NBER WORKING PAPER SERIES

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Working Paper 12015
http://www.nber.org/papers/w12015

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2006

We would like to thank Vikas Agarwal, Dmitri Alexeev, Torben Andersen, Duke Bristow, Art Bushonville, Bhagwan Chowdhry, Randolph Cohen, Kent Daniel, Harry DeAngelo, Dobrislav Dobrev, Shingo Goto, David Hsieh, Ken Judd, Robert Korajczyk, Ken Kroner, Ananth Madhavan, Rosa Matzkin, Narayan Naik, Todd Pulvino, Bryan Routledge, Che-Lin Su, Melvyn Teo, Sergey Tsyplakov, Motohiro Yogo, participants of the 2006 NBER Asset Pricing Program Meeting, 2006 Western Finance Association Meeting, 2007 American Finance Association Meeting, 2007 Advances in Theory Based Estimation: a Conference in Honor of Lars Hansen and Ken Singleton, and seminar participants at Barclays Global Investors, China Europe International Business School, East Carolina University, Georgia State University, Indian School of Business, National University of Singapore, Northwestern University, Singapore Management University, University of Arkansas, University of Illinois at Urbana-Champaign, University of Melbourne, University of New South Wales, University of North Carolina at Chapel Hill, University of South Carolina, University of Southern California, York University for their helpful discussions and suggestions. We are grateful to HFR Asset Management for providing us with the data. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 12015
February 2006, Revised August 2008
JEL No. I1

ABSTRACT

We examine whether hot hands exist among hedge fund managers. In measuring performance persistence, we use hedge fund style benchmarks. This allows us to identify managers with valuable skills, and also to control for option-like features inherent in returns from hedge fund strategies. We take into account the possibility that reported asset values may be based on stale prices. We develop a statistical model that relates a hedge fund's performance to its decision to liquidate or close in order to infer the performance of a hedge fund that left the database. While we find significant performance persistence among superior funds we find little evidence of persistence among inferior funds.

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1 Introduction

The hedge fund industry has grown at an astounding pace from 610 funds controlling $39 billion in 1990 to more than 9,000 funds with $1.9 trillion in 2007.[1] While it appears that investors have enthusiastically embraced hedge funds as an investment vehicle, and are especially eager to invest in hedge funds that have exhibited outstanding past returns, there is little consensus in the empirical finance literature on whether there is performance persistence among hedge funds. In part that is due to the fact that any rigorous research about hedge fund performance has to overcome numerous biases and irregularities in the available data. These biases arise due to the unregulated nature of the hedge fund industry. There are no legal requirements for hedge funds to report performance numbers, although there are several different databases, to which hedge funds provide information about themselves on a voluntarily basis.[2] Ackerman, McEnally, and Ravenscraft (1999), Liang (2000), Fung and Hsieh (2000) and Fung and Hsieh (2002) discuss the issues that arise when using data from these sources.

In this paper we study performance persistence among hedge fund managers, while correcting for measurement errors as well as for the backfill, serial correlation, and look-ahead biases in the data. We conjecture that certain types of skills are more valuable at certain points in time but the match decays over time. Given the decay, we cannot use a long time series to identify those managers whose skills will be in demand in the near future. Therefore, we use peer[3] evaluation to identify managers who are likely to have superior skills relative to their peer group, i.e., positive relative alpha. To the extent that there are common factors that affect all managers in a peer group, relative alphas can be estimated more precisely than alphas by controlling for these common effects. This is especially true with short time series of hedge fund return data on individual hedge fund managers. However, evidence of the relative performance persistence cannot be directly interpreted as superior fund performance to an investor. Indeed, outperforming the group of peers does not guarantee superior alpha in absolute terms, as the entire peer group may have inferior performance. We examine whether managers with superior historical relative alpha indeed also have superior future alpha in the following way. We construct managed portfolios of hedge funds based on their historical relative alpha, and examine their out-of-sample performance using the multifactor hedge fund performance evaluation model of Fung and Hsieh (2004).

An important feature of a hedge fund database is backfill bias - the case when hedge funds bring their history with them when they join a database. Since only funds with

[1] "Plenty of Alternatives," The Economist, Feb 28, 2008.

[2] Among them are CISDM, TASS and HFR (we use the HFR database in the paper).

[3] We define "peers" as a group of hedge funds pursuing similar strategies.

relatively superior historical performance enter a database, when possible backfilling of data is ignored, it results in a bias toward mistakenly assigning superior ability to managers of funds in their earlier years. Since our HFR data contains the information on when funds actually joined the database, we are able to eliminate the backfill bias by deleting all the backfill observations in our data set. Moreover, our data is survivorship bias free, since the HFR database retains all hedge funds, including those that ceased to exist.

Another issue with hedge fund analysis is that hedge fund returns exhibit substantial serial correlation, a feature that is extensively investigated in Getmansky, Lo, and Makarov (2004) and Okunev and White (2003). They showed that the presence of illiquid assets in hedge fund portfolios are the primary source for the serial correlation. If serial correlation is not accounted for properly, the manager's performance measure will be biased. Notice that when hedge fund returns exhibit serial correlation due to the presence of illiquid assets in the portfolio, benchmark style index factor returns will also exhibit such serial correlation. We assume that unobserved "true" returns on assets are serially uncorrelated, and identify them using the MA2 approach suggested by Getmansky, Lo, and Makarov (2004). We measure performance relative to a carefully chosen portfolio of fund specific style index benchmarks and a broad stock market index, i.e., we use alpha relative to peers. To the extent peers within each hedge fund style take similar risks, we are able to control for option-like features in returns.

We evaluate hedge fund performance persistence by comparing the alphas over consecutive nonoverlapping three year intervals. This is a fairly long time period relative to the time periods examined in the literature reviewed in the following section. Considering a three-year period allows us to accurately capture relative alphas for individual funds, and also provides us with a better sense of investor returns accounting for lockup, notice, and redemption periods. For example, an investor in a fund with a two year lockup period can realistically expect to receive her money from two years and three months to two years and six months later. Lockup periods vary among different funds, but periods of two years or more have gotten more common in recent years.[4] Following Hsieh,[5] we employ a method of weighted least squares in order to minimize the downward bias in persistence caused by measurement errors in alphas. We assign more weight to more precisely measured alphas in our sample. We further apply this approach to study persistence among the best performing and the worst performing funds separately.

[4] For example, in 1996, LTCM allowed to withdraw one third of investor's capital in years 2, 3, and 4 (Perold (1999)). The adoption of a new SEC rule in December 2004 provided further incentives for hedge funds to adopt lockup periods in excess of two years (the rule was struck down by the US Court of Appeals in June 2006).

[5] Mimeo, private communication.

Finally, some hedge funds stop reporting to the database before the end of the sample period used in the study.[6] That may lead to a biased estimate of alpha-persistence when the likelihood of a fund leaving the database is related to its past and expected future performance. Therefore, estimating performance persistence by regressing future alpha on past alpha without addressing conditional nature of the observed distribution of alphas may produce a biased estimate of alpha persistence. We follow the terminology of Baquero, Ter Horst, and Verbeek (2005), and refer to it as a look-ahead bias. We simultaneously address measurement errors and the look-ahead bias by building a statistical model that assumes that hedge funds that are liquidated are more likely to be ones with low past performance and those that are closed are more likely to be ones with high past performance. Our statistical model provides additional information about the unobserved performance of funds thereby reducing the measurement error in estimated alphas, provided the model is right. We assume that hedge funds that stop reporting but do not give a reason are drawn from the same distribution as funds that continue to report or stop reporting but tell us why. With these assumptions, which we empirically show are reasonable, we develop a GMM estimation method that estimates all parameters in the model and produces an estimate of performance persistence. Our approach is also consistent with the observation in Brown, Goetzmann, and Park (2001) and Liang (2000) that hedge funds with low past performance are primary candidates for liquidation. Overall, both weighted least squares and GMM approaches produce similar estimates of performance persistence.

The unobserved performance of a hedge fund after it stopped reporting to the database can result in a biased persistence estimate. For example, a fund that has a large positive alpha during the first three year period may perform poorly during the second three year period and liquidate; a fund that has a large negative alpha during the first three year period may perform extremely well during the second three year period and close; and both funds will stop reporting their performance data. That could cause a positive bias in measured persistence in the alphas of funds that survived during both three year periods. While it is a possibility, we provide diagnostics indicating that it is not a likely scenario.

We find relative performance persistence over a three year horizon, i.e. that managers with higher estimated alphas in one three year period tend to have higher estimated relative alphas in the following three year period. The average performance persistence parameter estimate is 28% from the weighted least squares approach,[7] and 31% from the GMM proce-

[6]Notice that the fact of nonreporting to a database does not mean fund liquidation. For example, a fund may stop reporting after it has been closed for *new* investors. Such a hedge fund will continue to manage funds of current investors.

[7]Individual cross-section estimates for the weighted least squares approach vary from 4.4% to 52.7%.

dure.[8] In comparison, a simple regression of future alphas on past alphas gives a downward biased average estimate of only 22% for alpha persistence.

