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Does Size Matter in the Hedge Fund Industry?*

Melvyn Teo**

Abstract

We document a negative and convex relationship between hedge fund size and future risk-adjusted returns. Small hedge funds outperform large hedge funds by 3.65 percent per year after adjusting for risk. This over performance is not driven by fund age, leverage, serial correlation, or self-selection biases. The capacity constraints manifest across various investment styles and regions. In particular, they are strongest for funds managed by multiple principals who trade small, illiquid securities, suggesting that the observed diseconomies can be traced to price impact and hierarchy costs (Stein, 2002). While investors direct disproportionately more capital to smaller funds, they do not do so quickly enough to eliminate this size effect. Interestingly, the capacity constraints facing individual hedge funds do not extend to funds of hedge funds.

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1. Introduction

How significant and pervasive are the capacity constraints facing individual hedge funds? Do small hedge funds deliver economically larger risk-adjusted returns than do large hedge funds? Which hedge funds are most affected by capacity constraints and why? The answers to these questions are relevant to investors and have important implications for performance persistence and the existence of incentive fees.

Recent studies have shed light on capacity constraints in the mutual fund industry (Chen, et al. 2004; Yan, 2008). However, unlike mutual funds, hedge funds typically trade complex and illiquid securities, including derivatives and over-the-counter securities. They exploit limited arbitrage opportunities through dynamic strategies that involve speed, leverage, and attention to execution costs. It seems that the impact of fund size, if any, should be amplified for hedge funds. Indeed, the widespread use of incentive fees by hedge fund management companies suggests that hedge fund investment opportunities are not as scalable as those for mutual funds (Goetzmann, Ingersoll, and Ross, 2003). As a result of possible diseconomies of scale, several successful hedge funds have stopped accepting new money. Some hedge funds that have ignored such scalability issues have perished (Lowenstein, 2001). Clearly, the hedge fund industry provides an interesting laboratory for studying the effects of diseconomies of scale on fund management.

Yet, the evidence in favor of capacity constraints in the hedge fund industry appears mixed. Goetzmann, Ingersoll, and Ross (2003) find that successful funds are less likely to accept new money while Fung, Hsieh, Naik, and Ramadorai (2008) show that inflows hurt the ability of Funds of Funds to deliver alpha. Naik, Ramadorai, and Stromqvist (2007) document investment strategy level capacity constraints. However, none of these studies focus on the fundamental relationship between fund assets under management and future fund performance. An exception is Getmansky (2005) who finds a positive and concave relationship between fund size and future performance; hedge funds initially benefit from an increase in fund size, but investment performance suffers once funds grow beyond a certain optimal level. Yet, given the logic of Berk and Green (2004), Getmansky's results[1] seem inconsistent with the dearth of performance

[1] We show that Getmansky's results are sensitive to the model of self selection and termination that she uses.

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persistence for hedge funds (Brown, Goetzmann, Ibbotson, 1999; Liang, 2000; Agarwal and Naik, 2000). Hence, we believe that the topic of capacity constraints in the hedge fund industry deserves a fresh look.

In this effort, we investigate the effects of fund size on the cross-section of future fund performance. We find using a Fama and MacBeth (1973) regression framework that the relationship between past fund size and fund performance is downward sloping and convex. Specifically, we estimate cross-sectional regressions on monthly fund abnormal returns with last month's fund size and square of fund size as independent variables. The regressions control for a kitchen sink of fund characteristics that may affect fund performance, and allow for style and investment region fixed effects. We adjust for hedge fund risk exposure using the Fung and Hsieh (2004) seven-factor model which has been shown to have considerable explanatory power over aggregate hedge fund returns. We find that the coefficient estimate on last month's fund size is negative and statistically significant (t-statistic = 2.54) while that on the square of last month's fund size is positive and statistically significant (t-statistic = 2.26). After controlling for the other variables, an increase in fund assets under management (henceforth AUM) from a small base of say US$10m to US$500m is associated with a reduction in annual abnormal returns of approximately 1.23 percent. As a manifestation of the convexity, a subsequent increase in fund AUM from US$500m to US$1bn is associated with additional reduction in risk-adjusted returns of only 0.57 percent.

Next, we evaluate the economic relevance of the capacity constraints by employing the portfolio sort methodology used by Carhart (1997) and others. We show that the portfolio of small funds outperforms the portfolio of large funds by about 3.65 percent per year (t-statistic = 6.64) after adjusting for covariation with the Fung and Hsieh (2004) seven risk factors.[2] The portfolios are formed every January 1st based on fund AUM last December. These results cannot be explained by self-selection induced backfill and incubation database biases (Fung and Hsieh, 2004), illiquidity induced serial correlation in returns, and differences in fund fees. The portfolio spread is still consistently above two percent per year and statistically significant (at the one percent level) regardless of whether we perform the sort analysis after removing the first 36

[2] We define as small funds those in the smallest two size quintiles and as large funds those in the largest two size quintiles.

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months of return data for each fund, after unsmoothing the returns using the Getmansky, Lo, and Makarov (2004) approach, or after adding back fees to the post-fee returns.

Can hedge fund investors benefit by choosing small funds instead of large funds? Since investors cannot short sell hedge funds (at least those funds that are not publicly listed), spread portfolios of hedge funds may not be particularly relevant to them. Hence, we consider the performance of a hypothetical Fund of Funds portfolio with the typical fee structure of one percent management fee and ten percent performance fee, and that only invests in small hedge funds. We show that this hypothetical Fund of Funds delivers an after-fee alpha of 3.99 percent per year (t-statistic = 3.97), which is both economically and statistically significant. In contrast, the hypothetical Fund of Funds portfolio comprising only large hedge funds earns an after-fee alpha of 1.32 percent per year that is statistically indistinguishable from zero. Our results are robust to requiring that the Fund of Funds invests only in small hedge funds that manage at least US$20 million.

What drives capacity constraints for hedge funds and how pervasive are they? We break down our fund universe into four broad investment styles (Security selection, Directional Traders, Relative Value, and Multi-process) and four investment regions (North America, Europe, Global, and Emerging Markets). We find that the portfolio sort results are robust across investment styles and regions. However, the spread alphas demonstrate substantial variation. For example, the spread alphas are relatively weak for Relative Value (1.86 percent) and Global (2.71 percent) funds who typically trade liquid and large-capitalization securities. Conversely, they are relatively strong for Emerging Market (8.02 percent) funds who typically trade illiquid and small-capitalization securities. These results suggest that price impact may lie at the root of the observed capacity constraints. Large hedge funds are likely to generate greater price impact with their trades than do small hedge funds as they attempt to deploy large amounts of capital in the markets. Moreover, the effects of price impact are especially severe for small capitalization and illiquid securities. Consistent with this view, we find that the capacity constraints are strongest for funds that by virtue of their tight share restrictions (long redemption and notification periods) are likely to hold more illiquid securities (Aragon, 2007).

We also show that the capacity constraints are related to the organization diseconomies proposed by Aghion and Tirole (1997) and Stein (2002). They argue that the process of agents jostling to get ideas implemented in large organizations can create diseconomies of scale.[3] According to Stein (2002), such diseconomies or hierarchy costs are particularly relevant when tasks involve the processing of soft information, e.g., information that cannot be verified by anyone but the agent. Chen et al. (2004) and Berger et al. (2005) find evidence of hierarchy costs in mutual funds and banks, respectively. Since the investment management process at hedge funds very often involves soft information, i.e., subjective opinions as to whether a security is over or under-valued, hierarchy costs should impact hedge fund performance as well. We show that consistent with this line of reasoning, the number of principals compounds the effects of size on hedge fund performance. Specifically, the alpha spread between small and large funds is almost 1.5 times for multi-principal funds as it is for single-principal funds.

Are hedge fund managers cognizant ex-ante of the diseconomies of scale that they will face? Evidence suggests that they are. We find that funds who are most affected by capacity constraints set higher performance fees and lower management fees than do funds who are least affected by capacity constraints. Funds who will potentially struggle with significant capacity issues benefit from high performance fees as such incentive fees allow fund managers to extract rents while curtailing asset growth and side-stepping diseconomies of scale. Conversely, funds who by the nature of their investment strategies eschew capacity issues are able to grow their assets without hurting future performance and can benefit from setting high management fees. Since hedge fund management contracts are inked prior to fund inception, it is likely that managers understand in advance, perhaps through past trading experience, the severity of capacity issues that they will face.

Do hedge fund investors direct more capital towards smaller hedge funds? If so, why does the size effect persist over time? We show that smaller funds attract disproportionately larger inflows than do larger funds even after controlling for the better performance of the former. Further, consistent with Berk and Green (2004), these fund inflows crimp the future performance of small funds. Small funds that subsequently experience above-median inflows underperform small funds that do not by 5.82 percent per year after adjusting for risk. However, these inflows do not erode performance quickly enough to eliminate the size effect. The alpha of the spread between the small and large fund portfolios falls from 3.64 percent to 2.49 percent per

[3] This line of research follows from theoretical work by Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995). They argue that agents who lack control over allocation decisions face weaker incentives.

annum when we wait 12 months before evaluating performance, but remains statistically significant at the 1 percent level. One view is that fund share restrictions, such as lock-ups and redemption notification periods, prevent hedge fund investors from swiftly redeploying capital from large to small funds and taking full advantage of the size effect.

