Anomalies and Multi-Factor Models in the Chinese Market

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Abstract. A stock market anomaly refers to the occurrence of excess returns in stocks that cannot be fully explained by traditional asset pricing models or the efficient market hypothesis. Studying these anomalies allows scholars to gain deeper insights into the stock market and provides investors with opportunities to capitalize on these irregularities for higher returns. In this paper, the size and value factors in the Chinese stock market are empirically tested for the period from January 2002 to December 2021, leading to several conclusions. First, the CH-3 model is found to be more suitable for the Chinese market compared to the FF-3 model. Additionally, the interpretation of anomalies using CH-3 differs from prior research, particularly regarding the CH-4 model, which incorporates a share turnover factor. These differences may stem from potential data mining effects.

Keywords: Anomalies, Multi-factor model, Investment strategy portfolio.

1. Introduction

Both domestic and international stock markets exhibit phenomena of excess returns that cannot be fully explained by asset pricing models or the efficient market hypothesis, which scholars refer to as stock market anomalies. In the United States, scholars have studied and published research on hundreds of stock market anomalies, while in China, the number of published studies on such anomalies remains relatively small, leaving many anomalies yet to be explored. From the perspective of the efficient market hypothesis, there should not be so many anomalies in the market, and two main reasons could explain their occurrence.

The first is data mining. In the United States, numerous scholars have demonstrated that many published stock market anomalies are actually spurious, resulting from data mining. For example, Linnainmaa and Roberts (2018) constructed new out-of-sample data to examine the performance differences of 36 accounting-based anomalies in the U.S. stock market, both in-sample and out-of-sample. Their analysis revealed that most of these anomalies failed out-of-sample, suggesting that they are more likely a product of data mining rather than unknown risks or mispricing. Similar research has been conducted in China as well. For instance, Hou, Xue, and Zhang (2017) replicated 447 anomalies proposed by the academic community, covering six categories: momentum, value/growth, investment, profitability, intangible assets, and trading frictions. After excluding the impact of small-cap stocks, 64% of these anomalies were no longer significant; if the t-statistic threshold was raised to 3.0, 85% of the anomalies lost significance. Furthermore, using the four-factor model proposed by Hou, Xue, and Zhang (2015) as the pricing model, 98% of the anomalies lost significance, with only 11 anomalies remaining valid.

The second possible reason for anomalies is related to the choice of regression models used to explain them. If only the CAPM model is used as the explanatory model, many anomalies will show significant alpha values that CAPM cannot explain. However, as pricing models become more refined and the number of factors increases, many anomalies become insignificant. Thus, there is still ample room for further exploration of anomaly factors in the Chinese market.

By conducting in-depth research on stock market anomalies, we can not only enhance our understanding of market mechanisms but also provide investors with strategic insights, enabling them to capitalize on these irregularities to achieve excess returns.

2. Literature review

Stock market anomalies (or market anomalies) refer to the phenomenon of excess returns in stocks that cannot be fully explained by asset pricing models or the efficient market hypothesis. Anomaly factors (or abnormal variables) are indicators that describe these phenomena, which may not have a specific meaning but can reliably explain average cross-sectional stock returns. Not long after the CAPM model was introduced, foreign scholars discovered the existence of stock market anomalies, and in the following decades, hundreds of anomalies were identified. Since the establishment of the Shanghai Stock Exchange at the end of 1990, although China's securities market has only had a history of over 20 years, the modern investment theories of Western securities markets have gradually drawn the attention of domestic scholars. Over the past two decades, Chinese scholars have conducted extensive research on China's stock market and have discovered numerous anomalies. According to the methodology of Hou, Xue, and Zhang (2018), these anomalies can be broadly categorized into five types: inertia, value and growth, investment, profitability, and trading frictions.

