# The Effectiveness Analysis of Fama-French Five-Factor Model in China A-share Market

Zhuo Chen, Jiarui Lu\*

Dong Wu School of Business, Soochow University, Suzhou 21500, China

These authors contributed equally to this work and should be considered co-first authors

## Abstract

Due to the important role of the stock market, the study of the factors influencing stock pricing and risk premiums has been a hot topic in finance. Since Fama & French proposed the three-factor model in 1992 and the improved five-factor model in 2015, the Capital asset pricing model (CAPM) has become a very powerful tool to measure asset prices in the modern stock market and an important element in the field of risk and return in modern finance. This paper draws on the mature asset pricing research theories at home and abroad, selects A-share market stocks as sample data, and studies its effectiveness in the Chinese A-share market through the five-factor model. The first empirical analysis of the validity of the five factors, take the size to book-to-market ratio, earnings, investment crossover way to group, take 2\*3 way to construct the factors, take 5\*5 way to construct the test portfolio, the regression results show that the five-factor model has some explanatory power for the A-share market, but the two factors RMW and CMA have less influence on the A-share market, indicating that Chinese stockholders mainly focus on stock value factors rather than company earnings and investment factors.

## **Keywords**

Fama-French Five-Factor Model; Asset Pricing; Value Factors.

## 1. Introduction

China's stock market was formed in 1990 and has been developing for about 30 years. Despite the rapid development and increasing transaction scale, there are still many imperfections compared with the mature capital markets in Europe and America. For example, Shao Jing (2019) proposed that the equity structure of China's stock market is unreasonable, the information disclosure system is defective, and the regulatory foundation is weak. Meanwhile, the A-share market, as the main stock market of China's stock market, has a longer development time, larger investment and financing scale and more mature development compared with the B-share market.

At the same time, capital asset pricing plays a very important role in the financial field. Its theoretical purpose is to quantitatively explain and analyze the factors affecting stock return rate from the perspective of risk and return. From the classic CAPM single factor model to explain the excess return of assets, to Fama & French's three factor model, Q factor model, five factor model, six factor model and other capital asset pricing models, these all provide a powerful help to explain the change of the return rate of investment portfolio in the US capital market. There is controversy about the applicability of the three-factor model of market factor, size factor, and book-to-market ratio to the Chinese stock market. Some studies have shown that the intercept terms of each portfolio are all significantly zero when applying the three-factor model to regression is valid, but some studies have also shown that the explanatory power of the three-factor model is weak for the main board of the Chinese stock market. Therefore, it

is meaningful to investigate the explanatory power of the three-factor for the Chinese stock market return data. The applicability of the five-factor model compared to the three-factor model for the Chinese stock market is also controversial in the current study. It is necessary to study whether these two factors should be added to the three-factor model or only one factor should be added to the three-factor model for the Chinese stock market, and further study whether different factor combination models should be applied to the Chinese stock market. From the domestic and international studies, there are also proposals to add other factors to the three-factor model, among which the momentum factor has received more attention. After testing the explanatory power of the three-factor model for Chinese stock market return data, we analyze whether the two factors added to the Fama-French Five-Factor model are applicable to the Chinese stock market, and for us to consider other proposed factors, such as the momentum factor, and combine behavioral finance and Internet big data to calculate the new sentiment factor and empirically analyze its applicability with other factors. It is also useful to analyze the applicability of the new factors, to further integrate them with other factors, to finalize the factor combination model for the Chinese stock market, and to analyze the improvement of the explanatory power of the five-factor model that has been conducted.

#### Therefore, this article through the Fama-French five factor model to verify its validity in the Ashare market research, not only to verify performance in foreign markets is relatively good five factor model is applied to in the development of China's A-share market, also be able to further perfect and development of China's capital markets to provide help, therefore has a certain value.

## 2. Literature Review

In 1952, Harry M. Markowitz introduced the theory of portfolio selection. Markowitz treats the price changes of a portfolio as random variables, measuring returns by their means and risk by their variances. The Capital Asset Pricing Model (CAPM) is the core of modern financial pricing theory and is used in many fields such as portfolio construction, investment decision making, and corporate finance. The CAPM model quantifies the relationship between the expected return of an individual portfolio of securities and the relative risk of that portfolio relative to the market portfolio using the formula that the expected return on a financial asset is equal to the risk-free rate of return plus a risk-adjusted excess compensation for the risk taken by the portfolio relative to the riskiness of the overall market portfolio. The earliest capital asset pricing model is the classic CAPM model proposed by Sharpe (1964), namely:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}$$

Where  $R_{it} - R_{ft}$  represents the excess rate of return on securities minus the return on risk-free assets at time t.  $\alpha_i$  represents the excess rate of return that cannot be explained by CAPM model.  $R_{mt}$  represents the expected rate of return on market portfolio at time t, and  $\varepsilon_{it}$  represents the residual term. However, through the practical application of the CAMP model in modern financial markets, it is found that the CAMP model ignores some realistic influencing factors and there are risk exposures that are not fully covered by the single explanatory variable of market risk, resulting in many capital asset pricing phenomena that cannot be explained by the CAMP model in financial markets, which reduces the value of the CAMP model in the securities market.