Thus far our analysis has focused on single-manager[4] hedge funds. When we run the same portfolio analysis for Funds of Funds we find that the spread is -0.46 percent per year. That is large Funds of Funds outperform small Funds of Funds. While the alpha spread is statistically indistinguishable from zero, it underscores the difference between single-manager hedge funds and Funds of Funds. Large Funds of Funds may be able to leverage on their size and negotiate for better terms with their underlying hedge funds or invest in successful hedge funds that are otherwise closed to new investors. The Fund of Funds results also shed light on an alternative, agency-based explanation for the diseconomies of scale facing single-manager hedge funds. Specifically, large single-manager funds may under perform small single-manager funds simply because fund managers do not care as much about maximizing returns after their funds reach a certain size. Since single-manager hedge funds and Funds of Funds face similar incentive structures[5], this agency-based story does not explain why we do not observe similar diseconomies with Funds of Funds. Conversely, the price impact story squares with the lack of capacity constraints for these funds. Since large Funds of Funds are composed of the smaller distinct portfolios run by their underlying hedge funds, they should be less affected by the liquidity costs associated with trading a large portfolio. Moreover, hierarchy costs are less relevant for Funds of Funds since the single-manager hedge funds within a Fund of Funds portfolio do not have to make coordinated investment decisions or compete directly with one another for assets.

Overall, the results suggest that hedge fund managers grapple with significant diseconomies of scale. In doing so, we build on several recent themes. In particular, our results complement earlier work on hedge fund performance persistence. Brown, Goetzmann, and Ibbotson (1999), Liang (2000), and Agarwal and Naik (2000) find that hedge fund performance does not persist at annual horizons. Berk and Green (2004) argue that even if fund managers possess investment skills, their future performance will deteriorate if fund flows chase returns

[4] Single-manager hedge funds refer to funds managed by a single management company. Hedge fund management companies may be run by one or multiple principals.
[5] This incentive structure consists of an AUM-based management fee and a return-based performance fee.

and capacity constraints are binding. Our work on capacity constraints helps us understand why hedge fund performance persistence, at least based on standard performance measures, remains elusive. More recently, Kosowski, Naik, and Teo (2007) propose alternative Bayesian performance measures for hedge funds and find substantial evidence of performance persistence especially with Funds of Funds.[6] Our results on Funds of Funds dovetail nicely with their findings. Since we find that size constraints are more relevant to individual hedge funds than to Funds of Funds, it is less likely that stellar Fund of Funds performance will be eroded away by asset growth.

We also extend work by Goetzmann, Ingersoll, and Ross (2003) on hedge fund management contracts. They conjecture that the use of incentive fees is due to decreasing returns to scale in the industry. We refine the link between capacity constraints and incentive fees. Our results suggest that fund managers who face significant capacity constraints set higher performance fees and lower management fees as they cannot grow assets without hurting future returns. Our analysis corroborates the Goetzmann, Ingersoll, and Ross (2003) view that the compensation structure in the fund management industry provides a key signal of how future returns depend on the amount of money chasing after limited opportunities.

The rest of this paper is structured as follows. Section 2 describes the data. Section 3 presents the main empirical results. A series of robustness tests follow in Section 4. Section 5 concludes.

2. Data

We evaluate the size and performance relationship of hedge funds using monthly net-of-fee[7] returns and assets under management (henceforth AUM) data of live and dead hedge funds reported in the TASS and HFR datasets between January 1994 to June 2008 – a time period that covers both market upturns and downturns, as well as relatively calm and turbulent periods. Since TASS and HFR started distributing their data in 1994, the datasets do not contain information on funds that died before December 1993. This gives rise to survivorship bias. We mitigate this bias by focusing on January 1994 onward data.

[6] See the decile spread alphas in their Table 7.
[7] Our results are robust to using pre-fee returns.

In our fund universe, we have a total of 4,556 live hedge funds and 5,442 dead hedge funds. However, due to concerns that funds with multiple share classes may cloud the analysis, we exclude duplicate share classes from the sample.[8] This leaves us with a total of 3,177 live hedge funds and 4,240 dead hedge funds. The breakdown of funds by database is illustrated in Figure 1. The Venn diagram in Figure 1 reveals that the funds are roughly evenly split between TASS and HFR. While there is some overlap between the two databases, there are many funds that belong to only one database. For example, there are 2,376 funds and 2,920 funds peculiar to the TASS and HFR databases, respectively. This highlights the advantage of obtaining our funds from more than one data source.

[Please insert Figure 1 here]

Other than monthly return and size information, our sample also captures data on fund characteristics such as management fee, performance fee, redemption frequency, notification period, lock-up period, investment style, investment geographical region, fund leverage indicator, fund family, and fund minimum investment. These fund characteristics are recorded in year 2008 and, for our purposes we take these characteristics as constant over the sample period. Since minimum investments are sometimes quoted in currencies other than U.S. dollar, we convert all minimum investments to U.S. dollars using exchange rates on 30 June 2008, so as to facilitate meaningful comparison.

Following Agarwal, Daniel, and Naik (2009), we classify funds into four broad investment styles: Security Selection, Multi-process, Directional Trader, and Relative Value. Security Selection funds take long and short positions in undervalued and overvalued securities, respectively, and reduce systematic risks in the process. Usually, they take positions in equity markets. Multi-process funds employ multiple strategies that take advantage of opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. Directional Trader funds bet on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash market. Relative Value funds take positions on spread relations between prices of financial assets and aim to minimize market exposure. Table 1 breaks down the funds in our sample by investment strategy and reports the size distribution as well as the number of live and dead funds in each strategy.

[8] Inferences do not change when we include multiple share classes of the same fund in the analysis

[Please insert Table 1 here]

We recognize that hedge fund data are susceptible to many biases (Fung and Hsieh, 2000). These biases stem from the fact that, due to the lack of regulation amongst hedge funds, inclusion in hedge fund databases is voluntary. As a result, there is a self-selection bias. For instance, funds often undergo an incubation period where they rely on internal funding before seeking capital from outside investors. Incubated funds with successful track records then go on to list in various hedge fund databases while the unsuccessful funds do not, resulting in an incubation bias. Separate from this, when a fund is listed on a database, it often includes data prior to the listing date. Again, since successful funds have a strong incentive to list and attract capital inflows, these backfilled returns tend to be higher than the non-backfilled returns. In the analysis that follows, we will repeat the tests after dropping the first 36 months of return data from each fund so as to ensure that the results are robust to backfill and incubation bias.

3. Empirical results

A. Size and the cross-section of fund alpha

To investigate the cross-sectional relationship between fund size and fund performance, we estimate Fama-MacBeth (1973) regressions on monthly hedge fund alpha with lagged fund size as an independent variable. Specifically, we first run cross-sectional regressions for each month. Then, we report the time series averages of the coefficient estimates, and use the time-series standard errors of the average slopes to draw inferences. The Fama-MacBeth methodology is a convenient and conservative way of accounting for potential cross-correlation in residuals. According to Fama and French (2002), Fama-MacBeth standard errors are often two to five times the OLS standard errors from pooled panel regressions that ignore cross-correlation.

Throughout this paper, we model the risks of hedge funds using the Fung and Hsieh (2004) seven-factor model. The set of factors comprises: the excess return on the S&P 500 index (*SNPMRF*); a small minus big factor (*SCMLC*) constructed as the difference between the Wilshire small and large capitalization stock indices; the yield spread of the U.S. 10-year

Treasury bond over the three month Treasury bill, adjusted for duration of the 10-year bond (*BD10RET*); the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond, also appropriately adjusted for duration (*BAAMTSY*), and the excess returns on portfolios of lookback straddle options on currencies (*PTFSFX*), commodities (*PTFSCOM*), and bonds (*PTFSBD*), which are constructed to replicate the maximum possible return on trend following strategies on their respective underlying assets. These seven factors have been shown by Fung and Hsieh (2004) to have considerable explanatory power on hedge fund returns. Agarwal and Naik (2004) present a factor model for hedge funds that includes some of the factors of the Fung and Hsieh (2004) model.

Following Carhart (1997), we first calculate monthly fund abnormal return or alpha as fund excess returns minus the factor realizations times loadings estimated over the entire sample period. Hence, we have

$$\begin{aligned} ALPHA_{im} \equiv r_{im} - (&b_{iM} SNPMRF_m + c_{iM} SCMLC_m + d_{iM} BD10RET_m + e_{iM} BAAMTSY_m \\ &+ f_{iM} PTFSBD_m + g_{iM} PTFSFX_m + h_{iM} PTFSCOM_m) \end{aligned} \tag{1}$$

where i = 1, …, *nfunds*, m = 1,…,M, $ALPHA_{im}$ is the abnormal return of fund i for month m, r_{im} is fund return in excess of the risk free rate. To facilitate the estimation of fund alpha, we only include results for funds with at least 24 months of return data.[9]

Next we estimate the following Fama-MacBeth cross-sectional regressions:

$$ALPHA_{im} = a + bFUNDSIZE_{im-1} + cFUNDSIZE^2_{im-1} + dFAMSIZE_{im-1} + eFAMSIZE^2_{im-1} + \varepsilon_{im} \tag{2}$$

$$\begin{aligned} ALPHA_{im} = a &+ bFUNDSIZE_{im-1} + cFUNDSIZE^2_{im-1} + dFAMSIZE_{im-1} + eFAMSIZE^2_{im-1} \\ &+ fPERFFEE_i + gMGTFEE_i + hREDEMP_i + kMININV_i \\ &+ lFUNDAGE_{im-1} + \sum_{w=1}^{W-1} o^w STYLEDUM_i^w + \sum_{y=1}^{Y-1} p^y GEODUM_i^y + \varepsilon_{im} \end{aligned} \tag{3}$$

[9] Similar results obtain for funds with at least 36 months of return data. Results are available upon request.

where *FUNDSIZE* is fund size or fund AUM, *FAMSIZE* is fund family size[10], *PERFFEE* is fund performance fee, *MGTFEE* is fund management fee, *REDEMP* is fund redemption period, *MININV* is minimum investment amount, *FUNDAGE* is fund age, *STYLEDUM* is investment style dummy, and *GEODUM* is investment region dummy.

