

Does Size Matter in the Hedge Fund Industry?*

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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 2.75 percent per year after adjusting for risk. This over performance cannot be explained by fund age, leverage, serial correlation, backfill bias, or incubation bias. The capacity constraints are not confined to the smallest funds, and manifest across various investment styles and regions. In particular, they are strongest for funds managed by multiple principals that trade small, illiquid securities, suggesting that the observed diseconomies can be traced to price impact and hierarchy costs (Stein, 2002). Interestingly, these 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 immensely 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, trading asset growth for future returns. 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 results¹ seem inconsistent with the dearth of performance persistence in the hedge fund industry (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 = 2.72) while that on the square of last month's fund size is positive and statistically significant (t -statistic = 3.24). After controlling for the other variables, an increase in fund AUM from a small base of say US\$10m to US\$500m is associated with a reduction in annual abnormal returns of approximately 1.5 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 0.5 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 (below median AUM) funds outperforms the portfolio of large (above median AUM) funds by about 2.75 percent per year (t -statistic = 6.15) after adjusting for covariation with the Fung and Hsieh (2004) seven risk factors. 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 12 months of return data for each fund, after

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

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 3.74 percent per year (t -statistic = 3.71), 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 1.30 percent per year that is statistically indistinguishable from zero. Our results are robust to requiring that the Funds of Funds invest only in 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 (1.29 percent) and Global (2.06 percent) funds who typically trade liquid and large-capitalization securities. Conversely, they are relatively strong for Emerging Market (6.75 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.² 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 twice as large 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 the 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 determined upon inception, it is likely that managers understand prior to setting up the fund, perhaps through past financial market experience, the severity of capacity issues that they will face.

Thus far our analysis has focused on individual hedge funds. When we run the same portfolio analysis for Funds of Funds we find that the spread is -0.67 percent per year. That is large Funds of Funds outperform small Funds of Funds. While this effect is statistically indistinguishable from zero, it highlights the difference between hedge funds and Funds of Funds. Large Funds of Funds may be able to leverage on their size and negotiate better terms with their underlying hedge funds or invest in successful hedge funds that are otherwise closed to new investors. Moreover, since they do not directly manage portfolios of securities, they should be less affected by the adverse price impact from trading a large portfolio.

² This line of research follows from theoretical work by Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995) who argue that agents who lack control over allocation decisions face weaker incentives.

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 performance will not persist if fund flows chase returns 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. Successful hedge funds attract inflows and experience significant asset growth. In the presence of the capacity constraints documented in this paper, this asset growth crimps future performance. 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.³ 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 tighten 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-

³ See the decile spread alphas in their Table 7.

fee⁴ 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.

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 analysis.⁵ 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 June 30, 2008 so as to facilitate meaningful comparison.

Following Agarwal, Daniel, and Naik (2008), 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

⁴ Our results are robust to using pre-fee returns.

⁵ Inferences do not change when we include multiple share classes of the same fund in the analysis

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.

[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 12 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

$$ALPHA_{im} \equiv r_{im} - (b_{im}SNPMRF_m + c_{im}SCMLC_m + d_{im}BD10RET_m + e_{im}BAAMTSY_m + f_{im}PTFSBD_m + g_{im}PTFSFX_m + h_{im}PTFSCOM_m) \quad (1)$$

where $i = 1, \dots, n_{funds}$, $m = 1, \dots, M$, $ALPHA_{im}$ 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.⁶

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

$$ALPHA_{im} = a + bFUNDSize_{im-1} + cFUNDSize_{im-1}^2 + dFAMSize_{im-1} + \varepsilon_{im} \quad (2)$$

⁶ Similar results obtain for funds with at least 36 months of return data. Results are available upon request.

$$\begin{aligned}
ALPHA_{im} = & a + bFUND SIZE_{im-1} + cFUND SIZE_{im-1}^2 + dFAM SIZE_{im-1} \\
& + ePER FFEE_i + fMGTFEE_i + gREDEMP_i + hMININV_i \\
& + kFUNDAGE_{im-1} + \sum_{y=1}^{Y-1} l^y STYLEDUM_i^y + \sum_{z=1}^{Z-1} o^z GEODUM_i^z + \varepsilon_{im}
\end{aligned} \tag{3}$$

where *FUNDSIZE* is fund size or fund AUM, *FAMSIZE* is fund family size, *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 squared of *FUNDSIZE* to capture potential non-linearity in the fund size and performance relationship. 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 (2008) 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. 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 $12 * (0.5 * 0.33 - 0.5^2 * 0.16)$ or 1.5 percent. For comparison, an increase in AUM from US\$10m to US\$1bn is associated with a decrease in alpha of approximately 2 percent per year and not 3 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 1 percent level. Interestingly, the coefficient estimate on the fund family variable is also statistically significant

for the regression without controls but is statistically indistinguishable from zero once we control for the other fund characteristics.

