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# The Performance of Emerging Hedge Funds and Managers

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# The Performance of Emerging Hedge Funds and Managers


**ABSTRACT**

This paper provides the first systematic analysis of performance patterns for emerging funds and managers in the hedge fund industry. Emerging funds and managers have particularly strong financial incentives to create investment performance and, because of their size, may be more nimble than established ones. Performance measurement, however, needs to control for the usual biases afflicting hedge fund databases. After adjusting for such biases and using a novel event time approach, we find strong evidence of outperformance during the first two to three years of existence. Each additional year of age decreases performance by 42 basis points, on average. Cross-sectionally, early performance by individual funds is quite persistent, with early strong performance lasting for up to five years.



**JEL Classifications**: G11 (portfolio choice), G23 (private financial institutions), G32 (financial risk management)

**Keywords**: hedge funds, emerging managers, incentives, performance evaluation

## I. Introduction

The hedge fund industry has grown very rapidly. Assets under management have increased from an estimated $39 billion in 1990 to more than $1.8 trillion in 2007.[1] Correspondingly, the number of funds has increased from 610 to more than 10,000. One immediate question with the large growth in the number of funds is whether all of these new managers and funds are capable of generating superior performance. This paper provides the first systematic evidence on whether emerging hedge funds and managers tend to outperform more established ones. We find that emerging funds and managers tend to add value in their early years. Thereafter, performance tends to deteriorate. Each additional year of fund age decreases fund performance by 42 basis points on average, although as we show below, this relation is better described as nonlinear. This result suggests that emerging funds, especially in the first two years of life, represent attractive investment opportunities. We also find that, at startup, larger funds run by multi-fund management companies tend to perform better. These results are consistent with emerging funds and managers having stronger incentive effects, and those that start up with a larger pool of capital and existing organizational infrastructure are able to capitalize on these advantages.

The growth of the hedge fund industry can be rationalized by the value added generated by hedge fund managers that we document. For example, over the period 1994 to 2007, the CSFB hedge fund index delivered an additional 6.7% annual return over cash.[2] Put differently, this performance is slightly greater than that of the S&P stock market index over the same period, but with half the volatility and very little systematic risk. These performance results are puzzling in view of the mutual fund literature, which finds that mutual funds generally fail to outperform their benchmarks even after adjusting for risk. Hedge funds, however, differ in a number of essential ways from mutual funds.

[1] According to the HFR (2008) survey, excluding funds of funds to avoid double-counting.

They provide more flexible investment opportunities and are less regulated. More flexible investment opportunities include the ability to short securities, to leverage the portfolio, to invest in derivatives, and generally to invest across a broader pool of assets. The lighter regulatory environment creates an ability to set performance fees, lockup periods, and other forms of managerial discretion such as limited reporting. Hedge fund managers also have a stronger financial motivation to perform because of the compensation structure typical of hedge funds: this includes both a fixed annual management fee that is proportional to assets under management and an incentive fee that is a fraction of the dollar profits. In addition, hedge fund managers often invest a large portion of their own wealth in the funds they manage, while many mutual fund managers never invest in their own funds (Kinnel 2008).

At the same time, there is a fair amount of interest in "emerging" managers and funds, defined as newly-established managers and funds. In this paper, we examine both emerging hedge fund managers and emerging hedge funds, using fund age or years of existence since inception as the primary sorting criterion.[3] We focus on emerging funds and managers for several reasons. Incentive effects should be stronger for this class of hedge fund managers. The marginal utility of a given annual profit should be higher for managers with lower initial wealth; given that emerging managers are likely to be on average younger than more established managers, profits can be expected to accrue over a longer lifetime. In addition, an existing manager starting a new fund has strong incentives to perform for both reputational reasons and to gather more assets for both the new and existing funds. Further, because of their size, emerging funds may be more nimble than established funds. Finally, emerging funds are more likely to be open to investors than established hedge funds, especially established funds with strong historical performance.

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[2] The CSFB hedge fund index, which in absolute terms returned 10.9% per year over this period, is representative of all hedge funds and does not represent the returns on just emerging hedge funds. For emerging hedge funds, see Table 1.

This is the first academic paper to focus on emerging funds and managers. Age sometimes appears as another factor explaining performance with generally insignificant effects. Crucially, the age factor in hedge funds is subject to a very significant backfill bias. This bias occurs because managers report their performance to the databases only voluntarily—there is no requirement that managers disclose performance. Typically, after inception, the fund's performance is not made public during some incubation period. Upon good performance, the manager is more likely to make the performance public. If so, the manager starts reporting to the database current performance and backfills the past performance, and not even necessarily over the entire incubation period. Funds that collapse due to poor performance may never appear in the database.

Our paper eliminates backfill bias by selecting a sample of funds with inception dates very close to the start dates in the database. We find that backfill bias would otherwise completely distort measures of early performance, imparting an upward bias of around 5% in the first three years. The common practice of arbitrarily dropping the first 12 or 24 months of the sample is insufficient to control for backfill bias. In addition, it may bias tests of persistence toward non-rejection because performance during the backfill period generally appears very high.

Our paper provides evidence on whether emerging hedge funds and managers tend to outperform more established ones. We examine fund performance in "event time" where the event is the start of fund performance. Examining funds in event time is a more powerful and direct method to assess the relationship between age and performance. To see this, suppose that every year a large number of new funds start up, and that new or emerging funds outperform existing funds. Running pooled cross-sectional regressions of fund returns on indices or factors (even with time fixed effects) in calendar time would imply that hedge funds outperform on average.

[3] Initially, we take recently established funds as a proxy for emerging managers. It is possible, however, that a recently established fund is run by a manager who has run other hedge funds. Later, in Section IV, we separately evaluate

However, the outperformance is actually generated by the new funds, an effect which will be captured in event time but missed in calendar time.

Our use of event time is novel in hedge fund research, and the event time approach is ideally suited for examining the performance of emerging hedge funds. Conventional event studies typically examine short horizon reactions to news or events. More recently, long horizon event studies have been used to examine differences in firm returns due to changes that cannot precisely be pinned down to the day. Our use of event time is long horizon in nature—we examine hedge fund performance over years—but we know precisely when the hedge fund starts reporting performance. We use event time to measure hedge fund aging, which is similar to a cohort analysis, while still allowing us to create portfolios of hedge funds.

Using portfolios allows us to test hypotheses while automatically accounting for correlations in returns across funds. This is because the standard errors we report are based on portfolio returns. In contrast, pooled cross-sectional regressions of individual fund returns are usually mis-specified due to cross-sectional correlations in fund returns. Our econometric approach yields robust evidence that emerging funds and managers tend to add value in their early years. This result holds regardless of organizational form (single product versus multi-product management companies) and also regardless of whether the manager has previously run another fund.

In addition, when we form portfolios of emerging funds, we find that early performance (up to five years) is persistent. The persistence we find is present both for the best performing quintile and the worst performing quintile of hedge funds. This result is important because earlier studies of performance persistence tend to find performance persistence amongst only the worst performing funds. As hedge funds become more established (i.e., age) the performance persistence that we document fades away, along with the outperformance exhibited in the funds' early years.

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managers of recently-established funds who have previously run a fund listed in TASS and those that have not.

In further tests, we perform a cohort analysis, where we track over time all funds that start within a given year. This analysis allows us to more precisely control for changes in fund size. One possibility is that past good performance may lead to inflows, which results in the deterioration of fund performance over time, as hypothesized by Berk and Green (2004). Under these conditions, the deterioration in fund performance is actually due to changes in fund size, and not fund age. When we control for fund size, we continue to find that younger funds perform better and this performance deteriorates over time. In addition, we find that, at startup, larger funds run by multi-fund management companies perform better, suggesting advantages to scale associated with organizational infrastructure.

This paper is structured as follows. We review the rationale for emerging funds and managers and relevant literature in Section II. Section III then describes the data and empirical setup. Section IV discusses the results. Concluding comments are contained in Section V.

## II. The Rationale for Emerging Managers

Emerging funds and managers may be attractive for a number of reasons. The first set of arguments is related to incentive effects. There are good reasons to believe that incentive effects are particularly important for the hedge fund industry. Incentives should help sort managers by intrinsic skills. We would expect the best asset managers to migrate to the hedge fund industry. In addition, incentives should induce greater effort by managers, as predicted by agency theory (e.g., Jensen and Meckling (1976)). In the mutual fund industry, Massa and Patgiri (2007) compare the usual fixed management fee setup with arrangements where this fee decreases as a function of asset size. This concave function provides a negative incentive effect, which is found to be associated with worse performance, as predicted. In the hedge fund industry, Agarwal et al. (2007) find that greater managerial incentives, managerial ownership, and managerial discretion are associated with superior performance. In addition, these effects explain the empirical evidence of return persistence for hedge funds, while little persistence has been reported for mutual funds.[4]

Relative to more established and older managers, incentive effects should be even more important for emerging managers because their initial wealth is smaller. The marginal utility of the same dollar amount of fees should progressively decrease as the manager gets richer. In addition, the benefits of high-powered incentive contracts carry over a longer period, since emerging managers are generally younger. So, emerging managers should put more effort into enhancing performance. In their starting years, managers may also be more focused on generating performance rather than spending time marketing to new investors. In addition, an existing manager starting a new fund has strong incentives to perform for both reputational reasons (the new fund has no pre-existing track record) and to gather more assets for both the new and existing funds.

The second set of arguments for emerging managers is related to size. They generally manage a smaller asset pool than the typical fund. Goetzmann et al. (2003) argue that arbitrage returns may be limited, leading to diseconomies of scale. They report that, in contrast with the mutual fund industry, large hedge funds frequently prefer not to grow. Diseconomies of scale also underpin Berk and Green (2004)'s model that explains many regularities in the portfolio management industry that are widely regarded as anomalous. Managers with skill attract inflows, but diseconomies of scale erode performance. As a result, the performance of skilled managers disappears over time. Getmansky (2004) studies competition in the hedge fund industry and finds decreasing returns to scale.

[4] Jagannathan et al (2007) find evidence of persistence in hedge fund returns over 3-year horizons. They also provide a review of the literature on persistence in hedge fund returns. Kosowski, Naik, and Teo (2007) report mild evidence of persistence using classical OLS alphas but much stronger evidence in a Bayesian analysis. Baquero et al. (2005) report persistence at the quarterly and annual horizons, using raw and style-adjusted returns. Aggarwal, Georgiev, and Pinato (2007) show performance persistence for time horizons ranging from six months to over two years. Carhart (1997) reports no evidence of persistence in mutual fund returns using abnormal returns defined by a 4-factor model. These conclusions are reinforced by Carhart et al. (2002), who deal with survivorship and look-ahead biases for mutual funds.

For mutual funds, however, the evidence is mixed. Grinblatt and Titman (1989) and Wermers (2000) find no significant difference across the net performance of small and large funds. Chen et al. (2004) report some evidence of a negative relationship between fund returns and size, but this is exclusively confined to funds that invest in small stocks, which tend to be illiquid. This is confirmed by Allen (2007), who reports no difference across size for institutional investors except for the small cap category, which is capacity-constrained and for which small funds perform better.