In their article published in 1996, Fama and French suggested that the historical average stock returns of firms with small market capitalization size and high book-to-market ratios are generally higher than those predicted by the CAPM model, and these observations suggest that

firm market capitalization size and book-to-market ratios can proxy for a portion of the systematic risk exposure that is not accounted for by the market risk beta of the CAPM model, thus generating a risk premium associated with its Fama and French further suggest that the variation in U.S. stock returns can be well explained by a three-factor model consisting of market factors, size factors, and book-to-market factors. Therefore, Fama and French (1992) proposed a three-factor model. They believe that in addition to market factors, there are other factors that can well explain the excess return of investment portfolio relative to risk-free assets, namely:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}$$

Where  $SMB_t$  denotes the scale factor.  $HML_t$  denotes the value factor. 2015, Fama and French find from the analysis of the empirical results that high levels of earnings and conservative investment styles The historical average stock returns of companies with high levels of earnings and a conservative investment style are generally higher than the returns predicted by the three-factor model, and therefore add to the Therefore, they add two factors to the three-factor model to represent the basic investment situation and operating profitability of the company, and construct the Fama-French Five-Factor model. Fama and French used the five-factor model to empirically test the five-factor model in North American, European, and Asia-Pacific stock markets. The results show that the model has good explanatory power and applicability in all of these stock markets. The results show that the model has good explanatory power and applicability in the above stock markets. Subsequently, Fama et al. added two further factors to the three-factor model and the dividend discounting model, i.e., the five-factor model:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it}$$

Where  $RMW_t$  represents profit factor and  $CMA_t$  represents investment factor. The emergence of five-factor model enhances the explanatory ability of portfolio excess return rate and greatly expands the theoretical system of CAPM.

Many domestic scholars have also done some research on multi-factor model. Zhao Shengmin, Yan Honglei, Zhang Kai (2016) studied which model was more suitable for China's stock market by comparing the five-factor model recently proposed by Fama with the previous three-factor model, and found that, contrary to the American research, the three-factor model was more suitable for China's stock market. Zhou Yan and Tang Yutong (2019) used the five-factor model to study the pricing factors of the main board and gem in China's stock market, and found that the value factor and profit factor were more significant in the main board market, while the investment factor was more significant in the GEM market. Li Hui (2018) used principal component analysis and five-factor model to analyze the influence of the new Third Board stock pricing, and found that the profit factor was the most important factor affecting the new Third Board stock pricing.

At the same time, due to the large difference between the domestic capital market and the foreign capital market, the explanatory power of the multi-factor model for the excess return of China's stock portfolio is obviously weaker than that of foreign countries. Therefore, Chinese scholars on the basis of the multi-factor model, based on the characteristics of China's market to construct other factors for empirical analysis. For example, Ouyang Zhigang and Li Fei (2016) analyzed the momentum effect and reversal effect of Chinese stock prices and added the momentum factor with a lag of six months to construct a four-factor asset pricing model, which was found to have more explanatory power than Fama's three-factor model. Based on the five-factor model, Wang Han (2020) constructed the quality factor QMJ, which is composed of three

dimensions of profitability, growth and safety of listed companies, for China's A-share market, and found that the added QMJ factor completely passed the test, enhancing the explanatory ability of the model.

# 3. Model Design and Data Sample Selection

#### (1) Model design

In order to study the effectiveness of the five-factor model in China's A-share market, this paper mainly studies the explanatory factors of the changes in excess return of stocks in the A-share market from the perspective of asset pricing of risk and return.

Therefore, this paper mainly adopts Fama-French's five-factor model for empirical validity test to study the magnitude of the effect of market factor  $R_{mt} - R_{ft}$ , size factor  $SMB_t$ , value factor  $HML_t$ , profit factor  $RMW_t$  and investment factor  $CMA_t$  on the excess return of stock  $R_{it} - R_{ft}$ :

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it}$$

Among them, the meanings and calculation methods of each variable in the model are listed in Table 1.

