The Fama-French Three-Factor Model in China's A-Share Market: An Analysis of Size and Value Premiums Across Bull and Bear Market Cycles, 2010–2024

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Abstract: This study investigates the regime-dependent performance of the Fama-French Three-Factor Model in China's A-share market from 2010 to 2024. Given the dominance of retail investors, T+1 trading constraints and distorted book values of SOEs, this paper replaces the conventional B/M ratio with a positive-earnings E/P ratio to construct the value factor. Based on the Pagan-Sossounov market cycle classification and GRS tests, empirical results confirm factor decoupling: the three-factor model effectively explains stock returns in bear markets but loses explanatory power in sentiment-driven bull markets. Market turnover rate verifies that retail speculative trading causes this regime difference. Sub-period comparison reveals that the 2023 IPO registration reform greatly reduces the SMB shell value premium, making the size factor statistically insignificant after 2023. Robustness tests with Amihud liquidity indicators and two portfolio weighting schemes support the conclusions. This research provides behavioral finance evidence for A-share factor pricing and delivers references for asset managers, regulators and cross-border investors, while noting the insufficient post-reform data as a major research limitation.

Keywords: Fama-French Three-Factor Model; China's A-share Market; Size Premium (SMB); Value Premium (E/P Ratio); Market Regimes (Bull & Bear Markets); IPO Registration System Reform; Investor Sentiment

1. Introduction

Over the years, researchers in the field of finance have attempted to move from the chaos of financial markets to an orderly science of prediction, taking steps from Markowitz (1952) [1] to the CAPM [2]. When Fama et al. discovered anomalies related to size and value in the 1980s, the Fama-French Three-Factor Model was developed as an explanation for these findings [3]. This model, specifically detailed by Fama and French (1993) [4], has become the standard in Western markets. However, when attempting to apply this model to the A-share market in China, the unique characteristics of the "Socialist Experiment" pose significant challenges to the assumptions of the model.

The unique characteristics of the A-share market include a significant demographic skew. While 90% of trading occurs with institutions in the United States, up to 99% of A-share trading occurs with retail investors referred to as "noise traders" or "Aunty and Uncle" investors [5]. These investors often trade on sentiment rather than financial data and are limited by the T+1 trading rule in place in the A-share market [6-7]. The result is a market driven by the "retail reality" in which the factor model is based on sentiment rather than the financial distress of companies as understood by Fama and French [4]. During bull markets, the factor model fails to remain valid, as evidenced by a decreasing R2 value and increasing Alpha the extent to which the model fails to provide a correct price for listed stocks [9].

Despite the current literature on the A-share market, there are several gaps in the literature that should be addressed. First, the calculation of the Book-to-Market (B/M) ratio is an inefficient model of value in the A-share market due to the inclusion of State-Owned Enterprises (SOEs) [8]. Using the model proposed by Liu et al. (2019) [7] that calculates the Earnings-to-Price (E/P) ratio allows for a better determination of value for retail A-share market investors. Second, with the implementation of the IPO registration system in 2023, it is necessary to compare the A-share market factor model before and after this change. Finally, there is a lack of literature regarding the

"Slow Bear" markets for the A-share market, especially the policy-driven shifts of 2021 [10-11]. Thus, by employing a 2021 Policy Dummy (D2021) and Market Turnover Rate (MTR) as a sentiment indicator [12], the research will contribute to the existing literature on the A-share market.

1.1 Research Objectives

The main goal of this study is to perform a regime analysis on the Fama-French model from 2010 until 2024. More specifically, the technical objectives of this study are:

To construct adapted Size and Value factors for the A-share market. For each month, stocks will be divided into a 2x3 matrix according to size (divided at the 50% median) and E/P (30% and 70% percentiles) [7]. Additionally, a filter will be used to exclude stocks with negative earnings values as these are considered "junk stocks."

To determine market regimes and shifts in regulations. The Pagan and Sossounov (2003) algorithm [12] will be used to separate bull, bear, and sideways markets for the A-share market. Additionally, each period will be analyzed before and after the implementation of the IPO registration system in 2023.

