Capital age and the cross-section of Chinese stock returns

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Abstract. This paper investigates the impact of capital age on the cross-section of stock returns in the Chinese stock market. Based on portfolio sorting and Fama-MacBeth regressions, we find a significant premium for stocks with low capital age, with monthly risk-adjusted returns that are 0.42%-0.49% higher than those of stocks with high capital age. Mechanism analysis shows that capital age affects expected stock returns through its influence on firms' investment efficiency and their ability to cope with technology shocks. The premium remains statistically significant after controlling for a comprehensive set of common risk factors and is robust across different weighting schemes and sample selection criteria. Our findings confirm that capital age can serve as a reliable incremental predictor of expected returns in the Chinese stock market.

Keywords: Capital age; Cross-section of stock returns; Return predictability; Chinese stock market; Fama-MacBeth regression.

1. Introduction

The aging and renewal of corporate capital constitute fundamental micro-level determinants of firm productivity, competitive resilience, and long-term value creation [1,2]. As technological progress accelerates and industrial upgrading deepens, a firm's capital age serves not merely as a proxy for the physical and technological obsolescence of its equipment, but also as a critical indicator of its flexibility in technology adoption and its capacity to adapt to evolving market conditions [3]. In recent years, a growing body of literature has turned its attention to the asset pricing implications of capital age, documenting a robust empirical link between capital age and expected stock returns [3,4,5]. Against this backdrop, investigating whether and how capital age influences the cross-sectional pricing of stocks in China carries substantial theoretical and practical significance.

Several motivations underpin our examination of the pricing role of capital age in the Chinese stock market. First, through decades of development, China's equity market has grown into the world's second largest by market capitalization, with its scale and influence steadily rising and attracting growing attention from both domestic and international investors [6,7,8]. Second, China's economy is at a pivotal stage of transformation and upgrading, where manufacturing equipment renewal, technological iteration, and capital deepening are central policy priorities [9,10]; capital age may thus serve as a meaningful barometer for tracking the progress and quality of firm-level transformation. Third, existing asset pricing studies on capital age have largely concentrated on developed markets [3,4], with limited evidence from emerging economies such as China. Given that Chinese firms exhibit distinctive capital composition, depreciation practices, and investment behavior, the capital age effect may manifest differently in this setting.

Based on this, we take Chinese A-share listed companies from 2008 to 2020 as our sample, construct a firm-level capital age measure, and systematically examine its predictive power for the cross-section of stock returns in China. First, using portfolio sorting, we find that portfolios with low capital age generate significantly positive excess returns relative to those with high capital age, with an average monthly premium of 0.47%. This premium remains robust after controlling the market, size, value, profitability, and investment factors. Second, employing Fama-MacBeth cross-sectional regressions, we find that capital age remains a significantly negative predictor after controlling for firm size, book-to-market ratio, profitability, illiquidity, and investment, suggesting that its pricing role is independent of these common determinants. In addition, we conduct a series of robustness checks, including alternative weighting schemes, excluding special years, and relaxing sample selection criteria, all of which support the reliability of the capital age premium.

This paper has several contributions. First, our research is closely linked to the growing literature on capital age and asset pricing. While existing studies have predominantly focused on developed markets, we complement this literature by introducing capital age, a fundamental real-economy variable, into the asset pricing framework of the Chinese stock market, thereby broadening the predictor space for cross-sectional return predictability. Second, we provide systematic empirical evidence for a significant "capital age premium" in China and document its distinct patterns relative to firm size, investment, and other key firm characteristics. Third, our findings have practical implications for investors seeking to identify firms with strong renewal momentum and technological adaptability, offering a new dimension for asset allocation and risk management in the Chinese equity market.

The remainder of the paper is organized as follows. Section 2 describes the data and variable construction. Section 3 presents the main empirical results. Section 4 discusses potential mechanisms. Section 5 provides robustness checks. Section 6 concludes.

2. Data and key variables

2.1. Capital age

We construct the capital age variable following the framework established in the literature [3,4,5]:

$$\mathrm{AGE}_{i,t} = (1 - \delta_j)\frac{K_{i,t-1}}{K_{i,t}}(\mathrm{AGE}_{i,t-1} + 1) + \frac{I_{i,t-1}}{K_{i,t}} \tag{1}$$

Where $K_{i,t}$ is the net fixed assets of firm i in period t, $I_{i,t}$ represents the net investment from period t to period t+1, and δ_j denotes the industry-specific depreciation rate calculated according to the CSRC 2012 industry classification. The initial capital age is the ratio of accumulated depreciation and amortization to current depreciation and amortization.