variable	meaning	How variables/proxy variables are calculated
R <sub>it</sub>	The return on a portfolio of stocks at time t	The portfolio is divided in different ways, and the monthly return rate of the portfolio is weighted according to the current market value
$R_{ft}$	The risk-free rate at time t	Use the 1 year bank time deposit rate
R <sub>mt</sub>	The return at time t of a market portfolio weighted by market capitalization	The average monthly yield of Shanghai Composite Index (000001.sh) and Shenzhen Composite Index (399001.sz) is used as a proxy variable. (Wang Hailing, 2017)
SMB <sub>t</sub>	The difference in returns between the portfolio of companies with low circulating market value and the portfolio of companies with high circulating market value in period t	The company's total market value is used as a proxy variable for size, i.e., the outstanding share capital of the year t-1 multiplied by the closing price of the last trading day.
HML <sub>t</sub>	The difference between the returns of the portfolio with a high book-to-market ratio and the portfolio with a low book-to-market ratio in the period t	The ratio of the company's owner's equity to the total market value in t-1 year is used as the proxy variable of book value
RMW <sub>t</sub>	The difference of profitability between the strong profitability portfolio and the weak profitability portfolio in period t	The ratio of operating profit to owner's equity at the end of t-1 was used as a proxy variable of profitability
CMA <sub>t</sub>	The yield difference between the corporate portfolio with low investment level and the corporate portfolio with high investment level in period t	The ratio of the total assets at the end of t-1 to the total assets at the end of t-2 was used as the proxy variable for investment

**Table 1.** Meanings of variables and calculation methods of variables/proxy variables

(2) Data sample selection and screening

In this paper, all A-share stocks in Shanghai and Shenzhen stock exchanges from January 1, 2010 to December 31, 2020 are selected as the original samples. ST stocks, \*ST stocks and

stocks with missing items in data are excluded, and stocks with negative book value are also excluded. In order to facilitate subsequent group analysis, 1400 stock samples are finally obtained. In this paper, the Wind information database is used to select the monthly return rate and closing price data of these 1400 listed companies during this period of time, and the total assets, total market value, owners' equity and operating profit data are selected according to the financial statements of each company. At the same time, the Wind information database is used to obtain the monthly yield of Shanghai Composite Index and Shenzhen Composite Index from 2010 to 2020, as well as the one-year bank time deposit interest rate.

# 4. Empirical Analysis

#### (1) Descriptive analysis of data

In this paper, we refer to the method of Fama & French (2015), which first divides all stocks into two dimensions, i.e., first into five categories according to size from small to large, and then into five categories according to book-to-market ratio, profitability and investment according to small to large respectively, constituting 25\*3 asset portfolios, and then calculate the return of each annual portfolio according to the weighted average of market capitalization outstanding, and finally calculate the the average of the returns for all years from the beginning of 2010 to the end of 2020, as shown in Table 2. In addition, the data used to calculate Table 2 are given in the Appendix.

From the return rate of various investment portfolios, the following rules can be seen: 1. Regardless of the portfolio, China's stock market has a very obvious scale effect, i.e., companies with smaller market capitalization tend to have higher returns than those with larger market capitalization. 2. As seen in Panel A, except for large companies, the returns of stocks with high book value (value stocks) are significantly higher than those of stocks with low book value (growth stocks), which is largely consistent with the findings of Huang Huiping, and Bloomberg (2010). 3. Panel B shows that as the profitability of a company increases, the return of a stock portfolio tends to increase, with larger companies performing more significantly, which is also consistent with the findings of Zhao Shengmin, Yan Honglei, and Zhang Kai (2016). 4. Panel C shows that in the Chinese stock market, the relationship between the return of stock investment and the change of firm investment level is not very obvious.

Stocks are allocated to five Size groups (Small to Big) using A-share market cap breakpoints. Stocks are allocated independently to five B/M groups (Low to High), again using A-share market break points. The intersections of the two sorts produce 25 value-weight Size-B/M portfolios. B is book equity at the end of the fiscal year ending in year t-1 and M is market cap at the end of December of year t-1, adjusted for changes in shares outstanding between the measurement of B and the end of December. The Size-OP and Size-Inv portfolios are formed in the same way, except that the second sort variable is operating profitability or investment. Operating profitability, OP is measured with accounting data for the fiscal year ending in year t-1 and is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Investment, Inv, is the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets. The table shows averages of monthly returns in excess of the one-month Treasury bill rate.

	Low	2	3	4	High				
Panel A: size-B/M combination									
Small	1.43	1.50	1.60	1.70	1.64				
2	0.89	1.14	1.05	1.09	1.30				
3	0.80	0.86	0.88	0.85	0.84				
4	0.90	0.78	0.74	0.80	0.67				
Big	1.06	0.29	0.43	0.32	0.37				
		Panel B: siz	e-op combinatio	on					
Small	1.60	1.60	1.44	1.55	1.66				
2	0.63	0.97	1.13	1.31	1.41				
3	0.80	0.57	0.80	1.02	1.01				
4	0.47	0.62	0.77	0.93	1.05				
Big	0.27	0.32	0.09	0.38	1.33				
		Panel C: size	e-INV combinati	on					
Small	1.57	1.39	1.57	1.52	1.57				
2	0.73	0.95	1.09	1.20	1.21				
3	0.97	0.87	0.82	0.83	0.74				
4	0.64	0.59	0.70	0.76	0.83				
Big	0.45	0.55	0.82	0.72	0.93				

