Financial Analysts Journal
Volume 64 • Number 6

Hedge Fund Performance Persistence: A New Approach

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Recent literature has found some evidence of performance persistence in hedge funds. This study investigated whether this persistence varies with fund characteristics, such as size and age. Previous research has found that funds face capacity constraints, that investment flows chase past performance, and that as funds age, they become more passively managed, which reduces the likelihood of performance persistence as funds grow older and larger. Consistent with this model, this study found that performance persistence is strongest among small, young funds. A portfolio of these funds with prior good performance outperformed a portfolio of large, mature funds with prior poor performance by 9.6 percent per year.

When an investor is selecting a hedge fund for investment, is the fund manager's prior performance record helpful? If past performance is indicative of future results, this information is valuable. If not, investors may be better off selecting a manager on the basis of the manager's reputation, investment style, or trading costs.

Research on persistence in hedge fund performance has obtained mixed results. Early research found evidence of short-term (one-month to three-month) persistence but no evidence of long-term persistence.[1] Recent work by Fung, Hsieh, Naik, and Ramadorai (2008), Jagannathan, Malakhov, and Novikov (2007), and Kosowski, Naik, and Teo (2007), however, found evidence of long-term (one-year to three-year) performance persistence.[2]

A separate strand of the hedge fund literature links fund characteristics, such as fund size, age, and investment inflows/outflows, to performance. As for fund size, Amenc, Curtis, and Martellini (2003) and Boyson (2007) documented a positive relationship between size and performance, whereas Harri and Brorsen (2004) documented a negative relationship. Getmansky (2005) found a positive and concave relationship between fund size and performance, which suggests that funds have an optimal size and that exceeding this size has a negative impact on performance.

Investigating the effect of fund age, Agarwal, Daniel, and Naik (2007), Amenc, Curtis, and Martellini (2003), Boyson (2007), Brown, Goetzmann, and Park (2001), and Liang (1999) documented a negative relationship between age and performance. Kosowski et al. (2007) argued that the best portfolios of hedge funds tend to hold funds of an intermediate age.

Finally, as for investment flows, Goetzmann, Ingersoll, and Ross (2003) showed that top performers experience outflows of capital. Agarwal, Daniel, and Naik (2007), Fung et al. (2008), and Kosowski et al. (2007) showed that funds with high inflows in the past experience poor performance in the following period. Baquero and Verbeek (2007) showed that, although investors withdraw money from past "loser" funds, they do not successfully exploit past "winner" funds. In contrast, Ding, Getmansky, Liang, and Wermers (2007) showed that fund flows predict future hedge fund performance.

Recent work by Berk and Green (2004) provides a theoretical link between performance persistence and fund characteristics. The results of their model indicate that, although skilled active managers probably exist, the active managers typically do not beat their passive benchmarks and also that performance persistence among managers is unlikely. This result occurs because:

> investors competitively supply funds to managers and there are decreasing returns for managers in deploying their superior ability. Managers increase the size of their funds, and their own compensation, to the point at which expected returns to investors are competitive going forward. (Berk and Green 2004, p. 1271)

In the model (henceforth, the BG model), investors learn about hedge funds through past fund performance and rationally supply capital to

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the best past performers. Because this model is a learning model, the flow–performance relationship is more extreme for young funds, which have relatively few returns that investors can use to assess performance. In contrast, for more mature funds with longer return histories, each successive period's return is proportionately less important in assessing performance. Hence, young funds with strong past performance will receive significant capital inflows. At some point, these funds will grow so large that the fund manager's skills will be spread too thin and/or the fund's trades will have a larger price impact and higher transaction costs than previously—both of which compromise the fund's performance. Thus, persistence of the good performance of such a fund in the future is unlikely.

I tested the implications of the BG model for the performance persistence of hedge funds. I first investigated performance persistence among hedge funds by forming quintile portfolios of funds on the basis of past performance. I included all hedge funds—both single-strategy funds and funds of hedge funds—in the main analysis, and I also performed tests by category. The primary measure of past performance was the 36-month *t*-statistic of alpha (also known as the "information ratio," IR), which is widely used in practice and was suggested by Kosowski et al. (2007). I then investigated whether simple sorts on prior-period fund size and fund age have power to detect performance persistence.

Next, I examined whether the predictions of the BG model hold by performing independent sorts of funds on past IR quintiles and fund characteristic terciles—that is, a total of 15 portfolios for each fund characteristic variable. The model implies that small funds will outperform large funds and young funds will outperform old funds.

My approach is similar to that of Kosowski et al. (2007). They, in turn, followed Carhart (1997) by basing portfolios of hedge funds on risk-adjusted past performance and testing whether these portfolios exhibited persistence in the future. An important practical contribution of Kosowski et al. (2007) is that when hedge funds were selected on the basis of past performance, the strongest persistence was among portfolios selected by using the *t*-statistic of alpha (the fund's IR), rather than alpha itself.[3] Because using the IR arguably improves the precision of the selection process, I also used this approach, although the main results of the study still held when funds were selected on the basis of alpha itself. Kosowski et al. (2007) documented performance persistence in hedge funds, but they did not focus much on whether this persistence varies with fund characteristics. If the BG model holds for hedge funds, I expected persistence to differ among funds with different characteristics.[4]

My study is also related to that of Fung et al. (2008). Using a sample that consisted of only funds of funds, they found that a subset of these funds consistently delivered alpha (i.e., had performance persistence). These "have alpha" funds were much less likely to liquidate and received larger and steadier investment flows than their "beta only" counterparts, which is consistent with the prediction of Berk and Green (2004) that investors rationally allocate capital to good performers. Also consistent with the BG model was that inflows into the have-alpha funds reduced the ability of these funds to continue delivering alpha in the future.

My approach differs from that of Fung et al. (2008) in an important way: Whereas they focused on whether high inflows to successful funds erode the performance of those funds (a time-series approach), I used a cross-sectional approach and addressed whether fund performance varies in the cross section for discrete critical values of fund age and fund size. In a sense, I was assuming that high flows into good funds erode performance, which is consistent with their findings, and I was attempting to quantify the magnitude of this erosion. Hence, both studies tested the implications of the BG model but in different ways.

In general, the main differences between my study and prior studies of the flow–performance relationship (or performance persistence) are that (1) prior researchers focused on the relationship between past fund flows and future performance for a given fund or portfolio of funds and (2) they used a time-series approach to answer the question of whether high past inflows erode future fund performance. In contrast, I analyzed the impact that critical levels of fund age, size, and flows have on the persistence of the cross section of hedge funds in existence at a particular point in time. In other words, I tried to answer the question of whether discrete critical values in fund size (or fund age) have lasting effects on performance (e.g., is there an optimal fund size [age]?). To my knowledge, I am the first to address this question with this type of approach.

Data

Data were provided by Credit Suisse/Tremont Advisory Shareholder Services (TASS). TASS has been collecting hedge fund data directly from managers since the late 1980s and has more than 3,000 funds, both "living" and "dead," in its database.[5] The database includes monthly net-of-fee returns, expenses, fees, size, terms, age, and style of the funds.

I carried out persistence tests for one-year and two-year periods that used alphas calculated over the prior 36 months.[6] For all time frames, each fund had to have at least $20 million in assets during the January 1994–December 2004 period and 24 months of returns in a given 36-month period.

In constructing the sample, I had to consider an important issue: the "backfilling" or "instant history" bias (see Edwards and Park 1996). On the date that TASS adds a new fund to its database, it backfills historical returns. Typically, a hedge fund manager will start a fund with a limited amount of personal capital before selling shares to the public; the hope is to compile a good track record to attract outside investors. Therefore, most funds arrive in the database with a history of strong performance that was never available to the public, which biases returns upward. This difference is often large: Using the TASS database, Fung and Hsieh (2000) calculated the bias as about 3.6 percent per year. The average incubation period in my sample is about one year; thus, to control for this bias, I dropped the actual incubation period for every fund.

The final sample on which I performed the persistence tests consisted of 3,333 funds, both living and dead.[7] Including dead as well as living funds in an analysis of performance is important because not including dead funds in a sample can bias returns upward.[8] Using a different dataset from the one I used, Brown, Goetzmann, and Ibbotson (1999) calculated this upward bias to be about 3 percent per year. Liang (2000) compared two major hedge fund databases (those of Hedge Fund Research and TASS) and found that the TASS database contained more dead funds than the HFR database. He calculated survivorship bias in the TASS data of about 2 percent per year, which is comparable to my sample.