All variables are adjusted to real values with 1990 as the base year using the fixed asset investment price index published by the National Bureau of Statistics of China. For the pre-2007 period, where official price index data is not available, we follow the standard methodology in the literature [11,12, 13] to estimate the missing index values.

When a firm has no positive investment, the capital age evolves as:

$$\mathrm{AGE}_{i,t} = \mathrm{AGE}_{i,t-1} + 1 \tag{2}$$

This specification implies that firms can only reduce their capital age through positive net investment.

2.2. Other variables

We begin with all listed firms on the Shanghai and Shenzhen stock exchanges, including the main boards, the growth enterprise market, the STAR market, and the Beijing Stock Exchange, over the period from 2008 to 2020. Following [4], we exclude firms in the following industries based on the CSRC 2012 industry classification: K70 (real estate), N78 (public facility management), C39 (computer, communication, and other electronic equipment), C27 (pharmaceutical manufacturing), J66 (monetary financial services), and J69 (other financial services). Firms with special treatment (ST) or particular transfer (PT) status are also removed. We drop observations with missing values for any key variable and winsorize all continuous variables at the 1st and 99th percentiles to mitigate the impact of outliers.

For the main financial variables, including capital age, book-to-market ratio (BM), and return on equity (ROE), we align them with the actual disclosure month of the annual report. When the disclosure month is unavailable in CSMAR, we follow the common practice of Chinese listed firms and assign April of each year by default.

When constructing the monthly analysis sample, we impose two additional conditions. First, a firm must have at least 60% of the month's total trading days. Second, its month-end tradable market capitalization must exceed the 30th percentile of the cross-sectional distribution for that month.

All financial data are sourced from the CSMAR database. After applying the above procedures, we obtain an unbalanced panel dataset.

3. Empirical results

3.1. Average and risk-adjusted returns of capital age quintile portfolios

To provide an initial examination of the relationship between capital age and the cross-section of stock returns, we follow the methodology of [14,15,16] and conduct a univariate portfolio sorting analysis. At the end of each month, we sort all sample firms by their capital age in ascending order and group them into five equally weighted quintiles. Quintile 1 (Low) contains firms with the smallest capital ages, while Quintile 5 (High) contains firms with the largest capital ages. We also construct a zero-cost hedge portfolio that takes a long position in the low capital age group and a short position in the high capital age group.

Table 1 reports the average capital age and monthly excess returns for each quantity. The sorting variable exhibits substantial cross-sectional variation, with average capital age increasing monotonically from 2.70 years in the lowest quintile to 9.53 years in the highest quintile. In terms of returns, excess returns exhibit a clear downward trend as capital age increases. Using [17] adjusted t-statistics, the monthly excess return on the low-minus-high hedge portfolio is 0.47% and is significant at the 5% level. This finding indicates that, under the univariate sorting framework, firms with low capital age significantly outperform those with high capital age, generating a pronounced negative return differential.

We further evaluate the risk-adjusted performance of these portfolios using the CAPM, the Fama-French three-factor model (FF3), and the five-factor model (FF5) [18,19]. The core finding remains robust: the alpha of the low-minus-high portfolio is significantly positive across all three models, with values of 0.43%, 0.45% and 0.49%, respectively. Notably, the high capital age group exhibits significantly negative alphas in most specifications, while the low capital age group shows positive but insignificant alphas. This pattern suggests that the pricing information embedded in capital age cannot be explained by commonly used asset pricing factors.

Table 1. Low capital age premium.

