What Can We Tell from Them?

A Study on Hedge Funds' Service Providers

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Abstract

By building a comprehensive numeric score of hedge funds' service providers, we study the relationship between hedge funds' use of service providers and funds' performance and characteristics. We find that using well-known service providers is associated with larger fund size, younger fund age, offshore domiciliation, better fund performance, and smaller and less volatile cash flow from investors, and it is also related to better fund performance in the future. Using one well-known service provider is associated with a 12 (48) basis point increase in overall (future) annual returns. Our results are robust across different fund sizes, investment strategies, and asset growths.

Keywords: hedge funds, service providers, performance, investor flow

JEL classification: G23; G24; H89; M41; P37

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 hedge funds have gained enormous attention from investors worldwide, their operational risk and fund governance have always been a major concern among investors, regulators, and academics (for example, Liang (2003), Bollen and Pool (2008), Brown, Goetzmann, Liang, and Schwarz (2008, 2009, 2012), and Cassar and Gerakos (2010)).[1] In the midst of this concern, hedge funds' service providers (SPs, hereafter) are definitely in the epicenter. After all, hedge funds' SPs are the ones that should provide the hedge fund industry with effective internal control. Therefore, we should expect that reputable and experienced SPs can help reduce operational risk and enhance fund governance for hedge funds.

A good example of the above projection is the hedge fund division within Bernard L. Madoff Investment Securities LLC. This firm turned out to be the largest Ponzi scheme by far, which allegedly attracted $41 billion from investors before its collapse in 2008.[2] Admittedly, in order to fully unravel this complicated fraud, one needs to conduct in-depth investigations. However, people could have sensed the fraud by simply looking at its SPs, because some of Madoff's SPs were neither reputable nor experienced. For example, despite its huge assets under management, Madoff's firm only hired a little-known accounting firm as its auditor. And it turned out that this accounting firm called Friehling & Horowitz only had three employees.[3]

This example emphasizes that SPs with little reputation are not likely to provide trustworthy services for complicated clients like hedge funds. Therefore, it is reasonable to conjecture that a hedge

[1] According to IAFE Operational Risk Committee (2001), operational risk is "losses caused by problems with people, processes, technology, or external events."
[2] See a Bloomberg article at http://www.bloomberg.com/apps/news?pid=newsarchive&sid=ax319OmN67Pg&refer=home.
[3] See http://en.wikipedia.org/wiki/David_G._Friehling and http://content.time.com/time/business/article/0,8599,1867092,00.html.

fund's SPs can serve as an indicator of the fund's governance. 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.

However, even though hedge funds' SPs are such an important topic, we find little research examining the relationship between hedge funds' SPs and hedge fund governance. The only exception we find so far 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. Unfortunately, however, this OS score is not a good representation of the SP community for hedge funds. First, OS only consider two types of SPs, legal counsels and auditors, but in reality, there are four types of key SPs used by hedge funds—not only legal counsel and auditor, but also prime broker and administrator.[4] Second, although the SPs that provide services for hedge funds are only one portion of the entire SP spectrum, OS still base their score on the whole spectrum, not the SPs actually used by the hedge fund industry.

In order to examine whether a hedge fund's use of SPs actually contains material information about the fund, we propose a new scoring system in this paper. This Service Provider score (referred to as the SP score, hereafter) quantifies the impact of SPs on hedge fund governance. Our SP score is

[4] 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.)

preferable to the OS score, because we take all four types of SPs into account, and we base the score on only the SPs used by the hedge fund industry.

We then study the impact of this SP score on hedge fund governance. To be specific, we compute seven indicators of fund governance. These seven indicators are also suggested by previous studies, either directly or indirectly—better fund governance (or lower operational risk) is possibly related to (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)),[5] (4) better overall fund performance (Liang (2003), Brown et al. (2008, 2009, 2012), and Aragon, Liang, and Park (2014)), (5) lower investor flow (Ozik and Sadka (2014)), (6) less volatile investor flow (Bollen and Pool (2008)), and even (7) better future performance (Amenc, El Bied, and Martellini (2003) and Baquero, Ter Horst, and Verbeek (2005)).

