Is Buffett indicator priced in Chinese stock markets?

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Abstract

How to explain the return in China's A-share market is a popular topic. I found the individual stock data of Shanghai and Shenzhen A-shares from 1998 to 2023 and compute Buffett's indicators with cheapness, safety, and quality. Then, I construct portfolios and use Fama-Macbeth two-stage regression to compare the empirical performances of traditional factor models and added Buffett's factors into them to gain the extended factor model of excess returns in China's stock market. The results show that the BIF factor can explain the existence of excess returns in China's stock market; the factor model containing the Buffett factor is more suitable to be used as the pricing model of China's stock market than conventional.

Keywords: Six-factor model, BIF factor, Fama-Macbeth two-stage regression

JEL classification: G10, G11, G13, G14

1. Introduction

The stock market in China is the world?s second-largest, financing an economy that might be potential to be the world?s largest within a decade(Liu et al., 2019). However, China's stock market is highly volatile. For instance, the Shanghai Composite Index fluctuated a lot since the end of 2021, dropping below 3,000 points and hitting another new low(Xinwen, 2023). The volatile price fluctuations in the stock market in China might be due to the Chinese stock market is characterized by a high proportion of retail investors, with their trading volume accounting for over 85% of the total (Wen and Zhifeng, 2012). These highly volatile price fluctuations indicate high risks faced by investors in Chinese stock market. Therefore,

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it is urgent to investigate risk factors that drive volatile fluctuations in stock markets in China(Chen and Yuan, 2021),which is important for the stable development of Chinese stock market, and even the global financial markets given the background of globalization.

There is a large number of literature on explaining stock returns from a risk-return perspective, which is a classic research topic in asset pricing. It is well documented that Fama-French three-factor and five-factor models are most widely used asset pricing models to explain asset returns. Although these asset pricing models have demonstrated satisfactory performance in explaining stock returns in the USA, these models fail to explain stock returns in China (Liu et al., 2019). For instance, Guo et al. (2017) believed that compared to size profitability and value, Investment is redundant. In order to better capture the uniqueness of the Chinese stock market, several new risk factors have been proposed, including asset growth factor (Cooper et al., 2024) and liquidity factors (Safdar et al., 2019). However, these factors can only explain stock returns of a certain stock sector or in a certain period of time. This might be attributed to the shell value problem(Liu et al., 2019). For instance, backdoor listing of certain smaller listed companies has resulted in stock pricing that often reflects substantial value unrelated to the fundamental business of the company, which is a consequence of the regulatory framework governing initial public offerings (IPOs) in the Chinese stock market(Lee et al., 2017). Therefore, which risk factors can explain stock returns in China satisfactorily are not clear yet, which warrants further investigation.

In the paper, we aim to investigate new risk factors that are potential to explain stock returns in China from a risk-return perspective. It is widely accepted that Warren Buffett's investments can achieve relatively stable and high returns(Rajablu, 2011). The Buffett's success lies in the selection of inexpensive, less risky and higher quality stocks (Frazzini et al., 2013). Therefore, risks related to safety, cheapness, and quality might satisfactorily represents systematic risks in stock markets, which guarantees the profits of Buffett's investments. Accordingly, Frazzini et al. (2019) further constructs a risk factor related to safety, cheapness, and quality of investors by measuring their Leverage and investment style and suggest that this track record can explain the returns in U.S. stock market. However, the risk factor related to safety, cheapness, and quality of companies in Chinese stock markets is relatively unexplored in the existing literature but this classification method is acceptable. Due to the retail investors account more than those in the U.S., it is not reasonable to characterize and measure investor leverage to describe the returns of China's stock market(Giglio et al., 2022).

Therefore, we propose a risk factor related to safety, cheapness, and quality of companies and then investigate the explanatory ability of this risk factor for Chinese stock returns. To do so, we first construct a Buffett index relating to the three aspects of safety, cheapness, and quality of companies, following Frazzini et al. (2013). Following the common practice of literature on classic asset pricing factors, we construct a Buffett factor by grouping companies into several portfolios with double sorts of the size and Buffett indicator. For the Buffett factor, the Buffett indicator is bounded by the 30% and 70% quartiles, respectively. Since the Buffett index and expected returns are positively correlated, the Buffett factor (Robust-Minus-Weak, RMW) is constructed using the difference between the returns of the Quality (Quality, S/Q and B/Q) and Inferior (Inferior, S/I and B/I) groups. The Buffett factor is then defined as BIF(Buffet Index Factor). Then, we investigate whether the Buffett factor can explain stock returns in China, joint with traditional asset pricing factors, including stock market excess return, size, value, investment, and probability risk factors. In order to avoid the ideocratic risks of individual companies, we use portfolios as test assets.

Using data spanning 1 January 1998 to 31 December 2023, we have some interesting results. Generally, we find that the Buffett factor has the ability to explain stock returns in China, by adopting the assumption of time-varying risk premiums. The one-factor model only incorporating the Buffett factor outperforms the considered classic asset pricing models and the ones augmented with the Buffett factor. The Fama-French three-factor model augmented with the Buffett factor also perform satisfactorily. These results indicate that the Buffett factor represents a systematic risk factor and incorporates important risk information to explain stock returns in China. Besides, we conduct several robustness checks. Particularly, we examine the performance of asset pricing models considered in this paper during bull and bear periods in Chinese stock markets, and suggest that the one-factor model including the Buffett factor significantly outperforms the others. In addition, we test whether the results are sensitive to sample selection, by using the 2008 economic crisis turmoil as the cut-off point, find that the Buffett factor is still significantly priced. Finally, we check whether the assumption of constant risk loading matters to the results, by estimating time-varying beta with a rolling window of three years, and show that the results are still robust.

The main academic contributions of this paper are as follows: Firstly, we extend the literature on explaining Chinese stock returns, by proposing a Buffett risk factor related to safety, cheapness, and quality of companies, motivated by the Buffett investment. We provide new evidence that the Buffett risk factor represents a systematic risk in Chinese stock markets. Second, we add value to the literature on the Buffett factor. Different from Frazzini et al. (2013), which start from select stocks and leverage, we use company business data to measure the Buffett index, which make the Buffett factor more suitable to the stock market in China.

The following arrangement of this paper is as follows: the second section introduces the method of constructing Buffett's three factors and the method of testing the empirical analyses of this strategy; the third section introduces the data sources and the selection of indicators; the fourth section reports the results of the empirical study; the fifth section is the robustness test; and the last section provides some concluding comments.

2. Methodology

2.1. The principle of building Buffett's index

We use the quality factor to refer to the safe, cheap, and quality of a company. The quality factor corresponding to the Buffett indicator is denoted as BIF(Buffet Index Factor), and its components are described below.

For safety aspect, β and IVOL are used as measures and they show a negative correlation.

Equity risk is usually divided into systemic risk and non-systemic risk and beta is usually used to measure systemic risk, while specific risk (IVOL) is used to measure non-systemic risk. Based on Markowitz modern Portfolio Theory (Markowitz, 1952), investors hold diversified portfolios, and trait risk will be eliminated. Investors will be compensated only by taking on systemic risk. Therefore, β is calculated using the CAPM model based on the past 60 months, which is widely used in the research. In contrast to previous studies, Ang and Zhang (2006) proposed the widely accepted conclusion that stocks with high heterogeneous volatility have lower expected returns in the future, which is also observed in China. Fu (2009) also support this conclusion. Stambaugh and Yuan (2015) have portrayed heterogeneous volatility from two perspectives: arbitrage risk and arbitrage asymmetry. They defined mispricing metrics and found that there is a negative correlation between heterogeneous volatility and future expected return in the overpriced group, while the underpriced group shows a positive correlation. Schneider et al. (2019) suggestion of the opposite, which is yet to be questioned, should be excluded due to lack of evidence. Combining the above, this paper defines the chemical IVOL metric as the daily residuals. Through a three-factor model, this method calculates the volatility of the residuals. The residuals of the current month are multiplied by the total number of trading days in the month to determine the idiosyncratic volatility.

$$R_{it} - r_f = \alpha + \beta_{1i}\left(R_{mt} - r_f\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it} \tag{1}$$

$$IV_{i,t} = \mathrm{std}\left(E_{it}, d\right) \times \sqrt{N_t} \tag{2}$$

For cheapness aspect, we use measures of book-to-market ratio (BM), advertising expenditure (ADV), and research and development expenditure (RD) for analysis, and they show a positive correlation. According to Basu (1977), who used the CAPM model, low P/E stocks can outperform the market. ”P/E effect”, as found by Rosenberg and Lanstein (1985), shows a negative correlation between price-to-book ratio and stock returns. Fama and French (1993) found that stocks with high BM have, on average, higher expected returns.