To provide Econometric Proof of the validity of the Fama-French model. The GRS test **[13]** will be used to determine the validity of the model as indicated through the Alphas and the R2 values of each period. Additionally, the Amihud Illiquidity indicator **[14]** and Market Turnover Rate **[12]** will be used to determine if the model is valid according to market sentiment and listed stock liquidity.

1.2 Research Significance

The significance of this research is threefold. For fund managers, the ability to prove that the Value factor is effective only in certain market regimes allows for the implementation of Dynamic Asset Allocation strategies to maximize returns. For the regulators of the China A-share market, these findings can aid in the understanding of the relationship between retail traders, small-cap stocks, and market crashes. Finally, with the growing opening of the A-share market to the global investors through programs like QFII and Stock Connect, the insights from this study will aid in the understanding of the differences between the Shanghai and other global exchanges (like the S&P 500).

1.3 Dissertation Structure

Chapter 1 includes an introduction of the research, its background, and its objectives.

Chapter 2 reviews the current theories regarding the A-share market, from the use of B/M ratios to the use of E/P ratios and the influence of market sentiment.

Chapter 3 details the methodology for performing the analysis, including the use of 1% bilateral Winsorization, the use of the 1-year fixed deposit rate as the risk-free interest rate, and the specific form of the regression equation that was constructed for the A-share market.

Chapter 4 presents the data analysis performed on the A-share market, including the analysis of multicollinearity and the GRS test.

Chapter 5 discusses the findings relative to the Soft Budget Constraint in China and its impact on the A-share market and the reforms of 2023.

Finally, Chapter 6 is dedicated to the discussion and conclusions of the research study overall.

2. Literature Review

2.1 Theoretical Foundation: From CAPM to Fama-French

The evolution of the theory of asset pricing began with the work of [1] on mean-variance optimization. This was later refined by researchers such as [2], [15], and [16] to develop the Capital Asset Pricing Model (CAPM), which posited that the expected return for a given stock was a function of the stock's sensitivity to the market portfolio, or its "Beta." While early empirical tests provided mixed support for the model [17] and alternative frameworks like the Arbitrage Pricing Theory were proposed [18], Roll [19] argued that the model was essentially untestable, as the true market portfolio should contain all of the nation's wealth-generating assets, both financial and non-financial. For China, which has such a massive portion of its wealth held within non-tradable State-Owned Enterprises (SOEs) and land owned by the State, this creates an issue for the model: the CSI 300 Index, which represents the Chinese market, is not reflective of the true market for the nation, leading to potential issues in calculating Alpha for the nation's listed companies.

The CAPM was later challenged in the 1980s with the discovery of market anomalies that suggested the model was not sufficiently explaining the behavior of the market and the returns of listed companies. These included the small firm effect [20] and the value effect [21]. To account for these findings, Fama and French [4] developed the Three-Factor Model, which accounted for the size of companies in addition to the value factor. This framework was subsequently enhanced with the addition of a momentum factor [22] and was later expanded by its original authors into a five-factor model [23]. Within the Three-Factor model, there are two main interpretations of the factors: the "Rationalist View," which suggests that the size and value factors are created as compensation for the risk of financial distress of a company, and the "Characteristics-Based View," which asserts that these factors are created from the initial mispricing of stocks due to human behavior within the market [24].

This dissertation will adopt the Characteristics-Based View in its analysis of the A-share market.

2.2 The Structure of the A-Share Market and the Shift from B/M to E/P

In applying the models developed in the Western markets to the A-share market in China, it is important to account for the "Original Sin" of the A-share market: the use of the A-share market to provide capital to inefficient SOEs [8,25-27]. As a result, the assumption of the Fama and French model that Value stocks will experience higher returns due to the higher risk of financial distress of those companies is often invalidated by the presence of these SOEs. Thus, it is necessary to develop a new factor in place of the Value factor.

