Should hedge funds deviate from the benchmark?

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Abstract

We examine the relationship between deviating from the benchmark and subsequent performance for hedge funds. We propose a simple new measure of benchmark deviations, termed the Dispersion Contribution Index (DCI), which is based on a fund's return-distance from the mean return of same-style funds. We find that funds which deviate the most from their benchmark tend to underperform relative to their less distinctive peers, after accounting for their idiosyncratic characteristics. This relative underperformance stems primarily from the higher risk exposure associated with pursuing a unique strategy. Our findings are robust to a wide array of additional tests.

JEL Classifications: G10; G11; G23

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1 Introduction

Hedge funds charge investors high fees on the expectation of delivering superior performance. This superior performance is typically believed to be driven by fund managers possessing unique skills that allow them to pursue unique investment ideas. However, the extent to which fund managers pursue investment strategies that deviate from their benchmark and, more importantly, whether these strategies lead to improved performance remains an open empirical question. In this paper,

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we contribute to this on-going debate in the literature on whether deviating from the benchmark reflects greater skill or merely a willingness to take more risk.

The empirical literature has yet to reach a consensus with respect to the relationship between funds deviating from their peers and their subsequent performance. For instance, a substantial debate has been developing on whether the Active Share (Cremers and Petajisto, 2009), one of the most commonly used measures of active portfolio management, can predict future fund performance. Computed as the proportion of the fund's holdings that are different from the holdings included in its respective benchmark (passive) index, the Active Share was reported by Cremers and Petajisto (2009) to be significantly positively related to future fund performance. This finding provided initial support for the hypothesis that fund managers who pursue highly active, distinctive strategies outperform their benchmark as well as their less distinctive peers. The notion that deviating from the benchmark, as reflected in a higher Active Share, results in improved performance is further supported by Petajisto (2013).[1]

However, these initial findings have been strongly challenged by Frazzini et al. (2016) who suggest that the Active Share is as likely to correlate positively as it is negatively with returns inside particular fund groups. The implication is that deviating from the benchmark does not necessarily reflect skills and it cannot predict future performance. The paper by Frazzini et al. (2016) has sparked a lively debate, with Cremers and Petajisto subsequently offering rebuttals (Cremers, 2015, 2017; Petajisto, 2016).

A number of other studies have also suggested that the relationship between performance and deviations from the benchmark is not necessarily straightforward. For instance, Jin et al. (2016) report an inverted-U relationship between Active Share and investment performance. Intuitively, it seems that fund managers who have performed poorly are more likely to subsequently pursue more distinctive strategies, essentially "gambling" in an attempt to make up for poor past performance. At the other end of the spectrum, the highest performing managers tend to also pursue even more distinctive strategies, which Jin et al. (2016) attribute to overconfidence built up from past success. Moreover, Cremers and Pareek (2016) document that deviating from the benchmark leads to outperformance only when managers trade relatively infrequently, whereas very active managers who trade frequently generally underperform.

[1]Sun et al. (2012; 2016) also provide support for the hypothesis that deviating from the benchmark leads to better fund performance. Sun et al. (2012; 2016) measure a fund's deviation from the benchmark as one minus the correlation between the funds returns and the mean return of same-style funds, and they label this measure the fund's Strategy Distinctiveness Index (SDI). Consistent with the argument in Cremers and Petajisto (2009), Sun et al. (2012; 2016) find that fund managers who correlate less with their benchmark tend to outperform their less distinctive peers.

In a similar vein, Brunnermeier and Nagel (2004) focus on the technology bubble and report that the effect of deviating from the benchmark was not unconditionally positive but, instead, depended on the stage of the bubble. In particular, they find that skilled managers of equity funds performed well by riding the bubble along with less skilled investors, suggesting that strategy uniformity, rather than distinctiveness, pays off during bubble formation. However, these skilled managers subsequently distanced themselves from the "herd" by reducing their positions in technology stocks and, thus, avoiding the losses incurred by most other investors.

Our paper contributes to the on-going debate in the literature about the relationship between deviating from the benchmark and fund performance. We use the distance of a fund's return from the mean return of its cohort (scaled by the mean distance among all the cohort's funds) as a simple measure of the extent to which a fund deviates from its peers. We label this measure the fund's Dispersion Contribution Index (DCI), and we argue that the DCI can serve as a useful measure. First, given that it is based on distances in terms of realized returns, the DCI is intuitively linked to deviations in terms of strategies by focusing on the actual performance that was delivered by the fund's strategy. Second, this measure can be easily computed using data on fund returns that are readily available, as opposed to data on fund holdings (e.g. as required to compute the Active Share measure) which, in the majority of cases, are not disclosed by fund managers.

Our paper also contributes to the growing literature on the determinants of hedge fund performance. Generally, existing empirical evidence suggests that the performance of funds with certain characteristics tends to be consistently better than that of other funds. More specifically, a number of studies have found that superior fund performance tends to be associated with longer lock-up periods (Aragon, 2007), lower age (Boyson, 2008), higher watermarks and greater managerial incentives (Agarwal et al., 2009), greater geographical proximity to investments (Teo, 2009), higher managerial education level (Li et al, 2011), lower exposure to systematic risk (Titman and Tiu, 2011), holding more illiquid assets (Schaub and Schmid, 2013), greater adoption of quantitative versus qualitative methods (Chincarini, 2014), higher maximum return over a fixed interval (Bali et al., 2015), smaller size (Clare et al., 2015), and higher exposure to sentiment risk (Chen et al., 2016).

We find a wide dispersion and evidence of a positively skewed distribution of DCI levels in the cross-section of hedge funds. The DCI for the majority of funds is less than 1 while a small number of funds have particularly high DCI levels. Furthermore, the DCI of an individual fund is found to be considerably persistent over time. The DCI appears to be significantly related to other fund characteristics, with higher DCI levels being more likely to be observed in funds with higher return volatility, longer redemption notice and lock up periods, higher performance fees, lower age and higher leverage.

More importantly, our empirical results strongly reject the hypothesis that deviating from the benchmark leads to improved fund performance. On the one hand, we find that funds with the highest (lowest) DCI indeed offer the highest (lowest) net returns and Fung and Hsieh (2004) alphas. On the face of it, this finding seems to suggest that deviating from the benchmark leads to higher returns, even after accounting for the funds exposure to a set of commonly used systematic factors. However, when we account for other sources of risk and other fund-specific characteristics, we find strong evidence of more distinctive funds underperforming relative to their less distinctive peers.

More specifically, we report a significantly negative and economically large Treynor and Black (1973) Appraisal Ratio (AR) earned by a spread portfolio that goes long in the quintile of highest DCI funds and short in the quintile of lowest DCI funds (essentially betting on distinctiveness). Given that the AR is a scaled version of a fund's alpha by its volatility, the previously reported higher alphas offered by higher-DCI funds seem to come at the cost of substantially higher idiosyncratic risk, with the overall risk-return trade-off being worse compared to that of funds with lower DCI levels. The relative underperformance of funds with the highest DCI levels is further supported by the finding that they offer significantly lower Omega and Sortino ratios compared to the lowest-DCI funds. Since these two performance measures are based on the lower partial moments of the returns' distribution, our results could indicate that managers who are skilled enough to deviate from their peers and implement unique strategies are exploiting the option-like features of their compensation contracts by increasing downside risk in pursuit of extremely high returns. Finally, this negative relationship between deviations from the benchmark and fund performance holds across several different re-balancing periods for the quintile portfolios, ranging from one month to two years.

The results from Fama and MacBeth (1973) regressions of performance measures against fund-specific characteristics further confirm the negative relationship between distinctiveness and performance. When fund-specific characteristics are taken into account, a fund's performance is found to be significantly negatively related to its DCI. This result also holds when performance is based on the Fung and Hsieh (2004) alphas, suggesting that the initially reported positive relationship between alphas and the DCI was most likely driven by other fund characteristics rather than reflecting a fundamentally positive effect of deviations from the benchmark on fund performance.

In order to better understand the relationship between the DCI and performance, we conduct a battery of additional tests. First, we explore the effect of managers' skills in timing the market return (Chen and Liang, 2007) and timing the market liquidity (Cao et al., 2013) on the relationship between deviations from the benchmark and fund performance. Second, in order to address the issue of DCI persistence, we re-sort portfolios based on a fund's mean DCI over the previous months. We also explore the incremental informational content of the DCI by examining the performance of funds that have been double-sorted in portfolios according to their DCI and their SDI levels. Furthermore, given that our results are based on the Joenvaara et al. (2016) classification of funds in style clusters, we explore the effect of different ways to group funds by using the original Barclay-Hedge style categories and by performing an alternative k-means clustering. We also compare results from equally-weighting to those from value-weighting funds within particular portfolios. We account for the Titman and Tiu (2011) hedging effect by examining the relationship between the DCI and the R-square obtained from the Fung and Hsieh (2005) regressions. Finally, we explore the possibility of survivorship bias driving the previous findings. We find that our results are robust to all these additional tests.

Overall, our empirical results cast substantial doubt on the notion that pursuing a strategy that deviates from the benchmark leads to improved performance. Hedge funds that deviate the most from their peers seem to take substantially higher levels of risk exposure without offering sufficiently higher returns, especially after taking into account their idiosyncratic characteristics. While some fund managers might be able to achieve higher risk-adjusted returns by timing the market return and/or liquidity, the practice of deviating from the style-group's consensus appears in itself to lead to deterioration in performance. This finding, along with the significantly positive relationship between the DCI and performance fees, also calls into question the perception that higher fees tend to be indicative of better fund performance.