Notice that an investor can only benefit from our approach by investing in hedge funds run by talented managers, and staying away from the ones that have not demonstrated persistent skill, since an investor cannot take a short position in a hedge fund. Hence we concentrate on investigating positive performance persistence, which could be interpreted as evidence of valuable managerial skill. We conduct out-of-sample portfolio tests based on historical alpha and relative alpha rankings, and find evidence of performance persistence among the top hedge funds. In contrast, there is no evidence of persistence among the bottom funds. Consistent with our conjecture of relative performance being a better measure of valuable managerial talent, we conclude that historical superior relative performance is a better predictor of superior future absolute performance, compared to historical superior absolute performance. We document that a portfolio of the top 33% of funds ranked by their historical *relative alpha* t-statistic retained 26% of its historical alpha in the out-of-sample period, while a similar portfolio formed by *alpha* t-statistic ranking only retained 19% of its historical alpha.[9]

Our findings are consistent with Berk and Green (2004) who show, using a rational model of active portfolio management, that in equilibrium more money will flow to managers with superior skills. This leads to an erosion of performance over time and equalization of after fee returns available to investors from managers with different levels of skills, when there are diminishing returns to scale. Nevertheless, only part of the superior performance erodes.

The rest of this paper is organized as follows. The next section provides a connection to the existing hedge fund performance persistence literature. Section 3 describes the methodology for empirical testing. The model of hedge fund performance is introduced, factor selection, return smoothing and look-ahead bias issues are discussed there. Tests for performance persistence are also explained. Section 4 contains data description, along with estimation of hedge fund performance persistence. Out-of-sample tests of performance persistence are performed in section 5. Section 6 concludes.

2 Related Literature

There are several papers in the literature that examine hedge fund managers' performance persistence. Brown, Goetzmann, and Ibbotson (1999) estimated the offshore hedge fund

[8] Individual cross-section estimates from the GMM procedure vary from 5.8% to 49.6%.

[9] A portfolio of the top 10% of funds ranked by their past *relative alpha* t-statistic retained 45% of its past alpha in the out-of-sample period, while a similar portfolio formed by *alpha* t-statistic ranking retained 28% of its past alpha.

performance using raw returns, risk adjusted returns using the CAPM, and excess returns over self reported style benchmarks. They found little persistence in relative performance across managers. On the contrary, Agarwal and Naik (2000a) and Agarwal and Naik (2000b) when using both offshore and onshore hedge funds found significant quarterly persistence - that is hedge funds with relatively high returns in the current quarter tend to earn relatively high returns in the next quarter. They used the return on a hedge fund in excess of the average return earned by all funds that follow the same strategy as a measure of performance.[10] They used both parametric and nonparametric tests for performance persistence. In their case the persistence was driven mostly by "losers". Edwards and Caglayan (2001) considered an eight-factor model to evaluate hedge fund performance. They found the evidence of performance persistence over one and two year horizons. They also showed that the persistence holds among both "winners" and "losers".

More recently, Bares, Gibson, and Gyger (2003) applied a non-parametric approach to individual funds, as well as an eight-factor APT model to fund portfolios with a conclusion of performance persistence only over one to three month horizons. Capocci and Hübner (2004) followed the methodology of Carhart (1997), discovering no evidence of performance persistence for best and worst performing funds, but providing limited evidence of persistence for middle decile funds. Boyson and Cooper (2004) have found no evidence of performance persistence if only common risk and style factors are used in estimation, but discovered quarterly persistence when manager tenure was taken into consideration. Baquero, Ter Horst, and Verbeek (2005) concentrated on accounting for the look-ahead bias in evaluating hedge fund performance. Comparing raw and style-adjusted performance of performance-ranked portfolios they found evidence of positive persistence at the quarterly level. Kosowski, Naik, and Teo (2007) used a seven-factor model and applied a bootstrap procedure, as well as Bayesian measures to estimate hedge fund performance. Considering performance-ranked portfolios they found evidence of performance persistence over a one year horizon. Finally, Fung, Hsieh, Naik, and Ramadorai (2007), using data for fund of hedge funds, show that it is possible to identify fund of funds that deliver superior alphas. However, they find that new money flows faster into such funds leading to a deterioration of their performance over time.

This paper contributes to the above literature in three ways. First, control for the measurement errors in alphas using weighted least squares and GMM procedure. The latter deals with measurement errors and the look-ahead bias simultaneously. Second, to our knowledge, this paper is first to study performance persistence to account for all three major

[10] They also examined the standardized measure of performance, i.e., the excess return dividend by its standard deviation.

biases in hedge fund data, i.e. backfill, serial correlation, and look-ahead biases. Third, we present evidence of hedge fund managers' performance persistence over longer (three year) horizons, especially among the top performing funds.

3 Econometric Methodology

In this section we describe the estimation of hedge fund performance and then we propose a method to check for performance persistence.

3.1 Modeling the Relative Performance of a Hedge Fund

Hedge fund returns have several distinctive features. This can make the analysis of hedge funds' performance different from the analysis of performance of other assets like stocks and mutual funds.

First, hedge funds are not required to reveal their financial information including their returns.[11] This raises a question about the selectivity of returns in hedge fund databases. We should take into account possible reasons for a hedge fund to reveal its performance information. One possible explanation is that some hedge funds need to raise funds. Reporting their returns could be a way to advertise themselves. This implies that we will probably not find the most and the least successful hedge funds in the database. The most successful funds most likely have enough clients without any additional promotions. The least successful funds probably would not reveal their information to a broad set of investors.

Second, hedge fund strategies produce returns that cannot be well explained by standard factors,[12] and they also exhibit option-like features.[13] The usual way to estimate the performance in such a case is to include options on factors in addition to these factors, following the suggestion made by Glosten and Jagannathan (1994).

Third, hedge funds often hold illiquid securities in their portfolios. Usually, it is difficult to obtain current prices for such securities. In this case, managers use past prices to estimate the current value of assets. Therefore, we may observe serial correlation in returns. If we completely ignore this issue, then we will get inconsistent estimates of hedge fund performance. Scholes and Williams (1977) proposed a simple way to account for stale prices. They

[11] According to SEC regulation 13F institutional investors with assets under management more than $100M are supposed to reveal their long position holdings on quarterly basis.

[12] See Fung and Hsieh (1997).

[13] See for example, Fung and Hsieh (1997), Fung and Hsieh (2001), Mitchell and Pulvino (2001), Okunev and White (2003), Agarwal and Naik (2004), and Bondarenko (2004) for the discussion of the issues that option-like features in managed portfolio returns create when measuring performance.

used lags of factors along with factors in estimating the asset performance. These lags control for the serial correlation in returns. Asness, Krail, and Liew (2001) using this technique showed that the performance of indices[14] may not be as attractive as it appears from a regular regression without including any lags. Lo (2002) showed that annualized Sharpe ratios can be significantly overstated if the serial correlation in returns is not taken into account. Getmansky, Lo, and Makarov (2004) and Okunev and White (2003) introduced models for hedge fund returns, taking into account stale prices and return smoothing practices among hedge funds. Getmansky, Lo, and Makarov (2004) also estimated smoothing patterns for individual hedge funds and indices.

Fourth, the history of hedge funds is relatively short. Even for long-livers the reliable data in most cases does not exceed ten years. This creates a problem in analyzing hedge fund risks. The hedge fund return history may simply be too short for a high risk (low probability) event to happen. Weisman (2002) explains several simple strategies[15] that can be successful for a relatively long period of time (several years), but finally lead to bankruptcy. Those strategies will not be correlated with systematic factors. Pastor and Stambaugh (2002b), Pastor and Stambaugh (2002a), and Ben Dor, Jagannathan, and Meier (2003) developed techniques for dealing with short histories. Ben Dor, Jagannathan, and Meier (2003) used two stage regressions; Pastor and Stambaugh (2002b) and Pastor and Stambaugh (2002a) used Bayesian analysis. Kosowski, Naik, and Teo (2007) applied Bayesian technique to the hedge fund performance analysis.

Finally, the life of hedge funds can be pretty short. Hedge funds can be liquidated or closed for new investments. Even if a database is survivorship bias free (that is, it stores all the liquidated and closed funds), there is the issue of how these hedge funds should be taken into account when analyzing performance persistence.

While analyzing the performance of hedge funds and performance persistence, we will try to control for the above features of hedge fund returns. We follow Getmansky, Lo, and Makarov (2004) in designing an appropriate model for the estimation of hedge fund performance.

Let the true equilibrium (unobserved) excess returns follow:

$$R_{i,t}^{un} = \alpha_i + X_t \beta_i + \varepsilon_{i,t} \tag{1}$$

where X_t is the vector of excess returns on factor portfolios $(T \times l)$, ε_{it} are i.i.d. We define

[14] In the case of Hedge Fund Research style indices.

[15] Consider for example a strategy from St. Petersburg Paradox. You place one dollar on a coin to be tossed heads. If you lose, then you double your bets (if you do not have your own capital then you have to borrow). If you play long enough, then with probability one you will face a borrowing constraint.

α_i as the performance of a hedge fund. We assume that the observed returns (as reported by the hedge fund managers) are smoothed. Hence we observe the following returns

$$\begin{aligned} R_{i,t} &= \theta_0^i R_{i,t}^{un} + ... + \theta_s^i R_{i,t-s}^{un} \\ R_{i,t} &= \alpha_i + X_t \theta_0^i \beta_i + ... + X_{t-s} \theta_s^i \beta_i + u_{i,t} \\ R_{i,t} &= \alpha_i + X_t \theta_0^i \beta_i + ... + X_{t-s} \theta_s^i \beta_i + u_{i,t} \end{aligned}$$

Note that s may be different for different hedge funds. For identification purposes we will use the following normalization on the parameters:

$$\theta_0^i + ... + \theta_s^i = 1 \text{ for any } i$$

Combining with equation (1) we can write the observed returns as follows:

$$R_{i,t} = \alpha_i + X_t \theta_0^i \beta_i + ... + X_{t-s} \theta_s^i \beta_i + u_{i,t} \tag{2}$$

where

$$u_{i,t} = \theta_0^i \varepsilon_{i,t} + ... + \theta_s^i \varepsilon_{i,t-s} \tag{3}$$

As we see from (3), the error term $u_{i,t}$ follows an $MA(s)$ process. The next step is to choose appropriate factors for the model given by (2) and (3).