We include the square of *FUNDSIZE* and *FAMSIZE* to capture potential non-linearities in the fund size and performance relationship.[11] The annual fund characteristic variables (i.e., fees, redemption period, minimum investments, fund age, investment style, and investment region) are included in the Eq. 3 regression as control variables to account for their potential impact on fund performance. For example, Agarwal, Daniel, and Naik (2009) show that funds with more high powered incentives deliver higher returns than do other funds. Aragon (2007) argues that funds with longer redemption periods may take on greater liquidity risk and achieve higher expected returns. Finally, managers of younger funds may outperform managers of older funds, regardless of the amount of assets they manage, simply because they are more driven. It is important to control for the effects of fund age when analyzing the capacity constraints facing the industry since younger funds typically also manage fewer assets.

[Please insert Table 2 here]

The coefficient estimates on the fund size variables reported in Table 2 reveal a strong negative and convex relationship between last month's fund AUM and this month's fund abnormal return.[12] They indicate that after controlling for the other variables, an increase in AUM from a small base of say US$10m to US$500m is associated with a reduction in annual abnormal returns of approximately $12*(0.5*0.26-0.5^2*0.11)$ or 1.23 percent. For comparison, an increase in AUM from US$10m to US$1bn is associated with a decrease in alpha of approximately 1.80 percent per year and not 2.46 percent as a linear relationship would suggest. This highlights the convexity of the relationship between fund size and performance. We note that both the coefficient estimates on the fund size variables are statistically significant at the 5 percent level. Interestingly, the coefficient estimate on the fund family variable is negative and statistically significant for the regression without controls but is statistically indistinguishable from zero once we control for the other fund characteristics. This contrasts with Chen et al.

[10] For each fund, fund family size is the sum of the AUM for all the other funds within the same fund family as the fund.
[11] Inferences do not change when we replace the size and size squared variables with the logarithm of size.
[12] The results also hold when we estimate the regressions on raw fund returns.

(2004) who find significant economies of scale at the family level for mutual funds. We believe that one reason for the difference may be that hedge fund families are more specialized in their investment process than are mutual fund families. As a result, individual hedge funds within a family are more likely to hold similar securities or engage in similar arbitrage opportunities. This ameliorates the potential family level economies of scale that come from reduced trading commissions and lending fees.

To illustrate the fund size and performance relationship, we sort fund monthly return and past AUM observations by AUM into 100 bins. Next, we plot the average monthly returns of the funds in each bin with their average past month's AUM. The resultant scatter plot of Figure 2 nicely summarizes the findings of Table 2. The downward sloping polynomial line of best fit drawn through the scatter plot is steeper in the region of small funds and gentler in the region of large funds, highlighting the convexity of the size and risk-adjusted performance relationship. This sharply contrasts with the concave relationship documented by Getmansky (2005) for size and raw fund performance.

[Please insert Figure 2 here]

There are concerns that the results may be due to differences in the way backfill and incubation bias affects small versus large. If small funds backfill or incubate their returns while large funds do not, it may explain the overperformance of the former group of funds. Also, there are concerns that small funds may trade illiquid securities. As a result, for these funds, reported returns tend to be smoother than true economic returns, which understates volatility and overstates the statistical significance of risk-adjusted measures like alpha. To cater for such concerns, we re-estimate the regressions with backfill and incubation bias-adjusted alpha and with alpha derived from unsmoothed returns using the Getmansky, Lo, and Makarov (2004) correction.[13] To adjust for backfill and incubation bias, we remove the first 36 months of return data from each fund and redo the alpha estimation for funds with at least 24 months of remaining return data. Lastly, to ensure that the underperformance of large funds is not simply due to their higher fees, we also re-do the analysis on pre-fee[14] alpha. The results from this robustness analysis are presented in columns three to eight of Table 2, and suggest that the overperformance

[13] We use the average values of $\theta_0, \theta_1,$ and θ_2 for the various investment styles reported in their Table 8 to effect the correction.

[14] Pre-fee alphas are computed from pre-fee returns. We derive pre-fee returns by taking the high watermark and hurdle rate as the T-bill, and assuming that the returns accrue to a first-year investor in the fund.

of small hedge funds is not driven by backfill bias, incubation bias, illiquidity, or lower fund fees. The coefficient estimates on the *FUNDSIZE* variable are statistically significant and economically relevant for all specifications and for the regressions with and without controls.

One shortcoming of the Fama-MacBeth (1973) procedure is that while it accounts for correlations between observations on different funds in the same month, it does not account for correlation between observations on the same fund across different months. Petersen (2009) calls the latter the firm effect. According to him, standard errors clustered by firm (Rogers, 1993) are unbiased and produce correctly sized confidence intervals whether the firm effect is permanent or temporary. The firm effect may be present in hedge fund data given that hedge fund returns are often serially correlated. To address this issue, we estimate the following pooled OLS regressions with standard errors clustered by fund.

$$\begin{aligned} ALPHA_{im} &= a + bFUNDSIZE_{im-1} + cFUNDSIZE^2_{im-1} + dFAMSIZE_{im-1} + eFAMSIZE^2_{im-1} \\ &+ fPERFFEE_i + gMGTFEE_i + hREDEMP_i + kMININV_i + lFUNDAGE_{im-1} \\ &+ \sum_{w=1}^{W-1} o^w STYLEDUM_i^w + \sum_{y=1}^{Y-1} p^y GEODUM_i^y + \sum_{z=1}^{Z-1} q^z YRDUM_i^z + \varepsilon_{im} \end{aligned} \tag{4}$$

where *YRDUM* is the year dummy and the other variables are as per defined earlier. We find that our results still hold when we adopt this alternate regression framework. Based on the clustered standard errors, the coefficient estimate on fund size is negative and statistically significant (*t*-statistic = 2.99). Conversely, the coefficient estimate on the square of fund size is positive and statistically significant (*t*-statistic = 2.42).

B. The performance of portfolios sorted on fund size

To gauge the economic relevance of the capacity constraints facing hedge funds, we first construct portfolios of funds based on fund size and compare their risk-adjusted performance. Specifically, every January 1st, we form an equal-weighted portfolio of small funds (Portfolio A) and an equal-weighted portfolio of large funds (Portfolio B) based on AUM in December[15] last year. We define as small funds those in the smallest two size quintiles. Conversely, we define as

[15] Recognizing that AUM data are often reported with a one month lag, we also sort funds every January 1st based on AUM in November of last year and find that the results are only marginally weaker.

large funds those in the largest two size quintiles.[16] Next, we evaluate the performance of the portfolios relative to the Fung and Hsieh (2004) model over the next 12 months. The alpha of the spread between Portfolios A and B represents the value added to investors of investing in small hedge funds and avoiding large hedge funds.

The results from this exercise are displayed in Panel A of Table 3. Consistent with the cross-sectional regression results, they reveal a negative relationship between fund size and performance. The strategy of investing in the small hedge funds and avoiding large funds yields a risk-adjusted return of 3.65 percent per year (*t*-statistic = 6.64). This suggests that size is detrimental to future performance. Can hedge fund investors benefit by choosing small funds instead of large funds? Since one cannot short sell hedge funds, we evaluate the performance of the small fund portfolio (portfolio A) after discounting the one percent management fee and ten percent performance fee charged by the typical Fund of Funds. We find that after fees, the hypothetical Fund of Funds portfolio comprising small hedge funds delivers an after-fee alpha of 4.34 percent per year, which is both economically and statistically significant (*t*-statistic = 4.07). In contrast, the hypothetical Fund of Funds portfolio comprising large hedge funds only earns an after-fee alpha of 1.09 percent per year that is statistically indistinguishable from zero.

[Please insert Table 3 here]

Consistent with the cross-sectional regression results, our findings are robust to adjustments for backfill and incubation bias, serial correlation in returns, and fund fees. All the spread alphas in Panels B, C, and D of Table 3 are at least 2 percent per year and statistically significant at the 1 percent level. It is reassuring to note that the portfolios returns (portfolios A and B) are well explained by the Fung and Hsieh (2004) factor model. The adjusted R-squares for portfolios A and B are consistently not lower than 55 percent.

Figure 3 illustrates the results from the baseline portfolio sorts. It shows the monthly cumulative average residuals (henceforth CARs) from the portfolio of small funds (portfolio A) and the portfolio of large funds (portfolio B). CAR is the cumulative difference between a portfolio's excess return and its factor loadings (estimated over the entire sample period) multiplied by the Fung and Hsieh (2004) risk factors. The CARs in Figure 3 indicate that

[16] The results are robust to defining small funds as funds with AUM below the median fund and defining large funds as funds with AUM above the median fund.

portfolio A consistently outperforms portfolio B over the entire sample period and suggest that the deleterious effects of fund size are not confined to a particular time period.

[Please insert Figure 3 here]

One concern is that small hedge funds may employ greater leverage and hence will mechanically outperform large hedge funds. This may well be the case if these small funds trade more aggressively in a bid to deliver greater returns and attract larger inflows. As a check, we compute the information ratio (alpha divided by tracking error) of the portfolios in Panel A of Table 3. We find that the annualized information ratios for portfolio A, portfolio B, and the spread are 1.78, 0.98, and 1.69, respectively. Since the information ratio adjusts for the additional volatility that leverage induces, the superior information ratio[17] of the small fund portfolio indicates that its overperformance is not simply a by-product of higher leverage.