Table 2. Average monthly returns of 25\*3 portfolios

### (2) Construction methods of various explanatory factors

In this paper, with reference to Fama & French (2015), the method of the interpretation of the outside market factor to adopt a more mainstream 2\*3 model. We use independent sorts to assign stocks to two Size groups, and three B/M, operating profitability (OP), and investment (Inv) groups. The VW portfolios defined by the intersections of the groups are the building blocks for the factors. We label these portfolios with two letters. The first always describes the Size group, small (S) or big (B). In the 2\*3 sorts, the second describes the B/M group, high (H), neutral (N), or low (L), the OP group, robust (R), neutral (N), or weak (W), or the Inv group, conservative (C), neutral (N), or aggressive (A). All the sample stocks are first divided into two categories equally according to the market capitalization size factor from smallest to largest, and then divided into the other dimension (book-to-market, profitability, and investment) after sorting them respectively according to the 30% and 70% quartiles of the market as the split point three categories, so a total of six asset portfolios are obtained for each classification, and then the factors are further processed according to Table 3 to obtain the SMB, HML, RMW and CMA factors. In this paper, Excel and Python programming software are mainly used in this data processing process.

We sort stocks independently into two Size groups, two B/M groups, two OP groups, and two Inv groups using A-shares medians as breakpoints. The intersections of the groups are 16 VW portfolios. The Size factor SMB is the average of the returns on the eight small stock portfolios minus the average of the returns on the eight big stock portfolios. The value factor HML is the average return on the eight high B/M portfolios minus the average return on the eight low B/M portfolios. The profitability factor, RMW, and the investment factor, CMA, are also differences between average returns on eight portfolios (robust minus weak OP or conservative minus aggressive Inv). We can, also interpret the value, profitability, and investment factors as averages of small and big stock factors.

Therefore, this paper uses Stata16 software to perform descriptive statistics and correlation analysis on the various factors obtained by sorting and grouping, as well as the previous market factors, to obtain data as in Tables 4 and 5: (Also: specific year data are attached in the Appendix)

Grouping method	quantile	Factor calculation method				
2*3 Size-B/M Size-OP Size-Inv	Size: small(S), big(B) B/M: low(L), neutral(N), high(H) OP: weak(W), neutral(N), robust(R) Inv: conservative(C), neutral(N), aggressive(A)	$SMB_{B/M} = \frac{SH + SN + SL}{3} - \frac{BH + BN + BL}{3}$ $SMB_{OP} = \frac{SR + SN + SW}{3} - \frac{BR + BN + BW}{3}$ $SMB_{Inv} = \frac{SC + SN + SA}{3} - \frac{BC + BN + BA}{3}$ $SMB = \frac{SMB_{B/M} + SMB_{OP} + SMB_{Inv}}{3}$ $HML = \frac{SH + BH}{2} - \frac{SL + BL}{2}$ $RMW = \frac{SR + BR}{2} - \frac{SW + BW}{2}$ $CMA = \frac{SC + BC}{2} - \frac{SA + BA}{2}$				

#### **Table 3.** Grouping and calculation methods of four explanatory factors

#### Table 4. Descriptive statistics of the five explanatory factors

Variable	The average	The standard deviation	The minimum value	The maximum
$R_{mt} - R_{ft}$	0.0599195	0.2519192	0.287882	0.4033954
$SMB_t$	0.491684	1.926212	2.380363	4.676151
$HML_t$	0.0034221	1.323641	2.162813	1.897583
RMW <sub>t</sub>	0.2782339	0.569961	0.5921984	1.347663
CMA <sub>t</sub>	0.1716069	0.757202	1.450089	0.7824535

#### Table 5. Correlation analysis diagram of five explanatory factors

	MKT_RF	SMB	HML	RMW	СМА
MKT_RF	1				
SMB	0.2697	1			
HML	-0.3963	-0.5510	1		
RMW	-0.1690	-0.5634	-0.0889	1	
СМА	-0.6078	-0.0316	0.7386	-0.4801	1

As can be seen from Table 4, the sample time period selected for this paper, January 2010 to December 2020, the market return does not significantly exceed the risk-free rate and therefore the mean value of the market factor is small, while the mean value of the investment factor return is negative, so it can be inferred that investment has a negative effect on stock returns. This is in line with the findings of Wanatabe et al. (2013).

As can be seen from Table 5, there is a more significant positive correlation between the value factor and the investment factor, as well as a more significant negative correlation between the investment factor and the market factor, which is also largely consistent with the findings of Wang, H. L. (2017).

