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Asset pricing and nominal price illusion in China

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Based on the Fama's three-factor model (FF3) and five-factor model (FF5), this study adds a low-priced stock premium factor LPP, and then builds a new four-factor and six-factor model respectively to examine the impact of low-price premium (LPP) on the pricing of China's stock market. The research indicates that LPP is a reliable and effective pricing component in China's A-share market, and it may be used as a systematic factor in the Chinese stock market's asset pricing model. The LPP factor shows a strong negative association with stock excess returns. And the inclusion of the LPP in the FF3 and FF5 still passes the robustness test. Meanwhile, the six-factor model created by combining the LPP factor with the FF5 could explain Chinese stock market pricing better.

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Introduction

The capital asset pricing model (CAPM) is the basic theory of current financial asset pricing. This model was respectively proposed by Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966). The theory holds that the expected return of securities is only determined by the expected rate of return (MKT) of the market portfolio, and the sensitivity of different securities to MKT is measured by the beta coefficient. So, the CAPM is often called the single factor model. However, the CAPM has been questionable in many aspects since the 1970s (Blume, 1970; Black, 1972). According to scholars, there are some exposures that cannot be explained by a single explanatory variable like market risk, rendering the CAPM ineffective for capital asset pricing. They began to make further extensions on the basis of CAPM. The Arbitrage Pricing Theory (APT) proposed by Ross (1976) constructed a linear multi-factor pricing model. Further, Fama and French (1992) have subverted the CAPM's viewpoint by including factors that CAPM could not explain. After that, Fama and French (1993) added two more components to the CAPM, High-Minus-Low (HML) and Small-Minus-Big (SMB), and developed the Fama-French three-factor model, which was the first multi-factor model. Since then, many scholars began to explore the field of the multi-factor model, (Jegadeesh and Titman, 1993; Carhart, 1997; Novy-Marx, 2013). Recently, the Daniel-Hirshleifer-Sun three-factor model was also proposed by Daniel et al. (2020). This model proposes two behavioural factors on both long- and short-time scales, which along with the market component create a composite three-factor model, in an attempt to apply behavioural finance to asset pricing. However, in general, CAPM is still a suitable starting point for capital asset pricing today because of its mathematical simplicity and easy understanding of the operation. But additional systemic risk variables that cannot be described by the CAPM could no longer be ignored.

The FF3 is a pioneer in the field of capital asset pricing, however, there are still numerous anomalies that cannot be explained. As a result, many researchers have developed other four-factor models based on the FF3, each model has with its own set of components. The cross-sectional momentum anomaly, first postulated by Jegadeesh and Titman, is the most prominent of the numerous unexplained anomalies (1993). Based on this, Carhart (1997), influenced by Jegadeesh and Titman (1993), added a cross-sectional momentum component (MOM) to the FF3, resulting in the Carhart four-factor model. Differently, Novy-Marx (2013) replaced the SMB factor in the FF3 with the UMD momentum component and PMU profitability factor, thus forming a new four-factor model. The difference is that the UMD momentum factor of Novy-Marx (2013) is constructed by the double ranking method, rather than the Carhart four-factor model's univariate ranking method. Unlike the Fama-French three-factor and Carhart four-factor models, Novy-Marx (2013) builds the factors in a sector-neutral method, that is, long a stock while shorting the sector index to which it belongs with equal weighting, resulting in a sector-neutral portfolio. After that, Stambaugh and Yuan (2017) introduced a management factor and a performance factor to create a distinct four-factor model based on the market factor (MKT) and the size factor (SMB) from different viewpoints.

Fama and French used the dividend discount model (DDM) to analyse earnings and investment determinants in 2006. As the study progressed, Fama and French (2015) included the earnings and investment components to their three-factor model and explicitly presented a five-factor model. The Fama five-factor model, however, has been criticized by Hou et al. (2015). They build a different four-factor model based on the economic theory of real investment. The Hou-Xue-Zhang four-factor model is

developed from the economics of corporate investment and is influenced by Cochrane (1991).

Fritzmeier discovered the low-priced effect in the stock market in 1936, demonstrating that low-priced stocks had both greater investment returns and higher price volatility than equities at higher prices. Using theories such as stock splits, size premium effects and earnings effects, several academics have ascribed the excess profits created by this occurrence to characteristics such as business size, book-to-market ratio, liquidity and momentum (Strong, 1983; Goodman and Peavy, 1986; Hwang and Liu, 2008). The extra risk of the low-priced effect is attributed to characteristics such as business quality and financial leverage by Heins and Allison (1966), Christie (1982), and Dubofsky and French (1988). These factors, however, do not entirely explain the effect of the low-priced stock, implying that the low share price premium effect persists after these factors are eliminated. From a behavioural economics viewpoint, Baker et al. (2009) and Chen et al. (2009), among others, suggest that the phenomenon is driven by investors' creation of the illusion of nominal pricing, which encourages investors to assume that low-priced stocks are cheaper and have greater upside (this is known as the low share price premium puzzle). According to the "investment style hypothesis", Lakonishok et al. (1992), Gompers and Metrick (2001) pointed out that individual investors preferred low-priced stocks to institutional investors. The trading range hypothesis proposes that listed companies tend to keep their stock prices within a reasonable range to attract small or non-institutional investors, namely noise traders (Copeland, 1979). Under the liquidity hypothesis, Black (1986) also believed that low-priced stocks were more likely to attract noise traders, who were crucial to market liquidity. Meanwhile, through the capital market equilibrium model with incomplete information, Merton (1987) proved that the expansion of the scale of noise traders could reduce the financing cost of the company, increase the stock liquidity and improve the market value of the company.

