November 2015

Three Essays on Hedge Funds

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THREE ESSAYS ON HEDGE FUNDS

A Dissertation Presented

by

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Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
of the requirements for the degree of

DOCTOR OF PHILOSOPHY

September 2015

School of Management

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DEDICATION

To my Lord Jesus Christ, my parents, and my brothers and sisters at Amherst Chinese Christian Church.

ACKNOWLEDGMENTS

I would like to thank my advisor, Bing Liang, for his many years of extraordinary guidance and support. Without him, I could not have finished my doctoral study and found a job. He has been my ideal advisor. I would also like to extend my gratitude to the members of my committee, Lei Lian, Mila Getmansky Sherman, and Bernard Morzuch, for their helpful comments and suggestions on all stages of this project.

I wish to express my appreciation to Stephen Kuselias, Nikki MacKenzie, Timothy Mech, Jun Pan, Jun Qian, Christopher Schwarz, Elaine Wang, Tan Wang, Hong Yan, Xiaoyan Zhang, and Lu Zheng for useful comments and suggestions.

Once again, as in my dedication page, I want to thank my Lord Jesus Christ for all His creation, redemption, and blessings upon every one of us! I would like to thank my parents, as well as my dear brothers and sisters at Amherst Chinese Christian Church. They are all wonderful presents to me from God.

ABSTRACT

THREE ESSAYS ON HEDGE FUNDS

SEPTEMBER 2015

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This dissertation consists of three chapters. The first two chapters focus on the Chinese hedge fund industry, and the third chapter focuses on American and offshore hedge funds.

In the first chapter, I study the Chinese hedge fund industry during its earliest development from 2003 to 2013. I find that it outperforms the Chinese stock market over this period by about 200% in cumulative returns. I also find that different investment strategies lead to significant differences in a fund's performance, risk taking behavior, and return generating process, although no investment strategy demonstrates persistence in performance during this period. Moreover, I point out that for any research on survival issues of Chinese hedge funds, it is necessary to distinguish between dissolved funds according to why a fund stops reporting to a database.

Chinese hedge funds are different from other hedge funds in the world because of their self-chosen disclosing mechanism, special legal structure, and constant policy changes. So in the second chapter, I investigate whether these special features affect the performance of Chinese hedge funds. I find strong evidence that better fund performance is associated with more frequent fund disclosure, higher complexity of trust companies and fund management companies, and slower speed of fund families in launching new funds. I also provide evidence that the new policy in July 2011, which allows trust companies to trade stock index futures, brings fundamental changes to the hedge fund industry, especially funds that focus on hedging techniques.

The third chapter studies hedge funds and their service providers. By building a comprehensive numeric score of hedge funds’ service providers, I study the relationship between hedge funds’ use of service providers and funds’ characteristics, performances, and investor flows. I find that using well-known service providers is associated with larger fund size, younger fund age, offshore domiciliation, better past performance, and smaller and less volatile cash flows from investors, and it can also predict better fund performance in the future. My results are robust across different fund sizes, investment strategies, and different levels of asset growth.

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CHAPTER 1

CHINESE HEDGE FUNDS: PERFORMANCE, RISK, STRATEGIES, AND SURVIVAL

1.1 Introduction

In this study I investigate the Chinese hedge fund industry during its earliest development, which is from 2003 to 2013. In China the term "hedge fund" usually refers to a legal structure that is different from hedge funds in other countries. Rather than directly launched by a fund management company (management company hereafter), Chinese hedge funds are jointly launched by a trust company (trust hereafter) and a separate management company. Legislatively, therefore, Chinese hedge funds are considered part of the trust rather than a separate entity. [1] People often refer them as "Sunshine" private funds in order to distinguish them from illicit, underground private funds.[2]

Focusing on markets in Mainland China, the Chinese hedge fund industry is a very special method of alternative investment in emerging markets. The distinctiveness of Chinese hedge funds arises on three aspects. First, the Chinese hedge fund industry is very young and fast growing. The first Chinese hedge fund was launched as recently as 2003, as shown in Figure

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[1] This is the definition of Chinese hedge funds by 2013, the end of the data sample in this research. However, with the implementation of Securities Investment Fund Law of the People's Republic of China (http://www.gov.cn/jrzg/2012-12/29/content_2301603.htm (in Chinese)) in June 2013 and of Registration Measures for Private Funds and Fund Managers (http://www.amac.org.cn/flfg/flfgwb/zlgz/385709.shtml (in Chinese)) in February 2014, management companies are now allowed to launch hedge funds autonomously, without the use of a trust. So the term "Chinese hedge funds" changed afterwards. In March 2014, Shanghai Chongyang Investment Management Co., Ltd., issued the first Chinese hedge fund (A-Share Alpha Hedge Fund) under the new definition. However, in the time horizon of this research, all funds are structured under the original definition.

[2] Illegal private funds in China are also referred to as "Grey" private funds, because they are unauthorized, highly opaque, and not subject to any regulation or monitoring. It is estimated that by the end of 2002 the grey private fund industry manages 25 to 113 billion USD (Yang (2002)).

1.[3] With only ten years of development, the numbers of active funds and fund families (or management companies) have already increased to 1,793 funds and 592 fund families in 2013. China Trustee Association estimates that as of the first quarter (Q1) of 2014, the Chinese hedge fund industry has total assets under management of 41.91 billion USD.[4] People often consider 2007 the year of the industry's real emergence, because before this year there were only a handful of funds and fund families.[5] Additionally, 2010 is often considered the real birth year of Chinese hedge funds, because in this year both funds and fund families double in number.[6]

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[3] This first fund in my data is China Dragon I issued by Yunnan International Trust Co., Ltd., in August 2003. In fact, however, the Chinese hedge fund industry began several months before this. In December 2002, Shanghai Guosen issued the first fund is Bond Portfolio Capital Plan (Chen, Chen, and Chen (2013)), but it is a short-lived, investment plan with a history of merely one year, and thus it is not included in my data. Another well-known fund is Pure Heart managed by Danyang Zhao and issued by Shenzhen International Trust (now China Resources ZITIC Trust Co. Ltd.) in February 2004. The media often regard it as the first Chinese hedge fund (see, for example, http://news.go-goal.com/86/494307.html (in Chinese)). However, in fact it is the first fund managed by overseas managers, and it is launched later than the first fund in my data. Pure Heart is unstable and not representative of the overall Chinese hedge funds. The clearest example is that in 2008 it abruptly stopped operation and liquidated all its assets. So it is also not included in my data.

[4] Data source: http://www.xtxh.net/xtxh/statistics/19746.htm (in Chinese). The original number is 261 billion CNY. This may not be an impressive figure worldwide. Indeed, it is merely two times the total stipend to the 25 top-earning hedge fund managers in the world in 2013, according to a report in the Institutional Investor's Alpha magazine (http://www.institutionalinvestorsalpha. com/HedgeFundRichList). However, given a short development of less than eleven years, the Chinese hedge fund industry obviously demonstrates a significant growth.

[5] According to an article on Go-Goal.com (http://news.go-goal.com/86/494307.html), the surge of the industry in 2007 coincides with two events. The first event is that many well-known mutual fund managers joined the hedge fund industry. The other event is the advent of personal banking services in China, which suggests that financial institutions in China have become ready to provide financial services to Chinese high net-worth investors.

[6] Several events may be related to the significant rise of hedge funds in 2010. For example, the state issued a new policy on March 31, 2010, which allows margin trading in China. Before this policy, there was virtually no direct hedging instrument in China. Another event is that in November 2011 the Securities Association of China listed hedge funds as one of the institutions for IPO pricing inquiry, which means that the general public recognizes Chinese hedge funds.

Second, most Chinese hedge funds claim to focus only on Chinese equity markets. This focus is called the Traditional Stock strategy in my database, similar to the Long/Short Equity strategy in other countries. The vast majority (79%) of funds in my sample use this strategy. Actually, such predominance is a unique feature in the early developing stage of all hedge fund industries. For example, by the mid-1970s, most US hedge funds used only the Equity Long/Short strategy (Langham and Raasch (2008)).

Finally, most Chinese hedge funds offer only investment contracts with finite time horizons, also known as limited contract duration. Therefore, Chinese hedge funds could exit from a database for a special reason—a fund may stop reporting simply because it has reached its contract duration, not necessarily because of poor performance or real fund failure. [7] Although this reason may also exist in other hedge fund industries, it is obviously far more predominant in China, because only 8% of funds claim that they do not operate with limited contract duration.

While the last aspect is probably unique to Chinese hedge funds, the first two are in fact universal features to early development of all hedge fund industries. Therefore, investigating Chinese hedge funds not only offers insight into this particular industry but also sheds light on the primary developing stage of all hedge funds globally. However, few studies have actually focused on Chinese hedge funds, with the exception of Chen, Chen, Chen, and Zhang (2012) and Chen, Chen, and Chen (2013). In this research, by using a large database that offers comprehensive Chinese hedge fund data, I provide insights into this industry from 2003 to 2013. Focusing on the three aspects above, this paper primarily investigates the industry's (i) general

[7] A common question about limited duration is what a fund will do after it reaches its contract duration. In reality, it will either extend the duration of the contract or be liquidated (Yu (2012)). In my data, 51 funds have reached their contract duration, but only nine report after expiration. Thus, it appears that most of the expired funds in my data are liquidated.

performance and risk, (ii) investment styles, and (iii) survival issues. The main findings are as follows.

First, I find that from 2003 to 2013 Chinese hedge funds yield higher returns with less volatility than the Chinese stock market. They outperform the Chinese stock market by about 200% in cumulative returns over these ten years. Hedge funds deliver a monthly excess return of 1.18% and a significant monthly Fama-French (1993) three-factor alpha of 0.85%, whereas the stock market delivers only 0.99%. Hedge funds are also less volatile. They bear a monthly standard deviation of only 4.63%, while that for the stock market is 9.26% more than two times higher.

Next, I study funds' investment strategies. I find large variation across different strategies in terms of risk and return. For risk, the difference across strategies can be as high as over ten times—the Bond strategy, the least risky strategy, has a monthly standard deviation lower than 1%, but the Trend Following strategy, the most risky strategy, has a monthly standard deviation more than 10%. Regarding returns, I first document that no single investment strategy shows persistence in performance over the years. Then, in order to explore the return generating process of each strategy, I perform stepwise regressions of fund returns on a series of Chinese asset-based style (ABS) factors. The regression results reveal that different investment strategies have disparate return generating process, and a fund's claimed investment strategy indeed indicates its real investment focus.

Finally, I focus on survival issues for Chinese hedge funds. I first document that from 2003 to 2013 the average fund attrition rate was 5% and the annual survivorship bias was 0.8%. Contrary to common beliefs, however, these numbers are not entirely caused by live funds' outperformance over dissolved (or dead) funds. My results show that nearly 50% of dissolved funds exit the database merely because they have reached contract duration, and these funds are the best performing ones among all dissolved funds, with their performance virtually no different than live funds. I then explore what fund characteristics could predict fund dissolution or real fund failure. I find that there are several fund characteristics related to fund dissolution, but only poor fund performance is associated real fund failure.

To the best of my knowledge, this study is the first comprehensive study on the performance, risk, strategies, and survival issues of Chinese hedge funds, so it enriches the existing literature. For example, Xia (2001) provides a theoretical framework on this business from the perspective of regulators and practitioners. Chen et al. (2012) focus on the impact of different managers' background on fund performance. Chen, Chen, and Chen (2013) study survival issues of Chinese hedge funds, although they do not distinguish among dissolved funds according to why a particular fund stops reporting to a database.

Compared to these studies, my research has two main contributions. First, I show that, for Chinese hedge funds, differences in return and risk are mainly caused by funds' investment styles. This cause is more direct than a fund manager's background. Second, I demonstrate that almost half of dissolved funds disappear due to limited contract duration rather than poor performance. Consequently, in order to study survival issues of Chinese hedge funds, one has to consider the reason why a fund drops out of a database; otherwise, the result could be misleading.

1.2 Legal Structure and Boom of Chinese Hedge Funds

As in previous discussion, the Chinese hedge fund industry is special for its unique legal structure and amazing economic growth. In this section, I offer the underlying causes for these two features. First, regarding their legal structure, Chinese hedge funds are organized differently than hedge funds in other countries. The key reason for this difference in legal structure is that

China has been very prudent in introducing hedge funds to its domestic markets. Therefore, from 2003 to 2013, Chinese authorities did not allow management companies to launch any privately offered fund directly. Instead, to launch a private fund, a management company had to collaborate with a trust, which is an already existing financial industry that the state can safely guard. Although the trust hires a management company to manage the fund, legislatively, the fund is still considered a special financial product offered by the trust. The fund can then be sold to general investors. Investors purchase and sell the fund shares completely via the trust and have no direct interaction with the management company. To ensure the transparency of the fund, the trust is responsible for regularly disclosing the fund's net asset value (NAV) to its investors. Additionally, the trust needs a third-party custodian bank to guard the fund's capital and a prime broker to provide a centralized securities clearing facility for the fund. Figure 2 illustrates such a special legal structure.

Although this unique setting obviously protects investors' interests, it costs the funds additional distribution channel fees and restricts them from using complicated financial instruments, as trusts are usually very conservative.[8]

Second, two main factors power the dramatic boom of the Chinese hedge fund industry from 2003 to 2013. The first factor is the asset management demand from the high net-worth investors due to the fast growing Chinese economy. Given limited investment channels and the

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[8] In fact, however, the Revised Fund Law of the People's Republic of China (http://www.gov.cn/jrzg/2012-12/29/content_2301603.htm (in Chinese)), which was approved in June 2013, expands the definition of Chinese hedge funds. The Revised Fund Law now allows management companies to launch hedge funds alone, without collaborating with any trust, so hedge funds can now operate under a different structure. The Chinese government also announced Registration Measures for Private Funds and Fund Managers (http://www.amac.org.cn/flfg/flfgwb/zlgz/385709.shtml (in Chinese)). The first fund totally run by a management company is A-Share Alpha Hedge Fund, launched by Shanghai Chongyang Investment Management Co, Ltd., which was founded in March 2014. But for the data range in my research, all funds are organized under the original structure.

disappointing performance of the Chinese stock markets, hedge funds are the only legal form of private funds available for these wealthy investors. Before the advent of Chinese hedge funds, many underground funds already existed in China due to the strong demand for alternative investment vehicles among Chinese investors. Investing flexibly in private equity and secondary market securities, hedge funds offer professional management and better asset allocation, and provide absolute returns to investors.

Another driving force for the industry's fast expansion has been the enactment of a series of beneficial policies. In the first few years of the industry, the Chinese government was very prudent. The state aims to pose as few abrupt changes as possible, so it has introduced hedge funds' sophisticated investment philosophy gradually. Thus, in the industry's earliest development, there were virtually no hedging instruments available to the funds. The first advantageous policy for hedge funds, issued in March 2010, allowed margin trading in China and provided the first tool for hedging. Later, the state issued a number of policies and laws that provided more and more flexibility to hedge funds. These changes included a system allowing hedge funds to use stock index futures in July 2011, the refinancing system in August 2012, the securities relending system in February 2013, the re-launch of Treasury futures in June 2013, and the revised Securities Investment Fund Law (Revised Fund Law hereafter) in June 2013.

1.3 Related Literature

This research is related to three aspects of the literature on hedge funds. Within the performance and risk literature, two groups of research are especially close to my study. On one hand, I investigate the return generating process of Chinese hedge funds, several studies provide insight into this process. For example, Ackermann, McEnally, and Ravenscraft (1999), Liang (1999), and Fung and Hsieh (2001) find that returns are much less correlated with the traditional market benchmarks commonly used for investigating mutual funds, and thus hedge funds have less systematic risk. Additionally, Fung and Hsieh (1997a), Mitchell and Pulvino (2001), and Agarwal and Naik (2004) provide evidence that hedge funds' return generating process is option-like due to both their flexibility in trading derivatives and the call option-like incentive fee structure. Fung and Hsieh (2004) present a regression model of hedge fund returns on a series of asset-based style (ABS) factors that other researchers use widely. In my approach, I compare the return of Chinese hedge funds with the return on the Chinese stock market, similar to previous studies. For hedge funds in developed countries, Liang (1999) finds that hedge funds provide higher Sharpe ratios than mutual funds. For the Chinese market, Chen et al. (2012) also document the outperformance of hedge funds over the stock market. Additionally, they document that the Fama-French three-factor model has the highest explanatory power. Similarly, I also find the outperformance of Chinese hedge funds using the Fama-French three-factor model.

The second aspect of the literature that relates to my study is differentiation among hedge fund styles (or strategies). In this research, I explore these differences across fund types and strategies. Much of the previous research is conducted in this direction also. For instance, Brown and Goetzmann (2001) find that different styles of hedge funds do exist, and that style differences contribute 20% of the cross-sectional variation of hedge fund performance. Fung and Hsieh (2004) provide theoretical insight into operations for major hedge investment strategies. Moreover, they introduce a regression model to explain hedge fund returns using seven asset-based style (ABS) factors, and they argue that using the model on bias-free hedge fund data delivers better and more meaningful results. Naik, Ramadorai, and Stromqvist (2007) find cash flows affect each investment strategy disparately. They show that for four out of eight major hedge investment strategies, cash inflows have statistically preceded the negative movement in alphas, but not for other strategies. Chen et al. (2012) study the differences for Chinese hedge funds caused by a manager's previous background. Their results demonstrate that managers with background in mutual funds or securities firms show superior performance and more skills in choosing stocks than other managers. Titman and Tiu (2011), and Sun, Wang, and Zheng (2012) indicate that fund managers who differ from their peers tend to possess superior managerial skills.

The third aspect of the literature is survival of hedge funds. For example, Fung and Hsieh (1997b) and Brown, Goetzmann, Roger G. Ibbotson, and Ross (1992), among others, report that alternative investment vehicles suffer from significant attrition each year. They report the annual attrition rate for Commodity Trading Advisors (CTAs) to be 19%; for offshore hedge funds, the attrition rate is 14%. Based on Lipper TASS data, Liang (2000) finds that the annual attrition rate for hedge funds averages around 8%.

However, hedge funds may stop reporting to a database for reasons other than fund failure. These reasons include: The database is unable to contact the fund, the fund is closed to new investment; the fund has merged with other funds; and the fund is in a dormant period (see, for example, Liang and Park (2010)). Therefore, the overall attrition rate does not indicate real hedge fund failure. Some research specifically investigates the differences between fund attrition and fund failure. For example, Liang and Park (2010) find that the annual attrition rate of hedge funds is between 8% and 9%, but only 3% of such attrition is due to real fund failure.

Other research measures the survivorship bias for hedge funds. Fung and Hsieh (1997b), Liang (2000), and Amin and Kat (2003) all find that such bias is between 2% and 4%. The research by Chen et al. (2012) is probably the closest to mine, since they also study the survival issue for Chinese hedge funds. Using a different database from mine, they document an attrition rate of 14% and a survivorship bias of 0.99% per year. They also investigate the causes of fund attrition and find that poor risk-adjusted performance, higher volatility, smaller fund size, and younger fund age are associated with fund attrition. In my data, however, I find that the average attrition rate is 5% and the annual survivorship bias is 0.8%. Additionally, the funds that dissolve only because they have reached the limit of their investment contract perform much better than funds that disappear due to other reasons. I also find evidence that several fund characteristics are associated with fund attrition, but only poor performance is related to both fund attrition and real fund failure.

1.4 Data

In this research, I use data for Chinese hedge funds provided by Howbuy, a leading investment advisor in China.[9] The raw data from Howbuy consists of two Excel files. The first data file contains the time-series disclosures of NAV per share for each fund. This file allows me to calculate both the monthly returns and the disclosing frequency of each fund. The disclosing frequencies, calculated as the difference in days between two adjacent disclosures, are approximately daily, weekly, monthly, or quarterly.[10] The second data file contains various characteristics for each fund. It also lists the management company and trust for each fund. Thus, I can obtain the characteristics at the fund level, family level, and trust level with this file.[11]

I obtain two snapshots from the Howbuy data—one on November 16, 2012, and the other on November 23, 2013. Including more than one snapshot allows me to obtain more

[9] The website of Howbuy is http://www.howbuy.com/ (in Chinese).

[10] Additionally, some funds do not disclose NAV with a stable frequency.

[11] This second file reports the following fund level information: Inception date, trust, custodian, prime broker, load fee, redemption fee, management fee, incentive fee, dates open to subscription and redemption, duration of investment, lockup period, soft lockup period, fund type, and investment strategy. Some funds also report monthly returns in this file, but I consider such returns only if the fund’s NAV for that month is not available in the NAV file.

comprehensive data for Chinese hedge funds.[12] I then combine the two Excel files from the two snapshots, where I calculate the monthly returns for each fund using month-end observations of NAV per share. The data period covers August 2003 to November 2013. Altogether, my data sample contains 2,195 funds and 733 fund families.

Figure 1 provides an overview of the industry based on this unscreened data sample. Subfigure (a) depicts the significant growth in the industry. In 2003, there was only one Chinese hedge fund and thus one fund family, but 1,793 funds and 592 fund families were operating as of November 2013. However, the numbers of new funds and fund families are not consistently increasing each year, with the peak reached in 2011, as shown in Subfigure (b).[13]

For my approach, I apply the following screening criteria to my sample. I require the funds to have at least a one-year history of NAV disclosure. I then delete the quarterly disclosing funds, because even if such funds have one year of history, there are as few as four observations. The top and bottom 2.5% raw return values are winsorized to control for outliers.[14] Such screening leads to a sample of 1,548 funds and 554 fund families. The rest of the

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[12] See, for example, Patton, Ramadorai, and Streatfield (2013) and Aragon and Nanda (2014) for discussions on using multiple snapshots. I follow the procedure of Aragon and Nanda (2014) in that I use only NAV values in the more recent snapshot, if the NAV for a certain fund at a certain month is included in both the two snapshots.

[13] The phenomenon may occur that new fund startups do not keep increasing in 2012 and 2013 for two reasons. First, in these two years, some hedge funds may already be operating but do not report to any database. Thus, the actual number of fund startups in 2012 and 2013 could well exceed what the database suggests. Later, hedge fund managers usually choose a successful fund and report its previous returns. This behavior of hedge funds causes a well-documented incubation bias. Second, Chinese hedge fund managers may really be reluctant to launch new funds in these two years. This hesitation may be due to the fact that they know the Revised Fund Law will be enacted very soon. This new law will allow them to launch funds completely autonomously. It finally was implemented in February 2014, so this hesitation paid off.

[14] I also try including the quarterly funds in the sample and try other thresholds for winsorization, and the results remain virtually unchanged.

study is based on this screened sample. Table 1 and Figure 3 provide summary information about this screened data sample.

Table 1 presents the summary statistics. Panel A of Table 1 reports the statistics for the funds, while Panel B of Table 1 reports for fund families. There are four fund types: Ordinary funds, which use conventional strategies, Innovative funds, which use newer strategies, Trust-of-Trusts (ToT) funds, which invest in a pool of hedge funds,[15] and Overseas Managed funds, which are managed by management companies outside Mainland China.[16] Together, the Ordinary and Innovative funds account for 95% of the funds in my data sample.

Panel A of Table 1 reveals that, compared to Ordinary funds, Innovative funds are newer, engage more in daily reporting, perform better, and offer more investor protection in incentive fee collection,[17] shorter contract duration, and stricter share restrictions. To be specific, Innovative funds are on average more than one year younger than Ordinary funds. Of Innovative funds 32% disclose NAV daily; 33% of Ordinary funds disclose weekly or monthly, and less than 1% of them do so on a daily basis. The difference in performance between these two fund types is always severalfold, regardless of the performance measurement (excess return, Sharpe ratio, or Fama-French three-factor alpha). Besides, Innovative funds on average offer six years shorter contracts but much tighter share restrictions (for example, lockup period, soft lockup period, and open frequency[18]) than Ordinary funds.

[15] ToT funds are the Chinese version of funds of funds.

[16] Managers from China start these overseas management companies, but they are registered overseas. They are not the leading management companies in developed countries.

[17] Such protection includes the use of the high water mark provision, the hurdle rate provision, or both, which set up higher return levels for the fund to reach before they can charge incentive fees from investors.

[18] Open frequency is almost the same as redemption frequency, except that when a Chinese hedge fund is open to redemption, for most cases, it is also open to new investment. Thus, I use the term open frequency.

Another interesting finding in Panel A of Table 1 is the negative first-order autocorrelations among Chinese hedge funds. This finding is different from previous hedge fund studies, which document positive autocorrelations (see, for example, Getmansky, Lo, and Makarov (2004) and Brown et al. (2008)). Two reasons could lead to such a discrepancy. First, the Chinese hedge fund returns are highly correlated with the stock market. Compared to hedge funds in developed countries, Chinese hedge funds have relatively fewer hedging instruments, so most of them take only long positions in stocks, especially before 2010. And the autocorrelations of stocks are generally negative, especially over longer intervals (French and Roll (1986) and Lo and MacKinlay (1986)). Second, Chinese hedge funds rarely use the high water mark provision. As Getmansky, Lo, and Makarov (2004) put forward, high water mark could increase positive autocorrelations for hedge funds. In developed countries, the percentage of hedge funds that have water mark provision is between 65% and 78% (Liang (1999) and Aragon and Nanda (2012)), but in China this percentage is only 6%.

I next examine two minor fund types. For performance, Overseas Managed funds also show superior returns, but because of higher risk, their Sharpe ratio is lower than Innovative funds. ToT funds always perform between Innovative and Ordinary funds. For fund characteristics, by using high water mark exclusively, 45% of the Overseas Managed funds have investor protection in incentive fee collection. Such a high percentage is consistent with the popular use of high water mark for hedge funds in developed countries (Liang (1999) and Goetzmann, Ingersoll, and Ross (2003)). Meanwhile, only two ToT funds offer such protection.

Panel B of Table 1 summarizes a few key statistics for fund families. Five categories of families exist in my data—the families that solely manage Innovative, Ordinary, Overseas Managed, or ToT funds; and the families that manage multiple types of funds. On average, Innovative families are 14 months younger than Ordinary families, which is consistent with the results for funds in Panel A of Table 1. The families with the longest history are Multiple Type families, followed by Overseas Managed families. Each Multiple Type family on average manages 7.37 funds, more than double the family complexity for Innovative families. Family complexity decreases monotonically in Ordinary, ToT, and then Overseas Managed families. Overseas Managed families are the most focused group, operating only one fund per family. Multiple Type and Overseas Managed families also seem the most cautious, as they on average spend five to six months to open a new fund, while it takes Innovative families less than three months to open a new one.

1.5 Tests and Results

1.5.1 General Performance and Risk

My first goal is to examine the general performance and risk taking behavior of Chinese hedge funds. Figure 3 reveals that Chinese hedge funds generate higher and less volatile returns than the Chinese equity market. To be specific, one dollar invested in hedge funds in 2003 becomes around four dollars in 2013, while the equity market generates only two dollars during the same time period. The only exception to such outperformance occurs during the first few months of 2007, when the Chinese equity market underwent striking growth—its index grows by roughly 200% from the beginning of 2007 to the all-time peak in October 2007. The return of hedge funds is much less volatile than the equity market, most likely due to the hedging instruments available to hedge funds. Overall, such outperformance of hedge funds over traditional investment vehicles is consistent with the findings of hedge funds in developed countries (see, for example, Ackermann, McEnally, and Ravenscraft (1999) and Liang (1999)).

Moreover, Figure 3 clearly reveals that January 2010 should serve as a cutoff point for Chinese hedge funds, which separates the period of volatile changes before this month and the smoother period afterward. Three reasons could lead to this difference. First, 2010 is the year when the Chinese stock market finished the period of volatile changes. And since hedge fund returns are closely related to the stock market, the funds also bear less risk after 2010. Second, in 2010, the Chinese government established the system for margin trading, which provides funds with an effective tool for hedging. Before this, there was no direct way for Chinese funds to hedge their portfolio. As a result, the standard deviation of the funds begins to drop significantly after 2010. Finally, the industry is becoming increasingly competitive over the years. Many more funds are launched after 2010, as shown in Figure 1. The number of funds and fund families in 2010 suddenly more than doubles the number in 2009. The increasingly competitive industry imposes pressure on fund managers, which could mean that they engage in less risky trading in order to avoid heavy losses. This possible cause is also found for investment vehicles in other countries. To sum up, the apparent difference before and after 2010 suggests that the divide of period into two subperiods when testing hypotheses.