In this research, we verify that higher SP scores are strongly associated with better fund governance on all seven indicators. All results are both economically and statistically significant, and are robust to different levels of fund sizes, investment strategies, and fund size changes. For example, hiring one additional well-known (Well, hereafter) SP is associated with a 12 basis point increase in overall annual returns, and a 48 basis point increase in future annual returns, ceteris paribus.[6]

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

[5] 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)).

[6] In this paper, a fund's overall performance is defined as its performance since inception, and its future performance is defined as its performance after it has updated its SP information.

The rest of the paper is organized as follows. Section 2 summarizes related literature and develops the three main hypotheses in this research. Section 3 describes the data we use, and Section 4 presents the main empirical findings. Section 5 discusses the robustness check, and Section 6 concludes.

2. Related Literature and Hypotheses Development

This research is related to two important areas in the literature: (1) hedge funds' SPs and (2) operational risk, fund governance, and other features of hedge funds. Some of the literature is based on mutual funds, not directly on hedge funds.

Hedge fund's SPs. Not all hedge funds are required to disclose their information, so hedge fund research relies on funds' voluntary report. Researchers find that hedge funds with better SPs report their data more reliably. Some of them focus on hedge funds' auditors, a key SP category. For example, Liang (2003) finds that hedge funds with adequate auditing (also a symbol for less operational risk) is associated with more consistent reporting.[7]

Literature also demonstrates that hiring better SPs is more common among lager hedge funds. For example, Liang (2003) also finds this fund size effect—larger funds are more inclined to hire Big 4 auditors than smaller funds are. Moreover, Malkiel and Saha (2005) show that larger mutual funds are much easier to survive than smaller ones. It is reasonable to expect that this higher surviving rate may be related to using more Well SPs.[8]

Though such researchers study hedge funds' SPs, to the best of our knowledge, almost no study has provided a quantitative measure of these SPs. The only exception we have found is a paper by Ozik

[7] For example, he investigates the discrepancies in hedge funds' reporting to two databases: the Tremont Advisory Shareholder Services (TASS) database and the US Offshore Fund Directory. He finds that the discrepancy in annual returns is 2.24% for funds with missing audit date information, but only 0.64% for funds with a Big Four auditor.

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

and Sadka (2014) (OS, here after). Their major focus in the paper is not on hedge funds' SPs, but on fund governance; however, they do suggest that hedge funds with better SPs experience lower investor flow. It is because their measure of fund governance includes the SP information—in their five-dimensional scoring system for fund governance, two of them are related to SPs: audit (a fund is assigned a score of one if it reports an audit date 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).[9] They suggest that higher OS scores, indicating better fund governance (and better SPs), implies smaller investor flow. This finding is implied in Table 6 of the OS paper. The regression results there demonstrate that the OS score and investor flow have offsetting effects on fund performance. Thus, ceteris paribus, the higher the OS score, the lower the investor flow.

Operational risk, fund governance, and other fund features. The paper by Brown et al. (2008) is a pioneer work regarding hedge funds' operational risk. They indicate that less operational risk (therefore better fund governance) is related to better fund performance. In their research, they divide hedge funds into a problem and a nonproblem group, 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. Thus, the problem and nonproblem groups represent high and low operational risk, respectively.[10] By comparing these two groups, they reveal an important pattern—the nonproblem group has significantly better performance.[11]

[9] The other three dimensions are: 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).

[10] 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."

[11] For example, they find that the average returns for problem and nonproblem funds are 0.77% and 0.91% per month (or 9.64% and 11.48% per annum), respectively. They continue this study in Brown et al. (2009, 2012).

Another fund characteristic that may be related to fund governance is the history length, or age, of a fund. A number of studies suggest that younger funds are more inclined to hire Well SPs. The reason is that younger funds tend to use newer trading techniques, which may cause funds to use better SPs, in order to be 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 did not directly cause the flash crash in the US 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, we expect that younger funds have greater incentive to use Well SPs.