First, in terms of inertia anomalies, the unexpected earnings effect is a typical example. Many scholars have conducted in-depth studies on the unexpected earnings phenomenon in China and have confirmed its existence. Furthermore, research has revealed different factors driving this phenomenon, with some scholars approaching it from the perspective of the efficient market hypothesis, while others explain it from a behavioral finance viewpoint. The research on inertia and reversal phenomena is also varied; some scholars have found that the Chinese stock market exhibits short-term and long-term inertia along with medium-term reversals, while other studies suggest that the reversal phenomenon is significant but inertia is not.

Second, regarding value and growth anomalies, the book-to-market ratio effect and the price-to-earnings ratio (P/E) have been widely studied. Liu et al. (2018), using data from the Chinese A-share market between 2000 and 2016, compared metrics such as earnings-to-price ratio (E/P), book-to-market ratio, asset-to-market ratio, and cash flow-to-market ratio, concluding that the E/P ratio is more suitable as a value factor in the Chinese market. Similarly, multiple studies have shown a significant negative correlation between the P/E ratio and stock returns, meaning that the higher the P/E ratio, the lower the future stock returns.

Regarding investment anomalies, domestic research generally suggests that there is a significant negative correlation between investment rates and stock returns in the Chinese stock market. For profitability anomalies, the applicability of the Fama-French five-factor model in the Chinese market has been repeatedly tested. While some studies have found that the profitability factor does not yield significant excess returns, others, such as Liu, Stambaugh, and Yuan (2018), have shown a significant positive correlation between the profitability factor and expected stock returns.

Lastly, trading friction anomalies include size effects and idiosyncratic volatility. Meng Yong et al. (2019) found that size effects are significantly present in the A-share market, with smaller firms earning higher average returns than larger firms. However, some studies show that size effects are not significant in other markets. Additionally, Zhang Bing (2021) used data from 1996 to 2016 to demonstrate that stable idiosyncratic volatility anomalies exist in the Chinese stock market, with higher idiosyncratic volatility stocks tending to have higher expected returns.

In terms of anomaly explanation models, Fama and MacBeth (1973) were the first to test the CAPM model, finding a significant positive relationship between market beta and returns. However, subsequent research uncovered numerous anomaly factors that CAPM could not explain. To better account for these market anomalies, Fama and French (1993) introduced the three-factor model, which added size and book-to-market factors to explain the excess returns that CAPM could not account for. However, the three-factor model also faced challenges, such as the presence of momentum effects, which raised questions about its explanatory power. Carhart (1997) added a momentum factor to the Fama-French three-factor model, resulting in the four-factor model.

Over time, more anomalies were discovered, prompting researchers to propose new pricing models. Hou, Xue, and Zhang (2015) introduced the q-factor model based on the q-theory, incorporating market, size, investment, and profitability factors. They demonstrated that the q-factor model

outperformed the Fama-French three-factor and Carhart four-factor models in explaining anomalies. Similarly, Fama and French (2015) recognized the need to add new factors to their pricing model, proposing a five-factor model that includes investment and profitability factors. Additionally, Stambaugh and Yuan (2017) constructed a mispricing four-factor model by aggregating multiple anomaly factors, showing that this model performed better than the q-factor model and the Fama-French five-factor model in explaining anomalies.

Liu, Stambaugh, and Yuan (2018) proposed the CH three-factor model for the Chinese market. After excluding the smallest 30% of stocks by market capitalization, they selected the earnings-to-price ratio (EP) as the value factor and demonstrated that the CH three-factor model is more suitable for the Chinese market than the Fama-French three-factor model. Lastly, Daniel, Hirshleifer, and Sun (2020) introduced the Daniel-Hirshleifer-Sun three-factor model, applying behavioral finance to asset pricing and explaining mispricing phenomena, further expanding the understanding of stock market anomalies.

3. Data and variable definitions

3.1. Data

The research subject of this paper includes all A-share stocks listed on the Shanghai and Shenzhen stock exchanges, excluding financial companies and stocks with missing data. The data types used include monthly stock trading data and financial statement data, with all raw data sourced from the GTA CSMAR financial database.