Next, I explore the differences in performance and risk across different fund types. I create six portfolios[19] based on the fund type criterion: One for each of the four fund types, one for domestic funds, and one for all funds in the database. I measure each portfolio's risk-adjusted return using the Fama-French three-factor model:

$$R_t - RF_t = \alpha + \beta_1 \times MKT_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \varepsilon_t. \qquad (1)$$

where R_t is the raw return of the portfolio in month t, RF_t is the interest rate of Chinese demand deposits in month t, MKT_t is the return on the Chinese Hushen 300 Index[20] in month t minus RF_t, SMB_t is the total return on the Russell China Small Cap Stock index minus the total return on the

[19] All portfolios in this research are equally weighted, because there is no fund size information in my database.

[20] The Hushen 300 Index is a widely recognized index for Chinese A-share stocks, compiled by China Securities Index Co., Ltd.

Russell China Large Cap Stock index in month t, and HML is the return on the Russell China Value Stock index minus the return on the Russell China Growth Stock index in month t.

Table 2 presents the differences in performance and risk across the four fund types. Overall, hedge funds outperform the stock market. Almost all fund type groups deliver higher excess return and Sharpe ratio than the stock market in the entire sample period and the two subperiods. For example, for the whole sample period, hedge funds' excess return is 29-basis-point higher than that of the Hushen 300 stock index (1.18% vs. 0.99%). ToT funds operate only in the second subperiod, and in this time range they do generate better performance, although they cannot outcompete the stock market's performance for the entire sample period. Two reasons could cause the fact that ToT funds deliver lower returns to investors. First, their investment philosophy determines that they can get only the average return from the pool of hedge funds they invest in. Second, these ToT funds charge higher service fees on investors, which in turn decreases their net returns (see, for example, Brown, Goetzmann, and Liang (2004)).

I then study the difference across fund types. First, I focus on the two major types, Innovative and Ordinary funds. I observe clearly that Innovative funds outperform Ordinary funds. Over the whole sample period from 2003 to 2013, the Innovative fund portfolio nearly doubles the excess return, Sharpe ratio, and Fama-French three-factor alpha compared to the Ordinary fund portfolio.

Then, using January 2010 as the cutoff point, I divide the whole sample period into two subperiods: 2003 to 2009 and 2010 to 2013. The first subperiod mainly drives the good

(http://www.csindex.com.cn/sseportal/csiportal/indexquery.do (in Chinese)). It is a free-float-weighted index consisting of 300 stocks, representing over 70% of the A-share stock market. The Chinese stock index future is built on this index. This index is also referred to as CSI 300 Index.

performance of the fund industry, because the Chinese stock market was going through drastic rises. During this period, funds yield higher but more volatile returns (excess return of 1.86% and standard deviation of 5.27% per month). The second subperiod features a bearish stock market. Hedge funds provide lower but smoother returns (excess return of 0.07% and standard deviation of 3.07% per month). This decline in hedge funds' performance caused by increasing competitiveness is also found for mutual funds and hedge funds in other countries (Berk and Green (2004), Naik, Ramadorai, and Stromqvist (2007) and Fung et al. (2008)).

Using Panel B in Table 2, I observe that Innovative funds' outperformance in the second period delivers 53 times higher excess return, 32 times higher Sharpe ratio, and over three times higher Fama-French alpha than those of the Ordinary portfolio.

The most likely cause for the expansion in Innovative funds' outperformance is the advent of beneficial policies. Starting in 2010, the Chinese regulators begin to enact a series of policies and laws that provide more hedging instruments to the funds. Since the Innovative funds consist mainly of funds using newer trading techniques, it is easier for them to benefit from these hedging instruments.

I then turn to the two minor types. I find that Overseas Managed funds show relatively mild performance and risk taking behavior. Like Innovative funds, they also realize significantly positive performance over the second subperiod. On the other hand, ToT funds are relatively the newest, with all such funds established after 2010, but their overall performance is not impressive.

1.5.2 Investment Strategies

So far, I have documented the performance and risk for the fund industry in general, as well as across the four fund types. However, these results tell me little about the industry at the investment strategy level. Next, I explore the differences among investment strategies. To be specific, I aim to answer three basic questions about investment strategies: (i) Whether different strategies lead to different patterns of performance and risk taking, (ii) whether any strategy maintains persistence in performance, and (iii) whether different strategies generate returns in different processes. Overall, my findings suggest that each strategy has unique return and risk taking behavior.

1.5.2.1 Classification by Investment Strategies

First, I have to understand the relation between two means of classification: The fund type criterion and the investment strategy criterion. The former criterion separates the funds into four subsets, but the latter one divides the funds into 15 subsets. However, despite this difference, funds report their investment style. In fact, originally the major classification criterion used by Howbuy was the fund type criterion, but later it had adopted the strategy criterion. My two snapshots reflect this change in the database. In the first snapshot on November 16, 2012, the fund type classification was the prevalent method, and the strategy classification was not widely used. But for the more recent snapshot on November 23, 2013, the Howbuy staff instructed me to focus instead on the strategy classification. One possible reason for this change is the fast growth of Chinese hedge funds. The simple fund type criterion was sufficient to distinguish the funds when the industry was small. Later, however, the dramatic growth of the industry demands the finer investment strategy criterion. Table 3 describes the close relation between fund type and investment strategy classifications.

In total, there are 15 groups based on the strategy criterion: 13 groups for each of the mainstream strategies; the Other group, which consists of funds that use rare strategies; and the N/A group, which consists of funds that do not report any strategy. Clearly, the Innovative fund type consists of strategies with shorter histories, while the Ordinary type consists of strategies with longer histories. So, again, I see that the Innovative type is younger than the Ordinary type.

Three other aspects of the strategy classification are worth noting. First, Overseas Managed and ToT are also self-reported strategies, although they are fund types also. Second, the category of Hedge-Strategy includes all funds self-labeling as Arbitrage, Hedge, or Multi-Strategy. These funds appear after March 2010, when China allowed margin trading, and subsequently this category has grown significantly. Third, this research does not include the Market Neutral strategy, even though it is a major strategy group in previous hedge fund research. I exclude it because this strategy group is dubious. In my data, the funds that claim using Market Neutral strategy began operating as early as in 2007, but that is before any hedging instrument is available to funds. In 2010, the authority introduced the first tool for hedging, which is the margin trading system. Therefore, the definition of the Market Neutral strategy is questionable.

1.5.2.2 Risk Difference

Next, I concentrate on differences in risk taking behavior across investment strategies. I first investigate whether they could lead to different patterns of risk. Figure 4 shows the risk taking behavior of each investment strategy, in which I form an equally weighted portfolio for each strategy.

Subfigure (a) includes the strategies with a history longer than 40 months. Their difference in risk is as much as 5%, and their risk shows a declining tendency in the long term.

Subfigure (b) includes the strategies with shorter histories. These strategies have even wider variation in risk. The least risky strategy is the Bond strategy with an average monthly standard deviation of lower than 1%, but the Trend Following strategy, the most risky strategy, has an average risk of over 10%. Overall, the risk patterns for these newer strategies are all relatively mild without any obvious declining tendency.

1.5.2.3 Performance Persistence

My next research question is whether any investment strategy has significant persistence in performance. After all, it is important for investors to know which funds or managers could consistently outperform their peers (Brown and Goetzmann (2001)). Table 4 shows that there is hardly any performance persistence across investment strategies. The coefficients in this table indicate the performance persistence from one year to the next, where a significantly positive coefficient suggests persistence in performance, and a significantly negative one suggests that the performance over these two years is actually reversed. Only 12 out of the 30 estimates of persistence coefficient are statistically significant, and even these significant estimates wander from negative to positive over the years, so there is no conclusive evidence for persistence in performance. The lack of performance persistence in hedge funds is also found in more established hedge fund industries (see, for example, Agarwal and Naik (2000), Brown and Goetzmann (2001), and Sun, Wang, and Zheng (2012)).

1.5.2.4 Return Generating Process

Since there is a clear difference but no significant persistence in performance across investment strategies, I am motivated to explore the return generating process of each strategy to understand more about each fund's investment style. To do so, I regress returns of each strategy on a series of asset-based style (ABS) factors. This is a standard method used in many studies (see, for example, Fung and Hsieh (2004)):

$$R_t = \alpha + \beta_1 \times MKT_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \beta_4 \times MOM_t + \beta_5 \times ChinaConcept_t + \beta_6 \times NationalBd_t + \beta_7 \times CorporateBd_t + \beta_8 \times COM_t + \varepsilon_t. \quad (2)$$

I explain R_t, MKT_t, SMB_t, and HML_t in Equation (1). In addition, MOM_t is the momentum factor in month t.[21] $ChinaConcept_t$ is the return on the MSCI Golden Dragon index in month t.[22] $NationalBd_t$ is the return on the CSMAR index for the national bonds listed in the Shanghai exchange in month t.[23] $CorporateBd_t$ is the return on the CSMAR index for the corporate bonds listed in the Shanghai exchange in month t. COM_t is the return on the Galaxy Futures comprehensive index for Chinese commodities in month t.[24] Fung and Hsieh (2004) introduce the methodology of using ABS factors for hedge fund studies, widely used afterwards.

Unlike most other studies, however, I use a stepwise version of the above regression, which considers only the significant (or marginally significant) contributing factors for returns.[25] To guarantee enough observations for regression, I consider strategies with a history longer than two years, leaving eight specific strategies and the Other strategy group. As reported in Table 5, the regression results document distinct return generating processes across strategies.

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[21] Following the method of Carhart (1997), the equally weighted return average of stocks with the highest 30% eleven-month returns lagged one month; the equally weighted return average of stocks with the lowest 30% eleven-month returns lagged one month. The portfolios include all Chinese A-share stocks and are re-formed monthly.

[22] The MSCI Golden Dragon index is designed to track the China-concept stocks listed in stock exchanges outside Mainland China.

[23] The website of CSMAR is http://www.gtarsc.com/ (in Chinese).

[24] The Galaxy Futures comprehensive index is designed to track the prices of the Chinese major commodity futures in many industries and is widely used for the overall performance of the Chinese commodity futures market. The website of Galaxy Futures is http://www.zs.yhqh.com.cn/ (in Chinese).

[25] See Liang (1999) and Agarwal and Naik (2000) for more detailed description of the stepwise regression mechanism.

Panel A of Table 5 reports the regression results for the entire sample period. I find that each strategy clearly has its own targeted market niche. No ABS factor is significantly associated with all strategies. The most popular investment focus among Chinese hedge funds is the domestic stock market, but even this focus is positively correlated with the returns of only four strategies. Other popular investment targets include Small minus Big (SMB), High minus Low (HML), and China-Concept stocks listed outside of Mainland China (ChinaConcept). All of these four targets focus on the equity market. This finding is consistent with the fact that most Chinese hedge funds use the Traditional Stock strategy.

Moreover, I find evidence that the name of the strategy correctly reveals the strategy's investment style, at least to some degree. For example, the Traditional Stock and the Private Placement strategies suggest that they mainly invest in the equity market, and unsurprisingly their returns are positively correlated with the stock market. Another example is the Bond strategy. Intuitively, it is not related to the stock market, such as Bond strategy, and it is the only strategy with a significantly positive correlation with the corporate bond market. Additionally, the Other group is not associated intuitively with any market niche.

The analysis in Panel A of Table 5 covers a period of more than 11 years. My analysis for this panel could be undermined if a strategy changes its investment style significantly over this long-term range. To reduce such concern, I divide the entire time window into two subperiods: 2003 to 2009 and 2010 to 2013, the same division mechanism used earlier. If I observe similar return generating processes for a strategy over the two subperiods, I have reason to believe that this strategy has consistent investment focus over the years. The result reported in Panel B Table 5 confirms the consistency in investment focus of a strategy. Only two strategies are long enough to be considered in Panel B of Table 5—the Traditional Stock and the Overseas Managed strategies. Both funds follow a similar investment focus over the two subperiods, with the adjusted R-squared for the stepwise regressions ranging between 0.5 and 0.8. The Traditional Stock strategy focuses consistently on MKT and SMB factors, and the Overseas Managed strategy focuses consistently on China-concept stocks listed overseas and the SMB factor.

1.5.3 Survival

In this subsection, I study the survival issue of the Chinese hedge fund industry. The industry has already witnessed significant fund attrition, despite its short history, as suggested in Figure 1. Overall, I find significant differences between live and dissolved funds, and there are different reasons for fund dissolution. The funds that disappear due to real fund failure perform the worst and lose roughly 30% of their capital for the last two years of operation. The funds that disappear because they have reached contract duration are the best performing group, and they keep their capital intact for the last two years towards disappearance. Other dissolved funds show better performance. To test what is related to fund failure or dissolution, I conduct a logistic regression by using fund characteristics as explanatory variables. I find that poor performance is the only factor that is strongly correlated with real fund failure, although more fund characteristics are related to fund dissolution.

First, I document the different reasons why Chinese hedge funds stop reporting to a database. Compared to hedge funds in other countries, Chinese funds have a unique reason for dissolution—limited contract duration. To be specific, most Chinese funds are designed to operate within a finite time period, and thus they have only a limited duration on their contract with investors.[26] Therefore, funds may stop reporting because they have reached their contract duration. To my knowledge, this reason for fund dissolution is not observed for other hedge fund industries. Aside from this unique feature, the literature documents other reasons for a

[26] Merely 8% of funds are designed to operate long term (infinite contract duration).

fund's disappearance from a database. For example, Liang and Park (2010) find that reasons include: The database is unable to contact the fund; the fund is closed due to a new investment; the fund is merged to other funds; and the fund is in a dormant period.

Next, I study the differences across different reasons for disappearance. First, I specify four groups of dissolved funds: (i) Total Dissolution group, including all dissolved funds, (ii) Matured group, including funds that stop reporting merely because they have reached the contract duration, (iii) Early Dissolution group, including all dissolved funds that are not in the Matured group, and (iv) Real Failure group, including the funds in the Early Dissolution group with a negative average return for the last six months before dissolution.[27] Similar grouping methods also appear in Brown, Goetzmann, and Park (2001) and Liang and Park (2010). For this analysis, I exclude funds that do not report information of their life cycle, and I also leave out nine funds that report shortly after their contract duration. Therefore, this sample includes 712 funds. Among them, 599 are live funds, and 113 are dissolved funds. All of these 113 dissolved funds are in the Total Dissolution group, 42 in the Matured group, 71 in the Early Dissolution group, and 45 in the Real Failure group. Table 6 presents these different types of fund dissolution in the industry.

Panel A of Table 6 reports the statistics over the years. The first fund dissolution occurred in 2010, when only two funds stop reporting to Howbuy. The number grows remarkably over the years, and in 2013 alone, already 51 funds disappear from the database. Over one-third of these 51 funds disappear because they have reached contract duration, and 13 of them disappear due to real failure. As a result, even though the total attrition rate has grown in 2013 to around 8%, the real failure rate is only 2%. On average, the attrition rate is

[27] The Real Failure group is a subset of the Early Dissolution group.

4.9% and the real failure rate is 2.04%. Overall, these results are consistent with the literature on hedge funds in other countries. For example, Liang (2000) finds that the attrition rate for the HFR database from 1994 to 1997 is 2.72% and that for the TASS database from 1994 to 1998 is 8.3%. Liang and Park (2010) discover that the attrition rate for the TASS database from 1995 to 2004 is 8.7%, but the real failure rate is only 3.1%. But the attrition rate I obtain is significantly less than the result of Chen, Chen, and Chen (2013); they find an attrition rate of 14% using another database for Chinese hedge funds and a different calculation method. I find that the annual survivorship bias is 0.8%. This is comparable to the 0.99% result of Chen, Chen, and Chen (2013), but less than the 2% result of Liang (2000).

Panel B of Table 6 reports the results across fund types and investment strategies.[28] First, across investment strategies, eight out of 13 strategy groups witness fund attrition, but there is attrition only in the Traditional Stock strategy and the N/A strategy group. Most fund attrition and failures are found in the Traditional Stock strategy. Second, I also find differences in fund attrition and failure across fund types. Almost half of the Innovative funds stop reporting to Howbuy, but they all exit because they have reached contract duration. On the contrary, the Ordinary funds do not feature an attrition rate as high, but all fund failure is in this fund type. The more attrition and failure in the Ordinary fund type is also driven by the fact that Traditional Stock is the worst strategy in terms of fund survival. The most likely reason for poor survival in this strategy is that it is the oldest strategy. It is less likely for funds to disappear or fail in strategies with much shorter histories.

The different kinds of dissolved funds also have different performance patterns. Figure 5 describes the performance of each group of dissolved funds before the fund's death. Only the

[28] None of the Overseas Managed funds report information on life cycle, so I do not include them in the analysis.

Matured funds are able to keep their capital virtually intact for the last two years before death, and other two groups perform much worse. Intuitively, the Real Failure group has the worst performance, with an average loss of about 28% in the last two years of operation, followed by the Early Dissolution group, which loses around 18% of its capital.

While Figure 5 covers the comparison only for the last two years before the fund dissolution, Table 7 offers the comparison of fund performance for the entire sample period. Live funds conspicuously outperform dissolved funds, where live funds deliver over 1% Fama-French alpha, and the Total Dissolution group fails to deliver any significant alpha. Again, however, the Matured funds are the best performing group among dissolved funds, and it is the only group of dissolved funds that can generate significantly positive alpha. The worst group is the Real Failure group, followed by the Early Dissolution group.

Undoubtedly, investors of hedge funds strive to avoid investing in funds that will dissolve or even fail in the future. Therefore, my next goal is to explore what fund characteristic or performance measure can best predict fund dissolution or failure. I conduct logistic regression and present the results in Table 8. Panel A reports the result for the forecast of fund dissolution. I find five significant indicators for fund dissolution. Funds are more likely to dissolve in the future—(i) with daily disclosing frequency, (ii) with finite contract duration, (iii) with poor performance, (iv) with higher redemption fees, or (v) without investor protection in incentive fee collection.

However, Panel B of Table 8 reveals that most of these indicators lose forecasting power for real fund failure. Although six of them are significant in the univariate regression, the only indicator that appears useful for fund failure is the fund's past performance. This finding is reasonable, because poor return history is undoubtedly the most direct reason why a fund fails.

Therefore, investors can somehow predict the probability of fund dissolution by examining a number of fund characteristics, but it is much harder for them to predict fund failure.

1.6 Conclusions

The decade of 2003 to 2013 marks the earliest development of the Chinese hedge fund industry. The first Chinese hedge fund was founded in 2003, and the industry has enjoyed tremendous growth ever since. Growth in hedge funds is powered by the increasing demand for alternative investment from Chinese high net-worth investors and a series of establishments of beneficial regulations. This industry also features dominant focus on Chinese equity markets, with 79% of funds claim to use the Traditional Stock strategy. Meanwhile, a significant number of funds have disappeared over these ten years. However, not all dissolved (or dead) funds cease to exist due to poor performance, because nearly 50% of them drop out from my database simply because they have reached their contract duration.

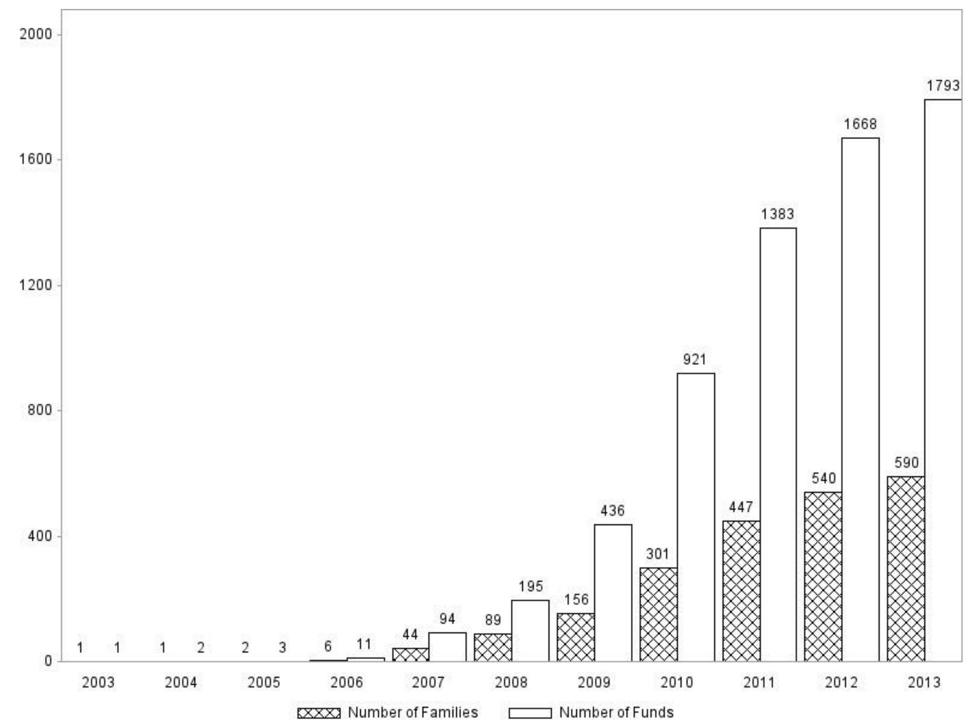
Overall, the Chinese hedge fund industry from 2003 to 2013 is a special sample for hedge fund research, not only because it allows people to investigate Chinese hedge funds themselves, but also because it sheds light on the early developing stage of all hedge funds worldwide. In this research, by using the data provided by Howbuy, I explore three main aspects of this new industry: (i) Performance and risk taking behavior, (ii) different investment styles, and (iii) survival issues.

I first find that Chinese hedge funds as a whole outperform the Chinese equity market during the decade of 2003 to 2013. The outperformance is about 200% in cumulative raw returns over these ten years. Chinese hedge funds also deliver a monthly excess return of 1.18%, whereas the stock market delivers only 0.99%. Chinese hedge funds also demonstrate less volatility. Their monthly standard deviation is only 4.63%, while that for the stock market is 9.26%, more than two times higher.

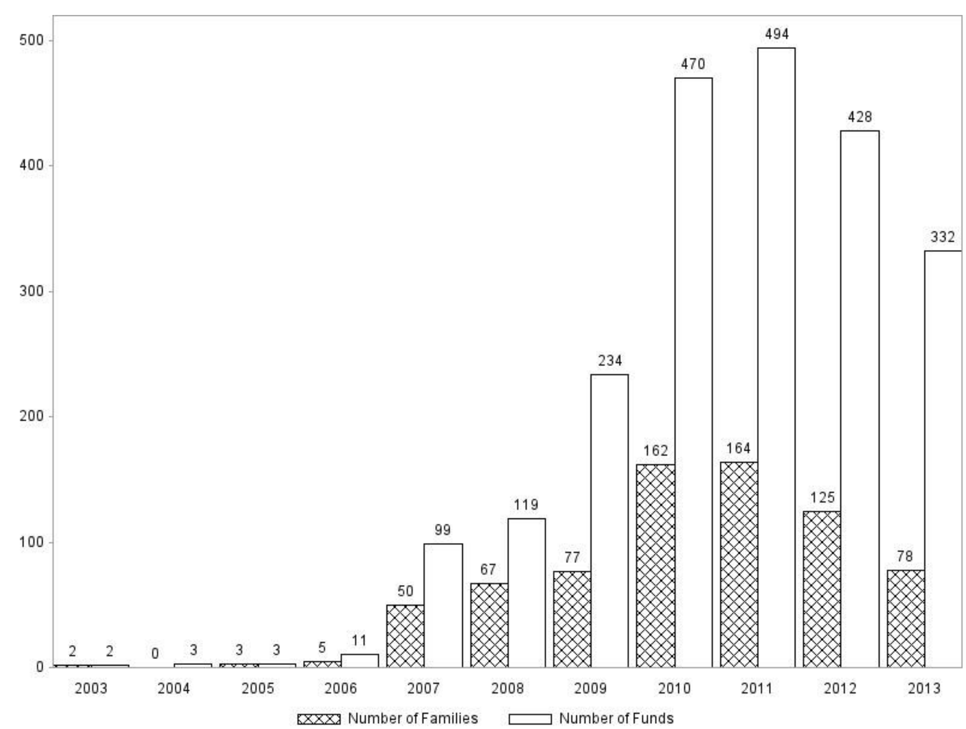
Second, I find strong evidence that different investment strategies lead to disparate patterns in performance and risk. Although no particular strategy shows persistence in performance from 2003 to 2013, each strategy has a unique return generating process. No common market exposure exists for all strategies. Also, the difference in risk across strategies can be as much as ten times.

Last, I document that from 2003 to 2013 the average fund attrition rate is 5% and the annual survivorship bias is 0.8%. However, nearly 50% of dissolved funds cease to exist merely because they have reached their contract duration. I show that these funds are the best performing ones among all dissolved funds, and their performance is virtually no different than live funds. I then explore what fund characteristics might be related to fund dissolution or real fund failure. I find that although there are several fund characteristics related to fund dissolution, only poor fund performance is associated real fund failure.

My research has two main contributions to the hedge fund literature. First, in order to explore a more direct cause for Chinese hedge funds' differences in return and risk, I focus on a fund's investment style rather than other fund characteristics. Second, I show the necessity of distinguishing between dissolved hedge funds according to their reason for dissolution, when people are to study survival issues of Chinese hedge funds; otherwise, the result could be misleading. In my future research, I aim to provide a closer examination of this industry, by studying more detailed fund characteristics.



(a) Numbers of Operating Funds and Fund Families



(b) Numbers of Startups of Funds and Fund Families

Figure 1. Numbers of Funds and Fund Families

This figure depicts the numbers of funds and fund families that are operating (Subfigure (a)) and that are founded (Subfigure (b)) in each year. The data is only through November 2013.

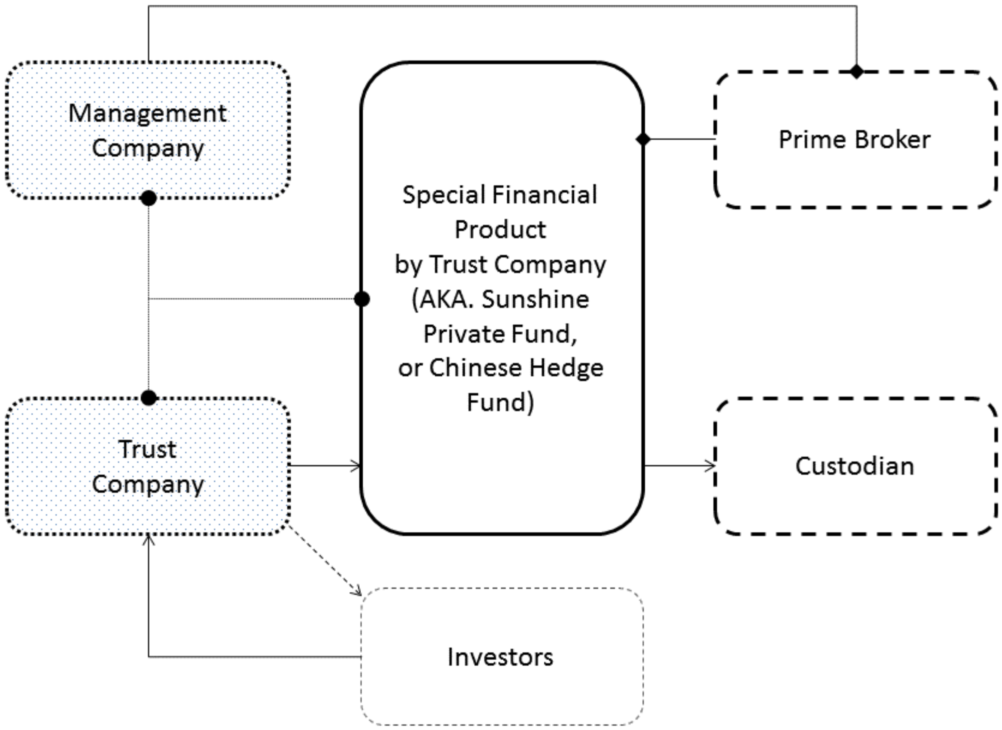


Figure 2. Fund Structure

This figure illustrates the legal structure of Chinese hedge funds from 2003 to 2013. The solid, shaded, dotted, and dashed rectangles represent the fund, its founding parties, investors, and key service providers, respectively. The round arrows, regular arrows, and diamond arrows denote the incubation, cash flows, and management procedure of the fund, respectively. The dotted arrow indicates that the trust is responsible for monitoring the fund and providing timely disclosure to investors.

