Empirical Asset Pricing Models: Evidence from the Chinese Stock Market

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Abstract. This study constructs conventional asset pricing models including the CAPM, the Fama and French three-factor model (FF3 hereafter), the Carhart four-factor model (FFC4 hereafter), and the Fama and French five-factor model (FF5 hereafter). Additionally, a six-factor model (FF5 model augments the Carhart momentum factor) is also constructed and it outperforms other conventional asset pricing models in the Chinese stock market while explaining the returns variation of cross-sectional indices and individual stocks. However, the explanatory power of models varies in explaining indices and individual stocks because of their own specificity. The models can capture most at 69.05% and least at 3.03% of the variation of the return in certain individual stocks. In light of indices, models account for the largest proportion of the variation of the return at 96.83% and the smallest proportion at 85.28%. Moreover, the predictive ability of the six-factor model is confirmed in this study, which implies the validity of constructed factors and the model.

Keywords: Asset pricing model; dimensional factors; Chinese stock market.

1. Introduction

Since the foundation of the stock market, enormous scholars and investors have been researching various methods or models to precisely explain or forecast the price of assets, stocks, and portfolios. Previous studies have proved that some models, such as the Sharpe (1964) - Linter (1965) CAPM, the FF3 model (1993), the FF5 model (2015), and the FFC4 (1997) model, have been proven to be effective in global stock markets including the Chinese stock market [1-5]. Guo, Zhang, Zhang, and Zhang (2017) proved out-of-sample tests for the FF5 model in the Chinese stock market [4, 6]. They found strong size, value, and profitability patterns in average returns, but insignificant investment patterns [6]. Huang (2018) has proven that the FF5 model was robust and it outperformed other models in the Chinese stock market over the 1994-2016 period [4, 7]. A similar study was done by Wang and Xu (2004), who claimed that because of the Chinese capital market's speculative nature, over the 1996-2002 period, the size factor could capture the cross-sectional discrepancy in returns, while the value factor was ineffective [8]. This study focuses on the explanatory power of each model on Chinese indices and individual stocks and explores whether they perform differently with the influence of the specificity of a certain index or individual stock.

The appearance of CAPM by Sharpe (1964) - Linter (1965) was the first model verifying the fundamental impacts of investor preferences and the physical characteristics of capital assets resulting in the price of risk. It also demonstrated a relationship between the price of an individual asset and the corresponding risk [1, 2]. Subsequently, the FF3 model and the FFC4 model were put forward, which were found to better explain the variation in the stock market [3, 5]. Following these researches, Fama and French (2015) ulteriorly proposed the FF-5 model based on their FF3 model and found it further enhanced the model’s explanatory power [4]. Furthermore, Fama and French (2016) proved the validity of the FF5 model by clearly dissecting some anomalies in the capital market [9]. Reasonably, a combination of the FF5 model and the momentum factor proposed in the FFC4 model can also explain the variation in the stock market [4, 5]. Huang (2018) performed regression on individual stocks, using the above-mentioned asset-pricing models, and proved that the six-factor model performed best among all models when utilizing Adj.R^2 to compare their performance [7].

However, factors such as policy, structure, constitution, etc. in each country's stock market vary, making scholars exert great effort to prove models' universality and availability in a certain country. This study constructs factors that influent stock markets, strictly and detailly following the procedures in the previous papers which will be described in the following sections. The significance and influence of each factor can be easily observed through a statistical summary. Then, the result of OLS regression on indices and individual stocks is going to verify their effectiveness and compare their performance in the Chinese stock market.

Moreover, some scholars also have done research on the out-of-sample forecast through asset pricing models. Ferson and Locke (1998) show that utilizing the historical average in the past leads to better market return forecasts than a 60-month historical average [10]. Griffin (2002) estimated five-year regressions, employing individual stocks for some asset pricing models. And he found that prediction errors were dramatically large for all models. But the result showed a clear ranking, which indicated that forecasting is probably a practical and reasonable way to embody the model's validity [11]. Consequently, out-of-sample predictions by models are made in this study to ulteriorly verify the availability of the above models in the Chinese stock market.