Although China's securities market has developed for over twenty years, the available historical data for research is not abundant, particularly in the early stages of market development, where the number of stocks was relatively small, making it difficult to meet the requirements for large-scale and repeated grouping. Additionally, cash flow statement data has only been disclosed since 1998, and quarterly financial statement data became gradually available from 2002. The factors constructed in this paper rely on data from the three major financial statements, with most factors being built based on quarterly data. To ensure consistency, the sample data period used for constructing the quarterly factors spans from January 2002 to December 2021.

We also impose several filters. First, we exclude stocks that have become public within the past six months. Second, we exclude stocks having (i) less than 120 days of trading records during the past 12 months or (ii) less than 15 days of trading records during the most recent month. The above filters are intended to prevent our results from being influenced by returns that follow long trading suspensions. Third, we eliminate the bottom 30% of stocks ranked by market capitalization at the end of the previous month. Market capitalization is calculated as the closing price times total shares outstanding, including nontradable shares.

3.2. Variable definitions

We survey the literature documenting anomalies in China and compile, to the best of our knowledge, an exhaustive list of stock characteristics identified as cross-sectional predictors of future returns. This list comprises nine categories: size, value, profitability, volatility, investment, accruals, illiquidity, reversal, and turnover. Within each category, one or more firm-level characteristics are identified as predictors of returns. The anomalies categorized are as follows:

Size: The stock’s market capitalization is used in this category. It is computed as the previous month’s closing price times total A shares outstanding, including nontradable shares.

Value: Three variables are used. Earnings-price ratio (EP). Earnings equals the most recently reported net profit excluding nonrecurring gains/losses. A stock’s EP is the ratio of earnings to the product of last month-end’s close price and total shares. Book-to-market ratio (BM). Book equity equals total shareholder equity minus the book value of preferred stocks. A stock’s BM is the ratio of book equity to the product of last month-end’s close price and total shares. Cash-flow-to-price (CP). Cash flow equals the net change in cash or cash equivalents between the two most recent cash flow

statements. A stock's CP is the ratio of cash flow to the product of last month-end's close price and total shares.

Profitability: Profitability is assessed using firm-level Return on Equity (ROE) calculated at a quarterly frequency. ROE is a key financial metric that measures a company's ability to generate profit from its shareholders' equity. Specifically, the value of ROE is determined by the ratio of a firm's earnings to its book equity.

Volatility: Stocks with lower historical volatility tend to provide better future performance. Volatility refers to the degree of variation in a stock's price over time, often measured by the standard deviation of returns. Stocks with lower historical volatility tend to provide better future performance. This observation can be attributed to the fact that lower volatility stocks are perceived as less risky by investors. Consequently, these stocks often attract a more stable investor base and can experience less dramatic price swings during market fluctuations.

Investment: Companies that invest less (or have lower asset growth) often generate higher returns.

Illiquidity: Stocks that are less liquid typically yield higher returns due to the liquidity premium.

Reversal: The sorting measure used is the stock's one-month return, computed as the cumulative return over the past 20 trading day

Turnover: Higher turnover rates may indicate momentum effects, where stocks with higher trading volumes can lead to greater future returns.

4. Methodology

4.1. Fama-French Three-Factor Model

Fama and French (1993) expanded on the Capital Asset Pricing Model (CAPM) by introducing two additional factors: value (FFHML) and size (FFSMB), proposing the Fama-French three-factor model, which is regarded as the pioneer of multifactor models:

$$E\left(R_t^i\right) - R_t^f = \beta_{MKT}^i\left[E\left(R_t^m - R_t^f\right)\right] + \beta_{FFSMB}^i E(FFSMB) + \beta_{FFHML}^i E(FFHML) \quad (1)$$

Where R_t^f represents the risk-free rate for stock i; R_t^m denotes the market return at time t; $\mathrm{E}\left(R_t^i\right)$ signifies the expected return of asset i at time t; $\mathrm{E}\left(R_t^i\right) - R_t^f$ is the market risk premium; $E(FFSMB)$ is the expected return of the size factor; $E(FFHML)$ is the expected return of the book-to-market ratio factor; and β_{MKT}^i, β_{FFSMB}^i, β_{FFHML}^i represent the stock's exposure to the respective factors.

