**NUS Financial Engineering Project**
**Cover Page**

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|---|---|
| Project Title | Betting Against Beta in China |
| Name | DING Xiangyu |
| Student ID | A0212112H |
| | |
| Itemized workload | |
| - Data collection | 3 hours |
| - Literature review | 12 hours |
| - Empirical research design | 12 hours |
| - Programming (for empirical analysis) | 72 hours |
| - Trading strategy design | 12 hours |
| - Programming (for trading strategy) | 12 hours |
| - Report writing | 24 hours |
| - Report revising | 12 hours |
| Total workload | 159 hours |
| | |
| Original contribution | This project has the following original contributions:<br><br>1. I use portfolio sort to empirically show that low-beta anomaly exists in Chinese stock market.<br><br>2. Based on Frazzini and Pedersen (2014), I design a feasible trading strategy to help investors in China to profit from low-beta anomaly.<br><br>3. To make the strategy feasible Chinese stock market, I make three major improvements to the trading strategy: excluding small stocks to avoid distortion of shell value, using value weight to avoid high transaction cost, and hedging by short position of stock index future.<br><br>4. I back test the trading strategy and the result shows my trading strategy provide decent return. |

# Betting Against Beta in China

NUS-PKU DDP Financial Engineering Project

**DING Xiangyu**

**A0212112H**

# Contents

# 1. Abstract

In this graduation project, I empirically demonstrate that low-beta anomaly exists in Chinese stock market. I further design a profitable trading strategy based on the *Betting Against Beta (BAB)* proposed by Frazzini and Pedersen (2014). I make several improvements on the trading strategy to make it feasible in Chinese stock market. Back testing finds that this trading strategy can generate good return in China.

# 2. Motivation

Frazzini and Pedersen (2014) *Betting Against Beta* (BAB) is one of the most influential finance papers in the last 20 years. The paper links the low-beta anomaly with borrowing constraints, and it implies that a zero-beta portfolio called BAB factor portfolio constructed by leveraged low-beta stocks and deleveraged short selling in high-beta stocks brings positive return. Their empirical analysis finds that this trading strategy brings decent return in most mature stock markets (e.g. US, UK, Japan, Hong Kong, etc.). Due to the good performance of this trading strategy, the paper became one of the most downloaded articles published on *Journal of Financial Economics* in recent years, and the defensive equity trading strategy represented by this paper also witnessed a large inflow of funds (Novy-Marx & Velikov, 2022).

Unfortunately, Frazzini & Pedersen (2014) do not provide empirical evidences from emerging market, especially China, which has become the second largest stock market measured by market capitalization. In addition, due to the limited historical data, leverage restrictions and short-selling restrictions, the beta estimation method and original BAB trading strategy are not feasible in China. Therefore, in this graduation project, I would like to extend the BAB trading strategy to make it applicable to Chinese stock market.

The remaining parts of this report are organized as follows: In Section 3, I review existing literature on low-beta anomaly and potential economic mechanisms causing the anomaly. In Section 4, I conduct empirical analysis to study whether low-beta anomaly exists in Chinese stock market. In Section 5, I design a feasible trading strategy based on BAB and test whether it can generate profit for investor. Section 6 concludes the project.

# 3. Literature Review

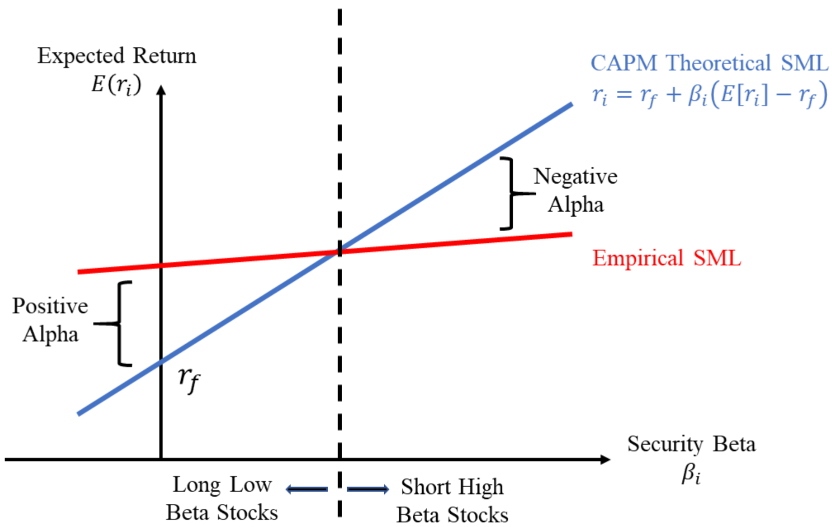
## 3.1 Low-beta Anomaly

The simplest and best-known asset pricing model, Capital Asset Pricing Model (CAPM), predicts that the relationship between asset betas and expected returns should be linearly positive with slope equals to the expected market excess return. This relationship between return and beta is known as the security market line (SML), shown as equation (1):

$$E(r_i) = r_f + \beta_i(E[r_i] - r_f) \qquad (1)$$

However, empirical analyses show that the SML in reality is fatter than CAPM predicts (Haugen & Heins, 1972, 1975). Further research, for example Baker et al. (2011), even finds the relationship is negative. Baker et al. (2011) sort all US listed stocks into five quintiles based on their estimated beta. They show that $1 investment in lowest-beta portfolio in January 1968 grows to $60.46 in December 2008, while the same $1 in the highest-beta portfolio only end up in $3.77. Because beta is highly correlated with volatility, Baker et al. (2011) also show that sorting portfolio based on volatility also gives a similar result. These puzzling results are called the low-beta anomaly and the low-volatility anomaly in asset pricing.

**Figure 1: Low-Beta Anomaly**




One may think that low-beta anomaly is a result of coincidence, however, a large body of empirical research shows that low beta anomaly exists almost universally in most markets and in many assets classes for a long period of time. Frazzini & Pedersen (2014) conduct empirical analyses using stock market data from 20 developed countries and find low-beta anomalies in 19 of them. In addition, they find low beta anomalies in stock indices, sovereign bonds, credit bonds, foreign exchange, and commodity markets. Dutt and Humphery-Jenner (2013) find low-volatility anomalies in stock markets of emerging market countries. Burggraf and Rudolf (2021) even show that less volatile cryptocurrencies give higher return. In these studies, the authors control for other common return factors and found that low beta anomalies cannot be not explained by correlation with other factors.

## 3.2 Economic Mechanisms

One of the corner stone of classical finance theory, the efficient market hypothesis proposed by Fama (1970) claims that asset prices reflect all the available information. If market is efficient, arbitrage quickly brings asset prices back to the fundamental values, and any trading strategy based on past asset price information should not generate long-term excess return. However, the existence of low-beta anomaly means that an investor can beat the market by estimating asset beta using past return and buys low-beta stocks. Therefore, low-beta anomaly attracts widespread attention in the academic community. Many literatures are trying to find the economic mechanisms behind the low-beta anomaly.

One key aspect to understand low-beta anomaly is to know why people have high demand on high-beta stocks. From the perspective of discounted cash flow, expected return is low when price is high. If people are risk-averse, high-beta assets with high risk should be priced lower, so higher returns are needed to encourage people to hold risky assets. Therefore, Low-beta anomaly means that high-beta assets are overvalued by investors, comparing to the prediction of CAPM. The over valuation of high-beta stock may cause by investors' high demand on high-beta assets. Some research argues that the preference for high-beta assets is a rational behavior under borrowing constraints, while other shows that irrational investment behavior can also lead to excess demand on high-beta financial assets.

The idea that borrowing restrictions can lead to low-beta anomaly dates back to the Black-CAPM proposed by Fischer Black (1972, 1993). Unlike classical CAPM models, Black-CAPM assumes that investors cannot borrow at risk-free rates. Because it is infeasible to leverage their investment in low-beta assets, investors looking for the high return can only invest in high-beta assets, causing excess demand on high-beta assets and lowering their return. Frazzini and Pedersen (2014) extend the Black-CAPM model by allowing heterogeneous borrowing constraints across investors, and they propose the BAB trading strategy to profit from low-beta anomaly.

