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 risk profile and various fund characteristics. This relative underperformance stems primarily from the higher subsequent risk exposure associated with pursuing a unique strategy. Our results are indicative of risk shifting by fund managers attempting to maximize the value of their compensation contracts.

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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

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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, 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 risks.

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, Cremers and Petajisto (2009) and Petajisto (2013) report that the Active Share is significantly positively related to future fund performance. Sun et al. (2012) construct the fund's Strategy Distinctiveness Index (SDI) and they find that fund managers who correlate less with their benchmark tend to outperform their less distinctive peers. Furthermore, Jiang and Verardo (2018) report that funds whose trades correlate the least with past institutional trades tend to make superior investment decisions and, hence, outperform funds which tend to herd around the trades of the institutional crowd.

On the other hand, Frazzini et al. (2016) strongly challenge the hypothesis of a positive relationship between deviating from the benchmark and fund performance, suggesting that the Active Share is as likely to correlate positively as it is negatively with returns inside particular fund groups (see subsequent rebuttals in Cremers, 2015, 2017; Petajisto, 2016). Moreover, Eshraghi and Taffler (2020) report an inverted-U relationship between the Active Share and investment performance, arguing that distinctive strategies are as likely to be associated with very poor or with very high fund performance. Finally, 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.

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. Third, we empirically show that the DCI has incremental explanatory power over subsequent fund performance, in excess to that already contained in other fund characteristics.

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 the mean of one, while a small number of funds have particularly high DCI levels. Furthermore, the DCI of individual funds is found to be considerably persistent over time, especially for the highest-DCI funds. 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. The results from DCI-sorted fund portfolios highlight a negative relationship between strategy distinctiveness and fund performance. In particular, we find that a spread portfolio that goes long in the quintile of highest DCI funds and short in the quintile of lowest DCI funds is associated with a significantly negative and economically large Treynor and Black (1973) Appraisal Ratio (AR), Omega, and Sortino ratio. In other words, betting on strategy distinctiveness results in a significantly worse risk-return trade-off when we consider the funds' exposure to idiosyncratic and downside risk. 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 on individual funds further confirm this negative relationship between deviating from the benchmark and subsequent fund performance, after accounting for a large set of fund-specific characteristics. In particular, we find that funds with higher DCI levels tend to subsequently offer significantly lower mean returns, Fung and Hsieh (2004) alphas, ARs, Omegas, and Sortino ratios, compared to lower-DCI funds. We also double-sort funds into portfolios based on their DCI and specific measures of risk and skill, to confirm the incremental informational content of the DCI.

Our results provide support for the risk shifting hypothesis (see, for instance, Goetzmann et al., 2003; Agarwal et al., 2009; Panageas and Westerfield, 2009; Aragon and Nanda, 2012). In particular, we report that high-DCI funds have significantly higher post-formation levels of systematic risk, idiosyncratic risk and tail risk compared to low-DCI funds. In the context of risk shifting, incentivized by compensation contracts that are linked to the fund's net profits, managers who actively deviate from the benchmark aim to maximize short-term expected returns at the cost of substantially higher risk. The resulting higher exposure to systematic, idiosyncratic and downside risk increases the expected value of managers' option-like compensation contracts. However, we document that fund performance deteriorates as a result, with investors earning significantly lower risk-adjusted returns compared to those offered by managers who stay closer to the benchmark.

Moreover, we show that the DCI is distinct from, and it contains incremental information to, the Sun et al. (2012) SDI. Although both measures are related to strategy distinctiveness, they are only weakly (and negatively) correlated across funds in the full sample, and separately in every strategy group. Consequently, the DCI seems to contain incremental information, as also evidenced by the significant performance of spread portfolios that have been double-sorted on the DCI and the SDI. A potential reason for this difference could be the fact that the DCI is a standardized measure, and thus comparable across funds in different groups, while the SDI is not. For instance, when we look at the extreme cases of the 5% most/least distinctive funds, the specific funds that populate these tail quantiles tend to come from markedly different strategy groups depending on which of the two measures is being used. Our findings suggest that sorting funds according to their SDI would result, to some extent, in an implicit sorting in terms of benchmark returns while, as a standardized measure, the DCI is not affected by the same limitation. In fact, we find that a standardized version of the SDI is significantly positively related to the DCI, although the latter is still found to contain significant incremental information.

We conduct a number of additional tests to better understand the robustness of the observed negative relationship between deviations from the benchmark and fund performance. First, in order to explore the issue of DCI persistence, we re-sort portfolios based on a fund's mean DCI over the previous months instead of the past month's point estimate. Furthermore, given that our results are based on the Joenväärä et al. (2019) classification of funds in style clusters, we explore the effect of different ways to group funds by using the original BarclayHedge style categories and by performing an alternative k-means clustering. We control 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 (2004) regressions. We also explore the impact of splitting funds into subsamples based on their past performance, lock up period, redemption notice period, and highwater mark. Finally, we repeat the analysis using gross fund returns in order to understand whether the relative underperformance of high-DCI funds could potentially be explained by fund managers extracting most of the economic rents. 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. Fund managers who deviate the most from their peers seem to be engaging in risk shifting, accepting substantially higher levels of systematic, idiosyncratic and tail risk without offering sufficiently higher returns. As a result, 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 discusses some descriptive statistics for the DCI. Section 4 examines the DCI's persistence and its relationship with other fund characteristics. Section 5 presents the empirical results on the relationship between deviations from the benchmark and fund performance, while Section 6 examines the relationship between the DCI and the SDI. Section 7 presents the results of various robustness tests, while Section 8 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" (see Chiang and Zheng, 2010; Galariotis and Spyrou, 2015) and idiosyncratic risk (see Angelidis et al., 2015; Verousis and Voukelatos, 2018). 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") a specific fund is. 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 running 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 Joenväärä et al. (2019) 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.

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 (Figure A1 in the Internet Appendix). 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).[1]

[Figure 1 about here]

4 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

[1]Table A1 in the Internet Appendix reports descriptive statistics for a large set of fund characteristics.

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. Panel A of Table 1 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 1 about 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.

Panel B of Table 1 reports the proportion of funds that remain in the same quintile portfolio across time, separately for holding periods of 1, 3, 6, 12 and 24 months. The DCI appears to exhibit a substantial level of persistence across time, consistent with the results in Panel A. Interestingly, this persistence is particularly more pronounced in the case of high-DCI funds compared to low-DCI funds. For instance, 40% of funds remain in the highest-DCI quintile portfolio P5 after one month (compared to 25% in the P1 quintile portfolio), with the proportion still being relatively high at 32% after 12 months. This difference could reflect the fact that pursuing a unique investment strategy represents a more conscious and active choice compared to simply following the benchmark. In other words, managers of the highest-DCI funds are much more likely to consistently pursue highly distinctive strategies for longer periods, while managers of the lowest-DCI funds are likely to follow their benchmark to varying degrees over time.

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 (3). The vector X of fund characteristics consists of the fund's redemption notice period, the lock up period, a dummy variable for highwater mark, the management and performance fees (in percentages), the fund's age, AUM, leverage, the Sun et al. (2012) SDI,[2] the previous period's return, the return volatility, skewness and kurtosis over the previous 24 months, the Fung and Hsieh (2004) alpha, Treynor and Black (1973) AR, Keating and Shadwick (2002) Omega, Sortino ratio, Idiosyncratic Volatility (measured as the variance of residuals from Fung-Hsieh regressions), Systematic Variance (measured as the total variance of fund returns minus idiosyncratic variance, following Bali et al., 2012), Fama and French (2015) factor betas (MKT, SMB, HML, RMW, CMA), 5% Value-at-Risk (VaR), 5% Expected Shortfall, and the Agarwal et al. (2017) Systematic Tail Risk measure. Table 2 reports the results from estimating the panel regression in (3) (with fund and time fixed effects).

$$DCI_{i,t} = \alpha + BX_{i,t-1} + \epsilon_{i,t} \tag{3}$$

The DCI is found to be significantly positively related to a fund's length of redemption period and length of lock up period. Furthermore, the DCI seems to increase with the fund's performance fee, suggesting that managers who are more skilled (and, thus, more likely to deviate from the benchmark) tend to charge higher fees. The DCI is also found to be higher for funds of lower age, lower AUM

[2] We follow Sun et al. (2012) and compute a fund's SDI as 1 minus the correlation of the fund's 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 Joenväärä et al. (2019) classification.

and higher leverage. The negative relationship between age and the DCI is not surprising, since we would have expected the managers of younger funds to be more flexible in pursuing unique strategies. The negative DCI-AUM relationship is consistent with the intuition that smaller funds can be more flexible in adopting new innovative strategies compared to larger funds.

We also find that the DCI is negatively correlated with past performance in terms of FH alphas, AR and Omega ratios, suggesting that funds are potentially more likely to deviate from their benchmark following a period of underperformance. Moreover, funds with higher DCI tend to have higher levels of risk as measured by Idiosyncratic Volatility, VaR, Expected Shortfall, and Systematic Tail Risk in the previous month, but they have lower levels of Systematic Variance. 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. We explore this negative DCI-SDI relationship further in Section 6.