#### (3) Regression test analysis

In this paper, Stata16 software and Python programming software are used for data processing. At the same time, the excess rate of return is obtained by subtracted from the stock portfolio return rate and risk-free interest rate, and then the group regression is carried out with each explanatory factor obtained above. A total of 75 regressions of 25\*3 are carried out, and the

results are as follows: Table 6, Table 7 and Table 8. Due to space limitations, this paper does not list the t values of each regression factor, but marks them with \*, \*\* and \*\*\* respectively represent significant at the 10%, 5% and 1% significance levels.

	Table 6. Test results of size-B / M combined model										
B/M	Low	2	3	4	High	Low	2	3	4	High	
	R <sub>it</sub>	$-R_{ft} = a$	$\alpha_i + \beta_i (R_m$	$_t - R_{ft} +$	$s_i SMB_t +$	h <sub>i</sub> HML <sub>t</sub> -	$+ r_i RMW_t$	$+ c_i CMA_t$	$+ \varepsilon_{it}$		
			α <sub>i</sub>					$\beta_i$			
Small	0.27	0.31	0.47*	0.45	0.48	3.22*	5.26*	5.61**	5.73**	7.92***	
2	0.33	0.13	0.15	0.20	0.08	5.74***	6.77***	7.02***	5.83***	6.72***	
3	0.48	0.43	0.16	0.24	0.15	5.39*	6.55**	5.34***	7.60**	4.89**	
4	0.27	0.40	0.58*	0.40	0.16	5.58*	6.61**	5.77***	7.73**	6.16***	
Big	0.57	0.41	0.13	0.22	0.14	5.90**	5.30*	7.23**	5.84**	4.11**	
			Si			h <sub>i</sub>					
Small	1.57***	1.43***	1.32***	1.27***	0.97***	1.42**	1.02	0.78*	0.97*	0.50	
2	1.27***	1.09***	0.93***	1.16***	0.99***	1.11**	0.39	0.46	0.98***	1.09**	
3	1.08**	1.03***	0.94***	0.82**	0.89***	0.78	0.41	0.68**	0.86	1.63***	
4	0.81*	0.75**	1.05***	0.69**	0.63***	0.30	0.51	1.31**	0.79	1.52***	
Big	0.51*	0.10	0.07	0.30	0.18	0.99	0.66	1.45*	1.44**	1.97***	
			r <sub>i</sub>					Ci			
Small	1.82**	1.1	0.95	0.84	0.002	2.89**	1.45	1.33	1.92	0.37	
2	1.00	0.02	0.15	0.14	0.05	2.28**	0.75	0.92	1.50**	1.26	
3	0.58	0.26	0.69	0.01	0.87	1.92	0.81	1.73**	0.90	2.57**	
4	0.06	0.08	0.31	0.54	0.52	1.55	1.41	2.06**	0.79	1.56**	
Big	0.34	0.14	1.10	0.26	1.27	0.59	1.79	2.45	1.23	2.21*	

**Table 6.** Test results of size-B /M combined model

OP	Low	2	3	4	High	Low	2	3	4	High	
	R <sub>it</sub>	$-R_{ft} = a$	$z_i + \beta_i (R_m$	$_t - R_{ft} +$	$s_i SMB_t +$	h <sub>i</sub> HML <sub>t</sub> -	$+ r_i RMW_t$	$+ c_i CMA_t$	$+ \varepsilon_{it}$		
			α <sub>i</sub>				$\beta_i$				
Small	0.75*	0.51	0.24	0.10	0.37**	4.93*	5.00**	6.80***	5.68**	5.65***	
2	0.74**	0.35**	0.03	0.06	0.33*	5.90**	9.13***	6.27***	6.00***	4.66***	
3	0.06	0.61*	0.39	0.07	0.37	6.29**	6.40**	7.13**	4.82**	5.12**	
4	0.26	0.67*	0.47	0.22	0.24	6.20***	7.50**	6.04*	6.81**	5.26**	
Big	0.01	0.54	0.61	0.32 *	0.55	5.92**	6.96**	8.98***	5.13***	4.52*	
			Si			h <sub>i</sub>					
Small	0.01	0.65 *	0.05	0.28 *	0.12	1.01	1.82**	0.91	0.50*	0.96	
2	1.18***	0.98***	0.97***	1.20***	1.12***	1.14**	0.60**	0.64*	0.97**	0.73**	
3	0.70**	1.01***	0.94**	1.02***	1.12***	0.88*	0.73	0.43	0.81	1.52**	
4	0.36*	0.84**	1.02**	0.76*	0.97***	1.13**	0.71	1.04	0.62	0.96*	
Big	0.51*	0.10	0.07	0.30	0.18	0.99	0.66	1.45*	1.44**	1.97***	
			r <sub>i</sub>					Ci			
Small	1.70*	1.46*	0.29	0.48	0.75**	1.76	2.10*	0.60	1.79*	1.53***	
2	0.12	0.55*	0.58	0.18	0.66	1.74	0.23	1.26*	1.80**	1.75**	
3	1.12	0.20	0.12	0.64	0.06	1.78	1.29	0.71	1.76	2.39**	
4	1.21*	0.60	0.02	0.43	0.33	2.54**	0.83	1.43	0.78	1.86	
Big	1.35	0.26	0.40	0.73	0.34	1.96	1.35	0.45	0.83	2.87	

