Bocconi University
Stockholm School of Economics
MSc in Finance

Empirical Study on the Performance of Hedge Funds in China

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Consists of:

Part A
Empirical Study on the Performance of Hedge Funds in China (I)

and

Part B:
Empirical Study on the Performance of Hedge Funds in China (II)

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PART A

Bocconi University
Stockholm School of Economics
Double Degree Master of Science in Finance

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Abstract

China is one of the most popular emerging markets, and the fund management industry has experienced rapid growth during the past decade, especially private funds. Although the regulatory regimes were underdeveloped at first, the government realized that it was important to improve the related regulation to address this problem. On June 1, 2013, Chinese new fund law was formally implemented, and hedge funds obtained a clear legal status for the first time, which started the rapid development of the hedge fund industry.

This paper investigates the performance of hedge funds in China, which was issued after the new fund law, in China. The sample is 54 picked hedge funds over the period 2014-2020. The performance is evaluated through the Sharpe ratio, Jensen alpha and the excess manipulation-proof performance measure. Then, using the Henriksson-Merton model and the Treynor-Mazuy model to examine the market-timing ability and stock picking skills of hedge fund managers. Lastly, we use the contingency table and recursive portfolio approach to analyze the short-term persistence in Chinese hedge funds.

The findings are as followed: firstly, according to the Jensen alpha, all the picked hedge funds are theoretically less volatile than the market, and some are even negatively correlated with the market. Besides, there are over half of the chosen funds outperform the market according to the excess manipulation-proof performance measure, which means that half of the managers have skills to earn abnormal returns. Then, based on the HM model, most hedge fund managers do not have market timing capacities, but some of them may have stock picking ability. However, according to the TM model, there is no evidence that Chinese hedge fund managers have significant stock picking ability. Yet, some managers have significant market-timing ability with respect to stocks and bonds. Lastly, through contingency table, there is some evidence of one-year persistence found. However, through recursive portfolio approach, it seems that no short-term persistence exists.

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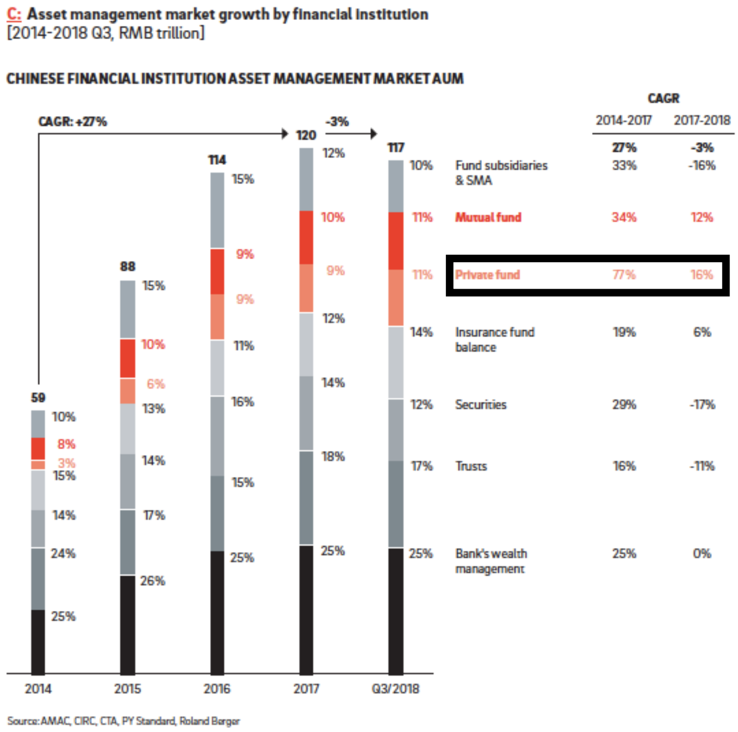
1. Introduction

In this part, we first present an overview of the development of hedge funds in China. Then we discuss the motivation of our study in order to show a full picture of the whole study. An outline of this paper is presented at the end of this part.

1.1 Background

China is one of the most popular emerging markets, and the fund management industry has experienced rapid growth. According to KPMG, since the asset management industry existed in China, China's fund management firms have achieved unrivalled growth in both size and maturity – growing their AUM from RMB10.4 billion (US$1.27 billion) in 1998 to RMB12.6 trillion (US$2.0 trillion) in 2018. The Chinese asset management market holds considerable potential for development. Based on the data collected by Roland Berger, the CAGR of the total Chinese asset management market is 17% from 2004 to 2018, much higher than that of the European or Japanese market. Additionally, the private fund sector has the highest CAGR among all Chinese financial institutions.

Graph 1: Chinese Asset Management Market Growth by Financial Institution (Roland Berger)



In China, because of the regulation and other related limitations, the private fund is included in private equity. There are three categories under private equity: privately offered securities investment funds, private equity, and venture capital. This paper will focus on the first category, privately offered securities investment funds, most of which is quite similar to the hedge fund in the Western.

1.1.1 The History of Hedge Funds in China

Private equity was introduced to China in the 1980s when Deng Xiaoping's open-door policy actively developed foreign economic cooperation and exchange. Previously, the government was the primary source of capital for domestic enterprises, but a large portion of that capital went to China's state-owned enterprises, which meant the private sector was experiencing a shortage of financial capital. Private equity helps fill this financing gap. However, private equity had not established a foothold in the 1980s until the early 1990s, when it begins to change.

The government created the Shanghai Stock Exchange and Shenzhen Stock Exchange in 1990 and 1991, respectively.[1] Then, under the approval of the State Council, the People's Bank of China (PBOC) promulgated the Administrative Measures on the Establishment of Chinese Industrial Investment Funds Abroad in 1995, the first nationwide regulation on private equity.[2]

China's accession to the World Trade Organization (WTO) in 2001 was partly based on the government's pledge to implement significant changes in the nation's financial system.[3] After that, many foreign private fund firms entered the Chinese market, but there were a lot of limitations hampering their investments and also the development of the Chinese market. The regulatory regimes were underdeveloped, and it was important to improve the related regulation to address this problem. In 2002, private funds appeared in the Chinese market. Then until 2010, the China Financial Futures Exchange introduced China stock index futures so hedge funds can use futures to hedge the risks and manage their assets.

On June 1, 2013, Chinese new fund law was formally implemented, and hedge funds obtained a clear legal status for the first time, which started the rapid development of the hedge fund industry. Hedge fund companies can issue products by themselves instead of through other channels. As of the end of May 2020, the scale of private fund management focused on stocks

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1 Martha Avery, Min Zhu, and Jinqing Cai, China's Emerging Financial Markets: Challenges and Global Impact (Singapore: John Wily & Sons, 2009).

2 Wang Bo, "Risk Prevention Measures for Private Equity in China" (paper presented at the International Conference on Management of e-Commerce and e-Government, Jiangxi, October 17-19, 2008).

3 Charles W. Calomiris, China's Financial Transition at a Crossroads (New York: Columbia UP, 2007),63.

reached RMB 2.64 trillion, accounting for 36.1% of the scale of total private funds and nearly one-tenth of worldwide AuM of the hedge fund.
However, because of the lack of enough experience and rules, there are some Black Swan events of hedge funds in China. For example, during the past decade, person-to-person(P2P) plays a very incredible role in the Chinese financial market. In 2013, the P2P explosion began. Approximately 150 platforms were set up in 2013, accounting for 50% of the total number of Internet financing platforms in China. This kind of Internet financing sector continued to mushroom in 2014; about 900 platforms were set up in 2014. More than 2,000 platforms were in operation by mid-2016, with loans outstanding reaching RMB 209 billion. However, most P2Ps marketed themselves as hedge funds with capacities of earning extremely high abnormal returns. However, in reality, most of them just ran capital pools and were not hedge funds at all. Then, in the first half of 2018 alone, 300 P2P platforms went out of business. Up to now, there is only one P2P existing. Several Chinese Ponzi scheme happened in P2P. Tens of thousands of investors lost their principles because of a lack of knowledge of hedge funds. Therefore, it is necessary to provide a well-known and fair evaluation system, and some performance characteristics of the hedge fund to protect investors. Because of a massive boom in the total number of hedge funds and P2Ps in China since 2013, stricter regulations were introduced to limit hedge funds in 2016. Therefore, since 2016, the development of hedge fund gradually enters a stable period. But in general, hedge fund has become a very important investment choice in China. There are some superstars among hedge funds in China, whose AuM can even be close to that of top mutual funds. At the same time, their managers have very excellent performance records, and many investors choose to invest a bunch of money in these funds because of the reputation of managers. Therefore, it is meaningful to investigate the skills of hedge fund managers and whether their performance can persist for some periods.

1.1.2 General Situation of Hedge Funds in China

Different managers will take different strategies to attempt to gain abnormal returns. Simultaneously, there are some limitations related to these strategies, like short. In China, mainly the following strategies are used by hedge funds: macro, equity long/short, equity long bias, NEEQ, multi-strategy, bond fund, arbitrage strategy, managed futures, equity market neutral, and other.
Regarding the asset under management, according to the data collected by the Asset Management Association of China (Table 1), up to the first season of 2020, total Asset under Management in China is RMB 53.93 trillion (USD 7.79 trillion). Among AuM, the private asset management sector holds RMB

14.3 trillion, accounting for 26.5% of total AuM. Currently, there is a total of 85085 private asset management products in China.

Table 1: General information on Chinese Asset under Management

Products Issuing Institutions	***Number of Products***	***Amount of Assets(billion)***
Mutual Fund	6819	16636.7
Asset Management (Security Company Subsidiaries)	17373	10465.3
Asset Management Company	10920	8142.4
Pension Fund	1841	2525
Asset Management (Future Company Subsidiaries)	1161	164.2
Private Asset Management Sector	85058	14312.3
Others	1723	1688.4
In Total	**124895**	**53934.3**

Source: Asset Management Association of China, 2020.06.

Table 2 is the detailed information related to the Chinese private asset management sector up to June 2020. The privately offered securities investment fund has the maximum number of products, which is 45278 and accounts for over half of the whole private asset management products. The total AuM of privately offered securities investment fund is RMB 2.65 trillion, making up 18.5% of total private AuM.[4]

Table 2: General information on Chinese Private Asset Management Sector

Products Issuing Institutions	***Number of Products***	***Amount of Assets(billion)***
Privately-offered Securities Investment Fund	45278	2652.3
Private Equity	28665	9004
Venture Capital	8866	1351.1
Others	3286	1340.2
In Total	**86095**	**14347.6**

Source: Asset Management Association of China, 2020.06.

Most privately offered securities investment funds in China are just hedge funds, although we cannot obtain the detailed data of hedge funds among privately offered securities investment funds. In the following research parts, we will set the limitation of hedge fund when we gather the data.

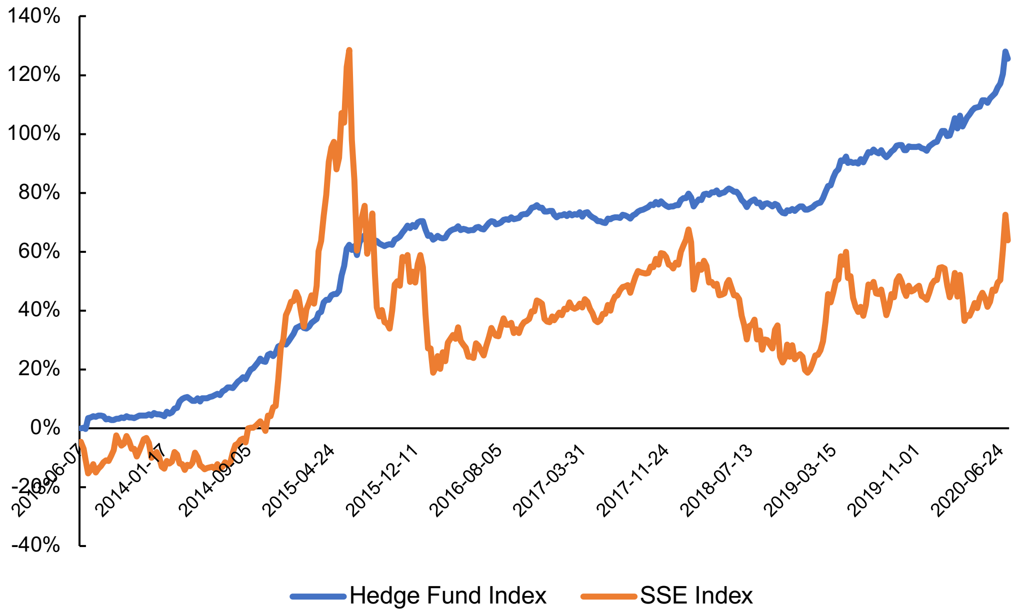
Do hedge fund managers deliver superior performance in China? Because hedge funds typically charge fixed management fees and performance fees, it is important to understand whether their performance justifies these fees. Gathering the data from the Suntime Private Funds Database, Graph 2 shows the accumulated return rate of the Chinese hedge fund index[5] and Shanghai Stock Exchange index, which takes 1st Jun 2013 as the beginning date. As we can see, the performance of the hedge fund index is much more stable, compared with the SSE index. The accumulated return rate of the hedge fund

[4] http://www.amac.org.cn/researchstatistics/datastatistics/privategravefundindustrydata/

[5] Chinese hedge fund index consists of 35 hedge funds in China, who is willing to provide the return information regularly, made by Suntime Private Funds Database.

index shows steady growth during the past seven years, even during the Covid-19 period. The only exception occurs during the first half-year of 2015, when it was the super bull market in China. During this period, the performance of the SSE index outperformed that of the hedge fund index. In the other period, the hedge fund index always outperforms.

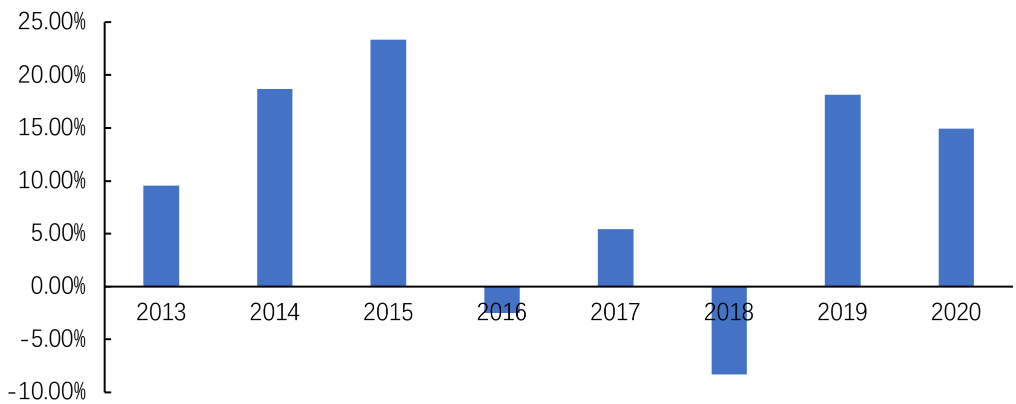
Graph 2: The Accumulated Return Rate of Hedge Fund Index and SSE Index



Source: Suntime Private Funds Database

Graph 3 shows the historical annual return of hedge funds in China. 2015 is the year having the best performance, 23.33%, mainly because of the super bull market. Then in 2016 and 2018, the annual returns of hedge funds are both negative. In 2019 and 2020, when the trade war and Covid-19 happened, the annual returns of hedge funds were still positive, 18.11% and 14.94% separately.

Graph 3: The historical Annual Return of Hedge Funds



Source: Suntime Private Funds Database

1.2 Motivation

In the face of the rapid development and the great potential development of the Chinese private asset management industry, it is meaningful to distinguish the possible factors that impacted the return, especially hedge funds which is more and more popular because of good performance among the investors. At the same time, most P2P acted as hedge funds to attract investors. In the past two years, thousands of Chinese P2Ps collapsed, and many investors cannot get back their principals. There has been a significant loss of household wealth, and the words “financial refugees” frequently appear in public opinion on the Internet.

Therefore, how to scientifically evaluate the performance of hedge funds and important characteristics of hedge funds have become the topics of most concern to investors. Besides, hedge funds always charge a much higher management fee, compared with mutual funds. Therefore, we want to check whether these hedge fund managers have some excellent investment skills. Additionally, whether hedge funds have persistent performance is also one of the most important factors for investors when they choose funds. Currently, most investors choose target funds mainly because of managers’ reputations. However, managers’ reputations are all coming from the past performance of their managed funds. Hence, it is necessary to check the performance sustainability of Chinese hedge funds and help investors to distinguish whether they can earn abnormal returns through buying past winners.

Lastly, the world has been more and more volatile during the past two years, especially in China. The trade war has caused huge impacts on the Chinese market, and we cannot estimate how will this trade war develop in the future even at this time. Also, at the end of 2019, Covid-19 was firstly identified in China and then impacted more and more countries, causing severe public health and economic consequences. This coronavirus pandemic has resulted in the most severe global economic contraction since at least the 1930s. The pandemic has disrupted factories, supply chains, and demand for goods, which all showed in the stock market. Therefore, we also want to check whether hedge fund is a good investment choice in China during this kind of volatile period with many uncertainties.

1.3 Outlines

This paper consists of five sections. The first part introduces the background and the development of Chinese private asset management and hedge funds. The second part is the literature review, mainly summarizing the theoretical research of fund performance evaluation, managers’ skill, and persistence of performance. Based on the classical theories, we will decide the suitable methodologies used in this paper in the third part: Sharpe ratio, Jensen alpha, and excess manipulation-proof performance measure will be used to measure the performance of hedge funds; the Henriksson-Merton model and the Treynor-Mazuy model will be used to examine the market-timing ability and stock-picking skills of hedge fund managers, then contingency table and recursive portfolio approach will be used to analyze the short-term persistence in Chinese hedge funds. Additionally, the third part also includes information about the data used in this paper. Then, in the fourth part, we will examine the empirical data of the Chinese hedge fund using the picked methodologies. Finally, the conclusion reviews the research objectives and methodological considerations and presents the main results and findings of the project. Additionally, we will also point out some main weaknesses in our research.

2 Literature Review

In this part, we review the theoretical research of foreign fund performance evaluation, managers' skill, and performance persistence. At the same time, we also gather some related domestic literature.

The topic of performance measurement is developing with the increasing number of professionally managed funds. Many performance measurements originate in modern portfolio theory. Beside models issued from portfolio theory, research in the area of performance measurement has also concerned the consideration of real market conditions and has developed techniques to fit cases where the restrictive hypotheses of portfolio theory are not observed. In general, there are three elements to be analyzed when we talk about performance evaluation: undertaking of risk, skill, and luck. The indicators for these three elements are risk-adjusted return indicators, stock-pricing and market timing indicators, and persistence analysis. The following parts will try to summarize these three indicators separately.

2.1 Risk-adjusted Return Indicators

At first, professionals use a basic formula to present the return of a portfolio. The basic formula of the return on a portfolio for a given period is obtained through an arithmetic calculation. The return R_{Pt} of the portfolio is given by:

$$R_{Pt} = \frac{V_t - V_{t-1} + D_t}{V_{t-1}}$$

Where V_t denotes the value of the portfolio at the end of the period, V_{t-1} denotes the value of the portfolio at the beginning of the period, and D_t

denotes the cash flows generated by the portfolio during the evaluation period. However, this formula is only valid for a fixed portfolio during the evaluation period and cannot explain the active investment process. But currently, many portfolio managers frequently change the composition based on the new information.
Therefore, we begin to take capital flows into account to get the internal rate of return, which mainly has two methods that take into account the volume of capital and the time that capital is present in a portfolio: the capital-weighted rate of return and the time-weighted rate of return. Although these methods improve the accuracy compared with the basic formula, they require more frequent calculation. DiBartolomeo (2003) asserts that applying to daily data leads to the conclusion that it is highly biased and unreliable. Besides, the returns of different portfolios under different situations are not comparable. Then, people propose risk-adjusted return indicators, which is a measure of return obtained for one unit of risk undertaken. Typically, combining a return measure and a risk measure presents the return of a portfolio.

2.1.1 Absolute risk-adjusted performance measures

Treynor ratio (1965) measures the relationship between the return on the portfolio over the risk-free rate and its systematic risk. This ratio is drawn directly from the Capital Asset Pricing Model.
Sharpe ratio (1966) measures the return of a portfolio above the risk-free rate, compared to the total risk of the portfolio, which is measured by its standard deviation. It is based on the capital market line, so it does not refer to a market index.

2.1.2 Relative risk-adjusted performance measures

Jensen's alpha (1968) measures the differential between the return on the portfolio above the risk-free rate and the return explained by the market model. This method is based on the CAPM, and the alpha measures the abnormal return due to the manager's choices.
McDonald (1973), using a portfolio of stocks invested in the French and American markets, proposed a performance measure which is an extension to the Jensen measure. This method allows us to evaluate the manager's capacity to select the best-performing international securities and to invest in the most profitable markets. Then Pogue, Solnik, and Rousselin (1974) proposed a performance measure without any limit on the number of countries.
Merton (1981) developed the non-parametric version of the model using options theory, whose principle is that of an investor who can split his portfolio

between a risky asset and a risk-free asset, and who modifies the split over time, according to his anticipations on the relative performance of the two assets.

Grinblatt and Titman (1989) present a decomposition of the Jensen measure in three terms: a term measuring the bias in the beta evaluation, a timing term, and a selectivity term.

Sortino ratio (1991), defined on the same principle as the Sharpe ratio, replaces the risk-free rate with the minimum acceptable return, i.e. the return below which the investor does not wish to drop, and the standard deviation of the returns with the standard deviation of the returns below the minimum acceptable return.

Sharpe (1994) presents the information ratio, which is defined by the residual return of the portfolio compared to its residual risk. This ratio allows us to check that the risk taken by the manager is sufficiently rewarded and also to evaluate the manager's skill in achieving a performance that is better than that of the average manager.

Modigliani and Modigliani (1997) propose the M2 measure, which evaluates the annualized risk-adjusted performance of a portfolio concerning the market benchmark. This measure can be expressed as the Sharpe ratio times the standard deviation of the benchmark index. Then, Muralidhar (2000) adds the consideration of relative risk to the M2 measure.

Following the same principle as M2 measure, Scholtz and Wilkens (2005) propose the Market Risk-Adjusted Performance measure, which measures returns relative to market risk instead of total risk.

Keating and Shadwick (2002) develop the omega measure, which involves partitioning returns into loss and gain above and below a return threshold and then considering the probability-weighted ratio of returns above and below the partitioning. This one is recommended for evaluating portfolios that do not exhibit normally distributed return distributions.

Most previous studying of performance is related to mutual funds because it is only a short time since hedge funds enter our horizon. However, since active management becomes more and more popular, and some hedge funds market their super skill of earning abnormal returns, some researchers are beginning to investigate hedge funds.

Lo (2002) points out that the Sharpe ratio could only be efficient under the standard independent and identical distribution assumption. In the empirical example of hedge funds, the Sharpe ratio will be overstated because of the presence of the serial correlation in returns.

Because of the limitations of the Sharpe ratio, Bailey and Prado (2014) develop the new uncertainty-adjusted investment skill metric (called the probabilistic Sharpe ratio), which models the trade-off between track-record length and undesirable statistical features.

Jonathan et al. (2007) find that numerous measures, like the Sharpe ratio, can be gamed among hedge funds, so they develop a manipulation-proof performance measure (MPPM), which can provide more robust performance information of hedge funds.
Then, Brown et al. (2010) develop the doubt ratio based on the MPPM, which can indicate whether the reported returns from hedge funds are suspicious.
Maria et al. (2016) use the Sharpe ratio, information ratio, Jensen alpha, and excess MPPM to examine whether persistence of hedge funds' performance is suspicious. They conclude that performance is more modest and less persistent when using EMPPM.

2.2 Skill indicators

The Treynor and Mazuy model (1966) used a quadratic version of CAPM and can be used to evaluate a manager's market timing capacity. Managers, who have a good market timing capacity, will have lower portfolio beta when the market falls. Therefore, their portfolio will depreciate less than if they had not adjusted.
Jensen (1972) finds that the timing ability can be evaluated by the correlation between the managers' forecast and the realized return.
Alexander and Stover (1980) study the market timing ability of fund managers by utilizing a non-linear CAPM, which uses a dummy variable in the model to determine whether the beta coefficient depends on the bull market or bear market. They concluded that managers generally have stock-picking skills but do not have timing capacity.
Henriksson and Merton (1981) develop the parametric version of the model, consisting of a modified version of the CAPM which takes the manager's two risk objectives into account, depending on whether he forecasts that the market return will or will not be better than the risk-free asset return.
Bhattacharya and Pfleiderer (1983) modify the Treynor-Mazuy model, minimizing the variance of the forecast error and adding the signal-to-noise ratio. They find that most managers do not have security selection and/or market timing skills.
Chang and Lewellen (1984), using the Henriksson-Merton model, jointly test monthly returns of mutual funds during the decade of the 1970s. They conclude that mutual funds are neither skilled market timer nor skilled stock selectors.
Lehmann and Modest (1987) find that the performance of funds is sensitive to the benchmark chosen to measure, including APT and CAPM benchmarks, and to the type of factor estimation procedure used.
Fama and French (1993) firstly developed a three-factor model for estimation of stock return, including market, size, and value. Then they try to combine

the three-factor model with the Treynor-Mazuy model and the Henriksson-Merton model separately.
Carhart (1997) adds the momentum factor to the three-factor model, which is called the four-factor model. The fourth factor increased the accuracy in measuring portfolio returns compared to the three-factor model.
Busse (1999) finds that volatility timing is an important factor in the returns of mutual funds and has led to higher risk-adjusted returns.

2.3 Persistence Analysis

Performance persistence is often addressed in two ways: the first is linked to the notion of market efficiency and the second is related to whether the winners are always the same.
Jensen (1968) shows that performance persistence in mutual funds is not a reflection of the manger’s superior stock pricing skills but is explained by the common asset return factors and the differences in fees and transaction costs. Additionally, he finds that the ranking of funds from one year to another is random, and the ranking can vary greatly from one year to the next.
Brown, Goetzmann, Ibbotson, and Ross (1992) find that short-term performance persisted, but the survivorship bias attached to the database.
Hendricks, Patel, and Zeckhauser (1993) observe the light persistence in the performance of mutual funds, for both good managers and bad managers.
Grinblatt and Titman (1994) find that using different benchmarks will impact the performance persistence and turnover is positively related to the ability of fund managers to earn abnormal returns.
Kahn and Rudd (1995) observe slight performance persistence for bond funds, but not for equity funds. Their conclusion is that it is most profitable to invest in index funds than in funds that have performed well in the past.
Brown and Goetzmann (1995) conclude that relative risk-adjusted performance persists, and poor performance also tends to increase the probability that the fund will disappear.
Carhart (1997) observed performance persistence for managers whose performance was negative. But the persistence he identified could be attributed either to survivorship bias or to a poor choice of benchmark. He also points out that the “hot hands” phenomenon is due to the momentum effect. Later, Carhart et al (2002) find that survivor conditioning weakens evidence of performance persistence.
Jan and Hung (2004) get the result that short-run mutual fund performance is likely to persist in the long run. They suggest that mutual fund investors may benefit from selecting funds based on not only past short-run performance but also past long-run performance.