Low-beta anomaly can also be explained by lottery preference, a theory of behavioral finance. Lottery preference refers to investors' preference for financial assets like lottery tickets which have a tiny probability of obtaining huge returns. Lottery-like assets typically have high-volatility and high-beta, so the irrational demand for lottery-like assets can explain the high prices and low returns of high-beta stocks. Kumar (2009) uses investor transaction data obtained from a U.S. brokerage and finds that individual investors prefer lottery-like stocks to institutional investors. In order to link the lottery preference with the cross-section stock return, Bali et al. (2011) use a stock's maximum one-day return over the previous month (MAX) to identify lottery like stocks. They find that stocks with high MAX significantly gives low return comparing other stocks, indirectly showing that overinvestment in lottery-like stocks inflate their price and lowering their return. Further, Bali et al. (2015) finds that the explained return of low-beta stocks disappeared if MAX is controlled, so they argues that the low-beta anomaly is a result of lottery preference.

In addition to the high demand on high-beta assets, another key aspect to understand low-beta anomaly is to know why *smart money* from institutional investors does arbitrage by investing in low-beta assets. Baker et al. (2011) find that the many active managed funds use information ratio (IR) to evaluate the performance of fund managers, and this evaluation standard, coupled with borrowing constraints, makes investors less motivated to invest in low-beta stocks. IR is defined as excess return relative to benchmark over tracking error, the standard deviation of the excess return:

$$IR = \frac{Portfolio\ Return - Benchmark\ Return}{std(Portfolio\ Return - Benchmark\ Return)} \tag{2}$$

Baker et al. (2011) demonstrate that while investing in low-beta assets can generate an increase in the numerator, the increase in the denominator is greater, making the IR decrease. Therefore, fund managers have no incentive to investor in low-beta assets.

# 4. Empirical Analysis

In this section, I will empirically test whether there is low-beta anomaly in Chinese stock market. If it exists, then I can design a trading strategy in Section 5, and show whether investors can profit from it.

## 4.1 Data

This research project requires two parts of data: the close-to-close daily returns of each stock listed in Chinese stock market, and the return of common return factors in China as control variables. The time window of the data is from January 1st, 2000 to December 31st, 2020. I do not use data after December 31st, 2020 because the data of Liu et al. (2019) Chinese factors ends on December 31, 2020.

The close-to-close daily returns of each stock are calculated as the simple return of dividend-adjusted close price compared to the last trading day. Dividend-adjusted close price of each trading date is downloaded from Wind Data Service (WDS) maintained by Chinese financial data service provider Wind Information Co., Ltd. It is widely used by quantitative funds in China. https://www.wind.com.cn/en/data.html is the webpage of their data service. Peking University HSBC Business School subscribes this database, and as a student of the school, I can use SQL to query data from it.

In order to control the effect of other factors, I need to calculate the alphas related to common return factors, including Fama and French (1993) three factors, Carhart

(1997) four factors, and Fama and French (2015) five factors. Shi et al. (2020) estimate the returns to these factors in the Chinese stock market in their book *Factor Investing*. They publish their results at https://www.factorwar.com/data/factor-models/, and I download their estimated results. In addition, Liu et al. (2019) develop their own version of Chinese three factors and Chinese four factors in their paper *Size and value in China* published on *Journal of Financial Economics*. One of the authors of this paper, Dr. Robert F. Stambaugh, posts their estimated Chinese factor returns on his webpage: https://finance.wharton.upenn.edu/~stambaug/. I download their estimated results.

## 4.2 Methodology

Following Baker et al. (2011) and Frazzini and Pedersen (2014), I use the standard portfolio sort to test the low-beta anomaly.

First of all, in order prevent the influence of extreme values, I winsorize the daily stock returns in beta estimation. An important feature of Chinese stock market is that China introduces daily stock price limit regulation of simple return +10% and -10% in December 1996. Usually, the close-to-close daily stock return should not be higher than 10% or lower than -10% during my sample period. However, stocks that have just been listed or stocks that have just been suspended from trading are not restricted by this price limit. In my sample period, 0.1% percentile of stock return is -10.03% around -10% and 99.9% percentile of stock return is around 10.14% around 10% (not exactly 10% because the limit is rounded to 0.01 RMB yuan). However, the min and max are -

68.72% and 2065.28% caused by listing and trading suspension. When estimating beta of each stock, I winsorize the extreme returns by 0.1% and 99.9% percentile. After estimating beta, return before winsorization is used for calculate portfolio return and back testing of my trading strategy.

Second, daily excess stock return is regressed on daily excess market return calculated by Liu et al. (2019) on 252 trading days (or 1 year) rolling window basis. The OLS estimator of slope is the estimated beta of each stock. Mathematically, the beta of stock $i$ at trading date $T$ is the ordinary least squares (OLS) estimator of $\beta_{i,T}$ in the following equation:

$$r_{i,\tau} - r_{f,\tau} \quad = \gamma_{i,T} + \beta_{i,T}(r_{m,\tau} - r_{f,\tau}) + \epsilon_{i,\tau} \tag{3}$$

$$\forall\, \tau \in \{T - 251, T - 250 \ldots, T\}$$

Notice that this method is different from the method used by Frazzini and Pedersen (2014) in which the authors separately estimate the one-year-rolling-window volatility of stocks and five-year-rolling-window correlation with the market. They claim that their method is better because return volatility changes faster than stocks' correlation with the market return. However, I choose the regression approach due to the following reasons: First, regression approach is supported by Novy-Marx and Velikov (2022) which shows that the method used by Frazzini and Pedersen (2014) tends to underestimate asset beta when the market is volatile. Second, the US stock return data used by Frazzini and Pedersen (2014) is much longer than our data. Because China's stock market has a short history and many stocks are listed in recent years, using a five-year rolling window to estimate correlations leads to a problem that I have to drop many new stocks in our dataset.

Third, stocks are divided into 5 groups according to their estimated betas, forming 5 different equal weight or value weight portfolios. Among them, Portfolio 1 has the smallest beta and Portfolio 5 has the highest beta. I rebalance each portfolio each month in the first trading date. Then, I calculate the excess return for each portfolio. Finally, in order to calculate the alpha of each portfolio, I regress the time series of excess returns each month on common factor returns, including Fama and French (1993) three factors, Carhart (1997) four factors, Fama and French (2015) five factors, Liu et al. (2019) Chinese three factors, and Liu et al. (2019) Chinese four factors. Mathematically, the alpha of portfolio $p$ is the OLS estimator of $\alpha_p$ in the following equation, in which $r_{jt}$ is the return factor $j$ and $\lambda_{pj}$ is the factor exposure of portfolio $p$ on return factor $j$.

$$r_{pt} - r_{ft} = \alpha_p + \sum_j \lambda_{pj} r_{jt} + \epsilon_{pt} \tag{4}$$

In addition, ex-ante beta (weighted average of estimated portfolio beta), realized beta (regression coefficient of realized portfolio excess return on market return), annualized volatility, and annualized Sharpe ratio are calculated.