3.2 Relative Performance Factor Selection

In measuring relative fund performance we employed the following factors:

Variable	Description
R_t^{mkt}	Excess return on the market portfolio (CRSP)
$I_t^{J,self}$	Excess return on the self-reported style index J from HFR
$I_t^{K,aux}$	Excess return on an additional style index K from HFR

Therefore, $X_t' = [R_t^{mkt}, I_t^{J,self}, I_t^{K,aux}]$. The first factor is the CRSP market portfolio, and the other two factors are HFR style indices.[16] Style indices are defined as an equally weighted average of returns for all hedge funds with the same strategy. The hedge funds themselves provide information about strategies they use. The list of strategies[17] defined in

[16] Although we end up using no more than three factors, we perform a third factor selection from 32 HFR style indices by applying a statistical model selection criterion. This helps avoid model overparametrization, or "overfitting". See Bossaerts and Hillion (1999) for a discussion about using statistical model selection criteria in finance.

[17] For the official definition of self reported index, please refer to the web page of Hedge Fund Research at http://www.hedgefundresearch.com/pdf/HFR_Strategy_Definitions.pdf.

the database can be found in table 1.

Style indices are good proxies for non-linear strategies of hedge funds, however there are problems with self reported styles. For all hedge funds in the database we can find the styles that were reported by the hedge funds themselves. However, hedge funds may change their styles over time, and this may not be reflected in the database. We observe only one style per hedge fund and we do not know if a hedge fund has been using this style lately or some time ago (it may depend on the willingness of a hedge fund to report any changes in its style). To account for this "unpleasant" feature, we are going to add one more style index[18] in addition to the self reported index to try to capture changes in hedge fund styles. This additional style index is chosen by the Schwarz's Bayesian criterion (SBC) (details are provided in the next subsection).

The second problem is with style indices as factors. We know that the reported hedge fund returns are smoothed. By definition, a style index is the (equally weighted) average of returns for all hedge funds with the same self-reported strategy. Therefore, we should expect style indices to display serial correlations (or be "smoothed") as well. To deal with this problem, we consider the following model of "smoothed" indices (again we follow here Getmansky, Lo, and Makarov (2004)):

$$I_t^J = \gamma_0^J \eta_t^J + ... + \gamma_l^J \eta_{t-l}^J \tag{4}$$

where η_t^J represents the unobservable "true" factor J at time t. Let us assume that $\eta_t^J \sim N\left(\mu_J, \sigma_J^2\right)$. Equation (4) is a moving average process of order l. To identify this process, as before we assume $\gamma_0^J + ... + \gamma_l^J = 1$. From equation (4) we see that I_t^J follow an $MA\left(l\right)$. Hence, the true factors η_t^J can be estimated from (4) by maximum likelihood. For this estimation we set $l = 2$ (i.e. we assume that indices are smoothed up to two lags[19]). We will use η_t^J as factors in (2).

The autocorrelations of orders from 1 to 12 for the original database indices I_t^J are presented in figure 1. We can see that several indices have significant[20] first and second order autocorrelation. The examples of such strategies are "convertible arbitrage", "distressed securities", "emerging markets", etc. These strategies involve heavy trading in illiquid securities. Figure 2 displays the autocorrelations of orders from 1 to 12 for unsmoothed indices η_t^J. None of the unsmoothed indices η_t^J have statistically significant autocorrelations, and their autocorrelations are substantially smaller than corresponding autocorrelations in figure

[18]We also found little evidence that adding more than one additional style index improves the fit of the model.

[19]Getmansky, Lo, and Makarov (2004) use two lags to estimate the smooth model of hedge fund returns.

[20]At the a 5% significance level.

1.

3.3 Estimation Procedure

In order to check for performance persistence we have to have at least two periods with performance estimates, see figure 3. For every period, we run the following regression based on the model given by (2) and (3):

$$\begin{aligned} R_{i,t} &= \alpha_{zi} + X_t\delta_{0,i} + ... + X_{t-s}\delta_{s,i} + u_{i,t} \quad (5) \\ u_{i,t} &= \theta_0^i \varepsilon_{i,t} + ... + \theta_s^i \varepsilon_{i,t-s} \quad (6) \end{aligned}$$

where z is either 0 or 1, depending on if $T \leq t < T + k$ or $T + k \leq t < T + 2k$; X_t is the vector of factors described in the previous subsection.

We estimate the alphas by Maximum Likelihood. We also take into account the fact that the error term $u_{i,t}$ follows moving average process of order s. As a result of the maximum likelihood estimation procedure, we obtain consistent and asymptotically efficient estimators.

For every hedge fund we have to determine how many lags s to include and which additional indices are to be used in (5). We use Schwarz's Bayesian Criterion (Schwarz (1978)) to select the best model:

$$SBC = -2\log(L) + l \times \log(n)$$

where L is the likelihood function, l is the number of parameters and n is the number of observations. Given a hedge fund, we estimate several models like (5) that will be different in the number of lags and additional style indices. We then pick a model with the highest value of the Schwarz's Bayesian Criterion. For different hedge funds we may have different number of lags[21] in regression (5) and different additional indices.[22]

We use primary and additional style indices as factors in estimation of hedge fund performance. Therefore, we look at the *relative* performance of hedge funds with respect to hedge funds that follow similar investment strategies.

3.4 Performance Estimation

Studying hedge fund performance persistence by using the performance measure relative to HFR style indices provides valuable insight into the role of talent in the industry. Indeed, a finding of positive performance persistence could be interpreted as evidence of a hedge fund

[21] We consider up to two lags for each hedge fund.

[22] We also consider a model without an additional style index.

manager's superior talent relative to his or her peers. However, such a conclusion could be of little comfort to an investor, if it does not result in a significantly positive performance measured against a set of market factors.

To capture such performance measure, alpha, we modify the Fung and Hsieh (2004) seven-factor model of hedge fund performance in order to account for potential smoothing of reported returns as described in the previous subsection. Ideally, such a procedure would require running a model given by (5) and (6), except the vector of factors, X_t, would be as follows:[23]

$$X_t' = [SP500_t, SizeSpr_t, Bd10Y_t, CredSpr_t, BdOpt_t, FXOpt_t, ComOpt_t],$$

where

Variable	Description
$SP500_t$	S&P 500 index excess return
$\mathrm{SizeSpr}_t$	Wilshire Small Cap 1750 - Wilshire Large Cap 750 return
$Bd10Y_t$	Excess return on Fama treasury bond portfolio with maturities greater than 10 years
$CredSpr_t$	Excess return on the CitiGroup Corporate BBB 10+ yr index less $Bd10Y_t$
$BdOpt_t$	Excess return on the bond trend-following factor
$FXOpt_t$	Excess return on the currency trend-following factor
$ComOpt_t$	Excess return on the commodity trend-following factor

Unfortunately, using all seven Fung and Hsieh (2004) factors along with their lags in (5) would certainly result in overparametrization, since we have only 36 monthly observation points for a three-year estimation period. Bossaerts and Hillion (1999) advocated using statistical model selection criteria to overcome model overparametrization, or "overfitting". Hence we employ the Schwarz's Bayesian Criterion as a statistical model selection criterion in selecting an appropriate number of factors and lags for each fund. For each fund, we estimate models with all possible combinations of factors including up to two lags for each factor.[24] We then select a model with the highest value of the Schwarz's Bayesian Criterion. This procedure mirrors our approach in selecting an additional HFR index factor and an appropriate number of lags in the relative performance evaluation.

In the remainder of this paper, we refer to the resulting measure as the Fung and Hsieh (2004) model alpha.

[23] Bond, currency, and commodity trend-following factors are constructed as portfolios of lookback straddle options on these assets. These factors were introduced in Fung and Hsieh (2001) to replicate returns from trend-following strategies in bonds, currencies, and commodities. The current data on these factors was obtained from David Hsieh's web site at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls.

[24] This results in testing 381 different models for each fund.

3.5 Testing Hedge Fund Performance Persistence

Here we provide an econometric framework for testing a hypothesis of performance persistence.

3.5.1 Simple (Naive) Regressions

Suppose we have obtained the hedge fund alphas for two periods α_{0i} and α_{1i}. Then we can run a simple regression

$$\alpha_{1i} = a + b\alpha_{0i} + \varepsilon_i \tag{7}$$

The persistence would mean that the slope coefficient b is statistically different from zero. However, a statistically insignificant slope coefficient would not necessarily mean the absence of persistence. That is because the slope estimate can be biased toward zero due to measurement errors. We discuss the nature of this bias in the next subsection.

3.5.2 Measurement Errors and Estimation Bias

If the true alphas were known, then the regression (7) would have given us an unbiased estimate of performance persistence. However, in reality there is always a measurement error present in our estimates of alphas. Assume that we observe

$$\begin{aligned} \alpha_{0i} &= \alpha_{0i}^* + u_i \\ \alpha_{1i} &= \alpha_{1i}^* + v_i \end{aligned}$$

where α_{0i}^* and α_{1i}^* are "true"measures of relative performance, and noise components u_i, v_i are independent from the "true" alphas and from each other.