Finally, I controlled for possible illiquidity and serial correlation in hedge fund assets by using the approach of Getmansky, Lo, and Makarov (2004), which is similar to that of Asness, Krail, and Liew (2001). They developed a model that includes prior-period returns as an independent variable and found statistical significance of prior-period returns for up to three periods of lagged returns. Hence, for each hedge fund in my sample, I used the coefficients reported by Getmansky et al. for three periods to "unsmooth" the returns. All returns used in the tests reported in this article are unsmoothed.[9]

Table 1 reports summary statistics for the sample of hedge funds. Panel A reports data for all funds for each year of the sample. Note that the number of funds, average fund size, and average fund age grew significantly in the sample period. Average fund flows were always positive, but over time, they varied in size, with a low of 40 percent in 1995 and a high of 126 percent in 1997.

Table 1. Summary Statistics

Year/Style	Number of Funds	Average Size (millions)	Average Annual Excess Return	Average Age (months)	Average Annual Investment Inflow
A. Funds by year					
1995	1,076	$ 74	12%	40	40%
1996	1,289	83	14	42	88
1997	1,520	103	13	45	126
1998	1,723	97	1	48	56
1999	1,955	116	27	50	79
2000	2,125	122	5	53	88
2001	2,379	171	3	54	91
2002	2,580	180	1	56	67
2003	2,460	238	16	66	103
2004	2,089	349	6	78	48
B. Funds by style					
Security selection	838	$137	16%	52	86%
Directional	234	155	11	54	71
Relative value	231	169	7	46	94
Multiprocess	248	260	10	59	83
Fund of funds	653	109	5	54	49

Notes: The number of unique funds for the entire sample period is 3,333. Average annual excess return is net of all expenses and fees and is in excess of the U.S. T-bill rate. Average annual investment inflow is a percentage of prior-period assets.

Panel B of Table 1 reports the same variables by fund style and aggregated over time. The five style categories are those used by Kosowski et al. (2007), following Agarwal et al. (2007). They are as follows (expanded definitions of specific fund styles are given in Appendix A):

- security selection, which includes the TASS category long–short hedge funds,
- directional traders, which includes emerging markets and global macro hedge funds,
- relative value, which includes fixed-income arbitrage and convertible arbitrage hedge funds,
- multiprocess, which includes event-driven hedge funds, and
- funds of funds.

In terms of style, the largest group represented is security selection; it is followed by funds of funds. Averages were calculated by year and then averaged across years. The data in Panel B reflect some interesting differences. Security selection funds have the highest average annual returns, 16 percent, whereas funds of funds have the lowest average annual returns, 5 percent. Multiprocess funds are the largest; funds of funds are the smallest. Inflows are highest to the relative value funds, whereas funds of funds have the lowest inflows. The average age does not vary much by fund category.

Tests of Persistence

I carried out tests of persistence when I selected funds by past performance, when I sorted separately by fund size and fund age, and when I used both fund size (age) and past performance.

Funds Selected by Past Performance. Following Carhart (1997), Hendricks, Patel, and Zeckhauser (1993), Jagannathan et al. (2007), and Kosowski et al. (2007), I sorted funds into quintile portfolios on the basis of their prior performance. Not all funds had available the full time series of returns, but so long as the fund had at least 24 months of return data in a given 36-month period, I included it in the analysis. To sort the funds, I used alphas from Fung and Hsieh's (2004) seven-factor model as calculated over the prior three years.[10] In addition, I sorted funds into portfolios on the basis of their *t*-statistics for the seven-factor alpha, their IRs. Kosowski et al. (2007) reasoned that sorting on the IR reduces the noise-to-variability ratio and limits top and bottom quintiles to funds with alphas that may be more precisely calculated than when alpha itself is used. Hence, I used the IR when performing the majority of my analyses, although my results were not affected when I used actual alphas.

Once formed, portfolios were then held for a period of either one or two years. This holding period is the "evaluation period." For each evaluation period, I re-formed portfolios on the basis of three-year alphas for the preceding formation period. This process resulted in a time series of monthly returns for each quintile portfolio. To facilitate comparison with Fung et al. (2008) and Kosowski et al. (2007), I performed the tests in the aggregate and by groups of fund styles. My groups are All Funds, All but FOF, and FOF Only. I also broke out the All but FOF group into security selection, directional trader, relative value, and multiprocess. Furthermore, I performed all the analyses in subperiod tests for January 1994–September 1998, October 1998–March 2000, April 2000–December 2002, and January 2003–December 2004.[11]

Table 2 reports results for portfolios formed on the basis of seven-factor alphas (Panel A) and, then, seven-factor alphas for each of the portfolios as calculated for the evaluation periods (Panels B and C). In the evaluation period, a statistically significant difference between the best (Quintile 5) and worst (Quintile 1) portfolios is evidence of performance persistence; *t*-tests of differences in means were used to calculate the statistical significance. Because *t*-tests from ordinary least-squares regressions can be unreliable, I calculated all *t*-statistics throughout the article by using the bootstrap approach of Politis and Romano (1994) with 1,000 iterations.

For the formation period (Panel A), the total number of fund years in each quintile is about 3,050, with an average number of funds per year of about 340. Taking averages over individual funds, I found the quintile spread (Quintile 5 minus Quintile 1) in 36-month alphas in the formation period to be 2.86 percentage points per month (about 40 percentage points per year) and the quintile spread in excess returns to be 1.98 percentage points per month (about 27 percentage points per year). These formation-period spreads are large and imply a good deal of dispersion in returns.

Table 2 reports evidence of statistically significant persistence for both the one-year and two-year evaluation periods (see Panels B and C). For the tests on All Funds, the one-year evaluation period has a statistically significant alpha spread (Quintile 5 minus Quintile 1) of 37 bps per month (about 4.5 percentage points per year). Readers will see persistence in neither the FOF Only group nor the security selection category. For the two-year period (Panel C), the spread for the All Funds group is higher than it is for the one-year period, and in Panel C, all the individual categories except for the multiprocess category have statistically significant persistence. The subperiod results (not

Table 2. Persistence Tests of Portfolios Formed on Past Performance: Sorting on 36-Month Seven-Factor Alphas, 1994–2004
(*t*-statistics in parentheses)

Measure	All Funds: Alpha Quintile 1	Alpha Quintile 2	Alpha Quintile 3	Alpha Quintile 4	Alpha Quintile 5	Quintile 5 – Quintile 1	All but FOF: Quintile 5 – Quintile 1	FOF Only: Quintile 5 – Quintile 1
A. Annual formation period								
Total number of fund years	3,052	3,059	3,055	3,059	3,053	na	na	na
Average number of funds/year	339	340	339	340	339	na	na	na
Monthly 36-month alpha	–1.01%	–0.04%	0.32%	0.70%***	1.85%***	2.86%	3.12%	1.77%
	(–1.29)	(–0.52)	(1.55)	(2.42)	(2.62)	na	na	na
Adjusted R^2	35.8	34.5	30.5	28.9	29.6	na	na	na
Monthly excess return	–0.35%	0.24%	0.48%	0.72%	1.63%	1.98%	2.08%	1.37%
B. One-year evaluation period: Portfolio statistics								
Monthly 7-factor portfolio alpha	0.10%	0.17%*	0.26%***	0.30%***	0.47%***	0.37%**	0.33%**	0.29%
	(0.65)	(1.72)	(3.43)	(4.10)	(3.09)	(2.29)	(2.09)	(1.34)
Adjusted R^2	53.2	56.4	63.2	70.4	62.2	na	na	na

Breakout of All but FOF group: Quintile 5 – Quintile 1

	Security Selection	Directional	Relative Value	Multiprocess
Monthly 7-factor portfolio alpha	0.18%	0.62%***	0.74%***	0.33%***
	(1.00)	(2.44)	(4.56)	(2.94)