Fund governance is related to fund domiciliation—offshore funds are expected to use more Well SPs. For instance, Cassar and Gerakos (2010) find that fund governance is related to a fund's domiciliation. The measure of fund governance they use is funds' 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 environments. They argue that "Although onshore and offshore funds are generally exempt from U.S. securities regulations, investors in onshore funds can use the US 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)). In summary, they indicate that offshore hedge funds have more incentive than onshore equivalents to rely on using Well SPs to enhance fund governance and mitigate operational risk.

Some scholars provide reasons why offshore funds tend to use more Well SPs. The reasons 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 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)).

Literature suggests that better fund governance is not only accompanied by smaller investor flow, but also by less volatile investor flow. Bollen and Pool (2008) study the "conditional serial correlation" phenomenon in hedge fund returns.[12] They argue that conditional serial correlation is a key signal 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 flow is positively associated with the magnitude of conditional serial correlation.[13] Namely, less volatile investor flow are related to less conditional serial correlation and, therefore, better fund governance.

Fund governance may also be related to future fund performance. The reasons are twofold. First, we have seen that fund governance is related to fund performance and fund characteristics. Second, a number of studies show that 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 performance can be used to predict future performance. In a different setting,

[12] 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.
[13] This result can be found in Table 13 of the paper.

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, we also focus on funds' share restrictions, i.e., funds whose total redemption period is greater than one day.[14]

Overall, existing literature suggests that using more Well SPs is a symbol of lower operational risk and better fund governance, and it is associated with a number of fund features, including a fund's performance and some characteristics. Therefore, we develop three testable hypotheses for this research.

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 fund performance and (2) smaller and less volatile investor flow.

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

[14] *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 our 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, our research and these studies all show that most hedge funds have share restrictions. For example, in our sample, the percentage of share-restricted funds is 79.19%.

3. Data

The main database in this study is the Tremont Advisory Shareholder Services (TASS) database, and we 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 SEC-registered management company. Consistent with previous literature, we apply the following screening criteria. First, we 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, we delete funds whose size is below $1 million. Third, we discard return observations that are exactly 0.0000 or consecutively 0.0001. Fourth, in order to mitigate backfill bias, we further delete a fund's first 12 monthly returns. Finally, as discussed before, we consider only share-restricted funds, i.e., funds that have a total redemption period greater than one day.

After data filtering, we have 9,485 funds with 804,347 monthly observations, including both hedge funds and funds of funds, both live and dead funds, and both onshore and offshore funds. For fund returns that are not denominated in USD, we use historical exchange rates to convert them to USD denominated returns. The returns are then winsorized at the 2.5% level (on each side).[15] For each of these funds, we observe its fund characteristics and calculate its SP score and OS score based on its most recent reporting, and calculate its fund performance and investor flow based on its historical reporting.

As mentioned before, existing literature has not yet provided any numeric measure designed for SPs for the hedge fund industry. Thus, one main contribution of this research is that we build an aggregate numeric SP score for hedge funds using the TASS data. The SP score is calculated in four

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

steps. First, for each SP, we calculate its total number of hedge fund clients.[16] Second, for each of the four SP categories (legal counsel, prime broker, auditor, and administrator), we 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.[17] 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. We follow the same procedure to assign each fund a prime broker score, an auditor score, and an administrator score. Finally, we calculate the aggregate SP score by summing all the four separate scores. Thus, our final SP score can be any integer from zero to four. Table 1 lists the Well SPs for each SP category.

[Insert Table 1]

In order to compare with our SP score, we also replicate the original OS score. Consequently, we use two other data sources: the worldwide rankings of auditors and legal counsels. Following OS's procedure, we use the list of the top 100 accounting firms in 2014 selected by accountingTODAY and the list of 100 law firms in 2014 on WIKIPEDIA.[18] By combining the TASS data and these two rankings, we are able to replicate completely the OS score. Table 2 reports the summary statistics of the SP score, and for comparison purposes, we also report the OS score in this table.