Inv	Low	2	3	4	High	Low	2	3	4	High	
	R <sub>it</sub>	$-R_{ft} = \alpha$	$x_i + \beta_i (R_m)$	$(t - R_{ft}) +$	$s_i SMB_t +$	$h_i HML_t +$	r <sub>i</sub> RMW <sub>t</sub> -	$+ c_i CMA_t -$	+ ε <sub>it</sub>		
			$\alpha_i$					$\beta_i$			
Small	0.37	0.37	0.60*	0.26	0.60	5.67**	7.37**	6.18**	9.20**	4.29*	
2	0.61	0.09	0.01	0.23	0.14	10.31**	8.80***	8.92***	4.00**	2.26*	
3	0.06	0.61*	0.39	0.07	0.37	6.29**	6.40**	7.13**	4.82**	5.12**	
4	0.34	0.41	0.19	0.06	0.34	5.10**	4.96**	6.22***	8.69***	7.29**	
Big	0.02	0.28	0.21	0.45	0.78	7.96**	4.81**	3.51*	6.00**	5.22*	
			s <sub>i</sub>			h <sub>i</sub>					
Small	1.40***	1.03**	1.10***	1.14**	1.30***	0.98	0.52	0.85	0.15	1.36**	
2	1.04**	0.76***	0.85***	1.0***	1.22*	0.08	0.29	0.57***	1.27**	2.03	
3	0.95***	0.93***	0.81***	1.00***	1.08**	1.42**	1.46**	1.16***	1.28**	1.19	
4	0.71***	0.81***	0.69**	0.33	0.89**	1.41***	1.69***	124**	0.72	1.39*	
Big	0.14	0.06	0.54	0.001	0.22	0.82	1.79***	3.35**	1.43*	1.88**	
			r <sub>i</sub>					Ci			
Small	0.51	0.39	0.64	0.76	1.49	1.62	0.87	1.15	0.59	2.62*	
2	1.29	0.44	0.16	1.00*	1.54	1.10	0.14	0.26	2.54**	4.21	
3	1.13	0.12	0.18	0.50	0.57	2.69**	1.85	1.69***	2.02*	1.57	
4	0.13	0.39	0.53	0.47	0.39	1.87*	2.15**	1.65	0.67	2.08	
Big	0.41	1.80**	1.32	1.67	2.30*	0.21	2.39**	5.11**	1.93	3.18	

Table 8. Check diagram of size-INV combination model

# 5. Conclusion

From Table 6 to Table 8, we can draw the following conclusions:

(1) The intercept terms of the three portfolios are hardly significant, indicating that the intercept terms cannot exclude the possibility that they are significantly non-zero after the regression of the five-factor model. At the same time the coefficients of the market factors  $\beta_i$  are all significantly positive, and the coefficients of most of the value factors  $h_i$  are also basically significant and positive. While  $r_i$  and  $c_i$  are almost all insignificant, indicating that the five-factor model has some explanatory power for the A-share market, but company profitability and investment level have little effect on the returns of Chinese companies, and the profitability factor and investment factor cannot help to verify the effectiveness of the A-share market in China, which is also consistent with the findings of Zhao Shengmin, Yan Honglei, and Zhang Kai (2016).

(2) The coefficients of the size factors of the three groups of investment portfolios  $s_i$  are basically more significant in companies with small market capitalization, while they are basically not significant in companies with large market capitalization, which proves that the size of small companies is more influential in China's A-share market, which is consistent with the data in Table 2 above.

(3) Compared with Fama & French (2015) who considered  $HML_t$  is a redundant factor, through the empirical results of this paper, for China's A-share market, the redundant factors of the fivefactor model should be  $RMW_t$  and  $CMA_t$ . The reason is that investors in China are more concerned about whether the stock valuation itself has the space to rise rather than analyzing the profitability and future investment value of the company itself, which also side shows that there are still some defects in the effectiveness of the current market investment strategy in China's A-share market. This paper speculates that the reason for this is that the proportion of retail investors in China's stock market is significantly higher than that in the U.S. stock market, which tends to follow short-term price fluctuations in stocks due to the "herding effect", while China's stock market has been developed for a relatively short period of time and is heavily regulated by the market, which has serious information asymmetry problems, resulting in a lack of stock market effectiveness.

