading volume plays a moderating role in the impact of mispricing on expected returns, enhancing the predictive ability of mispricing on returns.

Keywords: Behavioral Finance, Efficient Market Hypothesis, Investor Rationality, Information Transparency, Market Efficiency, Stock Prices.

1. Introduction

With the continuous development of the Chinese stock market, the position of the stock market in the national economy has gradually become significant. By the end of 2022, the A-share market has reached a scale of 78 trillion yuan. With the continuous accumulation of residents' wealth and the growing demand for asset management, the stock market has also undertaken the task of preserving and appreciating residents' wealth.

The pursuit of higher returns by investors has become a significant trend in the market, and factor pricing models have gradually developed into important tools in the field of investment research. From the classical Capital Asset Pricing Model (CAPM) to the three-factor model proposed by Jianan (2019) for the A-share market in recent years, factor pricing models have made significant progress. Investors and researchers expect to use these factor pricing models to delve into the pricing mechanism of stocks in the market, finding stocks that are mispriced to gain excess returns.

However, despite the application of pricing models providing sophisticated tools for investors, with the continuous progress of technology, new model tools, and quantitative investment methods emerging, the complexity of the market is increasing. This makes it increasingly difficult to find excess returns through pricing models. Jacobs et al. (2020) found that when new pricing models are announced to gain excess returns, the excess return rate will show a decline in economic significance.

In addition to relying on traditional pricing models to find excess returns, researchers are actively exploring behavioral finance to find new research methods and gain a deeper understanding of the irrational behavior and psychological biases of market participants. Behavioral finance emphasizes the impact of investors' emotions and sentiments on market trends. Researchers assess investor sentiment by analyzing market anomalies, major news, corporate events, and macroeconomic changes. Chiang et al.'s (2010) study points out that due to information asymmetry and frequent policy interventions in the Chinese stock market, significant herding effects exist, meaning investors follow the decisions of others. Herding effects can lead to excessive investor behavior in the market, causing stocks or asset prices to deviate from their true values, forming market bubbles or excessive short selling, increasing market instability.

As trading volume is the most fundamental indicator in the market, containing many effective market insights, and capturing investor disagreements, it is necessary to delve into the role of trading volume in the impact of mispricing on expected returns.

Generally speaking, trading volume can measure stock market volatility, and volatility is the main source of risk in the stock market, and risk can affect the asset value of investors. In addition, according to Yufeng's (2022) research, it is found that trading volume can capture investor disagreements. Investor disagreements represent the cross-sectional standard deviation of expected deviations of investors (Atmaz et al., 2018). Incorporating the influence of trading volume into pricing models can achieve higher excess returns than the original pricing models.

Therefore, this paper aims to delve into the impact of trading volume and mispricing on the expected returns of stocks. This paper will analyze how these variables function in the Chinese A-share market to help investors better understand the market and provide practical information to guide investment decisions. In the context of information asymmetry in the stock market and investor limited rationality, the occurrence of mispricing issues is inevitable. As one of the key indicators of market activity, trading volume is worth studying for its impact on the expected returns of mispricing. By delving into the impact of trading volume and mispricing on expected returns, this paper is expected to provide more insights and recommendations for investors and regulators in the Chinese stock market.

2. Literature Review

The capital asset pricing principle holds that the intrinsic value of a stock is determined by the expected future discount rate and cash flow of the enterprise, which means that the discounted cash flow value of the future value of the company should be equal to the stock price. That is to say, for an efficient market, the price can reflect all public information. However, the stock market in reality is not an efficient market because of information asymmetry and limited arbitrage, and the stock price does not respond to all information changes. According to the theory of behavioral finance, there are deviations and disagreements in investor expectations, and retail investors are vulnerable to the interference of external environment and emotional factors, which aggravates the deviation of stock price from its intrinsic value. Therefore, based on the research and definition of the existing literature, this paper defines stock mispricing as the deviation between the stock price and its intrinsic value in the stock market. (Dong et al., 2012; You and Wu, 2012; Lu et al., 2017) (Dong, Hirshleifer, & Teoh, 2017; Lu, Rong, He, & Cui, 2017; You & Wu, 2012)