Also, Hou (2022) suggests that the horizontal relationship between R&D intensity and equity returns is more likely to be attributed to risk premiums than to mispricing and the increase of RD will simulate returns. Madsen and Niessner (2019) studied advertising promotes a marginal improvement in liquidity by attracting investors' attention, which in turn constitutes a spillover effect of commercial advertising, which in turn boosts stock returns. This is because ADV and R&D expenses that are not capitalized can undermine current profits but enhance future return, however, investors often fail to realize this, leading to underestimation of companies with high ADV and R&D costs (Chan and Sougiannis, 2001). These indicators are considered to be positively correlated with Cheapness. In this case, we approximate the book-to-market ratio as the inverse of the price-to-return (PB) ratio calculation.

For quality aspect, we use Gross Profit Margin on Assets (GPOA), Accrued Compensation (ACC), and Net Operating Assets (NOA) as measures of quality. Asness and Pedersen (2014) suggests firms with high safety, well profitability, well growth and high level of payments are defined as high quality firms and it is found that such firms and returns show a positive correlation. Safety has been defined and we could use high GPOA to measure positive profitability (Novy-Marx, 2013), high ACC for negative growth because investors tend to overestimate the continuity of accrued income (Sloan, 1996), high NOA for negative payments level due to the fact that marginal investors do not realize high net operating assets have difficulty in maintaining current levels of profitability (Hirshleifer and Zhang, 2004).

Given that the original metrics for Safety, Cheapness, and Quality differ in measurement units, summing them directly would result in dimensional inconsistency. The construction of the HML factor in the Fama-French three-factor model employs standardized book-to-market ratios (Fama and French, 1993). Asness et al. (2019) demonstrate that equal-weighted aggregation of standardized portfolios inherently captures market pricing of heterogeneous risks, outperforming fixed-weight schemes. Furthermore, Hou et al. (2015) emphasize that factor construction should prioritize economic logic coherence over ex post statistical significance in weight calibration. Although our framework utilizes multiple financial indicators across these three dimensions, we deliberately avoid assigning subjective weights to individual metrics, as such arbitrary parameterization would introduce model specification bias. The equal-weighted aggregation of standardized Z-scores (Z1 + Z2 + Z3) essentially constitutes a "non-informative prior" Bayesian method. Crucially, the Z-scores inherently embed cross-sectional dispersion information from each dimension. Practically, the A-share market exhibits lower short-term pricing efficiency, rendering equal weighting preferable to mitigate overfitting to historical data—consistent with Warren Buffett's philosophy of "being vaguely right rather than precisely wrong." Additionally, rapid regulatory cycles and style rotations in China's market increase the fragility of fixed-weight models. The equal-weighted B-score dynamically adapts via Z-score normalization, enhancing robustness to environmental uncertainties (Chen et al., 2017). Synthesizing these considerations, our composite formula for each dimension is specified below. A summary of variable definitions is provided in Table 1.

Table 1: Description of variables

Name	Description	Method
BETA	beta	Coefficient of regression of each stock's excess return over the past 60 months on the market excess return from the Choice database
IVOL	heterogeneous volatility	Standard deviation of the residual term from regressing each stock's daily excess return over the past month on the Fama-French three factors
BM	Book-to-market ratio	The inverse of the price-to-book ratio
ADV	Advertising expenses	From Choice database, advertising and promotion expenses disclosed by listed companies
RD	Research and Development Expenses	From Choice database, R&D expenses disclosed by listed companies in the notes to their financial reports
GPOA	Gross Profit	(Operating Income - Operating Expenses) / Year-end Total Assets
ACC	Accrued profit	(net profit - operating cash flow) / total assets at year-end
NOA	Net Operating Assets	(Current Assets - Current Liabilities)/Total Assets at year-end
Cheapness	Cheapness	Cheapness=Z(Z(BM)+Z(ADV)+Z(RD))
Safety	Safety	Safety=Z(Z(BETA)+Z(IVOL))
Quality	Quality	Quality=Z(Z(GPOA)+Z(ACC)+Z(NOA))
B-index	B-index	B-index=Z(Cheapness)+Z(Safely)+Z(Quality)

2.2. Building the factors

To establish the extended factor model for analysis, we first build six factors including Fama-French 5 factors and Buffett's factor. The Fama-French five-factors (Fama and French, 2015) represents a significant theoretical tool in the field of finance, extending the CAPM (Capital Asset Pricing Model) by incorporating five additional risk factors: market risk (market factor), size risk (market value factor), book-to-market ratio risk (book-to-market ratio factor), profitability (profitability factor), and level of investment (investment factor). This enables a more comprehensive understanding of the factors influencing asset returns. The Fama-French five-factor model enhances the explanatory power and predictive accuracy of the CAPM by introducing these additional factors.

In order to construct value and size factors, Fama and French (1993) selected both BM and market capitalisation as company indicators and performed an independent double sorting with two variables and three categories. The first step in the classification of stocks is their division into two groups: large (B) and small (S). The basis for this differentiation is the market capitalisation of each respective stock. The value factor is defined in terms of the 30th and 70th percentiles of BM. In particular, small companies are classified into three categories based on their book-to-market ratios: high (S/H), medium (S/M), and low (S/L). Similarly, large companies are also divided into three categories based on their book-to-market ratios: high (B/H), medium (B/M), and low (B/L). The returns of each portfolio are calculated as the market value-weighted returns of the individual stocks within each group.

$$SMB = \frac{1}{3}(S/H + S/M + S/L) - \frac{1}{3}(B/H + B/M + B/L) \tag{3}$$

$$HML = \frac{1}{2}(S/H + B/H) - \frac{1}{2}(S/L + B/L) \tag{4}$$

In terms of the profitability factor, the ROE is defined by the 30th and 70th percentiles. The Dividend Discount Model (DDM) postulates that expected profitability is positively correlated with expected returns. In particular, small companies are classified into three categories based on their ROE: high (S/R), medium (S/N), and low (S/W). Similarly, large companies are also divided into three categories based on their ROE: high (B/R), medium (B/N), and low (B/W). Accordingly, the profitability factor (Robust-Minus-Weak, RMW) is calculated as the difference in returns between the robust (Robust, S/R and B/R) and weak

(Weak, S/W and B/W) groups.

$$\text{RMW} = \frac{1}{2}(S/R + B/R) - \frac{1}{2}(S/W + B/W) \tag{5}$$

With regard to the investment factor, the change in total assets is also defined by the 30th and 70th percentiles. In accordance with the DDM theory (Williams, 1938), the expected investment is inversely correlated with the expected returns. In particular, small companies are classified into three categories based on their change in total assets: high (S/A), medium (S/N), and low (S/C). Similarly, large companies are also divided into three categories based on their change in total assets: high (B/A), medium (B/N), and low (B/C). Accordingly, the investment factor (Conservative-Minus-Aggressive, CMA) is constituted by the discrepancy in returns between the conservative (Conservative, S/C and B/C) and aggressive (Aggressive, S/A and B/A) groups.