To construct the value and size factors, Fama and French (1993) utilized the book-to-market ratio (BM) and market capitalization, applying a 2×3 independent double sorting method. In the sorting process, they used the median market capitalization of firms listed on the New York Stock Exchange (NYSE) to categorize companies on the NYSE, NASDAQ, and American Stock Exchange (AMEX) into two groups: small-cap (Small) and large-cap (Big). Similarly, they divided the firms listed on the NYSE into three groups based on the 30th and 70th percentiles of the BM ratio: firms with BM above the 70th percentile were classified as High, those below the 30th percentile as Low, and those in between as Middle.

After these classifications, six groups were formed, labeled as S/H, S/M, S/L, B/H, B/M, and B/L. The returns of the stocks within each group were then value-weighted to create six investment portfolios. Using these portfolios, Fama and French (1993) constructed the HML and SMB factors using the following methodology:

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

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

4.2. CH Three-Factor and Four-Factor Models

The CH three-factor model differs from the Fama-French three-factor model in that its value factor is based on the earnings-price (EP) ratio. Additionally, to eliminate the influence of the "shell" effect, the model excludes the smallest 30% of companies by market capitalization when constructing its three factors. The model's specific form is as follows:

$$E(R_t^i) - R_t^f = \beta_{MKT}^i \left[E(R_t^m - R_t^f)\right] + \beta_{SMB}^i E(SMB) + \beta_{VMG}^i E(VMG) \quad (4)$$

Where R_t^f represents the risk-free rate for stock i; R_t^m denotes the market return at time t; $\mathrm{E}(R_t^i)$ signifies the expected return of asset i at time t; $\mathrm{E}(R_t^i) - R_t^f$ is the market risk premium; The terms $E(R_t^m - R_t^f)$, $E(SMB)$, $E(VMG)$ denote the expected returns of the market factor, size factor, and the earnings-price ratio factor, respectively. The coefficients β_{MKT}^i, β_{SMB}^i, β_{VMG}^i represent the stock's exposure to these respective factors.

The construction of the factors is similar to that of the Fama-French three-factor model, so it will not be discussed in detail here.

The high turnover rate of a stock may be driven by investor optimism. Regulations on short-selling not only limit the correction of overpriced stocks but also establish a link between sentiment and turnover. As Baker and Stein (2004) suggested, when investors are pessimistic about a stock, non-investors may avoid participating in the market because short-selling regulations prevent them from acting on their negative sentiment. Conversely, when investors are optimistic, they tend to buy stocks in large quantities. Therefore, short-selling regulations often associate high turnover (high liquidity) with optimism rather than pessimism.

Based on this sentiment-driven rationale, we construct a four-factor model using abnormal turnover (the ratio of last month's turnover to the previous year's average turnover). The construction of the turnover factor follows the same approach as that of the value factor. We replace the EP ratio with abnormal turnover, with the only difference being that we go long on stocks with low factor values (reflecting investor pessimism) and short on stocks with high factor values (reflecting investor optimism). We name this factor PMO, and by adding PMO to the three-factor model, we derive the CH four-factor model.

5. Empirical Results

5.1. Comparison of FF-3 and CH-3 Models

Table 1 lists the alpha coefficients and corresponding t-values of the size and value factors for each model compared to the other model. The CH-3 model effectively explains the size and value factors of the FF-3 model. Specifically, the alpha for FFSMB in CH-3 is only -0.0001 per month, with a t-value of -0.1249, while the alpha for FFHML is -0.0020, with a t-value of -0.7073. In contrast, FF-3 fails to adequately explain the size or value factors of CH-3. However, FF-3 has an SMB of 0.0024 and a t-value of 3.3202, while the alpha for VMG is 0.0070 with a t-value of 4.1446, indicating that the CH-3 model clearly outperforms the FF-3 model.