Quintile	Low	2	3	4	High	Low-High
capital_age	2.704489	3.920431	4.990272	6.368812	9.525166	-6.820677
Excess Return	0.006091	0.003915	0.004917	0.004475	0.001427	0.004665
	(0.72)	(0.49)	(0.61)	(0.56)	(0.18)	(2.15)
αCAPM	0.001233	-0.000696	0.000342	-0.000061	-0.003085	0.004340
	(0.51)	(-0.40)	(0.20)	(-0.03)	(-1.75)	(2.09)
αFF3	-0.002875	-0.004288	-0.003016	-0.003739	-0.007330	0.004540
	(-1.75)	(-3.68)	(-2.49)	(-2.79)	(-7.20)	(2.39)
αFF5	-0.003053	-0.003853	-0.002375	-0.002690	-0.006126	0.004946
	(-1.87)	(-3.08)	(-1.78)	(-2.06)	(-5.95)	(2.79)

To further illustrate the long-term performance of this strategy, we plot the logarithmic cumulative returns of the capital age spread portfolio and the market portfolio in Fig.1. As shown in the figures, over the entire sample period, the cumulative return of the low-minus-high strategy based on capital age exhibits a steady and significant upward trend, substantially outperforming the market benchmark. This visual evidence further confirms the effectiveness and economic significance of capital age as a predictor of stock returns.

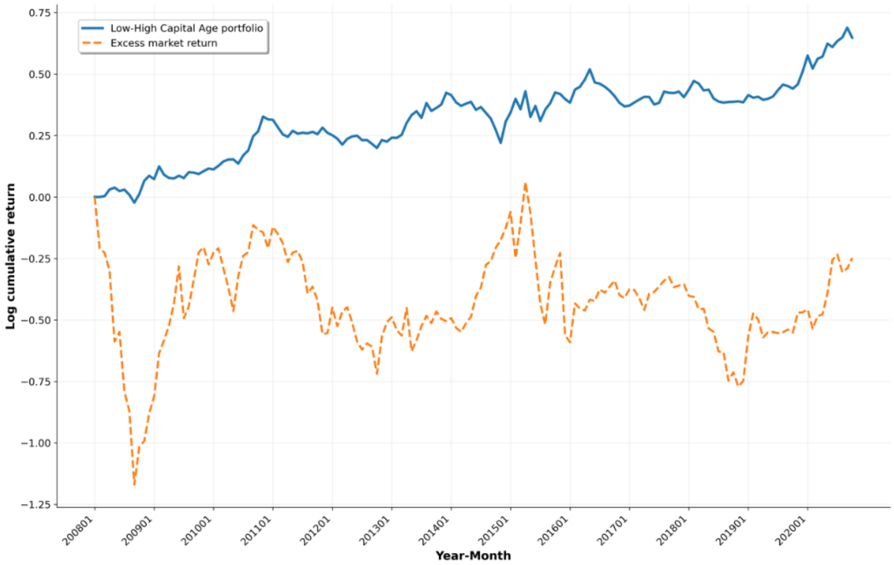

Fig. 1 Low capital age premium: cumulative performance.

3.2. Double sorts on capital age and size

[4] argue that firm size is correlated with capital age: larger firms tend to have older capital, while smaller firms tend to have younger capital. To explore whether capital age is incrementally informative relative to firm size, we conduct double sorts in this subsection. We follow [20] and use conditional double sorts which are rebalanced monthly on firm size and capital age. Specifically, we first form size quintiles by sorting out the previous month's market value. Within each size quintile, we then create five quintiles formed by sorting on capital age.

Table 2 reports double-sort results on firm size and capital age, including monthly average excess returns, alphas, and their [17] adjusted t-statistics. First, we find a significant downward trend in excess returns as capital age increases. Specifically, the lowest capital age quintile has an excess return of 0.73%, and the highest capital age quintile has an excess return of 0.26%, with the difference between the two being 0.47%. This evidence suggests that the predictive power of capital age for cross-sectional stock returns is not affected by firm size. Furthermore, from a risk-adjusted perspective, the double-sort portfolio generates significant abnormal returns ranging from 0.43% to 0.49% across the CAPM, the Fama-French three-factor model, and the five-factor model. That is, the factor models do not explain the double-sort portfolio well. This is consistent with the results in Table 1. In a word, the ability of capital age to explain future cross-sectional stock returns is not affected by firm size.

Table 2. Double sorts on capital age and size.