The remaining of the paper is organized as follows. Section 2 describes the construction of the DCI and the intuition behind it. Section 3 presents the data used in the empirical analysis and some descriptive statistics for the DCI. Section 4 discusses the empirical results on the relationship between deviations from the benchmark and fund performance. Section 5 describes the results of various robustness tests, while Section 6 concludes.

2 Dispersion Contribution Index (DCI)

In order to understand deviations from the benchmark at the level of the individual fund, we begin by quantifying how funds differ from one another at the aggregate level of the fund's cohort. In this context, the cross-sectional dispersion (CSD) of fund returns represents a natural candidate for a measure of heterogeneity at the aggregate level. We measure CSD as the mean absolute deviation of individual funds' returns from the mean return of all funds in a particular style group, as described in equation (1)

$$CSD_t = \frac{\sum_{i=1}^{N} |r_{i,t} - r_{G,t}|}{N} \tag{1}$$

where $r_{i,t}$ is the return of fund i at time t, $r_{G,t}$ is the cross-sectional mean return at t of all funds in the same style group, and N is the number of funds in that group. Recent studies have been paying increasing attention to the cross-sectional dispersion of returns, for instance in the context of "herding" (Chiang and Zheng, 2010; Galariotis et al., 2015) and idiosyncratic risk (Angelidis et al., 2015; Verousis and Voukelatos, 2017). Generally, CSD can serve as an economically meaningful measure of divergence of performance among assets at the aggregate level. By construction, CSD is bound from below at zero, which represents the hypothetical extreme case of all fund managers pursuing exactly the same strategy and, thus, earning exactly the same return. As managers start to deviate from their peers, the returns of individual funds will diverge more from the mean of the cohort and CSD will increase as a result.

Given that CSD reflects the aggregate level of distinctiveness within a particular style group, we then proceed to measure deviations from the benchmark at the level of the individual fund as the contribution of that fund to the total level of aggregate dispersion of the group. To this end, we propose the Dispersion Contribution Index (DCI) as an intuitive measure, computed as follows

$$DCI_{i,t} = \frac{|r_{i,t} - r_{G,t}|}{CSD_t} = \frac{|r_{i,t} - r_{G,t}|}{\frac{\sum_{j=1}^{N} |r_{j,t} - r_{G,t}|}{N}} \tag{2}$$

While CSD can be viewed as a measure of a cluster's "density" (i.e. how close together are the cluster's elements), the DCI represents a distance measure which reflects how far from the cluster's consensus ("centre") is a specific fund. In addition to its intuitive interpretation and ease of computation, the DCI has the advantage of being a relative measure, so that levels of DCI can be directly compared across funds irrespective of whether they belong to the same style group. More specifically, as an arithmetic average of absolute deviations, the CSD reflects the contribution of the average fund to the group's dispersion. By dividing the distance of a particular fund from the group's mean by the average distance, the DCI effectively translates into the distance of that fund from the consensus relative to the mean (expected) distance. For example, the mean DCI across all funds in a given style group is by construction equal to 1. Therefore, a fund with a DCI of 0.5 can be thought of as being away from its style group mean at half the distance that would have been expected on average, while a fund with a DCI of 2 can be thought of as being twice as far away than expected from the mean of its group.

3 Data

We examine a sample of hedge funds from the BarclayHedge database, with the sample period spanning from January 1994 to August 2015. The BarclayHedge database reports, among other fields, the monthly returns of hedge funds and a large set of fund characteristics. Our initial dataset comprises 6,489 live and 16,478 graveyard funds, for a total of 22,967 unique funds. Similarly to previous studies, we apply several filters on this dataset. First, we exclude non-monthly filing funds and those with unknown strategies. Second, we drop funds denominated at any currency other than USD. We then exclude funds for which average assets under management (AUM) are below 5 million USD. Similarly to Sun et al. (2012), we filter out funds that have fewer than 12 observations in any given 24-month period and we control for backfill bias by dropping the first 18 monthly observations for each fund. Finally, we exclude funds of funds. The resulting post-filtering dataset comprises 9,533 unique funds, with 2,961 funds being alive at end of the sample period and 6,572 funds having been defunct at some point during that period.

BarclayHedge classifies hedge funds into 96 groups based on the primary strategy that they follow. Given that such a number of strategy groups is significantly high (for instance compared to the number of strategy groups typically examined in the related literature) and that clear similarities exist between the strategies of different groups, we follow the classification approach proposed by Joenvaara et al. (2016) and assign funds to 12 main style categories. These "mapped" strategy categories consist of CTA, emerging markets, event-driven, global macro, long-only, long-short, market-neutral, multi-strategy, relative value, sector, short-bias, and others. The most populated strategy groups are the long/short and sector, while the least populated one is the short bias group.

Table 1 reports descriptive characteristics for the post-filtering sample of hedge funds for the period January 1994 to August 2015. Each column tabulates the time-series mean of a particular cross-sectional descriptive statistic (mean, median or standard deviation) for a given characteristic. The characteristics examined consist of the number of funds per period, the DCI computed using equation (2), the 24-month volatility of returns, the fund's redemption notice and lock up period, a dummy variable for high watermark, the fund's management and performance fees (in percentages), age, AUM, leverage, and the Sun et al. (2012) SDI. Descriptives are tabulated separately for the full sample, as well as for the live and graveyard subsamples.[2]

[2]We follow Sun et al. (2012) and compute a fund's SDI as 1 minus the correlation of the fund's

[Table 1 around here]

As has been previously discussed, the mean DCI is equal to 1 by default. However, the median DCI is found to be around 0.70 for both live and graveyard funds, which is substantially lower than the mean. The fact that the majority of funds exhibit a DCI that is lower than the expected value of 1, while a relatively small number of funds appear to follow very distinctive strategies, is also evidenced in the histogram of DCI presented in Figure 1. The frequency distribution of DCI across all funds is characterized by a substantial level of positive skewness, and this is also the case when the histograms are produced separately for live and graveyard funds (unreported to conserve space). This significant asymmetry in the DCI distribution indicates that funds which deviate substantially from their style-group's consensus are relatively rare, while funds which follow the group's consensus more closely are quite common. Although the relative scarcity of potentially skilled fund managers who pursue unique strategies and the relative abundance of managers who follow the trend to a significant extent is not necessarily surprising, the magnitude of this asymmetry is somewhat large compared to previously reported findings (see, for instance, Sun et al., 2012).

[Figure 1 around here]

4 Empirical Results

4.1 Performance measures

Our main focus is on understanding how hedge funds' tendency to deviate from their respective benchmark, as measured by DCI, relates to their performance. In order to form a comprehensive view of funds' performance, we examine their monthly returns (net of fees) as well as a set of commonly used performance measures. The first performance measure refers to the alpha obtained from the

returns with the mean return of all funds belonging in the same strategy group. We estimate the $SDI_{i,t}$ of fund i at time t using returns over the previous 24 months, as follows

$$SDI_{i,t} = 1 - \frac{\sum_{k=1}^{24} (r_{i,t-k} - \bar{r_i})(r_{G,t-k} - \bar{r_G})}{\sum_{k=1}^{24} (r_{i,t-k} - \bar{r_i})^2 \sum_{k=1}^{24} (r_{G,t-k} - \bar{r_G})^2}$$

In contrast to Sun et al. (2012), though, who follow Brown and Goetzmann (1997, 2003) to produce fund clusters, we assign funds to strategy groups according to the Joenvaara et al. (2016) methodology.

Fung and Hsieh (2004) 7-factor (FH) model. The FH model, arguably the most commonly used asset pricing model in the hedge fund literature, comprises 7 factors that have been shown to explain the cross-section of hedge fund returns better than the Capital Asset Pricing Model or other pricing models that have been traditionally used in the case of stocks. The 7 FH factors consist of a bond trend-following factor, a currency trend-following factor, a commodity trend-following factor, an equity market factor, a size spread factor, a bond market factor and a credit spread factor.[3] We measure the abnormal performance of a given fund at time t as the intercept from fitting the FH model using the past 24 months of that fund's returns. In order to obtain a time-series of FH alphas for each individual fund in the sample, we run the FH model on a rolling 24-month basis. Overall, the FH alpha measures a fund's risk-adjusted (or abnormal) return after accounting for the fund's exposure to a set of relevant risk factors.

Our second performance measure is a modification of the Treynor and Black (1973) Appraisal Ratio (AR). We compute a fund's AR at t by dividing the mean of its past 24 FH alphas by their standard deviation. Scaling alpha by its standard deviation produces a performance measure that captures abnormal returns in excess of exposure to a set of systematic risks, after also accounting for idiosyncratic risk. In this sense, the AR can serve as a more useful measure of hedge fund performance than the simple FH alpha, particularly since it mitigates problems stemming from survivorship bias (Sun et al., 2012) and it accounts for differences in leverage among different funds (Agarwal and Naik, 2000).

Moreover, we evaluate fund performance by computing the Keating and Shadwick (2002) Omega measure. The Omega shifts the emphasis from the returns distribution variance, or its co-variance with the group's mean return, to downside risk. In particular, the Omega is computed based on the distribution's first Lower Partial Moment (LPM), and it is defined as

$$Omega_i = \frac{\int_L^b [1 - F(r_i)] dr_i}{\int_a^L F(r_i) dr_i} \tag{3}$$

where L is a return threshold, F is the cumulative distribution function of the returns of fund i, and a and b are the upper and lower bounds of the returns distribution, respectively. We compute a fund's Omega at t using returns over the past 24 months and we set the threshold L equal to the risk-free rate (1-month T-bill rate). The Omega measures performance by focusing on returns below a

[3]Fung and Hsieh have recently introduced an additional factor in their model, namely the emerging market risk factor. Our subsequent analysis has been replicated using the extended FH model, with the results being similar to the ones obtained under the standard 7-factor model and, thus, omitted for brevity.

certain threshold as a proxy for risk, and it is flexible in dealing with the non-normal distributions of hedge fund returns.