2. Methodology

2.1 Data Sourcing

The stock market has developed quickly and thoroughly in China, providing a good environment for enterprises and investors to conduct financial activities. This study considers factors data on daily basis over the 2012-2020 period, which is computed by relevant data provided by CSMAR (China Stock Market & Accounting Research Database). Additionally, the database also provides the daily price of each individual stock during 2017-202, including all stocks publicly traded on A shares, which is used to compute the returns and perform OLS regression. To ensure validity and reliability, those stocks with less than 300 days of data are removed from the sample, and the number of available stocks for regression is 3603. Furthermore, missing data are also excluded, but extreme data are reserved, since the actual condition in the stock market is complex and we cannot ignore the abnormal situation, otherwise the result of this study can hardly be convincing. To verify model performance on Chinese indices, daily returns of 4 traditional indices in the Chinese stock market (SZI, SSEC, SPCITIC300, SCI1000I) over the 2012-2020 period are chosen in this study, which is downloaded from the website investing.com. The detailed description of selected indices will be shown in section 3.

2.2 Variables Definition

2.2.1 Market factor: MKT

The Sharpe (1964) -Linter (1965) CAPM indicates that the expected excess return $R_i - R_f$ (the asset's return (R_i) minus the risk-free interest rate (R_f)) is completely explained by its expected CAPM risk premium (its beta times the expected value of $R_m - R_f$) [1, 2]. On the above expressions, R_m represents the return of the market portfolio, which is the value-weighted returns of all stocks. In the following research, the expected value of $R_m - R_f$ is defined as market factor MKT.

2.2.2 Size factor: SMB (Small Minus Big)

Fama and French (1993) have proved that in the US stock market during the 1980s, if book-to-market equity was controlled, small enterprises performed worse than big ones [3]. They also claimed that small enterprises can experience a prolonged earnings depression that doesn't affect large enterprises, which shows that size is linked to a common risk factor that could interpret why the average return and the size move in the opposite direction. Therefore, the size of a firm influent the return of stocks for some reasons, which makes the construction of the size factor make sense. To be brief, the size factor SMB equals the value-weighted return of small groups minus the value-weighted return of big groups. The detailed procedures of the construction of size factor SMB can be seen in the study by Fama and French (1993) [3].

2.2.3 Value factor: HML (High Minus Low)

Fama and French (1993) have proved that BE (book equity) and BE/ME (book-to-market equity) are two cross-section variables that can capture a considerable proportion of the stock return [3]. All stocks are separated into two groups, big (B) and small (S), based on the median BE, and then inside each group, they will be divided once again into a high group (H) and a low group (L), based on the median BE/ME. Consequently, each stock will be in either B or S, and meanwhile in either H or L. For example, the S/L portfolio represents that it has low BE and low BE/ME. To make a definition, HML is the simple average returns on S/H and B/H MINUS that on S/L and B/L.

2.2.4 Momentum factor: UML (Up Minus Down)

Jegadeesh and Titman (1993) evidenced that over three to twelve months holding periods, purchasing stocks that have done well in the past and selling stocks that have underperformed leads to considerable positive returns [12]. Their study indicated that the previous performance can make some impact on future performance, which is similar to the definition of momentum in physics, describing that the previous state of an item can affect its future state. Based on the above analysis, Carhart (1997) proved that the one-year momentum effect had explained some phenomena in mutual funds, but the momentum strategy did not help to find profitable individual stocks [5]. Therefore, in this study, the momentum factor will be tested for its validity in the Chinese stock market. As for the procedures of construction, data of each month is sorted according to the cumulative returns in the previous 2-12 months, and the discrepancy between the high-return portfolio and the low-return portfolio which is weighted by market capital is the momentum factor UML. A more detailed procedure of construction can be seen in Carhart (1997) [5].

2.2.5 Profitability factor RMW (Robust Minus Weak) and investment factor CMA (Conservative Minus Aggressive)

The procedures of constructing RMW and CMA are extremely similar to HML. The difference is that the rank is on the basis of either profitability or investment. Like HML, RMW and CMA can be interpreted as averages of profitability and investment factors for small and big stocks. The construction of RMW and CMA strictly follows the procedures described in the study on constructing the FF5 model by Fama and French (2015) [4].