[Insert Table 2]

There are three interesting findings in Table 2, which, before we test the main hypotheses, already reveal some patterns in hedge funds' usage of SPs. First, offshore funds have a higher SP score than onshore funds (2.12 vs. 1.96). This difference reveals that offshore funds tend to use more Well SPs. Second, different investment strategies also cause difference in hiring SPs. For example, Funds

[16] 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.
[17] For robustness checks, we also use other thresholds of Well and Not Well SPs, and the results are generally unchanged.
[18] 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. Admittedly, 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.

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.

4. Tests and Results

4.1. Differences between the SP and OS Scores

If our 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, we first examine whether these two scores are different. Our SP score is better than the OS score for two reasons. First, hedge funds have four key SPs, but the OS score only considers two of them, legal counsel and auditor, and not the other two, prime broker and administrator. Second, the OS score uses general rankings of all legal firms and accounting firms, many of which actually do not even provide services for hedge funds. On the other hand, our SP score includes all four SP categories, and considers only the SPs specialized for the hedge fund industry. Thus, our SP score serves as a better measure of hedge fund's SPs. Table 3 reports the differences between these two scoring systems.

[Insert Table 3]

These results show that, again, many of the "top 100" firms considered by OS actually do not serve for hedge funds. To be specific, Panel A demonstrates that OS have a "top 100" legal firm list, only 67 of them serve the hedge fund industry. Since there are 526 legal counsels for hedge funds, these 67 legal firms account for only 11.36% of the entire spectrum. 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, there are 290 auditors for the hedge fund industry, but only 32 (or 11.03%) of them are considered a "top 100" accounting firm in the OS score. The mean of the actual rankings of these 32 auditors is 73.25, where the highest ranking is 1 and the lowest is 281. Therefore, overall, while our SP score measures actual popularity of the SPs among hedge funds, the OS score only describes a small portion of that.

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

4.2. Fund Characteristics

In the three following subsections, we present empirical evidence regarding our main hypotheses developed in Section 2. To test the Fund Characteristics Hypothesis, we examine whether the SP score is associated with certain fund characteristics. To be specific, we expect that higher SP scores are related to (1) larger fund size, (2) younger fund age, and (3) offshore domiciliation. We use the generalized linear model (GLM) regression:

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

where the dependent variable, SP_i, is Fund *i*'s SP score, and each of the independent variables, $Characteristic_{i,k}$ is Fund *i*'s *k*th characteristic. Per our previous discussion, we include the following characteristics in the 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, we also include the OS score as an independent variable.

Our Fund Characteristics Hypothesis is confirmed by the GLM regression results presented in Table 4. For example, 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 our sample is from 6 to 11. Therefore, on average, a Log (Size) = 11 fund (size greater than $100 billion) has an SP score that is 1.625 higher than a Log (Size) = 6 fund (size between $1 million and $10 million). Meanwhile, fund age is negatively associated (-0.001) with the SP score. Though this coefficient may seem small, note that the fund ages in our sample range from 12 to 222 months. Therefore, fund age alone could explain up to 0.21 (= $0.001 \times (222 - 12)$) 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 includes all these fund characteristics.

[Insert Table 4]

All of the results in Table 4 are intuitive. For fund size, there are two reasons why fund size is significantly positively associated with the SP score, similar to our discussion in Section 2. 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, because 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.

For fund age, there could be two reasons why younger funds are more likely to have well SPs. On one hand, younger funds are more eager to build up reputation fast. One possible way to do this is to hire Well SPs. After all, hiring Well SPs is usually perceived as a positive signal. On the other hand, people usually launch funds to take advantage of state-of-art trading techniques, like high-frequency trading. Thus, younger funds are more likely to engage in newer trading techniques, like high-frequency trading.

The third characteristic in this table is fund domiciliation—offshore funds are on average less likely to use Well SPs. This phenomenon 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. This factor is also suggested by Cumming and Dai (2010) and Aragon, Liang, and Park (2014). The second factor is fund size. Offshore funds are typically much larger than onshore funds. This fact is documented in a number of studies. For example, Aragon, Liang, and Park (2014) find that the average size of offshore funds is more than 200% of that 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 hedge funds' legal structures. 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. Most corporations are required by regulations to use SPs. Fourth, it may also be related to SP branching. In our 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.