The OLS slope estimator from the regression (7) is equal to

$$\hat{b}_{OLS} = \frac{cov\left(\alpha_{1i}, \alpha_{0i}\right)}{Var\left(\alpha_{0i}\right)} = \frac{cov\left(\alpha_{1i}^*, \alpha_{0i}^*\right)}{Var\left(\alpha_{0i}^*\right) + Var(u_i)} \tag{8}$$

It is easy to see from (8) that the error in measuring α_0 creates the downward bias in the naive OLS estimate $\hat{b}_{OLS}$ compared to the "true" persistence estimate $\hat{b}^*$, since

$$\left|\hat{b}_{OLS}\right| = \left|\frac{cov\left(\alpha_{1i}^*, \alpha_{0i}^*\right)}{Var\left(\alpha_{0i}^*\right) + Var(u_i)}\right| < \left|\frac{cov\left(\alpha_{1i}^*, \alpha_{0i}^*\right)}{Var\left(\alpha_{0i}^*\right)}\right| = \left|\hat{b}^*\right|$$

Further, notice that the error in measuring α_1 does not result in a biased estimate of persistence, and thus we assume without loss of generality that $\alpha_{1i} = \alpha_{1i}^*$ throughout the rest of the paper.

3.5.3 Weighted Least Squares Approach

We employ a method of weighted least squares in order to minimize the downward bias in persistence caused by measurement errors in alphas. Performing regression (7) in terms of the t-statistic of alpha would result in a more accurate estimate of persistence, since more accurately measured alphas would have higher absolute t-statistic values, while less accurately measured alphas would have lower absolute t-statistic values. Unfortunately, such regression results could be difficult to interpret as a measure of performance persistence, since the weights would be different across the evaluation and prediction periods.

We employ a stylized t-statistic of alpha that is obtained by dividing all alphas by their standard deviations during the evaluation period, i.e we consider

$$t^*_{\alpha_{1i}} = a + bt_{\alpha_{0i}} + \varepsilon_i, \tag{9}$$

where

$$t_{\alpha_{0i}} = \frac{\alpha_{0i}}{\sigma_{\alpha_0}}, \quad t^*_{\alpha_{1i}} = \frac{\alpha_{1i}}{\sigma_{\alpha_0}}.$$

This results in assigning more weight to more precisely measured alphas in our sample, and it also allows us to interpret the regression result as a measure of performance persistence. We further apply this approach to see whether performance persists among the best performing or the worst performing funds by running regression (9) for the upper and the lower terciles according to their alpha t-statistic during the evaluation period.

3.5.4 Selective Reporting Model

In this section we address the errors in variables problem and potential look-ahead bias by modeling the nature of the dependence of the closing/liquidation decision of a fund on its true "alpha". We estimate the model parameters using the generalized method of moments. While estimating alphas in the prediction period, one can notice that some hedge funds, which were available in the evaluation period, disappeared from the database. A hedge fund can be liquidated or closed.[25] Closed funds typically stop reporting to the database, since they do not need to attract any additional investments. In the HFR database, hedge funds that opt out of the database may indicate the reason (liquidated fund or closed for new investments fund). For some hedge funds this information is missing.

We build the following model. Suppose that the hedge fund performance is measured by alphas: α_{0i} - alpha in the evaluation period and α_{1i} - alpha in the prediction period. We

[25] A hedge fund is called closed if it is closed for new investors. It continues to manage capital of its current investors.

can observe α_{0i} for all funds in our sample during the evaluation period, but we can only observe α_{1i} for funds that were not liquidated or closed during the prediction period. We can also observe whether a hedge fund was liquidated or closed for new investments. We model the above pattern in hedge funds' performance and reporting as follows:

$$\alpha_{1i}^{*} = a + b\alpha_{0i}^{*} + \varepsilon_i \tag{M}$$

$$\alpha_{0i} = \alpha_{0i}^{*} + u_i$$

$$\alpha_{1i} = \begin{cases} \textit{liquidated}, & \text{with probability } p_0\left(\alpha_{0i}^{*}\right) \\ \alpha_{1i}^{*}, & \text{with probability } p_2\left(\alpha_{0i}^{*}\right) \\ \textit{closed}, & \text{with probability } p_1\left(\alpha_{0i}^{*}\right) \end{cases}$$

where $p_0\left(\alpha_{0i}^{*}\right) + p_1\left(\alpha_{0i}^{*}\right) + p_2\left(\alpha_{0i}^{*}\right) = 1$.

This model implies that we observe noisy[26] variables of hedge fund performance, however the decision on hedge fund liquidation, or closing is based on the "true" α_{0i}^{*} measure of performance.

The noise in this model follows

$$\begin{aligned} \varepsilon_i &\sim N(0, \sigma_\varepsilon^2) \\ u_i &\sim N(0, \sigma_u^2) \end{aligned}$$

and these random variables are independent.

We assume that hedge fund alphas are normally distributed as well.

$$\alpha_{0i}^{*} \sim N(\mu_\alpha, \sigma_{\alpha^*}^2)$$

and

$$\alpha_{0i} \sim N(\mu_\alpha, \sigma_\alpha^2)$$

One can easily establish the relationship between the variance of α_{0i}^{*} and α_{0i} :

$$\sigma_\alpha^2 = \sigma_u^2 + \sigma_{\alpha^*}^2 \tag{10}$$

For notational convenience, we consider σ_{α^*} as an unknown parameter, which is to be estimated (instead of σ_u), then σ_u can be easily found from (10).

[26] The measurment error can be attributed for example to the incomplete set of factors in the performance estimation regression.

3.5.5 GMM Estimation

Consider the following specification for probabilities of liquidation and closure:

$$p_0(\alpha_{0i}^*) = \begin{cases} \max\{\min\{g_0(\mu_\alpha - \alpha_{0i}^*) + c_0, 1 - c_1\}, 0\}, \text{ if } \alpha_{0i}^* \le \mu_\alpha \\ c_0, \text{ if } \alpha_{0i}^* > \mu_\alpha \end{cases} \tag{P}$$

$$p_1(\alpha_{0i}^*) = \begin{cases} c_1, \text{ if } \alpha_{0i}^* \le \mu_\alpha \\ \max\{\min\{g_1(\alpha_{0i}^* - \mu_\alpha) + c_1, 1 - c_0\}, 0\}, \text{ if } \alpha_{0i}^* > \mu_\alpha \end{cases}$$

Then model (M) with specification (P) has nine parameters: a, b, c_0, c_1, g_0, g_1, σ_ε, σ_{α^*}, and μ_α. Of these parameters, μ_α is obviously identified, and it is estimated by the sample mean of α_0. The remaining eight parameters $P = (a, b, c_0, c_1, g_0, g_1, \sigma_\varepsilon, \sigma_{\alpha^*})$ in model (M) with specification (P) are identified and can be estimated via GMM using the following moment conditions:

1) Conditional probability of liquidation, given $\alpha_{0i} \le \mu_\alpha$:

$$\Pr(liquidation|\alpha_{0i} \le \mu_\alpha) = \Pr(liquidation|\tilde{\alpha}_{0i} \le \mu_\alpha) \tag{11}$$

2) Conditional probability of liquidation, given $\alpha_{0i} > \mu_\alpha$:

$$\Pr(liquidation|\alpha_{0i} > \mu_\alpha) = \Pr(liquidation|\tilde{\alpha}_{0i} > \mu_\alpha) \tag{12}$$

3) Conditional probability of closure, given $\alpha_{0i} \le \mu_\alpha$:

$$\Pr(closure|\alpha_{0i} \le \mu_\alpha) = \Pr(closure|\tilde{\alpha}_{0i} \le \mu_\alpha) \tag{13}$$

4) Conditional probability of closure, given $\alpha_{0i} > \mu_\alpha$:

$$\Pr(closure|\alpha_{0i} > \mu_\alpha) = \Pr(closure|\tilde{\alpha}_{0i} > \mu_\alpha) \tag{14}$$

5) Expected value of alpha α_0 for liquidated funds::

$$E(\alpha_0|liquidation) = E(\tilde{\alpha}_{0i}|liquidation) \tag{15}$$

In the above equations (11) - (15), $\tilde{\alpha}_{0i}$ belongs to a simulated distribution F of α_0 according to the model specification with free parameters g_0, g_1, c_0, c_1, $\sigma^2_{\alpha^*}$. Further denote F^* to be a simulated distribution of α_0^* for observable funds that is derived from the model specification with parameters g_0, g_1, c_0, c_1, $\sigma^2_{\alpha^*}$. Then

6) Expected value of α_{1i}

$$\begin{aligned} E\left(\alpha_{1i}|\alpha_{1i} \text{ is observable}\right) &= E\left(\alpha_{1i}^{*}|\alpha_{0i}^{*} \sim F^{*}\right) \\ &= E\left(a + b\alpha_{0i}^{*} + \varepsilon_{i}|\alpha_{0i}^{*} \sim F^{*}\right) \\ &= a + bE\left(\alpha_{0i}^{*}|\alpha_{0i}^{*} \sim F^{*}\right) \end{aligned} \tag{16}$$

7) Variance of α_{1i}

$$\begin{aligned} Var\left(\alpha_{1i}|\alpha_{1i} \text{ is observable}\right) &= Var\left(a + b\alpha_{0i}^{*} + \varepsilon_{i}|\alpha_{0i}^{*}|\alpha_{0i}^{*} \sim F^{*}\right) \\ &= \sigma_{\varepsilon}^{2} + b^{2}Var\left(\alpha_{0i}^{*}|\alpha_{0i}^{*} \sim F^{*}\right) \end{aligned} \tag{17}$$