Quintile	Low	2	3	4	High	Low-High
Excess Return	0.007320	0.006038	0.006944	0.005927	0.002616	0.004704
	(0.89)	(0.76)	(0.88)	(0.74)	(0.35)	(2.13)
αCAPM	0.001646	0.000589	0.001597	0.000537	-0.002608	0.004253
	(0.68)	(0.28)	(0.85)	(0.26)	(-1.35)	(2.03)
αFF3	-0.000758	-0.001954	-0.000948	-0.001852	-0.005366	0.004608
	(-0.38)	(-1.18)	(-0.59)	(-1.07)	(-3.45)	(2.37)
αFF5	0.000032	-0.001275	-0.000470	-0.001325	-0.004873	0.004906
	(0.02)	(-0.79)	(-0.29)	(-0.82)	(-3.42)	(2.70)

3.3. Fama-MacBeth regressions

The foregoing analysis has demonstrated the importance of capital age as a cross-sectional determinant of future returns. However, portfolio-level analysis suffers from drawbacks such as the difficulty of controlling multiple factors at the same time [21]. Therefore, we use Fama-MacBeth regressions to investigate whether the capital age premium in the Chinese equity market is driven by other important determinants. Specifically, these factors include firm size (SIZE), log book-to-market ratio (BM), illiquidity (ILLIQ), return on equity (ROE), and investment (Investment), whose data definitions and sources are presented in Section 2.2. Specifically, monthly cross-sectional regressions, i.e., Fama-MacBeth regressions, can be expressed as:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_t^{capital\_age} \cdot capital\_age_{i,t} + \lambda_t^X \cdot X_{i,t} + \epsilon_{i,t+1} \quad (3)$$

Where $r_{i,t+1}$ is the excess return of stock i in month t+1, $capital\_age_{i,t}$ is the capital age of stock i in month t, and Xi, t represents an empty set or a collection of control variables (SIZE, BM, ILLIQ, ROE, and Investment). $\epsilon_{i,t+1}$ is the error term. All independent variables are winsorized at the 1st and 99th percentiles and then standardized to have zero mean and unit variance.

Table 3 reports the time-series averages of the slope coefficients and their Newey and West (1986) adjusted t-statistics. First, when $X_{i,t}$ is an empty set, the first column indicates a statistically significant negative relationship between capital age and the cross-section of future stock returns. The average slope of capital age is −0.000511, with a t-statistic of −2.03. This t-statistic has significant economic meaning. In the second column, we consider the case where $X_{i,t}$ represents only SIZE. The coefficient of capital age drops slightly to −0.000554 and the t-statistic remains largely unchanged. In the third column, we add BM. In the fourth column, we add ROE. In the fifth column, we add ILLIQ. In the sixth column, we include all control variables. The results show that the coefficient on capital age remains significantly negative after accounting for the control variables, with values ranging from −0.000556 to −0.000713. In model (6), the coefficient remains −0.000713. In short, the results of the Fama-MacBeth regressions display that the premium of capital age is robust after controlling the relevant factors and these factors only explain a small portion of the low capital age premium.

Table 3. Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
capital_age	-0.000511	-0.000554	-0.000577	-0.000556	-0.000646	-0.000713
	(-2.03)	(-2.25)	(-2.28)	(-2.24)	(-2.61)	(-2.85)
SIZE		-0.005846	-0.005811	-0.005984	-0.003216	-0.003124
		(-3.50)	(-3.60)	(-3.69)	(-1.95)	(-1.89)
BM			-0.000611	-0.000234	-0.000384	-0.000304
			(-0.25)	(-0.10)	(-0.16)	(-0.13)
ROE				0.008498	0.008385	0.009269
				(1.60)	(1.56)	(1.75)
ILLIQ					0.133878	0.133750
					(6.20)	(6.20)
INVESTMENT						-0.002129
						(-1.59)
R^2	0.0059	0.0315	0.0427	0.0462	0.0535	0.0558
Adj. R^2	0.0049	0.0296	0.0397	0.0422	0.0486	0.0499
Number of obs.	219,416	219,416	214,792	213,205	213,205	212,916

3.4. Explanation

So far, we have shown that capital age plays an important role in the cross-sectional pricing of individual stocks. In this section, we discuss the economic mechanisms underlying the low capital age premium.

First, capital age is closely tied to firms' financing and investment dynamics. [22] propose a theory of financing in which firms borrow to finance investment and deleverage as capital ages to accumulate sufficient financial slack for future replacement investments. In their framework, leverage and debt maturity are negatively related to capital age. This implies that firms with older capital tend to have lower leverage and shorter debt maturities, reflecting their need to prepare for costly capital replacement. In the Chinese context, where firms often face financing constraints and underdeveloped bond markets [20,23], the financial flexibility of low capital age firms may allow them to undertake more growth-oriented investments, thereby generating higher expected returns. This is consistent with our finding of a low capital age premium.