$$\text{CMA} = \frac{1}{2}(S/C + B/C) - \frac{1}{2}(S/A + B/A) \tag{6}$$

The study follows Fama and French (2015) in constructing the Buffett factor by weighted average of market capitalization outstanding using a 2×3 portfolio division method, and the other factors are constructed by referring to the Fama-French factor construction method. We do this classification annually to prevent overfitting of the data (Zhao, 2018). Besides, we aim to obtain factor exposures, which, if adjusted frequently, may lead to instability of the factor exposures, thus affecting the performance of the portfolios (Bender and Wang, 2015). The market capitalization is divided into 10 equal parts to exclude the smallest 30% of the market capitalization. We choose the median as the grouping point, so the first 50% is the small-sized group (S), the last 50 % is the large-sized group (B). Then we choose the 30th and 70th interquartile points, which are selected for the Warren Buffett grouping within the grouping of S and B respectively. After, they are recorded as low (BI, SI), medium (BM, SM), and high (BQ, SQ), and then obtained according to the following calculation methods

BIF factor.

$$\mathrm{BIF} = \frac{\mathrm{SQ} + \mathrm{BQ}}{2} - \frac{\mathrm{SI} + \mathrm{BI}}{2} \tag{7}$$

SQ denotes the small size (S) and high quality (Q) portfolio, and other symbol meanings analogously denote the difference between the monthly average return of the high value portfolio and the monthly average return of the low value portfolio after controlling for the size factor. Then, 50 portfolios are constructed by dividing listed companies into deciles according to each of the other five factors (SMB, HML, CMA, RMW, BIF).

2.3. Modelling and Test

Once the BIF factor variables have been obtained, the Buffett factor is added to the CAPM, Fama-French three-factor and five-factor models, respectively, to obtain the six-factor models that are the main focus of this paper. We constructed six risky factors as follows, $\mathrm{R_{i,t}}$ denotes the return of the asset in period t, R_{ft} denotes the risk-free rate, $R_{mt} - R_{ft}$ denotes the market risk premium factor MKT, and SMB denotes the size factor, HML is the book-to-market factor, RMW is the profitability factor with coefficient, CMA is the investment factor, BIF is the Warren Buffett factor; and α_t is the intercept.

$$R_{it} = \alpha_{it} + \beta'_i \lambda_t, i = 1, 2, ..., N \quad for \quad each \quad t \tag{8}$$

$$\hat{\lambda} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t \tag{9}$$

$$\widehat{\alpha}_t = \frac{1}{T} \sum_{t=1}^{T} \widehat{\alpha}_{it} \tag{10}$$

In constructing the 50 portfolios, different firm indicators were utilized, and companies were grouped according to percentiles each year. Companies are divided into 10 groups based on market capitalisation, book-to-market ratio, operating margin, investment and the Buffet index to obtain 50 portfolios. This process allowed for a refined analysis of investment portfolios by categorizing companies based on different indicators and annual percentiles.

Typical alpha tests can only test individual stocks. To test the stocks in a portfolio together, this paper uses the GRS test (Gibbons and Shanken, 1989). The GRS test is an important statistical test in stock analysis that is mainly used to test the risk factor pricing model of stock assets. It checks whether multiple intercept terms of asset regressions are jointly zero. In other words, the GRS test verifies that the pricing model fully explains the excess returns of all stock portfolios in the cross-section. Given the number of sample observations T and the number of portfolios N, the GRS test is highly accurate and produces very reliable results. The GRS test involves constructing an F-statistic based on the intercept term and residual term of the asset portfolio regression equation. The methodology determines whether the 100 intercepts are jointly 0 or not after the regression of each factor as a risk factor on the OLS regression of the 100 stock portfolios. This is done under the original hypothesis as follows,

$$\mathrm{H}_0: \quad \alpha_1 = \alpha_2 = \ldots = \alpha_{100} = 0 \tag{11}$$

where the joint test of the intercept terms of all portfolio regressions should not reject the original hypothesis of a simultaneous 0 if the pricing model can fully explain the excess returns of all stock portfolios The smaller the value of the GRS statistic, the smaller the unexplained portion of the stock returns inside the stock returns, implying that the current model's pricing factors are more efficient for the market and more closely resemble the true stock returns.

2.4. Fama-Macbeth two steps regression

In factor studies, the calculation of factor returns is primarily based on three methods: time-series regression, cross-sectional regression, and Fama-Macbeth regression. In time-series regression, factor returns, calculated using simulated portfolios constructed by grouping, are employed as independent variables, while the excess returns of assets are utilised as dependent variables. This method is appropriate for the calculation of style factors (e.g. financial indicators). The cross-sectional regression method comprises two stages. Initially, time-series regression is conducted for each asset, utilising excess returns and multiple factor values to derive the regression coefficients, otherwise known as factor exposures. Subsequently, at period T, the factor exposures of each asset obtained in the first stage are employed as independent variables, while the mean excess returns of the preceding T periods are used as dependent variables in cross-sectional regression. The resulting regression coefficients are designated as factor returns λ.

However, both methods are susceptible to the issue of standard error bias due to cross-sectional correlation. As Petersen (2009) notes, two principal types of correlation must be considered in the context of panel data: time-series correlation, which pertains to the correlation within each individual over time ($Cov(X_{i,t}, X_{i,s}) \neq 0$), and cross-sectional correlation or time effect, which concerns the correlation between different individuals within the same time period ($Cov(X_{i,t}, X_{j,t}) \neq 0$). The presence of these correlations gives rise to issues with the standard errors of regression coefficients estimated by Pool Regression. Cochrane (2005) emphasises that there is a significant probability of cross-sectional correlation in asset prices. When one asset demonstrates a high excess return in a specific month, it is probable that another asset will also exhibit a high excess return in the same month. The Fama-Macbeth regression method effectively addresses this issue by ensuring that cross-sectional correlation does not introduce errors into the computation of standard errors in cross-sectional regressions.

The 50 portfolios were constructed for a Fama-Macbeth two-stage regression as we said before. The seven models included CAPM, FF3, FF5 and factor models after incorporating BIF, as well as regression on the BIF alone. The two-stage regression theory proposed by Fama and MacBeth (1973) is a general methodology used by econometrics in the field of asset pricing. The Fama-Macbeth regression offers the advantage of enabling the exclusion of the effect of the correlation of $\alpha_{i,t}$ on the standard error. Furthermore, the method allows for the neat exclusion of the effect of the correlation of random perturbations in the cross section on the standard error. Therefore, we used this method to measure our factors.

The basic idea of this approach is to combine time series and cross-sectional data in a two-stage regression analysis. In the first step of the time series regression, the Fama-Macbeth two-stage regression is therefore able to effectively deal with the heteroskedasticity and autocorrelation of the cross-sectional data, thus improving the accuracy of the parameter estimates. The initial stage of the process is analogous to a rolling window cross-sectional regression. A cross-sectional regression is performed for each time point t, and the exposure of each portfolio to the factors in each model is obtained through time series regression β_i. Specifically, the returns of each stock at time t are first calculated, and then these returns are used as the dependent variable in a regression with pre-determined values of the six factors to obtain the regression coefficients at each time point t, where it is assumed that each time point's risk exposure is constant.

In the second stage, the regression coefficients obtained in the first stage are used as new dependent variables, and a cross-sectional regression is performed on them. This provides the average regression coefficients for each factor, which are the final parameter estimates of interest. It is important to note that there is a significant difference between Fama-Macbeth two-stage regression and general cross-sectional regression. In the general cross-sectional regression, the returns of each stock are usually averaged and then the regression is run using this average return. However, in Fama-Macbeth two-stage regression, each time point t is treated as a separate observation, and these observations are then regressed. This approach allows for a more accurate analysis of the data. This method has the advantage of providing more accurate estimates of standard errors, allowing for a more precise assessment of parameter significance.