8) Covariance between α_{1i} and α_{0i}

$$\begin{aligned} & cov\left(\alpha_{1i}, \alpha_{0i}|\alpha_{1i} \text{ is observable}\right) \\ = \; & cov\left(a + b\alpha_{0i}^{*} + \varepsilon_{i}, \alpha_{0i}^{*} + u_{i}|\alpha_{0i}^{*} \sim F^{*}\right) \\ = \; & bVar\left(\alpha_{0i}^{*}|\alpha_{0i}^{*} \sim F^{*}\right) \end{aligned} \tag{18}$$

Notice that estimates for parameters g_0, g_1, c_0, c_1, σ_{α^*} can be obtained by solving the system of equations (11), (12), (13), (14), (15). The estimate for the slope b can be found from (18), the intercept a estimate can be computed from (16), and the variance σ_{ε}^{2} estimate can be obtained from (17). This proves that the above eight moment conditions (11) - (18) specify the exactly identified case for estimating the set of parameters $P = (a, b, g_0, g_1, c_0, c_1, \sigma_{\varepsilon}, \sigma_{\alpha^*})$. We estimate the parameters and standard errors via the two step GMM procedure described in Hansen (1982) and Hansen and Singleton (1982) by numerically solving[27] the system of equations (11) - (18) for numerically simulated distributions F and F^*.

3.5.6 Monte Carlo Simulation

As a robustness check of the above GMM procedure, we used the Monte Carlo approach where we simulated 100 independent data sets. Each of these data sets has 493 observations[28] that were simulated with parameter values representative of our GMM estimates in section 4. The results are provided in table 2.

We observe a close match between the simulated parameter values and their average GMM estimates, which indicates an effective GMM procedure. We also observe a close

[27] We wold like to thank Ken Judd and Che-Lin Su for suggesting SNOPT software that we used in our algorithm.

[28] This replicates the size of the smallest cross-section in our study.

match in GMM-implied and observed standard deviations of estimates of a, b, and σ_ε. This indicates that the GMM inferences about statistical significance of the performance persistence coefficient, b, are efficient. It may be worth noting that while we observe some discrepancy between GMM-implied and observed standard deviations of estimates of g_0, g_1, c_0, c_1, and σ_{α^*}, these are mostly auxiliary parameters in our selective reporting model.

3.5.7 Biases in Simple vs. GMM Models

The OLS slope estimate from the naive regression (7) is equal to

$$\hat{b}_{OLS} = \frac{cov\,(\alpha_{1i}, \alpha_{0i})}{Var\,(\alpha_{0i})}, \tag{19}$$

and the consistent GMM estimator can be obtained from (18) as

$$\hat{b}_{GMM} = \frac{cov\,(\alpha_{1i}, \alpha_{0i})}{Var\,(\alpha^*_{0i}|\alpha^*_{0i} \sim F^*)}. \tag{20}$$

In order to compare $\hat{b}_{OLS}$ and $\hat{b}_{GMM}$ estimators we have to account for the two types of estimation bias:

1) Measurement bias: $Var\,(\alpha_{0i}) > Var\,(\alpha^*_{0i})$,

2) Look-ahead bias: $Var\,(\alpha^*_{0i}) > Var\,(\alpha^*_{0i}|\alpha^*_{0i} \sim F^*)$.

The combined effect of the above biases is that $Var\,(\alpha_{0i}) > Var\,(\alpha^*_{0i}|\alpha^*_{0i} \sim F^*)$, which results in

$$\left|\hat{b}_{OLS}\right| < \left|\hat{b}_{GMM}\right|.$$

This means that the naive regression OLS slope estimate (19) is biased toward zero compared to the GMM slope estimate (20).

4 Estimation Results

In this section we present the data and the results of the estimation of all the models proposed in the last section.

4.1 Data Description

The data for this research was generously provided by Hedge Fund Research. The database contains the history of monthly hedge fund returns beginning in 1990.[29] However, the

[29] For some funds, history dates back to the 1980s.

information about when a fund actually joined the database is only available since May 1996. Hence, we consider the time period from May 1996 until April 2005. We consider only hedge funds with dollar returns (both offshore and onshore), which report their returns as net of all fees. The yearly summary statistics is presented in table 3.

When a hedge fund joins the HFR database, it is given an option to select one strategy from the HFR list. These strategies are used in computation of monthly self reported style indices.[30] The indices are computed as returns on equally weighted portfolios of all funds using the same strategy.

4.2 Estimation of Hedge Fund Alphas

In order to evaluate performance persistence over three-year periods, we only consider hedge funds that had at least three years of observations. This leaves us with 1755 hedge funds. As described in the econometrics methodology section, in order to test for the persistence in hedge fund returns, we first estimate alphas α_{0i} in the evaluation period, then estimate alphas α_{1i} in the prediction period for the same hedge funds (if available) and proceed with a cross-section of hedge fund alphas (future and past alphas) which is tested for persistence. We form four overlapping cross-sections with three year evaluation and prediction periods using the nine years of available backfill bias free data. Table 4 shows the timeline for the estimation of alphas.

For each of the four resulting cross-sections, we compute relative performance alphas as well as the Fung and Hsieh (2004) model alphas. Comparing adjusted R-squares from the two models (provided in tables 5 and 6), we observe that the average mean adjusted R-square of the relative performance model is 68% higher, compared to the mean adjusted R-square of the Fung and Hsieh (2004) model. Consistent with our conjecture in the introduction, we conclude that the relative performance model estimates individual fund performance more precisely compared to the Fung and Hsieh (2004) model.

Following our conjecture that the relative performance could be more indicative of valuable managerial talent, we investigate relative alpha performance persistence in the remainder of this section. However, in section 5, we employ the Fung and Hsieh (2004) model alpha in order to demonstrate tangible benefit to an investor from our relative performance persistence analysis.

We show in section 5 that portfolios of winners selected on their relative performance exhibit a higher degree of out-of-sample Fung and Hsieh (2004) performance persistence,

[30] Only hedge funds with dollar returns reported on monthly basis, net of all fees are used in the computation of self reported indices. These indices are also free of the backfill bias, since backfill observations are excluded from index calculations.

as compared to portfolios selected on their Fung and Hsieh (2004) performance alphas. This confirms our conjecture, and validates our focus on the relative performance alphas in studying performance persistence.

We further eliminated outliers in the evaluation period by truncating the top and bottom 1% of the data. We did not do the same for the prediction period, since these outliers are not known ex-ante in the evaluation period, and thus cannot be used for out-of-sample predictions.

4.3 Performance Persistence

4.3.1 Simple (Naive) Regression

The first approach to check for persistence is to run the naive regression (7):

$$\alpha_{1i} = a + b\alpha_{0i} + \varepsilon_i.$$

The results of the naive regression are presented in table 7 and the scatter plots are presented in figure 4.[31] The slope coefficient b is significant in three out of four cross-sections,[32] and the average estimate of performance persistence across all cross-sections is 21.5%. However, the persistence estimate, b, suffers from the downward bias due to measurement errors, and it also does not account for the fact that some hedge funds disappeared from the database due to various reasons. We address these biases in subsections that follow. Moreover, our naive regression results are not very robust with respect to outliers in α_1 in the prediction period.[33] This further underscores the importance of weighted least squares and GMM approaches to measuring performance persistence.

4.3.2 Weighted Least Squares Regression

Here we employ a method of weighted least squares in order to minimize the downward bias in persistence caused by measurement errors in alphas. We estimate the regression (9), i.e.

$$t^*_{\alpha_{1i}} = a + bt_{\alpha_{0i}} + \varepsilon_i,$$

where

$$t_{\alpha_{0i}} = \frac{\alpha_{0i}}{\sigma_{\alpha_0}}, \quad t^*_{\alpha_{1i}} = \frac{\alpha_{1i}}{\sigma_{\alpha_0}}.$$

[31] A few outliers in α_1 are off the scale of the plots.

[32] At the 5% significance level.

[33] Naive regression results after truncating the top and bottom 1% of the data with respect to α_1 are presented in table 8.

The results of the weighted least squares regression are presented in table 9, and the scatter plots are presented in figure 5. The slope coefficient b is statistically significant[34] in three out of four cross-sections, and the average estimate of performance persistence across all cross-sections is 28.4%. While we did not eliminate outliers in the prediction period, they may obscure the out-of-sample persistence interpretations in this instance.[35] Weighted least squares regression results after truncating the top and bottom 1% of the data with respect to $t^*_{\alpha_{1i}}$ indicate a statistically significant[36] performance coefficient, b, across all cross-sections.[37] However, the magnitude of the persistence estimate, b, is noticeably smaller in the third cross-section. That cross-section has the closest breaking point to the worst overall performance year for the hedge fund industry over the study period.[38] This suggests that superior skill that is reflected in our measure of relative performance persistence may not be as valuable to an investor during periods of adverse economic conditions for the hedge fund industry as a whole. We conjecture that when there are fewer opportunities in the economy for hedge fund managers as a group, there will be less cross-sectional dispersion in managers' alphas, i.e., the performance differential between the more talented and the less talented managers is likely to be less pronounced. We leave modeling this dependence of relative performance on market conditions to future research.