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.⁷ To adjust for backfill and incubation bias, we remove the first 12 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-fee⁸ alpha. The results from this robustness analysis are presented in columns three to eight of Table 2, and suggest that the overperformance 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.

⁷ We use the average values of θ_0 , θ_1 , and θ_2 for the various investment styles reported in their Table 8 to effect the correction.

⁸ 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.

B. The performance of portfolios sorted on fund size

To gauge the economic relevance of the capacity constraints facing hedge funds, we 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. We define small funds as funds with AUM equal to or less than that of the median fund. Conversely, we define large funds as funds with AUM greater than that of the median fund. 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 portfolio A and portfolio 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 and show that the strategy of investing in small hedge funds and avoiding large funds yields a risk-adjusted return of 2.75 percent per year (t -statistic = 6.15). This suggests that managing many assets 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 Funds of Funds portfolio comprising small hedge funds delivers an after-fee alpha of 3.74 percent per year, which is both economically and statistically significant (t -statistic = 3.71). In contrast, the hypothetical Fund of Funds portfolio comprising large hedge funds only earns an after-fee alpha of 1.30 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 comfortably above 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 greater than 65 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 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 use greater leverage and hence 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 1.72, 1.10, and 1.55, respectively. Since the information ratio adjusts for the additional volatility that leverage induces, the higher information ratio of the small fund portfolio indicates that its overperformance is not simply a by-product of 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 (3.96 percent per year) and weakest for relative value (1.29 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 plague 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 risk-adjusted

returns that are slightly higher (though the difference is statistically indistinguishable from zero) than small Funds of Funds. Perhaps, large Funds of Funds are able to capitalize on their greater purchasing power and gain access to successful single-manager hedge funds that are otherwise closed to new investments. 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 illiquid securities. This is because it is much harder to move funds in and out of small capitalization illiquid securities without having price move against the trader. Conversely, it is significantly easier to shift funds in and out of large capitalization 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 knowing 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 6.75 percent per year (t -statistic =

2.47) 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 trading in the Global region. The small Global fund portfolio only outperforms the large Global fund portfolio by 2.06 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 categorize funds, 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 2.48 percent per year while that for hedge funds that allow for less frequent redemptions (every quarter at best) is 3.02 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 2.64 percent per year. For hedge funds managed by two principals, the alpha spread rises to 5.25 percent per year. When we analyze hedge funds managed by more than two principals, the alpha spread rises yet again to 6.65 percent per year. This monotonic relationship between the number of principals and the strength of the capacity constraints 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. On 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 < 20 percent), small funds outperform large funds by a modest 0.58 percent per year after adjusting for risk. Yet, within the high performance fee group of funds (performance fee \geq 20 percent), small funds outperform large funds by 3.40 percent per year after adjusting for risk.

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 dispel any residual leverage related concerns, we perform the sort analysis for funds with and without leverage. We can do so as HFR and TASS include an indicator variable for leverage. The results reported in Panels A and B 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 2.47 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 are not 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 kind of 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, e.g., US\$20 million. Hence in Panels C and D of Table 9, we report portfolio sort results for funds that manage less than US\$20 million and for funds that manage more than US\$20 million. The results in Panel D of Table 9 indicate that within the group of funds who manage more than US\$20 million, small funds continue to outperform large funds after adjusting for risk. Even with the size cutoff, the small fund portfolio trumps the large fund portfolio by a risk-adjusted 2.14 percent per year (t -statistic = 4.54). 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 2.79 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.

5. Conclusion

Inundated almost daily by news of large and successful hedge funds, readers of the financial press may well believe 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 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 2.75 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 some of the capacity constraints can be 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.