2.3 Modelling

In this study, the following 5 models will be utilized to capture the variation of individual stocks and cross-sectional indices in the Chinese market, and a comparison will be made to verify their explanatory power. Formula (1) - (5) are respectively the CAPM, the FF3 model, the FFC4 model, the FF5 model, and the six-factor model [1-5]. α_t is the intercept of the equation. If the model perfectly holds, α_t should be zero, and the t-test under $\alpha_t = 0$ hypothesis should not be rejected. ε_t is a random disturbance term.

$$R_{it} - r_{ft} = \alpha_t + \beta_1 MKT_t + \varepsilon_t \tag{1}$$

$$R_{it} - r_{ft} = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{2}$$

$$R_{it} - r_{ft} = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_t \tag{3}$$

$$R_{it} - r_{ft} = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon_t \tag{4}$$

$$R_{it} - r_{ft} = \alpha_t + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5 RMW_t + \beta_6 CMA_t + \varepsilon_t \tag{5}$$

To compare each model's performance in typical indices, OLS regression is performed on every index. Through the result of the regression, Adj.R^2 can be utilized to measure a model's explanatory power. It shows how much of the volatility in the target field can be attributed to the input(s). Furthermore, the coefficient of every factor and the corresponding value of t–statistic indicate the correlation and significance of the factor. Similarly, to compare their performance in individual stocks, for every model, OLS regression is performed on every available stock. Comparison between models can be made through the statistical characteristic of the regression result.

2.4 Forecasting

For every model, if the construction of factors is reasonable and valid, the model should have considerable predictive ability. In this study, for every model, OLS regression is performed to compute the coefficient of every factor through data of chosen indices over the 2012-2020 period. Then, the coefficient we get from the 2012-2020 period will be used to forecast the return of mentioned indices over Jan. 2021-July. 2021. And the real data of factors are given in this prediction. Knowing the actual values of factors over Jan. 2021-July. 2021 and constant coefficients of factors computed by data over the 2012-2020 period, prediction of returns of indices can be made. If the structure and condition of the index are stable and the model is valid in the Chinese stock market, the discrepancy between the actual value and predictive value should be subtle. In this study, RSS (residual sum of squares) is calculated to measure the discrepancy and measure the predictive ability of models.

3. Empirical Results and Analysis

3.1 Factor Returns

Table 1 reports the summary statistics for the factors mentioned before (using data from 2012 to 2020), showing the mean, standard deviation, minimum, 25 percentile, median, 75 percentile, maximum and t-statistic value of each factor. The hypothesized value for the t-test equals 0, to test if the factor should be 0. As is shown in Table 1, factor MKT is slightly higher than 0, which means the average market return excess risk-free asset by 0.0437% per day, equivalent to 17.29% per year, indicating that the Chinese stock market experienced an upward trend during the given period.

The size effect depicts a tendency that smaller companies tend to generate higher returns than larger ones because the size factor SMB is positive at 0.0307%, equivalent to 11.86% per year. The responding t-statistics value is about 1.936, which is the highest among all factors. It means that it is over 1.9 standard errors from zero and SMB is the most significant factor, which provides investors with a good indicator while choosing a profitable strategy in the Chinese stock market.

The value effect corresponds to the pattern that value stocks tend to perform better than growth stocks. However, the value factor HML in the Chinese market is negative, showing that growth stocks, such as low BE/ME ratio stocks, produce higher returns than value stocks by 0.0043% per day, equivalent to 1.58% per annum. The number is quite small, and simultaneously, the t-statistics value is also small at -0.29045. The result is similar to the previous study by Wang and Xu (2004), who also found tiny evidence of the factor HML in the Chines stock market [8]. Additionally, investment factor CMA and profitability factor RMW have small t-statistic values at about -1.34665 and 0.10469 respectively. The above statistical result implies that value factor HML, investment factor CMA and profitability factor RMW are probably redundant. In other words, they are weak in the Chinese stock market and their effectiveness and explanatory power are limited.

As Jegadeesh and Titman (1993) suggested, buying stocks which perform well in the past instead of which performed poorly in the past leads to higher earnings [12]. Therefore, a price momentum factor UMD is added to traditional models to capture the price variation. Momentum factor UMD exhibits an average return of 0.019% per day, equivalent to about 7.18% per annum. The corresponding t-statistics is over 0.88, implying considerable validity of this factor.

