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"Opinion is the medium between knowledge and ignorance."

– Plato

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RÉSUMÉ DE LA THÈSE

Ma thèse de doctorat consiste en trois articles scientifiques examinant plusieurs externalités qui imposent des impacts sur la performance des fonds de couverture : rendement d'échelle décroissant, réseaux sociaux, et limites de l'arbitrage.

Article 1. Non seulement le talent mais également les économies d'échelle : le cas des fonds de couverture

Nous testons empiriquement un modèle à deux niveaux de rendements d'échelle décroissants avec un échantillon de fonds de couverture. Le modèle à deux niveaux suppose que l'alpha brut d'un fonds est une fonction décroissante à la fois des économies d'échelle au niveau du fonds et des économies d'échelle au niveau du style. Cette dernière est mesurée par la taille totale des pairs déployant des stratégies d'investissement de même style. Nous constatons qu'un modèle au niveau du fonds sous-estime l'impact de la décroissance des économies d'échelle sur l'alpha brut mensuel de 55 points de base. Les résultats indiquent que les gestionnaires des fonds doivent tenir compte des contraintes imposées par les économies d'échelle du style lorsqu'ils optimisent la taille de leur fonds. Nous constatons aussi que les fonds de couverture n'ont pas investi à leur niveau optimal et confirmons que le talent et les capacités à résister à la décroissance des économies d'échelle sont deux éléments importants à considérer pour sélectionner les fonds performants.

Article 2. Influences sociales et caractère unique des stratégies de fonds de couverture

Différemment des études antérieures, nous examinons l'effet des réseaux sociaux sur la performance des fonds en tenant compte de la concurrence entre les différents fonds. Nous supposons que si les réseaux sociaux facilitent le regroupement dans les investissements des fonds, un fonds « central » aurait une stratégie moins unique, mesurée par l'indice de distinction des stratégies de Sun et al. (2012). Ceci entraîne une baisse de la performance lorsque les idées d'investissement uniques sont cruciales pour réussir au sein d'un environnement compétitif. Nous confirmons cet effet en examinant les réseaux des anciens diplômés et ceux du travail entre les fonds concurrents les plus proches. En particulier, les gestionnaires « intelligents » avec plus

d’ambition de carrière sont plus vulnérables à cet effet négatif. Nous confirmons également que le regroupement d'investissements se manifeste davantage sous les influences sociales.

Article 3. Les fonds de couverture avec moins de contraintes surperforment-ils ?

Cette étude examine si les fonds qui sont moins contraints par des limites d'arbitrage surperforment leurs pairs qui sont plus contraints à l’aide d’un bêta de mauvaise évaluation. Nous constatons qu'un tiers des fonds de notre échantillon de fonds de couverture ont tendance à remettre à plus tard l’exploitation des erreurs d'évaluation de titres au niveau du MGMT, tandis qu’au maximum 3% des fonds corrigent les prix sans délai. Néanmoins, un cinquième des fonds exploitent les erreurs au niveau du PERF et seulement 5% diffèrent l'arbitrage. Nous constatons également que les fonds de couverture avec les bêtas les plus élevés surperforment ceux avec les bêtas les plus faibles de 28 à 63 points de base par mois. Nous estimons aussi que la valeur économique provenant de la capacité des fonds à effectuer l’arbitrage dynamique correspond à un alpha de 69 points de base par mois à long terme.

DISSERTATION SUMMARY

My doctoral dissertation consists of three scientific articles examining several externalities that impact hedge fund performance: decreasing return to scale, social networks, and limits of arbitrage.

Paper 1. Not only skill but also scale: Evidence from the hedge fund industry

This paper empirically tests a two-level model of decreasing returns to scale using a sample of hedge funds. The two-level model assumes that a fund's gross alpha is a decreasing function of both the fund scale and the style scale measured by the aggregate size of peers in the hedge fund style. We find that a fund-level model underestimates the impact of diseconomies of scale on the gross alpha by 55 basis points. The results indicate that managers should consider the constraints imposed by the style scale when optimizing their portfolio sizes. We also provide evidence that hedge funds did not invest at their optimal amount and confirm that skill and the ability to resist decreasing returns to scale are two important components of selecting hedge fund performers.

Paper 2. Social influences and uniqueness of hedge fund strategies

Unlike previous studies, we explore a mechanism that explains how social networks could be detrimental to fund performance due to competition. We postulate that if social networks facilitate investment herding, then a central fund would have a less unique strategy, proxied by the strategy distinctiveness index of Sun et al. (2012), which leads to lower performance. We consider alumni and employment ties between the closest hedge fund competitors and confirm this point of view. Particularly, smart managers with career ambitions are more vulnerable to this negative effect. We also find that investment herding is encouraged under social influences.

Paper 3. Overcoming short-sale constraints and hedge fund returns

Our study explores the heterogeneous abilities of hedge funds to arbitrage overpricing and the impact of this ability on their performance. We find that on one side, one-third of funds in our sample tend to delay arbitrage on management (MGMT) mispricing, whereas no more than 3% of funds correct prices right away. On the other side, one-fifth of funds bet against performance

(PERF) mispricing, while only 5% delay arbitrage. We also find that funds with the highest mispricing betas outperform those with the lowest betas and show that the mispricing beta strongly predicts hedge fund performance in the long run.

PAPER 1. NOT ONLY SKILL BUT ALSO SCALE:

EVIDENCE FROM THE HEDGE FUND INDUSTRY

(*International Review of Financial Analysis, Volume 83, 2022*)

ABSTRACT

This paper empirically tests a two-level model of decreasing returns to scale using a sample of hedge funds. The two-level model assumes that a fund's gross alpha is a decreasing function of both the fund scale and the style scale measured by the aggregate size of peers in the hedge fund style. We find that a fund-level model underestimates the impact of diseconomies of scale on the gross alpha by 55 basis points. The results indicate that managers should consider the constraints imposed by the style scale when optimizing their portfolio sizes. We also provide evidence that hedge funds did not invest at their optimal amount and confirm that skill and the ability to resist decreasing returns to scale are two important components of selecting hedge fund performers.

JEL classification: G11; G23; J24

Keywords: Hedge funds; Decreasing returns to scale; Performance; Skill

1. Introduction

Managerial skill drives performance in active asset management. In 2013, North American hedge funds realized an annual net return of 16.55% and a 5-year annualized net return of 16.98%. In 2017, U.S. hedge funds achieved 12 consecutive months of positive performance.[1] This superior performance is likely an outcome of hedge fund managers' skills in developing trading strategies. Pástor, Stambaugh, and Taylor (2015) point out, however, that fund performance depends not only on the fund manager's skill but also on various constraints, such as decreasing returns to scale (DRTS). In other words, the hedge fund performance could be a mixed effect of hedge fund skill and DRTS. DRTS are a result of the constraints imposed by the scale (Berk and Green, 2004; Pástor et al., 2015; Perold and Salomon, 1991; Harvey and Liu, 2017; Phillips, Pukthuanthong, and Rau, 2018; and Zhu, 2018).[2] For example, large funds are more likely to face price pressures that erode their performance and several constraints when building their optimal portfolio.[3] Consequently, portfolio managers need to cap their funds to take advantage of investment opportunities. They also need to fit their fund size to their investment strategies and to the market where they operate.[4] Thus, as noted by Pástor, Stambaugh, and Taylor (2015, p.24), "*if scale impacts performance, skill and scale interact.*"

The purpose of this study is to answer the following questions: Do hedge funds face DRTS? How did the changes in hedge funds size affect the evolution of fund performance? How DRTS

[1] Data are from Preqin Global Hedge Fund Report (2014, 2018). Preqin is one of the biggest global alternative assets data and solutions providers.

[2] In this paper, we primarily interested in scale effects and not in competition effects. See, for example, Wahal and Wang (2011) that examine competition among mutual funds.

[3] For example, some strategies could highly weight a small-cap stock. When fund size is too large, the asset allocation to the small-cap stock (the weight of the small-cap stock (x) the fund size) is very likely to exceed the market capitalization of this stock. Consequently, large funds are forced to hold a sub-optimal portfolio or to forego these specific strategies.

[4] Fung and Hsieh (1997) note that "niche" hedge funds would be more suitable when operating in illiquid markets, rather than large hedge funds.

interact with skill to measure fund performance?

In this study, we consider a comprehensive sample of 4,960 U.S. hedge funds from the Lipper TASS database (TASS) between January 1994 and December 2018. Using a fund-level and style-level model, we find that the hedge fund's capacity depends on the manager's skill as well as the style scale. We also find that if an increasing amount of capital is invested in a particular hedge fund style, the return and the potential profits extracted from this strategy (the maximal value added) decrease. In other words, if style size imposes a constraint, fund's return and profits decrease even when the manager optimizes his(her) fund size. We test a fund-level model of DRTS and find that when an average hedge fund doubles its size (corresponding to an increase of 250 million dollars in the managed assets), its monthly gross alpha decreases by 9.90 bps, with a t-statistic of −3.49. Based on a two-level model, we find a similar level of coefficient estimate on the fund scale. For instance, an increase of 250 million dollars in the fund size decreases the gross alpha by 8.43 bps per month, with a t-statistic of −2.84. When an average fund's style scale doubles (corresponding to an increase of 90 billion dollars in the style size), its alpha reduces by 54 bps, with a t-statistic of −2.23.

We estimate skill for each fund and each month from 1994 to 2018. The average fund would have realized a gross alpha of 0.95% per month in the absence of DRTS. Over the period, about 70% of hedge funds had the skill to beat the market, but only one-half of hedge funds realized positive alphas in the presence of a diseconomy of scale. By analyzing the interaction of skill and scale in determining fund performance, we find that scale accounts for a large portion of hedge fund performance during the financial crisis, while the post-crisis performance of hedge funds declines due to skill.

Further, we find that hedge funds did not invest at their optimal level. About 30.69% (34.31%) of the funds in our sample are excessively (moderately) overfunded, and 35% are underfunded. About 36.33% (63.67%) of the funds destroyed (added) value. The average hedge fund added an economically and statistically significant value of $300,000 per month. Among the funds adding value, a larger fraction (34.17% of all funds) is underfunded, with an average size of $124 million versus the optimal size of $215 million. The underfunded funds added, on average, a value of $820,000 per month with an average skill of 1.67%. If they reached the optimal size, they could realize a value of $1,380,000 per month. We explain the underfunding of good performers by strict regulations regarding limited access to hedge funds and the prudent use of capacity by hedge funds.

Our paper makes several contributions to the literature. First, we provide robust evidence for DRTS in hedge funds. Previous studies focus mainly on mutual funds and report mixed results (e.g., Pástor, Stambaugh, and Taylor, 2015; Harvey and Liu, 2017; Phillips, Pukthuanthong, and Rau, 2018; and Zhu, 2018), while very few studies consider the case of hedge funds. Specifically, Rzakhanov and Jetley (2019) focus on a subcategory of hedge fund style (merger and arbitrage strategy) and find that fund size has no impact on alpha, while Teo (2012) focuses on fund-level scale constraints using a comprehensive sample of hedge funds. In this study, we find, however, that the hedge fund style scale is the more dominant factor than the fund scale. In addition, our empirical tests consider the critical issues in estimating DRTS caused by omitted skill, a finite sample, and the time trend of the unobserved variable.[5] Further, compared to mutual funds studies, we find more significant fund-level scale effects among hedge funds than mutual funds, a much

[5] We also eliminate the concern that the mechanic relation between net returns and fund size could drive a negative relation, which is not DRTS of interest (see Section 4.3).

smaller proportion of hedge funds are overfunded, and hedge funds destroy value due to a lack of skill rather than DRTS.[6]

Second, we extend the literature by providing evidence for the style-level DRTS in hedge funds. Previous studies on mutual funds also examine the nature of returns to scale at the industry-level (Pástor and Stambaugh, 2012; Pástor et al., 2015; and Harvey and Liu, 2017). Compared to mutual funds, hedge funds engage in various strategies using different investment instruments (e.g., leverage, derivatives, short-selling, and trading in a broader range of markets). Different hedge fund styles could also have different capacity limits. We complement these studies by testing the nature of returns to scale at the style-level, as proxied by the aggregate size of competitors who employ similar strategies.[7] Our rationale is that hedge fund's returns are decreasing as the style size increases. We also re-examine DRTS with a fund-level model and find that the fund-level model largely underestimates the impact of DRTS on the gross alpha by 55 bps per month on average. When AUM in a specific investment style grows, hedge funds in this style realize lower rates of return given the more severe price pressure, which is caused by more trades chasing the same opportunities among competitors.

Third, we advance the estimation method for scale-performance relationship, by tackling the endogeneity caused by the time trend of skill which the fixed effect (FE) model fails to capture. The FE model assumes that fund skill is heterogeneous across funds but constant over the lifetime of each fund. This assumption is challenged because the skill of funds could vary over time

[6] For instance, considering the same estimator (FE-RD2), an increase of $100 million in hedge fund size decreases alpha by 4.87 bps per month, compared with the result of Zhu (2018) of 0.485 bps for mutual funds. We find only 65% (30%) of hedge funds are (excessively) overfunded. Zhu (2018) finds that 82% (57%) of mutual funds are (excessively) overfunded. We find skill partially explains why some hedge funds destroyed value. Zhu (2018) finds that DRTS is the main reason for mutual funds destroying value.

[7] Our style scale equals the total AUM of the fund's peers in the same style, not including the fund itself. This eliminates concerns of whether style-level decreasing returns implies fund-level decreasing returns if a single fund represents a large fraction of the style and avoids multicollinearity problems in the multiple regression. Moreover, the coefficients on fund scale and style scale in the multiple regression represent the independent effects of two levels.

(Phillips et al., 2018). In the presence of the time trend of skill, the estimated scale effect falsely captures the correlation between the time trend of skill and the scale variable when using the FE model. To tackle this problem, we develop an RT-RD2 estimator under a random trend (RT) model, which allows a fund-specific time trend of skill. In the simulation exercise, we prove that the estimator developed under the FE model is biased at both fund-level and style-level if returns have a time trend, while our RT-RD2 unbiasedly estimates the two-level coefficients no matter whether there is a time trend of skill or not. We also confirm this bias in our empirical tests with the hedge fund sample.[8]

Fourth, we complement Harvey and Liu (2017) in examining the heterogeneity of the ability to resist DRTS among hedge fund managers. We confirm that this ability and skill are two important components to select hedge fund performers. For example, when one fund is better at managing the price pressure by trading with a large volume, it can outperform peers with the same level of skill. Moreover, we find small funds are more able to manage the constraints imposed by scale. Further, Yin (2016) examine the optimal size of hedge funds to maximize managers' compensation. We also complement this study by examining the optimal size of hedge funds under the context of DRTS.

The remainder of the paper is organized as follows. Section 2 discusses the hypothesis of two-level decreasing return to scale; Section 3 presents the method of our empirical tests and show the robustness of our estimator. Section 4 presents sample, data issues, and estimation of gross alphas; Section 5 presents the empirical results; Section 6 presents robustness tests; Section 7

[8] If there is no time trend, both FE-RD2 and RT-RD2 should have estimates at a similar level. However, two estimators have different estimates in Table 3. Moreover, by estimating the growth rate of skill, we confirm the presence of time trend. We find that 30% (52%) of hedge funds have significantly increasing (decreasing) skill. On average, hedge fund skill is decreasing at 0.07367% per year.

concludes.

2. Background and hypotheses

Pástor et al. (2015) investigate the nature of returns to scale in active mutual fund management at both the fund-level and industry-level. They note that the fund-level DRTS reflect the impact of liquidity constraints and price pressures within the fund. They also note that both levels of decreasing returns are motivated by liquidity constraints and that the aggregate size is more important in determining fund performance than the individual size, particularly for an industry where individual funds apply homogeneous strategies. The more funds follow the same strategy, and the fewer investment opportunities become available. However, hedge funds compete more rigorously within style groups. Hedge funds invest in markets, sectors, and asset classes and employ investment instruments—leverage, derivatives, and short selling, among others—that are distinct across hedge fund styles. Also, style-chasing by investors erodes fund performance. Getmansky (2012) finds that when a hedge fund strategy performs well, investors favorably position this strategy by increasing their fund inflows. Consequently, they increase the probability of liquidation of hedge funds in this strategy. To test whether these style-chasing flows impose constraints on fund performance, we propose a style-level scale measure. Our rationale is that hedge fund returns decrease at the style-level, which negatively affects fund performance when the style size increases.

Moreover, to consider the concern that style-level decreasing returns to scale implies fund-level DRTS, the style size takes a sum of the peers in style and excludes the fund itself. In this way, the two-level scale measures are as independent as possible, avoiding the multicollinearity problem when a fund accounts for a large fraction of the total AUM in a given style. Our nonmutually exclusive hypotheses are as follows: The first one concerns fund-level DRTS: as the size of an active hedge fund increases, the fund's performance declines. The second hypothesis is style-level DRTS: as the size of the active hedge fund style increases, the hedge fund's performance declines.

The two-level DRTS is described as $\alpha_i = a_i - \beta_1 q_i - \beta_2 q_s$, where q_i is the fund scale measured as the amount of the fund AUM, q_s is the style scale measured as the total AUM of the remaining funds in the style s, $q_s = \sum_{j \in s, j \neq i} q_j$, a_i is the fund's skill, α_i is the fund's gross alpha, and the scale coefficients $\beta_1 (\beta_2) > 0$. The model suggests that when the fund (style) size increases by \$1, the gross alpha decreases by $\beta_1 (\beta_2)$.

The two-level model has different implications from a fund-level model. To see the differences, we solve the optimization problem of the value-added (Berk and van Binsbergen (2015); Zhu (2018)). The value-added is the fund AUM times the gross alpha, $V_i = q_i \alpha_i$. The optimal fund size is the amount of fund AUM at which the fund maximizes its value-added, $q_i^* = \text{argmax}_{q_i} V(q_i)$, where $V(q_i) = q_i(a_i - \beta_1 q_i - \beta_2 q_s)$. By finding the first-order condition, $q_i^* = \frac{1}{2\beta_1}(a_i - \beta_2 q_s)$. Also, we get the gross alpha at the optimal size and the maximum value-added, $\alpha_i^* = \frac{1}{2}(a_i - \beta_2 q_s)$ and $V_i^* = \frac{1}{4\beta_1}(a_i - \beta_2 q_s)^2$, given that $\frac{\partial q_s}{\partial q_i} = \frac{\partial \sum_{j \in s, j \neq i} q_j}{\partial q_i} = 0$.

Below we explain the underlying rationale of the two-level hypothesis. The optimal size, q_i^*, reflects the capacity of the hedge fund, which is determined by not only the skill but also the style scale. Compared with the fund-level model's solution, $q_i^* = \frac{a_i}{2\beta_1}$, the two-level model tells us that managers must consider the constraints imposed by the style size to secure their capacity. More elusive investment opportunities explain these constraints — as more money chases the opportunities, price moves faster (Pástor et al., 2015). If there is an increasing amount of capital investing in the style, the fund should consider decreasing its size to realize the optimal value-added, V_i^*. The optimal value is the maximum the fund can extract from the strategy and is achieved based on the rationality of capital decision-makers. Note that the value of V_i^* depends on the style scale, which suggests that when the style scale increases, the return and the value-added of the fund decrease (even though the manager optimizes the fund size).[9]

3. Method

Previous empirical studies on DRTS have considered an FE model, in which skill is assumed to be heterogeneous across funds but constant over the lifetime of each fund (Pástor et al., 2015 and Zhu, 2018). However, the FE model is less evident as the skill of funds could potentially vary over time. Some funds could improve their skill, e.g., through knowledge spillovers in the economy, while others could fail to maintain their skill level. For example, fund location could explain the differences in the evolution of fund skill. Christoffersen and Sarkissian (2009) find that mutual funds located in financial centers are more likely to improve their skill than peers located in small towns. Pástor et al. (2015) also show a negative time trend in performance over a typical mutual fund's lifetime. For hedge funds, the constant skill assumption is even more questionable than for mutual funds given a higher degree of competition. Figure 1

[9] An alternative scale measure is the logarithm of the AUM, as used by Zhu (2018).We must be aware that the model implies different assumptions by choosing a different scale measure. Using the AUM, we assume each dollar has an equal effect on the return; using the logarithm of the AUM, each percent of changes in the AUM has an equal effect on the return. Whether the AUM or its logarithm is more appropriate depends on the question of whether hedge funds choose fees to reflect their skill. Take the fund-level model as an example, $\alpha_i = a_i - \beta x_i$, x_i is a fund scale measure. The fund AUM measure gives the optimal size (q_i^*) at $2a_i/\beta$ (Berk and van Binsbergen (2015)). The gross alpha (α_i^*) is equal to one half of the fund's skill ($a_i/2$). In equilibrium, management fees are equal to the gross alpha (making the net alpha zero), so fund fees reflect manager skill. On the other hand, the logarithm of fund AUM measure gives the optimal fund size q_i^* at $e^{a_i/\beta-1}$. The optimal gross alpha is equal to β, which is irrelevant to skill and homogeneous across funds. In equilibrium, all funds charge fees at the same level. In our main analyses, we use the AUM as scale measures. We also report the results with the log AUM in the Appendix D.

shows the dynamics of U.S. hedge funds in terms of AUM and the number of funds during the period 1994-2018.[10] The changes in the number of funds show a high rate of attrition in all the styles. Funds that fail to maintain and enhance their skill are dropped. Hence, we suppose that hedge fund returns to scale follow a random trend (RT) model as Eq (1), which allows each fund to have a fund-specific time trend of skill and a fund-specific intercept:

$$r_{it} = a_{i0} + g_i h_{it} + \beta x_{i,\,t-1} + \varepsilon_{it} \qquad (1)$$

Where r_{it} is the gross alpha of fund *i* in month t; $x_{i,\,t-1}$ is the one-month lagged fund scale; h_{it} is the age of the fund in years; a_{i0} and g_i are two unobserved individual effects, representing the level of skill at the inception of the fund and a yearly growth rate of skill, respectively, ε_{it} is unexpected return, with $E(\varepsilon_{it} \mid x_{i,t-1}) = 0$.

3.1. Endogeneity of the FE model

If the unobserved effect changes over time, FE models fail because of a violation of strict exogeneity. In their studies, Heckman and Hotz (1989), Polachek & Kim (1994), and Friedberg (1998) have indeed recognized the potential endogeneity caused by the time trend of unobserved individual effect in an FE model.[11] Phillips et al. (2018) argue that the potential time trend of skill could cause a biased estimate of scale effect under the FE model since skill is correlated with scale. Below we show that an estimator of scale effect developed under the FE model is biased in the presence of the time trend.

Suppose that fund returns to scale follow Eq (1), with a nonzero g_i, and consider an

[10] The hedge fund sample is described in detail in Section 4.1.

[11] For example, Friedberg (1998) examines the effect of divorce laws on divorce rates using state-level panel data. Without imposing state-specific trends, she finds no effect of divorce laws on divorce rates. If trends are considered, she finds that the effect becomes important and statistically significant (Wooldridge (2010)).

estimator of scale effect used by Zhu (2018), FE-RD2, which is developed under the FE model (see Appendix A). Recursively forward demeaning the variables of Eq (1), we have:

$$\bar{r}_{it} = g_i\bar{h}_{it} + \beta\bar{x}_{i,\,t\text{-}1} + \bar{\varepsilon}_{it} \qquad (2)$$

Applying FE-RD2 to Eq (2) and taking the expectation of the estimator, we obtain:

$$E[\hat{\beta}_{FE\text{-}RD2}] = \beta + \left[\left(\frac{1}{N}\sum_{i=1}^{N}\bar{\mathbf{x}}'_i\mathbf{z}_i\right)\left(\sum_{i=1}^{N}\mathbf{z}'_i\mathbf{z}_i\right)^{-1}\left(\sum_{i=1}^{N}\mathbf{z}'_i\bar{\mathbf{x}}_i\right)\right]^{-1} \cdot \left(\frac{1}{N}\sum_{i=1}^{N}\bar{\mathbf{x}}'_i\mathbf{z}_i\right)\left(\sum_{i=1}^{N}\mathbf{z}'_i\mathbf{z}_i\right)^{-1}\left(\sum_{i=1}^{N}\mathbf{z}'_i g_i\bar{\mathbf{h}}_i\right) \qquad (3)$$

When fund scale also has a time trend, i.e., $Corr(x_{i,\,t\text{-}1}, \bar{h}_{it}) \neq 0$, which is likely true, the second term of Eq (3) is not equal to zero.[12] The FE-RD2 estimator is not an unbiased estimator of β.

3.2. An RT-RD2 estimator for scale effect

We follow Wooldridge's (2010) approach to develop an unbiased estimator of scale effect under the RT model.[13] Defining $w_{i,t} \equiv \begin{pmatrix} 1 \\ h_{it} \end{pmatrix}$ and $\mathbf{a}_i \equiv \begin{pmatrix} a_{i0} \\ g_i \end{pmatrix}$, Eq (1) is rewritten as:

$$\mathbf{r_i} = \mathbf{W'_i a_i} + \boldsymbol{\beta}'\mathbf{x_i} + \boldsymbol{\varepsilon}_\mathbf{i} \qquad (1.1)$$

---

[12] FE-RD2 is a 2SLS estimator, with fund scale as the instrumental variable, $\mathbf{z}_i$. Notice that the forward-demeaned variable of age, $\bar{h}_{it}$, is still a time trend variable. If $Corr(x_{i,\,t\text{-}1}, \bar{h}_{it}) \neq 0$, then $\sum_{i=1}^{N}\mathbf{z}'_i g_i\bar{\mathbf{h}}_i \neq \mathbf{0}$ and $E[\hat{\beta}_{FE\text{-}RD2}] \neq \beta$.

[13] Heckman and Hotz (1989) and Polachek and Kim (1994) suggest a method of differencing away the intercept and applying FE-OLS to estimate effect of interest. However, this approach is problematic in our study. In a first difference of (1), $\Delta r_{it} = g_i + \beta'\Delta x_{i,\,t\text{-}1} + \Delta\varepsilon_{it}$, $\Delta x_{i,t-1}$ is correlated with $\Delta\varepsilon_{it}$, as $Corr(\Delta x_{i,t-1}, \Delta\varepsilon_{it}) = Corr(x_{i,\,t\text{-}1} - x_{i,\,t\text{-}2}, \varepsilon_{it} - \varepsilon_{i,\,t\text{-}1}) = Corr(x_{i,\,t\text{-}1}, -\varepsilon_{i,\,t\text{-}1}) \neq 0$.

where $\mathbf{r_i} = \begin{pmatrix} r_{i,2} \\ r_{i,3} \\ \vdots \\ r_{i,T_i} \end{pmatrix}$, $\mathbf{x_i} = \begin{pmatrix} x_{i,1} \\ x_{i,2} \\ \vdots \\ x_{i,T_i-1} \end{pmatrix}$, $\mathbf{W_i} = \begin{pmatrix} w'_{i,2} \\ w'_{i,3} \\ \vdots \\ w'_{i,T_i} \end{pmatrix} = \begin{pmatrix} 1 & h_{i,2} \\ 1 & h_{i,3} \\ \vdots & \vdots \\ 1 & h_{i,T_i} \end{pmatrix}$, and $\boldsymbol{\varepsilon_i} = \begin{pmatrix} \varepsilon_{i,2} \\ \varepsilon_{i,3} \\ \vdots \\ \varepsilon_{i,T_i} \end{pmatrix}$.

Multiplying all variables by $\mathbf{M_i} \equiv \mathbf{I}_{T_i-1} - \mathbf{W_i}(\mathbf{W'_i W_i})^{-1}\mathbf{W'_i}$, $\mathbf{a}_i$ is eliminated since $\mathbf{M_i W'_i} = \mathbf{0}$, and we have Eq (4):

$$\mathbf{M_i r_i} = \beta' \mathbf{M_i x_i} + \mathbf{M_i} \boldsymbol{\varepsilon_i} \qquad (4)$$

$$\text{Or:} \quad \ddot{\boldsymbol{r}}_i = \beta' \ddot{\mathbf{x}}_i + \ddot{\boldsymbol{\varepsilon}}_i$$

where $\ddot{\boldsymbol{r}}_i = \mathbf{M_i r_i}$, $\ddot{\boldsymbol{x}}_i = \mathbf{M_i x_i}$, and $\ddot{\boldsymbol{\varepsilon}}_i = \mathbf{M_i} \boldsymbol{\varepsilon}_i$.

$\mathbf{M_i r_i}$, $\mathbf{M_i x}_i$ and $\mathbf{M_i} \boldsymbol{\varepsilon}_i$ are the residuals of a projection of $\mathbf{r_i}$, $\mathbf{x}_i$ and $\boldsymbol{\varepsilon}_i$ on $\mathbf{W_i}$. The potential time trend in the variables is eliminated by this procedure.

Examining the strict exogeneity condition for Eq (4), we have $E(\ddot{x}_{i,t-1}\ddot{\varepsilon}_{it}) = 0$ but $E(\ddot{x}_{it}\ddot{\varepsilon}_{it}) \neq 0$. Indeed, $E(\ddot{x}_{it}\ddot{\varepsilon}_{it}) = E[(x_{it} - \hat{\beta}_{ix} h_{i,t+1})(\varepsilon_{it} - \hat{\beta}_{i\varepsilon} h_{it})] = E[(x_{it} - \hat{\beta}_{ix} h_{i,t+1})\varepsilon_{it}] = E[x_{it}\varepsilon_{it}] \neq 0$, where $\hat{\beta}_{ix} = \mathbf{W}_i(\mathbf{W'_i W_i})^{-1}\mathbf{W'_i x_i}$, $\hat{\beta}_{i\varepsilon} = \mathbf{W_i}(\mathbf{W'_i W_i})^{-1}\mathbf{W'_i} \boldsymbol{\varepsilon_i} = 0$, and $E[h_{i,t+1}\varepsilon_{it}] = 0$. An OLS estimator of Eq (4) seems to suffer the Stambaugh bias.

To eliminate this bias, we apply Zhu's (2018) RD2 estimator to Eq (4). Recursively forward demeaning the variables and implementing the 2SLS procedure to Eq (5):

$$\bar{\ddot{\mathbf{r}}}_i = \beta' \bar{\ddot{\mathbf{x}}}_i + \bar{\ddot{\boldsymbol{\varepsilon}}}_i \qquad (5)$$

In the first-stage regression, we include an intercept and use the fund scale $x_{i,t-1}$ as the instrumental variable (IV). $x_{i,t-1}$ is qualified as a valid IV because it is correlated with $\bar{\ddot{x}}_{i,t-1}$ but uncorrelated with $\bar{\ddot{\varepsilon}}_{i,t}$. Furthermore, $x_{i,t-1}$ contains full information about scale in the past so as to guarantee better goodness of fit in the first stage than $\ddot{x}_{i,t-1}$ or its backward-demeaned form as the IV. We call the RD2 estimator under the RT model RT-RD2. Our RT-RD2 estimator considers time-varying unobserved skill and is free of the omitted variable bias and Stambaugh bias (See discussions of both biases in Appendix A). It is written as:

$$\hat{\beta}_{RT\text{-}RD2} = \left[\left(\sum_{i=1}^{N} \bar{\ddot{\mathbf{x}}}'_i z_i \right) \left(\sum_{i=1}^{N} \mathbf{z}'_i \mathbf{z}_i \right)^{-1} \left(\sum_{i=1}^{N} \mathbf{z}'_i \bar{\ddot{\mathbf{x}}}_i \right) \right]^{-1}$$

$$\cdot \left(\sum_{i=1}^{N} \bar{\ddot{\mathbf{x}}}'_i \mathbf{z}_i \right) \left(\sum_{i=1}^{N} \mathbf{z}'_i \mathbf{z}_i \right)^{-1} \left(\sum_{i=1}^{N} \mathbf{z}'_i \bar{\ddot{\mathbf{r}}}_i \right) \qquad (6)$$

where $\bar{\ddot{\mathbf{r}}}_i = \begin{pmatrix} \bar{\ddot{r}}_{i,2} \\ \bar{\ddot{r}}_{i,3} \\ \vdots \\ \bar{\ddot{r}}_{i,T_i} \end{pmatrix}$, $\bar{\ddot{\mathbf{x}}}_i = \begin{pmatrix} \bar{\ddot{x}}_{i,1} \\ \bar{\ddot{x}}_{i,2} \\ \vdots \\ \bar{\ddot{x}}_{i,T_i-1} \end{pmatrix}$ and $\mathbf{z}_i = \begin{pmatrix} 1 & x_{i,1} \\ 1 & x_{i,2} \\ \vdots & \vdots \\ 1 & x_{i,T_i-1} \end{pmatrix}$.

3.3. Simulation exercise

We conduct a simulation exercise to show biased estimates under the FE model in the presence of the time trend and the performance of RT-RD2. One thousand simulated samples are constructed over 100 months for 300 funds. All funds start at $ 250 in million and at the age of 0. Benchmark-adjusted returns are generated from an RT model with the two-level scale, as Eq (7):

$$r_{it} = a_{i0} + g_i h_{it} + \beta_1 q_{i,\,t-1} + \beta_2 q_{s,\,t-1} + \varepsilon_{it} \qquad (7)$$

where $q_{s,\,t-1}$ is style scale measured as the total AUM of the remaining funds. Fund scale, q_{it}, is measured as the fund AUM, generated from Eq (8), in which we use the logarithm difference to guarantee the positive values of q_{it} in simulations:[14]

[14] Pástor et al. (2015) and Zhu's (2018) size models assume the monthly change in fund size is a function of returns. Pástor et al. (2015) use a simple percentage of changes ($q_{it}/q_{i,\,t-1} - 1$) in fund size (see Eq (A2)). For certain

$$\log(q_{it}) - \log(q_{i,t-1}) = c + \gamma r_{it} + v_{it} \qquad (8)$$

Consistent with the estimates from our sample, we choose the following values for the model parameters: the initial skill of funds, a_{i0}, follows a normal distribution $N(0.0121, 0.0271^2)$; g_i follows a normal distribution $N(-0.0007367, 0.0039^2)$; std(ε) = 0.0057, β_1 and β_2 take four different values: $-10^{-6} \times [0, 0; 5, 0; 3, 0.05; 5, 0.1]$. The first assumes scale effect is zero at both levels. The second assumes DRTS at the fund level but no effect at the style level. The third set of β parameters is close to our estimates (See Section 5.3). The other parameters c = 0.0107, std(v) = 0.1504. From Eq (8), we estimate γ as 0.5418. Thus, three values for γ, 0.5, 0.8, and 1.2, are considered in the simulations.[15]

With each sample, we estimate β_1 and β_2 using FE-RD2 and RT-RD2 estimators and report four performance metrics in Table 1: bias, standard deviation, root mean square error (RMSE) of the estimators, and the fraction of rejecting the null (β = 0) at the 5% confidence level.[16] The four performance measures are calculated across 1000 simulated samples.

In Table 1, we observe a significant bias in the FE-RD2 estimator of both β_1 and β_2. This bias becomes more significant when the coefficient of scale is greater. For example, when $\gamma = 0.5$

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extreme scenarios, simulated sizes could become negative when using simple percentage. Zhu (2018) uses the logarithm difference of fund size as in Eq (A3), which represents a continuously compound rate of changes. Positive simulated sizes can be guaranteed. We do not include the benchmark return as it does not influence the estimation of γ nor the generated fund sizes. As the gross alphas of hedge funds are estimated from Fung and Hsieh (2004)'s multifactor model (See Section 4.4), it is strictly orthogonal to the benchmark return of the fund. The mean of ρB_{it} enters c and its variance enters the innovation term, v_{it}.

[15] The initial skill and time trend of skill of individual hedge funds are estimated from Eq (15). We calculate the mean and standard deviation of a_{i0} and g_i across funds to obtain the simulation parameters. std(ε) is estimated from FE-OLS estimator of Eq (7), assuming constant g across funds. The parameters of size model are estimated from Eq (8).

[16] Bias is equal to $\bar{\hat{\beta}} - \beta$, $\bar{\hat{\beta}} = \frac{1}{n}\sum_{i=1}^{n} \hat{\beta}_i$, $\hat{\beta}_i$ is the estimate from the i^{th} sample, n = 1,000. The standard deviation (sd) of $\hat{\beta}$ is equal to $\sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{\beta}_i - \bar{\hat{\beta}})^2}$. The RMSE is equal to $\sqrt{bias^2 + sd^2}$.

and $[\beta_1, \beta_2] = [-3, -0.05] \times 10^{-6}$, the bias is as large as 2.21×10^{-6} and -1.70×10^{-8} for $\hat{\beta}_1$ and $\hat{\beta}_2$, respectively. Even with a high standard deviation, FE-RD2 rejects the null in 64-94% of cases when the null $\beta_1 = 0$ is true and in over 98% of cases when the null $\beta_2 = 0$ is true. However, when the null $\beta_1 = 0$ is false, in only 45-82% of simulations, the null is rejected because of biases. On the other side, we observe RT-RD2 is free of biases (less than 0.01×10^{-6} for $\hat{\beta}_1$ and less than 0.02×10^{-8} for $\hat{\beta}_2$). Regarding estimation uncertainty, RT-RD2 yields more precise estimates with much smaller standard deviations than FE-RD2. The RD procedure seems to increase estimation uncertainty when Stambaugh bias is less significant, i.e., when γ is smaller. We observe a higher standard deviation for smaller value of γ across all simulation scenarios. Combining the bias and standard deviation, RT-RD2 offers a much smaller RMSE consistently across all simulation scenarios. For example, when $\gamma = 0.5$ and $[\beta_1, \beta_2] = [-3, -0.05] \times 10^{-6}$, the RMSE of RT-RD2 is only one-fifth of that of FE-RD2 for $\hat{\beta}_1$ and one-tenth for $\hat{\beta}_2$. Regarding the power of test, RT-RD2 has approximately the right size. It rejects a true null in 6-7% of cases for $\hat{\beta}_1$ and 0-6% of cases for $\hat{\beta}_2$. RT-RD2 possesses adequate power to reject the null when the null is false. When the null $\beta_1 = 0$ is false, its power to reject is 76-100%. When the null $\beta_2 = 0$ is false, its power increases to 100%. We repeat the simulation exercise with returns generated from an FE model. The results are reported in Appendix B (Table A1). We find that RT-RD2 is an unbiased estimator with acceptable test power no matter whether returns have time trend or not. [17]

[17] RT-RD2 is still an unbiased estimator when returns have no time trend. To summarize the results in Table A1, RT-RD2 unbiasedly estimates the scale effect (less than 0.01×10^{-6} for $\hat{\beta}_1$ and less than 0.02×10^{-8} for $\hat{\beta}_2$). The fraction of rejecting a true null is less than 5% of simulations. The power to reject a false null is 87-100% for $\hat{\beta}_1$ and 100% for $\hat{\beta}_2$.

4. Data

In this section, we describe the sample of hedge funds, style classification, estimating gross returns, treatments of some conventional hedge fund data biases, estimating gross alpha, and the alternative performance measures and benchmarks used in the robustness tests.

4.1. Sample and style classification

We construct the sample by collecting U.S. hedge funds from the Lipper/TASS database. We keep funds reporting monthly net-of-return in U.S. dollars (USD) with an AUM of at least $5 million. TASS includes data on defunct funds starting from 1994. Our sample period ranges from January 1994 to December 2018. The initial sample covers 4,960 U.S. hedge funds: 614 live funds and 4,346 graveyard funds, as of December 2018. TASS classifies hedge funds into 11 strategy categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long-short equity, options strategy, multi-strategy, and other strategies.

Our style-level DRTS hypothesis implies that individual funds in the same style apply homogeneous strategies. However, the classification of hedge fund styles varies from one database to another. In their study, Agarwal et al. (2009) consider a hedge fund sample from multiple databases. Based on the fact that there are only a few distinct style factors in hedge fund returns (Fung and Hsieh, 1997), they classify funds into four broad strategies. Funds classified in a style group are assumed to have similar factor exposures and employ similar strategies. Therefore, in our main analysis, we adopt the method of Agarwal et al. (2009), classifying hedge funds into Directional traders, Security selection, Relative value, Multiprocess, and Other strategies. This classification helps adapt our style-level analysis to different hedge fund databases. In Section 6.4, we test the robustness of our results to the choice of hedge funds classification.

Specifically, we classify Dedicated Short Bias, Emerging Market, and Global Macro into Directional traders. These hedge funds bet on the direction of price changes in different markets. For example, Global Macro hedge funds invest in instruments that have prices that fluctuate with changes in economies and capital flows around the globe. Relative Value funds invest in opportunities from relative price changes between financial assets. We classify Convertible Arbitrage, Equity Market Neutral, and Fixed-income Arbitrage into this style. Security Selection includes Long/Short Equity funds, which take long and short positions in undervalued and overvalued securities in primary equity and equity derivatives markets. Event-Driven and Multi-Strategy are classified into Multiprocess. They invest in opportunities created by corporate events (e.g., risk arbitrage on mergers and acquisitions or investing in distressed securities. Finally, we join Options Strategy and other strategies into a group named Other.

4.2. Data biases

Research has shown that hedge fund data suffer survivorship, backfilling, and smoothed return biases. A sample including live funds and graveyard funds minimizes the survivorship bias (Titman and Tiu, 2011; Bali, Brown, and Caglayan, 2012; Agarwal and Naik, 2004; among others). Backfilling bias refers to the artificially inflated performance of fund managers who selectively do not report past underperformed returns. To mitigate the bias, we delete the returns before the listing date of the fund (Yin, 2016; Shi, 2017).[18] To have a sufficient number of observations to run regressions, we keep funds with more than 24 months of returns. This reduces the number of funds

[18] An alternative method is to delete returns of the first 24 months for each fund (Jagannathan, Malakhov, and Novikov, 2010; Titman and Tiu, 2011; Fung and Hsieh, 2000; Bali et al., 2012; among others). As a robustness check, we consider this alternative method and results remain qualitatively unchanged.

in our sample to 3,323 funds. Backfilling has a minor influence on the reported AUM. We consider the initial sample of 4,960 funds to calculate the style-level scale.

Further, we identify some funds which have missing values of AUM. For a given fund, when missing values occur in some months, we recursively estimate the fund's AUM, as $q^{E}_{i,t}$, using the following method:

$$q^{E}_{it} = \frac{1}{2}\left\{q_{i,t-1} \times (1+NR_{i,\,t}) + q_{i,t+1}/(1+NR_{i,t+1})\right\} \qquad (9)$$

where $q_{i,t-1}$ and $q_{i,t+1}$ are the values of AUM in the previous and the next month, NR_{it} is the net return. If the previous or the next AUM is not available, we use $q_{i,t+1}/(1+NR_{i,t+1})$ or $q_{i,t-1} \times (1+NR_{it})$. The funds without a value of AUM are dropped. The estimated values of AUM are only used to calculate the style-level scale. We omit these observations in the performance-scale regressions.