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) 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. Our results also suggest that hedge fund managers are aware of the capacity constraints that they will face prior to setting up their compensation structure. 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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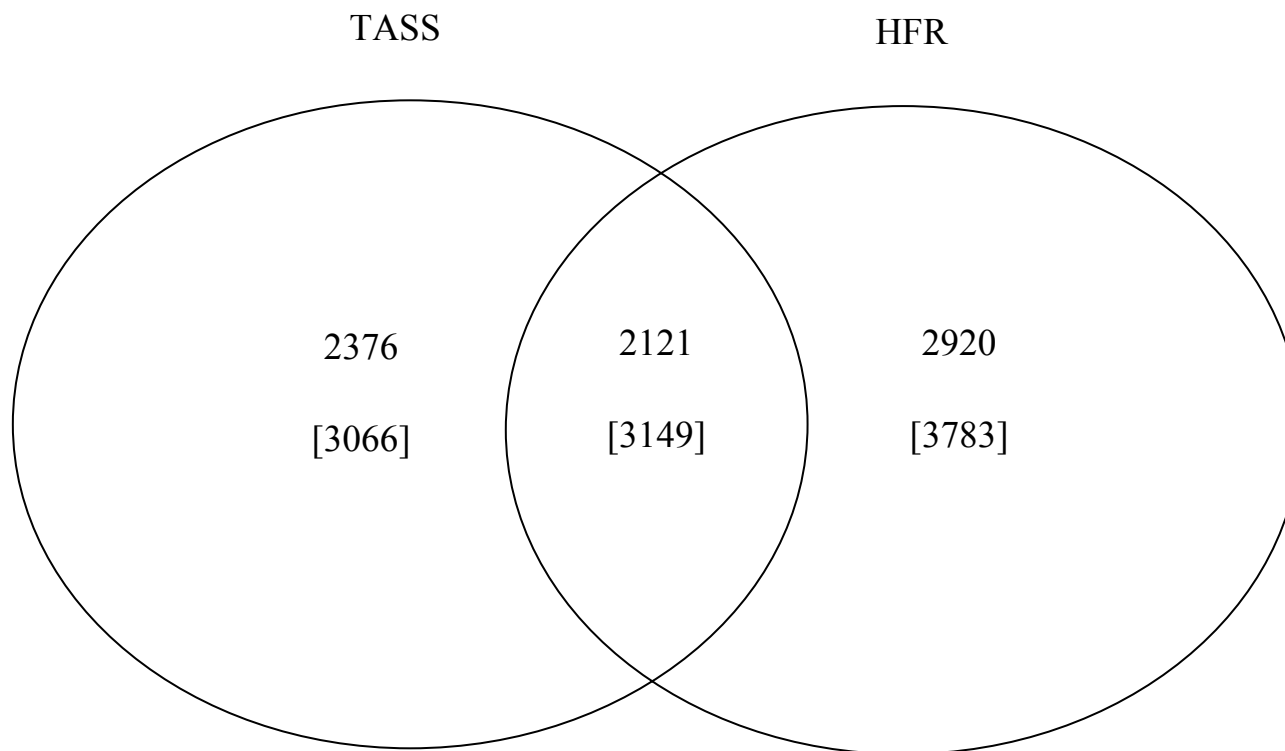


Figure 1: Break down of funds by database vendor. Fund numbers in brackets include duplicate share classes of the same fund. The sample period is from January 1994 to June 2008.