Multi-factor models, as evidenced by the current literature, take additional aspects into consideration to offer a more full and realistic view of share price movements. As a result, the multi-factor model may be utilized to characterize stock market fluctuations and could serve as a theoretical foundation for further improving China's capital market while also reflecting its efficacy. Whether the three-factor model proposed by Fama is applicable to China's stock market is still under debate. Zhan-hui (2004) and Lin et al. (2012) tested the relationship between the FF3 and the potential risk factors of the Chinese stock market. They believed this model could be well applied to the Chinese stock market. Jianlong et al. (2015) believes that the three-factor model has not been verified in China's stock market. After Fama put forward the five-factor model, many scholars compared the applicability of Fama's three-factor model and five-factor model in China's capital market. Among them, Guo et al. (2017), Zhang et al. (2021) and Lin (2017) found that the five-factor model performed better. Guo et al. (2017) and Zhang et al. (2021) found that investment factors contributed little to the investment portfolio. And Lin (2017) found that the disadvantage of the five-factor model was that it could not fully capture the high average return of stocks. Jiao and Lilti (2017) found no significant difference between the five-factor model and the three-factor model. Although there is no unanimous conclusion on whether the multi-factor model proposed by Fama is applicable to China's stock market, scholars still mainly use the FF3 and the FF5 in the empirical asset pricing field in China.

However, the empirical study discovered that in the Chinese stock market, there is a low-price premium effect, and the bigger the proportion of retail investors, the stronger the effect, and

small-cap stocks have a higher low-price premium (Luo et al., 2017). Over 200 low-priced stocks in China increased by an average of 699.1% between 2006 and 2007, compared to 299.76% for the same number of high-priced firms.

Based on the existing literature, it is found that the five-factor model cannot completely catch the high average return of stocks. The scholars have not enough research on the low-price stock effect of China's stock market, and rarely consider the unique investor structure of China's stock market. China's stock market is famous for its a large number of inexperienced individual investors. According to the annual statistics of the Shanghai Stock Exchange, individual investors contributed 85% of the total trading volume in 2020. Meanwhile, the research results of Liu et al. (2019) show that the investor structure has an important impact on the stock pricing of China's stock market, and individual investors prefer low-priced stocks. Few studies take the nominal price of the stock as one of the factors of its pricing and bring it into the multi-factor model for comprehensive analysis. Therefore, this study extends the five-factor model (including MKT, HML, SMB, CMA, and RMW) of Fama and French (2015), build the low-price premium effect factor from the perspective of behavioural finance, and creates a six-factor model to test the pricing of China's stock market by adding the influence component of the low-priced stock premium (LPP). The research makes up for the defect that the existing five-factor model cannot fully capture the high average return of stocks, and takes into account the unique investor structure of more individual investors in China's stock market. And we also attempt to explain the differences in the determinants of stock risk premium in the rapidly developing Chinese stock market.

In this study, Stata is the main tool used in this work. Specifically, firstly, the LX method (Luo et al. 2017) is used to build LPP indicators. Based on this, the factor cross-section technology is used to process the LPP factor data. Secondly, in order to create a new four-factor and six-factor models, LPP factor is added to the FF3 and FF5. Thirdly, the FF3 and FF5 are verified and compared with the four-factor model and six-factor model including the LPP factor. Finally, the four multi-factor models are applied to China's stock market. This is to test which model is the most effective for Chinese stock valuation. Our main results show that LPP could be used as a systematic pricing factor, and the six-factor model has also passed the robust test. Our research could provide some supplements and references for other scholars in the field of capital asset pricing and multi-factor model. In addition, our results cannot only provide different perspectives for investors and securities analysts in investment decision-making but also provide new ideas for the government to formulate capital market-related policies.

Methodology

China's capital market is developing rapidly, with its total market value increasing from 2.8 billion CNY in 1990 to 80 trillion CNY in 2020. It has become the second-largest capital market in the world. Meanwhile, China's capital market is not completely open, and its development level is still behind that of other developed countries such as Europe and the United States. China's capital market has its special characteristics. For example, its participants are mostly individual investors with relatively little investment experience. In terms of theoretical research, there are few studies on determinants of equity risk premium in China's capital market. Based on the above analysis, we choose China's stock market as the research object. In the related studies, most scholars like Liu et al. (2019) and Zhang et al. (2021) use China Stock Market & Accounting Research Database (CSMAR) for research, and the data of the database is accurate and comprehensive. So, in our

study, we collect the data from CSMAR in order to be consistent with other scholars. Since 2007, China began to implement the reform of non-tradable shares, which further standardized the operation of the capital market. Therefore, CSMAR data after 2007 could better reflect the real situation of China's stock market at this stage. So the sample period of our study is from 1 January 2007 to 31 December 2020, including stock data of all listed companies (4392). Market interest rate, risk-free rate, China's stock market index, stock market capitalization, book value, operating profit and other indicators are used to build the FF5 and the LPP. This is to study the determinants of risk premium in China's stock market.