The development of China's stock market is not yet perfect, and the intrinsic value of stocks often deviates from the stock price. First, from the perspective of market trading system, China's limit system is relatively special, and it is difficult for stock prices to return quickly after deviating from the basic value. (Chen and Long, 2003; Wang and Wang, 2017; Huang et al., 2018) (Chen & Long, 2003; Huang Yuan, Xie Quanbin, & Hu Xin, 2018; Wang & Wang, 2017) In addition, as the stocks on the first day of listing are easy to obtain high returns, the phenomenon of investors "speculation of new shares" often occurs in the stock market. (Han et al., 2007; Song and Tang, 2019) (Song and Tang, 2019; Wu & Han, 2007). Although the short sale restrictions have been eased to some extent after the emergence of the margin trading system in 2010, on the whole, the balance of short selling is much smaller than the balance of financing, which is still far behind the developed stock markets such as the US stock market. Second, the development history of China's stock market is only a few decades, the market norms are not yet sound, and the quality of individual investors is uneven, which makes the phenomenon of information asymmetry very serious. In addition, according to the theory of behavioral finance, many investors in the market are not rational, and their investment decisions will be interfered by investment experience, investment literacy, psychological emotions and other factors, leading to the occurrence of mispricing. (You and Wu, 2012; Xu et al., 2015) (Xu & Xu, 2015; You & Wu, 2012) Finally, under the influence of macro uncertainties such as economic and political factors and national economic policies, China's stock market shows the characteristics of a "policy market," which reduces the credibility of stock market indicators and leads to more serious mispricing. (Xie et al., 2002; Zhu and Li, 2013; Dai and Yin, 2017) (Dai and Yin, 2017; Xie Baohua, Gao Rongxing, & Ma Zheng, 2002; Zhu & Li, 2013)

Asset price return rate and trading volume are the two most concerned indicators in the securities market. Early researchers tried to find a direct positive or negative relationship between volume and return. Su and Mai (2004) (Su and Mai, 2004) found a negative correlation. Therefore, stock liquidity is one of the factors in asset pricing. Zhou and Wu (2009) (Zhou and Wu, 2009) found a positive correlation, which changed with the change of stock size, and was more significant in small-capitalization stocks. This opposite conclusion exists not only in the domestic market, but also widely in other stock markets. Bajzik et al. (2021) (Bajzik, 2021) conducted a review study on the relationship between trading volume and price, and believed that different research methods would bring opposite conclusions, and publication bias would also distort the results. If Granger causality test is used to evaluate the relationship between turnover and returns, it will again be found that this relationship is weak or does not exist.

Obstacles stand in the way of directly studying the effect of volume on expected returns. The research of Atmaz et al. (2018) (Atmaz & Basak, 2018) pointed out a new direction, and he proposed the concept of belief dispersion in the stock market. The reasons for stock price deviation from intrinsic value are divided into average expectation deviation and investor disagreement. The average expected deviation is the average deviation of investors in the market. Investor disagreement is the dispersion of investors' beliefs, defined as the standard deviation of investor belief bias, using the cross-sectional standard deviation of investor disagreement as belief dispersion. Moreover, the divergence of investors' beliefs magnifies the average expected deviation of investors. On the basis of this theory, Yufeng Han et al. (2021) (Han et al., 2022) used mispricing level (misp) to capture the average deviation of investors' expectations, and used the average turnover rate of the past three months to capture the divergence of investors' beliefs. Market cap weighted portfolios are constructed by independent double sorting of mispricing levels and volume. The results show that the impact of trading volume on expected returns shows heterogeneity, and in undervalued stocks, trading volume is positively related to expected returns. In the case of overvalued stocks, the correlation is negative.

