The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance

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Abstract

Basic economic principles suggest that a well-known trading strategy offers little economic profit. In this paper, we investigate whether skilled hedge fund managers are more likely to pursue unique investment strategies that result in superior performance. We propose a measure of the distinctiveness of a fund's investment strategy based on historical fund return data. Specifically, we examine the extent to which a fund's returns differ from those of its peer funds. We call the measure the "*Strategy Distinctiveness Index*" (*SDI*). The higher the *SDI,* the more distinctive is a fund's strategy. We document substantial cross-sectional variations as well as strong persistence over time in funds' *SDI*. Our main result indicates that, on average, a higher *SDI* is associated with better subsequent performance. Funds in the highest *SDI* quintile significantly outperform funds in the lowest quintile by about 3.5% in the subsequent year after adjusting for risk.

I. Introduction

Investors pay high fees for hedge fund performance.[1] Basic economic principles suggest that only unique investment ideas are likely to generate superior performance because any potential abnormal return resulting from a well-known and heavily traded strategy is likely to be competed away. Therefore, identifying fund managers with unique investment ideas is crucial for hedge fund investors. In this study, we make an initial attempt to estimate the uniqueness and distinctiveness of a fund's investment strategy. Further, we examine whether a distinctive investment strategy is an indicator of greater managerial talent, and hence superior fund performance. Our empirical findings contribute to the growing literature on the cross-sectional determinants and predictors of hedge fund performance.[2] The findings also provide new evidence on the effects of arbitrage activities on asset prices.

Economic theory suggests that unique investment ideas are important for delivering superior performance. The "zero-profit" condition for a competitive economy suggests that "enough money chasing a given pattern in returns will necessarily eliminate that pattern."[3] The Arbitrage Pricing Theory (APT) also predicts that arbitrage in expectations has diminishing returns to scale. The model of Berk and Green (2004) further indicates that diminishing returns to scale can reconcile the lack of average outperformance by mutual funds with the existence of managerial skill. Recent empirical studies of mutual funds provide evidence that it is difficult for funds to

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[1] Research on hedge fund performance in general suggests that hedge funds deliver positive excess returns, while the evidence on performance persistence has been rather mixed. See for example, Ackermann, McEnally, and Ravenscraft (1999); Agarwal and Naik (2000 and 2004); Brown and Goetzmann (2003); Brown, Goetzmann, and Ibbotson (1999); Brown, Goetzmann, Liang, and Schwarz (2008); Fung and Hsieh (1997, 2000, 2001, 2002); Goetzmann, Ingersoll, and Ross (2003); Griffin and Xu (2009); Ibbotson and Chen (2006); Jagannathan, Malakhov, and Novikov (2006); Kosowski, Naik, and Teo (2007); and Liang (1999, 2000).

[2] Recent papers on cross-sectional determinants of hedge fund performance include Agarwal, Daniel, and Naik (2009); Aggarwal and Jorion (2009); Aragon (2007); Li, Zhang, and Zhao (2011); Liang and Park (2008); Malkiel and Saha(2005);and Titman and Tiu (2011).

[3] See Stein (2009).

scale up their unique strategies.[4] Consistent with the "zero-profit" condition, recent papers show that profitable ideas are likely to be guarded by investors and stay localized, while less valuable investment ideas tend to be shared more widely.[5]

Developing unique ideas is especially important for hedge fund managers, among whom competition has intensified over the past 20 years due to the vast growth of the industry.[6] The notion of diminishing returns to scale suggests that the fierce competition would quickly reduce a strategy's economic profit as it becomes well known. Therefore, fund managers need to continually exploit new investment ideas to generate superior performance. Anecdotal evidence indicates that hedge fund managers are concerned about the commonality in the investment approach and protect their unique investment ideas by all means.[7,8] Developing effective new trading strategies, however, is costly and requires skill. Thus skilled managers are more likely to generate and pursue unique investment strategies that will result in superior performance, while less skilled managers are more likely to trade on known strategies. Following this hypothesis, we should observe a positive relation between distinctiveness in fund strategy and fund performance.

Moreover, hedge fund managers who pursue distinctive strategies may be less subject to negative externalities owing to the "crowded-trade" effect and the leverage effect, both of which are elaborated in Stein (2009). The "crowded-trade" effect occurs when an arbitrageur faces

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[4] See for example, Chen, Hong, Huang, and Kubik (2004); Pollet and Wilson (2008); and Wahal and Wang (2011).

[5] See Stein (2008) and Gray and Kern (2010) for theoretical and empirical evidence.

[6] The total assets under management of funds reporting to the Lipper TASS database have grown from $50 billion in 1994 to $1.2 trillion in 2009.

[7] Mark Carhart, a former manager of Goldman Sachs' Global Alpha Fund, commented on the economic crisis in 2007 and 2008 during an interview: "Probably the most important lesson was the magnitude of commonality in the investment approach we followed across the broader investment community. Success in quant investing in the future will hinge on developing unique ideas that are differential from competitors." (http://www.chicagomaroon.com/2010/4/23/uncommon-interview-with-mark-carhart)

[8] Related to the issue of protecting private information, the hedge fund industry strongly opposed the 2004 Securities and Exchange Commission disclosure requirement. In 2006, D.C. Circuit Court of Appeals vacated the new rule. In addition, hedge funds frequently file trade-secrets lawsuits against former employees for using the funds' proprietary trading strategies.

additional price uncertainty due to the inability to know how many others are using the same model and taking the same positions as the arbitrageur. The leverage effect occurs when traders follow the same set of signals and buy the same assets using leverage; they may incur significant losses in asset value if one of their peers holding similar portfolios is hit with a negative shock and is forced to liquidate the assets in a fire sale. These negative externalities associated with funds using similar trading strategies increase the risk of those strategies and may cause ex-ante profitable investment strategies to lose money ex post.

At the same time, a positive association between the distinctiveness of hedge fund strategies and future performance may be dampened or reversed by counteracting mechanisms. Unskilled managers may take excessive idiosyncratic risk due to a potential conflict of interest between fund managers and investors. For example, the option-like feature of the hedge fund manager's compensation contract may create an incentive for fund managers to make idiosyncratic bets in the hope of achieving extreme performance.[9] Funds that pursue such a gaming strategy would appear to be distinctive from their peers yet with no superior performance. Another counteracting mechanism is rooted in the limits of arbitrage. For example, when individual arbitrageurs face capital constraints, coordination and synchronization among multiple arbitrageurs may be necessary to successfully correct mispricing.[10] Therefore, hedge funds that do not coordinate with their peers may suffer temporary yet significant losses, especially in circumstances when the noise trader risk is high, such as bubble periods. In these cases, we would expect a negative relation or no relation between distinctiveness in fund strategy and fund performance.

This study empirically investigates the relation between strategy distinctiveness and future fund performance. We start by proposing a measure based on historical fund returns. Specifically, we

[9] See Goetzmann, Ingersoll, and Ross (2003).
[10] This is discussed in Abreu and Brunnermeier (2002) and is referred to as synchronization risk.

examine the correlation of individual hedge fund returns with the average returns of peer funds in the same style category. In this context, we term (1 minus correlation) the "*Strategy Distinctiveness Index*" (*SDI*). The *SDI* measures the extent to which a fund's returns differ from those of its peers. The higher the *SDI*, the more distinctive is the fund's investment strategy. We then examine how the *SDI* relates to fund performance and other fund characteristics.

In our main analyses, we define fund investment styles by clustering historic returns using a procedure similar to that used by Brown and Goetzmann (1997, 2003). The clustering method groups funds with their closest cohort by minimizing the sum of the distance of all funds to the corresponding clusters. The partition of funds is based on a systematic and quantitative approach rather than predefined categories. As suggested by Brown and Goetzmann (1997, 2003), the statistical approach precludes possible misclassification of fund styles due to strategic self-reporting. The clustering method also allows for time-varying grouping, as some funds may change investment strategies over time. In the section on robustness tests, we repeat the analyses using the predefined Lipper TASS styles.

Using monthly return data on about 3,900 hedge funds covered by the Lipper TASS database over the period from January 1994 to December 2009, we construct the *SDI* for individual funds. For the sample of funds, we control for survivorship and backfill biases to the extent that the data allow. We document a substantial cross-sectional variation in the *SDI*, indicating that some funds follow innovative investment strategies, while others tend to follow the herd. We also find strong persistence in individual fund *SDI* over time. This finding suggests that the *SDI* is likely driven by systematic fund characteristics, such as innovative managerial skills, that tend to persist over time, rather than by noise or transitory factors. Further, we find that the *SDI* is related to a number of fund characteristics. For example, high *SDI* funds are younger and smaller and have higher incentive fees. Moreover, the *SDI* increases with lagged performance and decreases with lagged idiosyncratic volatility of fund returns. These results are consistent with the skill hypothesis mentioned earlier - that skilled managers are more likely to pursue unique investment strategies resulting in superior performance, while less-skilled managers are more likely to trade on known strategies.

Our main test concerns the relation between the *SDI* and fund performance. We form portfolios of hedge funds based on their *SDI* levels and examine the subsequent performance of these portfolios. Consistent with the skill hypothesis, we find that the *SDI* helps predict future fund performance. Funds with more distinctive strategies tend to perform consistently better after adjusting for differences in their risks and styles. Specifically, when we sort funds into portfolios based on the *SDI* and hold them for a year, the highest *SDI* quintile outperforms the lowest by 3.5% per year in abnormal returns. The return difference between the two portfolios is statistically and economically significant.

Next, we examine the relation between the *SDI* and future fund performance using a multivariate regression approach. Specifically, we use both panel regressions with clustered standard errors as well as time and style fixed effects, and the Fama-MacBeth regressions with heteroscedasticity and autocorrelation adjusted (HAC) standard errors. Controlling for other fund characteristics, we confirm the positive relation between a fund's *SDI* and its subsequent performance in the multivariate regression setting.

We further examine the robustness of our results. First, we investigate whether the performance predictability of the *SDI* is driven by the hypothesis that more informed managers choose to hedge away systematic risks. As shown by Titman and Tiu (2011), funds with low R-square of returns on a set of systematic risk factors display better performance. We find moderate correlation between the *SDI* and the R-square measure. Furthermore, the portfolio sorting and regression results suggest that the *SDI* measure predicts future performance beyond the hedging effect.

Second, we examine whether the outperformance of the low *SDI* portfolio by the high *SDI* portfolio is attributable mainly to survivorship bias. We find a 3% difference in the dropout rate between the lowest and highest *SDI* quintile portfolios (18% and 21%, respectively) one year after portfolio formation. We use both the Heckman correction and back-of-the-envelope calculations to show that the differences in the dropout rate and the potential return bias are unlikely to explain away the outperformance by the high *SDI* portfolio.

Finally, we investigate whether our results hold up to alternative specifications of the strategy distinctiveness measure, and we consider an alternative method to control for backfill bias. The results are consistent with the main analysis.

The remainder of the paper is organized as follows. Section II discusses the related literature. Section III introduces the data. Section IV defines the *SDI* and examines its properties and determinants. Section V presents the empirical findings on the relation between the *SDI* and future fund performance as well as robustness tests. Section VI concludes.

II. Related Literature

Despite the importance of distinguishing skilled hedge fund managers from unskilled ones, research on the cross-sectional determinants of hedge fund returns has been rather limited until several recent papers started linking hedge fund performance to various fund and managerial attributes. Aragon (2007) and Liang and Park (2008) find that funds with more stringent share restriction clauses offer higher returns. Agarwal, Daniel, and Naik (2009) show that funds that offer their managers greater incentives and discretion in trading display superior performance.

Aggarwal and Jorion (2009) document strong outperformance by emerging hedge fund managers, especially during the first two to three years of fund existence. Li, Zhang, and Zhao (2011) find that both the educational background and work experience of managers are related to hedge fund performance. The study most related to this one is by Titman and Tiu (2011). They argue that skilled managers choose to hedge, and show that funds with lower R-squares with respect to systematic risk factors subsequently outperform those with higher R-squares. In the robustness section, we examine whether the *SDI* measure has additional predictive power for performance beyond the hedging effect.

The existing literature examining the effect of innovative managerial talent and distinctive fund strategy on fund performance has primarily focused on the mutual fund sector. Kacperczyk, Sialm, and Zheng (2005) argue that mutual fund managers may decide to deviate from a well-diversified portfolio and concentrate their holdings in industries in which they have informational advantages. Their results confirm that more concentrated funds perform better, after controlling for risk and style differences. In a related paper, Cremers and Petajisto (2009) propose a measure of Active Share for individual mutual funds to capture the share of portfolio holdings that differ from the benchmark index. They find that funds with the highest Active Share values significantly outperform their benchmark, both before and after expenses. In addition, several related papers propose to evaluate mutual fund performance by their use of public information (Kacperczyk and Seru, 2007), similarity of holdings to star funds (Cohen, Coval, and Pastor, 2005), and the effect of unobserved actions (Kacperczyk, Sialm, and Zheng, 2008).

In this study, we try to estimate the distinctiveness of a hedge fund strategy, a previously unstudied aspect of managerial quality. This task is especially important and challenging for hedge funds. First, hedge fund managers conduct their trading operations amid great secrecy, offering little disclosure in order to protect their investment ideas. Second, the rapid growth of the hedge fund industry has resulted in a wide range of strategies and a huge number of funds run by managers with diverse investment backgrounds and qualifications. Our paper attempts to assess the uniqueness of hedge fund strategies by analyzing the limited fund information in the public domain.

III. Data and Performance Measures

The hedge fund data are from the Lipper TASS database, recognized as one of the leading sources of hedge fund information. The main data include monthly hedge fund returns, as well as fund characteristics. We start with a total of 14,058 funds, including both live and graveyard funds. Then, following Aragon (2007), we filter out non-monthly filing funds, funds denoted in a currency other than US dollars, and funds with unknown strategies, leaving us with 8,808 unique funds. We also filter out observations before 1994 and after 2009, which yields 8,774 unique funds. To control for backfill bias, we further exclude the first 18 months of returns for each fund, yielding 7,834 unique funds.[11] We then filter out funds of funds (FoFs), reducing our sample to 6,012 funds.[12] To reduce the noise in the fund distinctiveness measures, we exclude funds with fewer than 12 monthly returns within each preceding 24-month period, leading to a sample of 4,814 unique funds. Finally, we filter out funds with assets under management *(*AUM*)* of less than 5 million dollars, resulting in a final sample with 3,896 unique funds.

[11] We also consider an alternative approach to controlling for backfill bias by removing returns before a fund joins the TASS database, following Aggarwal and Jorion (2009). The results are reported in the Robustness section, V.C.4.

[12] Our *SDI* measure may not work well to predict future performance for FoFs. First, overlapping holdings of the underlying hedge funds may reduce the spread of the *SDI* across FoFs, which is confirmed in our unreported analysis, available upon request. Furthermore, superior FoFs may invest in similar underlying hedge funds; therefore, there is a counteracting effect against finding a positive link between the *SDI* and FoFs' performance. In an unreported analysis, we find no significant association between the *SDI* and FoFs' performance. The results are available upon request.