Table 2 depicts the correlation matrix among all factors. Except for the momentum factor UMD, other factors show a strong correlation with certain factors. The size factor SMB shows a strong and negative correlation with HML and RMW, at -0.40 and -0.87 respectively. It indicates that small stocks most probably have smaller BE/ME ratios and lower profitability. On the contrary, SMB shows little and positive correlation with CMA and approximately no correlation with the UMD. As for the value factor HML, it indicates a relatively strong correlation with RMW at 0.39 and CMA at 0.55, showing that stocks with a high BE/ME ratio tend to conventionally invest and be more profitable. The momentum factor UMD implies a relatively low and negative correlation with HML and MKT, furthermore, UMD shows nearly no correlation with other factors. The above analysis indicates some rules in the Chinese stock market during the 2012-2020 period through the correlation between factors, but the result is not completely consistent with Huang (2017), which may imply that the correlation among factors varies when using data in different periods [7].

Table 1. Summary statistics of 6 factors

variable	mean	sd	min	P25	P50	P75	max	t-statistics
MKT	0.000437	0.016133	-0.09478	-0.00634	0.001088	0.008101	0.091656	1.257918
SMB	0.000307	0.007362	-0.05856	-0.00299	0.001045	0.004506	0.040162	1.936447
HML	-0.000043	0.006878	-0.04256	-0.00401	-0.00029	0.003479	0.036026	-0.29045
UMD	0.00019	0.00998	-0.06076	-0.00467	0.000446	0.005525	0.050135	0.885171
RMW	0.000021	0.009137	-0.05985	-0.00503	-0.00066	0.003982	0.085343	0.104685
CMA	-0.00017	0.005766	-0.03835	-0.0033	-0.00016	0.002953	0.041644	-1.34665

Table 2. Correlation matrix of 6 factors

variable	MKT	SMB	HML	UMD	RMW	CMA
MKT	1					
SMB	0.310895	1				
HML	-0.19988	-0.40062	1			
UMD	0.165007	-0.02487	-0.26898	1		
RMW	-0.44762	-0.86719	0.38617	0.001911	1	
CMA	-0.22337	0.102123	0.551164	-0.28828	-0.07355	1

3.2 Model Performance Comparison

3.2.1 Several typical indices in the Chinese stock market

In this section, 4 cross-sectional indices (SSEC, SPCITIC300, CSI1000I, SZI) between 2012 and 2020 are taken into consideration. (1) SSEC, which includes all stocks in the SH Exchange, reflecting the overall price changes on the SH Exchange. (2) SPCITIC300, the index's purpose is to assess the overall market performance of the China A-share. The index includes some of the companies with the best liquidity and the largest size from 24 industries, selected to represent the market's overall sectoral. (3) CSI1000I, the index contains 1,000 stocks with relatively small scale and good liquidity in A-share, comprehensively representing a collection of small-cap companies' stock price performance on the A-share market. (4) SZI, the index is compiled by the SZ Stock Exchange. Forty cross-sectional stocks are selected from all listed stocks, and the index is the average value calculated with the tradable shares as the weight. It comprehensively represents the trend of prices in the SZ Stock Exchange.

This section attempts to find the crucial and significant factors which influent stocks’ returns and compare the effectiveness of different models proposed by previous scholars. Table 3-7 reflects the OLS regression result on each index, using different models. The statistical result of coefficients and the responding significance level of factors are shown in the mentioned tables. The Adj.R^2 of every single index is computed to assess the explanatory power of the model in the certain index, and the mean value of Adj.R^2 of each model is utilized to compare the explanatory power of models.

The result depicts some empirical rules. The value of Adj.R^2 of all 5 models is all considerable, approaching 1, which represents that the majority of the variation of indices can be captured by the model. As for the CAPM, it captures about 88% of the variation, while others all capture more than 94% and the six-factor model can best explain the variation of the index. It shows great evidence of the strong explanatory capability of existing asset-pricing models in the Chinese stock market. Furthermore, the signs of the coefficients are not constant when a certain model is used to explain different indices. Each factor makes different impacts on different indices, which is due to the unique structure and component of each index.