Are the documented size constraints pervasive across the investment strategies or unique to a specific strategy? To check whether the documented capacity constraints apply broadly to hedge funds, we break down the sort analysis by investment strategy. That is, we redo the sorts for each of our four broadly defined investment styles: security selection, directional traders, relative value, and multi-process. The spread alphas reported in Panels A – D of Table 4 are all statistically significant at the 5 percent level and indicate that the capacity issues are robust across investment strategies. However, variations across styles do exist. The performance differential between small and large funds is greatest for security selection (5.49 percent per year) and weakest for relative value (1.86 percent per year). One view is that relative value funds trade mostly liquid fixed income securities and hence are less affected by price impact issues.

[Please insert Table 4 here]

Thus far the analysis has focused on single-manager hedge funds. However it may be instructive to separately analyze the size effect for Funds of Funds. This is because Funds of Funds invest in multiple hedge funds and do not manage a portfolio of securities. Hence they should be relatively immune to the price impact induced size constraints that plaque hedge funds. The results in Panel E of Table 4 are consistent with this line of reasoning. Small Funds of Funds do not outperform large Funds of Funds. In fact, large Funds of Funds deliver higher risk-adjusted returns than small Funds of Funds (though the difference is statistically

[17] Since the number of observations for each portfolio is the same, we can draw similar inferences by comparing the alpha *t*-statistics of the small and large fund portfolios.

indistinguishable from zero). Perhaps large Funds of Funds are able to capitalize on their greater bargaining power and gain access to successful single-manager hedge funds that are otherwise closed to new investments. Alternatively, Brown, Fraser, and Liang (2008) argue that large Funds of Funds are better able to bear the costs of the due diligence needed to select outperforming funds. In any case, following the logic of Berk and Green (2004), the lack of capacity constraints for Funds of Funds suggest that performance persistence should be strongest for Funds of Funds; since without such capacity constraints, inflows on the back of good performance no longer crimp future performance. The results in Panel E of Table 4 thus dovetail nicely with the strong evidence of performance persistence documented for Funds of Funds by Kosowski, Naik, and Teo (2007). They show in their Table 7 that the decile spread between fund portfolios sorted on past performance is most statistically significant for Funds of Funds.

C. Capacity constraints and price impact

Do the capacity constraints facing large hedge funds stem from the price impact of their trades? If so, then it must be the case that these capacity constraints are accentuated for funds that trade small and illiquid securities. This is because it is much harder to move funds in and out of small capitalization and illiquid securities without having price move against the trader. Conversely, it is significantly easier to shift funds in and out of large capitalization and liquid securities without changing prices. As a corollary to this, Carhart et al. (2002) show that small cap mutual funds can more effectively "lean for the tape" or ratchet up the price of their stock holdings with end-of-the-quarter purchases than can large cap mutual funds.

To test the hypothesis that the capacity constraints are driven by price impact effects, we redo the portfolio sort analysis on hedge funds stratified by the size and illiquidity of their underlying holdings. How does one distinguish between funds that trade small capitalization thinly-traded securities from funds that trade large capitalization frequently-traded securities without information on their underlying holdings? One way is to look at the geographical region that they invest in. For example, Emerging Market stocks tend to be smaller and more illiquid than Developed Market stocks. In this effort, we redo the analysis for funds investing in the North American, European, Global, and Emerging Market regions. The results reported in Table 5 corroborate the price impact hypothesis. The alpha of the spread between the small Emerging

Market fund and large Emerging Market fund portfolios is 8.02 percent per year (t-statistic = 3.12) and dwarfs the spread alphas for funds investing in the North American, European, and Global regions. Also given that global securities (e.g., components of the MSCI world indices) are the best capitalized and most frequently traded securities in the financial markets, and it is not surprising that the capacity constraints are weakest for funds investing in the Global region. The small Global fund portfolio only outperforms the large Global fund portfolio by 2.71 percent per year after adjusting for risk.

[Please insert Tables 5 and 6 here]

To shed further light on the drivers behind the capacity constraints, we stratify hedge funds based on the liquidity of their underlying holdings, by using fund share restrictions as a proxy, and redo the portfolio analysis. It has been argued by Aragon (2007) and others that funds with long redemption periods tend to hold more illiquid securities than do funds with short redemption periods. Such share restrictions allow funds sufficient time with which to exit from their illiquid positions. The results in Table 6 are broadly supportive of the price impact story. They indicate that regardless of whether we use redemption frequency or redemption notification period to proxy for fund illiquidity, funds trading illiquid securities tend to experience greater capacity constraints than funds trading liquid securities. For example, the spread alpha for hedge funds that allow for frequent redemptions (every month at worst) is 3.34 percent per year while that for hedge funds that allow for less frequent redemptions (every quarter at best) is 4.24 percent per year. Taken together, the results from Tables 5 and 6 suggest that price impact factors may lie at the root of the capacity constraints facing hedge funds.

D. Capacity constraints and hierarchy costs

Are organizational diseconomies also responsible for some of the capacity constraints that we observe for hedge funds? Chen et al. (2004) find that controlling for fund size, team managed mutual funds underperform single-manager mutual funds. They attribute this effect to the hierarchy costs proposed by Aghion and Tirole (1997) and Stein (2002). According to Stein (2002) the process of agents jostling to get their ideas implemented in large organizations can create diseconomies of scale especially when those ideas involve soft information, i.e., information that cannot be verified by anyone other than the agent herself. As a result of this competition for resources amongst agents, the best ideas do not always get implemented as agents choose ex-ante to focus on ideas supported by hard information, which can be easily verified. Such organizational diseconomies follow in the spirit of Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995) who argue that agents face weak incentives when they do not exercise control over the allocation of resources.

Since investment decisions at hedge funds often involve soft information, e.g., subjective opinions on whether a security is over or under-valued, we hypothesize that hierarchy costs can induce organization diseconomies in hedge funds as well. To test this, we redo the portfolio sorts for single principal hedge funds and for multi-principal hedge funds. Since only HFR includes principal information, we run this analysis for HFR funds only. Despite the reduced sample size, the findings reported in Table 7 are striking. For hedge funds managed by a single principal, the alpha spread between small and large hedge funds is 4.45 percent per year. For hedge funds managed by two principals, the alpha spread rises to 6.42 percent per year. When we analyze hedge funds managed by more than two principals, the alpha spread is also relatively high at 6.34 percent per year. The difference in the strength of the capacity constraints for multi- versus single principal funds suggests that hierarchy costs exacerbate the diseconomies faced by large hedge funds.

[Please insert Table 7 here]

E. Capacity constraints and fund incentives

Goetzmann, Ingersoll, and Ross (2003) argue that the existence of performance fees can be explained by the diseconomies of scale facing hedge funds. Because of capacity constraints, successful funds will want to curtail inflows if they wish to maintain their returns. With performance fees, investors can compensate managers based on their returns and not solely on the assets that their returns attract.

If hedge fund managers understand the severity of the capacity constraints that they face then they should structure their compensation contracts to accommodate those constraints. According to the Goetzmann, Ingersoll, and Ross (2003) line of reasoning, hedge funds who run into substantial capacity constraints will find it advantageous to receive more of their compensation in the form of performance fees. Conversely, hedge funds who are less affected by capacity constraints will find it in their best interests to receive more of their compensation in the form of management fees. Hence, on one hand, we should expect to find weak capacity constraints for asset gatherers or hedge funds with high management fees and low performance fees. One the other hand, we should expect to find strong capacity constraints for non-asset gatherers or hedge funds with low management fees and high performance fees.

[Please insert Table 8 here]

We test this hypothesis by stratifying funds based on their management and performance fees, and leveraging on the portfolio sort framework of Table 3. The results in Table 8 are broadly consistent with Goetzmann, Ingersoll, and Ross (2003) and the idea that hedge fund managers are cognizant of the capacity constraints that will they face prior to setting up the fund. The alpha spreads in Panels A and D of Table 8 indicate that fund managers who set high management fees or low performance fees typically do not experience significant diseconomies of scale. In contrast, the alpha spreads in Panels B and C of Table 8 suggest that fund managers who set low management fees or high performance fees typically have to contend with significant diseconomies of scale. For example, within the low performance fee group of funds (performance fee less than[18] 20 percent), small funds outperform large funds by a modest 0.90 percent per year after adjusting for risk. In contrast, within the high performance fee group of funds (performance fee greater than or equal to 20 percent), small funds outperform large funds by 4.45 percent per year after adjusting for risk.

F. Capacity constraints and hedge fund investors

Are hedge fund investors aware of the capacity issues confronting hedge funds? Do they direct disproportionately more capital to smaller funds? If so, why does the size effect documented in this paper persist over time?

To test whether hedge fund investors deploy more capital to small funds, we estimate the following Fama and MacBeth (1973) regressions on fund flow:

[18] Most hedge funds impose management and performance fees of 2 and 20 percent, respectively. Since we know that the majority of funds are affected by capacity constraints, we set the inequalities in Table 8 such that we have fewer funds in the low performance fee and high management fee groups. Inferences do not change when we omit funds with management and performance fees of 2 and 20 percent, respectively, from our sample.

$$
\begin{aligned}
FUNDFLOW_{im} &= a + bFUNDSIZE_{im-1} + c\left(\frac{1}{L}\right)\sum_{lag=1}^{L} FUNDRET_{im-lag} + dPERFFEE_i \\
&+ eMGTFEE_i + fREDEMP_i + gMININV_i + hFUNDAGE_{im-1} \\
&+ \sum_{w=1}^{W-1} k^w STYLEDUM_i^w + \sum_{y=1}^{Y-1} l^y GEODUM_i^y + \varepsilon_{im}
\end{aligned} \tag{5}
$$

where $L \in \{3, 6, 9, 12\}$ is the maximum return lag in months, *FUNDFLOW* is monthly fund flow as a percentage of AUM, *FUNDRET* is monthly fund return, and the other variables are as per defined in Section 3A. We seek to explain monthly fund flow with last month's fund AUM after controlling for past fund returns (averaged over the past 3, 6, 9, or 12 months), and other fund characteristics. We find that the coefficient estimate on *FUNDSIZE* is negative and statistically significant at the 1 percent level for all *L*. For example, the coefficient estimate on *FUNDSIZE* when the maximum return lag is 3 months (i.e., $L = 3$) indicates that a one standard deviation decrease in fund AUM increases monthly fund flow by 0.06 standard deviations or by 0.78% after controlling for past quarter's fund returns and other fund characteristics. It appears that hedge investors are aware of the superior performance of small funds and, consequently, direct more capital to these funds.