TASS groups these hedge funds into 10 self-reported style categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity hedge, managed futures, and multi-strategies. One-third of our sample funds are in the long/short equity hedge category. There are fewer than 30 funds in the dedicated short bias category. The rest of the sample is relatively evenly distributed across the remaining eight hedge fund categories.

The abnormal performance of a hedge fund is measured relative to certain benchmarks. Given the wide use of derivatives and dynamic trading strategies among hedge funds, the standard CAPM model cannot adequately capture the risk-return tradeoff for hedge funds. Therefore, we consider a few alternative choices as performance benchmarks. For our main results, we use the Fung and Hsieh (FH) 7-factor model (Fung and Hsieh, 2001),[13] which includes an equity market factor, a size spread factor, a bond market factor, a credit spread factor, and trend-following factors for bonds, currency, and commodities.

In addition, we use a modified appraisal ratio of Treynor and Black (1973), calculated by dividing the mean of the monthly abnormal returns by their standard deviation. Brown, Goetzmann, and Ross (1995) show that survivorship bias is positively related to fund return variance. Thus, the higher the return volatility, the greater the difference between the ex-post observed mean and the ex-ante expected return. Using the alpha scaled by the idiosyncratic risk as our performance measure mitigates such survivorship problems. Agarwal and Naik (2000) further point out that this measure is particularly relevant for hedge funds, given that it also accounts for differences in leverage across funds.

[13] http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

Moreover, we calculate the monthly Sharpe ratio to capture the risk-return tradeoff of hedge fund performance. It is defined as the ratio between the average monthly net fee returns in excess of the risk-free rate and the volatility in the monthly excess returns. For our main tests, we consider the smoothing-adjusted Sharpe ratio to control for illiquidity and smoothing in hedge fund returns, following Getmansky, Lo, and Makarov (2004). Details of the adjustment are provided in Appendix A.

Finally, we calculate the manipulation-proof performance measure (MPPM) as in Ingersoll, Spiegel, Goetzmann, and Welch (2007). The authors show that popular performance measures such as the alpha and Sharpe ratio can be gamed, and a non-skilled fund manager may appear skillful based on these measures. They propose a manipulation-proof measure based on historical hedge fund returns as follows:

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

Where T is the total number of observations over the performance evaluation period, Δt is the length of time between observations (i.e., 1/12 for our monthly return sample), r_t is a hedge fund's rate of return for month t , and r_{ft} is the risk-free rate at month t. ρ can be viewed as a relative risk-aversion coefficient, to make holding the benchmark portfolio optimal for uninformed managers. The authors estimated that ρ is between 2 and 4 if the CRSP value-weighted return is the benchmark portfolio. Our test results are qualitatively similar when we use ρ = 2 to 4 respectively. For brevity, we report results using ρ = 3 in the tables.

IV. Hedge Fund *SDI*

The goal of this study is to investigate whether a distinctive investment strategy reflects innovative and skillful managerial talent and is thus capable of predicting superior future performance. To measure the distinctiveness of a fund's investment strategy, we compare its historical returns with the average returns of its peers.

A. Quantifying Hedge Fund Strategy Distinctiveness

If a manager is skillful, she is likely to engage in an innovative and unique trading strategy, thereby delivering performance that co-moves less with the overall performance of the hedge fund sector, or with the performance of the specific style to which her fund belongs. This suggests an intuitive measure to capture the distinctiveness of a fund strategy: 1 minus the sample correlation of a fund's return (r_{it}) with the average return of all funds belonging to the same style (μ_{It}):

$$
\begin{aligned}
SDI_i &= 1 - corr(r_i, \mu_I) \\
&= 1 - \frac{\sum_{t=1}^{24}(r_{it} - \bar{r}_i)(\mu_{It} - \bar{\mu}_I)}{\sqrt{\sum_{t=1}^{24}(r_{it} - \bar{r}_i)^2 \sum_{t=1}^{24}(\mu_{It} - \bar{\mu}_I)^2}}
\end{aligned}
\quad (1)
$$

where $\mu_{It} = \frac{\sum_{i \in I} r_{it}}{count(i \in I)}$. The *SDI* ranges between 0 and 2 in theory. Graphically, *SDI* can be viewed as a "distance" measure: the higher the *SDI*, the farther a fund is from its cluster and the more distinctive the fund's strategy.

To gauge how distinctive a fund's strategy is from its cohort, we first need to define hedge fund styles appropriately. Although TASS offers a classification scheme of 10 styles based on survey and voluntary reporting of hedge fund managers, this classification has a number of limitations.

First, the TASS style classification is based on voluntary self-reporting. This process may be error-ridden and possibly subject to managerial manipulation. Despite the lack of direct evidence, we have designed a test that sheds light on this issue. The premise of our test is that if the TASS classification is accurate, we would expect returns of a fund to have the highest R^2 (or correlation) with the self-reported TASS style index returns. For each hedge fund, we estimate the R^2 (or correlation) of returns associated with each of the 10 TASS style indices using the whole time series. The index yielding the highest R^2 (correlation) is identified as the "best fit index" for that fund. We then calculate the fraction of hedge funds whose "best fit index" coincides with its self-reported TASS style index. The more accurate the TASS style classification is, the higher the fraction is expected to be. Our results show that only 36% (40%) of funds turn out to have a self-reported TASS style index that is the same as its "best fit index" based on R^2 (correlation). This evidence substantiates our concern about misspecification in the self-reported TASS styles.

Second, the TASS database only provides the most recent snapshot for fund style and characteristics. Therefore, we are unable to examine if, and to what extent, hedge funds' trading styles have changed over time. Ideally, if hedge fund holding and trading information were available, we could evaluate whether there is any style-switching by hedge funds. Such information, however, is unavailable. Therefore, we have designed another test to examine the stability of the "best fit index" for each fund. Specifically, at each quarter for each fund, we use a rolling window of 24 months to estimate the R^2 (correlation) of individual fund returns with each of the 10 TASS styles. We identify the "best fit index" for the fund that yields the highest R^2 (correlation) in that quarter. If the "best fit index" for a fund changes over 2 consecutive quarters, we consider this to be a style switch. We count the number of times a fund changes styles, then average across funds. We find that, on average, 31% (27%) of the time, a fund switches its style over time. This evidence suggests that the latest snapshot of the TASS styles may not be the most accurate in capturing the true investment and trading style for individual funds over time.

Third, and perhaps most problematic, funds with broadly defined styles may appear more distinctive than those with narrowly defined styles, not because they *are* more distinctive, but because they are more widely dispersed within the broadly defined style. In this case, the difference in the *SDI* measure may reflect the style difference. In Table B1 of the Appendix, we compare the distribution of the *SDI* for each style and find large variations across TASS styles. For example, the average *SDI* for the dedicated short bias is 0.28, while that for the equity market neutral is 0.83. This suggests a possible confounding style effect associated with the *SDI* measure based on TASS styles.

To address these issues, this paper defines styles (i.e., cluster styles) by clustering historic returns. At the beginning of each quarter, for funds with more than 12 monthly returns over the preceding 24-month period, we group them into *K* clusters, that is, *K* styles, based on the correlation of fund returns. The clustering procedure is similar to the method used by Brown and Goetzmann (1997, 2003). The goal of the procedure is to find a locally optimized partition among funds, so that it minimizes the sum of the distance of all funds to the corresponding clusters. This quantitative method, by design, groups each fund with its closest cohort and captures style-shifting by funds if it occurs. It also balances among all clusters so that the strategy distinctiveness measure is more comparable across clusters. For example, the lowest average *SDI* for a cluster is 0.30, while the highest for a cluster is 0.47. The difference of 0.17 is much smaller than the spread between TASS-based *SDI* measures. Therefore, the *SDI* based on cluster style is not as likely to be subject to the confounding style effect as the *SDI* based on TASS style.[14]

[14] In table B1 of the appendix, we also report the average R-squares and performance statistics of the style clusters and the TASS styles.

B. Properties of the Cluster Styles

To better understand the clustering results, first, we compare how much overlap exists between the statistically defined cluster styles and the self-reported TASS styles. In our study, we fix the number of clusters at 10, the same as the number of TASS styles. In Table B2 in the Appendix, we report the cross-tabulation of the cluster styles with the TASS styles. Since the self-reported styles are identified only at the end of the sample, we compare them with the end-of-sample clusters estimated based on the last 2 years of return data.[15] As seen from Table B2, the cluster styles and the TASS styles do not match perfectly. Each of the relatively narrowly defined styles, such as convertible arbitrage, dedicated short bias, emerging markets, and managed futures, tends to be concentrated in one or two clusters, which, when combined, constitute more than 50% of funds in that style. This confirms that the clustering methodology indeed groups together funds with similar strategies. On the other hand, funds in broadly defined styles such as equity market neutral, event driven, fixed-income, global macro, long-short equity, and multi-strategy spread widely across clusters. This further indicates that the TASS style classification may lump together funds that are fundamentally different, thus making it problematic to construct the strategy distinctiveness measure based on the TASS styles.

Second, we examine the stability of the clustering results. Since we update the clusters over time, funds belonging to one cluster this quarter may not necessarily be grouped together in the next quarter. However, if two funds are grouped together because of some fundamental link, then the clustering should remain relatively stable over time. We test this hypothesis by analyzing pair-wise connections between funds for each period. The results are summarized in Table B3 in the Appendix. For each year, we calculate the fraction of change in the pair-wise connections between funds, which we call the *switching rate.* We find an average annual switching rate of

[15] We also compare clusters defined based on the whole sample of returns with the TASS styles. The results are similar.

16.6%,[16] comparable with the 17.6% rate found by Brown and Goetzmann (1997) based on a mutual fund sample. The low switching rate confirms the stable grouping by the clustering procedures. We also bootstrap the switching rate under the null hypothesis that funds are grouped into clusters by random chance. The average switching rate under the null is 29.6%. Plotting the entire distribution of the null rate reveals that the sample switching rate for each year is below the 1 percentile of the bootstrapped distribution, suggesting that the clusters are significantly more stable than if they were grouped by random chance.

C. Properties of the *SDI*

In the following section, we investigate the properties of the *SDI*, based on the cluster styles.

C.1. Heterogeneity of the *SDI*

There is a clear pattern of large variation in the distinctiveness of trading strategies across hedge funds. Panel A of Table 1 reports the time-series averages of the cross-sectional summary statistics of the main variables. The *SDI* has a mean (median) of 0.32 (0.29), with a standard deviation of 0.18. The histogram presented in Figure 1A further confirms the heterogeneous pattern in the *SDI*. More than 80% of the sample funds exhibit an *SDI* lower than 0.50. The distribution is more than 15% in each of the 0.15 to 0.35 *SDI* bins, and about 10% in the 0.05,

[16] From the "best fit index" analysis in Section IV.A, we find that, on average, 31% of funds change their best fix index from quarter to quarter. However, this fraction cannot be directly compared with the switching rate of the pair-wise connection. As pointed out by Brown and Goetzmann (1997), the switching rate may be lower or higher than the style-switching rate. Two simple numerical examples can illustrate the point. Suppose there are four funds, with Funds 1 and 2 in Style A and Funds 3 and 4 in Style B at time 1. In example one, Fund 1 shifts from Style A to Style B, and all other funds remain unchanged at time 2. Then the switching rate for this case is 50% (3 out of 6 pair-wise connections change from time 1 to time 2), even though only 25% of the funds change styles. In example 2, all four funds change their styles. No pair-wise connections change from time 1 to time 2, resulting in a 0% switching rate, while 100% of the funds change styles. To compare the stability of the cluster styles and the "best fit index" styles, we calculate the same pair-wise switching rate for the "best fit index." We find an average annual switching rate of 18.5%, which is comparable to the switching rate of the cluster styles.

0.45, and 0.55 *SDI* bins. Funds scoring higher than 0.70 in *SDI* account for less than 5% of the total sample.

Figure 1B plots the histogram of the *SDI* based on the TASS styles. The mean is 0.52, considerably higher than the average cluster style-based *SDI* of 0.32. Also note that 10% of funds have a TASS style-based *SDI* greater than 1, indicating that these funds' returns are actually negatively correlated with the average returns of the funds within the same TASS styles. Overall, these patterns confirm that the clustering methodology better identifies funds with similar strategies.

A comparison of the cluster style-based *SDI* measures between the live and graveyard funds shows a similar level of *SDI*: the means of *SDI* for the live and graveyard funds are 0.31 and 0.32, respectively. Moreover, the proportion of the live and graveyard funds remains at about a 40/60 split across the *SDI* bins, as Figure 1A shows. These statistics suggest that findings on the relation between the *SDI* and fund performance are unlikely to be driven by the different levels of the *SDI* for live and graveyard funds.

In Figure 2, we examine the relative distribution of hedge funds across cluster styles in each of the *SDI* bins. The relative proportion of each cluster is stable across the bins. This finding suggests that the difference in the *SDI* measure is not driven by the difference in cluster styles, and hence, any performance difference associated with the *SDI* is also unlikely to be driven by the style difference.

To better understand how the *SDI* varies across funds with different characteristics, we report the time-series average of the pair-wise correlations between the *SDI* and the contemporaneous fund characteristics. Panel B of Table 1 yields several noteworthy points. First of all, there is a positive correlation between the *SDI* and fund performance as measured by alpha, appraisal ratio, and Sharpe ratio. Second, there is a negative correlation between the *SDI* and fund return volatility (*Vol*). Finally, younger funds, funds with a longer redemption notice period and funds with higher incentive fees tend to have a higher *SDI* in our sample.

C.2 Persistence in the *SDI*

If the deviation in hedge fund returns from its peers is driven by innovations in trading strategies and managerial skills, funds should display rather persistent *SDI* over time. For example, if a hedge fund exhibits high *SDI* in one period due to the manager's unique informational advantage or unique approach in processing information, its index level is likely to remain high in the future: managers are inclined toward their usual resources and styles, as long as the market capacity for this type of strategy has not been fully exhausted.

To examine whether the *SDI* is persistent, we sort all funds in our sample into quintile portfolios according to their lagged *SDI* measures and compute the average *SDI* for each quintile during the subsequent 3 months, 6 months, and 1–3 years. Note that the *SDI* measure is always constructed using a rolling 2-year window. Also note that there is no look-ahead bias, as we keep a fund whenever it exists within the next 3 months to 3 years. Table 2 reports the average index levels of the quintile portfolios, both at the sorting time and during the next 3 months to 3 years. The future index levels of the high *SDI* portfolios remain higher than those of the low *SDI* portfolios for all five holding horizons we considered. The difference in the *SDI* between the high and low *SDI* portfolios decreases over time, but remains economically and statistically highly significant even after 3 years, at a level of 0.20. These results suggest a strong persistence in the *SDI* measure.