Another set of arguments for emerging managers is that they may have newer ideas for trades, whose usefulness can fade away over time. New funds may be established to take advantage of new markets or financial instruments. Irrespective of a performance advantage, emerging funds are often open to new investors and, therefore, represent practical investment opportunities in hedge funds.

So far, no academic paper has directly investigated the performance of emerging hedge fund managers.[5] Age sometimes appears as another factor explaining performance in mutual funds, with generally insignificant effects. In addition, the age factor is subject to a very significant backfill bias or instant-history bias with hedge funds. This bias arises from the option to report performance or not, and if so, to backfill performance produced during an incubation period. To evaluate the effect of age, it is crucial to control for backfill bias, which would otherwise make early returns look better. Our analysis controls for both backfill and survivorship biases.

The age effect that is the focus of our study is also related to the literature on career concerns of portfolio managers. For mutual funds, Chevalier and Ellison (1999) indicate that termination is more sensitive to performance for younger managers. Combined with the incentive structure in this industry, they argue that this should lead to less risk taking in younger managers. This is confirmed by their data. Given the vastly different incentives schemes, it is not clear

[5] Some industry studies suggest that young funds perform better. For example, Howell (2001) claims that young funds outperform old funds by 970 basis points on average but fails to control for backfill bias (see also Jones (2007)).

whether these results should carry over to the hedge fund industry, however. Boyson (2008) finds that young hedge funds have marginally greater performance than old hedge funds. Her sample, however, does not focus on new or emerging managers.

## III. Data and Setup

### *A. Database*

The database employed has been collected by Tremont Advisory Shareholders Services (TASS), which compiles fund data over the period November 1977 to December 2006. The TASS database covers close to one-half of the estimated total number of hedge funds in existence. The database provides total monthly returns net of management and incentive fees, as well as assets under management (AUM). For our analysis, we use data starting in January 1996, the first year for which there is a non-trivial number of non-backfilled funds, using the method defined below.

TASS reports two separate databases, one with "live" funds and another with "graveyard" funds, which keeps track of dead funds and starts in 1994. Many funds stop reporting at some point, because of liquidation or some other reason. We include the graveyard database to minimize survivorship biases. We eliminate funds of funds as well as duplicate classes from the same fund family. In addition, we only retain funds that provide returns in U.S. dollars and net of fees.

While eliminating duplicate classes and funds providing returns in currencies other than US dollars is sufficient to eliminate most situations of the same fund appearing multiple times in the data, it does not completely resolve the problem. For example, two funds can appear in the database, be run by the same manager, and have the same name up to one fund having the designation "onshore" and the other having the designation "offshore." As another example, two funds can have the same manager and the same name up to one fund being an "LP" (limited partnership) and the other being "limited" or an "investment company." These situations often happen in fund companies set up with a master-feeder fund structure, where multiple feeder funds channel capital to one investing master fund. In these situations, if the funds are duplicates (for example, if the returns are 0.99 correlated or more), we eliminate one of the duplicates.[6]

More precisely, funds are selected as follows. If two (or more) funds from the same management company have a duplicate series of returns for the months in which both report, and one fund started later than the other, then we keep the oldest fund or the fund with the longest return series. If two funds have duplicate series for the months in which both report and one fund stops reporting before the other, we again keep the fund with the longer return series. If two funds have duplicate series and exactly the same months for which they report, we keep the larger of the two funds by initial assets under management (AUM). In order to avoid double-counting assets, we retain the assets under management only for the fund whose return series we include. This is because, in many cases, the smaller fund is a feeder fund for the larger master fund, which implies that the feeder funds' AUM could already be included in the master funds' AUM. On the other hand, situations may exist without double-counting of assets (e.g., side-by-side onshore and offshore funds or side-by-side funds denominated in different currencies); in such cases, we will understate the aggregate AUM for that manager.

### *B. Constructing Emerging Fund Returns*

It is well-known that the practice of backfilling returns causes severe biases in performance measurement.[7] Fung and Hsieh (2000) report that the median backfill period is about 12 months

[6] We note that much of the existing literature does not correct for such master-feeder duplicates, thereby imparting another potential bias to hedge fund research.
[7] Evans (2007) also reports a substantial incubation bias for mutual funds. Apparently, mutual fund families seed new funds without initially making their performance public. After a while, the fund may acquire a ticker symbol from the NASD, thus becoming public. He defines a fund as incubated if the period between the ticker creation date and the fund inception date is greater than 12 months. He reports a difference in performance of 4.7% between incubated funds during their incubation period and an age-matched sample of non-incubated funds.

based on the TASS database from 1994 to 1998. They adjust for this bias by dropping the first 12 months of all return series and report a bias estimate of 1.4% per annum (see also Malkiel and Saha (2005)). The common practice in hedge fund academic research is to drop the first 12 or 24 months to control for backfill bias (e.g., Kosowski, Naik, and Teo (2007)).

This adjustment, however, is peculiar. For funds with no backfill, this discards the first year of performance, which is perfectly valid and very informative. Moreover, for the 50% of funds with backfill longer than 12 months, this still preserves backfill bias. Whether this biases the results of the empirical analysis depends on the research objective. Clearly, backfill bias is of first-order importance when evaluating the initial performance of emerging funds. A better method to control for backfill bias is to minimize the period between inception of the fund and the first entry date into the database. Thus, we focus on the funds for which there is no (or very little) backfill bias.

TASS provides an "inception date," a "performance start date," as well as a "date added to database." The inception date is the inception date of the legal fund structure and generally will not coincide with the start of actual fund investment and performance. The performance start date is the date of the first reported monthly return. The date added to TASS is when the fund chooses to start reporting to TASS. For a typical fund in the TASS database, the inception date is prior to the performance start date, and the performance start date is prior to the date added to the database. Backfill occurs when the performance start date is before the date the fund was added to the database. The difference is the "backfill period." We find that the median backfill period in the entire database is 480 days, which is substantial. In addition, 37% of funds have a backfill period longer than two years; 25% of funds have a backfill period longer than 1165 days, which is more than three years. The obvious concern here is that funds only choose to report to TASS if past performance has been good and this performance is then allowed to be backfilled.

To control for this effect, we separate the sample into a non-backfilled sample and a backfilled sample. We define a fund as "non-backfilled" if the period between the inception date and date added to the database is below 180 days. Note that this definition slightly differs from the traditional definition of the backfill period, which is the difference between the performance start date and the date added to the database. Our definition takes into account the possibility that funds may have actual performance that they choose not to report between the inception date and the performance start date (which is self-chosen and reported). Our focus on the difference between the inception date and the date added to the database minimizes both backfill bias and the possibility of omitted performance. At the same time, the lag of 180 days is required because very few funds report to the TASS database immediately at inception. For most funds, not reporting performance at inception is entirely legitimate as the fund may be gathering assets rather than investing. The remaining period between the performance start date and date added to TASS is minimal, with a median of 82 days.[8] As we show later, our results are not driven by this window.

*C. Time Alignment*

We perform two types of analysis, based on "event time" and "cohort by calendar year." In the first type, the event is the start of fund performance. We form an equally-weighted portfolio of funds aligned on the first month of reported performance. Equal-weighting generates the expected return from a strategy of picking all managers meeting the relevant characteristics. To transform to yearly returns, we cumulate the first 12 months of performance, which is called year 1. The second twelve month period is then called year 2, and so on. From January 1996 to December 2006, we

[8] Our use of a window of 180 days for non-backfilled funds is in fact much more stringent than the 12-month window used by Evans (2007) in the context of mutual fund incubation bias.

have at most 132 months in event time, which could only be achieved by a fund starting in January 1996 that survives until December 2006 (there are three such funds).

Panel A in Table 1 reports raw returns for our portfolio of emerging funds. We have 923 funds that start (beginning of event year 1) over the period 1996 to 2006 that are free of backfill bias. By the beginning of event year 2, this number falls to 749, due to fund attrition as well as truncation at the end of the sample (i.e., a fund that starts in 2006 will not have two years of performance). By the beginning of event year 9, there are only 44 funds in the portfolio. The last two years are not reported in the table due to the small number of data points. This process leads to the largest number of funds in the first month, as every fund in the database with no backfill has at least one month of performance, and a smoothly decreasing number of funds in event time. Note that the first year performance for these funds is substantially higher than for subsequent years. The average raw return is 12.16% in the first year. This falls to 7.99% in the second year, which suggests outperformance by emerging managers. During the first two years, average performance is 10.1%, versus 9.1% during the remaining seven years.

Panel A also displays the portfolio volatility, annualized from monthly data. Volatility is very low given the large number of funds in the portfolio and the aggregation process across time. As event time goes by, the volatility increases due to the smaller number of funds in the portfolio. This volatility is also the standard error of the annual return.[9] Thus the estimated annual return becomes less reliable as time goes by. The table also shows the t-statistic that tests equality of consecutive annual returns. The return drop from the first to the second year is significant. Note that what matters is not the level nor sign of returns but rather their patterns over time. Performance is measured relative to the universe of funds, assuming all returns are drawn from the same

[9] Statistics are first computed from monthly returns (mean $\mu_m$ and volatility $\sigma_m$). The annual return is $\mu_a = 12\ \mu_m$ and the annual volatility is $\sigma_a = \sqrt{12}\ \sigma_m$.

distribution. Later, we will make adjustments for risk and contemporaneous correlations across funds. The last column in Table 1 reports the typical fund (not portfolio) volatility, taken as the cross-sectional average of this risk measure across all the funds in this group. Fund volatility is slightly higher in earlier years.

Given our interest in emerging managers, we need to correct for backfill bias in the TASS data. To illustrate this point, Panel B in Table 1 repeats the analysis using all emerging managers in the TASS data from 1996 to 2006 that do not meet our definition for no backfill. In other words, these are the backfilled funds. The returns are event time returns, which are therefore comparable to the returns in Panel A. There are many more backfilled funds than non-backfilled funds, 2267 initially versus 923. Backfilled funds exhibit much higher returns for the first four years than non-backfilled funds. The extent of backfill bias is substantial. During the first year, this bias is 6.44%, which is the difference between 18.60% and 12.16%. This bias persists for the first four years, dropping to 4.4%, 4.5%, and 2.4% in the years after the first year. The difference is significant at the one-sided 95% level during each of the first four years.

Our second type of time alignment groups funds according to the calendar year in which they start. A "cohort" is defined as a group of funds that start reporting during each of the years in our sample, from 1996 to 2006. For example, we have 74 funds with inception date and performance data starting during 1996 with no backfill. Each month, we construct an equally-weighted portfolio of returns across all funds for which we have data. Summing, this gives the average performance for that cohort (e.g., 1996) in year $t$, $\overline{R}_{1996,t}$. Note that, unlike the event-time analysis, there are fewer funds in January, which means that the weight of each fund and portfolio variability will be greater.[10] The size of each cohort successively shrinks as years go by; for example, the 1996 cohort decreases from $N_{1996,1}$=74 to $N_{1996,2}$=69 in January, 1997, and to only $N_{1996,11}$=10 in January, 2006.