Smoothed returns bias upward the Sharpe ratios and information ratios and could affect the estimation of alpha as well. Following the study of Titman and Tiu (2011), we consider Getmansky, Lo, and Makarov's (2004) method to adjust this bias. A smoothing coefficient θ of each fund is estimated in an MA(2) process as Eq (10) using maximum likelihood estimation via the "innovations algorithm" of Brockwell and Davis (1991):

$$GR^{o}_{t} = \mu + \theta_0\epsilon_t + \theta_1\epsilon_{t-1} + \theta_2\epsilon_{t-2} \qquad (10)$$

with the constraints, $1 = \theta_0 + \theta_1 + \theta_2$, and $0 < \theta_k < 1$, k = 0, 1, 2. GR^{o}_{t} denotes the observed returns. The actual returns, GR_t, are estimated by (11).

$$\text{GR}_t = \hat{\mu} + \hat{\epsilon}_t \qquad (11)$$

The average $\hat{\theta}_0$, $\hat{\theta}_1$, and $\hat{\theta}_2$ across the 3,233 funds is 0.80, 0.14, and 0.07, respectively. The estimated GR_t are winsorized at 1% level. The grand mean of the estimated "actual" gross returns remains at the level of 0.85% per month across the 3,233 funds.

4.3. Gross returns

Over 98% of U.S. hedge funds in the Lipper-TASS Database report net returns. However, given the particularity of hedge fund compensation structures, we cannot correctly infer the DRTS by using net returns. Specifically, the presence of a high-water mark provision for hedge funds may mechanically lead to DRTS. Let us consider a hedge fund with an exceptional run. Due to performance chasing by investors, the fund also attracts lots of inflows during this run. However, when the watermark is reached, there could be a large drop in net return because of the manager's incentive fees. In this case, we could conclude that there is a significant DRTS as a large inflow leads to lower future performance. Nevertheless, this is not the kind of DRTS we are interested in. To alleviate this problem, we need to consider gross returns.

For a fund that sets the high watermark provision, we estimate the gross returns of hedge funds based on Eq (12) and (13), assuming all fees are paid monthly. We are aware that they could be paid annually, semi-annually, or quarterly, depending on the fund.

$$q_{i,t-1} \times (1 + \text{NR}_{it}) + \text{Inflow}_{it} = q_{it} \qquad (12)$$

$$q_{i,t-1} \times (1+\text{GR}_{it})(1 - m\%) + \text{Inflow}_{it} - q_{i,t-1}\text{GR}_{it} \times \text{Inc}\% \times \mathbf{I}(\text{CGR}_{it} > \max_{\forall v<t}(\text{CGR}_{iv})) = q_{it} \qquad (13)$$

where GR_{it} is the gross return and NR_{it} is the net return, m% is the management fees, Inc% is the incentive fees, $Inflow_{it}$ is the amount of net inflows invested at the end of month, a negative value represents a net withdrawal of capitals by investors. The incentive fees ($q_{i,t-1} GR_{it} \times Inc\%$) are paid if and only if cumulative gross return at the end of the month, $CGR_{it} = \prod_{v=1}^{t} (1+GR_{iv})$, is greater than the maximum of the cumulative gross returns in the past. **I(.)** is a dummy variable equal to 1 when the watermark is reached, and 0 otherwise. If a fund does not set a high-water mark, we assume that incentive fees are paid if and only if the gross return is positive ($GR_{it} > 0$).

With Eq (12) and (13), we can recursively resolve the gross return (GR) and Inflow given the AUM, the net return, management fees, incentive fees, and high watermark variable provided by TASS.[19] The grand mean of estimated gross returns is 0.88% per month across the 3,233 funds in our final sample. Compared with the grand mean of net return of 0.74% per month, it will suggest that the total sum of management fees and incentive fees is equal to 0.14% per month on average.

4.4. Gross alpha

Benchmark adjustment for hedge fund returns is challenging. There is not yet a unanimous consensus on the choice of hedge fund benchmark. The used factor models vary from one study to another. For example, Titman and Tiu (2011) use the Fung and Hsieh (2004) seven-factor model and stepwise regressions to identify risk factors. Bali, Brown, and Caglayan (2012) use three-factor model specifications, a four-factor model of Fama and French (1993) and Carhart (1997), a six-factor model from Fama and French (1993), Carhart (1997), and Fung and Hsieh's (2004) two factors: changes in ten-year yield ($\Delta 10Y$) and changes in credit spread ($\Delta CredSpr$), and a nine-

[19] The algorithm for estimating the gross returns is available to interested readers upon request.

factor model from Fama and French (1993), Carhart (1997), and Fung and Hsieh's (2001, 2004) five factors: $\Delta 10Y$, $\Delta CredSpr$, bond trend-following factor (PTFSBD), currency trend-following factor (PTFSFX), and commodity trend-following factor (PTFSCOM). Shi (2017) use five alternative measures : raw returns, market-adjusted returns, Fama and French's (1993) three-factor model, Fama and French's(1993) and Carhart's (1997) four-factor model, and Pástor and Stambaugh's (2003) four-factor model augmented by a liquidity factor. Yin (2016) defines performance as style-adjusted return, which is equal to the fund's return minus the average return of all funds in the same style. Alternatively, performance can be measured as a return relative to a hedge fund index return (i.e., an index provided by Hedge Fund Research (HFR)). Style or HFR index-adjusted return provides valuable insight into the managers' talent if investors make capital investment decisions among the hedge funds in the same style. However, a conclusion based on such a measure is less interesting for investors whose choices are among a wider range of asset management vehicles other than hedge funds. Moreover, investors are comforted when a hedge fund realizes significantly positive performance against the markets (Jagannathan, Malakhov, and Novikov (2010)). In our main analysis, we use the Fung and Hsieh (2004) seven-factor model (FH7) to estimate alpha. To test the robustness of our results, we also consider the Fama and French (1993) three-factor model (FF3), the Fama and French (1993) and Carhart (1997) four-factor model (FFC4), and the five-factor model augmented by Pástor and Stambaugh (2003) with liquidity factor (FFCPS5).[20] Further, we consider alternative performance measures, namely, information ratio, Sharpe ratio, and manipulation-proof performance measure (MPPM) of

[20] At a minimal level, we consider the Fama-French three factors to adjust hedge fund returns. DRTS hypothesis implies that the performance of active management declines as more assets chase the same investment opportunities. A single market factor adjustment seems indeed insufficient. For example, assume that a manager allocates a fraction of his (her) portfolio to the market portfolio and the other fraction to the size factor. Using a single factor model such as CAPM, we would find a positive alpha that comes from the size factor. This alpha would not decrease as his (her) fund size increases, since the size factor returns would not be affected by his (her) fund size.

Ingersoll, Spiegel, Goetzmann, and Welch (2007).

The time-varying feature of hedge funds' risk characteristics is widely accepted in hedge fund research. Fung, Hsieh, Naik, and Ramadorai (2008) confirm hedge fund factor loadings change over time. To reflect this dynamic, Titman and Tiu (2011) estimate the risk exposure parameters of hedge funds by using a 24-month rolling window; Bali et al. (2012) use a 36-month rolling window; Shi (2017) uses a 24-month, non-overlapping window. The length of the test period should be as short as possible to capture time-varying risk characteristics, while a sufficiently long period is necessary to have stable estimates. Considering both aspects, we choose a 36-month rolling window to estimate gross alphas.[21] The process is as follows:

$$GR_{i,t:\,t+w-1} - R_{f,\,t:\,t+w-1} = \alpha_{i,t} + \sum_{k=1}^{K} \beta_{i,k,t} F_{k,\,t:\,t+w-1} + \varepsilon_{i,\,t:\,t+w-1} \tag{14}$$

where $GR_{i,\,t:\,t+w-1}$ is "actual" gross returns of fund i from month t to t+w-1 (estimated in Section 4.2); $R_{f,\,t:\,t+w-1}$ is risk-free rate; $F_{k\,,t:\,t+w-1}$ is the return of risk factor k, k = 1, 2, …, K; $\beta_{i,k,t}$ is risk exposure of fund i to factor k during the period t to t+w–1, w = 36. The intercept of regression, α_{it}, is the gross alpha, the performance measure we use in the main analysis. The Sharpe ratio is equal to the mean of "actual" excess gross returns divided by the standard deviation of "actual" gross returns; the information ratio is equal to the alpha divided by the regression error obtained from Eq (14); the MPPM is calculated using the observed return, GR_t^o, as it controls for the smoothed return issue.[22]

[21] Our results are robust to an alternative 48-month moving window. The estimates remain at a similar level compared with the 36-month window, $\hat{\beta}_1 = -3.45\times10^{-6}$ (t-statistic = –1.90), $\hat{\beta}_2 = -0.05\times10^{-6}$ (t-statistic = –2.03).

[22] Ingersoll, Spiegel, Goetzmann, and Welch's (2007) formula for MPPM:

5. Results

First, we present summary statistics and test the nature of returns to scale at the fund-level and the two-level scale using different estimators. Second, we present the evidence for the time trend of skill in our sample and then analyze the interaction of skill and scale in determining fund performance. Third, we examine the heterogeneous ability to resist the diseconomy of scale and analyze the relationship of this ability with fund performance. Fourth, we provide evidence for the rationality of capital invested in hedge funds.

5.1. Summary statistics

Panel A of Table 2 summarizes hedge fund performance over the period of 1994-2018. The average gross alpha across all the funds obtained from the FH7 model is 0.32% per month and is about 0.28% per month under the alternative models, FF3, FFC4, and FFCPS5. The Sharpe ratio, information ratio, and MPPM are, on average, 0.25, 0.21, and 0.04, respectively. All the performance measures (gross alpha and different performance measures) suggest that Security Selection funds underperform other styles, on average (with gross alphas varying from 0.21% to 0.25% per month).

Panel B of Table 2 reports the statistics of hedge fund characteristics. Management fees and incentive fees are, on average, 1.41% and 18.65%, respectively. Seventy-six percent of funds set high-water mark provisions. The average age of the hedge fund sample is 7.00 years. Panel C of Table 2 presents the statistics of scale measures. The average Fund AUM across all hedge funds is $244 million. The average Style AUM is $87,747 million. Security Selection and Multiprocess

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$$\mathrm{MPPM}_{\rho,t} = \frac{12}{(1\text{-}\rho)} \ln\left(\frac{1}{w}\sum_{s=t}^{t+\mathrm{w}-1}[(1+\mathrm{GR}_t^o)/(1+\mathrm{R}_{\mathrm{ft}})]^{1\text{-}\rho}\right), \text{ with } \rho=3$$

have a larger style scale relative to other styles. The total AUM of hedge funds in our sample is equal to \$353,129 million on average over the period 1994-2018.

Panel A of Figure 1 plots the evolution of the total AUM of hedge funds. We observe that the amount of managed assets by hedge funds changes significantly over time. Before the financial crisis in 2008, the total AUM increased from \$44 billion in 1994 to \$650 billion in 2007 and then decreased to \$250 billion in the following ten years. The number of funds increased from 375 in 1994 to 2,548 in 2007 and then decreased to 600 in 2018. Panel B to E plot the evolution of the total AUM of each hedge fund style. The 2008 financial crisis also represents a turning point for most hedge funds styles.

[Insert Table 1 and Figure 1 here]

5.2. Fund-level returns to scale

To examine the fund-level DRTS, we run the univariate regressions of the gross alpha on the fund scale. The gross alpha is estimated from the FH7 model. The results of the RT-RD2 estimates are reported in Table 3. We also report the results of the OLS, FE-OLS, and FE-RD2 estimates. OLS is the estimate obtained from a pooled OLS regression. FE-OLS is the fixed effect estimator of Eq (A1). FE-RD2 is Zhu's (2018) RD2 estimator developed under the FE model, as Eq (A7). All three estimators are, however, biased, and we should interpret their results with caution. RT-RD2 is the estimate from Eq (6), which is free of the omitted variable bias, Stambaugh bias, and the time trend bias, as established in Section 3.

In Panel A, we find the RT-RD2 estimate of β_1 is significantly negative under the fund-level model, at -2.13×10^{-6} (t-statistic = −3.89). The difference between RT-RD2 and FE-RD2

(-15.43×10^{-6}, t-statistic: −1.10) confirms a negative sample mean of the second term of Eq (3). The endogeneity caused by the time trend of skill in the estimates of the FE model is significant. In Panel B, we repeat the tests using a sample excluding the return observations from 2007 to 2009, considering the potential impact of these extreme returns on our estimated scale effect.[23] The RT-RD2 estimate of β_1 becomes -3.96×10^{-6} (t-statistic: −3.49). To interpret the coefficient, an increase of $250 million (a doubling size of an average fund) in the managed assets of a hedge fund decreases its gross alpha by 9.90 bps per month. We confirm DRTS at the fund level using the logarithm of fund AUM measure in Appendix D (Table A3). The RT-RD2 estimate of β_1 under the fund-level model is -1.15×10^{-3} (t-statistic: −5.74) with the full period sample and -2.69×10^{-3} (t-statistic: −5.24) after excluding Crisis 2008.[24]

Table 4 reports the results of the style sub-samples. For brevity, we only report results from RT-RD2. The estimates range from -1.14×10^{-6} to -12.77×10^{-6}. The estimated coefficients are statistically significant at the 1% confidence level across all styles except for Multiprocess in Panel B, after excluding returns during the financial crisis.

[Insert Table 3 and Table 4 here]

5.3. Two-level returns to scale

To examine the two-level DRTS, we run the multiple regression of the gross alpha on the lagged fund AUM and style AUM. The results are reported in Table 3, Panel A for the full period

[23] As in Figure 1, we observe that the financial crisis of 2008 has a dramatic impact on the sizes of hedge funds. Figure 2 plots the average gross returns of all hedge funds and different styles for each year over the period between 1994-2018. We observe dramatic negative returns (−0.30% to −1.52%) in the year 2008 across all hedge funds styles. The average returns across all funds in 2008 is −1.21%.

[24] However, the magnitude of estimated scale effect is noticeably different. Using log AUM, a doubling size of an average fund would decrease alpha by 18.6 bps (= $-2.69\times10^{-3}\times\text{Log}2$). A model assuming a log-linear form of DRTS predicts a more severe diseconomy for an average fund.

and Panel B excluding the financial crisis. With the style scale as a covariate, the RT-RD2 estimate for the fund-level scale effect remains negative and significant, at -3.37×10^{-6} (t-statistic: −2.84). Its magnitude remains at a level similar to that of the univariate regression.

Regarding the estimate of β_2, the coefficient in Panel A seems to exhibit increasing returns to style-level scale. However, this result should be interpreted with caution. It could be affected by the extreme returns which are beyond expectations of the normal distribution. As illustrated in Figures 1 and 2, sizes of all styles decreased dramatically during the 2008-2009 period. The dramatic decrease in style sizes is associated with underperformance and a significant attrition rate of hedge funds.[25] A systematic negative shock on returns could lead to significant capital outflows, devaluated assets under management, and a decreased style size. In this context, we test the impact of a systematic return shock on the RT-RD2 estimate of β_2. In Appendix C (Table A2), we find a significant upward bias in the estimated style-level scale effect.[26] However, we should interpret the estimates biased by extreme returns with caution as we could falsely confirm increasing returns to style-level scale while the true value of β_2 is negative, as shown in the simulation exercise of Appendix C.

[Insert Figure 2 here]

Considering their potential impact on the estimate of style-level effect, we rerun regressions by excluding the extreme return observations during the financial crisis. In Panel B, indeed, we find that the coefficient becomes negative and significant, at -0.06×10^{-6} (t-statistic: –

[25] In our sample, 565 funds were liquidated from 2007 to 2009.

[26] A one-sigma negative shock over a subperiod of 12 consecutive months causes a bias of 2.07×10^{-8} when γ=0.5 and $[\beta_1,\beta_2] = [-3, -0.05] \times10^{-6}$. If the shock is more severe (e.g., a three-sigma shock), the bias is more pronounced (5.69×10^{-8}). The null ($\beta_2 = 0$) is rejected in 74% of cases. However, we falsely confirm increasing returns to style-level scale, while the true value of β_2 is negative (-0.05×10^{-6}).

2.23). To interpret the two-level scale effect, the impact of fund size doubling (i.e., an increase of 250 million dollars in fund AUM) diminishes the fund's gross alpha by 8.43 bps per month; The impact of style size doubling (i.e., an increase of 90 billion dollars in the managed assets of the peers of this fund in the same style) deteriorates its gross alpha by 54 bps further.

The results of regressions with the style samples also provide evidence for the two-level DRTS. The estimate on the fund scale ranges from -1.50×10^{-6} to -11.63×10^{-6}. The estimate on the style AUM is significantly negative except for Multiprocess, ranging from -0.16×10^{-6} to -0.02×10^{-6}.

With the estimated coefficients on scale, -3.37×10^{-6} and -0.06×10^{-6} for β_1 and β_2, respectively, we can calculate the effects of the two-level scale on the fund performance. The two-level scale decreases monthly gross alpha by 0.63% on average, of which the fund-level and the style-level scale decrease the alpha by 0.08% and 0.55%, respectively.[27] An average fund realizes a gross alpha of 0.32%; in the absence of DRTS, it would have realized a gross alpha of 0.95% per month. This finding suggests that style scale accounts for a larger portion of DRTS of hedge funds. When the AUM for a particular investment style is growing, a hedge fund in this style realizes a lower rate of return because of the more severe price pressure, which is caused by more trades chasing the same opportunities among competitors. The style size is an important factor to consider for capital decision-makers.

[27] The two-level effect of scale is calculated as $\hat{\beta}_1$ times each observation of fund AUM, plus $\hat{\beta}_2$ times style AUM, and take the sample mean, i.e., the two-level scale effect $= \frac{1}{\sum_{i=1}^{N}(T_i-1)}\sum_{i=1}^{N}\sum_{t=2}^{T_i}(\hat{\beta}_1 q_{i,t-1}+\hat{\beta}_2 q_{s,t-1})$, with $[\hat{\beta}_1, \hat{\beta}_2] = [-3.37, -0.06] \times 10^{-6}$.

5.4. A close look at hedge fund skill

In this section, we first report the time trend of hedge funds skill and then examine the interaction of skill and scale in determining the hedge funds performance. In Eq (1.1), the parameters related to skill, $\mathbf{a_i}$, can be unbiasedly estimated as:

$$\hat{\mathbf{a}}_\mathbf{i} = (\mathbf{W'_iW_i})^{-1}\mathbf{W'_i}(\mathbf{r_i} - \widehat{\boldsymbol{\beta}}'_{\text{RT-RD2}}\mathbf{x_i}) \qquad (15)$$

$$\begin{aligned} \mathrm{E}(\hat{\mathbf{a}}_\mathbf{i}|\mathbf{W},\mathbf{x}) &= (\mathbf{W'_iW_i})^{-1}\mathbf{W'_i}\mathrm{E}\left(\mathbf{r_i} - \widehat{\boldsymbol{\beta}}'_{\text{RT-RD2}}\mathbf{x_i}\middle|\mathbf{W},\mathbf{x}\right) \\ &= (\mathbf{W'_iW_i})^{-1}\mathbf{W'_i}\mathrm{E}\left(\mathbf{W'_ia_i} + \boldsymbol{\beta}'\mathbf{x_i} + \boldsymbol{\varepsilon}_\mathbf{i} - \widehat{\boldsymbol{\beta}}'_{\text{RT-RD2}}\mathbf{x_i}\middle|\mathbf{W},\mathbf{x}\right) \\ &= (\mathbf{W'_iW_i})^{-1}\mathbf{W'_i}\mathrm{E}(\mathbf{W'_ia_i}) = \mathbf{a_i} \end{aligned}$$

given that $\widehat{\boldsymbol{\beta}}_{\text{RT-RD2}}$ is an unbiased estimator of $\boldsymbol{\beta}$, i.e., $\mathrm{E}(\widehat{\boldsymbol{\beta}}_{\text{RT-RD2}}|\mathbf{W},\mathbf{x}) = \boldsymbol{\beta}$. In the two-level scale model, $\mathbf{x_i}$ is a matrix of $\mathrm{T_i} \times 2$, whose columns are fund scale and style scale, and we take the estimated coefficients of the two-level scale, $\widehat{\boldsymbol{\beta}}_{\text{RT-RD2}} = \begin{pmatrix}-3.37\\-0.06\end{pmatrix} \times 10^{-6}$.

Using Eq (15), we estimate the time trend of skill, g_i, for each fund whose number of observations is greater than 20 months. Figure 3 plots the cross-sectional distribution of the growth rate of hedge funds skill. We find that 30% (52%) of hedge funds in our sample have a positive (negative) and statistically significant time trend of skill, with a t-statistic above (below) 1.96 (−1.96), while 18% of funds have heterogeneous but time-invariant skill. The mean of the time trend of skill across funds suggests a decrease of skill by −0.07367% per year on average, with a t-statistic of −8.26. Compared with a normal density, the empirical density of the time trend appears to be approximately symmetrical (skewness of −1.36) but considerably fat-tailed (kurtosis of 18.7).

[Insert Figure 3 here]

Next, we estimate time-varying skill. Similar in spirit to Pástor et al. (2015), we define hedge fund skill as the gross alpha earned on the first dollar invested in the fund and the hedge fund style. The time-varying skill of the fund is estimated as the initial skill plus the changes over time:

$$\hat{a}_{i,t} = \hat{a}_{i,0} + \hat{g}_i h_{i,t} = \mathbf{w'_{i,t}\hat{a}_i} \qquad (16)$$

Figure 4 plots the cross-sectional distribution of hedge fund skill and alpha in Panel A and Panel B, respectively. We calculate for each month between 1996-2016 the percentile of the estimated skill and the gross alphas across all operating funds in that month. The median of skill is around 0.97%. The 90^{th} (70^{th} and 30^{th}) percentile of skill is around 2.11% (1.31% and 0.55%). The 30^{th} percentile is above zero in most time, which indicates that about 70% of hedge funds have the skill to beat the market. The skill of the funds at the bottom 10% is below zero, indicating that at least 10% of hedge do not have the skill to beat the market. Influenced by scale, funds at the 30^{th} percentile sometimes fail to beat the market, but in all time, one-half of hedge funds realizes positive alphas.

[Insert Figures 4 here]

Figure 5 displays the equal-weighted average skill, the two-level DRTS, the average gross alpha, and the average gross alpha adjusted for DRTS over the period 1996-2016. Panel A shows the result across all funds. The average skill is between 0.15% and 1.34%, while the average DRTS is between −1.14% and −0.15%. The average skill exhibits a significant downward trend after 2008, and the most serious DRTS occur around 2008. The average (adjusted) gross alpha is between −0.20% (−0.03%) and 0.73% (1.87%). The gap between the alpha and the adjusted alpha (the DRTS) is minor before 2000 and is the most significant around 2008. Overall, scale accounts for a large portion of hedge fund performance during the financial crisis, while the post-crisis performance of hedge funds declines due to skill.

Panel B to Panel E plot the same graphs for each style. Still, the impact of scale is important around 2008 in all hedge funds styles. All styles, except Directional traders, have a decreasing skill since 2008. Scale constraints seem negligible among Directional traders before 2003. On average, DRTS is -0.18% before 2003 and -0.66% after 2003. The gap between the alpha and the adjusted alpha is small. Relative value has relatively minor DRTS in the post-crisis period, –0.35%, compared to –0.60% for Security Selection and Multiprocess.

[Insert Figure 5 here]

5.5. Heterogeneity of decreasing returns to scale

In the previous sections, we assume that the coefficient on scale, β, is constant across funds. However, this assumption is too restrictive to capture the potential heterogeneity of the ability to resist DRTS. For example, one fund is better than another fund at managing price pressure when trading stocks with a large volume so that its performance suffers less. As fund skill, the ability to resist DRTS should also be fund specific (Harvey and Liu, 2017 and Zhu, 2018). The purpose of this section is to examine whether the fund can outperform if it has a better ability to resist DRTS.

To answer this question, we extend our model by allowing fund-specific coefficients on scale (β_i). Nevertheless, fund by fund regressions may produce imprecise estimates for the short-lived funds. Harvey and Liu (2017) draw inference for such funds from the information of peers in the cross-section by using the Expectation-Maximization (EM) method. In this study, we apply a strategy that assumes that funds with similar features (size and style) share the same coefficient on scale. In each style, we sort funds into quintile portfolios by fund size and estimate β_1 and β_2 for each portfolio by RT-RD2. This approach allows us to run regressions with sufficient number of observations and reduce estimation error (Zhu, 2018).[28]

To examine the ability to resist DRTS, we exclude funds with positive parameters and report the estimated parameters for each size portfolio in Panel A of Table 5. We find that the magnitude of the estimated coefficients on the fund scale decreases with the fund size.

We measure the ability to resist DRTS (ARDRTS) as the effect of scale at the average size of each fund, i.e., $\text{ARDRTS}_i = \hat{\beta}_{1,i}\bar{q}_i + \hat{\beta}_{2,i} \times \bar{q}_s$, where $\hat{\beta}_{1,i}$ and $\hat{\beta}_{2,i}$ are the fund-specific coefficients estimated from the portfolio regressions, $\bar{q}_i$ and $\bar{q}_s$ are the average fund AUM and the average style AUM of the fund. We find that small funds are more able to manage the constraints imposed by the scale at the two levels. At the two levels, when the fund size and style size both double, the smallest fund suffers less severe decreasing returns (by 24 bps compared to the largest fund). The difference is statistically significant with a t-statistic of –3.92.

To examine the influence of the ARDRTS on fund performance, we create high-medium-low portfolios by sorting funds on their average skill and ARDRTS. A low-low portfolio consists of funds with low values of skill and low values of ARDRTS. Panel B of Table 5 reports the average gross alphas of nine skill-scale portfolios, calculated by taking the time-series mean for each fund first and then equally weighting the time-series mean across funds in the portfolio. We find that skill is a determinant of portfolio performance. In the columns of Panel B, all the high-minus-low (HML) portfolios on skill have a positive gross alpha, which is statistically significant

[28] Among the 25 style-size portfolios, we find one portfolio (Q5 of Other style) that has a positive fund scale parameter $\hat{\beta}_1$ and one-half of portfolios that has a positive style scale parameter $\hat{\beta}_2$.

at the 1% level. Also, we observe ARDRTS is a significant factor in determining performance. On the table rows, all HML portfolios on ARDRTS also have positive gross alphas from 0.73% to 1.31% per month (t-statistic: 5.67 to 14.43).

[Insert Table 5 here]

5.6. Do hedge fund managers invest at the optimal amount?

In the context of DRTS, the manager should invest at his optimal amount to realize the maximum profits, as discussed in Section 2, and we should observe the realized value-added of the fund at the optimal level. When investors provide excessive capital ($q_i > q_i^*$), the manager can actively manage his optimal amount q_i^* and index the excessive money ($q_i - q_i^*$). Since the indexed investments earn no alpha, the value-added of the fund is equal to $V = q_i^* \alpha_i^* + (q_i - q_i^*) \times 0 = q_i^* \alpha_i^* = V_i^*$. To answer the question, we investigate the realized value-added and the maximum value-added.

We calculate the realized value-added of a fund in a month as the AUM at the end of the previous month multiplied by the gross alpha, $S_{it} = q_{i,\,t-1} \alpha_{it}$. Then, the value-added of the fund is a time-series average of S_{it} over its lifetime, $S_i = \frac{1}{T_i - 1} \sum_{t=2}^{T_i} S_{it}$. The optimal size of the fund is estimated by using the fund-specific parameters, $\hat{q}_{i,\,t-1}^* = \max \{ -\frac{1}{2\hat{\beta}_{1i}} (\hat{a}_{it} + \hat{\beta}_{2i} q_{s,\,t-1}), 0 \}$. A negative term of $\hat{a}_{it} + \hat{\beta}_{2i} q_{s,\,t-1}$ indicates that the fund has little skill, which is not sufficient to offset the impact imposed by the style scale. In this case, the optimal size of the fund should be zero. Accordingly, the optimal value-added in the month is estimated as $\hat{V}_{it}^* = \hat{q}_{i,\,t-1}^* \hat{\alpha}_{it}^*$, where $\hat{\alpha}_{it}^* = \hat{a}_{it} + \hat{\beta}_{1i} \hat{q}_{i,\,t-1}^* + \hat{\beta}_{2i} q_{s,\,t-1}$. If a fund has little skill, the maximal value it can exploit from the strategy is zero too. Likewise, the optimal value-added of the fund is obtained by taking the time-series mean of $\hat{V}_{it}^*$,

$\widehat{V}_i^* = \frac{1}{T_i - 1}\sum_{t=2}^{T_i} \widehat{V}_{it}^*$.

Table 6 reports both realized value added (S_i) and optimal value-added ($\widehat{V}_i^*$). The second column is for the realized value added. Specifically, we report two versions of average value-added across funds: (1) the cross-sectional (ex-ante) mean, which is a simple average of value-added across all individual funds, and (2) the cross-sectional weighted (ex-post) mean, which is the average value-added across funds weighted by the number of periods it appears in the database. The ex-ante mean shows the average hedge fund added an economically and statistically significant value by $300,000 per month, with a t-statistic of 5.70. Successful funds are more likely to survive than unsuccessful funds. The ex-post mean of value added is greater, at $550,000 per month. We also observe that there is a large variation across funds. The fund at the 99th percentile cutoff generated close to $6.33 million per month, and the fund at the 90th percentile cutoff generated $1.18 million per month on average. The median fund earned an average of $50,000 per month. In total, we find that about 63.67% of the funds had a positive value-added, while 36.33% of funds destroyed value.

The third column of Table 6 reports the maximum value a fund could potentially extract from investment opportunities in the strategy. We observe that the optimal value the average fund could exploit from the strategy is $970,000 per month on average. Again, the ex-post mean is greater than the ex-ante mean, reflecting that skilled funds operate longer than less skilled funds.

[Insert Table 6]

There is a significant difference between realized value-added and optimal value. Hedge funds are often referred to as "smart money" attracting the brightest talents. Why then did hedge fund managers deviate from the optimal behavior?

In Table 7, we divide funds into three groups: excessively overfunded when $q_i > q_i^c, q_i^c = 2q_i^*$; moderately overfunded when $q_i^* < q_i \leq q_i^c$; and underfunded when $q_i < q_i^*$. Note that the gross alpha becomes negative when the fund AUM is greater than q_i^c, doubling the optimal size. The fund size q_i and two critical fund size are the average over a fund's existing period in the sample. About 30.69% of the funds are excessively overfunded. Their managers would destroy value if they actively manage all the money. Indeed, we find that most of these funds (30.06%) have a negative value added of \$–540,000 per month. If they maintain their size at the optimal level, they would realize a value added of \$320,000 per month.

On the other side, among funds increasing value, we find that about 28.88% of funds are moderately overfunded. The moderately overfunded group realized a value-added of \$670,000 per month, while their optimal value is \$1,210,000 per month. By examining their sizes, we find that the average AUM of the moderately overfunded group is \$191 million, which is slightly greater than their average optimal size of \$138 million. As the neoclassical assumptions state, if the manager invests at the optimal amount, even though he/she accepts excessive capital, he/she could index the excessive money and realize the maximum value-added. A plausible explanation for overfunding could be that these managers did not know their own capacity, as results in Table 7 show that their realized value added (S) is much smaller than V.

The underfunded group accounts for about 34.17% of the funds. On average, they added a value of \$820,000 per month, which could be maximized at \$1,380,000 per month. These funds seem to be too prudent to accept assets from investors. They have an average skill (a_{it}) of 1.67%, maintaining an average size of \$124 million, which is largely lower than their capacity of \$215 million. Overall, the results suggest that hedge funds did not invest at their optimal amount.

Note that sophisticated hedge fund investors chase performance and that overinvested funds are exposed as their subsequent profits decline. When additional capital inflows do not increase profits, investors can withdraw excess capital. This explains, in part, why only 30% of funds are excessively overfunded.[29] However, why did underfunded funds, which performed well, receive insufficient funding? The strict regulations regarding limited access to the hedge fund could be a plausible explanation. Regulation D specifies, indeed, that the requirements for private placement offerings like hedge funds are exempted from registration. Particularly, Rule 504 set ceilings (up to $5,000,000 in any 12-month period) on the size of the offerings for the exemption.[30] There is no capital limit on the eligibility, only when a fund raises capital from accredited investors listed in Rule 501.

Moreover, hedge funds use their capacity with caution. Limited partnership (LP) is a typical business organization form of hedge funds. The general partners (GP) are usually the sponsors of funds; they are also managers responsible for running funds. Mostly, they contribute their own capital. Investors are limited partners (LP), taking no responsibility for investment decisions. LP agreements are widely used to specify any restrictions on the percentage of investors' assets, while investors use side letters to ensure access to the fund's future capacity.

[Insert Table 7 here]

[29] Zhu (2018) finds that 57% of mutual funds are excessively overfunded.
[30] Please refer to the SEC website: https://www.investor.gov/introduction-investing/investing-basics/glossary/rule-504-regulation-d

6. Robustness checks

6.1. Closed hedge funds

First, we examine if past returns merely drive our findings. For example, if hedge funds carefully use their capacity, they would stop accessing new capital after they have reached their limit. In this case, the estimated scale effect could simply reflect how past returns affect current returns. To assess this issue, we investigate our sample and find that 326 funds have reported their closure to investors, of which 80 funds have reopened later. However, these funds account for less than 10% of our sample.

In addition, we repeat the RT-RD2 regressions by excluding funds that were closed to investors. The estimate of β_1 (β_2) remains negative and statistically significant, at -3.40×10^{-6} (-0.05×10^{-6}), with a t-statistic of −3.51 (−2.06). Further, we investigate capital flows in our data. We find that on average more than 56% of funds in our data have net flows greater than $100,000 each month over the period 1994-2018. Therefore, our results are unlikely to be driven by the relation between past returns and current returns.

6.2. Alternative performance measures

Second, we check whether our results are robust to alternative performance measures, namely Sharpe ratio, information ratio, and MPPM. The results are reported in Panel A of Table 8. With a fund-level model, we find evidence for fund-level DRTS. With a two-level model, we find again that the style-level DRTS is more dominant. For example, the estimate of β_1 is significantly negative at a confidence level lower than 10% under the fund-level model. With the style scale as covariant, although the estimate of β_1 remains negative, it becomes statistically insignificant for Sharp ratio and MPPM. The estimate of β_2 are all significantly negative at the 1% level for the three measures.

[Insert Table 8 here]

6.3. Alternative benchmarks

Another robustness check is to consider alternative benchmarks. To do so, we use three different factor models, namely the Fama and French (1993) three-factor model (FF3), the Fama and French (1993) and Carhart (1997) four-factor model (FFC4), and the five-factor model augmented by Pástor and Stambaugh (2003) liquidity factor (FFCPS5). The negative impacts of scale at the two levels are confirmed with the three alternative benchmarks, as in Panel B of Table 8. For example, under the two-level model, the estimate of β_1 is -3.31×10^{-6} with the FFCPS5 alpha (t-statistic: –4.52); the estimate of β_2 is -0.07×10^{-6} (t-statistic: –2.36). The magnitude of the estimates of scale effect remains at a level similar to our previous result using the FH7 model.

6.4. Alternative style classification

Hedge funds style classification varies from one study to another, depending on different hedge funds databases used by researchers. In our main analysis, we consider a broad style classification as suggested by Agarwal et al. (2009). This classification helps adapt our style-level analysis to different hedge fund databases. To examine whether our results are robust to the choice of style classification, we consider TASS database classification. TASS classifies hedge funds into 11 strategy categories: convertible arbitrage, dedicated short bias, emerging markets, event-driven, equity market neutral, fixed income arbitrage, global macro, long/short equity, multi-strategy, and others. We define an alternative style scale measure, Strat AUM, which is equal to the total AUM of the fund's peers in the same strategy category defined by TASS. We present the estimates of the two-level scale effect in Panel C of Table 8. Overall, our results hold for this alternative style classification. The estimate of β_1 is significantly negative at a confidence level lower than 10% for all alternative performance measures and alternative benchmarks, except for the Sharpe ratio. More importantly, the estimate of β_2 is consistently significant and negative at the 1% level across all performance measures and benchmarks. Our findings of style-level DRTS remain qualitatively unchanged using different style classifications.

7. Conclusion

This paper empirically tests a two-level model of DRTS with a sample of hedge funds. The two-level model assumes that a fund's gross alpha is a decreasing function of both the fund scale and the style scale, which is measured by the aggregate size of peers in the hedge fund style. Pástor et al. (2015) and Zhu (2018) addressed econometric biases that hamper the estimation of size-performance relationship and construct unbiased estimates for analyzing scale effect under an FE model assuming time-invariant fund skill. However, the FE model fails when there is a time trend of skill. As such, the estimators developed under this model are not bias-free. Under the FE model, the estimated scale effect falsely captures the correlation between skill and scale. Our results show that this endogeneity causes a significant bias in the estimated scale effect.

By heterogeneously considering the time trend of fund skill in the two-level model, we unbiasedly estimate the two-level scale effect. Assuming every dollar has an equal effect on the gross alpha, we find an increase of $250 million in the fund AUM reduces the alpha by 8.43 bps with a t-statistic of −2.84; an increase of 90 billion dollars in the style size reduces the alpha by 54 bps with a t-statistic of −2.23. The two-level scale decreases the alpha by 0.63% on average. The style-level effect (0.55%) accounts for a larger portion of DRTS. The results confirm the importance of hedge fund size. When an increasing amount of capital is invested in a given strategy, their hedge funds should consider decreasing their portfolio size to realize the maximal value-added.

We also estimate heterogeneous abilities to resist DRTS (ARDRTS) and find that small funds have better abilities to handle the constraints imposed by scale. Further, we examine the impact of skill and the ARDRTS on the gross alpha and find that both are determinants of performance. Specifically, funds with better ARDRTS outperform their peers with the same skill level but a lower ARDRTS. This difference in performance is statistically significant at the 1% level.

We also investigate whether hedge funds invest at the optimal amount and find that about 65% of funds are overfunded, and a large fraction (35%) of skilled funds are underfunded. Plausible explanations could be related to the strict regulations on accessing capital flows to hedge funds and the prudent use of capacity by hedge funds. We leave these to future research.

Appendix A: Omitted skill bias and Stambaugh bias

Previous empirical studies on DRTS have considered an FE model, in which skill (a_i) is assumed to be heterogeneous across funds but constant over the lifetime of each fund (Pastor et al. (2015) and Zhu (2018)). A fund-level model is as Eq (A1):

$$r_{it} = a_i + \beta x_{i,\,t-1} + \varepsilon_{it} \qquad \text{(A1)}$$

where r_{it} is the gross alpha of fund *i* at time *t*. $x_{i,\,t-1}$ is the lagged fund scale, either the fund AUM used by Pastor et al. (2015), or the logarithm of the fund AUM used by Zhu (2018). ε_{it} is the unexpected return, with $E(\varepsilon_{it} \mid x_{i,\,t-1}) = 0$.

In estimating the scale-performance relationship, the omitted-variable bias and the Stambaugh bias are two critical issues influencing the estimates of scale effect. Skill is unobservable but positively correlated with fund scale. The omitted variable could cause an upward bias in an OLS estimation. Ferreira et al. (2013), Yan (2008), Chen et al. (2004), Pástor et al. (2015), Zhu (2018), and among others confirm this bias in their tests with mutual funds. An OLS estimator with FE (FE-OLS) can eliminate the omitted-variable bias. However, the FE-OLS estimator still suffers the Stambaugh bias (1999) (or the finite sample bias). The Stambaugh bias (1999) is a case of violation of the strict exogeneity condition, i.e., $E(\varepsilon_{it} \mid x_{i1}, x_{i2},\ldots, x_{iT_i}) = 0$. In a regression of the return on the lagged scale, the unexpected return is correlated with the contemporaneous regressor, i.e., $E(\varepsilon_{it} \mid x_{it}) \neq 0$. An unexpected positive return ($\varepsilon_{it} > 0$) is associated with a higher contemporaneous fund scale, given the fact that fund size increases following a positive return and performance-chasing capital flows. This contemporaneous correlation is described by Pástor et al. (2015) as in Eq (A2) and in Eq (A3) by Zhu (2018), where B_{it} is the fund's benchmark return:

$$\frac{q_{it}}{q_{i,\ t-1}} - 1 = c + \gamma r_{it} + \nu_{it} \quad \text{(A2)}$$

$$\log(q_{it}) - \log(q_{i,\ t-1}) = \phi + \rho B_{it} + \gamma r_{it} + \xi_{it} \quad \text{(A3)}$$

A positive coefficient γ tends to cause a downward bias in the OLS estimator.