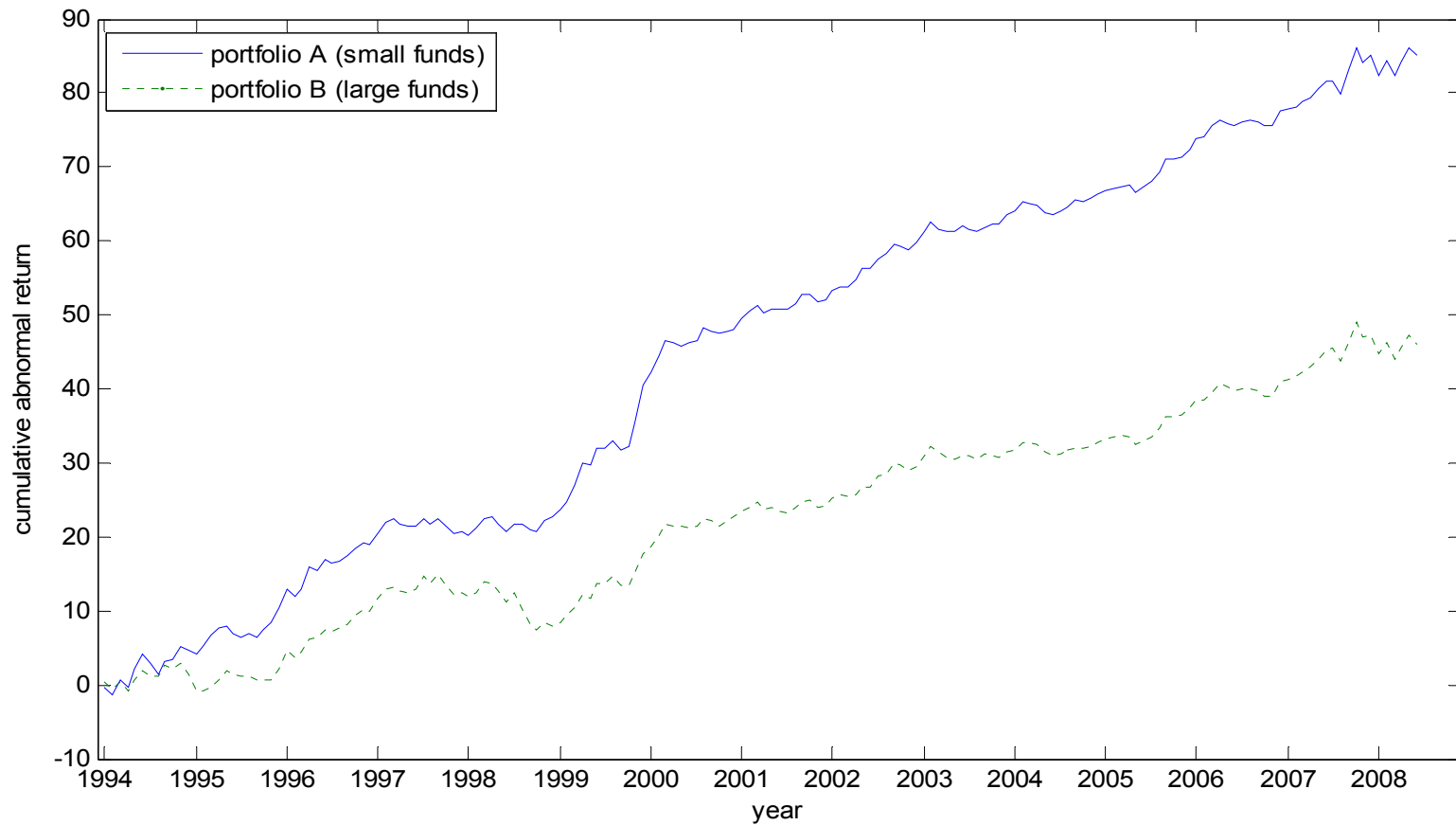


Figure 2: Cumulative abnormal return of small versus large hedge funds. Equal-weighted portfolios of hedge funds are constructed by sorting funds every January 1st based on fund size. Cumulative abnormal return is the difference between a portfolio's excess return and its factor loadings multiplied by 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.