3. Data

3.1. Data Sources

This paper selects stock from equity market of Shanghai and Shenzhen, including the main board, the STAR(The Science and Technology Innovation Board, STAR Market), and the GEM(Growth Enterprises Market), as the objects of empirical research. The sample period is from 1 January 1998 to 31 December 2023, and the original data is from the financial database called CSMAR. CSMAR database represents the inaugural domestic economic and financial database of its kind. It has been developed by drawing on the professional standards of CRSP at the University of Chicago, Standard & Poor's Compustat and other internationally renowned databases, and combining these with China's actual national conditions. The Cathay Pacific CSMAR financial data set encompasses China's stock market, company research, a listed company financial database, a financial notes database and so forth. The data quality is standardised. This database use different methods, including manual proofreading, database constraints, and strict process controls, to ensure the accuracy and reliability of the data. They also apply various balancing and empirical formulas to check the data for legitimacy, consistency, and statistical aspects.

The original data spans from 1990 to 2023, while the data used to calculate the six factors, after excluding missing data, spans from 1998 to 2023. Although the Chinese stock market started in 1990, there were fewer listed companies in the early days and the 10% limit on upward and downward movement started in December 1996, so after 1998 there were more listed companies in the Chinese stock market and the environment was relatively more stable. The grouping occurs at the end of June each year.

Due to the forward-looking bias and relevant Chinese securities laws, annual reports of listed companies cannot be used until May of the following year, as the publication month of the annual report is in April. Therefore, the book value is used as the book owner's equity at the end of December of the previous year(t-1). This calculation is based on the monthly A-share sample in April of the year t. The average market value is then measured. Although there is no standardized criterion for choosing the period over which beta is measured, data providers such as Standard & Poor's and Value Line are often referenced. They typically use monthly returns over the past five years to determine β, which is generally considered a comprehensive reflection of a security's performance in different market environments, hence we use 60 months' window to calculate β .

3.2. Data on company fundamentals

The Capital Asset Pricing Model (CAPM) is employed in order to derive the excess returns of stocks. Fixed deposits are typically considered to be one of the most secure investment instruments. One-year fixed deposits, being relatively short-term and highly liquid, are considered to more accurately reflect the market's risk-free interest rate and are widely accepted as the standard for measuring it. The market returns are calculated using the market value-weighted average method, which takes into account cash dividend reinvestment. The selected market type is that of the Chinese A-share market. The following data have been excluded from the analysis: stocks with ST and PT trading statuses, financial stocks, stocks with negative book values, data within the first six months post-IPO (including the listing month), and records with missing return data. The CAPM model has been applied to calculate the excess returns and the MKT factor, using the regression coefficients of the excess returns of each stock over the past 60 months relative to the excess returns of the SSE index, in order to derive the beta coefficients.

$$E(R_i) = R_f + \beta(R_m - R_f) \tag{12}$$

The company's fundamental data are derived from the balance sheet and income statement. Book value is defined as the company's book equity at the conclusion of the preceding fiscal year, whereas the term 'market value' refers to the total market value of the company at the end of the previous year. The annual market value is calculated as the mean of the market values observed in June of the grouping year, which are then categorised into circulating market value and total market value. The operating profit margin is defined as the ratio of operating profit to equity, while investment is defined as the growth rate of total assets, representing the difference between the current and previous periods' total assets divided by the previous period's total assets.

3.3. Measurement of the Buffett factor

The metrics we used follow description in the previous. It is worth noting that the beta estimation we used to measure IVOL methodology uses the monthly regression of Fama and MacBeth (1973) to ensure objectivity and precision. To ensure statistical accuracy, the data is standardized(denoted by Z) to construct indicators and dimensions. Table 1 shows the definitions and calculations of these indicators.

3.4. Descriptive statistics of variables

Based on the descriptive statistics presented in Panel A in Table 2, we observe notable results from the construction of the Buffett Factor and the 2×3 portfolios. The average monthly returns vary significantly, ranging from -0.157% for the BI portfolio to 1.895% for the SQ portfolio. Notably, these returns exhibit high volatility, as indicated by standard deviations ranging from 7.551% for BI to 9.589% for SQ. The range of returns is also substantial, with minimum returns between -32.145% for SM and -26.674% for BI, and maximum returns between 32.924% for SI and 42.810% for BI. These observations suggest that the BIF, derived from financial data and characteristics of stocks that are inexpensive and of high quality, demonstrates significant variation in returns across different size and value-quality dimensions. Consequently, the BIF factor, along with other traditional factors, appears to be capable of explaining cross-sectional variations in stock returns.

Panel B details the descriptive statistics for six factors over a specific period. The market factor (MKT) shows a relatively high average return of 0.635%, yet it carries the highest risk level with a standard deviation of 7.726%, indicating substantial market volatility. In contrast, the classic SMB and HML factors have lower average returns (0.536% and 0.237%, respectively) but also lower risk levels (standard deviations of 4.282% and 3.905%, respectively), suggesting they can provide more stable premiums for investment portfolios. The RMW and CMA factors, based on firm fundamentals, present relatively low average returns (0.068% and 0.079%, respectively) with moderate risk levels, indicating potential diversification benefits. Notably, the BIF factor exhibits the highest average monthly premium

(1.435%) with a contained risk level (standard deviation of 2.059%), highlighting the excess return opportunities from investing in high-quality companies.

Panel C shows the results of correlation analysis among the six factors. The correlation coefficients between BIF and the other factors are generally low (absolute values below 0.3), indicating low correlation. BIF is negatively correlated with SMB, HML, and CMA. In contrast, the correlation coefficient between SMB and RMW is relatively high (absolute value greater than 0.6), indicating a strong correlation. Overall, the low correlations among these factors suggest they provide different information for explaining asset return movements. Specifically, the low correlation between BIF and the base factors implies that the risks associated with percentage returns may be independent of the risks represented by traditional asset pricing factors.

Figure 1 visually illustrates the returns of the portfolios utilized in the analysis, spanning the period from January 1998 to December 2023, encompassing a total of 312 monthly observations. At the end of April each year, portfolios were constructed by sorting stocks into 50 groups based on five distinct characteristics: market capitalization, book-to-market ratio, operating profitability, investment, and the Buffett indicator. The average return of each portfolio is plotted as a scatter plot, ranging from -4% to +4%. The figure shows that the data points are not clearly clustered, but fluctuate around 0, indicating a lack of a clear linear relationship and some randomness in their distribution. This pattern suggests that the performance of these portfolios, although constructed from the same quantile points, varies due to differences in the specific assets included. It is therefore worth investigating complex risk factors to explain the observed return patterns.

4. Results

This section presents the results of the empirical analysis of the calculation method described in Section 3. The central research question of this paper is whether Buffett's value investment approach can explain the excess returns in the A-share market. To test this

Table 2: Descriptive statistics of variables

Panel A: MKT-BIF 2 × 3 Portfolios						
Portfolios	Obs.	Mean	Std.	Min	Median	Max
SQ	312	1.895	9.589	-30.278	1.563	34.282
SM	312	1.111	9.472	-32.145	0.324	36.409
SI	312	0.068	8.894	-31.603	-0.191	32.924
BQ	312	0.887	7.940	-27.758	0.449	41.881
BM	312	0.718	8.346	-30.874	0.294	36.187
BI	312	-0.157	7.551	-26.674	-0.651	42.810
Panel B: Descriptive statistics of the six factors						
Factors	Obs.	Mean	Std.	Min	Median	Max
MKT	312	0.635	7.726	-26.835	0.486	36.159
SMB	312	0.536	4.282	-21.203	0.631	21.028
HML	312	0.237	3.905	-19.696	0.029	20.007
RMW	312	0.068	3.264	-14.357	0.050	14.717
CMA	312	0.079	2.242	-6.028	-0.006	9.956
BIF	312	1.435	2.059	-5.518	1.265	8.530
Panel C: Six-factors correlation analysis						
	MKT	SMB	HML	RMW	CMA	BIF
MKT	1.000					
SMB	0.138	1.000				
HML	-0.101	-0.357***	1.000			
RMW	-0.314**	-0.714***	0.038	1.000		
CMA	0.079	0.233**	0.443***	-0.589***	1.000	
BIF	0.249*	-0.049	-0.172**	0.108	-0.127	1.000