Table 1. Comparison of FF and CH: Alpha

Factors	CH-3	FF-3
FFSMB	-0.0001 (-0.1249)	
FFHML	-0.0020 (-0.7073)	
SMB		0.0024*** (3.3202)
VMG		0.0070*** (4.1446)

The GRS test (Gibbons, Ross, and Shanken, 1989) is used to assess pricing errors of n assets under a given factor model, specifically testing whether the alpha values are jointly equal to zero. When comparing the two multifactor models, the factors from both models are tested as both assets and pricing models.The results in Table 2 indicate that when using SMB and VMG as factor models, the pricing errors for FFSMB and FFHML can be considered zero (p-value = 0.77); conversely, when using FFSMB and FFHML as pricing models, significant non-zero pricing errors for SMB and VMG remain (p-value = 0.00011914). This implies that SMB and VMG perform better than FFSMB and FFHML.

Table 2. Comparison of FF and CH: GRS

Factors	CH-3	FF-3
FFSMB, FFHML	0.5050 (0.7769)	
SMB, VMG		18.0705 (0.0001)

5.2. Explanation of Anomalies by FF-3 and CH-3 Models

Due to the relatively high size premium in the Chinese stock market, the anomaly variables and size may obscure the effect of anomalies on unconditional sorting. Therefore, we opted for a value-neutral alpha to screen for anomalies. The screening methods for the 14 anomalies are as follows:

For unconditional sorting, we construct deciles by sorting based on the anomaly variables (for CP and EP, only positive values are screened). Then, we create a long-short strategy using deciles one through ten, and within each decile, we form an equally weighted portfolio.

For value-neutral sorting, we first construct size deciles by sorting based on the market capitalization from the previous month. Within each size decile, we then sort based on the anomaly variables to create ten deciles. Finally, we build the anomaly decile portfolios used in our analysis. We extract the stocks within the anomaly deciles from each size decile, apply equal weights to their returns, and construct the return portfolios based on the market capitalization of the individual stocks. Similar to unconditional sorting, the long-short strategy is based on deciles one through ten.

Table 3. CH-3's Explanation of Anomaly Factors

Panel A:Unconditional sorts								
Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$
ME	-0.0008	0.0031	1.3966	-0.5287	-0.8498	0.1901	39.6614	-13.6113
EP	-0.0046	0.0380	0.6396	-1.0427	-2.1883	1.0731	8.7832	-14.4779
BM	0.0069	-0.1339	-0.3972	-1.2612	1.4883	-1.5282	-2.3841	-7.1119
CP	-0.0010	0.0211	0.1259	0.4629	1.2992	-1.0074	-0.0010	0.0211
ROE	-0.0114	0.0116	0.7818	-0.6683	-4.1157	0.2494	6.6736	-5.9871
1-month vol	-0.0010	-0.1875	0.2094	1.2512	-0.2612	-2.8863	1.3441	9.2106
MAX	0.0012	-0.2497	0.0984	0.7799	0.3365	-3.7156	0.6523	6.0541
1m return	0.0037	-0.0820	0.6681	0.2648	0.7900	-0.8945	4.0740	1.4084
12m return	-0.0106	0.0527	0.8935	0.6524	-2.0882	0.6567	5.6633	3.2336
1m turn	0.0095	-0.2393	0.2866	-0.0150	2.4234	-2.5405	1.5677	-0.0803
Panel B: Size-neutral sorts								
Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$
EP	0.0006	0.0374	0.1132	0.8664	0.4956	2.1286	2.5470	17.8364
BM	-0.0045	0.1663	0.2482	0.9197	-1.3463	3.0075	2.1384	6.9899
CP	-0.0008	-0.0157	-0.0091	0.1531	-0.6383	-0.7792	-0.2198	4.1902
ROE	0.0049	-0.0580	-0.0479	0.4533	2.1394	-1.5225	-0.6345	5.0956
1-month vol	-0.0069	0.1777	-0.2200	-0.8466	-2.4863	4.3130	-2.5943	-8.4624
MAX	-0.0081	0.0846	-0.2210	-0.5842	-3.3396	2.3781	-3.3072	-6.8519
1m return	-0.0081	0.0846	-0.2210	-0.5842	-3.3396	2.3781	-3.3072	-6.8519
12m return	-0.0094	0.1774	-0.1875	-0.6540	-4.2305	5.4532	-2.7893	-7.6726
1m turn	-0.0182	0.1358	-0.1713	-0.1870	-6.3385	2.4809	-1.5834	-1.4673