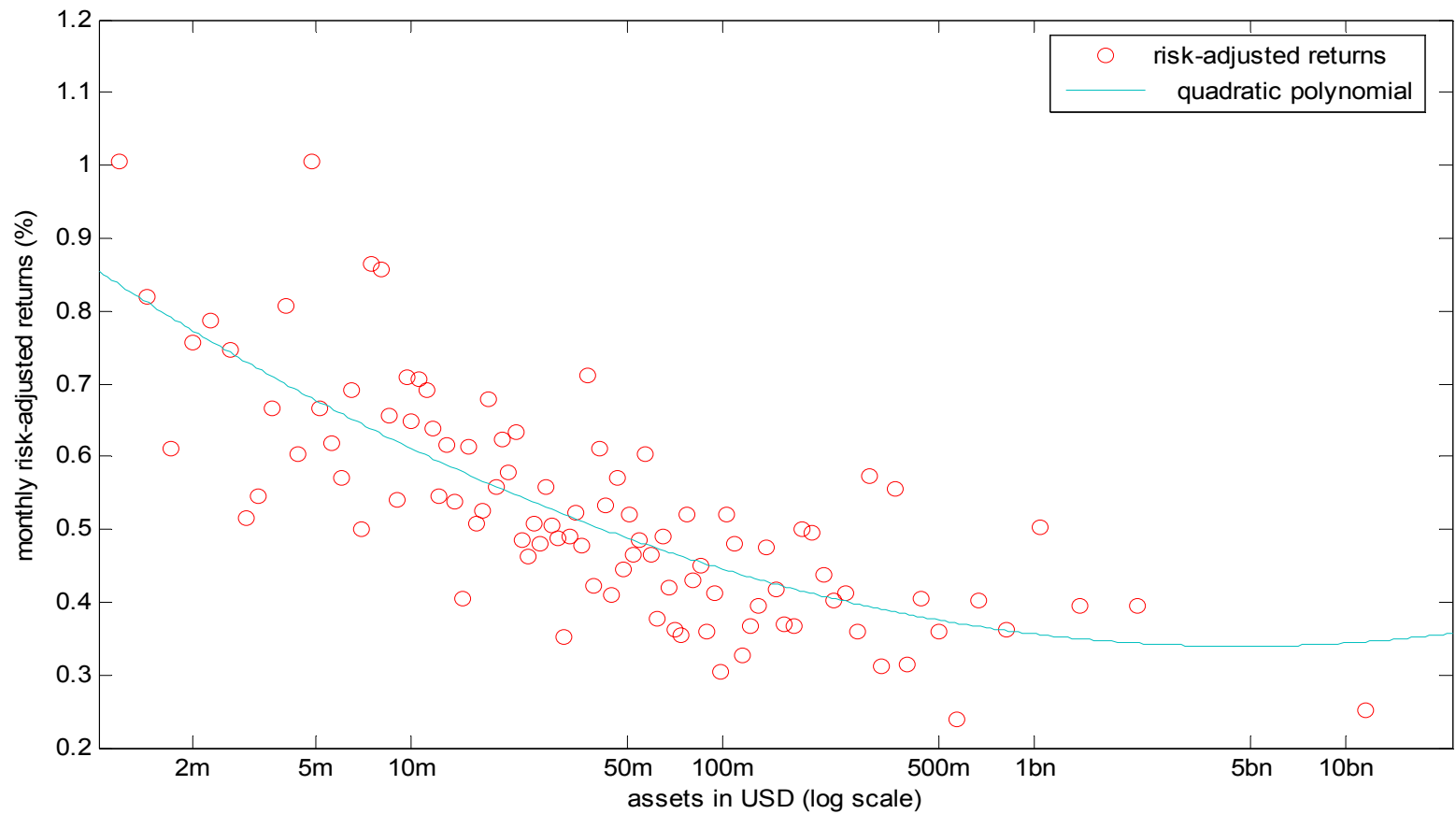


Figure 3: The relationship between hedge fund monthly abnormal returns and past assets. Monthly hedge fund abnormal return observations are sorted into 100 bins based on the funds' past month's assets. For each bin, we calculate the average monthly abnormal return and assets. These average monthly abnormal 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

Investment strategy	Total funds	Dead funds	Average AUM in US\$				Return months
			AUM<\$20m	\$20m≤AUM<\$100m	\$100m≤AUM<\$500m	AUM>\$500m	
Security Selection	2715	1234	1199	992	410	114	140710
Multi-process	999	483	349	355	221	74	45927
Directional Trader	1752	1184	885	600	194	73	83298
Relative Value	1308	787	474	503	272	59	62042
Others	643	552	446	155	34	8	26953
Total	7417	4240	3353	2605	1131	328	358930

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, and lagged monthly family size. 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.

Independent variables	Dependent variable							
	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)	-0.29** (-3.25)	-0.33** (-2.72)	-0.28** (-2.75)	-0.36** (-2.85)	-0.29** (-3.05)	-0.35** (-2.75)	-0.27** (-3.03)	-0.34** (-2.77)
lagged fund size squared	0.11** (2.84)	0.16** (3.24)	0.10* (2.43)	0.15** (2.98)	0.11* (2.57)	0.17** (3.15)	0.11** (2.72)	0.17** (3.37)
lagged family size	-0.06* (-2.13)	-0.03 (-1.02)	-0.03 (-0.98)	-0.02 (-0.45)	-0.06 (-1.93)	-0.03 (-0.92)	-0.09** (-2.98)	-0.04 (-1.30)