Notes: Panel A is the monthly summary statistics of portfolios constructed from the BIF(Buffet Index Factor) and the 2 × 3 portfolios. Panel B is the monthly summary statistics of risk factors. BIF is the Buffet Index Factor. MKT is the stock market excess return factor. SMB is the size factor. HML is the value factor. MOM is the stock momentum factor. RMW is the profitability factor. CMA is the investment factor. The sample period spans from January 1998 to December 2023. Panel C is the six-factors correalation analysis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Significance levels in Panel C are illustrative based on conventional thresholds. Actual significance requires calculation via $t = r\sqrt{(n-2)/(1-r^2)}$ with n as sample size. The monthly stock return used in the table with cash dividend reinvestment is calculated using the following formula: $r_{n,\ t} = \frac{P_{n,\ t}}{P_{n,\ t-1}} - 1$, where $P_{n,\ t}$ represents the adjusted closing price of stock n on the last trading day of month t, incorporating cash dividend reinvestment, and $P_{n,\ t-1}$ represents the corresponding adjusted closing price on the last trading day of month $t-1$.

question, Fama-Macbeth two-stage regression, GRS test, and other methods are used.

4.1. Fama-Macbeth time series regression

The Appendix A reports the results of the Fama-Macbeth first-stage regression. In the model that only includes the MKT factor, the portfolios R1-R40 show significant factors while the intercept term is not significant. This suggests that the MKT factor explains the excess returns. For portfolios R41-R50, which are constructed based on the Buffett factor, both the MKT and intercept terms are significant. This indicates that the MKT factor alone does not

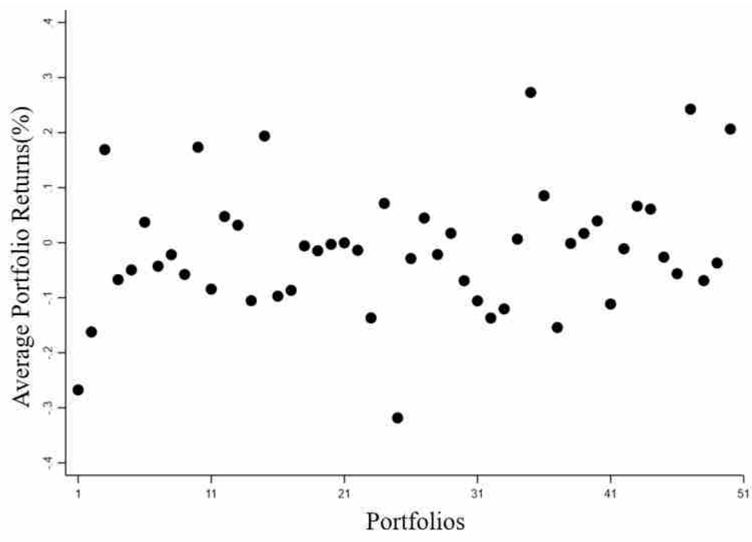

Figure 1: Scatterplot of the portfolio's return

*Note:*The scatter plot illustrates the returns of the portfolios utilized in the analysis, spanning the period from January 1998 to December 2023, encompassing a total of 312 monthly observations. At the end of April each year, portfolios were constructed by sorting stocks into 50 groups based on five distinct characteristics: market capitalization, book-to-market ratio, operating profitability, investment, and the Buffett indicator. Specifically, market capitalization is defined as the tradable market value of individual stocks at the time of sorting; the book-to-market ratio is calculated as the ratio of total equity reported in the annual financial statements to the market capitalization; operating profitability is derived as the ratio of operating profit to total equity from the annual report; investment is computed as the ratio of total assets from the previous year's annual report to the current year's total assets. The returns of each portfolio were calculated by weighting the individual stock returns within the portfolio by their respective market capitalization proportions, incorporating cash dividend reinvestment, and then subtracting the risk-free rate. The monthly stock return with cash dividend reinvestment is calculated using the following formula: $r_{n,\ t} = \frac{P_{n,\ t}}{P_{n,\ t-1}} - 1$, where $P_{n,\ t}$ represents the adjusted closing price of stock n on the last trading day of month t, incorporating cash dividend reinvestment, and $P_{n,\ t-1}$ represents the corresponding adjusted closing price on the last trading day of month $t-1$. In the scatter plot of portfolio returns, the horizontal axis denotes the group number: groups 1–10 are sorted by market capitalization, groups 11–20 by book-to-market ratio, groups 21–30 by operating profitability, groups 31–40 by investment, and groups 41–50 by the Buffett indicator. The vertical axis represents the portfolio returns.

reasonably explain the excess returns. After incorporating the Buffett factor model, the BIF factor of R41-R50 becomes significant while the intercept term is almost insignificant. The model's explanatory power improves, but the intercept term becomes significant in some R1-R40 portfolios. The FF3 model shows that the three factors are significant and the intercept term is insignificant in 20 portfolios constructed with market capitalization and investment factors. However, in other portfolios, FF3 are not sufficient to explain the excess market returns. In the FF5 model, compared to the FF3 model after adding the RMW and CMA factors, although RMW and CMA do not show significance in all portfolios, the intercept term is not significant, indicating that it is possible to price the stock portfolio returns, but it cannot be reasonably priced in the portfolios classified by the Buffett factor. In the FF3 and FF5 models, the intercept term's significance level is above 0.05 in almost all portfolios, even with the addition of the Buffett factor. The model's explanatory power is improved, although the Buffett factor does not show significance in all portfolios. In the one-factor model that includes only the Buffett factor, the Buffett factor is significant in 50 portfolios, and the intercept term is not significant. This suggests that the addition of the Buffett factor can reasonably explain the pricing rationality of different portfolios in the cross-section.

It is important to test whether a factor's good historical performance is due to sustained excess returns or its exposure to other outperforming factors. Additionally, it is necessary to confirm whether certain factors are generalizable in order to explain the performance of various asset classes and other factors. Therefore, factor pricing models should be tested. It is important to note that factor performance estimated from historical data is not necessarily indicative of future returns.

The statistical results reveal a strong correlation between several key metrics and model prediction accuracy. In general, a mean value of ? closer to 0 indicates a smaller deviation between the model's predicted excess return and the actual observed return. This results in a smaller GRS statistic, indicating better performance in the joint test. Additionally, a mean value of adjusted R2 close to 1 reflects the model's greater ability to explain changes in the return on assets.

Table 3 illustrates the GRS test of the 7 factor-models. As shown in the table, the CAPM model has an alpha mean of 0.11, indicating a positive bias in predicting excess returns. Its GRS statistic is 389.57, suggesting poor performance in the joint test. The model's adjusted R2 mean is 0.82, indicating that it can explain approximately 82% of the variation in asset returns. However, the SE mean is 0.16, suggesting that the standard error of its prediction is high, and therefore the prediction accuracy needs improvement. Introducing the Buffett factor to construct the BCAPM model results in an increase in its alpha mean to 0.25, indicating a decrease in the model's predictive ability. However, it is important to note that the GRS statistic decreases to 160.57, indicating a significant improvement compared to the FF5 model. This suggests that the model's predictive ability has improved in the joint test. Additionally, the BCAPM model's adjusted R2 mean of 0.84 indicates that it can explain approximately 84% of the variation in asset returns, which is a further improvement over the CAPM model. Although the SE mean of 0.19 is slightly higher in the FF5 model, the BCAPM model performs better overall in terms of explanatory power. Similar patterns are observed in the comparisons between the FF3 and BFF3, and FF5 and BFF5 models. The models with the addition of the Buffett factor generally have larger alpha means but smaller GRS statistics, indicating better performance in the joint test. Also, these models improved in terms of explanatory power, but with a slight decrease in predictive accuracy. However, the GRS statistics of model B are all on the large side, which seems to be inconsistent with expectations. However, this does not completely negate the validity of the joint test of these models. In the Fama-Macbeth first-stage regression, the factor exposures were treated as fixed values because they were not taken into account over time. This may have led to the models failing the GRS test. To more accurately assess the validity of the models, this assumption will be relaxed in a second-stage regression analysis to obtain more comprehensive and in-depth conclusions.