Bollen and Busse (2005) observe that superior performance is short-lived, and a short measurement horizon provides a more precise method of identifying top performers.

2.4 Chinese literature

Because of the limited development and the very early developing stage of Chinese asset management, Chinese literature related to performance are almost using foreign theories to do empirical test in the Chinese market.
Li Biao (2007) investigates mutual funds and hedge funds in China and finds that both are good at diversifying. The Jensen alphas are both positive, which means that funds win the market. Additionally, the performance of hedge funds is better than that of mutual funds.
Li and Lin (2011) find that large Chinese equity funds consistently outperform mid and small funds under various market conditions and different measurements.
Qiu Longmiao (2012) adopts the factor analysis method to analyze the performance of hedge funds. The conclusion is that if considering the risk, most hedge funds did not win the market.
Lan Haiping and Xu Rui (2014) uses the probability Sharpe ratio statistics to analyze the performance of hedge funds. They find that only less than 3% of fund products exhibited levelheaded investment skills, intermingled with good and bad in the overall performance.
Men Yao (2015) chooses the timing of return, volatility, and liquidity as the market timing factors to measure the timing skill of managers. Then, he finds that some Chinese hedge fund managers have the timing skills based on return and liquidity, but no skills based on volatility.
Wu Wei (2016) adopts both contingency tables and the portfolio approach to examine the performance persistence of private securities investment funds in China. He finds that the market timing factor was significant before 2014, and then the momentum factor becomes significant because of the change of regulation.

3 Methodology and Data

In this paper, we want to learn about the performance of different hedge funds, examine whether Chinese hedge fund managers own timing and stock picking capacity, and explore whether the performance persistence exists.
In this section, we first briefly introduce our primary methods and models applied to explore and rank the funds, at the same time, discuss the required

inputs of those methods and models. Then we talk about how we collect, clean, and construct the input data prepared for use.

3.1 Methodology

There are three different performance measures, two models to investigate managers' skills, and two approaches to test the short-term performance persistence in this essay. These are introduced and discussed respectively in the following parts below.

3.1.1 Return Rate

Here, we use the following formula to calculate the monthly return rate:

$$Monthly\ Return_m = \ln\left(\frac{NAV_{t,m} + Divident}{NAV_{t-1,m}}\right)$$

Then we need to transfer the monthly return into the manual return rate:

$$\begin{aligned} &Manual\ Return_m \\ &= (1 + Monthly\ Return_m) * (1 + Monthly\ Return_{m-1}) \\ &* (1 + Monthly\ Return_{m-2}) * \dots * (1 + Monthly\ Return_{m-11}) - 1 \end{aligned}$$

Therefore, we will take a rolling base to calculate the manual return rate.

3.1.2 Performance Measures

3.1.2.1 Sharpe Ratio and the Probabilistic Sharpe Ratio

The CAPM assumes either that all asset returns are normally distributed and thus symmetrical or that investors have mean-variance preferences and thus ignore skewness. These also cause limitations of the Sharpe Ratio. However, the Chinese market is far from the "perfect market", and it is necessary to check the actual distributions of asset returns. Therefore, we could firstly plot the distribution of historical returns.

Non-normal statistical characteristics of portfolios' performance have a great impact on the estimation errors of the Sharpe ratio, while the Probabilistic Sharpe ratio (PSR) statistics can comprehensively take the length, skewness, and kurtosis of track records into account for analyzing and evaluating the performance of funds. Consequently, it will be better to consider both the SR and PSR to evaluate the performance of funds.

To begin with, we need to review the Sharpe ratio. R_t presents the return of a portfolio during the period t and t+1. R_t satisfies:

$$\mathrm{R}_t \sim i.i.d$$

The average and variance of R_t are:

$$\mu = \mathrm{E}(\mathrm{R}_t)$$

$$\sigma^2 = \mathrm{Var}(\mathrm{R}_t)$$

Then, the Sharpe ratio is calculated by:

$$SR = \frac{\mu - \mathrm{R_f}}{\sigma}$$

R_f is the risk-free rate. We will take the 3-month SHIBOR (Shanghai Interbank Offered Rate) rate as R_f. If we have historical return data of the portfolio (R_1, R_2, R_3, ..., R_T), then we can get the sample average and variance:

$$\hat{\mu} = \frac{1}{\mathrm{T}}\sum_{t=1}^{T} R_t$$

$$\widehat{\sigma^2} = \frac{1}{\mathrm{T}}\sum_{t=1}^{T} (R_t - \hat{\mu})^2$$

Then the estimation of the Sharpe ratio will be:

$$\widehat{SR} = \frac{\hat{\mu} - \mathrm{R_f}}{\hat{\sigma}}$$

Under the assumption of i.i.d, we can estimate the standard error of the Sharpe ratio:

$$SE(\widehat{SR}) = \sqrt{\frac{(1 + \frac{1}{2}\mathrm{SR}^2)}{T}}$$

Then, if we want to calculate the PSR, we need to firstly pick a target Sharpe ratio (SR*) and calculate the probability that we get a real Sharpe ratio higher than SR*.

$$PSR(SR^*) = prob\left[\widehat{SR} > SR^*\right] = 1 - \int_{-\infty}^{SR^*} Prob(\widehat{SR})d\widehat{SR}$$

$$= Z\left[\frac{\left(\widehat{SR} - SR^*\right)\sqrt{n-1}}{\sqrt{1 - \widehat{\gamma_3}SR + \frac{\widehat{\gamma_4} - 1}{4}SR^2}}\right]$$

Where γ_3 represents the skewness of the return series, and γ_4 represents the kurtosis of the return series, and n is the number of observation periods. Through PSR, we can get the confidence of the Sharpe ratio. Because the returns of hedge funds are not necessarily i.i.d, using PSR can provide more robust results of the Sharpe ratio.

3.1.2.2 Jensen's Alpha

Inspired by Sharpe (1964) and Lintner (1965), Jensen (1968) proposed a more advanced way to measure performances by regressing the excess return of the portfolio on the excess return of the market portfolio. Specifically, he incorporated in his model market risk, which is defined as market return minus a risk-free rate. As he suggests, a positive and statistically significant alpha would demonstrate that the portfolio is outperforming the market on a risk-adjusted basis and vice versa.

$$R_p - R_f = \alpha + \beta_{p,m}(R_m - R_f) + \epsilon$$

$$\beta_{p,m} = \frac{cov(R_p, R_m)}{\sigma_m^2}$$

Where R_p is the return of the fund, and R_f is the risk-free rate, which we will take 3-month SHIBOR rate. α is the Jensen alpha. Then, $R_m - R_f$ is the excess return of the market portfolio, and $\beta_{p,m}$ presents the volatility of fund compared to the market as a whole.

3.1.2.3 Manipulation-proof Performance Measure

Jonathan et al. (2007) find that some common measures, like the Sharpe ratio, can be greatly impacted through some simple dynamic manipulation. Hence, they develop a more robust measure, called manipulation-proof performance measure. The MPPM is calculated as:

$$\Theta = [\frac{1}{(1-A)\Delta t}\ln\left(\frac{1}{T}\sum_{t=1}^{T}\left(\frac{1+r_t}{1+r_{ft}}\right)^{1-A}\right)]$$

The Θ is an estimate of the portfolio's premium return after adjusting for risk. Here, A is the risk aversion parameter, which we will take 2, 3, and 4[6]. Δt is one month, and r_t is the return of the hedge fund in month t. T is the number of observations and r_{ft} is the return on the 3-month SHIBOR on RMB in month t. Therefore, the Θ represents the equivalent excess monthly return for an investor with risk aversion A.

Then we can also use the same formula to calculate the MPPM of CSI 300 index as the market MPPM. Using the MPPM of hedge funds minus the market MPPM, we can get the excess MPPM (EMPPM), which can help us detect whether hedge funds outperform the market.

3.1.3 Skill Models

3.1.3.1 Henriksson-Merton Model

Henriksson and Merton modify the CAPM, taking the manager's two risk objectives into account, depending on whether he forecasts that the market return will or will not be better than the risk-free asset return. Therefore, this model can be good at indicating the timing and stock picking capacity of managers.

The model is presented in the following form:

[6] Jonathan et al. (2007) suggest that the market believes risk aversion varies between 2 and 4.

$$R_t - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2 D_t(R_m - R_f) + \epsilon$$

$$D_t = 0, when\ R_m - R_f > 0$$
$$D_t = -1, when\ R_m - R_f < 0$$

Where R_t is the return of the funds, and R_f is the risk-free rate, which we pick the 3-month SHIBOR rate. R_m is the market return, which we take the return of CSI 300 index. CSI 300 index is a capitalization-weighted stock market index designed to replicate the performance of the top 300 stocks traded on the Shanghai Stock Exchange and the Shenzhen Stock Exchange, which can present the performance of the Chinese market very well.
The first coefficient β_1 mainly measures the fund's exposure to the stock market. If it is positive, it means that this fund has positive exposure to the Chinese market. Then, β_2 helps us to evaluate the manager's ability to anticipate market evolution, because there is a dummy variable before the market excess return part. If the market outperforms the risk-free rate, the dummy variable will be zero. But if the market underperforms the risk-free rate, the dummy variable will be -1. If β_2 is positive and significantly different from zero, the manager has a good timing capacity. When β_2 is positive, the whole part ($\beta_2 D_t(R_m - R_f)$) will be positive too, which means that this part also makes contributions to the return of the fund. Therefore, even when the market is not very good, the manager with good timing capacity can still gain returns. We can estimate $\alpha, \beta_1\ and\ \beta_2$ through OLS regression based on the historical return data.

3.1.3.2 Treynor-Mazuy model

Cao and Jayasuriya (2001) employ the modified Treynor-Mazuy model to examine the performance of hedge fund index returns in emerging market regions, which can also investigate the market timing skills. Here we also take the Treynor-Mazuy model as our baseline to observe the marketing timing skills of Chinese managers, which can act as the supplement of the HM model.

$$R_{h,t} - R_{f,t} = \alpha + \beta_{s1}(R_{s,t} - R_{f,t}) + \beta_{b1}(R_{b,t} - R_{f,t}) + \beta_{s2}(R_{s,t} - R_{f,t})^2$$
$$+ \beta_{b2}(R_{b,t} - R_{f,t})^2 + \epsilon_{h,t}$$

Where
$R_{h,t}$ is the return of the hedge fund in month t
$R_{f,t}$ is the return on the 3-month SHIBOR on RMB in month t
$R_{s,t}$ is the return on the CSI 300 index in month t
$R_{b,t}$ is the return on the S&P China Bond index in month t

In this modified Treynor-Mazuy model, the only constant term is the α, which can present the manager's ability to generate excess returns, in other words, stock picking ability. Then, β_{s1} and β_{b1} indicate the risk exposures to Chinese stocks and bonds. Lastly, β_{s2} and β_{b2}, the coefficient estimates on the quadratic excess returns, capture the market timing ability of the hedge fund managers in changing their risk exposure according to the market risk. If β_{s2} is significant and positive, this indicates that managers may have the market-timing capacity with respect to stocks. Similarly, if β_{b2} is significant and positive, this implies the market-timing capacity of bonds.

3.1.4 Persistence Test

In this part, we use the non-parametric method, contingency table developed by Brown and Goetzman (1995), and the recursive portfolio approach proposed by Hendricks, Patel, and Zeckhauser (1993).

3.1.4.1 Contingency Table

Contingency table categories fund as winners or losers based on a predetermined standard. There are mainly two standards used: firstly, the stock market index can be used as a benchmark to distinguish winners and losers, and this is called the absolute benchmark; secondly, a relative benchmark which is based on the picked funds' data.

Kahn and Rudd (1995) choose relative benchmarks to distinguish the winner and loser. If a fund ranks at the top 50% of the list, it would be categorized as a winner, otherwise, it would be marked as a loser. The test consists of two periods, and each fund would be categorized independently in these two periods. If the fund is a winner in the first period and a loser in the second period, it would be marked as winner-loser (WL). Only WW and LL are seen as a persistent performance. If no persistence, the number of these four categories, which is WW, WL, LW, and LL, should be the same in different periods. And if there is performance persistence, it is reasonable to expect the total number of winner-winner and loser-loser should be statistically significantly higher than that of winner-loser and loser-winner. Therefore, the null hypothesis is there is no evidence of persistence, and the alternative hypothesis is that evidence for persistence is found. They use the Chi-square statistic to test this hypothesis. The formula is:

$$\chi = \sum \frac{(Q_i - E_i)^2}{E_i}$$

Where

Q_i is the number of funds observed in each category

E_i is the number of funds expected to be observed in each category

In their example, E_i should be half of the total number of funds, and test statistics follow Chi-square distribution with a degree of freedom of one. Brown and Goetzman (1995) also use this method but they choose different test statistics, which is called the Cross-Product ratio. The formula of the Cross-Product ratio is:

$$\text{Cross} - \text{Product Ratio} = \frac{WW * LL}{WL * LW}$$

They think that if the Cross-Product ratio is equal to one, then there is no persistence. A Cross-Product ratio is bigger than one and statistically significant, which means that persistence exists. However, if the statistically significant ratio is lower than one, negative persistence may exist, which means that the past performance predicts the opposite of future performance. Their null hypothesis is cross-product ratio is equal to one, and the alternative hypothesis is the cross-product ratio is bigger or smaller than one. They use z-statistic as their test statistic to check the significance of the cross-product ratio. The z-statistic is calculated as taking a log of the cross-product ratio and dividing it by its standard deviation. The detailed formula is:

$$\sigma_{\ln(cross-product\ ratio)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}$$

$$Z_{statistic} = \frac{\ln\left(\frac{WW * LL}{WL * LW}\right)}{\sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}}}$$

In this essay, we will replicate the method of Bronn and Goetzman (1995) using the contingency table and the cross-product ratio to check the persistence. The benchmarks that we choose include the abstract benchmark and relative benchmark. The abstract benchmark is CSI 300 index, Jensen's alpha, and EMPPM, and the relative benchmarks include the mean and median of those funds' returns.

3.1.4.2 Economic Predictability of Past Performance

Another quantitative method to test whether the performance of hedge funds shows persistent is to investigate the economic predictability of their past performance. Additionally, economic predictability is significant when an investor can earn abnormal returns by exploiting past performance.

In this essay, we will use the methodology proposed by Hendricks, Patel, and Zeckhauser (1993), but differ from them by using shorter ranking period. Firstly, we rank the funds at the start of each month from August 2017 to June 2020 based on a lagged one-month (one-quarter) performance measure, because most sample funds have return information during this period except ST1882. Then we divide those funds into six portfolios. The first-octile portfolio is composed of the best performers in the recent evaluation period;

the second-octile portfolio is composed of the next-poorer performers, and so on. The total number of 53 funds is used to form portfolios: therefore, there are 9 funds in portfolio 1-5 respectively and 8 funds in portfolio 6. Portfolios are equally weighted and rebalanced monthly (quarterly) to incorporate the deviation of weights. In this case, portfolio 1 should have funds with top sextile lagged one-month (one-quarter) performance in each month (quarter).
The economic predictability of past performance is evaluated by using CAPM, and we regress the monthly return of each portfolio on market excess return. A positive and statistically significant alpha of the difference return between top sextile and bottom sextile portfolio indicates the existence of positive performance persistence. In other words, buying past winners and selling past losers could create an abnormal return.

3.2 Data

In this part, we present our data source, show the data cleaning process, and elaborate the description of data.

3.2.1 Data Source

We mainly collect our funds' data from the Suntime Private Funds Database. Suntime, as the market leader in China's financial information service industry, provides accurate and real-time information for financial professionals. Its private fund database offers the most comprehensive, complete data on Chinese private funds.
Firstly, since the Chinese new fund law was formally implemented on June 1, 2013, hedge funds obtained a clear legal status for the first time. Therefore, we pick the funds which were issued after June 1, 2013.
When we choose the data, the sample meets the following criteria: private funds should be hedge funds, and the net asset value (NAV) information should be provided over 70% during its life. Besides, because we need enough NAV data to run the regression, we will select the funds with historical returns for more than three years, which means that the funds issued before July 22, 2017.
Additionally, we collect the time-series data of the CSI 300 index, which we take as the market return data, and the S&P China Bond Index, which we take as the bond return, from RESSET. RESSET database is the most comprehensive and commonly cited database for financial research on the Chinese market.

Then, we get the latest SHIBOR rate from the Shanghai Interbank Offered Rate website[7]. Up to July 25, 2020, the 3-month SHIBOR is 2.245%, which we will take as the risk-free rate.

3.2.2 Data Cleaning

We collect monthly NAV data in order to get the monthly return rate. However, because there is no strict disclosure rule for hedge funds, some funds did not report the NAV regularly. Therefore, there are only 54 funds entering our sample.
Among 54 funds, six funds did not regularly report their NAV during the beginning period. Therefore, we will ignore that long period and choose the period between the second reporting date and the first reporting date as the first period.
There are some funds not reporting NAV for a long period during the period that we choose. In order to run the regression of monthly return, we will divide the change of NAV equally during this period and then calculate the monthly return.

3.2.3 Data Description

Based on the set limitations, there are 54 funds entering our research. Table 3 shows the regression number, issued time, strategies, annual return from issuing, and maximum drawdowns of our picked funds. From the table we can see, the average annual return of these picked funds is 5.08%, and there are 31.48% of the sample (17 out of 54) with negative annual returns. The average age of these funds is over 4 years. As for maximum drawdown, the average level is 27.27% and the maximum one is 81.96%. Among these picked funds, the majority of funds (25 out of 54) take equity long bias as their strategy.

Table 3: The Information of Picked Funds

registration number	*issued time*	*strategies*	*Annual Return*	*Maximum Drawdown*
S20280	2014/7/9	*Equity Long Bias*	1.19%	31.17%
S21122	2014/9/10	*Equity Long Bias*	16.55%	50.79%
S21679	2014/10/27	*Equity Long/Short*	-9.04%	68.22%
S22382	2014/11/14	*Equity Long/Short*	-10.63%	71.15%
S22669	2014/12/16	*Equity Long/Short*	7.36%	28.22%
S23349	2014/12/24	*Macro*	16.2%	15.62%
S23350	2014/12/30	*Equity Long/Short*	-4.9%	53.68%
S26387	2015/2/25	*Equity Long Bias*	15.25%	36.37%

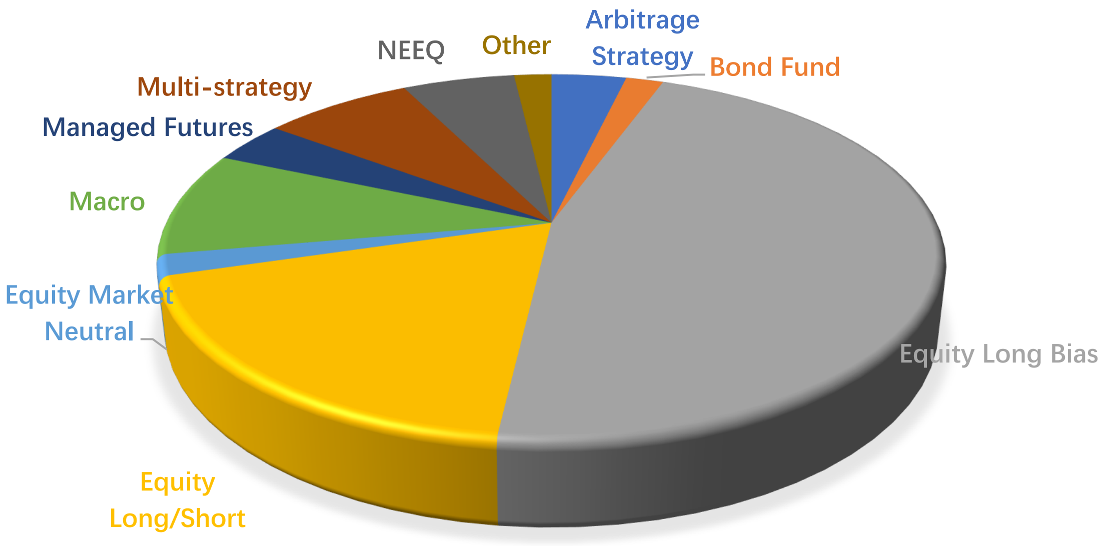
[7] http://www.shibor.org/shibor/web/html/index_e.html

S26379	2015/3/3	*Equity Long Bias*	-4.9%	53.68%
S27557	2015/3/6	*Equity Long Bias*	14.54%	19.59%
S26425	2015/3/20	*Equity Long Bias*	2.26%	40.83%
S28342	2015/3/23	*Equity Long Bias*	6.62%	23.21%
S29646	2015/4/9	*Equity Long Bias*	9.59%	20.2%
S28300	2015/4/16	*Equity Long Bias*	3.58%	26.08%
S28266	2015/4/21	*Equity Long Bias*	3.58%	26.08%
S35966	2015/6/17	*Macro*	6.89%	29.99%
S39727	2015/7/1	*Equity Long/Short*	-1.92%	28.99%
S37095	2015/7/15	*Equity Long Bias*	6.89%	29.99%
S62692	2015/7/17	*Equity Long/Short*	-7.4%	40.8%
S34823	2015/8/19	*Equity Long Bias*	-24.94%	81.96%
S68046	2015/9/29	*Equity Long/Short*	-1.78%	34.94%
S83243	2015/10/21	*NEEQ*	-0.32%	1.5%
S83527	2015/10/23	*Equity Long Bias*	0.04%	38.67%
S85118	2015/11/17	*Equity Long Bias*	39.32%	20%
SD0499	2015/11/23	*Multi-strategy*	-2.77%	36.34%
S83499	2015/12/10	*Equity Long/Short*	-0.32%	1.5%
SE1688	2015/12/24	*Equity Long Bias*	28.77%	27.07%
SE4488	2016/1/4	*Equity Long Bias*	31.54%	24.96%
SE4942	2016/1/8	*Equity Long Bias*	-1.11%	4.86%
S84129	2016/1/13	*Equity Long Bias*	13.15%	36.11%
S85603	2016/1/18	*Equity Long Bias*	-2.77%	36.34%
S69730	2016/1/22	*Equity Long Bias*	-1.78%	34.94%
S67536	2016/2/3	*NEEQ*	-1.64%	60.34%
SE5438	2016/2/4	*Equity Long Bias*	22.32%	25.27%
SH8698	2016/4/6	*Macro*	10.7%	19.69%
SE2421	2016/4/20	*Macro*	6.94%	23.22%
SH9398	2016/5/4	*Macro*	9.89%	17.97%
SJ5323	2016/5/11	*Equity Long Bias*	22.56%	20.56%
SK1674	2016/6/28	*NEEQ*	0.28%	10.44%
SL7844	2016/7/1	*Multi-strategy*	5.13%	10.23%
SK7292	2016/7/12	*Equity Long/Short*	-1.55%	33.27%
SJ4786	2016/7/14	*Bond Fund*	9.89%	17.97%
SM1268	2016/8/22	*Equity Long/Short*	9.76%	0.77%
SL8820	2016/9/14	*Arbitrage Strategy*	5.13%	10.23%
SN5118	2016/11/23	*Equity Long Bias*	5.17%	11.05%
SR3017	2017/1/3	*Equity Long Bias*	3.16%	28.97%
SR3434	2017/2/13	*Other*	6.44%	6.74%
ST1892	2017/5/9	*Managed Futures*	5.77%	0.59%
ST1882	2017/5/10	*Equity Market Neutral*	5.77%	0.59%
SR2083	2017/5/19	*Managed Futures*	5.17%	11.05%

ST0713	2017/5/22	*Multi-strategy*	5.77%	0.59%
SS9048	2017/5/23	*Multi-strategy*	6.44%	6.74%
ST5754	2017/6/26	*Arbitrage Strategy*	3.03%	10.48%
ST9165	2017/6/30	*Equity Long Bias*	-20.68%	72.23%

Source: Suntime Private Fund Database

Graph 4: The Strategies of Sample Funds



4. Empirical Results

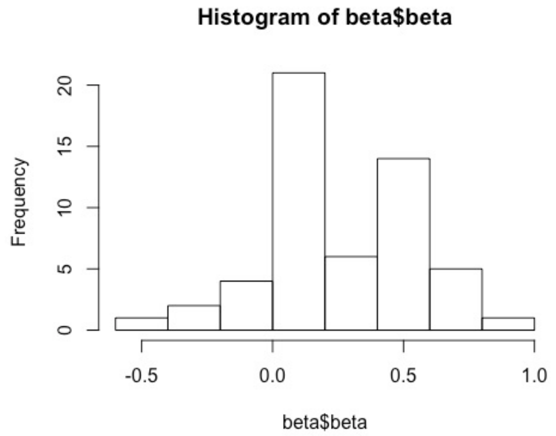
Empirical results are presented in this section. The following parts report the results of different measurements, models, and approaches, and provide some detailed analysis respectively.

4.1 Performance Measure

4.1.1 Jensen Alpha

We first calculate the Jensen alpha of every fund. But before calculating the Jensen alpha, the betas of different funds should be firstly calculated, which represents the volatility of funds compared with the market. In general, there is no one beta greater than one, which means that the fund is theoretically less volatile than the market. The average beta is 0.2578, and the median is 0.1788. Most betas are positive. The fund with the maximum beta is S29646, whose beta is 0.8951. In addition, there are 7 funds with a negative beta, which means that the volatility of funds is negatively related to the market. In general, hedge funds in China are theoretically less volatile than the market, and some are even negatively correlated with the market.

Graph 5: The Histogram of Sample's Beta



Then, the average Jensen alpha of these 54 picked hedge funds is 0.21%, and the median of them is 0.17%. There are 34 funds with positive Jensen alpha, which accounts for 63%. The minimum one is -2.4%, which is ST9165. ST9165 also has a negative Sharpe ratio, and the most negative annual return (-20.68%). The maximum one is 2.32%, which is S85118. S85118 is the one fund with the highest annual return (39.32%).