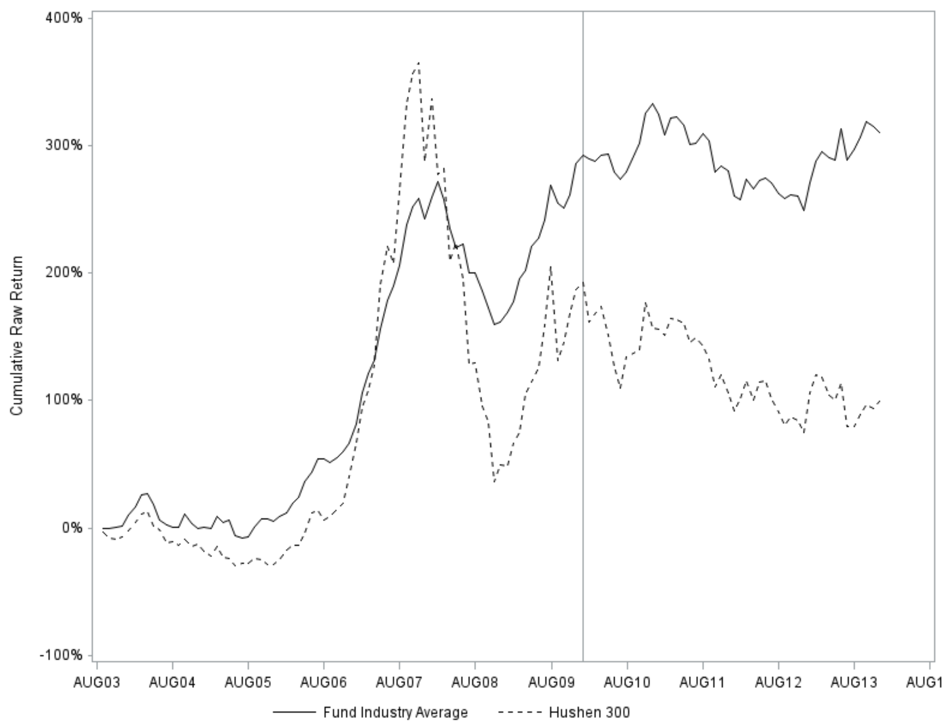
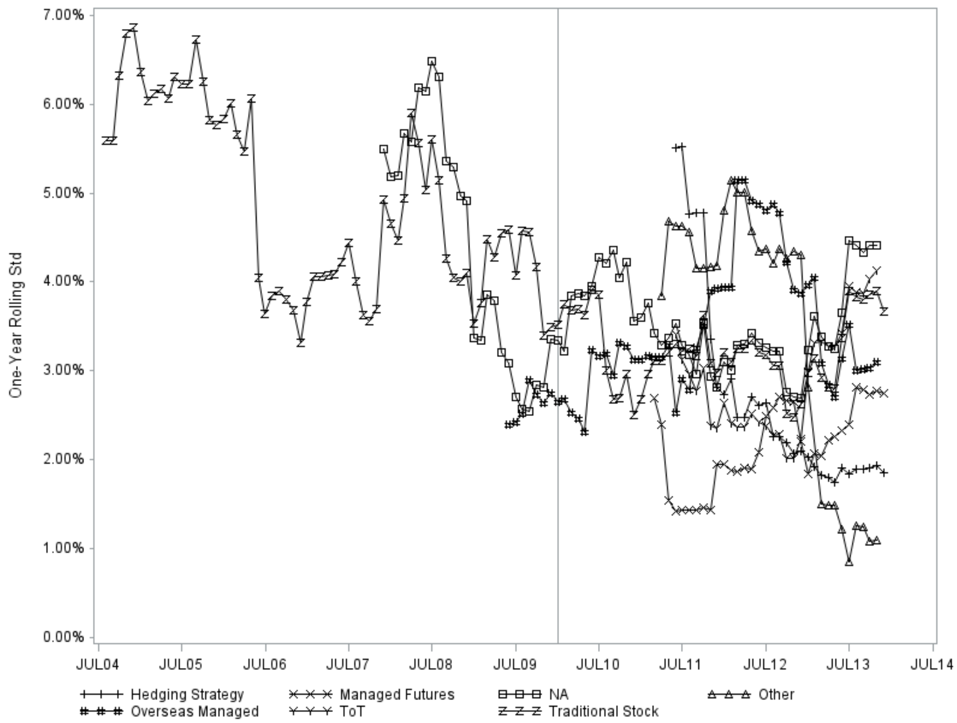
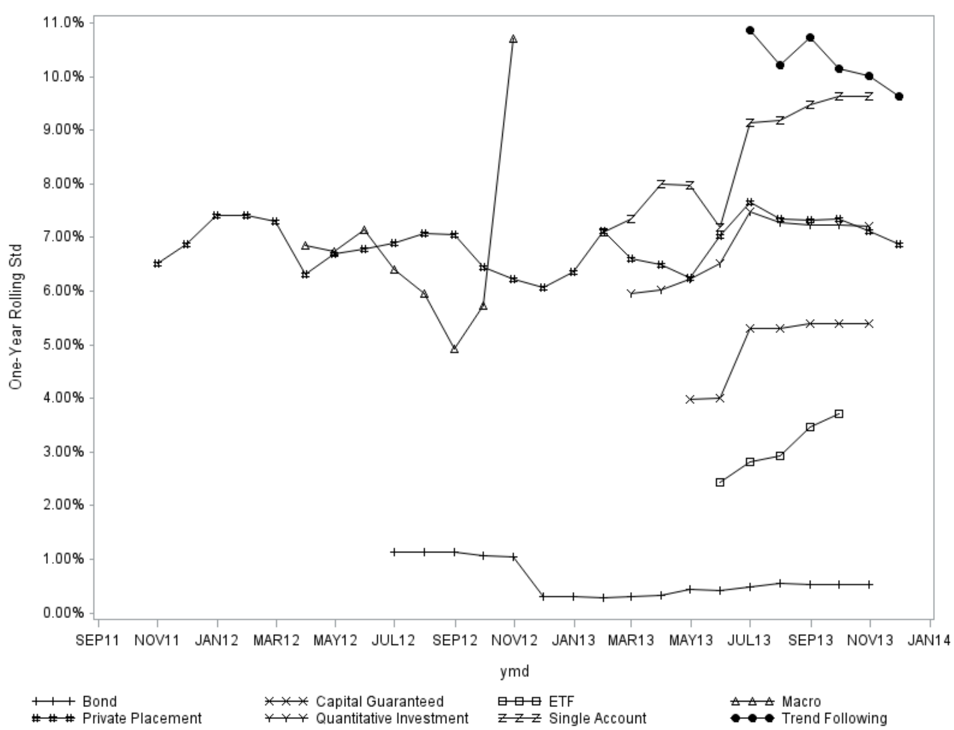


Figure 3. Cumulative Returns

This figure presents the cumulative returns. The vertical reference line of January 2010 is plotted to show the cutoff point. The cumulative return on the Hushen 300 index is also depicted for comparison.



(a) Strategies with Longer History



(b) Strategies with Shorter History

Figure 4. Risk Taking across Investment Strategies

This figure presents the one-year rolling standard deviation of different strategies. The vertical reference line of January 2010 is plotted to show the cutoff point. Subfigure (a) summarizes strategies with a history of longer than 40 months, and Subfigure (b) summarizes strategies with shorter histories.[29]

[29] The abrupt increase in rolling standard deviation of the Macro strategy in September and October of 2012 is driven by one fund in this strategy portfolio, which lost 11% and 30% in these two months, respectively. After these losses, the fund ceases reporting to the Howbuy database.

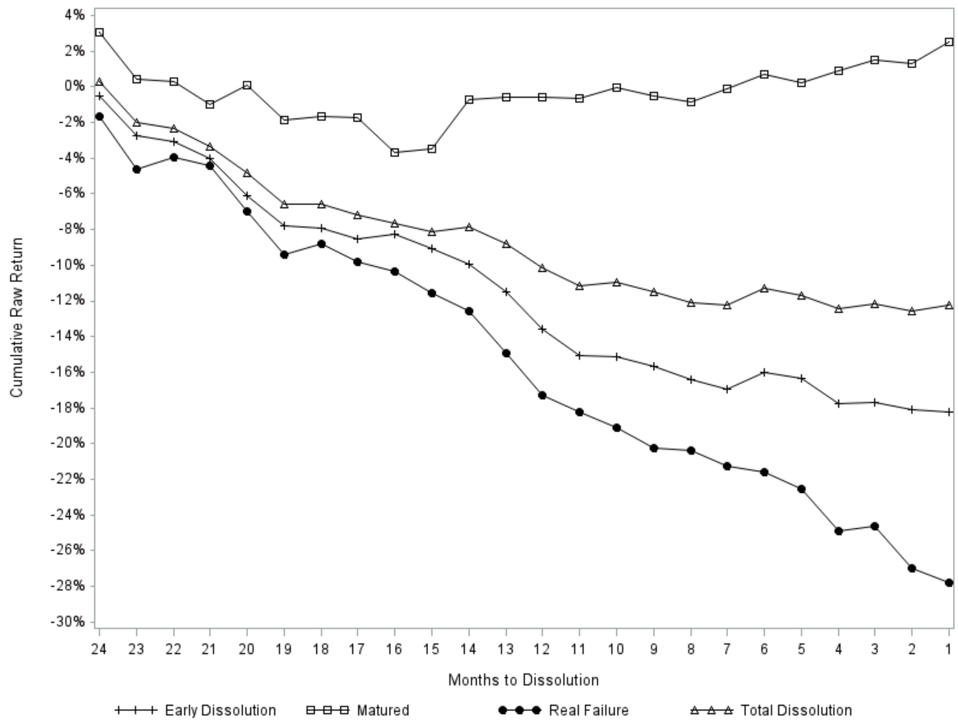


Figure 5. Cumulative Returns towards Fund Dissolution

This figure displays the cumulative returns for the last two years towards fund dissolution of the four groups of dissolved funds.

Table 1. Summary Statistics

This table presents the summary statistics of the Chinese hedge funds and fund families as of November 2013 based on the screened dataset. Panel A reports for all the funds and four fund types, and the t-test of the difference between Innovative and Ordinary funds. EarliestInception is earliest founding date. RepLength is the number of months of the fund's reporting history. ExRet is the fund's monthly excess return over Chinese demand deposit rate in that month, and ExRetStd is its standard deviation. FF3Alpha and FF3R^2 are the alpha and R-squared of the Fama-French three-factor regression of ExRet, respectively. Autocorrelation is the first order autocorrelation of the fund's raw return. LoadFee, RedeFee, ManFee, and IncFee denote the load fee, redemption fee, management fee, and incentive fee, respectively. RedeFee is typically charged for early redemptions within the lockup or soft lockup period. Lockup, SoftLockup, and OpenFreq are number of months of the fund's lockup period, soft lockup period, and frequency of opening to investment and redemption, respectively. Daily, Weekly/Monthly, SpecialIncFee, HWM, HurdleRate, and LongTerm equal one if the fund discloses daily, discloses weekly or monthly, has special provision in collecting incentive fee (high water mark provision, hurdle rate provision, or both), has high water mark provision, has hurdle rate provision, and is designed to operate long term (or not under limited contract duration), respectively, and equal zero otherwise. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Panel B reports for fund families (management company). FamilyComplexity is the number of funds run by a fund family. RepLength is the number of months of the family's reporting history. Speed is a family-specific measure, which is the average number of days the fund family spends in launching a new fund.

Panel A: Funds

	All Funds	Innovative Funds	Ordinary Funds	diff.		Overseas Managed Funds	ToT Funds
No. Funds	1,548	126	1,348			29	45
EarliestInception	1/16/2003	12/31/2007	8/1/2003			1/16/2003	5/26/2009
Daily	0.03	0.32	0.37	−0.05	***	0.00	.
Weekly/Monthly	0.31	0.21	0.33	−0.12	***	0.14	.
RepLength Avg. (Months)	34.36	20.13	35.73	−15.60	***	33.72	33.60
ExcRet Avg. (%)	0.18	0.72	0.11	0.61	***	0.90	0.31
ExRetStd Avg. (%)	4.90	5.28	4.85	0.75		6.39	4.34
ShapeRatio Avg.	0.07	0.25	0.05	0.20	***	0.20	0.08
FF3Alpha Avg. (%)	0.41	1.07	0.32	0.74	***	1.18	0.74
FF3R^2 Avg.	0.48	0.54	0.47	0.07	***	0.50	0.59
Skewness Avg.	0.13	0.31	0.12	0.19	***	0.01	0.06
Kurtosis Avg.	0.92	0.99	0.88	0.11		1.59	1.35
Autocorrelation Avg.	-0.08	-0.1	-0.08	−0.02		-0.07	-0.05
LoadFee Avg. (%)	0.96	0.75	0.95	−0.20	**	1.47	0.94
RedeFee Avg. (%)	2.12	1.08	2.17	−1.09	***	2.02	1.88
ManFee Avg. (%)	1.6	1.56	1.61	0.05		1.67	1.13
IncFee Avg. (%)	19.97	20.21	20.16	0.05		19.90	8.00
Special IncFee	0.1	0.2	0.08	0.12	***	0.45	0.04
HWM	0.06	0.01	0.06	−0.05	***	0.45	0.02
HurdleRate	0.04	0.2	0.03	0.17	***	0.00	0.02
Duration Avg. (Years)	8.48	3.00	9.14	−6.14	***	.	5.00
LongTerm	0.08	0.09	0.09	0.00		.	0.04
Lockup Avg. (Months)	7.67	10.07	7.61	2.46	**	6.64	6.75
SoftLockup Avg. (Months)	6.64	14	6.57	7.43		0.00	5.67
OpenFreq Avg. (Months)	1.29	2.61	1.25	1.36	*	1.17	1.50

Panel B: Fund Families

	All Families	Innovative Families	Ordinary Families	Overseas Managed Families	ToT Families	Multiple-Type Families
No. Families	554	27	468	13	8	38
RepLength Avg. (Months)	38.15	22.56	36.84	56.23	37.63	59.29
FamilyComplexity Avg.	2.78	3.22	2.45	1.15	1.88	7.37
Speed Avg. (Days)	102.68	86.55	96.2	163.54	44.96	185.27

Table 2. Performance and Risk Taking across Fund Types

Performance statistics across fund types are presented in this table. Six portfolios are formed based on fund type: All funds, Overseas Managed funds, Domestic funds (Innovative, Ordinary, or ToT funds), Innovative funds, Ordinary funds, and ToT funds. Panels A, B, and C give the statistics for the whole sample, 2003 to 2009, and 2010 to 2013, respectively. ExcessRet is the portfolio's monthly excess return over Chinese demand deposit rate, and Excess Return Std is its standard deviation. The Fama-French three-factor regression is performed on each portfolio. FF3Alpha is the regression intercept, and its corresponding p-value is reported in parentheses under it. Adj.R2 is the adjusted R-squared of this Fama-French regression. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The statistics of Hushen 300 stock index are also shown for comparison.

	No. Funds	Excess Ret (%)	Excess Return Std (%)	Sharpe Ratio	FF3Alpha (%)		Adj.R2
Panel A: Whole Sample							
All Funds	1,548	1.18	4.63	0.25	0.85	***	0.68
					(0.002)		
Overseas Managed Funds	29	0.80	3.38	0.24	0.87	***	0.53
					(0.004)		
Domestic Funds	1,519	1.18	4.64	0.25	0.84	***	0.68
					(0.002)		
Innovative Funds	126	1.64	3.63	0.45	1.52	***	0.11
					(0.000)		
Ordinary Funds	1,348	1.16	4.65	0.25	0.83	***	0.68
					(0.002)		
ToT Funds	45	0.15	3.26	0.05	0.30		0.64
					(0.336)		
Hushen 300		0.99	9.26	0.11			
Panel B: 2003–2009							
All Funds	415	1.86	5.27	0.35	1.15	***	0.65
					(0.004)		
Overseas Managed Funds	1	0.77	2.56	0.3	0.51		0.42
					(0.269)		
Domestic Funds	414	1.86	5.27	0.35	1.14	***	0.65
					(0.004)		
Innovative Funds	1	2.75	4.04	0.68	2.89	***	-0.01
					(0.003)		
Ordinary Funds	413	1.85	5.28	0.35	1.13	***	0.65
					(0.005)		
ToT Funds	0						
Hushen 300		1.95	10.42	0.19			
Panel C: 2010–2013							
All Funds	1,544	0.07	3.07	0.02	0.36		0.68
					(0.247)		
Overseas Managed Funds	29	0.81	3.69	0.22	1.18	***	0.65
					(0.002)		
Domestic Funds	1,515	0.06	3.08	0.02	0.35		0.68
					(0.258)		
Innovative Funds	117	1.08	3.31	0.33	1.29	***	0.36
					(0.002)		
Ordinary Funds	1,344	0.02	3.1	0.01	0.33		0.66
					(0.304)		
ToT Funds	45	0.15	3.26	0.05	0.30		0.64
					(0.336)		
Hushen 300		-0.59	6.76	-0.09			

Table 3. Fund Types and Investment Strategies

This table reports the statistics that indicate the relationship between fund types and investment strategies. There are three groups based on fund type: All funds, Innovative funds, and Ordinary funds, and 15 groups based on investment strategies. Strategy History is the number of months a strategy has been in the dataset. For each fund type group, the table reports the number of funds using a certain strategy and its percentage to the total number of funds in this fund type group. Except for the Other and NA strategy groups, the other 13 strategies are listed in the descending order of Strategy History.

	Strategy	All Funds		Innovative Funds		Ordinary Funds	
Strategy	History (Months)	No.	%	No.	%	No.	%
Traditional Stock	124	1,199	78.37	5	4.46	1194	88.84
Overseas Managed	65	29	1.90				
Managed Futures	45	23	1.50	2	1.79	21	1.56
Hedge-Strategy	42	27	1.76	26	23.21	1	0.07
ToT	41	45	2.94				
Private Placement	37	53	3.46	53	47.32		
Bond	28	22	1.44	8	7.14	14	1.04
Quantitative Investment	20	2	0.13	2	1.79		
Macro	19	1	0.07	1	0.89		
Capital-Guaranteed	18	2	0.13	2	1.79		
Single-Account	17	2	0.13	2	1.79		
Trend-Following	17	1	0.07	1	0.89		
ETF	16	3	0.20	3	2.68		
Other	42	2	0.13	2	1.79		
NA	83	119	7.78	5	4.46	114	8.48
Total		1530	100	112	100	1344	100

Table 4. Performance Persistence across Investment Strategies

Please see the associated file (name: Associated File_Tables) for this table.

Table 5. Stepwise Regression on Asset-Based Factors

This table gives the results of the stepwise regression of raw return on the eight asset-based style (ABS) factors, which considers only the significantly (or marginally significantly) explanatory factors. Eight portfolios are formed based on investment strategy, where only the strategies with at least two years of reporting history are considered. The stepwise regression is performed on each portfolio. ABS-Factor Alpha is the intercept of the regression. Estimates of the significant (or marginally significant) independent variables are also reported. Beta_MKT, Beta_SMB, Beta_HML, Beta_MOM, Beta_ChinaConcept, Beta_NationalBd, Beta_CorporateBd, and Beta_COM are the estimate of ABS factors. The p-value of the t-test on each estimate is reported below in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. No. Obs. is the number of months for each strategy portfolio. Adj. R2 is the adjusted R-squared of the regression. Panel A reports the statistics for the whole sample. Only two strategy portfolios are active in both subperiods of 2003 to 2009 and of 2010 to 2013, and so only the statistics for these two portfolios are reported in Panel B.

Panel A: Whole Sample

	Traditional Stocks	Overseas Managed	Managed Futures	Hedge-Strategy	ToT	Private Placement	Bond	Other
Excess Return (%)	1.15	0.80	0.92	1.49	0.86	0.15	0.66	1.61
Excess Return Std (%)	4.68	3.38	6.48	2.55	3.35	3.26	0.82	3.56
Sharpe Ratio	0.25	0.24	0.14	0.59	0.26	0.05	0.81	0.45
ABS-Factor Alpha (%)	0.89 ***	0.52	3.62 ***	1.61 ***	1.05 ***	0.31	0.29	0.82
	(0.001)	(0.115)	(0.001)	(0.000)	(0.003)	(0.315)	(0.163)	(0.278)
Beta_MKT	0.37 ***		0.83 ***		0.41 ***	0.34 ***		
	(0.000)		(0.000)		(0.000)	(0.000)		
Beta_SMB	0.15 **	0.52 ***				0.27 **		
	(0.034)	(0.000)				(0.019)		
Beta_HML			-0.37 **	-0.34 **	-0.34 **			
			(0.084)	(0.034)	(0.023)			
Beta_MOM								
Beta_ChinaConcept		0.22 ***		-0.17 **	-0.14 *			
		(0.000)		(0.013)	(0.057)			
Beta_NationalBd			-7.47 **					
			(0.027)					
Beta_CorporateBd		0.55					0.84 ***	1.9
		(0.110)					(0.009)	(0.112)
Beta_COM								
No. Obs.	124	65	37	45	42	41	28	42
Adj. R2	0.61	0.58	0.76	0.12	0.60	0.64	0.20	0.04

Panel B: Subperiods

	Traditional Stocks				Overseas Managed			
	2003-2009		2010-2013		2003-2009		2010-2013	
Excess Return (%)	1.85		0.00		0.77		0.81	
Excess Return Std (%)	5.31		3.12		2.56		3.69	
Sharpe Ratio	0.35		0.00		0.30		0.22	
ABS-Factor Alpha (%)	1.32	***	0.31		0.69		1.04	***
	(0.002)		(0.274)		(0.107)		(0.000)	
Beta_MKT	0.38	***	0.32	***			0.07	
	(0.000)		(0.000)				(0.147)	
Beta_SMB	0.14		0.27		0.21	*	0.75	***
	(0.142)		(0.101)		(0.083)		(0.000)	
Beta_HML								
Beta_MOM								
Beta_ChinaConcept					0.13	***	0.30	***
					(0.005)		(0.000)	
Beta_NationalBd	-0.25							
	(0.339)							
Beta_CorporateBd								
Beta_COM								
No. Obs.	77		47		19		46	
Adj. R2	0.60		0.64		0.53		0.78	

Table 6. Attrition and Real Failure

This table reports the statistics regarding fund attrition and real failure of Chinese hedge funds. The data is through November 2013. Panel A reports the statistics across years. Year Start and Year End are the number of funds at the beginning of the year and at the end of the year, respectively. Entry is the number of new funds founded in that year. Total Dissolution is the number of funds that disappear from the database each year. Matured, Early Dissolution, and Real Failure are the number of funds that disappear because they have reached the contract duration, that disappear before their contract duration, and that disappear due to real fund failure, respectively. Attrition Rate is the ratio of Total Dissolution to Year Start, and Real Failure Rate is the ratio of Real Failure to Year Start. Panel B reports the statistics across fund types and investment strategies. Only the funds that report information of life cycle are included. In the All Strategies row, the number of funds is the sum across strategies, but the attrition rate and real failure rate are the average across strategies.

Panel A: Attrition and Real Failure across Years

Year	Year Start	Entry	Total Dissolution	Matured	Early Dissolution	Real Failure	Year End	Attrition Rate (%)	Real Failure Rate (%)	Return of All Funds (%)	Return of Surviving Funds (%)
2003		1					1			1.94	1.94
2004	1	1					2			-0.60	-0.60
2005	2	0					2			0.76	0.76
2006	2	1					3			2.94	2.94
2007	3	25					28			3.50	3.81
2008	28	43					71			-1.44	-1.27
2009	71	103					174			2.74	2.84
2010	174	220	2		2	1	392	1.15	0.57	0.57	0.64
2011	392	208	6	2	4	4	594	1.53	1.02	-1.61	-1.56
2012	594	110	54	21	33	27	650	9.09	4.55	0.19	0.17
2013	650	0	51	19	32	13	.	7.85	2.00	1.25	1.26
Average								4.90	2.04	0.93	0.99
Annual Survivorship Bias (%)	0.76										

Panel B: Attrition and Real Failure across Fund Types and Investment Strategies

	Fund Type											
	Innovative Funds			Ordinary Funds			ToT Funds			All Types		
Investment Strategy	No. Funds	Attrition Rate (%)	Real Failure Rate (%)	No. Funds	Attrition Rate (%)	Real Failure Rate (%)	No. Funds	Attrition Rate (%)	Real Failure Rate (%)	No. Funds	Average Attrition Rate (%)	Average Real Failure Rate (%)
Bond	4	50.00	0.00	13	100.00	0.00				17	88.24	0.00
Capital Guaranteed	2	50.00	0.00							2	50.00	0.00
ETF	2	0.00	0.00							2	0.00	0.00
Hedging Strategy	7	14.29	0.00							7	14.29	0.00
Managed Futures				2	0.00	0.00				2	0.00	0.00
Market Neutral	5	40.00	0.00	1	0.00	0.00				6	33.33	0.00
NA				60	6.67	3.33				60	6.67	3.33
Other	1	0.00	0.00							1	0.00	0.00
Private Placement	35	57.14	0.00							35	57.14	0.00
Quantitative Investment	2	0.00	0.00							2	0.00	0.00
ToT							20	5.00	0.00	20	5.00	0.00
Traditional Stock	4	25.00	0.00	554	12.27	7.76				558	12.37	7.71
All Strategies	62	43.55	0.00	630	13.49	7.14	20	5.00	0.00	712	15.87	6.32

Table 7. Performance Based on Survival

This table reports the performance of live funds and different groups of dissolved funds. No. Months is the reporting length of the portfolio. Excess Return is the portfolio's monthly raw return over Chinese demand deposit rate, and Excess Return Std is its standard deviation. FF3Alpha is the intercept of the regression of excess return on the Fama-French three factors, and Adj. R2 is the adjusted R-squared of the regression. The p-value of the t-test on each estimate is reported below in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Live		Total Dissolution	Matured		Early Dissolution	Real Failure
No. Funds	599		113	42		71	45
No. Months	124		75	74		67	67
Excess Return (%)	1.40		0.29	0.60		-0.25	-0.58
Excess Return Std (%)	4.75		4.43	4.69		3.55	3.54
Sharpe Ratio	0.30		0.06	0.13		-0.07	-0.16
FF3Alpha (%)	1.07	***	0.41	0.76	**	0.05	-0.30
	(0.000)		(0.182)	(0.025)		(0.853)	(0.351)
Adj. R2	0.66		0.73	0.69		0.65	0.55

Table 8. Logistic Analysis of Fund Dissolution and Failure

Please see the associated file (name: Associated File_Tables) for this table.

CHAPTER 2

SPECIAL FEATURES OF CHINESE HEDGE FUNDS: DISCLOSING FREQUENCY, FUND STRUCTURE, AND POLICY CHANGES

2.1 Introduction

The Chinese hedge fund industry is a young but fast growing industry. The first Chinese hedge fund was launched in as recently as 2002, but by the end of 2013, there are already 1,793 funds and 592 fund families in operation (Liang and Zhang (2014a)).[30] Such figures may not appear significant, given that there are already nearly 10,000 funds operating worldwide.[31] However, I should keep in mind that before 2002, there was no such thing as a "Chinese hedge fund." Therefore, within only around a decade of development, the number of Chinese hedge funds increased from zero to 18% of the total number of hedge funds in other countries, which is obviously a significant growth.

Just like the fast growing Chinese economy, the quick expansion of the Chinese hedge fund industry has gained increasingly more attention from both practitioners and academics.