4.3. Performance and Flow

Our Performance and Flow Hypothesis states that higher SP scores should be associated with better overall fund performance and smaller, less volatile investor flow. For fund performance, we consider the following measures: (1) mean and (2) standard deviation of its monthly returns, (3) Sharpe ratio, (4) alpha in the corresponding size and strategy matched group, and (5) alpha based on the Fung-Hsieh eight factors.[19, 20]

For investor flow, we consider two measures: (1) mean and (2) standard deviation of a fund's monthly flows. A fund's monthly flows are calculated using the following equation:

$$Flow_{i,t} = \frac{Size_{i,t} - Size_{i,t-1} \times (1 + R_{i,t})}{Size_{i,t-1}}, \tag{2}$$

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.

In order to test this hypothesis, we first conduct a categorical analysis. The results of the categorical analysis are reported in Table 5. These results are consistent with our Performance and Flow Hypothesis. In this analysis, funds are grouped into three categories based on SP score: the Low (SP score = 0), Median (SP score = 1-3), and High (SP score = 4).[21] Namely, 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 other funds. Table 5 shows that (1) a fund's overall performance improves monotonically from the Low to High category, but (2) the magnitude of 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 categories is 17 basis points per month (equal to 205.92 basis points per year), ceteris paribus, a significant economic outperformance.

[Insert Table 5]

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[19] 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). We are also grateful to David Hsieh for providing some of the data on the website.

[20] Sharpe ratio is calculated as the 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. Alpha in the corresponding size and strategy matched group is calculated as 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. Alpha based on the Fung-Hsieh eight factors is calculated as the intercept of regressing a fund's returns on the Fung-Hsieh eight risk factors.

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

It is not surprising that the SP score is associated with better performance and smaller, less volatile investor flow. After all, higher SP scores indicate better fund governance and lower operational risk, which could cause improvement in fund's long-term, but not necessarily the short-term performance. Better long-term performance could attract long-term investors, who may not flood massively into any fund due to sudden outperformance, but are more consistent and less volatile. 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 5 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 our previous discussion) and (2) have better performance and smaller, less volatile investor flow (see, for example, Agarwal, Daniel, and Naik (2004) and Feng, Getmansky, and Kapadia (2011)). If this were the case, the SP effect in Table 5 would be nothing new, but merely a replication of the fund size effect. Therefore, to show that the SP effect contains different information from the fund size effect, we conduct the following GLM regression, which regress a fund's overall performance and investor flow on the SP score, while controlling for fund size, as well as for other fund characteristics:

$$PerfFlow_i = \alpha + \gamma_1 \times SP_i + \gamma_2 \times OS_i + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \qquad (3)$$

In this model, the dependent variable, $PerfFlow_i$ is Fund i's performance or flow measure; the independent variables include SP_i, Fund *i*'s SP score, OS_i, Fund i's OS score, and $Characteristic_{i,k}$, Fund *i*'s *k*th characteristic. Following Brown et al. (2008) and OS, we 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), and Flow (mean of Fund i's monthly investor flows). The fourth measure is a 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, we expect to see that higher SP scores are related to higher bars to new investment. For the independent variables, in order to show the similarities and differences between the SP and the OS scores, notice that we also include the OS score in the independent variables. We control for fund size, age, domiciliation, and investment strategy in this analysis.

[Insert Table 6]

If the SP effect contains different information from the fund size effect, we should expect that, after controlling for these factors, the SP effect found in Table 5 would disappear. The GLM regression results in Panel A of Table 6 further confirm that, even after controlling for fund size and other fund characteristics, higher SP scores are still significantly related to better overall performance and lower investor flow. Besides, we 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. The median value of minimum investment requirement in our sample is \$4,013,998, so at this level, this 0.08 increase in Log (Min Inv) would mean an \$811,889 (about 20%) rise in the minimum investment requirement. This phenomenon 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.[22]

Moreover, Table 6 also confirms that including the SP score is important in explaining fund performance and investor flow. To be specific, in Panel B we repeat the analysis in Panel A but using this model:

$$PerfFlow_i = \alpha + \gamma_1 \times OS_i + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \tag{4}$$

Notice that, compared to Equation (3), we only include the OS score in the independent variables this time. For Panel B to Panel A, the adjusted R-squareds increase and the Akaike information criterion

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

values decrease, suggesting that including both scores provides a better model than using just the OS score.