3. Data

This research sample covers all A-share stocks excluding the Science and Technology Innovation Board (STAR Market), including stocks listed on the main boards of the Shanghai Stock Exchange, Shenzhen Stock Exchange, ChiNext, and the Small and Medium Enterprise (SME) Board. In terms of the time span, the sample period starts from January 1, 2000, and ends on December 31, 2022. The choice to start from 2000 has two main reasons. Firstly, accounting standards gradually standardized and formed from 1999 onwards, and starting from 2000 ensures consistency in financial reporting. Secondly, starting from January 1, 2000, aims to ensure an ample number of samples and prevent statistical errors due to too few stocks or a too short sample period. The original data will be filtered based on the following principles:

(1) Excluding the 30% stocks with the smallest market value, according to the research of Jianan Liu (2019) (Liu et al., 2019), due to the unique IPO regulation in the Chinese market, the shell value problem will be caused, and the 30% stocks with the smallest market value will be disturbed by the

shell value pollution. As a result, the pricing model cannot reflect the difference in the expected return rate of the cross section of stocks. Therefore, in order to conduct in-depth research on the pricing mechanism of A-shares, it is necessary to discard the smallest 30% of companies by market capitalization.

(2) Excluding companies with abnormal financial conditions during the sample year, including ST, *ST stocks and PT stocks.

(3) Excluding the stock data in the first six months after IPO (including the listing month), because listed companies will be affected by many factors in the six months before IPO, such as IPO underpricing, which leads to a serious deviation of stock price from the actual value.

(4) Eliminating the stocks with missing data in the sample interval.

(5) Winsorizing the extreme values of all continuous variables at 1% and 99% can eliminate the influence of extreme outliers on the data structure.

(6) The rate of return is calculated by the closing price of the post-option. Post-restoration is to ensure that the historical price remains unchanged and adjust the current stock price after each stock equity change event, such as stock dividends. The post-option method can truly reflect the rate of return of investors.

All the data in this paper come from the CSMAR database, and the data processing and analysis are completed by Stata software.

4. Empirical Results

In academic research on market anomalies, double sorting is one of the most commonly used methods. To test whether new anomalies can achieve excess returns, scholars often use already researched factor variables and new anomaly variables for double sorting, thereby eliminating the influence of existing factors.

This paper forms 5x5 investment portfolios through the double sorting of mispricing degree and trading volume, with a monthly rotation of holdings for these 25 portfolios, held with market value weighting for one month. For further investigation, this paper constructs a new portfolio that buys the portfolio of stocks with the highest trading volume under the same mispricing degree (High volume group) and sells the portfolio of stocks with the lowest trading volume under the same mispricing degree (Low volume group), forming the H-L portfolio.

Table 1 shows the average returns for the 25 mispricing-trading volume investment portfolios for the next month. The results reveal that among the 5 portfolios of underpriced stocks, as trading volume increases, the average return also increases, ranging from 0.82% for the low trading volume portfolio to 1.65% for the high trading volume portfolio, with an average return of 0.83% for the H-L portfolio (t=1.71). Similarly, for the 5 portfolios of overpriced stocks, as trading volume increases, the average return decreases continuously, from 0.12% for the low trading volume portfolio to -0.65% for the high trading volume portfolio, with an average return of -0.77% for the H-L portfolio (t=-1.88). For portfolios with a moderate mispricing degree, although the average return of their H-L portfolio is not zero, it is not significant. Therefore, in underpriced stock portfolios, as trading volume increases, the expected stock returns also increase, while in overpriced stock portfolios, the expected stock returns decrease with the increase in trading volume.

Table 1. Average Returns of 5x5 Investment Portfolios

	Low volume	2	3	4	High volume	H-L
Underpriced	0.82	1.23	1.48	1.53	1.65	0.83(1.71)
2	0.85	1.02	1.2	1.29	1.44	0.59(1.23)
3	0.47	0.52	1.12	0.91	1.12	0.65(0.78)
4	0.22	0.13	0.09	-0.27	-0.38	-0.60(-0.79)
Overpriced	0.12	0.13	0.02	-0.15	-0.65	-0.77(-1.88)
UMO	0.70	1.10	1.46	1.68	2.30	1.6(2.90)
	(1.88)	(1.91)	(2.62)	(3.45)	(3.48)	

Based on the results in the table above, this study constructs a new investment portfolio. The portfolio buys stocks from the most underpriced group at the same trading volume level (Underpriced group) and sells stocks from the most overpriced group at the same trading volume level (Overpriced group), forming the UMO (Underpriced Minus Overpriced) portfolio. Since mispricing has predictive power for expected returns, the return of the UMO portfolio, representing the difference between underpricing and overpricing stocks, can be considered as a measure of the predictive ability of mispricing for future returns.