## 4.3 Empirical Result

Table 1, Table 2 and Table 3 below show the portfolio return formed by Chinese equity using different weighting method. All the stocks listed in Shanghai Stock Exchange and Shenzhen Stock Exchange are included. At the beginning of each month, stocks are sorted by their estimated beta. Beta is estimated as the OLS estimator of regression coefficient of stocks' excess return (relative to risk free rate) on the market excess return reported by Liu et al. (2019). The stocks are assigned to five different portfolios based on their beta rank: Portfolio 1 has the lowest beta and Portfolio 5 has the highest beta. In table 1, stocks are equal weighted in each portfolio. In table 2, stocks are weighted by total market value (total market cap). In table 3, stocks are weighted by circulated market value (total market value of listed stocks). Row 1 reports the monthly excess return relative to risk free rate. Row 2 to Row 7 report the alphas after controlling the market excess return [CAPM alpha], Fama and French (1993) three factors [FF3], Carhart (1997) four factors [Carhart4], and Fama and French (2015) five factors [FF5], Liu et al. (2019) Chinese three factors [LSY3], and Liu et al. (2019) Chinese four factors [LSY4]. Alphas are the OLS estimator of the intercept of regressing monthly excess return on return factors. Excess return and alpha are represented as percentage point per month. T-statistics calculated using robust standard error are listed in brackets. 5% significance is indicated in bold. Beta (ex-ante) is the weighted average of estimated beta, and beta (realized) is the regression coefficient of realized excess return on market excess return. Volatility is annualized, represented as percentage point per year, and Sharpe ratio is also annualized.

To illustrate the difference in portfolio alphas, Figure 2, Figure 4, and Figure 6 plot the estimated alphas of equal weight, total value weight, and circulated value weight portfolios. Figure 3, Figure 5 and Figure 7 show the cumulated value of 100 RMB yuan investment in equal weight, total value weight, and circulated value weight portfolios from January 1st, 2001.

**Table 1: Portfolio Sort of Chinese Equities, Equal Weight, 2000–2020.**

| | P1 (Low Beta) | P2 | P3 | P4 | P5 (High Beta) |
|---|---|---|---|---|---|
| Excess return % | **1.37** | 1.02 | 0.87 | 0.62 | 0.24 |
| | (2.17) | (1.51) | (1.18) | (0.80) | (0.29) |
| CAPM alpha % | **0.81** | 0.40 | 0.18 | -0.10 | -0.55 |
| | (2.59) | (1.33) | (0.59) | (-0.30) | (-1.65) |
| FF3 alpha | **0.60** | 0.17 | -0.08 | **-0.40** | **-0.79** |
| | (3.17) | (1.65) | (-0.80) | (-3.86) | (-4.92) |
| Carhart4 alpha % | **0.59** | 0.16 | -0.09 | **-0.40** | **-0.76** |
| | (3.06) | (1.47) | (-0.83) | (-3.68) | (-4.46) |
| FF5 alpha % | **0.60** | 0.09 | -0.11 | **-0.39** | **-0.64** |
| | (3.03) | (0.85) | (-1.22) | (-4.22) | (-4.12) |
| LSY3 alpha % | **0.72** | **0.35** | **0.33** | 0.15 | 0.13 |
| | (3.80) | (3.41) | (4.46) | (1.84) | (0.95) |
| LSY4 alpha % | **0.77** | **0.36** | **0.35** | **0.20** | 0.20 |
| | (3.80) | (3.48) | (4.39) | (2.35) | (1.44) |
| Beta (ex-ante) | 0.66 | 0.96 | 1.11 | 1.24 | 1.45 |
| Beta (realized) | 0.86 | 0.97 | 1.06 | 1.12 | 1.23 |
| Volatility % | 27.80 | 30.03 | 32.66 | 34.34 | 37.11 |
| Sharpe ratio | 0.59 | 0.41 | 0.32 | 0.22 | 0.08 |