[Table 2 about here]

5 DCI and hedge fund performance

5.1 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 evaluate 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 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

[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.

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.

The 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 (see Sun et al., 2012) and it accounts for differences in leverage among different funds (see 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

$$Omega_i = \frac{\int_L^b [1 - F(r_i)] dr_i}{\int_a^L F(r_i) dr_i} \tag{4}$$

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 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 (5). 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 (see Treynor and Black, 1973).

$$Sortino_i = \frac{\int_{-\infty}^{\infty} r_i dF(r_i) - L}{\sqrt{\int_{-\infty}^{L} (L - r_i)^2 dF(r_i)}} \tag{5}$$

5.2 DCI-sorted portfolios

In order to understand how deviations from the benchmark relate to subsequent 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. To this end, we evaluate fund performance for DCI-sorted portfolios under monthly rebalancing. Although we focus mainly on fund performance over the next month, we also consider longer holding periods of 3, 6, 12 and 24 months (see also Bali et al., 2019). At the beginning of each 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 holding period considered.

Panel A of Table 3 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) holding period, 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 holding periods.

[Table 3 about 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 the monthly holding period, 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 holding 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 accounting for relative changes in their DCI. However, P5-P1 returns are quite large even in the longest holding 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 Panel A of Table 3 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, Panel B of Table 3 reports the performance measures discussed earlier for the five DCI-sorted portfolios and the P5-P1 spread portfolio, for the 1-month holding period. Due to the non-normality of fund performance, we use bootstrapped error bounds on the empirical distribution of each performance measure for all subsequent portfolio analyses. 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.

As can be seen from Panel B, 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 the monthly holding period. 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, the results from alternative performance measures cast some doubt on the hypothesized positive relationship between the propensity to deviate from the benchmark and fund performance. In contrast to the mean returns and the FH alphas of DCI-sorted portfolios, the AR is found to be monotonically decreasing with the DCI, while the AR of the P5-P1 portfolio is significantly negative and economically large. This finding seems to suggest that managers who pursue more distinctive strategies are potentially chasing higher returns at the cost of much higher levels of idiosyncratic risk.

These results provide 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 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 and idiosyncratic volatility on the DCI reported in Table 2.[4]

Similarly to the results from the AR, the Omega and the Sortino ratios are

[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.

also found to be generally decreasing as we move from the lowest-DCI to the highest-DCI portfolio. Moreover, the Omega and the Sortino ratios of the spread P5-P1 portfolios are negative and statistically significant. 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. These findings on fund portfolios are consistent with the results reported in Table 2, where the DCI was found to be significantly positively related to lagged measures of downside risk (VaR, Expected Shortfall, and Systematic Tail Risk) at the level of the individual fund.

Overall, these 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 appear, at a first glance, to earn returns that are on average higher compared to those offered by less distinctive-strategy funds. However, these skilled managers seem to achieve higher returns 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 proceed by exploring this somewhat mixed relationship between deviating from the benchmark and fund performance, where the DCI has a positive impact on subsequent returns and alphas, and a negative impact on the AR, Omega and Sortino ratios. More specifically, we compute the exposure of the DCI-sorted quintile portfolios with respect to various types of risk. We compute the post-formation risk exposure of each quintile portfolio in terms of return volatility, skewness and kurtosis, idiosyncratic volatility (variance of the residuals from Fung-Hsieh regressions), systematic variance (total variance of fund returns minus idiosyncratic variance), 5% VaR, 5% Expected Shortfall, and the Agarwal et al. (2017) Systematic Tail Risk measure. Table 4 reports the risk profile of each quintile portfolio, as well as the difference between the high-DCI portfolio P5 and the low-DCI portfolio P1, measured over the 1-month post-formation period.

[Table 4 about here]

We find that high-DCI funds have substantially higher risk exposure compared to low-DCI funds, across all the risk measures that we consider. While risk is not always increasing monotonically across the quintile portfolios, the highest-DCI quintile P5 has consistently higher levels of risk relative to the lowest-DCI quintile P1, with the differences being statistically significant. For instance, the idiosyncratic volatility of high-DCI funds (0.33%) is around 4 times higher than that of low-DCI funds (0.08%). This finding is in line with our earlier results of high-DCI funds having lower ARs, and it suggests that fund managers who deviate the most from the benchmark load substantially more on idiosyncratic risk compared to managers who tend to follow the consensus. Moreover, high-DCI funds have significantly higher levels of tail risk relative to low-DCI funds, in terms of VaR (0.0313 against 0.0119, respectively) and Expected Shortfall (0.0088 against 0.0060, respectively).

Finally, funds in the highest DCI-quintile have around 4 times the level of systematic variance and almost twice the level of systematic tail risk compared to funds in the lowest DCI-quintile. In this sense, our results are consistent with the findings in Bali et al. (2012) and Agarwal et al. (2017) who report that hedge funds with higher levels of systematic variance and systematic tail risk, respectively, tend to earn higher mean returns and alphas than their counterparts with lower levels of systematic risk. However, although fund returns and alphas at a first glance seem to increase with the level of systematic risk, we find that this comes at a cost of significantly higher idiosyncratic and downside risk, as evidenced by the lower ARs, Omega and Sortino ratios.

5.3 Fama-MacBeth regressions

We proceed by employing the standard Fama and MacBeth (1973) two-pass methodology in order to control for fund characteristics when examining the DCI-performance relationship. In particular, in each month we run the following cross-sectional regression

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

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 2. 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, with the number of lags selected based on the Akaike Information Criterion (AIC). Table 5 reports the Fama-MacBeth second stage mean coefficients and statistical significance, tabulated separately for each performance measure (return, alpha, AR, Omega, and Sortino).

As can be seen from Table 5, the Fama-MacBeth results reject the hypothesis that deviating from the benchmark is associated with superior subsequent performance. More specifically, when we control for funds' other characteristics, performance measures are found to be significantly negatively associated with the lagged DCI. For instance, the coefficient of returns against the DCI is equal to -0.0005 and highly significant, implying that an 1-unit increase in a fund's DCI is expected to lead on average to a 0.05% decrease in the fund's monthly return. Similarly, the Fama-MacBeth mean coefficient of the DCI on alpha is negative (-0.0002) and statistically significant, 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. To put these results into context in terms of economic significance, if we consider the 1.23 standard deviation of DCI for the full sample (reported in Table A1 in the Internet Appendix), a one standard deviation increase in a fund's DCI is expected to lead to an annual decrease of 0.74% in subsequent fund returns and an annual decrease of 0.29% in subsequent alphas. Finally, the AR, Omega and Sortino ratios are also 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.

[Table 5 about here]

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.

At a first glance, the positive relationship between the DCI and returns/alphas that was reported in Table 3 seems to stand in contrast to the negative relationship reported in Table 5. One possible reason for this discrepancy is the fact that the Fama-MacBeth regressions in Table 5 examine the DCI-performance relationship in individual funds, while Table 3 reports the aggregate performance of fund portfolios. More importantly, though, the Fama-MacBeth regressions explore the

DCI-performance relationship after taking into account the funds' characteristics and exposure to various sources of risk, while the sorted portfolios by construction only consider variations in the DCI and ignore any other differences among funds.

For instance, Table 2 shows that high-DCI funds tend to have higher idiosyncratic volatility, generally higher market betas, and noticeably higher levels of tail risk and systematic tail risk. As a result, it would be reasonable to expect that, in additon to "betting" on strategy distinctiveness, the P5-P1 spread portfolio in Table 3 is likely to load significantly on idiosyncratic, systematic and tail risk. Therefore, the positive return and alpha offered by this portfolio could jointly reflect the spread in DCI as well as any other differences between funds in different DCI quintiles, including a compensation for different levels of risk exposure. In this sense, the Fama-MacBeth regressions in Table 5 are more likely to provide an accurate reflection of the DCI-performance relationship, as they control for various fund characteristics, including idiosyncratic and systematic tail risk.

5.4 Risk shifting

The DCI measures the extent to which a fund manager deviates from the benchmark, relative to all other funds in the same style-group. However, it is not immediately obvious whether deviations from the benchmark reflect managerial skill or a greater willingness to engage in risk shifting by trading in order to increase the value of managers' compensation contracts. If the DCI captures managerial skill, then we would expect high-DCI funds to offer superior performance at lower levels of risk relative to low-DCI funds. On the other hand, if the DCI reflects managers' propensity for risk shifting, then we would expect high-DCI funds to be more exposed to some sources of risk compared to their low-DCI counterparts.