Observing the performance of the UMO portfolio, the difference in the Low Volume group is 0.70 (t=1.88), and in the High Volume group, the difference is 2.30% (t=3.48). In the UMO portfolio, as trading volume increases, the expected return also increases. The corresponding value in the H-L column is 1.60% (t=2.90), and the result is significant. This suggests that trading volume plays a significant amplifying role in the relationship between mispricing and expected returns. As trading volume increases, the predictive ability of mispricing for future returns gradually strengthens.

To study the duration of the volume adjustment effect, Table 2 presents the average return of the 25 portfolios based on mispricing and volume over the next 3 months, 6 months, 12 months, 24 months, and 36 months.

Table 2, group A, provides the average return of the portfolios for the next 3 months. The UMO portfolio's return increases from 0.20% (t=2.69) for low-volume portfolios to 0.78% (t=4.86) for high-volume portfolios, with an H-L portfolio return of 0.58 (t=3.65). Group B gives the average return of the portfolios for the next 6 months. The UMO portfolio's return increases from 0.06% (t=1.76) for low-volume portfolios to 0.68% (t=2.99) for high-volume portfolios, with an H-L portfolio return of 0.62 (t=2.84). Group C provides the average return of the portfolios for the next 12 months. The UMO portfolio's return increases from 0.17% (t=1.27) for low-volume portfolios to 0.57% (t=2.52) for high-volume portfolios, with an H-L portfolio return of

0.40 (t=1.83).

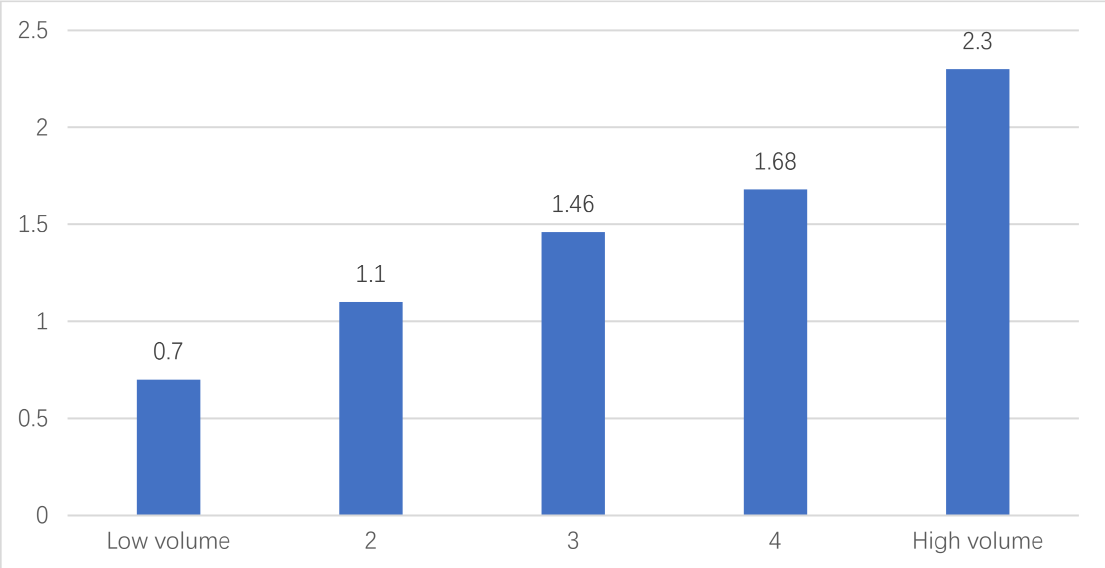

Figure 1. Average Return of the UMO Portfolio

It can be observed that over time, the t-values gradually decrease. By group D, the UMO portfolio's return increases from 0.13% (t=0.78) for low-volume portfolios to 0.31% (t=1.47) for high-volume portfolios, with an H-L portfolio return of 0.17 (t=1.35), no longer significant. In group E, the UMO portfolio's return of 0.12% (t=0.81) for low-volume portfolios is higher than the return of 0.09% (t=0.66) for high-volume portfolios, and the expected return no longer varies with volume.