Table 3
Sorts on fund size

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R ²
Panel A: All funds												
Portfolio A (small funds)	11.97	6.63	5.96	5.85	0.32	0.27	0.08	0.12	0.01	0.02	0.02	0.69
Portfolio B (large funds)	9.08	5.85	3.21	3.55	0.28	0.24	0.07	0.12	0.00	0.01	0.02	0.70
Spread (A-B)	2.89	1.94	2.75	6.15	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.20
Panel B: Adjusted for backfill and incubation bias												
Portfolio A (small funds)	11.09	6.69	5.07	4.87	0.32	0.26	0.09	0.15	0.01	0.02	0.02	0.68
Portfolio B (large funds)	8.90	5.82	3.05	3.41	0.28	0.23	0.06	0.12	0.00	0.01	0.02	0.70
Spread (A-B)	2.19	2.15	2.03	4.10	0.04	0.03	0.03	0.03	0.01	0.01	0.00	0.20
Panel C: Adjusted for serial correlation												
Portfolio A (small funds)	11.94	7.33	5.60	5.22	0.38	0.31	0.10	0.09	0.01	0.02	0.02	0.73
Portfolio B (large funds)	8.99	6.57	2.80	2.86	0.33	0.28	0.09	0.09	-0.01	0.01	0.02	0.73
Spread (A-B)	2.95	2.04	2.79	5.94	0.05	0.04	0.01	0.00	0.01	0.01	0.00	0.20
Panel D: Pre-fee returns												
Portfolio A (small funds)	16.87	6.77	10.83	10.38	0.33	0.27	0.08	0.13	0.01	0.02	0.02	0.69
Portfolio B (large funds)	13.07	5.94	7.17	7.80	0.29	0.24	0.06	0.13	0.00	0.01	0.02	0.70
Spread (A-B)	3.80	2.02	3.66	7.90	0.04	0.03	0.02	0.01	0.01	0.01	0.00	0.20

Table 4
Sorts on fund size stratified by fund investment strategy

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R ²
Panel A: Security Selection funds												
Portfolio A (small funds)	15.20	9.32	8.17	6.53	0.50	0.43	0.00	-0.02	0.00	0.01	0.00	0.77
Portfolio B (large funds)	11.11	8.56	4.21	3.75	0.46	0.39	0.02	0.00	-0.01	0.00	0.01	0.80
Spread (A-B)	4.08	2.43	3.96	6.75	0.04	0.04	-0.02	-0.02	0.01	0.01	-0.01	0.12
Panel B: Directional Trader funds												
Portfolio A (small funds)	11.48	8.06	4.85	3.58	0.37	0.32	0.13	0.18	0.00	0.02	0.02	0.61
Portfolio B (large funds)	8.45	7.67	2.06	1.50	0.33	0.29	0.12	0.16	-0.01	0.02	0.02	0.56
Spread (A-B)	3.03	2.52	2.79	4.43	0.04	0.03	0.02	0.02	0.01	0.00	0.00	0.05
Panel C: Relative Value funds												
Portfolio A (small funds)	9.00	2.86	4.26	7.49	0.08	0.08	0.04	0.16	-0.01	0.01	0.00	0.47
Portfolio B (large funds)	7.50	2.80	2.96	4.95	0.07	0.05	0.02	0.14	-0.01	0.00	0.00	0.30
Spread (A-B)	1.50	1.78	1.29	2.89	0.01	0.03	0.02	0.02	0.00	0.01	0.00	0.04
Panel D: Multi-process funds												
Portfolio A (small funds)	12.36	6.02	6.44	5.94	0.24	0.23	0.02	0.15	-0.01	0.00	-0.01	0.54
Portfolio B (large funds)	9.75	4.62	4.15	5.33	0.19	0.18	0.04	0.19	-0.01	0.00	0.01	0.63
Spread (A-B)	2.61	3.67	2.29	2.47	0.05	0.05	-0.02	-0.03	0.00	0.00	-0.01	0.03
Panel E: Fund of Funds												
Portfolio A (small funds)	7.10	5.64	1.51	1.42	0.20	0.21	0.06	0.21	0.00	0.01	0.02	0.51
Portfolio B (large funds)	7.81	5.42	2.18	2.18	0.21	0.19	0.09	0.12	-0.02	0.01	0.02	0.52
Spread (A-B)	-0.72	2.15	-0.67	-1.33	-0.01	0.03	-0.03	0.10	0.01	0.00	0.00	0.16

Table 5
Sorts on fund size stratified by fund investment region

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R ²
Panel A: North America funds												
Portfolio A (small funds)	14.06	6.69	7.74	9.16	0.35	0.31	0.03	0.09	0.00	0.01	0.00	0.80
Portfolio B (large funds)	10.30	5.43	4.48	6.66	0.28	0.27	0.05	0.03	-0.01	0.00	0.01	0.85
Spread (A-B)	3.76	2.55	3.26	5.63	0.07	0.04	-0.03	0.06	0.01	0.01	-0.01	0.22
Panel B: Europe funds												
Portfolio A (small funds)	12.81	7.02	7.22	4.55	0.19	0.12	0.05	0.23	-0.01	0.01	0.01	0.22
Portfolio B (large funds)	10.10	8.90	3.67	1.97	0.32	0.19	0.09	0.11	-0.03	0.01	0.01	0.33
Spread (A-B)	2.71	6.41	3.55	2.25	-0.12	-0.06	-0.03	0.12	0.02	0.00	-0.01	0.08
Panel C: Global funds												
Portfolio A (small funds)	10.39	6.92	5.77	4.10	0.17	0.18	0.22	0.05	0.02	0.03	0.04	0.40
Portfolio B (large funds)	8.79	5.67	3.71	3.24	0.18	0.16	0.14	0.13	0.01	0.02	0.02	0.41
Spread (A-B)	1.60	3.10	2.06	2.99	-0.02	0.02	0.08	-0.08	0.01	0.01	0.02	0.25
Panel D: Emerging Market funds												
Portfolio A (small funds)	22.22	23.09	12.30	2.40	0.75	0.37	-0.12	0.63	-0.04	0.01	0.03	0.26
Portfolio B (large funds)	15.55	19.37	5.55	1.33	0.55	0.40	-0.08	0.91	-0.06	0.00	0.03	0.30
Spread (A-B)	6.67	10.77	6.75	2.47	0.20	-0.02	-0.04	-0.28	0.02	0.01	0.01	0.03