4.2. Fama-Macbeth cross-sectional regression

The relatively poor performance of the models discussed in Appendix may be attributed to the assumption of constant risk premiums. This assumption may be subject to limiting sample bias as it restricts the risk premium to be equal to the average return on the risk factor. In this section, risk premiums are estimated based on all portfolios, while also allowing for variation over time. The risk premiums over time were estimated using the second step of Fama and MacBeth (1973) two-step procedure, based on the risk loadings estimated in the first step.

Table 3: The result of GRS

Model	p	α	GRS	Adj R^2	SE
B	0.00	-0.43	163.38	0.06	0.54
CAPM	0.00	0.11	389.57	0.82	0.16
FF3	0.00	0.02	371.37	0.92	0.11
FF5	0.00	0.07	330.39	0.94	0.10
BCAPM	0.00	0.25	160.57	0.84	0.19
BFF3	0.00	0.12	131.17	0.94	0.13
BFF5	0.00	0.15	125.37	0.96	0.12

Notes: This table reports the GRS tests for the models in the first stage of Fama-Macbeth regression. FF3 refers to Fama-French 3 factors model. FF5 refers to Fama-French 5 factors model. B refers to a model that includes only the BIF factors. BFF3 refers to a model that includes the MKT, SMB, HML, and BIF factors. BFF5 refers to a model that includes the MKT, SMB, HML, RMW, CMA, BIF factors. The p-value of the GRS test, which evaluates the joint hypothesis that all portfolio alphas are zero. α is the average abnormal return across the 50 portfolios, calculated as the intercept from the time series regressions. A statistically significant α suggests systematic mispricing unexplained by the model. The GRS statistic, testing whether all alphas are jointly zero. The average adjusted R^2 across portfolios, measuring the proportion of return variance explained by the model. SE is the average standard error of the regression residuals across portfolios, reflecting the precision of model predictions. The monthly stock return used in the table with cash dividend reinvestment is calculated using the following formula: $r_{n,\ t} = \frac{P_{n,\ t}}{P_{n,\ t-1}} - 1$, where $P_{n,\ t}$ represents the adjusted closing price of stock n on the last trading day of month t, incorporating cash dividend reinvestment, and $P_{n,\ t-1}$ represents the corresponding adjusted closing price on the last trading day of month $t-1$.

Table 4 displays the results of the cross-sectional regressions for the 50 portfolios, along with the average R^2. The average R^2 indicates the degree to which the model explains the average cross-sectional variation in investment returns. The traditional factor model does not explain the returns on the Chinese stock market well, and the results of the Table 4 corroborate this. The MKT factor in the CAPM model exhibits a significant performance, with a return on risk of approximately 3.05%, however, the significant intercept suggests that on average, a common return of around -2.46% bimonthly return is left unexplained by the CAPM model, which may be due to an omitted risk factor. Similarly, MKT factor also performed well in FF3 and FF5 model with 1.97% and 4.80% bimonthly return respectively and the estimator is significant. In particular, SMB and HML factor in the Fama and French (1993) three?factor model is not significantly priced, implying the poor performance of the FF3 model. Considering the risk related to the return, although FF5 model can explain about 47.7% return in the market, HML and RMW factor are not significant in the model and SMB and CMA factor performed not very well correspondingly. The significant of the interpret indicates the poor performance of the FF5 model, even they are negative. Notably, the HML factor in the FF3 and FF5 models is negative due to the negative risk loadings, as evidenced by the unreported results. This implies that investors are willing to pay the risk premiums to hedge against the aforementioned risks.

Table 4 also reports the performance of the four combined models. We first test the model only contained BIF factor. The first line of the Table 4 sees B model has an estimated risk premium of 0.97% and a non-significant intercept term that explains investment returns in the stock market. Then the three combined models incorporating the basis factor into the Fama and French three-factor and five-factor models. BIF factor carries 0.93% and 1.33% monthly return respectively in BCAPM and BFF5 model, and the interpret decreases compared to traditional factor models, proving that the basis factor model added BIF factor includes more risk information that help to explain the expected return. This suggests the conclusion we said in the introduction. Additionally, only SMB factor in BFF3 is weak significant and BIF factor is not significant and negative, even the interpret is not significant, perhaps due to the large comprehensive positive risk premium of the other positive factors. Finally, the estimated risk premiums for the risk factors diverge significantly from their average values, which I interpret as evidence in support of time-varying risk premiums. The cross-sectional regression results with time-varying risk premiums for the stock market also suggest a similar pattern of evidence.

To compare the performance of the models discussed in the Table 4, the figure plots the realized and predicted returns with time-varying risk premiums. Predicted returns are calculated by multiplying the risk factors with the estimated risk premiums shown in the Table 4. The pricing error, which reveals the difference between each scatter representing each portfolio and the 45 degree line, is a measure of the performance of asset pricing models. It is evident that all three traditional factor models exhibit suboptimal performance. However, the model incorporating the BIF factor demonstrates superior performance relative to the original factor model. Generally, the B and BFF3 model performs better best among all the

Table 4: The result of the second-stage regression for Fama-Macbeth

Model	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{BIF}	λ_0	**Avg.**R^2(%)
B						0.973***	-0.0806	6.70
						(5.27)	(-0.17)	
CAPM	3.053**						-2.459**	17.72
	(2.44)						(-2.16)	
FF3	1.966***	0.351	-0.119				-1.365***	25.97
	(2.90)	(1.38)	(-0.50)				(-2.77)	
FF5	4.795***	0.581**	-0.0297	0.306	0.276*		-4.171***	47.70
	(6.61)	(2.31)	(-0.13)	(1.50)	(1.91)		(-7.59)	
BCAPM	2.981**					0.926***	-2.284**	24.68
	(2.37)					(5.07)	(-1.98)	
BFF3	0.822	0.428*	-0.0356			-0.0356	-0.0711	46.57
	(1.23)	(1.68)	(-0.15)			(-0.15)	(-0.14)	
BFF5	2.324***	0.538**	0.0445	0.159	0.0620	1.329***	-1.581***	51.85
	(3.32)	(2.14)	(0.19)	(0.78)	(0.44)	(9.17)	(-2.90)	

Note: The table illustrates the result of the second-stage regression for Fama-Macbeth (Fama and MacBeth, 1973), spanning the period from January 1998 to December 2023, encompassing a total of 312 monthly observations. At the end of April each year, portfolios were constructed by sorting stocks into 50 groups based on five distinct characteristics: market capitalization, book-to-market ratio, operating profitability, investment, and the Buffett indicator. Specifically, market capitalization is defined as the tradable market value of individual stocks at the time of sorting; the book-to-market ratio is calculated as the ratio of total equity reported in the annual financial statements to the market capitalization; operating profitability is derived as the ratio of operating profit to total equity from the annual report; investment is computed as the ratio of total assets from the previous year's annual report to the current year's total assets. The returns of each portfolio were calculated by weighting the individual stock returns within the portfolio by their respective market capitalization proportions, incorporating cash dividend reinvestment, and then subtracting the risk-free rate. The monthly stock return with cash dividend reinvestment is calculated using the following formula: $r_{n,\ t} = \frac{P_{n,\ t}}{P_{n,\ t-1}} - 1$, where $P_{n,\ t}$ represents the adjusted closing price of stock n on the last trading day of month t, incorporating cash dividend reinvestment, and $P_{n,\ t-1}$ represents the corresponding adjusted closing price on the last trading day of month $t-1$. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. R^2 is the average R-value of T cross-sectional regressions.
B refers to a model that includes only the BIF factor. CAPM refers to a model that includes only the MKT factor. FF3 refers to a model that includes the MKT, SMB and HML factors. FF5 refers to the model that includes the MKT, SMB, HML, RMW and CMA factors. BCAPM, BFF3, BFF4 and BFF5 refer to the model that includes the BIF factors in addition to the CAPM, FF3, FF4 and FF5 factors respectively.

given models. This provides evidence that the BIF factor carries some valid information that can explain stock returns in China, and this risk factor can explain stock market returns.