As interest rates in China were not fully market oriented during the reporting period, we use the market interest rate to measure the combined monthly market rate of return on cash dividends reinvested and the risk-free rate is measured using the one-year time deposit rate, which is supported by Hou et al. (2019) and Liu et al. (2019). According to Fama and French (2015), financial data for publicly traded companies, such as the market value of shares, book value and operating profit, are derived from each company's consolidated financial statements, and calculated using the total market value from the previous year's financial report as weights. At the same time, the abnormal data from the sample, like yearly data of suspensions of more than 20 days, cumulative data of more than 200 days and stocks with negative book to value ratios, have been deleted in order to preserve the scientific quality of the study.

Our study uses the method of Fama and French (2015) to build the factors in order to make it comparable with the research of other scholars. SMB is the market value factor, that is the difference in the yield between the small market value and large market value stock portfolio. HML is the book to market ratio factor. It is the difference between the yield of a stock portfolio with a high book to market ratio and with a low book to market ratio. RMW is the profitability factor, which is the difference between the stock portfolio yield with a high operating profit margin and low operating profit margin. CMA is the factor of investment style, which is the difference between the return of a stock portfolio with a conservative investment style and a radical investment style. The factor construction method of the FF5 is as follows. Firstly, size of stocks (Market Value) is divided into two groups based on the median: small market value (S) and large market value (B). Secondly, according to the quantile of 30% and 70%, Earnings-to-Price (EP) is split into three groups: high (H), medium (M) and low (L). Low-Priced Premium (LPP) is split into three groups: front (F), medium (L) and rear (RE). Thirdly, by crossing the two indicators of market value and book to market value ratio, all stocks could be divided into six combinations of S/H, S/N, S/L, B/H, B/N and B/L. Similarly, the other two dimensions, Operating Profit (OP) and Investment Style (Inv), are separated into three groups, and the intersection of the size combinations is used to divide the total stock into 12 groups. The 12 combinations are S/R, S/N, S/W, B/R, B/N, B/W, S/C, S/N, S/A, B/C, B/N and B/A respectively. Among them, R represents steady profit, W is weak profit, C means conservative investment style, A is defined as aggressive investment style, and N denotes middle investment style. Then we calculate the weighted average return rate of each period of the above portfolios. Finally, the factors are constructed using the difference in the returns of the portfolios. These factors are as follows:

$$SMB_{EP} = \frac{(S/H + S/M + S/L)}{3} - \frac{(B/H + B/M + B/L)}{3} \quad (1)$$

$$SMB_{OP} = \frac{(S/R + S/O + S/W)}{3} - \frac{(B/R + B/O + B/W)}{3} \quad (2)$$

$$SMB_{Inv} = \frac{(S/I + S/N + S/V)}{3} - \frac{(B/I + B/N + B/V)}{3} \quad (3)$$

$$SMB_{LPP} = \frac{(S/F + S/L + S/RE)}{3} - \frac{(B/E + B/L + B/RE)}{3} \quad (4)$$

$$SMB = \frac{SMB_{BM} + SMB_{OP} + SMB_{INV} + SMB_{LPP}}{4} \quad (5)$$

$$HML = \frac{(S/H + B/H)}{2} - \frac{(S/L + B/L)}{2} \quad (6)$$

$$RMW = \frac{(S/R + B/R)}{2} - \frac{(S/W + B/W)}{2} \quad (7)$$

$$CMA = \frac{(S/C + B/C)}{2} - \frac{(S/A + B/A)}{2} \quad (8)$$

Fama’s three-factor (1992) and five-factor (2015) model are as follows.

$$R_{it} - R_{ft} = \alpha_i + \beta_{1,i}(R_{mt} - R_{ft}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \varepsilon \quad (9)$$

$$R_{it} - R_{ft} = \alpha_i + \beta_{1,i}(R_{mt} - R_{ft}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}RMW_t + \beta_{5,i}CMA_t + \varepsilon \quad (10)$$

where R_{it} is the yearly return on the equity portfolio i at time t , R_{ft} is the risk-free rate at time t , and R_{mt} is the return on the market portfolio weighted by circulation market value in December of year $t-1$. The difference in returns between a portfolio of small-cap shares and a portfolio of large-cap equities over time t is denoted by SMB_t . At time t , HML_t represents the return difference between a portfolio of stocks having a high profit-to-market ratio and with a low profit-to-market ratio. The difference between the return of a portfolio of high-profit companies and low-profit equities at time t is denoted by RMW_t . The difference in return of a portfolio of stocks having a conservative investment style and an aggressive investment style at time t is denoted by CMA_t . The sensitivity of stock returns to the SMB, HML, RMW, and CMA factors is measured by $\beta_{2,i}$, $\beta_{3,i}$, $\beta_{4,i}$, and $\beta_{5,i}$. With the greater the absolute value of the coefficient, the stronger the explanatory power of the factor on stock returns.