Table 4: Beta and Jensen Alpha

registration number	beta	Jensen α	registration number	beta	Jensen α
S28342	0.0514	0.0024	**SR3434**	-0.0100	0.0016
S35966	0.2731	0.0030	**SS9048**	0.0123	0.0012
SE2421	0.0491	0.0053	**SM1268**	-0.4014	0.0007
SH9398	0.0749	0.0061	**S39727**	0.4062	-0.0035
SR2083	-0.2940	0.0053	**S83243**	-0.0005	-0.0034
S85118	0.0422	0.0232	**SL7844**	0.0820	0.0043
SE5438	0.5603	0.0101	**S67536**	0.0025	-0.0040
SR3017	0.1764	-0.0009	**SK1674**	0.0030	-0.0029
S21122	0.5133	0.0063	**S28300**	0.0862	-0.0049
S68046	0.1291	-0.0047	**S37095**	0.5978	0.0098
S83499	0.0500	-0.0054	**SD0499**	0.4687	0.0039
ST0713	-0.0287	0.0135	**S28266**	0.6026	0.0029
SK7292	0.1419	-0.0051	**S26387**	0.5671	0.0116
S21679	0.3367	-0.0136	**SH8698**	0.4887	0.0017
S22382	0.1811	-0.0139	**S22669**	0.4931	-0.0009
S20280	0.0558	0.0012	**S69730**	0.3793	0.0155
S62692	0.1104	-0.0088	**S84129**	0.5198	0.0114
S23350	0.3233	-0.0081	**ST1882**	-0.3476	-0.0104
ST1892	0.0855	-0.0022	**SE4488**	0.6975	0.0165

SJ5323	0.5773	0.0126	**S29646**	0.8951	0.00004
S34823	0.1327	-0.0044	**SE4942**	0.7138	0.0080
SJ4786	-0.0498	0.0012	**S27557**	0.6199	0.0081
ST5754	0.0982	-0.0012	**SE1688**	0.1348	0.0177
SN5118	0.3962	0.0005	**S26379**	0.5626	0.0064
S83527	0.4685	-0.0037	**S26425**	0.4114	0.0030
SL8820	0.0171	0.0047	**S85603**	0.3812	0.0104
S23349	0.4101	0.0092	**ST9165**	0.6725	-0.0240

Source: Suntime Private Fund Database

4.1.2 Sharpe Ratio

Table 5: Probabilistic Sharpe Ratio of picked funds

	PSR(0)	PSR(0.5)	PSR(1)	SR		PSR(0)	PSR(0.5)	PSR(1)	SR
SR3434	1.00	1.00	1.00	6.09	S39727	0.73	0.00	0.00	0.09
S35966	1.00	1.00	1.00	5.96	SM1268	0.56	0.00	0.00	0.02
SE2421	1.00	1.00	1.00	5.86	S28342	0.34	0.00	0.00	-0.06
SH9398	1.00	1.00	1.00	5.49	SR2083	0.28	0.00	0.00	-0.11
ST0713	1.00	1.00	1.00	4.22	ST1892	0.01	0.00	0.00	-0.33
SL8820	1.00	1.00	1.00	3.64	S28300	0.00	0.00	0.00	-0.38
S85118	1.00	1.00	1.00	3.26	SK1674	0.01	0.00	0.00	-0.63
SR3017	1.00	1.00	1.00	2.87	S84129	0.00	0.00	0.00	-0.65
SE5438	1.00	1.00	1.00	2.61	SE4488	0.00	0.00	0.00	-0.71
ST5754	1.00	1.00	0.98	2.60	SD0499	0.00	0.00	0.00	-0.72
S21122	1.00	1.00	1.00	2.41	S37095	0.00	0.00	0.00	-0.86
S68046	1.00	1.00	0.98	1.94	S22669	0.00	0.00	0.00	-0.93
SK7292	1.00	1.00	0.93	1.54	ST9165	0.00	0.00	0.00	-1.06
S62692	1.00	1.00	0.92	1.48	ST1882	0.00	0.00	0.00	-1.10
S21679	1.00	0.97	0.87	1.46	S26387	0.00	0.00	0.00	-1.19
S83499	1.00	1.00	0.87	1.34	SH8698	0.00	0.00	0.00	-1.41
S20280	1.00	1.00	0.93	1.27	S28266	0.00	0.00	0.00	-1.55
S22382	1.00	1.00	0.79	1.25	S27557	0.00	0.00	0.00	-1.70
S23350	1.00	0.96	0.73	1.22	SE1688	0.00	0.00	0.00	-1.71
SS9048	1.00	1.00	0.53	1.02	S69730	0.00	0.00	0.00	-1.75
SN5118	1.00	0.93	0.17	0.76	SE4942	0.00	0.00	0.00	-1.75
SJ5323	1.00	0.84	0.07	0.67	S29646	0.00	0.00	0.00	-1.96
SL7844	1.00	0.98	0.00	0.66	S26425	0.00	0.00	0.00	-2.48
S83527	1.00	0.31	0.00	0.43	S26379	0.00	0.00	0.00	-3.20
S23349	1.00	0.22	0.00	0.42	S85603	0.00	0.00	0.00	-3.60
S34823	1.00	0.20	0.00	0.39	S67536	0.00	0.00	0.00	-59.93
SJ4786	0.88	0.01	0.00	0.17	S83243	0.02	0.02	0.00	-93.75

The above table displays the probabilistic Sharpe ratio of picked funds when we take 0, 0.5, and 1 as the target Sharpe ratios. In general, when the Sharpe ratio is close to 1, we can say that managers may have good investment management skills. The greater the value of the Sharpe ratio, the more attractive the risk-adjusted return. There are 20 funds with Sharpe ratios above 1 in total and 29 funds with positive Sharpe ratios.
The biggest Sharpe ratio of picked funds is 6.09, which is SR3434. SR3434 has a negative beta and a positive Jensen's alpha. Its maximum drawdown is 6.74%. Under these three target Sharpe ratios, the probabilities of its Sharpe ratio are always 1. There are 10 funds in total with a 100% probability to meet the target Sharpe ratio of 1.
When the target Sharpe ratio is 1, ST5754 meets this target with 98% confidence, even its Sharpe ratios higher than that of S21122. This may be caused by some risk factors that ST5754 has, i.e. more negative skewness and leptokurtic.
Although there are 20 funds with Sharpe ratio bigger than one, only 12 funds can have Sharpe ratios bigger than 1 with confidence over 95%. The Sharpe ratio of SS9048 is 1.02, but the probability with target Sharpe ratio 1 is only 53%.
Apart from the Sharpe ratio bigger than 1, there is only another one fund (SL7844) with confidence over 95% when taking 0.5 as the target Sharpe ratio. The maximum drawdown of this fund is 10.23%, lower than the average level. Its kurtosis is over 12, and its skewness is over 3, which means greater potential for extremely high returns.
There are over 50% (29 out of 54) funds with a positive Sharpe ratio, but only 26 funds among them with confidence 95% have positive Sharpe ratio. Therefore, according to the Probabilistic Sharpe Ratio, only 18.52% funds' Sharpe ratio can be 1 or above under 95% confidence.

4.1.3 Manipulation-proof Performance Measure

Then we calculate MPPM to provide a more robust measure of their performances, and EMPPM to examine managers' skill of earning abnormal returns.

Table 6: MPPM and EMPPM Results

	MPPM_2	MPPM_3	MPPM_4	EMPPM_2	EMPPM_3	EMPPM_4
S28342	-0.50%	-1.79%	-3.01%	14.71%	15.73%	16.94%
S35966	-2.19%	-4.65%	-7.12%	5.52%	5.49%	5.57%
S85118	23.76%	21.96%	20.20%	27.67%	27.85%	28.16%
SE2421	4.51%	3.51%	2.52%	2.74%	2.95%	3.18%
SH9398	5.79%	4.93%	4.07%	5.98%	6.43%	6.88%
SR2083	0.34%	-1.29%	-2.86%	-5.03%	-5.19%	-5.28%

SE5438	13.91%	12.73%	11.55%	8.70%	8.78%	8.87%
SR3017	-2.57%	-3.54%	-4.50%	-2.66%	-2.37%	-2.07%
S21122	-2.30%	-9.24%	-16.62%	-2.27%	-6.27%	-10.66%
S68046	-8.19%	-9.29%	-10.38%	-0.35%	1.25%	3.06%
S83499	-9.61%	-11.21%	-12.81%	-6.98%	-6.61%	-6.12%
ST0713	15.54%	15.31%	15.08%	17.49%	18.63%	19.76%
SK7292	-8.37%	-9.85%	-11.31%	-11.16%	-11.39%	-11.60%
S21679	-28.02%	-40.68%	-60.19%	-29.85%	-39.46%	-55.86%
S22382	-22.40%	-26.40%	-30.78%	-23.97%	-24.94%	-26.24%
S20280	-0.29%	-1.18%	-2.04%	1.10%	3.12%	5.23%
S62692	-13.50%	-14.59%	-15.70%	-1.57%	0.29%	2.34%
S23350	-15.74%	-20.25%	-26.01%	-12.38%	-14.25%	-17.27%
ST1892	-6.00%	-7.73%	-9.57%	-1.33%	-1.81%	-2.41%
SJ5323	13.76%	12.67%	11.56%	14.66%	14.81%	14.94%
S34823	-13.01%	-16.67%	-20.32%	-5.35%	-6.89%	-8.32%
SJ4786	0.94%	0.74%	0.53%	2.34%	3.42%	4.49%
ST5754	-1.52%	-1.64%	-1.76%	0.00%	1.34%	2.68%
SN5118	0.43%	-0.11%	-0.66%	0.94%	1.76%	2.58%
S83527	-9.33%	-11.93%	-14.56%	-6.04%	-6.63%	-7.14%
SL8820	5.51%	5.48%	5.44%	6.44%	7.67%	8.89%
S23349	7.18%	5.46%	3.78%	12.35%	13.14%	14.09%
SR3434	1.58%	1.44%	1.30%	2.88%	4.14%	5.39%
SS9048	1.35%	1.31%	1.26%	5.99%	7.27%	8.53%
SM1268	-8.11%	-11.53%	-14.94%	-10.59%	-12.72%	-14.85%
S39727	-4.23%	-5.43%	-6.61%	-7.53%	-7.43%	-7.31%
S83243	-4.13%	-4.14%	-4.14%	-1.94%	0.05%	2.17%
SL7844	4.55%	4.38%	4.22%	9.34%	10.36%	11.37%
S67536	-4.78%	-4.78%	-4.79%	-7.67%	-6.40%	-5.13%
SK1674	-3.66%	-3.79%	-3.92%	-3.59%	-2.51%	-1.43%
S28300	-7.85%	-8.78%	-9.70%	-1.96%	-0.20%	1.69%
S37095	3.05%	-0.36%	-4.11%	13.57%	13.32%	12.94%
SD0499	2.43%	1.23%	0.01%	6.00%	6.83%	7.74%
S28266	-1.18%	-2.44%	-3.78%	6.27%	6.98%	7.73%
S26387	11.22%	9.69%	8.15%	14.28%	14.79%	15.39%
SH8698	0.77%	-0.48%	-1.74%	0.81%	0.74%	0.65%
S22669	-3.51%	-4.84%	-6.21%	0.12%	0.85%	1.65%
S69730	15.68%	14.06%	12.44%	18.08%	18.55%	19.13%
S84129	10.29%	8.06%	5.86%	11.82%	11.67%	11.67%
ST1882	-21.62%	-24.01%	-26.53%	-31.28%	-31.94%	-32.74%
SE4488	15.20%	12.79%	10.41%	18.40%	18.05%	17.84%
S29646	-4.34%	-8.39%	-13.06%	-3.03%	-4.95%	-7.36%
SE4942	10.95%	9.37%	7.81%	7.09%	6.81%	6.55%

S27557	7.33%	5.36%	3.38%	8.64%	8.81%	9.08%
SE1688	16.50%	14.06%	11.55%	18.21%	17.81%	17.48%
S26379	0.60%	-1.57%	-3.71%	10.25%	10.78%	11.56%
S26425	2.20%	0.83%	-0.54%	2.67%	3.25%	3.95%
S85603	8.78%	7.22%	5.66%	14.08%	14.58%	15.20%
ST9165	-81.58%	-116.28%	-158.09%	-80.89%	-114.29%	-154.79%

Table 7: Summary of MPPM and EMPPM Results

	MPPM_2	MPPM_3	MPPM_4	EMPPM_2	EMPPM_3	EMPPM_4
Mean	-1.56%	-4.00%	-6.76%	0.59%	0.04%	-0.76%
Minimum	-81.58%	-116.28%	-158.09%	-80.89%	-114.29%	-154.79%
Maximum	23.76%	21.96%	20.20%	27.67%	27.85%	28.16%
Median	0.03%	-1.43%	-2.93%	1.72%	3.04%	3.56%

From Table 7, we can see, there is a great difference between different funds. The minimum MPPM under different risk aversion is that of ST9165, which is -81.58%, -116.28%, and -158.09% separately under different risk aversion. This fund also has a negative Sharpe ratio and Jensen alpha, and maximum downdraw. Checking the return data of this fund, we find that the monthly return of this fund is super volatile, whose standard deviation, skewness, and kurtosis are 0.19, -0.23, and 0.88 separately. The maximum monthly return of ST9165 is 42.76%, and the minimum monthly return of this fund is -54.01%, whose difference between the maximum and minimum monthly return is nearly 100%.

According to the EMPPM, which can provide more information related to managers' skill, the median EMPPMs of those picked funds are all positive under the different assumptions of risk aversion. Therefore, there are over half of picked hedge funds with returns above the market performance (CSI 300). Specifically, there are separately 31, 35, and 36 funds outperforming the market (whose EMPPM is positive) under the assumption of risk aversion 2, 3, and 4. These numbers are quite close to the number of positive Jensen alpha. Besides, all funds with positive EMPPMs also have positive Jensen alphas. However, there are 4 funds with positive Jensen alphas having negative EMPPMs. Therefore, we can conclude that over 54% of managers of picked hedge funds have stock-picking ability to earn an abnormal return, compared with the market performance.

Then we also investigate the EMPPM of these funds during some special periods in China, like the first half-year of 2020 and 2015-2016 Chinese stock market turbulence.

During the past half-year of 2020, there is a total of 33 funds winners with the risk aversion equal to 2 and 4, and 31 funds winners with the risk aversion equal to 3, which means positive EMPPMs. Therefore, even during this super volatile period, there are over half of hedge funds in China outperforming the market.

For the period 2015.01-2016.06, this period should be divided into two sample periods, 2015.01-2015.06 and 2015.07-2016.06. During the first period, the Chinese stock market is a typical bull market. Prices increased more than 150 percent on the Shanghai exchange, and even more on the Shenzhen Stock Exchange. Then during the second period, the Chinese stock market became the bear market, and a third of the value of A-shares on the Shanghai Stock Exchange was lost within one month of this period.
During the period of 2015.01-2015.06, there are only 6 funds having return information. Among these 6 funds, there are 3 funds outperform the market, and another 3 funds underperform.
During the second period, there are 22 funds having return information during the subperiod 2015.07-2015.12. Among these 22 funds, 10 samples outperform the market. Then during the subperiod 2016.01-2016.06, there are 36 samples. Among these samples, there are 22 funds outperforming the market, accounting for 61% of samples.
In general, we can choose hedge funds in China during the volatile period. Over half of the sample funds can outperform the market when faced with uncertainties. Additionally, the beta information suggests that hedge funds in China are theoretically less volatile than the market, and some are even negatively correlated with the market. Moreover, comparing with the market index, there are over half of the funds with positive abnormal returns. Therefore, nearly half of managers of those picked funds have stock-picking capacity.

4.2 Skill Models

4.2.1 Henriksson-Merton Model Regression Results

Firstly, we run the Henriksson-Merton model regression of these 54 funds through R. The detailed results are showed in Appendix I. Table 8 is the summary of HM model coefficients.

Table 8: Summary Statistics for the Henriksson-Merton Model coefficients

	N	mean	min	max	std.dev	N+	N+*	N-	N-*
alpha	54	0.0019	-0.034	0.021	0.0117	33	4	21	2
beta1	54	0.2766	-0.238	0.907	0.2706	46	18	8	0
beta2	54	0.0169	-0.85	1.339	0.3732	28	1	26	1

Note: The column N+(N-) reports the number of funds with positive (negative) estimates. The column N+* (N-*) reports the number of funds with parameter estimates that are positive (negative) and significant at the 5% level.

We observe that alpha is positive, on average. There are 33 funds with positive alpha but only four funds test statistically significant at the 5% level. The minimum alpha is -3.4%, the maximum one is 2.1%, and the median one is 0.2%. Besides, the standard deviation of alpha is the smallest among these three coefficients, which means that the abnormal returns of picked funds are very close and all close to zero. This indicates that most managers of Chinese hedge funds nearly do not have stock-picking capacity over the past 5 years. But there are still a few hedge fund managers in China (4 out of 54, that is SE5438, ST0713, SJ5323, and SE4942) are able to generate abnormal returns over the past 3 years, which means that they may have stock picking ability.

Then most funds have a positive β_1, which means that they all have positive exposure to the Chinese stock market. There are 85% (46 out of 54) funds with positive β_1, and only 8 funds with negative β_1, among which no one is statistically significant at the 5% level.

However, we observe that 28 funds' β_2 are positive, and only one (SL8820) is significant at the 5% level. On the other hand, 26 funds' β_2 are negative and also only one is significant at the 5% level. Additionally, the standard deviation of β_2 is the biggest among these three coefficients. The mean of β_2 is 0.0169. The results suggest that β_2 is insignificantly different from zero. Therefore, based on the HM model, we may conclude that, in China, most hedge fund managers do not have market timing capacity, but some of them may have stock picking ability.

4.2.2 Treynor-Mazuy Model Regression Results

Then, we also run the regression of picked funds using the Treynor-Mazuy model. The detailed results are showed in Appendix II. The modified TM model estimation results for the picked hedge funds are summarized in Table 9.

Table 9: Summary Statistics for the Treynor-Mazuy Model coefficients

	N	mean	min	max	std.dev	N+	N+*	N-	N-*
alpha	54	-0.0032	-0.086	0.02	0.0147	26	0	28	2
betaS1	54	0.2697	-0.523	0.8	0.2998	48	24	6	1
betaS2	54	0.3207	-3.029	5.737	1.7153	29	2	25	2
betaB1	54	0.2110	-3.57	8.304	1.9623	25	0	29	3
betaB2	54	313.2023	-362.324	3964.531	593.9519	43	7	11	0

Note: The column N+(N-) reports the number of funds with positive (negative) estimates. The column N+* (N-*) reports the number of funds with parameter estimates that are positive (negative) and significant at the 5% level.

The results of alpha here are similar to those of the HM model. The mean of alpha is -0.32%, and the standard deviation of alpha is very small, which may mean that the excess returns of each fund are close to zero. The minimum alpha is -8.6%, the maximum is 2%, and the median is -0.15%. Additionally, 26 funds have positive alpha but all of them are not statistically significant at the 5% level. But there is three positive alpha significant at the 10% level.

Therefore, according to the regression of the TM model, there is no enough evidence showing that hedge fund managers, in China, have stock picking ability.
About the exposure to stocks and bonds, the means of β_{s1} and β_{b1} are both above 20%. Almost 89% of hedge funds have positive exposures to stocks, among which 50% are statistically significant at the 5% level. However, only 46% of hedge funds have positive exposures to bonds, of which no one is statistically significant. Therefore, most hedge funds have significantly positive exposure to the Chinese stock market, but only half of the hedge funds have exposure to the Chinese bond market.
In addition, the regression shows that 54% of funds have positive β_{s2} for the quadratic excess equity returns, among which only 2 coefficients are statistically significant at the 5% level. The mean of β_{s2} is 0.32, and the standard deviation is 1.72. Hence, only a few managers (2 out of 54, S85118 and SL8820) have a significant market-timing ability with respect to stocks.
On the other hand, the β_{b2} for the quadratic excess bond returns is positive in general. In detail, nearly 80% of funds have positive coefficients and the mean of beta is 313.20, but only 13% of the total sample (S35966, SE2421, SH9398, SE5438, SJ5323, S39727 and S69730) obtains statistical significance for these positive β_{b2}. No funds have statistically significant and negative coefficients for market timing ability in bonds. Therefore, a few (7 out of 54) hedge fund managers have the market-timing ability with respect to bonds.
In general, according to the TM model, there is no evidence that Chinese hedge fund managers have significant stock-picking ability, but a few managers have significant market-timing ability with respect to stocks and bonds.

4.3 Persistence Test

In this part, we will investigate the performance persistence of hedge funds in China through a qualitative method and quantitative method.

4.3.1 Contingency Table

We will take three abstract benchmarks (CSI 300, Jensen's alpha, and EMPPM) and two relative benchmarks (mean and median) to conduct the contingency table separately. Besides, our sample has five test periods, i.e. 2015-2016, 2016 -2017, 2017-2018, 2018-2019, 2019-2020. Especially, when taking EMPPM as the benchmark, we also try to use half-year as the length of our sample period and conduct the contingency table.

4.3.1.1 Contingency Table Based on Abstract Benchmark (CSI 300)

Table 10: Contingency Table based on abstract benchmark (CSI 300)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	24	9	3	12	0	0	--
2016-2017	44	14	21	4	5	0.8333	-0.2417
2017-2018	54	18	0	32	4	_	--
2018-2019	54	12	38	2	2	0.3158	-1.0942
2019-2020	54	5	9	23	17	0.4106	-1.3843

Note: * significant level of 5%.

The above contingency table is based on the abstract benchmark, CSI 300. The winners will be defined as the funds with returns higher than the index return, and the losers will be defined as the funds with returns lower than or equal to the index return.

In 2015, comparing with CSI 300, 12 hedge funds outperformed, which accounts for 50% of observed funds. Among them, 9 funds were winners this year and also won the market next year. But 3 funds were winners this year but underperformed next year. There was no fund keeping losing two years. Therefore, the Cross-Product ratio of 2015-2016 was equal to 0, and the test statistic cannot be calculated.

In 2016, there were 35 funds wining the market, but only 14 out of them kept winning next year, accounting on 31.82% of total observed funds, and the rest turned into losers. 5 funds were loser this year and kept losing next year. Therefore, there was a total of 19 funds keep performance in this period, which accounts for 43.19% of observation. In this year, the cross-product ratio is lower than one but not statistically significant.

Then in 2017, 66.67% of funds underperformed, and there were 4 funds keeping losing next year. However, all the winners of this year outperformed next year, so no fund was categorized as WL. Hence, the cross-product ratio and z statistics cannot be calculated this year. During 2017-2018 this sample period, 22 out of 54 funds show performance persistence, and the rest show negative performance persistence.

During the sample period 2018-2019, 14 (12+2) out of 54 funds keep performance persistence. But 38 funds were winners in 2018, but turned into losers in 2019, accounting on 70.37%. During the period 2019-2020, there are 22 (5+17) funds to keep performance persistence. The cross-product ratios for these two periods are 0.3158 and 0.4106 separately, both of which are not significant at the 5% level.

However, all the calculated cross-product ratios are smaller than one, but there is no cross-product ratio statistically significant at the 5% level. Therefore, the results indicate that there is no persistence for Chinese hedge funds, taking the CSI 300 index as the abstract benchmark. In this situation, there is only one fund to keep the same results all the period (winner all the time), compared with the market, which is SJ5323. In the TM model, SJ5323 has positive and significant alpha, and in the HM model, it has positive and significant β_{b2}.

4.3.1.2 Contingency Table Based on Abstract Benchmark (Jensen's alpha)

Table 11: Contingency Table based on Abstract Benchmark (Jensen's Alpha)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	4	5	9	3	0.2667	-1.3976
2016-2017	45	18	4	10	13	5.8500*	2.5431
2017-2018	53	17	15	4	17	4.8167*	2.3855
2018-2019	54	14	7	13	20	3.0769	1.9241
2019-2020	54	12	15	15	12	0.6400	-0.8148

Note: * significant level of 5%.

We calculate the Jensen's alpha of every fund each year and defines winners as funds with Jensen's alpha higher than zero. Winners are considered to have an excess return after taking market risk into consideration. The repeated winners are funds that consistently outperform the market, and the repeated losers consistently underperform the market.

The above test categorizes funds based on Jensen's alpha. The results have some differences. The cross-product ratio of the sample period 2016-2017 is 5.85, which is statistically significant at the 5% level. This means that this period shows performance persistence. During this period, there are 18 WWs and 13 LLs, so persistence mainly comes from winners. Different from the previous situations, the sample period 2017-2018 also has a statistically significant cross-product ratio greater than one, so this period also shows performance persistence. During this period, persistence equally comes from winners and losers, both 17. Different from the previous situation, during the 2019-2020 period, although there are 12 WWs and 12 LLs, there are more funds showing reversals. There is only one fund (ST0713) having positive Jensen's alpha all the time since issuing, whose strategy is multi-strategy.

4.3.1.3 Contingency Table Based on Abstract Benchmark (EMPPM)

Table 12: Contingency Table based on Abstract Benchmark (EMPPM_2)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	6	4	10	1	0.1500	-1.5405
2016-2017	45	12	18	7	8	0.7619	-0.4264
2017-2018	53	18	1	30	4	2.4000	0.7566
2018-2019	54	12	37	1	4	1.2973	0.2232
2019-2020	54	4	9	27	14	0.2305*	-2.1418

Table 13: Contingency Table based on Abstract Benchmark (EMPPM_3)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	7	2	11	1	0.3182	-0.8697
2016-2017	45	13	20	5	7	0.9100	-0.1376

2017-2018	53	17	1	29	6	3.5172	1.1204
2018-2019	54	13	34	1	6	2.2941	0.7359
2019-2020	54	5	9	26	14	0.2991	-1.8600

Table 14: Contingency Table based on Abstract Benchmark (EMPPM_4)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	8	1	11	1	0.7273	-0.2139
2016-2017	45	13	21	5	6	0.7429	-0.4241
2017-2018	53	17	1	29	6	3.5172	1.1204
2018-2019	54	13	34	1	6	2.2941	0.7359
2019-2020	54	5	9	28	12	0.2381*	-2.1881

Note: * significant level of 5%.

The above three tables are contingency tables based on the EMPPM under different risk aversion assumptions. Because EMPPM is equal to the MPPM of hedge funds minus the MPPM of the market index, we define positive EMPPM as the winner and negative one or zero as the loser.

Under the risk aversion level equal to 2, there is only period 2019-2020 showing statistical significance under the 5% level, with a cross-product ratio equaling to 0.2305, which is lower than one. This indicates that during this period, the past performance of funds provides an opposite prediction of their future performance. The reversals mainly come from the losers of last year (27 out of 54).

A similar situation happens under the risk aversion level equal to 4. The cross-product ratio of the period 2019-2020 is equal to 0.2381, which is significant at the level of 5%. The majority of reversals also come from the losers of last year (28 out of 54).

Under the risk aversion level equal to 3, the cross-product ratio of the period 2019-2020 shows statistically significant at the level of 10%. Similarly, the ratio of this period is also lower than 1, and the reversals also mainly come from the losers of last year (26 out of 54).

Based on the previous research, we find that EMPPM is a much more robust measure, which has taken the market index into consideration and also is not impacted by the distribution of returns. Additionally, the number of our sample period is a little small, and also hedge funds always have large volatilities because of dynamic trading strategies. Therefore, we conduct the contingency table again based on the EMPPM but choose half-year as the length of the sample period. we have 10 sample periods: 2015H-2016, 2016-2016H, 2016H-2017, 2017-2017H, 2017H-2018, 2018-2018H, 2018H-2019, 2019-2019H, 2019H-2020, and 2020-2020H. As the same with the previous, we define a positive EMPPM as the winner and a negative one or zero as the loser.