Notice that an investor can only benefit from our approach by investing in hedge funds run by talented managers, and staying away from the ones that have not demonstrated persistent skill. Hence it may be of little value to an investor to find evidence of negative performance persistence, since an investor cannot take a short position in a hedge fund. On the other hand, evidence of positive performance persistence could be potentially valuable, since taking long positions in hedge funds run by talented managers could result in achieving superior returns. It is important to point out that although relative positive performance persistence could be interpreted as evidence of managerial talent, it does guarantee future superior performance as measured by the Fung and Hsieh (2004) model. We investigate the relationship between past relative performance and future performance in section 5, and conclude that superior relative performance is idicative of superior future performance as measured by the Fung and Hsieh (2004) model.

We study whether positive or negative performance persists by running regression (9) separately for funds in the upper and the lower terciles according to their alpha t-statistic

[34] At the 1% significance level.

[35] For example, a few large outliers may significantly influence regression results, while having a modest impact if considered as a part of a larger portfolio. Our analysis in section 5 confirms this observation.

[36] At the 10% significance level.

[37] See table 10.

[38] Measured by the HFR total index.

during the evaluation period. For robustness, we also perform this analysis after eliminating outliers in the prediction period. Remarkably, we find evidence of performance persistence among top hedge funds, while we find no evidence of persistence among bottom funds. These results are presented in tables 11 and 12. This is consistent with the interpretation of superior performance persistence as a result of superior managerial talent, which is also reflected in superior prior performance. Our findings also support the view that managers of superior skills restrict inflow of new money in order to maintain their performance.

4.3.3 GMM Estimation

During the prediction period, a hedge fund can either remain or drop out from the database. Funds may disappear from the database due to liquidation, closing, or stop reporting for unknown reasons. Summary statistics of hedge funds according to this decomposition are presented in tables 13 and 14. If probabilities of liquidation and closure are influenced by fund's "true" prior performance, α_0^*, it will result in biased persistence estimates, which is also known as a look-ahead bias. Considering histograms of distributions of liquidated and closed funds by deciles of α_0 (figure 6) and conditional probabilities of liquidation and closure conditional on α_0 being in top and bottom parts of its distribution (table 15), we conclude that there is a relationship between fund's prior performance and probabilities of fund's liquidation and closure. We model this relationship by specifying different patterns of liquidation and closure for the top and bottom parts of the true alpha distribution through model (M) with specification (P). This approach allows us take into account measurement errors along with the look-ahead bias, and it is estimated via the GMM procedure. Estimates from the GMM procedure are provided tables 16 and 17. The estimates of the persistence coefficient b are roughly consistent with the weighted least squares estimates from subsection 4.3.2, and the average GMM estimate of performance persistence across all cross-sections is 30.7% compared to the weighted least squares average of 28.4%. GMM estimated conditional probabilities of liquidation and closure (figure 7) are also consistent with observed probabilities in table 15 and figure 6.

Notice that in the first two cross-sections liquidated funds tend to have low alphas, while closed funds tend to have high alphas (see table 13). This is consistent with our statistical model (M) and the specification (P), but it is the only consequence of the model. In fact, the specification (P) is flexible to allow decreasing probabilities of closure with increasing α_0, as demonstrated by negative g_1 parameter estimates in third and fourth cross-sections. These estimates are consistent with descriptive statistics in the last two cross-sections, as closed funds do not outperform liquidated and observable funds (see table 14).

However, it is worth pointing out that the underlying fundamentals of the decision to close a fund to new investors might have changed after 2001. In order to test this conjecture we performed probit tests of the decision to liquidate vs. close among the funds that were either closed or liquidated in our data. The estimates of the probability of liquidation are provided in table 18. The results indicate the significance of α_0 in liquidation vs. closure decisions vanishes in the last two cross-sections, while the ratio of last flows to assets gains in significance in the last two cross-sections. This supports our conjecture that the role of the relative performance measure, α_0, in the decision to liquidate or close a fund has diminished since 2001.

4.3.4 Non-Reporting Funds

The non-reporting funds[39] comprise on average 15.6% of the data among all cross-sections. Can we use these funds in our further performance analysis? The answer to this question lies in the distribution of observable characteristics of the non-reporting funds during the evaluation period. We may attempt to classify the non-reporting funds as closed or liquidated on the basis of their evaluation period performance α_0. Such classification would be consistent with assumptions of the model (M) and the specification (P), but only if the distribution of the relative performance measure α_0 for non-reporting funds resembles the distributions of α_0 for funds that stopped reporting, but indicated a reason for doing so (i.e. liquidated and closed funds). Unfortunately, Kolmorogov-Smirnov test for distribution closeness does not indicate consistently close fit between the distribution of non-reporting funds and the distribution of liquidated and closed funds. In fact, the best match between the distribution of non-reporting funds and the distribution of liquidated and closed funds only come from the fourth cross-sections, while in the other three cross-sections the non-reporting funds distribution is closest to the distribution of all reporting funds.[40]

Hence we conclude that classifying non-reporting funds as either closed or liquidated would result in model (M) misspecification, and that treating non-reporting funds as missing data would be the most consistent approach.

4.3.5 Potential Biases

Here we consider a possibility of a scenario when funds with large positive alphas during the first three year period perform poorly during the second three year period and liquidate, and funds with large negative alphas during the first three year period perform extremely

[39] The non-reporting funds are those that dropped out of the HFR dataset without reporting a reason.

[40] See table 19 for Kolmorogov-Smirnov test results.

well during the second three year period and close. Such a pattern could contribute to findings positive measured persistence in alphas of funds that survived during both three year periods.

However, as seen in figure 6 and tables 13, 14, and 15 funds with lower performance during the first period were more likely to be liquidated. This indicates that the scenario of performance reversal for liquidated funds between the two periods is unlikely.

In case of closed funds, figure 6 along with tables 13 and 15 indicate that in the first two cross-sections funds with higher prior performance were more likely to be closed. This does not suggest performance reversal in the first two cross-sections. On the other hand, in the last two cross-sections (see figure 6 and tables 14 and 15) closed funds with lower first period performance were more likely to be closed, which could be an indication of performance reversal among a subset of underperforming funds in the first period. If that was the case, we would have been more likely to find an indication of stronger performance persistence among the lower performing hedge funds. Nevertheless, our weighted least squares analysis produced no evidence of performance persistence among the lower performing hedge funds, hence we conclude that it is unlikely that there could be a performance reversal pattern strong enough to significantly bias our previous findings of performance persistence.

While the above observations allow us to suggest that our finding of performance persistence is not a spurious phenomenon, a completely definitive answer on the matter could only be obtained by completely eliminating the bias caused by funds dropping out of the database by tracking down the performance of all the funds that dropped out without being completely liquidated.

5 Can Investors Benefit?

While we provide evidence of the relative performance persistence in the previous section, it is not obvious that an investor can achieve tangible superior performance, alpha, by using this knowledge. We construct portfolios of hedge funds based on their past relative performance in the evaluation period, and then track their absolute performance[41] during the prediction period. All the hedge funds are sorted by their evaluation period relative alpha t-statistic, $t_{\alpha_{0i}}$. We compose an inferior portfolio of all hedge funds in the bottom of the ranking, a superior portfolio of all funds in the top, and a neutral portfolio of all the remaining funds. For robustness, we used 33% and 10% cutoffs for the superior and inferior portfolios. We then invest one dollar to every portfolio in the beginning of the prediction period. One dollar

[41] Here we define absolute performance as the Fung and Hsieh (2004) seven-factor model alpha.

is equally split among all the hedge funds in a given portfolio. If a fund disappears during the prediction period, the money is reinvested among the surviving funds in a portfolio.[42]

The portfolio approach allows us to reduce performance measurement errors, and increase the accuracy of the Fung and Hsieh (2004) model. It also allows to take into account performance of funds that disappeared from the sample during the prediction period, as they remain in their portfolios up to the time of their disappearance from the database.

We calculate each out-of-sample portfolio performance during the prediction period and in-sample past performance during the evaluation period as Fung and Hsieh (2004) model alphas. We also consider appraisal ratios[43] to capture the robustness of managerial performance. The performance of the three portfolios in the evaluation and prediction periods are in tables 20 and 21. Notice that the relative performance measure is used for ranking purposed only.

As we see from tables 20 and 21, the superior portfolio provides consistent significantly positive[44] out-of-sample alphas, while inferior and neutral portfolios fail to provide a consistent statistically significant out-of-sample performance. Moreover, the superior portfolio consistently dominates other portfolios in appraisal ratios, indicating a robust out-of-sample persistence of superior performance.[45]

5.1 Why Use Past Relative Alpha to Predict Future Alpha?

Earlier we assumed that past relative alpha would be a better predictor of future alpha than past alpha itself. In this section we verify the veracity of that assumption. Tables 22 and 23 provide out-of-sample future alphas of inferiror, neutral, and superior performers identified using historical alphas estimated using the Fung and Hsieh (2004) model.

We again observe that the superior portfolio provides significantly positive[46] out-of-sample alphas, while inferior and neutral portfolios fail to provide a consistent statistically significant out-of-sample performance.

Since both predictions based on the relative alpha and the Fung and Hsieh (2004) model provide evidence of superior out-of-sample performance, we compare the effectiveness of

[42] We also consider a pessimistic scenario, under the assumption that the money invested into disappeared hedge funds cannot be recovered at all, regardless of the reason the hedge fund disappeared.

[43] Based on Fung and Hsieh (2004) model.

[44] With the exception of the second cross-section for the 33% cutoff.