Table 6
Sorts on fund size stratified by fund share restrictions

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -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)	14.19	8.48	7.24	6.53	0.44	0.41	0.02	0.07	0.00	0.01	0.00	0.78
Portfolio B (large funds)	10.72	6.97	4.22	4.68	0.36	0.33	0.03	0.09	-0.01	0.00	0.01	0.79
Spread (A-B)	3.48	2.83	3.02	4.69	0.08	0.08	-0.01	-0.02	0.01	0.00	0.00	0.22
Panel B: High redemption frequency funds (<=one month)												
Portfolio A (small funds)	10.65	6.09	5.26	4.70	0.25	0.19	0.12	0.12	0.01	0.02	0.02	0.54
Portfolio B (large funds)	8.19	5.43	2.78	2.74	0.22	0.17	0.09	0.14	0.00	0.02	0.02	0.53
Spread (A-B)	2.46	1.96	2.48	5.43	0.03	0.02	0.02	-0.02	0.01	0.01	0.00	0.18
Panel C: Long redemption notification period funds (>one month)												
Portfolio A (small funds)	14.33	7.67	7.74	7.11	0.37	0.36	0.00	0.10	-0.01	0.01	0.00	0.74
Portfolio B (large funds)	11.00	6.76	4.65	4.70	0.32	0.30	0.01	0.13	-0.01	0.00	0.01	0.72
Spread (A-B)	3.33	2.73	3.09	4.64	0.06	0.06	-0.01	-0.03	0.01	0.00	0.00	0.10
Panel D: Short redemption notification period funds (<=one month)												
Portfolio A (small funds)	11.49	6.65	5.59	5.25	0.32	0.27	0.11	0.11	0.01	0.02	0.02	0.66
Portfolio B (large funds)	8.55	5.83	2.74	2.90	0.27	0.23	0.09	0.10	-0.01	0.01	0.02	0.66
Spread (A-B)	2.94	2.32	2.85	5.33	0.04	0.03	0.02	0.01	0.02	0.01	0.00	0.19

Table 7
Sorts on fund size stratified by number of principals

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R ²
Panel A: Funds with one principal												
Portfolio A (small funds)	14.41	7.28	8.39	6.75	0.35	0.25	0.03	0.11	0.01	0.02	0.01	0.59
Portfolio B (large funds)	11.42	6.03	5.75	5.54	0.26	0.22	0.07	0.15	0.00	0.01	0.02	0.60
Spread (A-B)	2.99	3.20	2.64	3.44	0.09	0.02	-0.04	-0.04	0.00	0.00	-0.01	0.14
Panel B: Funds with two principals												
Portfolio A (small funds)	15.75	7.41	9.36	7.73	0.35	0.28	0.01	0.16	0.00	0.01	0.01	0.64
Portfolio B (large funds)	10.90	7.52	4.11	3.50	0.35	0.30	0.04	0.24	-0.01	0.00	0.01	0.66
Spread (A-B)	4.85	3.87	5.25	5.32	0.01	-0.03	-0.03	-0.07	0.01	0.01	-0.01	0.01
Panel C: Funds with more than two principals												
Portfolio A (small funds)	15.51	7.22	9.54	7.88	0.33	0.28	0.12	0.05	0.00	0.02	0.02	0.60
Portfolio B (large funds)	8.63	5.15	2.89	3.41	0.23	0.19	0.11	0.16	-0.01	0.01	0.02	0.65
Spread (A-B)	6.88	4.18	6.65	6.68	0.10	0.09	0.01	-0.11	0.01	0.01	0.01	0.14