D. Determinants of the *SDI*

To better understand what affects the level of distinctiveness of a hedge fund's strategy, in this subsection we examine the relation between the *SDI* and lagged fund-specific characteristics. Specially, we use a multivariate panel regression approach based on annual data, controlling for fund clustering and time and cluster-style fixed effects. The lagged fund characteristics considered include fund return volatility (*Vol*), lengths of redemption notice and lockup periods, an indicator variable for personal capital commitment, an indicator variable for high-water mark, management fees, incentive fees, fund age, natural logarithm of AUM, flow into funds, minimum investment, an indicator variable for the use of leverage, and FH 7-factor alpha over the past 2 years.

Table 3 summarizes the results, which are consistent with the overall patterns we observe from the correlation matrix in Panel B of Table 1. Specifically, the *SDI* increases with the past 2 year FH 7-factor alpha, which is consistent with the skill effect. Moreover, the *SDI* decreases with *Vol,* length of lockup period, high-water mark dummy, fund age, and fund size, while it increases with fund incentive fees, past fund flows, minimum investment, and use of leverage. The negative relation between the *SDI* and *Vol* suggests that our measure of fund performance deviation from its peers is not driven by managers making random bets and taking on excessive risk to maximize the option-like payoff. Instead, the deviation measured by our *SDI* is likely associated with managerial talents in designing and implementing innovative strategies. The results regarding fund age, size, and incentive fees are intuitive if the *SDI* reflects a talent for innovation. Managers of young funds are likely to pursue innovative ideas. Managers of small funds, being more nimble, can more readily incorporate innovations into their current practice. Higher incentive fees may better motivate managers to pursue innovative and profitable strategies. This is also consistent with the belief that more talented managers may charge higher fees.

We also study whether *SDI* captures a fund's ability to keep its trading secret. To do this, we include in the covariates an indicator variable for whether a hedge fund is required to file quarterly 13F filings about its holdings. The premise is that funds that disclose their holdings are less likely to be able to keep their strategies secret and distinctive; copycats will try to mimic their trading strategies by observing their holdings. We identify hedge fund families that report holdings by manually matching our sample to Thomson Financial CDA/Spectrum Institutional (13F) Holdings Database. We also check the starting and ending periods to pin down the exact timing of reports. We are able to identify 820 unique hedge funds managed by 250 management companies in our original sample that file holdings information. In general, these fund families may manage both equity and fixed-income funds; however, the holding disclosure is more likely to impact their equity funds, since 13F institutions are only required to report their long positions in equity and equity-like securities, such as equity options, warrants, convertible debt, etc.[17] Therefore, we separately look at funds with equity-related strategies and fixed-income strategies. For the equity- related strategies, we include long/short equity, event driven, equity market neutral, and dedicated short bias funds. As Table 3 shows, the coefficient on the disclosure variable is negative and significant for equity-related funds, while it is positive and insignificant for fixed-income funds. These results suggest that funds that are subject to holdings disclosure are less likely to have a secret or distinctive trading strategy.

V. *SDI* and Fund Performance

Until now, we have provided evidence that the *SDI* has appealing properties that are consistent with its potential of being an effective proxy for innovative managerial skills. In this section, we test the main hypothesis of the paper, that is, whether the *SDI* indeed contains valuable

[17] See http://www.sec.gov/divisions/investment/13ffaq.htm, Question #7.

information that can be used to predict future fund performance. We probe this question using both a portfolio sorting and a multivariate predictive regression approach.

A. Portfolio Sorting

To gauge the relative performance of funds with different *SDI* levels, at the beginning of each quarter we sort all hedge funds into five portfolios according to their *SDI* levels measured over a previous 24-month period. For each quintile portfolio, we compute the equally and value-weighted average buy-and-hold performance for the subsequent quarter. We also consider the performance of these quintile portfolios held for the subsequent 6 months and 1–3 years.[18]

We consider various performance measures for each quintile portfolio, including the average FH 7-factor adjusted alpha, a modified appraisal ratio of Treynor and Black (1973), the smoothing-adjusted Sharpe ratio, and the manipulation-proof performance measure. For each fund, we compute the monthly FH 7-factor alpha using a rolling estimation of the prior 24 months. We then compound the monthly alpha to derive the holding period alpha for each fund, and average across funds within each quintile to get the corresponding portfolio alphas. The appraisal ratio for each fund is calculated as the ratio between the mean of its monthly FH 7-factor adjusted returns over the holding period and the standard deviation of the monthly alphas. The Sharpe ratio is calculated in a similar way using the monthly net fee returns in excess of the risk-free rate and adjusted for smoothing as detailed in Appendix A. The manipulation-proof performance measure is calculated using monthly net fee return and risk-free rate with a relative risk-aversion coefficient of 3. We then take the average within each portfolio to derive the appraisal ratio, Sharpe ratio, and manipulation-proof performance measure of the quintile portfolios. Tables 4 and 5 summarize the time-series average of these performance measures for each quintile

[18] We consider quarterly overlapping trading strategies for holding horizons longer than 3 months so that we have sufficient observations for our tests.

portfolio, as well as the difference between the high and low *SDI* portfolios. The corresponding *t*-statistics are adjusted for heteroscedasticity and autocorrelation.

For the equally weighted portfolios, the FH 7-factor alphas increase almost monotonically with the past *SDI* measures for all five holding horizons. For a trading strategy with a one-year holding horizon, funds in the highest *SDI* quintile, in which managers tend to follow distinctive investment strategies, earn an abnormal return of 7.42% per annum, with a *t*-statistic of 7.25. Those in the lowest *SDI* quintile, in which managers tend to herd the most, on the other hand, yield a return of 3.88% each year, after controlling for the FH 7 factors. The performance difference between the top and bottom quintiles is 3.54% per annum and statistically significant. For other holding horizons, funds in the highest *SDI* quintile consistently outperform those in the lowest quintile by about 2–4% per annum, after adjusting for the FH 7 factors. To earn these return spreads, one has to set up a trading strategy going long on funds with the most innovative investment skills, and short on those most likely to herd. The long side of this trading strategy alone can actually secure a better abnormal return of 7–8% per annum for all holding horizons.

As a fund deviates from its benchmark performance, it will be exposed to idiosyncratic risk. To take into account the different levels of unique risk across our sample of funds, we use a modified appraisal ratio of Treynor and Black (1973). For the equally weighted portfolios, there is a clear tendency for the appraisal ratio to increase with the *SDI*. The difference between the top and bottom *SDI* portfolios is 0.44 with a *t*-statistic of 5.29 for a holding horizon of 3 months. When the holding horizon is extended to a one-year period, the difference in the appraisal ratio between the high and low *SDI* portfolios converges, but still remains highly significant at a level of 0.26 with a *t*-statistic of 5.48. The difference in the appraisal ratio shrinks to 0.19 and remains significant when the holding horizon is extended to 3 years.

To ensure that our portfolio sorting results are not specific to the FH 7-factor performance benchmark, we also consider the smoothing-adjusted Sharpe ratio that is based on the monthly net fee returns in excess of a risk-free rate.[19] The equally weighted portfolio Sharpe ratio increases monotonically from the lowest *SDI* quintile to the highest one for all five holding horizons. For the one-year holding horizon, the high *SDI* portfolio outperforms the low one by 0.15, significant at the 1% level. In general, the spread in the smoothing-adjusted Sharpe ratio ranges from 0.09 to 0.20 across various holding horizons and is significant at the 1% level.

Furthermore, in Table 5 we consider the manipulation-proof performance measure for the high and low *SDI* quintile portfolios. We use a bootstrap method as suggested by Titman and Tiu (2011) to gauge the statistical significance of the performance differences between the high and low *SDI* portfolios.[20] Specifically, we simulate the distribution of manipulation-proof performance measure under the null hypothesis that there is no relationship between *SDI* and fund performance. For each quarter, we randomly form 5 portfolios, each containing the same number of funds as each of the actual *SDI* portfolios. We then calculate the manipulation-proof performance measures for each of the simulated portfolios as well as the difference between high and low portfolios. We then calculate the time-series average of the performance measures for the simulated portfolios. We repeat the procedure 5,000 times to obtain a distribution. Based on the distribution of these differences, we report the *p*-value corresponding to the performance difference between the actual high and low *SDI* portfolios. The high *SDI* portfolio outperforms the low *SDI* portfolio by 2.62% per annum using the manipulation-proof performance measure, and is highly statistically significant based on the bootstrapped *p*-value.

[19] Results based on the raw Sharpe ratios yield similar findings and are available upon request.
[20] We use this method due to the concern that the distribution of the MPPM measure is not normal.

The value-weighted portfolio sorting results are qualitatively similar to the equally weighted ones. For example, based on a one-year holding period, funds in the highest *SDI* quintile significantly outperform those in the lowest quintile by 2.53% per annum, after controlling for the FH 7 factors. In general, the magnitude of the spread in the annualized FH 7-factor alpha and manipulation-proof performance measure between the value-weighted extreme quintiles is smaller than that of the equally weighted portfolios, but still remains significant except in the case of the 3-month and 6-month holding horizons. The results based on appraisal ratios and Sharpe ratios are essentially the same as the equally weighted ones, both in magnitude and in statistical significance.

B. Multivariate Predictive Regression Analyses

In this section, we further extend our analysis using a multivariate regression approach. The quintile portfolio analysis does not control for hedge fund characteristics that are known to affect future performance. For example, funds with more innovative investment strategies may be smaller than those that are likely to follow the herd. Moreover, more innovative fund managers may be offered different incentive contracts from those of go-along-with-the-crowd managers. Our previous finding that there is a positive association between the *SDI* and future fund performance may be driven by size or other fund characteristics. A multivariate regression framework can help differentiate the alternative explanations by simultaneously controlling for these different factors.

To investigate whether the *SDI* has predictive power for future fund performance after controlling for other fund-specific characteristics, we estimate the following regression:

$$AbnormalPerformance_{i,t} = c_{0i} + c_{1i}SDI_{i,t-1} + c_{2i}Control_{i,t-1} + e_{i,t} \quad (2)$$

where $AbnormalPerformance_{i,t}$ is the risk-adjusted fund performance within one year after the *SDI* is calculated. Specifically, we consider the alpha, the corresponding appraisal ratio, the smoothing-adjusted Sharpe ratio, and manipulation-proof performance measure.

We use the lagged control variables to mitigate potential endogeneity problems. The $Controls_{i,t-1}$ consist of performance volatility measured by the volatility of prior 24-month fund returns in percent (*Vol*), redemption notice period measured in a unit of 30 days, lockup months, indicator variables for whether personal capital is committed and whether there is a high-water mark requirement, management fees, incentive fees, ages of funds in years, natural logarithm of AUM, flows into funds within the last year as a percentage of AUM,[21] average monthly net fee returns in the preceding 24-month period, minimum investment, and an indicator variable for use of leverage. These variables are suggested by the existing literature on hedge fund characteristics and performance. If the distinctiveness index indeed reflects innovative and skillful managerial talent, we should expect its estimated coefficient to be significantly positive.

Our data are a time-series and cross-sectional unbalanced panel data. Given the stale price issue for hedge fund data documented by Getmansky, Lo, and Makarov (2004), the resulting alphas may be correlated over time for a specific fund; hence, we must correct for the fund-clustering effect. Moreover, hedge fund performance may also be correlated across funds at a given point in time. Therefore, we need to correct for the time effect. As Petersen (2009) shows, clustering standard error is the preferred approach in addressing the fund effect, while Fama-MacBeth is appropriate for correcting for the time effect. When both effects exist, we need to address one parametrically and then estimate standard errors clustered on the other dimension. We thus adopt two approaches. The first approach is the panel regression adjusting for both fund-clustering and

[21] To control for data errors, we excluded observations of flow higher than 1,000% or lower than –1,000%.

time and style fixed effects. The second approach is the Fama-MacBeth cross-sectional analysis with style fixed effects and the Newey-West heteroscedasticity and autocorrelation adjustment (HAC). Since there are only 14 years in our regression analysis, the annual regression, especially the Fama-MacBeth analysis, will be subject to the issue of limited statistical power. Therefore, our regressions use data of quarterly frequency.

B.1 Panel Regression

For the panel regression, we pooled the time series of all funds together to estimate Equation (2). The results are reported in Table 6, where the *t*-statistics are adjusted for fund-level clustering effect as well as time and cluster-style fixed effects. Since risk-adjusted returns better reflect managerial talent, we focus on the regression results with the FH 7-factor adjusted returns and the corresponding appraisal ratios, the smoothing-adjusted Sharpe ratios, as well as the manipulation-proof performance measure, as the dependent variables. Table 6 demonstrates that the *SDI* has an important impact on future fund abnormal performance, even after controlling for other fund characteristics.

For the panel regression of alphas, the estimated coefficient for the *SDI* is 3.35 with a *t*-statistic of 3.02, when time and cluster-style fixed effects are controlled. This implies that a one-standard-deviation increase in the *SDI* predicts an increase in the annualized FH 7-factor returns of 0.60% in the subsequent year, in the presence of a host of control variables. The signs of the coefficients for other fund characteristics are largely consistent with the existing literature. For example, the lengths of the redemption notice period and the lockup period are significantly and positively associated with future fund alpha. This corroborates the findings in Aragon (2007) and Liang and Park (2008) documenting that funds with more stringent share restriction clauses offer higher returns to compensate for illiquidity. The high-water mark dummy variable and management fees are significantly and positively related to future alpha. These results are similar to the findings by

Agarwal, Daniel, and Naik (2009) that hedge funds outperform when managers are better incentivized. AUM is negatively associated with the future alpha, consistent with the notion of performance erosion due to increased scale in the mutual fund sector, as discussed by Berk and Green (2004) and by Chen, Hong, Huang, and Kubik (2004).

The FH 7-factors cover a large span of major asset classes, allowing the model to capture the risk-return tradeoff for hedge funds with different strategies. Hence, we have chosen the FH 7-factor model as the primary benchmark to gauge abnormal returns of hedge funds thus far. However, there are alternative performance benchmarks that contain relevant factors to capture the risk-return tradeoff for hedge funds. Following Agarwal and Naik (2004), we consider as alternative performance benchmarks a model combining Carhart (1997) 4 factors and returns on the at-the-money and the out-of-the-money call and put options on the S&P 500 index. In an unreported test, the regression yields a similar effect of the *SDI* on the new alpha.

We also adopt the appraisal ratio as an alternative performance measure. The results indicate a strong positive association of the *SDI* and future appraisal ratio.[22] For example, a one-standard-deviation increase in the *SDI* will result in an increase in the FH 7-factor appraisal ratio of 0.06 when time and cluster-style fixed effects are controlled for. The effect of the *SDI* on the smoothing-adjusted Sharpe ratio is also strongly positive and significant. A one-standard-deviation increase in the *SDI* leads to an increase of 0.05 for the smoothing-adjusted SR. Finally, there is a strong positive association between *SDI* and the manipulation-proof performance measure, with a point estimate of 3.54 and a *t*-statistic of 4.41. One standard deviation increase in

[22] We exclude lagged volatility from the regressor set for the appraisal ratio and the smoothing-adjusted Sharpe ratio. Since both ratios are already scaled by volatility of alphas or excess returns, further regressing these variables on another return volatility measure may cause a mechanical negative link between them. Nevertheless, our main results on the positive association between the *SDI* and performance measures remain the same, regardless of the regression specification.

the *SDI* corresponds to an increase of 0.64% per year in the manipulation-proof performance measure, a magnitude similar to the effect on alpha.