# 6. Future Development

Carhart proposed an extended factor construction method and added the constructed momentum factors to the factor model. Antoniou and Galariotis conclude that by using stock market return data from Western countries as the subject of their study that these Antoniou and Galariotis use stock market return data from Western countries to find a certain degree of momentum (reversal) effect in these stock markets, and Fama and French examine a representative sample of European, North American, Japanese and Asia-Pacific stock markets. Fama and French applied three- and four-factor models to stock return data from representative European, North American, Japanese, and Asia-Pacific stock markets. for empirical analysis and found that the effectiveness of the momentum factor differs slightly in the stock markets of each country. Domestic scholars have also focused on this area, Shu and others concluded that the Chinese A-share market has a cyclical alternating momentum and reversal effects, while Qiuming Gao et al obtained empirical evidence that the Chinese stock market does not have a significant momentum effect. Due to the different lengths of the selected investment cycles, different time spans, and inconsistent sample subjects, there is no significant momentum effect in the Chinese stock market. It is still controversial to study whether there is a momentum effect (reversal) effect in the Chinese stock market, while if there is a significant effect, it is also controversial whether it is a momentum or reversal effect.

Behavioral finance combined with Internet big data to construct new factors and investigate the applicability to Chinese stock returns. The combination of behavioral finance and Internet big data, data mining, and machine learning may generate new factors. Hirshleifer et al. found that too much information on the Internet that is not relevant to investment decision making behavior can be distracting and make investors under-responsive to information that is relevant to real decisions. concluded that there is a significant negative relationship between media coverage and stock returns. Liu, Feng et al similarly concluded that stock returns are negatively affected by media coverage, while finding that stocks that receive attention from investors exhibit higher investment returns. Using media attention indicators, Jiang Yang et al. found that stock portfolios with higher media attention received lower returns. Yang and Zhou used data-like variables representing sentiment information such as stock trading volume and turnover rate to process sentiment indicators and empirically analyzed them to find a strong correlation between stock market trading behavior and stock excess returns. Further Bathia and Bredin conclude that sentiment information can cover the risk exposure that cannot be covered by the original three factors and enhance the explanatory effect of the traditional CAPM model on the dependent variable. Similar conclusions were also obtained by domestic scholars, Shi et al. found that the sentiment indicator after the three-factor adjustment still significantly enhances the explanatory power of the factor model for the dependent variable stock excess return. However, there are opposite findings on the role of sentiment information on stock pricing. Guo et al. find that sentiment information is significantly helpful for stock pricing only when stock prices are high.

In summary, the current research is consistent on the negative relationship between media attention and stock returns, but research related to the impact of sentiment indicators of media news content on stock returns that influence investors' decisions is in its infancy.

## References

- [1] Sharpe, W. Capital asset prices: a theory of market equilibrium under conditions of risk[J]. Journal of Finance, 1964, 19: 425-442.
- [2] Fama, E.F.& K.R. French. On the cross-section of expected stock returns[J]. Journal of Finance, 1992, 6: 427-465.
- [3] Wanatabe A., Xu Y., Yao T., Yu T. The Asset Growth Effect: Insights from International Equity Markets[J]. Journal of Financial Economics, 2013, 108(2): 529-563.
- [4] Fama, E.F.& K.R. French. A Five-Factor Asset Pricing Model[J]. Journal of Financial Economics, 2015, 116, (1): 1-22.
- [5] Wang J, Wang J, et al. The relationship between the market value and the market value [J]. Accounting Research, 2010(10): 40-46.
- [6] Zhao Shengmin, YAN Honglei, Zhang Kai. Is Fama-French Five-Factor model better than three-factor model: Empirical evidence from China's A-share market [J]. Nankai Economic Research Institute, 2016, (02): 41-59.
- [7] (IN Chinese with English abstract) [J]. Research in Financial Economics, 2016, 31(02): 84-96.
- [8] Wang H L. An empirical study on the effectiveness of Fama-French Five-Factor model in Chinese stock market [D]. Liaoning: Dongbei University of Finance and Economics, 2017.
- [9] Li Hui. Factors influencing stock pricing of The New Third Board: Empirical analysis based on principal component analysis and five factor model [J]. Journal of Hubei Second Normal University, 2018, 35(10): 43-48.
- [10] Zhou Y, Tang Y T. A comparative study of asset pricing factors in China's main board and gem market based on Fama-French Five-Factor model [J]. Zhejiang Finance, 2019, (03): 44-53.
- [11] Wang J, Wang J, Wang J, et al. A study on the effectiveness of stock markets in China [J]. Journal of Management Research, 2016, 25 (1) : 1-11.
- [12] Wang HAN. Research on improvement of five-factor model based on quality factor [J]. National Circulation Economy, 2020, (29): 132-134.
- [13] Yang C, Zhou L. Investor Trading Behavior, Investor Sentiment and Asset Prices[J]. North American Journal of Economics & Finance, 2015, 34:42-62.
- [14] Lin Q. The Fama-French Five-Factor Asset Pricing Model in China[J].Emerging Markets Review, 2017(31): 13-28.
- [15] Guo B, Zhang W, Zhang Y. The Five-Factor Asset Pricing Model Tests for the Chinese Stock Market[J]. Pacific-Basin Finance Journal, 2017, 43:84-106.
- [16] Carhart M M. On Persistence in Mutual Fund Performance[J]. The Journal of Finance,1997(3): 57-82.
- [17] Fama E F, French K R. Size, Value, and Momentum in International Stock Returns[J]. Journal of Financial Economics, 2012(3): 457-472.
- [18] Hirshleifer S A, Lim S S, Teoh S H. Driven to Distraction: Extraneous Events and Underrreaction to Earnings News[J]. Journal of Finance, 2009, 64(5): 2289-2325.
- [19] Fang L, Peress J. Media Corverage and the Cross-Section of Stock Returns[J]. 2009, 64(5): 2023-2052.
- [20] Guo K, Sun Y, Qian X. Can Investor Sentiment be Used to Predict the Stock Price? Dynamic Analysis based on China Stock Market[J]. Physica A: Statistical Mechanics & its Applications, 2017,469:390-396.
- [21] Barberis N, Shleifer A, Vishny R. A Model of Invest or Sentiment[J]. Journal of Financial Economics, 1998, 49(3):307-343.