To get the average return for the first year of our 11 cohorts, we take:

$$\overline{\overline{R}}_1 = \tfrac{1}{11}(\overline{R}_{1996,1} + \overline{R}_{1997,1} + \ldots + \overline{R}_{2006,1}) \tag{1}$$

The average return for the second year of our cohorts averages the second years of our funds ($\overline{R}_{cohortyear,2}$), i.e., 1997 returns for the funds started in 1996, 1998 returns for the funds started in 1997, and so on. We do this for all years up to the maximum of 11 years.

This cohort/calendar time analysis provides an alternative method of classifying funds. It also allows us to sort by size on an annual basis, which provides a more natural sorting for size than does the event time analysis. The results of this method will be presented later in Table 6, when discussing size effects.

*D. Performance Measures*

We use several measures of performance. The first measure is the raw return, as previously discussed. The advantage of this method is that it does not require estimation of any parameter. However, it does not control for risk or market movements. The second measure uses the TASS classification into one of twelve sectors. Of these twelve sectors or styles, funds in our sample belong to ten: convertible arbitrage, fixed income, event driven, equity market neutral, long-short equity, short bias, emerging markets, global macro, managed futures, and multi-strategy. For each sector, CSFB provides an index based on an asset-weighted portfolio return of funds selected from

[10] For example, there are 13 funds in operation in January 1996, so the January 1996 portfolio return is an equal weight average of the 13 funds' returns. There are 17 funds (13 one-month old funds and 4 new funds) in operation in

the TASS database. These CSFB indices include funds with at least one year of track record, with at least \$10 million in assets, and with audited financial statements.[11] These indices should be free from backfill and survivorship biases, because they are constructed 'live,' or from contemporaneous data.[12] Indeed, these indices are not recomputed to include previous returns and do include funds that may die later.

We use these sector returns to adjust fund returns for sector effects. Abnormal, style-adjusted, returns are measured as:

$$AR_{it}^{S} = R_{it} - \beta_{it} R_{St} \ , \qquad (2)$$

where $R_{it}$ is the return on fund $i$ at time $t$, $R_{St}$ is the return on the sector $S$ to which fund $i$ belongs, and $\beta_{it}$ is the sector exposure of fund $i$, computed over two calendar years or less if the series are shorter. To be specific, the exposure $\beta_{it}$ for years 1 and 2 is calculated using all of fund $i$'s return data from years 1 and 2; thereafter, $\beta_{it}$ is calculated using return data from years $t$ and $t-1$.[13]

The advantage of this approach is that it is simple to implement. It controls for sector effects, which is appropriate when comparing performance across funds. It also adjusts for general movements in fund returns, such as the period of negative returns experienced during the third quarter of 1998, at the time of the Long-Term Capital Management crisis. As a result, the variance

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February 1996, so the portfolio return is an equal weight average of the 17 funds' returns. The number of funds increases during the calendar year.

[11] After April 2005, the minimum size went up to \$50 million.

[12] These indices were constructed live since December 1999. Prior to that, however, the returns may have been backfilled. In addition, as Ackermann et al. (1999) indicate, a remaining bias might exist, called "liquidation" bias. This arises if a fund stops reporting and falls further in value thereafter. The authors indicate that the index providers take great pains to ensure that the final return is included. Even when not included, their paper reports that the remaining loss in value is estimated at minus 0.7%, which is small. For instance, the Bear Stearns High Grade Structured Credit Fund failed during June 2007. The June performance for this fund was announced too late to be included in the June returns for the index, but was included in the July index returns. The effect was small, however, because this fund had a weight of less than 0.2% in the broad index. For our purposes, the last month of performance was eventually included in the database.

[13] We have also performed the analysis using betas calculated over one year. The results are quite similar to all of those reported below. The advantage of using one year betas is that abnormal returns can be calculated out-of-sample (i.e., using the prior year's beta) in all years except the first year. The disadvantage is that the betas are noisier.

of abnormal returns should be less than that of raw returns, which should increase the power of the tests. This approach also controls for risk, taken as a factor exposure. For instance, keeping the correlation fixed, a fund with higher leverage should have higher volatility and hence higher beta.

On the other hand, the classification into sectors may be arbitrary. This can be an issue with funds that straddle several strategies, or with funds that change their investment themes over time. Note that this approach simply provides a measure of relative performance with respect to other funds with the same style. Because hedge funds are not compared to other asset classes, a negative alpha does not mean that a fund has poor absolute return performance.[14] One other concern with this approach is that we must estimate the abnormal returns and the betas (sector exposures) in-sample. In other words, there is no estimation period followed by a predictive period. Given our focus on emerging hedge fund managers (who, by definition, do not have past returns), this is simply a cost of making an adjustment for risk. More generally, the approach we use is the approach taken in most hedge fund research on performance and performance persistence (see, e.g., Jagannathan, et. al. (2007) and Kosowski, et. al. (2007)) which typically involves short time series.

## IV. Empirical Results

### *A. Style-Adjusted Performance Using Event Time*

We start by presenting style-adjusted returns for the event-time portfolio. Panel A in Table 2 presents alphas by age, ranging from one to nine years after inception. Panel A shows that first-

[14] We have also examined the Fung and Hsieh (2004) asset-based style (ABS) factors, with betas estimated over the entire period, with similar results. We choose not to report the Fung and Hsieh results because a large number of new funds stop reporting fairly quickly, creating unstable estimates. For example, of our 923 funds, 174 stop reporting within twelve months. 68 of these funds start in 2006 and survive, but cannot report more than twelve months of performance; the rest stop reporting mostly due to failure and liquidation. Estimating Fung and Hsieh seven factor exposures with less than 12 months of data is clearly problematic because we over-fit alphas. On the other hand, dropping these funds results in the elimination of almost 20% of our sample. Nonetheless, when we drop funds with fewer than 12 months of performance, we find results based on the Fung and Hsieh factors that are similar to the results reported based on style indices.

year alphas are 4.31%, falling substantially in years two to five, and then varying between positive and negative values thereafter.[15] Standard errors are systematically smaller than in Table 1, reflecting the increase in power due to the sector adjustment. The test column presents the t-statistic for the hypothesis of no change in annual return. The first-year drop is statistically significant. Performance continues to drop in the third and fourth years. To summarize the outperformance, the average alpha during the first four years is 1.57% per annum, versus 0.36% during the next five years. Emerging managers, narrowly defined over a time span of two years, generate an abnormal performance of 2.71% per annum relative to 0.38% later.[16] This difference is statistically and economically significant.

The last column reports the typical fund beta, taken as the arithmetic average of this risk measure across all the funds in this group. Average betas are around 0.7 relative to the style indices. This beta differs from unity because the typical fund may not be perfectly correlated with the style factor (e.g., the manager has new ideas), or may not have the same leverage or volatility.[17]

Panel B presents results from a regression of monthly portfolio alphas on a time trend. In the first column, we include a linear time trend. Each additional month of age decreases monthly performance by 0.29 basis points. Each additional year of age would decrease monthly performance by 0.29*12 = 3.5 basis points or yearly performance (annual alpha) by 3.5*12 = 42 basis points, on average. The time trend is even stronger and more statistically significant when

[15] To address concerns that there may be some residual backfill bias in our results, we have also examined the funds for which there is no backfill at all because they are added to TASS within 30 days of their first performance report. There are initially 243 such funds. The patterns we describe for the full no backfill sample are similar for this sample as well, but with less statistical power due to the smaller number of funds. In the first year in event time, the average alpha is somewhat smaller at 2.31% with a standard error of 1.19%.

[16] We have also assigned each of our hedge funds to one of ten sectors and formed a portfolio of the hedge funds in that sector. The largest sector is long-short equity, with 40.4% of the funds at inception. The results are not driven by any one sector. Most sectors display a decline in alphas in event time, including long-short equity. We do not report statistics for this decomposition because the number of funds is small for each sector and shrinks very quickly in event time, which creates more variability in the average alphas.

using the logarithm of age as the explanatory variable, as shown in the second column.[18] Thus, emerging managers display significantly better performance during their initial years.

Hedge funds can differ in their organizational form. Some hedge funds are run by large, multi-product fund management companies while others are run by a management company dedicated to that sole hedge fund. It is possible that single-fund management companies have stronger incentives to succeed as the managers' attention and efforts can be concentrated on a single fund. Conversely, for reputational spillover reasons, managers at multi-product management companies may have strong reasons to curtail poor performance and shut down underperforming hedge funds. Table 3, Panel A examines whether differences in organizational form matter for abnormal fund performance. The left sub-panel presents alphas for funds from multi-fund management companies; the right sub-panel presents alphas for funds from single-fund management companies. Most of the funds that start (576 out of 923 at the outset) belong to multi-fund management companies.[19] Performance is similar across funds from the two types of organizations, albeit slightly worse for funds from single-product management companies. This difference is consistent with the findings by Chen, et al. (2004) that mutual fund performance slightly increases when a fund is part of a larger fund group, probably due to economies of scale in trading commissions and marketing costs.

Up until this point, our focus has entirely been on emerging or new funds. However, it is likely that many managers of new funds have run other hedge funds before. For example, it is easy

[17] There does appear to be some tendency for beta to increase over time, which parallels the decrease in alpha. This is in part due to the negative correlation between alpha and beta due to the overlap in estimation period. Because style indices tend to have positive returns, if beta is underestimated, this will lead to an overestimation of alpha.
[18] We find similar results using the alphas from the Fung-Hsieh seven factor model.
[19] In an earlier version of this paper, we defined funds as belonging to multi-fund management companies if at any time the management company ran multiple funds. This definition allowed for the possibility that a management company might start a fund, generate strong performance, and then start additional funds. The initial fund would have been classified as belonging to a multi-fund management company. We now classify new funds as belonging to a multi-fund

for a successful manager to close a fund, perhaps because of a regulatory limit on the number of investors, and then to start a new fund with a similar investment strategy. In this case, the manager should not truly be considered emerging. In order to address this concern, we verify whether the manager (or any of the managers) of a fund in our sample has run any other funds that report to TASS. This approach, admittedly, does not account for managers that previously ran another fund not reported to TASS.

Using this classification scheme, we find that 397 of our sample of 923 funds have managers who have previously run another fund in TASS. There are 493 funds run by managers without a previous record in TASS.[20] The remaining 33 funds do not report managers' names and are excluded. Table 3, Panel B compares the alphas of managers who have and have not previously run another fund in TASS. Generally, the time patterns are similar for both groups. Managers who have previously run another fund have slightly higher abnormal performance than managers who have not previously run other funds. The first few years, however, are very similar. Overall, emerging funds seem to perform better in earlier years, and this is true as well of emerging managers who have not previously run another hedge fund, defined to the best extent possible with the available data.