A solution to the Stambaugh bias is applying a recursive demeaning (RD) process to all the variables of the regression, a method proposed by Moon & Phillips (2000). Using Pástor et al. (2015) and Zhu's (2018) notation, we write the recursively forward-demeaned variables as:

$$\bar{r}_{it} = r_{it} - \frac{1}{T_i - t + 1}\sum_{s=t}^{T_i} r_{is}$$

$$\bar{x}_{i,t-1} = x_{i,t-1} - \frac{1}{T_i - t + 1}\sum_{s=t}^{T_i} x_{i,s-1}$$

$$\bar{\varepsilon}_{it} = \varepsilon_{it} - \frac{1}{T_i - t + 1}\sum_{s=t}^{T_i} \varepsilon_{is}$$

The fund FE a_i is dropped in the forward-demeaned procedure. We estimate β from Eq (A4):

$$\bar{r}_{it} = \beta\bar{x}_{i,\ t-1} + \bar{\varepsilon}_{it} \quad \text{(A4)}$$

Though, after forward-demeaning, the lagged scale is correlated with the unexpected return, i.e., $E(\bar{\varepsilon}_{it}|\bar{x}_{i,\ t-1}) \neq 0$. Pástor et al. (2015) use the recursively backward-demeaned regressor as the instrumental variable (IV) and implement a two-stage least squares (2SLS) procedure to Eq (A4). The recursively backward-demeaned scale is defined as:

$$\underline{x}_{i,t-1} = x_{i,t-1} - \frac{1}{t-1}\sum_{s=1}^{t-1} x_{i,s-1} \qquad (A5)$$

Their estimator of β (called FE-RD1 thereafter) is written as:

$$\hat{\beta}_{\text{FE-RD1}} = \left(\sum_{i=1}^{N}\sum_{t=2}^{T_i} \bar{x}'_{i,t-1}\,\underline{x}_{i,t-1}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=2}^{T_i} \underline{x}'_{i,t-1}\,\bar{r}_{i,t}\right) \quad (A6)$$

The FE-RD1 estimator implies a zero intercept in the first-stage regression. Zhu (2018) points out that the zero-intercept entails an unrealistic assumption that a fund's past average size equals its future average size. Moreover, the nonconstant regression only decreases the goodness of fit of the first stage. A low first-stage R^2 results in a less efficient 2SLS estimator, given that the first-stage R^2 is inversely proportional to the asymptotic variance of β. Zhu (2018) proposes including an intercept in the first stage and using fund scale as the IV. Fund scale ($x_{i,t-1}$) is qualified as an IV because it is correlated with $\bar{x}_{i,t-1}$ and uncorrelated with $\bar{\varepsilon}_{i,t}$. An enhanced estimator (FE-RD2) of β is written as:

$$\hat{\beta}_{\text{FE-RD2}} = \left(\sum_{i=1}^{N} \hat{\bar{\mathbf{x}}}'_i\,\bar{\mathbf{x}}_i\right)^{-1}\left(\sum_{i=1}^{N} \hat{\bar{\mathbf{x}}}'_i\,\bar{\mathbf{r}}_i\right)$$

$$= \left[\left(\sum_{i=1}^{N} \bar{\mathbf{x}}'_i\mathbf{z}_i\right)\left(\sum_{i=1}^{N} \mathbf{z}'_i\mathbf{z}_i\right)^{-1}\left(\sum_{i=1}^{N} \mathbf{z}'_i\bar{\mathbf{x}}_i\right)\right]^{-1}\left(\sum_{i=1}^{N} \bar{\mathbf{x}}'_i\mathbf{z}_i\right)\left(\sum_{i=1}^{N} \mathbf{z}'_i\mathbf{z}_i\right)^{-1}\left(\sum_{i=1}^{N} \mathbf{z}'_i\bar{\mathbf{r}}_i\right) \qquad (A7)$$

$$\text{where } \bar{\mathbf{r}}_i = \begin{pmatrix} \bar{r}_{i,2} \\ \bar{r}_{i,3} \\ \vdots \\ \bar{r}_{i,T_i} \end{pmatrix}, \bar{\mathbf{x}}_i = \begin{pmatrix} \bar{x}_{i,1} \\ \bar{x}_{i,2} \\ \vdots \\ \bar{x}_{i,T_i-1} \end{pmatrix} \text{ and } \mathbf{z}_i = \begin{pmatrix} 1 & x_{i,1} \\ 1 & x_{i,2} \\ \vdots & \vdots \\ 1 & x_{i,T_i-1} \end{pmatrix}.$$

In the simulation exercise, Zhu (2018) proves $\hat{\beta}_{\text{FE-RD2}}$ has a much lower asymptotic variance than $\hat{\beta}_{\text{FE-RD1}}$ and then an improved power of test. The FE-RD2 estimator provides a bias-free and efficient estimate of the scale effect if hedge fund skill is constant over time.

Appendix B: Returns without time trend

Table A.1

The table shows the performance of the RT-RD2 estimator when returns have no time trend. We simulate one thousand of samples of fund returns (r) and fund size (q_i). We assume returns follow the fixed effect model: $r_{it} = a_i + \beta_1 q_{i,\,t-1} + \beta_2 q_{s,\,t-1} + \varepsilon_{it}$. The fund size follows $\log(q_{it}) - \log(q_{i,\,t-1}) = c + \gamma r_{it} + v_{it}$. The simulation parameters are as described in Section 3.3. In each sample, we estimate β_1 and β_2 using the RT-RD2 estimators. Four performance measures, bias, standard deviation, root mean square error (RMSE) and fraction of rejecting the null are calculated across the one thousand samples.

	$\hat{\beta}_1 \times 10^6$			$\hat{\beta}_2 \times 10^8$		
$[\beta_1, \beta_2] \times 10^6$	$\gamma = 0.5$	$\gamma = 0.8$	$\gamma = 1.2$	$\gamma = 0.5$	$\gamma = 0.8$	$\gamma = 1.2$
			Bias			
[0, 0]	0.00	0.00	0.00	0.00	0.00	0.00
[-5, 0]	-0.01	0.00	0.00	0.00	0.00	0.00
[-3, -0.05]	0.00	-0.01	-0.01	0.00	-0.01	0.00
[-5, -0.1]	-0.01	-0.01	0.00	-0.02	0.01	0.00
			Standard deviation			
[0, 0]	0.04	0.00	0.00	0.02	0.00	0.00
[-5, 0]	0.42	0.09	0.05	0.14	0.07	0.07
[-3, -0.05]	0.46	0.10	0.05	0.17	0.13	0.08
[-5, -0.1]	0.28	0.12	0.08	0.30	0.22	0.12
			RMSE			
[0, 0]	0.04	0.00	0.00	0.02	0.00	0.00
[-5, 0]	0.42	0.09	0.05	0.14	0.07	0.07
[-3, -0.05]	0.46	0.10	0.05	0.17	0.13	0.08
[-5, -0.1]	0.28	0.12	0.08	0.30	0.22	0.12
			Fraction of rejecting the null			
[0, 0]	0.04	0.05	0.05	0.04	0.05	0.05
[-5, 0]	0.95	1.00	1.00	0.00	0.00	0.00
[-3, -0.05]	0.87	1.00	1.00	1.00	1.00	1.00
[-5, -0.1]	0.99	1.00	1.00	1.00	1.00	1.00

Appendix C: Systematic shocks on returns

Table A.2

The table shows the RT-RD2 estimate of β_2 are upward biased due to systematic shocks on returns. We simulate one thousand of samples of fund returns following the random trend model: $r_{it} = a_{i0} + g_i h_{it} + \beta_1 q_{i,\,t-1} + \beta_2 q_{s,\,t-1} + \varepsilon_{it}$. The fund size follows $\log(q_{it}) - \log(q_{i,\,t-1}) = c + \gamma r_{it} + v_{it}$. The simulation parameters are described in Section 3.3. From month 31 to month 42, we impose a negative shock on the generated return. With three different degrees of severity, the shocks are equal to -0.0057, -0.0114, and -0.0171, corresponding to one, two, and three sigma of return residuals ($\text{std}(\varepsilon)$ = 0.0057), respectively. Four performance measures, bias, standard deviation, root mean square error (RMSE) and fraction of rejecting the null are calculated across the one thousand samples.

	$\hat{\beta}_2 \times 10^8$								
	one-sigma			two-sigma			three-sigma		
$[\beta_1, \beta_2] \times 10^6$	γ=0.5	γ=0.8	γ=1.2	γ=0.5	γ=0.8	γ=1.2	γ=0.5	γ=0.8	γ=1.2
				Bias					
[0, 0]	0.10	0.01	0.00	0.20	0.02	0.00	0.30	0.03	0.00
[-5, 0]	1.02	1.14	1.69	2.03	2.09	3.19	2.89	2.84	4.41
[-3, -0.05]	2.07	2.55	0.97	3.99	4.86	2.82	5.69	6.78	5.28
[-5, -0.1]	4.37	2.53	-1.54	8.51	5.29	-2.03	11.59	9.18	-1.40
				Standard deviation					
[0, 0]	0.10	0.01	0.00	0.12	0.02	0.00	0.18	0.02	0.00
[-5, 0]	0.76	0.39	0.37	1.48	0.77	0.73	2.38	1.04	1.16
[-3, -0.05]	0.87	0.82	1.05	1.94	1.58	2.25	2.93	2.42	3.30
[-5, -0.1]	2.49	3.08	1.94	5.06	5.97	4.81	7.00	8.47	7.69
				RMSE					
[0, 0]	0.14	0.01	0.00	0.23	0.03	0.00	0.35	0.04	0.00
[-5, 0]	1.27	1.21	1.73	2.51	2.22	3.28	3.75	3.02	4.56
[-3, -0.05]	2.24	2.68	1.43	4.44	5.11	3.61	6.40	7.20	6.23
[-5, -0.1]	5.03	3.98	2.48	9.90	7.98	5.22	13.54	12.49	7.81
				Fraction of rejecting the null					
[0, 0]	1.00	0.99	0.92	1.00	1.00	1.00	1.00	1.00	1.00
[-5, 0]	0.61	0.94	1.00	0.80	0.98	1.00	0.84	0.99	1.00
[-3, -0.05]	0.97	0.99	1.00	0.80	0.82	0.93	0.74	0.85	0.91
[-5, -0.1]	0.97	0.98	1.00	0.87	0.92	0.99	0.89	0.93	0.98

Appendix D: Logarithm of AUM as scale measure

Table A3.

The table reports the results which are parallel to Table 3, with the logarithm of AUM as scale measures. We regress gross alpha obtained from the FH7 model on the Log (Fund AUM) and Log (Style AUM). Panel A presents the results over the full sample period from January 1994 to December 2018. Panel B presents the results by excluding the return observations from 2007 to 2009. "OLS" presents the estimates from a pooled OLS regression. "FE-OLS" presents the estimates from a fixed effect estimator of Eq (A1). "FE-RD2" presents the estimates from a RD2 estimator developed under the FE model, as Eq (A7). "RT-RD2" represents the estimates from a RD2 estimator developed under the random trend (RT) model, as in Eq (6). We also report the first-stage R-squared for the 2SLS estimators. The *t*-statistics are reported below the estimates, calculated based on cluster standard errors by hedge fund style.

Panel A: Full period

	OLS		FE-OLS		FE-RD2		RT-RD2	
Log (Fund AUM)	0.08	0.11	-1.95	-2.14	-4.37	-4.57	-1.15	-1.90
($\times 10^3$)	1.14	1.37	-7.05	-6.92	-9.99	-11.48	-5.74	-8.46
Log (Style AUM)		-0.78		1.26		2.85		4.21
($\times 10^3$)		-2.21		1.42		3.81		5.26
First-stage R^2					0.11	0.17	0.13	0.20

Panel B: Excluding Crisis 2008

	OLS		FE-OLS		FE-RD2		RT-RD2	
Log (Fund AUM)	-0.11	-0.03	-2.60	-2.21	-4.76	-4.24	-2.69	-2.46
($\times 10^3$)	-0.57	-0.17	-4.98	-5.51	-5.35	-6.51	-5.24	-6.39
Log (Style AUM)		-2.12		-2.54		-0.87		-2.10
($\times 10^3$)		-4.04		-2.70		-0.87		-1.54
First-stage R^2					0.10	0.18	0.09	0.13

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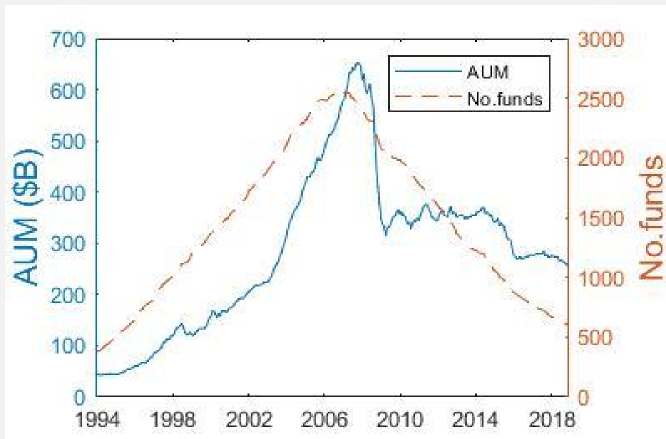
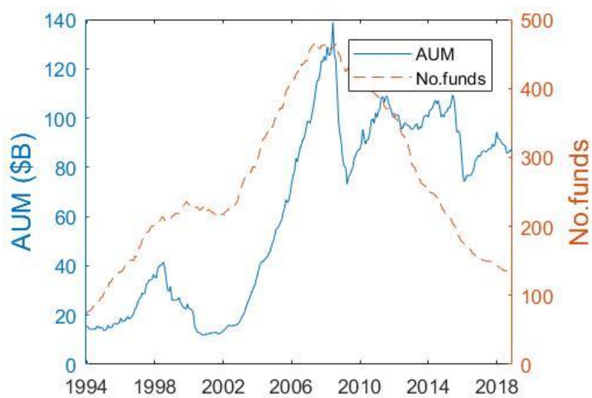
Figure 1 Evolution of the U.S. hedge funds

The figures plot the evolution of assets under management and the number of funds in our sample for each style during the period 1994-2018. The styles of hedge funds follow a definition of Agarwal et al. (2009).

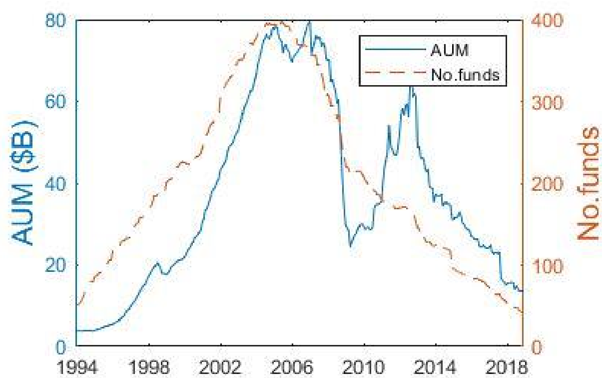
Panel A: All funds



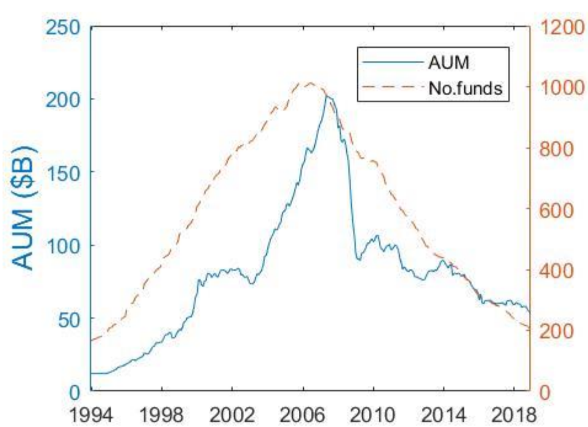
Panel B: Directional traders



Panel C: Relative value



Panel D: Security selection



Panel E: Multiprocess

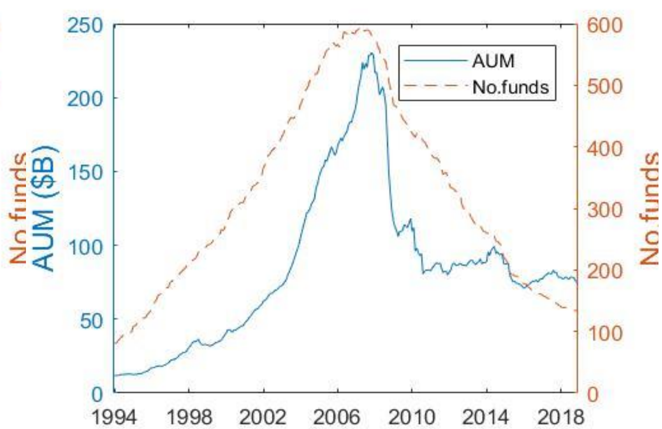


Figure 2 Gross returns of hedge funds over time

The figure plots the average of monthly gross returns across hedge fund styles from 1994 to 2018.

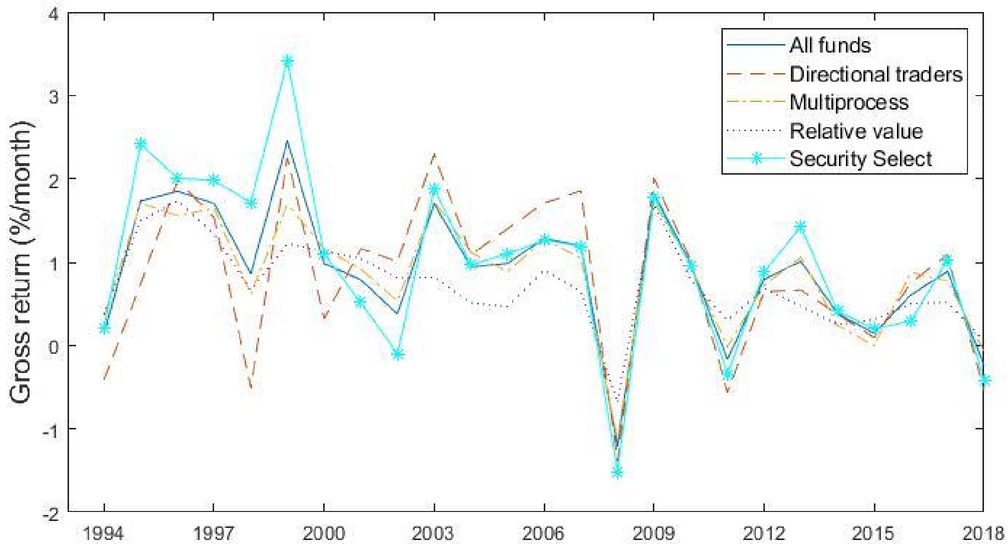


Figure 3 Distribution of the time trend of hedge fund skill

This figure presents a fitted normal distribution and a fitted nonparametric kernel distribution of the yearly growth rates of skill across funds. The growth rate is estimated from Eq. (15).

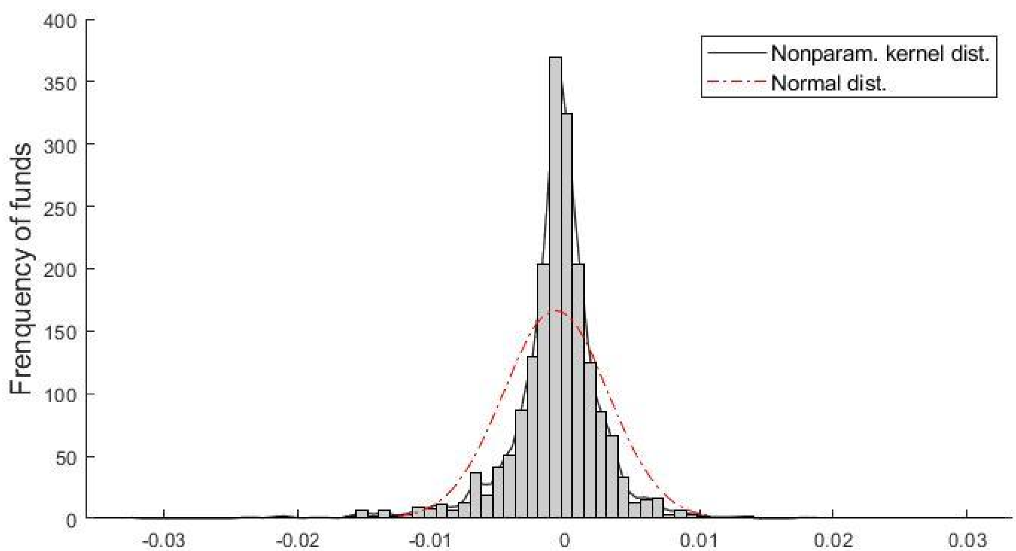
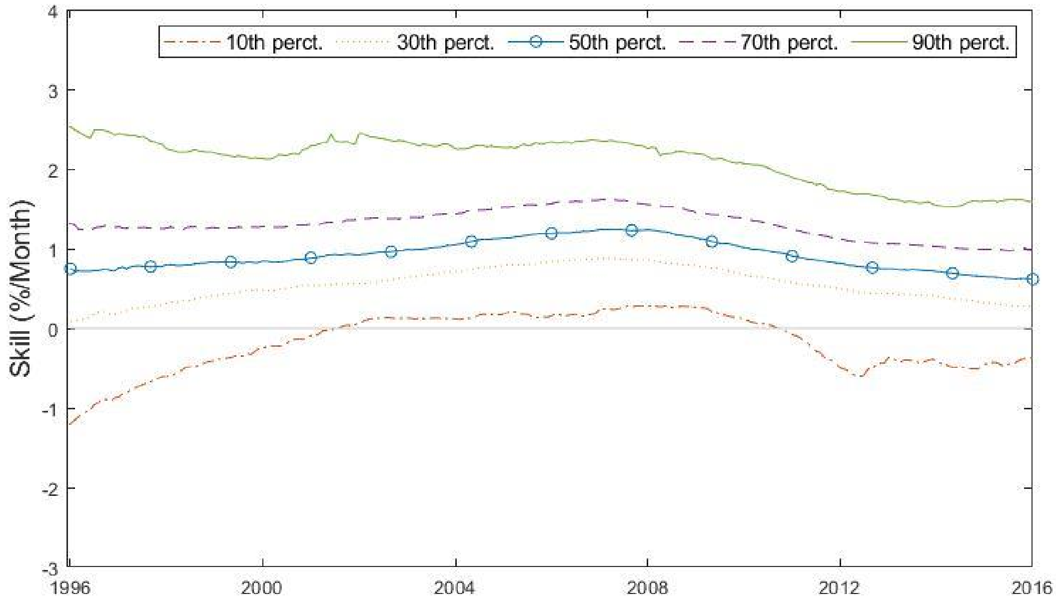


Figure 4 Distribution of hedge fund skill and gross alpha

The figure plots the cross-section of the hedge fund skill and alpha over the period 1996-2016. Time-varying skills of hedge funds are estimated by Eq. (16). Gross alphas are estimated under the FH7 model. Percentiles are calculated across all operating funds each month.

Panel A. Cross-sectional distribution of the hedge funds skill



Panel B. Cross-sectional distribution of gross alpha

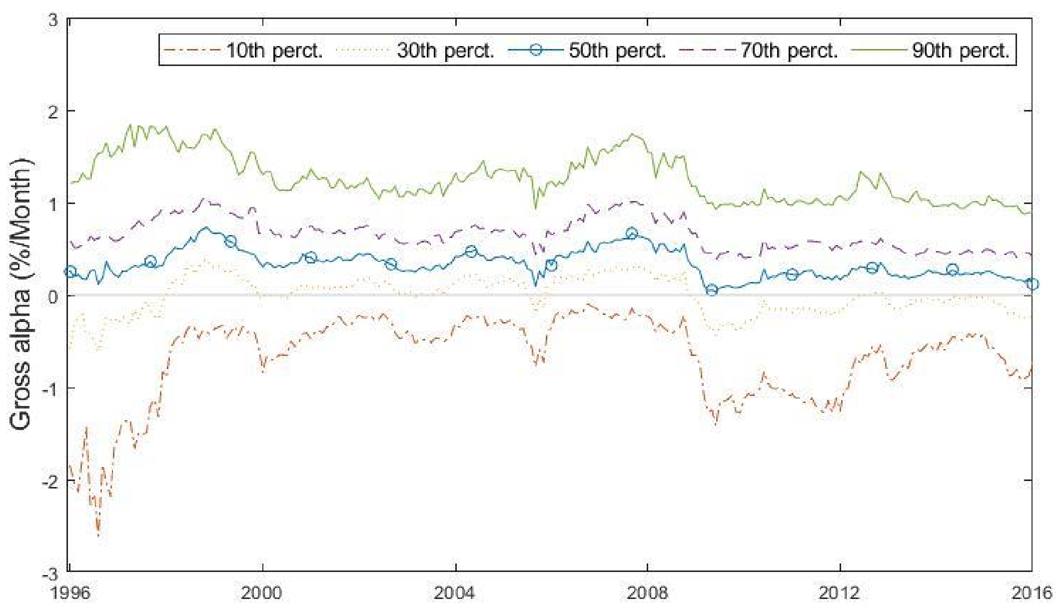
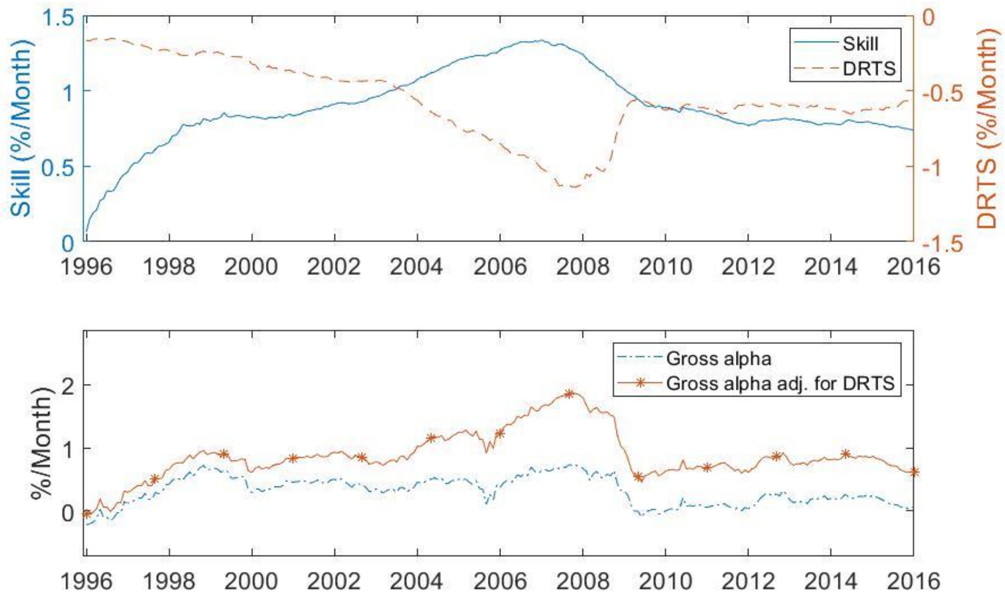


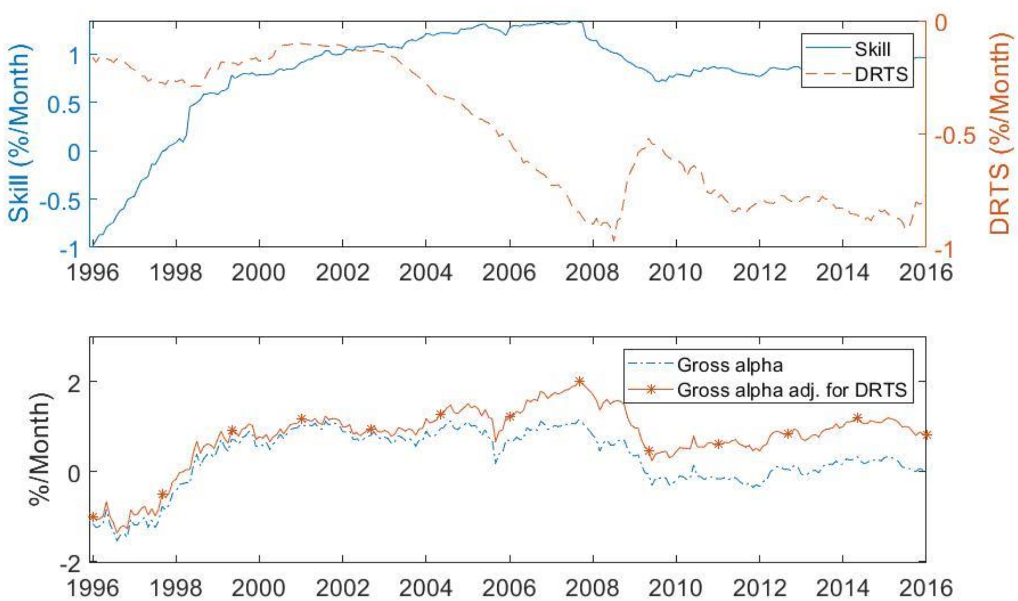
Figure 5 Interaction of skill and scale

The figure plots the evolution of hedge fund skill, DRTS, gross alpha, and gross alpha adjusted for DRTS from 1996 to 2016, Panel A for all funds in our sample and Panel B to E for funds in each style. Time-varying skills of hedge funds are estimated by Eq. (16). DRTS represents the total effect of scale at the fund and style levels. Gross alphas are estimated under the FH7 model. Gross alpha adjusted for DRTS is equal to gross alpha minus DRTS.

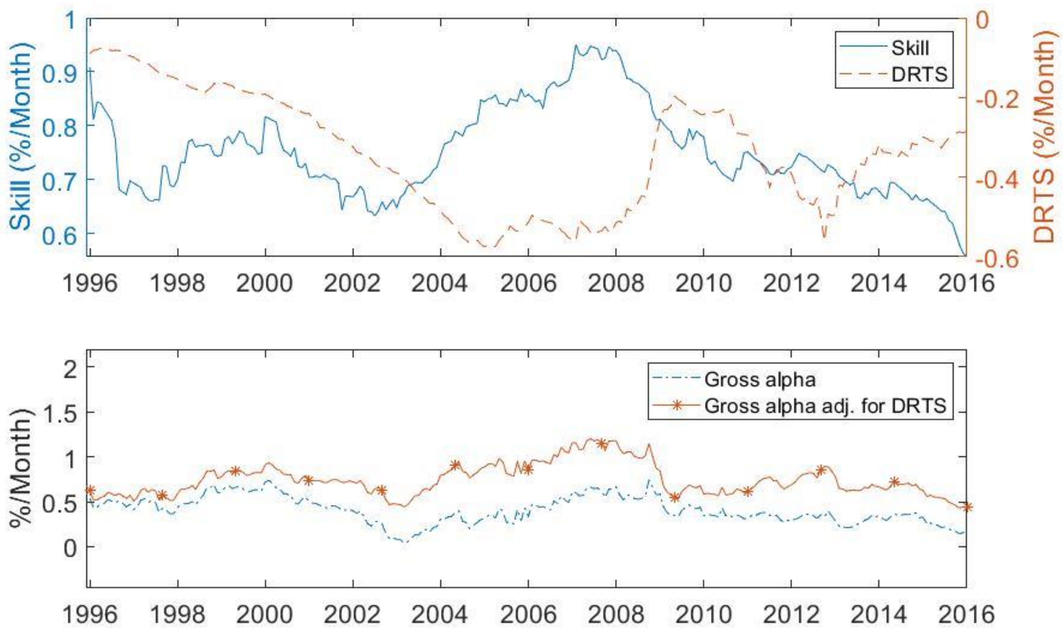
Panel A. All funds



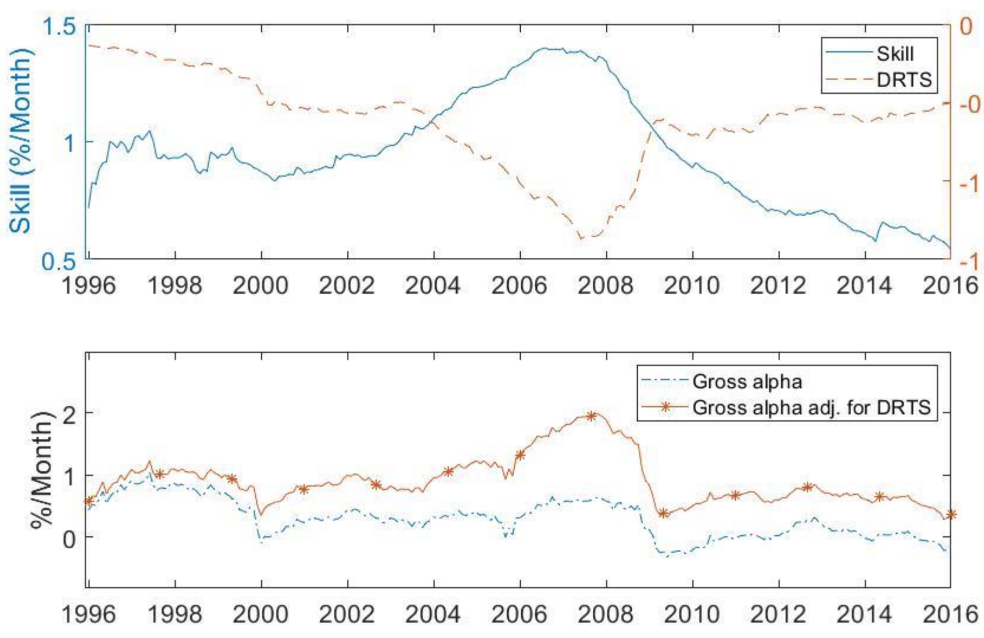
Panel B. Directional traders



Panel C. Relative value



Panel D. Security selection



Panel E. Multiprocess

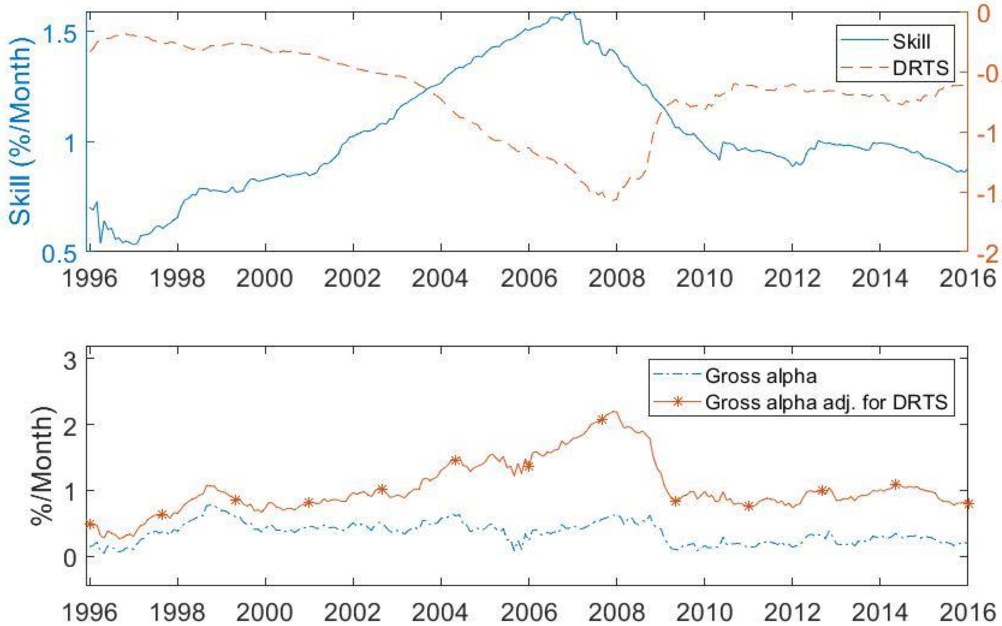


Table 1 Simulation exercise

The table reports the result of the simulation exercise. We simulate one thousand of samples of fund returns (r) and fund size (q_i). Simulated returns follow the random trend model: $r_{it} = a_{i0} + g_i h_{it} + \beta_1 q_{i,t-1} + \beta_2 q_{s,t-1} + \varepsilon_{it}$. The fund size follows $\log(q_{it}) - \log(q_{i,t-1}) = c + \gamma r_{it} + v_{it}$. The simulation parameters are described in Section 3.3. In each sample, we estimate β_1 and β_2 using the FE-RD2 and RT-RD2 estimators. Four performance measures, bias, standard deviation, root mean square error (RMSE) and fraction of rejecting the null at the 5% confidence level are calculated across the one thousand samples.

	FE-RD2						RT-RD2					
	$\hat{\beta}_1 \times 10^6$			$\hat{\beta}_2 \times 10^8$			$\hat{\beta}_1 \times 10^6$			$\hat{\beta}_2 \times 10^8$		
$[\beta_1, \beta_2] \times 10^6$	$\gamma = 0.5$	$\gamma = 0.8$	$\gamma = 1.2$	$\gamma = 0.5$	$\gamma = 0.8$	$\gamma = 1.2$	$\gamma = 0.5$	$\gamma = 0.8$	$\gamma = 1.2$	$\gamma = 0.5$	$\gamma = 0.8$	$\gamma = 1.2$
Bias												
[0, 0]	0.10	0.01	0.00	-0.24	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
[-5, 0]	2.81	4.19	6.35	-1.64	-1.94	-2.56	-0.01	0.00	-0.01	0.00	0.00	0.00
[-3, -0.05]	2.21	2.90	3.09	-1.70	-1.78	-1.82	-0.01	-0.01	-0.01	0.00	0.01	0.00
[-5, -0.1]	3.53	3.85	1.78	-2.87	-2.94	-2.27	-0.01	-0.01	0.00	0.02	0.01	-0.01
Standard deviation												
[0, 0]	0.09	0.01	0.00	0.13	0.03	0.00	0.03	0.00	0.00	0.01	0.00	0.00
[-5, 0]	1.96	2.82	8.58	0.71	0.96	2.83	0.56	0.12	0.06	0.18	0.07	0.07
[-3, -0.05]	2.09	3.45	7.17	0.79	1.14	2.31	0.58	0.15	0.07	0.19	0.12	0.10
[-5, -0.1]	6.68	9.91	16.26	2.19	3.21	5.13	0.37	0.17	0.10	0.29	0.26	0.15
RMSE												
[0, 0]	0.13	0.01	0.00	0.27	0.05	0.00	0.03	0.00	0.00	0.01	0.00	0.00
[-5, 0]	3.43	5.05	10.68	1.79	2.16	3.82	0.56	0.12	0.06	0.18	0.07	0.07
[-3, -0.05]	3.05	4.51	7.81	1.87	2.12	2.94	0.58	0.15	0.07	0.19	0.12	0.10
[-5, -0.1]	7.56	10.63	16.36	3.61	4.36	5.61	0.37	0.17	0.10	0.29	0.26	0.15
Fraction of rejecting the null												
[0, 0]	0.94	0.71	0.64	1.00	1.00	1.00	0.06	0.07	0.06	0.06	0.05	0.05
[-5, 0]	0.72	0.50	0.62	0.98	0.99	0.99	0.85	1.00	1.00	0.00	0.00	0.00
[-3, -0.05]	0.60	0.45	0.69	1.00	1.00	0.96	0.76	0.98	1.00	1.00	1.00	1.00
[-5, -0.1]	0.50	0.58	0.82	1.00	1.00	0.96	0.95	1.00	1.00	1.00	1.00	1.00

Table 2 Summary statistics

Panel A reports the statistics of performance measures. Gross alphas are estimated from Fung and Hsieh (2004) seven-factor model (FH7), Fama and French (1993) three-factor model (FF3), Fama and French (1993) and Carhart (1997) four-factor model (FFC4), and the four-factor model augmented by Pastor and Stambaugh (2003) liquidity factor (FFCPS5). Sharpe ratio is equal to the mean of monthly excess returns divided by their standard deviation. Information ratio is equal to alpha divided by regression standard error, estimated under the FH7 model. MPPM represents the manipulation-proof performance measure of Ingersoll et al. (2007). Panel B reports the statistics of hedge fund characteristics, management fee (MGMT_FEES), incentive fee (INCEN_FEES), high watermark (HWM), and AGE in years. Panel C reports the statistics of scale measures (in millions). Fund AUM is hedge fund size in dollars of assets under management. Style AUM is hedge fund style size, measured as the total AUM of the fund's peers in the same style. On the last row, we report the total AUM of all funds in our final sample over the period 1994-2018.

Panel A: Performance measures

	Gross alpha (%, per month)							
	FH7		FF3		FFC4		FFCPS5	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Directional traders	0.33	1.16	0.29	1.11	0.30	1.05	0.29	1.05
Relative value	0.36	0.58	0.31	0.60	0.30	0.59	0.30	0.61
Security Selection	0.25	0.85	0.22	0.79	0.21	0.76	0.22	0.76
Multi-Process	0.35	0.68	0.29	0.66	0.29	0.64	0.30	0.65
Others	0.55	0.80	0.53	0.78	0.54	0.75	0.54	0.75
All funds	0.32	0.86	0.28	0.82	0.28	0.79	0.28	0.79

Panel A (continued)

	Sharpe ratio		Information ratio (FH7)		MPPM			
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	No. Obs.	No. Funds
Directional traders	0.20	0.47	0.16	0.57	0.02	0.16	27,938	624
Relative value	0.33	0.63	0.33	0.74	0.04	0.09	19,021	501
Security Selection	0.19	0.63	0.12	0.74	0.04	0.11	59,805	1,334
Multi-Process	0.28	0.30	0.24	0.38	0.05	0.09	31,099	662
Others	0.49	0.80	0.52	0.94	0.06	0.11	9,105	202
All funds	0.25	0.57	0.21	0.67	0.04	0.12	146,968	3,323

Panel B: Fund characteristics

	MGMT_FEES (%)		INCEN_FEES (%)		HWM		AGE	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Directional traders	1.60	0.49	17.94	5.30	0.74	0.44	6.41	4.21
Relative value	1.38	0.42	18.96	4.64	0.73	0.45	6.50	4.58
Security Selection	1.32	0.41	18.91	3.83	0.78	0.41	7.21	4.98
Multi-Process	1.39	0.54	18.49	5.01	0.73	0.45	7.77	5.50
Others	1.49	0.43	18.96	5.47	0.88	0.33	5.93	4.16
All funds	1.41	0.47	18.65	4.63	0.76	0.43	7.00	4.90

Panel C: Hedge fund scale measures

	Fund AUM ($M)		Style AUM ($M)	
	Mean	Std. Dev.	Mean	Std. Dev.
Directional traders	320	1,457	76,328	35,328
Relative value	213	414	49,022	20,099
Security Selection	176	425	104,932	41,885
Multiprocess	321	800	106,010	52,437
Others	266	506	28,433	11,423
All funds	244	809	87,747	47,127
Total AUM ($M)	353,129	138,528		

Table 3 Diseconomy of scale – all hedge funds

The table reports the results of regressions of gross alpha on the fund-level scale and style-level scale. Gross alpha is the benchmark-adjusted return estimated under the FH7 factor model over 36-month moving windows. The fund-level scale measure is one-month lagged Fund AUM in million dollars. The style-level scale measure is one-month lagged Style AUM, which is the total AUM of the fund's peers in the same style. Panel A presents the results over the full sample period from January 1994 to December 2018. Panel B presents the results by excluding the return observations from 2007 to 2009. "OLS" presents the estimates from a pooled OLS regression. "FE-OLS" presents the estimates from a fixed effect estimator of Eq (A1). "FE-RD2" presents the estimates from a RD2 estimator developed under the FE model, as Eq (A7). "RT-RD2" represents the estimates from a RD2 estimator developed under the random trend (RT) model, as in Eq (6). We also report the first-stage R-squared for the 2SLS estimators. The *t*-statistics are reported below the estimates, calculated based on cluster standard errors by hedge fund style.