The results indicate that the predictive power of the volume adjustment effect gradually diminishes over time, remaining significant up to 12 months but completely disappearing after 24 months.

Table 2. Average Returns of 5x5 Investment Portfolios

	Low volume	2	3	4	High volume	H-L
Panel A：Month t + 3						
Underpriced	0.05	0.04	0.07	0.11	0.40	0.14(2.30)
Overpriced	-0.15	-0.17	-0.18	-0.24	-0.38	-0.23(2.05)
UMO	0.20	0.21	0.25	0.35	0.78	0.58(3.65)
	(2.69)	(1.97)	(3.85)	(2.63)	(4.86)	
Panel B：Month t + 6						
Underpriced	-0.10	-0.01	0.17	0.29	0.33	0.43(2.24)
Overpriced	-0.16	-0.15	-0.27	-0.28	-0.35	-0.19(1.85)
UMO	0.06	0.14	0.44	0.57	0.68	0.62(2.84)
	(1.76)	(1.56)	(1.05)	(1.77)	(2.99)	
Panel C：Month t + 12						
Underpriced	0.02	0.11	0.04	0.24	0.26	0.24(1.96)
Overpriced	-0.15	-0.08	-0.11	-0.23	-0.31	-0.16(1.24)
UMO	0.17	0.19	0.15	0.47	0.57	0.40(1.83)
	(1.27)	(1.77)	(0.80)	(2.18)	(2.52)	
Panel D：Month t + 24						
Underpriced	0.03	0.07	0.16	0.09	0.13	0.10(0.96)
Overpriced	-0.10	-0.17	-0.13	-0.19	-0.18	-0.08(1.15)
UMO	0.13	0.24	0.29	0.28	0.31	0.17(1.35)
	(0.78)	(1.54)	(0.64)	(1.70)	(1.47)	
Panel E：Month t + 36						
Underpriced	0.06	0.13	0.11	0.12	0.08	0.02(0.67)
Overpriced	-0.06	-0.15	-0.13	-0.18	-0.01	0.05(0.49)
UMO	0.12	0.28	0.24	0.30	0.09	-0.03(0.90)
	(0.81)	(0.63)	(1.35)	(0.90)	(0.66)	

5. Conclusion

From the perspective of the volume-adjusted effect, this paper explores the impact of trading volume and mispricing on expected returns, finding that in stocks with high trading volume, the predictive ability of mispricing is stronger. In contrast to traditional literature, which tends to construct new factor models to attempt to gain excess returns from factor model pricing anomalies, this paper departs from the theory of investor belief divergence, using trading volume to measure investor divergence and discovering that stocks with larger trading volumes that are undervalued have higher expected returns. The research findings of this paper have certain implications for both investors and regulatory authorities.

For investors, the study reveals that stocks with high trading volumes have better predictive ability for mispricing. Therefore, when formulating investment strategies, investors should pay attention to trading volume as an important indicator for evaluating the potential returns of stocks. Especially for undervalued stocks with relatively high trading volumes, investors have a better chance of gaining excess returns. In addition, investors should not blindly follow the trend after seeing favorable news, as these messages may be influenced by mispricing, leading to false market signals. Rational investment is the key to long-term returns, and investors should maintain a rational analysis of market information, not being swayed by short-term market fluctuations. For stocks with high trading volumes, investors need to be more cautious in decision-making, fully considering the possible factors of mispricing, and thereby formulating better risk management strategies.

For regulatory authorities, this research reveals the regulatory role of trading volume in the relationship between mispricing and expected returns, helping regulatory authorities to more comprehensively understand the pricing mechanism in the market. Regulatory authorities can draw on the research results to further improve market supervision systems, guide the healthy and orderly development of the market, and enhance the efficiency and transparency of market operations. In times of significant market volatility, regulatory authorities can also strengthen monitoring of stocks with high trading volumes, promptly respond to potential market anomalies, and maintain market stability and fairness.

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