## Figure 2: Alpha of Equal Weight Portfolio (Monthly, %)

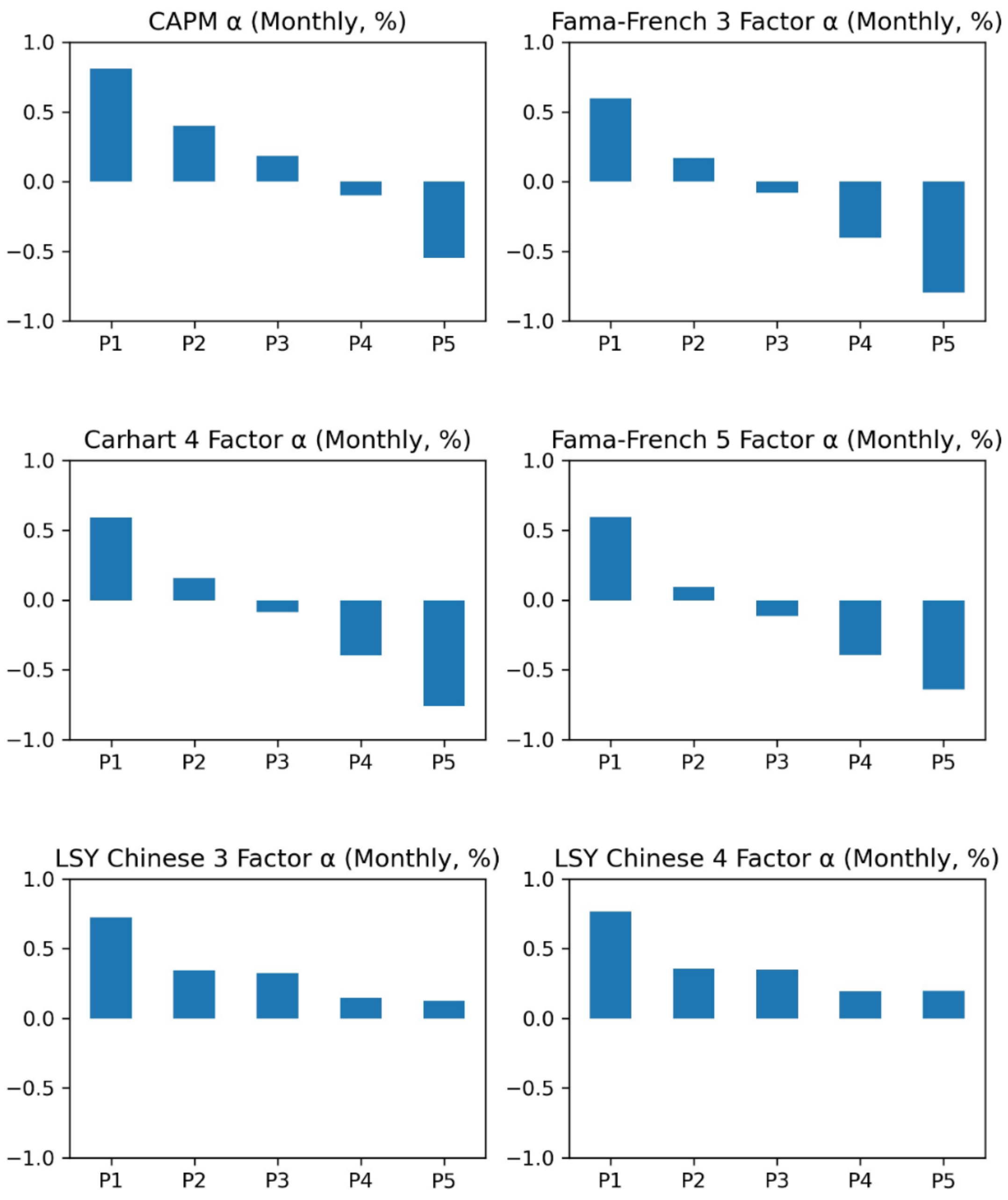


**Figure 3: Cumulative Value of 100 RMB Investment from Jan 1st, 2001**

**Equal Weight: P1 (Low Beta) to P5 (High Beta)**

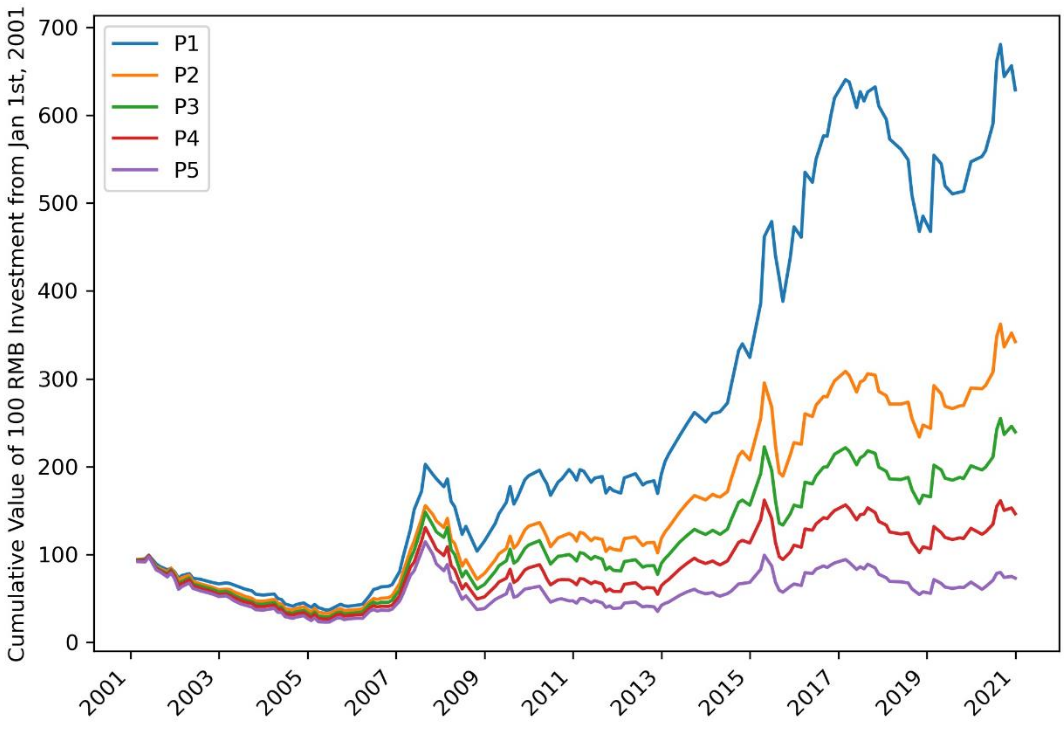


**Table 2: Portfolio Sort of Chinese Equities, Total Value Weight, 2000–2020.**

| | P1 (Low Beta) | P2 | P3 | P4 | P5 (High Beta) |
|---|---|---|---|---|---|
| Excess return % | **1.22** | **1.50** | **1.50** | 1.12 | 1.00 |
| | (2.48) | (2.39) | (2.03) | (1.54) | (1.17) |
| CAPM alpha % | **0.76** | **0.88** | **0.76** | **0.39** | 0.16 |
| | (3.59) | (4.70) | (4.25) | (2.22) | (0.62) |
| FF3 alpha | **0.83** | **1.06** | **0.89** | **0.38** | 0.08 |
| | (3.87) | (5.31) | (4.82) | (2.45) | (0.32) |
| Carhart4 alpha % | **0.83** | **1.10** | **0.90** | **0.40** | 0.14 |
| | (3.60) | (5.48) | (4.80) | (2.54) | (0.52) |
| FF5 alpha % | **0.77** | **1.04** | **0.88** | **0.46** | 0.27 |
| | (3.11) | (4.61) | (4.98) | (2.73) | (1.04) |
| LSY3 alpha % | **0.84** | **0.89** | **1.00** | **0.90** | **0.96** |
| | (3.23) | (4.31) | (6.78) | (4.84) | (3.86) |
| LSY4 alpha % | **0.80** | **0.76** | **0.95** | **0.94** | **1.11** |
| | (2.93) | (3.60) | (6.21) | (4.82) | (4.07) |
| Beta (ex-ante) | 0.60 | 0.95 | 1.11 | 1.24 | 1.43 |
| Beta (realized) | 0.70 | 0.95 | 1.15 | 1.13 | 1.31 |
| Volatility % | 21.72 | 27.74 | 32.58 | 32.21 | 37.97 |
| Sharpe ratio | 0.67 | 0.65 | 0.55 | 0.42 | 0.32 |