4.3. Redundancy test of factors

This section also presents evidence regarding the redundancy of the basis factor in the three combined models. The time series test is applied in this paper by regressing the basis factors of common asset pricing models, such as CAPM, Fama and French (1993) three-factor model and Fama and French (2015) five-factor model. The aim of the time series test is to assess whether the benchmark factors can be accounted for by the asset pricing factors. The regression results are presented in the Table 5. The intercepts of the four time series regressions are significant at the 1% level, indicating abnormal returns that cannot be explained by the underlying factors. Therefore, the BIF factor are not redundant in the portfolio model.

Table 5: Explaining the 6th factor using the other 5 factor regressions

	BIF	**BIF**	**BIF**
MKT	0.170***	0.175***	0.170***
	(7.648)	(9.024)	(7.648)
SMB		-0.117***	0.010
		(-3.449)	(0.197)
HML		-0.102**	-0.097
		(-1.990)	(-1.507)
RMW			0.176**
			(2.402)
CMA			0.082
			(0.694)
BIF			
_cons	3.384***	3.490***	1.382***
	(23.362)	(24.013)	(12.154)
N	312	312	312
adj. R2	0.209	0.251	0.111

Note: Above are the results of regressions where each factor is treated as the dependent variable, and the remaining factors serve as independent variables. BIF is the Buffet Index Factor. MKT is the stock market excess return factor. SMB is the size factor, HML is the value factor, MOM is the stock momentum factor, RMW is the profitability factor, and CMA is the investment factor. The sample period spans from January 1998 to December 2023. These regressions aim to examine the relationships and dependencies among the factors, providing insights into their individual explanatory power and potential interactions within the context of the specified time frame.t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Robustness Tests

5.1. Performance of Bear and Bull Markets in China

When determining whether the stock market is in a bear or bull market, market returns are typically used to compare with a certain assumed threshold. If the interval is higher than this value, it is defined as a bull market; otherwise, it is defined as a bear market. Foreign countries use real-time stock market movements and milestone events to classify bull and bear markets (Mansor F., 2011). Gonzalez et al. (2006) use two centuries of stock index returns to divide stocks into economic and statistically meaningful bull and bear market states. As defined by Pagan (2003) and Chauvet and Potter (2000), bear markets correspond to a period of general decline in asset prices characterized by negative returns and high volatility, whereas a bull market phase during which prices typically rise, often associated with positive returns and lower volatility. The study reveals that the base factor model demonstrates pricing power during bull markets, whereas the Buffett factor exhibits better pricing power during bear markets. Additionally, the B and BF models are found to be overestimated during bull markets and underestimated during bear markets.

China's stock market is known for its 'short bulls and long bears'. The difference between bull and bear markets is that bull markets have more money flowing into the stock market, resulting in a general rise in stock prices, including companies with poor performance. On the other hand, China's bear markets are more extreme, with all types of stocks generally falling. This is due to the socialist characteristics of China's 'market but no market' and the lack of a truly free market. It is important to note that this is a subjective evaluation. To improve objectivity, it is recommended to avoid such evaluations unless clearly marked as such. Additionally, the language used should be clear, concise, and value-neutral, avoiding biased, emotional, figurative, or ornamental language. The text should also adhere to conventional structure, use precise word choice, and be free from grammatical errors, spelling mistakes, and punctuation errors. Finally, the content of the improved text must be as close as possible to the source text, and the addition of further aspects must be avoided at all costs. However, China's bear market is more severe, and stocks across the board tend to decline. This is due, in part, to China's socialist market characteristics. This paper categorizes bear and bull markets based on three criteria: a 20% increase or decrease, a half-yearly increase or decrease, and an annual increase or decrease. The study focuses on the bull and bear markets that followed the stock reform in 2005. The bull market is divided into the period between June 2005 and October 2007, with the highest turnover of 257.2 billion yuan, while the bear market is divided into the period between November 2007 and September 2008, with the lowest turnover of 23.73 billion yuan. The bull market is further divided into the period between October 2008 and August 2009, with the highest turnover of 302.8 billion yuan, while the bear market is between September 2009 and June 2013, with the lowest turnover of \$33. From July 2013 to June 2015, the market experienced a bull run with the highest turnover of \$130.99 billion. This was followed by a bear market from July 2015 to January 2019, with the lowest turnover of \$123.4 billion. The market then entered another bull run from February 2019 to February 2021, with the highest turnover of 793.6 billion. Currently, from March 2021 to December 2023, the market is in a bear run.

Table B1 in Appendix B presents the performance of eight models during the bull market. There were 89 observations, and only the intercept terms of the traditional CAPM, FF3, and BFF3 models were insignificant. The Warren Buffett factor underperformed, which partially explains Warren Buffett's value investing strategy. Warren Buffett does not follow the trend of the bull market in the stock market. In fact, he sells his stocks when encountering a bull market in line with the models' performance. The model containing the Buffett factor does not explain the excess returns of the market. As shown in Figure B1, the underlying factor model better explains the market returns in the bull market.

Table B2 in Appendix B presents the performance of the eight models during the 134 observed bear markets. The results indicate that only CMA exhibits significance, while both CMA and Buffett factors show significance. The BCAPM, FF3, and BFF3 models have insignificant intercept terms for pricing the asset premium in bear markets. This outcome reinforces Warren Buffett's well-known quote, 'I am fearful when others are greedy, and I am greedy when others are fearful.' According to Figure B2 in Appendix B, the model that incorporates Buffett's factors provides a better explanation for market returns than the underlying factor model.

5.2. Dividing the sample period for robustness testing

The paper divides the entire sample period into two sub-periods to check whether the model performs similarly in different time periods. If the model comes to similar conclusions in different sub-periods or subsets of the data, we can be more confident that the model is robust. The paper divides the sample period into two distinct periods: 1998-2011 and 2012-2023, each containing 156 observations and bounded by the year 2012.

Table B3 of Appendix B shows that in the first sample period, the intercept term of the B model is not significant enough to price the stock market. Additionally, the model that includes the Buffett factor outperforms the model that includes only the underlying factor. The significance of the BFF5 model, which includes the Buffett factor, decreases compared to the FF5 model, even in the case where the intercept terms of both FF5 and BFF5 are significant. Based on the images, it appears that accurate pricing of the models is not possible. This may be due to various factors such as the early stage of China's securities market establishment, inadequate systems, data distortion, and small sample size. However, it is worth noting that the B model demonstrates better pricing explanatory ability.

Similarly, in the second sample period (see Table B4 in Appendix B), it can be observed that Model B performs well. The model containing the Buffett factor outperforms the base model, and Model B has better explanatory power, which confirms the previous conclusion.

5.3. Adjusting the rolling window

Another concern is related to the risk factor of the model. This paper assumes that the risk loadings are constant in the model, whereas they may be time-varying. This section estimates the risk loadings for the rolling window of the time series regression in the first step of the two-step procedure of Fama and MacBeth (1973). The time-varying risk loadings are then used to estimate the risk premium in the second step. It is important to note that a long window for estimating the time-varying loadings implies a short sample for estimating the risk premium. To ensure sufficient observations for estimating risk loadings and premiums, this paper employs a rolling window of three years. The Table B5 displays regression results for seven models. As shown in Appendix B, Table B5, the study indicates that portfolio returns can be explained by common asset pricing models and portfolio models, such as the BCAPM and the BFF5 model. However, the BFF3 model has less explanatory power compared to the FF3 model. Therefore, it can be concluded that returns compensate for risk, regardless of the estimation method used, including factors such as HML.