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[30] Liang and Zhang (2014a) document that it remains a bit controversial which fund was the first Chinese hedge fund. Chronologically, the first one is Bond Portfolio Capital Plan issued by Shanghai Guosen in December 2002 (see, for example, Chen, Chen, and Chen (2013)). But some people believe that the first fund should be Pure Heart managed by Danyang Zhao and issued by Shenzhen International Trust (now China Resources ZITIC Trust Co.,Ltd.) in February 2004. So in fact Pure Heart is founded later than the other funds, although it is indeed the first Chinese hedge fund managed by overseas fund management companies. Despite the above two funds, in Liang and Zhang's (2014) data, the first fund is China Dragon I issued by Yunnan International Trust Co., Ltd. They argue that the data does not include Bond Portfolio Capital Plan because it is a short-lived, investment plan with a history of merely one year. And they also lend evidence that Pure Heart is unstable and not representative of the overall Chinese hedge funds. They argue that the clearest example is that in 2008 Pure Heart abruptly stopped operation and liquidated all its assets. Therefore, Pure Heart is also not included in their data. I use the same data as Liang and Zhang (2014a).

[31] Data source: https://www.managedfunds.org/hedge-fund-investors/industry-fact-sheets/industry-size/.

Studies o Chinese hedge funds not only explore this particular industry, but also shed light on the early development of hedge funds in general, which is missing from the hedge fund literature due to lack of data in the early years of the hedge fund industry.

Some research has been conducted on Chinese hedge funds (for example, Chen et al. (2012), Chen, Chen, and Chen (2013), and Liang and Zhang (2014a)). For example, Liang and Zhang (2014a) summarizes four features of this industry: Unique legal structure, constant policy changes, less diversified but special investment styles, and an unusual reason for a fund's exit from a database. [32] None of these studies explores these unique features in details; however, although they all touch on them to some degree.

My goal in this paper is to explore these special features of Chinese hedge funds in details; more specifically, to study their impact on fund performance. By using data for Chinese hedge funds from 2003 to 2013, I focus on three aspects: If a fund's disclosing frequency; the special characteristics about a fund's legal structure; and the impact of new policies on the fund. Some of these features are new topics in hedge fund research. I explain these three aspects as follows.

The first topic is on the disclosing frequency of Chinese hedge funds. Different from hedge funds in other countries that usually disclose return or net asset value (NAV) on a monthly basis (for example, Liang (2000), Capocci and Hübner (2004), and Sadka (2010)), Chinese funds disclose NAV daily or weekly/monthly.[33] The reason for the special disclosing mechanism is twofold. On one hand, according to their legal structure, the funds need to

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[32] A fund may disappear from a database simply because it has reached the expiration of its contract with investors.

[33] There are still many funds that disclose NAV discretionarily to some degree, in the sense that their disclosures do not follow a stable frequency. These funds are not included in my comparison between the daily funds and weekly/monthly funds.

disclose weekly.[34,35] The China Banking Regulatory Commission, the regulator for Chinese hedge funds, issued Operating Guidelines for the Securities Investment Trust Business of Trust Companies in 2009, which requires Chinese hedge funds to disclose NAV weekly. On the other hand, a large number of funds do not follow this regulation. The most important reason is that they follow their contract with investors to disclose NAV.[36] Most Chinese hedge funds specify a weekly or monthly disclosing frequency in their contract.[37]

Therefore, most funds that do have a dominant disclosing frequency disclose NAV weekly or monthly. However, in my data I observe that a smaller percentage of funds follows an even higher frequency—daily disclosing. Disclosing more frequently is usually regarded as a signal of providing better transparency to investors, so the daily disclosing funds are obviously perceived better by potential investors. Therefore, I conjecture that higher disclosing frequency suggests improved fund performance, i.e., the daily disclosing funds should have better

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[34] Liang and Zhang (2014a) point out that the Chinese government has been prudent in introducing the hedge funds, and thus “from 2003 to 2013, it did not allow fund management companies to directly launch any privately offered fund”. In order to launch a private fund, a fund management company must collaborate with a trust company. The trust company is an already existing financial industry that the Chinese authority can effectively control. Although the trust company hires to the fund management company to manage the fund, legislatively, the fund is still considered a special financial product offered by the trust company.

[35] They also document that “the Revised Fund Law of the People’s Republic of China (http://www.gov.cn/jrzg/2012-12/29/content_2301603.htm, in Chinese), which was approved in June 2013, expands the definition of Chinese hedge funds. The Revised Fund Law now allows fund management companies to launch hedge funds alone, without collaborating with any trust company, so hedge funds can now operate under a different structure”. For the data range in this research, however, the original fund structure always holds.

[36] According to a number of articles by leading financial advisory firms, there are mainly two other reasons why a fund does not obey this regulation. First, the fund is suffering from bad performance, and thus the fund manager is afraid that more frequent disclosure would intimidate investors. Second, the fund is liquidated prematurely. However, those articles document that most funds that do not follow the regulation are not liquidated (see, for example, http://fund.sohu.com/20100812/n274153391.shtml, in Chinese). This research also investigates the impact of current performance on fund’s disclosing frequency.

[37] See, for example, http://www.licai.com/xuetang/simu.html (in Chinese).

performance than the weekly/monthly disclosing funds. Additionally, I conjecture that the sudden changes in disclosing frequency are related to fund performance; that is, in the months when the hedge funds do well, a fund is likely to switch to a higher frequency (from weekly/monthly to daily), and vice versa.

My second research focus is on special characteristics regarding a fund's legal structure. Chinese hedge funds between 2003 and 2013 are organized under a special legal structure, where there are two parties: The trust company (trust hereafter) and the fund management company (management company, or fund family, hereafter) (see Liang and Zhang (2014a)). In this paper, I focus on three features of these two parties: Trust complexity (the number of funds governed by the same trust), family complexity (the number of funds managed by the same management company) and family speed (the average number of days that a management company spends to open a new fund).

These three features figure largely in fund performance. The impact of family complexity on individual funds has been the subject of a number of studies, but the results lead to mixed findings. On one hand, existing research finds that families with larger complexity are associated with more significant persistence in a fund's performance (Guedj and Papastaikoudi (2005)) and better profitability (Gervais, Lynch, and Musto (2005)). On the other hand, studies also find that higher family complexity causes higher organizational cost and more conflict of interest inside a family (Bessler et al. (2014)).[38] In China, however, the hedge fund business has just started, and fund families are not as large as hedge fund families in developed countries. Therefore, organizational cost and conflict of interests may not be a major problem for Chinese fund families yet. Most Chinese investors, as well as leading financial advisory firms, believe that

[38] Some of these studies focus on mutual fund families rather than hedge fund families.

higher family complexity is associated with better future performance.[39] As a result, I expect that families with higher complexity should help deliver better future performance.

Trust complexity should have a similar effect on fund performance as family complexity. Higher trust complexity is a sign of larger trusts, and larger trusts have more resources to monitor funds effectively and provide good services to investors.[40] Therefore, I expect that trusts with higher complexity are more likely to provide investors with funds with good performance.

Family speed should also be a significant factor in fund performance. This feature reflects the management company's caution in business expansion. In China, well-known fund managers do run many funds at the same time,[41] but they achieve such high levels of family complexity through long periods of time. In addition, a significant number of management companies launch new funds very fast—64 (or 12%) management companies set up new funds at a speed of one fund within two months.[42] One motivation for this phenomenon is that these aggressive managers are able to collect more management fees. However, such reckless expansion could hurt fund's future performance for two reasons. First, managers would not have enough resources under aggressive expansion, so this prevents them from running each

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[39] See, for example, http://www.licai.com/zhuanti/simujijin.html (in Chinese).

[40] See, for example, http://trust.pingan.com/xintuojiangtang/licaijinnang/1379915447866.shtml and http://finance.people.com.cn/GB/1040/59941/136878/136886/136898/8431509.html (both in Chinese).

[41] For example, according to a report in 2013, the most "occupied" fund manager runs 31 individual funds at the same time, and the average number of funds run by the six most "occupied" managers is 28 (http://finance.people.com.cn/n/2013/0304/c355188-20669864.html in Chinese).

[42] In my data, 554 management companies report dates of fund inception, so 64 management companies account for 12% of them.

fund effectively.[43] Second, lack of resources could also increase operational risk of the management company (Brown et al. (2008, 2009)). Therefore, I conjecture that faster family speed is associated with lower fund's future performance.

My last research concentration is on the impact of new policies on Chinese hedge funds. As Liang and Zhang (2014a) suggest, before 2010, there were actually no effective hedging instruments available to the funds. The first breakthrough is the establishment of margin trading mechanism in January 2010, which allows market participants to borrow cash or securities they do not currently own. Another significant change occurred in July 2011, when Chinese regulators finally allowed Chinese hedge funds to trade stock index futures. This event is often considered as the groundbreaking event of "freedom" for the industry. A series of policy changes also took place afterwards, including the inception of the Securities Refinancing mechanism in August 2012 and the Securities Relending mechanism in February 2013. My expectation is that among all the other events and new policies, the new policy in July 2011 should have the largest impact on the fund industry, since it is directly related to the fund industry.

I find strong empirical evidence for the above three research questions. My major findings are as follows. First, I find strong evidence that higher disclosing frequency is associated with better fund performance. During 2010 to 2013, daily disclosing funds deliver five times higher excess return, and over-two-times-higher Sharpe ratio and Fama-French (1993) three-factor alpha than weekly/monthly disclosing funds. Moreover, funds' propensity to change their disclosing frequency is closely related to current performance of the hedge fund industry and of the China-concept stocks listed overseas. When these two markets realize higher returns, more

[43] See, for example, http://biz.zjol.com.cn/05biz/system/2011/06/10/017589942.shtml (in Chinese).

funds switch from lower disclosing frequency to higher frequency (from weekly/monthly to daily), but when these two markets show poor performance, more funds switch from higher disclosing frequency to lower frequency (from daily to weekly/monthly).

Second, I provide evidence that higher complexity of trusts and fund families is associated with a fund achieving better future performance. I separate funds into two groups based on trust complexity: Funds from funds from trusts monitoring only one fund (single-fund trusts hereafter) and funds from trusts with a complexity greater than one (complex trusts hereafter). Similarly, I build two groups based on family complexity: Funds from families running only one fund (single-fund families hereafter) and funds from families with a complexity greater than one (complex families hereafter). My results demonstrate that funds from trusts or families with higher complexity yield a one-to-three-times-higher Fama-French alpha than funds from single-fund trusts or single-fund families. I also find that family speed is negatively associated with fund performance. By forming four portfolios based on family speed, I show that the portfolio with the slowest speeds yield over one time higher excess returns, Sharpe ratio, and Fama-French alpha than the portfolio with the fastest speeds.

In order to examine the impact of the above three characteristics on fund performance, I conduct a regression of fund returns on disclosing frequency of the fund, trust complexity, family complexity, and family speed, while controlling for different fund types and investment strategies.[44] My results indicate that disclosing frequency and family complexity still contribute significantly to fund performance in this multivariate testing framework, while trust complexity loses its explanatory power. These results are reasonable because disclosing frequency and

[44] Liang and Zhang (2014a) provide evidence that differences in fund types and investment strategies often lead to great variations in a fund's returns and risk taking behavior.

family complexity are both associated with the management company, which is more involved in a fund's operation. In contrast, the trust is involved only in a relatively indirect way.

Finally, I show evidence that the policy in July 2011, which allows funds to trade stock index futures, is the most influential event for the Chinese hedge fund industry. It greatly boosts the expansion speed of the funds that self-label as using mainly hedging strategies, and causes a sharp drop in the expansion speed of other types of funds. I conduct a difference-in-differences (D/D) test in order to explore the impact of this event. This result is robust as a validity check on the D/D testing framework.

My research contributes to the existing hedge fund literature in that it offers more insight into the young Chinese hedge fund industry. Compared to prior studies, this research explores the special issues of Chinese hedge funds in details, especially on the disclosing mechanism, fund structure, and the impact of policy changes on the funds.

2.2 Related Literature

This research focuses on the special features of the Chinese hedge fund industry, including its disclosing frequency and fund structure, and the impact of policy changes on the funds. Therefore, my research is mainly related to three streams of literature.

First, this paper is linked with research on the disclosure of hedge funds and other investment vehicles. Most of the research focuses on hedge fund's disclosure of returns or net asset value (NAV). For example, on hedge fund's disclosure, Bollen and Pool (2008, 2009, 2010) discover a series of performance flags in disclosed returns and argue that these performance flags suggest fund manager's manipulation.[45] Similarly, Cumming and Dai (2010) find that

[45] These performance flags include conditional serial correlation (also found in Getmansky, Lo, and Makarov (2004)), the phenomenon that small gains outnumber small losses, and a finding that these performance flags link with the heightened risk of fraud.

misreporting and other performance flags are more common in funds with more restrictions. Moreover, Agarwal, Capocci, and Naik (2011) find the phenomenon of December pikes in the disclosed returns of hedge funds, which means that the returns in Decembers are significantly larger than the rest of the year. However, Jorion and Schwarz (2014) provide evidence that most of the above abnormalities in returns are mainly caused by hedge funds' high water mark provisions, not necessarily by manager's intentional manipulation.

Other research explores other types of fund disclosure. For example, Brown et al. (2008, 2009) concentrate on hedge funds' disclosure on Form ADV, which was once a required form for major hedge funds but was later overruled. Their results suggest that the Form ADV disclosure of hedge funds provides material information to investors concerning operational risk of hedge funds.

My research, on the other hand, focuses on funds' frequency of return disclosure. Some research directly lands on this topic, while some of it focuses on mutual funds, rather than hedge funds. For instance, Wermers (2001) argues that if mutual funds disclose more frequently than the semiannual requirement, they are likely to suffer from front running, free riding, and other speculative activities, which could hurt themselves. As a result, these funds are prone to charge higher fees on their investors. Ge and Zheng (2006) document that less frequent disclosures of mutual funds are a bad signal, because it is often associated with higher turnover, higher expense ratios, and higher likelihood of fund fraud.

Fewer studies have been done directly on the disclosing frequency of hedge funds. One good example is Aragon and Nanda (2014). They find evidence for "performance smoothing" for hedge funds disclosure. They show that hedge funds often disclose poor performance with delays, and that the delays are sometimes also associated with poor subsequent performance. They conclude that such delays could reveal poor managerial quality and/or operation risks of funds. My research enriches the literature on hedge funds' disclosing frequency by focusing on the disclosing frequency of Chinese hedge funds. My results suggest that a fund's disclosing frequency is largely associated with its performance and risk taking behavior.

The second strand of literature to which my research is related is the topic of fund families. Some studies are conducted in the realm of mutual funds. For example, Guedj and Papastaikoudi (2005) find it is easier to find consistency in mutual fund performance within a fund family than in the entire hedge fund universe. They argue that the main reason for more significant performance persistence within a fund family is that fund families, especially the more complex fund families, can allocate managers and other resources to favor their winner funds inside the family. Bessler, Kryzanowski, Kurmann, and Lückoff (2014) focus on the "past winner" mutual funds with low cash inflows. They find that although in general these funds all outperform other funds, funds in simpler fund families perform better than those in complex families. They argue that it is because complex fund families have higher organizational complexity costs and conflicts of interest inside the family.

Some studies are also conducted on hedge fund families. For example, McGuire and Tsatsaronis (2008) provide evidence that in the absence of more detailed information of hedge funds, a regression of fund returns on risk factors can serve as a good help for due diligence. However, they suggest that this method works much better for the funds in fund families whose returns are better captured by the risk factors in the analysis. Gervais, Lynch, and Musto (2005) find that larger hedge fund families with more managers are more apt to maintain profitability, because larger fund families are easier to fire inefficient managers and retain efficient ones. My research is on the relation between a Chinese fund's family complexity (number of funds in a family) and the fund's returns and risk taking behavior, so it contributes to this strand of literature.

Third, my research also connects with the studies on the relation between hedge funds and special events or policy changes. On one hand, some studies on this topic focus on the role played by hedge funds in these events. For example, Brunnermeir and Nagel (2004) provide analysis on how hedge funds involved in the technology bubble in mid-2000. They show evidence that hedge funds not only did not help correct the bubble but also deliberately invested in high-tech stocks heavily before the burst of the bubble. In order to support this finding, they provide evidence from the stocks in which hedge funds invested, the risk exposure of hedge funds (especially the technology factor), and their cash flows.

On the other hand, some research targets the impact of these events on hedge funds, which is more related to my research. Edwards (1999) and Borio (2008) provide a case study on the impact of the failure of Long-Term Capital Management in 1998 and of the financial turmoil in 2007 on hedge funds, respectively. In the paper, Borio (2008) gives a comprehensive list of the events that could impact the hedge fund industry and economy from April 2007 to February 2008.

Similarly, I also provide a list of events that could affect the Chinese hedge fund industry (from June 2008 to February 2013). In addition, I also adopt the D/D methodology in estimating their impact on funds. Some researchers have also used this methodology to study the impact of events, and most of them focus not only on hedge funds, but on the economy in a broader sense. For example, Gilje and Taillard (2014) use the D/D framework to study the impact of the sudden breakdown of Canadian oil producers' hedging system in first quarter of 2012 on the Canadian oil producing industry. They perform the D/D test on the Canadian companies as the treatment group and their U.S. counterparts as the control group. They show that the Canadian oil companies, especially those with high leverage, indeed significantly reduce their capital expenditures due to this event. I use the similar technique to test whether the event in July

2011, which allows the funds to use stock index futures, causes the most changes in the hedge fund industry.

2.3 Data and the Chinese Fama-French Three-Factor Model

2.3.1 Data

Data for this research come from two separate sources. The most important part is the Chinese hedge fund data provided by Howbuy, a leading investment advisor in China.[46] The raw data from Howbuy consist of two Excel files. The first file contains the time-series disclosures of NAV per share for each fund. This file allows me to calculate both the monthly returns and the disclosing frequency for each fund. The disclosing frequencies, calculated as the difference in days between two adjacent disclosures, are approximately daily, weekly, monthly, or quarterly.

The second file contains the characteristics for each fund. It also has information of the management company and trust company for each fund. Thus, I can obtain the characteristics at the fund level, family level, and trust level through this file.

Another part of my research data is a list of the important events in China concerning the hedge fund industry. I focus on two types of events. The first is about the fund industry itself, which records the dates when each type of funds and strategy of funds began to operate. The second is about the establishment of new financial markets policies. There are only a few of such events, and the information is readily available from the regulatory websites and news media.

I require the funds to have at least one year of NAV disclosure. I then delete the quarterly disclosing funds, because even if such funds have one year of history, there are only as

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[46] The website of Howbuy is www.howbuy.com (in Chinese).

few as four observations. The top and bottom 2.5% raw return values are then winsorized to control for outliers.[47] After combining all the data, I have a sample of 1,548 funds, 554 fund families, 37 trusts, and 6 important events in my sample. The included events are (1) the inception of overseas managed funds, (2) the policy in March 2010 that allows margin tradings, (3) the inception of funds that specifically label themselves as using hedging strategies, (4) the policy in July 2011 that allows trusts to trade stock index futures, (5) the policy in August 2012 that allows refinancing for brokers, and (6) the policy in February 2013 that allows securities relending for brokers.[48]

2.3.2 The Chinese Fama-French Three-Factor Model

To adjust Chinese hedge funds' returns for common risk factors, I adopt the Fama-French (1993) three-factor model, which is widely used in other financial studies. Rather than using the original model that has U.S. risk factors, I use Chinese data and compute the Chinese risk factors for the purpose of this study. The adjusted model is

$$R_t - RF_t = \alpha + \beta_1 \times MKT_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \varepsilon_t \,, \tag{3}$$

where R_t is the raw return of the fund (or fund portfolio) in month t; RF_t is the interest rate of the Chinese demand deposit in month t; MKT_t is the return on the Chinese Hushen 300 Index in month t minus RF_t;[49] SMB_t is the total return on the Russell China Small Cap Stock index minus the total return on the Russell China Large Cap Stock index in month t; HML_t is the return on the

[47] I also try other thresholds for winsorization, and the results remain virtually unchanged.

[48] I list all these policies and events in Table 13.

[49] The Hushen 300 Index is a widely recognized index for the Chinese A-share stocks, compiled by China Securities Index Co., Ltd. (http://www.csindex.com.cn/sseportal/csiportal/indexquery.do, in Chinese). It is a free float-weighted index consisting of 300 stocks, representing over 70% of the A-share stock market. The Chinese stock index futures are built on this index. This index is also referred to as CSI 300 Index.

Russell China Value Stock index minus the return on the Russell China Growth Stock index in month t. The intercept in the regression, α, is the Fama-French three-factor alpha of the fund (or fund portfolio). Model (3) is used whenever I refer to Fama-French three-factor alpha later in this research.

2.4 Tests and Results

2.4.1 Disclosing Frequency

My first research goal is to explore the impact of a fund's disclosing frequency on fund performance. To do so, I classify funds into categories based on disclosing frequency. I calculate disclosing frequencies as the difference in days between two adjacent disclosing dates. A fund obviously could have a number of frequencies, but a significant number of funds mainly stick to a dominant frequency. I define the dominant frequency of a fund as the frequency that it follows at least 95% of the time in its history.[50]

My next step is to classify the funds according to their disclosing frequency. First, some funds do not report any information of their disclosing dates to the Howbuy database, so I put them in the N/A category. Second, I classify the funds that do not have a dominant disclosing frequency in the Unstable category. Afterwards, there are only funds that do have a dominant frequency, and I find three frequencies: Daily, weekly, and monthly. I group funds disclosing weekly and funds disclosing monthly in one category, because, as discussed above, they are both legitimate disclosing frequency required by law or in the fund's investment contract. Most funds belong to this Weekly/Monthly category. Daily disclosing funds are grouped into a separate category, because such funds disclose their performance far more frequently than

[50] I have also tried other cutoff points for criterion of stable disclosing frequency, and the results are virtually unchanged.

mandated by regulation or by industrial standard. I focus only on the Daily category and the Weekly/Monthly category. Figure 6 shows the distribution according to this classification. Table 9 presents the fund characteristics and return statistics of the daily funds and monthly/weekly funds.

Panel A of Table 9 reports the fund characteristics. Compared to weekly/monthly funds, daily funds on average are founded 15 months later and have a significantly shorter investment duration, over six years shorter. To their investors, daily funds charge 29 basis points more in management fee; a higher percentage of them offer investor protection (high water mark, hurdle rate, or both) by collecting incentive fee or target to operate in the long run, and they require a lockup period of about five months shorter. Therefore, these daily disclosing funds appear more appealing to investors in terms of investor protection and share restrictions, but they do impose a higher fixed fee on investors.

Panel B of Table 9 focuses on the difference in fund performance between daily funds and weekly/monthly funds. The performance measures I consider here include: (1) ExRet (the mean of a fund's raw return in excess of Chinese demand deposit interest rate), (2) ExRetStdDev (the standard deviation of ExRet), (3) $SharpeRatio_{i,t}$, (calculated as ExRet / ExRetStdDev), and (4) FF3Alpha (as previously described, it is the intercept in the regression of ExRet on the Chinese Fama-French three factors).

For the whole sample period, daily funds and weekly/monthly funds do not differ much. Next I divide this entire time period into two subperiods: 2003 to 2008 and 2010 to 2013, where the year of 2009 is omitted. The reason is twofold. First, Liang and Zhang (2014a) find that the subperiods 2003 to 2009 and 2010 to 2013 function as the two disparate time periods for the Chinese hedge funds industry. Second, 2009 is not a reliable year to study disclosing frequency. China Banking Regulatory Commission issued Operating Guidelines for the Securities Investment

Trust Business of Trust Companies in this year, which requires funds to disclose NAV weekly. Consequently, in 2009 many funds change their disclosing policy to adjust for this new regulation, so I omit 2009 in the analysis on subgroups.[51]

Over the entire sample period, Daily funds deliver higher Fama-French three-factor alpha than Weekly/Monthly funds (1.13% vs. 1.05%), although their excess return and Sharpe ratio are slightly lower. However, the Daily funds operate only in the second subperiod. In this subperiod, Daily funds clearly perform better. They provide five times higher excess return and over two times higher Sharpe ratio than Weekly/Monthly funds. Besides they deliver a significant Fama-French alpha of 1.13%, whereas Weekly/Monthly funds fail to provide any risk-adjusted return. The reason why Weekly/Monthly funds do not underperform too much in the whole sample period is that they mainly get their positive performance from the first subperiod.

So far I have documented the phenomenon that daily funds, funds disclosing more frequently, have better performance than Weekly/Monthly funds, funds disclosing less frequently. Next, I conduct analyses to explore funds' motivation for choosing a particular disclosing frequency. My results indicate that the disclosing frequency of Chinese hedge funds is closely related to Chinese economic conditions—in months when the Chinese hedge fund industry and the Chinese stock market perform better, funds tend to switch from weekly/monthly frequencies to daily; otherwise, funds tend to switch from daily frequency to weekly/monthly. I present these results in Table 10.

[51] Interestingly, prior to 2009, there were only weekly and monthly funds, and the daily funds are all launched after the new policy in 2009. Therefore, it appears that this new policy on disclosing frequency serves as a major motivation for some funds to choose a daily disclosing frequency—by doing so they can show their superiority over the weekly and monthly frequency required by the regulation.

In Table 10 I focus on fund's sudden change in the disclosing frequency, i.e., whether a fund suddenly switches from weekly/monthly frequencies to daily or vice versa. There are two steps of my analyses in this table. The first is a categorical analysis, where I divide all monthly performance observations in my sample into three categories: (1) If the fund switches from weekly/monthly frequencies to the daily frequency in that month, (2) if the fund does not change its disclosing frequency, or (3) if the fund switches from the daily frequency to weekly/monthly frequencies. And then I build a portfolio for each category using its performance observations.[52] The performance measures I consider include ExRet, SharpeRatio, and FF3Alpha, and to show the differences among these three portfolios, I also consider the rankings of these three measures.

Based on my previous discussion, I expect to see that among these three portfolios, Portfolio (1) has the best performance, because when funds suddenly disclose performance more frequently, they should perform better recently. For these funds, they are able to give investors more good news by disclosing more frequently. For the same reason, I expect that Portfolio (3) has the worst performance, and Portfolio (2) ranks between Portfolios (1) and (3).

The results in Panel A of Table 10 confirm my expectation. Portfolio (1) obtains an average excess return of 82 basis points, almost twice as much as that of Portfolio (3). The Sharpe ratio of Portfolio (1) is 150% of that of Portfolio (3). Portfolio (1) realizes a significant Fama-French alpha of 81 basis points, while Portfolio (3) has no significant return after controlling for Fama-French factors. For all three performance measures, Portfolio (1) ranks first, Portfolio (3) last, and Portfolio (2) in between.

[52] All portfolios in this research are equally weighted because there is no fund size information in my database.

The second step of my analyses is a logistic regression model. The purpose of this analysis is to explore the reasons why Chinese hedge funds change the disclosing frequency from weekly/monthly to daily or vice versa. My logistic regression model is:

$$ToDaily_t = \alpha + \sum_{k=1} \beta_k \times Index_{t,k} + \varepsilon_{t.} \qquad (4)$$

In this model, for any variable, the subscript t denotes Month t. The dependent variable, $\mathrm{ToDaily_t}$, equals one if in that month more funds, percentage wise, switch from weekly/monthly frequencies to daily, and equals zero otherwise. The independent variables $\mathrm{Index_{t,k}}(\mathrm{k} = 1,2,, \ldots)$ are Chinese economic indices, which may include ExRet Avg. (the average return of the Chinese hedge fund industry in excess of Chinese demand deposit interest rate), MKT (the return on Chinese Hushen 300 A-Share Index in excess of Chinese demand deposit interest rate), MOM (the momentum factor based on Chinese A-Share stocks), ChinaConcept (the return on the index of China-concept stocks listed in markets outside Mainland China), Bond (the return on the comprehensive index of Shanghai bond market), and COM (the return on the index for Chinese commodity futures).

I use both the bivariate version and the multivariate version of this logistic model. The bivariate models consider only one economic index on the right hand side. The multivariate models consider two or more indices, where I include four combinations of these indices: Model 1 focuses on the equity markets; Model 2 focuses on bond market and futures market; Model 3 considers all of such markets; and Model 4 considers all these markets and also includes the performance of the overall Chinese hedge fund industry.