Do these additional capital flows erode away the over performance of small hedge funds? Berk and Green (2004) argue that inflows should crimp the future performance. When we perform two-pass sorts on past month's fund AUM and this month's fund flow, we find that the size effect is stronger for funds that attract less inflow. For funds who attract below-median flow, the alpha spread between the small and large fund portfolios is 5.30 percent per year (*t*-statistic = 9.46). Conversely, for funds who attract above-median flow, the corresponding alpha spread is only 2.11 percent per year (*t*-statistic = 3.70). Moreover, small funds who receive above-median flow underperform small funds who do not receive such high inflows by 5.82 percent per year (*t*-statistic = 9.56) after adjusting for risk. These results, which are available upon request, are consistent with the reasoning expounded by Berk and Green (2004).

Are the inflows large enough to completely eliminate the size effect? When we impose a gap between the formation and evaluation periods and redo the baseline portfolio sorts, we find that the alpha spread decays slowly as we lengthen the gap. Even if we wait 12 months before evaluation, the alpha spread is still 2.49 percent per year (*t*-statistic = 4.41). With a 18-month gap between formation and evaluation periods, the alpha spread shrinks further to 1.94 percent per year but is still statistically significant at the 1 percent level (t-statistic = 3.49). Clearly, inflows hurt future performance but not enough to completely eliminate the size effect. One view is that hedge fund investors, stymied by fund share restrictions (lock-ups and notification periods), often cannot rapidly redeploy capital from larger funds to smaller funds. Also, to keep monitoring and due diligence costs down, rather than investing in several small funds, some investors with significant capital may prefer instead to invest in a few large funds.

4. Robustness tests

In this section, we present robustness tests to evaluate the strength of our empirical results. One recurring concern is that the size effects may be caused by fund leverage. Small funds in their pursuit of high returns may take on more leverage. In our sort analysis, this will mechanically drive up the average risk-adjusted return of the small fund portfolio relative to that of the large fund portfolio. Still, as discussed in Section 3A, a comparison of the information ratios of the portfolios suggest that it is unlikely that leverage lies at the root of their performance differential. Nonetheless, to address any residual leverage related concerns, we perform the sort analysis for funds without leverage. We can do so as HFR and TASS include an indicator variable for leverage. The results reported in Panel A of Table 9 reaffirm our earlier conclusions that leverage does not drive the performance advantage of small funds. Small funds who eschew leverage outperform large funds who eschew leverage by 3.40 percent per year after adjusting for risk. While the performance differential is somewhat higher for funds who do employ leverage, the fact that the results still hold for funds who avoid leverage altogether make clear that leverage does not drive the bulk of the performance differential between small and large funds.

[Please insert Table 9 here]

Yet another concern is that the results thus far may not be particularly relevant to large institutional investors as the performance differential may be driven entirely by the smallest of funds. Given the convex relationship documented in Figure 2, the effects of size may not be meaningful for the larger funds that institutional investors focus on. Specifically, large institutional investors may find it difficult to invest in small funds who manage less than a certain size cutoff. Hence in Panel B of Table 9, we report portfolio sort results for funds that manage at least US$20 million. The results indicate that even with the size cutoff, the small fund portfolio trumps the large fund portfolio by a risk-adjusted 3.01 percent per year (*t*-statistic = 6.34). In addition, assuming that the small fund portfolio is part of a Fund of Funds charging the typical 1 percent management fee and 10 percent performance fee, it will generate a statistically significant alpha of 3.52 percent per year after fees. This suggests that while the capacity constraints are less striking in the region of large funds, they are still economically meaningful for hedge fund investors.

A related concern is that our methodology of sorting funds into only two groups based on size may mask perverse non-linearities in the size and performance relationship. To address this issue, in Panel C of Table 9, we report the performance of quintiles portfolios sorted on last December's AUM. The results are strongly consistent with capacity constraints in the hedge fund industry. There is a monotonic decrease in portfolio alpha as we move from portfolio Q1 (smallest funds) to portfolio Q5 (largest funds). Portfolio Q1 achieves an impressive risk-adjusted return of 7.84 percent per year while portfolio Q5 only delivers a risk-adjusted return of 2.90 percent per year. The alpha spread between these two portfolios is 4.94 percent per year. Noting that the smallest quintile may contain hedge funds that are too small for large institutional investors, we also compute the alpha spread between portfolio Q2 and Q5. We find that consistent with the convexity of the size/performance relationship, constraining the fund sample to larger funds weakens but does not knock out the size effect. It is reassuring to note that the spread between Q2 and Q5 is still economically and statistically significant at 2.59 percent per year (*t*-statistic = 4.77).

5. Conclusion

Given the media's perennial fascination with large and successful hedge funds[19], it is tempting for one to conclude that large hedge funds are also successful going forward. The results in this paper challenge that view. We show that large hedge funds grapple with significant

[19] See, for example, "Paulson & Co. scores again this year" The Wall Street Journal, 24 October 2008, and "Hedge fund pay equals Rwanda's GDP" The Financial Times, 8 April 2008. Understandably, given the current U.S. financial turmoil, such media reports have been less forthcoming lately. Large and erstwhile successful funds have started chalking up significant losses. See, "Crisis on Wall Street: more pain, less gain for large hedge funds" The Wall Street Journal, 26 September 2008.

diseconomies of scale, and consequently under perform small hedge funds, ex-post. The portfolio of small hedge funds outperforms the portfolio of large hedge funds by 3.65 percent per year after adjusting for risk. The capacity constraints are pervasive across the industry and cannot be explained by hedge fund database biases, leverage, fund age, and illiquidity-induced serial correlation. While the size and performance relationship is convex and strongest in the region of small funds, it is not confined to the smallest of funds. We show that such size effects are most apparent for funds trading small illiquid securities, i.e., Emerging Market funds and funds with high share restrictions, suggesting that price impact may lie at the root of the capacity constraints. In addition, we show that the capacity constraints can be partly traced to the hierarchy costs proposed by Stein (2002). As a result of hierarchy costs, the underperformance of large hedge funds is especially severe for hedge funds managed by multiple principals. These principals compete with one another to implement their investment ideas. Since information supporting the best investment ideas may not be verifiable, competition amongst principals creates organizational diseconomies as the best investment ideas are not always implemented. While investors recognize that smaller funds deliver superior returns and direct disproportionately more capital towards these funds, their actions do not completely eliminate the size effect.

Our results also have implications for the nascent literature on hedge funds. Together with the reasoning of Berk and Green (2004), they provide support for why Agarwal and Naik (2000), Liang (2000), and Brown, Goetzmann, and Ibbotson (1999) find scant evidence of performance persistence at annual horizons. They also corroborate evidence by Goetzmann, Ingersoll, and Ross (2003) who argue that fund capacity constraints may explain the use of incentive fees in the hedge fund industry. Indeed we sharpen their results and show that funds who experience greater capacity constraints adopt higher performance fees (and lower management fees) than do funds who are able to avoid such constraints. These findings also suggest that hedge fund managers are aware of the capacity constraints that they will face prior to fund inception. Finally, the size effects documented in this paper help us understand why some successful hedge funds close their funds to new investments.

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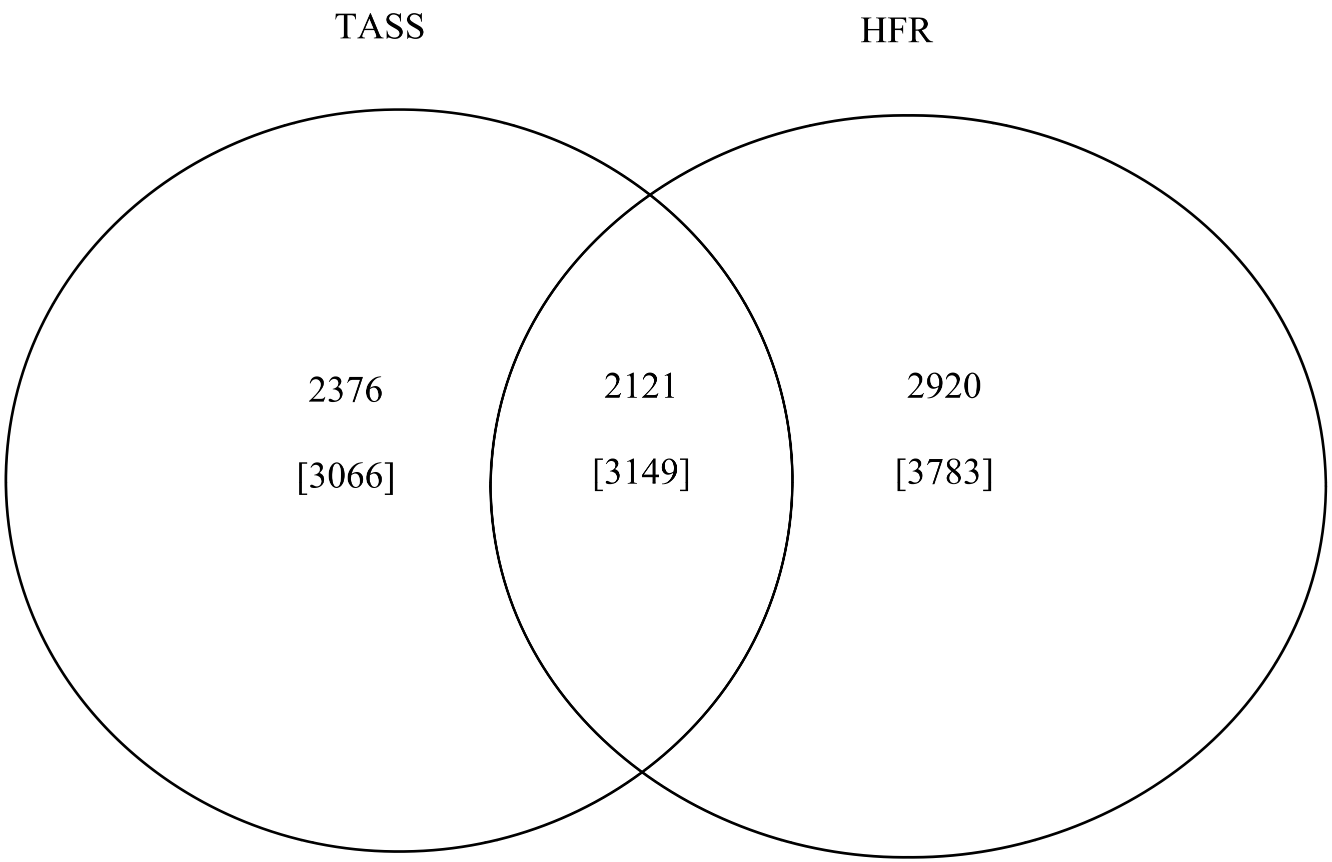