Panel C provides regression results to support the previous findings. Sub-panel 1 shows that the age effect is significant for both single and multi-funds, with a stronger effect for single funds. Sub-panel 2 shows that the age effect is significant and equally strong for managers who have and have not previously run a fund in TASS. As an additional test, we consider separately the live and dead funds from TASS. Out of the total sample of 923 funds, 493 funds died during our sample

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management company only if there are other funds run by the management company on or before the inception date of the new fund. All of our results are robust to this change in definition.

period. Sub-panel 3 shows that the age effect is very strong and significant for live funds. Not surprisingly, dead funds exhibit lower initial alphas than live funds, and the dead fund initial alphas are not statistically significant. While the age coefficient is negative for dead funds, the age effect is also not statistically significant. In general, the alpha series for dead funds is quite noisy, consistent with funds that die being much more volatile than funds that survive. This evidence is complementary to that of Chan, et al. (2006), which finds that young funds with poor performance are more likely to die than others. An open and interesting question is whether investors anticipate that poorly performing new funds are likely to fail and hasten their demise by withdrawing funds. Panel D then separates the sample into live single funds, live multi-funds, dead single funds, and dead multi-funds. The age effect is significant for live funds, whether from single or multi-funds, and is particularly strong for the single funds.

*B. Backfilled vs. Non-Backfilled Funds*

Table 4 presents alphas in event time for the backfilled funds. Panel A presents annual alphas from the first reported performance after inception. This sample fully incorporates all of the backfilled data. Not surprisingly, alphas are large but decreasing for the first four years of inception. To see how much of this performance is due to firms backfilling positive returns, we reexamine our backfilled sample by truncating all monthly return observations prior to the fund starting to report performance to the database. Since the database reports the date that the fund was added to the database, we treat all monthly return observations prior to this date as backfilled and eliminate them. We then compute alphas for the remaining (non-backfilled) observations in event time, where the event is the fund being added to the database. These results are presented in Panel

[20] It is worth noting that a random examination of fund manager backgrounds reveals that virtually all emerging fund managers have some prior trading experience either at an investment bank, institutional money management firm,

B of Table 4. The alphas plummet relative to those in Panel A. Interestingly, alphas are also lower than for the purely non-backfilled funds in Table 2, suggesting that there are important return effects during the first few years of a fund's life that can be missed by simply truncating all backfilled returns.

Panel C reports the alphas of backfilled hedge funds, separated into multi-product funds (1274) and single-product funds (992). The ratio of single-product funds in the backfilled sample is 992/2266=44%, which is slightly higher than that in the non-backfilled sample, 347/923=38%. Thus, single-product funds are somewhat more susceptible to backfill returns than are multi-product funds. In addition, we find that the performance in the first (backfilled) year is greater for single-product funds, by 12.68% - 9.61% = 3.07%, and remains much higher for the first four years of life.

Panel D reports the alphas of backfilled hedge funds separated into multi-product and single-product funds after eliminating all of the backfilled returns (i.e., the returns prior to the fund being added to the database). Eliminating the backfilled period for the backfilled funds dramatically shrinks the alphas, with single funds outperforming the multi-product funds in the first year only by 2.28% - 0.96% = 1.32%. The conclusion for the backfilled sample is that single funds seem to perform better, but most of this performance is attributable to greater backfill bias for single funds.

Figure 1 displays the cumulative alphas aligned by event time for our non-backfilled sample. The initial performance is very strong, and then tapers off as the fund ages. Note that the performance in the first year is not driven by the first three months alone, which should dispel concerns about the remaining 82-day median period between the performance start date and the date added to the database. Also note that the beginning of the line is rather smooth, due to the large number of funds in the series. Towards the end, however, the line is much more irregular. This

mutual fund, or as a junior manager at another hedge fund.

reflects the greater standard error due to the fact that the portfolio is less well diversified because it includes a smaller number of funds. Overall, the figure indicates that performance in the initial few years is better than average. One point worth noting is that emerging funds are open to investors, whereas many established funds (including those in the indices) that have performed well are not open to investors. Thus, in the space of investable funds, emerging funds are likely to be even better performers relative to established funds.

The figure also displays the cumulative alphas for backfilled funds. The vertical difference between the two top lines (backfilled versus non-backfilled funds) indicates that the backfill bias is very substantial. For example, the vertical difference between the two lines after four years is about 15%, which translates into a bias of about 4% per year. This comparison controls for the age of the fund, using the non-backfilled funds as a reference.

Alternatively, we can compare the performance of backfilled funds at different points in time. The third line in Figure 1 plots the cumulative alphas for the funds from our backfilled sample starting on the first date of reporting to TASS. In other words, these are the non-backfilled observations from our sample of backfilled funds. For the first four years, the cumulative alpha is essentially zero. Comparing the backfilled funds to the backfilled funds without the backfilled observations, the vertical difference between the two lines after four years is about 21.5%, which translates into a bias of almost 5.4% per year. Hence, a portfolio of backfilled funds that either includes the backfilled period or excludes the backfilled period gives an unrealistic view of the performance of emerging managers. The only proper approach is to examine a portfolio of non-backfilled funds.

In addition, we can now evaluate the standard practice of discarding the first two years of the sample to account for backfill bias. Figure 2 compares the cumulative performance of our non-backfilled sample starting in year 3 to that of the backfilled sample. Without bias, the two lines should be comparable to each other. In fact, the backfilled sample displays persistently higher performance than the non-backfilled sample. This is because 37% of funds still have backfilled numbers even after truncating the first two years. Over the next three years, the difference amounts to about 3%, which translates into a bias of about 1% per year. Thus, the usual practice of truncating the first two years is insufficient to purge the backfill bias. The key message here, however, is that even after carefully controlling for backfill bias, emerging funds perform well in the first two years of life. This actual effect is typically missed in hedge fund research when the first two years of performance is truncated.

One possibility that could explain the difference in the performance of the non-backfilled versus the backfilled sample is differences in management or incentive fees. It turns out that this is not the case. For the non-backfilled sample, the average management and incentive fees are 1.50% and 19.65%, versus 1.43% and 19.63% for the backfilled sample. Of course, effective fees can differ from the stated fees, which are the ones reported to the database and used to compute net returns. In particular, early investors in emerging funds may be able to get a fee break. This, however, would make returns for emerging funds even more attractive for early investors than those reported here.

### *C. Performance Persistence*

These results suggest that emerging funds and managers perform better during their earlier years, on average. An interesting question is whether these results are driven by specific funds or a subsample of funds. To check whether specific funds that have performed well continue to perform well, we examine whether performance is persistent in the cross-section of emerging funds. We address this question in two ways.

First, Table 5, Panel A presents the results from a regression of:

$$\alpha_{it} = b_0 + b_1\alpha_{it-1} + \varepsilon_{it} \qquad (3)$$

where α is the abnormal return as defined in Equation (2). This is a conventional regression approach where we simply ask whether future abnormal returns are associated with past abnormal returns. The regression is performed year-by-year in event time. We start by examining the association between year 2 abnormal returns and year 1 abnormal returns and then move forward in time. For the first two years, the coefficient on the previous year's alpha is approximately 0.30 and is significant. For the remaining years (with the exception of year 8), the coefficient on the prior year's alpha is insignificant. Thus, we find a high degree of performance persistence from years 1 to 2 and years 2 to 3 for emerging funds.[21] After year 3, when the funds are arguably no longer emerging, we do not find evidence of performance persistence. These results should be interpreted with caution, however, because the regression uses alphas with substantial estimation error as independent variables. Carpenter and Lynch (1999) provide a detailed study of the statistical efficiency and power for various measures of performance persistence and show that this type of test can be unreliable.

This is why we also use a second methodology recommended by Carpenter and Lynch (1999). In the absence of survivorship bias, which is appropriate in our context because we include graveyard funds, they recommend forming portfolios of funds based on performance deciles. Grouping decreases estimation error in the performance measures. Due to the smaller number of hedge funds relative to mutual funds, we choose to form quintiles instead. We use a one year ranking period and a one year evaluation period. In event year *t-1*, we form five portfolios based on average fund alphas sorted into quintiles. The highest average alphas are in Q5 and the lowest are

[21] Separating the sample into the 576 funds from multi-fund management companies and the 347 single funds, performance persistence lasts through the first four years for multi-funds, but only through the first three years for single funds. This evidence is consistent with the hypothesis that the multi-fund organizational structure provides more consistent performance.

in Q1. In year *t*, we calculate average annual alphas for each of the five portfolios. Partial observations for funds that disappear during that year are kept in the sample, so there is no look-ahead bias. We then take the difference between the average annual alpha for Q5 and Q1 and test whether the difference is statistically significant.

The results are presented in Panel B of Table 5. The differences between Q5 and Q1 are large in magnitude and statistically significant in years 2 through 5, with values of 17.2%, 13.4%, 8.8%, and 10.7%, respectively.[22] These spreads are much larger than the 5.8% spread for all large funds (assets under management greater than $20 million) in all years reported by Kosowski, et.al., using a Bayesian analysis. However, the spreads from year 6 on are smaller, consistent with the previous performance persistence results being driven by emerging funds. Moreover, Kosowski, et. al., along with most previous literature, eliminate the first 12 months of returns to control for backfill. This is precisely the period for which we find the results that are largest in magnitude (17.2%). Indeed, when we take a weighted average of the top-bottom quintile difference across all years, where the weights are the number of funds, we find that the average difference is 11.99%. Of this, the year 2 difference (based on the year 1 ranking) accounts for 6.05%. Eliminating the first year, we find that the remainder, 5.94%, is quite similar to the 5.8% found by Kosowski, et. al., although their sample and estimation procedure is markedly different.

In sum, we find performance persistence all the way to year 5.[23] Thereafter, the spread falls sharply. In addition, performance persistence occurs in both the top quintile and the bottom

[22] The t statistics assume independence across portfolios. This is a reasonable assumption because sorting by event time mixes calendar months, as in conventional event studies. Indeed the results are similar when using the time-series of the differences in portfolio returns to construct the t statistics.

[23] One concern with this result is that our alphas are calculated in-sample using betas estimated over two years. It is possible that this induces a spurious autocorrelation in the alphas. We address this in two ways. First, simulation results (not reported) show that any induced autocorrelation is small in magnitude and cannot account for the high degree of persistence we find. Second, we re-examine our results using alphas and betas estimated over one year. All of the results are quite similar, suggesting that the two-year beta estimation horizon does not account for our results. These results are available upon request.

quintile, with large positive alphas for the top quintile through year 5 and large negative alphas for the bottom quintile through year 6. This finding is important because performance persistence for poorly performing funds can happen mechanically—poor performance causes redemptions, which force liquidation of fund holdings generating additional poor performance. Overall, we conclude that not only does the average emerging fund perform well for the first few years, but the specific emerging funds (grouped into portfolios) that perform well in the first few years seem to continue to do so.

*D. Controlling for Size*

The evidence of better performance during the early years of a fund's life can be attributed to a number of explanations related to incentive effects, as previously discussed. Another explanation, however, could be size. It could very well be that outperformance is due to the small size of the fund instead of its age. Size is measured by assets under management (AUM) for each fund, as reported by TASS.[24] To check this hypothesis, we evaluate the performance of funds sorted by size quintiles. In this experiment, we sort funds using AUM at the time of inception. For consistency in reporting, AUM is reported in 2006 dollars adjusted for inflation.