**Figure 4: Alpha of Total Value Weight Portfolio (Monthly, %)**

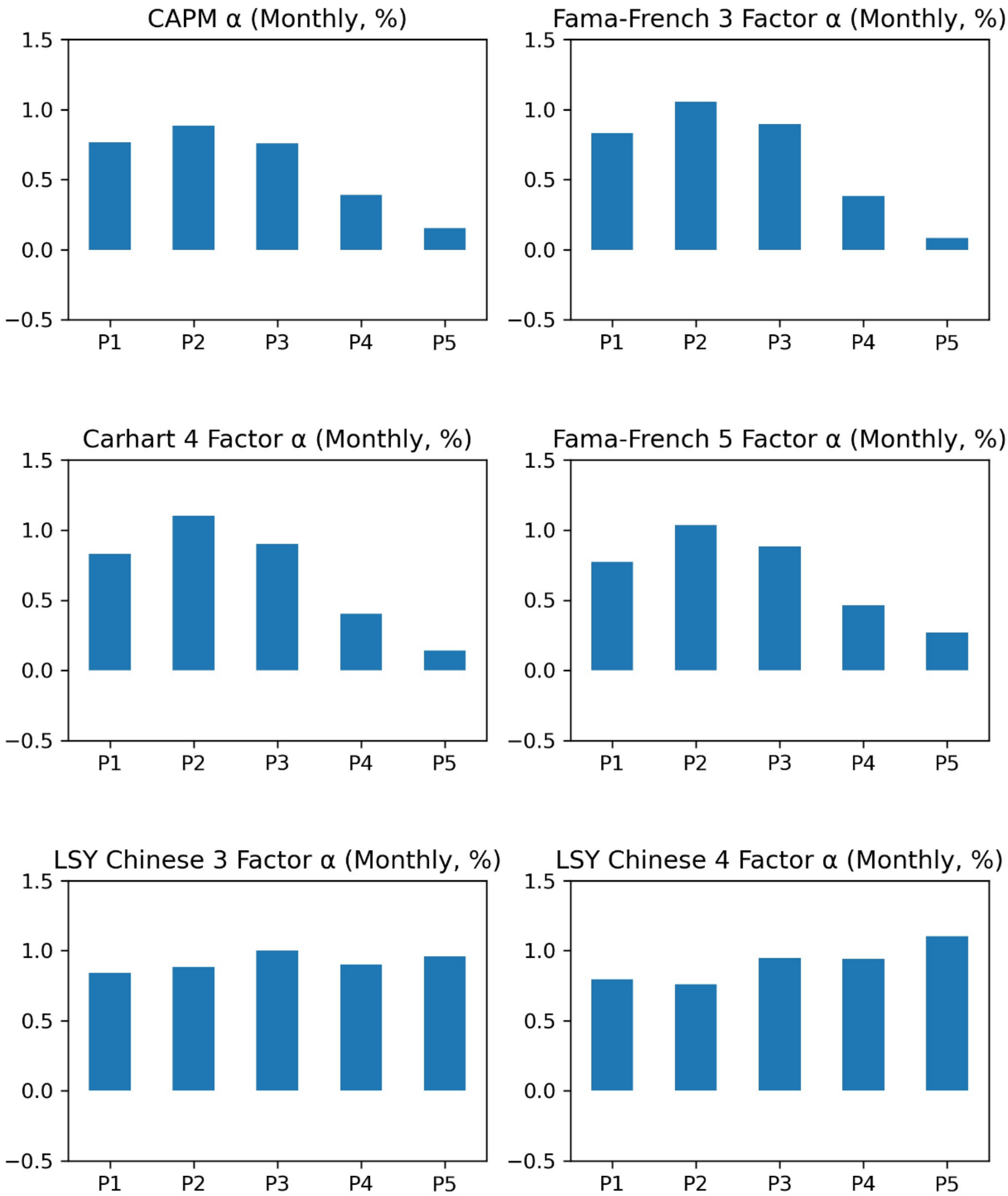


**Figure 5: Cumulative Value of 100 RMB Investment from Jan 1st 2001**

**Total Value Weight: P1 (Low Beta) to P5 (High Beta)**

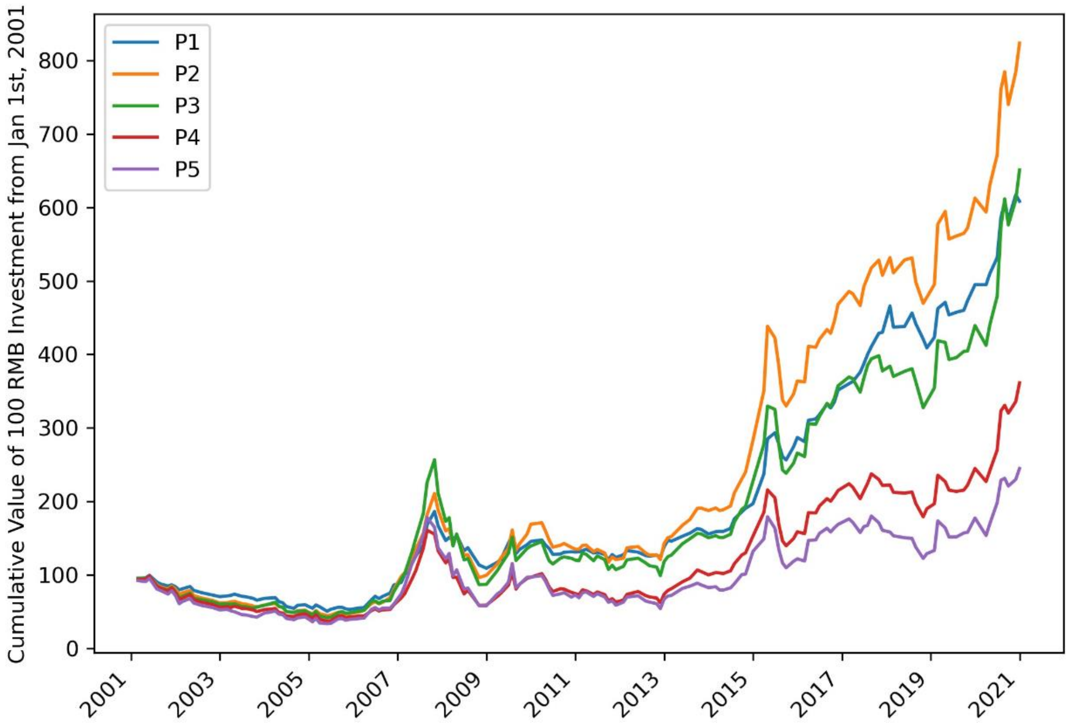


**Table 3: Portfolio Sort of Chinese Equities, Circulated Value Weight, 2000–2020.**

| | P1 (Low Beta) | P2 | P3 | P4 | P5 (High Beta) |
|---|---|---|---|---|---|
| Excess return % | **1.50** | **1.74** | **1.41** | 1.32 | 0.91 |
| | (2.92) | (2.68) | (2.00) | (1.75) | (1.05) |
| CAPM alpha % | **1.00** | **1.08** | **0.70** | **0.56** | 0.05 |
| | (5.71) | (6.87) | (4.15) | (3.04) | (0.22) |
| FF3 alpha | **0.95** | **1.08** | **0.72** | **0.46** | -0.07 |
| | (5.52) | (6.52) | (4.97) | (3.14) | (-0.31) |
| Carhart4 alpha % | **0.92** | **1.09** | **0.72** | **0.48** | 0.00 |
| | (5.03) | (6.56) | (4.94) | (3.22) | (-0.02) |
| FF5 alpha % | **0.96** | **1.13** | **0.77** | **0.59** | 0.19 |
| | (5.03) | (5.88) | (5.06) | (3.47) | (0.82) |
| LSY3 alpha % | **0.91** | **1.21** | **0.95** | **1.01** | **0.92** |
| | (4.23) | (6.37) | (5.57) | (5.17) | (4.13) |
| LSY4 alpha % | **0.91** | **1.23** | **0.93** | **1.07** | **1.09** |
| | (3.73) | (6.27) | (5.37) | (5.53) | (4.46) |
| Beta (ex-ante) | 0.60 | 0.96 | 1.11 | 1.25 | 1.43 |
| Beta (realized) | 0.77 | 1.01 | 1.10 | 1.17 | 1.32 |
| Volatility % | 22.68 | 28.68 | 31.24 | 33.44 | 38.23 |
| Sharpe ratio | 0.79 | 0.73 | 0.54 | 0.47 | 0.29 |

**Figure 6: Alpha of Circulated Value Weight Portfolio (Monthly, %)**

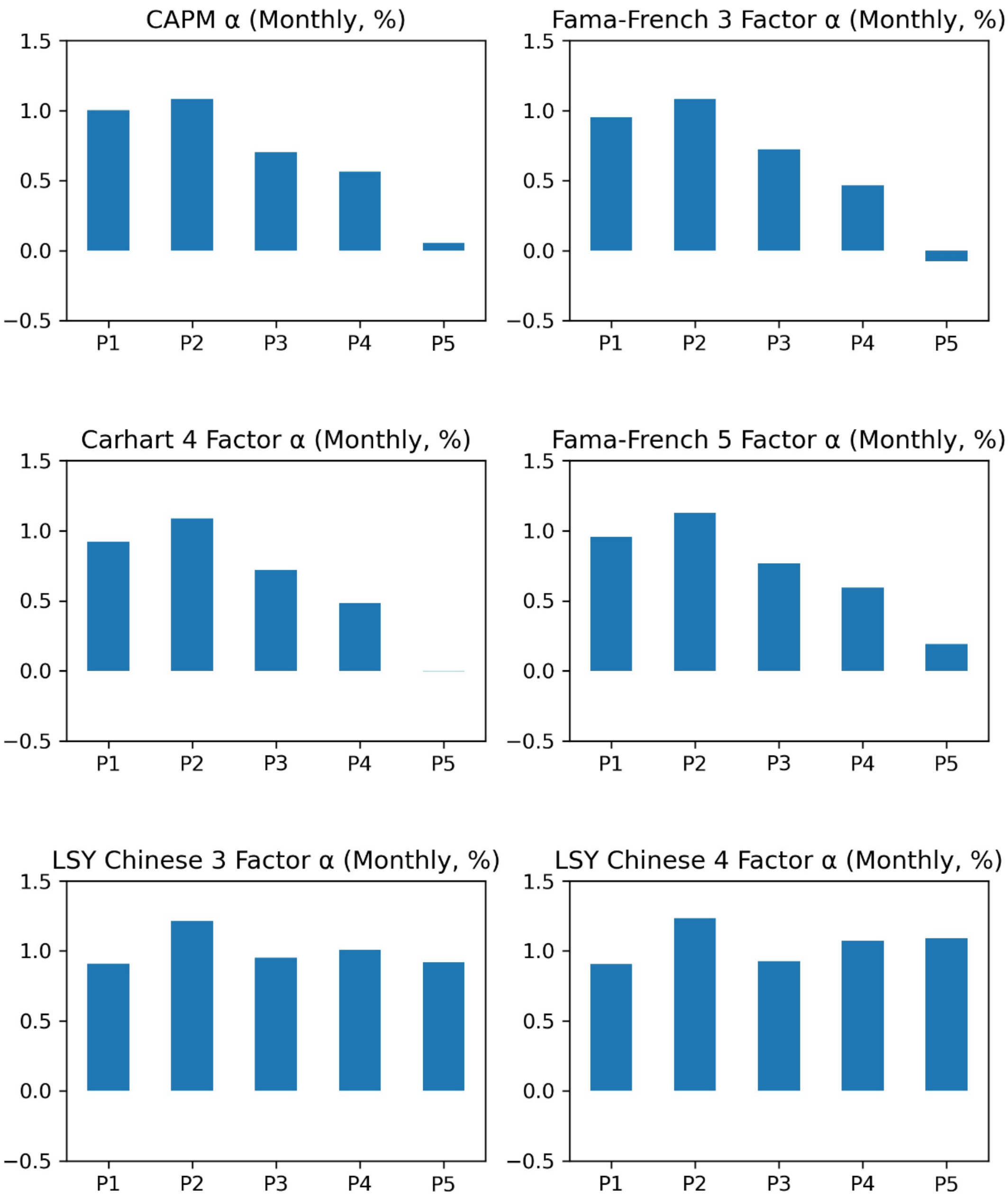
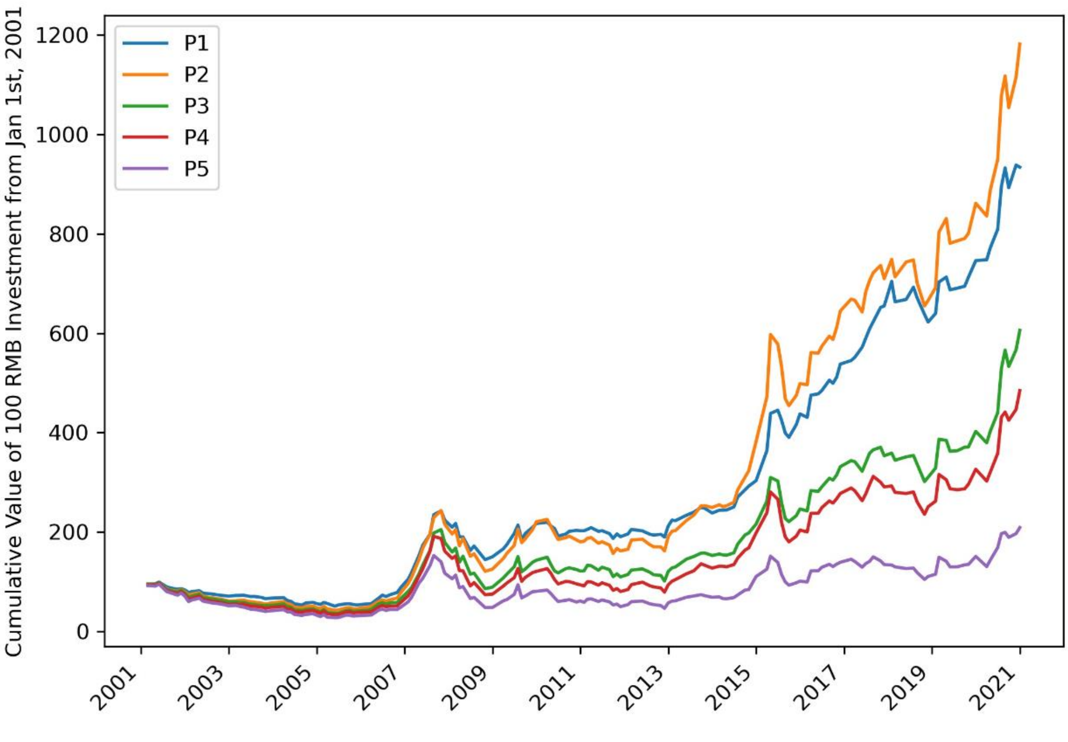