Table 4 reports that high-DCI funds load substantially more on systematic, idiosyncratic and tail risk compared to low-DCI funds. We further explore the risk shifting hypothesis by constructing fund portfolios that have been double-sorted according to their DCI and some other risk characteristic. More specifically, in each month we begin by sorting all funds in quintiles according to a specific risk characteristic. Then, inside each 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 initial quintiles that had been formed according to the specific risk characteristic. This process results in the construction of double-sorted quintile portfolios that have relatively homogeneous levels of a particular risk characteristic but varying levels of DCI. The double-sort is repeated every month, resulting in a time-series of returns across the five DCI-based portfolios.[5]

[5]Similarly to the Fama-MacBeth regressions in Table 5, the double-sorted portfolios are intended to capture the effect of the DCI on fund performance after controlling for other fund

We construct double-sorted portfolios according to the DCI and one risk characteristic in turn. In particular, we double-sort using some of the main risk characteristics that were explored earlier in Table 4 (namely idiosyncratic volatility, systematic variance, VaR, Expected Shortfall, and Systematic Tail Risk), the factor loadings from the Fung and Hsieh (2004) model (PTFSBD, PTFSFX, PTFSCOM, S&P, SCMLC, BD10RET, BAAMTSY), the factor loadings from the Fama and French (2015) model (MKT, HML, SMB RMW, and CMA), the loading on the Pastor and Stambaugh (2003) traded liquidity factor (LIQ)[6], the loading on the Bali et al. (2014) Macroeconomic Risk Index (MRI), and the loading on the Agarwal et al. (2017) Systematic Tail Risk Factor (STRF). The resulting double-sorted portfolios differ in terms of the DCI while having comparable levels of another characteristic. Table 6 reports the mean return, Fung-Hsieh alpha, Appraisal Ratio, Omega and Sortino ratio of the respective P5-P1 spread portfolios under double-sorting, separately for each risk characteristic.

[Table 6 about here]

The double-sorted portfolio results suggest that funds' *ex ante* risk characteristics cannot fully explain the negative relationship between the DCI and risk-adjusted performance. The first thing to notice is that the P5-P1 spread portfolios offer mean returns that are consistently positive and, in most cases, statistically significant. Consistent with our earlier findings, this result suggests that deviating from the benchmark is associated with higher returns on average, even after taking into account individual funds' risk profile at the portfolios' construction. However, all four measures of risk-adjusted performance of the double-sorted P5-P1 spread portfolio are universally negative and, with few exceptions, highly significant.

Deviating from the benchmark still seems to come at the cost of substantially higher systematic risk, idiosyncratic risk and downside risk, as reflected by the

characteristics. Although the Fama-MacBeth regressions allow us to simultaneously control for a number of fund characteristics, the double-sorts are based on varying DCI levels while keeping only one other characteristic fixed. However, the double-sorts can provide additional insight about the DCI-performance relationship as they (a) focus on fund portfolios instead of individual funds, and (b) move away from a cross-sectional analysis to the time-series of investing in funds with different DCI levels.

[6] 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.

spread portfolio's significantly negative alpha, AR, and Omega/Sortino ratios, respectively. Importantly, this relationship does not disappear when we account for funds' pre-formation risk profile. For example, even when we consider funds that have comparable levels of idiosyncratic volatility when the quintile portfolios are formed, the high-DCI funds are still found to subsequently offer a significantly lower AR compared to low-DCI funds (the respective double-sorted spread portfolio has an AR that is equal to -0.77 and highly significant).

We also explore how deviating from the benchmark affects a fund's exposure to downside risk by examining how the level of DCI relates to fund survival. Similarly to Bali et al. (2019), we estimate monthly cross-sectional logit regressions of hedge fund short-term and long-term survival (over the next 1, 3, 6, 12, and 24 months) on the DCI, with and without control variables. Table 7 reports the mean DCI slope coefficients and the associated t-statistics. The results highlight a strong negative relationship between a fund's DCI and its probability of subsequent survival. For instance, when we consider 1-month-ahead survival, the average DCI slope is equal to -0.19 and highly significant in the specification that does not include control variables. Importantly, this significantly negative relationship between DCI and subsequent fund survival persists for periods until 24 months and it is observed even after controlling for a large set of fund characteristics. These results provide further support for the hypothesis that funds which deviate more from the benchmark are exposed to significantly higher levels of downside risk, as evidenced by a significantly lower probability of survival over the next months.

[Table 7 about here]

Finally, we investigate whether managerial skill can explain the significant underperformance of high-DCI funds relative to low-DCI funds by examining the performance of portfolios that have been double-sorted based on the DCI and two commonly used measures of managerial skill, namely the Chen and Liang (2007) measure of market timing skill and the Cao et al. (2013) measure of market liquidity timing skill. Chen and Liang (2007) demonstrate that funds which self-report that they follow market timing strategies indeed show significant ability to time US market returns, while 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.[7]

Both the Chen and Liang (2007) and the Cao et al. (2013) measures of managerial skill apply to equity-oriented funds only. Therefore, we exclude from the subsequent analysis all funds with strategies that are not associated with equities (see also Sun et al., 2018).[8] After computing these two measures of managerial skill, we then double-sort funds into portfolios according to their DCI and a specific skill measure (separately for β_M^i and β_L^i). In each month, we begin by sorting all funds into quintiles according to their skill measure and then, inside each skill-based quintile we further sort the funds into quintiles according to their DCI. Finally, the monthly returns of the DCI-based quintiles are averaged across the skill-based quintiles, thus reflecting the returns of portfolios with homogeneous levels of managerial skill but across different levels of DCI. Table 8 reports the performance of P5-P1 spread portfolios of funds that have been double-sorted according to their DCI and each measure of managerial skill in turn.

[Table 8 about here]

The results from these double-sorted portfolios fail to provide support for the hypothesis that deviating from the benchmark reflects predominantly managerial skill. When we control for funds' level of managerial skill, high-DCI funds seem to offer higher mean returns than low-DCI funds. However, these higher mean returns still come at a substantially high cost in terms of systematic, idiosyncratic

[7]We follow Chen and Liang (2007) and measure the timing skills of fund managers as the β_M^i from the following regression

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

where r_t^i is the return of fund i at t, F_t is a vector of the values of the seven Fung and Hsieh (2004) factors, and MKT_t is the excess return of the market (also included in F_t). We run this time-series regression separately for each fund, with higher values of β_M^i being indicative of a greater market-timing ability. 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 as follows

$$r_t^i = \alpha^i + \beta_F^i F_t + \beta_L^i MKT_t \Delta L_t + \epsilon_t^i$$

where ΔL_t is the first difference of the Pastor and Stambaugh (2003) market liquidity factor. 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).

[8]Although any conclusions from these results cannot necessarily be extended to funds in non-equity style groups, this analysis can at least shed some additional light on the "skill vs risk" debate by accounting for two commonly used measures of managerial skill in a relatively large subsample of funds.

and downside risk. More specifically, the spread portfolio's alpha, AR, Omega and Sortino ratios are universally negative and statistically significant for holding periods of up to 6 months, and in most cases for longer holding periods as well, when we double-sort using either measure of managerial skill (see also Table A2 in the Internet Appendix). Overall, fund managers with comparable levels of managerial skill seem to offer substantially different performance depending on the extent to which they tend to deviate from the benchmark.

In theory, deviating from the benchmark could reflect genuinely higher levels of managerial skill. However, our empirical results suggest that pursuing a distinct strategy, as measured by a high DCI, is more likely to reflect managers' propensity for risk shifting. It should also be noted that, given the inherent difficulty in accurately measuring managerial skill (and even, to some extent, risk), it is possible that the DCI still reflects some level of skill and/or risk that cannot be fully captured by existing proxies. Overall, even though a skill-based explanation cannot be entirely ruled out, the results are more in line with a risk shifting explanation where managers who deviate from the benchmark are pursuing strategies with substantially higher levels of risk, at the expense of the funds' overall performance.

Interestingly, the higher risk exposure of high-DCI funds appears to stem from higher loadings across multiple types of risk. For instance, high-DCI managers seem to be achieving strategy distinctiveness by increasing their loading on systematic risk, as evidenced by the negative DCI-alpha relationship (Table 5) and the higher systematic variance of the spread portfolio (Table 4). Deviating from the benchmark also leads to significantly higher levels of idiosyncratic risk, reflected in negative ARs for the spread portfolio (Table 3) and higher levels of idiosyncratic volatility (Table 4). Importantly, managers who pursue unique strategies are also found to load substantially more on downside risk, achieving lower Omega and Sortino ratios (Table 3), exhibiting markedly higher levels of VaR, Expected Shortfall and Systematic Tail Risk (Table 4), and facing higher probabilities of going defunct in the short- and longer-term (Table 7) compared to managers who stay closer to the consensus in their group. This higher risk exposure in multiple fronts is also evident from the fact that controlling for each risk separately cannot fully explain the significant underperformance of high-DCI funds (Table 6).

These results can be interpreted in the context of the wider literature on managerial incentives. The option-like features of managers' compensation contracts stem from the fact that performance (incentive) fees are based on the fund's net profits. In fact, fund managers' compensation contracts are fairly similar to the OTM option compensation contracts typically awarded to CEOs, although the former often include hurdle rate and highwater mark provisions (Agarwal et al., 2009).[9] In this sense, the asymmetric nature of the incentive contract might in-

[9] A manager's incentive fee contract can be considered as equivalent to a portfolio of call

duce risk-taking behavior by managers, especially when the fund's value is below the highwater mark, since their compensation is linked to the fund's returns non-adjusted for risk (Goetzmann et al., 2003).