[45] In the pessimistic scenario, the superior portfolio consistently provides higher out-of-sample alphas compared to inferior and neutral portfolios. The average out-of-sample alpha for the superior portfolio of the top 33% of funds was -0.4774, while the average alpha for the bottom 33% of funds was -1.0206. The average out-of-sample alpha for the superior portfolio of the top 10% of funds was -0.4743, while the average alpha for the bottom 10% of funds was -2.3378. However, these results are heavily influenced by the attrition rates in the portfolios.

[46] With the exception of the second cross-section for both 33% and 10% cutoffs.

their predictions for superior portfolios, i.e. for portfolios of previous winners picked by different performance measures.[47] Consistent with our conjecture, we observe that portfolios of winners selected on their relative alphas exhibit a higher degree of out-of-sample absolute performance persistence as compared to portfolios selected on their Fung and Hsieh (2004) model alphas. Portfolios with superior past relative alphas outperformed portfolios with superior past Fung and Hsieh (2004) model alphas by delivering higher average alphas and appraisal ratios.[48] Moreover, on average, portfolios with superior past relative alphas retained a higher percentage of their past alphas during the out-of-sample period compared to portfolios with superior past Fung and Hsieh (2004) model alphas. This further validates our use of the relative performance model in our previous performance persistence analysis.

6 Conclusion

Hedge fund managers are given much more flexibility regarding where and how to invest compared to mutual fund managers. The growth of hedge funds, with 1.9 trillion dollars invested in assets by 2007, may well reflect the need for giving talented managers who know where superior opportunities exist at a given point in time the necessary flexibility to exploit that talent. A natural question that arises is whether it is possible to identify those hedge fund managers who are able to exploit the flexibility given to them better than others.

While the flexibility given to hedge fund managers may help in generating superior returns, it also makes performance evaluation more difficult. Hedge fund returns are unlike returns from standard asset classes, and exhibit option-like features that have to be taken into account when evaluating performance. Further, since hedge funds invest in illiquid assets, care has to be exercised in measuring their systematic risk. In this paper we develop a method for evaluating the performance of a hedge fund manager relative to a suitably constructed peer group. Our method takes into account option-like features in hedge fund strategies and serial correlation in hedge fund returns caused possibly by investments in illiquid assets. We also take into account the backfill bias in our data set and the look-ahead bias (i.e. the fact that a hedge fund may be liquidated or closed and exit the data set). We employ a method of weighted least squares in order to minimize the downward bias in persistence caused by measurement errors in alphas.

We find evidence of persistence in the performance of funds relative to their style bench-

[47] We cannot use the pessimistic scenario for comparing the effectiveness of the relative alpha and the Fung and Hsieh (2004) model alpha predictions, since out-of-sample pessimistic estimates are heavily influenced by portfolio attrition rates. Notice that portfolios formed on the basis of relative alphas have different attrition rates compared to portfolios formed on the basis of Fung and Hsieh (2004) model alphas.

[48] See table 24 for details.

marks. It appears that on average more than 25% of the abnormal performance during a three year interval will spill over into the following three year interval. We provider further support for the interpretation of performance persistence as evidence of superior managerial talent by finding strong evidence of performance persistence among top hedge funds, while finding little evidence of persistence among bottom funds. Our findings of performance persistence are also consistent with the evidence of out-of-sample superior performance of portfolios of past winners.

Our analysis highlights difficulties that arise in predicting how a hedge fund manager will perform in the future relative to his peer group. While the assumptions we had to make in order to answer the question of performance persistence among hedge fund managers appear reasonable, we need a better understanding of what happened to funds that vanished from publicly available databases to provide a quantitative answer to that question with utmost confidence. We hope that our findings will stimulate research examining how funds that discontinue reporting their performance do subsequently.

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#	HFR Strategy Style Index	#	HFR Strategy Style Index
1	Convertible Arbitrage	17	Fund of Funds: Conservative
2	Distressed Securities	18	Fund of Funds: Diversified
3	Emerging Markets: Asia	19	Fund of Funds: Market Defensive
4	Emerging Markets: E. Europe/CIS	20	Fund of Funds: Strategic
5	Emerging Markets: Global	21	Macro
6	Emerging Markets: Latin America	22	Market Timing
7	Equity Hedge	23	Merger Arbitrage
8	Equity Market Neutral	24	Regulation D
9	Equity Non-Hedge	25	Relative Value Arbitrage
10	Event-Driven	26	Sector: Energy
11	Fixed Income: Arbitrage	27	Sector: Financial
12	Fixed Income: Convertible Bonds	28	Sector: Health Care/Biotechnology
13	Fixed Income: Diversified	29	Sector: Miscellaneous
14	Fixed Income: High Yield	30	Sector: Real Estate
15	Fixed Income: Mortgage-Backed	31	Sector: Technology
16	Fund of Funds (Total)	32	Short Selling

Table 1: Style indices in Hedge Fund Research database.

	a	b	g_0	g_1	c_0	c_1	σ_ε	σ_{α^*}
Simulated values	-0.07	0.30	0.10	0.08	0.08	0.03	1.00	0.80
Observed means	-0.0576	0.2971	0.0893	0.0864	0.0801	0.0265	1.0004	0.8175
GMM-implied std dev	0.0422	0.0700	0.4050	0.3870	0.0716	0.1147	0.0301	2.0384
Observed std dev	0.0469	0.1008	0.0230	0.0372	0.0206	0.0330	0.0368	0.0962

Table 2: Summary statistics from the Monte Carlo GMM simulation. The results are based on 100 independent data sets of 493 simulated observations. The table presents the simulated values of selective reporting model parameters, the mean estimates of these parameters from 100 observed GMM estimates, the mean standard deviation of the estimates as implied by the GMM procedure, and the observed standard deviations of 100 parameter estimates.

year	total	entered	left	attrition	mean return	median return	std. dev.
1996	1123	1123	91	8.10%	0.57%	0.61%	5.10%
1997	1326	294	163	12.29%	1.14%	0.86%	5.31%
1998	1436	273	206	14.35%	-0.19%	0.23%	7.98%
1999	1479	249	199	13.46%	1.50%	0.67%	7.97%
2000	1546	266	251	16.24%	-0.40%	0.12%	7.12%
2001	1851	556	204	11.02%	0.12%	0.24%	4.64%
2002	2183	536	277	12.69%	-0.09%	0.13%	4.34%
2003	2744	838	281	10.24%	1.11%	0.76%	3.31%
2004	3274	811	364	11.12%	0.23%	0.20%	2.86%

Table 3: Yearly distribution of hedge funds. The table presents the total number of funds that reported during a year, the number of funds that entered and left the database, and mean, median, and standard deviation of monthly excess returns. A year represents the time period from May of that year until April of the next year.

	Evaluation Period		**Prediction Period**	
Cross-section	**Begins**	**Ends**	**Begins**	**Ends**
1	May 1996	April 1999	May 1999	April 2002
2	May 1997	April 2000	May 2000	April 2003
3	May 1998	April 2001	May 2001	April 2004
4	May 1999	April 2002	May 2002	April 2005

Table 4: Timeline for evaluation and prediction periods.

	Evaluation period adjusted R^2			Prediction period adjusted R^2		
Cross-section	mean	median	std.dev.	mean	median	std.dev.
1	0.49	0.52	0.26	0.45	0.46	0.28
2	0.50	0.55	0.26	0.44	0.45	0.27
3	0.50	0.52	0.25	0.47	0.51	0.27
4	0.44	0.45	0.28	0.53	0.58	0.26

Table 5: Summary statistics of relative performance model adjusted R-squares.

	Evaluation period adjusted R^2			Prediction period adjusted R^2		
Cross-section	mean	median	std.dev.	mean	median	std.dev.
1	0.33	0.31	0.26	0.22	0.19	0.26
2	0.30	0.30	0.25	0.26	0.23	0.26
3	0.30	0.28	0.25	0.31	0.30	0.28
4	0.21	0.18	0.25	0.35	0.34	0.26

Table 6: Summary statistics of Fung and Hsieh (2004) model adjusted R-squares.

	1996-1999 - 1999-2002			1997-2000 - 2000-2003		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.1462	-1.17	0.2445	-0.0493	-0.41	0.6822
b	**0.3795**	**3.15**	**0.0018**	**0.2899**	**2.40**	**0.0168**
	1998-2001 - 2001-2004			1999-2002 - 2002-2005		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.1457	-1.64	0.1016	-0.2693	-5.02	<.0001
b	**0.0564**	**0.69**	**0.4910**	**0.1341**	**2.97**	**0.0031**

Table 7: Naive regression results. Persistence is captured by the slope coefficient, b, which is statistically significant in two out of four cross-sections.

	1996-1999 - 1999-2002			1997-2000 - 2000-2003		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.0683	-1.01	0.3111	-0.0953	-1.64	0.1016
b	**0.1130**	**1.73**	**0.0855**	**-0.0108**	**-0.18**	**0.8549**
	1998-2001 - 2001-2004			1999-2002 - 2002-2005		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.1967	-4.55	<.0001	-0.2297	-7.65	<.0001
b	**0.0344**	**0.86**	**0.3883**	**0.1513**	**5.99**	**<.0001**

Table 8: Naive regression results without ouliers in a_1. Persistence is captured by the slope coefficient, b, which is statistically significant in two out of four cross-sections.