Table 15: Contingency Table (Half Year) based on Abstract Benchmark (EMPPM_2)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic

2015H-2016	6	2	1	2	1	1.0000	0.0000
2016-2016H	22	8	2	10	2	0.8000	-0.2016
2016H-2017	36	9	19	4	4	0.4737	-0.9172
2017-2017H	45	11	7	14	13	1.4592	0.6113
2017H-2018	50	17	8	3	22	15.5833*	3.6612
2018-2018H	53	16	4	24	9	1.5000	0.5944
2018H-2019	53	37	3	12	1	1.0278	0.0228
2019-2019H	54	7	43	1	3	0.4884	-0.5853
2019H-2020	54	7	1	14	32	16.0000*	2.4843
2020-2020H	54	7	14	24	9	0.1875*	-2.7630

Table 16: Contingency Table (Half Year) based on Abstract Benchmark (EMPPM_3)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015H-2016	6	2	1	1	2	4.0000	0.8004
2016-2016H	22	8	1	10	3	2.4000	0.7013
2016H-2017	36	9	19	3	5	0.7895	-0.2831
2017-2017H	45	10	7	15	13	1.2381	0.3436
2017H-2018	50	17	8	3	22	15.5833*	3.6612
2018-2018H	53	15	5	24	9	1.1250	0.1819
2018H-2019	53	36	3	13	1	0.9231	-0.0667
2019-2019H	54	9	41	1	3	0.6585	-0.3447
2019H-2020	54	6	4	14	30	3.2143	1.6170
2020-2020H	54	7	13	24	10	0.2244*	-2.4859

Table 17: Contingency Table (Half Year) based on Abstract Benchmark (EMPPM_4)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015H-2016	6	2	1	1	2	4.0000	0.8004
2016-2016H	22	8	1	11	2	1.4545	0.2860
2016H-2017	36	9	20	2	5	1.1250	0.1269
2017-2017H	45	9	7	16	13	1.0446	0.0696
2017H-2018	50	16	9	3	22	13.0370*	3.4549
2018-2018H	53	15	4	24	10	1.5625	0.6592
2018H-2019	53	37	2	12	2	3.0833	1.0686
2019-2019H	54	9	41	1	3	0.6585	-0.3447
2019H-2020	54	6	4	14	30	3.2143	1.6170
2020-2020H	54	7	13	26	8	0.1657*	-2.9039

Note: * significant level of 5%.

From the above tables, we can see, under different assumptions of risk aversion, sample period 2017H-2018 all have cross-product ratios greater than one, which is all statistically significant at the level 5%. Therefore, we can conclude that during 2017H-2018, the previous performance can provide a forecast for the next period. Under these three situations, all loser-losers (LLs) account for a larger percentage than winner-winners (WWs) during this sample period.

Besides, during the sample period of 2020-2020H, all three situations have statistically significant cross-product ratios lower than 1. All the reversals mainly come from the losers of last year.

Under the risk aversion equal to 2, the sample period 2019H-2020 also has a significant cross-product ratio, which is equal to 16. This indicates that if an investor has a higher risk tolerance than the average, the performance of hedge funds will show persistence during the uncertain period.

4.3.1.4 Contingency Table Based on Relative Benchmark (mean)

Table 18: Contingency Table based on Relative Benchmark (mean)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	24	1	7	3	13	0.6190	-0.3848
2016-2017	44	11	6	8	18	4.1250*	2.1409
2017-2018	54	6	13	19	16	0.3887	-1.5779
2018-2019	54	10	15	13	16	0.8205	-0.3576
2019-2020	54	5	18	17	14	0.2288*	-2.3748

Note: * significant level of 5%.

Then we take the mean return of the observed funds as the relative benchmark to conduct the contingency table. We define winners as funds with returns higher than or equal to the mean return and losers as funds with return lower than the mean return.

In total, there are two cross-product ratios statistically significant. In the sample period 2016-2017, the cross-product ratio is 4.1250, greater than 1. This indicates that for the period 2016-2017, there was persistence in performance. During this period, there are 11 WWs and 18 LLs, so persistence mainly comes from losers. Another significant cross-product ratio is that of 2019-2020, which is 0.2288 lower than one. This result indicates that the past performance of funds provides an opposite prediction of their future performance. The reversals come nearly equally from last year’s winners and losers.

Therefore, taking the mean return of observed funds as the relative benchmark, there is one period (2016-2017) showing persistence and another period (2019-2020) showing negative persistence. In this situation, there is one fund to keep the same results all the period (loser all the time).

4.3.1.5 Contingency Table Based on Relative Benchmark (Median)

Table 19: Contingency Table Based on Relative Benchmark (Median)

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	24	3	9	3	9	1.0000	0.0000
2016-2017	44	19	3	8	14	11.0833*	3.1520
2017-2018	54	13	14	14	13	0.8622	-0.2721
2018-2019	54	12	15	15	12	0.6400	-0.8148
2019-2020	54	10	19	16	9	0.2961*	-2.1311

Note: * significant level of 5%.

The above test categorizes funds based on the median return. We define winners as funds with returns higher than or equal to the median return and losers as funds with return lower than the median return.

The result is quite similar to that of taking the mean as the benchmark. There are also two sample periods with significant cross-product ratios, 2016-2017 and 2019-2020. In the sample period 2016-2017, there are 33 funds showing performance persistence in total, 19 WWs and 14 LLs. The ratio of this period is 11.08, which is greater than 1 and significant under a 95% confidence level. In this situation, persistence mainly comes from winners.

For the period 2019-2020, the cross-product ratio is smaller than 1 and statistically significant at a 5% significance level, which indicates that the past performance of funds provides an opposite prediction of their future performance. The reversals come nearly equally from last year's winners and losers. Total amounts of 19 of last year's winners became losers in the following year, and 16 of last years' losers turned into winners in the following year. At the same time, only 10 funds keep doing well during the two-year testing period, and 9 underperforming funds continued to underperform in the following year. Total testing funds were 54, and the majority of them experienced reversals.

In general, there is no enough evidence that Chinese hedge fund managers have abilities to keep performance persistence, especially some special periods. When we take relative benchmarks, some funds may have performance persistence in the period 2016-2017. Then some funds show negative performance persistence in the period 2019-2020 when reversals happened.

4.3.2 Economic Predictability

4.3.2.1 Portfolio of Hedge Funds Based on Lagged 1-month Returns

Table 20: Portfolio of Hedge Funds Based on Lagged 1-month Returns (CAPM)

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.004	0.004	0.002	0.002	-0.003	-0.001	-0.006
	(0.007)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
RMRF	0.641***	0.090	0.086	0.129	0.261*	0.232	0.652***
	(0.143)	(0.145)	(0.106)	(0.106)	(0.146)	(0.145)	(0.094)
R2	0.370	0.011	0.019	0.042	0.086	0.070	0.587
Adjusted R2	0.351	-0.018	-0.010	0.013	0.059	0.043	0.575

Note: *p<0.1; **p<0.05; ***p<0.01

Portfolios are formed at the beginning of August in 2017 based on the previous month's returns (July 2017). Portfolio 1 has funds with top sextile lagged one-month return, and portfolio 6 has funds with the bottom sextile lagged one-month return. Later, at the start of the following months, funds will be ranked again based on a lagged one-month return. The excess return is the return of the portfolio over the risk-free rate. The test result shows that no portfolio has statistically significant alpha under a 90% confidence level.

The 1-6 spread is the zero-investment strategy of long in the top performers' portfolio and short in the worst performers' portfolio. It displays a negative and insignificant alpha under a 90% confidence level. The alpha of the 1- 6 spread is -0.006, which means that this strategy cannot earn any abnormal return.

The result suggests that alphas of all portfolios are not significantly different from zero. Even portfolio 1 does not have a positive alpha through regression. Therefore, there is no short-term persistence existing in the Chinese hedge fund. Besides, the zero-investment strategy cannot gain any abnormal returns, which means that if you buy the past winners and short the past losers, you will not make money.

4.3.2.2 Portfolio of Hedge Funds Based on Lagged 1-quarter Returns

Table 21: Portfolio of Hedge Funds Based on Lagged 1-quarter Returns (CAPM)

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.014	-0.009	-0.016	0.012	0.018	0.021	-0.025
	(0.023)	(0.020)	(0.011)	(0.022)	(0.013)	(0.022)	(0.021)
RMRF	0.035	-0.303	-0.196	0.081	-0.228	-0.477	0.402**
	(0.252)	(0.278)	(0.126)	(0.216)	(0.155)	(0.350)	(0.131)
R2	0.002	0.116	0.211	0.015	0.192	0.171	0.510
Adjusted R2	-0.109	0.018	0.124	-0.094	0.103	0.079	0.456

Note: *p<0.1; **p<0.05; ***p<0.01

The above table shows the CAPM regression result that portfolios are formed based on lagged 1-quarter returns. As the same with that based on lagged 1-month returns, there are no significant alphas among these portfolios, which means that alphas are not significantly different from zero. Portfolio 1 even has a negative alpha but not significant. In other words, investors cannot earn abnormal returns by buying the past quarter winners.

If we use the zero-investment strategy based on 1-quarter lagged return, it seems that we cannot gain abnormal returns because the alpha of the spread 1-6 is negative and insignificant. In general, there is no short-term persistence of hedge funds existing in China based on the CAPM.

Therefore, through a quantitative method, there is no short-term (one month or quarter) persistence existing among the sample funds. Besides, we cannot earn abnormal returns through buying the winners of the past evaluation period, and the strategy that buying the past winners and shorting the past losers also does not provide positive abnormal returns. While analyzing through the contingency table, there is some short-term persistence existing during some periods, positive persistence during the period 2016-2017 and negative persistence during the period 2019-2020.

Table 22: Summary of Contingency Table Results Based on Different Benchmarks

Benchmark	persistence results		
CSI 300			
Jensen's alpha	2016-2017^{+}	2017-2018^{+}	
EMPPM		2017H-2018^{-}	2019-2020^{-}
mean	2016-2017^{+}		2019-2020^{-}
median	2016-2017^{+}		2019-2020^{-}

Note: $^{+}$ positive persistence, $^{-}$ negative persistence.

5. Conclusion and Discussion

5.1 Conclusions

In this paper, we mainly investigate 54 Chinese hedge funds and their managers' skills. Firstly, we calculate the Sharpe ratios and Jensen alphas of these picked funds. We found that all the picked funds are theoretically less volatile than the market, and some are even negatively correlated with the market. The majority of picked funds have positive Jensen alphas, which means that they have abnormal returns compared with the market. Then we also calculate the Probabilistic Sharpe Ratio to provide more information related to the Sharpe ratio of hedge funds. Nearly returns of all picked funds are not normal distributions, which means PSR can provide much correct information related to the Sharpe ratio. According to the Probabilistic Sharpe Ratio, only 18.52% funds' Sharpe ratio can be 1 or above with 95% confidence, although there are 20 funds with Sharpe ratio bigger than 1. Besides, there are over 50% (29 out of 54) funds with a positive Sharpe ratio, but only 26 funds among them with confidence 95% have positive Sharpe ratio. Based on the previous research of hedge funds, we find that the MPPM and EMPPM are much more exacting performance measures than the more traditional Sharpe ratio, alpha, so we calculate the MPPM and EMPPM of funds with different risk aversion assumptions, which can provide much more robust information of the performance. Based on the results of EMPPM, there are over half of picked hedge funds with returns above the market performance (CSI 300), which means outperforming the market index. These numbers are quite close to the number of positive Jensen alpha. Therefore, we can conclude that over 54% of managers have stock-picking ability to earn an abnormal return, compared with the market performance. During some special subperiods, we find that investing in hedge funds may be a good choice when faced with great uncertainties, like the current period.
Then, we use the Henriksson-Merton model and Treynor-Mazuy model to check the marketing-timing capacity of managers. Both models show that only

a few managers have the market-timing ability and stock picking ability. Most managers do not have these two skills.

As for short-term persistence, we mainly use the contingency table and recursive portfolio approach, but the evidence is mixed. Firstly, we use the contingency table, taking CSI 300 index, mean, median, EMPPM, and Jensen's alpha as the benchmarks separately. When taking CSI 300 index as the benchmark, the results indicate that there is no persistence for Chinese hedge funds. When taking mean and median as the benchmarks, the results indicate that there are persistence in the period 2016-2017 and negative persistence in the period 2019-2020. According to Jensen's alpha, there are two periods showing performance persistence: 2016-2017 and 2017-2018. When taking EMPPM as the benchmark, it shows that there is negative persistence during the period 2019-2020. Then we also shorten the sample periods and investigate the half-year EMPPMs. The result indicates that there are positive persistence in the period 2017H-2018 and negative persistence in the period 2019H-2020. In general, there are some periods showing persistence: positive persistence during the period 2016-2017 and negative persistence during the period 2019-2020. However, the recursive portfolio approach shows no evidence of abnormal return when using both lagged one-month return and lagged one-quarter return.

Based on our research, we find that in China hedge funds have lower betas, which means they are less volatile than the market. Therefore, during this volatile period, investing in hedge funds may be a good investment choice for Chinese investors if they want their investment much more stable. This also can be visualized by the EMPPM of these funds during the last half-year. During the past months in 2020, the market is very volatile because of the COV19. However, over half of these sample funds have positive EMPPMs, which means that they outperform the market index. But the performance of hedge funds does not show short-term persistence and only a few managers have the market-timing ability and stock-picking skill. Additionally, there are only a few hedge funds with Sharpe ratio bigger than one, so investors need to do more research about the fund before making the investment decision.

5.2 Weakness: Sample Representativity

The quality of hedge fund data is always a concern to academics as fund information is reported on a voluntary basis by managers. In China, there are only a few databases providing the private funds' data, and Suntime is one of the most professional private funds databases. However, Suntime also collects data based on funds self-reporting. Therefore, there is some self-selection bias related to our data.

In this paper, our sample consists of 54 Chinese hedge funds. The main picking procedure is as following:

Table 23: Sample Picking Procedure

Conditions	Number of Funds
Private Securities Investment Funds	19409
Hedge Funds	2025
NAV Information $\geq$ 70%	69
Issued Time Range	54

From Table 23, we can see, the main constrain of sample picking is the integrality of NAV information. Because it's still the early stage of Chinese hedge funds, the regulation related to hedge funds is still underdeveloped, especially the public reporting regulation. Therefore, although our sample is small, our sample has included all funds satisfied with our research standards. Additionally, among our sample, all the funds are live and their lives are all shorter than 6 years. There is maybe a potential problem of survivor bias. In general, there are some biases associated with our data, while we can still gain some basic insights of hedge funds in China.

Furthermore, the marketing of hedge funds is also prohibited in China. Most funds among our sample are issued by well-known private asset management companies in China, so they may try to market themselves through reporting their past performance. In other words, although our sample may be too small to get some general conclusions of hedge funds in China, our research provides some points related to top hedge funds in China. Since hedge funds become more and more common in the Chinese asset management industry, the regulation related to hedge funds and their public information will be developed a lot.

5.3 Contributions

Our research makes contributions to studies on Chinese hedge funds and their managers' skills. But because of the lack of the Fama-French factors and other factors data of Chinese hedge funds, we cannot use more advanced models to measure the performance of Chinese hedge funds. Therefore, there is still room for further research in order to understand the impact of other detailed factors on the performance of hedge funds. If some database can provide the data of the Fama-French factors and Carhart's momentum factor, we will test Chinese hedge funds again.

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Appendices

Appendix I: Henriksson-Merton Model Regression

Table 24: Henriksson-Merton Model Regression Results

Henriksson–Merton Model Regression Results Part I

Dependent variable: R – Rf

	S28342	S35966	S85118	SE2421	SH9398	SR2083	SE5438	SR3017	S21122	S68046	S83499	ST0713	SK7292	S21679
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
beta1	−0.113	−0.155	0.505*	−0.038	0.030	−0.238	0.379**	0.475**	0.403	0.125	0.129	0.001	0.244	0.191
	(0.230)	(0.278)	(0.268)	(0.233)	(0.217)	(0.335)	(0.181)	(0.234)	(0.261)	(0.199)	(0.249)	(0.128)	(0.285)	(0.227)
beta2	−0.285	−0.716*	0.791*	−0.223	−0.145	0.092	−0.477	0.600	−0.269	−0.018	0.128	0.033	0.193	−0.344
	(0.335)	(0.403)	(0.402)	(0.411)	(0.388)	(0.631)	(0.341)	(0.411)	(0.462)	(0.274)	(0.375)	(0.226)	(0.514)	(0.404)
alpha	0.008	0.018	0.008	0.009	0.009	0.003	0.018**	−0.011	0.013	−0.004	−0.008	0.013**	−0.009	−0.005
	(0.010)	(0.012)	(0.011)	(0.009)	(0.009)	(0.016)	(0.008)	(0.010)	(0.016)	(0.008)	(0.010)	(0.005)	(0.012)	(0.014)
Observations	61	60	58	50	46	36	53	43	69	57	57	38	47	68
R^2	0.016	0.115	0.068	0.011	0.017	0.061	0.374	0.096	0.135	0.039	0.006	0.002	0.023	0.090
Adjusted R^2	−0.018	0.084	0.034	−0.031	−0.028	0.005	0.349	0.051	0.109	0.003	−0.031	−0.055	−0.021	0.062

	S22382	S20280	S62692	S23350	ST1892	SJ5323	S34823	SJ4786	ST5754	SN5118	S83527	SL8820	S23349	SR3434
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
beta1	0.054	0.077	0.099	0.453**	0.232	0.368**	0.266	−0.029	0.062	0.346**	0.889***	0.116**	0.593***	0.103
	(0.197)	(0.114)	(0.186)	(0.220)	(0.317)	(0.179)	(0.370)	(0.111)	(0.076)	(0.135)	(0.282)	(0.044)	(0.199)	(0.089)
beta2	−0.309	0.043	−0.028	0.237	0.263	−0.461	0.220	0.015	−0.114	−0.124	0.724*	0.180**	0.320	0.202
	(0.350)	(0.202)	(0.253)	(0.349)	(0.541)	(0.306)	(0.543)	(0.190)	(0.137)	(0.238)	(0.421)	(0.076)	(0.306)	(0.155)
alpha	−0.006	0.0001	−0.008	−0.014	−0.007	0.021***	−0.009	0.001	0.001	0.003	−0.018	0.001	0.002	−0.002
	(0.012)	(0.007)	(0.008)	(0.011)	(0.013)	(0.007)	(0.015)	(0.004)	(0.003)	(0.006)	(0.011)	(0.002)	(0.009)	(0.004)
Observations	68	72	63	66	39	51	58	46	36	42	55	45	66	43
R^2	0.046	0.010	0.032	0.111	0.016	0.438	0.013	0.008	0.189	0.425	0.204	0.145	0.210	0.041
Adjusted R^2	0.017	−0.019	0.0002	0.083	−0.039	0.414	−0.023	−0.038	0.139	0.395	0.174	0.105	0.185	−0.007

Note: *p<0.1; **p<0.05; ***p<0.01

Henriksson–Merton Model Regression Results Part II

Dependent variable: R – Rf

	SS9048	SM1268	S39727	S83243	SL7844	S67536	SK1674	S28300	S37095	SD0499	S28266	S26387	SH8698
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
beta1	0.009	0.233	0.471*	−0.002	0.134	−0.001	0.094	0.091	0.464*	0.523***	0.369***	0.496**	0.356
	(0.056)	(0.416)	(0.235)	(0.014)	(0.104)	(0.014)	(0.088)	(0.167)	(0.247)	(0.172)	(0.136)	(0.191)	(0.222)
beta2	−0.047	1.339*	0.102	−0.017	0.066	−0.033	0.162	0.009	−0.214	0.089	−0.390*	−0.143	−0.331
	(0.096)	(0.738)	(0.417)	(0.021)	(0.179)	(0.026)	(0.152)	(0.241)	(0.341)	(0.258)	(0.195)	(0.286)	(0.387)
alpha	0.002	−0.023	−0.005	−0.003***	0.003	−0.003***	−0.006	−0.005	0.015	0.002	0.010*	0.014*	0.007
	(0.002)	(0.017)	(0.010)	(0.001)	(0.004)	(0.001)	(0.003)	(0.007)	(0.011)	(0.007)	(0.005)	(0.008)	(0.009)
Observations	37	48	46	56	47	53	48	64	60	55	55	55	50
R^2	0.037	0.120	0.194	0.029	0.069	0.077	0.027	0.018	0.349	0.347	0.607	0.396	0.264
Adjusted R^2	−0.019	0.081	0.156	−0.008	0.027	0.040	−0.016	−0.014	0.327	0.322	0.592	0.373	0.232

	S22669	S69730	S84129	ST1882	SE4488	S29646	SE4942	S27557	SE1688	S26379	S26425	S85603	ST9165
	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
beta1	0.408**	0.415*	0.697**	−0.175	0.788***	0.428*	0.479**	0.449**	0.068	0.760***	0.522**	0.386	0.907
	(0.174)	(0.238)	(0.265)	(0.366)	(0.256)	(0.221)	(0.202)	(0.219)	(0.311)	(0.265)	(0.204)	(0.236)	(1.161)
beta2	−0.174	0.038	0.302	0.397	0.141	−0.850**	−0.569	−0.326	−0.146	0.275	0.164	−0.008	0.548
	(0.258)	(0.356)	(0.401)	(0.722)	(0.385)	(0.337)	(0.379)	(0.334)	(0.468)	(0.360)	(0.309)	(0.350)	(2.088)
alpha	0.002	0.015	0.005	−0.019	0.014	0.018*	0.018**	0.015	0.021	0.001	−0.0001	0.011	−0.034
	(0.007)	(0.010)	(0.011)	(0.019)	(0.011)	(0.009)	(0.009)	(0.009)	(0.013)	(0.010)	(0.008)	(0.010)	(0.049)
Observations	55	53	54	23	54	55	53	55	54	55	55	52	36
R^2	0.390	0.167	0.226	0.114	0.355	0.572	0.436	0.384	0.019	0.328	0.233	0.175	0.030
Adjusted R^2	0.366	0.134	0.195	0.025	0.330	0.555	0.414	0.360	−0.019	0.302	0.204	0.141	−0.029

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix II: Treynor-Mazuy Model Regression

Table 25: Treynor-Mazuy Model Regression R

TM Model Regression Results Part I

Dependent variable: R - Rf

	S28342 (1)	S35966 (2)	S85118 (3)	SE2421 (4)	SH9398 (5)	SR2083 (6)	SE5438 (7)	SR3017 (8)	S21122 (9)	S68046 (10)	S83499 (11)	ST0713 (12)	SK7292 (13)	S21679 (14)
betaS1	0.024	0.186	0.198	0.090	0.118	-0.262	0.640***	0.106	0.539***	0.131	0.052	-0.047	0.099	0.298*
	(0.133)	(0.141)	(0.141)	(0.130)	(0.118)	(0.199)	(0.107)	(0.140)	(0.180)	(0.110)	(0.141)	(0.076)	(0.171)	(0.153)
betaS2	-0.550	-1.631	3.712***	-1.278	-1.030	-0.022	-2.414*	3.231*	0.031	-0.037	-0.096	0.295	0.022	-1.388
	(0.999)	(1.173)	(1.150)	(1.760)	(1.616)	(2.688)	(1.403)	(1.812)	(1.153)	(0.770)	(1.142)	(0.974)	(2.286)	(0.981)
betaB1	-1.286	1.952	-0.542	1.877	2.295	2.520	-0.928	-0.866	-0.562	-1.019	-0.723	-0.988	-3.068	-0.962
	(1.766)	(2.199)	(1.993)	(1.581)	(1.465)	(2.836)	(1.173)	(1.632)	(2.607)	(1.619)	(1.916)	(0.946)	(2.105)	(2.448)
betaB2	227.990	1,048.208***	-96.105	742.731***	707.465***	701.710	646.992***	392.391	-130.155	151.805	136.982	238.153	139.196	502.670
	(266.747)	(371.916)	(388.541)	(261.042)	(239.096)	(504.903)	(217.237)	(322.145)	(343.765)	(310.195)	(378.660)	(183.762)	(338.278)	(351.963)
alpha	0.001	-0.007	0.014	-0.003	-0.002	-0.004	0.004	-0.014	0.009	-0.007	-0.007	0.010*	-0.008	-0.016
	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.013)	(0.007)	(0.009)	(0.014)	(0.008)	(0.010)	(0.005)	(0.010)	(0.013)
Observations	61	60	58	50	46	36	53	43	69	57	57	38	47	68
R^2	0.040	0.222	0.175	0.170	0.203	0.144	0.495	0.152	0.133	0.054	0.011	0.080	0.086	0.139
Adjusted R^2	-0.028	0.166	0.113	0.096	0.125	0.034	0.452	0.063	0.079	-0.018	-0.065	-0.032	-0.001	0.084

	S22382 (15)	S20280 (16)	S62692 (17)	S23350 (18)	ST1892 (19)	SJ5323 (20)	S34823 (21)	SJ4786 (22)	ST5754 (23)	SN5118 (24)	S83527 (25)	SL8820 (26)	S23349 (27)	SR3434 (28)
betaS1	0.125	0.048	0.106	0.260**	0.037	0.589***	0.167	-0.040	0.132***	0.414***	0.573***	0.011	0.425***	-0.012
	(0.129)	(0.078)	(0.100)	(0.129)	(0.181)	(0.090)	(0.202)	(0.064)	(0.046)	(0.080)	(0.157)	(0.023)	(0.112)	(0.052)
betaS2	-1.014	-0.013	-0.054	0.269	1.783	-2.301*	0.705	0.250	-0.532	-0.652	2.251*	1.210***	1.204	1.230*
	(0.831)	(0.504)	(0.732)	(1.035)	(2.303)	(1.215)	(1.662)	(0.874)	(0.606)	(1.084)	(1.263)	(0.307)	(0.906)	(0.698)
betaB1	-1.781	-1.183	-0.908	-1.531	-1.682	-2.903**	0.021	-0.008	0.634	-0.033	1.589	-0.384	0.116	0.372
	(2.180)	(1.135)	(1.511)	(1.961)	(2.283)	(1.112)	(2.965)	(0.788)	(0.735)	(0.978)	(2.190)	(0.274)	(1.731)	(0.622)
betaB2	558.627*	19.131	102.914	402.951	762.311*	531.283**	-216.467	34.047	157.836	-18.162	-185.882	52.239	267.220	72.187
	(304.059)	(150.102)	(260.827)	(277.746)	(438.446)	(216.453)	(577.030)	(130.227)	(154.440)	(185.549)	(428.208)	(52.710)	(285.773)	(112.624)
alpha	-0.019*	0.001	-0.010	-0.017*	-0.015	0.009	-0.004	0.0001	-0.002	0.002	-0.007	0.001	0.0004	-0.003
	(0.011)	(0.006)	(0.007)	(0.009)	(0.011)	(0.006)	(0.014)	(0.004)	(0.003)	(0.005)	(0.011)	(0.001)	(0.008)	(0.004)
Observations	68	72	63	66	39	51	58	46	36	42	55	45	66	43
R^2	0.131	0.025	0.046	0.173	0.109	0.590	0.017	0.012	0.227	0.427	0.224	0.332	0.235	0.090
Adjusted R^2	0.076	-0.033	-0.020	0.118	0.004	0.554	-0.057	-0.085	0.127	0.365	0.162	0.265	0.185	-0.005