Figure 1: Break down of funds by database vendor. Fund numbers in brackets include duplicate share classes of the same fund. The sample period is from January 1994 to June 2008.

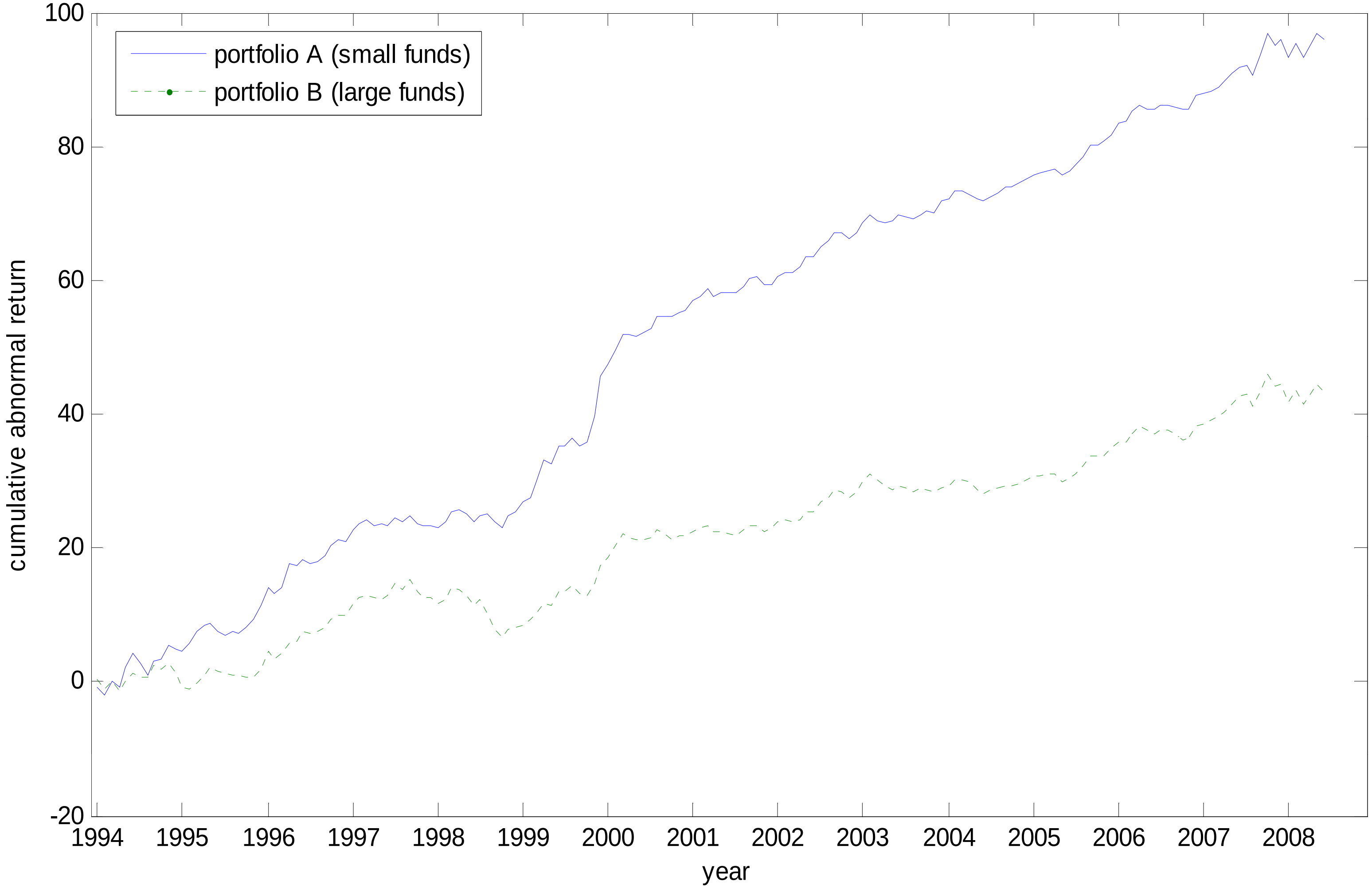

Figure 2: Cumulative abnormal return of small versus large hedge funds. Portfolios of hedge funds are constructed by sorting funds every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Cumulative abnormal return is the difference between a portfolio's excess return and its factor loadings multiplied by the Fung and Hsieh (2004) risk factors. Factor loadings are estimated over the entire sample period. The sample period is from January 1994 to June 2008.

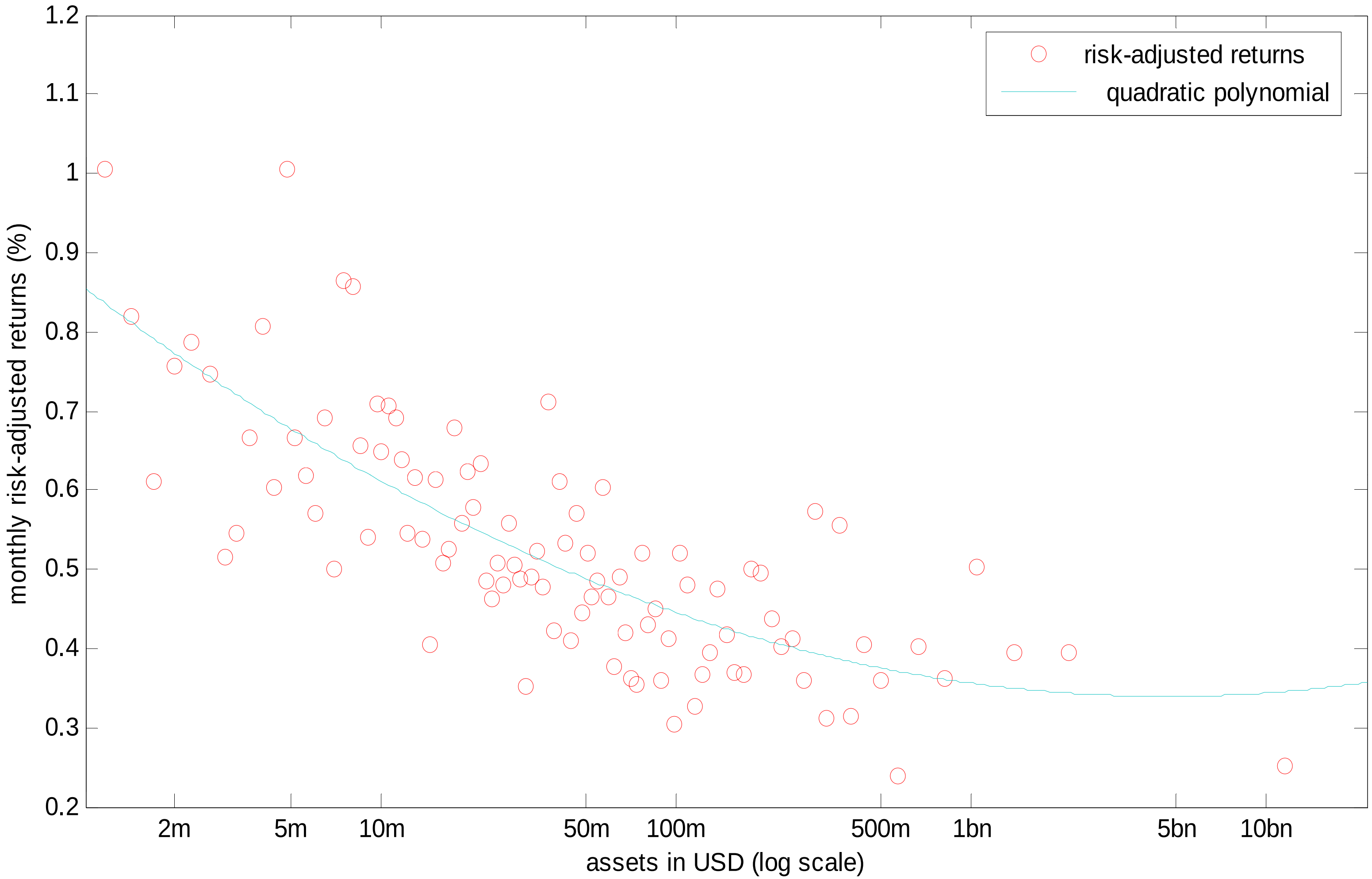

Figure 3: The relationship between hedge fund monthly abnormal returns and past assets. Monthly hedge fund abnormal return observations are sorted into 100 bins based on the funds' past month's assets. For each bin, we calculate the average monthly abnormal return and assets. These average monthly abnormal returns and assets data are plotted and a quadratic polynomial is fitted through them. Monthly abnormal return is the difference between a fund's excess return and its factor loadings multiplied by the Fung and Hsieh (2004) risk factors. Factor loadings are estimated over the entire sample period. The sample period is from January 1994 to June 2008.