However, Fama and French (2015) found that the HML is redundant for explaining the variation of average return in the U.S. data during 1963–2013 because the explanatory power of the FF5 model did not improve compared with the four-factor model which drops HML from the FF5 model [4]. However, this conclusion does not make sense in the Chinese stock market. Compared with the FF3 model (in Table 4) and the FF5 model (in Table 6), HML losses its statistically significant level only in SZI, while in other indices it is still significant at the level of 1%. The result implies that HML is not a redundant factor in the 2017-2020 period in the Chinese stock market. Moreover, a comparison between all six factors shown in Table 7 indicates that UMD seems to have the least explanatory power to the return of indices in the Chinese stock market. It is obvious that the absolute value of the coefficient of UMD is the smallest, proving that this factor affects the return to a trivial extent. The result is consistent with Huang (2019), who also found the invalidity of UMD in the Chinese stock market [7].

Table 3. Regression result for individual stocks on CAPM

CAPM	SSEC	SPCITIC300	CSI1000I	SZI	Mean
MKT	0.7989***	0.8059***	1.0254***	0.9631***	0.8983
	(0.0059)	(0.0074)	(0.0087)	(0.0067)	(0.0072)
Adj.R^2	0.8987	0.8528	0.8667	0.9087	0.8817

Table 4. Regression result for individual stocks on the three-factor model

3 Factors	SSEC	SPCITIC300	CSI1000I	SZI	Mean
MKT	0.8591***	0.8917***	0.9077***	0.9780***	0.9091
	(0.0044)	(0.0054)	(0.0046)	(0.0067)	(0.0053)
SMB	-0.2509***	-0.5003***	0.6457***	-0.2203***	-0.0814
	(0.0105)	(0.0131)	(0.0108)	(0.0161)	(0.0126)
HML	0.2939***	0.1388***	-0.3064***	-0.2035***	-0.0193
	(0.0109)	(0.0136)	(0.0112)	(0.0166)	(0.0131)
Adj.R^2	0.9497	0.9304	0.9663	0.9183	0.9412

Table 5. Regression result for individual stocks on the four-factor model

4 Factors	SSEC	SPCITIC300	CSI1000I	SZI	Mean
MKT	0.8652***	0.8953***	0.9124***	0.9895***	0.9156
	(0.0044)	(0.0055)	(0.0046)	(0.0066)	(0.0053)
SMB	-0.2666***	-0.5089***	0.6331***	-0.2502***	-0.0981
	(0.0105)	(0.0131)	(0.0109)	(0.0158)	(0.0126)
HML	0.2660***	0.1238***	-0.3274***	-0.2564***	-0.0485
	(0.0111)	(0.014)	(0.0116)	(0.0167)	(0.0133)
UMD	-0.0654***	-0.0400***	-0.0458***	-0.1243***	-0.0689
	(0.007)	(0.0088)	(0.0074)	(0.0107)	(0.0085)
Adj.R^2	0.9517	0.9310	0.9669	0.9234	0.9433

Table 6. Regression result for individual stocks on the five-factor model

5 Factors	SSEC	SPCITIC300	CSI1000I	SZI	Mean
MKT	0.8857***	0.9130***	0.9148***	0.9461***	0.9149
	(0.0049)	(0.006)	(0.0051)	(0.0074)	(0.0058)
SMB	-0.1237***	-0.2667***	0.5443***	-0.1867***	-0.0082
	(0.0189)	(0.0235)	(0.0195)	(0.0287)	(0.0227)
HML	0.2244***	0.1426***	-0.3931***	-0.0268	-0.0132
	(0.014)	(0.0175)	(0.0146)	(0.0213)	(0.0168)
RMW	0.1642***	0.2270***	-0.0481***	-0.0671***	0.069
	(0.016)	(0.0201)	(0.0165)	(0.0244)	(0.0192)
CMA	0.1073***	-0.0360*	0.1542***	-0.3054***	-0.02
	(0.016)	(0.0197)	(0.0166)	(0.0243)	(0.0191)
Adj.R^2	0.9527	0.9348	0.9679	0.9241	0.9449