Note: *p<0.1; **p<0.05; ***p<0.01

Henriksson-Merton Model Regression Results Part II

Dependent variable: R - Rf

	SS9048 (1)	SM1268 (2)	S39727 (3)	S83243 (4)	SL7844 (5)	S67536 (6)	SK1674 (7)	S28300 (8)	S37095 (9)	SD0499 (10)	S28266 (11)	S26387 (12)	SH8698 (13)
betaS1	0.025	-0.523**	0.412***	0.005	0.089	0.014*	0.013	0.117	0.552***	0.515***	0.536***	0.558***	0.500***
	(0.033)	(0.244)	(0.123)	(0.007)	(0.058)	(0.008)	(0.051)	(0.089)	(0.129)	(0.096)	(0.073)	(0.106)	(0.129)
betaS2	0.132	5.737*	0.726	-0.019	0.165	-0.103	0.449	0.521	-0.497	1.058	-1.406**	-0.551	-1.280
	(0.419)	(3.335)	(1.710)	(0.057)	(0.784)	(0.105)	(0.688)	(0.757)	(0.957)	(0.771)	(0.580)	(0.855)	(1.717)
betaB1	-0.443	-3.570	2.150	-0.260**	-1.166	-0.224**	0.494	1.134	1.560	0.169	-0.016	0.314	-1.563
	(0.418)	(2.978)	(1.468)	(0.101)	(0.701)	(0.098)	(0.608)	(1.430)	(1.926)	(1.341)	(1.001)	(1.483)	(1.504)
betaB2	-1.859	-249.379	756.358***	27.642	-49.211	27.635*	137.720	4.671	589.804*	16.847	157.776	312.895	326.817
	(79.263)	(567.880)	(256.860)	(16.929)	(133.338)	(16.201)	(98.190)	(280.983)	(350.558)	(257.928)	(171.144)	(286.079)	(250.297)
alpha	0.001	-0.009	-0.016*	-0.004***	0.004	-0.004***	-0.006*	-0.007	0.004	0.001	0.004	0.009	-0.001
	(0.002)	(0.016)	(0.008)	(0.0005)	(0.004)	(0.0005)	(0.003)	(0.007)	(0.010)	(0.007)	(0.005)	(0.008)	(0.008)
Observations	37	48	46	56	47	53	48	64	60	55	55	55	50
R^2	0.066	0.143	0.362	0.244	0.125	0.278	0.054	0.037	0.387	0.370	0.634	0.415	0.326
Adjusted R^2	-0.051	0.063	0.300	0.185	0.042	0.218	-0.034	-0.028	0.342	0.319	0.604	0.369	0.266

	S22669 (14)	S69730 (15)	S84129 (16)	ST1882 (17)	SE4488 (18)	S29646 (19)	SE4942 (20)	S27557 (21)	SE1688 (22)	S26379 (23)	S26425 (24)	S85603 (25)	ST9165 (26)
betaS1	0.506***	0.463***	0.609***	-0.309	0.747***	0.783***	0.800***	0.599***	0.159	0.687***	0.482***	0.440***	0.780
	(0.096)	(0.128)	(0.147)	(0.248)	(0.141)	(0.114)	(0.127)	(0.120)	(0.174)	(0.139)	(0.113)	(0.130)	(0.700)
betaS2	-0.048	1.479	1.968	2.606	0.719	-2.923***	-3.029*	-0.698	0.030	1.480	1.318	1.053	5.249
	(0.781)	(1.027)	(1.192)	(2.935)	(1.136)	(0.949)	(1.703)	(0.996)	(1.399)	(0.963)	(0.901)	(1.038)	(9.000)
betaB1	-1.219	1.450	1.710	5.898	2.089	1.373	1.668	0.948	0.437	1.312	-0.910	-0.263	8.304
	(1.357)	(1.813)	(2.183)	(3.934)	(2.009)	(1.566)	(1.420)	(1.644)	(2.407)	(1.908)	(1.550)	(1.790)	(10.084)
betaB2	-84.492	736.518**	103.825	414.890	-362.324	523.330*	85.284	338.927	-67.509	604.522	355.711	291.728	3,964.531*
	(233.208)	(351.704)	(406.763)	(795.984)	(387.685)	(287.775)	(231.858)	(301.971)	(411.589)	(366.902)	(299.817)	(351.821)	(1,954.101)
alpha	0.0002	0.0004	0.005	-0.025	0.020*	0.002	0.014*	0.005	0.019	-0.007	-0.007	0.003	-0.086*
	(0.007)	(0.009)	(0.010)	(0.019)	(0.010)	(0.008)	(0.008)	(0.009)	(0.012)	(0.010)	(0.008)	(0.009)	(0.047)
Observations	55	53	54	23	54	55	53	55	54	55	55	52	36
R^2	0.394	0.255	0.265	0.235	0.392	0.629	0.462	0.399	0.019	0.376	0.289	0.202	0.144
Adjusted R^2	0.346	0.193	0.205	0.065	0.342	0.599	0.417	0.351	-0.061	0.326	0.232	0.134	0.033

Note: *p<0.1; **p<0.05; ***p<0.01

PART B

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Master of Science in Finance

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Abstract

China is one of the most popular emerging markets, and the fund management industry has experienced rapid growth during the past decade, especially private funds. Although the regulatory regimes were underdeveloped at first, the government realized that it was important to improve the related regulation to address this problem. On June 1, 2013, the Chinese new fund law was formally implemented, and hedge funds obtained clearly legal status for the first time, which started the rapid development of the hedge fund industry.

This paper investigates the performance of hedge funds in China, which was issued after the new fund law, in China. The sample is 54 picked hedge funds over the period 2014-2020. The performance is evaluated through three models: Fama-French's three-factor model, Carhart's four-factor model, and a modified eight-factor model. According to the regression results, these three models do better than models in my previous research (CAPM, Henriksson-Merton model, and Treynor-Mazuy model). Then, we conduct the contingency table and the recursive portfolio approach based on three models to investigate the performance persistence of hedge funds in China. According to the results of the contingency table, all models show that our sample shows one-year persistence between 2016 and 2019, including past winners and losers. However, through the recursive portfolio approach, there is no enough evidence found.

Then I compare the results of this paper with the results of the Bocconi paper and summarize the whole conclusions of my study on the performance of hedge funds in China.

Contents

Content of Table

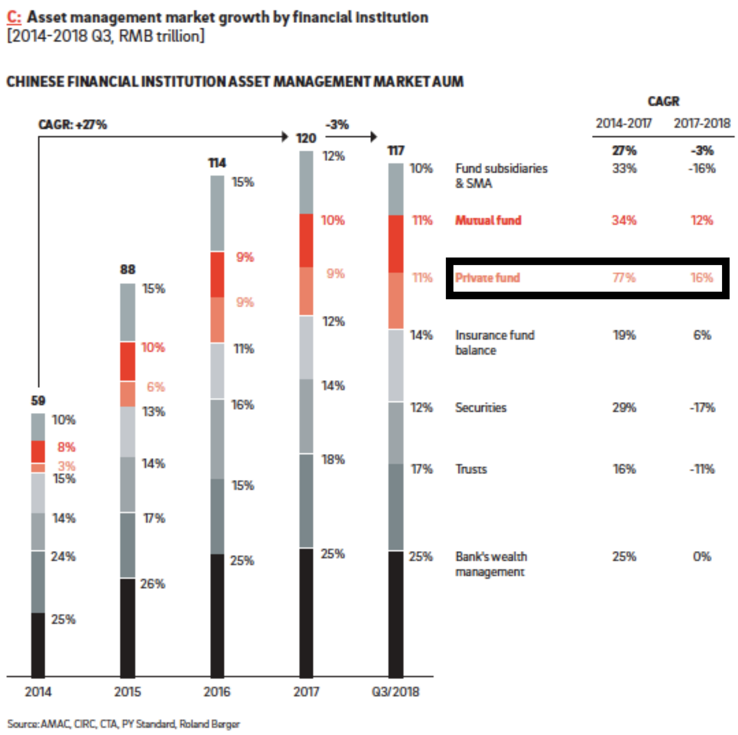
1. Introduction

The history and development of private fund in China has been discussed a lot in the first part of the Bocconi paper. Here we mainly discuss the differences between hedge funds in the US and privately offered securities investment funds in China, which is not discussed in the Bocconi paper. This comparison could give us a more detailed view of hedge funds in China, which is special because of the participation of the government in the market. Then we discuss the motivation of our study in order to show a full picture of the whole study. An outline of this paper is presented at the end of this part.

1.1 Background

China is one of the most popular emerging markets, and the fund management industry has experienced rapid growth. Based on the data collected by Roland Berger, the CAGR of the total Chinese asset management market is 17% from 2004 to 2018, much higher than that of the European or Japanese market. Additionally, the private fund sector has the highest CAGR among all Chinese financial institutions, although it only has a very short history in China.

Graph 1: Chinese Asset Management Market Growth by Financial Institution (Roland Berger)



In China, because of regulations and other related limitations, the private fund is included in the private equity. There are three categories under the private equity: privately offered securities investment funds, private equity, and venture capital. This paper will focus on the first category, privately offered securities investment funds operated in the mainland Chinese, which is quite similar to the hedge fund in the Western. Yet privately offered securities investment funds in China are not totally the same as hedge funds in developed countries. The main differences are as follows: firstly, investments of hedge funds in developed countries are allocated in many countries and areas, but privately offered securities investment funds in China mainly invest in China, which can also be visualized in the following regression results. Secondly, the strategies of those two funds may be different. There are more regulations in China. For instance, the Chinese new asset management rules in 2018 regulate the leverage ratio of privately offered securities investment funds, which should be lower than 200% (leverage ratio = the total value of holding assets/ the value of net assets). However, there are no maximum leverage constraints for hedge funds in the US. According to the data reported by the Federal Reserve Board, the median gross leverage of hedge funds in the US is higher than 2, and the average level is higher than 8. In addition, the permitted level of a short position is different. In the US, many hedge funds are taking the short-only strategy. However, in China, although there are no specific regulations prohibiting the short-selling strategy, some laws and regulators strictly limit short positions because the government is afraid that short-selling would trigger a collapse in the Chinese market. Therefore, there are nearly no privately offered securities investment funds in China taking the short-only strategy. Most privately offered securities investment funds in China just take equity long strategy, which is similar to mutual funds in China. Moreover, the new asset management rules also set the limitation of the long position, which said that for every hedge fund the direct long position of one company should not more than 30% of the outstanding shares of this company.

However, there are still some similarities between privately offered funds in these two countries. Firstly, both have strict requirements for qualified investors, like the total asset amount and the net financial asset amount of investors. Moreover, there are minimum investment requirements for different kinds of investors. Most importantly, different from the mutual funds, privately offered funds in both countries charge investors a higher management fee and performance fee, both mainly following 2 and 20 fee structure. In this paper, I collected the data of privately offered securities investment funds with exposure to the hedging strategy[8], which are called hedge funds in this paper.

[8] Hedge strategy means active taking an opposite position in a related asset in order to reduce exposures to risks.

With the development of asset management, the hedge fund has become a very important investment choice in China. There are some superstars among hedge funds in China, whose AuM even can be close to that of top mutual funds. At the same time, their managers have very excellent performance records, and many investors choose to invest a bunch of money in these funds regardless of the high management fee because of managers' reputation. Therefore, it is really meaningful to investigate the skills of hedge fund managers and whether their performance can persist for some periods.

1.2 Motivation

In the Bocconi paper, we have firstly measured the performance of samples using Sharpe ratio, Probability Sharpe ratio, Jensen's alpha, EMPPM (excess manipulation-proof performance measure). Then through the Henriksson-Merton model and the Treynor-Mazuy model, we try to examine the market-timing ability and the stock-picking skill of hedge fund managers, which are two essential skills to obtain excess returns. Lastly, in the persistence part, we firstly use Jensen's alpha, EMPPM, CSI 300 index, and the mean and median returns of our samples as benchmarks to conduct the contingency table. Then, through the recursive portfolio approach, we regress the monthly (quarterly) return of each portfolio on market excess return. In general, the whole research in the Bocconi paper is mainly based on the basic CAPM model with the stock market factor and the bond market factor. According to the results of models used in the Bocconi paper, our samples all have significantly positive exposure to the stock market. Hence, I would like to evaluate the performance of our samples using some models that could help capture the excess returns of investment, especially the premium in the stock market. For example, Fama-French's three-factor model and Carhart's four-factor model both provide some possible factors to explain the premium, like size factor and value factor.
Therefore, in this paper, I plan to use some more advanced models to investigate the performance of our sample, then mainly focus on the performance persistence of hedge funds in China. Through these advanced models, we explore some factors that could provide explanations of returns, which can help us find out more about hedge funds in China and their investment strategies. Through this study, I hope that this could provide some information to the investors of hedge funds and also help me to consider how to plan my own investment in the future.

1.3 Outlines

This paper consists of five sections. The first part mainly introduces the differences between Chinese privately offered securities investment funds and hedge funds in the US and defines the hedge fund in this paper. Then, the second part is the literature review, mainly summarizing the theoretical research of fund performance persistence. Based on the classical theories, we will decide the suitable methodologies used in this paper in the third part: Fama-French's three-factor model, Carhart's four-factor model, and a modified eight-factor model will be used to measure the performance of hedge funds, then the contingency table and the recursive portfolio approach will be used to analyze the short-term persistence in Chinese hedge funds. Additionally, the third part also includes information about the data used in this paper. Then, in the fourth part, we will examine the empirical data of the Chinese hedge fund using the picked methodologies. Finally, the conclusion reviews the research objectives and methodological considerations and presents the main results and findings of the whole project. Additionally, we will also point out some main weaknesses in our research.

2 Literature Review

We have reviewed the theoretical research of fund performance evaluation and manager's skill in the Bocconi paper. In this part, we mainly review the theoretical research of performance persistence. At the same time, we also gather some related domestic literature.
Performance persistence is often addressed in two ways: the first is linked to the notion of market efficiency and the second is related to whether the winners are always the same. Hedge funds in China have a much shorter history than that in the Western, so there are few studies focusing on the performance persistence of hedge funds in China. However, some studies focus on the performance persistence of hedge funds in the Western. The following discussion would present the findings of existing researches.

2.1 Long-term Persistence

A few researches find long-term persistence. Edwards and Caglayan (2001) use the six-factor Jensen's alpha to examine the persistence of hedge funds during the period of January 1990 through August 1998. They find evidence of performance persistence over 1-year and 2-year horizons.

Kosowski et al. (2007) is the first one to use Bayesian methods and bootstrap to investigate the performance persistence of hedge funds. They find that there is one-year persistence existing for abnormal returns of hedge funds, and the abnormal returns of hedge funds cannot be attributed to luck.
Ammann et al (2010) get the conclusion that long-term persistence of hedge funds exists. They investigate the performance persistence of hedge funds over time horizons between 6 months and 36 months based on the sample for the period from 1994 to 2008. Instead of using standard regression, they use a panel probit regression approach and find performance persistence over a 3-year horizon.
Jagannathan et al. (2010) create a statistical model to evaluate the performance of hedge funds relative to a suitably constructed peer group. They find long-term persistence over a 3-year horizon, especially for top hedge funds.

2.2 Short-term Persistence

However, there are more studies only finding short-term persistence, compared with the number of studies finding long-term persistence. Agarwal and Naik (2000) use the multi-period framework to investigate the performance persistence of hedge funds from January 1982 to December 1998. The result indicates that performance persistence among hedge fund managers is primarily short term (quarterly) in nature.
This finding is also supported by the study of Harry and Brorsen (2004). They use three methods: running the autoregression of returns, conducting style analysis, and using the Spearman rank correlation test. Their finding is short-term persistence over 3 to 4 months.
Koh, Koh and Teo (2003) investigate the hedge funds mainly investing Asia through the contingency table and the chi-square test at the two-period level and Kolmogorov-Smirnov test at the multi-period level. The key finding is that returns of Asian hedge funds strongly persist at monthly to quarterly horizon, but there is no evidence that persistence exists for a period longer than one quarter.
Manser and Schmid (2009) examine the persistence of risk-adjusted returns for equity long/short hedge funds using the portfolio approach and find that the persistence does not last longer than 1 year except for the worse performers.
María, Nicolas, and Frank (2016) also use the recursive portfolio method to investigate the performance persistence of hedge funds in the US. When they use different funds to form portfolios, the Sharpe ratio, alpha, information ratio, and EMPPM are used as benchmarks separately. They find that no matter benchmarks, top quintile funds are able to deliver long-term persistent

superior performance out of sample. But if using EMPPM to form portfolios, persistence is no longer than 12 months.

Rudin (2018) examines the persistence of two kinds of hedge funds: equity long/short and macro/managed futures through a novel fee-aware portfolio construction frame. He finds that there is a half-year period persistence existing.

In China, Wu Wei (2016) adopts both contingency tables and the portfolio approach to examine the performance persistence of private securities investment funds in China. He finds that persistence exists over a horizon shorter than one-year.

2.3 No Persistence

There are very few studies showing no persistence. The reason may be that if researchers find that no persistence exists, they may think it is meaningless to discuss this topic.

Capocci and Hübner (2004) use an extension of Carhart's (1997) model combined with the Fama and French (1998) and Agarwal and Naik (2002) models. They find that there is no persistence for extreme performers (the best and worst performers), but the performance of the middle performers shows persistence.

Table 1: Summary of Previous Researches (Europe and US)

The following table summarizes the results of previous researches on the performance persistence of hedge funds. The first column shows the information of authors, and the second column presents the period of data used in the researches. The third column simply summarizes the methods used in the researches. The last column shows the results of different research.

study	data period	methods	results
Grinblatt and Titman (1992)	January 1990 to December 2002	Bayesian methods and bootstrap	one-year persistence
Agarwal and Naik (2000)	January 1982 to December 1998	multi-period	short-term persistence
Edwards and Caglayan(2001)	January 1990 to August 1998	six-factor Jensen's alpha	long-term persistence over a 1-year and 2-year horizon
Harry and Brorsen (2004)	1977-1998	Autoregression style analysis the Spearman rank correlation test	short-term persistence over 3 to 4 months
Capocci and Hübner (2004)	January 1984 to June 2000.	an extension of Carhart's (1997) model combined with the Fama and French (1998) and Agarwal and Naik (2002) models	no persistence for extreme performers
Manser and Schmid (2009)	1994-2005	portfolio approach	short-term persistence for equity long/short hedge funds
Ammann et al (2010)	1994-2008	panel probit regression approach	long-term persistence over a 3-year horizon

Jagannathan et al. (2010)	May 1996 to April 2005	statistical model	long-term persistence over a 3-year horizon, especially top hedge funds
María, Nicolas, and Frank (2016)	January 31, 2001 to December 31, 2012	portfolio approach	persistence of no longer than 12 months (EMPPM)
Rudin (2018)		a novel fee-aware portfolio construction frame	half-year period persistence for equity long/short and macro/managed futures

3 Methodology and Data

According to the review of existing studies of persistence, there are mainly the following methods: two-period or multi-period, non-parametric method or parametric method. The following part will first show methods of performance measure used in this paper and choices of persistence test based on the characteristic of our sample data, which is the same as the methods used in the Bocconi paper. Then we talk about how we collect, clean, and construct the input data prepared for the study, mainly focusing on the collecting of new factors. Lastly, I would express my ex-ante expectations related to this study based on the previous study in the Bocconi paper and the understanding of the Chinese market.

3.1 Methodology

There are three models to evaluate the performance of hedge funds, and two approaches to test the short-term performance persistence in this essay. These are introduced and discussed respectively in the following parts below.

3.1.1 Return Rate

Here, we use the following formula to calculate the monthly return rate, which is the same as the calculation in the Bocconi paper:

$$Monthly\ Return_m = \ln\left(\frac{NAV_{t,m} + Divident}{NAV_{t-1,m}}\right)$$

Then we need to transfer the monthly return into the manual return rate:

$$\begin{aligned} Manual\ Return_m &= (1 + Monthly\ Return_m) * (1 + Monthly\ Return_{m-1}) \\ &* (1 + Monthly\ Return_{m-2}) * \dots * (1 + Monthly\ Return_{m-11}) - 1 \end{aligned}$$

Moreover, we will take a rolling base to calculate the manual return rate.

3.1.2 Performance Measures

In the Bocconi paper, I used the Sharpe ratio, Jensen's alpha, manipulation-proof performance measure, Henriksson-Merton model and Treynor-Mazuy model to measure the performance of hedge funds, which are mainly following the CAPM model. Moreover, from the Bocconi paper, I find that most funds have significantly large exposure to the stock market. Therefore, it may be better to use some models capturing some premium in the stock market, like Fama-French's three-factor model and Carhart's four-actor model. Consequently, in this paper, I plan to use some more sophisticated models to evaluate the performance in order to explore more impacted factors of performance.

3.1.2.1 Fama-French's Three-factor Model

Based on Jensen's model, Fama and French (1993) identify three stock factors: RMRF, SMB, and HML. RMRF is the excess return on a value-weighted market portfolio. SMB (small minus big) presents the difference between the return of small-size stock portfolios and large-size stock portfolios returns with about the same weighted-average book-to-market equity in China. HML (high minus low) refers to the difference between the return of high book-to-market stocks and low book-to-market stocks in China. These two kinds of data can be collected directly from RESSET, which is shown in the data part. The formula is as follows:

$$r_{it} = \alpha_{iT} + \beta_{RMRF}RMRF_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_{it} \qquad (1)$$

When β_{RMRF} is positive, it reflects that this fund has positive exposure to the stock market. If β_{SMB} and β_{HML} are significantly positive, we may conclude that this fund puts more weight on small company stocks and value stocks. A significantly positive alpha in this formula implies that this fund gains abnormal returns taking the market risk, size risk and value risk into consideration.

3.1.2.2 Carhart's Four-factor Model

Hendricks, Patel, and Zeckhauser (1993) observe the light persistence in the performance of mutual funds, for both good managers and bad managers, which is mostly driven by the one-year momentum effect. Grinblatt, Titman, and Wermers (1995) find that funds following momentum strategies show better performance. Wermers (1996) suggests that momentum strategies can generate short-term persistence. Based on Fama and French's (1993) three-factor model (1), Carhart (1997) constructs a four-factor model (2), which incorporates the momentum factor.

$$r_{it} = \alpha_{iT} + \beta_{RMRF}RMRF_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \epsilon_{it} \qquad (2)$$

UMD is a portfolio that long past 12-month return winners and short past 12-month return losers, which can also be collected directly from RESSET. A significantly positive β_{UMD} reflects that funds take the strategy that long past winners and short past losers. Carhart (1997) concludes that the persistence of fund performance is related to the momentum effect. As a consequence, β_{UMD} could also be considered when we investigate performance persistence. A significantly positive alpha in this formula implies that this fund gains abnormal returns taking the market risk, size risk, value risk and momentum effect into consideration.

3.1.2.3 Modified Eight-factor Model

Fung and Hsieh (1997) argue that hedge fund follows highly dynamic strategies and generates option-like returns. They (2001) use lookback straddles to model the payoff of actively managed funds that can perfectly predict price trends, which is called the "trend-following" strategy. Furthermore, they (2004) put the famous seven-factor model by combining four asset-based factors with three primitive trend-following strategy factors, which is commonly used to evaluate the performance of hedge funds. Then, they add the MSCI emerging market index as the eighth factor. The whole eight-factor model is as follows:

$$r_{it} = \alpha_{iT} + \beta_1 S\&P500 + \beta_2 SMB_t + \beta_3 10Y + \beta_4 CredSpr + \beta_5 BdOpt + \beta_6 FXOpt + \beta_7 ComOpt + \beta_8 MSCI\ Emerging\ Market\ Index + \epsilon_{it}$$

SMB is the return of small cap index minus that of large cap index;
$10Y$ is the change in the US Federal Reserve 10-year constant-maturity yield;
$CredSpr$ is the change in the difference between Baa yield and the Federal Reserve 10-year constant-maturity yield;
$BdOpt$, $FXOpt$, and $ComOpt$ are returns of a portfolio of lookback straddles on bond futures, currency futures, and commodity futures.
$MSCI\ Emerging\ Market\ Index$ is the return of this index.
However, considering the real future market in China, we decide not to use these primitive trend-following strategy factors. Additionally, China is one of the emerging countries, so it is not suitable to use the MSCI emerging market index. Therefore, we modified the 8-factor model to evaluate the performance of hedge funds in China.
In China, there are mainly four risks: market risk, operation risk, credit risk, and policy risk. We try to find out some factors that can present these risks. In addition, the regulation establishes the investment rule of hedge funds in China that hedge funds can only invest in stocks, futures, bonds, options, and so on. Therefore, we plan to add some factors, which could reflect the exposure of funds to these assets. The modified model is as follows:

$$r_{it} = \alpha_{iT} + \beta_1 CSI300 + \beta_2 SMB_t + \beta_3 10Y + \beta_4 CredSpr + \beta_5 HML + \beta_6 MOM + \beta_7 Future\ index + \beta_8 MSCI\ World\ Index + \epsilon_{it} \quad (3)$$

$10Y$: the change in the China national 10-year constant maturity yield.
$CredSpr$: the change in the difference yield between the corporate bond and China national 10-year bond.
$Future\ index$: the change in the Chinese future market index.

3.1.3 Persistence Test

In this part, we use a non-parametric method, the contingency table developed by Brown and Goetzman (1995), and the recursive portfolio approach proposed by Hendricks, Patel, and Zeckhauser (1993). This part is same with the content in the Bocconi paper, but because these two methods play an important role in this paper, therefore I repeat the main process of how to conduct these two methods here.

3.1.4.1 Contingency Table

Contingency table categories fund as winners or losers based on a predetermined standard. There are mainly two standards used: firstly, the stock market index can be used as a benchmark to distinguish winners and losers, and this is called the absolute benchmark; secondly, a relative benchmark which is based on the picked funds' data.