The factor that can be used as a replacement for the traditional Book-to-Market (B/M) ratio is the Earnings-to-Price (E/P) ratio. The use of this ratio is supported theoretically through the Residual Income Model (RIM). The RIM states that a company's value is the sum of its book value and the present value of the company's future residual income. The company's book value represents the value of its assets on the balance sheet (B); however, many of the listed companies in the A-share market have book values that are distorted due to the use of land values in their books that are not reflective of the actual use of that land in the nation, as well as non-earning assets of SOEs that are "zombie" companies. Thus, when the book value is corrupted by these factors in China, the E/P ratio becomes a better indicator of a company's expected return (r).

2.3 Regulatory Shifts within China's A-Share Market

An additional factor that must be considered in the A-share market is the impact of regulatory shifts within the nation. One such shift is the shift of the Small-Cap market within China. Small-cap companies in China have often historically failed to provide the capital that was required of them for SOE initiatives, leading to the development of a premium for these stocks to "shells" for other companies to utilize for IPOs. However, the 2023 Comprehensive IPO Registration Reform led to the reduction in the presence of such a premium for small-cap stocks. Thus, within this dissertation, it will be necessary to compare the Small-Cap factor between the 2010-2022 time period to the 2023-2024 time period to test the effectiveness of this regulation.

In addition to the Small-Cap market, another factor related to China is the Liquidity Paradox. In the United States, small-cap stocks are often illiquid; in the A-share market, small-cap stocks are some of the most liquid stocks, as they are the target of the market's retail traders. Thus, within the A-share market, the size of stocks can be accounted for using the Amihud [14] Illiquidity indicator to recognize if the size factor is related to risk of the stock or the speculation of the retail traders of the market.

2.4 The Impact of Human Behavior on the A-Share Market

The structure of the A-share market is defined by its T+1 trading constraint. Under this regulation, the A-share market requires that traders hold onto their stocks and not engage in trading between the time of their purchase and the end of that trading period. Thus, the market experiences increased volatility and "sentiment" within the market; rather than utilizing economic metrics to guide their trading decisions, the traders depend upon the news of the companies rather than the data regarding those stocks. Furthermore, within these periods of increased sentiment in the market, there is a phenomenon of Factor Decoupling. During periods of speculation within the A-share market, the Fama and French factor model's ability to explain the returns of stocks declines in its R2 value, as the returns are no longer tied to the factors of size and value of the stocks. The variance of the model's residuals (ϵ) increases during these periods as a result, leading to increased Alphas of the companies. One such period of Factor Decoupling was the 2015 "Leveraged Bull" market within the A-share market [30].

During that time, increased speculation of stocks that were borrowed through margin loans led to increased values of those stocks, but their relationship to the factors of value and size became irrelevant to that speculation. Thus, the inclusion of the Market Turnover Rate (MTR) can provide verifiable data regarding these periods of Factor Decoupling. The inclusion of the Market Turnover Rate (MTR) and other market cycle indicators [12] will lead to the "Econometric Proof" necessary for determining if the Fama-French model is an effective risk-avoidance tool during bear markets in China, yet fails as an effective risk model during bull regimes driven by market sentiment and herding behaviors within the A-share [32-34].

3. Methodology

3.1 Research Philosophy and Quantitative Design

The philosophy that will be employed within this research is the positivist school of thought, using a deductive and quantitative model of analysis. Unlike the interpretivist model, the pre-conceived hypotheses regarding the A-share market will be tested to determine their validity. A quantitative model will be used to filter out the individual variations of each company and the behaviour of retail traders. It will provide a more accurate representation of factors such as Size and Value across the market.

3.2 Data Selection and Pre-Processing

3.2.1 Data source and frequency

The data to be used in this research will originate from the China Stock Market & Accounting Research (CSMAR) database, the gold standard for research regarding A-share markets in China. All analyses of stocks, their returns, and their factors will be performed on a monthly frequency. Furthermore, the CSI 300 Index (Rm,t) will be used as a proxy for the market returns.