Overall, our findings are consistent with the risk shifting hypothesis. In other words, managers who deviate from the benchmark seem to be doing so to maximize expected returns by substantially increasing the fund's exposure to systematic, idiosyncratic and downside risk. This high return - high risk profile associated with pursuing a distinctive strategy potentially maximizes the value of the managers' option-like compensation contracts, as these are linked with the fund's non-risk-adjusted returns, at the possible cost of reputational damage (Carpenter, 2000) and lower value of future options.

Theoretically, the highwater mark provisions could either exacerbate or mitigate managers' incentives for risk shifting (see, for instance, Goetzmann et al., 2003; Panageas and Westerfield, 2009; Aragon and Nanda, 2012). The intuition behind this argument is based on the trade-off between management (regular) fees and performance (incentive) fees. More specifically, increasing portfolio risk increases the expected value of the performance fee, but it also increases the probability of investors exiting the fund due to poor subsequent fund performance (lowering the expected future management fee). We explore whether our previous findings of a negative DCI-performance relationship depend on the existence of a highwater mark provision by constructing DCI-sorted portfolios separately for funds with and without a highwater mark provision.[10]

As can be seen from Table 8, the DCI-performance relationship is broadly similar for funds with and without a highwater mark provision ("HWM" and "no HWM", respectively), with the P5-P1 spread portfolio offering positive returns and alphas, and negative AR, Omega and Sortino ratios (as was the case in the full sample). We also find that all performance measures are significantly negatively related to the DCI in Fama-MacBeth regressions for both subgroups. However, even though strategy distinctiveness seems to come at the cost of much higher risk irrespective of the existence of a highwater mark provision, risk shifting appears to be more pronounced in HWM funds (presumably because HWM managers face receiving zero performance fees if the fund does not exceed the highwater mark). This is evidenced by the fact that, in funds with a highwater mark the spread portfolio offers a poorer performance across all measures and almost all horizons,

options on the fund's AUM. The strike prices of these options are based on the Net Asset Value at which different investors have entered the fund, as well as the hurdle rate and the highwater mark provisions that might be embedded in the contract (see Goetzmann et al., 2003; Agarwal et al., 2009).

[10] Approximately 69% of funds in our sample have highwater mark provisions, against 31% that do not. These proportions are in line with the 65%-35% split documented in Aragon and Nanda (2012).

and it has a noticeably higher post-formation risk exposure (Tables A3-A4 in the Internet Appendix).

Finally, considering that the incentive for risk shifting is likely to depend on a fund's withdrawal policy (Goetzmann et al., 2003), we construct DCI-sorted portfolios separately for funds with lock up periods that are above or below the median, as well as for funds with redemption notice periods that are above or below the median. The results in Table 8 and Tables A5-A8 in the Internet Appendix are qualitatively similar to those found in the full sample, with the spread portfolio offering positive returns/alphas and negative AR/Omega/Sortino ratios in all subgroups. Moreover, the DCI slopes in Fama-MacBeth regressions are significantly negative across all measures.[11] Nevertheless, the negative DCI-performance relationship seems to be somewhat more pronounced in funds with longer lock up and redemption notice periods, consistent with the hypothesis that fund managers have a greater incentive to increase portfolio risk when investors need to wait longer to withdraw funds.

6 DCI's relationship with the SDI

The DCI and the Sun et al. (2012) SDI can both be considered as measures of strategy distinctiveness. However, the Fama-MacBeth regression results in Table 5 provide some initial evidence that these two measures are far from perfect substitutes, considering how the DCI was found to contain significant incremental information about a fund's subsequent performance, in excess of the information already contained in other fund-specific characteristics including the fund's SDI. In order to better understand the informational content of the DCI, we proceed to examine its relationship with the SDI.

We begin by computing contemporaneous correlations between funds' DCI and SDI levels. Table 9 reports the mean, median and standard deviation of DCI-SDI correlations, in the entire sample of funds as well as separately in each strategy group. In addition, Figure 2 plots the respective histogram of DCI-SDI correlations across all funds. The first thing to notice is that the contemporaneous DCI-SDI correlations across all sample funds are very close to zero on average, although slightly negative (the mean and the median in the full sample are equal to -0.06). This is also the case when we compute contemporaneous DCI-SDI correlations separately for funds in different strategy groups, with mean correlations per group ranging from -0.12 (Short Bias) to 0.00 (Relative Value). The fact that the DCI is only weakly and negatively correlated with the SDI provides further support for the notion that they are most likely complimentary, rather than substitute,

[11]The Fama-MacBeth regression results for subgroups based on lock up and redemption notice periods are unreported for brevity, but available upon request.

measures of strategy distinctiveness, consistent with the significant incremental explanatory power of the DCI over subsequent fund performance reported in Table 5.

[Table 9 about here]

[Figure 2 about here]

Although we find that the DCI correlates weakly negatively with the SDI, the reason why this should theoretically be the case is not immediately obvious. The two measures are similar in the sense that their construction is essentially based on the distances between the returns of a fund and the returns of a benchmark. The DCI is a relatively simpler measure since it is computed as the absolute scaled distance at a single point in time, while the SDI aggregates squared distances across time. These two differences in the construction of the two measures (absolute vs squared, and single-point vs time-series) do not readily allow for a prediction on the nature of the DCI-SDI relationship ex ante. In other words, while both measures reflect a fund's propensity to deviate from a benchmark, it is not possible to determine whether they are *theoretically* expected to be negatively or positively correlated (or even correlated at all).[12]

In order to explore the incremental informational content of the DCI further, we examine the performance of portfolios of funds that have been double-sorted on SDI and DCI, using the same double-sorting approach that was adopted in Section 5.4. The resulting double-sorted portfolios are constructed so that they vary in terms of their DCI levels while having approximately equal SDI levels.

Table 10 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 Table 3, 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, results in positive returns and alphas, and significantly negative ARs, Omega and Sortino ratios. In other words, funds that are the most distinctive in terms of their DCI tend to perform significantly worse than their low-DCI peers, even when they are comparably distinctive in terms of their SDI. Overall, these results further confirm that the DCI contains

[12]It is also worth noting that, as a proxy for unique investment ideas, the DCI is predominantly empirically motivated. We argue that deviations from the benchmark are intuitively linked to the concept of a fund pursuing a strategy that is distinct from the consensus, but we do not explicitly attempt to develop a theoretical model where fund performance is determined by the DCI. The Sun et al. (2012) SDI is a measure that is intuitively appealing for the same reasons but, similarly to the DCI, not as a result of a specific theoretical model of hedge fund returns.

incremental information that is not contained in the historical correlations between fund and benchmark returns.

[Table 10 about here]

We proceed by examining how the DCI and the SDI vary across different benchmarks. Table 11 presents descriptive statistics of the DCI (Panel A) and the SDI (Panel B) across different strategy groups. More specifically, we report the mean of the respective measure, the number of funds in each strategy group as a proportion of all sample funds, and the proportion of funds from each group that belong in the bottom/top 5% and 1% quantiles of the respective measure.

[Table 11 about here]

As can be seen from Panel B of Table 11, the mean SDI varies considerably across different benchmarks. For instance, the mean SDI is equal to 0.47 when computed across all funds, but it ranges from a minimum of 0.21 (CTA) to a maximum of 0.77 (Long Only) when computed in specific strategy groups. Furthermore, strategy groups are far from uniformly represented in quantiles that have been formed according to their mean SDI. When we look at the 5% of funds with the lowest SDI, these are heavily populated by funds that come from just 3 strategy groups (out of 11 groups in total). For example, 24% of these lowest-SDI funds come from the "Long-Only" group which, for context, accounts for only 3% of funds in the full sample. At the other end of the spectrum, the funds in the "Sector" group account for a very small proportion of total funds (approximately 0%) but they contribute 20% of funds in the 5% set of funds with the highest SDI. The results are relatively similar (and, arguably, more extreme) when we look at the lower/upper 1% of funds based on their SDI. For instance, more than half (51%) of the 1% lowest SDI funds come from the "Long Only" strategy group, while "Sector" funds are substantially over-represented in the 1% of funds with the highest SDI (17%).