Panel B of Table 10 reports the results, and the specific indices included in each version of the logistic model are also specified in this panel. The bivariate results show that switching to the daily frequency is positively correlated with the performance of the overall Chinese hedge fund industry, Chinese A-Share stocks, and China-concept stocks listed in overseas markets. The multivariate results demonstrate a similar pattern. For example, a one-percentage-point increase in ExRet Avg. causes a 15.96-percentage-point increase in the probability of more funds switching from weekly/monthly to daily than from daily to weekly/monthly. The multivariate regression results reveal a similar pattern. The impact of ExRet Avg. and ChinaConcept is still significant, but MKT loses the explanatory power. This could be caused by multicollearity problems. Overall, Panel B of Table 10 shows that Chinese hedge funds tend to switch to higher disclosing frequency if macro economic conditions are good, where the two most significant economic conditions are the overall Chinese hedge fund industry and China-concept stocks listed in overseas markets.

2.4.2 Fund Structure

Next I study whether a fund's legal structure affects fund performance. As previously discussed, I focus my investigation on three characteristics: Trust complexity, family complexity, and family speed. I divide funds into groups according to these three features. Frist, two groups are formed based on trust complexity: (1) Trust Complexity = 1, including funds offered by single-fund trusts and (2) Trust Complexity > 1, including funds offered by complex trusts, i.e., trusts that monitor multiple funds. Therefore, the Trust Complexity > 1 group consists of funds with more resources. Second, two groups are formed based on family complexity: (1) Family Complexity = 1, including funds run by single-fund families and (2) Family Complexity > 1, including funds run by complex families. Therefore, the Family Complexity > 1 group consists of funds with more resources. Last, four groups are formed based on family speed: (1) Single-Fund, including funds run by single-fund families, (2) 0-60 days, including funds run by families whose family speed is shorter than two months, i.e., families that on average launch a new fund in less than 60 days, (3) 60-120 days, including funds run by families with family speed of one new fund in two to four months, and (4) > 120 days, including funds run by families with family speed of one new fund in longer than four months.[53] Therefore, in terms of the speed of launching new funds, the 0-60 days group consists of the most reckless fund families, and the > 120 days group consists of the most cautious families.

Per previous discussion, I expect that (1) the Trust Complexity > 1 group outperforms the Trust Complexity = 1 group, (2) the Family Complexity > 1 group outperforms the Family Complexity = 1 group, and (3) the > 120 days group outperforms the 60-120 days group, which in turn outperforms the 0-60 days group. The results in Table 11 confirm all these expectations.

Panel A shows that the Trust Complexity > 1 group outperforms the Trust Complexity = 1 group in all three performance measures: ExRet (1.16% vs. -0.09%), SharpeRatio (0.25 vs. -0.02), and FF3Alpha (0.78% vs. insignificant alpha). The comparison in this panel demonstrates that funds monitored by larger trusts perform better. This could be attributed to the fact that larger trusts are more resourceful and can provide more effective inspection.

Panel B shows similar results. The Family Complexity > 1 group shows better performance than the Family Complexity = 1 group in all three performance measures as well. This performance difference between the two groups suggests that funds managed by more complex fund families perform better. The reason, again, is that these fund families enjoy more capital and managerial resources.

Panel C reports the performance differences across the groups formed by family speed. Because the purpose of this panel is to examine whether a fund family's speed of starting new

[53] In the group criterion of family speed, the four groups divide my sample roughly into quartiles. Groups (ii) to (iv) are complex families.

funds affects fund performance, I do not focus on single-fund families.[54] Remember that the slower the family speed is, the more cautious is the fund family. Panel C indicates that funds managed by more cautious fund families have better performance. ExRet (0.19%, 1.25%, 1.24%), SharpeRatio (0.06, 0.26, 0.27), and FF3Alpha (insignificant, 0.85%, 0.91%) almost always increase monotonically with the increase in family speed.

There are two reasons for the underperformance of fund families that start new funds too fast. One reason is that fast expansion prevents managers from running each fund effectively. Another reason seems more rational—fast expansion could increase operational risk of management companies. Brown et al. (2008, 2009) conduct important research on operational risk, and my results regarding family speed are consistent with their findings both theoretically and empirically. First, in the theoretical framework, they state that loses due to operational risk "include the risks of failure of the internal operational, control, and accounting systems; failure of the compliance and internal audit systems; and failure of personnel oversight systems, that is, employee fraud and misconduct." Obviously, management companies with a high family's speed are very likely to induce all the above failure. Moreover, my analysis also leads to consistent empirical results. In Panel C of Table 11, the Speed 0-60 group has the lowest returns and return standard deviation, and the youngest age (measured by number of months of the group's time range). Brown et al. (2008) also find that operational risk is negatively correlated with previous fund returns, return standard deviation, and fund age. Therefore, higher operational risk could cause the low performance of less-than-cautious families in business expansion.

[54] Notice that the number of single-fund families is 303 in Panel B but only 265 in Panel C. This difference is because only 265 of the 303 single-fund families actually report a fund's inception date information.

So far in this subsection, trust complexity and family complexity are calculated as of the end of my dataset, which is November 2013. For example, if a trust is monitoring only one fund as of November 2013, I consider its trust complexity to be one, i.e., it is a single-fund trust, regardless of how many funds it monitored before this month. Therefore, if single-fund trusts (families) were not monitoring (managing) only one fund before November 2013, my analysis in this subsection would be seriously undermined.

To dismiss this concern, I calculate historical means and medians of trust complexity (trust complexity) for single-fund trusts (families). If the means and medians are historically very close to one, I have reasons to believe that my calculation of trust complexity and trust complexity is reliable over the years.

Figure 7 confirms this reliability. For trust complexity, the historical means range from 1.2 to 1.33 (Subfigure (a)), and the historical medians are always 1 (Subfigure (b)). For family complexity, the range of the historical means is from 1.11 to 1.23 (Subfigure (c)), and the historical medians are, again, always 1 (Subfigure (d)). For comparison purposes, the historical means and medians for more complex trusts or families are also reported in this figure.

2.4.3 The Joint Effect of Disclosing Frequency and Fund Structure on Fund Performance

So far I have examined four China-specific characteristics: Disclosing frequency, trust complexity, family complexity, and family speed, and I have studied their separate effect on fund performance. However, in reality a fund generally has these four characteristics simultaneously. Thus, it is necessary that I study their joint effect on fund performance, which is the focus in this subsection.

The methodology of my test for joint effect is the following general regression model:

$$
\begin{aligned}
FF3Alpha_i = \alpha + \beta_1 \times Daily_i + \beta_2 \times Weekly/Monthly_i + \beta_3 \\
\times TrustCcompGT1_i + \beta_4 \times FamilyCompGT1_i \qquad (5) \\
+ \beta_5 \times Speed0 - 60_i + \beta_6 \times SpeedGT120_i + \varepsilon_{i.}
\end{aligned}
$$

In this model, for any variable, the subscript i denotes Fund i. The dependent variable $FF3Alpha_i$ is Fund i's Fama-French three-factor alpha (in percentage points). Two independent variables are dummy variables based on disclosing frequency: $Daily_i$ (equals one if Fund i is a daily disclosing fund, and zero otherwise) and $Weekly/Monthly_i$ (equals one if Fund i is a weekly/monthly disclosing fund, and zero otherwise).[55] One independent variable is the dummy variable based on trust complexity: $TrustCompGT1_i$ (equals one if Fund i belongs to a trust that monitors more than one fund, and zero otherwise). One independent variable is the dummy variable based on family complexity: $FamilyCompGT1_i$ (equals one if Fund i belongs to a management company that runs more than one fund, and zero otherwise). The last two independent variables are dummy variables based on family speed: $Speed0–60_i$ (equals one if Fund i belongs to a management company that on average starts a new fund within 60 days, and zero otherwise) and $SpeedGT120_i$ (equals one if Fund i belongs to a management company that on average starts a new fund in greater than 120 days, and zero otherwise). [56] Furthermore, I have three models for this test. The first is the original Model (5); in the second model I also control for fund's investment strategy; and in the third model I further control for fund type. I control for these two characteristics because, as Liang and Zhang (2014a) suggest, different fund types and investment strategies indicate different return generating processes.

[55] The two variables, $Daily_i$ and $Weekly/Monthly_i$ do not cause perfect collinearity problems, because, as described in Figure 6, 60.92% of the funds in my dataset do not follow a stable disclosing frequency.

[56] The two variables, $Speed0–60_i$ and $SpeedGT120_i$ do not cause perfect collinearity problems, because some fund families launch a new fund in an average between 60 and 120 days.

The regression results are reported in Table 12. Tested for both the entire sample period (Panel A) and the 2010-2013 subperiod (Panel B), my results are consistent over time. There are three patterns in the results in Panel A. First, both the Daily and Weekly/Monthly dummies are positively related to the dependent variable, a fund's Fama-French three-factor alpha, indicating that funds disclosing at a consistent frequency, either daily or weekly/monthly, outperform funds that do not disclose consistently. Moreover, the coefficients on Daily are always larger than those on Weekly/Monthly, suggesting that daily disclosing funds are even better in performance than weekly/monthly disclosing funds.

Second, family complexity is also positively related to fund performance. The coefficients on the FamilyCompGT1 variable are around 0.3, which means that if a fund is managed by a fund family that runs multiple funds, its Fama-French three-factor alpha will rise by 0.3 percentage point per month (equivalent to 3.66 percentage points per year) from if it is managed by a single-fund family. This increase is both economically and statistically significant, and it shows that the more complex a fund family is, the better its funds perform. The reason for this is, again, more complex fund families have more resources to manage funds effectively. On the other hand, trust complexity does not have significant impact on fund performance. The reason for the loss of its explanatory power is thatits effect is probably captured by other characteristics in this joint test.

Third, the Speed0-60 dummy variable is negatively related to fund performance. Its coefficients range from -0.28 to -0.23, suggesting that a fund's Fama-French three-factor alpha will drop by 0.23 to 0.28 percentage point per month (equivalent to 2.73 to 3.31 percentage points per year) if its fund family launches one new fund within two months. These figures confirm my previous test, which is fund families that are reckless in starting new funds will actually hurt its funds in performance.

All three patterns are both economically and statistically significant; these results hold for the 2010-2013 subperiod (Panel B). Overall, these three patterns suggest that better fund performance is expected in funds that (1) disclose information on a daily basis, (2) belong to a fund family that manages multiple funds, or (3) belong to a fund family that is cautious in launching new funds.

2.4.4 The Most Influential Policy Change

Besides these four China-specific characteristics I have studied (disclosing frequency, trust complexity, family complexity, and family speed), Chinese hedge funds are also distinguishable because of a fifth special feature; i.e., they have been facing constant policy changes. In this subsection, I investigate all major policy changes between 2003 and 2013, identify the most influential one of them, and examine its impact on the Chinese hedge fund industry.

The reason why Chinese hedge funds witness more policy changes than other hedge funds is their significant growth during a short period of time. As documented in prior research (for example, Chen et al. (2012), Chen, Chen, and Chen (2013), and Liang and Zhang (2014a)), the first few Chinese hedge funds came out between 2003 and 2004, when China was not really ready for them. For example, there were no real hedge instrument in China during that time, so these “hedge funds” could only go long on securities then. Hedging instruments became available for them only at a later time However, with a series of new policies over the years, Chinese hedge funds are now a well-established industry. Therefore, many policy changes regarding the industry took place between 2003 and 2013.

Table 13 lists four major policy changes as well as two critical events during this period of time. The first policy changes is that margin trading was allowed in China on March 31, 2010, which is the first hedging instrument available for Chinese hedge funds. With this new policy, they can now go short on securities. The second policy change is that trusts are allowed to trade stock index futures, which occurred on July 12, 2011. Stock index futures are a major hedge technique for hedge funds in other countries, but there was no stock index future available in China until April 2010. This is when China officially launched its stock index futures market. However, for the first 15 months of this market, Chinese hedge funds were not allowed to participate, primarily because the market was considered immature for sophisticated investors, like hedge funds. Only on July 12, 2011 did Chinese authorities allow trusts to enter this market, and since, legally speaking, a Chinese hedge fund is part of a trust, Chinese hedge funds have been able to use stock index futures since then. The next two policy changes took place in 2012-2013, which launched the Chinese refinancing system and securities relending system, respectively. [57] All of these four major policy changes provide hedging instruments for Chinese hedge funds.

I also consider two critical events for the Chinese hedge fund industry. The first is that funds that label themselves as Overseas Managed started to report to my database from June 30, 2008. Before this time, all hedge funds in my sample were managed by Chinese managers, even though some managers appear to have overseas background to some degree. Overseas Managed funds attract investors probably because they are perceived as superior to domestic funds. The second event is that funds that self-label as Hedge-Strategy started reporting to my database from June 30, 2010. It appears that these funds have superior trading technique,

[57] The refinancing and the securities relending systems are actually extensions of the Chinese margin trading system. Before these two systems, Chinese investors could borrow money or securities only from the securities firms they use; but with these two systems, investors can now borrow from other securities firms as well. The central broker in these two systems is China Securities Finance Corporation Ltd.

because they were operating even before July 12, 2011, when hedge funds were actually allowed to use stock index futures.

Table 13 also shows the impact of these policy changes and events of the Chinese hedge fund industry. Per my discussion above, I investigate three groups of hedge funds: Funds (1) that specifically label themselves as Hedge-Strategy;[58] (2) that are managed in Mainland China (domestic); and (3) that are managed overseas.[59] I expect that the Hedge-Strategy fund group is the most sensitive to the policy changes and events in Table 13, because all of them provide Chinese hedge funds with more hedging instruments.

To emphasize the impact of these policy changes and events on the industry, I calculate the growth speed in the number of funds in each fund category, i.e., how fast a particular fund group has expanded during a specific period of time. The equation I use is as follows:

$$Growth\ Speed = \frac{No._t - No._{t-1}}{(Time_t - Time_{t-1})/365}. \tag{6}$$

The subscript t denotes that the variable is observed at the tth policy change or event, No. is the number of funds, and Time is the date of the policy change or event.

The results in Table 13 show that the policy change on July 12, 2011, when trusts are allowed to trade stock index futures, is the most influential event. I see this pattern in all three fund groups. First, before the new policy, the Hedge-Strategy fund group was rather silent. There were only four Hedge-Strategy funds, and on average only 2.9 funds were launched per

[58] The Hedge-Strategy fund group includes all the funds that report of using strategy of Hedging, Arbitrage, or Multi-Strategy. These funds are all managed in Mainland China. The hedging strategies group is a subset of the domestic fund group, and the domestic group and the overseas managed group are mutually exclusive and altogether form the whole sample of 1,548 funds.

[59] As Liang and Zhang (2014a) document, the overseas management companies all feature Chinese managers, but the companies are registered overseas. The overseas managed funds mainly trade Chinese stocks listed in Mainland China and China-concept stocks listed overseas.

year. Afterwards, however, there has been a significant surge in this group, with over 20 new funds coming out every year. Therefore, this policy greatly boosts funds that specifically label themselves as Hedge-Strategy funds. Second, for the domestic fund group, although its expansion has been dramatic, its largest growth occurred before the policy in July 2011 (537.33 new funds launched per year). After the policy change, the growth speed for the domestic fund group decreases fast—it drops to 178.49 new funds per year with in two years after the policy. Combining the results in these two fund groups, I see that this new policy significantly boosts the Hedge-Strategy sector and reduces the attractiveness of other domestic funds. The third trend is seen in the Overseas Managed fund group. Similar to the domestic fund group, the Overseas Managed fund group enjoyed fast growth before the policy, with three to four new funds lunched every year. After the policy, however, the growth speed has plummeted, and on February 28, 2013, it even became negative growth of -2.01, which suggest that between August 30, 2012 and February 28, 2013, no new Overseas Managed fund was founded, and on average two funds disappeared from my database.

In summary, Table 13 shows that the policy change on July 12, 2011 is the most influential event for the Chinese hedge fund industry, and because it provides funds with an effective hedging instrument, it most directly affects funds that self-label as Hedge-Strategy funds. To measure its quantitative impact on Hedge-Strategy funds, I conduct the following difference-in-difference (D/D) test.

The purpose of the D/D test is test the impact of a special event on a certain subject, and it is used in many financial studies (see, for example, Gilje and Taillard (2014)). In this research, I focus on the policy change in July 2011 on the performance of Chinese hedge funds. The D/D test requires the use of two groups: A treatment group, the group of subjects that are directly affected by the event, and a control group, a group of similar subjects that are not affected by the event. In my situation, the treatment group is of course all Hedge-Strategy funds. To choose funds for the control group, I must select funds that have similar history length, are also managed by domestic managers, and the selected funds must represent the majority of Chinese hedge funds. Therefore, I choose Traditional Stock funds and Private Placement funds as the control group.[60] I present the preliminary similarities and differences between these two groups in Figure 8.

These two groups have similar returns before the July 2011 event. However, right after the event, the difference started to expand. By the end of my data in November 2013, funds using hedging strategies cumulate nearly 40% more monthly returns than the funds of Traditional Stock strategy or Private Placement strategy.

Besides using two groups for the D/D test, I also need to select two time windows: One before and the other one after the event. These two time windows must satisfy three conditions: They must be long enough, they must be of the same length, and they should not overlap with any other major events. Therefore, I choose 12 months before and after the July 2011: July 2010-June 2011, and August 2011-July 2012. These two time windows are the longest ones that do not overlap with any other major policy change or event in Table 13.

My baseline model for the D/D test is as follows:

$$Perf_{i,t} = \alpha + \beta_{Hedge} \times Hedge_i + \beta_{Post} \times Post_t + \beta_{Hedge*Post} \times Hedge_i \times Post_t + \varepsilon_{i,t} \,. \tag{7}$$

The subscripts i and t denote Fund i and Time Window t, respectively. Therefore, I have altogether four combinations based on groups and time windows: The treatment group (1)

[60] Traditional Stock and Private Placement are fund's investment strategies. According to Liang and Zhang (2014a), Traditional Stock funds and Private Placement funds have similar history to Hedge-Strategy funds, and they two represent 81.83% of the entire Chinese hedge fund industry.

before the event and (2) after the event, and the control group (3) before the event and (4) after the event. The dependent variable Perf is the fund performance measure I want to test. For the independent variables, $\mathrm{Hedge_i}$ is a dummy variable that equals one if Fund i is from the treatment group, Hedge-Strategy funds, and equals zero otherwise; $\mathrm{Post_t}$ is a dummy variable that equals one if Time Window t is before the event in July 2011, and equals zero otherwise.

The three coefficients on the right hand side have different meanings. β_{Hedge} suggests the difference between the treatment and control groups. β_{Post} suggests the impact of the policy change in July 2011 on the treatment and control groups combined. $\beta_{\mathrm{Hedge*Post}}$ suggests the impact on the treatment group alone. Therefore, if this policy change significantly affects the performance of the treatment group, but not so for the control group, the coefficient $\beta_{\mathrm{Hedge*Post}}$ will be significant. On the contrary, if $\beta_{\mathrm{Hedge*Post}}$ is not significant, then I cannot say that the event significantly affects the treatment group.

The performance measure I examine is $\mathrm{ExRet}_{i,t}$, the mean of Fund i's raw returns in excess of the Chinese demand deposit interest rate in Time Window t. For comparison purposes, I also test a risk measure, $\mathrm{ExRetStdDev}_{i,t}$, the standard deviation of $\mathrm{ExRet}_{i,t}$, as well as a performance measure that considers risk factor, $\mathrm{SharpeRatio}_{i,t}$, which is calculated as $\mathrm{ExRet}_{i,t}$ / $\mathrm{ExRetStdDev}_{i,t}$. I expect that the policy change in July 2011 greatly increase the performance of Hedge-Strategy funds, but not so much for their risk. Therefore, if I use $\mathrm{ExRet}_{i,t}$ as the dependent variable in Model (7), I expect a significantly positive $\beta_{\mathrm{Hedge*Post}}$ coefficient; but if I use $\mathrm{ExRetStdDev}_{i,t}$, or $\mathrm{SharpeRatio}_{i,t}$ as dependent variable in Model (7), I expect that the $\beta_{\mathrm{Hedge*Post}}$ coefficient to be insignificant.

The D/D test results are reported in Panel A of Table 14, which are consistent with my expectations. When $\mathrm{ExRet}_{i,t}$ is the dependent variable, the $\beta_{\mathrm{Hedge*Post}}$ coefficient is 2.19, and the β_{Post} coefficient is significantly at -1.85. These two number imply that after the policy change, the mean of excess returns of the treatment group, Hedge-Strategy funds, increases by 34 percentage points per month (= 2.19 - 1.85). This has great economic significance. When $ExRetStdDev_{i,t}$ or $SharpeRatio_{i,t}$ is the dependent variable, $\beta_{\mathrm{Hedge*Post}}$ is insignificant. Therefore, the policy change in July 2011 only increases the excess returns of Hedge-Strategy funds, but does not reduce its risk.

A key issue for the D/D test is the validity of the test. Namely, I must verify that before the policy change in July 2011, the $\beta_{\mathrm{Hedge*Post}}$ coefficient is insignificant. Otherwise, the significant coefficient found in Panel A could be caused by some other reasons, not necessarily by this particular policy. To address this issue, I conduct a validity check as follows. I create a placebo event before July 2011, repeat the D/D test, and check if the $\beta_{\mathrm{Hedge*Post}}$ coefficient is significant for this placebo event. If it is, then my D/D test will not be proper for the policy change in July 2011; if it is not, however, then my test should be reasonable. I choose December 2010 to January 2011 as the time for the placebo event, because this two-month placebo event separates the time period between July 2010 and June 2011 into three parts: Five months before the placebo event, two months during it, and five months afterwards.

The results of this validity check are reported in Panel B of Table 14. The $\beta_{\mathrm{Hedge*Post}}$ coefficient is never significant. Therefore, my test results for the July 2011 policy should be reliable; this particular policy largely increased the returns of Hedge-Strategy funds, but did not significantly reduce their risk.

2.5 Conclusion

The Chinese hedge fund industry has enjoyed dramatic growth since its start in 2002. Chinese hedge funds have several unique features that distinguish them from other hedge funds in the world. These features include: Self-chosen disclosing frequency (Chinese hedge funds choose how often they update their information to a data vendor, rather than doing so just on a monthly basis, which is popular among other countries); special legal structure (Between 2003 and 2013, Chinese hedge funds must be offered to the public via a trust company, although they are in fact run by a fund management company.); and constant policy changes (Since they were founded, Chinese hedge funds have witnessed many policy changes, which have provided these funds with more and more hedging instruments.). In this research, I investigate whether these special features affect the performance of Chinese hedge funds. To be specific, I focus on three questions: (1) Is a fund's disclosing frequency related to its performance, (2) Are characteristics of a fund's trust company (or trust) and management company (or fund family) related to the fund's performance, and (3) Among all the policy changes, which has been the most influential one for the fund industry, and which fund sector is the most affected by this change? My main findings are summarized as follows.

First, I discover that if a Chinese hedge fund discloses its information to a data vendor with a consistent frequency, there are three frequencies it can choose: Daily, weekly, or monthly. I find that daily disclosing funds show the best performance. For example, between 2003 and 2013, they outperform weekly/monthly disclosing funds by 8 basis points in the risk-adjusted return per month (equal to 96 basis points per year). I also find that daily funds charge higher management fees to investors than weekly/monthly funds. This is likely due to the fact that fund managers of daily funds are more confident about fund performance. Moreover, I find that the disclosing frequency is strongly related to Chinese economic conditions. If the entire Chinese hedge fund industry or China-concept stocks listed overseas do well, more funds would switch to daily disclosure; otherwise, more funds would switch to weekly/monthly disclosure. This pattern is probably because fund managers want to provide investors with more good news and less bad news.

Second, I find that a fund's legal structure strongly affects its performance. I focus on three features of the legal structure: Trust complexity (the number of funds monitored by a trust), family complexity (the number of funds run by a management company), and family speed (the average length of time that a management company needs to launch a new fund). I find that fund performance is positively related to its trust complexity and family complexity. Fund performance of trusts (families) with high complexity is significantly better than that of single-fund trusts (families). This is because single-fund trusts and families lack resources to monitor or manage funds effectively. For family speed, I find that the more cautious a fund family is in starting new funds, the better its funds perform. This phenomenon is, again, due to a management company's resources—if it launches new funds too fast, it will not have enough managerial resources for each fund, and it will be more likely to suffer from operational risk problems (Brown et al. (2008, 2009)).

Last, I find that among all the policy changes and events between 2003 and 2013, the new policy in July 2011, which allows trusts to trade stock index futures, has been the most influential one for the Chinese hedge fund industry. This event has greatly boosted the expansion of Hedge-Strategy funds. Before this policy, there were only about three Hedge-Strategy funds founded per year, but after this policy there have been over 20 such funds launched per year. Furthermore, this policy has also greatly increased the performance of Hedge-Strategy funds. My D/D test results indicate that this policy causes the excess return of Hedge-Strategy funds to increase by 34 basis points per month.