Table 7. Regression result for individual stocks on the six-factor model

6 Factors	SSEC	SPCITIC300	CSI1000I	SZI	Mean
MKT	0.8916 ***	0.9166 ***	0.9187 ***	0.9580 ***	0.9212
	(0.0048)	(0.006)	(0.0051)	(0.0071)	(0.0058)
SMB	-0.1305 ***	-0.2714 ***	0.5392 ***	-0.2007 ***	-0.0158
	(0.0185)	(0.0233)	(0.0194)	(0.0276)	(0.0222)
HML	0.2020 ***	0.1304 ***	-0.4075 ***	-0.0723 ***	-0.0369
	(0.0139)	(0.0175)	(0.0147)	(0.0207)	(0.0167)
UMD	-0.0658 ***	-0.0449 ***	-0.0394 ***	-0.1341 ***	-0.071
	(0.0069)	(0.0086)	(0.0073)	(0.0102)	(0.0082)
RMW	0.1699 ***	0.2292 ***	-0.0447 ***	-0.0556 **	0.0747
	(0.0157)	(0.0199)	(0.0164)	(0.0234)	(0.0189)
CMA	0.0968 ***	-0.0444 **	0.1475 ***	-0.3268 ***	-0.0317
	(0.0157)	(0.0196)	(0.0165)	(0.0234)	(0.0188)
Adj.R^2	0.9547	0.9357	0.9683	0.9299	0.9471

3.2.2 Individual stocks

To verify if these models still hold for individual stocks, time series regressions of 3603 individual stocks in the SH stock market and the SZ stock market (2017-2020) are run in this section. To assure the accuracy of regression, stocks with less than 300 transaction days of data are excluded from the sample. As is shown in Table 8-12, the intercept α and the Adj.R^2 can be utilized to estimate the model performance.

The average value of α in all models are approaching 0, the maximum (0.00015) appears in the six-factor models while the minimum (-0.00057) appears in CAPM. It is worth mentioning that the addition of the value factor and size factor significantly improves the model's explanatory power. The value of Adj.R^2 in the FF3 model increases to over 0.304 from about 0.25 in the CAPM. While the addition of the momentum, profitability and investment factors only leads to a subtle increment on Adj.R^2, in which the value of the FFC4 model, the FF5 model and the six-factor model is about 0.308, 0.311, and 0.315 respectively.

In addition to Adj.R^2, α can also be used to estimate the model. If the model perfectly holds, the absolute value of α should be zero. Although the value of α shown in the tables is not zero, the t-value and corresponding p-value indicate that α is not significant and it is probably equal to zero. Overall, conventional asset pricing models can capture part of the variation of returns in the Chinese stock market to some extent.

Table 8. CAPM performance on individual stocks

CAPM	Mean	sd	Median	Min	Max
α	-0.00057	0.00130	-0.00065	-0.01069	0.00664
$\|\alpha\|$	0.00108	0.00092	0.00090	0.00000	0.01069
t_value	-0.66630	1.28671	-0.75460	-5.87506	4.63865
p_value	0.36808	0.29972	0.30111	0.00000	0.99972
Adj.R^2	0.25016	0.08233	0.24849	0.03030	0.62299

Table 9. Three-factor model performance on individual stocks

3-Factor	Mean	sd	Median	Min	Max
α	0.00005	0.00110	0.00000	-0.00978	0.00637
$\|\alpha\|$	0.00076	0.00080	0.00054	0.00000	0.00978
t_value	0.00741	1.05809	0.00033	-5.51697	4.08769
p_value	0.50671	0.29564	0.51549	0.00000	0.99983
Adj.R^2	0.30381	0.09381	0.30299	0.03424	0.66763

Table 10. Four-factor model performance on individual stocks

4-Factor	Mean	sd	Median	Min	Max
α	0.00014	0.00108	0.00010	-0.00953	0.00588
$\|\alpha\|$	0.00075	0.00078	0.00052	0.00000	0.00953
t_value	0.12030	1.02823	0.12564	-5.55391	4.05668
p_value	0.51446	0.29340	0.53807	0.00000	0.99970
Adj.R^2	0.30830	0.09500	0.30617	0.03782	0.69064

Table 11. Five-factor model performance on individual stocks

5-Factor	Mean	sd	Median	Min	Max
α	0.00006	0.00111	0.00002	-0.00977	0.00633
$\|\alpha\|$	0.00078	0.00079	0.00055	0.00000	0.00977
t_value	0.01370	1.06627	0.02496	-5.49035	3.90552
p_value	0.49831	0.29570	0.50531	0.00000	0.99980
Adj.R^2	0.31061	0.09688	0.30800	0.03587	0.67119