B.2 The Fama-MacBeth Regression

Using the Fama-MacBeth approach, for each quarter, we perform the cross-sectional regression of Equation (2) together with cluster-style indicator variables to obtain the estimated coefficients. Then, we use the time series of the estimated coefficients to derive the final Fama-MacBeth regression results with the Newey-West heteroscedasticity and autocorrelation adjustment on standard errors. The results are reported in Table 7. For the regression of the FH 7-factor alphas, the estimated coefficient on the *SDI* is 3.82 with a *t*-statistic of 2.51. Since the difference in the *SDI* between the high and low portfolios up to one year post-formation falls between 0.31 and 0.50 according to Table 2, the implied difference in the FH 7-factor alpha between the extreme quintiles is about $0.31 \times 3.82 = 1.18\%$ to $0.50 \times 3.82 = 1.91\%$. The magnitude is smaller than the portfolio sorting results, but remains economically important. Overall, the results from the Fama-MacBeth analysis are consistent with those from the panel regression and the portfolio analysis.

C. Robustness

In this section, we discuss the robustness tests of our main findings. First, we investigate whether the performance predictability of the *SDI* is driven by the hedging hypothesis discussed in Titman and Tiu (2011). Second, we examine whether our results are due to a survivorship bias, resulting from the fact that no performance records are available after funds stop reporting to the TASS database. Third, we consider alternative measures for strategy distinctiveness, including the absolute correlation-based *SDI* and the TASS style-based *SDI*. Finally, we use an alternative approach to screen out back-filled data.

C.1 *SDI* and Hedging

The superior performance delivered by the distinctive hedge funds can be driven by multiple sources of skills, one of which might be related to hedging away systematic risk. Titman and Tiu (2011) show that more skilled hedge fund managers will choose less exposure to systematic risk, hence their funds will exhibit lower R-square of returns on the FH 7-factors. It is possible that the low R-square funds also tend to have high *SDI*. Therefore, we investigate whether the forecasting power of the *SDI* is a manifestation of the hedging effect.

First, we examine the correlation between the *SDI* and 1 minus *R-square* (denoted as "*1 – R2(FH)*"). The time-series average of the cross-sectional correlation is 0.57. We further examine the extent of overlapping between the two sets of quintile portfolios sorted on the *SDI* and on *1-R2(FH)*, respectively. Panel A of Table 8 shows an overlapping pattern, albeit modest, between the two sets of portfolios. On average, about 50% (48%) of funds in the lowest (highest) *SDI* quintiles also fall into the lowest (highest) quintiles sorted on *1-R2(FH)*.

Second, we exclude the overlapping funds from the *SDI* quintiles, and then repeat the portfolio analysis. For example, in this case, the lowest *SDI* quintile consists of funds with the lowest *SDI* but not the lowest *1-R2(FH)*. Panel B of Table 8 shows that for the equally weighted portfolios, under a trading strategy with a one-year holding horizon, funds in the highest quintile outperform those in the lowest one by 3.69% per annum measured by the FH 7-factor alpha. The performance difference is 0.18 and 0.07 based on the AR(FH) and the Sharpe ratio, respectively. And the high *SDI* portfolio outperforms the low *SDI* portfolio by 3.13% per annum if the manipulation-proof performance measure is considered. The value-weighted analysis yields qualitatively similar but weaker results. These findings suggest that even after taking out the hedging effect, funds with high *SDI* continue to outperform those with low *SDI*.

Finally, we include both the *SDI* and *1-R2(FH)* in the panel and Fama-MacBeth regressions discussed in Section V.B. In particular, we estimate the following model:

$$AbnormalPerformance_{i,t} = c_{0i} + c_{1i} SDI_{i,t-1} + c_{2i}(1 - R2(FH))_{i,t-1} + c_{3i} Control_{i,t-1} + e_{i,t} \qquad (3)$$

For brevity, we do not report the estimation results of the control variables in Panel C of Table 8. After controlling for *1-R2(FH)*, the coefficient on the *SDI* is reduced in magnitude for alpha and AR but remains similar for SR and the manipulation-proof performance measure.[23] Overall, the coefficient on SDI remains positive and significant for most of the specifications. Thus the performance predicting power of the *SDI* measure is beyond the hedging effect documented by Titman and Tiu (2011).

C.2 Control for Survivorship Bias

Our analysis may be subject to a typical survivorship bias problem. Although we include both live and graveyard funds in the portfolio analysis, there is no return data available after funds voluntarily stop reporting and drop out of the data set. If the dropped-out funds continue to operate and the unreported performance of these funds is substantially different from the performance of existing funds, the observed portfolio return based on existing funds would be biased. This potential bias raises the concern that the observed performance difference across the *SDI* quintiles might be due to the difference in the survival rate, rather than true performance.

We take two approaches to assess whether survivorship biases might be responsible for the cross-sectional patterns we find in fund performance. First, we analyze the dropout property of the *SDI* portfolios and gauge the impact of the potential bias on our findings via some back-of-the-

[23] Even though we include the results for alpha (FH) and AR (FH), there is a potential concern of regressing alpha (FH) and AR (FH) on 1-R2 (FH): correlated estimation errors problem may arise when the same factor model is used in both the sorting and performance evaluation stages.

envelope calculations. Second, we use the Heckman correction to explicitly control for the survivorship bias in the multivariate regression.

Panel A of Table 9 reports the survival rate for the *SDI* sorted portfolios corresponding to the ones reported in Table 2. In general, funds in the high *SDI* portfolios have a slightly lower survival rate than funds in the low *SDI* portfolios. For example, about 81.6% of the funds in the lowest *SDI* quintile remain in the data set 1 year after portfolio formation, while 78.8% of the funds in the highest *SDI* quintile remain.

To examine whether the 3% difference in the survival rate between the extreme quintiles explains away the observed performance difference across the *SDI* quintiles, we need to know the performance of the funds after they drop out. Unfortunately, such data are not readily available. Funds drop out of the database for many reasons, such as liquidations, mergers, name changes, or they voluntarily stop reporting. As a result, even the sign of the bias is not clear. We assess the potential impact of survivorship bias through the following back-of-the-envelope calculations. For each portfolio, the true risk-adjusted return can be denoted as:

$$alpha^{True} = w^{Surviving} alpha^{Surviving} + w^{Dropout} alpha^{Dropout} \quad (4)$$

The difference in the true performance between the high and low *SDI* portfolios is then given by:

$$\begin{aligned} &alpha_{Hi}^{True} - alpha_{Low}^{True} = \\ &w_{Hi}^{surviving} alpha_{Hi}^{Surviving} + w_{Hi}^{Dropout} alpha_{Hi}^{Dropout} - w_{Low}^{surviving} alpha_{Low}^{Surviving} - w_{Low}^{Dropout} alpha_{Low}^{Dropout} \end{aligned} \quad (5)$$

Since there is no direct way to measure the performance of funds after they leave the database, assuming $alpha_{Low}^{Dropout} = alpha_{Hi}^{Dropout} = alpha^{Dropout}$, we will explore at what level $alpha^{Dropout}$ would eliminate the difference in the true performance between the high and low *SDI* portfolios.

Take the equally weighted one-year post-formation case as an example. Based on Table 4A and Table 9, $alpha_{Hi}^{True} - alpha_{Low}^{True} = 0.79 \times 7.42\% - 0.82 \times 3.88\% + (0.21 - 0.18) alpha^{Dropout}$. As long as the annualized $alpha^{Dropout} \geq -89\%$ for funds one year after dropping out, the true performance of the high *SDI* portfolio beats that of the low *SDI* portfolio.

While the true performance of dropped-out funds is unobservable, the existing literature provides some clues. For instance, Ackerman, McNally and Ravenscraft (1999) report an average loss of -0.7% for terminating funds beyond the information contained in the database according to a poll by the a major hedge fund database. Noticeably, this number subjects to the self-reporting bias and needs to be interpreted with caution. In addition, Fung and Hsieh (2000) argue while individual hedge funds drop out of the database, their performance is reflected in the performance of funds of funds if they continue to be present in the market. Thus, the return of funds of funds is not subject to the "drop out" bias. Comparing the return of funds of funds with that of survived individual funds yields an implied return on the dropped-out funds of 0.14%.[24]

Second, we use the Heckman correction, a two-step statistical procedure, to correct for the nonrandom selection in the sample. We first estimate a probit model on hedge funds' survival probability over the next 12 months, then include the inverse mills ratio from the probit regression as an additional control variable in our multivariate regression analysis. Brown, Goetzmann, and Park (2001) find that hedge fund survivorship depends on net fee return, past alpha, excess volatility, and fund age. Besides these variables, we also include *SDI*, fund size, and past flow as additional explanatory variables in the probit regression. Table C in the Appendix reports the results of the first-step regression of the Heckman correction. The results are highly

[24] Table 4 of Fung and Hsieh (2000) shows that for the period 1994 to 1998, the average return on the surviving portfolio measured by individual hedge fund returns was 10.24%, and the average return on the true portfolio proxied by implied hedge fund returns using funds-of-funds data was 8.22%. Assuming the drop-out rate to be 20%, the implied return on the drop-out funds was 0.14%.

consistent with the previous studies. We find that older and larger funds with better past performance and lower return volatility are associated with a higher probability of survival. We also find that funds with higher *SDI* are more likely to drop out of the sample after 12 months. This finding confirms the need for using a Heckman correction in our multivariate regression.

We include the inverse mills ratio computed from the probit regression as an additional control variable and repeat the multivariate regression as in Tables 6 and 7. The results are summarized in Table 9, Panel B. As can be seen, after controlling for the difference in surviving probability, the coefficient on *SDI* is only slightly reduced and remains statistically significant across all specifications. This result further confirms that our findings of a positive association between *SDI* and fund performance are not likely to be driven by survivorship bias.

C.3 Alternative *SDI* Measures

C.3.1 Absolute Correlation-Based *SDI*

Under our *SDI* specification, a hedge fund may have a high *SDI* if its manager pursues unique investment ideas unrelated to known systematic factors, or if the manager "bets against the tide," i.e., taking opposing views from his peers on how to load on systematic factors. The literature on limits to arbitrage suggests that the second approach may not generate superior performance, due to noise trader risk and synchronization risk.[25] To separate out the two mechanisms, we re-cluster funds and define a new distinctiveness measure, $SDI(|corr|)$, as one minus the absolute value of the correlation. Under this specification, a manager who simply bets against the peer group funds

[25] Base on stock holdings from 1998 to 2000 for 53 hedge fund managers, Brunnermeier and Nagel (2004) document outperformance by those hedge funds that successfully timed and rode the tech bubble instead of betting against the tide and trying to correct the mispricing right away.

will not have a high *SDI* measure, while one pursuing unique strategies unrelated to systematic factors will have a high *SDI.*

We start by comparing the two *SDI* measures. First, the time-series average of the cross-sectional correlation between the *SDI* and the $SDI(|corr|)$ is 0.91. In addition, Panel A of Table 10 shows a substantial amount of overlapping between the two sets of portfolios sorted on the S*DI* and the $SDI(|corr|)$, respectively. On average, about 79% (82%) of funds in the lowest (highest) *SDI* quintiles also fall into the lowest (highest) quintiles sorted on the $SDI(|corr|)$. These descriptive statistics suggests that overall there are not many hedge fund managers consistently betting against their peer groups.

We then sort funds into quintiles based on the $SDI(|corr|)$. Panel B of Table 10 shows that for the equally weighted portfolios, under a trading strategy with a one-year holding horizon, funds in the highest $SDI(|corr|)$ quintile outperform those in the lowest quintile by 3.50% per annum using the FH 7-factor alpha. The outperformance is 0.24, 0.10 and 2.34% per year based on the AR(FH), the Sharpe ratio, and the manipulation-proof performance measure, respectively. The differences are statistically significant. The value-weighted results are qualitatively similar.

Third, we run both panel and Fama-MacBeth regressions as in Section V.B. For brevity, we do not report the estimation results of the control variables in Panel C of Table 10. The results show that the $SDI(|corr|)$ remains highly significant in predicting future hedge fund performance. Overall, the findings suggest that the *SDI* effect is not largely driven by managers "betting against the tide."

C.3.2 TASS Style-Based *SDI*

In this section, we repeat the analyses using the TASS style classifications. Despite the caveats associated with the TASS style classifications detailed in Section IV.A, these classifications are readily available and easy to incorporate. Results reported in Table 11 agree with our main findings.

First, the time-series average of the cross-sectional correlation between the two *SDI* measures is 0.63. In addition, Panel A of Table 11 shows a modest overlap between the cluster-based *SDI* and the TASS style-based *SDI* measures. On average, about 57% (55%) of funds in the lowest (highest) *SDI*(cluster) quintiles also fall into the lowest (highest) *SDI*(TASS) quintiles.

Second, as reported in Panel B of Table 11, under a trading strategy with a one-year holding horizon, the difference in the annualized FH 7-factor alpha between the equally weighted high and low TASS style-based *SDI* quintiles is 3.27%. The difference is 0.18, 0.11, and 1.96% for the FH 7-factor based appraisal ratio, the Sharpe ratio, and the manipulation-proof performance measure, respectively. These findings are consistent with the results based on the cluster styles.

Finally, results in Panel C of Table 11 show that in the panel and Fama-MacBeth regression analysis, while the *SDI*(TASS) continues to predict future alpha, its predictive power for the appraisal ratio, Sharpe ratio, and manipulation-proof performance measure are not as robust as the cluster style-based *SDI* measure. The weaker result is likely due to the confounding style effect associated with *SDI*(TASS), which motivated us to focus on a cluster style-based *SDI* in the first place.

C.4 An Alternative Method to Control for Backfill Bias

In our main analyses, we try to mitigate the backfill bias by excluding the early months of a fund's return series. An alternative method used in the literature is to exclude the returns prior to a fund's entry date into the TASS database (Aggarwal and Jorion, 2009).[26] As a robustness check, we repeat the entire analyses using the second method to control for backfill bias.

In Table 12, we report some key test results for the sample period of 1997 to 2009.[27] Using a trading strategy of a one-year holding period, the difference in the annual alpha between the equally weighted high and low *SDI* quintiles is 4.88%. The difference in the appraisal ratio, the Sharpe ratio, and the manipulation-proof performance measure is 0.25, 0.16, and 4.92%, respectively. Moreover, the results in Panel B show that in both the panel and the Fama-MacBeth regressions, the *SDI* continues to significantly predict all four future performance measures. We also note that the sample size after applying the entry date filter is smaller than that used in the previous analysis. The new analysis includes 3,622 funds and 41,415 fund-quarter observations in the main regressions, while the previous analysis consists of 3,686 funds and 53,071 fund-quarter observations. Overall, the alternative method to control for backfill bias yields similar results as our previous analyses.