We sort funds by year of inception rather than pooling all of the funds and forming quintiles because the average size of new funds has increased significantly over time. If we pooled all of the funds to form quintiles, the funds in the largest quintile would predominantly come from 2006 and our largest quintile would disappear after a year. So, we form quintiles of funds starting in 1996,

[24] One concern with our results based on fund size is that there may be multiple classes of a fund, or onshore and offshore versions of a fund, or some other master-feeder structure between several funds such that when we eliminate duplicate funds, we also eliminate some of the assets managed by that fund, broadly defined. This would induce mismeasurement in the assets under management ascribed to a manager. However, simply aggregating the assets for all of the potential duplicates of a fund creates another problem of potentially double-counting assets that are already contained in the larger, master fund. We prefer to be conservative in our estimates of assets under management but acknowledge that this may create noise in our estimates.

quintiles of funds starting in 1997, and so on. We then aggregate all of the funds in the smallest quintiles, all of the funds in the second quintiles, etc., to create the final five quintiles.[25]

Next, we run the analysis in event time, keeping each fund in the same quintile. In other words, funds may grow or shrink over time, but their assigned quintile does not change. This analysis can be viewed as choosing funds strictly based on size when they start. This answers the question of whether funds that are small initially outperform or not. A disadvantage of this sorting method is that it does not ensure a continuously balanced allocation to quintiles. Each quintile contains 20% of the 923 funds during the first month. Over event time, however, the number of funds decreases sharply and the allocation of funds to quintiles becomes unbalanced as funds disappear. After 10 years, for instance, there are no remaining funds in the smallest quintile. This effect also shows up as larger standard errors.

The results are displayed in Panel A of Table 6. The panel does not show a uniform size effect in the alphas. The last column presents the average alpha and standard error by quintile over the first nine years. The average alpha for the smallest quintile is −1.96% and for the largest quintile is +0.01%. The bottom two rows of Panel A present the results of a joint test of equality of alphas across the five quintiles. Only for the first year do we reject the hypothesis of equality of alphas, with a p-value of 0.10. In general, variations across quintiles are less important than variations across years. In other words, picking a manager by age is more informative than by size.

To the extent that there are significant patterns due to size effects, larger managers seem to do better, especially in the first year or two of existence. This is contrary to the hypothesis that small managers should outperform others. One possible explanation is that the funds in our sample are rather small at inception. Funds in the smallest quintile have average assets under management of less than $1 million. Only in the largest quintile do funds start with average AUM in excess of

[25] For reference, we also report the average AUM in 2006 dollars for the final five quintiles.

$50 million, which, incidentally, is the cutoff size for inclusion in hedge fund style indices. Given that this is still a relatively small size, emerging funds are unlikely to suffer from diseconomies of scale. If anything, this sample may benefit from greater economies of scale, such as decreased trading costs and better access to information. Put differently, the relationship between performance and size is probably not linear. Very small funds could underperform because they lack economies of scale. On the other hand, very large funds could underperform because they became too big. In addition and not surprisingly, smaller managers at inception seem to exit at a more rapid rate over time than larger managers. This is consistent with the hypothesis that investors can identify managers with greater skill and provide them with more funds. Thus, investors seem to be able to successfully screen new managers.

One possibility is that size is proxying to a certain extent for funds from multi-fund management companies. We would certainly expect that multi-funds have an organizational advantage in gathering new assets, and they may also be better positioned to enter new markets, styles, or trades. We address this question in the Table 6, Panels B and C. The first column of Panel B shows that in a simple regression, only ln(age) is significant while fund size is not in explaining alphas. When we split the sample by single or multifund status (Columns 2 and 3), we continue to find a significant age effect. In addition, large funds from multifund companies have significantly higher alphas than small funds from multifund companies. In Panel C, we split the sample by size and find that large funds from multifund companies have significantly higher alphas than large funds from single fund companies. Among single fund companies, size does not matter. Again, in all cases, there is a negative and significant age effect. The key conclusion is that large funds from multi-fund companies have higher alphas, consistent with the hypothesis that multi-fund families have a competitive advantage.[26]

*E. Cohort by Calendar Year Analysis*

To further examine the effects of age and size, we provide an alternative time alignment classification based on a cohort by calendar year analysis. Here we keep track of the calendar year in which the fund is started so that we can reform size portfolios for funds started in a specific year (e.g., 1996) in every subsequent January. Before examining size, we present aggregate statistics on raw returns and alphas over time for the cohort by calendar year time alignment in Table 7, Panel A. First-year returns are computed by averaging returns in 1996 for funds started in 1996 with returns in 1997 from funds started in 1997, and so on. Second-year returns are computed by averaging returns in 1997 for funds started in 1996 with returns in 1998 for funds started in 1997, and so on. The rest of the returns are calculated in analogous fashion.

The results in Table 7, Panel A, are comparable to those in Tables 1 and 2 with two exceptions. First-year performance is higher under this method. Also, the portfolio volatility is systematically higher. This reflects the fact that, at the beginning of the calendar year, there are fewer funds in these portfolios than in Tables 1 and 2. In particular, there are many fewer funds in January and February of the first calendar year of existence.[27] As previously documented, early performance tends to be good, so that the months of January and February will tend to have very strong performance in the first year of existence. When we average across months to get yearly performance, we generate first-year results that seem much better than in the event-time analysis.

[26] We also analyzed the first year alphas by calendar year. In all years except one, this is positive, which indicates that our results are not due to a small cluster of years. We thank the referee for suggesting this analysis.
[27] For example, if all funds were to start uniformly during the first year, the number of funds in the December portfolio would be 12 times that in January.

Next, we want to examine more closely the effects we find for age and size in the previous section. Recall that we found evidence that initial fund performance is strong, especially for larger managers. Each fund was assigned to a quintile constructed using equal weights, and stayed in the same quintile over time. These results, however, could be obscuring an interaction between size and age. Specifically, our results could be obscuring better performance over time by larger funds and worse performance by smaller funds. When we form equally-weighted portfolios, we essentially dilute the strong performance of the larger funds.

To see this, suppose investors start with diffuse priors about the ability of fund managers and the distribution of initial fund sizes is random. As in the Berk and Green (2004) model, now assume that a fund performing well early will attract investor inflows that increase its assets under management; at least for a while, the fund continues to perform well in absolute terms even as its performance erodes. Conversely, firms that initially perform badly show a decrease in assets and, either due to liquidations or in absolute terms, continue to perform badly. Under these conditions, equally-weighted portfolios will overweight poorly performing small funds and underweight the strong performance of large funds. This effect is not captured by the design of the previous section because funds were frozen into the quintiles they occupied at inception. No allowance was made for the possibility that funds might grow or shrink over time based on their performance.

To address these concerns, we want to allow the fund classification and size portfolios to change over time. In order to do so, we re-sort all funds at the beginning of each subsequent year into size quintiles.[28] This method also ensures that the quintiles are equally balanced throughout time, which is not the case with the event time method where we left the quintiles frozen over time.

[28] Performing this analysis in event time is problematic because resorting by size every 12 months without regard to calendar year mixes funds from different years, and we know that there is a calendar time component to fund size (e.g., the average size of a new fund increases over time).

Panel B in Table 7 displays alphas from size quintile portfolios where the portfolios are reformed every year. In general, the results are similar to those in Table 6, Panel A. For the most part, differences across size portfolios are not statistically significant. Even so, large funds seem to perform better than smaller funds. The smallest funds do very well in the first year, after which performance worsens significantly. Compared to the fixed quintiles in Table 6, Panel A, large funds in the top quintile in Table 7, Panel B, perform better. Thus, while there is some evidence of a size effect—large funds do better—there is also evidence of an age effect—younger funds do better and then performance deteriorates.

To examine these competing effects, Panel C presents the results of a regression of portfolio alphas on both age and size quintiles. We find that the time trend is negative and significant, while the effect of size is positive but insignificant. This confirms that, even after controlling for possible performance persistence due to size, emerging hedge funds and managers do perform better than their older counterparts.

## V. Conclusion

While recent research has analyzed various facets of hedge fund performance, none has focused on emerging managers and funds. This is a particularly interesting category given the incentive features of the hedge fund industry. Emerging managers have particularly strong financial incentives to create performance and may be more nimble than established ones. In addition, emerging funds are more likely to be open to new investors whereas older, strongly-performing hedge funds may not be. This paper provides the first systematic analysis of performance patterns for emerging hedge funds and managers and makes several contributions to the literature.

First, we examine how hedge funds perform over time and what role age plays in performance. Prior work which pools hedge funds over time or examines hedge fund performance cross-sectionally misses the role of age. For example, if new hedge funds do well initially, and many new hedge funds are started every year, then one might (mistakenly) conclude that hedge funds do well over time. Our cohort analysis and event time analysis indicate that the performance of new hedge funds does deteriorate over time. Importantly, we find this result after controlling for backfill bias. Because reporting is voluntary, managers are more likely to report good results rather than bad results, leading to a backfill bias in performance evaluation that is particularly severe for emerging funds. We find that the usual practice in empirical research of eliminating the first 12 or 24 months of the sample is insufficient to purge the backfill bias.

Second, using a novel event time approach, we find evidence of outperformance during the first two or three years of existence. Emerging funds and managers, narrowly defined as the first two years of a hedge fund's life, generate an abnormal performance of 2.3% relative to the later years. This difference is statistically and economically significant. A simple linear regression of abnormal returns on time reveals that each additional year of age decreases performance by 42 basis points, on average. This effect holds across various organization types, i.e. single-fund and multi-fund management companies. This alpha also exists whether or not the manager has previously run another fund that appears in the TASS database. This effect does not seem to have a simple relationship with size. Large emerging funds do better, but the relationship is not uniform. We do find that large funds from multi-product management companies tend to perform better, which is consistent with the hypothesis of a competitive advantage due to their organizational infrastructure.

Third, we find strong evidence that, for individual funds, early performance is quite persistent. We find persistence for up to five years for emerging funds. Thereafter, performance persistence fades away, along with the outperformance we also document. Thus, as predicted by theory, emerging funds and managers tend to add value relative to their more established peers.

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## Table 1
## Hedge Fund Portfolios in Event Time: Raw Returns

This table presents the performance of portfolios aligned by event time, which is the first month of reported performance. Portfolios are constructed as equal-weighted averages of fund raw returns during each month. Returns are then grouped by year, i.e., first twelve months for year 1 and so on. Annualized volatility is reported for each year, from the portfolio time series. The t-statistic tests the hypothesis of equal annual return from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Average of fund volatility is the cross-sectional average of annualized volatility for each fund over 12 months. Panel A presents results for funds with no backfill, i.e., with the inception date very close to the date first reported to the database. Panel B presents results for funds with backfill, i.e., which do not satisfy the previous definition. Number of funds is at the start of each cohort year.