Table 3 lists the corresponding results of CH-3: in the empirical study of the U.S. stock market, the results confirmed that CH-3 can fully explain the profitability anomaly related to Return on Equity (ROE). In the U.S. market, the positive correlation between profitability and average returns led to the inclusion of this factor in the models of Hou et al. (2015) and Fama and French (2015). However, in the Chinese stock market, the explanatory power of CH-3 differs. Specifically, the monthly average alpha of ROE is -0.0114 under unconditional screening and 0.0049 under market capitalization screening, with corresponding t-values of -4.1157 and 2.1394, respectively. In terms of the volatility anomaly, under unconditional screening, the alpha generated by the previous month's average daily volatility and the single-day maximum return is not significant. However, under market capitalization screening, both show significant alpha.

For the size and value anomalies, CH-3 performs well under both unconditional and market capitalization screening, explaining the size (ME), earnings yield (EP), book-to-market ratio (BM), and cash flow yield (CP), with insignificant alpha. However, for the turnover and reversal anomalies, CH-3 shows different results. Under unconditional screening, CH-3 can explain the 1-month return reversal factor but fails to explain the 12-month and 1-month turnover rates. Under market capitalization screening, both the turnover factor and the reversal factor exhibit significant alpha.

Table 4. FF-3's Explanation of Anomaly Factors

Panel A:Unconditional sorts								
Anomaly	α	β_{MKT}	β_{FFSMB}	β_{FFHML}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{FFSMB}))$	$t(\beta_{FFHML})$
ME	-0.0010	0.0298	1.4759	-0.1663	-0.9733	1.4753	38.2928	-3.7932
EP	-0.0117	0.1228	1.1201	-0.2121	-4.6307	3.3462	15.0814	-3.7383
BM	0.0012	0.0505	-0.0702	-1.5105	0.6389	1.4702	-1.3829	-32.9840
CP	-0.0021	0.0211	0.1821	0.1330	-0.8647	0.4671	1.9777	2.5069
ROE	-0.0167	0.0423	1.1520	0.2361	-6.2648	0.9782	14.9978	3.5071
1-month vol	0.0080	-0.3288	-0.3528	0.7375	2.1496	-4.7863	-2.8119	6.4446
MAX	0.0069	-0.3325	-0.2872	0.4234	1.9143	-5.1328	-2.1122	3.5932
1m return	0.0075	-0.1194	0.4324	0.1442	1.7289	-1.3137	2.9488	0.7969
12m return	-0.0061	-0.0568	0.6376	0.8663	-1.4102	-0.8216	4.3373	6.5545
1m turn	0.0116	-0.2264	0.1320	-0.2589	2.8114	-2.8133	0.8423	-1.5152
Panel B: Size-neutral sorts								
Anomaly	α	β_{MKT}	β_{FFSMB}	β_{FFHML}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{FFSMB})$	$t(\beta_{FFHML})$
EP	0.0080	-0.0492	-0.3376	0.2353	4.1282	-1.5137	-6.5566	5.0632
BM	-0.0008	0.0304	0.0297	1.1518	-0.6054	1.2928	0.6679	31.6786
CP	0.0010	-0.0261	-0.1113	-0.0735	0.7280	-1.2637	-3.1430	-2.3729
ROE	0.0106	-0.0822	-0.3963	-0.2921	4.8448	-2.2401	-6.2004	-5.6765
1-month vol	-0.0129	0.2790	0.1359	-0.5335	-4.6579	6.5866	1.8620	-7.3115
MAX	-0.0128	0.1509	0.0690	-0.2880	-5.0831	4.2491	1.0326	-3.7706
1m return	-0.0128	0.1509	0.0690	-0.2880	-5.0831	4.2491	1.0326	-3.7706
12m return	-0.0144	0.2555	0.0887	-0.3685	-6.0394	7.4538	1.4466	-5.6259
1m turn	-0.0213	0.1456	0.0293	0.1426	-7.0082	3.0202	0.3041	1.3158