VI. Conclusion

[26] In 1999, TASS sold its database to Tremont, and the consolidation of the two data sources resulted in a significant increase in the number of new funds. As a result, in 2001 many "new" funds entered the TASS database from the external source. This in turn artificially increased the observed distance between the fund inception date and the database entry date. Hence, using the entry date as a cutoff point for eliminating backfilling bias may be misleading in this case.

[27] Note that we had to exclude 1994 because the small number of funds resulting from the new entry date filter is insufficient for the clustering analysis. We use the first two years (1995 and 1996) to run the cluster analysis.

Investors want to identify talented hedge fund managers who have unique alpha-generating investment ideas. Since little information about funds' security holdings or trading strategies is disclosed to investors, assessing managerial ability is a challenging task that relies mainly on learning from funds' historical return information and managers' track records. Academic literature has studied how past fund performance relates to future fund performance. In this paper, we examine a different aspect of fund historical returns, namely the extent to which a fund's return series resembles the return series of its peer funds. We hypothesize that skilled managers with innovative ideas will herd less frequently, and thus their returns will display less resemblance to those of an average fund.

To measure the distinctiveness of a fund's investment strategy, we estimate the correlation of a fund's returns with the average returns of its peer funds. We term (1 minus correlation) the *SDI*. Using fund return data from January 1994 to December 2009, we document a substantial cross-sectional variation in the *SDI*, indicating much heterogeneity in the distinctiveness of funds' styles. We also find strong persistence in the individual funds' *SDI* for years into the future, suggesting that the *SDI* reflects persistent, fund-specific factors. Further analysis indicates that the *SDI* is related to a number of fund characteristics, for example, past fund performance, return volatility, fund age, size, the length of the redemption notice period and the lockup period, incentive fees, minimum investment, leverage usage, and disclosure of holdings.

Our main result shows that the *SDI* is associated with significantly better future fund performance. Funds with a high *SDI* tend to perform consistently better, after adjusting for differences in their risks and styles. We show this finding using a portfolio approach, a panel regression approach, and the Fama-MacBeth regression. Overall, our evidence indicates that the *SDI* is a potentially useful indicator of innovative managerial talent, and it can be used to good effect by investors in selecting funds. The findings also indicate that arbitrage in expectations has diminishing returns to scale as predicted by the APT.

Appendix A: Smoothing-adjusted Sharpe Ratio

We use the smoothing-adjusted Sharpe ratio rather than the regular Sharpe ratio. Lo (2002) points out that hedge fund returns are subject to high serial correlations that can bias the *annualized* Sharpe ratio, measured using monthly returns if autocorrelation in returns is not taken into account. Moreover, Getmansky, Lo, and Makarov (hereafter GLM, 2004) show that due to illiquidity and smoothing, the unobserved true economic returns differ from the observed smoothed returns. Therefore, even the *monthly* Sharpe ratio, which itself is based on the observed returns, will be biased. GLM (2004) further propose an econometric model of return smoothing, as well as an estimator for the smoothing-adjusted Sharpe ratio. In particular, the true return of a hedge fund R_t is determined by a linear factor model, as described below:

$$R_t = \mu + \beta\Lambda_t + \varepsilon_t, \quad \varepsilon_t, \Lambda_t \sim IID \quad \text{(A1)}$$

The true return R_t is not observable; instead we observed the smoothed returns R_t^o as follows:

$$\begin{aligned} &R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \ldots + \theta_k R_{t-k} \\ &\theta_j \in [0,1],\ j = 0,\ldots,k \quad \text{and}\ \theta_0 + \theta_1 + \ldots\theta_k = 1 \end{aligned} \quad \text{(A2)}$$

Their paper shows that the Sharpe ratio of the true unobserved return can be obtained by multiplying the regular Shaper ratio based on the smoothed return by $\sqrt{\theta_0^2 + \theta_1^2 + \ldots + \theta_k^2}$. The coefficients ($\theta_0, \theta_{1,} \ldots\theta_k$) in Equation (A2) can be estimated by the maximum likelihood method. We assume that the observed returns depend on lagged true returns up to time (t - 2). Thus, the smoothing-adjusted Sharpe ratio is

$$SR = \sqrt{\theta_0^2 + \theta_1^2 + \theta_2^2}\, SR^o$$

where SR^o is the regular Sharpe ratio calculated using observed monthly hedge fund returns.

Appendix B: More Results on Cluster Styles

Table B1: SDI and Performance across Styles (1996–2009)

Table B1 reports the time-series average of the cross-sectional mean on SDI, 1-R2(FH), and performance measures for cluster and TASS styles. SDI is constructed based on cluster styles and TASS styles in Panel A and Panel B, respectively.

Panel A: Cluster Styles

		SDI	1-R2(FH) (%)	Alpha(FH) (%pm)	SR	AR	MPPM (%p.a.)
Cluster	1	0.47	57.14	1.21	0.33	0.77	2.30
	2	0.34	50.18	0.55	0.30	0.46	2.10
	3	0.32	49.32	0.77	0.19	0.33	1.20
	4	0.35	51.72	0.60	0.25	0.45	3.70
	5	0.40	55.97	0.90	0.35	0.70	3.51
	6	0.30	48.99	0.75	0.32	0.51	1.48
	7	0.33	53.28	0.99	0.37	0.74	5.96
	8	0.35	45.61	0.62	0.28	0.45	4.48
	9	0.36	50.89	0.67	0.30	0.66	4.41
	10	0.34	51.66	0.99	0.30	0.61	3.21

Panel B: TASS Styles

	SDI	1-R2(FH) (%)	Alpha(FH) (%pm)	SR	AR	MPPM (%p.a.)
Convertible Arbitrage	0.42	56.20	0.74	0.48	0.96	4.53
Dedicated Short Bias	0.28	26.83	0.76	-0.03	0.37	-7.45
Emerging Markets	0.37	48.51	0.49	0.22	0.28	4.41
Equity Market Neutral	0.83	57.91	0.68	0.36	0.67	2.75
Event Driven	0.48	48.40	0.80	0.41	0.85	4.74
Fixed-Income Arbitrage	0.71	54.75	0.75	0.59	1.25	3.04
Global Macro	0.68	52.30	0.66	0.18	0.33	3.34
Long/Short Equity Hedge	0.48	42.44	0.78	0.22	0.34	4.22
Managed Futures	0.47	49.97	0.92	0.13	0.22	1.08
Multi-Strategy	0.67	49.92	0.75	0.41	0.81	4.73

Table B2: Cross-Tabulation of Self-Reported TASS Styles and Cluster Styles (200801-200912)

Table B2 reports the cross-tabulation of cluster styles with the styles reported by hedge funds in TASS. The TASS styles are those attributed to the funds as of December 2009. The clusters are based on hedge fund returns from January 2008 to December 2009.

TASS Style/Cluster Style	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Row Total**
Convertible Arbitrage	1	1	1	1	16	0	4	20	1	2	47
Dedicated Short Bias	0	11	0	0	0	1	0	0	0	0	12
Emerging Market	18	10	6	14	67	2	134	39	5	10	305
Equity Market Neutral	9	12	9	9	15	2	3	5	30	11	105
Event driven	18	11	1	33	85	2	9	17	11	21	208
Fixed-Income Arbitrage	2	5	5	3	17	0	2	17	1	6	58
Global Macro	19	10	22	7	4	20	16	10	12	4	124
Long/Short Equity Hedge	123	26	34	199	106	25	140	54	60	15	782
Managed Futures	3	15	20	7	4	137	4	10	12	9	221
Multi-Strategy	25	11	9	22	59	11	23	13	17	11	201
Column Total	218	112	107	295	373	200	335	185	149	89	2063

Table B3: Switching Rate of Pair-Wise Connections between Funds

Table B3 summarizes the pattern of the switching rate of fund clustering results. We study the pair-wise connection between funds based on the cluster groupings obtained at the end of each year; the connection takes the value of 1 or 0, depending on whether the two funds under study fall into the same cluster or not. We then calculate the percentage of pair-wise connections that remain unchanged from year to year. The higher the percentage, the higher the stability of clustering. Column 2 is the sample switching rate, the percentage of connections changed from the previous year clustering results. Column 3 reports the bootstrapped switching rate under the null of random grouping. The null is constructed by forming samples via random draws without replacement from actual fund returns. We follow Abraham, Goetzmann, and Wachter (1994) and Goetzmann and Wachter (1995) for the bootstrap procedure. For each round of the bootstrap procedure, we set the number of clusters and the total number of funds equal to those statistics from the real sample. The last column reports the standard deviation of the bootstrapped null distribution.

Year	Sample Switching Rate	Null Switching Rate	Std. Dev. of Null Switching Rate
1996	14.63%	29.25%	0.22%
1997	14.74%	29.50%	0.22%
1998	16.78%	29.58%	0.23%
1999	13.86%	29.75%	0.20%
2000	17.90%	29.63%	0.24%
2001	14.04%	29.60%	0.20%
2002	15.79%	29.76%	0.20%
2003	16.77%	29.82%	0.23%
2004	16.22%	29.70%	0.22%
2005	16.99%	29.80%	0.21%
2006	17.32%	29.50%	0.21%
2007	19.86%	29.54%	0.22%
2008	20.25%	29.83%	0.24%
2009	17.20%	29.60%	0.22%
Mean	16.60%	29.63%	

Appendix C: Heckman Correction - Probit Model

Table C: Hedge Fund Survivorship

Table C presents the probit regression results on hedge funds' survival probability. The dependent variable is indicator variation that takes a value of one if a fund survives till the end of the next 12 months and zero otherwise.

Variable Name	Coef.	Wald Chi_Squared	Pr>ChiSq	
SDI	-0.2743	59.88	<.0001	***
Ln(Age)	0.1233	88.73	<.0001	***
Ln(AUM)	0.1024	692.10	<.0001	***
FlowPast1Y	0.0000	0.16	0.6876	
VolPast2Y(%p.m)	-0.0042	3.54	0.0598	*
AvgPast2YRet	0.1343	536.67	<.0001	***
AlphaPast2Y	0.0024	4.66	0.0308	**
Time Fixed Effect	Yes			
#FundQtrObs	60621			

*** 1% significance; ** 5% significance; * 10% significance

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Figure 1: Histogram of Hedge Fund *SDI*

Figure 1A represents the histogram of the *SDI* based on the cluster styles for all funds for the period 1996–2009. It also depicts a breakdown between the live and graveyard funds in the distribution. Figure 1B represents the histogram of the *SDI* based on the TASS styles.

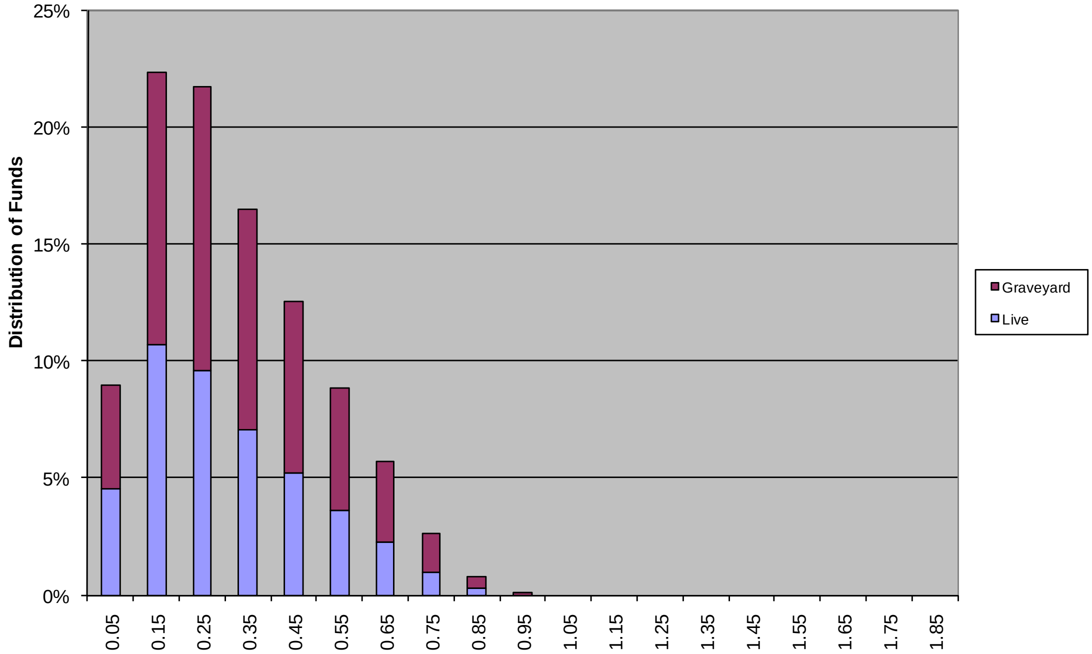

Figure 1A: SDI based on Cluster Styles

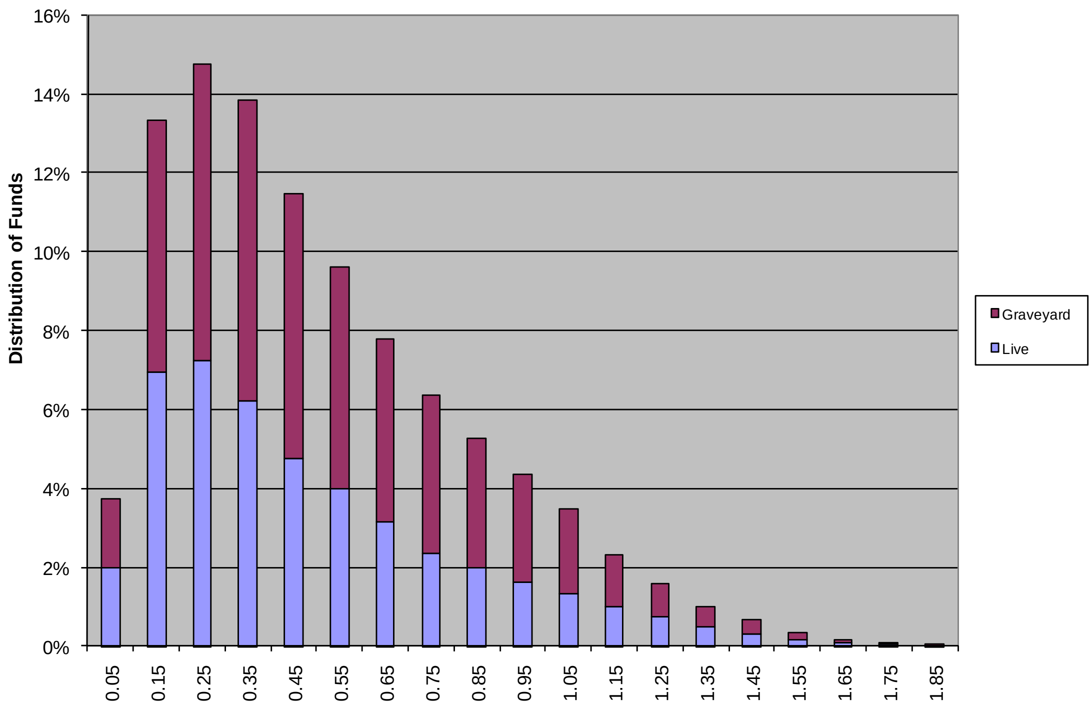

Figure 1B: SDI based on TASS Styles

Figure 2: Histogram of Hedge Fund *SDI*

Figure 2 represents the relative distribution of funds across the cluster styles for the *SDI* bins.