However, the variation of the DCI across strategy groups is very different to that of the SDI. For instance, funds in the "Relative Value" group account for the biggest proportion of funds in the bottom 5% of funds with the lowest DCI as well as the top 5% quintile of funds with the highest DCI (43% and 39%, of total funds in the quantile respectively). In contrast, funds in the "Long Only" group (which represented the largest proportion of the lowest-SDI funds) are found to only account for 0% of the lowest-DCI funds. Similarly, CTA funds that constitute 4% of all sample funds account for 15% of the lowest-DCI funds but effectively 0%

of the lowest-SDI funds.[13]

These results confirm that the DCI provides substantially different information regarding a fund's distinctiveness compared to the SDI. For instance, funds in certain groups would appear to follow extremely distinctive strategies when measured by their SDI, while the same cannot be said when looking at their DCI (and vice versa). We argue that this effect stems partly from the fact that the DCI is a standardized measure while the SDI is not. In this sense, sorting funds by their SDI is likely to result in an ordering that is far from independent from the funds' specific benchmarks. If this is indeed the case, any comparisons of performance according to SDI levels will, to some extent, also reflect a comparison of benchmark returns. Nevertheless, this limitation does not apply to performance comparisons of funds that have been sorted by their DCI, given how the latter is a standardized measure.

We explore the issue of non-comparability of the SDI across funds from different groups by computing a standardized version of the measure. In particular, we compute the Standardized Strategy Distinctiveness Index (SSDI) by dividing a fund's SDI at time t with the mean SDI of all same-style funds at t.[14] The observed relationship between the DCI and the SSDI is markedly different compared to the one reported earlier with respect to the SDI. For instance, the results from an explanatory regression of DCI against its determinants (Table A9 in the Internet Appendix) suggest that the DCI is positively, and significantly, related to the lagged SSDI (coef = 0.14, t-stat = 20.15). This stands in stark contrast to our original results, where the DCI was found to be negatively related to the lagged non-standardized SDI. Moreover, Fama-MacBeth regressions of performance measures against fund characteristics (Table A10 in the Internet Appendix) suggest that the SSDI is positively related to subsequent fund performance in the cross-section, with the associated coefficients being significant at 5% for all performance measures except returns. For comparison, the original Fama-MacBeth regression coefficients of the SDI (Table 5) were consistently negative (and, again, significant at 5% for all performance measures except returns).

Nevertheless, the relationship between fund performance and the DCI does not seem to change when we use the standardized SSDI instead of the SDI. The DCI slopes in Fama-MacBeth regressions when we control for SSDI are broadly similar to the original results reported in Table 5 (controlling for SDI), in the sense that fund performance is negatively related to the lagged DCI, with coefficients being

[13]The first column of Table 11 reports the average measure across each fund's mean across time. Given that the composition of each strategy group changes across time, this cross-sectional mean of time-series means will not necessarily be exactly equal to 1 in the case of the DCI.

[14]We would like to thank an anonymous reviewer for suggesting standardization as a potential explanation for the observed DCI-SDI relationship and for suggesting exploring a standardized version of the SDI.

statistically significant for all measures except returns. Moreover, double-sorting portfolios according to funds' DCI and SSDI (Table A11 in the Internet Appendix) results in performance patterns that are similar to the ones observed when double-sorting according to the DCI and SDI. In other words, high-DCI funds appear to load substantially more on risk compared to low-DCI funds, even after accounting for their strategy distinctiveness in terms of the standardized SSDI.

Overall, our results provide strong support for the hypothesis that the DCI contains incremental information and is complimentary to the commonly used SDI measure of strategy distinctiveness. Although the weak negative correlation between the DCI and the SDI is empirical rather than theoretical, part of the difference between the two measures seems to stem from the different variation of each measure across benchmarks. In this sense, the advantage of standardization embedded in the DCI allows us to directly compare and rank funds across different strategy groups, without this comparison being affected by the different levels of benchmark returns. However, standardization cannot fully explain the incremental information contained in the DCI, as evidenced by the performance of DCI-SSDI double-sorted portfolios.[15]

7 Robustness

In this Section, we consider several additional tests to determine the robustness of our main results regarding the negative DCI-performance relationship. The results of these robustness checks are reported in Table 8 as well as in Tables A14-A24 in the Internet Appendix.

1. **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. 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 performance of the P5-P1 spread portfolio when funds have been sorted according to their mean

[15] We also explore if the difference between our findings and those reported in Sun et al. (2012) is due to the use of different sample periods. More specifically, we re-do the analysis for the Sun et al. (2012) sample period of 1996 to 2009. The empirical results (Tables A12 and A13 in the Internet Appendix) are qualitatively similar to those reported in the paper, for example in terms of a negative DCI-SDI correlation and a negative correlation between the DCI and all performance measures (except mean returns). It should be noted that another reason for the difference in the empirical results between this paper and Sun et al. (2012) and could potentially be the use of different data sources (Lipper TASS vs BarclayHedge). On this issue, Joenväärä et al. (2019) provide an excellent discussion of the challenges associated with using specific databases of hedge fund data.

DCI over the previous 2, 3, and 6 months, while Table A14 in the Internet Appendix reports the results from the respective Fama-MacBeth regressions. The results continue to show a negative relationship between deviating from the benchmark and subsequent fund performance.

2. **Strategy classification**: 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. We also group funds according to the relative proximity of their historical returns, by assigning funds into 10 groups following the k-means clustering procedure (MacQueen, 1967; Brown and Goetzmann, 1997; Sun et al., 2012). The results based on these two alternative classifications are very similar to our original results that were obtained under the Joenväärä et al. (2019) classification (see Table A15 in the Internet Appendix). The DCI is negatively related to all performance measures in the Fama-MacBeth regressions, while the P5-P1 spread portfolio offers a signficantly negative AR, Omega and Sortino ratio.

3. **Hedging effect**: Titman and Tiu (2011) find that fund managers who maintain a lower exposure to factor risk are more likely to deliver superior performance. We start by sorting funds into quintiles according to their DCI and, independently, into quintles according to the Titman and Tiu (2011) hedging effect, measured as the 1 minus the R-square from regressions of fund returns against the Fung and Hsieh (2004) factors. We then create a 5×5 grid of these funds by the combining the previous two sets of quintiles. 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. Instead, we find that the proportion of funds that falls under each of the 25 quintile combinations seems to be distributed in a consistently uniform way around the expected 1/25=4%, with proportions ranging from a minimum of 3.79% to a maximum of 4.12% (in contrast to the non-trivial overlap between the SDI and $1 - R^2$ reported by Sun et al., 2012). We also find that double-sorting funds into portfolios based on their DCI and $1 - R^2$ again produces a significantly negative relationship between the DCI and risk-adjusted performance. The results are reported in Table 8, as well as in Table A16 in the Internet Appendix.

4. **Gross returns**: The empirical results so far have been based on net-of-fees fund returns, which reflect more accurately an investor's payoff from

investing in a particular fund. However, given that fee structures can vary widely across different funds, the relationship between fund performance and any measure of strategy distinctiveness could potentially be affected by a systematic relationship between that measure and the fees charged by fund managers. This is especially important in the context of understanding whether the relative underperformance of high-DCI funds reflects genuinely poorer investment decisions or whether fund managers are simply extracting most of the economic rents. We follow the simple approach in Teo (2009) and Chen et al. (2020) to compute gross returns by adding back management fees and performance fees under certain conditions. The P5-P1 spread portfolio earns a positive mean return and alpha, but a significantly negative AR, Omega and Sortino ratio, consistent with our earlier results using net returns. Moreover, all performance measures are lower than the ones reported when using net returns. These results are consistent with the hypothesis that managers of high-DCI funds tend to charge higher fees compared to managers of low-DCI funds. However, accounting for the varying magnitude of economic rents extracted by managers across different funds does not appear to change the fundamental relationship between deviations from the benchmark and fund performance. The results are reported in Table 8 and Table A17 in the Internet Appendix.

5. **Underperforming vs outperforming funds**: We explore if the previously reported risk shifting can be attributed only to underperforming managers who could be less skilled. To this end, we re-examine the DCI-performance relationship separately for funds with mean returns that are above or below the mean return of the median fund. While the results are somewhat stronger in the underperforming group, the negative effect of the DCI on performance is observed in both fund groups, with high-DCI funds having negative AR, Omega and Sortino ratios, as well as higher post-formation risk exposure (see Table 8 and Tables A18-A19 in the Internet Appendix).

6. **Strategy**: We explore whether the negative DCI-performance is concentrated in specific types of funds by constructing spread portfolios separately for each strategy group. The negative DCI-performance relationship is robust across all strategy groups (see Tables A20-A21 in the Internet Appendix).

7. **Learning**: We split the sample into two sub-periods (01/1994-10/2004 and 11/2004-08/2015) in order to explore if there any evidence of managers learning over time. We find that the performance of high-DCI managers somewhat improves in the later sub-period, as evidenced by relatively less negative ARs, Omega and Sortino ratios. However, the DCI is still found to be negatively

related to fund performance, consistent with the results in the full sample (see Table 8 and Tables A22-A23 in the Internet Appendix).

8. **Value-weighing**: We replace equal-weighing with value-weighing funds in the quintile portfolios. The results are consistent with those reported earlier, highlighting a negative relationship between a fund's DCI and its subsequent performance (Table 8 and Table A24 in the Internet Appendix).

Taken together, these findings suggest that the negative DCI-performance relationship is a robust characteristic of our sample of hedge funds.