We also compute the Sortino ratio as given in equation (4). Similarly to the Omega, the Sortino ratio is also a performance measure that adjusts mean returns for their level of downside risk. The main difference between the two is that the Omega is based on the first LPM while the Sortino ratio is based on the second LPM (Kaplan and Knowles, 2004).

$$Sortino_i = \frac{\int_{-\infty}^{\infty} r_i dF(r_i) - L}{\sqrt{\int_{-\infty}^{L} (L - r_i)^2 dF(r_i)}} \tag{4}$$

4.2 DCI persistence and relationship with fund characteristics

If the DCI is to be considered a meaningful measure of a fund manager's tendency to deviate from her peers, it should exhibit some level of persistence over time. In this context, a manager who possesses unique skills and resources during a particular period would be expected to exhibit the same characteristics in the future. Moreover, a manager who pursues a unique strategy that proves to be profitable would also be expected to continue trading in that fashion in the future, at least until the uniqueness of that strategy in the market has been exhausted. At the other end of the spectrum, a manager with a low level of skills/resources who tends to invest as a trend-follower in a given period is likely to pursue non-unique strategies in future periods as well, consistently displaying low levels of DCI.

We examine the persistence of the DCI by looking at the differences in future DCI levels among portfolios that have been originally sorted by their DCI. More specifically, in each month, we sort all sample funds into five portfolios according to their lagged DCI. We then compute the mean DCI of each portfolio when held for the next 1, 3, 6, 12 and 24 months. Whenever a fund ceases to trade during a particular holding period, it simply exits its respective portfolio so there is no look-ahead bias. Table 2 presents the mean DCI levels of these quintile portfolios at the time of sorting and across the different holding periods. We also report the difference between the mean DCI of the highest-DCI and lowest-DCI portfolios, and its respective t-statistic.

[Table 2 around here]

At the time of sorting, the lowest quintile portfolio has a mean DCI of 0.13, while the highest quintile portfolio has a mean DCI of 2.69. Consistent with the positively skewed DCI distribution that was discussed earlier, the first three quintiles have mean levels of DCI below 1. Unsurprisingly, the difference between the mean DCI of the first and last quintile (2.56) is statistically significant at any meaningful significance level. More importantly, the persistence of the DCI is supported by the fact that the mean DCI levels of the quintile portfolios at the end of the holding period are still monotonically increasing, with this finding being consistent across all holding periods from 1 to 24 months. The difference between the DCI levels of the first and last quintile diminishes as the holding period increases, reaching a minimum of 0.62 for the holding period of 24 months, but all these DCI differences are highly statistically significant. Overall, these results are indicative of a significant persistence in the DCI, with funds that exhibit a low (high) DCI at a given period being more likely to have a low (high) DCI in subsequent periods.

Having established that the DCI is a relatively persistent measure, we proceed to examine the fund characteristics that might affect strategy distinctiveness. In particular, we estimate a panel regression of funds' DCI levels against lagged fund-specific characteristics, as given in equation (5). The vector X of fund characteristics consists of the fund's volatility of returns during the previous 24 months, the redemption notice period, the lock up period, a dummy variable for high watermark, the management and performance fees (in percentages), the fund's age, AUM, leverage, and its Sun et al. (2012) SDI. Table 3 reports the results.

$$DCI_{i,t} = \alpha + BX_{i,t-1} + \epsilon_{i,t} \tag{5}$$

The DCI is found to be significantly positively related to a fund's return volatility, length of redemption period and length of lock up period. Furthermore, the DCI seems to increase with the funds performance fee, suggesting that managers who are more skilled (and, thus, more likely to deviate from the benchmark) tend to charge higher fees. However, the relationship between the DCI and the fund's management fee is statistically insignificant. Moreover, the DCI is found to be higher for funds of higher age, lower AUM and higher leverage. The negative relationship between age and the DCI is potentially surprising, since we would have expected the managers of younger funds to be more flexible in pursuing unique strategies. The negative DCI-AUM relationship, though, is consistent with the intuition that smaller funds can be more flexible in adopting new innovative strategies compared to larger funds. Interestingly, we find that the DCI is negatively related to the SDI in our sample. This result seems to suggest that higher correlations with the benchmark in previous periods are likely to be followed by larger absolute deviations from the benchmark in subsequent periods.

[Table 3 around here]

4.3 DCI and fund performance

In order to explore if deviating from the benchmark is related to hedge fund performance, we begin by looking at whether portfolios of funds with markedly different levels of DCI at a given point in time perform differently during subsequent periods. More specifically, we evaluate fund performance for portfolios rebalanced every 1, 3, 6, 12 and 24 months. At the beginning of each rebalancing period, we sort all funds in our sample into quintile portfolios based on their DCI levels computed in the previous month. Within each portfolio, we compute the equally-weighted mean return (net of fees). This approach results in one time-series of returns per quintile portfolio, with the length of each time-series varying according to the length of the rebalancing period considered.

Table 4 summarizes the mean returns offered by the above quintile portfolios. The first thing to notice is that, with few exceptions, returns increase monotonically with the portfolio's DCI. For example, at the shortest (monthly) rebalancing frequency, the lowest-DCI portfolio earns on average 0.75% per month while the highest-DCI portfolio earns 1.19% per month. Moreover, this relationship holds across all five rebalancing periods. Overall, these findings seem to support the hypothesis that funds which deviate more from their peers tend to outperform.

[Table 4 around here]

To put the return differential between funds with different levels of DCI into perspective, we also report the mean return (and associated t-statistic) of a spread portfolio that goes long in the highest-DCI funds of the last quintile and short in the lowest-DCI funds of the first quintile. We find that this zero-cost portfolio, termed P5-P1, offers a statistically significant and economically large mean return which, for instance in the case of monthly rebalancing, is approximately equal to 0.43% per month. The mean return of the spread portfolio seems to be somewhat decreasing as the length of the rebalancing period increases, potentially as a result of differences in the DCI between portfolios becoming less pronounced as funds remain for longer periods inside particular portfolios without rebalancing to account for relative changes in their DCI. However, P5-P1 returns are quite large even in the longest rebalancing period that we consider (24 months), where the zero-cost spread portfolio is found to earn a mean 0.24% per month (t-statistic is 3.08).

Even though the results reported in Table 4 suggest that funds which pursue more unique investment strategies tend to offer higher returns, these returns need to be evaluated against the funds' exposure to risk in order to understand the effect on overall fund performance. To this end, Table 5 reports the performance measures discussed in subsection 4.1 for the five DCI-sorted portfolios across the five different rebalancing periods. We also report the performance of the P5-P1 spread portfolio and the respective t-statistics. Due to the non-normality of fund performance, we use bootstrapped error bounds on the empirical distribution of each performance measure. In particular, in each case we obtain 1,000 non-parametric bootstrapped samples by sampling with replacement from the time-series of a particular performance measure. We then compute standard errors based on the distribution of these bootstrapped samples.

[Table 5 around here]

As can be seen from Panel A, the FH alpha increases monotonically as the DCI increases for portfolios 2 to 5, although the alpha of the first (lowest-DCI) portfolio is found to be higher than those of the medium-DCI portfolios 2 to 4. Importantly, going long in funds with the highest DCI (last quintile) and short in funds with the lowest DCI (first quintile) results in positive and highly significant alphas. For instance, the P5-P1 spread portfolio offers an alpha of 0.20% per month under monthly rebalancing, with FH alphas increasing as the rebalancing period increases. In general, funds that deviate more from the benchmark appear to offer higher risk-adjusted returns, i.e. perform better after accounting for their exposure to a set of relevant systematic risks, compared to funds that follow the "herd" more closely.

However, this positive relationship between the propensity to deviate from the benchmark and fund performance (when the latter is measured by returns or alphas) is not supported by the results obtained when we examine alternative performance measures. Panel B of Table 5 reports the AR of the five sorted portfolios and the spread P5-P1 portfolio. In sharp contrast to the results reported in Table 4 (returns) and Panel A of Table 5 (FH alphas), the AR is found to be monotonically decreasing with the DCI. This negative relationship is robust across all rebalancing periods, and the AR of the P5-P1 portfolio is significantly negative and economically large. The finding that the DCI is positively related with returns and alphas but negatively related with the AR seems to suggest that managers who pursue more distinctive strategies earn larger returns without being exposed to higher levels of systematic risk, but these higher returns come at the cost of much higher levels of idiosyncratic risk.

This finding provides evidence against the Sun et al. (2012) "skills hypothesis" which postulates that unskilled managers are more likely to take on higher levels of idiosyncratic risk while skilled managers are more likely to pursue unique strategies that enhance performance without the need of excessive idiosyncratic risk. Based on the DCI measure, we find that managers who are more skilled (in the sense of adopting strategies that deviate more from the benchmark) tend to avoid excessive systematic risk but still load substantially more on idiosyncratic risk, thereby increasing alpha but decreasing the AR. This relationship is further supported by the significantly positive coefficient of return volatility on the DCI reported in Table 3.[4]

Panels C and D of Table 5 report the respective results from measuring performance by the Omega and Sortino ratios, respectively. Similarly to the results from the AR, the Omega and the Sortino ratios are found to be generally decreasing as we move from the lowest-DCI to the highest-DCI portfolio, across the different rebalancing periods. Moreover, the Omega and the Sortino ratios of the spread P5-P1 portfolios are negative and statistically significant in all cases (with the exception of a negative but insignificant Sortino ratio under the longest 24-month rebalancing period). Given that both metrics measure fund performance relative to the Lower Partial Moments of the returns' distribution, our results suggest that performance deteriorates as deviations from the benchmark increase because of an increasing level of downside risk. This result runs, again, contrary to what might have been expected, since it indicates that it is potentially the skilled fund managers (rather than the unskilled ones) who might be exploiting the option-like feature of their compensation contracts by increasing downside risk in the hope of achieving substantially high returns.