### Panel A: Funds With No Backfill

| Cohort Year | Raw Returns (Annual) | Annualized Volatility (Portfolio) | Number of Funds | T-statistic of Equal Return | Average of Fund Volatility |
|---|---|---|---|---|---|
| 1 | 12.16% | 1.27% | 923 | | 12.73% |
| 2 | 7.99% | 0.82% | 749 | 2.76* | 12.52% |
| 3 | 7.30% | 1.26% | 505 | 0.46 | 12.01% |
| 4 | 8.32% | 1.07% | 324 | -0.61 | 11.19% |
| 5 | 8.90% | 1.12% | 221 | -0.38 | 9.93% |
| 6 | 6.69% | 1.03% | 143 | 1.45 | 9.78% |
| 7 | 11.06% | 1.54% | 92 | -2.36* | 8.97% |
| 8 | 9.97% | 1.95% | 67 | 0.44 | 8.77% |
| 9 | 11.83% | 2.88% | 44 | -0.53 | 10.13% |

### Panel B: Backfilled Funds

| Cohort Year | Raw Returns (Annual) | Annualized Volatility (Portfolio) | Number of Funds | T-statistic of Equal Return | Average of Fund Volatility |
|---|---|---|---|---|---|
| 1 | 18.60% | 0.62% | 2266 | | 14.22% |
| 2 | 12.42% | 0.99% | 2115 | 5.27* | 13.19% |
| 3 | 11.84% | 1.21% | 1787 | 0.37 | 12.59% |
| 4 | 10.73% | 0.64% | 1399 | 0.82 | 11.90% |
| 5 | 8.26% | 1.32% | 1064 | 1.68 | 11.52% |
| 6 | 9.13% | 0.92% | 806 | -0.54 | 10.58% |
| 7 | 11.72% | 1.51% | 579 | -1.46 | 10.28% |
| 8 | 11.51% | 1.54% | 377 | 0.09 | 9.97% |
| 9 | 11.34% | 1.39% | 261 | 0.08 | 9.63% |

## Table 2
## Non-Backfilled Hedge Fund Portfolios in Event Time: Alphas

This table presents the performance of portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. Panel A presents hedge fund portfolio alphas. Portfolios are constructed as equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_S$ is the style index and beta is estimated over a 2-year window. Alpha and its standard error are annualized. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Average of fund beta is the cross-sectional average of beta for each fund. Panel B presents the results of a regression of alphas on a monthly time trend. Standard errors are in parentheses.

Panel A: Abnormal Performance

| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha | Average of Fund Beta |
|---|---|---|---|---|---|
| 1 | 4.31%* | 1.12% | 923 | | 0.660 |
| 2 | 1.10% | 0.78% | 749 | 2.35* | 0.686 |
| 3 | 0.59% | 0.79% | 505 | 0.45 | 0.775 |
| 4 | 0.26% | 1.13% | 324 | 0.24 | 0.742 |
| 5 | 1.99%* | 0.82% | 221 | -1.23 | 0.711 |
| 6 | -0.37% | 0.78% | 143 | 2.09* | 0.789 |
| 7 | 0.13% | 1.00% | 92 | -0.39 | 0.876 |
| 8 | 1.51% | 1.93% | 67 | -0.63 | 0.705 |
| 9 | -1.48% | 2.08% | 44 | 1.06 | 0.743 |

Panel B: Regression of Portfolio Alphas on Age (Monthly)

| | (1) | (2) |
|---|---|---|
| Independent Variables: | | |
| Constant | 0.2324* | 0.5597* |
| | (0.0700) | (0.1398) |
| Age | -0.0029* | |
| | (0.0011) | |
| Ln(Age) | | -0.1307* |
| | | (0.0365) |
| Adj. R-squared | 0.0509 | 0.0993 |
| N | 108 | 108 |

## Table 3
## Non-Backfilled Hedge Fund Portfolios Alphas Analysis by Category

This table presents the performance of portfolios for non-backfilled funds aligned by event time. Portfolios are constructed as equal-weighted averages of funds' alphas, measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_S$ is the style index and beta is estimated over a 2-year window. Alpha and its standard error are annualized. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Panel A splits the sample into funds from management companies with multiple and single funds. Panel B splits the sample into funds with managers who have and have not previously run a fund reporting to TASS. Because the name of the portfolio manager is not reported in TASS for 33 of our non-backfilled funds, the total number of funds in this panel is 890, not 923. Panel C presents regressions of alphas on age, with various groupings. Panel D presents separate regressions for live single funds, live multi-funds, dead single funds, and dead multi-funds. There are only 96 monthly observations for the dead single funds as the number of dead single funds falls to one after 96 months.

Panel A: Abnormal Performance Split by Hedge Funds Belonging to Multi-fund Management Companies and Single-fund Companies

| Funds from Management Companies with Multiple Funds | | | | | Funds from Management Companies with a Single Fund | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha | Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha |
| 1 | 4.53%* | 1.14% | 576 | | 1 | 3.96%* | 1.44% | 347 | |
| 2 | 0.41% | 0.93% | 475 | 2.80 | 2 | 2.32%* | 1.11% | 274 | 0.90 |
| 3 | 0.09% | 0.95% | 326 | 0.24 | 3 | 1.46% | 1.44% | 179 | 0.47 |
| 4 | 0.16% | 1.29% | 203 | -0.04 | 4 | 0.44% | 1.36% | 121 | 0.52 |
| 5 | 4.26%* | 1.30% | 137 | -2.24 | 5 | -1.76% | 0.95% | 84 | 1.33 |
| 6 | 0.56% | 1.23% | 90 | 2.07 | 6 | -1.96% | 1.83% | 53 | 0.09 |
| 7 | 1.51% | 1.29% | 60 | -0.53 | 7 | -2.36%* | 1.06% | 32 | 0.19 |
| 8 | 0.39% | 2.90% | 42 | 0.35 | 8 | 3.59%* | 1.44% | 25 | -3.33 |
| 9 | -0.67% | 2.65% | 28 | 0.27 | 9 | -3.15% | 1.80% | 16 | 2.93 |

Panel B: Abnormal Performance Split by Hedge Funds with Managers Who Have Previously Run a Fund and Funds with Managers Who Have Not Previously Run a Fund

| Funds with managers who have previously run a fund in TASS | | | | | Funds with managers who have <u>not</u> previously run a fund in TASS | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha | Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha |
| 1 | 4.25%* | 1.37% | 397 | | 1 | 4.04%* | 1.14% | 493 | |
| 2 | 1.73% | 0.92% | 325 | 1.52 | 2 | 1.27% | 1.14% | 392 | 1.72 |
| 3 | 1.75% | 1.13% | 227 | -0.01 | 3 | 0.27% | 1.32% | 254 | 0.58 |
| 4 | 0.38% | 1.34% | 145 | 0.78 | 4 | -0.44% | 1.39% | 167 | 0.37 |
| 5 | 5.56%* | 1.57% | 97 | -2.51 | 5 | -1.21% | 0.85% | 116 | 0.47 |
| 6 | -0.33% | 1.11% | 74 | 3.07 | 6 | -0.38% | 1.17% | 64 | -0.57 |
| 7 | 1.52% | 1.79% | 49 | -0.88 | 7 | -1.36% | 1.83% | 39 | 0.45 |
| 8 | 0.21% | 2.20% | 38 | 0.46 | 8 | 2.83% | 2.76% | 26 | -1.27 |
| 9 | -1.57% | 2.57% | 26 | 0.52 | 9 | -2.86% | 2.48% | 15 | 1.54 |

Panel C: Regression of Portfolio Alphas on Age (Monthly), Splits

Sub-Panel 1: Split by whether the fund is from a single fund management company or a multifund management company
Sub-Panel 2: Split by whether managers have previously run a fund in TASS
Sub-Panel 3: Split by Live versus Dead Funds.

| | Sub-Panel 1 | | Sub-Panel 2 | | Sub-Panel 3 | |
|---|---|---|---|---|---|---|
| | Single | Multifund | Previously Run | Not Previously Run | Live | Dead |
| Independent Variables: | | | | | | |
| Constant | 0.6467* | 0.5148* | 0.6370* | 0.5364* | 0.8652* | 0.3135 |
| | (0.1665) | (0.1893) | (0.1878) | (0.1914) | (0.1576) | (0.2669) |
| Ln(Age) | -0.1679* | -0.1106* | -0.1379* | -0.1391* | -0.1783* | -0.1123 |
| | (0.0435) | (0.0494) | (0.0491) | (0.0500) | (0.0412) | (0.0698) |
| Adj. R-squared | 0.0634 | 0.0360 | 0.0606 | 0.0592 | 0.1421 | 0.0147 |
| N | 108 | 108 | 108 | 108 | 108 | 108 |

Panel D: Regression of Portfolio Alphas on Age (Monthly),
Split by live/dead and single/multifund

| | Live, Single | Live, Multifund | Dead, Single | Dead, Multifund |
|---|---|---|---|---|
| Independent Variables: | | | | |
| Constant | 1.2065* | 0.7094* | 0.2444 | 0.3906 |
| | (0.1945) | (0.2022) | (0.3575) | (0.3391) |
| Ln(Age) | -0.2646* | -0.1384* | -0.1148 | -0.1212 |
| | (0.0508) | (0.0529) | (0.0963) | (0.0886) |
| Adj. R-squared | 0.1961 | 0.0519 | 0.0044 | 0.0080 |
| N | 108 | 108 | 96 | 108 |

**Table 4**
**Backfilled Hedge Fund Portfolios in Event Time: Alphas**

This table presents the performance of portfolios aligned by event time, which is the first month of reported performance. Funds are backfilled. In Panels A and C, event time starts with the first month of reported performance after inception. In Panels B and D, event time starts with the first month of reported performance after the fund starts reporting to the database. Portfolios are constructed as equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_S$ is the style index and beta is estimated over a 2-year window. Alpha and its standard error are annualized. The t-statistic tests the hypothesis of equal annual alpha from one year to the next. Statistical significance at the two-sided 95% level indicated by *. Average of fund beta is the cross-sectional average of beta for each fund. Standard errors are between parentheses

Panel A: Abnormal Performance from Inception

| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha |
|---|---|---|---|---|
| 1 | 10.96%* | 0.77% | 2266 | |
| 2 | 5.17%* | 0.51% | 2115 | 6.27* |
| 3 | 3.40%* | 0.45% | 1787 | 2.60* |
| 4 | 2.00%* | 0.59% | 1399 | 1.90 |
| 5 | 0.64% | 0.70% | 1064 | 1.48 |
| 6 | 0.99%* | 0.41% | 806 | -0.43 |
| 7 | -0.32% | 0.64% | 579 | 1.72 |
| 8 | -0.86% | 0.68% | 377 | 0.59 |
| 9 | -0.77% | 0.69% | 261 | -0.10 |