4.4. Future Performance

Our Future Performance Hypothesis is that using more Well SPs can help predict better fund performance in the future. In order to test this hypothesis, we conduct an out-of-sample test on the relationship between the SP score and fund performance. To the best of our knowledge, this research is the first one that examines whether a hedge fund's SPs can affect its performance in the future. We expect that higher SP scores lead to better future performance. A truly out-of-sample test would require studying fund performance after a fund has reported its SP information. Unfortunately, it is not possible to conduct such a test, because the TASS database does not have the dates when a hedge fund reports its SPs.

However, we can work around this shortcoming, because the hedge funds in this database are believed to update their SP information to the most recent audit date.[23] 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. And because auditor is a key SP category, it is reasonable to believe that when funds update the audit information in TASS, they also update the information of other SPs. Therefore, we define a fund's report date of the SP information as its most recent audit date, and the time period after this date is considered the out-of-sample period.

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

$$Perf_{i,t1_i} = \alpha + \gamma_1 \times SP_{i,t0_i} + \gamma_2 \times OS_{i,t0_i} + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i, \qquad (5)$$

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

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

We control for fund characteristics such as fund size, age, domiciliation, and strategy. And we only consider live funds, because we are only interested in seeing, as of right now, whether a fund's current SP score predicts its future performance, not such a predictability a number of years ago. The dependent variables considered in this out-of-sample test 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. Again, for the independent variables, to show the similarities and differences between the SP and the OS scores, we also include the OS score.

[Insert Table 7]

Panel A of Table 7 reports the main results, which verify our Future Performance Hypothesis. There are two patterns worth noticing. First, higher SP scores lead to higher, less volatile future performance. This pattern is statistically significant and consistent across all performance measures. 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, our SP score provides a more accurate measure of hedge funds' SPs. Therefore, the results suggest that it is the SPs, not the OS score or any fund characteristics it considers, that help predict future performance.

We replicate the analysis in Panel A using a different model:

$$Perf_{i,t1_i} = \alpha + \gamma_1 \times OS_{i,t0_i} + \sum_{k=1} \beta_k \times Characteristic_{i,k} + \varepsilon_i. \tag{6}$$

We report the results of this model in Panel B. Notice that the only difference between Models (5) and (6) is that Model (6) 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 rise from Panel B to Panel A, and the Akaike information criterion values drop.

Even though previous literature suggests that it is difficult to investigate future performance of hedge funds (see, for example, Li, Zhang, and Zhao (2011)), the results in Table 7 demonstrate that the SP score is useful in predicting future fund performance. To the best of our knowledge, the SP score is by far the only measure that is both related to fund governance and future fund performance.

5. Robustness Checks

The TASS database does not provide historical information of a fund's SPs, but only the most recently reported information. That is to say, so far our research is built on the assumption that a fund's appointment of SPs remains unchanged over its entire life cycle. If hedge funds tended to change SPs significantly during the life cycle, then the SP information we obtain from TASS would be of little use. Hence, it is logical to argue that a fund could change SPs significantly over time. Especially, one concern is that a hedge fund tends to change SPs as it grows larger, 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 undermine this study.

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

$$Size\ Growth_i = \frac{Fund\ Size_{i,last\ month} - Fund\ Size_{i,first\ month}}{Fund\ Size_{i,first\ month}}. \tag{7}$$

This rate measures how much a fund's size has grown from its first month to its last month in the TASS database. Next, we divide funds into terciles based on this rate: the Low, Median, and High size growth terciles, where the Low tercile includes funds with the least change in fund's size, and the High tercile includes the largest.[24] Finally, we repeat the analyses in Table 4 and Table 6 (for the Fund Characteristics Hypothesis and the Performance and Flow Hypothesis, respectively). If the above concern were realistic, then we would see that only the Low tercile has results similar to Table 4 and Table 6, and the Median and High terciles have very different results.