Second, capital age reflects the firm’s exposure to technology adoption risk. [3] develop a dynamic model featuring a stochastic technology frontier and costly technology adoption. In their framework, firms operating with old capital face higher costs of upgrading to frontier technology, making them more vulnerable to technology frontier shocks. This mechanism is particularly relevant in the Chinese context, where the pace of technological catch-up and creative destruction is especially rapid [10]. Using US data, [3] show that the value-weighted return spread between old and new capital firms reaches 9% per annum, and they further demonstrate that the capital age premium is driven by firms' differential exposure to technology frontier shocks. Extending this logic to China, where technological upgrading has been a central policy priority [10], the productivity gap between new and old capital is likely to be even more pronounced. A large body of literature has established that more productive firms tend to generate higher stock returns, as their growth prospects are more favorably valued by the market [25, 26]. Thus, the low capital age premium we document may partly reflect a technology renewal premium. Investors reward firms that maintain young capital and remain competitive in a rapidly evolving technological landscape, while firms with older capital suffer from declining productivity and loss of competitiveness more quickly than the market can fully price in the associated risks.

Third, capital age is linked to the information environment and market learning.[4] introduce imperfect information and learning into a production-based asset pricing model, in which firms accumulate information about their productivity over time, leading to more efficient capital allocation for older capital firms. In the Chinese stock market, however, where retail investors account for over 99% of market participants and information dissemination is less efficient [23], the learning process may operate through a different channel. Specifically, firms with newly installed capital have shorter performance histories and higher information uncertainty. A growing literature documents that stocks with higher information uncertainty earn higher expected returns as compensation for delayed price discovery [27,28] This implies that the low capital age premium we observe may also capture an information uncertainty premium. The market requires higher returns to hold younger capital firms whose true productivity and profitability are harder to assess immediately, particularly in an environment where retail investors dominate and information frictions are prevalent.

In sum, we believe that capital age captures a new source of systematic risk that affects multiple aspects of a firm, including its financing flexibility, technology adoption capacity, and exposure to aggregate productivity shocks. Thus, while financing dynamics, technology adoption risk, and learning can partially explain our results, they cannot fully account for the low capital age premium, as evidenced by the results in Section 3.3. Due to space constraints, we leave more in-depth explanations for future research.

3.5. Robustness check

To ensure the robustness of the capital age premium, we conduct a series of tests. First, we use value-weighting rather than equal-weighting in portfolio construction. The capital age premium is 0.46% (t-statistic = 1.98). Second, we exclude the financial crisis in the year 2008. The premium is 0.44% (t-statistic = 1.95). Third, we retain all industries without excluding specific sectors. The premium is 0.43% (t-statistic = 2.07). Fourth, we use the one-year deposit rate from CSMAR as the alternative risk-free return. The premium is 0.47% (t-statistic = 2.13). Fifth, we relax the 60% trading days threshold. The premium remains 0.47% (t-statistic = 2.13). Finally, as can be seen in Fig. 1, the performance of the capital age strategy is also robust for all periods. In summary, the capital age premium is robust for a range of different settings.

4. Conclusion

This paper explores the relationship between capital age and cross-sectional returns in the Chinese stock market. Based on the capital age measures constructed from firms' fixed asset depreciation and investment data, we document a significant low capital age premium. The empirical results show that firms with low capital age generate higher future stock returns. Accordingly, quintile portfolios that are long on stocks with the lowest capital ages and short on stocks with the highest capital ages generate excess returns of up to 0.47% per month. This evidence suggests a significant negative correlation between capital age and future stock returns. Double-sort portfolio-level analysis controlling for firm size demonstrates similar results. When we control various anomalies and risks, including firm size, BM, ILLIQ, ROE, and Investment, the low capital age premium remains. Moreover, we consider a range of alternative settings and demonstrate the robustness of the premium capital age. Finally, the relationship between financing flexibility, technology adoption risk, and learning and capital age can partially explain the premium. In conclusion, this paper documents the importance of capital age in the cross-sectional pricing of individual stocks and provides a new dimension to asset allocation for Chinese stock market investors.

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