Overall, our results suggest that the relationship between deviations from the benchmark and hedge fund performance is more nuanced than what might have been expected, reflecting the lack of a consensus that seems to characterize the related literature. Managers who have the skills and resources to deviate from their peers are indeed found to earn returns that are on average higher compared to less distinct-strategy funds, even after adjusting for their exposure to the most commonly used systematic risk factors. However, these skilled managers seem to achieve higher returns and alphas by taking on higher levels of idiosyncratic and downside risk, with overall performance actually being worse, as a result, compared to their peers who stay closer to the benchmark.

We employ the standard Fama-MacBeth (1973) two-pass methodology to further explore the relationship between fund performance and deviations from the benchmark. More specifically, in each month we run the following cross-sectional regression

[4] In addition to sorting funds based on different measures, the differences between our findings and those reported by Sun et al. (2012) are also confounded by a set of practical differences, such as the use of different databases of US hedge funds and different sample periods. Perhaps more importantly, we evaluate fund performance by computing the performance measures for the time-series of quintile portfolio returns, while Sun et al. (2012) report portfolio performance as the average performance measure across the funds in that portfolio.

$$perf_i = \alpha + \beta_{DCI} DCI_i + B_X X_i + \epsilon_i \tag{6}$$

where $perf_i$ is the value of a particular performance measure for fund i, DCI_i is the level of the fund's DCI in that month, and X_i is a vector of fund characteristics lagged by one period. The X vector comprises the same fund characteristics examined in Table 3, namely return volatility, redemption notice, lock up period, dummy variable for high watermark, management fee, performance fee, age, AUM, leverage, and the SDI. In addition to the fund characteristics in X, we also include strategy dummy variables in the cross-sectional regressions to control for the funds' different styles. At the second stage, we use the time-series of the estimated coefficients to obtain the mean loading of the performance measure on each characteristic and to determine its statistical significance. Statistical inference is based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors.

Table 6 reports the Fama-MacBeth second stage mean coefficients and t-statistics (in brackets), tabulated separately for each performance measure (return, alpha, AR, Omega, and Sortino). Consistent with our findings from the DCI-sorted portfolios, the Fama-MacBeth results reject the hypothesis of funds which deviate from the benchmark subsequently offering superior performance. One of the most important findings of the two-stage regressions is that, when we control for funds' other characteristics, returns are found to be negatively associated with the DCI (albeit with a statistically insignificant coefficient). It seems that the previously reported positive relationship between the DCI and net returns most likely stems from funds' other characteristics, rather than from a fundamentally positive returns-DCI relationship. When we account for a fund's idiosyncratic profile, deviating from the benchmark tends in fact to lead to lower returns in subsequent periods.

Similarly, FH alphas are found to be significantly negatively related to the DCI after controlling for fund characteristics, in contrast to the previous finding of portfolios' alphas increasing with their DCI level. The Fama-MacBeth mean coefficient of the DCI on alpha is negative (-0.06%) and statistically significant (t-stat is -5.16), suggesting that funds with a lower DCI earn higher risk-adjusted returns compared to funds that have a higher DCI but are comparable in terms of other characteristics.

[Table 6 around here]

Moreover, the results from the Fama-MacBeth regressions for the AR, Omega and Sortino ratio are consistent with the respective results from the sorted portfolios. All three performance measures are found to be negatively and significantly related to the DCI, supporting the hypothesis that funds which deviate more from their cohort's mean tend to perform worse than their less distinctive peers, after accounting for the various fund characteristics and adjusting for risk. Overall, the Fama-MacBeth results stand in stark contrast to the hypothesis of deviations from the benchmark being positively related to performance. When we account for an extensive set of funds' idiosyncratic characteristics, all the performance measures examined are significantly negatively related to the funds' DCI levels, indicating that pursuing a distinctive strategy decreases performance relative to funds with similar characteristics but with a higher propensity to follow the benchmark.

5 Robustness

5.1 Market timing

Cao et al. (2013) show that skilled managers can improve fund performance by timing market liquidity and adjusting their funds' exposure to the market accordingly. Given that the willingness to deviate from the benchmark is directly related to managers' skills, we examine if market liquidity timing skills could potentially explain the previously reported relationship between the DCI and fund performance.

We follow Cao et al. (2013) and regress fund returns against a set of systematic factors and an interaction term between liquidity changes and the market return, given in equation (7)

$$r_t^i = \alpha^i + \beta_F^i F_t + \beta_L^i MKT_t \Delta L_t + \epsilon_t^i \tag{7}$$

where r_t^i is the return of fund i at t, F_t is a vector of the values of the seven Hung and Hsieh (2004) factors, MKT_t is the excess return of the market (also included in F_t), and ΔL_t is the first difference of a market liquidity factor.[5] The Cao et al. (2013) timing model applies to equity-oriented funds, so we exclude funds with strategies that are not associated with equities (see also Sun et al., 2016). We run

[5]We follow Pastor and Stambaugh (2003) and measure market liquidity as the γ_t coefficient from the following regression

$$MKT_{t+1} = \theta_t + \phi_t MKT_t + \gamma_t sign(MKT_t) v_t + \epsilon_t^i$$

where MKT_t is the CRSP value-weighted index return at t and v_t is the corresponding dollar trading volume at the aggregate market level. We run this regression for every month using daily observations over the previous month, resulting in a time-series of monthly values for the aggregate market liquidity.

the time-series regression in (7) separately for each fund. The β_L^i coefficient of the interaction term can be considered as a measure of a fund manager's skills in timing the market liquidity, with larger values indicating a greater timing ability, since the fund would exhibit a higher market beta during good market conditions (i.e. during periods with higher market liquidity).

After computing managers' timing skills, we then double-sort funds in portfolios according to their β_L^i and DCI. In each month, we begin by sorting all funds in quintiles according to their β_L^i. Then, inside each β_L^i-based quintile we further sort the funds in quintiles according to their DCI. Finally, the monthly returns of the DCI-based quintiles are averaged across the β_L^i-based quintiles, thus reflecting the returns of portfolios with homogeneous β_L^i levels but across different levels of DCI. This two-way sort is repeated every month, resulting in a time-series of portfolio returns across the five DCI-based portfolios. The double-sorting has the advantage of ensuring that the final quintile portfolios have comparable mean levels of β_L^i and are only expected to differ in terms of their DCI levels.

Panel A of Table 7 reports the returns and performance measures of the P5-P1 portfolios under this double-sorting. Our results suggest that market liquidity timing skills seem to be, to an extent, related to our previous findings on the relationship between DCI and fund performance. More specifically, the spread P5-P1 portfolios are still found to earn positive returns and significantly negative AR, Omega, and Sortino ratios across all five rebalancing periods, similarly to the results previously reported. However, under double-sorting with market liquidity timing skills, FH alphas become negative (and statistically significant for rebalancing periods up to 6 months).

[Table 7 around here]

Chen and Liang (2007) demonstrate that funds which self-report following market timing strategies indeed show significant ability to time US market returns, especially during up markets. In order to explore the potential effect of the ability to time market returns on our results, we follow Chen and Liang (2007) and measure the respective timing skills of fund managers as the β_M^i of the following regression

$$r_t^i = \alpha^i + \beta_F^i F_t + \beta_M^i (MKT_t)^2 + \epsilon_t^i \tag{8}$$

Higher values of β_M^i are indicative of a greater market-timing ability. After computing managers' skills to time market returns for equity-oriented funds, we double-sort funds in portfolios according to their timing ability and their DCI. Panel B of Table 7 reports the performance of the resulting spread portfolios across different rebalancing periods. The results are very similar to those obtained from accounting for the managers ability to time market liquidity (reported in Panel A), with positive but mostly insignificant returns, and significantly negative alphas, AR, Omega and Sortino ratios.

Overall, these results seem to suggest that the initially reported superior alphas earned by funds which deviate the most from the benchmark can be, at least partially, attributed to managers' timing skills in the subsample of equity-oriented funds. Once we account for exposure to systematic factors and the ability to time the market return and/or liquidity, equity-oriented funds with the highest (lowest) DCI levels are found to earn the lowest (highest) returns. This negative relationship between deviating from the benchmark and subsequent fund performance is further supported by the AR, Omega, and Sortino ratios.

5.2 Sorting on the mean DCI

One of the advantages of the DCI is that its value for a particular fund at t only requires a cross-section of comparable fund returns at that time to be computed. In the interest of robustness, though, we examine if using a short-term mean DCI as an alternative measure (instead of the point estimate) produces different results.

Table 8 reports the results from using the DCI mean computed over the previous 2, 3 and 6 months.[6] Panel A tabulates the returns and performance measures of the P5-P1 spread portfolios, while Panel B tabulates the coefficients of the DCI from the Fama-MacBeth regressions in (6). Our results are very similar to those obtained when the point estimate of DCI is used, with the spread portfolios earning significantly positive returns and FH alphas, and significantly negative AR, Omega, and Sortino ratios. Also, all performance measures have negative and (almost always) statistically significant Fama-MacBeth loadings on the DCI. Moreover, these results are consistent across mean levels of the DCI computed in periods of different length. Overall, our finding that funds which deviate less from the benchmark tend to outperform their more distinctive peers does not appear to be driven by potential noise from computing the DCI as a point estimate.