# Appendix

#### Some of the core Python code used to process time series data:

```
Def size_BM (self) :
 Data = XLRD. Open_workbook (' size - temp. XLSX ')
 table-data.sheet_by_index(0)
 market=table.col_values(5)[1:]
 pcg=table.col_values(6)[1:]
 For I in range (0140 0700).
 Sum=0
 for j in range(210):
 Sum=Sum+market[i+j]*pcg[i+j]
 pcg_result.append(Sum/su
m(market[i:i+210]))
 Sum=0
 for j in range(280):
 Sum=Sum+market[i+210+j]*pcg[i+210+j]
   pcg_result.append(Sum/sum(market[i+210:i+490]))
   Sum=0
 for j in range(210):
 Sum=Sum+market[i+490+j]*pcg[i+490+j]
   pcg_result.append(Sum/sum(market[i+490:i+700]))
 return pcg_result
```

# **Table 9.** Annual weighted returns of the size-B/M portfolio (in order of market value and<br/>book value from smallest to largest)

2010	2011	2012	 2017	2018	2019	2020	The average
3.166373	1.43448	1.614878	 2.45878	3.73527	1.956967	0.692852	1.427725
3.419643	2.13921	0.338713	 2.7689	2.33642	2.316177	0.534853	1.490541
0.9055	1.39583	0.505002	 1.822684	2.06894	0.495739	0.225202	0.320468
1.25958	1.45983	0.664423	 1.539533	1.1725	1.357875	0.65319	0.372517

<b>Table 10.</b> Annual weighted return rate of size-OP investment portfolio	(ranked from smallest
to largest in terms of market value and profitability	7)

2010	2011	2012	 2017	2018	2019	2020	The average
2.9641	1.2899	1.772395	 2.44129	3.01111	2.539224	1.799348	1.604259
3.476547	1.96708	0.991285	 2.18137	2.90823	2.911223	1.338954	1.597085
0.49938	1.20013	0.736413	 1.158903	1.53273	1.812278	1.602099	0.382448
2.703073	2.27674	0.899195	 3.62127	1.52355	4.380576	3.290356	1.333828

Table 11. Annual portfolio weighted returns of SI-INV (listed from smallest to largest by
market value and investment, respectively)

2011	2012	2013		2017	2018	2019	2020	The average		
2.06439	1.647445	2.436766		1.58487	2.72223	2.255593	1.922666	1.56911		
2.55251	0.675228	1.880126		1.46242	2.30742	2.787197	2.174056	1.391919		
1.92904	1.529592	0.91553		0.616717	1.65844	2.181902	0.754305	0.715159		
1.60168	2.385314	1.82879		2.080609	1.72019	2.877905	1.017608	0.932153		

#### Table 12. Time series diagram of each explanatory factor

Year	$R_{mt} - R_{ft}$	$SMB_t$	HMLt	RMW <sub>t</sub>	CMA <sub>t</sub>
2011	0.2839	0.08466	0.647344	0.28662	0.782453
2012	0.01194	0.184997	0.324788	0.420807	0.2447
2013	0.00701	2.562225	0.44644	0.255536	0.02021
2014	0.403395	0.071537	1.897583	0.5922	0.515797
2015	0.321183	4.676151	2.16281	0.23968	0.70729
2016	0.13409	0.979879	1.07434	0.088052	0.579601
2017	0.037162	2.38036	1.060331	1.347663	0.63548
2018	0.28788	0.81729	0.536868	0.622281	0.421328
2019	0.274544	0.13321	1.46638	0.391378	1.45009
2020	0.287725	0.14242	1.4314	0.775119	0.99791