**Figure 7: Cumulative Value of 100 RMB Investment from Jan 1st 2001**

**Circulated Value Weight: P1 (Low Beta) to P5 (High Beta)**



In the tables and figures above, I show the empirical result of portfolio sort in Chinese stock market.

The empirical result of equal weight portfolios gives support to the existence of low-beta anomaly in Chinese stock market. Table 1, Figure 2 and Figure 3 give the performance of equal weight portfolio constructed by stock sorted by their estimated beta. According to Table 1 and Figure 2, excess returns, alphas and Sharpe ratios decrease monotonically as the portfolios' beta and volatility increases. This result means that low-beta anomaly and low-volatility exists in Chinese stock market. Furthermore, Figure 3 shows the accumulated value of 100 RMB yuan investment from January 1st, 2001: 100 RMB yuan investment in Portfolio 1 with lowest beta, the money grew up to 628.64 RMB yuan in nominal term (equals to 397.28 RMB yuan in real term scaled by CPI). In comparison, same investment in the Portfolio 5 with highest beta only ended up in 73.12 RMB yuan in nominal term (equals to 46.21 RMB yuan in real term). This result is similar to Baker et al. (2011), which show that low-beta portfolios in US stock market greatly overperform the high-beta portfolios. In general, the empirical results support that low-beta anomaly exists in Chinese stock market so investing in low-beta stocks generate excess return comparing to the market.

Although the empirical result shows that equal weight portfolio of low-beta stocks perform well, Figure 3 indicates that unhedged low-beta portfolio have high exposure to market risk, and can cause great loss in bull market. Chinese stock market has experienced two major bull market in the last 20 years, and both of them are caused by burst of stock bubbles (Song & Xiong, 2018): The first bubble was from 2006 to 2007, and it burst in 2008 with the global financial crisis. The second bubble was from mid-2014 to mid-2015, and the bull market started in mid-2015. As we can see from figure 3, all the portfolios witnessed great loss during the bull market. For mutual funds and hedge funds, large losses in a short period of time may lead to investor withdrawals, resulting in fire sale and liquidity crisis. Therefore, it is important to hedge the market risk in designing the trading strategy.

In addition to great loss during the burst of stock bubbles, the empirical results of value weight portfolios show another problem: the influence of shell value. Table 2, Figure 4, and Figure 5 give the performance of total value weight portfolio, and Table 3, Figure 6, and Figure 7 show the performance of circulated value weight portfolio. On one hand, we can see that the portfolio with the highest beta still gives the worst return, so we expect that trading strategy based on low-beta anomaly is still profitable if I use total value weight or circulated value weight. On the other hand, figure 4 and figure 6 shows that there is no significant difference in alpha after controlling the Liu et al. (2019) Chinese three factors. Although, Liu et al. (2019) construct Chinese three factors by following the idea of Fama and French (1993), they change the factor construction method based on an important feature of Chinese stock market: the distortion of stock price due to initial public offering (IPO) regulations. Most of the IPO in China requires inspection and approval from China Securities China Securities

Regulatory Commission (CSRC) and the process is complicated, risky and time-consuming for firms. Therefore, some firms choose to acquire listed companies to bypass the inspection. Then, these firms inject assets to the acquired listed companies and indirectly list their shares. Since listed companies with small market value are good acquisition targets, there is an upward distortion in their stock value, usually called the shell value. Those small firms with high shell value have high exposure to regulation risk, so it is reasonable for investors to require a high return on these stocks. To prevent the influence of shell value, Liu et al. (2019) exclude the smallest 30% of firms in constructing Chinese factors to prevent the influence of shell value. The fact that low-beta anomaly exists after controlling for Fama and French (1993) three factors but vanishes after controlling for Liu et al. (2019) Chinese three factors indicates that the returns of low-beta stocks may partly come from the shell value.

In general, the empirical results predict that trading strategies based on low-beta anomaly may be profitable in China. However, the results also show that it is necessary to hedge market risks and to avoid the influence of shell value.

# 5. Trading Strategies

Because many empirical results have shown that low-beta anomaly exists in many financial assets and markets, trading strategies based on low-beta anomaly, usually called defensive equity strategies, have become a focus of the financial industry in the developed countries. Generally speaking, these strategies seek to invest in financial assets that have small risk (i.e. low beta, low volatility), but give similar return to the market. Unfortunately, while there are many studies in the US, few research studies trading strategies based on low-beta anomaly in China. Therefore, I will try to design and test several trading strategies in China.

## 5.1 Benchmark: Betting Against Beta

Frazzini and Pedersen (2014) *Betting against beta* (BAB) is one of the most influential defensive equity strategies. The authors show that BAB factor portfolio, constructed by investing in leveraged low-beta stocks and short selling in deleveraged low-beta stocks, provides monthly 0.70% return in US stock market.