[Table 8 around here]

5.3 Controlling for the SDI

The Fama-MacBeth results that were discussed in the previous section show that the DCI contains incremental information about a fund's performance, in excess of

[6]This analysis has been replicated with DCI means computed over longer horizons (up to 18 months). The results are qualitatively similar and, thus, omitted to conserve space.

the information already contained in other fund-specific characteristics, including the fund's SDI. In order to explore the incremental informational content of the DCI further, we proceed to examine the performance of portfolios of funds that have been double-sorted on SDI and DCI, similarly to our approach in subsection 5.1. The resulting double-sorted portfolios are constructed so that they vary in terms of their DCI levels without being overpopulated by funds that exhibit particularly low or high SDI levels.

Table 9 reports the returns and performance measures, along with the associated t-statistics, of the respective P5-P1 spread portfolios under double-sorting. The main thing to notice is that the results are very similar to those obtained in Tables 4 and 5, when funds had been sorted only on their DCI levels. Going long in the highest-DCI funds and short in the lowest-DCI ones, and simultaneously ensuring that the position is neutral with respect to the SDI, is found to offer positive returns and FH alphas which are statistically significant in most cases. Furthermore, all the other performance measures take negative values across all rebalancing periods, and they are consistently statistically significant (with the only exception of the Sortino ratio under 24-month rebalancing). In other words, funds which deviate more from the benchmark, according to their DCI, tend to perform worse than their peers, even when they are characterized by the same SDI levels. Overall, these results confirm that the proposed DCI contains information about a funds tendency to deviate from the benchmark that is not contained in the historical correlations with benchmark returns.

[Table 9 around here]

5.4 Alternative groupings of funds

In this subsection, we re-examine the relationship between the DCI and performance using the original BarclayHedge classification of hedge funds into 96 strategy groups. Even though this number of style groups is arguably too large, the BarclayHedge classification is nevertheless readily available and it could perhaps highlight important differences between niche fund markets. The results based on the original BarclayHedge style groups, reported in Panel A of Table 10, are very similar to those obtained under the Joenvaara et al. (2016) classification.

[Table 10 around here]

First, the returns and FH alphas of the P5-P1 spread portfolios are positive and statistically significant across the five rebalancing periods, while the ARs are significantly negative. The downside risk measures (Omega and Sortino) are significantly negative for the shorter rebalancing periods and insignificant for the longer ones. Second, the Fama-MacBeth regressions indicate that the loadings of the performance measures on the DCI are significantly negative.

In addition to basing the style groups on funds' self-reporting, i.e. using the original BarclayHedge or the Joenvaara et al. (2016) classifications, we also group funds according to the relative proximity of their historical returns. More specifically, we assign funds in 10 groups following the k-means clustering procedure. First developed by MacQueen (1967), the k-means procedure groups elements into clusters by minimizing the sum of Euclidian distances of all elements from their respective group means (see Brown and Goetzmann, 1997, and Sun et al., 2012, for a more detailed discussion of k-means clustering). The resulting clusters are not affected by the way in which funds self-report their own strategies, but they are solely driven by the funds actual performance history.

The results, presented in Panel B of Table 10, are again very similar to those obtained under the Joenvaara et al. (2016) classification. Portfolios with higher DCI levels are found to offer significantly higher returns and alphas but significantly lower AR, Omega and Sortino ratios. Also, all performance measures are significantly negatively related to the DCI in the Fama-MacBeth regressions. Overall, these results confirm that the previously reported negative relationship between deviations from the benchmark and performance measures is not simply an artefact of the specific way in which we group funds.

5.5 Value-weighted portfolios

Our previous results were based on equally-weighing funds within particular portfolios. We repeat the analyses by value-weighing funds instead. On each calendar month, the returns (and associated performance measures) are computed assuming that each fund enters a portfolio at a weight proportional to its AUM in that month relative to the portfolio's total AUM. Table 11 reports the resulting returns and performance measures of the P5-P1 value-weighted spread portfolios across the five rebalancing periods.

[Table 11 around here]

It appears that the weighing scheme does not affect the main relationship of interest. Going long in a value-weighted portfolio with the highest DCI and short in the portfolio with the lowest DCI is still found to offer significantly positive returns and alphas. However, consistent with our previous results, funds with the highest deviations from the benchmark considerably underperform relative to their least distinctive peers in terms of AR, Omega, and Sortino ratio, with the spread performance measures being statistically significant across most of the rebalancing periods.

5.6 The hedging effect

Titman and Tiu (2011) demonstrate that fund managers who maintain lower exposures to factor risk are more likely to deliver superior performance. In our context of deviating from the benchmark, this finding could be interpreted as more skilled fund managers tending to target superior performance through the implementation of more distinctive strategies rather than as compensation for simply bearing higher systematic risk. We follow Titman and Tiu (2011) and measure a fund's exposure to systematic risk at t as the R-square obtained from regressing the fund's returns over the previous 24 months against the 7 Fung and Hsieh (2004) factors. If a fund manager's propensity to seek exposure to systematic risk is indeed related to the fund's tendency to deviate from its peer group, we would expect the DCI to be negatively correlated with the R-square or, alternatively, positively correlated with 1 minus the R-square (see also Sun et al., 2012).

We examine the relationship between the DCI and the Titman and Tiu (2011) "hedging effect' in two ways. First, we sort funds into quintiles according to their DCI levels, as before. Then, we sort all funds according to their $1 - R^2$ measure, independently from the first sort. Finally, we compute the proportion of funds that simultaneously fall in a particular DCI quintile and a particular $1 - R^2$ quintile, for all 25 possible quintile combinations. If deviations from the benchmark are independent from the hedging effect, we would expect a uniform overlap among quintiles, with each quintile combination representing roughly $1/25 = 4\%$ of the total sample of funds. On the other hand, if the tendency to deviate from the group's consensus is associated with a lack of need for exposure to systematic risk, we would expect quintile combinations that are equally low (or equally high) in DCI and $1-R^2$ to be populated by more funds compared to low-high combinations.

Panel A of Table 12 reports the proportion of funds that falls under each of the 25 quintile combinations. This proportion seems to be distributed in a consistently uniform way, with each quintile combination being populated by approximately 4% of funds. For instance, the least populated combination includes 3.79% of all funds, while the most populated one includes 4.12% of funds. Furthermore, none of the proportions is found to be statistically different from the 4% threshold at any meaningful significance level. In other words, no discernible pattern is detected between the DCI and the hedging effect (in contrast to a non-trivial overlap between the SDI and $1 - R^2$ reported by Sun et al., 2012).

[Table 12 around here]

Our second test involves examining the performance of funds that have been double-sorted according to their DCI and $1 - R^2$. Similarly to the double sorts discussed in previous subsections, these portfolios are constructed so that they vary in terms of the DCI levels while having similar levels of $1 - R^2$. Panel B of Table 12 reports the returns and performance measures of the P5-P1 spread portfolios under this double-sorting. The results are broadly similar to those reported thus far. More specifically, funds with higher levels of DCI seem to offer higher returns than funds with lower DCI levels, although the difference is statistically significant only for the shortest 1-month rebalancing period. However, higher-DCI funds underperform considerably compared to their less distinctive peers after accounting for risk, with the spread portfolios being associated with negative (but mostly insignificant) alphas and significantly negative AR, Omega, and Sortino ratios.

5.7 Survivorship bias

Our dataset contains both live and graveyard funds, so we would expect any concerns related to survivorship bias not to be particularly pronounced. However, it could still be the case that funds which drop out of the sample because they stop reporting while still trading earn markedly different returns compared to funds that stay in the sample. In order to make sure that our findings are not driven by differences between live funds and graveyard funds that still operate, we examine the survivorship ratios among the five DCI-sorted quintile portfolios.

More specifically, Table 13 reports the survivorship ratios for each portfolio over the 1, 3, 6, 12 and 24 months post-formation. We also report the difference in survivorship ratios between the highest-DCI portfolio P5 and the lowest-DCI portfolio P1, and their associated t-statistics. The differences between survivorship ratios are found to generally increase as the period for which survivorship is computed increases. Furthermore, the majority of these differences are statistically significant, while the P5-P1 differences are always significant. However, the actual magnitude of these differences is very small (ranging from 0.20% to 1.59%), suggesting that the probability of a fund exiting the sample is not related to its DCI in a substantial way. Overall, these results confirm that the previously reported relationship between the DCI and fund performance is unlikely to be driven by survivorship bias.

[Table 13 around here]

6 Conclusion

This paper focuses on the current debate in the literature about whether a fund deviating from the benchmark reflects higher skills or simply a willingness to gamble in pursuit of higher returns. We use a simple measure of deviations from the benchmark, based on the distance between the return of the fund and the mean return of its cohort, and we label this measure the fund's Dispersion Contribution Index (DCI).

Our empirical results strongly reject the hypothesis that funds which deviate from their benchmark outperform their less distinctive peers. We examine a large sample of hedge funds during 1994-2015 and find that, after accounting for various sources of risk and for a set of idiosyncratic characteristics, funds that deviate the most from their peers offer the worst performance. At the other end of the spectrum, funds that deviate the least from the consensus of their cohort are found to offer the highest risk-adjusted returns.

These findings challenge the commonly held view that higher performance fees are justified in order to invest in hedge funds that are more actively managed by skilled managers pursuing more distinctive strategies. It might well be the case that more skilled managers seek to achieve elevated performance by deviating from the ideas implemented by their peers. However, these distinctive strategies seem to come at a significant cost to investors, both in terms of risk exposure and higher fees.