Table 4 lists the corresponding results of FF-3. FF-3 can only explain the size (SIZE) and value (Value) anomalies among the six anomaly factors. Under unconditional screening, only size (ME), book-to-market ratio (BM), cash flow yield (CP), and 12-month return show non-significance and can be explained by FF-3. In the case of market capitalization screening, only the book-to-market ratio (BM) and cash flow yield (CP) can be explained by FF-3. Compared to CH-3, FF-3 explains significantly fewer anomalies.

5.3. Explanation of Anomalies by the CH-4 Model

In the article by Liu, Stambaugh, and Yuan (2018), the Chinese version of the three-factor model proves ineffective against reversal and turnover anomalies. The reversal phenomenon is well established; it is so pronounced that one can construct portfolios based on returns sorted over nearly any time window, resulting in observable return reversals in the future. Conversely, turnover is closely related to the structure of retail-dominated traders and the constraints associated with short

selling. High turnover often indicates a greater presence of irrationality and excessive attention from sentiment-driven traders toward certain stocks. Frequent trading tends to inflate the recent prices of these stocks, leading to a decline in future returns. The restrictions on short selling mean that short sellers cannot capitalize on this irrationality, thus failing to suppress the price increases of high-turnover stocks.

To address these issues, Liu et al. (2018) introduced a fourth factor—the turnover factor PMO (Pessimistic Minus Optimistic)—in addition to the original three-factor model. The core logic behind this addition is that factors with low turnover tend to achieve higher returns compared to those with high turnover. This adjustment resulted in the development of a four-factor model specifically for the Chinese market.