The premium effect of low-priced stocks is measured using the Luo et al. (2017) approach (referred to as the LX method). After the LPP is constructed according to formula (11), it is incorporated into the FF5 to form a six-factor model. The following is the construction formula of LPP index.

$$LPP_{i,t} = \beta_0 + \beta_1PRICE_{i,t-1} + \beta_1X_PRICE_{i,t-1} + \beta_2RETAIL_{i,t-1} + \beta_3INSTI_{i,t-1} + \beta_4ANALY_{i,t-1} + \beta_5SELL_{i,t-1} + \sum Controls_{i,t-1} + \sum Industry + \sum Year + \varepsilon \quad (11)$$

where $PRICE_{i,t-1}$ is stock prices, $RETAIL_{i,t-1}$ denotes the size of retail investors in listed companies, $INSTI_{i,t-1}$ means the shareholding ratio of institutional investors in listed companies, and $ANALY_{i,t-1}$ denotes the shareholding ratio of securities analysts in listed companies. $SELL_{i,t-1}$ is a dummy variable for the mechanism of short selling. The interaction term between any of the moderating factors and $PRICE_{i,t-1}$ is represented by $X_PRICE_{i,t-1}$. $\sum Industry$ and $\sum Year$ are industry variables and time variables respectively, and ε is the random perturbation term.

We compute the LPP for each stock at different time using the algorithm above. The LPP factor is built in the same way as other Fama and French (2015)’s factors such as CMA and RMW. So,

the LPP factor is built as follows:

$$LPP = \frac{(S/F + B/F)}{2} - \frac{(S/RE + B/RE)}{2} \quad (12)$$

In order to see if the new factor LPP is a systematic asset pricing factor, we add it to the FF3 and FF5, respectively. This is accomplished in the following way:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1,i}(R_{mt} - R_{ft}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}LPP_t + \varepsilon \quad (13)$$

$$R_{it} - R_{ft} = \alpha_i + \beta_{1,i}(R_{mt} - R_{ft}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}RMV_t + \beta_{5,i}CMA_t + \beta_{6,i}LPP_t + \varepsilon \quad (14)$$

where LPP_t is the difference in return between a portfolio with a high and a low-price stock premium at time t . The objective of introducing the LPP_t component, in contrast to the Eqs. (9) and (10), is to evaluate the explanatory power of LPP on stock excess returns. The sign of $\beta_{6,i}$ is negative if the LPP factor is positively linked with a stock’s excess return, and the bigger $\beta_{6,i}$, the higher the excess return.

GRS statistic test was introduced by Gibbons et al. (1989) for assessing the validity of a model. If the pricing model’s variables fail to adequately describe stock portfolio returns, the regression intercept term matrix will most likely be statistically significant non-zero, resulting in a high GRS statistic, and the GRS test’s initial hypothesis will be rejected. On the basis of the FF3 and FF5, we test the LPP factor in different models by GRS test, and get GRS statistics for different models. Furthermore, we compare the GRS statistics of various models to see if the LLP factor are valid.

Empirical research

Table 1 shows the descriptive statistics including mean, standard deviation and t -statistic for each factor, as well as the correlation among them. The mean, standard deviation and t -statistics are shown in descriptive statistics. The Rm-Rf, MKT, and SMB factors have positive average return, whereas all other factors have negative average return. SMB has a strong linear correlation with other factors, such as RMW, CMA, and HML, as shown in the correlation table. In the next section, we will study whether this will impact the estimation efficiency of the factor models and the significance of the factors. In fact, the mean values of the factor return derived from Table 1 are only preliminary descriptive statistics and are insufficient to determine the significance of each factor in the Chinese stock market, as it could be influenced by sample intervals, grouping patterns, and other relevant factors.

Factor spanning regressions use the returns of five factors as explanatory variables to explain the returns of the sixth factor. The regression intercept term represents the risk premium of the other five factors after risk adjustment. The regression results in Table 2 show that after adjustment of several other five risk factors, the A-share market still has a significant size effect, book-to-market effect, profitability effect, and low-priced stock premium effect. The regression intercept of CMA factor on the other four factors cannot reject the null hypothesis that the intercept term is zero, indicating that the CMA factor in the six-factor model is a “redundant” factor for explaining the return rate of a stock portfolio, which is consistent with the result of Guo et al. (2017).

The usage of two-dimensional groups of size, EP, OP, and Inv is a common approach for determining if the influence of a new component is significant. We create two-dimensional groups of LPP-size, LPP-EP, LPP-OP, and LPP-Inv in this article. The 25 excess returns for the four grouping situations are shown in Table 3. Through the excess return, we could observe if there is a premium effect on low-priced companies. We divide the companies into five

Table 1 Descriptive statistics for factor return.

	Rm-Rf	MKT	SMB	HML	RMW	CMA	LPP
<i>Descriptive statistics for factor return</i>							
Mean (%)	1.21	0.65	0.32	-0.13	-0.01	-0.08	-0.23
Std dev. (%)	13.84	7.04	5.05	4.90	4.46	2.70	3.70
t-statistic	32.79	34.30	23.06	-9.86	-0.85	-11.00	-23.09
<i>Correlations</i>							
Rm-Rf	1.00	0.52	0.31	-0.20	-0.36	0.14	-0.05
MKT	0.52	1.00	0.20	-0.15	-0.26	0.02	-0.11
SMB	0.31	0.20	1.00	-0.52	-0.90	0.67	-0.07
HML	-0.20	-0.15	-0.52	1.00	0.34	0.11	0.77
RMW	-0.36	-0.26	-0.90	0.34	1.00	-0.72	-0.13
CMA	0.14	0.02	0.67	0.11	-0.72	1.00	0.45
LPP	-0.05	-0.11	-0.07	0.77	-0.13	0.45	1.00

Table 2 Factor spanning regressions.