Table 8
Sorts on fund size stratified by fund fee

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -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)	11.03	10.03	7.30	3.50	0.12	0.20	0.30	-0.10	0.04	0.05	0.06	0.37
Portfolio B (large funds)	10.08	9.46	6.23	3.05	0.09	0.14	0.31	-0.02	0.03	0.05	0.05	0.31
Spread (A-B)	0.94	3.96	1.06	1.06	0.04	0.06	-0.01	-0.08	0.01	0.00	0.01	0.03
Panel B: Low management fee funds (management fee <=2%)												
Portfolio A (small funds)	12.15	6.72	5.93	6.10	0.34	0.29	0.06	0.12	0.00	0.01	0.01	0.73
Portfolio B (large funds)	9.00	6.04	2.93	3.26	0.30	0.25	0.05	0.12	-0.01	0.01	0.01	0.72
Spread (A-B)	3.14	2.02	3.00	6.33	0.04	0.04	0.01	0.00	0.01	0.00	0.00	0.17
Panel C: High performance fee funds (performance fee >= 20%)												
Portfolio A (small funds)	12.93	6.50	7.10	6.85	0.30	0.27	0.08	0.13	0.01	0.02	0.02	0.66
Portfolio B (large funds)	9.40	5.57	3.70	4.26	0.26	0.24	0.06	0.11	0.00	0.01	0.02	0.69
Spread (A-B)	3.52	2.04	3.40	7.29	0.04	0.03	0.01	0.02	0.01	0.01	0.00	0.21
Panel D: Low performance fee funds (performance fee < 20%)												
Portfolio A (small funds)	9.28	7.69	2.68	2.30	0.40	0.28	0.07	0.17	0.01	0.02	0.01	0.69
Portfolio B (large funds)	8.70	7.34	2.10	1.78	0.36	0.24	0.07	0.18	-0.01	0.01	0.02	0.67
Spread (A-B)	0.58	2.83	0.58	0.84	0.03	0.04	0.00	-0.01	0.02	0.01	0.00	0.10

Table 9
Sorts on fund size, robustness tests

Hedge funds are sorted every January 1st based on fund size. Portfolio A is the equal-weighted portfolio of funds with below median AUM. Portfolio B is the equal-weighted portfolio of funds with above median AUM. Alpha is estimated relative to the Fung and Hsieh (2004) factors. The Fung 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 sample period is from January 1994 - June 2008.

Portfolio	Mean Ret. (pct/year)	Std. Dev.	Alpha (pct/year)	<i>t</i> -stat of alpha	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	Adj. R ²
Panel A: Unleveraged funds												
Portfolio A (small funds)	11.24	7.29	4.66	4.80	0.39	0.30	0.03	0.12	0.00	0.01	0.01	0.78
Portfolio B (large funds)	8.44	6.52	2.19	2.25	0.34	0.25	0.04	0.11	-0.01	0.01	0.01	0.70
Spread (A-B)	2.80	2.54	2.47	4.07	0.06	0.06	0.00	0.01	0.01	0.00	0.00	0.14
Panel B: Leveraged funds												
Portfolio A (small funds)	12.34	6.65	6.60	5.82	0.29	0.26	0.11	0.13	0.01	0.02	0.02	0.60
Portfolio B (large funds)	9.45	5.67	3.82	4.06	0.25	0.23	0.08	0.12	0.00	0.01	0.02	0.64
Spread (A-B)	2.89	2.12	2.78	5.61	0.04	0.03	0.03	0.01	0.01	0.01	0.00	0.17
Panel C: Funds with AUM <= US\$20m												
Portfolio A (small funds)	12.98	7.25	6.94	5.91	0.33	0.30	0.11	0.12	0.01	0.02	0.02	0.65
Portfolio B (large funds)	8.75	6.29	2.66	2.85	0.33	0.23	0.06	0.16	0.00	0.02	0.01	0.73
Spread (A-B)	4.23	3.07	4.28	5.75	0.01	0.08	0.05	-0.04	0.01	0.00	0.01	0.11
Panel D: Funds with AUM > US\$20m												
Portfolio A (small funds)	10.78	6.15	4.87	5.14	0.29	0.28	0.10	0.07	0.00	0.01	0.02	0.70
Portfolio B (large funds)	8.47	5.67	2.73	2.99	0.27	0.21	0.06	0.12	0.00	0.01	0.02	0.66
Spread (A-B)	2.31	1.96	2.14	4.54	0.02	0.07	0.04	-0.05	0.00	0.00	0.00	0.13