[Insert Table 8]

However, all three terciles show very similar patterns to those in Table 4 and Table 6.[25] As reported in Table 8, for all three terciles, higher SP scores are significantly associated with (1) larger fund size, (2) smaller fund age, (3) offshore domiciliation, (4) better overall performance, (5) lower and less volatile investor flow, and (6) higher requirement of minimum investment. Thus, the concern does not pose a serious threat our results are robust across different levels of asset growth, suggesting that hedge funds tend to keep using the same SPs over time.

This find is also supported by a considerable body of accounting literature, which suggests that large institutions are unlikely to change SPs over time. For example, Beattie and Fearnley (1995),

[24] 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.

[25] For simplicity, we only report the replication results of Panel A of Table 6.

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 after switching to another auditor, and large clients' agency concerns. Although the focus of these papers is on auditors, it is reasonable to conjecture that such stability also applies to other SP categories. In summary, it is unlikely for hedge funds to change SPs considerably over their life cycles.

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 performance and a number of key characteristics. Focusing on share-restricted funds, we find that using well-known SPs is associated with larger fund size, younger fund age, offshore domiciliation, better overall performance, and smaller and less volatile investor flow, and it is also related to better future performance. For example, using one more Well SP is associated with a 12 basis point increase in overall annual returns and a 48 basis point increase in future annual returns, ceteris paribus. We also provide evidence that our 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 performance and characteristics. Therefore, it offers a new perspective that could assist investors, as well as regulators, to prevent hedge fund fraud. Our research could be further extended by conducting similar studies across multiple databases.

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Table 1. Well-Known SPs for the Hedge Fund Industry

This table lists the Well SPs for the hedge fund industry, based on each SP's number of hedge fund clients. Well SPs are defined as those with at least 100 clients. The TASS database includes four SP categories: legal counsel, prime broker, auditor, and administrator. Each of them 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 2. Summary Statistics of the SP Score and OS Scores

This table reports the summary statistics of each fund's SP score (an integer from 0 to 4) and OS score (an integer from 0 to 5). Funds are divided into categories based on fund characteristics. *Onshore* and *offshore* denote that funds are domiciled within the U.S. and 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.) 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 scores. We 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 3. 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 in the *Actual Rankings*, 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 2. We 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 4. 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, SP_i is Fund *i*'s SP score, and $Characteristic_{i,k}$ ($k = 1,2,3,4$) 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. We 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 5. Categorical Analysis of the SP Score, Performance, and Flow

This table presents the categorical analysis results of the SP score, overall performance, and investor flow. 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, we 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. We 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 6. 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

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

$PerfFlow_i$ is Fund i's performance or flow measure, SP_i is Fund *i*'s SP score, OS_i is Fund i's OS score, and $Characteristic_{i,k}$ ($k = 1,2,3,4$) 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 4. *Adj* R^2 is the adjusted R-squared of the model.[26] *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. We 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 (%)			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 R^2 (%)	7.99			7.48			1.85			8.18		
AIC	18180.22			29932.04			20922.41			23557.14		

[26] We follow Shtatland, Moore, and Barton (2000) to calculate the adjusted R-squared.

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 R^2 (%)	7.97			7.34			1.79			7.88		
AIC	18184.20			29981.53			20935.53			23634.83		

Table 7. 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, $t0_i$ denotes that this variable is observed on Fund i's most recent audit date, and $t1_i$ denotes that it is calculated using the monthly returns after that date. $Perf_i$ is Fund i's performance variable, SP_i is Fund *i*'s SP score, OS_i is Fund i's OS score, and $Characteristic_{i,k}$ ($k = 1,2,3,4$) 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 4. *Adj* R^2 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. We 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 R^2 (%)	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 R^2 (%)	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 8. 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 4 across the terciles, respectively. Panels D-F repeat the analysis in Table 6 across the terciles, respectively. The description of these panels can be found in Table 4 and Table 6, 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 R^2 (%)	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 R^2 (%)	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 R^2 (%)	9.26			9.18			1.72			12.64		