Kahn and Rudd (1995) choose relative benchmarks to distinguish the winner and loser. If a fund ranks at the top 50% of the list, it would be categorized as a winner, otherwise, it would be marked as a loser. The test consists of two periods, and each fund would be categorized independently in these two periods. If the fund is a winner in the first period and a loser in the second period, it would be marked as winner-loser (WL). Only WW and LL are seen as a persistent performance. If no persistence, the number of these four categories, which is WW, WL, LW, and LL, should be the same in different periods. And if there is performance persistence, it is reasonable to expect the total number of winner-winner and loser-loser should be statistically significantly higher than that of winner-loser and loser-winner. Therefore, the null hypothesis is there is no evidence of persistence, and the alternative hypothesis is that evidence for persistence is found. They use the Chi-square statistic to test this hypothesis. The formula is:

$$\chi = \sum \frac{(Q_i - E_i)^2}{E_i}$$

Where

Q_i is the number of funds observed in each category

E_i is the number of funds expected to be observed in each category

In their example, E_i should be half of the total number of funds, and test statistics follow Chi-square distribution with a degree of freedom of one. Brown and Goetzman (1995) also use this method but they choose different test statistics, which is called the Cross-Product ratio. The formula of the Cross-Product ratio is:

$$\text{Cross} - \text{Product Ratio} = \frac{WW * LL}{WL * LW}$$

They think that if the Cross-Product ratio is equal to one, then there is no persistence. A Cross-Product ratio is bigger than one and statistically significant, which means that persistence exists. However, if the statistically significant ratio is lower than one, negative persistence may exist, which means that the past performance predicts the opposite of future performance. Their null hypothesis is cross-product ratio is equal to one, and the alternative hypothesis is the cross-product ratio is bigger or smaller than one. They use z-statistic as their test statistic to check the significance of the cross-product ratio. The z-statistic is calculated as taking a log of the cross-product ratio and dividing it by its standard deviation. The detailed formula is:

$$\sigma_{\ln(cross-product\ ratio)} = \sqrt{\frac{1}{WW}+\frac{1}{WL}+\frac{1}{LW}+\frac{1}{LL}}$$

$$Z_{statistic} = \frac{\ln\left(\frac{WW*LL}{WL*LW}\right)}{\sqrt{\frac{1}{WW}+\frac{1}{WL}+\frac{1}{LW}+\frac{1}{LL}}}$$

In this essay, we will replicate the method of Bronn and Goetzman (1995) using the contingency table and the cross-product ratio to check the persistence. The benchmarks that we choose include the alphas of Fama-French's three-factor model, the alphas of Carhart's four-factor model and the alphas of the modified eight-factor model.

3.1.4.2 Economic Predictability of Past Performance

Another quantitative method to test whether the performance of hedge funds persists is to investigate the economic predictability of their past performance. Additionally, economic predictability is significant when an investor can earn abnormal returns by exploiting past performance.

In this essay, we will use the methodology proposed by Hendricks, Patel, and Zeckhauser (1993), but differ from them by using a shorter ranking period. Firstly, we rank the funds at the start of each month from August 2017 to June 2020 based on a lagged one-month (one-quarter) performance measure, because most sample funds have return information during this period except ST1882. Then we divide those funds into six portfolios. The first-sextile portfolio is composed of the best performers in the recent evaluation period, the second-sextile portfolio is composed of the next-poorer performers, and so on. The total number of 53 funds is used to form portfolios: therefore, there are 9 funds in portfolio 1-5 respectively and 8 funds in portfolio 6. Portfolios are equal-weighted and rebalanced monthly (quarterly) to incorporate the deviation of weights. In this case, portfolio 1 should have funds with top sextile lagged one-month (one-quarter) performance in each month (quarter).

The economic predictability of past performance is evaluated by using the previous three models, and we regress the monthly return of each portfolio on

RMRF, SMB, HML, MOM, and other assets index. A positive and statistically significant alpha of the difference return between top sextile and bottom sextile portfolio indicates the existence of positive performance persistence. In other words, buying past winners and selling past losers could create abnormal returns.

3.2 Data

In this part, we present our data source, show the data cleaning process, and elaborate the description of data. The data of hedge funds are the same as that in the Bocconi paper, but the data of factors used in the Fama-French three-factor model, Carhart's four-factor model and the modified eight-factor model are the new things.

3.2.1 Data Source

We mainly collect our funds' data from the Suntime Private Funds Database. Suntime, as the market leader in China's financial information service industry, provides accurate and real-time information for financial professionals. Its private fund database offers the most comprehensive, complete data on Chinese private funds.
Firstly, since the Chinese new fund law was formally implemented on June 1, 2013, hedge funds obtained the clear legal status for the first time. Therefore, we pick the funds which were issued after June 1, 2013.
When we choose the data, we set some limitations: private funds should be hedge funds, and the net asset value (NAV) information should be provided over 70% during its life. Besides, because we need enough NAV data to run the regression, we will select the funds with historical returns for more than three years, which means that the funds issued before 22nd July 2017.
Additionally, we collect data related to Carhart's four-factor, bond and future from RESSET. RESSET database is the most comprehensive and commonly cited database for financial research on the Chinese market. As for RMRF, SMB, HML and MOM factors, we choose monthly value-weighted data from RESSET. As reported in the RESSET, RMRF is calculated as the capitalization-weighted return of all stocks listed in the Chinese equity market, including Shanghai and Shenzhen, minus the three-month Shanghai interbank rate. SMB is the difference between the monthly returns of the portfolio from the smallest 30% of the stocks and the largest 30%, including both Shanghai and Shenzhen. HML is the difference between the monthly return of the portfolio of stocks at the bottom 30% book-to-market ratio and

that of stocks with the highest 30% book-to-market ratio. The momentum factor is the difference between the 11-month return of equally-weighted portfolios of the top 30% stocks and the bottom 30% stocks.
Then, we use the CSI 10-year bond index (930916) to represent the 10Y bond factor and calculate the difference between the corporate bond index (000013) and the CSI 10-year bond index, which would be used as $CredSpr$. Future index data is also obtained from RESSET. MSCI world index data is downloaded from the MSCI official website. Then, we get the latest SHIBOR rate from the Shanghai Interbank Offered Rate website[9], which will be used as the risk-free rate.

3.2.2 Data Cleaning

We collect monthly NAV data in order to get the monthly return rate. However, because there is no strict disclosure rule for hedge funds, some funds did not report the NAV regularly. Therefore, there are only 54 funds entering our sample.
Among 54 funds, six funds did not regularly report their NAV during the beginning period. Therefore, we will ignore that long period and choose the period between the second reporting date and the first reporting date as the first period.
There are some funds not reporting NAV for a long period during the period that we choose. In order to run the regression of monthly return, we will divide the change of NAV equally during this period and then calculate the monthly return, which may cause some bias.

3.2.3 Data Description

Based on the set limitations, there are 54 funds entering our research. The detailed information of our samples refers to 3.2.3 in the Bocconi paper. Among these picked funds, the majority of funds (25 out of 54) take equity long bias as their strategy, which is similar with the discussion of the first part of this paper (Chinese hedge funds, as one kind of privately offered securities investment funds, are commonly taking long position and limited in the short position).

[9] http://www.shibor.org/shibor/web/html/index_e.html

3.3 Hypothesis

The main research questions in this paper are as follows: Do the advanced three models do better than CAPM? Does the performance of hedge funds in China persist? Before conducting the empirical research, I would prefer to show some ex-ante expectations based on my own understanding of the Chinese market.

Firstly, I believe that these three advanced models could do better than CAPM, especially Carhart's four-factor model. Because, as discussed in the first part, the main characteristics of hedge funds in China is taking the long position in the equity market and limited the short position, hedge funds in China usually have large exposure to the Chinese stock market. The key target of hedge funds is earning abnormal returns, and many studies find that all SMB, HML, and MOM have average premiums over a long period in China. Therefore, I suppose that those three factors and the market premium factor could do better at explaining the performance than CAPM did. As for the modified model, adding all the investable assets into the formula may not be useful, because most hedge funds do not have significant long-term exposures to some assets, like commodities.

Then about the persistence of performance in China, based on the previous study in the Bocconi paper, it is reasonable to suppose that there is some persistence existing. Moreover, when collecting the return data of hedge funds, I found that only a very small part of Chinese hedge funds report the performance regularly, most of which are mainly following the regulation[10]. During my sample period, there are no funds disappearing in the sample, which may imply that the performances of all samples are not such bad.

4. Empirical Results

Empirical results are presented in this section. The following parts report the results of different measurements, models, and approaches, and provide some detailed analysis respectively.

4.1 Performance Measure

According to the previous study in the Bocconi paper, there are over half of my sample showing excess returns using EMPPM or Jensen's alphas. Here,

[10] the Measures for the Administration of the Disclosure of Information on Privately Offered Investment Funds regulate that privately offered securities investment funds should regularly report their return data to their investors if the total AuM of this fund is over 50 million RMB.

we can check whether the result is the same using these three advanced models.

4.1.1 Fama-French's Three-factor Model

We first run the regression based on Fama-French's three-factor model. The following table is the summary of the regression result, and the detailed regression results are presented in the Appendix.

Table 2: Summary of Fama-French's Three-factor Model

The table reports the regression result using Fama-French's three-factor model. The second column N presents the number of observations. The rows from the third to the fifth are the beta estimations of RMRF, SMB, and HML factors separately. The columns from the third to the sixth are the mean, minimum, maximum and standard deviation of different coefficients, which can provide a whole view of the results. The seventh column N+ presents the number of positive results, and the eighth column N+* presents the number of significant positive results at the 5% level. Then the following two columns show the number of negative results and significant negative results separately.

	N	mean	min	max	std.dev	N+	N+*	N-	N-*
alpha	54	0.0030	-0.014	0.021	0.0080	37	11	17	2
betaRmrf	54	0.3179	-0.412	1.261	0.3896	44	25	10	0
betaSmb	54	-0.0401	-0.645	1.222	0.3849	23	2	31	11
betaHml	54	0.1976	-0.746	3.415	0.6247	33	12	21	1
Adjusted R2	54	0.1912	-0.083	0.696	0.2156				

Note: The column N+(N-) reports the number of funds with positive (negative) estimates. The column N+* (N-*) reports the number of funds with parameter estimates that are positive (negative) and significant at the 5% level.

The alpha in the Fama-French three-factor model reflects the abnormal return after taking the market risk, size effect and value effect into consideration. There are 37 positive Fama-French's alphas among our sample, accounting for 68.52%, and 11 of them are significant at the 5% level. Comparing with the results of Jensen's alpha, there are 3 more positive alphas than Jensen's alpha.

Additionally, most funds have positive exposures to the market index, and nearly half of the samples have positive and significant β_{Rmrf}. Among our samples, nearly half of them take the equity long strategy. Therefore, we can conclude that most hedge funds have positive exposures to the stock market. As for the size effect, the average level is smaller than zero, and over half of the samples have negative exposure to the size effect. This may imply that many managers do not necessarily put more weights on small size stocks. However, as for the value factor, 61% of our samples have positive exposure to the HML factor, which implies positive weights on the value stocks. The maximum significant exposure is 3.415.

4.1.2 Carhart's Four-factor Model

Table 3: Summary of Carhart's Four-factor Model

The table reports the regression result using Carhart's four-factor model. The second column N presents the number of observations. The rows from the third to the sixth are the beta estimations of RMRF, SMB, HML and MOM factors separately. The columns from the third to the sixth are the mean, minimum, maximum and standard deviations of different variables. The seventh column N+ presents the number of positive results, and the eighth column N+* presents the number of significant positive results at the 5% level. Then the following two columns show the number of negative results and significant negative results separately.

	N	mean	min	max	std.dev	N+	N+*	N-	N-*
alpha	54	0.0026	-0.0170	0.0200	0.0086	36	10	18	3
betaRmrf	54	0.3107	-0.4170	1.1850	0.4021	44	22	10	0
betaSmb	54	0.0108	-0.7690	2.5540	0.5592	27	2	27	9
betaHml	54	0.2031	-0.7400	3.4020	0.6252	34	12	20	1
betaMOM	54	0.0763	-0.5430	1.3210	0.3251	32	8	22	2
Adjusted R2	54	0.2063	-0.1050	0.6900	0.2165				

Note: The column N+(N-) reports the number of funds with positive (negative) estimates. The column N+* (N-*) reports the number of funds with parameter estimates that are positive (negative) and significant at the 5% level.

The above table summarizes the regression result of Carhart's four-factor model. The average adjusted R^2 has been improved by 1% compared with that of Fama-French's model. The results of alpha and β_{Rmrf} are similar to those of Fama-French's model. 67% of our samples have positive alphas, but only 19% of them are significant at the 5% level. Besides, nearly half of our samples have positive and significant exposure to the market index.

After adding the momentum factor, exposure to the size effect has changed. The average of β_{Smb} has been positive, and the numbers of funds with positive or negative exposure to the size effect are equal. However, there are only 2 positive significant betas, but 9 negative significant betas. Hence, we may conclude that managers of hedge fund do not have a preference for small size stocks.

As for the value factor and momentum factor, over half of our samples have positive exposure to these two factors. Among these positive betas, there are 12 significant β_{Hml} and 8 significant β_{MOM} at the 5% level separately. There are over 59% of our samples with positive coefficients of MOM. Moreover, most of the funds with significantly positive factor loading on the momentum factor have alphas nearly close to zero. We may conclude that the momentum factor could partly explain abnormal returns.

4.1.3 Modified Eight-factor Model

Then we use the modified eight-factor model to evaluate the performance of our samples. The following table is a summary of the regression results.

Table 4: Summary of Modified Eight-factor Model

The table reports the regression result using the modified eight-factor model. The second column N presents the number of observations. The rows from the third to the tenth are the beta estimations of different variables. The columns from the third to the sixth are the mean, minimum, maximum and standard deviations of different variables. The seventh column N+ presents the number of positive results, and the eighth column N+* presents the number of significant positive results at the 5% level. Then the following two columns show the number of negative results and significant negative results separately.

	N	mean	min	max	std.dev	N+	N+*	N-	N-*
alpha	54	0.0034	-0.0140	0.0190	0.0080	36	3	18	2
betaRmrf	54	0.3043	-0.4100	1.2480	0.3395	46	22	8	0
betaSmb	54	0.0251	-0.7810	3.4380	0.6580	24	4	30	8
betaHml	54	0.1537	-0.7660	3.1270	0.6026	33	11	21	3
betaMOM	54	0.0752	-0.5760	0.8070	0.3215	32	8	22	2
betaMSCI	54	-0.0707	-0.9140	0.6220	0.3266	27	3	27	7
beta10Y	54	-0.3843	-1.8250	0.9900	0.6256	12	0	42	3
betaCredSpr	54	0.6134	-14.2340	7.4450	3.7787	32	4	22	0
betaFutures	54	0.0777	-0.2290	2.8860	0.4270	31	1	23	0
Adjusted R2	54	0.2456	-0.0840	0.6760	0.2294				

Note: The column N+(N-) reports the number of funds with positive (negative) estimates. The column N+* (N-*) reports the number of funds with parameter estimates that are positive (negative) and significant at the 5% level.

From the above table, we can see, the average level of adjusted R^2 has improved by 4% after adding four factors.

The average coefficients of the MSCI world index and 10Y bond are both negative, especially that of the 10Y bond. Most hedge funds (42 out of 54) among our samples have negative coefficients of 10Y bonds. As for the MSCI world index, the number of positive coefficients and negative coefficients are the same, but the number of significant negative coefficients is smaller than that of significant positive coefficients. Therefore, this may imply that only a few managers would choose to invest in other countries, like the USA.

As for the coefficients of Carhart's four factors, the results are pretty similar to that of Carhart's four-factor model. In this model, we also find that most of the funds with significant factor loading on MOM have negative alphas, which are close to zero. This implies that MOM may be related to excess returns.

In general, according to the adjusted R2, these three models do better than Henriksson-Merton model and Treynor-Mazuy model.

4.2 Persistence Test

In this part, we will investigate the performance persistence of hedge funds in China through a qualitative method and a quantitative method.

4.2.1 Contingency Table

We will take the alphas of three models as abstract benchmarks to conduct the contingency table separately. Besides, our sample has five one-year test periods, i.e. 2015-2016, 2016 -2017, 2017-2018, 2018-2019, 2019-2020, and nine half-year periods, i.e. 2015H-2016, 2016-2016H, 2016H-2017, 2017-2017H, 2017H-2018, 2018-2018H, 2018H-2019, 2019-2019H, 2019H-2020.

4.2.1.1 Contingency Table Based on Fama-French's Alpha

Table 5: Contingency Table based on Fama-French's Alpha

The table reports the result of the one-year persistence test using the contingency table method based on Fama-French's alpha. The second column N presents the number of observations during this sample period. The columns from the third to the sixth show the numbers of WW, WL, LW and LL during the sample periods. WW means that fund is a winner both in the first test period and the second test period. For example, the result of the test during the period 2015-2016 shows 4 WWs, which means that there are 4 funds with positive alphas during the period 2015-2016 and these 4 funds show positive alphas during the period 2016-2017. The cross-product ratios test the persistence of sample periods using the standard Z-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level. If the cross-product ratio is greater than one and significant, it implies that persistence exists and past performance could predict future performance. If the cross-product ratio is smaller than 1, it implies negative persistence exists and past performance could oppositely predict future performance.

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	4	7	3	7	1.3333	0.3086
2016-2017	45	21	2	10	12	12.6000***	2.9635
2017-2018	53	19	17	2	15	8.3824***	2.5819
2018-2019	54	16	5	13	20	4.9231**	2.5542
2019-2020	54	13	16	16	9	0.4570	-1.3995

Note: *** significant level of 1%, ** significant level of 5%, * significant level of 10%.

The above contingency table is based on the abstract benchmark, Fama-French's alpha. The funds with alphas higher than zero will be defined as the winners, and the funds with alphas lower than or equal to zero will be defined as the losers.

In 2015, 11 hedge funds have positive Fama-French's alphas, which accounts for 50% of observed funds. Among them, 4 funds were winners this year and also gained positive abnormal returns next year. However, 7 funds were winners this year but underperformed next year. There were 7 funds keeping losing two years. Therefore, half of the samples show persistence, including 4 winner-winners and 7 loser-losers.

In 2016, there were 23 funds wining the market, and 21 of them kept winning next year, accounting for 47% of the total observed funds. 12 funds were losers this year and kept losing next year. Therefore, there was a total of 33 funds keeping performance in this period, which accounts for 73% of the observations. In this year, the cross-product ratio is bigger than one and statistically significant at the 5% level. Therefore, persistence during the period 2016-2017 mainly comes from winner-winners.

Then in 2017, over half of the observations gain positive abnormal returns and 19 funds continue to earn abnormal returns in the next year. There were 17 funds with negative alphas, and 15 of them are still losers in the next year. During 2017-2018 this sample period, 34 out of 54 funds show positive persistence, and the rest show negative performance persistence. The cross-product ratio of this period is significantly bigger than 1, so the performance of this period also shows positive persistence.

During the sample period 2018-2019, 36 out of 54 funds keep performance persistence, including 16 winner-winners and 20 loser-losers. The cross-product ratio of this period is also significantly bigger than 1 at the 5% level.

During the period 2019-2020, there are 32 (16+16) funds showing reversal. The cross-product ratio for this period is 0.4570, which is not significant at the 5% level.

Therefore, the above results indicate that there is one-year persistence for Chinese hedge funds during 2016-2019, taking Fama-French's alpha as the abstract benchmark.

Table 6: Contingency Table (Half- year) based on Fama-French's Alpha

The table reports the result of the half-year persistence test using the contingency table method based on Fama-French's alpha. The second column N presents the number of observations during this sample period. The columns from the third to the sixth show the numbers of WW, WL, LW and LL during the sample periods. WW means that fund is a winner both in the first period and the second period. For example, the result of the test during the period 2015H-2016 shows 5 WWs, which means that there are 5 funds with positive alphas during the period 2015H-2016 and these 5 funds showing positive alphas during the period 2016-2016H. The cross-product ratios test the persistence of sample periods using the standard Z-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level. If the cross-product ratio is greater than one and significant, it implies persistence exist and past performance could predict future performance. If the cross-product ratio is smaller than 1, negative persistence exists and past performance could oppositely predict future performance.

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015H-2016	22	5	3	3	11	6.1111*	1.8498
2016-2016H	39	11	7	10	11	1.7286	0.8398
2016H-2017	46	19	5	10	12	4.5600**	2.2980
2017-2017H	50	24	8	11	7	1.9091	1.0219
2017H-2018	53	17	19	5	12	2.1474	1.2163
2018-2018H	53	12	10	11	20	2.1818	1.3701
2018H-2019	54	14	9	18	13	1.1235	0.2074
2019-2019H	54	23	9	8	14	4.4722**	2.5282
2019H-2020	54	12	19	17	6	0.2229**	-2.4966

Note: *** significant level of 1%, ** significant level of 5%, * significant level of 10%.

After investigating the one-year persistence, we then test whether persistence exists for the half-year period. The above table shows the result that we use the contingency table to check performance every half year based on Fama-French's alphas.

Different from one-year performance, there are only 2016H-2017 and 2019-2019H periods with significant cross-product ratios bigger than one under a 95% confidence level. During these two periods, persistence mainly comes from winner-winners. Additionally, during the 2019H-2020 period, the cross-product ratio is 0.2229 and significant at the 5% level. It implies that negative persistence may exist during this period. The reversal of performance comes nearly equally from winners and losers in the second half of 2019.

4.2.1.2 Contingency Table Based on Carhart's Alpha

Table 7: Contingency Table based on Carhart's Alpha

The table reports the result of the one-year persistence test using the contingency table method based on Carhart's alpha. The second column N presents the number of observations during this sample period. The columns from the third to the sixth show the numbers of WW, WL, LW and LL during the sample periods. WW means that fund is a winner both in the first period and the second period. For example, the result of test during the period 2015-2016 shows 5 WWs, which means that there are 5 funds with positive alphas during the period 2015-2016 and these 5 funds also show positive alphas during the period 2016-2017. The cross-product ratios test the persistence of sample periods using the standard Z-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level. If the cross-product ratio is greater than one and significant, persistence exists and past performance could predict future performance. If the cross-product ratio is smaller than 1, negative persistence exists and past performance could oppositely predict future performance.

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	5	6	2	8	3.3333	1.2090
2016-2017	45	20	2	9	14	15.5556***	3.2065
2017-2018	53	19	16	3	15	5.9375**	2.4818
2018-2019	54	17	5	13	20	5.2308***	2.6640
2019-2020	54	11	17	14	12	0.5546	-1.0682

Note: *** significant level of 1%, ** significant level of 5%, * significant level of 10%.

We use the same way to calculate the Carhart's alpha of every fund each year and define winners as funds with Carhart's alpha higher than zero. Winners are considered to have an excess return after taking the market risk, size risk, value risk and momentum factor into consideration. The repeated winners are funds that consistently earn abnormal returns.

The results are very similar to that of Fama-French's alpha. The cross-product ratios of the sample period 2016-2017, 2017-2018, and 2018-2019 are all significant and greater than one. This implies that those periods show performance persistence. During these three periods, persistence almost equally comes from winner-winners and loser-losers.

During the sample period 2019-2020, the cross-product ratio is smaller than one but not statistically significant. Different from the situation of Fama-French's alpha, the reversals mainly come from the winners of last year. There are 17 funds with positive Carhart's alphas in 2019 but with negative one in 2020.

Table 8: Contingency Table (Half-year) based on Carhart's Alpha

The table reports the result of the half-year persistence test using the contingency table method based on Carhart's alpha. The second column N presents the number of observations during this sample period. The columns from the third to the sixth show the numbers of WW, WL, LW and LL during the sample periods. WW means that fund is a winner both in the first period and the second period. For example, the result of the test during the period 2015H-2016 shows 4 WWs, which means that there are 4 funds with positive Carhart's alphas during the period 2015H-2016 and these 4 funds also show positive Carhart's alphas during the period 2016-2016H. The cross-product ratios test the persistence of sample periods using the standard Z-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level. If the cross-product ratio is greater than one and significant, persistence exists and past performance could predict future performance. If the cross-product ratio is smaller than 1, negative persistence exists and past performance could oppositely predict future performance.

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic

2015H-2016	22	4	4	4	10	2.5000	0.9939
2016-2016H	39	12	6	8	13	3.2500*	1.7533
2016H-2017	46	18	5	11	12	3.9273**	2.0866
2017-2017H	50	25	8	9	8	2.7778	1.6131
2017H-2018	53	17	19	5	12	2.1474	1.2163
2018-2018H	53	11	11	11	20	1.8182	1.0524
2018H-2019	54	13	9	24	8	0.4815	-1.2272
2019-2019H	54	24	13	6	11	3.3846**	1.9879
2019H-2020	54	9	21	16	8	0.2143**	-2.6180

Note: *** significant level of 1%, ** significant level of 5%, * significant level of 10%.

Then we shorten the sample period to conduct the contingency table. Different from the result of the Fama-French model, the cross-product ratio of the period 2016-2016H is significant at the 10% level, but that of the period 2015H-2016 is not significant now. Except for those differences, other periods with significant cross-product ratios are the same as those based on the Fama-French model. During the sample period 2016H-2017 and 2019-2019H, the performance of these periods could predict the performance of the next half year. However, during the period 2019H-2020, the performance of hedge funds may provide an opposite prediction of their future performance.

4.2.1.3 Contingency Table Based on Alpha of Eight-factor Model

Table 9: Contingency Table based on Alpha of Eight-factor Model

The table reports the result of the one-year persistence test using the contingency table method based on the alpha of the modified eight-factor model. The second column N presents the number of observations during this sample period. The columns from the third to the sixth show the numbers of WW, WL, LW and LL during the sample periods. WW means that fund is a winner both in the first period and the second period. For example, the result of the test during the period 2015-2016 shows 5 WWs, which means that there are 5 funds with positive alphas during the period 2015-2016 and these 5 funds continually show positive alphas during the period 2016-2017. The cross-product ratios test the persistence of sample periods using the standard Z-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level. If the cross-product ratio is greater than one and significant, persistence exists and past performance could predict future performance. If the cross-product ratio is smaller than 1, negative persistence exists and past performance could oppositely predict future performance.

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015-2016	21	5	7	5	4	0.5714	-0.6285
2016-2017	45	21	3	8	13	11.3750***	3.1847
2017-2018	53	23	12	3	15	9.5833***	3.1138
2018-2019	54	21	5	12	16	5.6000***	2.7465
2019-2020	54	16	17	11	10	0.8556	-0.2791

Note: *** significant level of 1%, ** significant level of 5%, * significant level of 10%.

The above table is a summary of the contingency table based on the modified eight-factor model. As same to the other two alphas, funds with positive alphas are identified as winners, and vice versa.

Under this model, the result is also similar to previous results. The cross-product ratios of sample periods 2016-2017, 2017-2018, and 2018-2019 are all statistically significant at the 1% level and bigger than 1. As a consequence, the performances of these three periods all show persistence.

However, based on this modified eight-factor model, persistence mainly comes from winner-winners.
Similar to the previous case, the cross-product ratio of the period 2019-2020 is smaller than one but not statistically significant. In this case, the reversals (17 winner-losers and 11 loser-winners) mainly come from the winners of last year.