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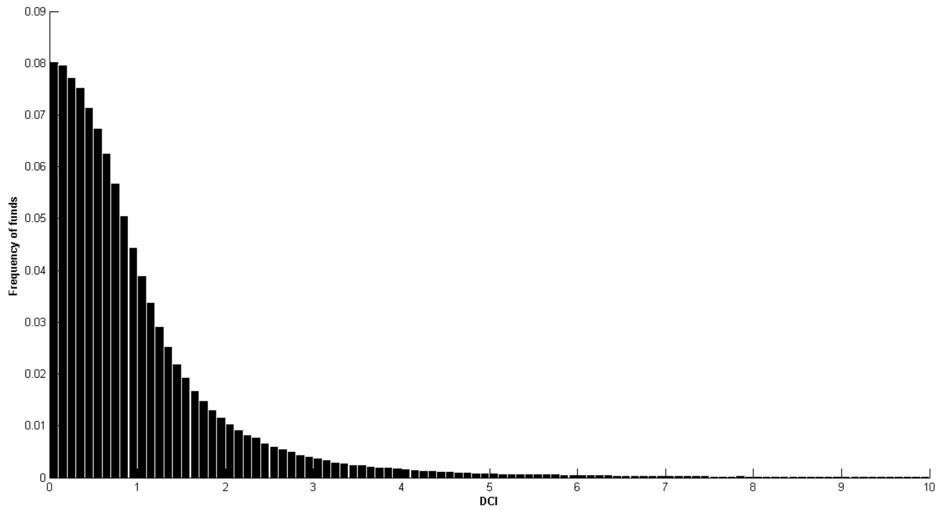
Figure 1: DCI Histogram



Notes: This Figure plots the histogram of DCI across the full sample (live and graveyard funds). The sample period is January 1994 to August 2015.

Table 1: Fund characteristics

	All Funds			Live Funds			Graveyard Funds		
	Mean	Median	St.dev	Mean	Median	St.dev	Mean	Median	St.dev
Funds per period	2,906	3,267	1,093	1,136	858	903	1,769	1,897	799
DCI	1.00	0.68	1.23	1.00	0.69	1.18	1.00	0.69	1.27
Return Volatility	0.04	0.03	0.03	0.04	0.03	0.03	0.04	0.03	0.03
Redemption Notice	34.7	30.00	39.20	32.22	30.00	33.45	35.84	30.00	41.54
Lock Up	9.38	0.00	17.60	9.17	0.00	18.35	9.48	0.00	17.24
High Watermark	0.69	1.00	0.46	0.75	1.00	0.43	0.66	1.00	0.47
Management Fee	1.52	1.50	0.68	1.47	1.50	0.59	1.54	1.50	0.71
Performance Fee	17.75	20.00	6.50	15.90	20.00	7.83	18.58	20.00	5.61
Age	11.87	11.17	6.40	8.48	7.00	6.03	13.40	12.59	5.97
AUM	17.02	17.21	2.11	17.40	17.58	2.14	16.75	16.95	2.11
Leverage	0.44	1.00	0.36	0.52	1.00	0.41	0.40	1.00	0.48
SDI	0.47	0.53	0.33	0.51	0.59	0.32	0.44	0.50	0.33

Notes: This Table reports descriptive statistics for a number of hedge fund characteristics. Each column tabulates the time-series average of the respective cross-sectional statistic. Statistics are tabulated separately for the full sample, and for the live and graveyard subsamples. The sample runs from January 1994 to August 2015.

Table 2: DCI persistence

	$t = 0$	1m	3m	6m	12m	24m
P1 (Low DCI)	0.13	0.76	0.78	0.79	0.81	0.82
P2	0.39	0.77	0.80	0.81	0.81	0.83
P3	0.68	0.83	0.84	0.85	0.86	0.88
P4	1.11	0.98	0.98	0.99	0.99	1.00
P5 (High DCI)	2.69	1.66	1.59	1.54	1.50	1.44
P5 - P1	2.56	0.90	0.81	0.75	0.70	0.62
(*t-stat*)	(363.3)	(91.7)	(93.4)	(82.4)	(79.1)	(62.8)

Notes: This Table reports the time-series average *DCI* of five portfolios for the current month and for the subsequent 1, 3, 6, 12 and 24 months. The five portfolios have been sorted based on the *DCI* at $t = 0$.The Table also reports the difference between the mean *DCI* in the first and last portfolio and the respective t-statistic (in brackets). The sample runs from January 1994 to August 2015.

Table 3: DCI determinants

Constant	0.5724
	(25.23)
Return Volatility	18.1413
	(129.77)
Redemption Notice	0.0003
	(2.61)
Lock Up	0.0009
	(3.33)
High Watermark	0.0641
	(6.04)
Management Fee	-0.0011
	(-0.17)
Performance Fee	0.0015
	(2.15)
Age	-0.0076
	(-10.66)
AUM	-0.0008
	(-0.96)
Leverage	0.0071
	(3.10)
SDI	-0.5078
	(-36.37)
Adj.R2	0.65

Notes: This Table reports the results from estimating a panel regression of individual funds' *DCI* against a set of fund characteristics. The set of fund characteristics is lagged by one period. The Table reports the estimated coefficients, the respective t-statistics (in brackets), and the Adjusted R-square. The sample runs from January 1994 to August 2015.

Table 4: Returns of portfolios sorted on DCI

	1m	3m	6m	12m	24m
P1 (Low DCI)	0.0075	0.0075	0.0077	0.0078	0.0071
P2	0.0075	0.0074	0.0076	0.0075	0.0069
P3	0.0079	0.0078	0.0076	0.0072	0.0068
P4	0.0080	0.0082	0.0081	0.0078	0.0076
P5 (High DCI)	0.0119	0.0110	0.0110	0.0110	0.0096
P5 - P1	0.0043	0.0036	0.0033	0.0032	0.0024
(*t-stat*)	(4.52)	(2.76)	(3.13)	(2.83)	(3.08)

Notes: This Table reports the time-series mean returns of five portfolios sorted on the funds' levels of *DCI*. Returns are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. The Table also reports the difference between the mean returns of funds in the highest-*DCI* quintile portfolio and those in the lowest-*DCI* quintile portfolio, as well as the respective t-statistic. The sample runs from January 1994 to August 2015.

Table 5: Performance measures of portfolios sorted on DCI

	1m	3m	6m	12m	24m
Panel A: Alpha (Fung-Hsieh)					
P1 (Low DCI)	0.0073	0.0073	0.0073	0.0073	0.0071
P2	0.0072	0.0072	0.0072	0.0071	0.0067
P3	0.0072	0.0073	0.0072	0.0072	0.0067
P4	0.0074	0.0074	0.0073	0.0073	0.0072
P5 (High DCI)	0.0093	0.0093	0.0097	0.0101	0.0101
P5 - P1	0.0020	0.0021	0.0024	0.0028	0.0030
(*t-stat*)	(10.35)	(5.79)	(5.14)	(4.25)	(3.62)
Panel B: Appraisal Ratio					
P1 (Low DCI)	2.9388	3.0164	3.0644	3.1299	3.1015
P2	2.8823	2.8738	2.9248	2.9987	3.0778
P3	2.6791	2.7478	2.7851	2.8233	2.8276
P4	2.1678	2.1350	2.1720	2.2328	2.2466
P5 (High DCI)	1.5794	1.5635	1.5720	1.5924	1.6808
P5 - P1	-1.3595	-1.4529	-1.4924	-1.5375	-1.4206
(*t-stat*)	(-30.59)	(-16.94)	(-16.78)	(-16.46)	(-16.96)
Panel C: Omega					
P1 (Low DCI)	3.6428	3.9342	3.7997	4.0394	3.8759
P2	3.7838	4.0506	4.3336	4.9867	4.4503
P3	3.4414	3.6204	3.7817	3.6943	3.1483
P4	2.4973	2.6541	2.8573	2.9152	2.5290
P5 (High DCI)	1.8006	1.8864	2.0501	2.1687	2.5487
P5 - P1	-1.8421	-2.0478	-1.7496	-1.8707	-1.3272
(*t-stat*)	(-13.82)	(-7.63)	(-5.84)	(-5.30)	(-3.56)
Panel D: Sortino					
P1 (Low DCI)	1.5723	1.6067	1.5727	1.7638	1.6593
P2	1.5464	1.6456	1.8172	1.9083	1.7013
P3	1.3486	1.4898	1.4315	1.4583	1.1257
P4	0.9746	1.0283	1.1833	1.0986	1.2526
P5 (High DCI)	0.7452	0.7961	0.8634	1.1372	1.2420
P5 - P1	-0.8270	-0.8105	-0.7093	-0.6266	-0.4173
(*t-stat*)	(-12.52)	(-7.00)	(-4.51)	(-2.20)	(-1.49)
Panel E: MPPM					
P1 (Low DCI)	0.3214	0.3669	0.4328	0.5457	0.3943
P2	0.3164	0.3605	0.4183	0.5485	0.3751
P3	0.3158	0.3677	0.4331	0.5642	0.4106
P4	0.3155	0.3772	0.4401	0.5787	0.4012
P5 (High DCI)	0.2782	0.3287	0.4025	0.5205	0.3844
P5 - P1	-0.0432	-0.0382	-0.0303	-0.0252	-0.0099
(*t-stat*)	(-7.28)	(-3.56)	(-1.98)	(-1.15)	(-0.39)

Notes: This Table reports the time-series means of a set of performance measures for five portfolios sorted on the funds' levels of *DCI*. The performance measures examined comprise the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. The Table also reports the difference between the mean performance measure of funds in the highest-*DCI* quintile and those in the lowest-*DCI* quintile, as well as the respective t-statistic. The sample runs from January 1994 to August 2015.