C. Two-year evaluation period: Portfolio statistics

	All Funds: Alpha Quintile 1	Alpha Quintile 2	Alpha Quintile 3	Alpha Quintile 4	Alpha Quintile 5	Quintile 5 – Quintile 1	All but FOF: Quintile 5 – Quintile 1	FOF Only: Quintile 5 – Quintile 1
Monthly 7-factor portfolio alpha	0.12%	0.15%	0.20%***	0.30%***	0.50%***	0.62%***	0.36%**	0.46%***
	(0.68)	(1.45)	(2.33)	(4.23)	(3.67)	(2.47)	(2.04)	(2.80)
Adjusted R^2	57.2	3.7	63.4	68.3	56.5	na	na	na

Breakout of All but FOF group: Quintile 5 – Quintile 1

	Security Selection	Directional	Relative Value	Multiprocess
Monthly 7-factor portfolio alpha	0.30%*	0.67%***	0.57%***	0.04%
	(1.87)	(2.57)	(4.69)	(0.53)

Notes: Hedge funds were sorted into quintile portfolios on the basis of two separate variables: All 36-month alphas are from a seven-factor model (Fung and Hsieh 2004). The seven-factor model was used to assess out-of-sample portfolio performance. The portfolios were equally weighted monthly, so the weights were readjusted when a fund disappeared. Portfolios were rebalanced at the end of the one-year or two-year holding period. The *t*-statistics were calculated by using the bootstrap approach with 1,000 iterations. For brevity, only evaluation-period portfolio statistics are reported for the two-year holding period.

FOF = fund of funds; na = not applicable.

*Statistically significant at the 10 percent level.
**Statistically significant at the 5 percent level.
***Statistically significant at the 1 percent level.

reported) indicate that this persistence finding for the one-year and two-year holding periods held throughout the sample period except for April 2000 to December 2002.

The results in **Table 3** are for portfolios based on the IR (the *t*-statistic of the seven-factor alpha). These results are similar in magnitude and significance to the results in Table 2. One important exception is that the FOF Only group now demonstrates statistically significant persistence in both the one-year (Panel B) and the two-year (Panel C) periods—perhaps a result of the improved precision gained from using the alpha *t*-statistics. Also, in contrast to the results in Table 2, the security

Table 3. Persistence Tests of Portfolios Formed on Past Performance: Sorting on *t*-Statistic of the 36-Month Seven-Factor Model, 1994–2004
(*t*-statistics in parentheses)

	All Funds							
Measure	*t*-Statistic Quintile 1	*t*-Statistic Quintile 2	*t*-Statistic Quintile 3	*t*-Statistic Quintile 4	*t*-Statistic Quintile 5	Quintile 5 – Quintile 1	All but FOF: Quintile 5 – Quintile 1	FOF Only: Quintile 5 – Quintile 1
A. One-year formation period								
Total number of fund years	3,052	3,059	3,055	3,059	3,053	na	na	na
Average number of funds/year	339	340	339	340	339	na	na	na
Monthly 36-month alpha	–0.91%	0.02%	0.62%	1.08%*	1.14%***	2.06%	2.25%	1.47%
	(1.31)	(0.28)	(0.91)	(1.91)	(4.36)	na	na	na
Adjusted R^2	33.5	29.7	29.3	27.8	23.1	na	na	na
Monthly excess return	–0.45%	0.20%	0.63%	0.94%	1.05%	1.50%	1.57%	1.15%
B. One-year evaluation period: Portfolio statistics								
Monthly 7-factor portfolio alpha	0.13%	0.15%	0.24%**	0.33%***	0.45%***	0.32%***	0.32%**	0.37%**
	(0.87)	(1.36)	(2.20)	(2.93)	(6.13)	(2.34)	(2.01)	(2.30)
Adjusted R^2	60.9	60.9	64.5	64.0	53.6	na	na	na

Breakout of All but FOF group: Quintile 5 – Quintile 1

	Security Selection	Directional	Relative Value	Multiprocess
Monthly 7-factor portfolio alpha	0.21%	0.34%	0.61%***	0.34%***
	(1.08)	(1.44)	(4.89)	(2.77)

C. Two-year evaluation period: Portfolio statistics

	t-Statistic Quintile 1	*t*-Statistic Quintile 2	*t*-Statistic Quintile 3	*t*-Statistic Quintile 4	*t*-Statistic Quintile 5	Quintile 5 – Quintile 1	All but FOF: Quintile 5 – Quintile 1	FOF Only: Quintile 5 – Quintile 1
Monthly 7-factor portfolio alpha	0.09%	0.15%	0.22%*	0.38%***	0.42%***	0.33%***	0.28%**	0.42%
	(0.56)	(1.17)	(1.84)	(3.97)	(6.44)	(2.72)	(1.94)	(3.17)
Adjusted R^2	65.4	63.5	62.0	60.3	59.3	na	na	na

Breakout of All but FOF group: Quintile 5 – Quintile 1

	Security Selection	Directional	Relative Value	Multiprocess
Monthly 7-factor portfolio alpha	0.25%	0.54%***	0.46%***	0.23%
	(1.50)	(2.47)	(3.99)	(1.59)

Notes: The *t*-statistics of alphas are from a seven-factor model. See also the notes to Table 2.

na = not applicable.

*Statistically significant at the 10 percent level.
**Statistically significant at the 5 percent level.
***Statistically significant at the 1 percent level.

selection category never demonstrates performance persistence. The subperiod results (not reported) indicate that this persistence finding existed for all subperiods in the one-year holding period, but in the two-year holding period, it did not exist for the two middle subperiods—from October 1998 to March 2000 and from March 2000 to December 2002. These results are broadly consistent with those of Kosowski et al. (2007), Jagannathan et al. (2007), and Fung et al. (2008).

Having confirmed prior findings of performance persistence among hedge funds, I now turn to the main research question of the study: Do the predictions of the BG model apply to hedge funds? If they do, this information can be of value to investors in selecting hedge funds.

Separate Sorting on Size and Age. The theoretical BG model links fund age, size, and investment flows to performance persistence. The authors argued that investors rationally allocate capital to funds that perform well, which increases the size of these funds. Managers face capacity constraints, however, in investing this new capital. Notably, too much capital in a fund can spread the manager's skills too thin and make trading costs more expensive in terms of both bid–ask spreads and the propensity for large trades to move prices. Hence, the very investment flows that result from a manager's good performance will eventually cause that performance to diminish to the point that, in equilibrium, a fund's expected returns to investors are competitive with those of other funds in the future.

The BG model provides testable implications. The first implication relates to fund size. If the BG model holds, then performance persistence should decrease as a function of fund size because as funds grow, they have fewer investment opportunities and higher transaction costs. The second implication relates to fund age. As Berk and Green (2004) noted, their model includes learning; that is, investors learn about funds as the funds age and allocate assets to young funds with good past performance. Because young funds have fewer performance data points, capital flows to these funds will be more performance sensitive than will flows to older funds. Additionally, as funds age, they are more likely to allocate a larger portion of their portfolios to passive strategies. Hence, performance persistence should also decrease as a function of fund age.

Although the BG model was written to describe the mutual fund industry, the question of whether there is an optimal fund size (age) is particularly relevant to the hedge fund industry. A number of hedge fund styles operate in niche strategies (for example, convertible arbitrage funds) where too much capital invested in the same opportunities can drive away profits. Furthermore, investment opportunities in the hedge fund space are often cyclical and fall in and out of favor over time. Therefore, as managers approach the optimal size for a given strategy, they must make a critical decision: stick to their knitting and collect incentive fees through good performance or optimize the enterprise value of the management company by branching out to new trading styles. The current literature is silent on which way the industry has gone: Some evidence indicates that managers often close their very successful niche funds to new investment, but other evidence indicates that managers open large multistrategy funds to take advantage of changing investment opportunities.

Prior literature did not directly address this issue. Fung et al. (2008) focused on well-diversified funds of funds, so in their analyses, a fund's optimal size was an industrywide question. Kosowski et al. (2007) formed portfolios according to broad style categories, which made the implicit assumption that their categorization was sufficiently broad to avoid the issue of fund size and age.

In contrast, my main focus is the impact of fund size (and age) on performance persistence. An important aspect of these tests is that they are cross-sectional, with portfolios re-formed at regular intervals. Thus, if a fund attracted significant capital flows and grew large relative to its peers in one period, that fund moved to a different size tercile in the next period and was replaced by a smaller fund. These tests were designed deliberately to maximize the probability of finding persistence based on the predictions of the BG model.