Panel A: Full period

	OLS		FE-OLS		FE-RD2		RT-RD2	
Fund AUM ($\times 10^6$)	0.06	0.06	-2.18	-2.46	-15.43	-15.07	-2.13	-3.02
	3.97	3.39	-6.39	-5.12	-1.10	-1.12	-3.89	-6.71
Style AUM ($\times 10^6$)		0.00		0.02		0.04		0.04
		-0.19		2.03		1.59		5.09
First-stage R^2					0.03	0.05	0.05	0.07

Panel B: Excluding Crisis 2008

	OLS		FE-OLS		FE-RD2		RT-RD2	
Fund AUM ($\times 10^6$)	0.02	0.08	-2.18	-1.58	-4.87	-1.69	-3.96	-3.37
	0.71	1.42	-2.80	-1.82	-1.03	-0.56	-3.49	-2.84
Style AUM ($\times 10^6$)		-0.05		-0.09		-0.09		-0.06
		-4.69		-3.36		-3.33		-2.23
First-stage R^2					0.05	0.07	0.04	0.05

Table 4: Diseconomy of scale – hedge fund styles

The table reports the RT-RD2 estimates of scale effect from the regressions of gross alpha on the fund-level scale and style-level scale. Gross alpha is the benchmark-adjusted return estimated under the FH7 factor model over 36-month moving windows. The fund-level scale measure is one-month lagged Fund AUM in million dollars. The style-level scale measure is one-month lagged Style AUM, which is the total AUM of the fund's peers in the same style. "RT-RD2" represents the estimates from a RD2 estimator developed under the random trend (RT) model, as in Eq (6). Panel A presents the results over the full sample period from January 1994 to December 2018. Panel B presents the results by excluding the return observations from 2007 to 2009. The t-statistics are reported below the estimates, calculated based on White's robust standard errors.

Panel A: Full period

	Directional traders		Relative value		Security selection		Multi-process	
Fund AUM ($\times 10^6$)	-2.12	-3.38	-5.94	-7.05	-1.14	-2.39	-6.27	-6.80
	-4.26	-5.23	-6.29	-7.00	-4.88	-9.47	-3.71	-3.82
Style AUM ($\times 10^6$)		0.07		0.03		0.05		0.03
		15.85		9.40		41.38		13.34

Panel B: Excluding Crisis 2008

	Directional traders		Relative value		Security selection		Multi-process	
Fund AUM ($\times 10^6$)	-3.07	-1.50	-5.52	-5.19	-12.77	-11.63	-2.63	-2.74
	-4.17	-2.54	-3.91	-3.67	-7.73	-7.20	-0.79	-0.81
Style AUM ($\times 10^6$)		-0.16		-0.02		-0.06		0.02
		-14.68		-4.06		-11.90		4.48

Table 5 Heterogeneity of decreasing returns to scale

Panel A reports the heterogeneity of scale effect across size quintile portfolios of hedge funds. To estimate fund specific scale coefficients, we sort funds in each style into quintiles by Fund AUM. Then, we estimate β_1 and β_2 by RT-RD2 for each style-size portfolio. For each fund, we measure the ability to resist DRTS (ARDRTS) as the effect of scale at the average Fund AUM and Style AUM, i.e., $\text{ARDRTS}_i = \hat{\beta}_{1i}\bar{q}_i + \hat{\beta}_{2i} \times \bar{q}_s$. Panel B reports the mean of gross alpha in each skill-scale portfolio. Gross alpha is first averaged over time for each fund and then equally weighted averaged across funds in the portfolio. The nine portfolios are created by independently sorting funds on skill and on ARDRTS. The time-varying skill is estimated using Eq (16), using fund specific coefficients.

Panel A: Fund specific scale effects and ARDRTS

	Size quintiles						
	Q1	Q2	Q3	Q4	Q5	Q5-Q1	*t*-stat
Fund AUM ($ mil.)	10.99	29.61	56.06	113.00	589.22		
$\beta_{1,i}(\times 10^6)$	-545.36	-371.77	-80.92	-48.70	-5.82		
t-stat.	-7.17	-10.20	-9.56	-13.41	-5.33		
$\beta_{2,i}(\times 10^6)$	-0.02	-0.17	-0.07	-0.11	-0.08		
t-stat.	-1.79	-6.96	-5.39	-8.23	-13.57		
ARDRTS	-0.74	-2.03	-0.92	-1.36	-0.98	-0.24	-3.92

Panel B: Gross alpha of skill-scale portfolios

		ARDRTS				
		Low	Medium	High	High minus Low	t-stat
Skill	Low	-1.44	-0.51	-0.18	1.25	5.67
	Medium	-0.12	0.34	0.61	0.73	14.43
	High	0.43	1.13	1.74	1.31	11.57
	High minus Low	1.86	1.64	1.92		
	t-stat	8.41	19.50	17.05		

Table 6 Value added of hedge funds

The table report the realized value added (S_i) and the optimal value added ($\widehat{V}_i^*$). For each fund, we first calculate the realized value added in a month, $S_{it} = q_{i,t-1}\alpha_{it}$, and then take the average monthly value added, $S_i = \frac{1}{T_i-1}\sum_{t=2}^{T_i} S_{it}$. The optimal value added of the fund in month t is estimated as $\widehat{V}_{it}^* = \hat{q}_{i,t-1}^*\hat{\alpha}_{it}^*$, where $\hat{q}_{i,t-1}^* = \max\{-\frac{1}{2\hat{\beta}_{1i}}(\hat{a}_{it} + \hat{\beta}_{2i}q_{s,t-1}),0\}$, $\hat{\alpha}_{it}^* = \hat{a}_{it} + \hat{\beta}_{1i}\hat{q}_{i,t-1}^* + \hat{\beta}_{2i}q_{s,t-1}$, $\hat{a}_{i,t}$, $\hat{\beta}_{1i}$, and $\hat{\beta}_{2i}$ are the fund specific parameters estimated from the size portfolios. The cross-sectional mean, standard error of mean, t-statistic, and percentiles are the statistical properties of the distribution of S_i ($\widehat{V}_i^*$) across funds. Percent with less than zero is the fraction of the distribution that has value added estimates less than zero. The Overall mean, standard error, and t-statistic are computed by computing the average value added in the dataset. The numbers are reported in $ millions per month.

	S_i	$\widehat{V}_i^*$
Cross-Sectional weighted Mean	0.55	1.38
Standard Error of the Mean	0.08	0.12
t-Statistic	7.19	12.00
Cross-Sectional Mean	0.30	0.97
Standard Error of the Mean	0.05	0.07
t-Statistic	5.70	13.68
1st Percentile	-2.31	0.00
5th Percentile	-0.76	0.00
10th Percentile	-0.36	0.01
50th Percentile	0.05	0.21
90th Percentile	1.18	2.31
95th Percentile	2.40	4.24
99th Percentile	6.33	11.73
Percent with S_i less than zero	36.33	0
No. of Funds	1437	

Table 7 Distribution of funds destroying and adding value

The table reports the distribution of the funds that destroyed and added value. The realized (optimal) value added of a fund S_i ($\widehat{V}_i^*$) is calculated as in Table 6. We divide funds into three groups: excessively overfunded when $q_i > q_i^c, q_i^c = 2q_i^*$; moderately overfunded when $q_i^* < q_i \le q_i^c$; and underfunded when $q_i < q_i^*$. $q_i, q_i^*$and q_i^c are the average over a fund's existing period in the sample. The numbers of S_i ($\widehat{V}_i^*$) are reported in $ millions per month.

	% of all funds	S_i	$\widehat{V}_i^*$
$S_i<0$			
Excessively Overfunded	30.06	-0.54	0.32
Moderately Overfunded	5.43	-0.21	0.75
Underfunded	0.84	-0.19	0.77
Total	36.33	-0.49	0.40
$S_i \ge 0$			
Excessively Overfunded	0.63	0.55	1.63
Moderately Overfunded	28.88	0.67	1.21
Underfunded	34.17	0.82	1.38
Total	63.67	0.75	1.30
All funds			
Excessively Overfunded	30.69	-0.52	0.35
Moderately Overfunded	34.31	0.53	1.13
Underfunded	35.00	0.80	1.36
Total	100.00	0.30	0.97

Table 8 Robustness check

The table reports the RT-RD2 estimates from the robustness tests. In Panel A, we use alternative performance measures other than alpha. In Panel B, we use alternative factor models for estimating alpha. In Panel C, we consider an alternative style classification. Sharpe ratio (SR) is equal to the mean of monthly excess returns divided by their standard deviation; information ratio (IR) is equal to the alpha divided by the regression standard error estimated under FH7; MPPM of Ingersoll et al. (2007). "FF3" is the Fama-French (1993) three factor model, "FFC4" is a four-factor model augmented with the Carhart (1997) momentum factor, and "FFCPS5" is a five-factor model augmented with the liquidity factor of Pastor and Stambaugh (2003). "Strat AUM" is a style scale measure, which is equal to the total AUM of the fund's peers in the same strategy category defined by TASS. The sample period is from January 1994 to December 2018 excluding the financial crisis 2007-2009. The t-statistics are reported below the estimates, calculated based on clustered standard errors by hedge fund style.

Panel A: Alternative performance measures

	SR		IR		MPPM	
Fund AUM ($\times 10^6$)	-79.18	-49.28	-185.34	-161.98	-39.85	-27.12
	-1.85	-1.37	-4.73	-4.87	-2.26	-1.46
Style AUM ($\times 10^6$)		-3.05		-2.21		-1.37
		-2.81		-2.47		-2.57

Panel B: Alternative benchmarks

	FF3		FFC4		FFCPS5	
Fund AUM ($\times 10^6$)	-3.28	-2.53	-3.93	-3.33	-3.89	-3.31
	-3.66	-3.23	-4.64	-3.92	-6.29	-4.52
Style AUM ($\times 10^6$)		-0.08		-0.07		-0.07
		-2.54		-2.48		-2.36

Panel C: Alternative style classification

	FH7	FF3	FFC4	FFCPS5	SR	IR	MPPM
Fund AUM ($\times 10^6$)	-3.67	-2.88	-3.63	-3.64	-60.18	-171.96	-32.99
	-2.83	-3.02	-4.04	-4.84	-1.56	-4.63	-1.87
Strat AUM ($\times 10^6$)	-0.06	-0.09	-0.07	-0.06	-3.96	-2.41	-1.56
	-2.62	-3.25	-3.18	-2.94	-4.25	-3.37	-3.34

PAPER 2. SOCIAL INFLUENCES AND UNIQUENESS OF HEDGE FUND STRATEGIES

ABSTRACT

Unlike previous studies, we explore a mechanism that explains how social networks could be detrimental to fund performance due to competition. We postulate that if social networks facilitate investment herding, then a central fund would have a less unique strategy, proxied by the strategy distinctiveness index of Sun et al. (2012), which leads to lower performance. We consider alumni and employment ties between the closest hedge fund competitors and confirm this point of view. Particularly, smart managers with career ambitions are more vulnerable to this negative effect. We also find that investment herding is encouraged under social influences.

JEL classification: G11; G23; J24

Keywords: Hedge funds; Social networks; Strategy uniqueness; Performance

1. Introduction

"Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."

– John Maynard Keynes, in General Theory (1936)

Studies of social network influence in the field of money management have significantly expanded in recent years (Cohen et al., 2008, 2010; Pool et al., 2015; Rossi et al., 2018; Qi et al., 2020; Lin et al., 2021; Spilker, 2022). A dominant paradigm of these studies rooted in information economics recognizes the beneficial effect of social networks on fund performance, given that networks provide essential channels for transmitting important information. The negative externalities of social networks are not yet thoroughly discussed in the literature. Our study is motivated by Scharfstein and Stein's (1990) discussion on reputational herding among professional managers. Managers choose to follow the crowd to "share the blame" in case of unsuccessful investment decisions. In this context, social networks may play an important role in facilitating herding behavior among managers with the reputation concern. However, "following the crowd" may be inefficient in a highly competitive environment. Our objective is to explore a mechanism that explains how social networks could be detrimental to fund performance due to competition.

We consider the hedge fund industry as a case study given that it is characterized by intense competition. The industry is crowded with the most knowledgeable and experienced financial market participants,[31] to whom investors pay the highest fees for performance. In general, each fund employs one or a combination of particular investment strategies in a specific style.

[31] A large number of hedge fund managers in our sample are top graduates from the most prestigious universities of the U.S. and are experienced at reputable financial services companies. Please see Table 1.

Competition is even more vigorous within a style category where funds exploit similar investment opportunities. As documented by Sun et al. (2012), to succeed in a highly competitive economy like the hedge fund industry, uniqueness of strategies is crucial for generating superior performance. Indeed, when a profitable strategy becomes well-known and heavily traded, the superior return of such opportunity would be competed away (Stein, 2009). The style-level diseconomy of scale also suggests that competition of funds chasing the same opportunity decreases the alpha of a fund (Pastor et al., 2015; Kooli and Zhang, 2022). Therefore, it becomes puzzling that competitors would exchange valuable information with each other since hedge fund managers have strong incentives to care about relative performance (Stein, 2008). Behavioral economists have long recognized that rational speculations of individuals can cause collective irrationality or even systematic mistakes (Keynes, 1936; Bikhchandani et al., 1992; Banerjee, 1992; Avery and Zemsky, 1998; Hirshleifer, 2020). Scharfstein and Stein (1990) discuss that reputational herding could be rational from the perspective of mangers, but it may be inefficient from a social standpoint. Therefore, we postulate that the social network effects could be twofold in their nature in a highly competitive economy. On the one hand, social networks have an information-benefit impact on fund performance; on the other hand, networks could be detrimental to performance in facilitating manager herding. Herding managers tend to be reluctant to develop and pursue unique strategies. As competition intensifies, manager herding would quickly diminishes the superior return of a novel strategy.

We empirically examine this mechanism by constructing an alumni and employment networks among the closest hedge fund competitors. An alumni tie indicates the managers of two funds are alumni of the same school; an employment tie indicates their managers have worked at the same employer. Unlike previous studies that examine the beneficial effect of networks

(Gerritzen et al., 2020; Lin et al., 2021; Spilker, 2022), we focus on the social influences from a fund's closest competitors and find strong and robust evidence that the negative effect of social networks is amplified due to competition. Specifically, we investigate how social networks affect uniqueness of hedge fund strategies, proxied by the "Strategy Distinctiveness Index" (SDI) of Sun et al. (2012). We postulate that if social networks influence funds toward similar investments, a fund at a central position in the networks would have a less unique strategy (i.e., a lower SDI) due to higher exposure to this kind of social influences. Consequently, this fund would perform less than its peers at the periphery of networks given all else being equal.

Therefore, our baseline analysis consists of two tests using a multivariate panel regression: the first tests the relation between social networks and the SDI[32] , and the second tests the relation between social networks and future fund performance. Following Sun et al. (2012), we construct the SDI for individual funds using monthly return data on about 2,711 hedge funds whose managers are located in the U.S. and covered by the Lipper TASS database from January 1994 to December 2018. At the end of each quarter, we classify funds into five styles by the K-mean clustering approach (Brown and Goetzmann, 2003; Sun et al., 2012). In each style, we define ANW and ENW pairwise connections between funds using the biographical data of hedge fund managers collected from LinkedIn.

In the first test, we find strong evidence that a central position in social networks, measured in three dimensions (degree, closeness, and betweenness), is associated with a lower SDI. The estimate coefficients on the centrality measures are consistently significant and negative at the 1%

[32] Sun et al. (2012) document a cross-sectional heterogeneity in the SDI. Our first test also serves to analyze the role of social networks as a determinant of SDI, in addition to fund characteristics such as fund size, age, incentive fees and return volatility.

confidence level or lower across both networks, even after controlling for various fund characteristics that are potential determinants of SDI as well as style and time fixed effect. For example, a one-standard-deviation increase in the ANW and ENW degree corresponds to a decrease in the SDI of – 1.40% and – 0.45% (t-stat: – 13.75 and – 4.64), respectively. In addition, we show that when social connections increase strategy similarity between two funds, the social network effect on a fund's SDI is a decreasing function of the fund's centrality. Indeed, we find that connectedness in the ANW and ENW increases the returns correlation between two funds by 5.15% and 6.22% (t-stat: 9.01 and 4.51), after controlling for the effect of networking in cities, influences from shared media markets, similar fund features and investment focuses, and style and time fixed effects. These findings are consistent with the herding theory, which recognizes that social networks bring the crowd into conformism in financial markets (Keynes, 1936; Scharfstein and Stein, 1990; Bikhchandani et al., 1992; Banerjee, 1992).

In the second test, we find that a central position in networks predicts lower abnormal performance, measured by a Fung and Hsieh (2004) seven-factor adjusted alpha, an FFCPS five-factor adjusted alpha, an appraisal ratio, and a smoothing-adjusted Sharpe ratio, respectively. The coefficients on all centrality measures, except for the ENW betweenness, are significant and negative at the 10% confidence level or lower after controls across the four performance measures and both networks. For example, a one-standard-deviation increase in the ANW and ENW degree predicts a decrease in the annual FH alpha of – 0.28% and – 0.30% (t-stat: – 3.04 and – 3.79) in the following year. Particularly, the use of appraisal ratio as an alternative performance measure mitigates the concern that the higher abnormal return of funds situated on the periphery of the network is a result of taking excessive idiosyncratic risk. Our results are robust to different subsamples of styles, the financial crisis and non-crisis subperiods, a subsample of funds whose managers are located in the U.S. financial centres, and after controlling for city fixed effect. The aggregate network effects become larger in magnitude when we sum up influences from both types of social ties. To summarize, our findings provide strong and robust evidence supporting that the negative influence of social networks is strengthened by competition and becomes more dominant than the information-benefit effect. A plausible explanation is that managers' desire for conformity, e.g., for a reputational reason, impedes the development of unique strategies that bring superior returns.

We also examine heterogeneous network effects from different manager characteristics, as well as social network influence on style-shifting of funds and their risk hedging. We find that smart managers with less established careers, who are more likely to pursue unique strategies because of their skill and ambition, are more vulnerable to the negative effect of social influence. We also find alumni ties increase (decrease) the probability that two funds remain in the same style (switch to different styles) in the future, while employment ties seem to have less influence on style-shifting. By investigating the relation between network centrality and the R2 of a fund's returns against risk factors (Titman and Tiu, 2011), we find that funds more exposed to social influence are also more exposed to systematic risk.

This paper makes several contributions to the literature. First, our paper adds to the fast-growing literature on social network effects in financial markets using a unique dataset about U.S. HF managers' biographical information hand-collected from LinkedIn. Second, we focus on relationships between the closest competitors instead of examining networks across all hedge funds. By doing so, we find that the negative network effect on performance is amplified due to competition. In an environment where unique ideas are crucial for success, managers would concern themselves with this negative externality in their decision-making. Third, we postulate a mechanism through which social networks impact hedge fund performance. We show that social networks are a strong determinant of SDI. Using the SDI as a proxy for strategy uniqueness, we show that social networks can impair performance by deterring managers from pursuing unique strategies when these information channels bring managers into conformity in their decision-making. Fourth, our paper provides empirical evidence supporting that social networks induce inefficient herding behavior among institutional investors, which is consistent with the conceptual framework of Keynes (1936), Scharfstein and Stein (1990), Bikhchandani et al. (1992), Banerjee (1992), and Avery and Zemsky (1998). Prior empirical studies on institutional herding mostly focus on examining institutional investors' shareholdings or trading activities on securities and the corresponding impacts on security prices (Sias, 2004; Boehmer and Kelley, 2009; Cai et al., 2019). Our study explores another important aspect of institutional herding, i.e., the role of social ties in facilitating this behavior and its impact on fund performance.

The remainder of the paper is organized as follows. Section 2 presents the literature review and hypotheses. Section 3 introduces data and variables. Section 4 presents empirical results and robustness tests. Section 5 concludes.

2. Literature review and hypotheses

Literature in economics and finance shows that the behaviors of economic agents are influenced by their social ties (Ellison and Fudenberg, 1995; Uzzi and Lancaster, 2003; Larcker et al., 2013; Fracassi, 2017; among others). One of the most addressed topics is the social influences on investment behavior and performance.[33] In the area of hedge funds, previous studies have

[33] Studies addressing social influences on investment behaviors and performance include: Hong et al. (2004, 2005), Cohen et al. (2008, 2010), Brown et al. (2008), Kuhnen (2009), Hochberg et al. (2010), Han and Yang (2013), Pool et al. (2015), Bajo et al. (2016), Rossi et al. (2018), Qi et al. (2020), Lin et al. (2021), Spilker (2022), etc.

examined alumni ties and employment ties between hedge fund funds. They find evidence supporting that social networks provide informational benefits that enhance fund performance. For example, Lin et al. (2021) examine alumni ties between managers and find that information advantage brought by central positions in networks can influence managers' investment styles and thus improve hedge fund performance. Spilker (2022) examines employment ties based on managers' past hedge fund management experiences and finds stronger ties lead to more similar and profitable investments.

Hedge funds operate in a highly competitive industry where unique talent is best rewarded. Sun et al. (2012) propose a "Strategy Distinctiveness Index" (SDI) for measuring the level of uniqueness of a fund's strategy relative to its cohorts investing in the same style. They find that high-SDI funds have better abnormal performance, suggesting that unique strategies are important for generating superior performance. They also find that small, young, and high incentive fees hedge funds are more likely to pursue unique strategies. Interpersonal relationships allow managers to observe and talk to each other. These interactions play an important role in diffusing investment information which constitutes a decision externality for managers. A manager in a central position is more exposed to information flowing through networks and thus would be more significantly influenced by the behaviors of his peers. We develop two hypotheses about how social networks influence hedge fund strategy uniqueness based on different economic theories.

The first hypothesis is based on the herding theory, which can be traced back to Keynes (1936). Conformism, i.e., the tendency of individuals to make decisions by following the actions of others rather than using owned information, is one of the most striking regularities of human society. Jones (1984) discusses various explanations for the desire to conform. An explanation of imitation can be due to socio-psychological factors (Baddeley, 2010). In behavioral economics, information cascades and herding are generated by Bayesian learning of individuals (Bikhchandani et al., 1992; Banerjee, 1992; and Avery and Zemsky, 1998). In their models, a player can observe previous actions of other players before making his/her decision. His/her observations provide information for adjusting his/her probabilistic judgment to make the decision. From the perspective of professional money managers, in a short-run view, it may be rational to simply follow the investment decisions of other managers for a reputational reason (Keynes, 1936; Scharfstein and Stein, 1990). Money managers operate their funds usually on a large scale with borrowed money. Behaving in a contrarian fashion by ignoring near-term market fluctuations needs greater resources and will receive the blame if the decision turns out to be unsuccessful. In contrast, "following the crowd" can share the blame if many others make the same mistake. For this reason, a manager would concern himself with foreseeing impending changes in the conventional basis of valuation, rather than making superior long-term forecasts of the probable yield. Prior empirical studies also find social networks bring the crowd into conformism in financial markets. For example, Pool et al. (2015) find that neighbor managers have similar investments due to word-of-mouth communications. Fracassi (2017) examines various social ties between executives and directors of U.S. public companies. They find that the more connections two companies share, the more similar their capital investments are. Qi et al. (2020) focus on alumni ties between mutual fund managers and find connected managers have similar portfolio allocations. Consistent with the view that social networks influence managers toward conforming behavior, we present the following hypothesis:

H1. Conformism hypothesis. When all else equal, a hedge fund located in a central position in social networks has a less unique strategy and lower performance than its peers on the periphery of networks.

Under certain circumstances, informed individuals might exhibit contrarianism. For example, Park and Sabourian (2011) show that contrarianism occurs when investors have hill-shaped signals. As one of the most sophisticated arbitrageurs, hedge fund managers would be concerned about the commonality of an investment approach and thereby intentionally differentiate their investments from peers. The first concern would be the profitability of a well-known, heavily traded strategy. Any superior abnormal return of such a strategy will likely be competed away (Berk and Green, 2004; Pastor et al., 2015; Zhu, 2018; Kooli and Zhang, 2022). The second concern is the "crowded-trading" effect, which suggests a price uncertainty faced by each arbitrageur when other arbitrageurs are using the same model and taking the same positions (Stein, 2009). In such circumstances, the inability of traders to condition their behavior on current market-wide arbitrage capacity creates a coordination problem, which drives prices further away from fundamental values. The uncertainty grows with leveraged arbitrageurs forced to liquidate the assets in a fire sale. Hence, managers would leverage their information and make contrarian decisions due to decreasing returns to scale and the crowded trading effect. Our alternative hypothesis is, therefore, as follows:

H2. Contrarianism hypothesis. When all else equal, a hedge fund located in central positions in social networks has a unique strategy and better performance than its peers on the periphery of networks.

3. Data and variables

In this section, we describe the hedge fund sample, biographical data of hedge fund managers, manager tenures, and the variables used in this study. Our main variables are fund performance measures, the strategy distinctiveness index (SDI), and network centrality measures.

Control variables include various hedge fund characteristics. Our data are collected from two sources, the Lipper TASS hedge fund database (TASS) and LinkedIn, a platform for professional networking with worldwide users. This online service allows users to create profiles based on their educational backgrounds and work experiences. TASS is recognized as one of the leading sources of hedge fund information and has been widely used in the hedge fund literature. It retains data on dead funds since 1994, which are less subject to the survivorship bias. Besides fund returns and characteristics, TASS provides information about portfolio managers, manager workplace location (country, city, and zipcode), and hedge fund firms.

3.1. Hedge fund sample

Our initial sample consists of hedge funds that report monthly net returns in U.S. dollars to TASS between January 1994 and December 2018. Considering the backfilling issue, we remove each fund's first 12-month return observations and keep funds with at least 24-month return observations. TASS classifies hedge funds into 12 self-reported strategy categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long-short equity, multi-strategy, managed future, options strategy, and funds of funds. We filter out funds of funds and funds with undefined strategies. Then, we keep funds with portfolio managers located in the United States. Our final sample consists of 2711 hedge funds, including 228 live funds and 2483 graveyard funds, and 2036 portfolio managers. Among these HFs, 2181 funds are managed by a single manager, and 530 funds are managed by multiple managers.

3.2. Manager biographical backgrounds and tenure at hedge fund

Biographical information of hedge fund managers is collected from LinkedIn. We match a LinkedIn user profile with a manager from the hedge fund sample by checking three conditions: (1) matched manager name, (2) matched employer name, i.e., the hedge fund firm name from TASS must appear on the LinkedIn profile as one of the employers, and (3) work position at the matched employer are among President, CEO, Founder, Co-founder, Partners, Chief Investment Officer, Vice president, Director, and Portfolio Manager. In total, we match 1713 out of 2036 managers. For each matched manager, we collect from his or her LinkedIn profile the education records (universities, colleges, degrees) and the work experience information (employer names and employment periods).

TASS does not provide information about manager tenure at a fund. For a fund with multiple managers, their tenures can span different periods over the fund's lifetime. In this case, we determine tenure for each manager based on employment information collected from LinkedIn. Specifically, we determine a manager's tenure as the employment period at the hedge fund firm.[34] The manager tenure is the fund's lifetime for a fund with a single manager. In total, we determine 2818 manager tenures (fund-manager pairs) for 2571 funds and 1712 managers. Figure 1 shows the geographical distribution of hedge fund managers in our sample. We cluster managers with the same zip code in a circle. The size of the plotted circle is determined by the number of managers located in this district. There are about one-half of hedge fund managers (862) clustered in the U.S. financial centers.[35]

[34] If the employment period is outside of the period the fund has performance records in TASS, we drop the observation of this manager. We find only one such manager.

[35] They are New York City, Boston, Chicago, Los Angeles, Philadelphia, and San Francisco, as referred by Christoffersen and Sarkissian (2009).

[Insert Figure 1 Here]

Hedge fund managers are recognized for their top-tier talent and extensive experience in financial markets. Indeed, we find that a substantial proportion of managers are graduates from the most prestigious business schools in the U.S., such as Wharton and Harvard. Panel A of Table 1 presents the top ten schools (among 777 schools) by the number of alumni in our sample. For example, the Wharton School is ranked number one, with 70 alumni managing 124 funds. Harvard Business School is ranked number four, with 46 alumni managing 93 funds. In total, 388 managers are alumni from the top ten schools, managing 656 funds. Also, we find that many managers are experienced at reputable financial services companies such as Morgan Stanley and Goldman Sachs. Panel B of Table 1 presents the top ten employers of managers. For instance, Morgan Stanley is ranked number one, with 46 managers managing 68 funds. Goldman Sachs is ranked number three, with 43 managers managing 67 funds. In total, 350 managers have worked at the top ten companies, managing 578 funds.

[Insert Table 1 Here]

3.3. Performance measures

We adopt four risk-adjusted performance measures widely used in the hedge fund literature, A Fung and Hsieh (FH, 2004) seven-factor adjusted alpha, a FFCPS five-factor adjusted alpha, an appraisal ratio, and a smoothing-adjusted Sharpe ratio. The FH model includes an equity market factor (the return on S&P 500 in excess of the risk-free rate), a size spread factor (Russell 2000 index total return minus S&P 500 total return), a bond market factor (change in the 10-year treasury constant maturity yield), a credit spread factor (change in the spread between Moody's Baa yield and the 10-year treasury), and three trend-following factors for bonds, currency, and commodities.

Different benchmarks for hedge funds have been used in prior studies. For example, Bali et al. (2012) use the Fama-French three-factor model and the Carhart four-factor model. Shi (2017) uses a five-factor model as an alternative benchmark adjustment, the Carhart four-factor model augmented by the liquidity factor of Pástor and Stambaugh (2003). We also consider this five-factor model as an alternative benchmark adjustment, and we call it the FFCPS model for brevity. The FFCPS model includes the Fama and French (1993) three factors, a momentum factor (Jegadeesh and Titman, 1993) and a liquidity factor (Pastor and Stambaugh, 2003). For each fund at the end of each month, we regress the excess return of a fund (R_{it}) on the risk factors ($\mathbf{F}_t$) over the prior 24 months. The fund's alpha in month *t*+1 is equal to the next month's excess return ($R_{i,\, t+1}$) minus the products of the estimated factor loadings $\hat{\boldsymbol{\beta}}_i$ and factor returns in month *t*+1, as in Eq (1):

$$R_{it} = \alpha_i + \boldsymbol{\beta}'_i \mathbf{F}_t + \varepsilon_{it}$$

$$\hat{\alpha}_{i,t+1} = R_{i,t+1} - \hat{\boldsymbol{\beta}}'_i \mathbf{F}_{t+1} \quad (1)$$

The appraisal ratio measures a fund's abnormal return relative to its idiosyncratic risk, which is calculated as the mean of the monthly alphas (FH) divided by their standard deviation. Illiquidity and smoothing in hedge fund returns can cause an upward bias in Sharpe ratios. We follow Getmansky, Lo, and Makarov's (2004) method to adjust hedge fund returns for the bias of the smoothing return.[36] Then, the smoothing-adjusted Sharpe ratio is defined as the ratio between the mean of monthly smoothing-adjusted excess returns and their standard deviation.

[36] Specifically, we estimate the smoothing coefficient (θ) of each fund in a MA(2) process using maximum likelihood estimation via the "innovations algorithm" of Brockwell & Davis (1991): $R_t^o = \mu + \theta_0 \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}$, with $1 = \theta_0 + \theta_1 + \theta_2$, and $\theta_k \in [0,1]$, k=0, 1, 2. R_t^o denotes the observed excess returns. The smoothing-adjusted return, $\hat{R}_t$, is estimated by $\hat{R}_t = \hat{\mu} + \hat{\epsilon}_t$.

Panel A of Table 2 reports the summary statistics of hedge fund performance. The variables are winsorized at the 1% level. At the end of each quarter, we annualize alpha by compounding the monthly alphas obtained from Eq (1) over the following 12 months. On average, hedge funds in our sample generate an annual FH alpha of 3.19%, with a standard deviation of 15.13%, and an annual FFCPS alpha of 2.87%, with a standard deviation of 13.60%. The reported appraisal ratio and smoothing-adjusted Sharpe ratio are also calculated over the 12-month rolling periods. The mean of the appraisal ratio is 0.16, with a standard deviation of 0.44. The mean of the smoothing-adjusted Sharpe ratio is 0.21, with a standard deviation of 0.39.

[Insert Table 2 Here]

3.4. Hedge fund styles and the SDI

Following Sun et al. (2012), we use SDI as a proxy for the uniqueness of hedge fund strategies. The SDI measures how much a fund's returns are correlated with those of its cohorts in the same style. Suppose a fund *i* belongs to the style *I*. When it employs a unique strategy, its returns ($\mathrm{R_i}$) would be less correlated with the return of a typical strategy of its style (μ_I), where μ_I can be measured as the average return of all funds in style *I*, i.e., $\mu_{\mathrm{It}} = \sum_{i \epsilon I} \mathrm{R_{it}} \,/\, \mathrm{count}\,(i \epsilon I)$. Therefore, the SDI of the fund is calculated as one minus the sample correlation between the fund's return and the average return of all funds in style *I* over a period of T months:

$$\mathrm{SDI}_i = 1 - \mathrm{corr}\,(\mathrm{R_i}, \mu_\mathrm{I}) = 1 - \frac{\sum_{s=1}^{T}(\mathrm{R_{it}} - \bar{\mathrm{R}}_\mathrm{i})(\mu_{\mathrm{It}} - \bar{\mu}_\mathrm{I})}{\sqrt{\sum_{s=1}^{T}(\mathrm{R_{it}} - \bar{\mathrm{R}}_\mathrm{i})^2 \sum_{s=1}^{T}(\mu_{\mathrm{It}} - \bar{\mu}_\mathrm{I})^2}} \tag{2}$$

To calculate the SDI, we need to define hedge fund styles. Given the limitations of TASS style classification,[37] we define styles by the K-mean clustering approach following Brown and Goetzmann (2003, 1997) and Sun et al. (2012). The SDI can be viewed as a distance metric used in a clustering program. Graphically, a higher metric value indicates a farther distance to the center of the cluster. A K-mean clustering algorithm is a procedure to find a locally optimized partition of funds that minimizes the sum of the distance of all funds to their corresponding cluster.

In this procedure, the number of clusters (styles) K is a prespecified parameter. Tuning this parameter is crucial for guaranteeing the quality of clustering. In previous studies, Brown and Goetzmann (2003) considered an adjusted R^2 as a performance measure for comparing different K, K = 5 and K = 8, and find the performance of K = 8 is better than K = 5. Sun et al. (2012) fixed K at 10, the same number of TASS styles. The optimal K in a clustering program is usually sample-specific. Undoubtedly, the TASS hedge fund sample has dramatically changed over time. Since style classification is an important instrument of our study, it affects not only the calculated SDI but also the construction of hedge fund social networks, we examine the optimal K for our sample. In Appendix A, we compare performance between K = 5 and K = 10 based on two performance measures, adjusted $R^{2,}$ and silhouette value. We find the performance of K = 5 is better than K = 10. Therefore, in our study, we fix the number of hedge fund styles at 5.

At the end of each quarter, we group funds with at least 24 prior month returns into five style clusters based on their return correlation over the period. These procedures generate time-varying, dynamic, and sufficiently stable hedge fund styles. The annual switching rates are equal

[37] TASS classification is based on self-reporting by funds. Sun et al. (2012) summarize its limitations as follows: 1) potential misclassification, 2) the database provides only the most recent snapshot of style reporting, whereas a fund's style could change over time, and 3) most importantly, some of TASS styles are more broadly defined than others. In consequence, the SDI calculated based on these classifications may merely capture a dispersion of a broader definition.

to the percentage of fund pairs that change status from belonging to the same style to switching to different styles and vice versa, ranging from 15% to 27% between 1996-2018 (with an average of 20.76%.) With the defined styles, we calculate the SDI for each fund by Eq (2). The mean of SDI is 0.37, with a standard deviation of 0.21. For a better understanding of the variable, we report the properties of the SDI in Appendix B. Figure A2 presents its cross-sectional distribution, which shows a pattern of a large variation in the SDI across funds, as found by Sun et al. (2012). The histogram displays the percentages of funds with the time-series average SDI at different values. About 73% of the sample funds exhibit an average SDI lower than 0.50. The distribution is more than 15% in each of the 0.25 to 0.45 SDI bins, and about 10% in the 0.15, 0.55, and 0.65 SDI bins. Figure A3 plots the SDI across styles with different popularity. The popularity of a style is measured by the number of funds as members. In Panel A, we find that Style 1, the most popular style (also called the mainstream style), accounts for about 30-50% of all hedge funds over the period 1996-2018, Style 2 accounts for about 20% of all funds, and Style 5, the least popular style, has only about 10% of funds as members. In Panel B, we find that larger styles tend to have a lower average SDI than smaller ones.

3.5. HF networks and centrality measures

To construct social networks of the closest competitors, we consider all cohorts in a given style at a given point in time. This approach allows us to have a time series of networks whose evolution is caused by the style-shifting of funds, the entrance of new funds, the attrition of liquidated funds, and manager tenure. At the end of each quarter, we define the pairwise connections between funds within each style based on social relationships between their managers. Using the manager biographical data collected from LinkedIn, we identify two types of social ties, Alumni Network (ANW) and Employment Network (ENW), and we call them the HF networks.

An alum connection indicates that managers of the two funds are alumni of the same school. An employment connection indicates that managers of the funds have worked at the same employer. In the case that multiple managers manage a fund, a connection between funds indicates at least one manager from one fund is connected with a manager from the other fund by alumni or employment tie. In addition, we require that the two funds do not have common managers to ensure that the estimated effect does not reflect the preferences of the same manager. The alumni and employment relationships of managers have been examined by prior studies (Gerritzen et al., 2020; Qi et al., 2020; Lin et al., 2021; Spilker, 2022). Shared educational backgrounds increase the probability of exchanging information between two managers based on mutual recognition. We take a weaker form for the employment ties by not requiring employment overlap in time. Shared experience backgrounds could drive similar investments, e.g., due to having been exposed to common training at the prior employer or firm culture, even though there is no exchange of ideas (Gerritzen et al., 2020).

Figure 2 displays a snapshot of the HF networks as of December 2007. The size of a node represents its level of degree centrality. The color of a node denotes the style it belongs to. The color of the edge denotes the type of relationship: a lighter line for ENW and a darker line for ANW. We observe that one or two styles are more popular with more funds as members. A larger style also tends to have more connections than a smaller style. For example, there are 716 connections in the largest style and only 45 connections in the smallest style.

[Insert Figure 2 Here]

Network centrality measures the importance of a position in social networks and has been used in prior studies to examine social influences on the behaviors of economic agents (Larcker et al., 2013; Bajo et al., 2016; Fracassi, 2017; Rossi et al., 2018; Qi et al., 2020; Lin et al., 2021; etc.). Different measures capture different dimensions of the network effect. We adopt three centrality measures commonly used in the literature. The first measure is *degree* centrality, which is equal to the number of connections of a node divided by the total number of nodes in the network minus one. This measure can be interpreted as an immediate probability that the fund catches information flowing through the network. The second measure is *closeness* centrality, which is equal to the inverse of the average distance between a node and all other nodes in the network. This measure indicates the average distance that randomly generated information in networks travels to reach the fund. The third measure is *betweenness* centrality, which measures how many shortest paths between other nodes go through a particular node. This measure captures bridge roles of a position in networks, e.g., a degree of control over important paths of information flows.

We calculate the three centrality measures in the ANW and ENW, respectively, for each fund at the end of each quarter between 1996-2018. Panel A of Table 2 reports the summary statistics. For the ANW, the means of the degree, closeness, and betweenness centrality measures are 0.24%, 0.51%, and 0.0047%, with a standard deviation of 0.52%, 1.08%, and 0.03%. For the ENW, the means of the three measures are 0.08%, 0.15%, and 0.0008%, with a standard deviation of 0.25%, 0.44%, and 0.01%. To examine their evolution over our sample period, for each measure, we first calculate its cross-sectional mean at a given time ($\mathrm{Net}_t = \mathrm{N}_t^{-1} \sum_{i=1}^{N_t} \mathrm{Net}_{it}$) and then standardize the time-series of Net_t. The standardized Net_t has a zero mean and unit variance. Figure 3 plots the time series of the standardized centrality over the period 1996-2018. All three measures exhibit averagely lower values in earlier years than in later years of the period. For example, the standardized ENW degree was below zero before 2004 and became positive in most years after that. Moreover, all three measures seem to fluctuate more violently over the post-2008 crisis period. When we plot the standardized SDI in the figure, we notice that the SDI appears to mirror the pattern of the centrality measures, indicating a negative correlation between the SDI and centrality. As a result, we calculate the correlation between the series of SDI and centrality. For example, for the ENW closeness, the correlation is – 0.24.

[Insert Figure 3 Here]

We examine their cross-sectional correlation for a basic understanding of the relation between our main variables. We first calculate the time-series average of each variable for each fund and then the pairwise correlations between the mean variables. Panel B of Table 2 reports the correlation matrix. Firstly, we confirm a positive correlation between the SDI and future fund performance across all four alternative measures, consistent with Sun et al. (2012). Secondly, we find a negative correlation between the SDI and centrality across all six centrality measures, ranging from – 0.18 to – 0.04. Thirdly, we also find a negative correlation between centrality and fund performance across all performance measures and centrality measures.

3.6. Control variables

Control variables are various fund characteristics, including fund return volatility (Vol), R2(FH), assets under management, fund age, redemption notice period, lockup period, personal capital commitment, high water mark, management fees, incentive fees, minimum investment, and leverage. Vol is the standard deviation of monthly net-fee-returns over the prior 24 months of each quarter. R2(FH) denotes the R-squared obtained from the 24-month rolling window regressions of Eq (1) with the FH model. RedempNotice is the redemption notice period in days. Lockup is the lockup period in months. PersonalCapital is an indicator of personal capital commitment. HWM is an indicator that the fund sets a high water mark provision. MGMT_FEE and INC_FEE are management fees and incentive fees in percentage. MIN_INV is the required minimum investment by fund in $million. Leverage is an indication of whether the fund uses leverage. Panel C of Table 2 summarizes the statistical properties of these variables. The average return volatility is 3.32% per month. The mean of R2(FH) is 0.54, with a standard deviation of 0.21. An average fund has a size of $258.78 million and an age of 8.46 years. Across funds, the average redemption notice period is 42.65 days, the lockup period is 5.51 months, management fees are 1.35%, incentive fees are 18.84%, and the required minimum investment is $1.58 million. About 43% of funds have personal capital commitment, 73% set high water mark provisions and 64% use leverage.

4. Results

4.1. Baseline results

Our baseline analysis consists of two tests using a multivariate panel regression. We first examine how HF networks influence a fund's SDI. Then, we examine how networks affect the fund's future abnormal performance. The two tests serve to examine our hypotheses. As discussed in Section 2, social networks could influence strategy uniqueness in two possible ways. Consistent with the conformism hypothesis that assumes social ties bring funds toward similar investments, a central position in the networks is associated with a lower SDI. It predicts lower performance due to a declined novelty of the fund's strategy. Based on the contrarianism hypothesis that assumes managers with information advantage intentionally differentiate themselves from peers due to the concern of commonality of a well-traded strategy, a central position is associated with a higher SDI and predicts higher performance.