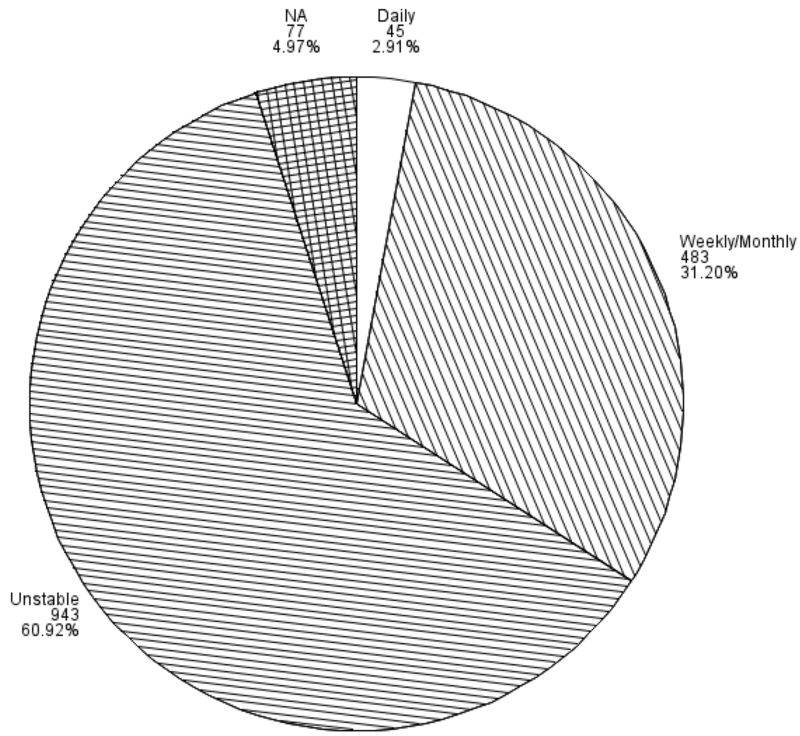
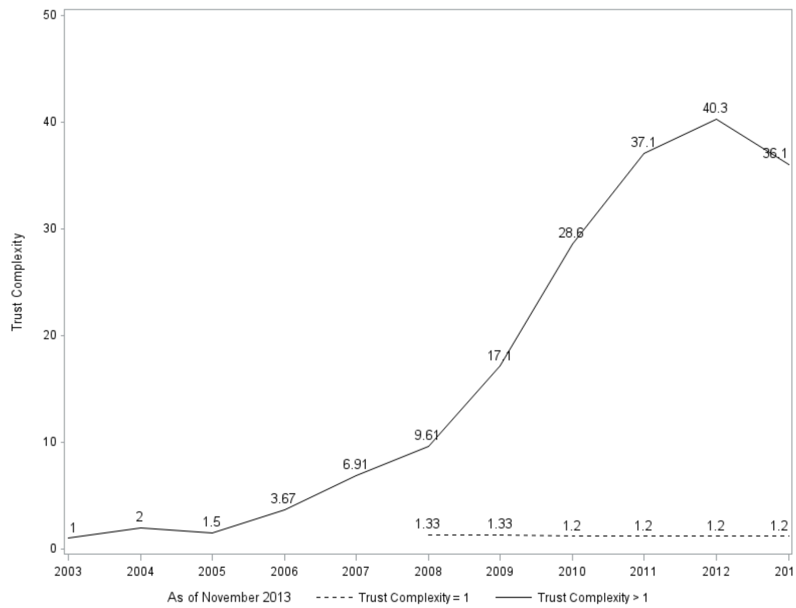
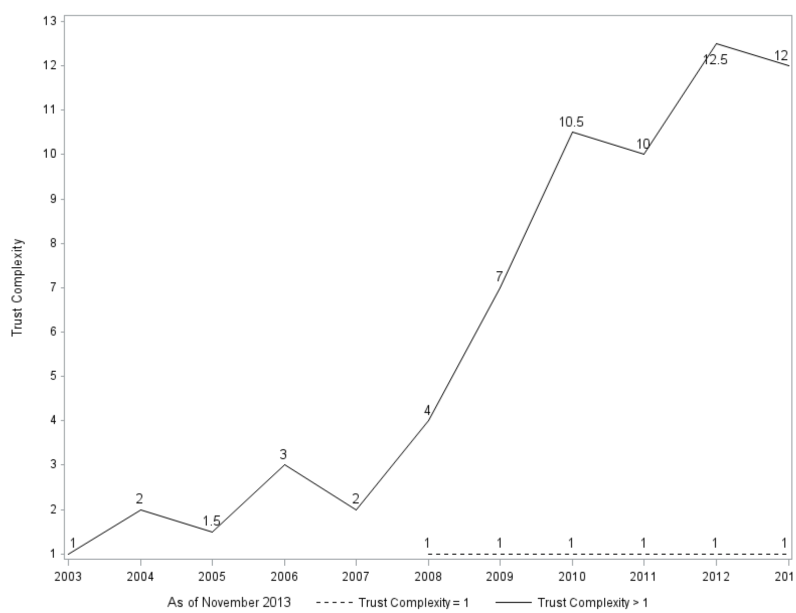


Figure 6. Distribution of Disclosing Frequency

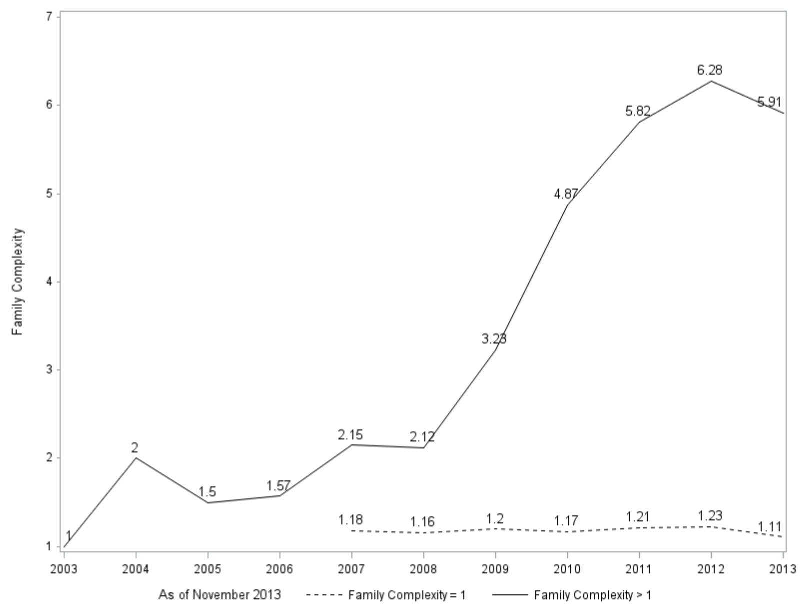
This figure shows the distribution of funds' disclosing frequency. My sample includes 1,548 funds between 2003 and 2013. If I cannot find a fund's reporting date information, then this fund is classified in the N/A group, i.e., it does not have any disclosing frequency. In my sample, 77 funds are in the N/A group. For other funds, if it discloses its information to my database at a particular frequency (daily, weekly, or monthly) for over 95% of its reporting time period, I consider it as using a stable frequency; otherwise, a fund is considered as using an unstable disclosing pattern.



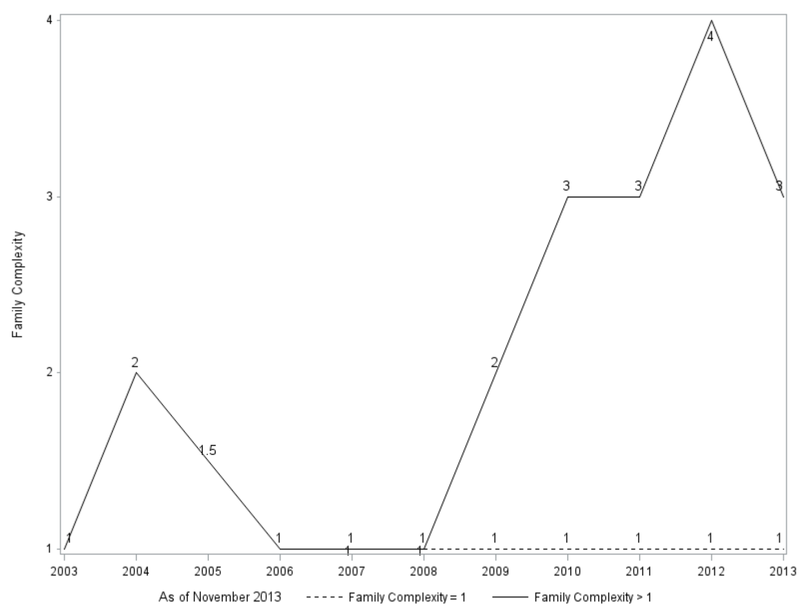
(a) Historical Means of Trust Complexity



(b) Historical Medians of Trust Complexity



(c) Historical Means of Family Complexity



(d) Historical Medians of Family Complexity

Figure 7. Historical Means and Medians of Trust Complexity and Family Complexity

This figure plots the historical means and medians of trust complexity and family complexity. If a trust (family) has only one fund as of November 2013, its complexity is considered 1; otherwise, its complexity is considered greater than 1. The vertical axis denotes the complexity, and the horizontal axis denotes the years.

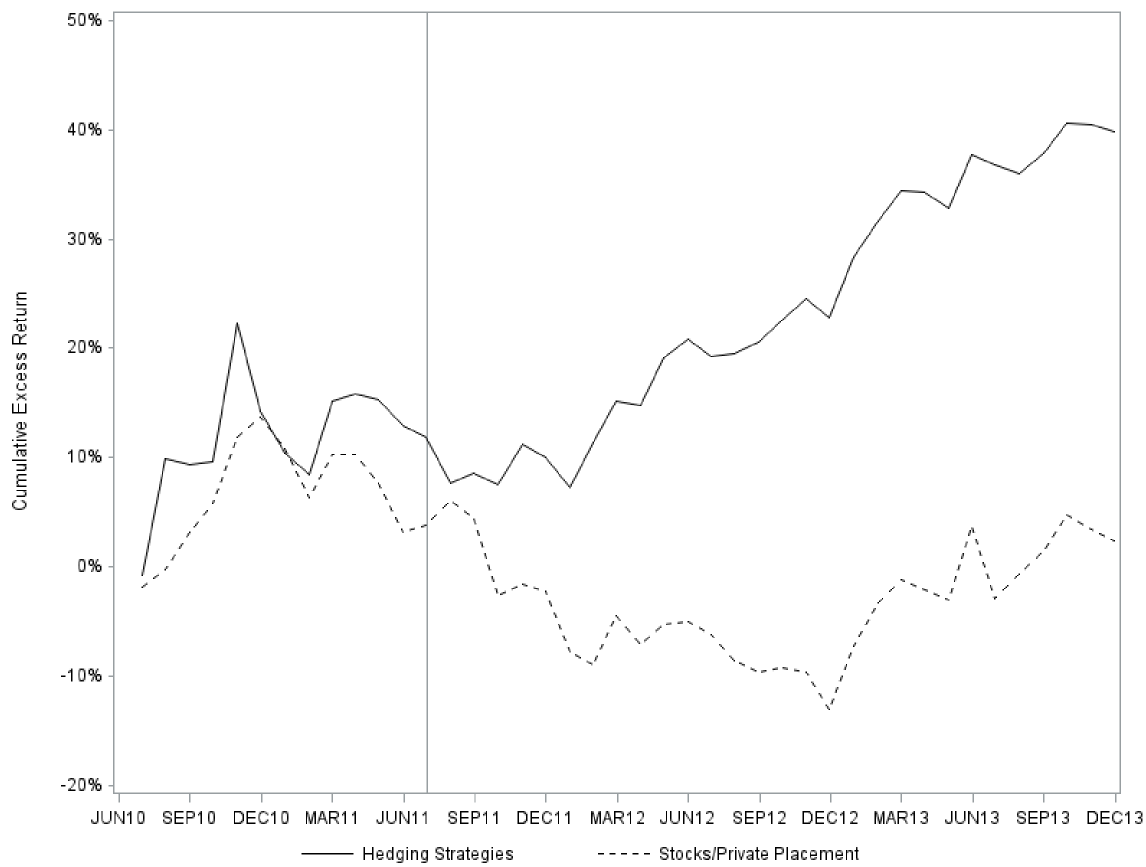


Figure 8. Cumulative Excess Return of Hedge-Strategy Funds and of Traditional Stock and Private Placement Funds

This figure plots the cumulative excess returns of Hedge-Strategy funds (treatment group) and of Traditional Stock and Private Placement funds (control group). Excess return is calculated as the difference between a fund's raw return and Chinese demand deposit interest rate. The vertical line is plotted as of July 2011 in the horizontal axis, denoting the then established policy that allows trusts to trade stock index futures.

Table 9. Comparison of Daily and Weekly/Monthly Disclosing Funds

This table gives the statistics based on a fund's disclosing frequency. Panel A reports fund characteristics. RepLength, Lockup, SoftLockup, and OpenFreq are the number of months of the fund's reporting history, lockup period, soft lockup period, and frequency of accepting new investment and redemption, respectively. LongTerm, SpecialIncFee, HWM, and HurdleRate equal one if the fund is designed to operate under unlimited duration, has investor protection in collecting incentive fee (either high water mark provision, hurdle rate provision, or both), has high water mark provision, and has hurdle rate provision, and equal zero otherwise, respectively. Duration is number of years of the fund's duration of contract if it is not a long-term fund. The detailed description of these fund characteristics can be found in Liang and Zhang (2014a). The differences between daily disclosing funds and weekly/monthly disclosing funds are also reported, witrh their p-values reported in parentheses. Panel B reports the performance of daily disclosing funds and of weekly/monthly disclosing funds. ExRet is the mean of the portfolio's raw return in excess of Chinese demand deposit interest rate, and ExRetStdDev is its standard deviation. FF3Alpha is the fund's Fama-French three-factor alpha, with the corresponding p-value reported in parentheses under it. Adj.R2 is the adjusted R-squared of this Fama-French three-factor regression. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fund Characteristics

	Daily			Weekly/Monthly			Difference		*p*-value
	N	Mean	Median	N	Mean	Median			
RepLength	45	21.51	16.00	483	36.78	33.00	−15.27	***	(0.000)
LoadFee (%)	0	.	.	227	1.00	0.01	.		
RedFee (%)	0	.	.	223	2.00	3.00	.		
ManFee (%)	16	1.86	1.95	203	1.57	1.50	0.29	***	(0.001)
IncFee (%)	16	20.00	20.00	194	20.00	20.00	0.00		
SpecialIncFee	45	0.36	0.00	483	0.06	0.00	0.30	***	(0.000)
HWM	45	0.02	0.00	483	0.04	0.00	−0.02		(0.531)
HurdleRate	45	0.36	0.00	483	0.02	0.00	0.34	***	(0.000)
Duration	32	1.27	1.25	134	7.49	5.00	−6.22	***	(0.000)
LongTerm	34	0.59	0.00	184	0.27	0.00	0.32	***	(0.000)
Lockup	4	4.25	4.50	250	8.74	6.00	−4.49	**	(0.023)
SoftLockup	0	.	.	38	6.30	6.00	.		
OpenFreq	2	1.00	1.00	282	1.25	1.00	−0.25		

Panel B: Portfolio Performance

Disclosing Frequency	No. Funds	ExRet (%)	ExRetStdDev (%)	SharpeRatio	FF3Alpha (%)	Adj. R2
Whole Sample: 2003–2013						
Daily	45	1.09	5.42	0.20	1.13**	0.62
					(0.031)	
Weekly/Monthly	483	1.27	4.39	0.29	1.05***	0.48
					(0.003)	
Subperiod: 2003–2008						
Daily	0					
Weekly/Monthly	96	2.19	5.89	0.37	2.03**	0.54
					(0.017)	
Subperiod: 2010–2103						
Daily	45	0.73	5.15	0.14	1.13**	0.69
					(0.011)	
Weekly/Monthly	481	0.12	2.84	0.04	0.37	0.53
					(0.238)	

Table 10. Analyses of Funds Switching Disclosing Frequency

Please see the associated file (name: Associated File_Tables) for this table.

Table 11. Performance Comparison based on A Fund's Legal Structure

This table reports the performance comparison based on a fund's legal structure features. Panel A, B, and C report for Trust Complexity, (the number of funds monitored by the same trust), Family Complexity (the number of funds run by the same management company), and Family Speed (the average number of days the management company needs to start a new fund), respectively. For each panel, funds are formed into equally weighted portfolios. The performance measures I consider here include ExRet (the mean of the portfolio's raw return in excess of Chinese demand deposit interest rate), ExRetStdDev (the standard deviation of ExRet), SR (the Sharpe ratio of the portfolio, calculated as ExRet / ExRetStdDev), and FF3Alpha (the portfolio's Fama-French three-factor alpha, with its corresponding p-value reported in parentheses under it). Adj.R2 is the adjusted R-squared of this Fama-French three-factor regression. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Trust Complexity

Trust Complexity	No. Funds	No. Months	ExRet (%)	ExRetStdDev (%)	SharpeRatio	FF3Alpha (%)	Adj.R2
= 1	8	71	-0.09	4.37	-0.02	0.30 (0.441)	0.58
> 1	1355	124	1.16	4.65	0.25	0.78*** (0.006)	0.71

Panel B: Family Complexity

Family Complexity	No. Funds	No. Months	ExRet (%)	ExRetStdDev (%)	SharpeRatio	FF3Alpha (%)	Adj.R2
= 1	303	83	0.42	4.51	0.09	0.21 (0.535)	0.56
> 1	1037	124	1.26	4.64	0.27	0.92 *** (0.001)	0.67

Panel C: Family Speed

Family Speed	No. Families	No. Funds	No. Months	ExRet (%)	ExRetStdDev (%)	SharpeRatio	FF3Alpha (%)	Adj.R2
Single-Fund	265	265	80	0.56	4.61	0.12	0.42 (0.292)	0.58
0-60 days	64	423	76	0.19	3.41	0.06	0.39 (0.134)	0.56
60-120 days	69	385	86	1.25	4.80	0.26	0.85 *** (0.001)	0.79
> 120 days	156	469	124	1.24	4.61	0.27	0.91 *** (0.001)	0.69

Table 12. Joint Effect of Disclosing Frequency and Fund Structure on Fund Performance

Please see the associated file (name: Associated File_Tables) for this table.

Table 13. Policy Changes and Critical Events

This table lists all the policy changes and critical events for Chinese hedge funds between 2003 and 2013, and also reports its impact on the number of funds. Using the following equation, I calculate the growth speed in the number of funds in each fund category, i.e., how fast a particular fund group has expanded during a specific period of time:

$$Growth\ Speed = \frac{No._t - No._{t-1}}{(Time_t - Time_{t-1})/365}$$

The subscript t denotes that the variable is observed at the tth policy change or event, No. is the number of funds, and Time is the date of the policy change or event. I consider three groups of funds here: (1) Hedge-Strategy funds, (2) all funds that are managed in Mainland China (domestic), and (3) all funds that are managed by overseas managers. The policy in July 2011, which allows trusts to use stock index futures, is listed in bold. [61]

		Hedge-Strategy Funds		All Domestic Funds		Overseas Managed Funds	
Time	Event	No.	No. Growth per Year	No.	No. Growth per Year	No.	No. Growth per Year
06/30/08	First Overseas Managed Fund Reported	0	.	175	.	16	.
03/31/10	Margin Trading Allowed	0	.	521	197.64	22	3.43
06/30/10	First Hedging-Strategy Fund Reported	1	.	626	421.15	23	4.01
07/12/11	**Trusts Allowed for Stock Index Futures**	**4**	**2.90**	**1181**	**537.33**	**26**	**2.90**
08/30/12	Refinancing Allowed	29	21.99	1460	245.39	29	2.64
02/28/13	Securities Relending Allowed	42	26.07	1549	178.49	28	-2.01

[61] The event on April 8, 2010 is not included in this analysis, which is the Chinese authority established the stock index futures. It is not directly linked to the Chinese hedge fund industry, because at time these funds were still not allowed to use these futures. Rather than this event, I list the policy on July 12, 2011 that allows trusts to use stock index futures, because the 2011 event is directly related to the hedge fund industry.

Table 14. Difference-in-Differences Test of the Policy Change in July 2011

This table reports the results of the difference-differences test. Panel A reports for the true policy change in July 2011, which allows trusts to trade stock index futures. Two groups of funds are considered: (1) Hedge-Strategy funds (treatment group) and (2) Traditional Stock funds and Private Placement funds (control group). I also consider two time windows around this policy: (1) 12 months before it and (2) 12 months after it. Three unrelated models are performed on the observations:

$$ExRet_{i,t} = \alpha + \beta_{Hedge} \times Hedge_i + \beta_{Post} \times Post_t + \beta_{Hedge*Post} \times Hedge_i \times Post_t + \varepsilon_{i,t},$$

$$ExRetStd_{i,t} = \alpha + \beta_{Hedge} \times Hedge_i + \beta_{Post} \times Post_t + \beta_{Hedge*Post} \times Hedge_i \times Post_t + \varepsilon_{i,t}, \text{ and}$$

$$SharpeRatio_{i,t} = \alpha + \beta_{Hedge} \times Hedge_i + \beta_{Post} \times Post_t + \beta_{Hedge*Post} \times Hedge_i \times Post_t + \varepsilon_{i,t}.$$

The subscripts i and t denote Fund i and Time Window t, respectively. For the dependent varibles, $ExRet_{i,t}$ is Fund i's raw return in excess of Chinese demand deposit interest rate in Time Window t, $ExRetStdDev_{i,t}$ is the standard deviation of $ExRet_{i,t}$, and $SharpeRatio_{i,t}$ is Fund i's Sharpe ratio in Time Window t, calculated as $ExRet_{i,t}$ / $ExRetStdDev_{i,t}$. For the independent variables, $\mathrm{Hedge_i}$ is a dummy variable that equals one if Fund i is from the treatment group, Hedge-Strategy funds, and equals zero otherwise; $\mathrm{Post_t}$ is a dummy variable that equals one if Time Window t is before the event in July 2011, and equals zero otherwise. Panel B reports for the placebo event in December 2010 and January 2011, which is designed to check the validity of the results in Panel A. In Panel B, I repeat the same models as in Panel A. The only difference is that in this panel I consider two time windows around the placebo event: (1) Five months before it and (2) five months after it. Thus, the independent variable $\mathrm{Post_t}$ equals one if Time Window t is before this placebo event, and equals zero otherwise. The p-value of each coefficient is reported under it in parentheses. Adj.R2 is the adjusted R-squared of the model. For falsification check, the same tests are performed for a placebo event assumed to occur in December 2010 to January 2011. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	No. Obs.	β_{Hedge}	β_{Post}		$\beta_{Hedge*Post}$		Adj. R2
Panel A: True Event (Trusts Allowed for Stock Index Futures in July 2011)							
ExRet	108	-0.28	−1.85	***	2.19	**	0.39
		(0.640)	(0.000)		(0.012)		
ExRetStdDev	108	-1.46	−0.54		3.08		0.03
		(0.235)	(0.258)		(0.975)		
SharpeRatio	108	0.33	−0.08		0.02		0.00
		(0.693)	(0.810)		(0.987)		
Panel B: Placebo Event in Dec 2010–Jan 2011							
ExRet	102	0.11	−3.60	***	1.15		0.44
		(0.957)	(0.000)		(0.699)		
ExRetStdDev	102	2.27	−1.41	**	−4.12		0.08
		(0.411)	(0.011)		(0.293)		
SharpeRatio	102	0.34	−0.29		0.18		0.00
		(0.925)	(0.689)		(0.972)		

CHAPTER 3

WHAT CAN WE TELL FROM THEM? A STUDY ON HEDGE FUNDS' SERVICE PROVIDERS

3.1 Introduction

Unlike traditional investment vehicles such as mutual funds, hedge funds are known for their proprietary techniques, secret positions, and lack of regulations. Although they have gained enormous attention from investors worldwide, people are raising increasingly more concerns about hedge funds' operational risk and fund governance (for example, Liang (2003), Bollen and Pool (2008), Brown, Goetzmann, Liang, and Schwarz (2008, 2009, 2012), and Cassar and Gerakos (2010)). [62] In the midst of this concern, hedge funds' service providers (SPs, hereafter) are an unavoidable topic because SPs are supposed to provide services and internal control for hedge funds. Therefore, I should expect that SPs that are more reputable and more experienced can better assist hedge funds in reducing operational risk and enhancing fund governance.

A good example is the hedge fund division within Bernard L. Madoff Investment Securities LLC. This firm actually turned out to be the largest Ponzi scheme so far, and it allegedly attracted $41 billion from investors before its collapse in 2008.[63] Admittedly, in order to fully discover the extent of this fraud, one needs to conduct many careful investigations. However, it would have been possible to sense Madoff's suspicious undertakings simply by investigating its SPs, because some of them were either disreputable or unqualified. For example, despite its huge assets under management, the firm did not hire any reputable auditor

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[62] According to IAFE Operational Risk Committee (2001), operational risk is "losses caused by problems with people, processes, technology, or external events."

[63] See a Bloomberg article at http://www.bloomberg.com/apps/news?pid= newsarchive&sid=ax319OmN67Pg&refer=home.

with extensive experience but rather Friehling & Horowitz, a little-known accounting firm called, with only three employees.[64] This example emphasizes that SPs with little reputation are not likely to provide trustworthy services for complicated clients like hedge funds.

Therefore, a hedge fund's SPs can serve as an indicator for the fund's quality. This point is supported by a number of academic studies. For example, Liang (2003) argues that hedge funds hire auditors (a key SP category) "for reasons of professionalism and to signal fund quality to investors." He indicates that only large funds can afford to hire reputable auditing firms like the Big 4. Similarly, Brown et al. (2008, 2009, 2012), who study hedge fund's operational risk, propose that "filing alone may be a potential signal of quality." They also indicate that reputable lenders are less likely to provide funding for hedge funds with high operational risk. As a result, I expect that hedge funds' use of SPs can also be a useful indicator for fund's quality.

Although hedge funds' SPs are such an important topic, I find little research examining the general relationship between hedge funds' SPs and hedge funds themselves. One exception is a recent paper by Ozik and Sadka (2014) (OS, hereafter). In their research, they establish a scoring system that measures hedge fund governance, where they do consider, to some degree, hedge funds' SPs. However, this OS score does not fully represent the SP community for hedge funds. First, OS consider only hedge funds' legal counsels and auditors, whereas a hedge fund actually has four key types of SPs (legal counsel, prime broker, auditor, and administrator).[65]

[64] See http://en.wikipedia.org/wiki/David_G._Friehling and http://content.time.com/time/business/article/0,8599,1867092,00.html.

[65] Per the tradition in the hedge fund industry, (1) legal counsels give guidance on issues regarding legal, regulatory, compliance, etc.; (2) prime brokers offer advice on issues regarding capital raising and provide services of legally forming the funding; (3) auditors provide auditing services; (4) administrators offer accounting and back office services at a certain frequency. (See, for example, http://www.investopedia.com/articles/trading/11/hedge-fund-startup-services.asp and http://www.lucasgroup.com/executive-jobs/attorney-recruiters/hedge-fund-attorney-jobs-careers/#m0eb6iBcX8xvEAL9.97.)

Second, OS base their score on the rankings of all legal counsels and auditors, rather than the ones that actually provide services for the hedge fund industry. Therefore, the OS score is not a perfect measure for hedge funds' SPs.

In this paper, I propose a new scoring system (referred to as the SP score, hereafter) to measure the impact of SPs on hedge funds. Compared to OS, I take all four SP categories into account, and I compute the SP score using the real number of hedge fund clients of each SP. Therefore, my SP score provides a better measure for the SPs for hedge funds.

The most fundamental question here is whether a hedge fund's use of SPs actually contains material information about the fund. To answer this question, I conduct empirical studies based on the SP score. To be specific, I focus on the relationship between hedge funds' SP score and certain fund features such as characteristics, performance, and investor flows.

Previous research suggests, directly or indirectly, that better fund governance (or lower operational risk) is possibly related to a number of fund features, including (1) larger assets under management, or fund size, (Liang (2003) and Malkiel and Saha (2005)), (2) younger fund age (Patton and Ramadorai (2013) and Kirilenko, Kyle, Samadi, and Tuzun (2014)), (3) offshore domiciliation (Cassar and Gerakos (2010), Cumming and Dai (2010), and Aragon, Liang, and Park (2014)),[66] (4) better past performance (Liang (2003), Brown et al. (2008, 2009, 2012), and Aragon, Liang, and Park (2014)), (5) lower investor flows (Ozik and Sadka (2014)), (6) less volatile investor flows (Bollen and Pool (2008)), and even (7) better future performance (Amenc, El Bied, and Martellini (2003) and Baquero, Ter Horst, and Verbeek (2005)). Therefore, I focus my study on these seven features. Using a novel measure that is based on hedge funds' SPs, I verify all the

[66] Hedge funds are usually divided into onshore funds, which are domiciled within the U. S., and offshore funds, which include all other funds (see, for example, Aragon, Liang, and Park (2014)).

above conjectures. For example, hiring one additional well-known (Well, hereafter) SP is associated with a 12 basis point increase in past annual returns and a 48 basis point increase in future annual returns, ceteris paribus. All of these results are both economically and statistically significant, and are robust to different levels of fund sizes, investment strategies, and fund size changes.

The main contribution of this paper is twofold. First, I establish a numeric scoring system that measures the impact of SPs on hedge funds. Second, I provide empirical evidence that a hedge fund's appointment of SPs actually conveys useful information of the fund, such as fund characteristics, performance, and investor flows.

3.2 Related Literature and Hypotheses Development

This research focuses on two important areas in the literature: (1) SPs and their relationship with operational risk or fund governance and (2) hedge fund characteristics, performance and investor flows.

Brown et al. (2008) is a pioneer work, which indicates that less operational risk (therefore better fund governance) is related to better fund performance. In their research, they divide hedge funds into problem and nonproblem groups according to funds' Form ADV filing with the Securities and Exchange Commission (SEC, hereafter). In this filing, hedge funds are required to disclose whether their management company has prior "problems" such as regulatory issues and investment-related misdemeanors. The problem and nonproblem groups represent high and low operational risk, respectively.[67] By comparing these two groups, they

[67] They also point out that operational risk more specifically includes "the risks of failure of the internal operational, control, and accounting systems; failure of the compliance and internal audit systems; and failure of personnel oversight systems, that is, employee fraud and misconduct."

reveal an important pattern in the relationship between operational risk and fund performance—the nonproblem group, the one with less operational risk, has significantly better performance.[68] This relationship is also suggested in an earlier paper by Liang (2003), who finds that funds with adequate auditing, which is also a symbol for less operational risk, is associated with better and more consistent fund performance.

Cassar and Gerakos (2010) find that fund governance is related to a fund's domiciliation. The fund governance measure they use is the fund's internal control, where better internal control is related to better fund governance. They find evidence that offshore hedge funds exhibit stronger internal control, and suggest that the key reason for this finding is the difference in regulatory environment. They argue that "Although onshore and offshore funds are generally exempt from U.S. securities regulations, investors in onshore funds can use the U.S. legal system to redress fraud and financial misstatements." Moreover, they point out that Caribbean islands, the domiciliation of most offshore funds, are known for their history in secret bank accounts and money laundering (citing Suss, Williams, and Mendis (2002)), and that fund managers in such a lax banking environment find it easier to commit fraud (citing Blum, Levi, Naylor, and Williams (1998)). Therefore, offshore hedge funds have more incentive to rely on using Well SPs to enhance fund governance and mitigate operational risk.