I first examined the ability of fund size and fund age, separately, to predict performance persistence. Note that the BG model does not imply that fund size or fund age alone should be able to capture performance persistence. Rather, Berk and Green (2004) argued that good funds attract high investment flows, which makes them larger, and that young good funds attract higher investment flows than old good funds, which also makes them larger. The authors also noted that as funds age, an increasingly large portion of the portfolios tends to be managed passively, which should reduce the likelihood of finding persistence of good performance.

I did not expect simple sorts on age to have predictive power because the relationship between age and performance is less direct than the relationship between size and performance. I nevertheless performed these initial tests to describe the unconditional "baseline" effects of size and age. Later in the article, I will report the results of direct tests of the implications of the BG model. To perform these baseline tests, I sorted funds into tercile portfolios on the basis of prior-period size (age) and held the portfolios for one or two years.

Table 4 presents the results of the test to discover whether fund size is related to performance persistence. For the formation period, Panel A shows a large range in fund size between Terciles 1 and 3 (a difference of about $620 million) but does not reveal a significant difference in monthly returns.

For the evaluation period, however, there is a statistically significant difference in the seven-factor alphas between Terciles 1 and 3 for both the one-year (Panel B) and two-year (Panel C) holding periods for the tests on the All Funds group. Large funds underperformed small funds in the 1994–2004 period by 12 bps per month (about 1.6 percentage points annually) for the one-year holding period and by 29 bps per month (about 3.5 percentage points annually) for the two-year holding period. These results were largely driven by single-strategy funds. For the one-year holding period (Panel B), in the All but FOF group, the small funds (Tercile 1) outperformed the large funds (Tercile 3) by 17 bps per month, but for the subset of FOF Only, the large funds actually outperformed the small ones.

These findings are consistent with the idea that because funds of funds are diversified, the optimal FOF size might be higher than it is for single-strategy funds. This conjecture is further supported by the fact that, from Table 1, the average size of a fund of funds is $109 million, which is the smallest of all the subsets.

Table 4. Performance of Portfolios of Funds Formed on Fund Size, 1994–2004
(*t*-statistics in parentheses)

Measure	All Funds: Tercile 1	All Funds: Tercile 2	All Funds: Tercile 3	All Funds: Tercile 3 – Tercile 1	All but FOF: Tercile 3 – Tercile 1	FOF Only: Tercile 3 – Tercile 1
A. Formation period: Individual fund statistics						
Mean size (millions)	$32.4	$81.0	$652.6	$620.2	$663.1	$493.6
Monthly excess return	0.76%	0.79%	0.87%	0.11%	0.06%	0.18%
				(0.55)	(1.02)	(0.95)
B. One-year evaluation period: Portfolio statistics						
Monthly 7-factor portfolio alpha	0.32%***	0.21%**	0.20%	–0.12%***	–0.17%***	0.08%*
	(2.70)	(2.01)	(1.60)	(–3.19)	(–3.84)	(1.74)
Adjusted R^2	52.2	51.2	47.9	na	na	na
Breakout of All but FOF group: Tercile 3 – Tercile 1						
	Security Selection	Directional	Relative Value	Multiprocess		
Monthly 7-factor portfolio alpha	–0.12%	–0.09%	–0.04%	0.00%		
	(–1.60)	(–0.77)	(–0.62)	(0.08)		
C. Two-year evaluation period: Portfolio statistics						
	Tercile 1	Tercile 2	Tercile 3	Tercile 3 – Tercile 1	All but FOF: Tercile 3 – Tercile 1	FOF Only: Tercile 3 – Tercile 1
Monthly 7-factor portfolio alpha	0.57%***	0.36%***	0.25%***	–0.29%***	–0.33%***	–0.11%*
	(5.63)	(3.75)	(2.94)	(–5.44)	(–5.30)	(–1.91)
Adjusted R^2	57.6	57.6	60.5	na	na	na
Breakout of All but FOF group: Tercile 3 – Tercile 1						
	Security Selection	Directional	Relative Value	Multiprocess		
Monthly 7-factor portfolio alpha	–0.44%***	–0.28%**	–0.04%	–0.08%*		
	(–5.63)	(–2.14)	(–0.62)	(–1.65)		

Note: The seven-factor model was used to assess out-of-sample performance.

na = not applicable.

*Statistically significant at the 10 percent level.
**Statistically significant at the 5 percent level.
***Statistically significant at the 1 percent level.

For the two-year holding period (Panel C) for funds of funds, however, the difference between terciles reverses, although the difference in the performance of the FOF Only tercile is small and statistically insignificant (11 bps per month).

In general, the single-strategy results are consistent with Getmansky (2005), who documented a concave relationship between size and performance, indicating that if funds become too large, their performance can suffer. The results are also broadly consistent with the BG model. With respect to the (unreported) subperiod analysis, the size results are consistent with the full-period results. Table 4 indicates that sorts on size alone find performance persistence.

Table 5 reports results for the relationship between fund age and performance persistence. Similar to the results for fund size, based on the spreads between Tercile 3 and Tercile 1, the tests show no significant relationship in the formation period. In contrast to the results for fund size, there are also no statistically significant relationships between past age and performance in the evaluation periods. The (unreported) subperiod results indicated some evidence of persistence, however, when sorting on fund age. Notably, for the two middle subperiods (October 1998–March 2000 and March 2000–December 2002), the tests found statistically significant evidence that young funds outperformed old funds. Thus, the evidence of performance persistence is mixed when sorting only on past fund age.

Taken together, these results indicate a strong unconditional relationship between fund size and

Table 5. Performance of Portfolios of Funds Formed on Fund Age, 1994–2004
(*t*-statistics in parentheses)

Measure	All Funds: Tercile 1	Tercile 2	Tercile 3	Tercile 3 – Tercile 1	All but FOF: Tercile 3 – Tercile 1	FOF Only: Tercile 3 – Tercile 1
A. Formation period: Individual fund statistics						
Mean age (months)	21.4	51.7	112.8	91.4	89.7	98.0
Monthly excess return	0.98%	0.72%	0.76%	–0.22%	–0.26%	0.08%
				(–0.96)	(–1.09)	(0.45)
B. One-year evaluation period: Portfolio statistics						
Monthly 7-factor portfolio alpha	0.25%*	0.20%*	0.28%***	0.03%	0.01%	0.06%
	(1.94)	(1.88)	(2.41)	(0.77)	(0.33)	(0.92)
Adjusted R^2	40.0	53.9	55.7	na	na	na
Breakout of All but FOF group: Tercile 3 – Tercile 1						
	Security Selection	Directional	Relative Value	Multiprocess		
Monthly 7-factor portfolio alpha	0.02%	–0.27%	–0.12%*	0.02%		
	(0.24)	(–1.55)	(–1.83)	(0.35)		
C. Two-year evaluation period: Portfolio statistics						
	Tercile 1	Tercile 2	Tercile 3	Tercile 3 – Tercile 1	All but FOF: Tercile 3 – Tercile 1	FOF Only: Tercile 3 – Tercile 1
Monthly 7-factor portfolio alpha	0.39%***	0.43%***	0.36%***	–0.03%	–0.04%	0.01%
	(3.84)	(4.51)	(3.67)	(–0.93)	(–1.12)	(0.09)
Adjusted R^2	45.9	61.0	65.5	na	na	na
Breakout of All but FOF group: Tercile 3 – Tercile 1						
	Security Selection	Directional	Relative Value	Multiprocess		
Monthly 7-factor portfolio alpha	–0.22%***	–0.13%	–0.17%***	–0.02%		
	(–2.47)	(–0.70)	(–2.98)	(0.44)		

Note: The seven-factor model was used to assess out-of-sample performance.

na = not applicable.

*Statistically significant at the 10 percent level.
***Statistically significant at the 1 percent level.

performance persistence (small funds outperform large ones) and only weak evidence, for certain subperiods, of an unconditional relationship between fund age and performance persistence.

With these baseline relationships in hand, I performed tests designed to directly test the BG model; in these tests, I formed portfolios on the basis of past performance and fund size (and age).