Panel B: Abnormal Performance from Date Added to the Database

| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha |
|---|---|---|---|---|
| 1 | 1.53%* | 0.45% | 2116 | |
| 2 | 0.52% | 0.45% | 1538 | 1.60 |
| 3 | -0.62% | 0.39% | 1038 | 1.90 |
| 4 | -1.42%* | 0.67% | 708 | 1.04 |
| 5 | -0.54% | 0.73% | 474 | -0.89 |
| 6 | -2.13%* | 0.64% | 300 | 1.63 |
| 7 | -0.25% | 0.93% | 134 | -1.67 |
| 8 | 0.37% | 1.26% | 90 | -0.40 |
| 9 | -0.06% | 1.32% | 52 | 0.24 |

Panel C: Abnormal Performance from Inception Split by Hedge Funds Belonging to Multi-fund Management Companies and Single-fund Companies

| Funds from Management Companies with Multiple Funds | | | | | Funds from Management Companies with a Single Fund | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha | Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha |
| 1 | 9.61%* | 0.89% | 1274 | | 1 | 12.68%* | 0.98% | 992 | |
| 2 | 3.92%* | 0.60% | 1190 | 5.29* | 2 | 6.78%* | 0.60% | 925 | 5.13* |
| 3 | 2.46%* | 0.40% | 998 | 2.02* | 3 | 4.58%* | 0.56% | 789 | 2.67* |
| 4 | 1.52%* | 0.68% | 758 | 1.20 | 4 | 2.57%* | 0.77% | 641 | 2.11* |
| 5 | 0.46% | 0.72% | 552 | 1.07 | 5 | 0.82% | 0.90% | 512 | 1.48 |
| 6 | 2.01%* | 0.44% | 405 | -1.83 | 6 | -0.03% | 0.76% | 401 | 0.73 |
| 7 | -0.05% | 0.53% | 289 | 2.98* | 7 | -0.59% | 0.93% | 290 | 0.46 |
| 8 | -1.77% | 1.12% | 174 | 1.39 | 8 | -0.07% | 0.66% | 203 | -0.46 |
| 9 | -0.32% | 0.84% | 126 | -1.04 | 9 | -1.19% | 0.77% | 135 | 1.11 |

Panel D: Abnormal Performance from Date Added to Database Split by Hedge Funds Belonging to Multi-fund Management Companies and Single-fund Companies

| Funds from Management Companies with Multiple Funds | | | | | Funds from Management Companies with a Single Fund | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha | Year | Alpha (Annual) | Standard Error | Number of Funds | T-statistic of Equal Alpha |
| 1 | 0.96%* | 0.45% | 1187 | | 1 | 2.28%* | 0.58% | 929 | |
| 2 | 0.54% | 0.53% | 860 | 0.60 | 2 | 0.49% | 0.54% | 678 | 2.24* |
| 3 | -0.22% | 0.61% | 576 | 0.93 | 3 | -1.06% | 0.66% | 462 | 1.81 |
| 4 | -0.25% | 0.67% | 370 | 0.04 | 4 | -2.72%* | 0.90% | 338 | 1.50 |
| 5 | 0.77% | 0.65% | 248 | -1.09 | 5 | -1.93% | 1.44% | 226 | -0.47 |
| 6 | -1.11% | 0.90% | 154 | 1.70 | 6 | -3.22%* | 0.69% | 146 | 0.81 |
| 7 | -0.75% | 0.69% | 69 | -0.32 | 7 | 0.18% | 1.48% | 65 | -2.09* |
| 8 | 0.31% | 1.29% | 46 | -0.72 | 8 | 0.46% | 1.56% | 44 | -0.13 |
| 9 | -2.00% | 2.08% | 26 | 0.94 | 9 | 1.46% | 2.21% | 26 | -0.37 |

## Table 5
## Performance Persistence in Event Time—Non-Backfilled Hedge Funds

Panel A: Alpha Regressions

This panel presents the results of year-by-year cross-sectional regressions of: $\alpha_{it} = b_0 + b_{t-1}\alpha_{it-1} + \varepsilon_{it}$. We use the non-backfilled funds. Funds are aligned in event time: the first twelve months of performance are year 1, the second twelve months are year 2, etc. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_S$ is the style index and beta is estimated over a 2-year window. The regression tests for persistence in alphas year to year. The constant is not reported. Statistical significance at the two-sided 95% level indicated by *.

| Year t | Coefficient, Alpha Year t-1 | Standard Error of Coefficient | Number of Observations | Adj. R-squared |
|---|---|---|---|---|
| 2 | 0.290* | 0.046 | 749 | 0.049 |
| 3 | 0.278* | 0.046 | 505 | 0.065 |
| 4 | 0.100 | 0.065 | 324 | 0.004 |
| 5 | 0.119 | 0.124 | 221 | 0.000 |
| 6 | 0.076 | 0.063 | 143 | 0.003 |
| 7 | 0.127 | 0.104 | 92 | 0.005 |
| 8 | -0.278* | 0.121 | 67 | 0.060 |
| 9 | -0.115 | 0.185 | 44 | -0.014 |

Panel B: Portfolios

This panel presents differences in performance between top and bottom portfolio quintiles sorted by prior performance. Hedge funds are sorted into five portfolios by alpha quintiles in year t-1 (the ranking period); performance is then measured from the annualized average portfolio alpha in year t (the evaluation period). Funds may have partial observations during the evaluation period, so there is no look-ahead bias. Each quintile's alpha during the evaluation period is reported with standard errors in parentheses. The "difference" column reports the difference in annual alpha between the top quintile (Q5) portfolio and the bottom quintile (Q1) portfolio. The t statistic for the difference is reported in brackets below the difference. Statistical significance at the two-sided 95% level indicated by *.

| Year t | Alpha, Q5 (Top) | Alpha, Q4 | Alpha, Q3 | Alpha, Q2 | Alpha, Q1 (Bottom) | Difference Q5-Q1 |
|---|---|---|---|---|---|---|
| 2 | 6.71%* | 3.36%* | 3.20%* | -0.81% | -10.54%* | 17.25%* |
| | (0.93%) | (0.96%) | (0.83%) | (1.07%) | (3.00%) | [5.49] |
| 3 | 5.44%* | 1.87%* | -0.09% | -1.49% | -7.92%* | 13.36%* |
| | (1.35%) | (0.61%) | (0.98%) | (1.35%) | (3.56%) | [3.50] |
| 4 | 4.04% | -0.93% | 0.08% | 0.70% | -4.75% | 8.79%* |
| | (2.45%) | (1.38%) | (1.13%) | (1.38%) | (3.15%) | [2.20] |
| 5 | 8.09%* | -1.59% | 4.67%* | 0.63% | -2.65% | 10.74%* |
| | (2.46%) | (1.63%) | (1.84%) | (1.28%) | (3.88%) | [2.34] |
| 6 | 1.80% | 1.63% | 0.34% | -3.80%* | -3.90% | 5.69% |
| | (1.82%) | (1.96%) | (1.21%) | (1.55%) | (2.74%) | [1.73] |
| 7 | 1.21% | 2.76% | 3.93% | -6.22%* | -2.31% | 3.52% |
| | (1.41%) | (1.99%) | (2.29%) | (1.12%) | (4.70%) | [0.72] |
| 8 | -1.10% | 1.25% | 3.33%* | 0.48% | 3.50% | -4.60% |
| | (1.87%) | (2.06%) | (1.52%) | (3.09%) | (8.41%) | [0.53] |
| 9 | 0.46% | -5.21%* | -11.00%* | 7.29%* | 1.18% | -0.72% |
| | (5.02%) | (2.36%) | (2.49%) | (2.62%) | (7.98%) | [0.08] |

**Table 6**
**Non-Backfilled Hedge Fund Portfolios:**
**Alphas Sorted by Year of Inception, then by Size Quintile**

This table presents the performance of portfolios aligned by event time, which is the first month of reported performance. Funds are non-backfilled. Portfolios are constructed as equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_S$ is the style index and beta is estimated over a 2-year window. Funds are classified into size quintiles formed by assets under management (AUM) at the performance start date and then held constant through time. Panel A presents the average alpha and other statistics. Quintiles are classified by calendar year to account for the growth in assets in the hedge fund industry, after adjusting for inflation, and measured in 2006 dollars. The first row presents the average alpha. The second is the standard error. The third row is the number of funds in each year since inception and the fourth row reports the average AUM at inception. The bottom two rows report the F statistic and the p value for the test of the joint hypothesis that the five quintiles have the same alpha. Panel B presents the results of a regression of alphas on a time trend and size for all funds, single funds and multifunds. Panel C presents the results of a regression of alphas on a time trend and multifund dummy variable for small and large funds. Standard errors are in parentheses. Statistical significance at the two-sided 90% and 95% level indicated by $^+$ and *, respectively.

Panel A: Alphas Sorted by Year of Inception, then by Size Quintile

| Size Quintile | Year 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **Total** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Smallest** | 2.54% | -0.10% | 2.50% | -3.45% | 2.49% | -2.88% | 1.59% | -3.64% | -16.67% | -1.96% |
| | 2.03% | 2.24% | 1.96% | 2.23% | 2.39% | 1.86% | 2.55% | 2.59% | 4.23% | 0.85% |
| | 182 | 135 | 91 | 55 | 38 | 27 | 17 | 9 | 6 | |
| | $874,989 | | | | | | | | | |
| **2** | 0.31% | -0.27% | -0.11% | -1.57% | 14.80% | 2.81% | -1.01% | -0.76% | 7.88% | 2.45% |
| | 1.53% | 2.10% | 2.71% | 4.11% | 6.58% | 5.64% | 4.30% | 5.55% | 7.12% | 1.59% |
| | 184 | 147 | 95 | 59 | 35 | 23 | 15 | 13 | 9 | |
| | $2,602,771 | | | | | | | | | |
| **3** | 8.20% | -0.54% | 0.75% | 2.37% | -1.33% | -1.11% | 1.40% | 0.25% | 3.14% | 1.46% |
| | 1.09% | 1.27% | 1.75% | 2.07% | 2.65% | 2.78% | 1.63% | 1.86% | 0.94% | 0.63% |
| | 185 | 151 | 101 | 60 | 45 | 29 | 18 | 12 | 4 | |
| | $6,072,739 | | | | | | | | | |
| **4** | 8.16% | 4.05% | 2.22% | 4.34% | 2.88% | 0.62% | 0.07% | 3.41% | 0.20% | 2.88% |
| | 1.11% | 1.01% | 1.44% | 1.28% | 1.46% | 1.33% | 2.93% | 2.54% | 3.51% | 0.68% |
| | 186 | 154 | 101 | 75 | 53 | 33 | 22 | 16 | 12 | |
| | $13,470,266 | | | | | | | | | |
| **Largest** | 4.42% | 0.84% | 0.46% | -2.48% | 0.91% | -1.85% | 0.02% | 0.40% | -2.63% | 0.01% |
| | 1.29% | 1.08% | 1.08% | 1.24% | 1.23% | 2.16% | 2.21% | 1.36% | 1.64% | 0.51% |
| | 186 | 162 | 117 | 75 | 50 | 31 | 20 | 17 | 13 | |
| | $55,937,174 | | | | | | | | | |
| F statistic | 2.061$^+$ | 0.678 | 0.183 | 1.921 | 0.963 | 0.551 | 0.141 | 0.724 | 1.639 | |
| p value | 0.100 | 0.611 | 0.946 | 0.129 | 0.442 | 0.700 | 0.965 | 0.591 | 0.256 | |