Ozik and Sadka (2014) (OS, here after) also focus on fund governance; they indicate that hedge funds with better fund governance experience lower investor flows.[69] To measure fund

[68] They continue this study in Brown et al. (2009, 2012).

[69] Such findings are implied in the Tables 4 and 6 of OS, which can be summarized in two aspects. For one thing, their evidence shows that the performance differences caused by investor flows are smaller for funds with higher OS scores, and larger for funds with lower OS scores. This implies that higher OS scores are associated with smaller investor flows. For another, their regressions of fund performance on fund characteristics demonstrate that the OS score and investor flows have offsetting effects on performance. This finding also suggests that higher OS scores link with smaller investor flows, ceteris paribus.

governance, they build a five-dimensional aggregate governance score. The five dimensions are audit (a fund is assigned a score of one if it reports an audit date and zero otherwise), high water mark (a fund is assigned a score of one if it has high water mark provision and zero otherwise), domiciliation (a fund is assigned a score of one if it is an onshore fund and zero otherwise), SEC registration (a fund is assigned a score of one if it belongs to an SEC registered management company and zero otherwise), and quality service providers (a fund is assigned a score of one if its legal counsel or auditor is a "top 100" firm and zero otherwise). Therefore, the aggregate OS score can be any integer ranging from zero to five, where a higher OS score indicates better fund governance.

Literature suggests that better fund governance is not only accompanied by smaller investor flows, but also by less volatile investor flows. Bollen and Pool (2008) study the "conditional serial correlation" phenomenon in hedge fund returns.[70] They argue that conditional serial correlation is a major indicator of hedge fund fraud. In other words, higher conditional serial correlation indicates poorer fund governance. Their regressions of conditional serial correlation on fund characteristics show that the volatility of investor flows is positively associated with the magnitude of conditional serial correlation. Namely, less volatile investor flows are related to less conditional serial correlation and, therefore, better fund governance.

The second stream of the related literature is on hedge fund (or mutual fund) characteristics and performance. Although it does not directly focus on fund governance or operational risk, it suggests that some hedge fund features may be related to them. One such feature is fund's assets under management (size)—larger funds have more incentive and can

[70] In order to measure conditional serial correlation, they first calculate the total serial correlation in hedge fund returns, then compute the "unconditional serial correlation" following Getmansky, Lo, and Makarov (2004), and then define conditional serial correlation as the part of total serial correlation that cannot be explained by the unconditional part.

afford to hire more Well SPs. For example, by studying hedge funds' auditors, Liang (2003) finds that larger funds are more inclined to hire Big 4 auditors than smaller funds are. Moreover, Malkiel and Saha (2005) show that larger funds are much easier to survive than smaller funds. It is reasonable to expect that this higher surviving rate may be related to using more Well SPs.[71]

Another fund characteristic that may be related to fund governance is the age of a fund. A number of studies suggest that younger funds are more inclined to hire Well SPs. The reason is that they tend to use newer trading techniques, which may cause funds to use more caution in operation. One example of these newer techniques is high-frequency trading. Patton and Ramadorai (2013) show that high-frequency variation provides a better explanation for hedge fund risk exposures than traditional models do. Therefore, they propose that such newer mechanisms emphasize the "importance of accounting for the dynamic nature of the risk exposures of these actively managed investment vehicles." That is to say, they suggest that funds using newer techniques find it more important to use Well SPs. A recent study by Kirilenko et al. (2014) shows the enormous power of hedge funds' high-frequency trading and argues that although such a technique of hedge funds did not directly cause the flash crash in the U.S. stock market in 2010, it did aggravate that crash. As a result, it is very important that funds with these new techniques receive proper inspection and monitoring. Therefore, I expect that younger funds have greater incentive to use Well SPs.

Another fund characteristic that may be related to fund governance is fund domiciliation—offshore funds are expected to use more Well SPs. The reasons for this phenomenon include (1) offshore funds rely more on Well SPs to provide internal control, since they are facing fewer external regulations; (2) offshore funds are much larger than onshore

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[71] The phenomenon that larger funds survive longer is not unique to the U.S. For example, Liang and Zhang (2014b) also find a similar pattern in the Chinese hedge fund industry.

funds, and larger size is related to more Well SPs; (3) offshore funds are usually organized as corporations that specifically require the use of SPs (Cassar and Gerakos (2010), Cumming and Dai (2010), and Aragon, Liang, and Park (2014)).

Fund governance may also be related to future fund performance. The reasons are twofold. First, I have seen that fund governance is related to past fund performance and fund characteristics. Second, a number of studies show that past fund performance and fund characteristics have a connection with future fund performance. For example, Baquero, Ter Horst, and Verbeek (2005) show evidence that a hedge fund's past performance can be used to predict future performance. In a different setting, Amenc, El Bied, and Martellini (2003) also show that hedge funds' future performances can be predicted by past performance and fund characteristics.

Furthermore, existing literature also suggests that fund governance is more important for funds with share restrictions on investors than funds without such restrictions. This is because if a hedge fund does not have any restriction on its investors, then they can flee from the fund whenever they sense any trace of poor governance. Therefore, investors in nonshare-restricted funds are unlikely to suffer from fund governance problems. For this reason, many studies on fund governance or related issues (for example, OS and Jorion and Schwarz (2015)) consider only share restricted funds. Similarly, I also focus on funds' share restrictions, i.e., funds whose total redemption period is greater than one day.[72]

[72] Total redemption period is defined as the sum of (1) redemption notice period and (2) redemption period (indicated by redemption frequency). If a fund has no restrictions on investors' redemption, its total redemption period would be one day—its investors can withdraw their money every day. Although my definition of share restriction is slightly different from that of OS or Jorion and Schwarz (2015), all definitions reflect hedge funds' prevention of investors' withdrawals. Moreover, my research and these studies all show that most hedge funds have share restrictions. For example, in my sample, the percentage of share restricted funds is 79.19%.

In summary, existing literature suggests that using more Well SPs is a symbol for lower operational risk and better fund governance and is associated with a number of fund features in terms of fund characteristics, performance, and investor flows. Therefore, for this research I have the following three testable hypotheses.

Fund Characteristics Hypothesis: Using more Well SPs is associated with (1) larger fund size, (2) younger fund age, and (3) offshore domiciliation.

Performance and Flow Hypothesis: Using more Well SPs is associated with (1) better past performance and (2) smaller and less volatile investor flows.

Future Performance Hypothesis: Using more Well SPs can predict better future fund performance.

3.3 Data

The main database in this study is the Tremont Advisory Shareholder Services (TASS) database, and I use the data from January 1995 to June 2013. The TASS database has rich information about hedge fund returns and characteristics, which include a fund's key SPs, most recent audit date, domicile country, and whether it belongs to an the SEC registered management company. Consistent with previous literature, I apply the following screening criteria. First, I select only funds that (1) report for at least 24 months, (2) report on a monthly basis, and (3) report returns net of all fees. Second, I delete funds whose size is below $1 million. Third, I discard return observations that are exactly 0.0000 or consecutively 0.0001. Fourth, in order to mitigate backfill bias, I further delete a fund's first 12 monthly returns. Finally, as discussed before, I consider only share restricted funds, i.e., funds that have a total redemption period greater than one day.

After data filtering, I have 9,485 funds with 804,347 monthly observations, including both hedge funds and funds of funds, both live and dead, and both onshore and offshore funds. For fund returns that are not denominated in USD, I use historical exchange rates to convert them to USD denominated returns. The returns are then winsorized at the 2.5% level (on each side).[73]

As mentioned before, existing literature has not yet provided any specific measure for SPs for the hedge fund industry. Thus, one main contribution of this research is that I build an aggregate numeric SP score for hedge funds using the TASS data. The SP score is calculated in the following four steps. First, I calculate the total number of hedge fund clients of each SP.[74] Second, for each of the four SP categories (legal counsel, prime broker, auditor, and administrator), SPs are ranked based on their number of clients. I define well-known SPs as those with at least 100 hedge fund clients, and all other SPs are considered not well-known (Not Well, hereafter) SPs.[75] Third, for the legal counsel category, a fund is assigned a legal counsel score of one if it reports a Well legal counsel and zero if it does not. I follow the same procedure to assign each fund a prime broker score, an auditor score, and an administrator score. Finally, I calculate the aggregate SP score by summing all the four separate scores. Thus, the range of my final SP score is from zero to four. Table 15 lists the Well SPs for each SP category.

Another source of information in this research is the worldwide rankings of auditors and legal counsels. The purpose of using these rankings is to replicate the OS score and check for differences with my SP score. Following OS's procedure, I use the list of the top 100 accounting

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[73] I also test other levels for winsorization, and the results remain generally the same.

[74] All branches of the same SP family are considered one SP. For example, in the auditor category, all offices of KPMG are considered one SP, including KPMG LLP, KPMG (Canada), KPMG (Cayman Islands), etc.

[75] For robustness checks, I also use other thresholds of Well and Not Well SPs, and the results are generally unchanged.

firms in 2014 selected by accountingTODAY and the list of 100 law firms in 2014 on WIKIPEDIA.[76] By combining the TASS data and these two rankings, I am able to replicate completely the OS score. Table 16 reports the summary statistics of the SP score, and for comparison purposes, I also report the OS score in this table.

There are three interesting findings in Table 16, which, before I test the main hypotheses, already reveal some patterns in hedge funds' SPs. First, offshore funds have a higher SP score than onshore funds (2.12 vs. 1.96). This difference reveals that different fund domiciliations result in different conventions of choosing SPs. Second, different investment strategies also cause difference in hiring SPs. For example, Funds of funds have the lowest SP mean score (1.64). This is probably because their major strategy is to invest in other hedge funds, which should already have SPs, thereby reducing funds of funds' need to hire their own Well SPs. Third, different fund size groups also show difference in using SPs—larger hedge funds tend to use more Well SPs. All these three patterns indicate the importance of controlling fund domiciliation, strategy, and size.

Based on a fund's most recent reporting, I observe its fund characteristics and calculate its SP score and OS score; based on its historical reporting, I calculate its fund performance and investor flow. Therefore, I mainly conduct cross-sectional analyses in the rest of this paper.

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[76] The accounting firm list is at http://digital.accountingtoday.com/accountingtoday/top_100_firms_supplement_2014#pg1. The legal firm list is at http://en.wikipedia.org/wiki/List_of_100_largest_law_firms_by_revenue. These sources are different from the one in the original paper of OS, but given the nature of these worldwide rankings in the same year, they should lead to similar results.

3.4 Tests and Results

3.4.1 Differences between the SP and OS Scores

If my SP score and the OS score were essentially the same, then there would be no novelty in this research. Therefore, before studying for the main hypotheses, I first examine whether these two scores are different. As discussed before, although the OS score does have a dimension for SPs, it is not a perfect measure for the hedge fund industry. First, the OS score only considers two SP categories, legal counsel and auditor, but not the other two categories, prime broker and administrator. Second, it uses general rankings of all legal firms and accounting firms, many of which actually do not even provide services for hedge funds. My SP score, on the other hand, includes all four SP categories, and considers only the SPs specialized for the hedge fund industry. Thus, my SP score serves as a better measure for hedge fund's SPs. Table 17 reports the differences between these two scoring systems.

These results show that, again, many of the top 100 firms considered by OS do not serve for hedge funds. To be specific, Panel A demonstrates that only 67 of the "top 100" legal firms provide services for hedge funds. Since the total number of legal counsels for hedge funds is 526, these 67 legal firms account for only 11.36% of the entire legal counsel community that provides services for hedge funds. Moreover, these 67 legal counsels are not even the top ones. Panel A shows that the real rankings of these 67 firms have a mean value of only 171.30. That is to say, on average, they are ranked the 171th in the entire 526 firms. The most popular one of them is ranked the fifth, and the least popular one is ranked as low as the 514th.

Similarly, the total number of auditors that serve for hedge funds is 290, but only 32 (or 11.03%) of them are found in the "top 100" accounting firm list in the OS scoring system. The mean of the real rankings of these 32 auditors is 73.25, where the highest ranking is 1 and the lowest is 281. Therefore, the OS score represents only a small percentage of the entire SP community for hedge funds. Overall, my SP score is more accurate in measuring hedge funds' SPs.

To further show the difference between these two scores, I report the correlation between them in Panel C. This panel reveals that the correlation between these two scores is actually very low, with the correlation coefficients ranging from only 0.10 to 0.47. The low correlations also corroborate my conjecture that these two scoring systems are essentially different.

3.4.2 Fund Characteristics

In the following three subsections, I present empirical evidence regarding my three main hypotheses. To test the Fund Characteristics Hypothesis, I examine whether the SP score is associated with certain fund characteristics. To be specific, my conjecture is that higher SP scores are related to (1) larger fund size, (2) younger fund age, and (3) offshore domiciliation. I make use of the generalized linear model (GLM) regression. This modeling approach is used by Liang and Zeger (1986) and Brown et al. (2008), for example. My GLM for the Fund Characteristics Hypothesis is:

$$SP_i = \alpha + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \quad (8)$$

where the dependent variable, $\mathrm{SP_i}$, is Fund i's SP score, and the independent variables, $\mathrm{Characteristic_{i,k}}$ $(\mathrm{k} = 1,2,3,4)$, are Fund i's characteristics. Per my previous discussion, the following are included as independent variables: Fund size, fund age (number of monthly observations in the TASS database), and domiciliation. To show the similarities and differences between the SP and the OS scores, I also include the OS score as an independent variable.

The GLM regression results in Table 18 confirm my Fund Characteristics Hypothesis. First, fund size is positively associated with the SP score. A one-unit increase in Log (Size) (the integer part of the decimal logarithm of a fund's size) is associated with a 0.325 increase in the SP score. Notice that the range of Log (Size) in my sample is from 6 to 11. Therefore, a Log (Size) = 11 fund (size greater than $100 billion) on average has an SP score that is 1.625 higher than a Log (Size) = 6 fund (size between $1 million and $10 million). Second, fund age is negatively associated (-0.001) with the SP score. The fund ages in my sample range from 12 to 222 months, so fund age alone could explain up to 0.21 (= 0.001 × (222 - 12)) of the difference in the SP score. Third, offshore funds are more likely to use Well SPs, because the Onshore dummy results in a 0.429 decrease in the SP score, ceteris paribus. All of these results are still significant in Model 5 that considers all these fund characteristics.

As previously discussed, there are two reasons why fund size is significantly positively associated with the SP score. First, Well SPs usually charge much higher fees than Not Well SPs, and so larger funds have more capital resources to hire Well SPs. Second, Well SPs are expected to provide more efficient services and more thorough inspection. This is a major attraction for larger funds since they typically have more complicated trading techniques and conduct broader investment operations. Therefore, hiring Well SPs is a positive signal to investors, which larger funds are more likely to afford than smaller funds.

I also find that younger funds are more likely to have well SPs. There could be two reasons for this finding as well. On one hand, younger funds are more eager to build up reputation fast. One possible way to do this is to hire Well SPs, because hiring Well SPs is often perceived as a positive signal. On the other hand, younger funds are more likely to engage in newer trading techniques, like high-frequency trading. As previously mentioned, using newer, more complicated techniques make younger funds more inclined to hire Well SPs.

The phenomenon that offshore funds are on average less likely to use Well SPs can be attributed to four factors. The first factor is different regulatory environments. As Cassar and Gerakos (2010) point out, offshore hedge funds are subject to far fewer regulations and much easier to commit fraud. That is to say, offshore funds have fewer external inspections and constraints than onshore funds do. Therefore, to improve fund governance, offshore funds are expected to rely more on hiring Well SPs than onshore funds. Cumming and Dai (2010) and Aragon, Liang, and Park (2014) show similar evidence for this factor as well. The second factor is that offshore funds are typically much larger than onshore funds. For example, Aragon, Liang, and Park (2014) find that the average size of offshore funds is more than 200% of onshore funds. And since larger funds are more inclined to use Well SPs, offshore funds are supposed to hire more Well SPs. The third factor is the difference in a fund's legal structure. As mentioned in Aragon, Liang, and Park (2014), most onshore funds (83.08%) are organized as limited partnership, whereas most offshore funds (96.49%) are organized in more complicated structures, such as corporation, which are required to use SPs. Finally, this phenomenon may also be related to SP branching. In my sample, it is mainly the Well SPs that have offshore branches, while most Not Well SPs operate only within the U.S. As a result, it is more likely for offshore funds to use Well SPs. Due to these reasons, offshore funds are more inclined to hire Well SPs.

3.4.3 Performance and Flow

My Performance and Flow Hypothesis states that higher SP scores should be associated with better past performance and smaller, less volatile investor flows. In order to test this hypothesis, I first conduct a categorical analysis based solely on the SP scores and then use GLM regressions to examine the impact of the SP score on past fund performance and investor flows, while controlling for other fund characteristics.

I consider the following five performance and flow measures: (1) Mean and (2) standard deviation of a fund's monthly returns, (3) Sharpe ratio based on the hedge fund industry average (alpha over the hedge fund industry, which is the intercept of regressing a fund's returns on the industry average, divided by the standard deviation of the industry averages), (4) Alpha based on size and strategy (the intercept of regressing a fund's returns on the matched group average, where the matched group consists of all funds with similar size and the same investment strategy), and (5) Alpha based on the Fung-Hsieh eight factors (the intercept of regressing a fund's returns on the Fung-Hsieh eight risk factors).[77]

And I consider two measures for investor flows: (1) Mean and (2) standard deviation of a fund's monthly flows. A fund's monthly flows are calculated using the following equation:

$$Flow_{i,t} = \frac{Size_{i,t} - Size_{i,t-1} \times (1 + R_{i,t})}{Size_{i,t-1}}, \qquad (9)$$

where i and t denote Fund i and Month t, respectively; Size is the fund's estimated assets of at the end of that month; R is the fund's return in that month. The results of the categorical analysis are reported in Table 19.

These results are consistent with my Performance and Flow Hypothesis. In this analysis, funds are grouped into three categories based on SP score: Low (SP score = 0), Median (SP score = 1-3), and High (SP score = 4), i.e., the Low category contains funds that never hire Well SPs, the High category contains funds that always hire Well SPs, and the Median category contains all

[77] A description of the Fung-Hsieh risk model can be found in Fung and Hsieh (2001) and in David Hsieh's data library (https://faculty.fuqua.duke.edu/~dah7/HFData.htm). I am also grateful to David Hsieh for providing some of the data on the website.

other funds.[78] Table 19 shows that all performance variables increase monotonically from the Low to High category, while investor flows and their standard deviations decrease monotonically. And the differences between the Low and High categories are all statistically significant. For example, the difference in raw returns between these two groups is 17 basis points per month (equal to 205.92 basis points per year), ceteris paribus, a significant economic outperformance.

The finding that the SP score is associated with better performance and smaller, less volatile investor flows is not surprising. After all, higher SP scores indicate better fund governance and lower operational risk, which could cause improvement of fund performance. And better fund performance could attract long-term investors, therefore reducing the volatility of investor flows. Similar reasoning can also be found in previous literature (for example, Liang (2003), Brown et al. (2008), Bollen and Pool (2008), and OS).

One may raise the concern that the results in Table 19 are merely driven by the fund size effect, not by the SP effect, because, after all, larger funds tend to (1) have higher SP scores(see my previous discussion) and (2) have better performance and smaller, less volatile investor flows (see, for example, Agarwal, Daniel, and Naik (2004) and Feng, Getmansky, and Kapadia (2011)). If this were the case, the SP effect on past performance and investor flows that I observe here would be nothing new, but a mere replication of the fund size effect. Therefore, to show that the SP effect contains different information than the fund size effect, I conduct the following GLM regression, which regress past performance and investor flows on the SP score, while controlling for fund size, as well as for other fund characteristics:

[78] I also use other SP scores as the cutoff points for this categorical analysis, and the results are virtually the same.

$$PerfFlow_i = \alpha + \gamma_1 \times SP_i + \gamma_2 \times OS_i + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \tag{10}$$

In this model, $\mathrm{PerfFlow_i}$ is Fund i's performance or flow measure, $\mathrm{SP_i}$ is Fund i's SP score, $\mathrm{OS_i}$ is Fund i's OS score, and $\mathrm{Characteristic_{i,k}}$ $(\mathrm{k} = 1,2,3,4)$ are Fund i's characteristics. Following Brown et al. (2008) and OS, I focus on four performance and flow variables in this stage of analysis: Mean (mean of Fund i's monthly raw returns), Std Dev (standard deviation of Fund i's monthly raw returns), Flow (mean of Fund i's monthly investor flows). Moreover, I include another flow measure, Log (Min Inv) (the decimal logarithm of Fund i's required minimum investment). This measure is included because it reflects fund manager's confidence in raising capital. Since using Well SPs is a positive signal to investors, I expect to see that higher SP scores are related to higher bars to new investment. To show the similarities and differences between the SP and the OS scores, I also include the OS score in the independent variables. I control for fund size, age, domiciliation, and investment strategy in this analysis.

The GLM regression results in Panel A of Table 20 further confirm that, even after controlling for fund size and other fund characteristics, higher SP scores are still significantly related to better past performance and lower investor flows. Besides, I find that higher SP scores are also related to higher minimum investment requirement. Hiring one additional Well SP is associated with a 0.08 increase the decimal logarithm of the minimum investment requirement. This increase is economically significant. For example, the median value of minimum investment requirement in my sample is $4,013,998, so at this level, such an increase would mean an $811,889 (about 20%) rise in this requirement. This phenomenon demonstrates that funds using more Well SPs are likely to impose higher restrictions on new investment. This is probably due to fund manager's skill, because higher SP scores could indicate better managerial skills, which is a key factor in minimum investment requirement.[79]

Moreover, Table 20 also confirms that including the SP score is important in explaining fund performance and investor flows. To be specific, in Panel B I repeat the analysis in Panel A but using this model:

$$PerfFlow_i = \alpha + \gamma_1 \times OS_i + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \quad (11)$$

Notice that I only include the OS score in the independent variables in this model. The adjusted R-squareds increase from Panel B to Panel A, while the Akaike information criterion values decrease, suggesting that including both scores provides a better model than using just the OS score.

3.4.4 Future Performance

My Future Performance Hypothesis is that using more Well SPs can help predict better fund performance in the future. In order to test this hypothesis, I conduct an out-of-sample test on the relationship between the SP score and future fund performance. To the best of my knowledge, this research is the first one that examines whether a hedge fund's SPs can affect its performance in the future. I expect that higher SP scores lead to better future performance.

One disadvantage of the TASS database is that it does not disclose the dates when a hedge fund reports its SPs. As a result, it is not possible to spot the exact out-of-sample time periods to study the relationship between the SP score and future fund performance. However, I can work around this shortcoming, because the hedge funds in this database are believed to

[79] For example, Teo (2009) provides evidence that skillful fund managers often demand higher minimum investment.

update their SP information to the most recent audit date. The reason is that, as Liang (2003) and Bollen and Pool (2009, 2010) suggest, many funds, especially the ones with good fund governance, do update their audit information on a regular basis.[80] And because auditor is a key SP category, it is reasonable to believe that when funds update the audit date in TASS, they also update the information of other SPs. Therefore, I define the report date of the fund's SP information as the fund's most recent audit date, and the time period after this date is considered the out-of-sample period.

My GLM regression for this out-of-sample analysis is

$$Perf_{i,t1_i} = \alpha + \gamma_1 \times SP_{i,t0_i} + \gamma_2 \times OS_{i,t0_i} + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i, \tag{12}$$

where, for any variable, $\mathrm{t0_i}$ denotes that this variable is observed on Fund i's most recent audit date; $\mathrm{t1_i}$ denotes that it is calculated using the information after that date; $\mathrm{Perf_i}$ is Fund i's performance variable; $\mathrm{SP_i}$ is Fund i's SP score; $\mathrm{OS_i}$ is Fund i's OS score; $\mathrm{Characteristic_{i,k}}$ $(\mathrm{k} = 1,2,3,4)$ are Fund i's characteristics.

The out-of-sample dependent variables considered here include (1) mean and (2) standard deviation of Fund i's monthly raw returns, (3) Fund i's excess return over the industry average, (4) Fund i's excess return over the matched group average (the matched group consists of all funds with similar size and the same investment strategy), (5) Fund i's Sharpe ratio calculated based on the industry average, and (6) Fund i's Sharpe ratio calculated based on the matched group average. I control for fund characteristics such as fund size, age, domiciliation, and strategy. Here I only consider the funds in the live fund category, because the purpose of this analysis is to see whether a fund's current SP score can predict its performance in the

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[80] In the TASS data, most audit dates are recorded as December 31 of a certain year.

future. Again, to show the similarities and differences between the SP and the OS scores, I also include the OS score in the independent variables.

Panel A of Table 21 reports the main results, which verify my Future Performance Hypothesis. There are two patterns worth noticing. First, higher SP score leads to higher fund performance in the future. This pattern is statistically significant and consistent across all performance measures, and the magnitudes of the coefficients are all economically significant. For example, other things equal, hiring one more Well SP leads to a 4 basis point increase in raw returns per month (equal to over 48 basis points per year). Moreover, using more Well SPs is also related to less volatile performance, because the Std Dev coefficient is significantly negative, which indicates that funds using more Well SPs enjoy not only higher, but also less volatile future performance.

Second, the SP score always has the opposite effect of the OS score. This discrepancy is, again, due to the essential differences between these two scoring systems. By design, my SP score provides a more accurate measure for hedge funds' SPs. Therefore, the results suggest that it is the SPs, not other fund characteristics the OS score considers, that help predict future performance.

Again, I replicate the analysis in Panel A using a different model:

$$Perf_{i,t1_i} = \alpha + \gamma_1 \times OS_{i,t0_i} + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \tag{13}$$

I report the results of this model in Panel B. Notice that the only difference between Models (12) and (13) is that Model (13) does not have the SP score on the right hand side. The comparison between Panels A and B shows that including the SP score increases the predicting power of future performance, because the adjusted R-squareds improve from Panel B to Panel A, and the Akaike information criterion values drop.

Even though previous literature suggests that it is difficult to indicate future performance of hedge funds (for example, Li, Zhang, and Zhao (2011)), the results in Table 21 demonstrate that higher SP scores are useful in predicting future fund performance. Moreover, to my knowledge, the SP score is by far the only measure regarding fund governance that can significantly predict future fund performance.

3.5 Robustness Check

The TASS database does not provide historical information of a fund's SPs, but just the most up to date information. Therefore, so far my research is built on the assumption that a fund's appointment of SPs remains unchanged over its entire life cycle. Indeed, if hedge funds tended to change SPs significantly during the life cycle, then the SP information I obtain from TASS would be of little use. Hence, one may argue that a fund could change SPs significantly over time. Especially, one concern is that a hedge fund tends to change SPs if its size changes by a great deal since its inception, i.e., a fund may have used Not Well SPs when it was just founded, but as it grows larger and becomes more resourceful, it may start to hire Well SPs. If this were the case, it would result in limitations to the conclusions of this study.

To address this concern, I design the following robustness check. First, I calculate the growth rate of a fund's size by using the following equation:

$$Size\ Growth_i = \frac{Fund\ Size_{i,last\ month} - Fund\ Size_{i,first\ month}}{Fund\ Size_{i,first\ month}}. \qquad (14)$$

This rate measures how much a fund's size has grown from its first month to its last month in the TASS database. Next, I divide funds into terciles based on this rate: Low, Median, and High size growth terciles.[81] Finally, I repeat the analyses in Table 18 and Table 20 (for the Fund Characteristics Hypothesis and the Performance and Flow Hypothesis, respectively). If funds indeed change their SPs considerably as their size changes, then I would see that only the Low tercile has results similar to Table 18 and Table 20, and the Median and High terciles have very different results.

However, all three terciles show very similar patterns to those in Table 18 and Table 20.[82] As reported in Table 22, for all three terciles, higher SP scores are significantly associated with (1) larger fund size, (2) smaller fund age, (3) offshore domiciliation, (4) better past performance, (5) lower and less volatile investor flows, and (6) higher requirement of minimum investment. Thus, my results are robust across different levels of asset growth, suggesting that hedge funds tend to keep using the same SPs over time.