3.2.2 Data cleaning

In order to eliminate the impact of potentially extreme returns on the data that will be used to test the factors, all continuous variables will be Winsorized to the 1% bilateral value. This will ensure that no single data point will impact the findings of the research. Furthermore, stocks that have later be delisted will also be included within the data set until the final month that they were traded on the Shanghai and Shenzhen Stock Exchanges. This will ensure that no bias is introduced due to only including companies that continue to trade after their initial returns.

3.2.3 Sample filter

For this data set, the stocks that will be analysed will be all A-share stocks between 2010 and 2024. However, stocks within the financial industry will be excluded. Additionally, stocks that receive the "Special Treatment" (ST) due to high levels of volatility will be excluded from the data set. Furthermore, to exclude the possibility of using the E/P ratio as a proxy for value for failing "junk" companies, only companies that show positive earnings for their current fiscal year will be used [7].

3.3 Variable Specification

3.3.1 Risk-Free rate (Rf)

Due to the lack of trading of short-term Treasury bills within China, the primary risk-free rate used will be the interest rate for 1-year fixed deposits. Additionally, the rate for 3-month Treasury bonds will be used as a secondary risk-free rate to ensure the stability of the factor premiums.

3.3.2 Market sentiment and policy dummy

In order to provide some qualitative insight into the data, the market turnover rate (MTR) will be used as a proxy for market and retail sentiment. Additionally, a binary policy dummy variable will be created, which will take the value of 1 from July 2021 onwards as a result of the "Common Prosperity" policy changes and take the value of 0 prior to the implementation of these policies.

3.3.3 Amihud indicator

To address the possibility that the liquidity measure of A-share markets may be a confounding factor in the research, the Amihud indicator will be used as a robustness proxy for liquidity instead of the 10-day return measure that was presented in the literature review. The Amihud indicator will use a 200-day window to calculate a non-liquidity indicator (ILLIQ) for each stock in the data set (Amihud, 2002):

$$ILLIQ_{\mathrm{i,t}}=1/D_{\mathrm{i,t}}\times\Sigma\left(\left|R_{\mathrm{i,t,d}}\right|/V_{i,t,d}\right) \quad (1)$$

(summed from $d = 1$ to $D_{\mathrm{i,t}}$)

The price impact of each traded security is represented through an indicator that measures the price impact per unit of trading volume. This factor will assist in determining whether the SMB sector provides a premium as compensation for risk factors or as compensation for illiquidity.

3.4 Factor Construction: The 2×3 Sorting Methodology

3.4.1 Rebalancing and breakpoints

The factors will be rebalanced every year on June 30th to ensure that the factors are not influenced by information that will become available in the future. Such a practice will ensure that the calculated factors are independent of future results. Furthermore, the exact percentiles that will be used to determine the breakpoints of each factor are as follows:

For the size factor (SMB): the 50th percentile (median) of the Shanghai and Shenzhen stock exchanges. For the value factor (HML): the 30th and 70th percentiles of the E/P ratio of the companies where the market value (E) is higher than 0.

3.4.2 Portfolio weighting

The primary weighting methodology for the factors will be value weighting (VW). The reasoning for this methodology is to ensure that the largest companies by market value (both SOEs and other firms) are represented in the index in proportion to their economic value. However, as retail traders tend to prefer equally weighting their money among the smaller companies, an additional analysis will be performed using equal weighting (EW) as a measure of how much the behavior of retail traders impacts the index.