Panel B: Regression of Portfolio Alphas on Age (Monthly) and Size, Sorted by Single vs. Multifund

| | All | Single | Multifund |
|---|---|---|---|
| Independent Variables: | | | |
| Constant | 0.5645* | 0.5259* | 0.6031* |
| | (0.1435) | (0.1934) | (0.2115) |
| Ln(Age) | -0.1506* | -0.1428* | -0.1584* |
| | (0.0365) | (0.0491) | (0.0537) |
| Size (Dummy) | 0.1051 | 0.0173 | 0.1930$^{+}$ |
| | (0.0676) | (0.0911) | (0.0996) |
| Adj. R-squared | 0.0390 | 0.0292 | 0.0463 |
| N | 432 | 216 | 216 |

Panel C: Regression of Portfolio Alphas on Age (Monthly) and Single vs. Multifund, Sorted by Size

| | Small | Large |
|---|---|---|
| Independent Variables: | | |
| Constant | 0.4377$^{+}$ | 0.6893* |
| | (0.2451) | (0.1482) |
| Ln(Age) | -0.1190$^{+}$ | -0.1821* |
| | (0.0622) | (0.0376) |
| Multifund (Dummy) | 0.0194 | 0.1951* |
| | (0.1154) | (0.0698) |
| Adj. R-squared | 0.0078 | 0.1196 |
| N | 216 | 216 |

## Table 7
## Non-Backfilled Hedge Fund Portfolios:
## Alphas Sorted by Cohort and Calendar Year

This table presents the performance of portfolios aligned by cohort and calendar year (instead of by event time). Non-backfilled funds are selected each month for funds that start within the year. Portfolios are constructed as equal-weighted averages of funds' raw returns and alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_S$ is the style index and beta is estimated over a 2-year window. Panel A presents statistics for raw returns and alphas. Statistical significance at the two-sided 95% level indicated by *. Panel B reforms size quintiles every year. The first row presents the average alpha. The second is the standard error. The third and fourth report the average AUM and number of funds for each cell. Panel C presents the results of a regression of alphas on a time trend and size. Standard errors are in parentheses.

Panel A: Raw Returns and Alphas

| Year | Raw Returns (Annual) | Annualized Volatility (Portfolio) | Alpha (Annual) | Standard Error | Number of Funds |
|---:|---:|---:|---:|---:|---:|
| 1 | 18.54% | 2.99% | 9.77%* | 1.82% | 923 |
| 2 | 8.11% | 2.06% | 1.23% | 0.79% | 749 |
| 3 | 6.63% | 1.94% | 0.79% | 0.83% | 505 |
| 4 | 8.79% | 1.92% | 1.29% | 1.03% | 324 |
| 5 | 7.10% | 1.98% | 0.97% | 1.02% | 221 |
| 6 | 7.92% | 2.16% | 1.20% | 1.29% | 143 |
| 7 | 8.34% | 2.18% | -0.37% | 0.98% | 92 |
| 8 | 12.24% | 2.57% | 1.76% | 1.49% | 67 |
| 9 | 9.64% | 3.79% | 0.46% | 2.01% | 44 |

Panel B: Alphas Sorted by Age and Size (Size Quintiles Reformed Every Year)

| Size Quintile | Cohort 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | **Total** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Smallest** | 13.70% | -4.15% | -1.89% | -1.25% | -3.68% | -4.41% | -3.85% | 9.87% | -9.03% | -0.52% |
| | 3.75% | 2.16% | 2.54% | 4.12% | 3.75% | 3.62% | 2.79% | 5.86% | 5.39% | 1.32% |
| | 184 | 161 | 114 | 72 | 49 | 32 | 20 | 14 | 10 | |
| **2** | 3.13% | 2.35% | 1.62% | 4.76% | 1.73% | 0.81% | -0.44% | -0.26% | 3.42% | 1.90% |
| | 3.36% | 1.53% | 2.18% | 2.03% | 2.16% | 2.09% | 2.33% | 3.33% | 5.64% | 0.99% |
| | 185 | 162 | 116 | 74 | 49 | 34 | 22 | 15 | 11 | |
| **3** | 6.21% | 1.53% | -0.31% | 3.32% | -0.48% | -0.06% | 0.19% | -2.46% | 0.41% | 0.93% |
| | 1.47% | 1.51% | 1.57% | 1.59% | 2.23% | 1.59% | 1.67% | 1.70% | 1.73% | 0.56% |
| | 185 | 161 | 114 | 74 | 51 | 32 | 20 | 14 | 11 | |
| **4** | 14.56% | 2.93% | 2.75% | -0.75% | 4.85% | 2.97% | 1.06% | 1.03% | 4.00% | 3.71% |
| | 3.17% | 1.14% | 1.19% | 1.27% | 2.14% | 3.16% | 1.30% | 1.80% | 2.17% | 0.69% |
| | 184 | 162 | 114 | 74 | 49 | 32 | 22 | 15 | 11 | |
| **Largest** | 7.16% | 2.79% | 1.72% | -0.36% | 0.53% | 4.64% | 0.10% | 1.41% | 0.79% | 2.09% |
| | 2.19% | 1.04% | 1.00% | 0.92% | 1.15% | 0.98% | 1.27% | 1.25% | 2.46% | 0.49% |
| | 184 | 161 | 114 | 72 | 49 | 32 | 20 | 14 | 10 | |
| F statistic | 1.701 | 1.083 | 0.494 | 1.588 | 0.383 | 1.742 | 0.259 | 0.869 | 3.472* | |
| p value | 0.164 | 0.376 | 0.740 | 0.199 | 0.819 | 0.172 | 0.901 | 0.505 | 0.050 | |

Panel C: Regression of Portfolio Alphas (Monthly) on Age and Size Quintiles

| | Calendar Month Alphas |
|---|---|
| Independent Variables: | |
| Constant | 0.9611* |
| | (0.1583) |
| Ln(Age) | -0.2410* |
| | (0.0391) |
| Size | 0.0339 |
| | (0.0256) |
| R-squared | 0.0653 |
| N | 540 |

**Figure 1**
**Cumulative Abnormal Performance: Non-Backfilled and Backfilled Hedge Funds, Alphas Sorted by Event Time**

This graph presents the cumulative abnormal performance of portfolios aligned by event time, which is the first month of reported performance. Cohorts of hedge funds are displayed (1) with no backfill, i.e., for those funds with the inception date very close to the date first reported to the database, (2) with backfill, and (3) with backfill, but with the monthly observations prior to the fund being added to the database (the backfill period) eliminated. Portfolios are constructed as equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_i$ is the fund return, $R_S$ is the style index return, and beta is estimated over a 2-year window.

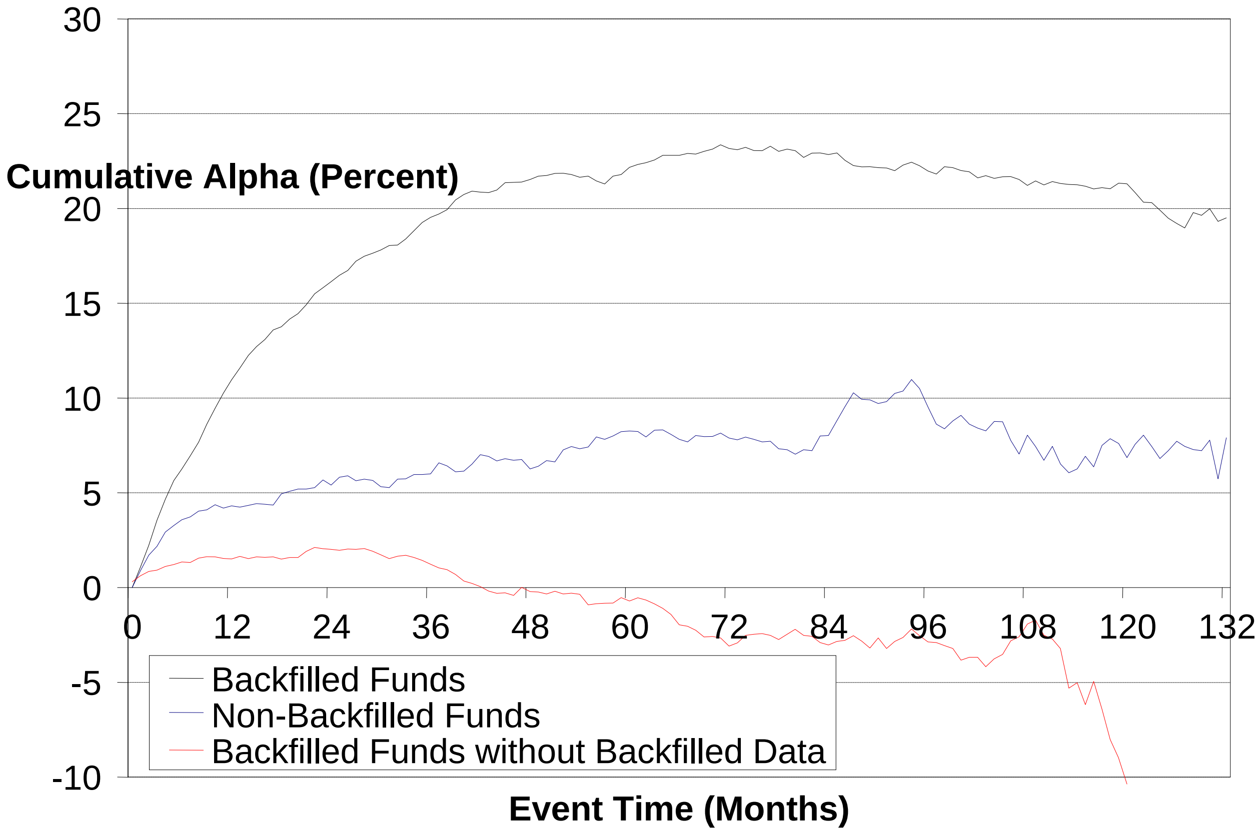

**Figure 2**
**Cumulative Abnormal Performance: Non-Backfilled and Backfilled Hedge Funds, Alphas Sorted by Event Time Eliminating the First 24 Months**

This graph presents the cumulative abnormal performance of portfolios aligned by event time, which is the first month of reported performance. Cohorts of hedge funds are displayed (1) with no backfill, i.e., for those funds with the inception date very close to the date first reported to the database, and (2) with backfill. Cohorts are shown after elimination of the first 24 months of alphas. Portfolios are constructed as equal-weighted averages of funds' alphas during each month. Alpha is measured as $\alpha_{it} = R_{it} - \beta_i R_{St}$, where $R_i$ is the fund return, $R_S$ is the style index return, and beta is estimated over a 2-year window.