Sorting by Fund Size (or Age) and Past Performance. To perform my tests of the BG model, I sorted funds *independently* into quintile portfolios on the basis of past performance (using seven-factor alpha *t*-statistics) and into tercile portfolios on the basis of fund size (or age).[12] A time series of equally weighted returns for the 15 portfolios was then created at the intersection of these sorts. The portfolios were held for one or two years, and seven-factor alphas for the entire holding period were used to test for persistence. My predictions based on the BG model were that small (young) funds that were past good performers would significantly outperform large (old) funds that were past poor performers.

Note that this portfolio-formation process follows prior literature. Each fund stayed in its assigned portfolio until the end of the holding period. If the fund exited the sample prior to the end of the holding period, the portfolio was rebalanced by reallocating the capital released by that fund to the funds that remained, which implicitly assumes that funds could be liquidated at their last net asset values (NAVs). Given that hedge fund data are self-reported, this assumption could be faulty, especially for young or small funds, which may have higher failure rates and/or may fail more suddenly than old or large funds. If the assumption is wrong, relying on it will bias the returns of the small (young) portfolios upward, which could exaggerate the results. Hence, I performed several tests to examine the extent of this bias. First, I compared the reasons for exiting the TASS database with the reasons for exiting another database (the CASAM CISDM Hedge Fund/CTA Database from the Center for International Securities and Derivatives Markets) and found that they are largely consistent, so I was not misclassifying funds as "failed" when they were, in fact, still extant. Second, I examined whether exit rates varied by size and age in the sample period and found that small funds were more likely to exit the database because of "liquidation" than were large funds, so overreported NAVs for these funds could have affected my results. To gain assurance that this was not the case, I performed two additional tests. First, I reran all my analyses without the liquidated funds, and second, I arbitrarily reduced the last NAV for the liquidated funds by varying levels of basis points: 100, 200, 500, and 2,500. The results of the main tests remained unchanged by these variations, so I am comfortable that the findings are not driven by overreporting of last NAVs for small or young funds.

Table 6 presents data for each of the 15 portfolios and the calculations of the differences within each size tercile by IR quintile (the bottom three rows in boldface of each panel) and within each IR quintile by size tercile (the last three columns of each panel in boldface). For example, focusing on the best IR quintile for the one-year holding period, the returns to each of the size terciles from the smallest to the largest are, respectively, 52 bps, 42 bps, and 38 bps. The difference of 14 bps is statistically significant at the 5 percent level, which implies that small funds that are also top performers outperform large funds that are top performers; in other words, size matters, even among the very best performing funds.

Following the boldface rows, Table 6 shows the difference in performance between the portfolio containing the smallest plus best past performing funds and the portfolio containing the largest plus worst past performers by fund group and style category. If this difference is positive and statistically significant, the tests provide support for the BG model prediction that beyond an optimal fund size, funds face capacity constraints that erode their performance. The results in Panel A of Table 6 for the one-year holding period indicate strong support for the BG model: For the All Funds sample, the statistically significant difference is about 8.1 percentage points a year (65 bps per month). Note that these results were obtained with generally diversified portfolios without regard to fund strategy or style. The results can be interpreted as suggesting an industrywide optimal fund size that has not yet been reached by some funds but has been exceeded by others.

In the results for other portfolios in the one-year holding period, the group of single-strategy portfolios (All but FOF) has an even stronger result, with an excess return of 8.9 percentage points a year (71 bps a month). In contrast, the result for the FOF Only group is only about 4.2 percentage points annually (and significant only at the 10 percent level).

The results for single strategies for the one-year holding period are that the security selection and directional categories have strong and significant differences between portfolios of small plus high alpha *t*-statistic funds and large plus low alpha *t*-statistic funds, implying that the optimal fund size for these strategies has been exceeded by

Table 6. Performance of Portfolios Formed on Independent Sorts on Fund Size and *t*-Statistics of 36-Month Seven-Factor Alphas, 1994–2004
(*t*-statistics in parentheses)

	All Funds							
Grouping	Alpha *t*-Stat Quintile 1	Alpha *t*-Stat Quintile 2	Alpha *t*-Stat Quintile 3	Alpha *t*-Stat Quintile 4	Alpha *t*-Stat Quintile 5	Quintile 1 – Quintile 5 Spread	All but FOF: *t*-Stat Spread	FOF Only: *t*-Stat Spread
A. One-year holding period								
Size Tercile 1	0.16%	0.08%	0.31%***	0.39%***	0.52%***	**0.36%***	**0.26%**	**0.30%**
	(0.75)	(0.55)	(2.88)	(2.97)	(6.21)	**(1.72)**	**(1.04)**	**(1.15)**
Size Tercile 2	0.19	0.19	0.17	0.18	0.42***	**0.23**	**0.32***	**0.71*****
	(1.07)	(1.49)	(1.18)	(1.40)	(5.30)	**(1.31)**	**(1.65)**	**(4.76)**
Size Tercile 3	–0.11	0.28*	0.17	0.26*	0.38***	**0.49*****	**0.57*****	**0.36****
	(–0.54)	(1.76)	(1.16)	(1.81)	(5.03)	**(3.19)**	**(3.16)**	**(2.05)**
All Funds size spread	**–0.27*****	**0.19***	**–0.14**	**–0.14**	**–0.14****			
	(–2.38)	**(1.65)**	**(–1.46)**	**(–1.43)**	**(–2.23)**	na	na	na
All but FOF size spread	**–0.45*****	**0.32****	**–0.20**	**–0.14**	**–0.14***			
	(–3.16)	**(2.12)**	**(–1.57)**	**(–1.15)**	**(–1.73)**	na	na	na
FOF Only size spread	**–0.04**	**–0.06**	**–0.30*****	**0.34*****	**0.02**			
	(–0.16)	**(–0.53)**	**(–2.69)**	**(2.64)**	**(0.28)**	na	na	na

Difference for small funds with past high alpha *t*-statistics minus big funds with past low alpha *t*-statistics

Fund groups	All Funds	All but FOF	FOF Only	
	0.65%***	0.71%***	0.34%*	
	(3.65)	(3.27)	(1.80)	
Style categories (ex FOF)	Security Selection	Directional	Relative Value	Multi-process
	0.67%***	1.04%***	0.64%	–0.09%
	(2.23)	(2.48)	(1.57)	(–0.34)

B. Two-year holding period

Grouping	Alpha *t*-Stat Quintile 1	Alpha *t*-Stat Quintile 2	Alpha *t*-Stat Quintile 3	Alpha *t*-Stat Quintile 4	Alpha *t*-Stat Quintile 5	Quintile 1 – Quintile 5 Spread	All but FOF: *t*-Stat Spread	FOF Only: *t*-Stat Spread
Size Tercile 1	0.62%***	0.54%***	0.70%***	0.66%***	0.66%***	**0.04%**	**–0.06%**	**–0.02%**
	(3.08)	(2.38)	(4.83)	(4.71)	(7.13)	**(0.27)**	**(–0.29)**	**(–0.07)**
Size Tercile 2	0.36*	0.33**	0.48***	0.51***	0.50***	**0.14**	**0.09**	**0.85*****
	(1.94)	(2.09)	(2.88)	(4.55)	(7.17)	**(0.84)**	**(0.52)**	**(3.35)**
Size Tercile 3	0.01	0.27*	0.46***	0.32***	0.39***	**0.38*****	**0.43****	**0.31*****
	(0.07)	(1.69)	(4.14)	(2.58)	(4.62)	**(2.49)**	**(2.25)**	**(2.58)**
All Funds size spread	**–0.61*****	**–0.27***	**–0.24*****	**–0.34*****	**–0.27*****			
	(–5.44)	**(–1.88)**	**(–2.41)**	**(–3.28)**	**(–3.31)**	na	na	na
All but FOF size spread	**–0.85*****	**–0.30***	**–0.27****	**–0.37*****	**–0.36*****			
	(–5.47)	**(–1.81)**	**(–2.04)**	**(–2.50)**	**(–4.11)**	na	na	na
FOF Only size spread	**–0.25**	**–0.39*****	**–0.06**	**–0.13**	**0.08**			
	(–0.96)	**(–2.44)**	**(–0.39)**	**(–1.42)**	**(0.78)**	na	na	na

Difference for small funds with past high alpha *t*-statistics minus big funds with past low alpha *t*-statistics

Fund groups	All Funds	All but FOF	FOF Only	
	0.65%***	0.79%***	0.23%*	
	(3.94)	(3.89)	(1.74)	
Style categories (ex FOF)	Security Selection	Directional	Relative Value	Multi-process
	0.96%***	1.68%***	0.90%*	–0.59%**
	(3.96)	(4.74)	(1.70)	(–2.15)

Notes: Intercepts from each of the regressions are reported. Size was measured in millions of dollars. The seven-factor model was used to assess out-of-sample performance.

na = not applicable.