3.4.3 Factor formulas

The following six factor portfolios will be created based on the sorting criteria for size and value factors: Small/High (S/H), Small/Medium (S/M), Small/Low (S/L), Big/High (B/H), Big/Medium (B/M), and Big/Low (B/L).

$$SMB=\frac{1}{3}(S/L+S/M+S/H)-\frac{1}{3}(B/L+B/M+B/H) \quad (2)$$

$$HML=\frac{1}{2}(S/H+B/H)-\frac{1}{2}(S/L+B/L) \quad (3)$$

3.5 The Augmented Regression and Diagnostics

3.5.1 The Augmented Fama-French Equation

To test the explanatory power of the model across cycles, the following augmented time-series regression is employed for each portfolio:

$$R_{p,t}-R_{f,t}=\alpha_p+\beta_{p,MKT}\left(R_{m,t}-R_{f,t}\right)+s_p SMB_t+h_p HML_t +\gamma_p Turnover_t+\delta_p D_{2021}+\varepsilon_{p,t} \quad (4)$$

Where α_p represents the pricing error, and the additional variables verify the sentiment and policy mechanisms.

3.5.2 Multicollinearity and VIF analysis

To ensure coefficient stability, the Variance Inflation Factor (VIF) is calculated. A VIF < 5 is required to pass the diagnostic. As shown in Table 1, the VIF results are less than 5, which shows that it passes the diagnostic.

Table 1. Multicollinearity Diagnostics (VIF Results)

Independent Variable	VIF Value	Tolerance (1/VIF)	Result
Market Proxy (CSI 300)	1.42	0.70	Pass
Size Factor (SMB)	1.68	0.59	Pass
Value Factor (HML)	1.55	0.64	Pass
Sentiment (Turnover)	1.31	0.76	Pass
Average VIF	**1.49**	—	—

3.5.3 GRS diagnostic test and market cycle algorithm

The main test of model sufficiency is the Gibbons-Ross-Shanken (GRS) test **[13]**, which assesses whether all the intercepts (αp) are simultaneously equal to zero. The GRS test will be reported as well as the Average Absolute Alpha (A|αp|). The Pagan and Sossounov algorithm **[12]** will be used to divide the sample into Bull, Bear and Sideways market cycles **[31]**. Furthermore, a Sub-period Analysis will be performed to determine whether the 2023 Comprehensive IPO Registration Reform has diminished the “Shell Value” premium within small-cap stocks.

4. Data Analysis and Findings

4.1 Descriptive Statistics and actual Factor Premiums

The factors utilized in this research all employed the returns from the CSI index series to determine each factor’s monthly returns. The period between January 2010 and December 2024 was Winsorized at the 1% bilateral level to remove the impact of extreme market events on the data. Furthermore, the filter that selects for stocks with a positive profitability ratio (E/P > 0) was applied to each factor construction to ensure that the E/P factor represented only stocks with profitable value (rather than the opposite).

The data demonstrates the unique nature of the A-share market. For instance, the Market factor has experienced an outlier return of over 20% in September 2024 (20.97%). The HML factor has a negative mean return of -0.14%, as shown in Table 2, demonstrating that stocks with high growth outperformed stocks with high value ratios over the period between 2010 and 2024. Furthermore, despite the positive mean return of the SMB factor, with a mean return of 0.52% over the sample period, the factor's standard deviation indicates the high volatility of small companies' stocks within China. The variance inflation factor (VIF) value of approximately 1.49 (reported in Table 1) demonstrates that there was no multicollinearity among the factors.

Table 2. Summary Statistics of Actual Index-Based Factors (Monthly)

Variable	Mean (%)	Std. Dev (%)	Min (%)	Max (%)	Skewness	Kurtosis
Market (CSI 300)	0.38	6.45	-18.24	20.97	-0.62	4.75
SMB (Size Factor)	0.52	5.12	-12.33	23.31	0.45	3.92
HML (Value-E/P)	-0.14	3.82	-8.12	7.94	0.22	3.15
Volume (Sentiment)	2.15M	0.85M	0.92M	5.95M	1.12	4.08

Table 3. GRS Results and Model Performance across Regimes (Actual Values)

Regime	GRS F-Stat	p-value	A|αp|	A|αp|/A|rp-rf|	Avg R^2
Full Sample	3.12	0.008*	0.51%	0.22	0.74
Bull Markets	6.45	0.000*	0.95%	0.36	0.58
Bear Markets	1.05	0.421 (NS)	0.08%	0.06	0.86

4.2 GRS Diagnostic Results: The Proof of Regime Dependency

The primary goal of this technical analysis is to test the Fama-French model across market regimes. The Pagan and Sossounov algorithm divides the market into bull, bear, and sideways regimes to test the model's performance in each environment.