Table 12. Six-factor model performance on individual stocks

6-Factor	Mean	sd	Median	Min	Max
α	0.00015	0.00108	0.00011	-0.00948	0.00585
$\|\alpha\|$	0.00076	0.00078	0.00053	0.00000	0.00948
t_value	0.12858	1.02739	0.13668	-5.47246	3.83965
p_value	0.50870	0.29359	0.52090	0.00000	0.99977
Adj.R^2	0.31505	0.09772	0.31226	0.04114	0.69051

3.3 Out-of-Sample Forecast

In the previous section, each model's coefficients of factors (2012-2020) are computed through OLS regression. In this section, these coefficients will be used to forecast the time series of four indices in the Chinese market mentioned before in 2021, based on the actual data of factors in the corresponding period.

$$RSS = \sum_t^D (y_t - \hat{y})^2 \tag{6}$$

RSS, residual sum of squares, is used to compare the accuracy of the prediction, which is defined by equation (6). y_t and $\hat{y}$ are the predicted and the actual returns of the index respectively. The smaller the RSS is, the more accurately the model can predict. The prediction can be visualized in Figure 1, using the six-factor model to forecast SZI for example, to compare the predicted and the actual time series. As the complete result is shown in Table 13, a conclusion can be made that all models perform extremely well in predicting. The addition of the value factor and size factor significantly increases the accuracy of model prediction, while other factors slightly improve the models' predictive ability. The tendency of RSS's variation is opposite with Adj.R^2 which is used to measure the validity of a model, showing that a model with higher Adj.R^2 tends to perform better in forecasting and own smaller RSS.

As this prediction requires actual data on factors, the strong predictive power of models may not be able to be utilized to generate a practical strategy for forecasting stock price. However, it still has its meaning. As it is described in the former section, factors are constructed based on actual data of returns. On the contrary, in this section, returns are predicted based on actual factors, and the perfect result demonstrates that these factors are valid and their construction is reasonable from an opposite perspective.

Table 13. RSS of the prediction

RSS	SSEC	SPCITIC300	CSI1000I	SZI
CAPM	0.0011	0.0041	0.0059	0.0026
three-factor model	0.0013	0.0014	0.0022	0.0008
four-factor model	0.0011	0.0014	0.0022	0.0010
five-factor model	0.0011	0.0010	0.0018	0.0013
six-factor model	0.0009	0.0010	0.0019	0.0012