4.1.1. Relation between network centrality and SDI

We run the regression of the SDI on the network centrality controlling for fund characteristics and style and time fixed effects, as in Eq (3):

$$\mathrm{SDI}_{i,I,t} = \mathrm{c_I} + \mathrm{c_t} + \gamma \mathrm{Net}_{i,I,t} + \boldsymbol{\varphi}'\mathbf{FundChar}_{i,I,t} + \epsilon_{i,I,t} \quad (3)$$

where $\mathrm{SDI}_{i,I,t}$ is the SDI of fund *i* in the style *I* at the end of quarter *t*; $\mathrm{c_I}$ and $\mathrm{c_t}$ represent style and time-fixed effects; $\mathrm{Net}_{i,I,t}$ is one of the six network centrality measures among degree, closeness, and betweenness, calculated in the ANW and ENW, respectively; $\mathbf{FundChar}_{i,I,t}$ is a vector of control variables, including fund return volatility (Vol), redemption notice period, leverage lockup period, personal capital commitment, fund size measured by the natural logarithm of assets under management, management fees, incentive fees, high water mark, the logarithm of minimum investment, fund age, and average FH alpha over the past one year.

Table 3 reports the estimated coefficients and their corresponding t-statistics, calculated based on clustered errors by style and time. Overall, we find strong evidence that a central position in the network is associated with a lower SDI. The estimate coefficients on all centrality measures are negative and statistically significant at the 1% confidence level or lower. Across all centrality measures, a one-standard-deviation increase in centrality corresponds to a 2% to 7% standard deviation decrease in the SDI, in the presence of a host of potential determinants of SDI. For example, the coefficients on the ANW and ENW degrees are – 2.69 and – 1.87 (t-stat: – 13.75 and – 4.64). Between the two types of relationships, the alumni network strongly influences the SDI than the employment network. A one-standard-deviation increase in the ANW degree corresponds to a decrease in the SDI of – 1.40%, while the increase in the ENW degree suggests a decrease in the SDI of – 0.45%. The results suggest that central managers under the influence of the social networks invest in a less distinct way. By contrast, when all else equal, managers located on the periphery of the networks might behave in a unique fashion.

Regarding the coefficients on the fund characteristics, we find that the SDI decreases with fund return volatility, fund size, high-water-mark dummy, minimum investment, and fund age, while it increases with the use of leverage, personal capital commitment, management and incentive fees, and past average alpha.

[Insert Table 3 Here]

4.1.2. Relation between network centrality and fund performance

In the second test, we run the regression of abnormal performance on lagged network centrality, controlling for fund characteristics and style and time fixed effects, as in Eq (4):

$$\text{AbnormalPerf}_{i,I,t+1} = \mu_{\text{I}} + \mu_{\text{t}} + \beta\text{Net}_{i,I,t} + \boldsymbol{\theta}'\mathbf{FundChar}_{i,I,t} + \epsilon_{i,I,t+1} \quad (4)$$

where $\text{AbnormalPerf}_{i,I,t+1}$ is the risk-adjusted performance of fund *i* in the style *I* in the following year, which is measured by the FH alpha, the FFCPS alpha, the appraisal ratio, and the smoothing-adjusted Sharpe ratio, respectively. Control variables include the average and standard deviation of monthly net fee returns in the preceding 24-month period (*AvgPast2YRet* and *Vol*), and redemption notice period, leverage lockup period, personal capital commitment, the logarithm of fund size, management fees, incentive fees, high water mark, the logarithm of minimum investment, and fund age.

Panel A of Table 4 reports the results with the FH alpha as the dependent variable. We find evidence that a central position in the networks predicts lower performance at the l% confidence level or lower across all centrality measures except for the ENW betweenness. For example, the estimated coefficients on the ANW and ENW degrees are – 0.53 and – 1.25 (t-stat: – 3.04 and – 3.79), implying that a one-standard-deviation increase in degree centrality predicts a decrease in the annualized alpha of – 0.28% and – 0.30% in the subsequent year. A one-standard-deviation increase in the ANW and ENW closeness predicts a decrease in the annualized alpha of – 0.23% and – 0.26%. Regarding the coefficients on the fund characteristics, we find the lengths of the redemption notice period, the high-water-mark dummy variable, management fees, and minimum investment requirement are significantly and positively associated with future fund alpha, and the fund size and age tend to predict a lower alpha.

Panels B to D of Table 4 present the results with the FFCPS alpha, the appraisal ratio, and the smoothing-adjusting Sharpe ratio as the dependent variable. For brevity, we report only the coefficients and t-statistics on the centrality measures. We also find the coefficients are negative and significant at the 10% confidence level or lower across all centrality measures, except for the ENW betweenness, across the three performance measures. Specifically, the significant results with the appraise ratio eliminate a concern that the negative relation between alpha and centrality could reflect an alternative mechanism, i.e., an eccentric manager who invests in an idiosyncratic way has a superior return by taking an excessive idiosyncratic risk. The coefficients on the ANW and ENW degree are – 3.39 and – 4.33 (t-stat: – 6.31 and – 4.52), suggesting a one-standard-deviation increase in degree centrality predicts a decrease in the appraisal ratio (FH) of – 1.76% and – 1.04%. When it comes to the smoothing-adjusting Sharpe ratio, a one-standard-deviation increase in the ANW and ENW degree predicts a decrease of – 1.20% and – 0.60% (t-stat: – 6.24 and – 3.23).

To summarize, our baseline results are consistent with the conformism hypothesis, which implies that social networks bring funds toward similar investments. We will investigate this assumption further in Section 4.2. A fund more exposed to this kind of influence tends to have a less unique strategy. When unique strategies are important for superior performance, the negative externality of social networks becomes more dominant than the information-benefit effect.

[Insert Table 4 Here]

4.1.3. Robustness

In this section, we consider three robustness tests, in which we rerun the regressions (3) and (4) with different subsamples. The first robustness check ensures that SDI heterogeneity across styles does not drive our findings. As shown in Figure A3, larger styles tend to have a lower average SDI than smaller styles. Figure 2 shows that larger styles have more connections than smaller styles, so funds in large styles tend to possess higher network centrality. In a panel regression that includes observations of all styles, our inference would be biased if this heterogeneity across styles drives a negative relation between centrality and SDI.

The style and time-fixed effects mitigate this issue to some extent. To eliminate this concern, we run regressions (3) and (4) with the subsample of each style, controlling for time fixed effect. For brevity, we report only the results using degree measures in Panel A of Table 5. The relations remain negative in most style subsamples. Particularly, in the mainstream style (Style 1), the negative effect on the SDI as well as performance remains strong and robust in both networks with t-statistics lower than – 2.00, except that the alumni network effect on alpha is negative but insignificant. The results of using closeness and betweenness are mostly consistent. For example, when using closeness, the alumni network effect on SDI and AR are – 0.63 and – 0.52 (t-stat: – 6.89 and –2.60) in the mainstream style. Therefore, our results are not driven by the heterogeneity across styles.

We investigate whether our results hold during different subsample periods in the second robustness test. During financial crisis periods, significant structural breaks are observed in the hedge fund industry; for example, returns, as well as the AUM and the number of funds, dramatically dropped during the period 2008-2010 (Bali et al., 2012; Kooli and Zhang, 2022). Liquidation of funds is one of the factors causing the HF networks' evolution. As in Figure 3, the centrality measures fluctuate more violently over the post-2008 crisis period. Therefore, we rerun regressions (3) and (4) over two subperiods: the financial crisis (1999-2002 and 2008-2010) and the non-crisis period. In Panel B of Table 5, we find that the negative network effects remain significant at 10% or lower over each of the two subperiods, except that the employment network effect on alpha is insignificant during the financial crisis period. The results suggest that structural breaks caused by the financial crisis do not impact our inference about social network effects.

In the third test, we investigate whether the observed effects from the HF networks manifest networking of managers in big cities. From Hong et al. (2005), we know that information is transferred between fund managers in a city. Big cities attract managers by offering better job opportunities and benefits from extensive information flow. It is possible that managers in big cities also possess high centrality in the HF networks since graduates from top schools and professionals at famous financial companies are very likely to work in big cities. Figure 1 shows that half of the managers in our sample are located in financial centers. To ensure our findings are still robust after controlling for the effect of networking in cities, we rerun the regressions by adding city fixed effect and using a subsample of funds whose managers are located in the U.S. financial centers. The results using degree centrality are reported in Panel C of Table 5. After controlling for the city fixed effect, the social network effects remain significantly negative at 1% or lower across both networks, and similar results when using closeness centrality. Our results are also robust to using the subsample of managers in financial centers. Thus, the observed effects from the HF networks are not a manifestation of the impact of networking in big cities documented by Hong et al. (2005).

[Insert Table 5 Here]

4.1.4. Aggregate network effect

To examine the aggregate effect of two types of relationships, we define the AGG degree as the number of both types of ties divided by the number of funds minus one. The mean and standard deviation of AGG degree is equal to 0.32% and 0.63% across 53,332 observations. We repeat the baseline analysis, with the full sample, and the robustness tests, with different subsamples using the AGG degree as the independent variable. Table A1 in Appendix C summarizes the results. Overall, we observe that the effects become larger in magnitude when summing up influences from both networks, especially for alpha and AR. A one-standard-deviation increase in AGG degree predicts a decrease of – 0.36% and – 1.92% (t-stat: – 3.78 and – 6.77), respectively.

4.2. Social connections and strategy similarity

Our conformism hypothesis is based on the herding theory that suggests social networks influence funds toward similar investments. In this section, we investigate this underlying assumption and explain the link between network centrality and the SDI. In Appendix D, we decompose the network effect on a fund's SDI into individual influences from the fund's social connections. Eq (A4) shows that the SDI of a fund is a decreasing function of the average return covariance with its cohorts. We describe the influence of social connectedness on strategy similarity between two funds in Eq (A5). The return covariance or correlation can measure strategy similarity since similar investments lead to more correlated returns. It is worth noticing that the model in (A5) allows for $b > 0$, $b < 0$, or $b = 0$. Particularly, a positive b indicates that connected funds employ more similar strategies and then have more correlated returns, which is consistent with herding theory. Replace (A5) with (A4) and take the partial derivative of the SDI with regard to connectedness with another particular fund. Eq (A6) shows the influence on the SDI from a social connectedness. When $b > 0$, it represents a decrease in the SDI. To gauge the total effect from all connections, we sum up (A6) across all cohorts of the fund in the same style, and Eq (A7) shows the total effect is a decreasing function of the degree centrality given $b > 0$.

In the following, we empirically test the relation between social connectedness and strategy similarity between two funds, i.e., the sign of b. Specifically, we use each pair of funds in the same style as the unit of analysis and run a multivariate panel regression under the pair model based on annual data. At the end of each year t, for each fund pair in style, we measure the strategy similarity between the fund pair by their return correlation as well as covariance over prior 24 months ($StratSim_{ijt}$). The social connectedness ($Connected_{ij,\,t-1}$) is a dummy variable, which is equal to 1 if the fund pair is socially connected at the end of year *t*-1, otherwise 0. We regress $\text{StratSim}_{\text{ijt}}$ on $\text{Connected}_{\text{ij, t-1}}$, controlling for location proximity of managers and similar fund features, which potentially explain their strategy similarity, and for style and time fixed effects, as in Eq (5):

$$\text{StratSim}_{\text{ijt}} = \rho_{\text{I}} + \rho_{\text{t}} + \delta\text{Connected}_{\text{ij, t-1}} + \boldsymbol{\tau}'\mathbf{Controls}_{\text{ij}} + \text{e}_{\text{ijt}} \qquad (5)$$

where δ is the coefficient of interest, measuring social influence from a connectedness on the strategy similarity after controls. **Controls** is a vector of *SameCity, SameMediaMkt, FdCharSim, AssetSim, APRSim, SecSim, GeoSim,* and *InvSim*. *SameCity* is an indicator that equals 1 if the managers of fund *i* and fund *j* are located in the same city, controlling for the networking effect in the same city (Hong et al., 2005). *SameMediaMkt* is an indicator that equals 1 if their managers are located within 50 miles of each other, controlling for a community effect from shared media markets (Pool et al., 2015).[38] *FdCharSim, AssetSim, SecSim, APRSim, GeoSim,* and *InvSim* are Jaccard coefficients, measuring the similarity in fund features, invested asset classes, investment approaches, sector focuses, geographic focuses, and investment focuses, respectively.

To calculate the Jaccard coefficients, we create for each fund (*i*) a n-dimension Boolean vector (BV_{i}) to indicate whether the fund possesses certain features. For example, a BV of fund features includes indicators for redemption notice period longer than 30 days, redemption frequency lower than monthly, minimum investment greater than $1 million, with lockup periods,

[38] The geographical distance between two managers is calculated using the manager workplace location zip code information from TASS. A U.S. zipcode can be converted into a pair of latitude and longitude (ϕ_i, λ_i). The distance (in miles) between manager *i* and manager *j* can be calculated using the Vincenty formula for distances on ellipsoids:

$$\text{distance} = 3963.19 \times \arctan\left(\frac{\sqrt{\left(\cos\phi_i \sin(\lambda_i - \lambda_j)\right)^2 + \left(\cos\phi_j \sin\phi_i - \sin\phi_j \cos\phi_i \cos(\lambda_i - \lambda_j)\right)^2}}{\sin\phi_j \sin\phi_i + \cos\phi_j \cos\phi_i \cos(\lambda_i - \lambda_j)}\right)$$

with personal capital commitment, using leverage, and setting high water mark. Moreover, each fund has a BV of 48 indicators for asset classes, 18 indicators for used investment approaches, 32 indicators for sector focuses, 16 indicators for geographic focuses, and 15 indicators for investment focuses. Using these BV, we calculate the Jaccard coefficients for each fund pair.[39] These variables range from 0 to 1. For example, *AssetSim* equal to 1 implies that two funds invest exactly in the same asset classes, and a value of 0 means investing in entirely different assets.

Table 6 reports the results of the regressions (5). We find strong evidence supporting that social networks influence funds toward similar investments. Specifically, a connectedness in the ANW increases the returns correlation between two funds by 5.15% (t-stat: 9.01) and increases their covariance by 0.75% (t-stat: 2.37), after controlling for the effect of networking in cities, influences from shared media markets, similar fund features and investment focuses, and style and time fixed effects. Connectedness in the ENW increases return correlation by 6.22% (t-stat: 4.51) and increases covariance by 0.58% (t-stat: 1.37) after controls. Regarding control variables, all coefficients are positive and statistically significant when using the correlation as the dependent variable, except for *GeoSim*. For example, consistent with Hong et al. (2005) and Pool et al. (2015), we find evidence that managers in the same city or media market tend to have more similar investments. Moreover, fund features information based on self-reporting by funds seems to explain the similarity in their employed strategies. For example, our result shows that when two funds report employing exactly the same approaches, their return correlation increases by 12.88%, compared with two funds that report using entirely different approaches. When two funds report

[39] The Jaccard similarity is defined as the size of the intersection divided by the size of the union. The value can be interpreted as a percentage of shared features between two data sets.

$$\text{Jaccard}\left(\text{BV}_\text{i}, \text{BV}_\text{j}\right) \equiv \frac{|\text{Intersection}\left(\text{BV}_\text{i}, \text{BV}_\text{j}\right)|}{|\text{Union}\left(\text{BV}_\text{i}, \text{BV}_\text{j}\right)|}$$

investing in exactly the same asset classes, their correlation increases by 6.75%, compared with two funds investing in entirely different asset classes.

[Insert Table 6 Here]

4.3. Manager talent, career establishment, and social network effects

Smart and less established managers are more likely to pursue unique strategies because of their skills and ambitions. In this section, we investigate heterogenous social network effects among managers with different characteristics (i.e., smartness and career establishment). Li et al. (2011) find hedge fund managers from higher SAT (Scholastic Aptitude Test) colleges perform better than managers from lower SAT, suggesting that better-educated managers are more skilled. They also find more experienced managers exhibit lower performance, suggesting that established managers are less motivated to work hard and reluctant to take investment opportunities that could risk their careers. Similarly, we measure the smartness of a manager by the average SAT of the college/university he attended and his career establishment by the length of work experience. We collected SAT scores of the U.S. colleges/universities from College Simple and PrepScholar.[40] The SAT scores in our sample range from the lowest of 900 to the highest of 1555, with a mean/median of around 1293/1295. WORK is defined as the number of years of work experience at financial service companies, using the employment information of managers collected from LinkedIn. Financial work experience is more relevant for measuring the degree of professional career establishment. The mean and median of WORK are 14.70 and 14.04 years, respectively; the shortest is 0 years, and the longest is 45.95 years.

[40] From College Simple, we collect a list of the 1066 colleges in the U.S. with the highest SAT Score for freshmen, at https://www.collegesimply.com/colleges/rank/colleges/highest-sat-scores/. We also search SAT scores from PrepScholar, an online SAT instructor. Both sources generate very similar results.

To examine heterogeneous effects, we apply regressions (3) and (4) to two subsamples with SAT or WORK above and below the sample median. In Panel A of Table 7, we report the results using the ANW degree centrality. With the subsample SAT >= 1295, we find the effect on the SDI is negative at a larger magnitude, with a coefficient of – 4.34 (t-stat: – 17.98). A one-standard-deviation increase in the ANW degree (0.675%) corresponds to a decrease in the SDI of – 2.93%. With the subsample SAT < 1295, we find the coefficient becomes less significant statistically and economically. A one-standard-deviation increase in degree (0.23%) suggests a decrease in the SDI of – 0.66% (t-stat: – 1.83). Similarly, we find the effect on alpha is also more negative with the subsample SAT >= 1295. A one-standard-deviation increase in degree predicts a decrease in the annual alpha of – 0.39% (t-stat: – 2.58), whereas the effect becomes statistically insignificant with the subsample SAT < 1295. In results not reported, our findings remain similar when using the closeness or betweenness centrality.

Panel B of Table 5 reports the results with the subsample WORK >=14 and WORK <14, where the degree centrality is calculated in the employment network. We find that the negative network effect is more significant in magnitude among managers with less experience. Among managers with financial work experience of less than 14 years, a one-standard-deviation increase in degree (0.21%) corresponds to a decrease in the SDI of – 1.16% (t-stat: – 5.70) and a decrease in alpha of – 0.44% (t-stat: – 2.93). Among more established managers, a one-standard-deviation increase in degree (0.37%) corresponds to a decrease in the SDI of – 0.40% (t-stat: – 2.21) and a decrease in alpha of – 0.17% (t-stat: – 1.33). To summarize, results suggest that smart managers with career ambition, who are more likely to pursue unique strategies, are more vulnerable to the negative effect of social networks.

[Insert Table 7 Here]

4.4. Style shifting and social ties

In this section, we examine another important aspect of social influences – how the HF networks affect funds' investment styles. Previously, we show that social networks increase strategy similarity between funds, but do they also increase the probability that two funds will invest in the same style in the future? Our time-varying style grouping allows us to examine the style-shifting of funds from year to year. Using the pair model, we define a dummy variable for each fund pair in the same style, $\text{StyleShift}_{ij,\,t+1}$, which is equal to 1 if the fund *i* and *j* s still belong to the same style in the next year and 0 if they switch to different styles. On average, about 30% of fund pairs in our sample remain in the same style for the next year. Mainstream funds are more likely to stay mainstream; 43.5% of fund pairs remain in the next year. We estimate the following logistic model with the same controls as used in Eq (5), where Pr (·) means probability:

$$\Pr\left(\text{StyleShift}_{ij,\,t+1}\right) = \Pr\left(\rho_I + \rho_t + \delta \text{Connected}_{ijt} + \boldsymbol{\tau}'\textbf{Controls}_{ij} + e_{ijt} > 0\right) \quad (6)$$

Table 8 reports the results with the full sample and a subsample of fund pairs in the mainstream style. We find that an alum tie increases (decreases) the probability of two funds remaining in the same style (switching to different styles) in the next year. With the full sample, an alum connectedness would increase the probability of remaining in the same style by about 3% (t-stat: 2.36). For mainstream funds, the connectedness would increase the probability of remaining in the mainstream by about 6% (t-stat: 2.68). However, we do not find evidence that employment ties impact the style-shifting of hedge funds. Regarding control variables, we find that funds whose managers are in the same city and have similar asset classes, sector focuses, and investment approaches are more likely to remain in the same style.

[Insert Table 8 Here]

4.5. Social influence and hedging

Under a rational model, a hedge fund manager optimizes his portfolio allocation between an indexed investment and a proprietary strategy. Managers possessing profitable proprietary strategies tend to have lower indexed allocations and, thus a lower R2 of returns against risk factors (Titman and Tiu, 2011). The purpose of this section is to examine how HF social networks influence a fund's exposure to systematic risk.

As previously shown, herding leads to a less profitable proprietary strategy. Under the rational expectation, a herding manager would tilt toward indexed investments. Therefore, due to herding, similar and indexed investments are two sides of the same coin. A central manager would have higher exposure to systematic risk. To investigate this relation, we run the regression (7) using the quarterly panel data:

$$R2_{i,I,t} = c_I + c_t + \theta Net_{i,I,t} + \boldsymbol{\vartheta}'\mathbf{FundChar}_{i,I,t} + NL\_FAC_{i,I,t} + Kurt_{i,I,t} + \epsilon_{i,I,t} \quad (7)$$

where $R2_{i,I,t}$ is the R2 (FH) of fund *i* at the end of quarter *t*. $\mathbf{FundChar}_{i,I,t}$ is the vector of control variables as used in Eq (3). In addition, we add two variables, the importance of nonlinear factors (NL_FAC) and the kurtosis of the residuals (Kurt) from Eq (1). NL_FAC is equal to the sum of absolute betas on three PTFS nonlinear factors divided by the sum of absolute betas across all seven factors. Funds being more exposed to nonlinear factors tend to have a smaller R2 (Ingersoll et al., 2007), and "fat" tails in fund returns also lead to a smaller R2 (Titman and Tiu, 2011).

Table 9 reports the results of the regression (7) using the degree centrality measure. We find strong evidence that a central network position is associated with a higher R2. All of the coefficients on the centrality measures, including untabulated results with closeness and betweenness, are consistently positive and significant at the 1% confidence level or lower. For example, a one-standard-deviation increase in the ANW and ENW degree corresponds to an increase of 0.89% and 0.50% (t-stat: 6.96 and 5.15) in a fund's R2 after controls. The results show that central funds more exposed to social influences are also more exposed to systematic risk.

The R2 increases with fund return volatility, fund size, high-water-mark dummy, minimum investment, and fund age, while it decreases with leverage, personal capital commitment, management and incentive fees, and past average alpha. We also find that funds with higher importance of nonlinear factors and kurtosis of the return residuals have a lower R2, consistent with the prediction of Ingersoll et al. (2007) and Titman and Tiu (2011).

[Insert Table 9 Here]

5. Conclusion

Academic research has focused on the beneficial influence of social networks in fund management. In this paper, we explore a mechanism that explains how social networks could be detrimental to fund performance due to competition. Social networks can facilitate investment herding among fund managers. This behavior deters the development of unique strategies and thus harms performance when unique investments are important for success in competition. We find strong and robust evidence supporting this point of view. Using a sample of hedge funds over the period 1994-2018, we examine two types of social ties (alumni and employment) between the closest competitors investing in the same style. We find that a central manager in social networks tends to have a less unique strategy and lower abnormal performance. We also find that managers connected by a social tie tend to have more correlated returns, supporting that investment herding is encouraged under social influences. This kind of influence also increases the probability that managers will invest in the same style in the future. A plausible explanation for herding can be due to reputation concerns for managers, which deserves further examination. Furthermore, our results show that smart and less established managers are more vulnerable to the negative effect of social influence. Central managers also tend to choose more exposure to systematic risk due to a declined return in their proprietary strategy.

Appendix A: Optimal number of hedge fund styles

The number of clusters (styles) K is a prespecified parameter in a K-mean clustering program. Tuning this parameter is crucial to guarantee the quality of classifications. In the previous studies, for example, Brown and Goetzmann (2003) consider an adjusted R^2 as a performance measure for comparing five style classification ($K = 5$) to eight styles ($K = 8$). The adjusted R^2, which is obtained from the regression of fund returns on styles classifications, measures the extent to which the classifications explain cross-sectional variability in future returns. They find five style classifications have a lower fitness than eight styles, with a TASS hedge fund sample between 1989-1999. The study of Sun et al. (2012) fixed the style number at $K = 10$, which is the same number of TASS styles. Given potential changes over time in the TASS hedge fund sample and the importance of the optimal K in our study, we revisit the subject and evaluate comparative performance of five style classifications and ten styles, i.e., $K = 5$ and $K = 10$. In addition to the adjusted R^2, we also consider an alternative performance measure, the silhouette value. We describe the calculations of two performance measures as below.

To implement the adjusted R^2 measure, at the end of each quarter between 1996-2018, we classify funds into five (or ten) styles using the prior two-year fund returns, and then regress the third year returns of each fund (R_{it}) on their corresponding style return (μ_{It}). These procedures allow us to have a time-series of the adjusted R^2 measure. We plot the time-series for $K = 5$ and for $K = 10$ in Panel A of Figure A1. The second measure is the silhouette value (Rousseeuw, 1987). The silhouette criterion is one of the most prominent methods to find the optimal number in a K-mean clustering program. This criterion measures how close a member to its own cluster compared to other clusters. In our style clustering program, the silhouette value can be interpreted as a measure of how similar a fund's strategy to its own style compared to other styles. The silhouette value is defined as Eq (A1):

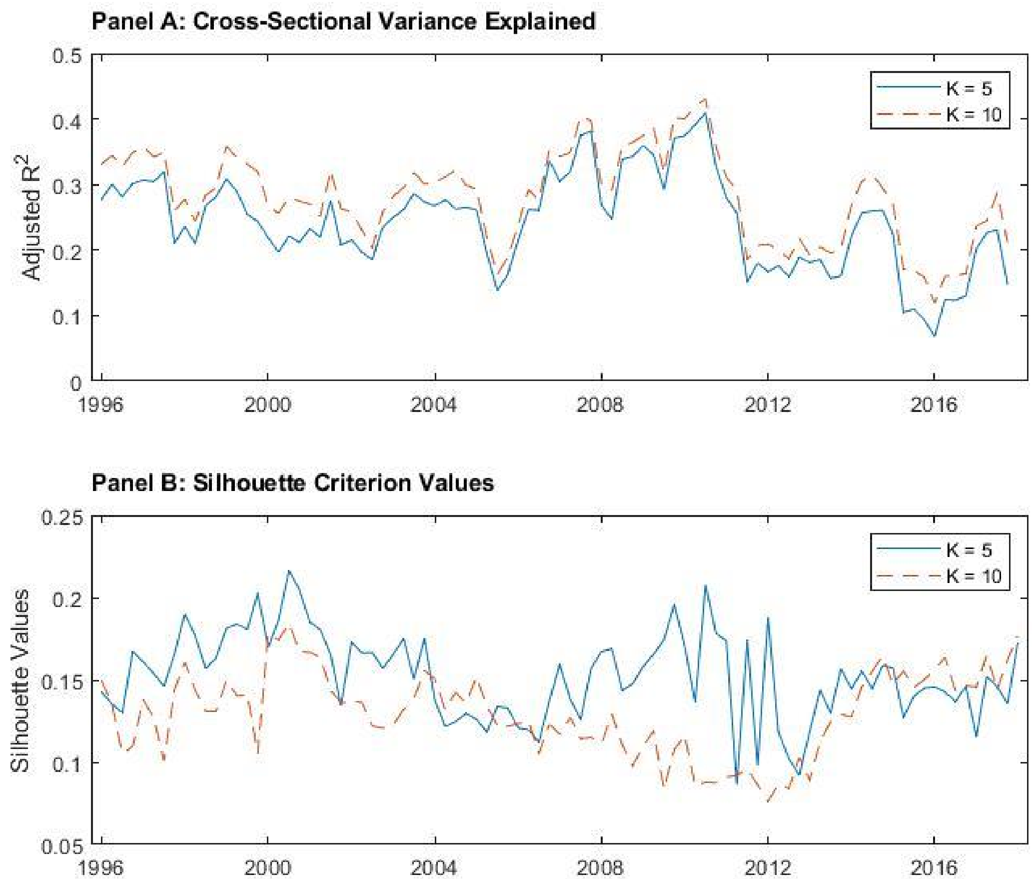
$$S(i)=\frac{a(i)-b(i)}{\max(a(i),\, b(i))} \qquad \text{(A1)}$$

where a(i) is the average distance between fund i and all other funds of the same cluster, b(i) is the minimum of the average distances between fund i and all the funds in each other cluster. S(i) measures how well fund i matches its style. For example, when S(i) is negative, i.e., a(i) is much larger than b(i), we can conclude fund i has been misclassified. After implementing the clustering program of each quarter, we calculate the silhouette value for each fund and take an average of the values across funds. This also generates a time-series of average silhouette value over the period 1996-2018. We plot the time-series in Panel B of Figure A1.

In Panel A, we observe a minor gap between the adjusted R^2 of five style and ten style classifications. On average, five style clusters explain 24.39% of the cross-sectional variability of subsequent returns, which is comparable to the fitness of ten styles (28.11%). It is worthy noticing the adjusted R^2 is strictly increasing with K. For example, in the extreme case K = the number of funds, the fitness would increase to 100%. Comparing with the results of Brown and Goetzmann (2003), who find the fitness of five styles is averagely at 13.28%, we find the fitness of five styles has substantially improved in a sample with more recent observations. In Panel B, we observe that the silhouette values of five styles are above those of ten styles in most of years, indicating a better quality of five style classifications than ten styles. Based on the results of both analyses, we conclude that five style classifications are sufficient for explaining cross-sectional return variations in our hedge fund sample. In our study, we cluster hedge funds into five styles.

Figure A1

The figure compares the performance of clustering with five styles (K = 5) and ten styles (K = 10) based on two performance measures, adjusted $R^{2,}$ and silhouette value. At the end of each quarter between 1996-2018, the hedge fund style clusters are defined by K-mean clustering programs using the prior 24-month fund returns. These procedures allow us to calculate a time-series of each measure. Panel A plots the time-series of adjusted R^2 from the regression of a fund's returns on its style returns over the year following the quarter the clustering is implemented. Panel B plots the time-series of the average silhouette value across all funds in a quarter. The silhouette value is defined by Eq (A1).



Appendix B: Properties of hedge fund styles and the SDI

Figure A2 Cross-sectional distribution of the SDI

The histogram plots the percentage of funds with the time-series average SDI at different values. The SDI of each fund at each quarter is calculated over the prior 24 months based on the five style clusters by Eq (2). We calculate the time-series average SDI for each fund over its lifetime period.

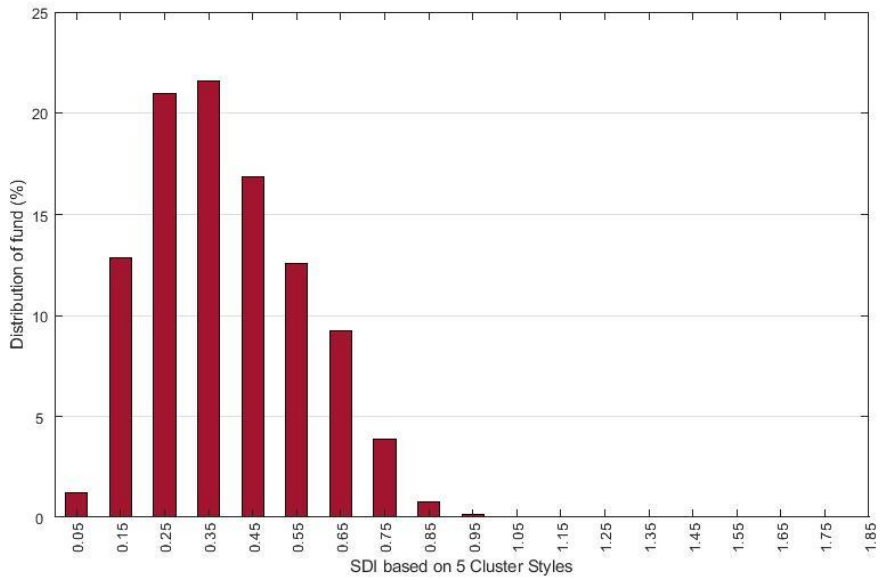
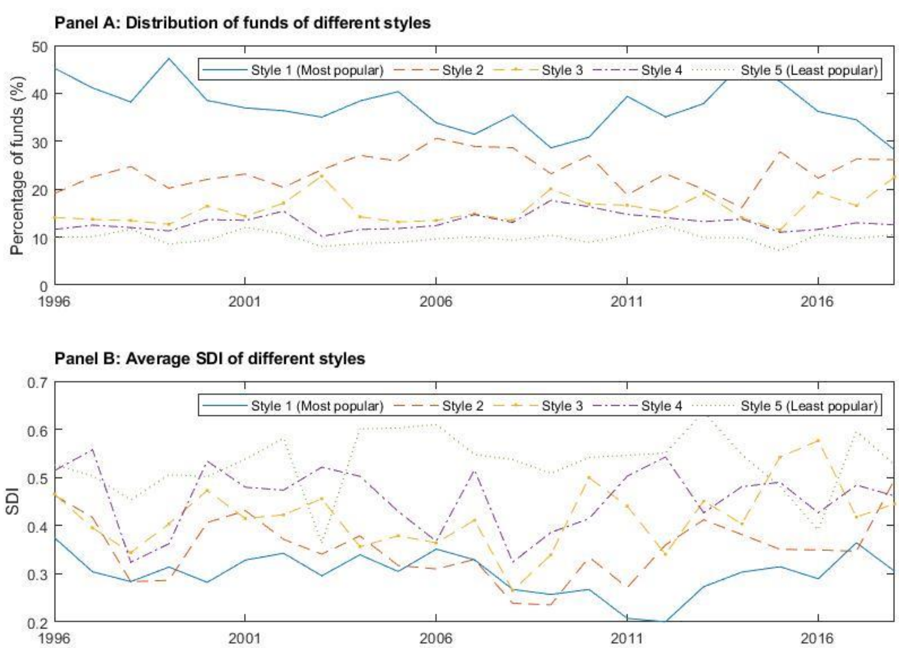


Figure A3 SDI and style popularity

Panel A illustrates the percentage of funds in five styles over 1996-2018. Style 1 to Style 5 denote styles ordered by their popularity, which is measured by the number of funds as members. Style 1, also called the mainstream style, has the largest number of funds as members, and Style 5 has the smallest number. Panel B plots the cross-sectional average SDI of each style over time.



Appendix C: Aggregate network effect

Table A1

The table reports the baseline results, with the full sample and the robustness tests, with different subsamples, in which the independent variable is the degree centrality measure calculated in the aggregate network. For brevity, we report only the coefficients and the corresponding t-statistics on the AGG degree centrality. The aggregate (AGG) network includes both alumni and employment ties. The AGG degree of a fund is then equal to the number of both types of ties divided by the total number of funds in the AGG network minus one.

DepVar:	SDI		Alpha (FH)		AR (FH)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Full sample	-2.18	-13.08	-0.57	-3.78	-3.05	-6.77
Subsamples:						
Financial crisis	-2.29	-7.92	-0.60	-1.92	-2.66	-3.16
Noncrisis	-2.06	-10.18	-0.54	-3.27	-3.26	-6.18
Financial centers	-1.81	-8.42	-1.19	-6.48	-5.16	-8.36
Style 1	-1.32	-8.07	-0.20	-1.40	-1.66	-4.57
Style 2	0.04	0.16	-0.56	-2.27	-3.47	-5.38
Style 3	-1.22	-2.23	-2.14	-4.93	-8.07	-6.32
Style 4	-0.51	-0.63	-1.32	-2.59	-5.01	-2.68
Style 5	-3.51	-3.22	1.70	1.55	2.98	0.89

Appendix D: Decomposition of the network effect on SDI

To explain the link between network centrality and the SDI, we decompose the total network effect into individual influences from the fund's connections. We start the analysis from the formula of SDI of fund *i*, which belongs to style *I*:

$$\mathrm{SDI}_i = 1 - \mathrm{corr}\,(\mathrm{R_i}, \mu_\mathrm{I}) = 1 - \frac{\mathrm{cov}\,(\mathrm{R_i}, \mu_\mathrm{I})}{\sigma_\mathrm{i}\sigma_\mathrm{I}} \tag{A2}$$

with:

$$\begin{aligned}\mathrm{cov}\,(\mathrm{R_i}, \mu_\mathrm{I}) &= \mathrm{cov}\,(\mathrm{R_i}, \frac{1}{N_\mathrm{I}}\sum_{\mathrm{j \in I}} \mathrm{R_j}) \\ &= \mathrm{cov}\,(\mathrm{R_i}, \mathrm{R_i} + \frac{1}{N_\mathrm{I} - 1}\sum_{\mathrm{j \in I, j \neq i}} \mathrm{R_j}) \\ &= \mathrm{cov}\,(\mathrm{R_i}, \mathrm{R_i}) + \frac{1}{N_\mathrm{I} - 1}\sum_{\mathrm{j \in I, j \neq i}} \mathrm{cov}\,(\mathrm{R_i}, \mathrm{R_j}) \\ &= \sigma_\mathrm{i}^2 + \frac{1}{N_\mathrm{I} - 1}\sum_{\mathrm{j \in I, j \neq i}} \sigma_\mathrm{ij}\end{aligned} \tag{A3}$$

where σ_i and σ_I denote the standard deviation of $\mathrm{R_i}$ and μ_I, $\sigma_\mathrm{ij} \equiv \mathrm{cov}\,(\mathrm{R_i}, \mathrm{R_j})$, $N_\mathrm{I} = \mathrm{count}\,(i \in I)$, the total number of funds in Style *I*. Replacing (A3) into (A2), we have:

$$\mathrm{SDI}_i = 1 - \frac{\sigma_\mathrm{i}}{\sigma_\mathrm{I}} - \frac{1}{\sigma_\mathrm{i}\sigma_\mathrm{I}(N_\mathrm{I} - 1)}\sum_{\mathrm{j \in I, j \neq i}} \sigma_\mathrm{ij} \tag{A4}$$

The SDI of fund *i* is a function of the average covariance with its cohorts, $\sum_{\mathrm{j \in I, j \neq i}} \sigma_\mathrm{ij}/(N_\mathrm{I}-1)$.

Now, we describe the influence from the social connectedness between fund *i* and fund *j* on their strategy similarity by Eq (A5):

$$\sigma_{ij} = a + b\text{Conn}_{ij} \tag{A5}$$

where Conn_{ij} is a dummy variable denoting a social connectedness between fund *i* and fund *j*, which is equal to 1 if their managers are socially connected, otherwise 0; the coefficient *b* denotes the social influence from the connectedness on the strategy similarity, which is measured by the return covariance; the coefficient *a* denotes the covariance in the absence of social influence. The model in Eq (A5) allows for $b > 0$, $b < 0$, or $b = 0$. Particularly, a positive *b* implies that connected funds employ more similar strategies and then have more correlated returns.

The effect of a social connectedness between fund *i* and fund *j* (Conn_{ij}=1) on the strategy distinctiveness of fund *i* (SDI_i) can be measured by the partial derivative of SDI_i with respect to Conn_{ij}. Replacing (A5) into (A4) and taking the partial derivative, we have:

$$\frac{\partial \text{SDI}_i}{\partial \text{Conn}_{ij}} = -\frac{b}{\sigma_i \sigma_I (N_I - 1)} \tag{A6}$$

To gauge the network effect on fund *i*'s SDI, we sum up the individual social influence, $\partial\text{SDI}_i/\partial\text{Conn}_{ij}$, across all connections of the fund. Then, we have the network effect on SDI is a decreasing function of the fund's network centrality when *b* is positive, as in Eq (A7):

$$\sum_{j\epsilon I, j\neq i} \frac{\partial \text{SDI}_i}{\partial \text{Conn}_{ij}} = -\frac{b}{\sigma_i \sigma_I (N_I - 1)} \sum_{j\epsilon I, j\neq i} \text{Conn}_{ij} = -\frac{b}{\sigma_i \sigma_I} \text{Degree}_i \tag{A7}$$

with: $$\text{Degree}_i \equiv \frac{\sum_{j\epsilon I, j\neq i} \text{Conn}_{ij}}{N_I - 1}$$

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Figure 1: Geographical distribution of hedge fund managers

The figure displays the geographical distribution of hedge fund managers in our sample. We cluster managers with the same zip code into a circle, whose size indicates the number of managers. The total number of managers is equal to 1712, and 862 managers are located in the U.S financial centers (New York City, Boston, Chicago, Los Angeles, Philadelphia, and San Francisco).