Table 10: Contingency Table (Half-year) based on Alpha of Eight-factor Model

The table reports the result of the half-year persistence test using the contingency table method based on the alpha of the modified eight-factor model. The second column N presents the number of observations during this sample period. The columns from the third to the sixth show the numbers of WW, WL, LW and LL during the sample periods. WW means that fund is a winner both in the first period and the second period. For example, the result of the test during the period 2015H-2016 shows 3 WWs, which means that there are 3 funds with positive alphas during the period 2015H-2016, and these 3 funds continually show positive alphas during the period 2016-2016H. The cross-product ratios test the persistence of sample periods using the standard Z-test. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level. If the cross-product ratio is greater than one and significant, persistence exists and past performance could predict future performance. If the cross-product ratio is smaller than 1, negative persistence exists and past performance could oppositely predict future performance.

period	N	WW	WL	LW	LL	Cross-product Ratio	Z statistic
2015H-2016	22	3	5	4	10	1.5000	0.4314
2016-2016H	39	8	10	11	10	0.7273	-0.4938
2016H-2017	46	17	5	11	13	4.0182**	2.1293
2017-2017H	50	26	6	9	9	4.3333**	2.2431
2017H-2018	53	25	12	3	13	9.0278***	3.0122
2018-2018H	53	15	13	10	15	1.7308	0.9848
2018H-2019	54	15	10	22	7	0.4773	-1.2415
2019-2019H	54	24	13	6	11	3.3846**	1.9879
2019H-2020	54	11	19	16	8	0.2895***	-2.1546

Note: *** significant level of 1%, ** significant level of 5%, * significant level of 10%.

When using the alpha of our modified 8-factor model as the abstract benchmark to evaluate the half-year persistence, the result changed a lot. The cross-product ratio is significant at the 5% level during 2016H-2017, 2017-2017H, 2017H-2018, 2019-2019H, and 2019H-2020. Except for the ratio of 2019H-2020, significant ratios of other periods are all bigger than 1. Only the ratio of 2019H-2020 is smaller than 1 and significant under a 99% confidence level, which is similar to the results using the other two models.
From the previous results of the contingency table based on different models, we find that all models show one-year persistence during the period 2016-2019 including past winners and losers, which is totally different from the results when taking CSI 300 index, Jensen's alpha, EMPPM, mean and median as benchmarks. In the previous research, there is no enough evidence to prove that one-year performance persistence exists. However, when we shorten the sample period, the results have changed a lot. As the following table shown, all models show performance persistence during 2019-2019H and negative persistence during 2019H-2020, which is similar to results using EMPPM as the abstract benchmark.

Table 11: Summary of Contingency Table Results

The table reports the results of the persistence test using the contingency table method in this paper. The first row shows the three benchmarks that we used: alphas of Fama-French's three-factor model, Carhart's four-factor model and the modified eight-factor model. The tests using different alphas all consist of two sub-tests with different lengths of sample periods: one-year and half-year. + means that the cross-product ratio is bigger than one and significant during this sample period, and – means that cross-product ratio is smaller than one and significant. H means the beginning of the second half-year of each year, e.g. 2015H~2016 presents the period from July 2015 to December 2015.

	Fama-French 3-factor model		Carhart's 4-factor model		modified 8-factor model	
period	**One-year**	**Half-year**	**One-year**	**Half-year**	**One-year**	**Half-year**
2015-2016		2015H~2016+				
2016-2017	+	2016H~2017+	+	2016~2016H+ 2016H~2017+	+	2016H~2017+
2017-2018	+		+		+	2017~2017H+ 2017H~2018+
2018-2019	+		+		+	
2019-2020		2019~2019H+ 2019H~2020-		2019~2019H+ 2019H~2020-		2019~2019H+ 2019H~2020-

Note: + cross-product ratio bigger than 1, - cross-product ratio smaller than 1.

4.2.2 Economic Predictability

As same as the previous research, we investigate the performance persistence of hedge funds through the recursive portfolio approach. The whole process of creating portfolios is the same as that in the previous research based on lagged 1-month returns and 1-quarter returns. However, different from the previous research, we use Fama-French's three-factor model, Carhart's four-factor model, and the modified eight-factor model to evaluate the performance of different portfolios.

4.2.2.1 Economic Predictability Based on Lagged 1-month Returns

When constructing the portfolios based on lagged 1-month returns, portfolios are formed at the beginning of August in 2017 based on the previous month's returns (July 2017). Portfolio 1 has funds with top sextile lagged one-month return, and portfolio 6 has funds with the bottom sextile lagged one-month return. Later, at the start of the following months, funds will be ranked again based on the lagged one-month return. The excess return is the return of the portfolio over the risk-free rate.

Table 12: Portfolio of Hedge Funds Based on Lagged 1-month Returns (Fama-French's Model)

The table reports the result that the persistence test using the recursive portfolio approach based on lagged 1-month returns. We regress the portfolio returns using Fama-French's three-factor model. The portfolios are constructed based on lagged 1-month returns, and portfolios are formed at the beginning of August in 2017 based on the previous month's returns (July 2017). Portfolio 1 has funds with top sextile lagged one-month return, and portfolio 6 has funds with the bottom sextile lagged one-month return. Besides, spread 1-6 is the portfolio using the strategy that long portfolio 1 and short portfolio 6. The alpha row presents the excess returns of different portfolios, and the following rows show the coefficients of three factors. The last rows are the adjusted R-square information of different portfolios. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.003	0.0004	0.002	0.006	-0.003	0.002	-0.009
RMRF	0.468***	0.342***	0.195**	0.323***	0.500***	0.502***	-0.022
SMB	0.093	-0.19	0.01	-0.123	-0.527***	-0.390**	0.472
HML	0.055	-0.171	0.032	0.319*	0.201	0.318*	-0.258
Adjusted R2	0.207	0.408	0.06	0.277	0.579	0.549	0.081

Note: *p<0.1; **p<0.05; ***p<0.01

The above table is the regression result based on lagged 1-month returns using Fama-French's three-factor model. There is no significant Fama-French's alpha under a 10% significance level. Additionally, the alpha of portfolio 6 is positive, but that of portfolio 1 is negative and that of spread 1-6 is even more negative.

The RMRF coefficients of portfolio 1 to portfolio 6 are all significant at the 5% level, and only that of spread 1-6 is not statistically significant. Among these 6 portfolios, portfolio 6 has the biggest exposure to the RMRF, which is 50.2%.

As for the exposure to the size risk, only portfolio 5 and 6 have significant coefficients of SMB, which are both negative. It implies that these two portfolios put more weights on the large company stocks.

Compared with the adjusted R2 of the CAPM model in the previous research, Fama-French's three-factor model explains better for portfolio 2 to 6, but does poorly in explaining the spread 1-6, which is only 8.1% for Fama-French's model but 57.5% for the CAPM model.

Table 13: Portfolio of Hedge Funds Based on Lagged 1-month Returns (Carhart's Model)

The table reports the result that the persistence test using the recursive portfolio approach based on lagged 1-month returns. We construct the portfolios based on lagged 1-month returns, and portfolios are formed at the beginning of August in 2017 based on the previous month's returns (July 2017). Portfolio 1 has funds with top sextile lagged one-month return, and portfolio 6 has funds with the bottom sextile lagged one-month return. Besides, spread 1-6 is the portfolio using the strategy that long portfolio 1 and short portfolio 6. The alpha row presents the excess returns of different portfolios, and the following rows show the coefficients of four factors. The last rows are the adjusted R-square information of different portfolios. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.002	0.0005	0.003	0.005	-0.003	0.002	-0.008
RMRF	0.474***	0.343***	0.200**	0.315***	0.493***	0.494***	-0.009
SMB	-0.079	-0.23	-0.137	0.111	-0.315*	-0.167	0.085
HML	0.045	-0.173	0.024	0.332**	0.213	0.329*	-0.279
MOM	-0.167	-0.039	-0.143	0.227*	0.206*	0.217*	-0.375
Adjusted R2	0.198	0.391	0.069	0.343	0.607	0.585	0.123

Note: *p<0.1; **p<0.05; ***p<0.01

After adding the momentum factor, Carhart's four-factor does better in explaining the spread 1-6 compared with the Fama and French's three-factor model, but still does worse than the CAPM model.

Similarly, there is no alpha statistically significant under a 90% confidence level. Portfolio 1 and Spread 1-6 both have negative alphas but not significant.

As for the momentum factor, coefficients of portfolio 4 to 6 are both significantly positive at the 10% level. However, coefficients of portfolio 1 to 3 and spread 1-6 are all negative but not significant. It implies that portfolio 4 to 6 are more concentrate on stocks with momentum effect.

Table 14: Portfolio of Hedge Funds Based on Lagged 1-month Returns (Eight-factor Model)

The table reports the result that the persistence test using the recursive portfolio approach based on lagged 1-month returns. We construct the portfolios based on lagged 1-month returns, and portfolios are formed at the beginning of August in 2017 based on the previous month's returns (July 2017). Portfolio 1 has funds with top sextile lagged one-month return, and portfolio 6 has funds with the bottom sextile lagged one-month return. Besides, spread 1-6 is the portfolio using the strategy that long portfolio 1 and short portfolio 6. The alpha row presents the excess returns of different portfolios, and the following rows show the coefficients of different variables. The last rows are the adjusted R-square information of different portfolios. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.004	0.002	0.003	0.008	-0.006	0.001	-0.009
RMRF	0.714***	0.426***	0.350***	0.245*	0.457***	0.545***	0.172
SMB	-0.263	-0.267	-0.266	0.18	-0.32	-0.222	-0.039
HML	0.123	-0.149	0.059	0.305*	0.207	0.340*	-0.214
MOM	-0.13	-0.012	-0.042	0.242*	0.18	0.259**	-0.382
MSCI	-0.513**	-0.260**	-0.19	0.094	0.056	-0.019	-0.504*
Bond	-0.235	-0.609	-0.276	-0.407	0.28	0.054	-0.359
CredSpr	6.614	2.779	1.584	-1.429	1.942	0.125	7.204
Futures	0.125	0.101	-0.328**	-0.06	-0.0004	-0.197	0.333
Adjusted R2	0.286	0.498	0.223	0.275	0.564	0.556	0.207

Note: *p<0.1; **p<0.05; ***p<0.01

Then we use the modified eight-factor model to investigate the persistence of portfolios. According to the adjusted R2, using the modified eight-factor model improves by 8%, but still does poorer than the CAPM model does. The estimations of alpha are similar to those of Fama-French's three-factor model and Carhart's four-factor model. No portfolio has significant alpha at the 10% level. But portfolio 6 has significant exposure to MOM at the 5% level, whose coefficient is 0.26. It implies that the bottom sextile portfolio is more concentrated on stocks with momentum effect compared with other sextile portfolios.

In this case, the MSCI world index has a significant impact on spread 1-6 under a 90% confidence level, whose coefficient is negative.

In general, there is no enough evidence to show that performance persistence exists based on lagged one-month returns. Besides, we cannot make money by holding a long position of the past winners and a short position of the past losers. Moreover, we find that the bottom portfolios have significantly positive exposure to the momentum factor.

4.2.2.2 Economic Predictability Based on Lagged 1-quarter Returns

Now we construct the portfolios based on lagged 1-quarter returns, and portfolios are formed at the beginning of the fourth quarter in 2017 based on the previous quarter's returns (2017Q3). Portfolio 1 has funds with top sextile lagged one-quarter return, and portfolio 6 has funds with the bottom sextile lagged one-quarter return. Later, at the start of the following quarters, funds will be ranked again based on a lagged one-quarter return.

Table 15: Portfolio of Hedge Funds Based on Lagged 1-quarter Returns (Fama-French's Model)

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.035*	-0.014	-0.013	0.005	0.012	0.034*	-0.081**
RMRF	0.358*	0.527***	0.265*	0.266	0.247**	0.638***	-0.247
SMB	-0.972**	-0.725***	-0.263	-0.075	0.124	0.354	-1.402***
HML	-0.193	0.209	0.191	-0.268	-0.19	0.474	-0.636
Adjusted R2	0.581	0.771	0.277	0.069	0.564	0.72	0.531

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16: Portfolio of Hedge Funds Based on Lagged 1-quarter Returns (Carhart's Model)

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	-0.035	-0.014	-0.012	0.006	0.012	0.032*	-0.079**
RMRF	0.358*	0.527***	0.264*	0.265	0.247*	0.638***	-0.247
SMB	-0.812	-0.707*	-0.09	0.066	0.216	0.122	-0.999
HML	-0.092	0.22	0.299	-0.179	-0.132	0.328	-0.382
MOM	0.136	0.015	0.147	0.121	0.079	-0.199	0.345
Adjusted R2	0.533	0.733	0.244	-0.067	0.51	0.718	0.542

Note: *p<0.1; **p<0.05; ***p<0.01

Table 17: Portfolio of Hedge Funds Based on Lagged 1-quarter Returns (8-factor Model)

	1(High)	2	3	4	5	6 (Low)	spread 1 - 6
alpha	0.157**	0.065	-0.006	0.232*	0.105	-0.034	0.183
RMRF	0.446*	0.301	-0.025	1.872**	0.692*	0.559	-0.1
SMB	0.589	0.084	0.153	0.84	0.507	-0.517	1.094
HML	0.105	0.066	0.012	1.676*	0.339	0.082	0.032
MOM	0.251	-0.013	0.014	1.177**	0.179	-0.528	0.777
MSCI	-0.533*	0.164	0.305	-1.872**	-0.928*	-0.263	-0.278
Bond	-7.994**	-3.712	-0.735	-6.887	-3.014	2.668	-10.961*
CredSpr	-17.150**	-6.013	1.26	-31.111*	-11.46	7.905	-25.007
Futures	0.143	-0.384	-0.287	0.815	1.125*	0.975	-0.849
Adjusted R2	0.973	0.774	-0.686	0.818	0.86	0.641	0.857

Note: *p<0.1; **p<0.05; ***p<0.01

These above tables report results that the persistence test using the recursive portfolio approach based on lagged 1-quarter returns. we construct the portfolios based on lagged 1-quarter returns, and portfolios are formed at the beginning of the fourth quarter in 2017 based on the previous quarter's returns (2017Q3). Portfolio 1 has funds with the top sextile lagged one-quarter return, and portfolio 6 has funds with the bottom sextile lagged one-quarter return. Besides, spread 1-6 is the portfolio using the strategy that long portfolio 1 and short portfolio 6. The above three tables show the regression results of formed portfolios using Fama-French's three-factor model, Carhart's four-factor model and the modified eight-factor model separately. The alpha row presents the excess returns of different portfolios, and the following rows show the coefficients of different variables. The last rows are the adjusted R-square information of different portfolios. *, **, and *** indicates statistical significance on the 90%, 95%, and 99% confidence level.

The above three tables show the regression results based on lagged 1-quarter returns using three models separately. In general, all models do much better than previous research (based on lagged one-month returns), especially the modified eight-factor model.
When we use Fama-French's three-factor model, the alphas of portfolio 1 and 6 are both significant under a 90% confidence level. However, portfolio 1 has a negative alpha and portfolio 6 has a positive alpha, which implies that past winners cannot keep outperforming and past losers may show reversals. The alpha of spread 1-6 is significantly negative under a 95% confidence level, which is more negative than that of portfolio 1. Because portfolio 1 gains a negative alpha and portfolio 6 gains a positive alpha, holding a long position of portfolio 1 and a short position of portfolio 6 may lose more. In addition, spread 1-6, portfolio 1 and 2 have significantly negative exposure to the SMB factor at the 1% level, which means that these three portfolios are more concentrated on large-company stocks not small-company stocks. The same result comes when evaluating through Carhart's 4-factor model. The alpha of spread 1-6 is significantly negative under a 95% confidence level.
Evaluating through the modified 8-factor model, the alpha of spread 1-6 is positive but not significant, but now the alpha of portfolio1 is significantly positive at the 5% level, which is 15.7%. For the portfolio spread 1-6, the adjusted R2 has improved a lot compared with the other three models (CAPM, Fama-French's 3-factor model, and Carhart's 4-factor model), which is 85.7%.
According to the above regressions, there is still no enough evidence to conclude that short-term performance persistence exists.

5. Conclusion and Discussion

5.1 Conclusions of this paper

In this paper, we use three different models to investigate the performance of hedge funds in China again in order to have more detailed insights into performance persistence.
Firstly, we use Fama-French's three-factor model, Carhart's four-factor model, and the modified 8-factor model to estimate the performance of our samples. In general, these three models do better than CAPM, Henriksson-Merton model and Treynor-Mazuy model based on the regression results.
Then we conduct the contingency table and use the recursive portfolio approach to explore the performance persistence of our sample hedge funds. Through the contingency table, we find that one-year persistence exists

during 2016-2019 using alphas of three models as abstract benchmarks, including past winners and losers. However, when we shorten our sample period from one-year to half-year, there are only some half-year periods during 2016-2019 showing persistence, and there is an opposite persistence during 2019H-2020, which implies that history performance could oppositely predict future performance. This reversal mainly comes from past winners. This result is similar to that of EMPPM. Because the period after 2019H-2020 is very volatile and uncertain, the economy of the whole world has been shut down for a while.

Lastly, through forming portfolios based on lagged 1-month returns and 1-quarter returns, we run the regression analysis of portfolios using three models. According to the results, there is no enough evidence to show the performance persistence of our sample hedge funds in China. Besides, bottom portfolios have significant and positive exposure to the momentum factor.

5.2 The Whole Conclusions

According to the Bocconi paper and this paper, I have gained these following understandings of hedge funds in China.

Firstly, based on the performance measure, the performance of hedge funds is less volatile than the market based on the calculation of the beta in the CAPM model. Besides, through different measurements, we all conclude that over half of our samples could earn abnormal returns, even during the first half-year of 2020. Therefore, I conclude that investing in hedge funds may be a good choice during the volatile period.

Then I use the Henriksson-Merton model and the Treynor-Mazuy model to test the market timing capacity and stock picking ability of managers. Both results show that only a few managers of hedge funds in China own these two skills.

Lastly, I investigate the persistence of performance. The following table combines the results got from the Bocconi paper and this paper using the two-period contingency table method.

Table 18: Summary of Contingency Table Results (Both Bocconi Paper and SSE Paper)

This table shows the persistence results of the whole study using the contingency table. The first column is the information of benchmarks, which are used to distinguish winners and losers. Then + means that during this period positive persistence exists, and – means that during this period negative persistence exists. There are 8 benchmarks used in my study including the Bocconi paper and the SSE paper. There are over half of my picked benchmarks showing that persistence exists during the period 2016-2018 and negative persistence exists during the period 2019-2020.

persistence results					
Benchmark	**2015-2016**	**2016-2017**	**2017-2018**	**2018-2019**	**2019-2020**
CSI 300					

Jensen's alpha		2016-2017+	2017-2018+		
EMPPM			2017H-2018-		2019-2020-
mean		2016-2017+			2019-2020-
Median		2016-2017+			2019-2020-
Fama-French 3-factor model	2015H-2016+	2016-2017+	2017-2018+	2018-2019+	2019-2019H+ 2019H-2020-
Carhart 4-factor model		2016-2017+	2017-2018+	2018-2019+	2019-2019H+ 2019H-2020-
modified 8-factor model		2016-2017+	2017-2018+	2018-2019+	2019-2019H+ 2019H-2020-

As we can see, during the one-year period 2016-2017, nearly all the tests show positive persistence, and during the half-year period 2019H-2020, nearly all the tests show negative persistence. Except for these two periods, there are four tests presenting positive persistence during the one-year period 2017-2018, including Jensen's alpha and alphas of three advanced models. However, when I use the recursive portfolio approach to test monthly and quarterly persistence of performance, both papers do not find the existence of persistence.

Based on the above results, I conclude that the one-year and half-year persistence performance of hedge funds in China may exist during some periods, but there is no evidence that monthly or quarterly persistence exists. Compared with the previous research of persistence in the US and Europe (Table1), more researches find that short-term persistence in Western, but here I only find short-term persistence over a half-year horizon. The possible reason may be that most hedge funds in China have great exposure to the Chinese stock market. However, the Chinese stock market is volatile over a short-term horizon but outperforms the world stock market over a long-term horizon. If in the future more data of hedge funds in China could be collected, it may be meaningful to check the short-term persistence again.

5.3 Contributions and Weaknesses

In this paper, I use the same sample as that of the previous paper, which consists of 54 hedge funds in China. The sample may be too small to get more general conclusions. However, the quality of hedge fund data is always a concern for academics. Suntimes, the database we choose here, is one of the most professional private funds databases, but its data is also based on funds self-reporting. Therefore, there is some self-selection bias related to our data.

Because of this bias, many hedge funds do not report return information monthly, which is the main reason that our sample is such small.

Moreover, because hedge funds do not have a very long history in China, our sample period is a little short for the economical prediction regression based on the half-year period or the one-year period.
In general, there are some biases associated with our data, while we can still gain some basic insights into hedge funds in China.

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Appendices

Appendix I: Fama-French Three-factor Model Regression Results

Fama French Three–Factor Model Regression Results Part I

	Dependent variable:																											
	R − Rf																											
	S28342	S35966	S85118	SE2421	SH9398	SR2083	SE5438	SR3017	S21122	S68046	S83499	ST0713	SK7292	S21679	S22382	S20280	S62692	S23350	ST1892	SJ5323	S34823	SJ4786	ST5754	SN5118	S83527	SL8820	S23349	SR3434
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
betaRmrf	−0.046	0.244	0.167	0.021	0.076	−0.378*	0.531***	0.153	0.857***	0.073	−0.071	−0.024	0.211	0.394***	0.375***	0.129*	0.040	0.376***	0.391**	0.569***	0.605***	−0.012	0.082	0.421***	0.571***	−0.020	0.324***	0.031
	(0.120)	(0.147)	(0.142)	(0.146)	(0.140)	(0.212)	(0.122)	(0.147)	(0.130)	(0.108)	(0.140)	(0.079)	(0.179)	(0.149)	(0.123)	(0.072)	(0.093)	(0.125)	(0.191)	(0.108)	(0.167)	(0.069)	(0.049)	(0.090)	(0.151)	(0.029)	(0.102)	(0.059)
betaSmb	−0.154	−0.070	−0.051	0.062	0.084	0.203	−0.597***	0.251	0.295	−0.446**	−0.109	0.225*	−0.465*	0.098	−0.164	−0.168	−0.074	−0.004	0.229	−0.593***	0.641**	0.044	−0.201**	0.017	0.256	0.061	0.447**	0.189*
	(0.221)	(0.270)	(0.243)	(0.220)	(0.217)	(0.354)	(0.192)	(0.235)	(0.272)	(0.180)	(0.234)	(0.132)	(0.276)	(0.311)	(0.254)	(0.147)	(0.179)	(0.240)	(0.315)	(0.160)	(0.286)	(0.107)	(0.082)	(0.149)	(0.280)	(0.047)	(0.196)	(0.094)
betaHml	−0.484*	−0.241	−0.493	−0.436*	−0.269	−0.746*	−0.274	−0.309	−0.342	−0.053	−0.198	−0.044	0.093	0.066	−0.238	−0.294*	−0.005	0.286	0.258	−0.418**	0.226	0.158	−0.148	−0.073	0.079	0.015	0.207	0.105
	(0.267)	(0.341)	(0.306)	(0.237)	(0.237)	(0.381)	(0.213)	(0.256)	(0.310)	(0.231)	(0.301)	(0.144)	(0.303)	(0.355)	(0.288)	(0.170)	(0.216)	(0.279)	(0.346)	(0.175)	(0.360)	(0.117)	(0.089)	(0.158)	(0.321)	(0.050)	(0.227)	(0.103)
alpha	0.0003	0.002	0.021***	0.005	0.006	−0.002	0.009*	0.001	0.002	−0.005	−0.006	0.015***	−0.007	−0.013	−0.014*	−0.00000	−0.009	−0.007	0.001	0.009**	−0.005	0.002	−0.003	0.001	−0.002	0.005***	0.008	0.004
	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)	(0.010)	(0.005)	(0.006)	(0.009)	(0.006)	(0.007)	(0.004)	(0.008)	(0.010)	(0.008)	(0.005)	(0.006)	(0.008)	(0.009)	(0.004)	(0.009)	(0.003)	(0.002)	(0.004)	(0.008)	(0.001)	(0.006)	(0.003)
Observations	61	60	58	50	46	36	53	43	69	57	57	38	47	68	68	72	63	66	39	51	58	46	36	42	55	45	66	43
R^2	0.056	0.086	0.129	0.111	0.081	0.190	0.387	0.190	0.508	0.120	0.011	0.123	0.103	0.112	0.151	0.091	0.005	0.133	0.119	0.521	0.341	0.055	0.267	0.439	0.285	0.052	0.288	0.096
Adjusted R^2	0.007	0.037	0.081	0.053	0.016	0.114	0.350	0.128	0.485	0.070	−0.045	0.045	0.040	0.070	0.111	0.051	−0.045	0.091	0.044	0.490	0.304	−0.013	0.198	0.395	0.243	−0.017	0.254	0.026

Fama French Three–Factor Model Regression Results Part II

	Dependent variable:																									
	R − Rf																									
	SS9048	SM1268	S39727	S83243	SL7844	S67536	SK1674	S28300	S37095	SD0499	S28266	S26387	SH8698	S22669	S69730	S84129	ST1882	SE4488	S29646	SE4942	S27557	SE1688	S26379	S26425	S85603	ST9165
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
betaRmrf	0.007	−0.412	0.015	0.008	0.095	0.013	0.016	−0.008	0.934***	0.421***	−0.132	0.270**	0.588***	0.506***	0.897***	0.692***	−0.191	0.850***	1.169***	0.851***	0.822***	0.825***	0.928***	0.625***	0.027	1.261*
	(0.036)	(0.273)	(0.164)	(0.008)	(0.061)	(0.009)	(0.053)	(0.087)	(0.101)	(0.099)	(0.115)	(0.126)	(0.142)	(0.093)	(0.112)	(0.131)	(0.284)	(0.130)	(0.104)	(0.122)	(0.106)	(0.126)	(0.106)	(0.086)	(0.172)	(0.703)
betaSmb	−0.003	0.581	0.512*	−0.013	0.147	−0.005	−0.136	0.165	−0.484**	−0.548***	0.064	−0.645***	−0.155	−0.490***	−0.311*	−0.396	0.784	−0.343	−0.288	−0.525***	−0.531***	−0.436*	−0.295	−0.444***	0.399	1.222
	(0.060)	(0.421)	(0.254)	(0.013)	(0.093)	(0.015)	(0.082)	(0.154)	(0.187)	(0.184)	(0.213)	(0.233)	(0.214)	(0.171)	(0.176)	(0.253)	(0.471)	(0.251)	(0.193)	(0.191)	(0.197)	(0.245)	(0.197)	(0.159)	(0.270)	(1.177)
betaHml	−0.020	0.315	0.246	0.019	0.283***	0.025	0.031	0.058	0.654***	0.008	0.150	−0.050	0.406*	−0.215	1.028***	1.055***	0.476	1.023***	1.055***	0.712***	0.683***	0.704**	1.019***	0.860***	0.303	3.415**
	(0.065)	(0.444)	(0.277)	(0.017)	(0.103)	(0.016)	(0.087)	(0.183)	(0.236)	(0.211)	(0.244)	(0.267)	(0.230)	(0.196)	(0.195)	(0.280)	(0.560)	(0.277)	(0.222)	(0.212)	(0.226)	(0.270)	(0.226)	(0.183)	(0.299)	(1.265)
alpha	0.001	0.003	0.002	−0.003***	0.006**	−0.004***	−0.004	−0.005	0.014**	0.003	0.001	0.010	0.002	−0.002	0.015***	0.014**	−0.007	0.019***	0.005	0.009*	0.010*	0.019***	0.006	0.005	0.012	0.012
	(0.002)	(0.011)	(0.007)	(0.0004)	(0.003)	(0.0004)	(0.002)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.007)	(0.014)	(0.007)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.004)	(0.007)	(0.033)
Observations	37	48	46	56	47	53	48	64	60	55	55	55	50	55	53	54	23	54	55	53	55	54	55	55	52	36
R^2	0.007	0.097	0.088	0.071	0.162	0.077	0.086	0.022	0.607	0.327	0.050	0.182	0.287	0.449	0.621	0.431	0.188	0.491	0.713	0.554	0.562	0.475	0.612	0.581	0.047	0.198
Adjusted R^2	−0.083	0.036	0.023	0.017	0.103	0.020	0.024	−0.027	0.586	0.288	−0.006	0.133	0.241	0.417	0.598	0.397	0.059	0.460	0.696	0.527	0.536	0.443	0.590	0.556	−0.013	0.123
Note:	*p<0.1; **p<0.05; ***p<0.01																									