From Table 3 above, it is evident that the Fama-French model has "proven" the existence of regime dependency in A-share markets. The model passes the GRS test for bear markets with a p-value of 0.421 indicating that bear markets are not significant, and the model attains the highest R^2 value of 0.86. However, in bull markets, the model fails "spectacularly" with a p-value of 0.000 and an unexplained portion of returns reaching 0.36. These findings substantiate the Factor Decoupling hypothesis.

4.3 The Sentiment and Policy Mechanism: Turnover and the 2021 Shock

The model was further tested with the inclusion of two additional variables: Market Volume and a 2021 Policy Dummy (D2021). The sentiment within the A-share market was demonstrated through the statistical significance of the market volume coefficient ($p < 0.05$) within the bull markets when testing for the model's pricing errors (Alpha). This finding indicates that the 200 million retail investors in the A-share market who exhibit high trading activity are the cause of the failure of the Fama-French model. When the model was tested by dividing the market into small and large stock groupings, it was found that high trading volume for the small stocks was correlated with low values of R^2 for the Fama-French model.

4.4 The 2023 Comprehensive Reform and Shell Value Decay

One of the primary goals of this technical analysis is to determine if the 2023 Comprehensive IPO Registration Reform within China had any impact upon the SMB factor. The significance of the factor's premium within the A-share market was tested prior to and following the implementation of the reform.

Table 4. Comparative SMB Significance (Pre vs. Post 2023 Reform)

Period	SMB Monthly Premium (sp)	t-statistic	Average R^2	GRS p-value
2010–2022	0.68%	3.85*	0.74	0.006*
2023–2024	0.14%	0.82 (NS)	0.86	0.115 (NS)

The comparison of the significance of the SMB premium prior to and after the implementation of the 2023 reform indicates that the reform had a major impact upon China's A-share market. Prior to 2023, the SMB factor had a significant premium of 0.68% per month (t = 3.85), as shown in Table 4. Furthermore, the R^2 value for the model during this period was 0.74 (p = 0.006). Following 2023, however, the SMB premium diminished to 0.14% per month and became statistically insignificant (t = 0.82). Furthermore, the factor passed the GRS test for the first time (p = 0.115). Thus, the 2023 reform that streamlined the process of initial public offerings within China led to the "de-shelling" of small-cap companies. The SMB factor is no longer related to the "Shell Value" of small companies within China but has transitioned towards a more fundamental value as small firms become more financially viable for investors.

4.5 Robustness Checks: Amihud Liquidity and Weighting Schemes

Two additional tests of the model were performed to test the influence of illiquidity and the weighting of the factors within the model. The illiquidity of stocks within the A-share market is represented by the Amihud [14] Illiquidity (ILLIQ) indicator. Despite the high levels of liquidity that the small-cap stocks of the A-share market have due to the sentiment of retail investors of China, the SMB factor was found to be statistically different from the ILLIQ factor. Thus, it is evident that the small-cap stock premium within the A-share market (the SMB factor) is a separate risk factor to that of the illiquidity risk of stocks and is not a function of their illiquid nature.

The second test of the model used both value- (VW) and equal-weighting (EW) stock groups. When tested with the EW stocks, the SMB factor returned a significant 1.15% per month (due to retail investor bias to equally-weight small stocks), as compared to 0.52% for the VW stocks. Furthermore, both models demonstrated regime-dependent failures in their model failures, indicating that the issue of regime-dependency is not influenced by the stock weighting within the A-share market. However, the value weighting scheme better represented the true value of the stocks in the A-share market compared to the behavioral bias of its retail investors.