Table 1

Summary statistics

The sample period is from January 1994 to June 2008. Funds are grouped according to their primary investment strategy. Security Selection funds take long and short positions in undervalued and overvalued securities, respectively, and reduce systematic risks in the process. Usually, they take positions in equity markets. Multi-process funds employ multiple strategies that take advantage of opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks. Directional Trader funds bet on the direction of market prices of currencies, commodities, equities, and bonds in the futures and cash market. Relative Value funds take positions on spread relations between prices of financial assets and aim to minimize market exposure. AUM is average assets under management (averaged over time). The total number of funds is 7,417. The total number of dead funds is 4,240. And the total number of fund months with return information is 358,930

			Average AUM in US$				
Investment strategy	Total funds	Dead funds	AUM<\$20m	\$20m≤AUM<\$100m	\$100m≤AUM<\$500m	AUM>\$500m	Return months
Security Selection	2,715	1,234	1,199	992	410	114	140,710
Multi-process	999	483	349	355	221	74	45,927
Directional Trader	1,752	1,184	885	600	194	73	83,298
Relative Value	1,308	787	474	503	272	59	62,042
Others	643	552	446	155	34	8	26,953
Total	7,417	4,240	3,353	2,605	1,131	328	358,930

Table 2

Fama MacBeth cross-sectional regressions on hedge fund alpha

Fama-MacBeth (1973) regressions are estimated on the cross-section of hedge fund alpha. The dependent variable is hedge fund monthly alpha. The independent variables are hedge fund characteristics such as lagged monthly fund size, lagged monthly fund size squared, lagged monthly family size, and lagged monthly family size squared. In the regressions with controls we also include as independent variables fund management fee, performance fee, redemption period, minimum investment, and fund age in months, as well as style and geographical region dummies. The *t* -statistics, derived from White (1980) standard errors, are in parentheses. The coefficient estimates on the control variables and dummies are omitted for brevity. The fund and family size variables are in US$bn. The sample period is from January 1994 to June 2008. * Significant at the 5% level; ** Significant at the 1% level.

	Dependent variable							
Independent variables	monthly alpha		backfill and incubation bias-adjusted alpha		unsmoothed alpha		pre-fee alpha	
	without controls	with controls	without controls	with controls	without controls	with controls	without controls	with controls
lagged fund size (US$bn)	-0.25**	-0.26*	-0.22*	-0.23*	-0.25**	-0.29*	-0.25**	-0.27*
	(-3.05)	(-2.54)	(-2.08)	(-2.01)	(-2.80)	(-2.54)	(-3.04)	(-2.57)
lagged fund size squared	0.06	0.11*	0.06	0.08	0.06	0.11*	0.05	0.11
	(1.66)	(2.26)	(1.25)	(1.62)	(1.44)	(2.16)	(1.43)	(2.30)
lagged family size (US$bn)	-0.20*	-0.16	-0.11	-0.10	-0.21	-0.16	-0.27**	-0.20*
	(-2.16)	(-1.76)	(-0.90)	(-0.84)	(-1.91)	(-1.58)	(-2.73)	(-2.19)
lagged family size squared	0.07	0.07	0.00	0.00	0.07	0.07	0.08	0.09
	(0.88)	(0.97)	(0.03)	(0.05)	(0.83)	(0.91)	(1.08)	(1.26)
fund characteristics	N	Y	N	Y	N	Y	N	Y
style dummies	N	Y	N	Y	N	Y	N	Y
region dummies	N	Y	N	Y	N	Y	N	Y

Table 3
Sorts on fund size

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: All funds												
Portfolio A (small funds)	12.60	6.78	6.62	6.13	0.32	0.27	0.08	0.14	0.01	0.02	0.02	0.66
Portfolio B (large funds)	8.95	6.02	2.98	3.19	0.29	0.24	0.07	0.13	-0.01	0.01	0.02	0.69
Spread (A-B)	3.65	2.36	3.65	6.64	0.03	0.03	0.01	0.01	0.02	0.01	0.00	0.18
Panel B: Adjusted for backfill and incubation bias												
Portfolio A (small funds)	10.99	7.08	5.20	4.11	0.30	0.24	0.09	0.20	0.01	0.02	0.03	0.55
Portfolio B (large funds)	8.95	5.95	3.05	3.27	0.29	0.22	0.07	0.15	0.00	0.01	0.02	0.68
Spread (A-B)	2.04	2.93	2.15	3.07	0.00	0.02	0.02	0.05	0.01	0.01	0.01	0.14
Panel C: Adjusted for serial correlation												
Portfolio A (small funds)	12.59	7.46	6.29	5.56	0.38	0.31	0.10	0.11	0.01	0.02	0.02	0.70
Portfolio B (large funds)	8.89	6.77	2.59	2.56	0.34	0.28	0.09	0.10	-0.01	0.01	0.02	0.72
Spread (A-B)	3.70	2.45	3.70	6.48	0.03	0.03	0.01	0.01	0.02	0.01	0.00	0.18
Panel D: Pre-fee returns												
Portfolio A (small funds)	17.66	6.94	11.66	10.49	0.33	0.27	0.08	0.15	0.01	0.02	0.02	0.65
Portfolio B (large funds)	12.83	6.10	6.83	7.22	0.29	0.24	0.06	0.14	-0.01	0.01	0.02	0.69
Spread (A-B)	4.83	2.46	4.83	8.44	0.03	0.03	0.01	0.01	0.02	0.01	0.00	0.18

Table 4

Sorts on fund size stratified by fund investment strategy

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: Security Selection funds												
Portfolio A (small funds)	16.21	9.39	9.16	7.07	0.50	0.41	0.01	-0.01	0.00	0.01	0.00	0.76
Portfolio B (large funds)	10.65	8.72	3.66	3.16	0.46	0.40	0.03	0.01	-0.01	0.00	0.01	0.79
Spread (A-B)	5.56	2.84	5.49	7.93	0.04	0.02	-0.02	-0.02	0.01	0.01	-0.01	0.10
Panel B: Directional Trader funds												
Portfolio A (small funds)	12.16	8.30	5.54	3.84	0.37	0.31	0.15	0.19	0.00	0.02	0.02	0.58
Portfolio B (large funds)	8.61	7.97	2.09	1.43	0.34	0.28	0.10	0.21	0.00	0.02	0.02	0.53
Spread (A-B)	3.55	3.21	3.45	4.22	0.03	0.02	0.05	-0.02	0.01	0.00	0.00	0.02
Panel C: Relative Value funds												
Portfolio A (small funds)	9.42	2.93	4.71	7.88	0.09	0.07	0.04	0.16	-0.01	0.01	0.00	0.42
Portfolio B (large funds)	7.45	2.93	2.85	4.57	0.08	0.04	0.02	0.16	-0.01	0.00	0.00	0.32
Spread (A-B)	1.97	2.06	1.86	3.56	0.01	0.03	0.01	0.00	0.00	0.01	0.00	0.03
Panel D: Multi-process funds												
Portfolio A (small funds)	13.27	6.58	7.22	6.04	0.26	0.25	0.02	0.15	-0.01	0.00	-0.01	0.52
Portfolio B (large funds)	10.40	4.70	4.82	5.94	0.19	0.18	0.04	0.19	-0.01	0.00	0.01	0.60
Spread (A-B)	2.86	4.25	2.40	2.27	0.08	0.07	-0.02	-0.04	0.00	0.00	-0.01	0.06
Panel E: Fund of Funds												
Portfolio A (small funds)	7.30	5.70	1.79	1.64	0.20	0.21	0.06	0.21	0.00	0.01	0.02	0.48
Portfolio B (large funds)	7.90	5.48	2.26	2.19	0.21	0.18	0.09	0.14	-0.02	0.01	0.02	0.50
Spread (A-B)	-0.60	2.50	-0.46	-0.78	-0.01	0.03	-0.03	0.07	0.02	0.00	0.00	0.16