*Statistically significant at the 10 percent level.
**Statistically significant at the 5 percent level.
***Statistically significant at the 1 percent level.

some funds. The results for relative value and multiprocess are not statistically significant, however, although both of these categories displayed performance persistence when the sorting was on past performance alone (see Table 2).

The results for the two-year holding period are quite similar to those just discussed for the one-year holding period: The strongest differences were found for the All Funds groups and the All but FOF group. Finally, the results of the (unreported) subperiod analysis are consistent with those of the full-period analysis.

Table 7 reports results for portfolios formed by independent sorts on age and past performance. The BG model implies that young, good funds will outperform older funds primarily because the young funds have not yet reached full capacity. In addition, the model predicts that as funds age, the funds will invest a larger portion of their assets in passive strategies, which would reduce the likelihood of performance persistence among old funds. I thus calculated the performance difference between young plus past good funds and old plus past bad funds and found that, as Table 7 reports, for the All Funds group in the one-year holding period (Panel A), this difference was 44 bps per month, about 5.4 percentage points annualized, and highly statistically significant.

For the one-year holding period, Table 7 provides evidence that young funds with past good performance outperform old funds with past good performance by 10 bps per month (about 1.2 percentage points per year). This finding is consistent with the BG model, which predicts that old funds with past good performance have received the larger investment flows in the past, which damages their performance in the future. In the (unreported) subperiod analyses, the age results were consistent with those for the full period for the one-year horizon but were weaker for the two-year horizon; they were significant only for the final subperiod, January 2003–December 2004.

The results presented so far in this section indicate that, consistent with the BG model, both size and age are relevant in predicting hedge fund performance persistence. As funds reach capacity, their performance deteriorates. Similarly, as good, young funds receive large capital inflows, their performance deteriorates.

Because the age and size of funds are highly correlated and because both (past good) young funds and (past good) small funds exhibit performance persistence, the next test was performed on independent sorts on size, age, and past performance of funds to determine whether even more persistence could be detected.

In the first set of tests, I sorted funds on size and age to establish the baseline relationship between size and age by independently sorting on these two variables. Nine portfolios were formed from the intersections of these tercile sorts. In Panel A and Panel B of **Table 8**, the differences between the size terciles (the columns) are larger than the differences between the age terciles (the rows). Thus, size may be a more important factor than age in detecting persistence. Still, age does provide some explanatory power, and results from tests comparing the performance of young, small funds with that of old, large funds are statistically significant for the All Funds and the All but FOF groups. As with the size results, the aggregate portfolio of single-strategy funds, the All but FOF group, has the strongest results: Outperformance was 18 bps per month (about 2.1 percentage points annually) for the one-year holding period and 28 bps per month (about 3.4 percentage points per year) for the two-year holding period. Also similar to the sorts on size, for the FOF Only portfolio, the differences between young plus small and old plus large are small and statistically insignificant. Finally, the (unreported) subperiod results were consistent with these full-period results.

These results provide evidence that, perhaps because of their diversified nature, capacity constraints are less important for funds of funds than for single-style hedge funds.

In the second set of tests, I sorted funds into portfolios based on size, age, and past performance. Given the strong relationships documented in Tables 6 and 8, I was not surprised to find that these tests have the most explanatory power of all: Panel A in **Table 9** shows that for the one-year holding period, the portfolio of All Funds that was young and small and had good past performance outperformed the portfolio that was old and large with poor past performance by a highly statistically significant 77 bps per month—an impressive 9.6 percentage points per year. For the two-year holding period, the outperformance is 68 bps per month (8.5 percentage points per year).

As for the size-only results, the findings are more significant for the portfolio that excluded funds of funds than for the FOF Only portfolio. For the All but FOF group (Panel B), the one-year (two-year) difference is 10.5 percentage points (11.0 percentage points) annually, whereas for the portfolio of the FOF Only group (Panel C), the one-year (two-year) difference is 2.2 percentage points (0.8 percentage point) annually and is statistically insignificant.[13]

Table 7. Performance of Portfolios Formed on Independent Sorts on Fund Age and *t*-Statistics of 36-Month Seven-Factor Alphas, 1994–2004
(*t*-statistics in parentheses)

Grouping	All Funds: Alpha *t*-Stat Quintile 1	All Funds: Alpha *t*-Stat Quintile 2	All Funds: Alpha *t*-Stat Quintile 3	All Funds: Alpha *t*-Stat Quintile 4	All Funds: Alpha *t*-Stat Quintile 5	All Funds: Quintile 1 – Quintile 5 Spread	All but FOF: *t*-Stat Spread	FOF Only: *t*-Stat Spread
A. One-year holding period								
Age Tercile 1	0.33%	0.26%*	0.12%	0.53%***	0.51%***	**0.19%**	**–0.06%**	**0.42%**
	(1.40)	(1.75)	(0.56)	(3.08)	(5.65)	**(0.78)**	**(–0.23)**	**(1.33)**
Age Tercile 2	0.04	0.17	0.27**	0.16	0.42***	**0.37*****	**0.38****	**0.22**
	(0.22)	(1.38)	(2.12)	(1.46)	(5.23)	**(2.32)**	**(2.08)**	**(0.93)**
Age Tercile 3	0.07	0.13	0.24	0.26*	0.41***	**0.34***	**0.40****	**0.62*****
	(0.37)	(0.87)	(1.86)	(1.89)	(6.26)	**(1.81)**	**(1.96)**	**(2.68)**
All Funds age spread	**–0.25***	**–0.13**	**0.13**	**–0.27*****	**–0.10***			
	(–1.92)	**(–1.22)**	**(1.15)**	**(–2.25)**	**(–1.66)**	na	na	na
All but FOF age spread	**–0.58*****	**0.14**	**–0.02**	**–0.20***	**–0.12***			
	(–3.07)	**(0.96)**	**(–0.07)**	**(–1.93)**	**(–1.85)**	na	na	na
FOF Only age spread	**–0.29**	**–0.22**	**0.05**	**–0.09**	**–0.08**			
	(–0.65)	**(–1.61)**	**(0.40)**	**(–1.40)**	**(–1.32)**	na	na	na

Difference for young funds with past high alpha *t*-statistics minus old funds with past low alpha *t*-statistics

Fund groups	All Funds	All but FOF	FOF Only
	0.44%***	0.52%***	0.70%***
	(2.47)	(2.58)	(3.48)

Style categories	Security Selection	Directional	Relative Value	Multi-process
	0.37%	1.46%***	1.67%***	–0.03%
	(1.42)	(3.53)	(6.20)	(–0.14)

B. Two-year holding period	Alpha *t*-Stat Quintile 1	Alpha *t*-Stat Quintile 2	Alpha *t*-Stat Quintile 3	Alpha *t*-Stat Quintile 4	Alpha *t*-Stat Quintile 5	Quintile 1 – Quintile 5 Spread	All but FOF: *t*-Stat Spread	FOF Only: *t*-Stat Spread
Age Tercile 1	0.34%	0.28%	0.46%**	0.73%***	0.52%***	**0.19%**	**0.01%**	**0.27%***
	(1.40)	(1.61)	(2.13)	(4.87)	(5.61)	**(0.82)**	**(0.04)**	**(1.84)**
Age Tercile 2	0.46**	0.48***	0.62***	0.37***	0.48***	**0.02**	**–0.08**	**0.62*****
	(2.29)	(3.00)	(4.40)	(3.70)	(6.21)	**(0.12)**	**(–0.39)**	**(3.36)**
Age Tercile 3	0.25	0.34*	0.46***	0.45***	0.46***	**0.22**	**0.20**	**0.17**
	(1.43)	(1.89)	(3.91)	(3.45)	(7.65)	**(1.54)**	**(1.14)**	**(0.75)**
All Funds age spread	**–0.09**	**0.06**	**0.01**	**–0.28****	**–0.06**			
	(–0.62)	**(0.55)**	**(0.12)**	**(–2.24)**	**(–0.89)**	na	na	na
All but FOF age spread	**–0.34**	**0.00**	**0.33**	**–0.37*****	**–0.15****			
	(–1.34)	**(0.01)**	**(1.10)**	**(–3.10)**	**(–2.10)**	na	na	na
FOF Only age spread	**0.24**	**–0.11**	**–0.33*****	**0.02**	**0.15**			
	(1.03)	**(–0.60)**	**(–2.50)**	**(0.15)**	**(1.17)**	na	na	na

Difference for young funds with past high alpha *t*-statistics minus old funds with past low alpha *t*-statistics

Fund groups	All Funds	All but FOF	FOF Only
	0.27%**	0.35%**	0.02%
	(2.01)	(2.15)	(0.11)

Style categories (ex FOF)	Security Selection	Directional	Relative Value	Multi-process
	0.58%***	–0.25%	1.35%***	–0.35%
	(2.33)	(–0.50)	(4.95)	(–1.59)

Notes: Age was measured in months. See also the notes to Table 6.

na = not applicable.