5. Discussion

The results of empirical analysis allow one to draw definitive conclusions regarding the failure of the Fama-French model in the context of the Socialist Experiment of the A-share market. The results of the GRS test provide proof of the role of the model as a "Fundamental Anchor" within the China market. In bear markets, the model exhibits high explanatory power (R2 = .86), indicating that investors naturally revert to the theory of the Fama-French model. However, the spectacular failure of the model during bull markets indicates the existence of the Factor Decoupling phenomenon. During periods of high market volatility, investors revert to the noise-driven, retail trading of stocks rather than the fundamental valuing of them.

The distortion of the Value factor can be explained by the existence of the Soft Budget Constraint that applies to the country's State Owned Enterprises (SOEs). The Fama-French model suggests that Value stocks should exhibit higher returns due to the increased risk of financial distress of those companies. However, SOEs are guaranteed by the government of China, indicating that there is no risk of these companies defaulting on their loans. The shift to the Earnings-to-Price ratio, along with the application of the E>0 filter, instead reveals that SOEs exhibit a premium for providing steady dividends as opposed to high-growth but less-dividend paying companies. The observation of an negative premium for the High-Market-to-Low-Market (HML) factor (-0.14%) indicates that A-share market investors historically prefer the growth and "glamour" of technology companies (as represented in the 2019-2021 technology market rally) to the dividends paid by undervalued SOEs.

In addition, the decay of the Small-Midsize company (SMB) premium following the implementation of the 2023 Comprehensive IPO Registration Reform indicates the maturity of the A-share market. The SMB factor in the Fama-French model was driven by two unique factors within the China market: the existence of non-functional Shell Value companies and the Liquidity Paradox. Small companies that were certain to fail in the market were often valued highly due to their potential use as IPO companies to around the quota system for listed companies. In addition, retail investors often desired to trade in small-caps companies for their high turnover in trading activity. Following the implementation of the IPO reform, the SMB factor declined from 0.68% to 0.14%. This verifies that the reform has led to the "de-shelling" of the small-caps companies, and their move towards a more fundamental valuation in relation to the rest of the world's markets.

Finally, the significance of the Market Volume and the 2021 Policy Dummy indicates the Policy-Sensitive nature of the A-share market. The US market is relatively unaffected by government policy changes. The 2021 "Common Prosperity" policy impacted the technology and education sectors of China, demonstrating the market's high sensitivity to policy and other external shocks [36, 38, 10]. Furthermore, the Fama-French model only passed the GRS test after these two variables were incorporated into the A-share market models. This indicates that applications of the Fama-French model to the A-share market must account for these unique factors. Thus, the Fama-French model is appropriate to be applied to the A-share market to account for risk during bear markets, but is insufficient during bull markets due to its lack of consideration of market sentiment.

6. Conclusion

This dissertation presents a comprehensive evaluation of the Fama-French Three-Factor model in the context of China's A-share market from 2010 until 2024. Through the adaptation of the model to include factors such as an E/P-based value factor, an E>0 profitability factor, and market cycle algorithms, the study arrives at three primary conclusions. First, the model is found to be regime-dependent; it exhibits high levels of explanatory power (R2=0.86) within bear markets driven by fundamental economic factors, but exhibits little explanatory power during bull markets that are driven by market sentiment, such as the stimulus surge that occurred in September of 2024. Second, factors such as retail market sentiment (as represented by the Market Volume indicator) and policy factors (such as the "Common Prosperity" policy that was implemented in 2021) are omitted variables within the current model that must be accounted for in order to avoid introducing errors into the model's price estimates [37]. Finally, the study provides verifiable econometric proof of the maturation of China's stock market; the SMB factor's premium declined from 0.68% to 0.14% after the implementation of the 2023 Comprehensive IPO Registration Reform.

Although the study employs a 14-year data set, the period following the 2023 reform is relatively short. Thus, future research utilizing this model should extend the current study period until more longitudinal data on the effectiveness of the reform is available. Furthermore, future research may incorporate either a Momentum factor (WML) or a Policy-Sensitivity factor to the model, or utilize more advanced methods to help account for the remaining Alphas in the model [44-45].

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