Table 5

Sorts on fund size stratified by fund investment region

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: North America funds												
Portfolio A (small funds)	14.68	6.81	8.36	9.14	0.35	0.30	0.02	0.12	0.00	0.01	0.00	0.76
Portfolio B (large funds)	9.84	5.50	3.99	5.76	0.29	0.26	0.04	0.05	-0.01	0.00	0.01	0.84
Spread (A-B)	4.85	3.05	4.37	6.06	0.07	0.04	-0.02	0.07	0.01	0.01	-0.01	0.15
Panel B: Europe funds												
Portfolio A (small funds)	13.01	6.87	7.90	4.91	0.16	0.09	-0.02	0.25	0.00	0.01	0.01	0.16
Portfolio B (large funds)	9.91	8.81	3.58	1.91	0.31	0.17	0.09	0.11	-0.03	0.01	0.01	0.31
Spread (A-B)	3.10	7.72	4.32	2.28	-0.15	-0.08	-0.11	0.14	0.03	0.00	0.00	0.09
Panel C: Global funds												
Portfolio A (small funds)	10.71	7.27	6.18	4.17	0.16	0.17	0.23	0.08	0.03	0.03	0.05	0.40
Portfolio B (large funds)	8.73	5.76	3.47	3.00	0.19	0.16	0.14	0.17	0.01	0.02	0.02	0.42
Spread (A-B)	1.98	3.79	2.71	3.35	-0.03	0.02	0.09	-0.09	0.02	0.01	0.03	0.32
Panel D: Emerging Market funds												
Portfolio A (small funds)	24.30	22.99	14.23	2.67	0.69	0.34	-0.25	0.70	-0.03	0.02	0.03	0.24
Portfolio B (large funds)	17.52	20.22	6.20	1.38	0.59	0.40	-0.01	0.86	-0.07	0.00	0.03	0.31
Spread (A-B)	6.78	9.96	8.02	3.12	0.10	-0.06	-0.24	-0.16	0.04	0.02	0.00	0.06

Table 6

Sorts on fund size stratified by fund share restrictions

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: Low redemption frequency funds (>one month)												
Portfolio A (small funds)	15.20	8.65	8.24	6.94	0.44	0.40	0.01	0.08	0.00	0.01	0.00	0.75
Portfolio B (large funds)	10.62	7.26	4.00	4.08	0.36	0.33	0.03	0.11	-0.01	0.00	0.01	0.76
Spread (A-B)	4.57	3.22	4.24	5.59	0.08	0.07	-0.01	-0.03	0.01	0.01	-0.01	0.16
Panel B: High redemption frequency funds (<=one month)												
Portfolio A (small funds)	11.20	6.22	5.86	5.08	0.25	0.19	0.12	0.13	0.02	0.02	0.03	0.52
Portfolio B (large funds)	7.96	5.38	2.53	2.53	0.22	0.17	0.09	0.15	0.00	0.02	0.02	0.53
Spread (A-B)	3.24	2.25	3.34	6.63	0.03	0.02	0.03	-0.02	0.02	0.01	0.00	0.24
Panel C: Long redemption notification period funds (>one month)												
Portfolio A (small funds)	15.29	7.66	8.75	7.74	0.37	0.35	-0.01	0.12	0.00	0.01	0.00	0.71
Portfolio B (large funds)	10.90	6.85	4.54	4.24	0.31	0.28	0.00	0.19	-0.01	0.00	0.01	0.67
Spread (A-B)	4.39	3.05	4.20	5.69	0.06	0.07	-0.01	-0.07	0.01	0.01	-0.01	0.11
Panel D: Short redemption notification period funds (<=one month)												
Portfolio A (small funds)	12.10	6.89	6.19	5.50	0.32	0.27	0.11	0.11	0.01	0.02	0.02	0.64
Portfolio B (large funds)	8.35	5.88	2.49	2.63	0.28	0.23	0.09	0.10	-0.01	0.01	0.02	0.66
Spread (A-B)	3.74	2.75	3.71	5.92	0.05	0.03	0.02	0.01	0.02	0.01	0.00	0.22

Table 7

Sorts on fund size stratified by number of principals

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
					Panel A: Funds with one principal							
Portfolio A (small funds)	15.53	7.72	9.54	7.01	0.37	0.24	0.04	0.10	0.01	0.02	0.01	0.56
Portfolio B (large funds)	10.92	6.06	5.09	5.05	0.28	0.22	0.07	0.16	0.00	0.01	0.02	0.63
Spread (A-B)	4.61	3.72	4.45	4.97	0.09	0.01	-0.02	-0.06	0.01	0.01	-0.01	0.12
					Panel B: Funds with two principals							
Portfolio A (small funds)	16.49	7.20	10.40	8.19	0.32	0.27	0.00	0.12	0.00	0.01	0.01	0.57
Portfolio B (large funds)	10.46	7.13	3.97	3.46	0.33	0.28	0.04	0.21	-0.01	0.01	0.01	0.64
Spread (A-B)	6.04	4.03	6.42	6.16	-0.01	0.00	-0.04	-0.09	0.01	0.00	-0.01	-0.02
					Panel C: Funds with more than two principals							
Portfolio A (small funds)	15.40	7.34	9.30	7.50	0.34	0.25	0.13	0.05	0.00	0.02	0.02	0.60
Portfolio B (large funds)	8.59	4.90	2.96	3.51	0.23	0.14	0.11	0.16	-0.01	0.01	0.01	0.61
Spread (A-B)	6.80	4.72	6.35	5.76	0.12	0.11	0.02	-0.11	0.00	0.02	0.01	0.18

Table 8

Sorts on fund size stratified by fund fee

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: High management fee funds (management fee > 2%)												
Portfolio A (small funds)	12.45	10.28	8.54	3.90	0.15	0.18	0.31	-0.06	0.04	0.04	0.05	0.33
Portfolio B (large funds)	10.37	9.65	6.52	3.11	0.10	0.14	0.32	-0.06	0.03	0.05	0.05	0.30
Spread (A-B)	2.08	4.33	2.02	1.84	0.05	0.05	-0.01	-0.01	0.02	0.00	0.01	0.03
Panel B: Low management fee funds (management fee <=2%)												
Portfolio A (small funds)	12.77	6.82	6.58	6.43	0.34	0.29	0.05	0.14	0.00	0.01	0.01	0.71
Portfolio B (large funds)	8.89	6.21	2.73	2.92	0.30	0.26	0.06	0.13	-0.01	0.01	0.01	0.71
Spread (A-B)	3.89	2.33	3.85	6.94	0.03	0.03	-0.01	0.01	0.01	0.01	0.00	0.14
Panel C: High performance fee funds (performance fee >= 20%)												
Portfolio A (small funds)	13.83	6.76	8.00	7.13	0.31	0.26	0.07	0.15	0.01	0.02	0.02	0.63
Portfolio B (large funds)	9.30	5.72	3.55	3.89	0.26	0.24	0.06	0.12	0.00	0.01	0.02	0.66
Spread (A-B)	4.54	2.44	4.45	7.85	0.04	0.02	0.01	0.03	0.02	0.01	0.00	0.19
Panel D: Low performance fee funds (performance fee < 20%)												
Portfolio A (small funds)	8.91	7.56	2.41	2.13	0.39	0.29	0.07	0.15	0.01	0.02	0.01	0.70
Portfolio B (large funds)	8.25	7.52	1.51	1.26	0.37	0.25	0.07	0.22	-0.01	0.01	0.02	0.68
Spread (A-B)	0.66	3.29	0.90	1.13	0.02	0.04	0.01	-0.07	0.02	0.01	0.00	0.12

Table 9

Sorts on fund size, robustness tests

Hedge funds are sorted every January 1st into quintiles based on fund size. Portfolio A is the equal-weighted portfolio of funds in the two smallest size quintiles. Portfolio B is the equal-weighted portfolio of funds in the two largest size quintiles. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung and and Hsieh (2004) factors are S&P 500 return minus risk free rate (SNPMRF), Wilshire small cap minus large cap return (SCMLC), change in the constant maturity yield of the U.S. 10-year Treasury bond adjusted for the duration of the 10-year bond (BD10RET), change in the spread of Moody's BAA bond over 10-year Treasury bond appropriately adjusted for duration (BAAMTSY), bond PTFS (PTFSBD), currency PTFS (PTFSFX), and commodities PTFS (PTFSCOM), where PTFS is primitive trend following strategy. The *t*-statistics are derived from White (1980) standard errors. The sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/ year)	Std. Dev.	Alpha (pct/ year)	*t*-stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R^2
Panel A: Unleveraged funds												
Portfolio A (small funds)	12.02	6.80	5.66	6.02	0.37	0.27	0.03	0.13	0.00	0.01	0.01	0.76
Portfolio B (large funds)	8.53	6.55	2.25	2.22	0.33	0.24	0.04	0.12	-0.01	0.01	0.01	0.67
Spread (A-B)	3.49	2.55	3.40	5.42	0.04	0.03	-0.01	0.01	0.01	0.00	0.00	0.08
Panel B: Funds with AUM > US$20m												
Portfolio A (small funds)	11.66	6.09	5.84	6.13	0.28	0.29	0.09	0.05	0.00	0.01	0.01	0.69
Portfolio B (large funds)	8.63	5.80	2.83	3.01	0.28	0.22	0.06	0.11	-0.01	0.01	0.02	0.65
Spread (A-B)	3.02	1.99	3.01	6.34	0.00	0.07	0.03	-0.06	0.01	0.00	-0.01	0.14
Panel C: Quintile portfolios												
Portfolio Q1 (smallest)	13.80	7.24	7.84	6.37	0.32	0.27	0.10	0.16	0.01	0.02	0.03	0.60
Portfolio Q2	11.49	6.57	5.49	5.39	0.32	0.26	0.06	0.12	0.01	0.02	0.01	0.68
Portfolio Q3	10.45	6.07	4.51	4.82	0.30	0.25	0.06	0.11	0.00	0.01	0.01	0.70
Portfolio Q4	9.25	6.42	3.05	3.16	0.31	0.28	0.08	0.13	-0.01	0.01	0.02	0.71
Portfolio Q5 (largest)	8.65	5.76	2.90	3.05	0.27	0.20	0.05	0.13	0.00	0.01	0.02	0.64
Spread (Q1-Q5)	5.15	3.40	4.94	6.16	0.05	0.07	0.04	0.02	0.02	0.01	0.01	0.16
Spread (Q2-Q5)	2.84	2.36	2.59	4.77	0.05	0.06	0.01	-0.01	0.01	0.01	-0.01	0.20