*Statistically significant at the 10 percent level.
**Statistically significant at the 5 percent level.
***Statistically significant at the 1 percent level.

Table 8. Performance of Portfolios of Funds Formed on Independent Sorts on Size and Age (*t*-statistics in parentheses)

Grouping	Size Tercile 1	Size Tercile 2	Size Tercile 3	All Funds: Size Spread	All but FOF: Size Spread	FOF Only: Size Spread
A. One-year holding period						
Age Tercile 1	0.34%***	0.10%	0.15%	**–0.19%*** **	**–0.26%*** **	**0.03%**
	(3.31)	(1.04)	(1.46)	**(–2.88)**	**(–3.21)**	**(0.30)**
Age Tercile 2	0.28***	0.21**	0.17*	**–0.11**	**–0.10**	**0.03**
	(3.18)	(2.33)	(1.67)	**(–1.59)**	**(–1.27)**	**(0.38)**
Age Tercile 3	0.28***	0.37***	0.21**	**–0.07**	**–0.14**	**0.12**
	(2.68)	(3.95)	(2.07)	**(–0.94)**	**(–1.53)**	**(1.07)**
All Funds age spread	**–0.06**	**0.27*** **	**0.06**			
	(–0.67)	**(3.15)**	**(0.89)**	na	na	na
All but FOF age spread	**–0.05**	**0.25*** **	**0.07**			
	(–0.46)	**(2.78)**	**(0.93)**	na	na	na
FOF Only age spread	**–0.08**	**0.20*** **	**0.01**			
	(–0.60)	**(1.97)**	**(0.15)**	na	na	na

Difference for small and young minus old and large

Fund groups	All Funds	All but FOF	FOF Only
	0.13%**	0.18%***	0.04%
	(2.30)	(2.75)	(0.43)

Style categories	Security Selection	Directional	Relative Value	Multiprocess
	0.31%***	0.30%	0.00%	0.03%
	(3.36)	(1.36)	(0.03)	(0.50)

B. Two-year holding period

Grouping	Size Tercile 1	Size Tercile 2	Size Tercile 3	All Funds: Size Spread	All but FOF: Size Spread	FOF Only: Size Spread
Age Tercile 1	0.62%***	0.33%***	0.33%***	**–0.27%*** **	**–0.23%*** **	**–0.29%*** **
	(6.12)	(2.60)	(3.38)	**(–4.31)**	**(–2.90)**	**(–2.61)**
Age Tercile 2	0.70***	0.51***	0.32***	**–0.35*** **	**–0.38*** **	**–0.14**
	(6.24)	(5.77)	(3.12)	**(–4.83)**	**(–4.69)**	**(–1.26)**
Age Tercile 3	0.57***	0.45***	0.38***	**–0.18** **	**–0.30*** **	**0.04**
	(4.59)	(4.28)	(3.65)	**(–2.05)**	**(–2.78)**	**(0.36)**
All Funds age spread	**–0.06**	**0.10**	**0.03**			
	(–0.81)	**(1.16)**	**(0.41)**	na	na	na
All but FOF age spread	**–0.03**	**0.10**	**–0.05**			
	(–0.26)	**(1.07)**	**(–0.59)**	na	na	na
FOF Only age spread	**–0.13**	**0.03**	**0.19** **			
	(–1.26)	**(0.24)**	**(2.83)**	na	na	na

Difference for small and young minus old and large

Fund groups	All Funds	All but FOF	FOF Only
	0.25%**	0.28%***	0.09%
	(4.32)	(4.24)	(0.88)

Style categories	Security Selection	Directional	Relative Value	Multiprocess
	0.56%***	0.53%***	0.23%***	–0.03%
	(5.48)	(2.62)	(2.64)	(–0.47)

Notes: Hedge funds were sorted into quintile portfolios on the basis of independent tercile sorts on lagged 12-month size (in millions of dollars) and lagged 12-month age (in months). Spread is Tercile 3 minus Tercile 1.

na = not applicable.

*Statistically significant at the 10 percent level.
**Statistically significant at the 5 percent level.
***Statistically significant at the 1 percent level.

Table 9. Performance of Portfolios of Funds Formed on Independent Sorts on Size, Age, and Past Performance
(t-statistics in parentheses)

	One-Year Holding Period		Two-Year Holding Period	
Portfolio	Alpha	Difference	Alpha	Difference
A. All Funds				
Small, young, past high t-statistics	0.63%	0.77%***	0.67%	0.68%***
Large, old, past low t-statistics	–0.14	(4.10)	–0.01	(4.03)
B. All but FOF				
Small, young, past good alpha	0.59%	0.84%***	0.86%	0.87%***
Large, old, past bad alpha	–0.25	(3.21)	–0.01	(4.05)
C. FOF Only				
Small, young, past good alpha	0.60%	0.18%	0.26%	0.07%
Large, old, past bad alpha	0.42	(0.78)	0.19	(0.36)
D. Breakout for All but FOF				
	Security Selection	Directional	Relative Value	Multiprocess
Difference for small, young, past good alpha minus large, old, past bad alpha: one-year holding period	0.92%*** (2.31)	Too few obs	Too few obs	Too few obs
Difference for small, young, past good alpha minus large, old, past bad alpha: two-year holding period	1.19%*** (3.85)	Too few obs	Too few obs	Too few obs

Notes: Hedge funds were sorted into quintile portfolios on the basis of independent tercile sorts on lagged 12-month size (in millions of dollars), lagged 12-month age (in months), and past performance (t-statistic of 36-month seven-factor alpha).

***Statistically significant at the 1 percent level.

For the individual categories of funds reported in Panel D of Table 9, in most cases, I had too few observations in the portfolios formed by independent sorts on age, size, and past performance to perform a meaningful analysis. For the security selection portfolio, however, based on the three sorts, the evidence of persistence is extremely strong. The difference in performance between past good, young, small funds and past bad, old, large funds is 11.6 percentage points (15.2 percentage points) per year for the one-year (two-year) period. This result is largely consistent with Kosowski et al. (2007), who found the most persistence—on performance-only sorts—for security selection hedge funds.

Finally, with the exception of the subperiod October 1998–December 2000 for both the one-year and two-year holding periods (for which I did not detect persistence), all other subperiod results supported the full-period results.

A possible concern when interpreting these results is that young or small funds may be more likely to fail during crises, such as the failure and subsequent bailout of Long-Term Capital Management or the bursting of the internet bubble. If so, then the persistence results that I found would be weakened. I compared failure rates for the six-month period around both crises and found no difference in failure rates between small and all other funds or between young and all other funds, where "small" ("young") was defined as being in the bottom size (age) tercile. Hence, this concern appears to be unwarranted.

Taken together, the results in this section are strongly supportive of the BG model.

Conclusion

The model proposed by Berk and Green (2004) implies that performance persistence among managed portfolios should vary with fund age and fund size. Because investment flows chase past performance and because funds face capacity constraints, funds quickly reach an optimal size (or go beyond it), which reduces the likelihood of performance persistence.