Table 6: Fama-MacBeth regressions of hedge fund performance

	Return	Alpha	AR	Omega	Sortino	MPPM
Constant	-0.0054	-0.0012	2.7826	1.8954	1.6479	0.0266
	(-1.25)	(-1.54)	(10.50)	(4.07)	(4.40)	(0.58)
DCI	-0.0003	-0.0006	-0.1148	-0.3832	-0.1437	0.0282
	(-0.60)	(-5.16)	(-9.20)	(-11.14)	(-5.46)	(1.08)
Return Volatility	0.0816	0.1006	-19.3222	-4.6941	-7.0700	-3.1550
	(3.15)	(14.86)	(-28.58)	(-2.62)	(-5.09)	(-2.33)
Redemption Notice	0.0000	0.0000	0.0017	0.0068	-0.0019	-0.0001
	(0.34)	(-3.37)	(5.62)	(3.64)	(-1.31)	(-1.09)
Lock Up	0.0000	0.0000	0.0010	-0.0025	-0.0070	0.0001
	(0.74)	(3.48)	(1.54)	(-0.86)	(-3.11)	(0.47)
High Watermark	0.0004	0.0003	0.0268	-0.6231	0.1561	0.0017
	(0.88)	(3.86)	(0.96)	(-5.19)	(1.91)	(0.35)
Management Fee	0.0003	0.0000	-0.1267	-0.0761	-0.0562	-0.0144
	(0.97)	(-0.63)	(-5.56)	(-1.20)	(-2.94)	(-1.62)
Performance Fee	0.0000	0.0000	0.0076	0.0382	-0.0109	-0.0002
	(-0.75)	(4.72)	(6.42)	(6.57)	(-2.01)	(-0.24)
Age	-0.0001	0.0000	0.0022	0.0444	-0.0354	0.0001
	(-1.33)	(-3.12)	(1.35)	(4.73)	(-2.53)	(0.30)
AUM	-0.0001	0.0001	0.0056	-0.0388	0.0733	0.0021
	(-0.46)	(5.59)	(1.22)	(-2.06)	(3.82)	(0.90)
Leverage	-0.0001	0.0001	0.0294	-0.1416	-0.1195	-0.0019
	(-0.56)	(2.67)	(2.92)	(-4.57)	(-5.09)	(-1.10)
SDI	-0.0009	-0.0042	-0.8172	-2.8805	-1.8017	0.0156
	(-0.69)	(-13.10)	(-10.83)	(-13.28)	(-8.38)	(1.07)
Adj.R2	0.22	0.23	0.22	0.10	0.10	0.26

Notes: This Table reports the results of Fama-MacBeth regressions of hedge fund performance against the *DCI* and a set of other fund characteristics. The regression is estimated separately for each performance measure, namely the fund's return, the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio (AR), the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). The fund characteristics are lagged by one period. Statistical inference is based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. The Table reports the estimated coefficients, the respective t-statistics (in brackets) and the Adjusted R-square. The sample runs from January 1994 to August 2015.

Table 7: P5-P1 portfolios double-sorted on DCI and alternative skill measures

	1m	3m	6m	12m	24m
Panel A: Timing of market liquidity					
Return	0.0026	0.0026	0.0044	0.0068	0.0095
	(2.19)	(1.16)	(1.93)	(1.75)	(1.20)
Alpha	-0.0013	-0.0013	-0.0009	-0.0007	0.0002
	(-8.48)	(-4.27)	(-2.11)	(-1.18)	(0.27)
AR	-1.1267	-1.1606	-1.0847	-1.0450	-1.0052
	(-32.80)	(-17.89)	(-11.13)	(-12.06)	(-8.51)
Omega	-1.6203	-1.6244	-1.3063	-1.2740	-1.2332
	(-13.79)	(-7.45)	(-6.78)	(-4.78)	(-3.64)
Sortino	-0.7277	-0.7414	-0.5460	-0.5142	-0.3947
	(-11.01)	(-6.24)	(-4.54)	(-3.44)	(-1.73)
MPPM	0.6231	0.6112	0.6065	0.5717	0.4029
	(24.98)	(13.56)	(9.71)	(5.77)	(3.59)
Panel B: Timing of market return					
	1m	3m	6m	12m	24m
Return	0.0028	0.0023	0.0039	0.0088	0.0101
	(2.37)	(1.00)	(1.48)	(2.10)	(1.25)
Alpha	-0.0012	-0.0012	-0.0010	-0.0008	0.0003
	(-7.90)	(-4.01)	(-2.36)	(-1.38)	(0.47)
AR	-1.1264	-1.1704	-1.0844	-1.0322	-0.9678
	(-31.79)	(-17.82)	(-11.31)	(-11.94)	(-8.81)
Omega	-1.6776	-1.7035	-1.3315	-1.4202	-1.2112
	(-14.20)	(-7.07)	(-6.07)	(-4.92)	(-3.04)
Sortino	-0.7186	-0.6888	-0.5093	-0.5310	-0.3857
	(-10.94)	(-6.22)	(-4.43)	(-3.69)	(-1.90)
MPPM	0.6190	0.6043	0.5993	0.5712	0.4029
	(24.84)	(13.36)	(9.37)	(5.49)	(3.58)

Notes: This Table reports the performance of spread portfolios that have been double-sorted on the *DCI* and a measure of managerial skill. The P5-P1 spread portfolio goes long in the quintile with the highest *DCI* funds and short in the quintile with the lowest *DCI* funds, keeping the funds' levels of a given skill measure approximately equal. Panel A refers to the skill of timing market liquidity (Cao et al., 2013), while Panel B refers to the skill of timing the market return (Chen and Liang, 2007). The performance measures examined comprise the return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. The respective t-statistics are tabulated in brackets. The sample runs from January 1994 to August 2015.

Table 8: Portfolios sorted on mean DCI

Panel A: Performance of P5-P1 spread portfolios

	1m	3m	6m	12m	24m
2-month mean DCI					
Return	0.0049*	0.0043*	0.0040*	0.0041*	0.0031*
Alpha	0.0027*	0.0028*	0.0032*	0.0036*	0.0036*
AR	-1.8420*	-1.8996*	-1.9289*	-1.9759*	-2.1106*
Omega	-2.4985*	-2.9016*	-2.7488*	-3.1362*	-2.4239*
Sortino	-1.0881*	-1.1993*	-1.1639*	-0.9935*	-0.6766*
MPPM	-0.0478*	-0.0420*	-0.0358*	-0.0426	-0.0521
3-month mean DCI					
Return	0.0059*	0.0054*	0.0046*	0.0046*	0.0035*
Alpha	0.0031*	0.0033*	0.0036*	0.0039*	0.0038*
AR	-2.1333*	-2.1473*	-2.1299*	-2.2154*	-2.2347*
Omega	-2.9103*	-3.2407*	-3.0567*	-3.4360*	-2.4507*
Sortino	-1.1893*	-1.2828*	-1.2032*	-1.0051*	-0.6483*
MPPM	-0.0502*	-0.0452*	-0.0368	-0.0582*	-0.0629
6-month mean DCI					
Return	0.0066*	0.0059*	0.0054*	0.0055*	0.0042*
Alpha	0.0036*	0.0038*	0.0042*	0.0044*	0.0044*
AR	-2.5494*	-2.5682*	-2.6830*	-2.7091*	-2.7486*
Omega	-3.3232*	-3.5194*	-3.3934*	-3.3366*	-2.7043*
Sortino	-1.3238*	-1.4107*	-1.2353*	-0.8785*	-0.7545*
MPPM	-0.0550*	-0.0516*	-0.0364	-0.0796*	-0.0679

Panel B: Fama-MacBeth coefficients of mean DCI

	Return	Alpha	AR	Omega	Sortino	MPPM
2-month mean DCI						
coef	0.0003	-0.0010	-0.1785	-0.5827	-0.2269	-0.0043
(*t-stat*)	(0.51)	(-5.95)	(-10.22)	(-11.95)	(-6.09)	(-0.11)
3-month mean DCI						
coef	0.0007	-0.0014	-0.2264	-0.6956	-0.2674	-0.0843
(*t-stat*)	(0.91)	(-7.07)	(-10.83)	(-11.73)	(-6.19)	(-2.19)
6-month mean DCI						
coef	0.0010	-0.0017	-0.3256	-0.9448	-0.4003	-0.1320
(*t-stat*)	(0.90)	(-6.54)	(-12.22)	(-13.68)	(-8.23)	(-2.12)

Notes: This Table examines the performance of funds according to their mean *DCI* levels. Panel A tabulates the performance of P5-P1 spread portfolios that go long in the quintile with the highest *DCI* funds and short in the quintile with the lowest *DCI* funds. The performance measures examined comprise the return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. Statistical significance at the 5% level is denoted by *. Panel B reports the results of Fama-MacBeth regressions of hedge fund performance against the *DCI* and a set of other fund characteristics. The regression is estimated separately for each performance measure, across the same measures examined in Panel A. The fund characteristics are lagged by one period. We report the estimated coefficients for the *DCI* and the associated t-statistics. In both Panels, the analysis is done separately using the mean *DCI* computed over 2, 3 and 6 months. The sample runs from January 1994 to August 2015.