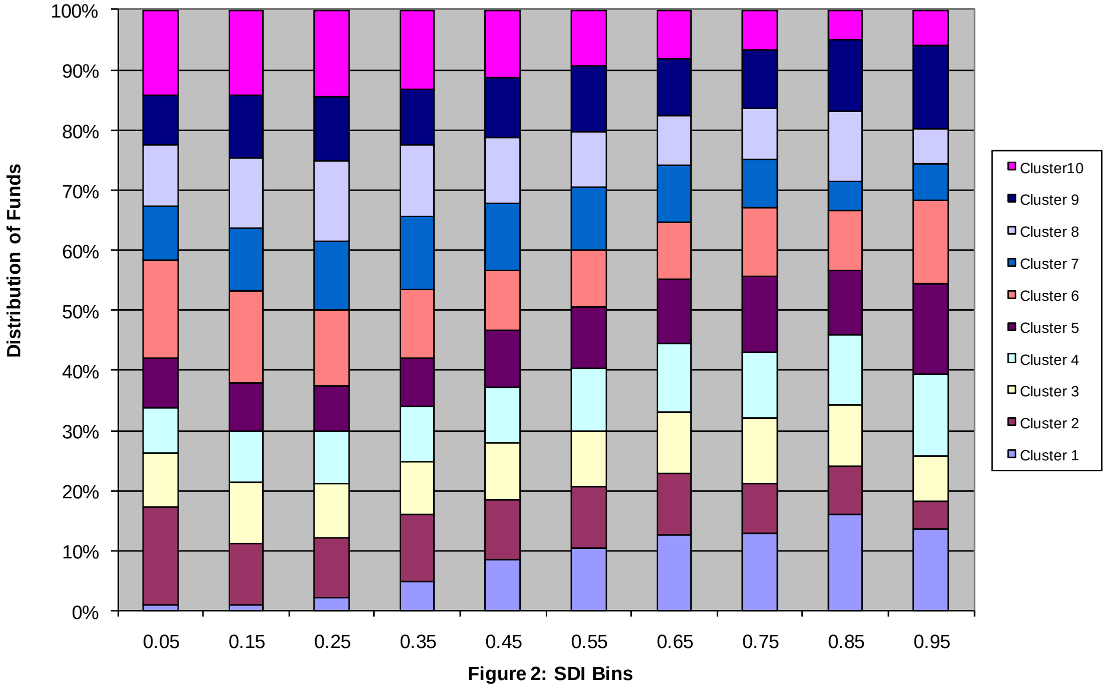

Table 1: Summary Statistics (1996–2009)

Panel A summarizes the time-series average of cross-sectional summary statistics for the main variables for the full sample, and for the live and graveyard fund subsamples. Variables considered are number of funds per period, the *SDI*, measured as (1 – correlation) from the clustering program, and contemporaneous fund characteristics including monthly net of fee returns, FH 7-factor adjusted alphas and the corresponding appraisal ratio (*AR*), Sharpe ratio (*SR*), manipulation-proof performance measure (MPPM), volatility of monthly net fee returns (*Vol*), length of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the past 12 months as a fraction of AUM, minimum investment, and an indicator variable for using leverage. Panel B reports the time-series average of the pair-wise correlation between these variables.

Panel A: Fund Performance and Characteristics

	Full Sample (3,896 unique funds)					Live Funds (1,537 unique funds)					Graveyard Funds (2,359 unique funds)				
	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std
#Funds per period	1,030	1,075	291	1,657	410	456	336	61	1,234	364	574	638	45	866	228
SDI	0.32	0.29	0.00	0.91	0.18	0.31	0.27	0.00	0.85	0.18	0.32	0.29	0.00	0.88	0.18
NetFeeRet(% p.m.)	0.99	0.74	-25.07	63.76	5.33	1.17	0.86	-17.28	24.61	4.52	0.83	0.63	-21.92	59.72	5.47
Alpha(% p.m.)	0.75	0.68	-5.99	30.34	1.78	0.84	0.75	-3.69	8.29	1.31	0.67	0.62	-5.90	29.07	1.94
AR	0.51	0.38	-1.96	7.50	0.79	0.51	0.40	-1.36	5.44	0.72	0.50	0.37	-1.87	6.94	0.83
SR	0.28	0.22	-1.21	5.42	0.44	0.29	0.25	-0.55	3.26	0.40	0.27	0.20	-1.19	4.90	0.48
MPPM (% p.a.)	3.70	3.86	-89.83	91.41	26.17	5.03	4.79	-80.40	84.55	26.55	2.08	2.55	-86.43	87.85	25.60
Vol(%p.m)	3.99	3.23	0.09	88.79	4.32	4.12	3.41	0.12	24.58	3.06	3.84	3.08	0.13	81.68	4.66
RedemptionNotice (days)	34.35	29.02	0.00	186.61	26.61	35.87	30.00	0.00	186.61	28.20	34.52	28.30	0.00	161.84	26.35
Lockup(months)	3.56	0.00	0.00	58.82	6.38	3.86	0.00	0.00	57.54	6.76	3.55	0.00	0.00	43.73	6.26
PersonalCapDummy	0.46	0.38	0.00	1.00	0.49	0.48	0.48	0.00	1.00	0.49	0.44	0.36	0.00	1.00	0.48
HighWaterMarkDummy	0.56	0.59	0.00	1.00	0.46	0.63	0.96	0.00	1.00	0.47	0.53	0.57	0.00	1.00	0.45
MgmtFee(%)	1.42	1.19	0.00	7.09	0.74	1.50	1.37	0.00	6.79	0.78	1.39	1.17	0.02	5.97	0.70
IncentiveFee(%)	18.17	20.00	0.00	49.40	5.83	19.10	20.00	0.00	35.92	4.32	17.73	20.00	0.00	47.86	6.39
Age(years)	6.63	5.62	2.50	32.07	3.78	6.91	5.88	2.51	25.71	3.90	6.53	5.48	2.50	31.98	3.80
AUM(M$)	192.47	57.88	5.00	7289.08	492.51	194.31	66.90	5.15	4086.93	393.75	211.66	53.14	5.04	7138.99	596.74
Flowpast1Y(%p.a.)	16.22	-0.66	-159.09	812.92	80.98	19.95	2.36	-108.47	659.88	77.28	13.77	-1.79	-142.78	745.35	81.28
MinInvestment(M$)	0.98	0.56	0.00	36.61	1.92	1.10	0.54	0.00	33.21	2.26	1.01	0.64	0.00	24.55	1.92
Leverage	0.64	1.00	0.00	1.00	0.48	0.71	1.00	0.00	1.00	0.45	0.61	0.96	0.00	1.00	0.49

(*continued*)

Table 1 – *continued*

Panel B: Correlations

	SDI	NetFee Ret	Alpha	AR	SR	MPPM	Vol	Redemp-tion Notice	Lockup	Personal Cap	High Water Mark	Mgmt Fee	Incentive Fee	Age	AUM	Min Invest-ment	Leverage
NetFeeRet(% p.m.)	0.01																
Alpha(% p.m.)	0.08	0.70															
AR	0.18	0.18	0.35														
SR	0.17	0.37	0.30	0.82													
MPPM (% p.a.)	0.00	0.95	0.50	0.35	0.35												
Vol(%p.m)	-0.17	0.37	0.28	-0.27	-0.24	0.00											
RedemptionNotice	0.04	0.02	0.04	0.20	0.21	0.06	-0.15										
Lockup(months)	-0.03	0.06	0.06	0.05	0.06	0.04	0.00	0.31									
PersonalCap	0.02	0.01	-0.01	-0.03	-0.02	0.01	0.03	0.04	-0.01								
HighWaterMark	0.01	0.05	0.05	0.09	0.10	0.04	-0.05	0.25	0.27	-0.08							
MgmtFee(%)	-0.02	0.06	0.06	-0.05	-0.04	-0.02	0.14	-0.18	-0.12	-0.06	-0.10						
IncentiveFee(%)	0.10	0.07	0.07	0.07	0.07	0.01	0.02	0.14	0.10	0.10	0.23	0.04					
Age(years)	-0.06	-0.02	-0.03	-0.06	-0.06	-0.01	0.02	-0.08	-0.04	0.13	-0.18	0.03	-0.10				
AUM(M$)	-0.02	0.06	0.03	0.07	0.10	0.00	-0.05	0.08	0.04	0.02	0.01	0.01	-0.03	0.16			
Flowpast1Y(%p.a.)	0.04	0.10	0.08	0.06	0.10	0.01	-0.02	0.01	0.01	-0.02	0.05	0.01	0.02	-0.07	0.03		
MinInvestment(M$)	0.03	0.01	0.02	0.16	0.14	0.03	-0.12	0.17	0.12	0.04	0.17	-0.05	0.05	0.05	0.21	0.01	
Leverage	0.04	0.03	0.02	0.02	0.03	0.00	0.04	-0.04	-0.06	0.15	0.03	0.09	0.18	0.02	0.04	0.01	-0.02

Table 2: Persistence of the *SDI* (1996–2009)

Table 2 reports the time-series means of the average *SDI* for the current quarter and the subsequent 3 months, 6 months, and 1–3 years for each of the quintile portfolios sorted on the previous 24-month *SDI*. It also reports the difference between the high and low portfolios and the corresponding *t*-statistics. In addition, we report the time-series means of number of funds per period at the sorting and at the end of each holding horizon.

	Time 0	3m	6m	1y	2y	3y
SDI						
Low SDI Port	0.10	0.14	0.16	0.19	0.22	0.23
Port2	0.20	0.22	0.23	0.24	0.25	0.26
Port3	0.29	0.30	0.30	0.31	0.31	0.30
Port4	0.40	0.40	0.40	0.39	0.36	0.35
Hi SDI Port	0.60	0.56	0.54	0.50	0.44	0.43
Hi-Lo (SDI)	0.50***	0.42***	0.38***	0.31***	0.22***	0.20***
(*t*-stat)	(107.20)	(71.42)	(48.87)	(30.32)	(20.87)	(24.68)
#Funds	1,025	981	935	850	707	592

*** 1% significance; ** 5% significance; * 10% significance

Table 3: Determinants of the *SDI* (1996–2009)

Table 3 reports the panel regression of the *SDI* on lagged fund characteristics using annual data: $SDI_{i,t} = c_{0i} + c_{1i} FundCharacteristics_{i,t-1} + e_{i,t}$ Survivorship and backfill biases are controlled for to the extent the data allow. FH 7-factor alpha and volatility of net fee returns (*Vol*) are measured over a window of 24 months and are lagged by one year. Other characteristics include lengths of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds, minimum investment, an indicator variable for leverage. Column I includes all funds in the sample. Column II includes only equity related funds, ie. Long/short equity, event driven, dedicated short bias, and equity market neutral. Column III includes only fixed income funds. The coefficients are multiplied by 100. The *t*-statistics in parentheses are adjusted for fund-clustering effect and time and cluster-style fixed effects.

	I	II	III
VolPast2Y(%p.m.)	-0.58**	-1.46***	-1.46**
(*t*-stat)	(-2.39)	(-6.48)	(-2.53)
RedemptionNoticePeriod(30 Days)	0.47	0.15	2.78**
	(1.34)	(0.36)	(2.51)
Lockup(months)	-0.09**	0.00	0.01
	(-2.16)	(0.09)	(0.07)
PersonalCapitalDummy	0.90	0.68	0.30
	(1.64)	(1.05)	(0.15)
HighWaterMarkDummy	-1.11*	-1.28*	-3.71*
	(-1.71)	(-1.66)	(-1.66)
MgmtFee(%)	-0.04	2.43***	-2.47
	(-0.09)	(2.96)	(-1.60)
Incentive Fee(%)	0.30***	0.37***	0.16
	(5.76)	(5.47)	(0.91)
Age(years)	-0.19***	-0.04	0.57*
	(-3.03)	(-0.43)	(1.66)
ln(AUM)	-0.85***	-1.36***	-0.46
	(-4.43)	(-6.13)	(-0.62)
FlowPast2Y in %	0.01***	0.00	0.01
	(3.19)	(1.20)	(1.47)
ln(MinInvestment+1)	0.66***	0.53*	-0.56
	(3.32)	(1.86)	(-0.66)
Leverage	1.02*	0.33	1.15
	(1.89)	(0.52)	(0.41)
AlphaPast2Y(%p.m)	1.49***	1.10***	-0.85
	(9.93)	(5.02)	(-0.89)
Disclosure		-1.92**	2.79
		(-2.50)	(1.05)
AdjR2(%)	11.05	15.61	16.75
#FundYearObs.	14,511	8,422	760

*** 1% significance; ** 5% significance; * 10% significance

Table 4: Portfolio Performance Based on the *SDI* (1996–2009)

Table 4 reports the time-series means and *t*-statistics of the post-formation FH 7-factor alphas, FH 7-factor based appraisal ratios (*AR*), and the smoothing-adjusted Sharpe ratios (*SR*) for the quintile portfolios sorted on the *SDI*. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every 3 months and held for 3 months, 6 months, and 1–3 years. The *SDI* is measured as (1 − correlation), estimated using the clustering procedure. The *t*-statistics reported below in parentheses are adjusted for heteroscedasticity and autocorrelation.