Appendix II: Carhart Four-factor Model Regression Results

Carhart Four-Factor Model Regression Results Part I

Dependent variable: R − Rf

	S28342 (1)	S35966 (2)	S85118 (3)	SE2421 (4)	SH9398 (5)	SR2083 (6)	SE5438 (7)	SR3017 (8)	S21122 (9)	S68046 (10)	S83499 (11)	ST0713 (12)	SK7292 (13)	S21679 (14)
betaRmrf	−0.057	0.197	0.095	0.014	0.071	−0.346*	0.502***	0.136	0.918***	0.003	−0.128	−0.018	0.194	0.183
	(0.134)	(0.166)	(0.151)	(0.147)	(0.140)	(0.204)	(0.121)	(0.129)	(0.143)	(0.110)	(0.147)	(0.079)	(0.177)	(0.153)
betaSmb	−0.135	0.008	0.117	0.196	0.258	−0.345	−0.408*	0.823***	0.221	−0.263	0.039	0.109	−0.148	0.355
	(0.245)	(0.300)	(0.271)	(0.264)	(0.272)	(0.442)	(0.222)	(0.261)	(0.282)	(0.197)	(0.263)	(0.171)	(0.336)	(0.300)
betaHml	−0.484*	−0.266	−0.516*	−0.436*	−0.275	−0.740*	−0.275	−0.307	−0.362	−0.060	−0.203	−0.045	0.068	0.133
	(0.270)	(0.345)	(0.304)	(0.237)	(0.236)	(0.365)	(0.209)	(0.225)	(0.311)	(0.225)	(0.300)	(0.144)	(0.298)	(0.331)
betaMOM	0.036	0.157	0.310	0.181	0.208	−0.543*	0.273	0.635***	−0.228	0.340**	0.274	−0.118	0.397	0.795***
	(0.190)	(0.255)	(0.227)	(0.195)	(0.197)	(0.280)	(0.166)	(0.178)	(0.227)	(0.167)	(0.223)	(0.110)	(0.249)	(0.242)
alpha	0.0001	0.001	0.018**	0.004	0.005	0.001	0.007	−0.002	0.003	−0.008	−0.008	0.015***	−0.010	−0.016
	(0.007)	(0.009)	(0.008)	(0.006)	(0.006)	(0.010)	(0.005)	(0.006)	(0.009)	(0.006)	(0.007)	(0.004)	(0.008)	(0.010)
Observations	61	60	58	50	46	36	53	43	69	57	57	38	47	68
R^2	0.057	0.092	0.159	0.128	0.105	0.278	0.420	0.393	0.516	0.185	0.039	0.152	0.154	0.241
Adjusted R^2	−0.010	0.026	0.096	0.051	0.018	0.184	0.371	0.330	0.485	0.122	−0.035	0.050	0.073	0.193

	S22382 (15)	S20280 (16)	S62692 (17)	S23350 (18)	ST1892 (19)	SJ5323 (20)	S34823 (21)	SJ4786 (22)	ST5754 (23)	SN5118 (24)	S83527 (25)	SL8820 (26)	S23349 (27)	SR3434 (28)
betaRmrf	0.264**	0.171**	0.024	0.227	0.366*	0.569***	0.675***	−0.018	0.079	0.423***	0.527***	−0.019	0.211*	0.030
	(0.116)	(0.079)	(0.098)	(0.136)	(0.183)	(0.109)	(0.178)	(0.066)	(0.050)	(0.091)	(0.159)	(0.029)	(0.112)	(0.060)
betaSmb	0.017	−0.214	−0.037	0.154	0.727*	−0.607***	0.479	0.222*	−0.145	−0.032	0.418	0.019	0.567***	0.229*
	(0.237)	(0.151)	(0.192)	(0.242)	(0.388)	(0.193)	(0.321)	(0.129)	(0.108)	(0.193)	(0.333)	(0.060)	(0.198)	(0.121)
betaHml	−0.073	−0.306*	0.0003	0.278	0.265	−0.418**	0.247	0.152	−0.149	−0.075	0.075	0.016	0.200	0.105
	(0.266)	(0.170)	(0.217)	(0.269)	(0.331)	(0.177)	(0.360)	(0.112)	(0.089)	(0.160)	(0.322)	(0.050)	(0.221)	(0.104)
betaMOM	0.685***	−0.157	0.080	0.458**	0.515**	−0.020	−0.298	0.212**	0.055	−0.050	0.228	−0.048	0.348**	0.045
	(0.183)	(0.126)	(0.142)	(0.194)	(0.252)	(0.145)	(0.268)	(0.093)	(0.068)	(0.126)	(0.252)	(0.042)	(0.159)	(0.082)
alpha	−0.017**	0.001	−0.010*	−0.009	−0.0004	0.009**	−0.003	0.001	−0.004	0.001	−0.003	0.005***	0.006	0.003
	(0.008)	(0.005)	(0.006)	(0.008)	(0.009)	(0.005)	(0.009)	(0.003)	(0.002)	(0.004)	(0.008)	(0.001)	(0.006)	(0.003)
Observations	68	72	63	66	39	51	58	46	36	42	55	45	66	43
R^2	0.305	0.112	0.011	0.205	0.215	0.521	0.356	0.160	0.282	0.442	0.296	0.083	0.340	0.103
Adjusted R^2	0.261	0.059	−0.057	0.153	0.123	0.479	0.307	0.078	0.190	0.381	0.240	−0.009	0.297	0.009

Carhart Four-Factor Model Regression Results Part II

Dependent variable: R − Rf

	SS9048 (1)	SM1268 (2)	S39727 (3)	S83243 (4)	SL7844 (5)	S67536 (6)	SK1674 (7)	S28300 (8)	S37095 (9)	SD0499 (10)	S28266 (11)	S26387 (12)	SH8698 (13)
betaRmrf	0.005	−0.417	0.012	0.006	0.094	0.012	0.016	−0.032	1.038***	0.479***	−0.152	0.304**	0.595***
	(0.036)	(0.275)	(0.165)	(0.008)	(0.062)	(0.010)	(0.054)	(0.092)	(0.111)	(0.102)	(0.122)	(0.133)	(0.143)
betaSmb	0.026	0.739	0.607*	−0.007	0.174	−0.0003	−0.113	0.204	−0.658***	−0.761***	0.136	−0.769***	−0.278
	(0.079)	(0.529)	(0.322)	(0.015)	(0.117)	(0.017)	(0.104)	(0.163)	(0.200)	(0.213)	(0.255)	(0.277)	(0.257)
betaHml	−0.020	0.317	0.243	0.018	0.281***	0.025	0.031	0.070	0.710***	0.013	0.148	−0.047	0.407*
	(0.066)	(0.448)	(0.280)	(0.017)	(0.104)	(0.016)	(0.088)	(0.184)	(0.231)	(0.206)	(0.246)	(0.268)	(0.231)
betaMOM	0.029	0.193	0.114	0.011	0.034	0.007	0.029	0.101	−0.349**	−0.299*	0.101	−0.173	−0.166
	(0.050)	(0.384)	(0.233)	(0.013)	(0.087)	(0.013)	(0.075)	(0.128)	(0.170)	(0.161)	(0.193)	(0.210)	(0.190)
alpha	0.001	0.002	0.002	−0.003***	0.005*	−0.004***	−0.004	−0.006	0.017***	0.005	0.001	0.011*	0.003
	(0.002)	(0.012)	(0.007)	(0.0004)	(0.003)	(0.0004)	(0.002)	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)
Observations	37	48	46	56	47	53	48	64	60	55	55	55	50
R^2	0.017	0.103	0.094	0.084	0.165	0.082	0.089	0.032	0.635	0.370	0.055	0.192	0.299
Adjusted R^2	−0.105	0.019	0.005	0.013	0.085	0.006	0.005	−0.033	0.608	0.320	−0.020	0.128	0.237

	S22669 (14)	S69730 (15)	S84129 (16)	ST1882 (17)	SE4488 (18)	S29646 (19)	SE4942 (20)	S27557 (21)	SE1688 (22)	S26379 (23)	S26425 (24)	S85603 (25)	ST9165 (26)
betaRmrf	0.531***	0.908***	0.791***	−0.172	0.883***	1.166***	0.873***	0.856***	0.855***	0.948***	0.665***	0.037	1.185*
	(0.098)	(0.114)	(0.132)	(0.290)	(0.137)	(0.111)	(0.122)	(0.112)	(0.134)	(0.113)	(0.090)	(0.175)	(0.695)
betaSmb	−0.581***	−0.379*	−0.739**	1.039	−0.457	−0.278	−0.671***	−0.658***	−0.538*	−0.368	−0.592***	0.327	2.554
	(0.204)	(0.208)	(0.281)	(0.623)	(0.292)	(0.232)	(0.223)	(0.234)	(0.286)	(0.235)	(0.187)	(0.319)	(1.508)
betaHml	−0.213	1.028***	1.071***	0.553	1.028***	1.055***	0.713***	0.686***	0.709**	1.021***	0.863***	0.304	3.402**
	(0.197)	(0.196)	(0.267)	(0.581)	(0.278)	(0.224)	(0.211)	(0.226)	(0.272)	(0.227)	(0.181)	(0.302)	(1.248)
betaMOM	−0.126	−0.098	−0.501**	0.228	−0.168	0.014	−0.210	−0.178	−0.150	−0.103	−0.207	−0.105	1.321
	(0.154)	(0.156)	(0.208)	(0.357)	(0.217)	(0.175)	(0.168)	(0.177)	(0.212)	(0.178)	(0.142)	(0.241)	(0.955)
alpha	−0.001	0.016***	0.017**	−0.009	0.020***	0.004	0.011**	0.011*	0.020***	0.007	0.006	0.013*	0.006
	(0.005)	(0.005)	(0.007)	(0.014)	(0.007)	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)	(0.004)	(0.008)	(0.033)
Observations	55	53	54	23	54	55	53	55	54	55	55	52	36
R^2	0.456	0.625	0.492	0.206	0.497	0.713	0.568	0.570	0.480	0.615	0.598	0.051	0.244
Adjusted R^2	0.413	0.593	0.450	0.029	0.456	0.690	0.533	0.536	0.438	0.584	0.566	−0.030	0.147

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix III: Modified Eight-factor Model Regression Results (Part 1)

Eight–Factor Model Regression Results Part I

Dependent variable: R – Rf

	S28342	S35966	S85118	SE2421	SH9398	SR2083	SE5438	SR3017	S21122	S68046	S83499	ST0713	SK7292	S21679
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
betaRmrf	0.275	0.373*	0.056	0.151	0.193	−0.216	0.271*	0.064	0.933***	0.125	0.122	0.102	0.557**	0.264
	(0.171)	(0.217)	(0.201)	(0.189)	(0.176)	(0.277)	(0.146)	(0.172)	(0.165)	(0.139)	(0.186)	(0.104)	(0.207)	(0.177)
betaSmb	−0.379	−0.190	0.152	0.027	0.108	−0.466	−0.317	0.940***	0.271	−0.324	−0.050	0.042	−0.305	0.263
	(0.251)	(0.317)	(0.293)	(0.285)	(0.272)	(0.489)	(0.224)	(0.283)	(0.307)	(0.204)	(0.272)	(0.184)	(0.322)	(0.328)
betaHml	−0.458*	−0.366	−0.598*	−0.460*	−0.345	−0.766*	−0.430**	−0.388	−0.365	−0.124	−0.168	−0.030	0.049	0.026
	(0.269)	(0.357)	(0.323)	(0.245)	(0.240)	(0.373)	(0.202)	(0.236)	(0.328)	(0.226)	(0.302)	(0.144)	(0.284)	(0.348)
betaMOM	0.167	0.167	0.317	0.219	0.276	−0.576*	0.229	0.658***	−0.226	0.411**	0.429*	−0.072	0.620**	0.807***
	(0.191)	(0.262)	(0.241)	(0.208)	(0.197)	(0.300)	(0.165)	(0.191)	(0.244)	(0.169)	(0.226)	(0.114)	(0.235)	(0.259)
betaMSCI	−0.715***	−0.562*	0.018	−0.405*	−0.449**	−0.439	0.275	−0.016	−0.103	−0.347*	−0.520**	−0.234**	−0.788***	−0.303
	(0.229)	(0.288)	(0.267)	(0.205)	(0.186)	(0.303)	(0.168)	(0.185)	(0.289)	(0.184)	(0.246)	(0.114)	(0.225)	(0.308)
beta10Y	−0.107	−0.540	−0.542	−0.388	−0.449	−0.346	−0.598	−1.024	−0.385	−0.643	−0.735	−0.333	−1.308	−1.266
	(0.826)	(1.041)	(0.974)	(0.757)	(0.708)	(1.264)	(0.624)	(0.689)	(0.900)	(0.688)	(0.918)	(0.459)	(0.859)	(1.029)
betaCredSpr	5.347	0.125	2.847	3.607	5.157	4.125	3.936	−2.385	−5.521	4.132	3.220	0.103	−0.636	0.001
	(4.145)	(5.223)	(4.899)	(3.787)	(3.482)	(6.238)	(3.104)	(3.479)	(4.466)	(3.477)	(4.642)	(2.332)	(4.200)	(5.252)
betaFutures	−0.112	0.279	0.014	0.054	0.090	0.399	−0.033	0.126	−0.056	0.043	−0.229	0.017	−0.056	−0.130
	(0.180)	(0.227)	(0.204)	(0.166)	(0.174)	(0.366)	(0.131)	(0.187)	(0.249)	(0.141)	(0.189)	(0.127)	(0.205)	(0.265)
alpha	0.0001	0.006	0.017	0.003	0.003	−0.00005	0.004	0.003	0.012	−0.008	−0.005	0.017***	−0.004	−0.010
	(0.009)	(0.012)	(0.010)	(0.008)	(0.007)	(0.014)	(0.006)	(0.007)	(0.012)	(0.007)	(0.010)	(0.005)	(0.009)	(0.013)
Observations	61	60	58	50	46	36	53	43	69	57	57	38	47	68
R^2	0.210	0.183	0.187	0.219	0.271	0.357	0.545	0.435	0.534	0.285	0.155	0.272	0.380	0.275
Adjusted R^2	0.088	0.055	0.055	0.067	0.114	0.167	0.462	0.302	0.472	0.166	0.014	0.071	0.250	0.177

	S22382	S20280	S62692	S23350	ST1892	SJ5323	S34823	SJ4786	ST5754	SN5118	S83527	SL8820	S23349	SR3434
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
betaRmrf	0.345**	0.248***	0.155	0.381**	0.283	0.338***	0.765***	−0.053	0.110	0.237**	0.512**	0.019	0.369***	0.073
	(0.137)	(0.087)	(0.137)	(0.160)	(0.249)	(0.121)	(0.227)	(0.084)	(0.067)	(0.113)	(0.213)	(0.039)	(0.126)	(0.081)
betaSmb	−0.023	−0.385**	−0.102	−0.029	0.964**	−0.346*	0.490	0.308**	−0.199	0.039	0.476	0.004	0.332	0.217
	(0.250)	(0.163)	(0.208)	(0.260)	(0.442)	(0.183)	(0.331)	(0.129)	(0.119)	(0.194)	(0.381)	(0.063)	(0.204)	(0.133)
betaHml	−0.117	−0.421**	0.022	0.183	0.225	−0.540***	0.090	0.134	−0.142	−0.113	0.085	0.048	0.107	0.109
	(0.282)	(0.174)	(0.229)	(0.270)	(0.345)	(0.160)	(0.365)	(0.114)	(0.091)	(0.152)	(0.344)	(0.053)	(0.211)	(0.111)
betaMOM	0.690***	−0.119	0.170	0.486**	0.556*	−0.017	−0.204	0.242**	0.074	−0.120	0.233	−0.036	0.377**	0.070
	(0.204)	(0.128)	(0.153)	(0.195)	(0.275)	(0.136)	(0.273)	(0.094)	(0.073)	(0.123)	(0.274)	(0.044)	(0.153)	(0.090)
betaMSCI	−0.276	−0.278*	−0.296	−0.430*	0.045	0.366***	−0.366	0.095	−0.028	0.266**	0.031	−0.014	−0.381**	−0.097
	(0.254)	(0.153)	(0.193)	(0.242)	(0.272)	(0.133)	(0.301)	(0.089)	(0.074)	(0.122)	(0.291)	(0.041)	(0.190)	(0.087)
beta10Y	−0.968	−0.159	−0.225	−1.550*	−1.353	−1.392***	−1.825	−0.587*	0.121	0.187	−0.343	0.123	−0.893	−0.170
	(0.828)	(0.468)	(0.692)	(0.821)	(1.020)	(0.494)	(1.100)	(0.337)	(0.307)	(0.442)	(1.067)	(0.157)	(0.644)	(0.324)
betaCredSpr	−2.334	5.302**	2.905	−0.102	−5.963	−3.762	4.108	−1.328	1.844	3.030	−3.804	0.497	7.445**	0.160
	(4.068)	(2.331)	(3.478)	(4.227)	(5.177)	(2.471)	(5.533)	(1.656)	(1.517)	(2.218)	(5.344)	(0.769)	(3.316)	(1.634)
betaFutures	−0.049	0.001	−0.118	−0.187	0.146	−0.074	0.017	−0.136	−0.127	−0.020	0.003	−0.071*	−0.155	0.008
	(0.213)	(0.131)	(0.154)	(0.199)	(0.304)	(0.104)	(0.231)	(0.083)	(0.089)	(0.122)	(0.223)	(0.038)	(0.156)	(0.088)
alpha	−0.009	−0.005	−0.010	−0.0001	0.010	0.016***	0.001	0.003	−0.006	−0.002	0.001	0.005***	0.003	0.004
	(0.010)	(0.006)	(0.008)	(0.010)	(0.012)	(0.005)	(0.012)	(0.003)	(0.003)	(0.005)	(0.011)	(0.002)	(0.008)	(0.003)
Observations	68	72	63	66	39	51	58	46	36	42	55	45	66	43
R^2	0.337	0.203	0.067	0.299	0.266	0.670	0.432	0.309	0.366	0.570	0.304	0.176	0.466	0.138
Adjusted R^2	0.247	0.101	−0.071	0.201	0.071	0.607	0.339	0.160	0.178	0.466	0.184	−0.007	0.392	−0.065

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix III: Modified Eight-factor Model Regression Results (Part 2)

Eight–Factor Model Regression Results Part II

	Dependent variable:																									
	R – Rf																									
	SS9048	SM1268	S39727	S83243	SL7844	S67536	SK1674	S28300	S37095	SD0499	S28266	S26387	SH8698	S22669	S69730	S84129	ST1882	SE4488	S29646	SE4942	S27557	SE1688	S26379	S26425	S85603	ST9165
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
betaRmrf	0.022	0.185	0.201	0.001	0.069	−0.005	−0.007	−0.091	0.986***	0.430***	−0.205	0.169	0.323*	0.450***	0.841***	0.700***	−0.410	0.757***	1.248***	0.678***	0.671***	0.598***	0.989***	0.559***	−0.126	0.345
	(0.046)	(0.331)	(0.217)	(0.007)	(0.081)	(0.008)	(0.073)	(0.132)	(0.149)	(0.136)	(0.160)	(0.175)	(0.183)	(0.127)	(0.150)	(0.168)	(0.439)	(0.179)	(0.146)	(0.157)	(0.142)	(0.158)	(0.146)	(0.107)	(0.223)	(0.884)
betaSmb	−0.022	0.534	0.617*	−0.004	0.182	0.005	−0.116	0.233	−0.640***	−0.726***	0.292	−0.643**	−0.140	−0.520**	−0.404*	−0.781**	1.444*	−0.437	−0.337	−0.668***	−0.525**	−0.528*	−0.426	−0.542***	0.549	3.438**
	(0.082)	(0.517)	(0.335)	(0.010)	(0.125)	(0.013)	(0.115)	(0.180)	(0.217)	(0.244)	(0.286)	(0.313)	(0.275)	(0.227)	(0.230)	(0.303)	(0.715)	(0.323)	(0.262)	(0.241)	(0.255)	(0.285)	(0.261)	(0.193)	(0.342)	(1.559)
betaHml	−0.013	0.553	0.231	0.003	0.219*	0.004	0.026	0.031	0.778***	−0.011	0.115	−0.108	0.304	−0.294	0.962***	1.004***	0.411	0.942***	1.050***	0.626***	0.598**	0.598**	0.966***	0.754***	0.177	3.127**
	(0.064)	(0.428)	(0.296)	(0.011)	(0.111)	(0.011)	(0.095)	(0.194)	(0.244)	(0.220)	(0.258)	(0.282)	(0.236)	(0.205)	(0.208)	(0.273)	(0.633)	(0.291)	(0.236)	(0.218)	(0.230)	(0.257)	(0.236)	(0.174)	(0.309)	(1.190)
betaMOM	0.038	0.415	0.275	0.014*	0.043	0.008	0.012	0.065	−0.383**	−0.318*	0.150	−0.202	−0.286	−0.144	−0.118	−0.563**	0.008	−0.238	0.059	−0.321*	−0.240	−0.351*	−0.081	−0.234*	−0.043	0.669
	(0.051)	(0.368)	(0.243)	(0.008)	(0.091)	(0.009)	(0.082)	(0.138)	(0.179)	(0.176)	(0.206)	(0.225)	(0.201)	(0.163)	(0.170)	(0.217)	(0.396)	(0.231)	(0.188)	(0.178)	(0.184)	(0.204)	(0.188)	(0.138)	(0.255)	(0.955)
betaMSCI	0.011	−0.914**	−0.374	−0.004	−0.067	0.003	0.032	0.096	0.198	0.090	0.077	0.257	0.399*	0.091	0.030	0.180	0.081	0.217	−0.208	0.288	0.354*	0.521**	−0.175	0.135	0.195	0.622
	(0.051)	(0.359)	(0.230)	(0.009)	(0.088)	(0.010)	(0.080)	(0.186)	(0.198)	(0.186)	(0.218)	(0.239)	(0.198)	(0.173)	(0.173)	(0.228)	(0.417)	(0.244)	(0.199)	(0.181)	(0.195)	(0.215)	(0.199)	(0.147)	(0.256)	(0.965)
beta10Y	0.251	−0.311	−1.238	−0.140***	−0.424	−0.146***	0.158	0.139	0.950	−0.100	−0.942	−0.353	−0.285	−0.550	−0.072	0.669	0.950	0.102	−0.193	0.387	−0.234	0.990	−0.384	−0.378	−1.621*	−0.278
	(0.211)	(1.321)	(0.873)	(0.033)	(0.335)	(0.035)	(0.293)	(0.581)	(0.713)	(0.684)	(0.801)	(0.877)	(0.730)	(0.635)	(0.642)	(0.855)	(1.881)	(0.912)	(0.733)	(0.671)	(0.715)	(0.805)	(0.732)	(0.539)	(0.952)	(4.029)
betaCredSpr	1.777*	−7.610	−2.896	0.700***	−0.099	0.553***	0.437	−0.192	−0.008	−0.424	−1.498	−0.680	−2.550	1.020	3.687	6.626	−2.041	2.452	3.180	2.592	−0.143	2.410	4.191	4.401	−0.582	−14.234
	(1.043)	(6.614)	(4.291)	(0.168)	(1.636)	(0.176)	(1.466)	(3.199)	(3.578)	(3.427)	(4.011)	(4.393)	(3.652)	(3.182)	(3.196)	(4.201)	(10.047)	(4.479)	(3.669)	(3.341)	(3.582)	(3.954)	(3.668)	(2.701)	(4.762)	(19.886)
betaFutures	−0.126*	−0.003	−0.105	−0.012*	0.089	−0.004	0.031	0.131	0.055	0.028	−0.123	0.005	0.172	0.057	0.004	0.057	0.941	0.119	−0.042	0.102	0.058	0.323*	0.034	0.046	−0.171	2.886**
	(0.062)	(0.325)	(0.214)	(0.007)	(0.080)	(0.007)	(0.072)	(0.145)	(0.156)	(0.143)	(0.167)	(0.183)	(0.160)	(0.133)	(0.135)	(0.176)	(0.684)	(0.188)	(0.153)	(0.141)	(0.149)	(0.166)	(0.153)	(0.113)	(0.201)	(1.168)
alpha	−0.002	0.013	0.009	−0.004***	0.007*	−0.004***	−0.005	−0.007	0.012	0.005	0.005	0.012	0.005	−0.002	0.012*	0.007	−0.014	0.015	0.003	0.006	0.010	0.010	0.005	0.002	0.018*	0.019
	(0.002)	(0.014)	(0.009)	(0.0003)	(0.003)	(0.0004)	(0.003)	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.009)	(0.022)	(0.009)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.010)	(0.045)
Observations	37	48	46	56	47	53	48	64	60	55	55	55	50	55	53	54	23	54	55	53	55	54	55	55	52	36
R^2	0.202	0.311	0.198	0.669	0.236	0.624	0.105	0.053	0.655	0.375	0.100	0.222	0.383	0.492	0.646	0.543	0.337	0.525	0.724	0.614	0.612	0.600	0.641	0.679	0.163	0.414
Adjusted R^2	−0.025	0.170	0.025	0.612	0.075	0.556	−0.079	−0.084	0.601	0.267	−0.056	0.087	0.262	0.403	0.581	0.461	−0.041	0.441	0.676	0.543	0.545	0.528	0.578	0.623	0.008	0.240

Note: *p<0.1; **p<0.05; ***p<0.01