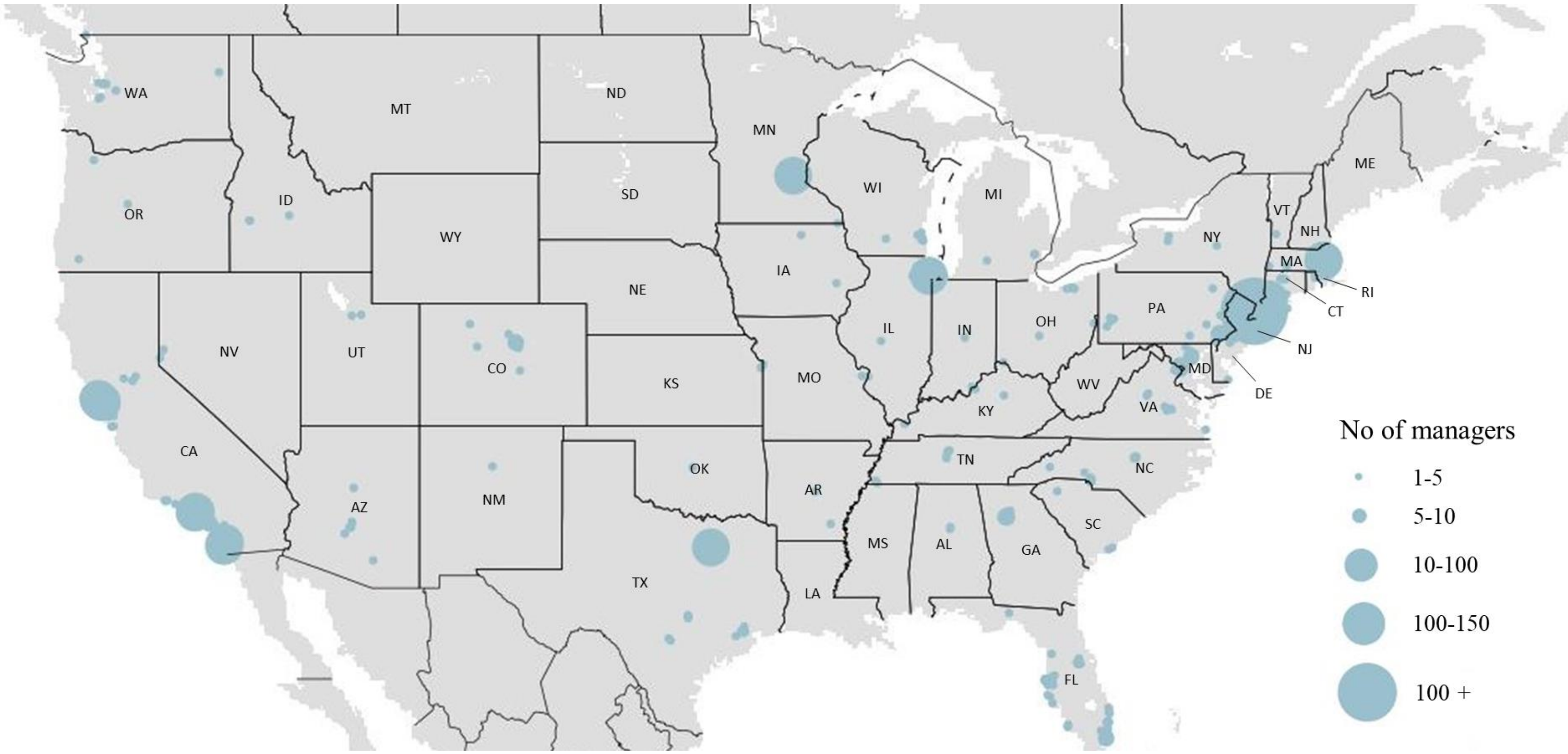

Figure 2: HF Networks as of December 2007

The figure displays a snapshot of the HF networks at the end of the year 2007. The size of a node indicates its level of degree centrality. The color of a node denotes the style the fund belongs to. The color of the edge denotes the type of social ties: a lighter line for the employment ties and a darker line for the alumni ties.

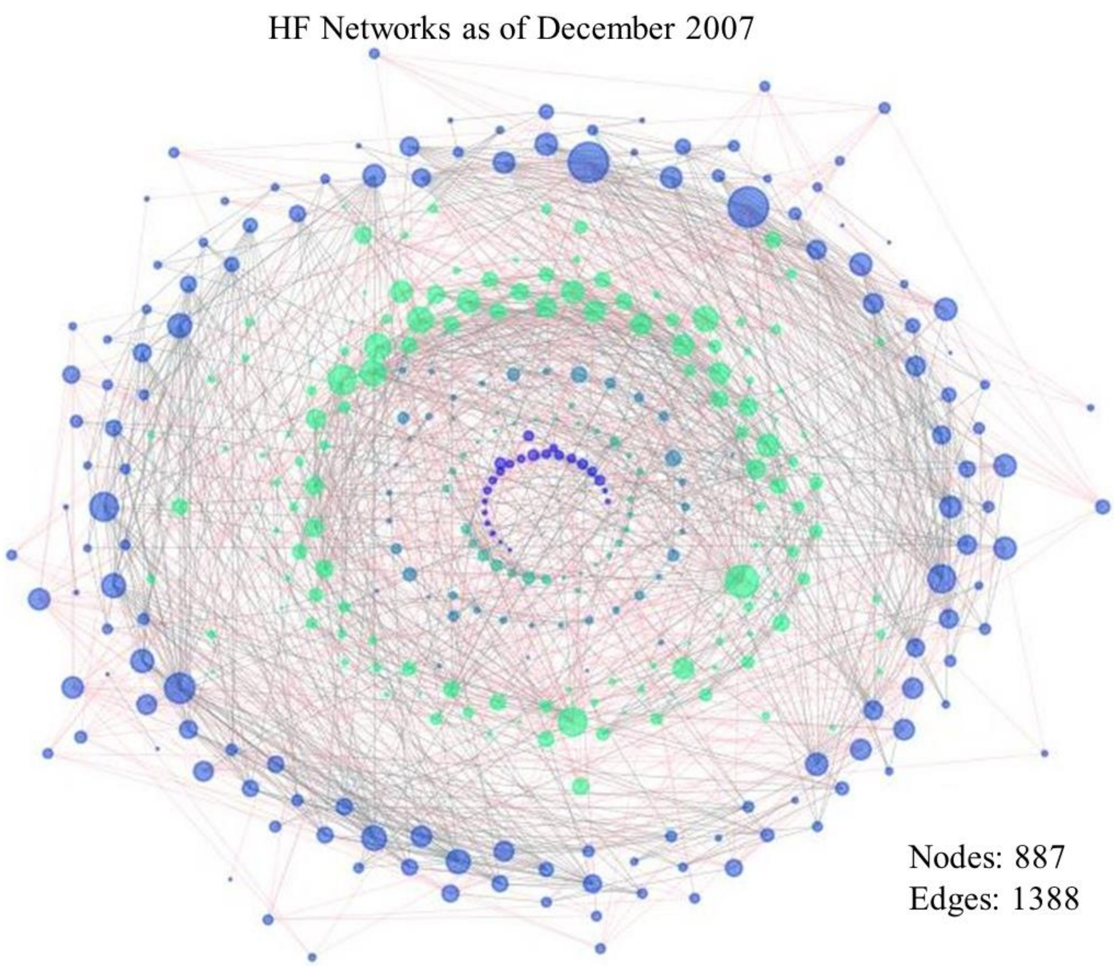

Figure 3: Evolution of HF network centrality

The figure displays the evolution of standardized centrality measures and SDI over the period 1996-2018. We first calculate the cross-sectional mean of each measure at a given time ($Net_t = N_t^{-1} \sum_{i=1}^{N_t} Net_{it}$), and then standardize the time-series of Net_t. The standardized variables have a zero mean and a unit variance.

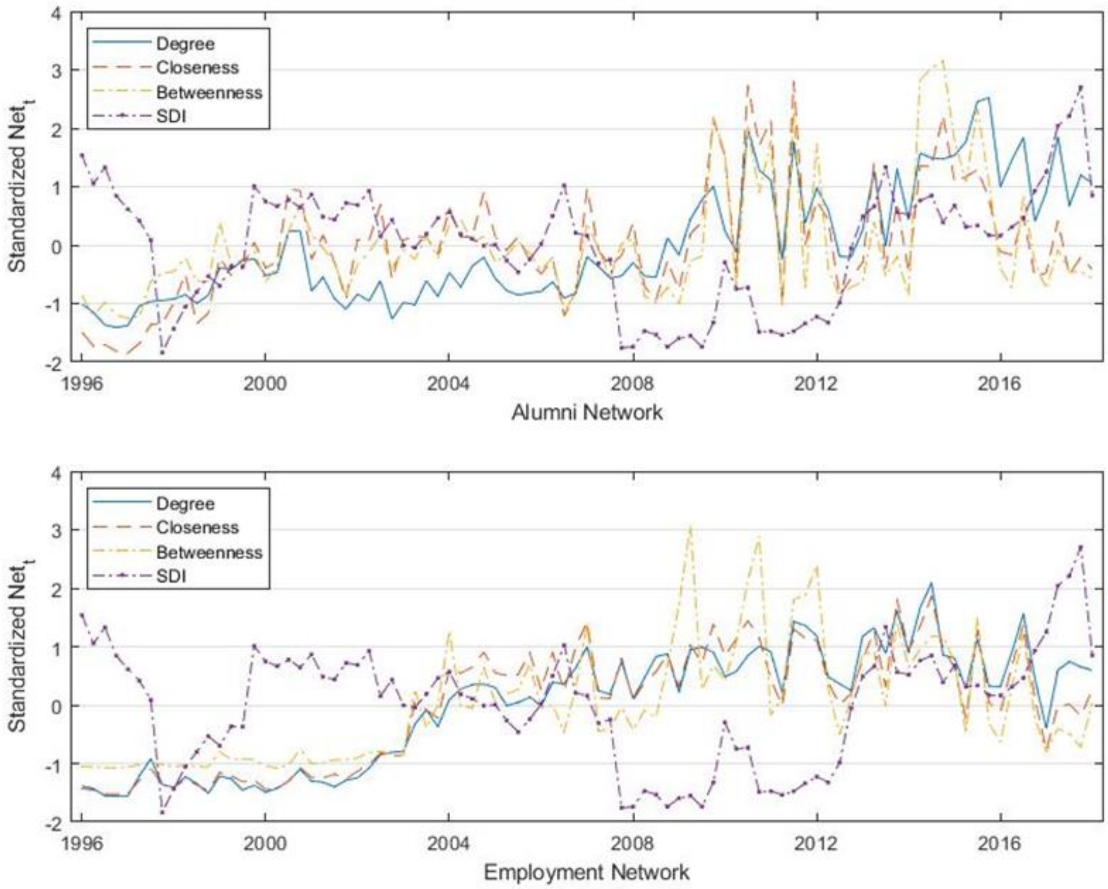

Table 1 Top ten schools and employers of hedge fund managers

Panel A and Panel B display the top ten schools and employers of hedge fund managers, respectively. The second column of Panel A presents the number of alumni of the school in our sample, while that of Panel B presents the number of managers having work experience at the company. The third column presents the number of funds managed by these managers.

Panel A Top ten schools of hedge fund managers

		No Mgr.	No Fund
1	Wharton School, University of Pennsylvania	70	124
2	New York University - Leonard N. Stern School of Business	51	82
3	The University of Chicago - Booth School of Business	50	68
4	Harvard Business School	46	93
5	Columbia Business School	42	65
6	Harvard University (Excluding Harvard Business School)	29	53
7	Yale University	28	51
8	University of Pennsylvania (Excluding Wharton School)	25	40
9	Princeton University	24	45
10	Massachusetts Institute of Technology	23	35
	Total	388	656

Panel B Top ten employers of hedge fund managers

		No Mgr.	No Fund
1	Morgan Stanley	46	68
2	Merrill Lynch	44	72
3	Goldman Sachs	43	67
4	JP Morgan	42	68
5	Lehman Brothers	39	65
6	Bear Stearns	33	67
7	UBS	30	49
8	Salomon Brothers	25	46
9	Citigroup	24	32
10	Credit Suisse	24	44
	Total	350	578

Table 2 Summary statistics

Panel A reports the summary statistics of the main variables, fund performance, the SDI, and the centrality measures. We estimate monthly alphas under the FH seven-factor model and the FFCPS five-factor model by Eq (1). At the end of each quarter, we annualized alphas by compounding monthly alphas over the following one year. Also, the appraisal ratio (AR) and the smoothing-adjusted Sharpe ratio (SR) are calculated over the 12-month rolling periods. The SDI is calculated over the previous 24 months and measured as 1 minus correlation between the fund' return and the return of its corresponding style cluster. Network centrality is measured in three dimensions and in the Alumni Network (ANW) and Employment Network (ENW), respectively. Degree is equal to the number of connections of a manager in the network divided by the total number of managers minus one. Closeness is the inverse of the average distance between the manager and all the other managers in the network. Betweenness is the average proportion of the shortest paths between other managers in the network that pass through the manager. Panel B reports the correlation matrix between the main variables. Panel C summarized statistical properties of the control variables. *Vol* is the standard deviation of net-fee returns over the prior 24 months. R2(FH) denotes the R-squared obtained from the 24-month rolling window regressions of Eq (1) with the FH model. RedempNotice is the redemption notice period in days. Lockup is the lockup period in months. PersonalCapital is an indicator for personal capital commitment. HWM is an indicator if the fund sets high water mark provision. MGMT_FEE and INC_FEE are management and incentive fees. MIN_INV is the required minimum investment. Leverage is an indication if the fund uses leverage.

Panel A Main variables

	Mean	Std	Min	Max	Obs
Alpha (FH%p.a.)	3.19	15.13	-37.09	57.83	44,575
Alpha (FFCPS%p.a.)	2.87	13.60	-33.16	51.54	44,575
AR (FH)	0.15	0.44	-0.79	1.64	44,575
SR	0.21	0.39	-0.63	1.49	44,575
SDI	0.37	0.21	0.01	1.21	53,332
Alumni network:					
Degree (%)	0.24	0.52	0.00	4.78	53,332
Closeness (%)	0.51	1.08	0.00	7.37	53,332
Betweenness (%)	0.0047	0.03	0.00	0.99	53,332
Employment network:					
Degree (%)	0.08	0.25	0.00	3.83	53,332
Closeness (%)	0.15	0.44	0.00	4.37	53,332
Betweenness (%)	0.0008	0.01	0.00	0.29	53,332

Panel B Correlation matrix of main variables

	(FH) Alpha	(FFCPS) Alpha	AR	SR	SDI	ANW Deg.	ANW Close.	ANW Btw.	ENW Deg.	ENW Close.	ENW Btw.
Alpha (FH)	1.00										
Alpha (FFCPS)	0.76	1.00									
AR (FH)	0.71	0.58	1.00								
SR	0.55	0.56	0.83	1.00							
SDI	0.12	0.13	0.23	0.13	1.00						
Alumni network:											
Degree	-0.05	-0.05	-0.10	-0.07	-0.15	1.00					
Closeness	-0.04	-0.04	-0.12	-0.07	-0.18	0.91	1.00				
Betweenness	-0.04	-0.05	-0.08	-0.03	-0.11	0.65	0.61	1.00			
Employment network:											
Degree	-0.03	-0.03	-0.03	-0.03	-0.04	0.29	0.28	0.25	1.00		
Closeness	-0.01	-0.02	-0.02	-0.02	-0.05	0.31	0.32	0.27	0.95	1.00	
Betweenness	-0.02	-0.02	-0.02	0.00	-0.05	0.18	0.18	0.16	0.71	0.65	1.00

Panel C Control variables

	Mean	Std	Min	Max	Obs
NetFeeReturn (%p.a.)	8.61	18.99	-69.55	214.41	44,575
Vol (%p.m.)	3.32	2.32	0.00	13.31	44,575
R2(FH)	0.54	0.21	0.02	0.99	44,575
AUM($M)	258.78	1028.66	0	38700	42,129
Age(years)	8.46	4.78	2	33	44,575
Redemp_Notice (days)	42.65	29.39	0	365	2,711
Lockup (months)	5.51	7.86	0	84	2,711
PersonalCapital	0.43	0.50	0	1	2,711
HWM	0.73	0.44	0	1	2,711
MGMT_FEE (%)	1.35	0.49	0	4	2,710
INC_FEE (%)	18.84	4.94	0	50	2,705
MIN_INV ($M)	1.58	19.37	0	1000	2,705
Leverage	0.64	0.48	0	1	2,711

Table 3 SDI and network centrality

The table reports the panel regressions of hedge fund SDI on network centrality, controlling for hedge fund characteristics and style and time fixed effects, as in Eq (3). *Net* represents one of centrality measures among degree, closeness, and betweenness in the Alumni (ANW) or Employment (ENW) network. Volatility of net fee returns (Vol) are measured over a window of 24 months. PastAvgAlpha is the average FH alpha over the past year. Other characteristics include the lengths of the redemption notice and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, minimum investment, and an indicator variable for leverage. The coefficients are multiplied by 100. The t-statistics are calculated based on clustered errors by style and time.

	ANW						ENW					
	Degree		Closeness		Betweenness		Degree		Closeness		Betweenness	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Net (%)	-2.69	-13.75	-1.18	-9.47	-10.54	-4.21	-1.87	-4.64	-1.28	-5.21	-54.22	-3.63
Vol (%p.m.)	-2.31	-23.73	-2.31	-23.71	-2.31	-23.60	-2.31	-23.63	-2.31	-23.64	-2.31	-23.63
Redemp_Notice (30 days)	-0.01	-0.07	-0.01	-0.09	-0.03	-0.23	-0.05	-0.37	-0.04	-0.36	-0.05	-0.37
Leverage	1.84	8.12	1.88	8.30	2.01	8.83	2.01	8.83	2.00	8.76	2.01	8.82
Lockup (months)	0.00	-0.3	-0.01	-0.45	-0.01	-0.64	-0.01	-0.54	-0.01	-0.41	-0.01	-0.65
PersonalCapital	0.84	3.69	0.79	3.49	0.65	2.85	0.70	3.06	0.71	3.12	0.64	2.77
ln(AUM)	-1.35	-17.86	-1.34	-17.77	-1.32	-17.53	-1.33	-17.74	-1.33	-17.72	-1.33	-17.74
MGMT_FEE (%)	2.57	9.29	2.53	9.16	2.50	9.05	2.56	9.3	2.56	9.31	2.52	9.15
INC_FEE (%)	0.29	10.71	0.29	10.75	0.29	10.79	0.29	10.93	0.29	10.90	0.29	10.93
HWM	-1.81	-6.86	-1.76	-6.63	-1.85	-6.94	-1.81	-6.77	-1.81	-6.77	-1.83	-6.87
ln(MIN_INV)	-0.66	-5.83	-0.66	-5.89	-0.67	-5.96	-0.69	-6.09	-0.69	-6.16	-0.67	-5.94
Age(years)	-0.48	-20.22	-0.48	-20.17	-0.48	-20.07	-0.49	-20.45	-0.49	-20.63	-0.48	-20.07
PastAvgAlpha(%p.m.)	0.95	7.2	0.95	7.20	0.96	7.26	0.96	7.24	0.96	7.26	0.96	7.28
AdjR2	0.20		0.20		0.19		0.19		0.19		0.19	
Obs	41,702		41,702		41,702		41,702		41,702		41,702	

Table 4 Hedge fund performance and network centrality

The table reports the panel regressions of hedge fund abnormal performance on one-year lagged network centrality, controlling for hedge fund characteristics and style and time fixed effects, as in Eq (4). Panel A reports the results with the FH alpha as the dependent variable. *Net* represents one of centrality measures among degree, closeness, and betweenness in the Alumni (ANW) or Employment (ENW) network, respectively. AvgPast2YRet and Vol are the average and the standard deviation of net-fee-returns measured over the preceding 24 months. Other characteristics include the lengths of the redemption notice and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, minimum investment, and an indicator variable for leverage. Panel B to D report the results with alternative performance measures, the FFCPS alpha, the appraisal ratio, and the smoothing-adjusted Sharpe ratio, as the dependent variable, respectively. For brevity, we report only the coefficients on centrality measures and the corresponding t-statistics. The t-statistics are calculated based on clustered errors by style and time.

Panel A Dependent variable: FH alpha

	ANW						ENW					
	Degree		Closeness		Betweenness		Degree		Closeness		Betweenness	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Net (%)	-0.53	-3.04	-0.23	-2.55	-6.18	-2.56	-1.25	-3.79	-0.60	-2.88	-8.09	-0.93
Vol (%p.m.)	-0.14	-1.3	-0.14	-1.29	-0.14	-1.28	-0.14	-1.32	-0.14	-1.32	-0.14	-1.29
Redemp_Notice (30 days)	0.85	8.22	0.85	8.24	0.85	8.22	0.84	8.14	0.84	8.15	0.85	8.18
Leverage	0.32	1.65	0.33	1.69	0.35	1.80	0.35	1.79	0.35	1.77	0.35	1.81
Lockup (months)	0.02	1.75	0.02	1.72	0.02	1.69	0.02	1.77	0.02	1.81	0.02	1.68
PersonalCapital	-0.08	-0.48	-0.09	-0.54	-0.10	-0.64	-0.07	-0.44	-0.08	-0.49	-0.12	-0.72
ln(AUM)	-0.13	-2.09	-0.13	-2.07	-0.12	-2.00	-0.13	-2.04	-0.13	-2.02	-0.13	-2.02
MGMT_FEE (%)	1.47	7.77	1.47	7.74	1.46	7.70	1.50	7.96	1.49	7.88	1.46	7.72
INC_FEE (%)	0.00	0.11	0.00	0.12	0.00	0.08	0.00	0.19	0.00	0.16	0.00	0.16
HWM	1.33	5.5	1.34	5.54	1.32	5.44	1.34	5.56	1.34	5.54	1.33	5.48
ln(MIN_INV)	0.27	2.98	0.27	2.96	0.27	2.94	0.26	2.83	0.26	2.82	0.27	2.95
Age(years)	-0.04	-2.01	-0.04	-2.04	-0.04	-1.99	-0.04	-2.38	-0.04	-2.31	-0.04	-2.02
AvgPast2YRet(%p.m.)	-0.21	-0.87	-0.21	-0.88	-0.22	-0.88	-0.22	-0.9	-0.22	-0.89	-0.21	-0.88
AdjR2	0.05		0.05		0.05		0.05		0.05		0.05	
Obs	41,702		41,702		41,702		41,702		41,702		41,702	

Panel B Dependant variable: Alpha (FFCPS)

	ANW						ENW					
	Degree		Closeness		Betweenness		Degree		Closeness		Betweenness	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Net (%)	-0.35	-2.37	-0.19	-2.40	-5.40	-2.32	-0.74	-2.47	-0.31	-1.70	-6.41	-0.71
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
AdjR2	0.08		0.08		0.08		0.08		0.08		0.08	
Panel C Dependant variable: AR												
Net (%)	-3.39	-6.31	-1.65	-5.96	-34.93	-5.64	-4.33	-4.52	-2.00	-3.49	-25.79	-0.98
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
AdjR2	0.13		0.13		0.13		0.13		0.13		0.13	
Panel D Dependant variable: SR												
Net (%)	-2.30	-6.24	-0.96	-4.92	-13.78	-3.44	-2.51	-3.23	-1.62	-3.61	16.14	0.78
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
AdjR2	0.24		0.24		0.24		0.24		0.24		0.24	
Obs	41,702		41,702		41,702		41,702		41,702		41,702	

Table 5 Robustness

Panel A reports the results of the regressions (3) and (4) with the style subsamples. Style 1 is the mainstream style with the largest number of funds as members and Style 5 is the least popular style with the smallest number of members. The t-statistics are calculated based on heteroskedasticity-consistent standard errors. Panel B reports the results over the financial crisis (1999-2002 and 2008-2010) and non-crisis subperiods. Panel C reports the results controlling for city fixed effect and the results with a subsample of funds whose managers are located in financial centers. For brevity, we report only the coefficients of centrality measured by degree. The t-statistics in Panel B and C are calculated based on clustered errors by style and time.

Panel A: Style subsamples

	ANW						ENW					
DepVar:	SDI		Alpha (FH)		AR (FH)		SDI		Alpha (FH)		AR (FH)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Style 1 (Obs: 14,623)	-1.64	-8.77	-0.12	-0.73	-1.52	-3.59	-0.99	-2.01	-0.89	-2.21	-4.37	-4.33
Style 2 (Obs: 10,492)	-0.31	-0.99	-0.53	-1.77	-4.50	-5.69	1.64	2.11	-1.09	-2.02	-1.63	-1.05
Style 3 (Obs: 7,346)	-1.77	-2.70	-2.16	-4.22	-8.58	-5.50	-0.13	-0.11	-3.08	-3.50	-10.32	-4.00
Style 4 (Obs: 5,400)	-1.06	-0.94	-1.71	-2.23	-8.72	-3.42	0.00	0.00	-1.54	-1.74	-2.50	-0.73
Style 5 (Obs: 3,841)	-4.53	-2.67	0.04	0.03	-0.58	-0.14	-3.31	-2.14	3.95	2.08	7.68	1.36

Panel B: Subperiods

	ANW						ENW					
DepVar:	SDI		Alpha (FH)		AR (FH)		SDI		Alpha (FH)		AR (FH)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Financial crisis period (Obs: 14,945)												
Degree	-2.80	-8.40	-0.67	-1.84	-2.97	-3.01	-1.69	-2.50	-0.87	-1.11	-3.66	-1.85
Noncrisis period (Obs: 26,757)												
Degree	-2.56	-10.74	-0.46	-2.39	-3.67	-5.70	-1.83	-3.74	-1.35	-3.88	-4.51	-4.15

Panel C: Control for networking in cities

	ANW						ENW					
DepVar:	SDI		Alpha (FH)		AR (FH)		SDI		Alpha (FH)		AR (FH)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
City fixed effect (Obs: 38,862)												
Degree	-2.50	-12.73	-0.57	-3.12	-3.82	-6.65	-1.00	-2.37	-1.09	-2.91	-4.98	-4.55
Managers in financial centers (Obs: 22,009)												
Degree	-2.34	-9.85	-1.33	-6.24	-5.60	-7.66	-0.50	-0.89	-1.30	-2.80	-6.44	-4.36

Table 6 Social connectedness and hedge fund strategy similarity

The table reports the panel regressions in Eq (5) of strategy similarity on social connectedness between funds, controlling for the effect of location proximity, similar fund features, and investment focuses and for style and time fixed effects. The regressions use annual data between 1996-2018. The strategy similarity is measured either by the return correlation or covariance between two funds, which is calculated at the end of each year for each fund pair in the same style with prior 24-month net-fee returns. *Connected* is an indicator for the connectedness between two funds lagged by one year, defined in the Alumni (ANW) and Employment network (ENW), respectively. *SameCity* is an indicator that equals 1 if their managers are located in the same city; *SameMediaMkt* equals 1 if the managers are located within 50 miles to each other; *FdCharSim*, *AssetSim*, *SecSim*, *APRSim*, *GeoSim*, and *InvSim* are the Jaccard coefficients calculated using 136 indicators for various fund features and investment focuses. The regression coefficients are multiplied by 100. The t-statistics are calculated based on clustered errors by style and time.

	ANW				ENW			
Dep Var:	Correlation		Covariance		Correlation		Covariance	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Connected	5.15	9.01	0.75	2.37	6.22	4.51	0.58	1.37
SameCity	1.37	3.57	-0.70	-3.78	1.36	3.56	-0.70	-3.62
SameMediaMkt	6.63	14.44	1.47	5.10	6.67	14.49	1.48	5.32
FdCharSim	1.16	2.10	1.06	4.02	1.16	2.11	1.06	3.28
AssetSim	6.75	9.21	3.33	5.33	6.74	9.20	3.33	4.83
SecSim	6.58	5.48	4.18	4.73	6.59	5.49	4.18	3.78
APRSim	12.88	15.76	4.36	7.46	12.89	15.77	4.36	6.26
GeoSim	0.14	0.34	-0.28	-1.73	0.13	0.34	-0.28	-2.44
InvSim	9.72	7.62	-3.33	-6.25	9.72	7.62	-3.33	-4.42
AdjR2	0.18		0.26		0.18		0.26	
Obs	1,139,160		1,139,160		1,139,160		1,139,160	

Table 7 Manager talent, career establishment, and social network effect

Panel A reports the panel regressions in Eq (3) and (4) with two subsamples of hedge funds whose managers went to a college/university with an average SAT score above and below 1295, respectively. Panel B reports the panel regressions with two subsamples of funds whose managers have financial work experience of more than and less than 14 years, respectively. The control variables *FundChar* are the same as in Table 3 when SDI is the dependent variable and the same as in Table 4 when Alpha is the dependent variable. We report only the coefficient on Degree centrality, which is calculated in the Alumni network in Panel A and in the Employment network in Panel B, for brevity. The t-statistics are calculated based on clustered errors by style and time.

Panel A: Alumni network

Dep Var:	SDI				Alpha (FH)			
Subsample:	SAT>=1295		SAT<1295		SAT>=1295		SAT<1295	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Degree	-4.34	-17.98	-2.85	-1.83	-0.57	-2.58	0.34	0.32
AdjR2	0.22		0.24		0.05		0.09	

Panel B: Employment network

Dep Var:	SDI				Alpha (FH)			
Subsample:	WORK>=14		WORK<14		WORK>=14		WORK<14	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Degree	-1.07	-2.21	-5.52	-5.70	-0.47	-1.33	-2.08	-2.93
AdjR2	0.21		0.20		0.04		0.06	

Table 8 Style shifting and social ties

The table reports the logistic regressions Eq (6) with a sample of fund pairs across all styles and a subsample of fund pairs in the mainstream style (MSS). The dependent variable, *StyleShift*, is equal to 1 if a pair of funds remain in the same style in the next year, otherwise 0. The explanatory variable, *Connected*, is an indicator for the social connectedness between two funds, defined under the Alumni network (ANW) and the Employment network (ENW), respectively. The regressions control for manager location proximity, similar fund features, and style and time fixed effect. These control variables are defined the same as in Table 6. The t-statistics are calculated based on clustered errors by style and time.

	ANW				ENW			
Sample:	All styles		MSS		All styles		MSS	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Connected	0.19	2.36	0.30	2.68	-0.07	-0.47	-0.01	-0.06
SameCity	0.18	3.43	0.14	1.92	0.18	3.41	0.13	1.91
SameMediaMkt	-0.03	-0.67	-0.01	-0.15	-0.03	-0.63	-0.01	-0.09
FdCharSim	0.07	0.83	0.21	1.76	0.07	0.84	0.22	1.79
AssetSim	0.41	3.62	0.49	3.28	0.41	3.62	0.49	3.27
SecSim	0.26	1.62	0.66	3.18	0.26	1.62	0.66	3.18
APRSim	0.44	3.63	0.59	3.83	0.44	3.64	0.59	3.83
GeoSim	0.05	0.61	0.13	1.14	0.05	0.61	0.13	1.14
InvSim	0.27	1.30	-0.35	-2.11	0.27	1.30	-0.35	-2.11
Pseudo R2	0.20		0.18		0.20		0.18	
Obs	820,652		407,356		820,652		407,356	

Table 9 R2 and network centrality

The table reports the panel regressions of the R2 (FH) on network centrality, as in Eq (7). The R2 is estimated under the FH seven-factor model from the regression in Eq (1) over quarterly 24-month moving windows. *NL_FAC* denotes the importance of nonlinear factors, which is equal to the sum of absolute betas on three PTFS nonlinear factors divided by the sum of absolute betas across all seven factors. *Kurt* is the kurtosis of the residuals from the regressions (1). The other variables are described in Table 3. The coefficients are multiplied by 100. The t-statistics are calculated based on clustered errors by style and time.

	ANW		ENW	
	Coef.	t-stat	Coef.	t-stat
Degree (%)	1.72	6.96	2.10	5.15
Vol (%p.m.)	2.13	23.86	2.13	23.78
Redemp_Notice (30 days)	-0.68	-5.86	-0.66	-5.7
Leverage	-2.38	-10.5	-2.48	-10.92
Lockup (months)	-0.02	-1.61	-0.02	-1.52
PersonalCapital	-0.37	-1.57	-0.31	-1.33
ln(AUM)	0.50	7.43	0.48	7.27
MGMT_FEE (%)	-4.88	-18.03	-4.91	-18.07
INC_FEE (%)	-0.28	-11.27	-0.28	-11.47
HWM	1.49	6.07	1.48	5.96
ln(MIN_INV)	0.49	4.87	0.52	5.09
Age(years)	0.39	15.62	0.40	15.86
PastAvgAlpha(%p.m.)	-0.70	-5.53	-0.70	-5.59
NL_FAC (%)	-1.35	-12.97	-1.36	-13.09
Kurt	-2.49	-21.98	-2.52	-22.14
AdjR2	0.30		0.30	
Obs	41,702		41,702	

PAPER 3. OVERCOMING SHORT-SALE CONSTRAINTS AND HEDGE FUND RETURNS

ABSTRACT

Our study explores the heterogeneous abilities of hedge funds to arbitrage overpricing and the impact of this ability on their performance. We find that on one side, one-third of funds in our sample tend to delay arbitrage on management (MGMT) mispricing, whereas no more than 3% of funds correct prices right away. On the other side, one-fifth of funds bet against performance (PERF) mispricing, while only 5% delay arbitrage. We also find that funds with the highest mispricing betas outperform those with the lowest betas and show that the mispricing beta strongly predicts hedge fund performance in the long run.

JEL classification: G11; G23; J24

Keywords: Hedge funds; Overpricing; Performance; Short-sale constraints

1. Introduction

In financial markets, mispricing exists to the extent that the limits of arbitrage deter rational speculators from fully eliminating inefficiencies.[41] Abreu and Brunnermeier (2002) note that mispricing disappears only if a threshold proportion of arbitrageurs have traded in the direction of stabilizing prices. In practice, arbitrage is, however, particularly costly when betting against overpricing due to short-sale constraints (Pontiff, 2006). Professional arbitrageurs are a relatively small number of highly specialized investors using other people's capital. As well-known arbitrageurs in financial markets, hedge funds may have different abilities to overcome these constraints, for example, due to different capital structures (Gromb and Vayanos, 2002; Liu and Mello, 2011) or different contractual protections from withdrawals (Hombert and Thesmar, 2014). The objective of this study is to investigate the heterogeneity in the cross-section of hedge funds' ability to arbitrage overpricing as well as the relation between the heterogeneous abilities and fund performance.

To measure the ability of hedge funds to overcome short-sale constraints, we propose a mispricing beta, estimated from a regression of a fund's return on the mispricing factors constructed by Stambaugh and Yuan (2017). The exposure of a hedge fund to the mispricing factor can reflect the extent to which the fund can overcome arbitrage constraints and thus exploit the opportunity created by overpricing, given the arbitrage asymmetry (Stambaugh et al., 2012, 2015, 2017). When investor sentiment is high (low), many securities are potentially overpriced (underpriced). Stambaugh et al. (2012) observe significantly lower returns on overpriced stocks

[41]Numerous studies have discussed that arbitrage fails to eliminate anomalies that appear in financial markets because of constraints such as shorting costs, holding costs, noise trader risk, synchronization risk, institutional constraints, and fragile capital structure (Shleifer and Vishny (1997), Abreu and Brunnermeier (2002), Gromb and Vayanos (2002), Pontiff (2006), Tuckman and Vila (1992), Liu and Mello (2011), among others).

following high sentiment but do not observe significantly higher returns on underpriced stocks following low sentiment. These observations reflect that overpricing gets corrected less than underpricing due to short-sale impediments. For example, overpricing persists longer due to low supplies of stock loans from institutional investors (D'Avolio, 2002) or difficulty in short-sell high idiosyncratic-volatility stocks (Stambaugh et al., 2015). These constraints reduce the willingness of arbitrageurs to short-sell stocks. From another perspective, the potential arbitrage profits created by these anomalies, which are not sufficiently exploited, are substantially attributable to overpriced stocks through short-selling them. Arbitrageurs less constrained by short sale impediments would be more able to exploit these opportunities. Hedge funds' short-selling data are not publicly available to researchers. However, their exposure to overpriced stocks can provide insights into how they arbitrage overpricing. Therefore, less constrained hedge funds that are able to exploit overpricing would have returns more correlated with the mispricing factor return and exhibit a higher mispricing beta than more constrained hedge funds.

Using a sample of 3,584 hedge funds over the period 1995-2016, we regress each fund's return on the two mispricing factors of Stambaugh and Yuan (2017), MGMT and PERF, controlling for ten risk factors, MKTRF, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF. Our main findings are as follows. First, by employing an unconditional model and a conditional model, we find that about one-fifth of funds arbitrage PERF mispricing, given positive and significant t-statistics of the PERF betas greater than 1.96, only about 5% delay arbitrage, given significant and negative t-statistics smaller than –1.96; by contrast, more of hedge funds (about one third) tend to delay their arbitrage on MGMT mispricing; no more than 3% of funds correct prices right away. Using the conditional model, we estimate the dynamic arbitrage coefficients of each fund and find that 7.53% of funds employ dynamic arbitrage on MGMT mispricing; these funds increase their MGMT betas in response to higher sentiment. Furthermore, we estimate the portfolio weight of overpriced stocks for each fund and find that funds with positive mispricing betas have weights on overpriced stocks in their portfolios ranging from – 9% to – 6%, which implies a short position on overpriced stocks among hedge funds betting against mispricing on average. Also, we find that hedge funds with negative mispricing betas have a long position on overpriced stocks, ranging from 14% to 19%, which are significantly higher than the weights (about 4%) in the market portfolio. These results confirm again that hedge funds delay arbitrage by investing in overpriced stocks instead of short-selling them.

Second, we find that hedge funds with the highest mispricing betas outperform those with the lowest betas, with outperformance ranging from 28 to 63 bps per month under the conditional model. These results support our hypothesis that less constrained hedge funds (by short-sale impediments) outperform. We also find that hedge funds that employ dynamic arbitrage perform better than their peers with mispricing betas at a similar level and with lower dynamic arbitrage coefficients. For example, among funds with the lowest MGMT betas (– 0.40), those funds with the highest dynamic arbitrage coefficients (0.48) outperform their peers with the lowest dynamic arbitrage coefficients by 45 bps per month (t-stat: 4.01). This performance is comparable to that of funds with the highest MGMT betas. The result indicates that arbitrage profits are considerably derived from sentiment-driven overvaluation through short sales by reacting to higher sentiment.

Third, our out-of-sample tests show that the mispricing beta and the dynamic arbitrage coefficient both predict the cross-sectional variation in hedge funds' performance in the short and long run. For example, when the PERF beta increases by one, the fund's average alpha over the next 12 months increases by 1.31% per month (t-stat: 4.53). When the dynamic arbitrage coefficient on MGMT increases by one, the fund's 12-month leading alpha increases by 0.83% per month (t-stat: 3.94). The results show that hedge funds' ability to arbitrage overpricing is one of the sources of hedge fund performance, and this performance persists for up to two years. In addition, the economic value of hedge funds' dynamic arbitrage is noticeable. Particularly, less constrained funds with the best ability to arbitrage MGMT in response to higher sentiment outperform their peers with the lowest ability by 69 bps per month on a risk-adjusted basis, corresponding to 8.28% per year (t-stat: 5.50).

Finally, we analyze the sentiment exposure of hedge funds that bet against mispricing and find that hedge funds with significant and positive PERF mispricing betas possess significant and positive sentiment betas. For example, 708 out of 3,584 funds with a t-statistic of PERF beta greater than 1.96 have significant and positive sentiment exposure at 0.09 on average (t-stat: 2.53). We also find that hedge funds with the highest PERF betas have sentiment betas of 0.50 higher (t-stat: 2.67) than those with the lowest PERF betas. Overall, we confirm a positive cross-sectional relation between hedge fund mispricing betas and sentiment betas as well as hedge fund performance.

Our contribution is threefold. First, our study contributes to the literature on hedge funds' arbitrage on mispricing in stock markets. Previous studies focus mainly on hedge funds' arbitrage on underpricing, and few empirical studies examine hedge funds' arbitrage on overpricing due to the unavailability of hedge funds' short-selling data.[42] Our study extends previous literature by investigating hedge funds' arbitrage on overpricing. Consistent with Abreu and Brunnermeier (2002, 2003)'s model, we find evidence supporting a lack of coordination in arbitrage among hedge funds and show that some hedge funds are more able to overcome the limits of arbitrage than others.

[42] As the SEC does not require institutions to disclose their short positions, Cao et al. (2018) consider hedge funds' long equity position data and find that hedge funds ownership is not significantly related to negative-alpha stocks (i.e., overpriced stocks).

For example, a large proportion of hedge funds in our sample with a positive PERF beta, compared with a smaller proportion of funds with a negative PERF beta, indicates that more hedge funds tend to exploit PERF arbitrage right away rather than delay arbitrage. Further, the outperformance of hedge funds with higher mispricing betas relative to those with lower betas reflects their strength in overcoming short-selling constraints.

Second, we contribute to the ongoing debate over the impact of hedge funds' heterogeneous sentiment-related trading strategies on their performance. Perhaps the study most closely related to ours is Chen et al. (2021), who find that hedge funds with high-sentiment betas outperform those with low-sentiment betas. They conclude that this outperformance reflects managerial skill and sentiment timing, a strategy of investing in overpriced securities when sentiment is expected to increase. A key difference between our study and theirs is that by considering the ability of sentiment to predict mispricing, we prove that the outperformance of hedge funds with high sentiment betas reflects arbitrage profits from betting against mispricing. We provide strong evidence that hedge funds with high mispricing betas also possess high sentiment betas and outperform those with low mispricing betas and low sentiment betas. Our results also suggest that, on average, following high sentiment, hedge funds that bet against mispricing outperform those following sentiment trading strategies, supporting the conventional wisdom that hedge funds generate alphas by betting against mispricing and that their main strength lies in overcoming short-sale constraints.

Third, our study adds to the strand of literature on the determinants of hedge fund performance. Existing studies document various sources of hedge fund performance, such as hedge funds' systematic risk exposure, fund location, timing skill, fund characteristics, and manager personality traits (Bali et al. (2012), Titman and Tiu (2011), Chen and Liang (2007), Cao et al.

(2013), Brown et al. (1999), Teo (2009), Avramov et al. (2011), Brown et al. (2018), among others). We provide strong evidence that the ability to arbitrage overpricing is one of the sources of hedge fund performance. Moreover, our results suggest that hedge funds' mispricing betas and dynamic arbitrage coefficients predict the cross-section of future fund performance in the long run, which is consistent with Jagannathan et al. (2010)'s finding of the persistence in hedge fund alphas.

The remainder of the paper is organized as follows. Section 2 presents the literature background and hypotheses; Section 3 presents data and methods; Section 4 presents results; Section 5 checks the robustness of the results; Second 6 concludes.

2. Background and hypotheses development

Classical finance theory argues that security prices equal the rationally discounted value of expected cash flows. Even though irrational investors drive prices away from the rational present value, arbitrageurs who trade against them stabilize prices. In a standard finance model (e.g., Fama and French, 1993), the cross-section of expected returns of securities only depends on factor sensitivities, which reflect their exposure to systematic risks. Numerous studies have identified asset-pricing anomalies that violate the Fama and French (1993) three-factor model despite its widespread use.

To explain observed mispricing, behavioral finance researchers propose an alternative model which is built on two concepts: 1) the presence of market-wide sentiment and 2) the limits of arbitrage (DeLong et al., 1990a and 1990b; Shleifer and Vishny, 1997; Abreu and Brunnermeier, 2002; Pontiff, 2006; and others). For example, DeLong et al. (1990b) laid out the first assumption that investors are subject to sentiment. The market-wide investor sentiment influences security prices in the same direction simultaneously. When sentiment is high, many securities are potentially overpriced. Nevertheless, speculators may be reluctant to correct prices due to the uncertainty of arbitrage. As Shleifer and Vishny (1997) and Pontiff (2006) discussed, trading against sentimental investors is costly and risky, especially when betting against overpricing due to short-sale impediments. Short-sale impediments, such as institutional constraints, shorting costs, holding costs, and wealth constraints, deter rational speculators from arbitraging overpricing and explain why overpricing is more prevalent than underpricing in financial markets (Miller, 1977 and Stambaugh et al., 2012). For example, institutional investors such as mutual funds are prohibited from taking short positions. Many stocks are costly to "short" due to low supplies of stock loans from institutional investors (D'Avolio, 2002). High transaction costs reduce arbitrageurs' willingness to take short positions. Stambaugh et al. (2015) find that overpricing is even more pronounced among hard-to-arbitrage stocks (i.e., high idiosyncratic volatility stocks) with low institutional ownership. Arbitrageurs shorting overpriced stocks must wait until prices fall to fair values to cover their short positions. Holding costs during this period, such as margin calls for additional capital and fund outflows through investor withdrawals, make even seemingly riskless arbitrage risky (Tuckman and Vila, 1992; Shleifer and Vishny, 1997; Brunnermeier and Nagel, 2004). Gromb and Vayanos (2002) show that if arbitrageurs' wealth is insufficient, they may be unable to eliminate price discrepancies between the risky assets.