Panel A: Equally Weighted Portfolios

	Alpha (FH 7-factor)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
	(%p.q.)	(%p.sa.)	(%p.a)	(%p.2y.)	(% p.3y.)										
LowSDIPort	0.91**	1.80**	3.88***	8.46***	12.69***	0.20***	0.16***	0.15***	0.14***	0.13***	0.23***	0.14**	0.09	0.08**	0.09***
(*t*-stat)	(2.18)	(2.33)	(3.14)	(5.44)	(9.95)	(2.97)	(3.65)	(4.25)	(5.25)	(6.83)	(2.80)	(2.08)	(1.36)	(2.27)	(3.55)
Port2	1.27***	2.62***	5.08***	10.24***	16.36***	0.29***	0.23***	0.21***	0.18***	0.17***	0.31***	0.18***	0.13**	0.11***	0.12***
(*t*-stat)	(3.66)	(4.29)	(4.88)	(6.81)	(12.44)	(4.85)	(6.05)	(6.90)	(7.50)	(9.49)	(4.35)	(3.31)	(2.31)	(3.18)	(4.89)
Port3	1.67***	3.35***	6.76***	13.77***	18.82***	0.40***	0.29***	0.26***	0.23***	0.22***	0.33***	0.21***	0.15***	0.14***	0.14***
(tstat)	(4.71)	(5.13)	(5.48)	(9.28)	(22.10)	(7.70)	(8.16)	(9.40)	(10.65)	(13.01)	(4.94)	(3.95)	(2.93)	(3.96)	(5.65)
Port4	1.79***	3.81***	6.87***	14.00***	20.42***	0.51***	0.40***	0.32***	0.28***	0.26***	0.36***	0.25***	0.18***	0.16***	0.15***
(*t*-stat)	(5.15)	(5.48)	(5.81)	(10.11)	(22.17)	(8.28)	(8.89)	(9.27)	(13.38)	(21.19)	(6.10)	(5.44)	(4.20)	(5.20)	(8.55)
HiSDIPort	1.91***	3.83***	7.42***	14.04***	20.73***	0.64***	0.50***	0.42***	0.36***	0.32***	0.44***	0.30***	0.24***	0.19***	0.17***
(*t*-stat)	(8.30)	(7.84)	(7.25)	(11.01)	(16.40)	(9.65)	(10.63)	(10.97)	(15.65)	(22.60)	(9.76)	(10.48)	(9.32)	(12.05)	(14.65)
Hi-Low	1.00***	2.03***	3.54***	5.57***	8.04***	0.44***	0.34***	0.26***	0.23***	0.19***	0.20***	0.17***	0.15***	0.11***	0.09***
(*t*-stat)	(2.69)	(3.03)	(3.26)	(4.28)	(7.18)	(5.29)	(5.82)	(5.48)	(8.03)	(9.12)	(2.89)	(3.48)	(3.38)	(3.83)	(4.12)
Annualized Alpha Hi-Low(%p.a.)	4.05	4.10	3.54	2.75	2.61										

(continued)

Table 4 – *continued*

Panel B: Value-Weighted Portfolios

	Alpha (FH 7-factor)					Appraisal Ratio					Sharpe Ratio				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
LowSDIPort	0.94*	1.63*	3.70**	8.28***	14.44***	0.26***	0.20***	0.21***	0.20***	0.21***	0.28***	0.18**	0.13*	0.13***	0.13***
(*t*-stat)	(1.92)	(1.79)	(2.44)	(4.36)	(8.05)	(2.77)	(3.18)	(3.91)	(5.18)	(6.74)	(2.70)	(2.40)	(1.76)	(2.99)	(5.01)
Port2	1.44***	2.70***	4.27***	8.72***	15.27***	0.41***	0.32***	0.26***	0.24***	0.24***	0.42***	0.26***	0.17**	0.16***	0.17***
(*t*-stat)	(3.39)	(3.26)	(2.91)	(3.46)	(4.93)	(4.84)	(5.91)	(5.89)	(5.89)	(6.33)	(4.80)	(3.61)	(2.53)	(3.32)	(5.15)
Port3	1.60***	3.38***	7.18***	14.62***	21.38***	0.50***	0.37***	0.32***	0.29***	0.28***	0.37***	0.25***	0.20***	0.19***	0.17***
(*t*-stat)	(3.03)	(3.76)	(4.28)	(5.49)	(9.54)	(6.54)	(6.83)	(7.23)	(7.83)	(8.29)	(3.22)	(3.65)	(3.14)	(4.07)	(4.74)
Port4	1.69***	3.55***	5.25***	11.71***	18.19***	0.61***	0.46***	0.36***	0.33***	0.32***	0.38***	0.29***	0.21***	0.19***	0.20***
(*t*-stat)	(3.30)	(3.54)	(2.66)	(4.03)	(7.87)	(8.40)	(8.40)	(6.42)	(7.50)	(9.91)	(4.79)	(5.21)	(3.67)	(4.07)	(5.20)
HiSDIPort	1.48***	2.80***	6.24***	12.92***	19.13***	0.83***	0.67***	0.57***	0.51***	0.43***	0.54***	0.38***	0.29***	0.23***	0.21***
(*t*-stat)	(2.64)	(3.14)	(4.87)	(9.20)	(11.70)	(8.16)	(8.01)	(7.70)	(10.82)	(16.97)	(7.45)	(6.16)	(5.21)	(6.74)	(8.57)
Hi-Low	0.54	1.16	2.53*	4.64***	4.69***	0.58***	0.47***	0.36***	0.31***	0.23***	0.26**	0.20***	0.16***	0.10**	0.08***
(*t*-stat)	(0.99)	(1.24)	(1.75)	(3.17)	(2.85)	(4.80)	(4.90)	(4.42)	(6.08)	(6.28)	(2.28)	(2.71)	(2.74)	(2.56)	(2.63)
Annualized Alpha Hi-Low(%p.a.)	2.18	2.34	2.53	2.29	1.54										

*** 1% significance; ** 5% significance; * 10% significance

Table 5 Manipulation-Proof Performance for *SDI* Portfolios (1996–2009)

Table 5 reports the time-series means of the post-formation manipulation-proof performance measure (MPPM), for the quintile portfolios sorted on the *SDI*. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every 3 months and held for 3 months, 6 months, and 1–3 years. The *SDI* is measured as (1 – correlation), estimated using the clustering procedure. The *p*-values for the high-low portfolio results are based on a bootstrap procedure described in the text.

	Equally Weighted Portfolios (% p.a.)					Value-Weighted Portfolios (% p.a.)				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
LowSDIPort	2.74	1.19	-0.79	-1.68	-1.47	2.63	1.28	-0.09	-0.89	-0.25
Port2	3.72	2.52	0.73	-0.62	-0.32	4.67	3.16	1.31	-0.26	0.05
Port3	3.73	2.94	1.33	0.02	-0.22	4.09	3.57	2.20	0.62	-0.21
Port4	3.86	3.19	1.27	0.11	0.11	2.60	2.48	-0.55	-0.96	-0.95
HiSDIPort	3.39	2.68	1.83	0.42	0.26	3.09	2.10	1.32	0.42	0.37
Hi-Low	0.66*	1.49***	2.62***	2.11***	1.73***	0.47	0.82	1.41*	1.31**	0.62
bootstrapped *p*-value	(0.05)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.35)	(0.24)	(0.06)	(0.03)	(0.15)

Table 6: Panel Regression of Hedge Fund Performance on the *SDI* (1996–2009)

Table 6 reports the panel regression results for hedge fund performance on *SDI* at the quarterly frequency as follows: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i}SDI_{i,t-1} + c_{2i}Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent the data allow. Alpha is the FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR, SR,* and *MPPM* are the corresponding appraisal ratio, smoothing-adjusted Sharpe ratio, and manipulation-proof performance measure, respectively. Control variables are the lagged fund characteristics, including volatility of monthly net fee returns (*Vol*), length of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the preceding 12 months as a fraction of AUM, in percent, minimum investment, and an indicator variable for using leverage. The *t*-statistics reported in parentheses are adjusted for fund-clustering effect and time and cluster style fixed effects.

	Panel Regression			
	alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	MPPM (% p.a.)
SDI	3.35***	0.34***	0.27***	3.54***
(*t*-stat)	(3.02)	(6.86)	(6.56)	(4.41)
VolPast2Y(%p.m)	0.13			-0.32***
	(0.85)			(-3.80)
RedemptionNotice(30Days)	0.55**	0.08***	0.05***	0.71***
	(2.12)	(3.76)	(3.84)	(3.54)
Lockup(months)	0.08**	0.00*	0.00	0.02
	(2.37)	(-1.75)	(-1.60)	(0.86)
PersonalCapitalDummy	-0.32	-0.04**	-0.01	0.62*
	(-0.79)	(-1.99)	(-0.56)	(1.88)
HighWaterMarkDummy	1.22**	0.01	0.02	1.62***
	(2.40)	(0.59)	(0.99)	(4.20)
MgmtFee(%)	0.78**	-0.01	0.01	1.01***
	(2.28)	(-0.82)	(0.75)	(4.18)
IncentiveFee(%)	0.04	0.00	0.00	0.05
	(0.80)	(-1.25)	(-0.97)	(1.51)
Age(years)	-0.01	0.00	0.00	0.13***
	(-0.27)	(1.52)	(1.31)	(3.40)
ln(AUM)	-0.57***	0.02***	0.01***	-0.39***
	(-4.23)	(4.61)	(3.36)	(-3.36)
FlowPast1Y(%)	0.00*	0.00	0.00	0.00
	(-1.79)	(0.73)	(1.15)	(1.24)
AvgPast2YRet(% p.m.)	0.08	-0.01***	0.02***	0.33*
	(0.28)	(-3.12)	(4.27)	(1.73)
ln(MinInvestment+1)	0.68***	0.03***	0.02***	0.57***
	(4.84)	(5.08)	(5.43)	(4.04)
Leverage	0.25	0.02	0.03*	0.30
	(0.59)	(0.92)	(1.80)	(0.88)
AdjR2(%)	5.39	8.86	14.82	19.26
#FundQtrObs.	53,071	53,071	47,643	52,311

*** 1% significance; ** 5% significance; * 10% significance

Table 7: Fama-MacBeth Analysis of Hedge Fund Performance on the *SDI* (1996–2009)

Table 7 reports the Fama-MacBeth regression results for hedge fund performance on the *SDI* and other fund characteristics at the quarterly frequency as the following: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i}SDI_{i,t-1} + c_{2i}Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent the data allow. Alpha is the FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR, SR,* and *MPPM* are the corresponding appraisal ratio, smoothing-adjusted Sharpe ratio, and manipulation-proof performance measure, respectively. Control variables are the lagged fund characteristics, including volatility of monthly net fee returns volatility, length of redemption periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the preceding 12 months as a fraction of AUM, in percentage, minimum investment, and an indicator variable for using leverage. Cluster-style dummies are included in the regressor set. The *t*-statistics (reported below the estimated coefficients in italicized font) are adjusted for heteroscedasticity and autocorrelation.

	Fama-MacBeth Regression			
	alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	MPPM (% p.a.)
SDI	3.82**	0.38***	0.22***	3.00*
(*t*-stat)	(2.51)	(5.27)	(5.02)	(1.78)
VolPast2Y(%p.m)	0.07			-0.45**
	(0.30)			(-2.01)
RedemptionNotice(30Days)	0.58**	0.08***	0.05***	0.60**
	(2.20)	(6.34)	(5.09)	(2.53)
Lockup(months)	0.14***	0.00*	0.00	0.05
	(2.63)	(-1.78)	(-1.38)	(1.09)
PersonalCapitalDummy	-0.33	-0.03***	-0.02	0.12
	(-0.71)	(-3.69)	(-1.62)	(0.33)
HighWaterMarkDummy	0.96	0.03	0.02	1.43***
	(1.13)	(1.44)	(1.58)	(2.89)
MgmtFee(%)	1.03**	-0.01	0.01*	1.25***
	(2.42)	(-0.89)	(1.73)	(3.88)
IncentiveFee(%)	0.01	0.00	0.00	0.02
	(0.32)	(-1.50)	(-1.64)	(0.57)
Age(years)	-0.05	0.00	0.00	0.04
	(-0.82)	(0.74)	(0.19)	(0.76)
ln(AUM)	-0.57**	0.03***	0.01***	-0.35**
	(-2.43)	(3.83)	(2.99)	(-1.96)
FlowPast1Y(%)	0.00	0.00**	0.00	0.00
	(-1.35)	(2.33)	(0.91)	(-0.38)
AvgPast2YRet(% p.m.)	0.50	-0.02	0.02**	1.16*
	(0.74)	(-1.04)	(2.50)	(1.95)
ln(MinInvestment+1)	0.76***	0.03***	0.02***	0.47***
	(3.42)	(5.19)	(7.83)	(3.27)
Leverage	0.50	0.02	0.03**	0.33
	(1.22)	(1.33)	(2.41)	(0.82)
AdjR2(%)	17.59	15.84	13.57	21.59

*** 1% significance; ** 5% significance; * 10% significance

Table 8: Robustness: Hedging Effect (1996-2009)

Panel A of Table 8 reports the summary statistics of the percentage of funds in the *SDI*-sorted quintile portfolios that fall into the same quintile sorted according to *1-R2(FH)*. Panel B reports the time-series means of the post-formation FH 7-factor alphas, FH 7-factor based appraisal ratios (*AR*), the smoothing-adjusted Sharpe ratios (*SR*), and the manipulation-proof performance measure (*MPPM*), for the *SDI*-sorted quintile portfolio using funds that do not fall into the same quintile when sorted on *1-R2(FH)*. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every 3 months and held for 1 year. We report below in parentheses *t*-statistics for alpha, AR, and SR, and bootstrapped *p*-value for MPPM. The *t*-statistics are adjusted for heteroscedasticity and autocorrelation. Panel C reports the panel regression and Fama-MacBeth regression results for hedge fund performance on *SDIs, 1-R2(FH)* and other fund characteristics at the quarterly frequency as the following: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i}SDI_{i,t-1} + c_{2i}(1 - R2(FH7))_{i,t-1} + c_{3i}Control_{i,t-1} + e_{i,t}$. Control variables are the lagged fund characteristics, including volatility of monthly net fee returns (*Vol*), length of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the preceding 12 months as a fraction of *AUM,* in percentage, minimum investment, and an indicator variable for using leverage. Panel regression is adjusted for fund-clustering effect and time and style fixed effects, and Fama-MacBeth regression controls for style dummies and adjusts for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for the *SDI* and *1-R2(FH)* are reported here. Survivorship and backfill biases are controlled for to the extent the data allow.

Panel A: Ratio of Overlapped Funds in Quintile Portfolios Sorted by SDI and by 1-R2(FH 7-factor)

	Low SDI	Port 2	Port 3	Port 4	Hi SDI
Mean	0.50	0.31	0.27	0.30	0.48
Median	0.51	0.32	0.27	0.29	0.47
Min	0.34	0.16	0.19	0.20	0.29
Max	0.64	0.43	0.36	0.41	0.62
Std	0.07	0.05	0.04	0.05	0.07

Panel B: Returns on Quintile Portfolios Sorted by SDI While Excluding Funds in the Same Rank Sorted by 1-R2(FH 7-factor)

EW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	VW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
Low SDI Port	3.71*	0.17***	0.08	-1.30	Low SDI Port	3.04	0.21***	0.13*	-0.69
	(1.72)	(3.31)	(1.38)			(1.12)	(2.86)	(1.89)	
Port 2	5.32***	0.21***	0.13**	0.52	Port 2	4.42***	0.26***	0.17***	1.17
	(4.65)	(7.07)	(2.47)			(3.25)	(6.71)	(2.65)	
Port 3	6.77***	0.26***	0.15***	1.21	Port 3	7.31***	0.34***	0.20***	2.23
	(5.39)	(9.57)	(2.92)			(4.56)	(7.04)	(3.14)	
Port 4	6.71***	0.31***	0.18***	1.18	Port 4	5.02**	0.35***	0.21***	-0.41
	(6.31)	(9.34)	(4.13)			(2.46)	(6.86)	(3.69)	
Hi SDI Port	7.40***	0.36***	0.20***	1.84	Hi SDI Port	6.02***	0.48***	0.24***	1.57
	(7.95)	(10.56)	(9.16)			(3.94)	(7.63)	(5.13)	
Hi-Lo	3.69**	0.19***	0.12**	3.13***	Hi-Lo	2.98	0.27***	0.11*	2.26**
	(1.97)	(2.97)	(2.43)	(<0.01)		(1.17)	(2.70)	(1.65)	(0.03)

Panel C: Regression Analysis (Other control variables in Table 6 are included in the regression but not reported below for brevity.)