	(1) MKT	(2) SMB	(3) HML	(4) RMW	(5) CMA	(6) LPP
SMB	-0.45 (-1.43)		-0.52** (-5.90)	-0.67** (-11.70)	0.31** -5.13	0.05 -0.56
HML	0.24-0.91	-0.35** (-5.90)		0.06 -0.87	0.20** -3.93	0.67** -15.1
RMW	-1.47** (-4.80)	-0.70** (-11.70)	0.09 -0.87		-0.21** (-3.15)	-0.25** (-2.92)
CMA	-1.11** (-2.95)	0.46** -5.13	0.44** -3.93	-0.29** (-3.15)		0.11 -1.05
LPP	-0.41 (-1.38)	0.04 -0.56	0.88** -15.1	-0.21** (-2.92)	0.07 -1.05	
MKT		-0.03 (-.43)	0.02 -0.91	-0.09** (-4.80)	-0.05** (-2.95)	-0.03 (-1.38)
_cons	0.45 (-0.77)	0.41*** (-2.89)	0.34* (-1.91)	0.26** (-1.85)	-0.07 (-0.56)	-0.18** (-2.07)
N	162	162	162	162	162	162
R ²	0.178	0.894	0.814	0.88	0.762	0.773

T statistics are given in brackets. Asterisk symbols *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

categories based on their market capitalization, book-to-market ratio, operational profit and investment, and then sort them by 20% quartile. Each of these five groups is cross-combined with the LPP in the same grouping method, yielding a total of 100 regressions. The low-priced stock premium effect may be seen in these four panels, because the excess return diminishes as the LPP grouping increases. This is the first indication that the Chinese capital market has a low-priced stock premium effect.

The regression results of the factor models for the FF3 and FF5, as well as each of them with the inclusion of LPP factor, are shown in Table 4. This is due to a lack of scholarly consensus on which of the FF3 and the FF5 is more suited for the Chinese capital market. So, we examine both the FF3 and FF5 in this study. The purpose of adding LLP to the FF3 and FF5 to construct a four-factor model and a six-factor model is to investigate if the additional factor might increase the factor models' explanatory ability. As shown in Table 4, the LPP factor is all statistically significant, indicating that it is an effective asset pricing factor. With the LPP component included, the models' explanatory power is increased further. In all models, the coefficients of LPP are negative, demonstrating that the larger the premium impact of low-priced stocks, the less the return of them.

Then we obtain intercept terms of the various factor models by ranking size, B/M, profit, investment, and LPP in quintiles, so as to further investigate the explanatory power of LPP in the factor models. If the intercept term is larger, the explanatory power of LPP factor will be stronger. Only the Size-BM and Size-Inv groups are given due to the page limit. On the basis of Table 5,

Table 3 LPP with 25 regression intercept terms in four dimensions.

LPP	Low	2	3	4	High	
<i>LPP-Size</i>						
Size	Small	0.8739	0.8523	0.8029	0.8529	0.7363
	2	0.8098	0.4930	0.3745	0.5113	0.4582
	3	0.5051	0.4933	0.2072	0.1326	0.1300
	4	0.4421	0.2328	0.0856	0.3356	0.6379
	BIG	0.3027	-0.0189	0.6310	0.5448	0.9576
<i>LPP-EP</i>						
EP	Small	0.6092	0.1891	0.4023	0.2247	0.6037
	2	0.5263	0.3817	0.4228	0.4888	0.5976
	3	0.5824	0.5345	0.3266	0.5423	0.3002
	4	0.5496	0.5547	0.5602	0.4784	0.5149
	BIG	0.7404	0.5377	0.4102	0.6899	0.4666
<i>LPP-OP</i>						
OP	Small	0.7895	0.6343	0.3991	0.6141	1.0367
	2	0.7374	0.6820	0.2838	0.2435	0.6892
	3	0.4275	0.3641	0.3912	0.7125	0.2127
	4	0.4578	0.2005	0.4961	0.4527	0.4795
	BIG	0.4539	0.3087	0.5707	0.2838	0.6852
<i>LPP-Inv</i>						
Inv	Small	0.7745	0.5790	0.2766	0.4924	0.1979
	2	0.8006	0.5921	0.2129	0.6664	0.6836
	3	0.5009	0.4911	0.7467	0.4865	0.4508
	4	0.6669	0.2982	0.5195	0.4004	0.5297
	BIG	0.5841	0.3566	0.3296	0.3272	0.2895

Table 4 Regression results for the four models.