8 Conclusion

This paper focuses on the ongoing debate in the literature about whether a fund deviating from the benchmark reflects higher managerial skill or simply a willingness to load more on risk in pursuit of higher returns. We use a simple measure of deviations from the benchmark, based on the standardized 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 and find that, after accounting for various sources of risk and a set of fund-specific 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. Overall, we find little support for a skill-based explanation of why managers pursue distinctive investment strategies, and strong support for a risk shifting explanation where high-DCI funds are exposed to disproportionately higher levels of idiosyncratic, systematic and tail risk.

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. While it might still be the case that more skilled managers seek to achieve elevated performance by deviating from the ideas implemented by their peers, 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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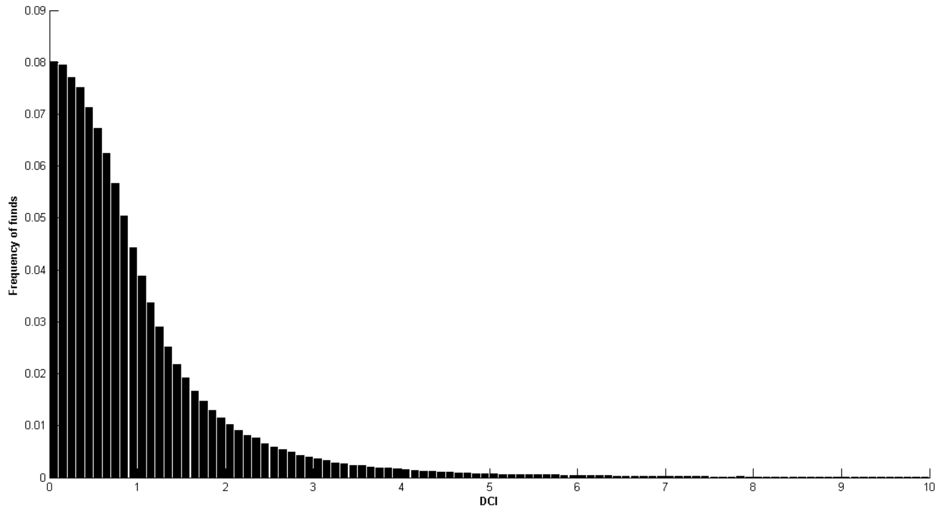

Figure 1: DCI Histogram

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.

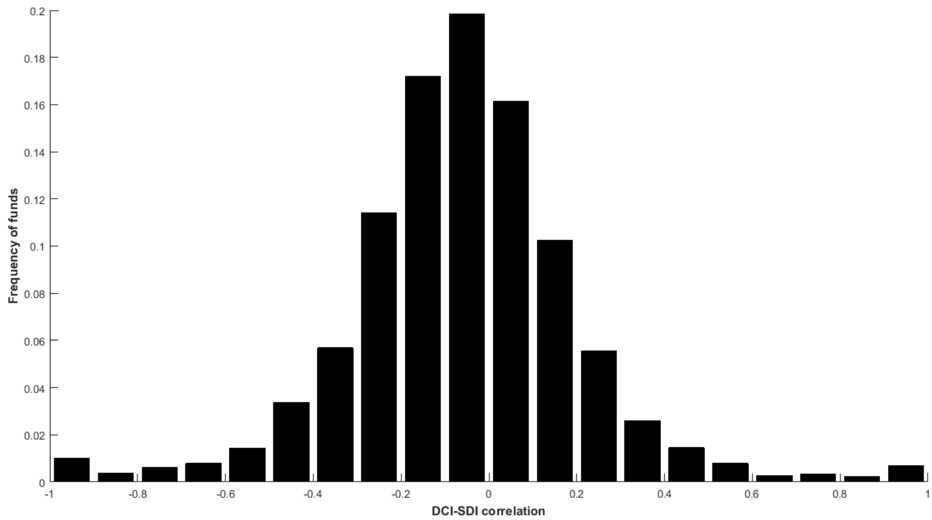

Figure 2: DCI-SDI correlations histogram

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

Table 1: DCI persistence

Panel A: Mean portfolio DCI across time						
	$t = 0$	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)

Panel B: Proportion of funds remaining in the same portfolio across time						
		1m	3m	6m	12m	24m
P1 (Low DCI)		25%	24%	24%	23%	23%
P2		23%	23%	23%	22%	22%
P3		22%	22%	22%	21%	21%
P4		23%	22%	22%	22%	19%
P5 (High DCI)		40%	37%	35%	32%	28%

Notes: Panel A of 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). Panel B reports the mean proportion of funds that remain in the same quintile portfolio in the subsequent 1, 3, 12 and 24 months. The sample runs from January 1994 to August 2015.

Table 2: DCI determinants

	Model I	Model II	Model III	Model IV
Constant	0.5724***	0.7813***	0.7864***	0.7323***
Redemption Notice	0.0003***	0.0008***	0.0008***	0.0009***
Lock Up	0.0009***	0.0002	0.0003**	0.0004**
Highwater Mark	0.0641***	0.0337***	0.0340***	0.0359***
Management Fee	-0.0011	0.0354***	0.0391***	0.0203***
Performance Fee	0.0015**	0.0007	0.0014***	-0.0008
Age	-0.0076***	-0.0047***	-0.0041***	-0.0040***
AUM	-0.0008	-0.0071***	-0.0071***	-0.0070***
Leverage	0.0071***	0.0038***	0.0040***	0.0026**
SDI	-0.5078***	-0.3958***	-0.4197***	-0.3469***
Return		-0.6773***	-0.4907***	-0.4567***
Volatility		15.0785***	15.4623***	7.8103***
Skewness		-0.0312***	-0.0275***	-0.0355***
Kurtosis		-0.0241***	-0.0228***	-0.0228***
Alpha			-5.2690***	-6.5902***
AR			-0.0097***	-0.0041***
Omega			-0.0047***	-0.0036**
Sortino				0.0188***
Idiosyncratic Volatility				16.4167***
Systematic Variance				-21.1267***
MKT beta				0.0762***
SMB beta				0.0867***
HML beta				0.0696***
RMW beta				-0.0309***
CMA beta				0.0349***
VaR				0.5385**
Expected Shortfall				1.1672**
Systematic Tail Risk				0.1209

Notes: This Table reports the results from estimating a panel regression (with fund and time fixed effects) of individual funds' DCI against a set of fund characteristics, namely the redemption notice (in days, excluding lock up), lock up period (in months), a dummy variable for highwater mark, management fee (in %), performance fee (in %), age (in years), Assets Under Management (AUM, in $ millions), a dummy variable for leverage, the Strategy Distinctiveness Index (SDI), return, return volatility, return skewness, return kurtosis (annualized 24-month estimates based on monthly returns), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio (AR), the Keating and Shadwick (2002) Omega, the Sortino ratio, idiosyncratic volatility (measured as the variance of residuals from Fung-Hsieh regressions), systematic variance (measured as the total variance of fund returns minus idiosyncratic variance), Fama and French (2015) factor betas (MKT, SMB, HML, RMW, CMA), 5% Value-at-Risk (VaR), 5% Expected Shortfall, and the Agarwal et al. (2017) Systematic Tail Risk measure. The set of fund characteristics is lagged by one period relative to the DCI. The Table reports the estimated coefficients. Statistical inference is based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The data panel consists of monthly observations across 9,533 individual funds for the period January 1994 to August 2015, for a total of 755,361 fund-month observations.

Table 3: Performance of DCI-sorted portfolios

Panel A: Mean returns across holding periods					
	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)
Panel B: Performance measures					
	Return	Alpha	AR	Omega	Sortino
P1 (Low DCI)	0.0075	0.0073	2.9388	3.6428	1.5723
P2	0.0075	0.0072	2.8823	3.7838	1.5464
P3	0.0079	0.0072	2.6791	3.4414	1.3486
P4	0.0080	0.0074	2.1678	2.4973	0.9746
P5 (High DCI)	0.0119	0.0093	1.5794	1.8006	0.7452
P5 – P1	0.0043	0.0020	-1.3595	-1.8421	-0.8270
(*t-stat*)	(4.52)	(10.35)	(-30.59)	(-13.82)	(-12.52)

Notes: This Table reports the performance of five portfolios sorted on the funds' levels of DCI. Panel A reports the time-series mean returns of the DCI-sorted quintile portfolios, separately for holding periods of 1, 3, 6, 12 and 24 months. Panel B reports a set of performance measures for the DCI-sorted portfolios (for a monthly holding period). The performance measures examined comprise the mean return, the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio (AR), the Keating and Shadwick (2002) Omega, and the Sortino ratio. The Table also reports the differences between the returns and performance measure of funds in the highest-DCI quintile and those in the lowest-DCI quintile, as well as the respective t-statistics (based on bootstrapped standard errors). The sample runs from January 1994 to August 2015.