	Panel Regression				Fama-MacBeth			
	alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	MPPM (% p.a.)	alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	MPPM (% p.a.)
SDI	2.10*	0.18***	0.23***	4.25***	1.07	0.29***	0.21***	3.21
(tstat)	(1.78)	(4.24)	(5.62)	(4.93)	(0.48)	(3.34)	(4.07)	(1.48)
1-R2(FH 7-factor)	2.22**	0.27***	0.08***	-1.27	4.45	0.16***	0.01	-0.22
(tstat)	(2.13)	(7.49)	(2.59)	(-1.58)	(1.52)	(2.77)	(0.26)	(-0.11)

*** 1% significance; ** 5% significance; * 10% significance

Table 9: Robustness: Survivorship Bias (1996–2009)

Table 9 Panel A reports the time-series means of the survival rate, in percentage, for quintile portfolios sorted on the *SDI*. The portfolios are sorted every 3 months and held for 3 months, 6 months, and 1–3 years. It also reports the difference between the high and low portfolios, and the corresponding *t*-statistics. Panel B reports the regression analysis with Heckman adjustment. The control variables for the regression are the same as the regression reported in Table 6 and 7.

Panel A: Portfolio Sorting

	3m	6m	1y	2y	3y
SDI					
Low SDI Port	95.41	90.75	81.55	67.93	55.32
Port2	95.28	90.57	82.03	67.68	55.86
Port3	95.06	90.18	80.99	66.23	54.52
Port4	94.94	89.73	80.28	65.09	53.00
Hi SDI Port	94.40	88.82	78.76	63.63	51.41
Hi-Lo (SDI)	-1.01**	-1.93***	-2.79**	-4.30***	-3.91***
(tstat)	(-2.36)	(-2.80)	(-2.22)	(-4.04)	(-2.95)

Panel B: Regression Analysis with Heckman Adjustment (Other control variables in Table 6 are included in the regression but not reported for brevity.)

	Panel Regression				Fama-MacBeth			
	alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	MPPM (% p.a.)	alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	MPPM (% p.a.)
SDI	3.31***	0.34***	0.27***	3.73***	3.67**	0.38***	0.21***	2.87*
(*t*-stat)	(3.01)	(6.92)	(6.64)	(4.66)	(2.38)	(5.36)	(4.95)	(1.69)
Heckman Lambda	4.13***	0.10***	0.10***	4.21***	4.31***	0.11***	0.10***	4.26***
(*t*-stat)	(18.36)	(10.43)	(10.49)	(16.06)	(10.16)	(8.96)	(8.20)	(6.35)
AdjR2(%)	6.65	9.60	15.81	20.59	18.80	16.92	15.44	23.70
#FundsQtr Obs.	52,947	52,947	47,531	52,189				

*** 1% significance, ** 5% significance, * 10% significance

Table 10: Robustness: Absolute Correlation-Based *SDI* (1996-2009)

Panel A of Table 10 reports the summary statistics of the percentage of funds in the *SDI*-sorted quintile portfolios that also fall into the same quintile sorted according to $SDI(|corr|)$. Panel B reports the time-series means of the post-formation FH 7-factor alphas, FH 7-factor based appraisal ratios (*AR*), the smoothing-adjusted Sharpe ratios (*SR*), and the manipulation-proof performance measure (*MPPM*), for the $SDI(|corr|)$-sorted quintile portfolio. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every 3 months and held for 1 year. We report below in parentheses *t*-statistics for alpha, AR, and SR, and bootstrapped *p*-value for MPPM. The *t*-statistics are adjusted for heteroscedasticity and autocorrelation. Panel C reports the panel regression and Fama-MacBeth regression results for hedge fund performance on $SDI(|corr|)$ and other fund characteristics at the quarterly frequency as the following: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} SDI(|corr|)_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. Alpha is the compounded FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR* and *SR* are the corresponding appraisal ratio and smoothing-adjusted Sharpe ratio. Control variables are the lagged fund characteristics including volatility of monthly net fee returns (*Vol*), length of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, *AUM*, new money flow into funds within the preceding 12 months as a fraction of AUM, in percentage, minimum investment, and an indicator variable for using leverage. Panel regression is adjusted for fund-clustering effect and time- and style-fixed effects, and Fama-MacBeth regression controls for style dummies and adjusts for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for the *SDIs* are reported here. Survivorship and backfill biases are controlled for to the extent the data allow.

Panel A: Ratio of Overlapped Funds in Quintile Portfolios Sorted by SDI(Corr)- and SDI(|corr|)

	Low SDI	Port 2	Port 3	Port 4	Hi SDI
Mean	0.79	0.63	0.63	0.66	0.82
Median	0.78	0.60	0.59	0.64	0.81
Min	0.66	0.50	0.46	0.44	0.63
Max	1.00	1.00	1.00	1.00	1.00
Std	0.07	0.11	0.12	0.11	0.06

Panel B: Returns of Quintile Portfolios Sorted on SDI(|corr|)

EW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	VW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
Low SDI Port	3.53***	0.15***	0.09	-0.84	Low SDI Port	3.67**	0.21***	0.13*	0.17
	(2.61)	(3.70)	(1.36)			(2.39)	(3.89)	(1.76)	
Port 2	5.70***	0.21***	0.13**	0.95	Port 2	5.70***	0.28***	0.17**	2.14
	(5.42)	(7.47)	(2.31)			(3.72)	(6.96)	(2.53)	
Port 3	6.37***	0.25***	0.15***	1.01	Port 3	6.47***	0.30***	0.20***	1.12
	(5.65)	(8.53)	(2.93)			(3.73)	(6.26)	(3.14)	
Port 4	7.38***	0.33***	0.18***	1.75	Port 4	5.59***	0.39***	0.21***	-0.07
	(5.81)	(10.77)	(4.20)			(2.78)	(6.58)	(3.67)	
Hi SDI Port	7.03***	0.41***	0.24***	1.50	Hi SDI Port	6.09***	0.57***	0.29***	1.45
	(7.14)	(10.67)	(9.32)			(4.82)	(8.62)	(5.21)	
Hi-Lo	3.50***	0.26***	0.15***	2.34***	Hi-Lo	2.41*	0.36***	0.16***	1.28*
	(2.77)	(5.09)	(3.38)	(<0.01)		(1.75)	(4.76)	(2.74)	(0.08)

Panel C: Regression Analysis (Other control variables in Table 6 are included in the regression but not reported below for brevity.)

	Panel Regression				Fama-MacBeth			
	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
SDI(|Corr|)	4.50***	0.38***	0.23***	3.18***	4.04**	0.34***	0.15***	2.19
(tstat)	(3.61)	(7.07)	(5.79)	(3.53)	(2.17)	(3.99)	(3.44)	(1.16)
AdjR2(%)	5.06	8.69	14.92	18.99	17.11	16.54	15.23	21.02
#FundsQtrObs	53,071	53,071	47,643	52,311				

*** 1% significance; ** 5% significance; * 10% significance

Table 11: Robustness: TASS Style-based *SDI* (1996–2009)

Panel A of Table 11 reports the summary statistics of the percentage of funds in the *SDI*-sorted quintile portfolios that also fall into the same quintile sorted according to *SDI(TASS)*. Panel B reports the time-series means of the post-formation FH 7-factor alphas, FH 7-factor based appraisal ratios (*AR*), the smoothing-adjusted Sharpe ratios (*SR*), and the manipulation-proof performance measure (*MPPM*), for the *SDI(TASS)*--sorted quintile portfolio. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every 3 months and held for 1 year. We report below in parentheses *t*-statistics for alpha, AR and SR, and bootstrapped *p*-value for MPPM. The *t*-statistics are adjusted for heteroscedasticity and autocorrelation. Panel C reports the panel regression and Fama-MacBeth regression results for hedge fund performance on *SDI(TASS)* and other fund characteristics at the quarterly frequency as the following: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} SDI(TASS)_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. We report results for both the raw and standardized *SDI*, which is the difference between the raw *SDI* and the average *SDI* of the corresponding style scaled by the cross-sectional standard deviation of *SDI* within the same style. Alpha is the compounded FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR* and *SR* are the corresponding appraisal ratio and smoothing-adjusted Sharpe ratio. Control variables are the lagged fund characteristics including volatility of monthly net fee returns (*Vol*), length of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the preceding 12 months as a fraction of AUM, in percentage, minimum investment, and an indicator variable for using leverage. Panel regression is adjusted for fund-clustering effect and time- and style-fixed effects, and Fama-MacBeth regression controls for style dummies and adjusts for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for the *SDI*s are reported here. Survivorship and backfill biases are controlled for to the extent the data allow.

Panel A: Ratio of Overlapped Funds in Quintile Portfolios Sorted by SDI and by SDI(TASS)

	Low SDI	Port 2	Port 3	Port 4	Hi SDI
Mean	0.57	0.36	0.32	0.35	0.55
Median	0.58	0.36	0.32	0.35	0.54
Min	0.34	0.21	0.19	0.19	0.37
Max	0.72	0.48	0.45	0.50	0.74
Std	0.09	0.07	0.07	0.07	0.10

Panel B: Portfolio Sorting Results

EW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	VW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
Low SDI Port	3.85***	0.18***	0.10	-0.75	Low SDI Port	3.34	0.24***	0.16**	0.08
	(2.67)	(4.37)	(1.55)			(1.51)	(3.93)	(2.01)	
Port 2	5.94***	0.23***	0.14**	1.32	Port 2	9.10***	0.35***	0.20***	2.93
	(5.99)	(7.80)	(2.52)			(4.19)	(7.36)	(2.94)	
Port 3	6.50***	0.26***	0.15***	1.35	Port 3	6.45***	0.33***	0.19***	0.26
	(5.64)	(9.82)	(2.75)			(4.25)	(7.36)	(2.85)	
Port 4	6.59***	0.33***	0.18***	1.24	Port 4	6.44***	0.44***	0.21***	0.87
	(5.43)	(10.99)	(4.11)			(4.38)	(7.55)	(3.58)	
Hi SDI Port	7.12***	0.36***	0.21***	1.21	Hi SDI Port	2.73	0.38***	0.22***	-0.22
	(6.60)	(8.54)	(10.20)			(1.62)	(5.87)	(5.99)	
Hi-Lo	3.27**	0.18***	0.11**	1.96***	Hi-Lo	-0.61	0.13**	0.06	-0.30
	(2.14)	(3.76)	(2.41)	(<0.01)		(-0.40)	(2.42)	(1.04)	(0.63)

Panel C: Regression Analysis (Other control variables in Table 6 are included in the regression but not reported below for brevity.)

		Panel				Fama-MacBeth			
		alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
Reg 1	SDI(TASS)	2.27***	0.05***	0.07***	2.57***	3.23**	0.07	0.02	0.17
	(*t*-stat)	(3.45)	(3.16)	(4.91)	(5.22)	(2.08)	(1.54)	(0.40)	(0.09)
Reg 2	SDI(Cluster)	3.35***	0.34***	0.27***	3.54***	3.82**	0.38***	0.22***	3.00*
	(*t*-stat)	(3.02)	(6.86)	(6.56)	(4.41)	(2.51)	(5.27)	(5.02)	(1.78)

*** 1% significance; ** 5% significance; * 10% significance

Table 12: Robustness: Alternative Backfill Bias Control (1997–2009)

Table 12 summaries the results, where the backfill bias is controlled by filtering out data prior to a fund entering the TASS database. Panel A reports the time-series means of the post-formation FH 7-factor alphas, FH 7-factor based appraisal ratios (*AR*), the smoothing-adjusted Sharpe ratios (*SR*), and the manipulation-proof performance measure (*MPPM*), for the *SDI*-sorted quintile portfolio. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every 3 months and held for 1 year. We report below in parentheses *t*-statistics for alpha, AR and SR, and bootstrapped *p*-value for MPPM. The *t*-statistics are adjusted for heteroscedasticity and autocorrelation. Panel B reports the panel regression and Fama-MacBeth regression results for hedge fund performance on *SDI* and other fund characteristics at the quarterly frequency as the following: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i}SDI_{i,t-1} + c_{2i}Control_{i,t-1} + e_{i,t}$. Alpha is the compounded FH 7-factor adjusted performance over the subsequent 1 year in percentage terms. *AR* and *SR* are the corresponding appraisal ratio and smoothing-adjusted Sharpe ratio. Control variables are the lagged fund characteristics including volatility of monthly net fee returns (*Vol*), length of redemption notice periods and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the preceding 12 months as a fraction of *AUM,* in percentage, minimum investment, and an indicator variable for using leverage. Panel regression is adjusted for fund-clustering effect and time- and style-fixed effects, and Fama-MacBeth regression controls for style dummies and adjusts for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for the *SDI*s are reported here.

Panel A: Returns of Quintile Portfolios Sorted on SDI

EW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	VW	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
Low SDI Port	1.70	0.12***	0.06	-4.01	Low SDI Port	1.66	0.20***	0.12	-2.81
	(0.91)	(2.82)	(0.95)			(0.65)	(2.90)	(1.62)	
Port 2	3.29**	0.18***	0.10*	-1.73	Port 2	2.48	0.24***	0.13	-0.77
	(2.01)	(4.55)	(1.67)			(0.95)	(3.99)	(1.62)	
Port 3	4.44***	0.23***	0.11**	-1.14	Port 3	2.85	0.28***	0.18***	-0.35
	(3.14)	(6.62)	(2.22)			(1.14)	(4.33)	(2.83)	
Port 4	6.10***	0.29***	0.16***	0.46	Port 4	2.13	0.35***	0.24***	-0.76
	(4.50)	(9.29)	(3.86)			(0.98)	(6.16)	(3.80)	
Hi SDI Port	6.58***	0.37***	0.22***	0.91	Hi SDI Port	4.59***	0.52***	0.28***	0.43
	(5.06)	(10.52)	(8.41)			(2.96)	(6.97)	(5.39)	
Hi-Lo	4.88***	0.25***	0.16***	4.92***	Hi-Lo	2.93	0.33***	0.16**	3.25***
	(3.16)	(5.56)	(3.33)	(<0.01)		(1.17)	(4.37)	(2.52)	(<0.01)

Panel B: Regression Analysis

Other control variables in Table 6 are included in the regression but not reported below for brevity.

	Panel Regression				Fama-MacBeth			
	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)	alpha(% p.a.) FH 7-factor	AR (FH)	SR	MPPM (% p.a.)
SDI	5.71***	0.38***	0.31***	5.49***	6.95***	0.41***	0.29***	7.55***
(*t*-stat)	(4.63)	(7.94)	(7.10)	(5.83)	(3.66)	(5.61)	(4.12)	(3.47)
AdjR2(%)	5.93	8.59	14.00	19.92	15.70	15.88	15.20	21.34
#FundsQtrObs	41,415	41,415	32,916	40,239				

*** 1% significance; ** 5% significance; * 10% significance