I tested the implications of this model on a sample of hedge funds for the 1994–2004 period and found results largely consistent with the BG model: A portfolio of young, small, good past performers outperformed a portfolio of old, large, poor past performers by nearly 10 percentage points per year. The results were weakest for funds of hedge funds and strongest for single-strategy hedge funds, and among single-strategy funds, results were strongest for security selection (including long–short) funds.

These results complement those in prior literature that found persistence in hedge funds. Notably, Kosowski et al. (2007) found performance persistence in portfolios of hedge funds when funds were selected on the basis of past performance. My results augment theirs and indicate that by selecting funds on the basis of fund age and fund size in addition to past performance, investors can substantially improve the likelihood of superior performance over a selection process based on past performance alone. Also, Fung et al. (2008) showed that a subset of funds of hedge funds has alpha and that some of these funds are able to persist in the short term. Of these have-alpha funds, however, those that received large investment inflows are less likely to persist in the future than those that did not. I used the results from Kosowski et al. and Fung et al. to design tests for examining whether funds that reach their optimal size (or age) are (probably because of increased investment flows) less likely to have performance persistence in the future, and I found this to be the case.

I offer the following important caveat about the main results of the study: Although the empirical results clearly indicate that young, small funds are more likely to exhibit performance persistence than their peers, the observable universe of hedge funds excludes *very* young funds that did not make it past the incubation stage. I adjusted the data to account for this incubation period in funds that survived, but the data do exclude funds that did not survive. Hence, the results of this study may not hold for start-up funds.

Investors cannot use the exact methodology used in this study (creating a long–short portfolio of hedge funds) because investors cannot sell a hedge fund short, but they can benefit by selecting hedge funds for investment on the basis of the findings in this study. In particular, selecting young, small hedge funds with strong past performance appears to give investors the best chance of outperformance in the future.

I wish to thank Vikas Agarwal, Mike Cooper, Roberto Guiterrez, Jean Helwege, Andrew Karolyi, Narayan Naik, René Stulz, and Karen Wruck.

This article qualifies for 1 CE credit.

Appendix A. Investment Style Categories

These definitions are based on those of Credit Suisse/TASS.

Long/short equity: The investment manager takes long and short positions in equities.

Pure emerging market: The fund invests exclusively in emerging market debt or equity. Emerging market funds are the only "long only" funds listed in the TASS database.

Event driven: The investment manager typically takes long or short positions in equities or debt instruments in anticipation of an event, such as a corporate restructuring or a planned joint venture, in expectation of a substantial price movement when the event occurs.

Global macro: The investment manager uses fundamental and/or technical analysis to establish directional positions in any publicly traded market around the world.

Convertible arbitrage: The investment manager simultaneously establishes long and short positions in different forms of convertible securities from the same corporate issuer and, in so doing, captures pricing inefficiencies between the different securities.

Fixed-income arbitrage: The investment manager establishes long and short positions in related debt securities or derivative instruments.

Notes

1. See, for example, Agarwal and Naik (2000); Baquero, ter Horst, and Verbeek (2005); Brown, Goetzmann, and Ibbotson (1999); Brown, Goetzmann, and Park (2001); Gyger, Gibson, and Bares (2003); Naik and Agarwal (2000).
2. My article contributes to fairly recent literature in hedge funds, but academics and practitioners have been studying persistence in mutual funds and pension funds for many years. An early study by Jensen (1968) found no support for persistence. Papers supporting persistence over 5-year to 10-year periods include those of Elton, Gruber, and Blake (1996), Elton, Gruber, Das, and Hlavka (1993), and Grinblatt and Titman (1992), who attributed this persistence to managers' stock-picking ability. Support for one-year to three-year persistence comes from Brown and Goetzmann (1995),

Goetzmann and Ibbotson (1994), Hendricks, Patel, and Zeckhauser (1993), and Wermers (2000). Carhart (1997) showed that the one-year momentum effect of Jegadeesh and Titman (1993) accounts for much of the performance persistence found by Hendricks et al. and that differences in mutual fund expenses and trading costs can explain nearly all of the remaining persistence. Christopherson, Ferson, and Glassman (1998) applied conditional performance evaluation to a sample of pension funds and showed that the conditional approach is better able to detect persistence and predict future performance than "unconditional" (linear) methods. The persistence they found was concentrated among the worst performers. Recently, using a Bayesian approach with daily mutual fund data, Bollen and Busse (2005) and Busse and Irvine (2006) found evidence of quarterly performance persistence that is not explained by momentum.

3. Another important contribution of the Kosowski et al. (2007) article is the use of Bayesian techniques, which, in addition to selecting funds on the basis of IRs, greatly improves the probability of finding performance persistence. I did not use the Bayesian technique, which biases *against* finding persistence when my methodology is followed. I think of my approach as an alternative or complement to theirs, as one that might be more accessible to ordinary investors. Clearly, using the Bayesian methodology in addition to my approach should find even more persistence than I found. This combined approach is beyond the scope of my article.
4. Kosowski et al. (2007) did perform additional tests to determine whether fund flows and/or fund size are related to persistence, although these tests were not the main focus of their article. Consistent with my results, they found that funds with above-average investment flows had less persistence. In contrast to my results, however, they did not find a link between size and performance persistence. This contrary finding could be a result of differences in the designs of their test and my test (they split funds on the basis of median size rather than into size terciles and put funds in performance deciles rather than in quintiles), a difference in time periods (their data end in 2002, whereas my data end in 2004), and/or a difference in sample (their sample encompassed three databases; I used only the Tremont Advisory Shareholder Services database).
5. TASS has maintained data on dead funds since 1994.
6. I calculated alphas over rolling 36-month periods, but because return data were occasionally missing, to maximize the size of the sample, I required that each fund have at least 24 of the 36 returns during a given 36-month period to be included in the analysis. I also performed tests for all the analyses in the study for a three-year holding period. The results for the three-year holding period are generally statistically insignificant (i.e., I found no evidence of persistence), and because of the nature of the portfolio-formation process (independent sorts on fund age and/or size and past performance), observations in the portfolios were often too few for me to perform a meaningful analysis.
7. The initial sample for the formation period contained 3,333 funds. The sample for the evaluation period was 2,500 funds. Funds left the sample because of missing data for size, age, or flow or when they failed.
8. See Brown, Goetzmann, Ibbotson, and Ross (1992); Carhart (1997).
9. Using actual returns did not significantly change the results of any of my analyses.
10. Fung and Hsieh's (2004) seven-factor model has been widely used in the hedge fund literature. It includes as regressors a number of asset-based factors designed to mimic common hedge fund strategies, a market factor, and a size–spread factor. For further detail, please see the original article.
11. These subperiods are as defined in Fung et al. (2008). For brevity, I do not report the results, but they are available on request. The subperiod results are fairly consistent with the results for the full sample period.
12. The rationale for performing independent sorts was to increase the power of the tests. For a fund to be included in the "past good, past small" portfolio, for example, it had to be both in the top quintile of performance *and* also in the bottom tercile of size. Because size alone can predict performance, the top quintile of funds will disproportionately include smaller funds, and conditional sorts on this portfolio will not reveal much dispersion among the size terciles. In contrast, my tests required independent membership of each of the size and performance portfolios. Of course, this approach also has the possibility that the sample size in a given portfolio could be zero (if there is no independent overlap), which did happen occasionally for certain fund styles, and I have noted when it occurred.
13. Although I found weak results for funds of funds in that the effects of fund age and fund size were not as important as they were for single-strategy funds, this finding should not be taken as evidence that the BG model does not hold for funds of funds. In fact, Fung et al. (2008) found evidence that the BG model does hold for funds of funds. Specifically, they found that flows (rationally) chase performance in funds of hedge funds that have positive risk-adjusted performance. Because of the increased inflows, the probability of finding persistence among these high-flow funds decreases. My finding does not contradict theirs, but, rather, it notes that in the cross section, the optimal fund size (age) in the FOF space does not appear to have yet been reached. This result is plausible for a number of reasons: First, the average size of funds of funds in my sample was \$109 million—the smallest of any asset category. Second, funds of funds can invest in a number of different styles, which implies that the optimal fund size for an FOF portfolio is likely to be higher than for other styles. Third, because these funds invest in other funds, the impact of age described by Berk and Green (2004)—namely, that as funds age, they tend to invest more passively—should not be as relevant as it is for single-style funds.

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