	FF3	FF3 + LPP	FF5	FF5 + LPP
MKT	0.9574*** (0.0102)	1.0461*** (0.0149)	0.9956*** (0.0119)	1.0406*** (0.0221)
SMB	0.6441*** (0.0736)	0.1550*** (0.0527)	0.6083*** (0.0777)	0.4006*** (0.1107)
HML	-0.2326*** (0.0570)	0.0878 (0.0732)	-0.1654*** (0.0604)	0.0288 (0.1154)
RMW			0.2282*** (0.0567)	-0.3626*** (0.0858)
CMA			-0.1000 (0.0700)	0.0152 (0.1279)
LPP		-0.3068*** (0.662)		-0.5080*** (0.0856)
Constant	0.0003 (0.0099)	-0.0095 (0.0105)	0.0412*** (0,0121)	-0.0409 (0.0207)
R ²	0.6083	0.4935	0.6099	0.4949

T statistics are given in brackets.
Asterisk symbols *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

Table 5 Size-BM grouping intercept terms and t-tests for the four models.

B/M	Low	2	3	4	High	Low	2	3	4	High
<i>Panel A: 3 factor</i>										
Size			A					t(A)		
Small	0.2743**	0.6235***	0.9417***	0.7026***	0.6856***	Small	1.5994	4.4633	6.0899	4.6842 3.7805
2	0.1695*	0.4582***	0.2925***	0.2257**	0.5302***	2	0.9883	2.8986	2.0040	1.6798 3.1806
3	-0.0383	-0.1100	0.0806	0.2268**	0.2646**	3	-0.2410	-0.7022	0.5968	1.6453 1.8039
4	0.1840**	0.2602**	-0.2744**	0.1573**	0.1444**	4	1.1810	1.7033	-1.9065	1.0721 1.0697
Big	0.8302***	0.2185**	0.0653	0.1603*	0.1568**	Big	5.5913	1.2988	0.3717	1.0241 1.7779
<i>Panel B: 4 factor</i>										
Size			A					t(A)		
Small	0.3715**	0.6607***	0.9859***	0.7654***	0.8209***	Small	2.1505	4.6808	6.2995	4.9867 4.4077
2	0.2625**	0.5155***	0.3860**	0.3347***	0.7357***	2	1.4933	3.1517	2.5942	2.4636 4.2358
3	-0.0447	-0.0431	0.1752**	0.4023***	0.4245**	3	-0.2749	-0.2702	1.2849	2.8357 2.8542
4	0.2128**	0.3560**	-0.1289	0.2726**	0.2941**	4	1.3077	2.2768	-0.8771	1.8287 2.1420
Big	0.9000***	0.3488**	0.2084**	0.2732**	0.2628**	Big	6.0108	2.0056	1.1591	1.6821 2.9012
<i>Panel C: 5 factor</i>										
Size			A					t(A)		
Small	0.3788**	0.7384***	1.0972***	0.9118***	0.9243***	Small	2.2282	5.2321	7.0408	5.8580 4.9941
2	0.2967 *	0.6255***	0.4972***	0.3847**	0.8231***	2	1.7167	3.9341	3.3788	2.8721 4.7618
3	0.0891	0.0822	0.2825**	0.4534***	0.5215***	3	0.5528	0.5243	2.0872	3.2279 3.5198
4	0.3947**	0.4801***	0.0063	0.3965**	0.3662**	4	2.4258	3.0878	0.0435	2.6807 2.6810
Big	1.0556***	0.5424***	0.2337*	0.3387**	0.3285***	Big	7.0499	3.1452	1.3266	2.1674 3.6910
<i>Panel D: 6 factor</i>										
Size			A					t(A)		
Small	0.4030**	0.7332***	1.0971***	0.9156***	0.9928***	Small	2.3591	5.1837	7.0155	5.8377 5.3016
2	0.3127*	0.6253**	0.5107***	0.4187***	0.9053***	2	1.7909	3.8765	3.4507	3.1190 5.1641
3	0.0563	0.0886	0.2977**	0.5025**	0.5786**	3	0.3466	0.5606	2.1957	3.5535 3.9077
4	0.3765**	0.4982***	0.0384	0.4102**	0.4000**	4	2.2775	3.1838	0.2635	2.7690 2.9240
Big	1.0658***	0.5724***	0.2862*	0.3646***	0.3397***	Big	7.1160	3.2825	1.6184	2.2975 3.7954

T statistics are given in brackets.
Asterisk symbols *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

we preliminarily evaluate the applicability of these four models in China’s capital market, and analyse which of the new models incorporating LPP performs better.

Table 5 shows that there is a total of 21 significant non-zero intercept terms (10%) in the FF3, the non-significant intercept terms are mainly concentrated in the Size group 3. On the whole, the FF5 has stronger explanatory power than the FF3, which is attributable to the fact that there are more variables significant at the 5% significance level in the FF5 (There are 20 significant regression results in the FF5, while only 19 in the FF3). This also helps to overcome the Size group 3’s weak explanatory power. The four-factor model has considerably superior intercept terms than the FF3. Because there are three intercept terms that are completely statistically insignificant in the four-factor model, while there are four such intercept terms in the FF3. With the addition of LPP, the FF3 appears to have better explanatory power. When comparing Panel C

and Panel D, we find that the six-factor model outperforms the FF5. Many intercept terms in Panels C and D are statistically significant. The addition of the additional variable (LPP), to some extent, enhances the t-statistic much more (Tables 6 and 7).