To construct factor portfolios, Frazzini & Pedersen (2014) divide stocks equally into two portfolios according to their estimated beta. The weight within each portfolio is determined by the stock's beta rank within the portfolio. For the low-beta portfolio, the stock with the highest beta in the portfolio has a weight of 1/total weight, the stock with the second highest beta has a weight of 2/total weight, ... and the stock with the lowest beta has a weight of 0.5n/total weight. n is the total number of stocks. Similarly, for the high beta portfolio, the stock with the lowest beta in the portfolio has a weight of 1/total weight, the stock with the second lowest beta has a weight of 2/total weight, ..., the stock with the highest beta has a weight of 0.5n/total weight. Formally, we can express the weight of stock $i$ in each portfolio as:

$$w_i^{Low} = \frac{1}{0.5\sum_n |z_n - \bar{z}|} max[\bar{z} - z_i, 0] \tag{5}$$

$$w_i^{High} = \frac{1}{0.5\sum_n |z_n - \bar{z}|} max[z_i - \bar{z}, 0] \tag{6}$$

$$\text{where } z_i = rank(r_i)$$

For example, if there are 7 stocks in total, weights are given using the table below:

**Table 4: Portfolio Weight: Example of 7 Stocks**

| | **Stock 1** | **Stock 2** | **Stock 3** | **Stock 4** | **Stock 5** | **Stock 6** | **Stock 7** |
|---|---|---|---|---|---|---|---|
| Beta rank | 1(Low) | 2 | 3 | 4 | 5 | 6 | 7(High) |
| Portfolio | Low | Low | Low | Neither | High | High | High |
| Weight Before Scaled | 3 | 2 | 1 | | 1 | 2 | 3 |
| Total Weight | 6 | 6 | 6 | | 6 | 6 | 6 |
| Weight | 1/2 | 1/3 | 1/6 | | 1/6 | 1/3 | 1/2 |

The final BAB factor portfolio combines a leveraged low-beta portfolio and a deleveraged high-beta portfolio. The leverage of the two portfolios are the inverse of the estimated beta, which makes the ex-ante beta of the constructed factor portfolio 0. Without transaction fees, the return is calculated as:

$$r_{t+1}^{BAB} = \frac{1}{\hat{\beta}_t^{Low}}(r_{t+1}^{Low} - r^f) - \frac{1}{\hat{\beta}_t^{High}}(r_{t+1}^{High} - r^f) \tag{7}$$

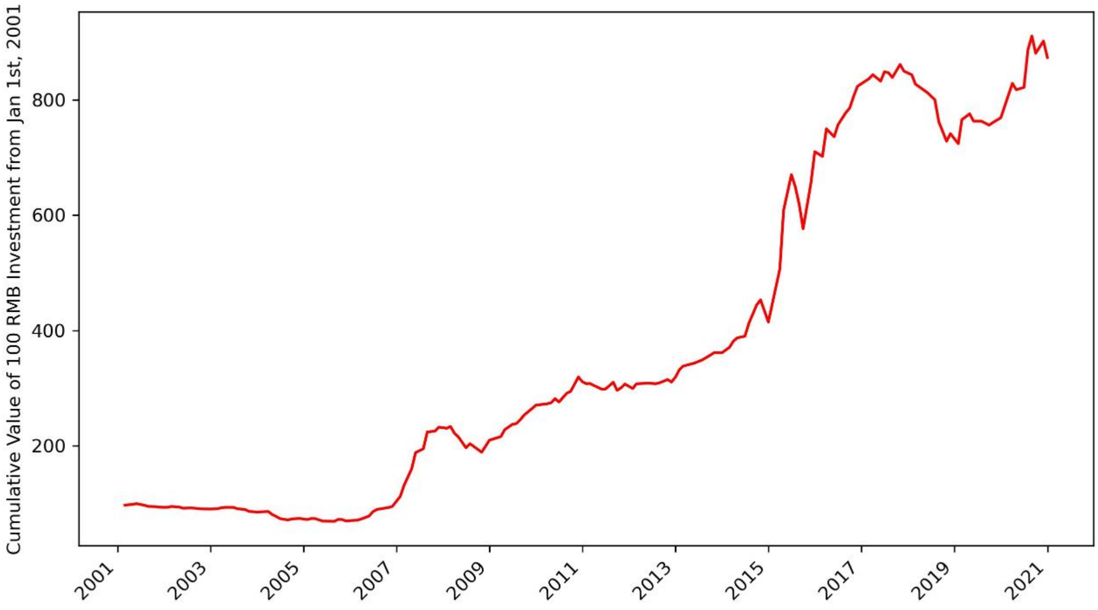
I use the return of Chinese equites to back test the BAB strategy. Table 5 shows the excess return, alphas after controlling for common return factors, realized beta, volatility and Sharpe ratio. Figure 8 illustrates the cumulative value of 100 RMB yuan investment from January 1st, 2001.

**Table 5: Original BAB Strategy (Frazzini & Pedersen, 2014)), 2000–2020.**

| Return % | CAPM alpha % | FF3 alpha % | Carhart4 alpha % | FF5 alpha % |
|---|---|---|---|---|
| **1.50** | **1.28** | **1.17** | **1.10** | **1.08** |
| (3.65) | (3.97) | (4.09) | (3.76) | (3.33) |

| LSY3 alpha % | LSY4 alpha % | Beta(realized) | Volatility % | Sharpe ratio |
|---|---|---|---|---|
| **0.73** | **0.75** | 0.36 | 17.91 | 1.00 |
| (2.47) | (2.33) | | | |

**Figure 8: Cumulative Value of 100 RMB Investment in BAB from Jan 1st 2001**



The back testing shows that BAB trading strategy can generate an astonishing return of 1.50% per month or 17.96 per year in China. Also, the alphas after controlling for other return factors are large and significant.

## 5.2 Drawbacks of BAB

Although the empirical result shows that BAB bring good return in Chinese stock market, the original BAB trading strategy also have many drawbacks that make it not feasible to implement in China.

First, BAB constructs portfolio by using the rank as weight, and it leads to huge transaction cost and risk exposure to shell value. Novy-Marx and Velikov (2022) show that the rank weight portfolio gives high weights on small illiquid stock. Frequent buying and selling of small stocks will greatly erode the high return because investor need to rebalance on a monthly basis. Novy-Marx and Velikov (2022) further show that using total value weight rather than rank weight makes the BAB return decrease. In addition, excess weight on small firms also makes the BAB expose to the risk of shell value brought by regulation.

Second, the original BAB trading strategy is also not suitable for Chinese stock market because it uses leverage and hedges by shorting individual stocks. Using leverage in stock market is illegal for most institutional and individual investors in China (Song & Xiong, 2018). Although short selling through securities borrowing is legal for Chinese institutional investors, CSRC imposes strict supervision on securities borrowing, making short selling of individual stocks very inconvenient and costly.

## 5.3 Feasible BAB Strategy in China

To address the above issues, I make the following improvements to the original BAB strategy to make it feasible in China. First of all, following Liu et al. (2019), I exclude stocks with a total value below the 30% percentile before equally dividing stocks into low-beta and high-beta groups. Liu et al. (2019) claims that this can rule out the influence of shell value. Second, I use total value weight and circulated value weight in forming portfolio. Finally, because it is not feasible to use leverage and short sell individual stock, the low-beta portfolio is combined with a short position in the index future to hedge the market risk. There are three stock index futures tradeable in China Financial Futures Exchange, CSI 300 index futures, CSI 500 index futures, and SSE 50 index futures. FTSE China A50 Index future traded in Singapore Exchange can also be used. In this project, I used the short position of CSI 300 futures main contract to hedge the market risk.

It is worth noticing that hedging using stock future in China is costly: Due to short selling restrictions and huge demand of hedging market risk in China, CSI 300 future price deviates from the no arbitrage price and the future price is often at discount, lower than spot price. However, this is one of the few ways to hedge market risk in China.