A considerable body of accounting literature also suggests that it is unlikely for large institutions to change SPs over time. For example, Beattie and Fearnley (1995), Davidson III, Jiraporn, and DaDalt (2006), and Blouin, Grein, and Rountree (2007) provide evidence that it is very costly to change auditors, due to reasons such as fee reduction of the incumbent auditor, client's aversion to disruption, same audit quality a client may still receive from another auditor, and large clients' agency concerns. Although the focus of these papers is on auditors, it is reasonable to conjecture that such stableness also applies to other SP categories. In summary, it is unlikely for hedge funds to change SPs considerably over time.

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[81] The Low tercile contains funds whose size growth is below the 33.33 percentile of the hedge fund industry, the High tercile contains funds whose size growth is greater than the 66.67 percentile of the industry, and the Median tercile contains all other funds.

[82] For simplicity, I only report the replication results of Panel A of **Error! Reference ource not found.**.

3.6 Conclusions

By establishing a comprehensive scoring system based on hedge funds' service providers, this paper studies the relationship between hedge funds' SPs and a number of fund features, including fund characteristics, performance, and investor flows. Focusing on share restricted funds, I find that using well-known SPs is associated with larger fund size, younger fund age, offshore domiciliation, better past performance, and smaller and less volatile investor flows, and it can also predict better performance in the future. For example, using one more Well SP is associated with a 12 basis point increase in past annual returns and a 48 basis point increase in future annual returns, ceteris paribus. I also provide evidence that my results are robust to fund sizes, investment strategies, and different levels of fund size growth.

This research is of practical importance because it shows that a fund's SPs contain a great deal of information about the fund's characteristics, performance, and investor flows. Therefore, it provides a new perspective that could assist investors, as well as regulators, to prevent hedge fund fraud. My research could be further extended by conducting similar studies across multiple databases.

Table 15. Well-Known SPs for the Hedge Fund Industry

This table lists the Well SPs for the hedge fund industry, ranked by each SP's number of hedge fund clients. Well SPs are defined as those with at least 100 clients in the TASS database. The TASS database includes four SP categories: Legal counsel, prime broker, auditor, and administrator, and each is reported in a separate panel. For each category, Client Market Share is the SP's number of clients divided by the total number of clients in that category, and Cumulative Market Share is the rolling sum of Client Market Shares from the highest ranked SP.

Panel A: Legal Counsels

Total Number of SPs = 526; Total Number of Clients = 7,125			
SP Name	N. Clients	Client Market Share	Cumulative Market Share
Maples & Calder	1,000	14.04%	14.04%
Walkers	568	7.97%	22.01%
Seward & Kissel LLP	479	6.72%	28.73%
Conyers Dill & Pearman	297	4.17%	32.90%
Schulte Roth & Zabel LLP	274	3.85%	36.74%
Dechert LLP	262	3.68%	40.42%
Simmons & Simmons	259	3.64%	44.06%
WS Walker & Company	217	3.05%	47.10%
Elvinger, Hoss & Prussen	166	2.33%	49.43%
Sidley Austin LLP	158	2.22%	51.65%
Appleby Corporate Services	138	1.94%	53.59%
Akin Gump Strauss Hauer & Feld LLP	129	1.81%	55.40%
Carey Langlois	111	1.56%	56.95%
Sadis & Goldberg LLC	103	1.45%	58.40%
Harney Westwood & Riegels	100	1.40%	59.80%

Panel B: Prime Broker

Total Number of SPs = 361;Total Number of Clients = 5,830			
SP Name	N. Clients	Client Market Share	Cumulative Market Share
Goldman Sachs & Co	927	15.90%	15.90%
Morgan Stanley	907	15.56%	31.46%
Bear Stearns Asset Management Inc	476	8.16%	39.62%
UBS Fund Services	433	7.43%	47.05%
Citigroup Global	266	4.56%	51.61%
Credit Suisse First Boston	246	4.22%	55.83%
Deutsche Bank AG	233	4.00%	59.83%
Banc of America Securities LLC	205	3.52%	63.34%
Merrill Lynch	182	3.12%	66.47%
JP Morgan	179	3.07%	69.54%
HSBC Institutional Trust Services	112	1.92%	71.46%
Man Group Plc	107	1.84%	73.29%

Panel C: Auditor

Total Number of SPs = 290; Total Number of Clients = 8,214			
SP Name	N. Clients	Client Market Share	Cumulative Market Share
PricewaterhouseCoopers	2,032	24.74%	24.74%
Ernst & Young Accountants	1,925	23.44%	48.17%
KPMG	1,460	17.77%	65.95%
Deloitte & Touche	971	11.82%	77.77%
Rothstein Kass & Company PC	438	5.33%	83.10%
Goldstein Golub & Kessler LLP	171	2.08%	85.18%
BDO Cayman Islands	156	1.90%	87.08%
Grant Thornton LLP	146	1.78%	88.86%
Richard A Eisner & Co LLP	133	1.62%	90.48%

Panel D: Administrator

Total Number of SPs = 997; Total Number of Clients = 9,564			
SP Name	N. Clients	Client Market Share	Cumulative Market Share
Citco Fund Services	816	8.53%	8.53%
HSBC Bank Bermuda Limited	676	7.07%	15.60%
BNY Alternative Investment Services Ltd	451	4.72%	20.32%
Citi Hedge Fund Services North America Inc	432	4.52%	24.83%
Fortis Fund Services Limited	305	3.19%	28.02%
UBS Fund Services	248	2.59%	30.61%
SS&C Fund Services Ltd	241	2.52%	33.13%
Northern Trust International Fund Administration Services	237	2.48%	35.61%
CACEIS	195	2.04%	37.65%
Goldman Sachs & Co	174	1.82%	39.47%
PFPC Inc	164	1.71%	41.19%
Credit Suisse Asset Management Limited	162	1.69%	42.88%
JP Morgan	154	1.61%	44.49%
Mellon Brascan Servicos Financeiros DTVM S	141	1.47%	45.96%
BNP Paribas Fund Services	136	1.42%	47.39%
State Street Cayman Trust Co Ltd	125	1.31%	48.69%
Banco Itau SA	117	1.22%	49.92%
Royal Bank of Canada	116	1.21%	51.13%
SEI Investments Management Corporation	116	1.21%	52.34%
GAM London Limited	114	1.19%	53.53%
Custom House Administration & Corporate Services Ltd	105	1.10%	54.63%
Admiral Administration Ltd	102	1.07%	55.70%

Table 16. Summary Statistics of the SP Score and OS Scores

This table reports the summary statistics of each fund's SP score (ranging from 0 to 4) and OS score (ranging from 0 to 5). The number of funds is reported, as well as the mean, standard deviation, minimum value, maximal value, and 25th, 50th, and 75th percentiles of the SP and OS scores. Funds are divided into categories based on fund characteristics. Onshore and offshore denote that funds are domiciled within the U.S. and that funds are domiciled elsewhere, respectively; HWM and No HWM denotes funds with and without a high water mark provision, respectively; Convertible Arbitrage through Other are the names of a fund's primary strategy in the TASS data; Log (Size) is the integer part of the decimal logarithm of a fund's size. (For example, the Log (Size) = 6 category includes funds whose size is equal to or greater than $1 million and less than $10 million.) I consider only share restricted funds (funds that have a total redemption period greater than one day).

		SP Score (0-4)							OS Score (0-5)						
Fund Category	N	Mean	Std Dev	Min	Max	P25	Median	P75	Mean	Std Dev	Min	Max	P25	Median	P75
All funds	9,485	2.01	1.21	0.00	4.00	1.00	2.00	3.00	2.69	0.97	0.00	5.00	2.00	3.00	3.00
Onshore	2,476	1.69	1.13	0.00	4.00	1.00	2.00	2.00	3.49	0.91	1.00	5.00	3.00	4.00	4.00
Offshore	7,009	2.12	1.21	0.00	4.00	1.00	2.00	3.00	2.40	0.82	0.00	4.00	2.00	2.00	3.00
HWM	6,022	2.21	1.20	0.00	4.00	1.00	2.00	3.00	3.17	0.75	1.00	5.00	3.00	3.00	4.00
No HWM	3,463	1.66	1.14	0.00	4.00	1.00	2.00	2.00	1.85	0.70	0.00	4.00	1.00	2.00	2.00
Convertible Arbitrage	209	2.50	0.99	0.00	4.00	2.00	3.00	3.00	2.99	0.87	1.00	5.00	2.00	3.00	4.00
Dedicated Short Bias	38	2.05	1.18	0.00	4.00	1.00	2.00	3.00	3.00	1.04	1.00	5.00	2.00	3.00	4.00
Emerging Markets	585	2.35	1.10	0.00	4.00	2.00	2.00	3.00	2.66	0.85	0.00	5.00	2.00	3.00	3.00
Equity Market Neutral	426	2.24	1.14	0.00	4.00	1.00	2.00	3.00	2.88	0.90	1.00	5.00	2.00	3.00	3.00
Event Driven	601	2.34	1.06	0.00	4.00	2.00	2.00	3.00	2.97	0.91	1.00	5.00	2.00	3.00	4.00
Fixed Income Arbitrage	228	2.17	1.18	0.00	4.00	1.00	2.00	3.00	2.87	0.95	1.00	5.00	2.00	3.00	3.00
Fund of Funds	3,259	1.64	1.09	0.00	4.00	1.00	2.00	3.00	2.39	0.93	0.00	5.00	2.00	2.00	3.00
Global Macro	343	2.04	1.22	0.00	4.00	1.00	2.00	3.00	2.66	1.00	0.00	5.00	2.00	3.00	3.00
Long/Short Equity Hedge	2,328	2.35	1.23	0.00	4.00	1.00	2.00	3.00	2.94	0.94	0.00	5.00	2.00	3.00	4.00
Managed Futures	589	1.57	1.14	0.00	4.00	1.00	2.00	2.00	2.58	0.89	0.00	5.00	2.00	3.00	3.00
Multi-Strategy	576	1.86	1.26	0.00	4.00	1.00	2.00	3.00	2.60	1.00	0.00	5.00	2.00	3.00	3.00
Options Strategy	26	2.27	1.43	0.00	4.00	1.00	2.50	3.00	3.00	0.94	1.00	5.00	3.00	3.00	4.00
Other	276	2.42	1.34	0.00	4.00	1.00	3.00	4.00	3.17	1.00	0.00	5.00	3.00	3.00	4.00
Log (Size) = 6	688	1.52	1.14	0.00	4.00	1.00	1.00	2.00	2.38	0.98	0.00	5.00	2.00	2.00	3.00
Log (Size) = 7	3,611	1.81	1.17	0.00	4.00	1.00	2.00	3.00	2.60	0.98	0.00	5.00	2.00	3.00	3.00
Log (Size) = 8	4,231	2.15	1.20	0.00	4.00	1.00	2.00	3.00	2.77	0.95	0.00	5.00	2.00	3.00	3.00
Log (Size) = 9	867	2.52	1.14	0.00	4.00	2.00	3.00	3.00	2.88	0.91	1.00	5.00	2.00	3.00	3.00
Log (Size) = 10	78	2.55	1.24	0.00	4.00	2.00	3.00	4.00	2.65	0.74	1.00	4.00	2.00	3.00	3.00
Log (Size) = 11	9	2.67	1.41	1.00	4.00	1.00	3.00	4.00	2.78	0.97	1.00	4.00	2.00	3.00	3.00

Table 17. Differences between the SP and OS Scores

This table summarizes the differences between the SP score and the OS score. Panels A and B report the ranking differences for legal counsel and auditor, respectively. N. Specialized in Hedge Funds is the number of SPs that (1) are in OS's "top 100" firm list and (2) actually provide services for hedge funds. The summary statistics of the SP score are then reported, including the mean, standard deviation, minimum value, maximal value, and 25th, 50th, and 75th percentiles. Panel C reports the correlation, as well as its p-value, between the SP and OS scores for each fund category. The description of these categories can be found in the table description of Table 16. I consider only share restricted funds (funds that have a total redemption period greater than one day).

Panel A: OS's Top 100 Legal Counsels

	Actual Rankings						
N. Specialized in Hedge Funds	Mean	Std Dev	Min	Max	P25	Median	P75
67	171.30	152.96	5	514	50.00	113.00	273.00

Panel B: OS's Top 100 Auditors

	Actual Rankings						
N. Specialized in Hedge Funds	Mean	Std Dev	Min	Max	P25	Median	P75
32	73.25	88.13	1	281	9.50	30.50	119.50

Panel C: Correlation between SP and OS Scores

Fund Category	N	Correlation	*p*-value
All Funds	9,485	0.305	0.000
Onshore	2,476	0.376	0.000
Offshore	7,009	0.470	0.000
HWM	6,022	0.142	0.000
No HWM	3,463	0.362	0.000
Convertible Arbitrage	209	0.347	0.000
Dedicated Short Bias	38	0.285	0.083
Emerging Markets	585	0.281	0.000
Equity Market Neutral	426	0.098	0.043
Event Driven	601	0.143	0.000
Fixed Income Arbitrage	228	0.279	0.000
Fund of Funds	3,259	0.353	0.000
Global Macro	343	0.304	0.000
Long/Short Equity Hedge	2,328	0.144	0.000
Managed Futures	589	0.163	0.000
Multi-Strategy	576	0.375	0.000
Options Strategy	26	0.149	0.467
Other	276	0.299	0.000
Log (Size) = 6	688	0.278	0.000
Log (Size) = 7	3,611	0.287	0.000
Log (Size) = 8	4,231	0.286	0.000
Log (Size) = 9	867	0.314	0.000
Log (Size) = 10	78	0.240	0.035
Log (Size) = 11	9	-0.243	0.530

Table 18. SP Score and Fund Characteristics

This table reports the results of the following generalized linear model regression:

$$SP_i = \alpha + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i.$$

In this regression, $\mathrm{SP_i}$ is Fund i's SP score, and $\mathrm{Characteristic_{i,k}}$ $(\mathrm{k} = 1,2,3,4)$ are Fund i's characteristics. The fund characteristics that may be considered include Log (Size) (the integer part of the decimal logarithm of Fund i's size), Age (Fund i's number of monthly observations), Onshore (a dummy variable that is one if Fund i is onshore and zero if Fund i is offshore), and OS Score (Fund i's OS score). Fund strategies may or may not be controlled for in the regression models, and Y denotes that they are and N denotes otherwise. Chi / DF is the model's Chi-squared divided by its degrees of freedom, where a value closer to 1 indicates a better model. In each model, coefficients and the corresponding p-values are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. I consider only share restricted funds (funds that have a total redemption period greater than one day).

	Model 1			Model 2			Model 3			Model 4			Model 5		
Independent Variable	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
Log (Size)	0.325	0.000	***										0.191	0.000	***
Age (month)				-0.001	0.009	***							-0.001	0.000	***
Onshore							-0.429	0.000	***				-1.143	0.000	***
OS Score										0.380	0.000	***	0.537	0.000	***
Control for															
Strategy	N			N			N			N			Y		
N. Obs	9,484			9,485			9,485			9,485			9,208		
Chi / DF	1.39			1.45			1.42			1.32			1.03		

Table 19. Categorical Analysis of the SP Score, Performance, and Flow

This table presents the categorical analysis results of the SP score, past performance, and investor flows. The performance and flow measures include Mean (mean of a fund's monthly raw returns), Std Dev (standard deviation of a fund's monthly raw returns), Sharpe Ratio (industry) (a fund's Sharpe ratio calculated based on the industry average in the TASS database), Alpha (size and strategy matched) (a fund's risk-adjusted return calculated based on the matched group average, where the matched group consists of funds with similar size and the same investment strategy), FH8 Alpha (a fund's risk-adjusted return calculated based on the Fung-Hsieh eight-factor model), Flow (mean of a fund's monthly investor flows), and Flow Std Dev (standard deviation of a fund's monthly investor flows). Funds are divided into three categories based on the SP score: Low (SP score = 0), Median (SP score = 1-3), and High (SP score = 4). For each performance or flow variable, I report the means in the three SP score categories, and the difference between the High and Low categories, as well as the p-value. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. I consider only share restricted funds (funds that have a total redemption period greater than one day).

	SP Score					
	Low [0]	Medium [1, 3]	High [4]	High - Low		
				diff.	*p*-value	
N	1,204	7,155	1,126			
Mean (%)	0.28	0.39	0.45	0.17	0.000	***
Std Dev (%)	3.12	3.03	3.03	-0.09	0.097	*
Sharpe Ratio (industry)	-0.08	-0.06	-0.02	0.07	0.000	***
Alpha (size and strategy matched) (%)	-0.04	-0.04	0.01	0.06	0.036	**
FH8 Alpha (%)	0.16	0.28	0.34	0.18	0.000	***
Flow	0.25	0.20	0.17	-0.08	0.013	**
Flow Std Dev	1.37	1.05	0.96	-0.41	0.008	***

Table 20. Regression Analysis of Service Provider Score, Performance, and Flow

This table reports the regression results of the following models. Panel A reports for

$$PerfFlow_i = \alpha + \gamma_1 \times SP_i + \gamma_2 \times OS_i + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i.$$

Panel B reports for

$$PerfFlow_i = \alpha + \gamma_1 \times OS_i + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i.$$

$\mathrm{PerfFlow_i}$ is Fund i’s performance or flow measure, $\mathrm{SP_i}$ is Fund i's SP score, $\mathrm{OS_i}$ is Fund i’s OS score, and $\mathrm{Characteristic_{i,k}}$ $(\mathrm{k} = 1,2,3,4)$ are Fund i's characteristics. The performance or flow measures include Mean (mean of Fund i’s monthly raw returns), Std Dev (standard deviation of Fund i’s monthly raw returns), Flow (mean of Fund i’s monthly investor flows), and Log (Min Inv) (the decimal logarithm of Fund i’s required minimum investment). Fund characteristics are included here to control for the fund fixed effect, and Y denotes that this characteristic has been controlled for. The description of the fund characteristics controlled for can be found in the table description of Table 18. Adj R2 is the adjusted R-squared of the model.[83] AIC is the value of the Akaike information criterion of the model, where a smaller value indicates a better model. In each regression, the coefficients and the corresponding p-values are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. I consider only share restricted funds (funds that have a total redemption period greater than one day).

[83] See Shtatland, Moore, and Barton (2000) for detailed explanation of calculating the adjusted R-squared.

Panel A: Independent Variables Include Both the SP Score and the OS Score

	Mean (%)			Std Dev (%)			Flow			Log (Min Inv)		
	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
SP	0.01	0.056	*	-0.09	0.000	***	-0.03	0.000	***	0.08	0.000	***
OS	-0.01	0.286		-0.05	0.003	***	-0.05	0.000	***	0.08	0.000	***
Control for												
Log (Size)	Y			Y			Y			Y		
Age (month)	Y			Y			Y			Y		
Onshore	Y			Y			Y			Y		
Strategy	Y			Y			Y			Y		
N. Obs	9,208			9,208			9,199			9,005		
Adj R2 (%)	7.99			7.48			1.85			8.18		
AIC	18180.22			29932.04			20922.41			23557.14		

Panel B: Independent Variables Include Only the OS Score

	Mean (%)			Std Dev (%)			Flow			Log (Min Inv)		
	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
OS	0.00	0.691		-0.10	0.000	***	-0.06	0.000	***	0.12	0.000	***
Control for												
Log (Size)	Y			Y			Y			Y		
Age (month)	Y			Y			Y			Y		
Onshore	Y			Y			Y			Y		
Strategy	Y			Y			Y			Y		
N. Obs	9,208			9,208			9,199			9,005		
Adj R2 (%)	7.97			7.34			1.79			7.88		
AIC	18184.20			29981.53			20935.53			23634.83		

Table 21. Out-of-Sample Analysis of the SP Score on Fund Performance

This table reports the results of out-of-sample analysis using the following generalized linear model regressions. Panel A reports for

$$Perf_{i,t1_i} = \alpha + \gamma_1 \times SP_{i,t0_i} + \gamma_2 \times OS_{i,t0_i} + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i.$$

Panel B reports for

$$Perf_{i,t1_i} = \alpha + \gamma_1 \times OS_{i,t0_i} + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i.$$

For any variable, $\mathrm{t0_i}$ denotes that this variable is observed on Fund i's most recent audit date, and $\mathrm{t1_i}$ denotes that it is calculated using the monthly returns after that date. $\mathrm{Perf_i}$ is Fund i's performance variable, $\mathrm{SP_i}$ is Fund i's SP score, $\mathrm{OS_i}$ is Fund i's OS score, and $\mathrm{Characteristic_{i,k}}$ $(\mathrm{k} = 1,2,3,4)$ are Fund i's characteristics. The dependent variable is one of the performance variables, which include Mean (mean of Fund i's monthly raw returns), Std Dev (standard deviation of Fund i's monthly raw returns), ExRet (industry) (a fund's excess return over the industry average in the TASS database), ExRet (size and strategy matched) (a fund's excess return over the matched group average, where the matched group consists of funds with similar size and the same investment strategy), Sharpe Ratio (industry) (a fund's Sharpe ratio calculated based on the industry average), Sharpe Ratio (size and strategy matched) (a fund's Sharpe ratio calculated based on the matched group average). Fund characteristics are included here to control for fund fixed effect, and Y denotes that this characteristic has been controlled for. The description of the fund characteristics can be found in the table description of Table 18. Adj R2 is the adjusted R-squared of the model. AIC is the value of the Akaike information criterion of the model, where a smaller value indicates a better model. In each regression, the coefficients and the corresponding p-values are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

I consider only share restricted funds (funds that have a total redemption period greater than one day).

Panel A: Independent Variables Include Both the SP Score and the OS Score

	Mean			Std Dev			ExRet (industry)			ExRet (size and strategy matched)			Sharpe Ratio (industry)			Sharpe Ratio (size and strategy matched)		
	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
SP	0.04	0.006	***	-0.08	0.002	***	0.05	0.005	***	0.05	0.000	***	0.01	0.095	*	0.02	0.005	***
OS	-0.09	0.000	***	0.06	0.120		-0.07	0.002	***	-0.07	0.003	***	-0.02	0.111		-0.02	0.043	**
Control for																		
Log (Size)	Y			Y			Y			Y			Y			Y		
Age (month)	Y			Y			Y			Y			Y			Y		
Onshore	Y			Y			Y			Y			Y			Y		
Strategy	Y			Y			Y			Y			Y			Y		
N. Obs	2,179			2,174			2,179			2,178			2,174			2,173		
Adj R2 (%)	3.31			6.57			3.61			1.65			7.36			7.43		
AIC	5152.07			7269.88			5168.63			4937.11			1464.77			1535.12		

Panel B: Independent Variables Include Only the OS Score

	Mean			Std Dev		ExRet (industry)			ExRet (size and strategy matched)			Sharpe Ratio (industry)		Sharpe Ratio (size and strategy matched)	
	coeff.	*p*-value		coeff.	*p*-value	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	coeff.	*p*-value
OS	-0.06	0.002	***	0.01	0.796	-0.04	0.041	**	-0.03	0.094	*	-0.01	0.326	-0.01	0.355
Control for															
Log (Size)	Y			Y		Y			Y			Y		Y	
Age (month)	Y			Y		Y			Y			Y		Y	
Onshore	Y			Y		Y			Y			Y		Y	
Strategy	Y			Y		Y			Y			Y		Y	
N. Obs	2,179			2,174		2,179			2,178			2,174		2,173	
Adj R2 (%)	3.21			6.48		3.51			1.45			7.23		6.98	
AIC	5157.76			7277.79		5174.43			4947.51			1465.56		1541.06	

Table 22. Analyses over Size Growth Groups

This table reports the results of the analyses across different size growth groups. Fund size growth are calculated as

$$Size\ Growth_i = \frac{Fund\ Size_{i,last\ month} - Fund\ Size_{i,first\ month}}{Fund\ Size_{i,first\ month}}.$$

This rate measures how much a fund's size has grown from its first month to its last month in the TASS database. Funds are divided into terciles based on this rate: Low, Median, and High size growth terciles. Panels A-C repeat the analysis in Table 18 across the terciles, respectively. Panels D-F repeat the analysis in Table 20 across the terciles, respectively. The description of these panels can be found in Table 18 and Table 20, respectively.

Panel A: SP Score and Fund Characteristics, Low Size Growth Tercile

	Model 1			Model 2			Model 3			Model 4			Model 5		
Independent Variable	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
Log (Size)	0.230	0.000	***										0.118	0.000	***
Age (month)				-0.005	0.000	***							-0.003	0.000	***
Onshore							-0.149	0.056	**				-1.008	0.000	***
OS Score										0.552	0.000	***	0.583	0.000	***
Control for															
Strategy	N			N			N			N			Y		
N. Obs	2,269			2,269			2,269			2,269			2,269		
Chi / DF	1.46			1.51			1.49			1.23			1.02		

Panel B: SP Score and Fund Characteristics, Median Size Growth Tercile

	Model 1			Model 2			Model 3			Model 4			Model 5		
Independent Variable	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
Log (Size)	0.265	0.000	***										0.172	0.000	***
Age (month)				-0.004	0.000	***							-0.004	0.000	***
Onshore							-0.345	0.000	***				-1.120	0.000	***
OS Score										0.414	0.000	***	0.572	0.000	***
Control for															
Strategy	N			N			N			N			Y		
N. Obs	2,993			2,993			2,993			2,993			2,993		
Chi / DF	1.37			1.39			1.39			1.25			0.89		

Panel C: SP Score and Fund Characteristics, High Size Growth Tercile

	Model 1			Model 2			Model 3			Model 4			Model 5		
Independent Variable	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
Log (Size)	0.381	0.000	***										0.229	0.000	***
Age (month)				-0.001	0.008	***							0.000	0.124	
Onshore							-0.701	0.000	***				-1.198	0.000	***
OS Score										0.237	0.000	***	0.475	0.000	***
Control for															
Strategy	N			N			N			N			Y		
N. Obs	3,946			3,947			3,947			3,947			3,946		
Chi / DF	1.32			1.46			1.29			1.36			0.99		

Panel D: SP Score, Performance, and Flow, Low Size Growth Tercile

	Mean (%)			Std Dev (%)			Flow			Log (Min Inv)		
	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
SP	0.03	0.019	*	-0.06	0.025	**	-0.04	0.008	***	0.09	0.000	***
OS	-0.01	0.474		-0.07	0.033	**	-0.03	0.218		0.03	0.322	***
Control for												
Log (Size)	Y			Y			Y			Y		
Age (month)	Y			Y			Y			Y		
Onshore	Y			Y			Y			Y		
Strategy	Y			Y			Y			Y		
N. Obs	2,269			2,269			2,263			2,189		
Adj R2 (%)	2.84			5.39			2.03			6.06		

Panel E: SP Score, Performance, and Flow, Median Size Growth Tercile

	Mean (%)			Std Dev (%)			Flow			Log (Min Inv)		
	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
SP	0.01	0.156		-0.06	0.001	***	-0.03	0.048	**	0.09	0.000	***
OS	-0.03	0.016	**	-0.05	0.061	*	-0.03	0.091	*	0.10	0.000	***
Control for												
Log (Size)	Y			Y			Y			Y		
Age (month)	Y			Y			Y			Y		
Onshore	Y			Y			Y			Y		
Strategy	Y			Y			Y			Y		
N. Obs	2,993			2,993			2,992			2,918		
Adj R2 (%)	6.81			7.47			1.54			6.65		

Panel F: SP Score, Performance, and Flow, High Size Growth Tercile

	Mean (%)			Std Dev (%)			Flow			Log (Min Inv)		
	coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value		coeff.	*p*-value	
SP	-0.02	0.004	***	-0.07	0.001	***	-0.02	0.096	*	0.06	0.000	***
OS	-0.02	0.054	*	-0.04	0.134		-0.07	0.000	***	0.11	0.000	***
Control for												
Log (Size)	Y			Y			Y			Y		
Age (month)	Y			Y			Y			Y		
Onshore	Y			Y			Y			Y		
Strategy	Y			Y			Y			Y		
N. Obs	3,946			3,946			3,944			3,899		
Adj R2 (%)	9.26			9.18			1.72			12.64		

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