5.4. *Using only long stratgies*

A critical concern arises from the unique regulatory constraints inherent in China's capital markets. While empirical studies on U.S. and European equity markets predominantly rely on long-short portfolio strategies to capture factor premia, the prohibition of short-selling in China—a common feature in emerging markets to curb speculative volatility (**?**). To address this institutional constraint, we explicitly evaluate the performance of long-only portfolios, which circumvent short-selling restrictions while preserving exposure to the BIF factor. As shown in Appendix, the BIF factor exhibits statistically significant excess returns even within this constrained setup(see Table B5 in Appendix B). The persistence of the Buffett-style premium under long-only constraints suggests that China's regulatory environment exacerbates mispricing persistence. Our results imply that Buffett-style investing retains its empirical validity even in markets with asymmetric trading rules, provided the factor construction emphasizes cash-flow-driven fundamentals over technical reversals. This has practical implications for global asset allocators navigating heterogeneous regulatory regimes.

6. Conclusions and Policy Implications

This paper tries to explain the risk factors in the Chinese stock market. We study the data of China's A-share market from 1998-2022 and explain it with the help of Buffett factor and multi-factor models, taking into account the changes in accounting standards and the latest research results. Firstly, we found that traditional factor models do perform poorly in the Chinese stock market, which is consistent with the findings of other scholars. In addition, the model containing only the Buffett factor outperforms all other models, which can indicate that safety, cheapness, and quality can measure the risk characteristics of the Chinese stock market. Thirdly, the BIF factor strategy exhibits robust stability, with the BIF factor demonstrating the capacity to explain stock returns in the Chinese market across a range of market conditions, including both bull and bear markets, as well as in rolling sample periods. It is of great importance for investors and policymakers alike to gain an understanding of the factor model that contains BIF and their sources. This is because it is vital for the development of profitable trading strategies within the stock market as an asset class.

This paper demonstrates the relevance of current policy research and practical operations in domestic value investment for investors. It is challenging for the majority of investors to anticipate all the variables that affect stocks in advance, and establishing the efficient market hypothesis in China is deemed difficult. Although brokerage business departments aim to serve retail investors by sharing and explaining stock market and investment knowledge, many retail investors view stocks as equivalent to lottery tickets and lack understanding of basic financial concepts such as stocks and bonds. Therefore, it is unlikely that they will use a factor model to select stocks or consider timing and contingency factors. When selecting a database, it was discovered that most stock market software offers historical and real-time quotes, as well as the latest data indicators from both domestic and international sources. Additionally, some software provides quantitative strategies, which can be accessible to those with higher education in science and technology. However, it is important to consider the history of computer development and China's national conditions. It may be necessary to exercise patience when using quantitative trading strategies and rely more on the guidance of opinion leaders rather than an abundance of information. In terms of policy, there is a need to strengthen market regulation, improve information disclosure, and entry and exit mechanisms for listed companies. It is important to give full play to the competitiveness of the capital market and correct mispricing in the stock market. In addition, it is necessary to improve people's knowledge of financial management publicity in a clear and objective manner. This will counteract any subjective evaluations made by opinion leaders, calm and improve market confidence, and help solve the problem of equating stocks with speculation for retail investors. Anti-counterfeiting propaganda can be used to complement the correct understanding of financial management. Practice has shown that promoting entrepreneurship and media accountability, transparent and effective disclosure of corporate and market information, and simplifying the threshold for investment strategies can help investors make more rational decisions and improve the nation's overall economic quality.

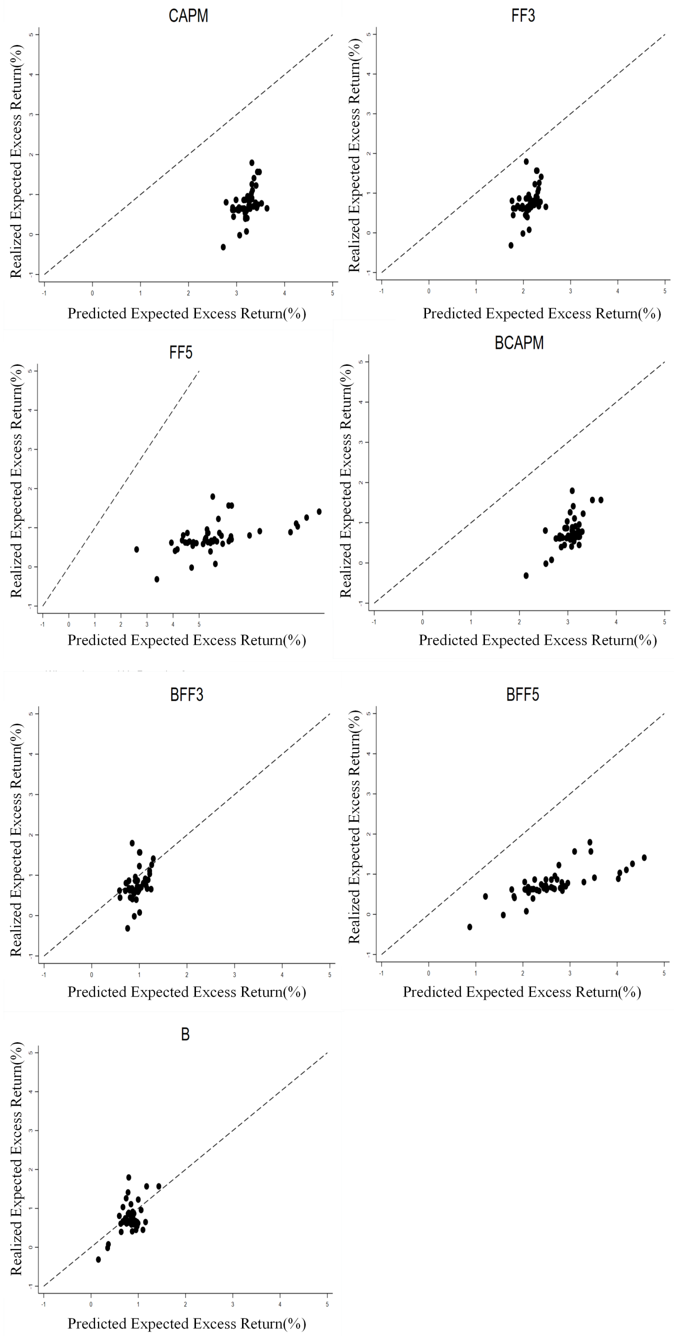

Figure 2: The fitting result of 7 Models

*Note:*Realized and expected have average returns with time-varying risk premiums. Forecasted expected returns are calculated using $E_{r,t} = \alpha_i + f_t' \beta_{i,f} + \varepsilon_{i,t} \quad t = 1, \ldots, T,, f_t'$ is Fama and MacBeth (1973) β estimated from the time-series regression (Step 1). $\hat{\lambda}_f$ is the risk premium for the risk factor estimated from the cross-sectional regression (Step 2) of Fama and MacBeth (1973). The realized expected return is the average return of the sample from 1998 to 2023. R^2 is the average of R^2 from the T cross-sectional regression. That is, $R^2 = \frac{\sum_{t=1}^{T} R_t^2}{T}$. CAPM refers to a model that includes only the MKT factor. FF3 refers to a model that includes the MKT, SMB, and HML factors. FF5 refers to a model that includes the MKT, SMB, HML, RMW, and CMA factors. BCAPM, BFF3 and BFF5 refer to models that include the BIF factor in addition to the CAPM, FF3, and FF5 factors, respectively. Bin refers to models that include only the BIF factor.

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