Table 4: Risk exposure of DCI-sorted portfolios

	P1 (Low)	P2	P3	P4	P5 (High)	High minus Low
Volatility	0.0143	0.0144	0.0147	0.0169	0.0283	0.0140
Skewness	-0.4977	-0.4381	-0.3009	-0.3328	-0.1162	0.3815
Kurtosis	5.2137	4.6261	4.0687	3.7006	4.7527	-0.4610
Idiosyncratic Volatility	0.0008	0.0006	0.0008	0.0009	0.0033	0.0025
Systematic Variance	0.0002	0.0002	0.0002	0.0003	0.0008	0.0006
VaR	0.0119	0.0135	0.0143	0.0186	0.0313	0.0194
Expected Shortfall	0.0060	0.0059	0.0063	0.0062	0.0088	0.0028
Systematic Tail Risk	0.0486	0.0376	0.0507	0.2557	0.0768	0.0282

Notes: This Table reports the post-formation risk exposure of quintile portfolios that have been created by sorting individual funds according to their DCI. The last column reports the difference in terms of each risk measure between the high-DCI portfolio (P5) and the low-DCI portfolio (P1). The Table reports the post-formation mean of a set of portfolio characteristics, namely idiosyncratic volatility (measured as the variance of residuals from Fung-Hsieh regressions), systematic variance (measured as the total variance of fund returns minus idiosyncratic variance), 5% Value-at-Risk (VaR), 5% Expected Shortfall, and the Agarwal et al. (2017) Systematic Tail Risk measure. The sample period runs from January 1994 to August 2015.

Table 5: Fama-MacBeth regressions of hedge fund performance

	Return	Alpha	AR	Omega	Sortino
Constant	-0.0004**	-0.0026***	3.3329***	1.5824***	3.6997***
DCI	-0.0005***	-0.0002***	-0.0223***	-0.0791***	-0.2286***
Redemption Notice	-0.0026	-0.0275***	1.1622***	4.1548***	15.2533***
Lock Up	0.0668***	0.0337***	6.1544***	-1.3852***	7.8140***
Highwater Mark	-0.0007***	-0.0003***	0.1012***	-0.1029***	-0.7788***
Management Fee	0.0005***	0.0000***	-0.2700***	0.0589***	0.2096***
Performance Fee	0.0001***	0.0001***	-0.0007***	-0.0076***	0.0266***
Age	-0.0001***	-0.0001***	0.0077***	-0.0169***	0.0066***
AUM	-0.0018***	0.0048***	0.8013***	8.0409***	13.1496***
Leverage	0.0000	0.0001***	0.0157***	-0.0431***	0.0366***
SDI	0.0011***	0.0007***	-0.1143***	-1.3076***	-3.3031***
Volatility	0.0082	0.0016	0.0019	0.0047	0.0070
Skewness	0.0001***	0.0001***	-0.0180***	0.5320***	1.3603***
Kurtosis	-0.0003***	-0.0001***	0.0161***	-0.0528***	-0.0365***
Idiosyncratic Volatility	0.0166***	0.0162***	49.2082***	0.6818**	-11.9190***
Systematic Variance	0.7623***	0.3224***	73.9900***	19.9273***	62.7705***
VaR	-0.0013***	-0.0073***	-0.3403***	-0.2952***	0.1354***
Expected Shortfall	-0.0900***	-0.7752***	-16.1100***	-11.6640***	-27.6080***
Systematic Tail Risk	0.0026***	-0.0005***	0.2821***	1.4472***	6.5697***
MKT	-0.0029***	0.0011***	-0.1603***	-0.4738***	-1.4645***
SMB	-0.0005**	-0.0002***	0.4121***	-0.1040***	-1.0373***
HML	0.0048***	0.0000	-0.4290***	-0.0954***	-0.2067***
RMW	0.0008***	-0.0007***	-0.4101***	-0.3305***	-0.6052***
CMA	0.0038***	0.0006***	-0.3293***	0.0050	-0.2541***
LIQ	-0.0413***	-0.0608***	59.7663***	15.5401***	39.3771***
MRI	0.0540***	-0.0190***	-6.0311***	12.5201***	9.7771***
STRF	-0.0068***	-0.0004***	-0.2504***	-1.0869***	-2.7480***
n	2,993	2,993	2,993	2,993	2,993

Notes: This Table reports the results of Fama-MacBeth regressions of individual hedge fund performance against the DCI and a set of other fund characteristics, namely the funds' redemption notice (in days, excluding lock up, $\times 10^{-3}$), lock up period (in months, $\times 10^{-3}$,), a dummy variable for highwater mark, management fee (in %), performance fee (in %), age (in years), Assets Under Management (AUM, in $), a dummy variable for leverage, the level of funds' Strategy Distinctiveness Index (SDI), return volatility (annualized 24-month volatility of monthly returns, in %), return skewness and kurtosis, idiosyncratic volatility (measured as the variance of residuals from Fung-Hsieh regressions), systematic variance (measured as the total variance of fund returns minus idiosyncratic variance), 5% Value-at-Risk (VaR), 5% Expected Shortfall, the Agarwal et al. (2017) Systematic Tail Risk measure, Fama and French (2015) factor betas (MKT, SMB, HML, RMW, CMA), the Pastor and Stambaugh (2003) traded liquidity factor beta (LIQ), the Bali et al. (2014) Macroeconomic Risk Index beta (MRI), and the Agarwal et al. (2017) Systematic Tail Risk Factor beta (STRF). The regression is estimated separately for each performance measure, namely the fund's mean return, the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio (AR), the Keating and Shadwick (2002) Omega, and the Sortino ratio. The fund characteristics are lagged by one period. Statistical inference is based on Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors, with the number of lags selected based on the Akaike Information Criterion. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The Table reports the second-stage mean estimated coefficients and the number of observations n. The sample runs from January 1994 to August 2015.

Table 6: Double-sorting on DCI and risk characteristics

	Return (%)	Alpha (%)	AR	Omega	Sortino
Idiosyncratic Volatility	0.14*	-0.20***	-0.77***	-0.89***	-0.48***
Systematic Variance	0.36***	-0.12***	-2.79***	-0.64***	-0.63***
VaR	0.04	-0.28***	-0.93***	-1.34***	-0.64***
Expected Shortfall	0.35***	0.09***	-0.96***	-1.83***	-0.75***
Systematic Tail Risk	0.29**	0.00	-1.26***	-1.54***	-0.56***
PTFSBD	0.30***	-0.12***	-1.10***	-1.60***	-0.72***
PTFSFX	0.40***	-0.09***	-1.14***	-1.66***	-0.70
PTFSCOM	0.41***	-0.11***	-1.12***	-1.53***	-0.68***
S&P	0.40***	-0.08***	-1.16***	-1.59***	-0.70***
SCMLC	0.32***	-0.13***	-1.16***	-1.54***	-0.70***
BD10RET	0.20**	-0.12***	-1.13***	-1.59***	-0.71***
BAAMTSY	0.43***	-0.09***	-1.16***	-1.70***	-0.74***
LIQ	0.34***	-0.08***	-1.14***	-1.60***	-0.70***
MRI	0.32***	-0.11***	-1.12***	-1.64***	-0.73***
STRF	0.03***	-0.10***	-1.14***	-1.59***	-0.69***
MKT	0.29***	-0.08***	-1.17***	-1.67***	-0.73***
SMB	0.28***	-0.12***	-1.15***	-1.57***	-0.69***
HML	0.31**	-0.12***	-1.13***	-1.54***	-0.72***
RMW	0.21**	-0.13***	-1.14***	-1.69***	-0.74***
CMA	0.29**	-0.11***	-1.12***	-1.53***	-0.70***

Notes: This Table reports a set of performance measures for P5-P1 spread portfolios that have been double-sorted based on the funds' levels of DCI and on a specific risk characteristic of the fund in turn. Each P5-P1 spread portfolio has been constructed by going long in the quintile of funds with the highest DCI and short in the quintile of funds with the lowest DCI, with the two quintile portfolios P5 and P1 having approximately the same level of the other fund risk characteristic. The set of fund risk characteristics consists of idiosyncratic volatility (measured as the variance of residuals from Fung-Hsieh regressions), systematic variance (measured as the total variance of fund returns minus idiosyncratic variance), 5% Value-at-Risk (VaR), 5% Expected Shortfall, and the Agarwal et al. (2017) Systematic Tail Risk measure, the 7 Fung and Hsieh (2004) factor betas (PTFSBD, PTFSFX, PTFSCOM, S&P, SCMLC, BD10RET, BAAMTSY), the 5 Fama and French (2015) factor betas (MKT, HML, SMB RMW, and CMA), the Pastor and Stambaugh (2003) traded liquidity factor beta (LIQ), the Bali et al. (2014) Macroeconomic Risk Index beta (MRI), and the Agarwal et al. (2017) Systematic Tail Risk Factor beta (STRF). The performance measures examined comprise the mean return, the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio (AR), the Keating and Shadwick (2002) Omega, and the Sortino ratio. Mean returns and alphas are tabulated in percentages. The performance measures refer to portfolios rebalanced at a monthly frequency. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The sample runs from January 1994 to August 2015.