Overall, a small fraction of the Inv3, Inv4 and high group have significantly non-zero intercept terms in Size-Inv, probably because the investment effect is not large in the Chinese stock market, as researchers like Hou et al. (2019) and Liu et al. (2019) have shown. In the FF3, there are only 14 intercept terms that are significantly non-zero (10%), and this number reduces to 7 when the significance level is increased to 1%. With the LPP component included, the number of significantly non-zero intercept terms increase to 18 (10%), and it increases to 10 with a significance level of 1%. This tendency could be seen in both the FF5 and six-factor model, with 21 intercept terms significantly non-zero (5%) in the six-factor model and

Table 6 Size-Inv grouping intercept terms and t-tests for the four models.

Inv	Low	2	3	4	High	Low	2	3	4	High	
<i>Panel A: 3 factor</i>											
Size	A							t(A)			
Small	0.4939***	0.7062***	0.8112***	0.7450***	0.6105**	Small	3.7861	5.0858	4.8570	4.2131	2.8156
2	0.3848*	0.4341**	0.2462**	0.3126**	0.1856*	2	2.5879	2.8822	1.6334	1.9504	1.1289
3	0.0375	0.0024	0.0774	0.1522*	0.0440	3	0.2476	0.0171	0.5380	1.0367	0.2796
4	-0.0576	-0.0251	0.1440	0.2820*	0.0616	4	-0.3157	-0.1669	0.9998	1.9915	0.4459
Big	-0.1627	0.1716	0.4737***	0.3701***	0.5484***	Big	-0.9230	1.0999	3.4078	3.0890	4.3124
<i>Panel B: 4 factor</i>											
Small	0.6320***	0.7376***	0.8398***	0.7718***	0.6643***	Small	4.7766	5.2216	4.9540	4.3548	3.0060
2	0.5485***	0.5859***	0.3060**	0.3754**	0.2603**	2	3.6065	3.7210	1.9859	2.3103	1.5553
3	0.1793	0.1471*	0.1500	0.2270*	0.1073	3	1.1652	1.0336	1.0186	1.5093	0.6680
4	0.1809	0.0517	0.2380*	0.3663**	0.1467	4	0.9570	0.3371	1.5971	2.5201	1.0443
Big	-0.0045	0.3009**	0.5904***	0.4729***	0.6465***	Big	-0.0245	1.9117	4.1356	3.8837	4.9513
<i>Panel C: 5 factor</i>											
Small	0.7212***	0.8960***	0.8998***	0.7986***	0.6982***	Small	5.4873	6.3068	5.2870	4.5987	3.2311
2	0.6104***	0.7081***	0.4043**	0.4641**	0.2312*	2	4.1005	4.5437	2.6611	2.8890	1.4158
3	0.3040**	0.2572*	0.2985**	0.3106**	0.1411	3	1.9782	1.8193	2.0445	2.0923	0.8997
4	0.2708*	0.2020*	0.3436**	0.5115***	0.3161***	4	1.4515	1.3165	2.3071	3.5193	2.2664
Big	0.1496	0.5237***	0.7496***	0.4788***	0.7459***	Big	0.8408	3.3406	5.3127	3.9578	5.7848
<i>Panel D: 6 factor</i>											
Small	0.7658***	0.8774***	0.9005***	0.7912***	0.7004***	Small	5.8055	6.1530	5.2532	4.5423	3.2294
2	0.6710***	0.7651***	0.4091**	0.4648**	0.2351*	2	4.4631	4.8111	2.6759	2.8880	1.4267
3	0.3420**	0.2906**	0.3056**	0.3234**	0.1427	3	2.2213	2.0526	2.0748	2.1607	0.9033
4	0.3344**	0.2060*	0.3574**	0.5237***	0.3167***	4	1.7765	1.3370	2.3728	3.5830	2.2662
Big	0.1734	0.5364***	0.7679***	0.5095***	0.7763***	Big	0.9603	3.4190	5.3983	4.1980	5.9788

T statistics are given in brackets. Asterisk symbols *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

Table 7 GRS test for four models.

	FF3					FF3 + LPP				
	GRS	SR(α)	A α _i	s(α)	Adj-R ²	GRS	SR(α)	A α _i	s(α)	Adj-R ²
Size-B/M	2.0927***	0.6333	0.2887	0.3176	0.8359	2.0822***	0.6399	0.3514	0.3185	0.8385
Size-OP	1.4634*	1.3913	0.3234	0.3299	0.8247	1.4025*	0.5254	0.3491	0.3307	0.8274
Size-Inv	1.3936**	0.5166	0.2885	0.3127	0.8347	1.3173**	0.5092	0.3301	0.3137	0.8371
Size-PI	1.9267***	0.6075	0.3531	0.3228	0.8291	1.7916***	0.5938	0.3486	0.3179	0.8372
	FF5					FF5 + LPP				
	GRS	SR(α)	A α _i	s(α)	Adj-R ²	GRS	SR(α)	A α _i	s(α)	Adj-R ²
Size-B/M	1.9431***	0.6293	0.4800	0.3081	0.8523	1.9451***	0.6351	0.4972	0.3087	0.8530
Size-OP	1.2681**	0.4781	0.4700	0.3155	0.8461	1.2017*	0.4992	0.4884	0.3162	0.8467
Size-Inv	1.1617**	0.4873	0.4750	0.3010	0.8536	1.1460*	0.4875	0.4911	0.3015	0.8543
Size-PI	1.8954**	0.6225	0.4895	0.3146	0.8445	1.8534***	0.6200	0.4945	0.3092	0.8505

T statistics are given in brackets. Asterisk symbols *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

19 intercept terms with the same degree of significance in the FF5.