Table 5. CH-4's Explanation of Anomaly Factors

Panel A:Unconditional sorts										
Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	β_{PMO}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB}))$	$t(\beta_{VMG})$	$t(\beta_{PMO})$
ME	-0.0012	0.0092	1.3876	-0.5356	0.0500	-1.1692	0.6133	42.2023	-13.6416	1.1091
EP	-0.0041	0.0311	0.6498	-1.0349	-0.0561	-1.9576	0.8107	8.1230	-14.7232	-0.6677
BM	0.0040	-0.0876	-0.4659	-1.3140	0.3786	0.8278	-1.1109	-2.8857	-7.6657	1.8497
CP	-0.0014	0.0277	0.1160	-0.0879	0.0543	-0.6047	0.5480	1.0946	-1.0922	0.5089
ROE	-0.0100	-0.0111	0.8154	-0.6424	-0.1854	-3.4501	-0.2439	6.6309	-5.8177	-1.8256
1-m vol	-0.0061	-0.1043	0.0860	1.1563	0.6804	-1.8190	-1.9299	0.5612	9.2746	4.3107
MAX	-0.0054	-0.1430	-0.0600	0.6583	0.8727	-1.8405	-2.5255	-0.4937	7.5231	7.5899
1m return	-0.0022	0.0140	0.5256	0.1554	0.7849	-0.4557	0.2150	3.8258	0.9307	4.3722
12m return	-0.0133	0.0956	0.8299	0.6036	0.3506	-2.6041	1.1405	5.1704	2.8570	1.5920
1m turn	-0.0026	-0.0415	-0.0070	-0.2405	1.6182	-1.3318	-1.1842	-0.1118	-3.8612	27.1777
Panel B: Size-neutral sorts										
Anomaly	α	β_{MKT}	β_{SMB}	β_{VMG}	β_{PMO}	$t(\alpha)$	$t(\beta_{MKT})$	$t(\beta_{SMB})$	$t(\beta_{VMG})$	$t(\beta_{PMO})$
EP	0.0006	0.0378	0.1127	0.8660	0.0029	0.4609	2.2203	2.4404	17.6086	0.0704
BM	-0.0029	0.1394	0.2882	0.9504	-0.2204	-0.8334	2.6203	2.4444	7.4163	-1.4497
CP	-0.0006	-0.0196	-0.0033	0.1575	-0.0318	-0.4503	-0.9309	-0.0764	4.1585	-0.7221
ROE	0.0035	-0.0352	-0.0817	0.4273	0.1864	1.4859	-1.0169	-1.0859	-4.7865	2.0737
1-m vol	-0.0039	0.1288	-0.1474	-0.7908	-0.3999	-1.5672	2.9788	-1.8036	-7.9214	-3.4802
MAX	-0.0041	0.0203	-0.1257	-0.5110	-0.5256	-1.9766	0.5977	-2.3925	-7.8564	-8.2673
1m return	-0.0041	0.0203	-0.1257	-0.5110	1.9766	-2.3925	0.8564	-8.2673	-0.0041	0.0203
12m return	-0.0079	0.1532	-0.1516	-0.6264	-0.1978	-3.5154	4.5610	-2.2947	-7.1719	-2.3561
1m turn	-0.0104	0.0077	0.0189	-0.0409	-1.0482	-6.7834	0.2628	0.2984	-0.7063	-17.5742

After incorporating the PMO factor, let's examine the explanatory power of the new four-factor model on the ten anomalies discussed in the previous section. Under unconditional screening, the model shows improved explanatory power for the reversal and turnover anomalies. However, the alpha of the 12-month return anomaly remains significant, with a t-value of -2.6041, indicating that it still cannot fully explain the turnover anomaly.

In the case of market capitalization screening, CH-4 still fails to explain the reversal and turnover anomalies, with the 1-month return, 12-month return, and 1-month abnormal turnover remaining significant. This contrasts with the original claim that the newly added PMO effectively addresses the shortcomings of the three-factor model, allowing all ten anomalies to be well explained by the four-factor model. This discrepancy suggests that the inclusion of the PMO factor in the formation of the CH-4 model may involve a degree of data mining.

6. Summary

First, the comparison between CH-3 and FF-3 shows that, whether in terms of alpha or GRS tests, CH-3 can effectively explain the size and value factors of FF-3, while FF-3 lacks corresponding explanatory power in return. Furthermore, CH-3 demonstrates a significantly stronger explanatory ability for anomaly factors compared to FF-3, indicating that CH-3 is more suitable for application in the Chinese market. This finding not only highlights CH-3's advantage in capturing market characteristics but also reveals FF-3's limitations in the Chinese context, suggesting that investors may achieve more accurate predictions by considering CH-3 in asset pricing and investment decision-making.

Second, the explanatory results of CH-3 for anomaly factors in this paper do not entirely align with related studies, particularly in the case of the CH-4 factor constructed after incorporating the turnover factor. This discrepancy may be associated with factors related to data mining. The introduction of the turnover factor during the construction of CH-4 may have triggered complex interactions with other anomaly factors, leading to inconsistencies with existing literature. Therefore, although CH-4 provides a new perspective, its results should be interpreted with caution to avoid biases stemming from excessive reliance on data mining. Further research could examine the robustness of these factors by using different samples or employing alternative validation methods to enhance the reliability of the conclusions.

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