Table 7: Logit regressions of fund survival on DCI

	1m	3m	6m	12m	24m
without controls					
mean	-0.1870	-0.0954	-0.0851	-0.0146	-0.0182
(*t-stat*)	(-41.24)	(-27.77)	(-34.32)	(-15.65)	(-43.60)
with controls					
mean	-0.6669	-0.2487	-1.1493	-1.3426	-1.6003
(*t-stat*)	(-13.07)	(-11.85)	(-21.60)	(-25.24)	(-28.35)

Notes: This Table reports the results of cross-sectional logit regressions of fund survival on the lagged DCI. The dependent variable is a dummy that takes the value of 1 if the fund is still in existence in the next 1, 3, 6, 12, or 24 months, and the value of 0 otherwise. Each cross-sectional regression is estimated separately for every sample month, with the Table reporting the mean DCI slope coefficient and the associated t-statistic (in brackets). The regression is estimated with and without control variables. The control variables are also lagged and they include the fund's redemption notice, lock up period, a dummy variable for highwater mark, management fee, performance fee, age, Assets Under Management, a dummy variable for leverage, the Strategy Distinctiveness Index, return, return volatility, return skewness, return kurtosis, idiosyncratic volatility, systematic variance, the Fama and French (2015) factor betas, 5% Value-at-Risk (VaR), 5% Expected Shortfall, and the Agarwal et al. (2017) Systematic Tail Risk measure.The sample runs from January 1994 to August 2015.

Table 8: Robustness checks

	Return	Alpha	AR	Omega	Sortino
Double-sort on DCI and market timing skill	0.003**	-0.001***	-1.126***	-1.678***	-0.719***
Double-sort on DCI and liquidity timing skill	0.003**	-0.001***	-1.127***	-1.620***	-0.728***
Double-sort on DCI and SSDI	0.007*	0.007***	-0.007***	-0.007***	-0.009***
Double-sort on DCI and $1 - R^2$	0.005***	-0.001***	-1.475***	-2.063***	-0.854***
HWM	0.004***	0.001***	-1.626***	-2.406***	-1.154***
no HWM	0.005***	0.003***	-0.902***	-1.005***	-0.305***
Long LockUp	0.004***	0.002***	-1.675***	-2.942***	-1.562***
Short LockUp	0.004***	0.002***	-1.256***	-1.572***	-0.573***
Long RedNot	0.004***	0.002***	-1.917***	-3.410***	-1.600***
Short RedNot	0.005***	0.002***	-1.040***	-1.077***	-0.417***
Underperforming funds	-0.002***	-0.002***	-1.303***	-1.383***	-0.479***
Outperforming funds	0.007***	0.003***	-1.520***	-2.458***	-1.180***
Sort on 2-month mean DCI	0.005*	0.003*	-1.842*	-2.499*	-1.088*
Sort on 3-month mean DCI	0.006*	0.003*	-2.133*	-2.910*	-1.189*
Sort on 6-month mean DCI	0.007*	0.004*	-2.549*	-3.323*	-1.324*
BarclayHedge groups	0.003*	0.001*	-1.010*	-0.978*	-0.412*
k-means clustering groups	0.003*	0.001*	-1.519*	-2.124*	-0.868*
Gross returns	0.005***	0.002***	-1.591***	-2.911***	-0.884***
01/1994 - 10/2004	0.007***	0.003***	-1.731***	-2.545***	-1.039***
11/2004 - 08/2015	0.002***	0.001***	-1.102***	-1.357***	-0.620***
Value-weighted	0.004***	0.002***	-1.291***	-1.486***	-0.860***

Notes: This Table reports the results of additional robustness checks on the performance of spread portfolios that go long in the quintile with the highest DCI funds and short in the quintile with the lowest DCI funds (for monthly holding periods). The set of robustness checks includes double-sorting funds according to their DCI and a number of variables that reflect managerial skill and/or strategy distinctiveness, namely the Chen and Liang (2007) measure of market timing skill, the Cao et al. (2013) measure of market liquidity timing skill, the Standardized Strategy Distinctiveness Index (SSDI), and the Titman and Tiu (2011) "hedging effect" $1 - R^2$ (measured as 1 minus the R-square obtained when regressing the fund's returns against the Fung and Hsieh (2004) seven factors). Additional robustness checks include computing the performance of the spread portfolio separately for funds with and without highwater mark provisions ("HWM" and "no HWM", respectively), with lock up periods that are above or below the median ("Long LockUp" and "Short LockUp", respectively), with redemption notice periods that are above or below the median ("Long RedNot" and "Short RedNot", respectively), and funds that offer mean returns that are below or above the median fund return ("Underperforming" and "Outperforming", respectively). The Table also reports the performance of spread portfolios that have been constructed by sorting funds according to their mean DCI levels over the previous 2, 3 and 6 months, as well as the performance of spread portfolios based on the original BarclayHedge fund strategy classification and a k-means clustering of funds in 10 groups according to their historical returns. Finally, the Table reports the performance of a spread portfolio based on *gross* returns (computed from net returns following the approach in Teo, 2009), computed separately for the two sub-periods 10/1994-10/2004 and 11/2004-08/2015, as well as based on value-weighing funds in each quintile. The performance measures examined comprise the mean return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, and the Sortino ratio. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The full sample runs from January 1994 to August 2015.

Table 9: DCI-SDI correlations

	mean	median	st.dev
CTA	-0.03	-0.03	0.31
Emerging Markets	-0.09	-0.09	0.24
Event Driven	-0.06	-0.07	0.24
Global Macro	-0.09	-0.07	0.30
Long Only	-0.11	-0.11	0.25
Long/Short	-0.08	-0.08	0.25
Market Neutral	-0.03	-0.05	0.29
Multi-Strategy	-0.07	-0.08	0.23
Relative Value	0.00	0.01	0.30
Sector	-0.06	-0.06	0.26
Short Bias	-0.12	-0.12	0.23
Others	-0.07	-0.06	0.27
ALL	-0.06	-0.06	0.27

Notes: This Table presents descriptive statistics on the pairwise correlations between funds' DCI and SDI levels. The Table reports the mean, median and standard deviation of DCI-SDI correlations across funds. The first rows present correlation descriptives separately for same-strategy fund groups (based on the classification proposed in Joenväärä et al., 2019), while the last row reports correlation descriptives computed across all sample funds.

Table 10: Double-sorting 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)

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 mean return (net of fees), the Fung and Hsieh (2004) alpha, the Treynor and Black (1973) Appraisal Ratio, the Keating and Shadwick (2002) Omega, and the Sortino ratio. Performance measures are tabulated separately for holding periods of 1, 3, 6, 12 and 24 months. The respective t-statistics (based on bootstrapped standard errors) are tabulated in brackets. The sample runs from January 1994 to August 2015.

Table 11: DCI and SDI across fund groups

	mean	n(%)	lower 5%	upper 5%	lower 1%	upper 1%
Panel A: DCI						
CTA	0.99	4%	15%	3%	10%	4%
Emerging Markets	0.98	11%	3%	3%	5%	7%
Event Driven	1.05	7%	0%	15%	3%	10%
Global Macro	0.98	5%	3%	0%	5%	3%
Long Only	0.97	3%	0%	0%	1%	2%
Long/Short	1.01	21%	5%	13%	8%	17%
Market Neutral	1.06	3%	1%	0%	1%	1%
Multi-Strategy	0.99	5%	0%	6%	3%	4%
Relative Value	1.05	15%	43%	39%	35%	25%
Sector	0.99	20%	4%	9%	14%	16%
Short Bias	1.06	0%	0%	0%	0%	0%
Others	1.05	7%	25%	11%	17%	11%
ALL	1.00	100%	100%	100%	100%	100%
Panel B: SDI						
	mean	n(%)	lower 5%	upper 5%	lower 1%	upper 1%
CTA	0.21	4%	0%	4%	0%	2%
Emerging Markets	0.62	11%	29%	8%	27%	6%
Event Driven	0.56	7%	5%	7%	0%	4%
Global Macro	0.34	5%	0%	6%	0%	8%
Long Only	0.77	3%	24%	2%	51%	1%
Long/Short	0.51	21%	25%	20%	9%	22%
Market Neutral	0.28	3%	0%	3%	0%	6%
Multi-Strategy	0.46	5%	3%	5%	2%	3%
Relative Value	0.34	15%	4%	13%	2%	15%
Sector	0.35	20%	0%	20%	0%	17%
Short Bias	0.71	0%	4%	0%	7%	0%
Others	0.38	7%	5%	12%	1%	15%
ALL	0.47	100%	100%	100%	100%	100%

Notes: This Table presents descriptive statistics of funds' DCI (Panel A) and SDI (Panel B) across different strategy groups. The Table reports the mean DCI and SDI levels, the proportion of the full sample attributed to each strategy group, while the last four columns report the proportion of funds in the bottom/top 5% and 1% DCI- and SDI-based quantiles that belong in each strategy group. The allocation of funds into strategy groups is based on the classification proposed in Joenväärä et al. (2019).