Robust test

A common test used in academia to test the robustness of factor models is the GRS. This test was generalized by Gibbons et al. (1989) from Malinvaud’s (1980) “Hotelling’s T2 Test”. It is calculated as follows:

$$GRS\ Statistic = \frac{T}{N} \times \frac{T - N - L}{T - L - 1} \times \frac{\alpha' \epsilon^{-1} \alpha}{1 + \mu' \Omega^{-1} \mu} \quad (15)$$

The statistic follows a non-central F distribution with the degrees of freedom N and (T-N-L). Where T is the number of

the units of time; N represents the number of portfolios on the left side of the equation; L is the number of the factors in multi-factor model; α is a matrix of intercept terms of dimension (N, 1); ε is a matrix consisting of the variance and covariance of the residual terms with dimension (N, N); μ represents the average return matrix of the factors in multi-factor model with dimension (L, 1); Ω is a matrix consisting of the variance and covariance of μ with dimension (L, L).

In this paper, the robustness of the FF3, the four-factor model, the FF5 and the six-factor model are tested using the GRS test. If the pricing model’s variables fail to adequately explain the return of the equity portfolio, the regression intercept term will be significantly non-zero, resulting in a high GRS statistic and the GRS test’s null hypothesis will be rejected.

The models that include the LPP component all pass the GRS test. It has the lower GRS statistics than the FF3 and FF5, showing that the LPP factor have a better influence on the model's explanatory power. The LPP factor is an effective pricing factor according to this test. Both the FF3 and FF5 pass the GRS test, and the GRS statistics of the FF3 is smaller to the FF5. It indicates that from the perspective of robustness, the FF5 is more applicable to the Chinese capital market. Meanwhile, the six-factor model obtained by adding LPP to the FF5 is more robust.

Conclusion

We select the monthly data of listed companies in China's A-share market from January 2007 to December 2020, and use the LX technology to evaluate the LPP factor. This is to study whether the LPP factor is an effective and systematic asset pricing factor. Then, we compare the FF3 and FF5. According to the empirical research results, LPP is an effective pricing component, which has a strong negative correlation with the excess return of stocks.

The conclusion of this study shows that the low-priced stock premium effect is an important factor that influences the efficiency of the capital market, and the six-factor model outperforms the FF5 in the Chinese A-share market. Moreover, under the full sample, the scale effect and book-to-market ratio effect are statistically significant. After the adjustment of the FF3 and FF5, there are still significant profitability effect, investment style effect and low-priced stock premium effect in China's capital market. Besides, consistent with the study conclusions of Guo et al. (2017), Zhang et al. (2021) and Lin (2017), the FF5 has a strong explanatory power, which is better than the FF3.

In China's stock market, considering the transaction cost and wealth constraints, retail investors prefer to buy low-priced stocks. It further expands the volatility of low-priced stocks, promotes the liquidity of stocks and increases the attraction to individual investors. Moreover, the reduction of liquidity risk reduces the overall risk of stocks to a certain extent, and finally shows the special phenomenon of high returns and low risk of low-priced stocks relatively. Compared with the securities market dominated by institutional investors in developed countries, China's stock market is dominated by retail investors. With the decrease of the average age of retail investors, it leads to the decline of financial literacy and the increase of irrational behaviour, resulting in a more obvious low-price stock effect. However, when the price of low-priced stocks rises gradually, individual investors will be affected by liquidity constraints. This weakens the attractiveness of low-priced stocks to retail investors, reduces the liquidity of stocks, and finally decreases the effect of low-priced stocks. LPP factor has more pricing power than the book value factor, which also shows that the irrational investor structure in China's stock market and the rationality of investment are low.

China should further and continuously open its capital market. It could attract institutional investors from other countries to participate in China's stock market. On the one hand, this could increase the degree of competition in China's capital market, thus forcing China's institutional investors to strengthen their professional construction. On the other hand, the entry of institutional investors from various countries could further improve the proportion of institutional investors in China's stock market. And the entry of them could also force Chinese regulators to issue corresponding laws and regulations to further improve the market standardization. Based on the three aspects above, the irrational level and low-price premium of investors in China's capital market will be reduced.

The findings of this article could not only help foreign investors better understand the Chinese A-share market, but also contribute to the empirical research on China's asset pricing. We will utilize more complex testing in future research, including but not limited to the factor pricing models discussed in this work. And we will go deeper into the theoretical basis of the models. Despite three experiments in our study show the six-factor model created by adding LPP to the FF5 is more successful, we should also admit that no model is flawless. Therefore, we need to maintain logical thinking and adopt scientific methods to honestly evaluate the advantages and disadvantages of various models.

Data availability

All data used in this study can be obtained from CSMAR or requested to the corresponding author.

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Additional information

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