Stambaugh et al. (2012) explore sentiment-related overpricing, which persists due to short-sale impediments, to explain 11 well-documented asset-pricing anomalies in the finance literature. These anomalies reflect differences in cross-sectional average returns that survive adjustment for the Fama and French (1993) three-factor model by sorting stocks on measures that include financial distress, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profit-to-assets, asset growth, return-on-assets (ROA), and investment-to-assets. Further, Stambaugh et al. (2012) find that each anomaly is stronger following high sentiment levels. A long-short strategy constructed based on the anomaly's sorts, with the long leg being the highest-performing decile and the short leg the lowest-performing decile, realizes higher returns resulting from significantly lower returns on the short leg consisting of the most potentially overpriced stocks. On the other side, the evidence for the sentiment effect on underpriced stocks is weak. They do not find significantly higher returns following low sentiment for most anomalies.

In the following study, Stambaugh and Yuan (2017) construct two mispricing factors, MGMT and PERF, which aggregate information across the 11 anomalies previously examined by Stambaugh et al. (2012). The MGMT (PERF) factor is constructed using sorts on an average ranking across a cluster of six (five) anomalies related to firms' management (performance). The factor returns are the spread portfolio returns between the long leg consisting of the most potentially underpriced stocks and the short leg consisting of the most potentially overpriced stocks. The six anomalies related to firms' management include net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. The five anomalies related to firms' performance include distress score, O-score, momentum, gross profitability, and return on assets. They find that investor sentiment predicts mispricing factor returns, especially short-leg returns. Following higher sentiment levels, both factors have significantly higher returns, resulting from significantly lower returns on the short leg of the factor.[43] To interpret the findings of Stambaugh

[43] We regress each mispricing factor on the lagged BW sentiment-level index (2006) over our sample period 1997-2016. The BW sentiment-level index is constructed based on the first principal components of five sentiment proxies excluding turnover, as described in Section 3.2, over the period 1965-2018. We find that a one-standard-deviation increase of the sentiment level, increase the MGMT and PERF factors by 1.01% and 1.51% per month (t-stat: 2.24 and 2.59), respectively. We also regress the mispricing factors on the BW sentiment change index (2007), which is constructed based on the first principal components of changes in the five variables. Nevertheless, the slopes on the sentiment change are statistically insignificant, at – 0.24 and – 0.11 (t-stat: – 0.98 and – 0.30) for the MGMT and PERF factors respectively. Thus, in this study, we use the BW sentiment level (2006) as our main sentiment metric, following Stambaugh et al. (2012, 2017).

et al. (2012, 2017), sentiment-related mispricing reflects that overpricing resulting from high sentiment gets corrected less by arbitrage than underpricing resulting from low sentiment, given that speculators are less willing or able to short stocks than to buy them.

Armed with an understanding of the limits of arbitrage and mispricing, we postulate first that there is heterogeneity in the ability to arbitrage overpricing in the cross-section of arbitrageurs such as hedge funds. In other words, hedge funds less constrained by short-sale impediments would be more able to exploit the profit opportunities created by mispricing than their more constrained peers.[44] Then we would observe that some less constrained hedge funds exhibit higher exposure to the mispricing factors (i.e., mispricing beta). Second, the heterogeneity in hedge funds' ability to arbitrage overpricing leads to heterogeneous performance in the cross-section. Arbitrage on overpricing could be one of the sources of expected returns of hedge funds. We expect that less constrained hedge funds with higher mispricing betas have better performance than more constrained hedge funds with lower mispricing betas, resulting from a better ability to arbitrage overpricing. Lastly, as shown by Stambaugh and Yuan (2012, 2017), betting against overpricing would be more profitable following high sentiment levels as sentiment-related overvaluation prevails in the markets. Less constrained hedge funds actively shorting overpriced stocks in response to high sentiment levels (i.e., dynamic arbitrage) would exhibit higher mispricing betas in higher sentiment periods than their average mispricing betas. Moreover, we expect that hedge funds that employ dynamic arbitrage strategies have even better performance than their peers who do not.

[44] For example, Hombert and Thesmar (2014) find some hedge funds are more protected by contractual impediments from withdrawals. Some arbitrageurs can partially overcome limits to arbitrage by securing a strong capital structure (Stein, 2009).

3. Data and method

3.1 Hedge funds

We employ a sample of hedge funds from the Lipper TASS database, which provides an extensive hedge funds sample covering both live and defunct funds since 1994 and has been widely used in the hedge fund literature. TASS classifies hedge funds into 12 strategy categories: convertible arbitrage, dedicated short-bias, emerging markets, event-driven, equity market neutral, fixed income arbitrage, global macro, long/short equity, managed futures, multi-strategy, option strategy, and funds of funds. We focus on equity-oriented hedge funds by following the screening method used by Chen et al. (2021). We first exclude funds in the primary categories of emerging markets, fixed-income arbitrage, option strategy, and managed futures.[45] To address the backfilling issue that hedge funds may choose only to backfill returns when their past returns are favorable, we drop the first 12 months of returns for each fund. Then we keep funds with average assets under management (AUM) of at least $5 million, which report monthly net-of-fee returns, allow for redemption at a monthly or higher frequency, and have at least 36 months of return observations. Our final sample is free of backfilling and survivorship biases and includes 3584 hedge funds over the period 1995-2016.[46]

Panel A of Table 1 reports descriptive statistics for the final hedge fund sample based on fund-month observations. All variables are winsorized at the 1% and 99% levels. The average fund return is 0.44% per month. The mean (median) AUM is $272 million ($51 million), and the average fund age is 75 months. The mean (median) management fee is 1.42% (1.50%), while the mean

[45] Dedicated short-bias funds are also excluded since no funds satisfy the following data filters.

[46] Our results are robust to excluding funds with AUM below $10 million and the first 24 months of fund returns and including all strategy categories and all redemption frequencies in the sample. See Section 5.3 for details.

(median) incentive fee is 12.98% (15%). About 57% of the funds use a high-water mark provision that requires the funds to recover previous losses before charging the incentive fee. The lockup period and the redemption notice period are 1.11 and 0.96 months on average, respectively.

3.2 Mispricing factors and investor sentiment

Panel B of Table 1 reports the summary statistics of the mispricing factors and the BW sentiment level over the period 1995-2016. The monthly returns of the MGMT and PERF factors are downloaded from Stambaugh's website.[47] On average, the MGMT (PERF) factor has a mean of 0.54% (0.72%) per month and a standard deviation of 3.07% (4.73%), with 25th and 75th percentiles of − 1.17% (− 1.64%) and 1.86% (3.05%), respectively. We also use a combined mispricing factor (COMB), constructed based on a single composite ranking by averaging all 11 anomalies (Stambaugh et al., 2012, 2015). The COMB factor returns are the value-weighted returns on a spread strategy between the 10th decile and the 1st decile portfolios of stocks sorted on the mispricing score of Stambaugh et al. (2015). The COMB factor has a mean of 0.16% per month and a standard deviation of 5.27%, with 25th and 75th percentiles of − 2.39% and 2.81%, respectively.

Our measure of market-wide investor sentiment is the monthly sentiment-level index constructed by Baker and Wurgler (2006), based initially on the first principal component of six sentiment proxies: closed-end fund discount (CEFD), New York Stock Exchange (NYSE) share turnover, number and average first-day returns of initial public offerings (NIPO and RIPO), equity share in new issues (S), and dividend premium (PDND). Given the explosion of high-frequency institutional trading in recent years, we use a sentiment-level index (SENT_O) constructed over

[47] See https://finance.wharton.upenn.edu/~stambaugh/M4.csv

the period 1965-2018 based on the first principal component of the five proxies, excluding turnover orthogonalized against the six macroeconomic variables.[48] The monthly index is downloaded from Wurgler's website.[49] Over the sample period 1995-2016, the BW sentiment level has a mean of 0.21 and a standard deviation of 0.66, with 25th and 75th percentiles of − 0.13 and 0.42, respectively.

3.3 Risk factors

To measure hedge funds' benchmark-adjusted performance (i.e., alpha), we consider the risk factors as commonly used to evaluate hedge fund performance in previous studies (Kosowski et al., 2007; Cao et al., 2013; Bali et al., 2011; Chen et al., 2021; and among others). The risk factors include the market excess returns (MKTRF) and the size factor (SMB) from the M4 model of Stambaugh and Yuan (2017), the change in the constant-maturity yield of the 10-year Treasury (ΔTERM), the change in the yield spread between Moody's Baa bond and the 10-year Treasury bond (ΔCredit), and the three trend-following factors for bonds, currencies, and commodities (Ptfsbd, Ptfsfx, and Ptfcom) of Fung and Hsieh (2004), the Pastor and Stambaugh (2003) liquidity factor (LIQ), the inflation rate (INF), and the default spread between the yield on Baa-rated and Aaa-rated corporate bonds (DEF). Panel C of Table 1 reports the correlation coefficients between the mispricing factors, the one-month-lagged BW sentiment level, and the risk factors. We observe the mispricing factors MGMT, PERF, and COMB are positively correlated with the lagged sentiment level at 0.21, 0.19, and 0.17, respectively, and statistically significant at the 1% level, confirming again that higher mispricing factor returns follow higher sentiment levels (Stambaugh

[48] The six macroeconomic variables include industrial production index, nominal durables consumption, nominal nondurables consumption, nominal services consumption, NBER recession indicator, employment, and consumer price index.

[49] See http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx

and Yuan, 2017). On the contrary, lower market returns follow higher sentiment levels, given a significant and negative correlation of −0.14 at the 5% level. Overall, most of risk factors are uncorrelated with the lagged sentiment level, except for ΔCredit and DEF.

[Insert Table 1 here]

3.4 Mispricing beta

In this study, we propose a mispricing beta to measure the ability of hedge funds to exploit profits created by mispricing in financial markets. Our empirical model for estimating the mispricing beta builds on the conditional framework of Ferson and Schadt (1996) and Christopherson et al. (1998). Suppose the returns of a hedge fund arbitraging mispricing (MISP) follow the process as Eq (1):

$$r_{i,t} = \beta_i(Z_{t-1})\mathrm{MISP}_t + v_{i,t} \qquad (1)$$

where $r_{i,t}$ is the excess return in month *t*, MISP_t is the mispricing factor return, $\beta_i(Z_{t-1})$ is the fund's mispricing beta, corresponding to an information variable Z available to investors at time $t-1$. We specify the information variable as the market-wide sentiment level and approximate the fund's mispricing beta as a linear function of the past sentiment level, which is demeaned as $S_{t-1} - \bar{S}$:

$$\beta_i(Z_{t-1}) = b_i + B_i(S_{t-1} - \bar{S}) + u_{i,t-1} \qquad (2)$$

Replace (2) into (1), we obtain:

$$r_{i,t} = b_i\mathrm{MISP}_t + B_i(S_{t-1} - \bar{S})\mathrm{MISP}_t + \varepsilon_{i,t} \qquad (3)$$

For the purpose of comparison, we proceed with tests under two regression models controlling for a set of risk factors $\boldsymbol{F_t}$, which are described in Section 3.3, an unconditional model (4) in which we assume the mispricing beta is time-invariant and a conditional model (5), which is the regression form of Eq (3):

$$r_{i,t} = \alpha_i + b_i \mathrm{MISP}_t + \boldsymbol{\gamma'}_i \boldsymbol{F_t} + \varepsilon_{i,t} \quad (4)$$

$$r_{i,t} = \alpha_i + b_i \mathrm{MISP}_t + B_i (S_{t-1} - \bar{S}) \mathrm{MISP}_t + \boldsymbol{\gamma'}_i \boldsymbol{F_t} + \varepsilon_{i,t} \quad (5)$$

The estimate of b_i represents fund i's average mispricing beta over the regression period, which reflects, averagely, to what extent the fund exploits the arbitrage opportunity created by the mispricing factor. Less constrained hedge funds that are more able to bet against overpricing would have a higher b_i than more constrained hedge funds. The coefficient B_i under the conditional model measures to what extent the fund employs dynamic arbitrage (called dynamic arbitrage coefficient thereafter). A positive B_i indicates the manager increases mispricing beta by more actively short-selling overpriced stocks in response to a higher sentiment level.

4. Empirical results

In this section, we first present the results of our in-sample analysis, which answer the following questions: do hedge funds bet against overpricing? Do less constrained hedge funds outperform? Does dynamic arbitrage deliver better performance? Next, we show evidence from our out-of-sample analysis that hedge funds' mispricing betas and dynamic arbitrage coefficients predict their future performance in the short and long run. Finally, we examine the relation between hedge funds' mispricing beta and sentiment exposure and estimate hedge funds' positions on overpriced stocks.

4.1 Do hedge funds bet against overpricing?

For each hedge fund, we estimate their average MGMT and PERF mispricing betas (b_i) and the dynamic arbitrage coefficients (B_i) under the unconditional model Eq (4) and the conditional model Eq (5) over their lifetime, controlling for the risk factors, MKTRF, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF, which are described in Section 3.3. We also run the regressions by replacing the MGMT and PERF factors with the COMB factor. The t-statistics of the coefficient estimates are calculated based on Newey-West standard errors with two lags. Table 2 reports the cross-sectional distributions of t-statistics of the estimated mispricing beta b_i and the dynamic arbitrage coefficient B_i across individual funds. Specifically, Table 2 displays the percentage of t-statistics exceeding the indicated cut-off values.

Under the unconditional model, we find that around 19.75% of hedge funds in our sample have t-statistics of the PERF beta (b_{PERF}) greater than 1.96, and 4.32% of funds have t-statistics smaller than – 1.96. The results suggest that around one-fifth of hedge funds bet against PERF mispricing, with a confidence level of 5%, while about 5% of funds tend to delay their arbitrage (by buying overpriced stocks). Nevertheless, less than 3% of funds exploit mispricing profits on the MGMT factor, while 31.86% of funds tend to delay arbitrage, as their t-statistics of b_{MGMT} are smaller than – 1.96.[50] Overall, more funds tend to correct PERF mispricing than to delay arbitrage, given that the distribution of b_{PERF} has thicker right tails than left tails. On the contrary, more funds tend to delay MGMT mispricing than to correct prices right away, given that the left tails are thicker than the right tails. As for the COMB factor that aggregates the information across the 11

[50] Abreu and Brunnermeier (2002) discuss the lack of coordination among arbitrageurs, i.e., synchronization risk. Speculators delay arbitrage when they face uncertainty about when their peers will exploit a common arbitrage opportunity. Our results also confirm the lack of coordination among hedge funds. Some hedge funds tend to delay arbitrage by increasing long positions of overpriced stocks and then have negtaive mispricing betas; nevertheless, there are some hedge funds stabilizing prices.

anomalies, we observe that 12.03% of funds exploit mispricing profits, while 5.52% of funds tend to delay arbitrage.

Under the conditional model, we find that the percentages of funds with significant t-statistics of b_i remain at a similar level, and around 8-10% of funds have t-statistics of the dynamic arbitrage coefficient (B_i) greater than 1.96, and 18-24% of funds have t-statistics greater than 1.282. For example, even though a small proportion (1.65%) of funds have, on average, a significant MGMT beta, a larger proportion (7.53%) of funds employ dynamic arbitrage strategies by actively short-selling overpriced stocks when sentiment is higher.

[Insert Table 2 here]

4.2 Do less constrained hedge funds outperform?

To examine the performance of hedge funds betting against overpricing, we form decile portfolios of hedge funds by independently sorting funds on their mispricing beta b_i and the dynamic arbitrage coefficient $B_{i,}$ which are estimated in Eq (4) and Eq (5), respectively. Panel A of Table 3 reports the average performance of the decile portfolios. The performance of each fund is measured as the alpha α_i from the following regression Eq (6) over their lifetime, where $\boldsymbol{F_t}$ is a vector of risk factors, MKTRF, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF, described in Section 3.3:

$$r_{i,t} = \alpha_i + \boldsymbol{\gamma'}_i \boldsymbol{F_t} + \varepsilon_{i,t} \qquad (6)$$

Columns (1) to (3) of Panel A present the results under the unconditional model. We observe the performance of the decile portfolio is an increasing function of the mispricing beta. For example, Portfolio 1 with the lowest b_{MGMT} has an average alpha of – 4 bps per month, while

Portfolio 10 with the highest b_{MGMT} has an average alpha of 46 bps per month. The difference in performance between Portfolio 10 and Portfolio 1 is 51 bps per month (t-stat: 3.37). We observe similar results in Columns (4) to (6) of Panel A under the conditional model. Overall, the results show that hedge funds with the highest mispricing beta outperform those with the lowest beta by 28–63 bps per month, supporting our hypothesis that less constrained hedge funds outperform their peers that are more constrained by short-sale impediments.

Columns (7) to (9) of Panel A reports the performance of the decile portfolios of hedge funds sorted on the dynamic arbitrage coefficient B_i estimated under the conditional model. We find that hedge funds employing dynamic arbitrage strategies also display higher alphas. For example, Portfolio 10 with the highest B_{PERF} outperforms Portfolio 1 with the lowest B_{PERF} by 45 bps per month (t-stat: 2.68). The results support that less constrained hedge funds, especially which are more able to bet against mispricing in high sentiment periods, deliver a better performance.

Further, we show the outperformance of dynamic arbitrage strategies by constructing 3×3 portfolios. We first sort hedge funds on the coefficients b_i, forming tertiles, and then sorting funds in each tertile by B_i, again forming tertiles. Panel B of Table 3 reports the performance of the 3×3 portfolios sequentially sorted on the mispricing beta and dynamic arbitrage. We observe that hedge funds with higher dynamic arbitrage coefficients have a better performance than their peers with similar levels of mispricing betas but lower dynamic arbitrage coefficients. The effect of dynamic arbitrage is the most significant in the lowest b_i tertile. For example, while the average mispricing beta of the lowest b_{MGMT} tertile portfolio is negative (– 0.40), funds with the lowest b_{MGMT}but the highest B_{MGMT} (0.48) outperform their peers with the lowest b_{MGMT} and the lowest B_{MGMT} (–0.80) by 45 bps per month (t-stat: 4.01), a performance comparable to that of hedge funds with high mispricing betas. Again, the results support that less constrained hedge funds actively betting against mispricing in high sentiment periods have better performance, even though their average mispricing beta is low over time. Moreover, in the last row and the last column (H – L), we report the difference in performance between the portfolio with the highest b_i and B_i and the portfolio with the lowest b_i and B_i, and the corresponding t-statistic. These differences range from 32 to 50 bps per month for all three mispricing factors, with t-statistics greater than 2.33.

[Insert Table 3 here]

4.3 Do hedge funds' mispricing betas predict their future performance?

The objective of this section is to test the significance of the mispricing betas and the dynamic arbitrage coefficients on predicting the cross-sectional variation in hedge funds' performance in the short and long run. To do so, we run two-stage Fama-MacBeth regressions. At the end of each month (*t*), in the first stage, we regress the excess return of each fund (*i*) on a mispricing factor, MISP_t, over the previous 36 months, controlling for the risk factors described in Section 3.3 and sentiment hedging against market risk (Zheng et al. (2018)), as in Eq (7).[51] We also require each fund has at least 36 months of return observations in the first stage regression. In the second stage, we run the cross-sectional regressions of the fund's future performance, $\text{Perf}_{i,t+1}$, on the estimated mispricing beta (b_{it}), dynamic arbitrage (B_{it}), and sentiment hedging (B_{it}^m), controlling for hedge fund characteristic, as in Eq (8).

$$r_{it} = \alpha_i + b_{it}\text{MISP}_t + B_{it}(S_{t-1} - \bar{S})\text{MISP}_t + B_{it}^m(S_{t-1} - \bar{S})\text{MKTRF}_t + \boldsymbol{\gamma'}_i\boldsymbol{F_t} + \varepsilon_{it} \quad (7)$$

$$\text{Perf}_{i,t+1} = w_t + \theta_{1,t}b_{it} + \theta_{2,t}B_{it} + \theta_{3,t}B_{it}^m + \boldsymbol{\theta'}_t\mathbf{FundChar}_t + \epsilon_{i,t+1} \quad (8)$$

[51] Since lower market returns follow higher levels of sentiment (as shown in Section 3.3), investors hedging against market risk by decreasing their market exposure in high sentiment periods would have better performance in the following month.

where, $\mathbf{FundChar}_t$ is a vector of variables including fund age, fund size, management fees, incentive fees, high-water mark, leverage, lockup period, and redemption period.

4.3.1 Predictability in the short run

We first use one-month leading alpha as the dependent variable in the second stage regression, which is the difference between the excess return $r_{i,t+1}$ and the products of the fund's risk factor loadings and factor returns in month *t*+1, as in Eq (9).

$$\hat{\alpha}_{i,t+1} = r_{i,t+1} - \hat{\boldsymbol{\gamma}}'_{it}\boldsymbol{F}_{t+1} \qquad (9)$$

where the fund's risk factor loadings, $\hat{\boldsymbol{\gamma}}'_{it}$, are estimated with the regression Eq (6) over the previous 36 months. Table 4 reports the results of the Fama-MacBeth second stage cross-sectional regressions. The reported t-statistics are calculated based on Newey-West standard errors with two lags. We find that the average slopes on the PERF and COMB betas are positive and significant. However, the average slope on the MGMT beta is insignificant. For example, when the average PERF beta increases by one, the fund's alpha increases by 1.25% per month in the next month (t-stat: 2.79). The average slopes on the dynamic arbitrage coefficients are all positive and significant for the three mispricing factors, with t-statistics greater than 2.326. For example, when the dynamic arbitrage coefficient on MGMT increases by one, the fund's alpha in the next month increases by 0.81% per month (t-stat: 3.46). For the MGMT factor, the dynamic arbitrage coefficient exhibits a better ability to predict hedge fund performance in the cross-section than the average mispricing beta. A plausible explanation could be that a larger number of funds adjust their MGMT beta in response to a higher level of sentiment. However, on average, only a small number of funds have positive MGMT betas. Table 4 also reports the average slopes on hedge fund characteristics. The coefficients on fund characteristics are in line with previous studies. For example, hedge funds that have a larger size, use a high-water mark provision, require a longer lockup period, or require a longer redemption notice period tend to perform better. Moreover, as expected, the average slopes on sentiment hedging (B_{it}^{m}) is negative and significant at the 1% level, confirming that investors that decrease their market exposure when sentiment is higher have better performance in the following month.

Overall, our results show a positive and significant relation between hedge fund performance and heterogeneity in hedge funds' ability to arbitrage mispricing, especially the ability to short sell overpriced stocks in response to high sentiment levels. The positive relation is significant even after adjusting for common risk exposures and controlling for fund characteristics.

[Insert Table 4 here]

4.3.2 Predictability in the long run

In this sub-section, we rerun the second-stage regressions by replacing the dependent variable with the alpha over a long-term period (3, 6, 9, 12, 18, and 24 months). For example, the 12-month leading alpha is the average of alphas estimated by Eq (9) from *t*+1 to *t*+12. If a fund disappears over the next 12-month period, its 12-month leading alpha is calculated by including alphas until its disappearance. We find similar results for all different periods in Table 5. The average slopes on the PERF and COMB betas remain positive and significant when the long-term performance is the dependent variable, indicating that hedge funds' ability to arbitrage mispricing persists in the long run. Particularly, the slopes on the PERF beta range from 1.12 to 1.31 (t-stat: 3.00 to 5.28) over the period from 3 months to 24 months. For example, when the PERF beta increases by one, the fund's average alpha over the next 12 months increases by 1.31% per month (t-stat: 4.53). Also, the average slopes on the dynamic arbitrage coefficients remain all positive and significant for all periods (except for the PERF factor under the 24-month period). For example, when the dynamic arbitrage coefficient on MGMT increases by one, the fund's alpha over the next 12 months increases by 0.83% per month (t-stat: 3.94). The results suggest that hedge funds' ability to arbitrage overpricing, measured by their mispricing beta and dynamic arbitrage coefficient, is an important source of fund alphas. We also show that this ability persists over time in out-of-sample tests.

[Insert Table 5 here]

4.3.3 Predictability over subperiods

In this section, we investigate further the predictive power of the mispricing beta and the dynamic arbitrage coefficient on future hedge fund performance during different subsample periods. We divide our full sample period 1997-2016 into two subperiods: the financial crisis period, including years from 1998 to 2001 (i.e., Technology bubble and Crash), and from 2007 to 2009 (i.e., 2008 Financial crisis) and the non-financial crisis period, which excludes the above years. The financial crisis period is also the period of market-wide sentiment levels experiencing dramatic changes. For example, the BW sentiment level increased from 0.58 in January 1998 to 0.97 in December 2001 and reached its peak at 3.20 in February 2001. During the 2008 financial crisis period, the sentiment level decreased from 0.48 in January 2007 to – 0.68 in December 2009 and reached its lowest level at – 0.89 in April 2009. We report the average slope of the second-stage regressions over the two subperiods in Panel A and B of Table 6, with the 1-, 3-, or 6-month leading alpha as the dependent variable. Panel A of Table 6 provides evidence of a stronger positive relation between dynamic arbitrage and performance when the market-wide sentiment level experiences dramatic changes. For example, when the 6-month leading alpha is the dependent variable, the average slope on MGMT (PERF) dynamic arbitrage is 1.20 (0.79) over the crisis subperiod. Further, Panel B shows that the slope on MGMT (PERF) dynamic arbitrage is lower over the non-crisis time (0.62 and 0.37, respectively) and, particularly, the slope on PERF dynamic arbitrage is statistically insignificant. By contrast, we find the positive relation between the mispricing beta and performance becomes weaker in the crisis period. For example, when the COMB beta increases by one, the 6-month leading alpha increases 0.41 bps per month (t-stat: 0.55) over the crisis period, whereas the increase is 0.84 bps per month (t-stat: 3.27) over the non-crisis period.

Overall, our results show hedge funds react to past market-wide sentiment levels to various extents over different subsample periods. During these periods, sentiment experienced dramatic changes, and stocks prices moved further away from their fundamentals. Limits of arbitrage impose more constraints on arbitrageurs who tend to correct overpricing (e.g., the liquidation of Tiger Management funds during the Technology bubble).[52] We explain their ability to arbitrage overpricing in high sentiment periods by being less constrained by the limits of arbitrage. For example, being more able to negotiate with investors to secure their capital in case of underperformance or being more protected by contractual impediments from withdrawals. Prior studies support that such hedge funds recover from underperformance more quickly (Hombert and Thesmar, 2014). Their findings are consistent with the idea that some hedge funds overcome the limits to arbitrage.[53]

[52]Value managers such as Tiger funds invested only little in technology stocks during the bubble time. However, due to accentuated sentiment-driven overpricing, Tiger funds suffered serious losses of its assets through investor withdrawals. Even though the manager increased the redemption period in order to curb outflows, he announced the fund's liquidation in March 2000, just when prices of technology stocks started to tumble (Brunnermeier and Nagel, 2004).

[53]However, the bubble-riding type of sentiment trading could be rational among a few more skilled hedge funds, such as Soros funds (Brunnermeier and Nagel (2004)). Particularly, we investigate the mispricing betas of Soros funds

[Insert Table 6 here]

4.4 Economic value of dynamic arbitrage

We continue our out-of-sample tests with non-parametric portfolio analysis. Each month, we form ten portfolios based on hedge funds' dynamic arbitrage coefficients, as estimated in Eq (7) over the past 36 months, and then hold the portfolios for a subsequent 1-, 3-, 6-, 9-, 12-, 18-, or 24-month holding period. These portfolios consist of funds that react to past market-wide sentiment levels to various extents in their arbitrage on mispricing. Portfolio 10 (1) includes hedge funds with the best (lowest) dynamic arbitrage ability. For each of the ten portfolios, we obtain seven different time series of holding-period alphas, one for each holding period, from 1997 to 2016. For example, for a portfolio formed in month *t*, its 12-month holding period alpha is the average of alphas from *t*+1 to *t*+12. The alphas are estimated for each fund by Eq (9), in which the fund's risk factor loadings are estimated with the regression Eq (6) over the previous 36 months. If a fund disappears over the holding period, the portfolio alpha is calculated by including its alphas until its disappearance. The difference in performance between Portfolio 10 and Portfolio 1 represents economic value derived from hedge funds' dynamic arbitrage ability.

Panels A, B, and C of Table 7 report the time-series average of alpha for each holding period. Each portfolio is sorted on the dynamic arbitrage on MGMT, PERF, and COMB factors, respectively. We observe strong evidence of the economic value of hedge funds' dynamic arbitrage ability. As reported in the sixth column in Panel A, for a 12-month holding period, the alpha of the portfolio consisting of hedge funds with the highest ability is 49 bps per month (5.9% per year),

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during the Technology Bubble and we indeed find their funds significantly increase exposure to overpriced stocks (i.e., decrease mispricing betas) and also have significant and positive performance on a risk adjusted basis.

compared with the average alpha of – 20 bps per month realized by the portfolio of hedge funds with the lowest ability. In the last two rows of each panel, we report the differences between Portfolio 10 and Portfolio 1 for each holding period and the corresponding t-statistics, which are calculated based on Newey-West standard errors with two lags. For all three mispricing factors, we observe that the outperformance of Portfolio 10 relative to Portfolio 1 persists for a significant period of time (i.e., with a holding period of 6 months or longer). This outperformance ranges from 33 bps to 69 bps per month, with t-statistics greater than 2.84. The economic value is the most noticeable when the holding period is around 12 months. For example, funds with the best ability to employ dynamic arbitrage on MGMT (PERF) factor outperform their peers with the lowest ability by 69 (42) bps per month on a risk-adjusted basis, corresponding to 8.28% (5.04%) per year, with a t-statistic of 5.50 (4.25). Among the three factors, the dynamic arbitrage ability to exploit profits from MGMT overpricing brings the most outstanding value. The evidence is again consistent with our hypothesis that less constrained arbitrageurs who are more able to bet against overpricing when sentiment is higher outperform their peers who are more constrained, even though their average mispricing beta over time is insignificant. Finally, we find that hedge funds with the lowest arbitrage ability (Portfolio 1) cannot beat the benchmark (given the negative alpha on average).

[Insert Table 7 here]

4.5 Sentiment exposure of hedge funds betting against overpricing

Sentiment trading of rational arbitrageurs has been examined by prior studies, e.g., DeLong et al. (1990a), Brunnermeier and Nagel (2004), Griffin et al. (2011), and Chen et al. (2021), which argue it can be optimal for arbitrageurs to invest in overpriced securities. When sentiment is expected to increase, bubble-riding appears to be rational. So, hedge funds that can time sentiment tend to have higher sentiment betas and display higher alphas. Concerning arbitrageurs who bet against mispricing, Chen et al. (2021) argue that they should have negative sentiment exposure because overpriced stocks are more sensitive to sentiment than undervalued stocks. In this section, we analyze the sentiment exposure of hedge funds that bet against overpricing. To do so, we consider the return process in Eq (1), by posing a constant mispricing beta without losing generality:

$$r_{i,t} = \beta_i \text{MISP}_t + v_{i,t} \tag{1.1}$$

Given that higher returns on the mispricing factor follow higher levels of sentiment, i.e.,

$$\text{MISP}_t = a + b(S_{t-1} - \bar{S}) + u_t, \text{ with } b > 0,\ a = E(\text{MISP}_t) \tag{10}$$

Replace (10) into (1.1), we have:

$$\begin{aligned} r_{i,t} &= \beta_i(a + b(S_{t-1} - \bar{S}) + u_t) + v_{i,t} \\ r_{i,t} &= \delta_i + \beta_i^S(S_{t-1} - \bar{S}) + e_{i,t}, \\ &\text{with } \delta_i = \beta_i a,\ \beta_i^S = \beta_i b,\ e_{i,t} = \beta_i u_t + v_{i,t} \end{aligned} \tag{11}$$

The fund's exposure to the sentiment level (β_i^S) is equal to its mispricing beta β_i times b and the fund's alpha (δ_i) is equal to its mispricing beta times a, which reflects the profits derived from betting on the mispricing factor. A hedge fund arbitraging the mispricing factor would have a positive β_i and therefore, a positive sentiment exposure β_i^S, given that $b > 0$. The fund's sentiment exposure seems able to predict its alpha, given the positive relation between the mispricing beta and the sentiment beta as well as the fund alpha.

To empirically test whether higher sentiment betas are associated with higher mispricing betas among hedge funds, we run the regressions Eq (12) of the excess return of each fund on the BW sentiment level without lag over their lifetime, controlling for the risk factors described in Section 3.3:[54]

$$r_{i,t} = \alpha_i + \beta_i^S S_t + \boldsymbol{\gamma'}_i \boldsymbol{F_t} + e_{i,t} \qquad (12)$$

In Panel A of Table 8, we report the average sentiment beta of hedge funds with significant mispricing betas at different confidence levels (i.e., with different levels of t-statistics). The mispricing beta of each fund (b_i) is estimated under the unconditional model in Eq (4) over their lifetime, as described in Section 4.1. We observe hedge funds with significant and positive PERF or COMB mispricing betas also possess a significant and positive sentiment beta on average. For example, 708 funds with a t-statistics of PERF beta greater than 1.96 also have a significant and positive sentiment exposure of 0.09 (t-stat: 2.53), on average. The sentiment exposure is even higher among the funds with t-statistics of PERF beta greater than 2.326, at 0.12 (t-stat: 3.24). However, we do not have such observation with the MGMT factor, probably because only a small number of funds have a significant and positive MGMT beta. Only 84 hedge funds in our sample have a t-statistic of MGMT beta greater than 1.96. We also observe that hedge funds with significant and negative mispricing betas tend to have a negative sentiment exposure. For the three mispricing factors, the sentiment beta of hedge funds at the left tails of the distribution of t-statistics on mispricing betas is averagely negative, even though not all statistically significant.

In Panel B of Table 8, we report the average sentiment beta of the decile portfolios of hedge funds sorted on their mispricing betas. We find evidence that higher sentiment betas are associated

[54]The first order autocorrelation of the BW sentiment-level index (ρ_1) is equal to 0.98.

with higher mispricing betas with the PERF and COMB factors. On average, the funds with the lowest PERF and COMB betas, respectively, have a sentiment beta of – 0.09 and – 0.11 (t-stat: – 0.66 and – 0.77), while the funds with the highest mispricing betas have a sentiment beta of 0.40 and 0.35 (t-stat: 3.34 and 2.94). The difference between Portfolio 10 and Portfolio 1 is economically and statistically significant at 0.50 and 0.46 (t-stat: 2.67 and 2.44). Combining these results with Table 3, we confirm the positive cross-sectional relation between hedge funds' mispricing beta and sentiment beta as well as their performance.

Prior studies (DeLong et al., 1990; Abreu and Brunnermeier, 2002; Griffin et al., 2011; Brunnermeier and Nagel, 2004; Chen et al., 2021) explain that when sentiment is expected to increase, it can be optimal for arbitrageurs to invest in overpriced assets so that hedge funds which are able to time sentiment tend to have higher sentiment beta and display higher alpha. In a different way, we explain that the outperformance of high sentiment-beta hedge funds can reflect the profits derived from betting against overpricing. We also show that in the presence of market-wide sentiment and limits of arbitrages, hedge funds employing arbitrage on the mispricing factors tend to have a positive sentiment exposure, resulting from lower returns on the short-leg of the mispricing factors (i.e., overpriced stocks) following high sentiment levels.

[Insert Table 8 here]

4.6 Portfolio weights on overpriced stocks of hedge funds betting against overpricing

To eliminate the concern that underpriced stocks could drive our results, we examine in this section, hedge funds' exposure to overpriced stocks by estimating their portfolio weights. Similar in spirit to Brunnermeier and Nagel (2004), we assume that the asset allocation decision of hedge fund managers involves two steps. First, allocate a fraction *b* of the total portfolio to the market portfolio. Second, reallocate a fraction g of the total portfolio value from the initial market investment to overpriced stocks. For an overpricing arbitrageur, g should be negative, and we assume the additional capital from shorting positions is added to the fund's market investment. So, the return of this hedge fund can be written as:

$$R_t = (b - g)R_{Mt} + gR_{St} + e_t \quad (13)$$

where, R_{Mt} is the market portfolio return, R_{St} is the value-weighted return of a portfolio of overpriced stocks, and e_t is the idiosyncratic return. We use the short-leg return of the COMB factor for the following tests, which corresponds to the return of the decile portfolio consisting of stocks with the highest mispricing scores (Stambaugh et al., 2015).[55] In this model, the fraction of the total portfolio invested in overpriced stocks, w_S, is equal to $(b - g)m_S + g$, where m_S is the weight of overpriced stocks in the market portfolio. To estimate w_S, we run the OLS regression (14) for each fund in each year from 1995 to 2016, where $R_{St} - R_{Mt}$ represents an "overpricing factor".

$$R_t = \alpha + bR_{Mt} + g(R_{St} - R_{Mt}) + \epsilon_t \quad (14)$$

Hedge funds could invest in other omitted asset classes, whose returns are correlated with $R_{St} - R_{Mt}$, then our results could be biased. Considering this potential problem, we also run the regression (14) with an overpricing factor which is orthogonalized to the risk factors, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF, i.e., the residuals from the regression of the overpricing factor on the risk factors.

[55]Our analysis in this section focuses on the COMB factor because of the unavailability of composite ranking data on PERF and MGMT.

At the end of each year, we estimate the portfolio weights of overpriced stocks for each hedge fund with a significant mispricing beta and report the average weight over the period 1995-2016 in Table 9. The left of Table 9 reports the results from the regressions with the overpricing factor. For example, the average market exposure is about 0.26 among hedge funds with COMB betas greater than 2.326, and these funds have, on average, significant and negative exposures to the overpricing factor (– 0.10, t-stat: – 2.73). The net investment on overpriced stocks in hedge funds' portfolios is about – 9% (t-stat: – 2.49). The portfolio weights of overpriced stocks among hedge funds with different t-statistics of mispricing beta greater than 1.282 are averagely negative, ranging from – 9% to – 6%. The results imply hedge funds betting against mispricing have on average short positions on overpriced stocks. On the right of Table 9, which reports the regressions with the orthogonalized overpricing factor, results remain qualitatively unchanged, and the estimated weights are even more negative.

Table 9 also reports the weights of overpriced stocks for each hedge fund with negative mispricing betas. The results show that hedge funds have positive exposure to overpriced stocks. For example, among funds with t-statistics of COMB betas smaller than – 2.326, the exposure is about 0.18, and the net investment on overpriced stocks represents a long position, on average, of 19%, compared with the market portfolio weights of about 4%. The results confirm that some hedge funds delay arbitrage by investing in overpriced stocks.

[Insert Table 9 here]

5. Robustness

5.1 Bootstrap analysis of mispricing betas

Firstly, we check the statistical significance of the estimated coefficients in our in-sample analysis. As Cao et al. (2013) discussed, conventional inference can be misleading for several reasons. For example, hedge fund returns may not follow normal distributions. By random chance, some funds may appear to have significant t-statistics under the conventional levels even if the true value of their coefficients is not different from zero. Therefore, we employ a bootstrap analysis similar to Cao et al. (2013) to assess the significance of the MGMT and PERF betas and the dynamic arbitrage coefficients under each of the two models. The basic idea of the bootstrap analysis is that we randomly resample regression residuals from our model to generate hypothetical fund returns that have the same factor loadings as the actual fund except for the coefficient to be assessed (e.g., the MGMT beta), which is assumed to be zero for the pseudo fund. Then, we evaluate if the t-statistics of the estimated coefficients for the actual funds are different from the pseudo funds. Details on the procedure of this bootstrap analysis are provided in the Appendix.

Table 10 reports the empirical p-values corresponding to the t-statistics of each coefficient at different extreme percentiles from the bootstrap analysis. Under the unconditional model, for the top-ranked funds at the extreme percentiles from 1% to 10%, the t-statistics of b_{MGMT} are 0.78, 1.42, 1.79, and 2.53, respectively, with empirical p-values close or equal to 1, suggesting the MGMT betas of top-ranked funds cannot be distinguished from zero. Meanwhile, we find that the empirical p-values of b_{PERF} for top-ranked funds are all close to zero, indicating that their PERF betas are significantly positive. Under the conditional model, we find evidence supporting that the MGMT betas of top-ranked funds cannot be distinguished from zero, and the PERF betas as well as both dynamic arbitrage coefficients are significantly positive. Figure 1 plots the kernel density distributions of bootstrapped top 10th percentile t-statistics in shaded areas, as well as the actual t-statistics of each coefficient as a vertical line. Panel A and B of the figure display the coefficients estimated under the unconditional model and the conditional model, respectively. At the bottom percentiles, we find the negative MGMT betas cannot be attributed to random chance, given that the empirical p-values are all close to zero. Overall, the results of the bootstrap analysis confirm that some hedge funds bet against PERF mispricing, but more hedge funds tend to delay arbitrage on MGMT mispricing. By reacting to higher sentiment levels, some hedge funds increase their mispricing betas to exploit profits from both mispricing factors.

[Insert Table 10 and Figure 1 here]

5.2 Does hedge funds' arbitrage on underpricing drive the results?

In our main analysis, we make inferences about hedge funds' arbitrage on overpricing based on their exposure to the mispricing factors. However, if arbitrage profits from the mispricing factors are more closely related to the long leg of the factor, i.e., underpricing stocks, our inference could be biased. In Section 4.6, we have estimated exposure to overpriced stocks of hedge funds with positive mispricing betas by regression (14). We indeed find significant and negative exposures among these funds, which we identify as arbitrageurs who bet against mispricing by shorting overpricing securities. For a further robustness check, we also run the regression (14) by replacing the overpricing factor with an underpricing factor, which is equal to the long leg return of the COMB factor minus the market return. We find that the exposure to the underpricing factor (g) among hedge funds with positive mispricing betas is economically and statistically insignificant, suggesting that these hedge funds do not excessively invest in underpriced stocks. For example, among hedge funds with t-statistic of mispricing betas greater than 1.96, the average exposure to the underpricing factor is 0.04 (t-stat: 0.48). In sum, the results in our main analysis could not be driven by underpriced stocks.