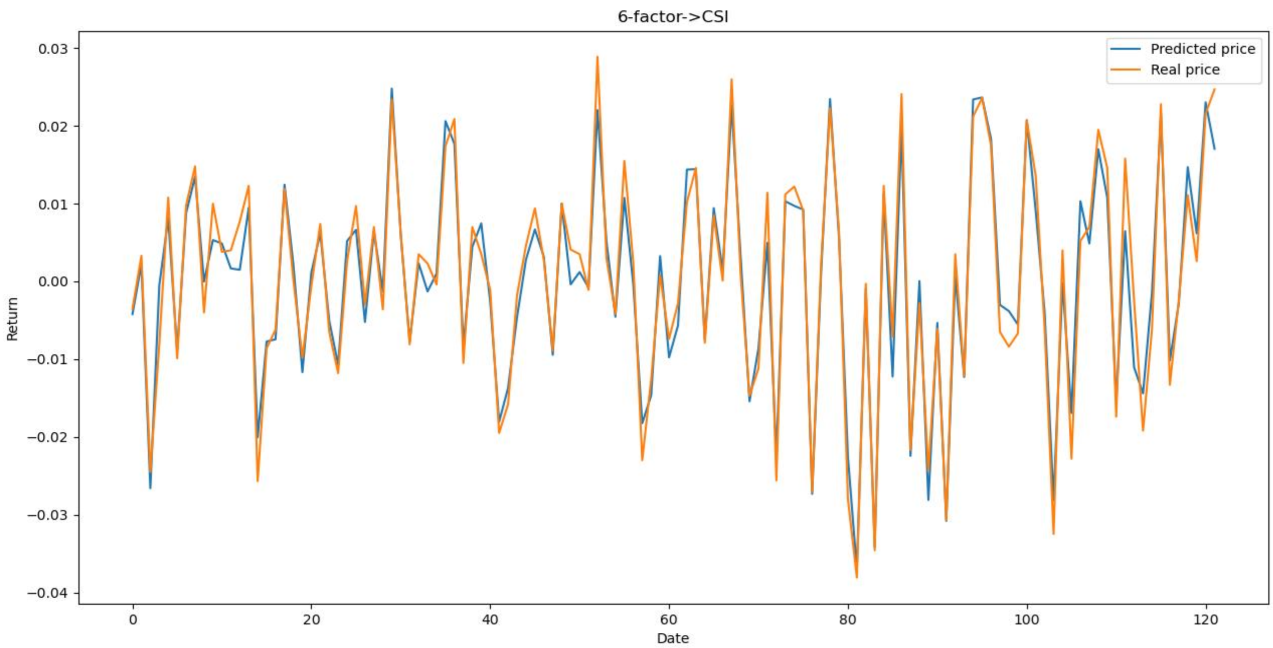

Fig. 1 Prediction on SZI by six-factor model

(Photo credit: Original)

4. Conclusion

This paper focuses on several traditional asset pricing models, involving the Sharpe-Linter CAPM, the FF3 model, the FF5 model, the FFC4 model, and a six-factor model. In most previous studies, they have verified the effectiveness and validity of these models by performing them on portfolios. On the contrary, this paper tries to utilize these models in explaining cross-sectional indices and individual stocks. Expectedly, models perform much better in explaining indices compared with individual stocks. As for indices, these models can capture most of the variance of indices, ranging from 85.28% to 96.83%. In comparison, conventional models account for 3.03%-69.05% variation of individual stocks. In a word, conventional assess-pricing models perform perfectly in explaining indices, and their performance show an enormous discrepancy between different individual stocks, but overall, models perform better in indices than in individual stocks.

On the other hand, each model's performance varies. Among conventional asset pricing models, the Sharpe-Linter CAPM performs the worst, which represents an average Adj.R^2 of 0.8817 among indices and 0.2502 among individual stocks. With the increment of the size and the value factor, the model's explanatory power dramatically increases to an average of 0.9401 among indices and 0.3038 among individual stocks. Compared with the FF3 model, the addition of the momentum factor slightly improves the model's validity, and its average Adj.R^2 reaches 0.9517 and 0.3083 respectively. Similarly, the addition of the profitability factor and the investment factor also just subtly increases the model's explanatory power to 0.9527 and 0.3106 respectively among indices and individual stocks. Eventually, the six-factor model with all the above-mentioned 6 factors has the greatest performance with an average Adj.R^2 of 0.9547 and 0.3151. Overall, the difference between Sharpe-Linter CAPM and the FF3 model is a qualitative change, enormously improving the model's effectiveness. However, the four- to six-factor model perform similarly to the FF3 model. However, it still shows a clear ranking, the more factors the model involves, the more explanatory power the model has. For further verification, the result of the out-of-sample forecast indicates the validity of the six-factor model, depicting that the investment strategy based on the six-factor model may be practical.

This paper has detailly explained the relation between indices or stocks' returns and traditional asset pricing models constructed by previous scholars and compared the performance of those models in the Chinese stocks market by explaining the returns variation of indices and individual stocks. However, much remains to be answered due to the limitation of this paper. The method and procedure of factors construction set by Fama and French and Carhart are on the basis of the American stock market, which has a different structure and characteristics compared with China. Therefore, the construction of factors in the Chinese capital market should vary from that in the US. A relative paper left a 17% annual alpha on the earnings-price factor and found that the Chinese version of a modified FF3 model can explain the Chinese capital market better. Afterwards, an empirical q-factor model was constructed by relative papers to fit the Chinese capital market. Subsequently, some studies found that the model with a modified size factor and modified profitability factor can better explain the Chinese stock market. In a word, the construction of factors can affect the model's effectiveness in the Chinese capital market to some extent. Therefore, how to modify the construction of factors to improve model performance is probably an attractive issue for the following scholars. Furthermore, which is the best model to explain the Chinese capital market is still a controversial topic to be researched.

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