In conclusion, my feasible BAB strategy includes investing in a low-beta portfolio after excluding 30% of small stocks, and a short position in CSI 300 index future with same beta as the portfolio. Short position of future contract is rolled over to next main contract on expiry date. Without transaction fees, the return on this investment strategy is:

$$r_{t+1}^{Feasible\ BAB} = (r_{t+1}^{Low} - r^f) - \hat{\beta}_t^{Low} r_{t+1}^{future} \tag{8}$$

I use the return of Chinese equites and CSI 300 future to back test my feasible BAB strategy. The data of future contract also comes from Wind Data Service (WDS) database. Only data after April 16th, 2010 is used because CSI 300 index future is available since then. Table 6 and Figure 9 show the result using total value weight in constructing the portfolio. Table 7 and Figure 10 show the result using circulated value weight.

**Table 7: Feasible BAB Strategy, Total Value Weight**

**Apr 16th, 2010 – Dec 31st, 2020**

| Return % | CAPM alpha % | FF3 alpha % | Carhart4 alpha % | FF5 alpha % |
|---|---|---|---|---|
| **0.86** | **0.77** | **0.65** | **0.60** | **0.84** |
| (3.00) | (3.21) | (2.97) | (2.85) | (3.20) |

| LSY3 alpha % | LSY4 alpha % | Beta(realized) | Volatility % | Sharpe ratio |
|---|---|---|---|---|
| **0.68** | **0.57** | 0.10 | 9.25 | 1.12 |
| (2.99) | (2.81) | | | |

**Figure 9: Cumulative Value of 100 RMB Investment in Feasible BAB Portfolio,**

**Total Value Weight, From Apr 16th, 2010**

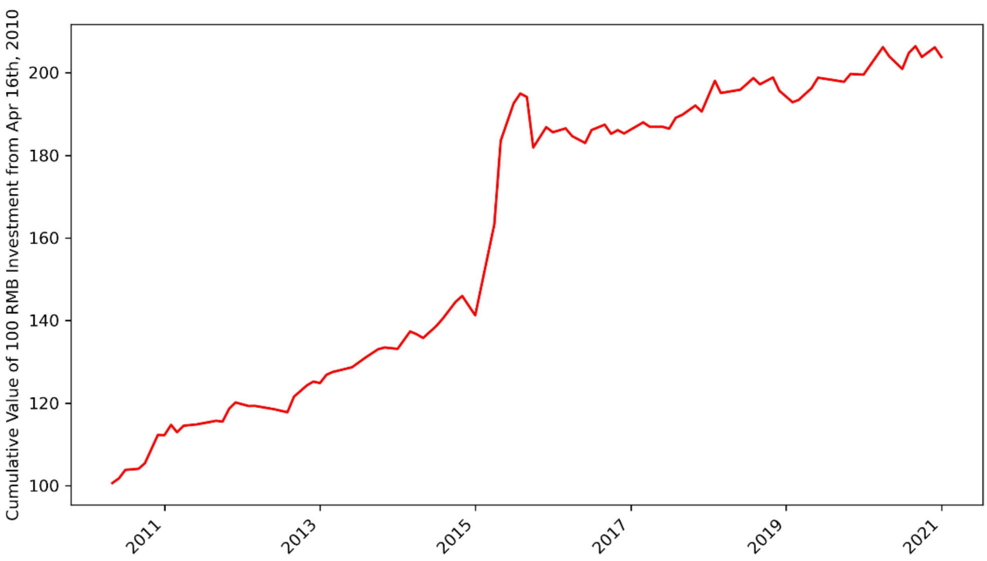


**Table 8: Feasible BAB Strategy, Circulated Value Weight**

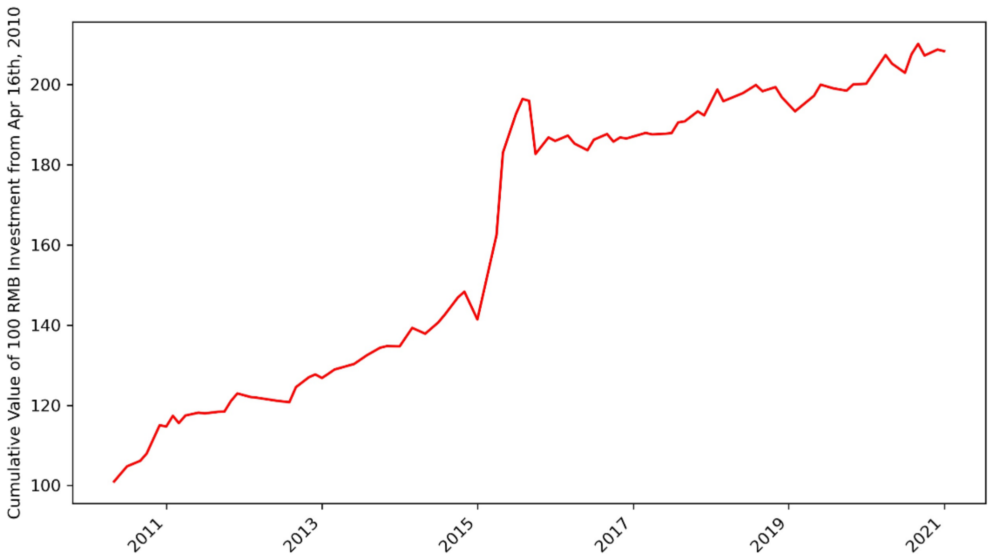
**Apr 16th, 2010 – Dec 31st, 2020**

| Return % | CAPM alpha % | FF3 alpha % | Carhart4 alpha % | FF5 alpha % |
|---|---|---|---|---|
| **0.89** | **0.81** | **0.71** | **0.66** | **0.93** |
| (3.10) | (3.36) | (3.15) | (3.01) | (3.47) |

| LSY3 alpha % | LSY4 alpha % | Beta(realized) | Volatility % | Sharpe ratio |
|---|---|---|---|---|
| **0.79** | **0.68** | 0.08 | 9.24 | 1.15 |
| (3.44) | (3.29) | | | |

**Figure 10: Cumulative Value of 100 RMB Investment in Feasible BAB Portfolio,**

**Circulated Value Weight, from Apr 16th, 2010**



The back testing shows that my feasible BAB trading strategy can generate a return of 0.86% per month or 10.38% per year using total value weight, or 0.89% per month or 10.69% per year using circulated value weight. Even after controlling for common return factors, there are alphas remained.

From Figure 9, we can see that 100 RMB yuan investment in my total value weight feasible BAB strategy from April 16th, 2010 grew up to 203.80 RMB yuan in the end of 2020. Figure 10 shows that the return is similar for circulated value weight strategy. An interesting feature is that a large part of the gains came from the period of 2015 Chinese stock market bubble and its burst. Therefore, from a factor timing perspective, my BAB strategy may be more suitable when market is volatile.

# 6. Conclusion

In this graduation project, I use portfolio sort to empirically test the low-beta anomaly in Chinese stock market. Empirical result shows that low-beta stocks overperform high beta stocks in Chinese stock market, providing support to the existence of low-beta anomaly. However, the empirical result also indicates that low-beta portfolio may have exposure on the risk of shell value.

Based on the empirical result, I improve the Frazzini and Pedersen (2014) BAB trading strategy to make the strategy feasible in China: First, I exclude 30% of small stocks with large shell value distortion to avoid risk exposure on regulation. Second, I use total and circulate value as weight to avoid high transaction cost brought by high turnover on small stocks. Finally, I use short position in CSI 300 index future rather than shorting individual stocks to hedge against the market risk. Back testing shows that my trading strategy can generate decent return in Chinese stock market, and the return is high when market is volatile.

I think my trading strategy can be used by quantitative mutual funds or hedge funds in China. In order to make the trading strategy more feasible and profitable, further research can be done in the following directions: First, advanced time series analysis methods can be used to estimate and forecast the market risk exposure of the stock portfolio. If the market is forecast to slump in near further, investor can increase the short positions in index futures because beta of the portfolio usually rises when market collapses. Second, the factor timing of BAB also needs further study so investor can adjust their trading strategy dynamically.

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