5.3 Alternative data filters

Lastly, we check whether our results are robust to alternative data filters. We repeat the previous tests with sample filters by deleting the first 24 months of fund returns and funds with AUM less than \$10 million from the sample. To save space, we summarize the results. From the in-sample analysis, we find about 20.20% (2.49%) out of 2857 funds have t-statistics of PERF (MGMT) betas greater than 1.96, and 4.73% (32.80%) of funds have t-statistics smaller than –1.96. About 8.44% (7.39%) of funds have t-statistics of PERF (MGMT) dynamic arbitrage coefficient greater than 1.96. The return spread between the top and bottom deciles of hedge funds ranked by mispricing betas ranges from 27 to 61 bps per month on a risk-adjusted basis (t-stat: between 1.65 and 3.58). From the out-of-sample analysis, we find that when the PERF (MGMT) beta increases by one, the fund's 12-month leading alpha increases by 1.16% (0.07%) per month (t-stat: 4.24 (0.38)). When the dynamic arbitrage coefficient on PERF (MGMT) increases by one, the fund's 12-month leading alpha increases by 0.56% (1.13%) per month (t-stat: 2.44 (4.34)). The economic value of hedge funds' ability to apply dynamic arbitrage on PERF (MGMT) mispricing corresponds to 22 (63) bps per month on a risk-adjusted basis over a 12-months period (t-stat: 2.75 (6.49)). From the sentiment exposure analysis, the sentiment beta is, on average of 0.15 (0.14) among funds with t-statistics of PERF (MGMT) beta greater than 1.96 (t-stat: 3.28 (0.81)). The sentiment beta difference between the top and bottom deciles of hedge funds ranked by PERF (MGMT) betas is 0.81 (0.17) (t-stat: 4.14 (1.02)).

Our results are also robust to including all strategy categories and all redemption frequencies in the sample. Considering the assumption of DeLong et al. (1990b) and Chen et al.

(2021) that arbitrageurs often have short horizons, our hedge fund sample in the main analysis keeps funds allowing for redemption at a monthly or higher frequency. However, this contractual feature can reflect the heterogeneous strength of capital structure among hedge funds across different strategy categories. Funds that set a lower redemption frequency tend to have a stronger capital structure and are more likely to overcome the limits of arbitrage (Hombert and Thesmar, 2014). Therefore, we relax the data filter conditions used by Chen et al. (2021) by including funds with different redemption frequencies. Below we summarize the results. From the in-sample analysis, we find about 16.08% and 3.09% out of 8545 funds have t-statistics of PERF and MGMT betas greater than 1.96, and 5.42% (27.06%) of funds have t-statistics smaller than –1.96. About 9.37% (7.21%) of funds have t-statistics of PERF (MGMT) dynamic arbitrage coefficient greater than 1.96. The return spread between the top and bottom deciles of hedge funds ranked by mispricing betas ranges from 29 to 49 bps per month on a risk-adjusted basis (t-stat: 2.32-4.09). From the out-of-sample analysis, we find when the PERF (MGMT) beta increases by one, the fund's 12-month leading alpha increases by 1.05% (0.01%) per month (t-stat: 3.82 (0.05)). When the dynamic arbitrage coefficient on PERF (MGMT) increases by one, the fund's 12-month leading alpha increases by 0.52% (0.65%) per month (t-stat: 2.49 (3.77)). The economic value of hedge funds' ability to apply dynamic arbitrage on PERF (MGMT) mispricing corresponds to 26 (62) bps per month on a risk-adjusted basis over a 12-months period (t-stat: 2.54 (6.14)). From the sentiment exposure analysis, the sentiment beta is, on average, of 0.10 (0.33) among funds with t-statistics of PERF (MGMT) beta greater than 1.96 (t-stat: 3.83 (3.73)). The sentiment beta difference between the top and bottom deciles of hedge funds ranked by PERF (MGMT) betas is 0.42 (0.10) (t-stat: 3.54 (0.88)).

6. Conclusion

This paper explores the relation between heterogeneity in hedge funds' arbitrage on overpricing and their fund performance. On the one side, we find that some hedge funds tend to delay arbitrage by investing in overpricing, and on the other side, some hedge funds bet against overpricing right away. Different arbitrage strategies by hedge funds lead to cross-sectional variation in their mispricing betas. We find robust evidence that hedge funds betting against overpricing tend to have positive mispricing betas. By estimating portfolio weights of overpriced stocks among hedge funds with positive mispricing betas, we find that these funds possess, on average, a short position on overpriced stocks (ranging from – 9% to – 6%). Moreover, the insignificant exposures to underpriced stocks among these hedge funds indicate that they do not excessively invest in underpriced stocks. We show robust evidence that hedge funds with positive mispricing betas outperform other funds. The risk-adjusted return spread between the top and bottom deciles of hedge funds ranked by mispricing betas ranges from 28 to 63 bps per month (t-stat: 1.69-4.03). Following high sentiment levels, arbitrage opportunities created by overpricing are more prevalent in the markets. We find that some hedge funds increase their mispricing betas in response to higher past sentiment levels. The economic value which can be exploited from hedge funds dynamic arbitrage ability is noticeable, corresponding to 69 bps per month on a risk-adjusted basis over a 12-months period (t-stat: 5.50). We investigate sentiment exposure of hedge funds betting against overpricing. We find that they possess positive exposure to sentiment levels. Our result supports the conventional idea that hedge funds generate alphas by betting against mispricing.

Appendix: Procedures of the bootstrap analysis

The bootstrap approach follows Cao et al. (2013). The basic idea is to resample regression residuals from our model to generate hypothetical fund returns with zero-mispricing beta (or a zero dynamic arbitrage coefficient) but the same factor exposures as the actual funds. Empirical p-values are computed by comparing t-statistics of the estimated mispricing beta (dynamic arbitrage coefficient) of the actual funds at various cut-off percentiles with the distribution of the t-statistics of the pseudo-funds at the same cut-off percentiles.

1. Run the regression under our model (e.g., the unconditional model) for fund i over its lifetime with T_i month return observations and store the estimated coefficients ($\hat{\alpha}_i$, $\hat{b}_{i,\mathrm{MGMT}}$, $\hat{b}_{i,\mathrm{PERF}}$, $\hat{\boldsymbol{\gamma}}'_i$) as well as the time series of regression residuals $\{\hat{\varepsilon}_{i,t}, t = 1, \ldots, T_i\}$:

$$r_{i,t} = \alpha_i + b_{i,\mathrm{MGMT}}\mathrm{MGMT}_t + b_{i,\mathrm{PERF}}\mathrm{PERF}_t + \boldsymbol{\gamma}'_i\boldsymbol{F_t} + \varepsilon_{i,t} \quad (4.1)$$

2. Resample the residuals with replacement and obtain a randomly resampled residual time series $\{\hat{\varepsilon}^{bs}_{i,t}\}$, where *bs* is the index of bootstrap iteration. Then, generate monthly excess returns for a pseudo-fund by setting $b_{i,\mathrm{MGMT}} = 0$ and $b_{i,\mathrm{PERF}} = 0$, respectively. For example, setting first $b_{i,\mathrm{MGMT}} = 0$, the returns of the pseudo fund are generated as Eq (A1):

$$r^{bs}_{i,t} = \hat{\alpha}_i + \hat{b}_{i,\mathrm{PERF}}\mathrm{PERF}_t + \hat{\boldsymbol{\gamma}}'_i\boldsymbol{F_t} + \hat{\varepsilon}^{bs}_{i,t} \quad (A1)$$

3. Estimate Eq (4.1) using the generated returns $r^{bs}_{i,t}$ as the dependent variable and store the t-statistic of $\hat{b}^{bs}_{i,\mathrm{MGMT}}$.

4. Complete Steps 1–3 across all funds in our sample for i = 1, …, N (e.g., N = 3584), to obtain the cross-sectional t-statistics of $\hat{b}_{i,\mathrm{MGMT}}^{bs}$ (e.g., the top 10th percentile).

5. Repeat Steps 1–4 for 1000 iterations to generate the empirical distribution for the cross-sectional t-statistics of $\hat{b}_{i,\mathrm{MGMT}}^{bs}$. For the right-tail statistic (e.g., the top 10th percentile), calculate the empirical p-value as the frequency that the values of the bootstrapped cross-sectional statistic for the pseudo-funds exceed the actual value of the cross-sectional statistic. For the left-tail statistic (e.g., the bottom 10th percentile), the empirical p-value is calculated as the frequency that the values of the bootstrapped cross-sectional statistic for the pseudo-funds are smaller than the actual value of the cross-sectional statistic.

6. Repeat Steps 2–5 by setting $b_{i,\mathrm{PERF}} = 0$, and repeat Steps 1–5 for each coefficient estimated under the conditional model (5.1).

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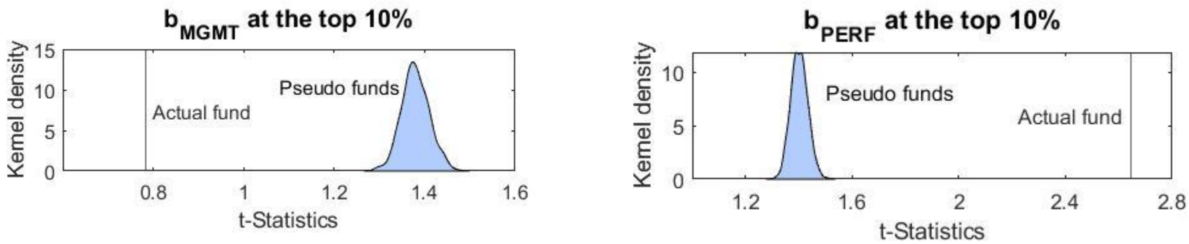
Figure 1 Mispricing t-statistics at the top 10th percentile: actual versus bootstrapped funds

Panel A of the figure displays the t-statistics of the mispricing betas at the top 10th percentile for actual fund versus bootstrapped funds, which are estimated under the unconditional model Eq (4.1). Panel B displays the t-statistics of the mispricing betas and the dynamic arbitrage coefficients for the top 10th percentile for actual funds versus bootstrapped funds, which are estimated under the conditional model Eq (5.1). The shaded area represents the density distribution of t-statistics of the coefficient for 1000 pseudo-funds that appear at the top 10th percentile in each of 1000 bootstrap simulations for the cross-section of sample funds. The vertical line corresponds to the actual fund at the top 10th percentile. The sample period is from January 1995 to December 2016.

Panel A: Unconditional model



Panel B: Conditional model

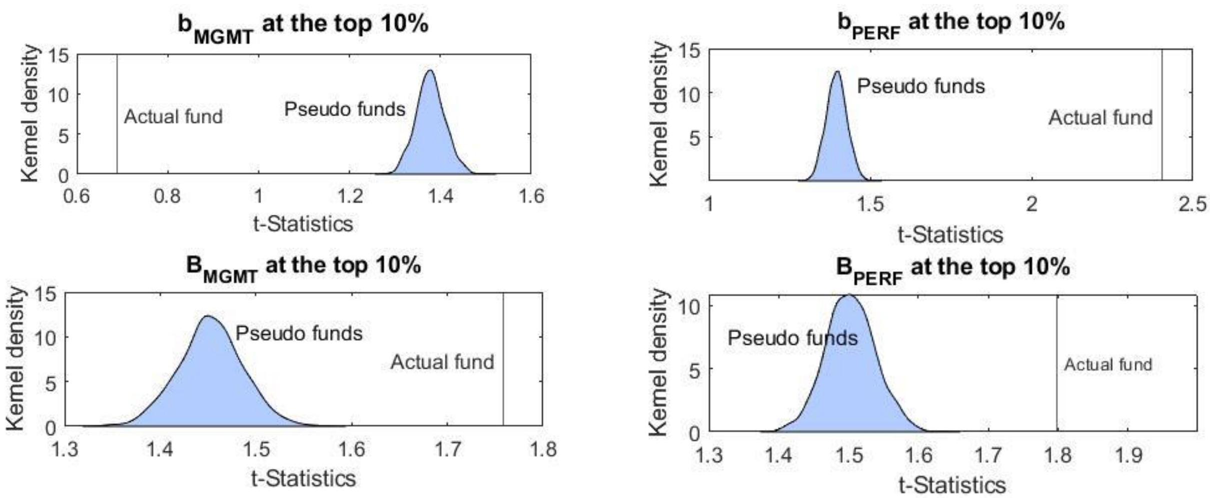


Table 1 Summary statistics

Panel A summarizes our final sample of 3584 equity-oriented hedge funds in primary categories of convertible arbitrage, event-driven, equity market neutral, global macro, long/short equity, multi strategy, and funds of funds, which have an average AUM of at least $5 million, report monthly net-of-fee returns, allow for redemption at a monthly or higher frequency, and have at least 36 months of returns. Our sample covers both active and defunct hedge funds. For each fund, the first 12 months of returns are excluded to mitigate backfill bias. The summary statistics are based on fund-month observations. All variables are winsorized at the 1% and 99% levels. Panel B reports the summary statistics of the mispricing factors, MGMT, PERF, and COMB, and the orthogonalized BW sentiment level (SENT_O). MGMT (PERF) is constructed by Stambaugh and Yuan (2017) based on the average ranking across a cluster of 6 (5) asset-pricing anomalies related to firms' management (performance). COMB is a combined mispricing factor constructed from a long-short strategy based on the composite ranking of the 11 anomalies as Stambaugh et al. (2012, 2015). Panel C reports the correlation coefficients between the mispricing factors, the sentiment level, and risk factors. The risk factors include the market excess returns (MKTRF) and the size factor (SMB) from the M4 model of Stambaugh and Yuan (2017), the change in the constant-maturity yield of the 10-year Treasury (ΔTERM), the change in the yield spread between Moody's Baa bond and the 10-year Treasury bond (ΔCredit), and the three trend-following factors for bonds, currencies, and commodities (Ptfsbd, Ptfsfx, and Ptfcom) of Fung and Hsieh (2004), the Pastor & Stambaugh (2003) liquidity factor (LIQ), the inflation rate (INF), and the default spread between the yield on Baa-rated and Aaa-rated corporate bonds (DEF). The sample period is from January 1995 to December 2016.

Panel A: Summary statistics of the hedge fund sample

	Mean	SD	10%	25%	Median	75%	90%
Fund return (%/month)	0.44	2.95	-2.55	-0.67	0.49	1.60	3.31
Fund size ($million)	272.21	884.46	7.12	17.67	51.17	155.87	449.00
Fund age (month)	75.40	52.49	21.03	35.88	61.93	101.92	148.90
Management fee (%)	1.42	0.56	0.80	1.00	1.50	1.80	2.00
Incentive fee (%)	12.98	8.22	0.00	5.00	15.00	20.00	20.00
High-water mark (dummy)	0.57	0.49	0.00	0.00	1.00	1.00	1.00
Lockup period (month)	1.11	3.90	0.00	0.00	0.00	0.00	0.00
Notice period (month)	0.96	0.87	0.00	0.17	1.00	1.17	2.17

Panel B: Summary statistics of the mispricing factors and the sentiment level

	Mean	SD	10%	25%	Median	75%	90%
MGMT (%/month)	0.54	3.07	-2.37	-1.17	0.39	1.86	4.41
PERF (%/month)	0.72	4.73	-4.46	-1.64	0.40	3.05	6.56
COMB (%/month)	0.16	5.27	-5.31	-2.39	0.14	2.81	5.65
SENT_O	0.21	0.66	-0.54	-0.13	0.09	0.42	0.87

Panel C: Correlation coefficients

	MGMT	PERF	COMB	SENT_O	MKTRF	SMB	ΔTERM	ΔCredit	Ptfsbd	Ptfsfx	Ptfcom	LIQ	INF	DEF
MGMT	1.00													
PERF	0.18	1.00												
COMB	0.50	0.81	1.00											
SENT_O	0.21	0.19	0.17	1.00										
MKTRF	-0.45	-0.50	-0.53	-0.14	1.00									
SMB	-0.23	-0.09	-0.17	0.07	0.19	1.00								
ΔTERM	-0.18	-0.22	-0.27	-0.08	0.24	0.20	1.00							
ΔCredit	0.29	0.39	0.42	0.17	-0.47	-0.23	-0.53	1.00						
Ptfsbd	-0.01	0.10	0.05	0.10	-0.24	-0.08	-0.31	0.27	1.00					
Ptfsfx	0.12	0.13	0.13	0.01	-0.20	0.00	-0.16	0.29	0.32	1.00				
Ptfcom	0.02	0.15	0.16	0.01	-0.17	-0.07	-0.10	0.16	0.20	0.35	1.00			
LIQ	-0.20	0.06	-0.10	0.12	0.16	0.09	0.25	-0.29	-0.07	-0.11	-0.08	1.00		
INF	-0.12	-0.04	-0.09	0.04	0.02	0.02	0.19	-0.15	-0.19	-0.16	-0.08	0.11	1.00	
DEF	-0.05	0.01	-0.10	-0.35	-0.12	0.04	-0.02	-0.03	0.03	0.03	-0.06	-0.08	-0.22	1.00

Table 2 Cross-sectional distribution of mispricing t-statistics

The table reports the cross-sectional distributions of t-statistics for the estimate b_i and for the dynamic arbitrage coefficient B_i, which are estimated under an unconditional and a conditional model, respectively, for each fund over their lifetime:

Unconditional model: $r_{i,t} = \alpha_i + b_{i,\mathrm{MGMT}}\mathrm{MGMT}_t + b_{i,\mathrm{PERF}}\mathrm{PERF}_t + \boldsymbol{\gamma'}_i\boldsymbol{F_t} + \varepsilon_{i,t}$ (4.1)

Conditional model: $r_{i,t} = \alpha_i + b_{i,\mathrm{MGMT}}\mathrm{MGMT}_t + b_{i,\mathrm{PERF}}\mathrm{PERF}_t + B_{i,\mathrm{MGMT}}(S_{t-1} - \bar{S})\mathrm{MGMT}_t + B_{i,\mathrm{PERF}}(S_{t-1} - \bar{S})\mathrm{PERF}_t + \boldsymbol{\gamma'}_i\boldsymbol{F_t} + \varepsilon_{i,t}$ (5.1)

Where $r_{i,t}$ is the excess return of hedge fund i, $\boldsymbol{F_t}$ is a vector of risk factors, MKTRF, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF, which are described in Section 3.3, $S_{t-1}$is the one-month lagged BW sentiment-level index, and $\bar{S}$ is the average BW sentiment level. We also run the regressions by replacing the MGMT and PERF factors with the COMB factor. The t-statistics are calculated based on Newey-West standard errors with 2 lags.

			Percentage of the funds							
		No. funds	t≤−2.326	t≤−1.960	t≤−1.645	t≤−1.282	t≥1.282	t≥1.645	t≥1.960	t≥2.326
Unconditional Model	b_{MGMT}	3584	24.75	31.86	38.70	47.21	5.89	3.77	2.34	1.34
	b_{PERF}	3584	2.46	4.32	6.47	9.49	35.49	26.31	19.75	13.76
	b_{COMB}	3584	3.38	5.52	8.12	12.70	24.92	17.38	12.03	7.53
Conditional Model	b_{MGMT}	3584	25.17	32.87	40.12	50.17	4.38	2.62	1.65	0.86
	B_{MGMT}	3584	2.15	3.82	6.61	10.85	17.89	11.38	7.53	4.97
	b_{PERF}	3584	3.10	4.69	6.45	9.65	31.17	22.54	16.35	10.91
	B_{PERF}	3584	2.71	4.44	7.03	11.55	19.95	12.39	8.26	5.47
	b_{COMB}	3584	3.46	5.66	8.57	12.97	24.44	16.96	11.44	6.95
	B_{COMB}	3584	3.18	5.13	8.12	12.36	23.35	15.35	10.60	6.42

Table 3 Outperformance of less constrained hedge funds

Panel A reports the performance of decile portfolios of hedge funds independently sorted on their mispricing beta b_i and dynamic arbitrage coefficients B_i, which are estimated for each fund under the unconditional model Eq (4) and the conditional model Eq (5) over their lifetime. The performance of each fund is measured as the alpha from the regression: $r_{i,t} = \alpha_i + \boldsymbol{\gamma}'_i \boldsymbol{F_t} + \varepsilon_{i,t}$ (6), where $\boldsymbol{F_t}$ is a vector of risk factors, MKTRF, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF, described in Section 3.3. Panel B reports the performance of 3×3 portfolios sorted on the mispricing beta and dynamic arbitrage. To construct the 3×3 portfolios, we first sort hedge funds on the coefficients b_i, forming tertiles, and then sort funds in each tertile by B_i, again forming tertiles. In the first column of Panel B, we also report the average mispricing beta b_i of each tertile; in the last row and the last column (H-L), we report the difference in performance between the portfolio with the highest b_i and B_i and the portfolio with the lowest b_i and B_i, and the corresponding t-statistic.

Panel A: Performance of decile portfolios sorted on the mispricing beta and dynamic arbitrage

	Unconditional Model			Conditional Model					
	b_{MGMT}	b_{PERF}	b_{COMB}	b_{MGMT}	b_{PERF}	b_{COMB}	B_{MGMT}	B_{PERF}	B_{COMB}
Portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	-0.04	0.22	0.06	-0.04	0.20	0.09	0.14	0.22	0.25
2	0.17	0.23	0.17	0.18	0.24	0.11	0.21	0.27	0.26
3	0.32	0.31	0.23	0.32	0.29	0.21	0.28	0.34	0.41
4	0.33	0.27	0.30	0.32	0.32	0.36	0.25	0.28	0.34
5	0.35	0.28	0.36	0.36	0.29	0.34	0.36	0.34	0.35
6	0.42	0.27	0.32	0.32	0.34	0.31	0.37	0.27	0.39
7	0.27	0.32	0.38	0.36	0.33	0.38	0.40	0.32	0.24
8	0.50	0.41	0.38	0.37	0.41	0.42	0.23	0.23	0.38
9	0.53	0.41	0.47	0.60	0.42	0.36	0.42	0.38	0.26
10	0.46	0.58	0.64	0.51	0.48	0.73	0.68	0.67	0.44
Port. 10 – Port. 1	0.51	0.36	0.59	0.55	0.28	0.63	0.54	0.45	0.18
t-statistics	3.37	2.18	3.63	3.59	1.69	4.03	3.42	2.68	1.14

Panel B: Performance of 3×3 portfolios sorted on the mispricing beta and dynamic arbitrage

MGMT:	b_i	Low B_i	Med B_i	High B_i	H – L	t-stat
Low b_i	-0.40	-0.04	0.13	0.41	0.45	4.01
Med b_i	-0.14	0.33	0.37	0.40	0.07	0.71
High b_i	0.07	0.45	0.47	0.46	0.02	0.13
H – L	0.47	0.48	0.35	0.05	0.50	2.67
t-stat		3.90	4.77	0.40	3.96	
PERF:						
Low b_i	-0.09	0.17	0.22	0.34	0.17	1.27
Med b_i	0.04	0.27	0.32	0.41	0.14	1.81
High b_i	0.15	0.42	0.34	0.50	0.08	0.62
H – L	0.24	0.25	0.12	0.15	0.32	1.95
t-stat		1.97	1.58	1.16	2.63	
COMB:						
Low b_i	-0.10	0.03	0.20	0.25	0.22	1.72
Med b_i	0.02	0.32	0.35	0.36	0.04	0.51
High b_i	0.13	0.59	0.45	0.44	-0.15	-1.28
H – L	0.23	0.55	0.25	0.18	0.40	0.60
t-stat		4.82	2.65	1.43	3.52	

Table 4 Predictability of mispricing beta on performance in the short run

The table reports the results of the Fama-MacBeth second stage cross-sectional regressions: in the first stage Eq (7), we regress at the end of each month (t) the excess return of each fund on a mispricing factor MISP_t over the previous 36 months, controlling for risk factors, MKTRF, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF, described in Section 3.3. and sentiment hedging against market risk; in the second stage Eq (8), we run the cross-sectional regressions of one-month-ahead fund performance $Perf_{i,t+1}$ on the average mispricing beta (b_{it}), dynamic arbitrage (B_{it}), and sentiment hedging (B_{it}^m), controlling for fund characteristics ($\mathbf{FundChar}_t$), fund age, fund size, management fees, incentive fees, high-water-mark, leverage, lockup period, and redemption period.

$$r_{it} = \alpha_i + b_{it}\text{MISP}_t + B_{it}(S_{t-1} - \bar{S})\text{MISP}_t + B_{it}^m(S_{t-1} - \bar{S})\text{MKTRF}_t + \boldsymbol{\gamma}'_i\boldsymbol{F}_t + \varepsilon_{it} \quad (7)$$

$$\text{Perf}_{i,t+1} = w_t + \theta_{1,t}b_{it} + \theta_{2,t}B_{it} + \theta_{3,t}B_{it}^m + \boldsymbol{\theta}'_t\mathbf{FundChar}_t + \epsilon_{i,t+1} \quad (8)$$

Where S_{t-1} is the one-month lagged BW (2006) sentiment-level index, $\bar{S}$ is the average of the sentiment level, the performance $\text{Perf}_{i,t+1}$ is measured as the one-month leading alpha, which is the difference between the excess return $r_{i,t+1}$ and the products of the fund's risk factor loadings and factor returns in month t+1, as in Eq (9). The fund's risk factor loadings are estimated using regression Eq (6) over the previous 36 months. The reported t-statistics are calculated based on Newey-West standard errors with 2 lags.

Dependent variable: One-month leading alpha

	MGMT		PERF		COMB	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
b_{it}	-0.33	-0.95	1.25	2.79	0.72	2.10
B_{it}	0.81	3.46	0.58	2.44	0.67	2.40
B_{it}^m	-1.02	-3.54	-0.97	-3.44	-0.91	-3.39
Log (Age)	-0.07	-1.33	-0.09	-1.68	-0.07	-1.23
Log (Size)	0.12	7.1	0.13	7.02	0.12	6.67
Mgmtfee	-0.07	-1.84	-0.07	-1.94	-0.08	-1.97
Incfee	-0.01	-2.82	-0.01	-2.81	0.00	-1.71
HWM	0.08	1.98	0.09	1.96	0.11	2.06
Leverage	0.02	0.55	0.04	1.18	0.01	0.36
Lockup	0.28	3.23	0.36	4.33	0.25	2.31
Redemp.	0.60	2.27	0.86	3.03	0.83	2.91
Constant	-1.72	-5.39	-1.90	-5.64	-1.76	-5.25
Obs	200,292		200,292		200,292	
Adj-R^2	0.08		0.07		0.07	

Table 5 Predictability of mispricing beta on performance in the long run

The table reports the results of the Fama-MacBeth second stage cross-sectional regressions: at the end of each month (t), in the first stage, we regress with Eq (7); in the second stage, we run the cross-sectional regressions with Eq (8), in which the dependent variable is the 3-, 6-, 9-, 12-, 18-, or 24-month leading alpha. For example, the 12-month leading alpha is the average of alphas estimated by Eq (9) from t+1 to t+12. The reported t-statistics are calculated based on Newey-West standard errors with 2 lags.

Dependent variable: N-month leading alpha

	3-month		6-month		9-month		12-month		18-month		24-month	
MGMT:	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
b_{it}	-0.33	-1.00	-0.28	-0.89	-0.22	-0.80	-0.15	-0.67	-0.09	-0.49	-0.07	-0.44
B_{it}	0.82	3.42	0.83	3.36	0.84	3.58	0.83	3.94	0.74	4.27	0.62	4.25
B_{it}^m	-1.01	-3.51	-0.97	-3.53	-0.92	-3.65	-0.88	-3.85	-0.71	-3.99	-0.53	-3.87
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R^2	0.08		0.09		0.09		0.09		0.08		0.07	
PERF:												
b_{it}	1.24	3.00	1.27	3.41	1.31	4.00	1.31	4.53	1.21	4.85	1.12	5.28
B_{it}	0.55	2.53	0.53	2.45	0.47	2.39	0.43	2.34	0.28	1.87	0.15	1.17
B_{it}^m	-0.99	-3.51	-0.97	-3.65	-0.94	-3.84	-0.92	-4.05	-0.79	-4.31	-0.61	-4.31
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R^2	0.08		0.08		0.08		0.08		0.07		0.07	
COMB:												
b_{it}	0.69	2.11	0.68	2.06	0.73	2.32	0.80	2.79	0.82	3.37	0.80	3.82
B_{it}	0.70	2.65	0.77	3.00	0.75	3.22	0.71	3.33	0.58	3.38	0.46	3.17
B_{it}^m	-0.94	-3.47	-0.94	-3.58	-0.93	-3.79	-0.90	-4.02	-0.77	-4.29	-0.61	-4.27
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R^2	0.07		0.07		0.07		0.08		0.07			
Obs	200,292		200,292		200,292		200,292		200,292		200,292	

Table 6 Predictability over subperiods

The table reports, in Panel A, the results of the Fama-MacBeth second stage cross-sectional regressions over two sample subperiods: the financial crisis period including years from 1998 to 2001 (i.e., Technology Bubble) and from 2007 to 2009 (i.e., 2008 Financial Crisis) and in Panel B, the results over the non-financial crisis period. The dependent variable is the 1-, 3-, 6-month leading alpha. The reported t-statistics are calculated based on Newey-West standard errors with 2 lags.

	Panel A: Subperiod 1998-2001 and 2007-2009						Panel B: Subperiod excluding 1998-2001 and 2007-2009					
	1-month		3-month		6-month		1-month		3-month		6-month	
MGMT:	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
b_{it}	-1.08	-1.40	-1.16	-1.55	-1.16	-1.70	0.11	0.39	0.15	0.55	0.24	0.98
B_{it}	**1.08**	2.18	**1.12**	2.26	**1.20**	2.30	**0.65**	2.94	**0.65**	2.72	**0.62**	2.62
B_{it}^m	-0.68	-1.65	-0.63	-1.55	-0.67	-1.68	**-1.22**	-3.20	**-1.23**	-3.22	**-1.14**	-3.21
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R^2	0.09		0.09		0.09		0.08		0.08		0.09	
PERF:												
b_{it}	1.88	1.79	**1.93**	2.00	**2.08**	2.38	**0.89**	2.68	**0.84**	2.78	**0.80**	3.00
B_{it}	**1.17**	4.48	**0.92**	4.59	**0.79**	3.89	0.24	0.70	0.33	1.04	0.37	1.17
B_{it}^m	-0.61	-1.39	-0.56	-1.35	-0.59	-1.56	**-1.18**	-3.25	**-1.23**	-3.37	**-1.19**	-3.42
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R^2	0.08		0.08		0.08		0.07		0.08		0.08	
COMB:												
b_{it}	0.08	0.11	0.21	0.29	0.41	0.55	**1.10**	3.51	**0.98**	3.38	**0.84**	3.27
B_{it}	**0.73**	2.40	**0.73**	2.73	**0.84**	3.04	0.63	1.57	0.69	1.77	0.72	1.95
B_{it}^m	-0.67	-1.57	-0.62	-1.46	-0.64	-1.57	**-1.05**	-3.04	**-1.12**	-3.24	**-1.12**	-3.34
FundChar	Yes		Yes		Yes		Yes		Yes		Yes	
Adj-R^2	0.06		0.06		0.07		0.07		0.07		0.07	
Obs	63,281		63,281		63,281		137,011		137,011		137,011	

Table 7 Economic value of dynamic arbitrage

This table presents the results of our univariate portfolio analysis on the economic value of hedge funds' dynamic arbitrage ability. Each month, we form ten portfolios based on hedge funds' dynamic arbitrage coefficients estimated over the past 36 months and then hold the portfolios for a subsequent 1-, 3-, 6-, 9-, 12-, 18-, or 24-month holding period. Portfolio 10 (1) includes funds with the highest (lowest) dynamic arbitrage coefficients. Panel A, B, and C report, for different holding periods, the time-series average alpha (in percent per month) of each portfolio consisting of funds dynamic arbitrage ability in their arbitrage on MGMT, PERF, and COMB mispricing, respectively. The alphas are estimated for each fund by Eq (9), in which the fund's risk factor loadings are estimated with the regression Eq (6) over the previous 36 months. In the last two rows of each panel, we report the time-series average difference in performance between Portfolio 10 and Portfolio 1 and the corresponding t-statistic, which is calculated based on Newey-West standard errors with 2 lags.

Panel A:	Dynamic arbitraging on MGMT factor						
Portfolio	1-month	3-month	6-month	9-month	12-month	18-month	24-month
1	-0.17	-0.18	-0.20	-0.20	-0.20	-0.21	-0.21
2	0.09	0.08	0.08	0.09	0.09	0.08	0.09
3	0.07	0.07	0.09	0.09	0.08	0.10	0.11
4	0.16	0.16	0.17	0.19	0.20	0.21	0.22
5	0.18	0.18	0.20	0.22	0.22	0.23	0.23
6	0.29	0.31	0.30	0.31	0.32	0.32	0.31
7	0.27	0.27	0.29	0.29	0.30	0.29	0.27
8	0.24	0.25	0.25	0.27	0.29	0.30	0.28
9	0.16	0.22	0.26	0.29	0.33	0.33	0.31
10	0.28	0.35	0.41	0.46	0.49	0.47	0.40
Port. 10 – Port. 1	0.45	0.54	0.61	0.66	0.69	0.68	0.61
t-statistics	2.93	3.89	4.72	5.12	5.50	6.96	7.14

Panel B:	Dynamic arbitraging on PERF factor						
Portfolio	1-month	3-month	6-month	9-month	12-month	18-month	24-month
1	-0.01	-0.05	-0.09	-0.10	-0.11	-0.11	-0.10
2	0.22	0.23	0.20	0.18	0.18	0.16	0.15
3	0.16	0.19	0.20	0.20	0.21	0.23	0.23
4	0.28	0.24	0.25	0.26	0.26	0.25	0.24
5	0.20	0.23	0.23	0.24	0.24	0.23	0.22
6	0.13	0.17	0.20	0.22	0.23	0.23	0.23
7	0.15	0.16	0.17	0.21	0.23	0.25	0.24
8	0.19	0.20	0.22	0.24	0.25	0.26	0.25
9	0.12	0.16	0.24	0.28	0.31	0.32	0.31
10	0.12	0.18	0.24	0.28	0.31	0.29	0.24
Port. 10 – Port. 1	0.13	0.23	0.33	0.39	0.42	0.39	0.34
t-statistics	0.90	1.92	2.94	3.65	4.25	4.33	4.22

Panel C:	Dynamic arbitraging on COMB factor						
Portfolio	1-month	3-month	6-month	9-month	12-month	18-month	24-month
1	-0.01	-0.04	-0.10	-0.14	-0.16	-0.20	-0.19
2	0.19	0.18	0.15	0.12	0.11	0.10	0.09
3	0.25	0.26	0.24	0.25	0.26	0.27	0.26
4	0.22	0.22	0.23	0.24	0.25	0.26	0.25
5	0.13	0.15	0.17	0.20	0.21	0.21	0.21
6	0.17	0.17	0.19	0.22	0.24	0.24	0.24
7	0.13	0.19	0.22	0.25	0.28	0.28	0.26
8	0.16	0.15	0.18	0.22	0.26	0.28	0.28
9	0.23	0.26	0.31	0.34	0.37	0.37	0.34
10	0.10	0.18	0.25	0.30	0.31	0.29	0.27
Port. 10 – Port. 1	0.11	0.21	0.35	0.43	0.47	0.49	0.45
t-statistics	0.66	1.59	2.84	3.75	4.39	5.29	5.62

Table 8 Sentiment betas versus mispricing betas

Panel A of the table reports the average sentiment beta of hedge funds with significant mispricing betas at different confidence levels (i.e., different t-statistics). The mispricing beta of each fund (b_i) is estimated under the unconditional model in Eq (4) over their lifetime. The sentiment beta of each fund (β_i^S) is estimated by the regressions of the excess return of the fund on the BW sentiment level without lag controlling for the risk factors described in Section 3.3, as in Eq (12), over their lifetime. Panel B reports the average sentiment beta of the decile portfolios of hedge funds sorted on their mispricing betas.

Panel A: Sentiment betas of funds with different mispricing betas

	MGMT			PERM			COMB		
	No. funds	Sentiment beta	t-stat	No. funds	Sentiment beta	t-stat	No. funds	Sentiment beta	t-stat
$t \leq -2.326$	887	-0.05	-1.21	88	-0.03	-0.19	121	-0.24	-1.09
$t \leq -1.960$	1,142	-0.05	-1.39	155	-0.13	-1.38	198	-0.15	-0.94
$t \leq -1.645$	1,387	-0.04	-1.24	232	-0.15	-1.97	291	-0.12	-1.01
$t \leq -1.282$	1,692	-0.02	-0.58	340	-0.11	-1.04	455	0.02	0.20
$t \geq 1.282$	211	0.11	1.05	1,272	0.09	3.24	893	0.13	3.96
$t \geq 1.645$	135	0.18	1.28	943	0.10	3.14	623	0.15	3.49
$t \geq 1.960$	84	-0.01	-0.08	708	0.09	2.53	431	0.19	3.36
$t \geq 2.326$	48	0.12	0.43	493	0.12	3.24	270	0.18	2.19

Panel B: Sentiment betas of decile portfolios sorted on mispricing betas

	MGMT		PERM		COMB	
Portfolio	Sentiment beta	t-stat	Sentiment beta	t-stat	Sentiment beta	t-stat
1	-0.05	-0.39	-0.09	-0.66	-0.11	-0.77
2	0.17	1.51	-0.14	-1.96	-0.17	-2.38
3	0.13	2.12	-0.08	-1.58	0.01	0.12
4	0.00	0.00	-0.12	-2.18	-0.08	-1.38
5	-0.10	-1.96	0.02	0.44	-0.06	-1.58
6	-0.04	-0.78	-0.07	-1.45	0.00	0.09
7	-0.02	-0.43	-0.02	-0.39	0.00	0.02
8	-0.03	-0.70	0.07	1.86	0.04	0.77
9	0.04	0.70	0.08	1.27	0.07	1.34
10	-0.04	-0.43	0.40	3.34	0.35	2.94
Port. 10 – Port. 1	0.01	0.09	0.50	2.67	0.46	2.44

Table 9 Portfolio weights of overpriced stocks of hedge funds betting against overpricing

The table reports the estimated portfolio weights of overpriced stocks of hedge funds with significant mispricing betas at different confidence levels (i.e., different t-statistics). The mispricing beta of each fund is estimated under the unconditional model in Eq (4) over their lifetime with the COMB factor. Each year, we run the regression (14) of each fund's return on the market return and the (orthogonalized) overpricing factor. The overpricing factor is the difference in returns between a portfolio of overpriced stocks and the market portfolio, $R_{St} - R_{Mt}$. The orthogonalized overpricing factor is the residuals of the regression of the overpricing factor on the risk factors, SMB, ΔTERM, ΔCredit, Ptfsbd, Ptfsfx, Ptfcom, LIQ, INF, and DEF. The portfolio weights of overpriced stocks of each hedge fund in each year, w_S, are estimated as $(b - g)m_S + g$, where m_S is the weight of overpriced stocks in the market portfolio. We report the average of estimated coefficients b, g, and w_S over the period 1995-2016.

	Overpricing factor				Orthogonalized overpricing factor			
	b	g	w_S	Adj. R^2	b	g	w_S	Adj. R^2
$t > 2.326$	0.26	-0.10	-0.09	0.28	0.26	-0.14	-0.12	0.28
	6.51	-2.73	-2.49		5.95	-3.70	-3.48	
$t > 1.96$	0.26	-0.10	-0.08	0.26	0.25	-0.13	-0.11	0.26
	6.49	-2.56	-2.33		5.93	-3.48	-3.26	
$t > 1.645$	0.26	-0.09	-0.07	0.26	0.25	-0.12	-0.10	0.26
	6.76	-2.33	-2.09		6.21	-3.22	-3.00	
$t > 1.282$	0.25	-0.07	-0.06	0.25	0.25	-0.10	-0.09	0.25
	6.69	-2.02	-1.78		6.26	-2.89	-2.66	
$t < -2.326$	0.32	0.18	0.19	0.27	0.35	0.17	0.18	0.27
	8.43	5.28	5.69		8.74	5.07	5.51	
$t < -1.96$	0.29	0.18	0.19	0.29	0.32	0.17	0.17	0.28
	13.05	6.36	6.80		14.34	6.06	6.53	
$t < -1.645$	0.25	0.16	0.16	0.28	0.28	0.15	0.15	0.27
	11.24	5.43	5.79		11.54	5.53	5.95	
$t < -1.282$	0.23	0.14	0.14	0.25	0.26	0.12	0.13	0.24
	11.05	5.36	5.75		11.95	5.33	5.76	

Table 10 Bootstrap analysis of mispricing betas

The table reports the results of the bootstrap analysis for assessing the significance of the mispricing betas (b_{MGMT} and b_{PERF}) and the dynamic arbitrage coefficients (B_{MGMT} and B_{PERF}) estimated under the unconditional model Eq (4.1) and the conditional model Eq (5.1), respectively. For each coefficient, the first row reports the t-statistics of the coefficient at different extreme percentiles across the sample of 3584 actual funds, and the second row is the empirical p-values from bootstrap simulations. The number of resampling iterations is 1000.

		Bottom t-stat				Top t-stat			
Coefficient		1%	3%	5%	10%	10%	5%	3%	1%
		Unconditional model							
b_{MGMT}	t-stat	-5.28	-4.46	-4.01	-3.36	0.78	1.42	1.79	2.53
	p-value	0.00	0.00	0.00	0.00	1.00	1.00	1.00	0.82
b_{PERF}	t-stat	-3.07	-2.22	-1.86	-1.23	2.64	3.29	3.67	4.25
	p-value	0.00	0.01	0.24	1.00	0.00	0.00	0.00	0.00
		Conditional model							
b_{MGMT}	t-stat	-5.20	-4.50	-4.03	-3.38	0.69	1.21	1.55	2.22
	p-value	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
b_{PERF}	t-stat	-3.20	-2.34	-1.87	-1.25	2.41	2.97	3.41	4.11
	p-value	0.00	0.00	0.11	1.00	0.00	0.00	0.00	0.00
B_{MGMT}	t-stat	-2.76	-2.14	-1.79	-1.34	1.76	2.32	2.69	3.23
	p-value	0.57	0.82	1.00	1.00	0.00	0.00	0.00	0.00
B_{PERF}	t-stat	-3.02	-2.24	-1.90	-1.41	1.80	2.39	2.71	3.34
	p-value	0.06	0.58	0.82	0.99	0.00	0.00	0.00	0.00