Table 9: P5-P1 portfolios double-sorted on DCI and SDI

	1m	3m	6m	12m	24m
Return	0.0024	0.0035	0.0054	0.0099	0.0124
	(2.34)	(1.86)	(2.33)	(2.47)	(1.65)
Alpha	0.0012	0.0010	0.0013	0.0010	0.0018
	(6.17)	(2.87)	(2.32)	(1.53)	(2.19)
AR	-1.3978	-1.4495	-1.3658	-1.3225	-1.1966
	(-31.79)	(-16.69)	(-10.64)	(-11.72)	(-7.26)
Omega	-1.6837	-1.7374	-1.5314	-1.5200	-1.1729
	(-13.45)	(-7.57)	(-5.19)	(-4.14)	(-2.32)
Sortino	-0.7208	-0.7445	-0.5925	-0.6401	-0.2131
	(-11.46)	(-6.35)	(-4.11)	(-3.06)	(-1.01)
MPPM	-0.0519	-0.0481	-0.0498	-0.0533	-0.0480
	(-11.70)	(-7.39)	(-5.35)	(-3.48)	(-2.42)

Notes: This Table reports the performance of spread portfolios that have been double-sorted on the *DCI* and the *SDI*. The P5-P1 spread portfolio goes long in the quintile with the highest *DCI* funds and short in the quintile with the lowest *DCI* funds, keeping the funds' *SDI* levels approximately equal. The performance measures examined comprise the return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. The respective t-statistics are tabulated in brackets. The sample runs from January 1994 to August 2015.

Table 10: Alternative strategy groups

Panel A: BarclayHedge groups						
Performance of P5-P1 spread portfolios						
		1m	3m	6m	12m	24m
Return		0.0034*	0.0028*	0.0024*	0.0025*	0.0020*
Alpha		0.0015*	0.0017*	0.0018*	0.0020*	0.0023*
AR		-1.0097*	-1.0266*	-1.0327*	-1.0801*	-1.0149*
Omega		-0.9782*	-0.9341*	-0.7474*	-0.4501	0.1583
Sortino		-0.4120*	-0.4080*	-0.2255	-0.1010	0.4648
MPPM		-0.0107*	-0.0086	-0.0004	0.0098	0.0215
Fama-MacBeth coefficients of DCI						
	Return	Alpha	AR	Omega	Sortino	MPPM
coef	0.0002	-0.0004	-0.1394	-0.2400	-0.0718	0.0369
(*t-stat*)	(0.49)	(-4.44)	(-11.74)	(-6.59)	(-2.59)	(1.42)
Panel B: k-means clusters						
Performance of P5-P1 spread portfolios						
		1m	3m	6m	12m	24m
Return		0.0031*	0.0021*	0.0021*	0.0018*	0.0017*
Alpha		0.0012*	0.0012*	0.0013*	0.0016*	0.0020*
AR		-1.5190*	-1.6019*	-1.6531*	-1.6938*	-1.6433*
Omega		-2.1241*	-2.5953*	-2.7647*	-3.1465*	-1.7862
Sortino		-0.8684*	-1.0582*	-1.1108*	-0.7169*	-0.4930
MPPM		0.0101*	0.0182	0.0122	0.0292	0.0162
Fama-MacBeth coefficients of DCI						
	Return	Alpha	AR	Omega	Sortino	MPPM
coef	0.0005	-0.0003	-0.1842	-0.3537	-0.1861	0.0318
(*t-stat*)	(2.00)	(-3.89)	(-15.52)	(-8.55)	(-7.46)	(1.49)

Notes: This Table examines the performance of funds according to their mean *DCI* levels using alternative fund strategy classifications. Panel A refers to classifying funds according to the BarclayHedge original style groups, while Panel B refers to a k-means clustering of funds in 10 groups according to their historical returns. Each Panel tabulates the performance of P5-P1 spread portfolios that go long in the quintile with the highest *DCI* funds and short in the quintile with the lowest *DCI* funds. The performance measures examined comprise the return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. Statistical significance at the 5% level is denoted by *. We also report the results of Fama-MacBeth regressions of hedge fund performance against the *DCI* and a set of other fund characteristics. The regression is estimated separately for each performance measure, across the measures described above. The fund characteristics are lagged by one period. We report the estimated coefficients for the *DCI* and the associated t-statistics. The sample runs from January 1994 to August 2015.

Table 11: Value-weighted portfolios

	1m	3m	6m	12m	24m
Return					
P5 - P1	0.0043	0.0030	0.0030	0.0034	0.0018
(*t-stat*)	(4.52)	(2.06)	(2.58)	(2.77)	(1.64)
Alpha					
P5 - P1	0.0020	0.0014	0.0017	0.0022	0.0020
(*t-stat*)	(10.35)	(3.35)	(2.67)	(2.65)	(2.31)
AR					
P5 - P1	-1.2906	-0.9784	-1.0617	-1.1885	-1.3802
(*t-stat*)	(-27.41)	(-15.83)	(-15.97)	(-17.07)	(-16.16)
Omega					
P5 - P1	-1.8421	-1.9494	-1.7441	-1.6144	-1.0123
(*t-stat*)	(-13.82)	(-7.70)	(-5.05)	(-3.03)	(-1.28)
Sortino					
P5 - P1	-0.8270	-0.6632	-0.9027	-0.9401	-0.6033
(*t-stat*)	(-12.52)	(-5.45)	(-2.94)	(-1.61)	(-1.38)
MPPM					
P5 - P1	-0.0432	-0.052	-0.0164	-0.0167	0.0046
(*t-stat*)	(-7.28)	(-2.13)	(-0.79)	(-0.45)	(0.13)

Notes: This Table reports the performance of value-weighted spread portfolios that have been sorted on the *DCI*. The P5-P1 spread portfolio goes long in the quintile with the highest *DCI* funds and short in the quintile with the lowest *DCI* funds. Within each portfolio and on each month, fund returns are weighted according to their AUM in that month. The performance measures examined comprise the return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. The respective t-statistics are tabulated in brackets. The sample runs from January 1994 to August 2015.

Table 12: DCI and the hedging effect

	Panel A: Proportion of funds overlapping in portfolios sorted based on DCI and $1 - R^2$				
	P1 (Low $1 - R^2$)	P2	P3	P4	P5 (High $1 - R^2$)
P1 (Low DCI)	0.0412	0.0398	0.0397	0.0394	0.0401
P2	0.0397	0.0400	0.0392	0.0404	0.0408
P3	0.0389	0.0397	0.0400	0.0402	0.0410
P4	0.0397	0.0395	0.0401	0.0404	0.0403
P5 (High DCI)	0.0406	0.0410	0.0410	0.0396	0.0379
	Panel B: Performance of P5-P1 portfolios double-sorted on DCI and $1 - R^2$				
	1m	3m	6m	12m	24m
Return	0.0048	0.0037	0.0045	0.0098	0.0159
	(3.09)	(1.46)	(1.56)	(2.00)	(1.95)
Alpha	-0.0007	-0.0007	-0.0004	-0.0003	0.0011
	(-3.78)	(-1.96)	(-0.86)	(-0.48)	(1.14)
AR	-1.4745	-1.5210	-1.4339	-1.3767	-1.2621
	(-32.98)	(-18.92)	(-11.66)	(-11.96)	(-8.88)
Omega	-2.0630	-2.0672	-1.7649	-1.7639	-1.5078
	(-15.78)	(-8.45)	(-7.73)	(-5.09)	(-2.80)
Sortino	-0.8544	-0.8498	-0.6750	-0.6251	-0.4785
	(-12.40)	(-7.19)	(-5.30)	(-3.99)	(-1.99)
MPPM	0.6566	0.6420	0.6336	0.5906	0.4230
	(25.84)	(14.13)	(9.70)	(5.76)	(3.88)

Notes: This Table examines the relationship between the *DCI* and the Titman and Tiu (2011) "hedging effect". The tendency of a fund manager to avoid exposure to systematic risk is measured as 1 minus the R-square obtained when regressing the fund's returns against the Fung and Hsieh (2004) seven factors. Panel A reports the proportion of funds belonging to a given quintile when sorted according to their *DCI* and simultaneously belonging to a given quintile when sorted according to their $1 - R^2$. Panel B reports the performance of spread portfolios that have been double-sorted on the *DCI* and $1 - R^2$. The P5-P1 spread portfolio goes long in the quintile with the highest *DCI* funds and short in the quintile with the lowest *DCI* funds, keeping the funds' levels of $1 - R^2$ approximately equal. The performance measures examined comprise the return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, the Sortino ratio, and the Ingersoll et al. (2007) Manipulation-Proof Performance Measure (MPPM). Performance measures are tabulated separately for rebalancing periods of 1, 3, 6, 12 and 24 months. The respective t-statistics are tabulated in brackets. The sample runs from January 1994 to August 2015.

Table 13: Survivorship ratios

	1m	3m	6m	12m	24m
P1 (Low DCI)	0.9932	0.9795	0.9565	0.9102	0.8191
P2	0.9925	0.9776	0.9554	0.9095	0.8186
P3	0.9914	0.9764	0.9535	0.9073	0.8135
P4	0.9923	0.9763	0.9535	0.9062	0.8121
P5 (High DCI)	0.9913	0.9741	0.9493	0.8986	0.8033
P5 - P1	0.0020	0.0054	0.0072	0.0115	0.0159
(*t-stat*)	(3.27)	(4.74)	(4.58)	(5.34)	(6.03)

Notes: This Table reports the survivorship ratios of funds when sorted in quintile portfolios according to their *DCI*. Survival at t is measured by whether a given fund exits the sample permanently at that time. We tabulate the mean survivorship ratios across the five portfolios, and the difference between the ratios of the highest *DCI* and the lowest *DCI* quintiles (and their associated t-statistics). The results are reported separately for survival periods of 1, 3, 6, 12 and 24 months. The sample runs from January 1994 to August 2015.