	1996-1999 - 1999-2002			1997-2000 - 2000-2003		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	0.1291	0.63	0.5308	-0.2929	-1.42	0.1569
b	**0.5267**	**4.48**	**<.0001**	**0.3532**	**2.90**	**0.0040**
	1998-2001 - 2001-2004			1999-2002 - 2002-2005		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.2622	-0.94	0.3456	-0.7273	-5.91	<.0001
b	**0.0435**	**0.26**	**0.7921**	**0.2120**	**3.28**	**0.0011**

Table 9: Weighted least squares regression results. Persistence is captured by the slope coefficient, b, which is statistically significant in all cross-sections.

	1996-1999 - 1999-2002			1997-2000 - 2000-2003		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	0.1653	1.04	0.2978	-0.0620	-0.53	0.5993
b	**0.3878**	**4.25**	**<.0001**	**0.1882**	**2.65**	**0.0033**
	1998-2001 - 2001-2004			1999-2002 - 2002-2005		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.4146	-4.74	<.0001	-0.5871	-6.47	<.0001
b	**0.1043**	**1.91**	**0.0568**	**0.1990**	**4.16**	**<.0001**

Table 10: Weighted least squares regression results without ouliers in $t^*_{a_{1i}}$. Persistence is captured by the slope coefficient, b, which is statistically significant in all cross-sections.

		Top 33%			Bottom 33%		
Cross-section	Parameter	Estimate	t-stat	p-value	Estimate	t-stat	p-value
1996-1999 - 1999-2002	b	1.3188	4.36	<.0001	0.4336	0.72	0.4728
1997-2000 - 2000-2003	b	1.0517	4.58	<.0001	0.3804	1.01	0.3161
1998-2001 - 2001-2004	b	-0.4285	-0.79	0.4314	-0.1801	-0.72	0.4748
1999-2002 - 2002-2005	b	0.2719	2.25	0.0253	0.0421	0.16	0.8749

Table 11: Weighted least squares regression results. Persistence is estimated separately for the top and the bottom of the t_{α_0} ranking.

		Top 33%			Bottom 33%		
Cross-section	Parameter	Estimate	t-stat	p-value	Estimate	t-stat	p-value
1996-1999 - 1999-2002	b	1.2689	6.03	<.0001	-0.1714	-0.41	0.6794
1997-2000 - 2000-2003	b	0.9463	4.62	<.0001	0.0458	0.18	0.8581
1998-2001 - 2001-2004	b	0.2427	1.78	0.0770	-0.0659	-0.30	0.7634
1999-2002 - 2002-2005	b	0.2284	2.23	0.0270	-0.1446	-0.66	0.5104

Table 12: Weighted least squares regression results without ouliers in $t^*_{a_{1i}}$. Persistence is estimated separately for the top and the bottom of the t_{α_0} ranking.

1996-1999 - 1999-2002	Observable	Liquidated	Closed	Non-Reporting	Total
number of hedge funds	313	64	25	91	493
percent	63.49%	12.98%	5.07%	18.46%	100%
α_0 mean	-0.0832	-0.1037	0.0916	-0.2097	-0.1003
α_0 median	0.0306	-0.2378	0.1515	0.0181	0.0228
α_0 std. dev.	1.0378	1.3317	1.1029	1.4083	1.1561
assets ($M) mean	239.43	38.27	58.52	92.97	176.84
assets ($M) median	56.54	7.72	31.25	21.34	39.63
assets ($M) std. dev.	658.17	96.52	71.04	178.18	536.61
1997-2000 - 2000-2003	Observable	Liquidated	Closed	Non-Reporting	Total
number of hedge funds	456	75	32	110	673
percent	67.76%	11.14%	4.75%	16.34%	100%
α_0 mean	0.0934	-0.3380	0.2286	-0.0901	0.0217
α_0 median	0.1641	-0.1788	0.4533	0.0426	0.1045
α_0 std. dev.	1.0002	1.3642	1.5400	1.1464	1.1076
assets ($M) mean	225.50	32.77	55.46	71.00	170.17
assets ($M) median	54.91	7.76	10.50	18.40	37.32
assets ($M) std. dev.	621.75	88.10	94.06	142.28	521.25

Table 13: Distribution of hedge funds in the prediction period from the first and second cross-sections. Alphas are measured as monthly percentage returns.

1998-2001 - 2001-2004	Observable	Liquidated	Closed	Non-Reporting	Total
number of hedge funds	508	82	37	96	723
percent	70.26%	11.34%	5.12%	13.28%	100%
α_0 mean	0.0610	-0.4090	-0.2909	-0.1686	-0.0408
α_0 median	0.1336	-0.1301	0.0032	0.0032	0.0828
α_0 std. dev.	1.0843	1.2830	1.3552	1.4191	1.1811
assets ($M) mean	301.91	58.43	59.24	77.28	231.37
assets ($M) median	69.00	9.98	11.18	17.76	44.95
assets ($M) std. dev.	722.15	265.56	105.38	155.68	623.05
1999-2002 - 2002-2005	Observable	Liquidated	Closed	Non-Reporting	Total
number of hedge funds	519	103	31	109	762
percent	68.11%	13.52%	4.07%	14.30%	100%
α_0 mean	0.1100	-0.1676	-0.6037	-0.0580	0.0194
α_0 median	0.1753	0.0575	-0.0681	-0.0445	0.1033
α_0 std. dev.	1.1848	1.2578	1.5462	1.1137	1.2103
assets ($M) mean	326.26	33.11	51.59	180.11	255.30
assets ($M) median	79.60	9.98	10.10	10.30	41.00
assets ($M) std. dev.	685.47	100.57	100.45	926.32	675.97

Table 14: Distribution of hedge funds in the prediction period from the third and fourth cross-sections. Alphas are measured as monthly percentage returns.

Cross-section	$\Pr(\mathrm{L}\vert\alpha_0 \leq \mu_{\alpha_0})$	$\Pr(\mathrm{L}\vert\alpha_0 > \mu_{\alpha_0})$	$\Pr(\mathrm{C}\vert\alpha_0 \leq \mu_{\alpha_0})$	$\Pr(\mathrm{C}\vert\alpha_0 > \mu_{\alpha_0})$
1996-1999 - 1999-2002	0.2143	0.1197	0.0476	0.0726
1997-2000 - 2000-2003	0.1807	0.0955	0.0361	0.0732
1998-2001 - 2001-2004	0.1860	0.0921	0.0698	0.0515
1999-2002 - 2002-2005	0.1714	0.1475	0.0607	0.0375

Table 15: Observed probabilities of liquidation and closure conditional on observed values of α_0.

	1996-1999 - 1999-2002			1997-2000 - 2000-2003		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.1687	-1.7528	0.0796	-0.0528	-0.5971	0.5504
b	**0.4956**	**2.4465**	**0.0144**	**0.4032**	**1.5714**	**0.1161**
g_0	0.1268	1.2236	0.2211	0.1384	0.6050	0.5452
g_1	0.0322	3.0140	0.0026	0.0768	0.5363	0.5918
c_0	0.1479	10.3059	<.0001	0.0886	1.8474	0.0647
c_1	0.0595	6.8046	<.0001	0.0289	0.9718	0.3312
σ_ε	2.1965	7.0974	<.0001	2.5665	4.1042	<.0001
σ_{α^*}	0.9486	3.0592	0.0022	0.8908	1.0842	0.2783

Table 16: Results of the GMM procedure for the first two cross-sections.

	1998-2001 - 2001-2004			1999-2002 - 2002-2005		
Parameter	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
a	-0.1465	-2.0607	0.0393	-0.2721	-6.2971	<.0001
b	**0.0577**	**1.3860**	**0.1657**	**0.2707**	**4.1214**	**<.0001**
g_0	0.1106	0.6351	0.5254	0.0459	1.1248	0.2607
g_1	-0.0112	-1.3048	0.1920	-0.0388	-2.3711	0.0177
c_0	0.1091	2.2626	0.0237	0.1060	6,7898	<.0001
c_1	0.0750	8.8217	<.0001	0.0697	11.5243	<.0001
σ_ε	1.9976	3.7028	0.0002	1.2051	7.7121	<.0001
σ_{α^*}	1.1071	1.3256	0.1850	0.8361	1.6502	0.0989

Table 17: Results of the GMM procedure for the last two cross-sections.

	1996-1999 - 1999-2002			1997-2000 - 2000-2003		
Parameter	Estimate	ChiSq	Pr>ChiSq	Estimate	ChiSq	Pr>ChiSq
Intercept	0.5131	10.31	0.0013	0.4085	8.14	0.0043
α_0	-0.1175	0.81	0.3683	-0.1790	3.54	0.0600
last_returns	-0.1097	4.64	0.0313	-0.0865	3.75	0.0527
last_flows_to_assets	-0.0136	0.15	0.6962	-0.0264	0.44	0.5070
	1998-2001 - 2001-2004			1999-2002 - 2002-2005		
Parameter	Estimate	ChiSq	Pr>ChiSq	Estimate	ChiSq	Pr>ChiSq
Intercept	0.3584	6.17	0.0130	0.6233	17.99	<.0001
α_0	-0.0640	0.42	0.5181	0.0625	0.39	0.5330
last_returns	0.00084	0.03	0.8673	0.0398	0.34	0.5621
last_flows_to_assets	-0.1801	2.68	0.1016	-0.4549	5.23	0.0222

Table 18: Probit estimates of the probability of liquidation. α_0 is estimated over the evaluation period. *last returns* is the cumulative fund's return over the last year of a fund's presence in the database. *last flows to assets* is a ratio of cumulative cash flows over a fund's last assets over the last year of a fund's presence in the database.

	1996-1999 - 1999-2002		1997-2000 - 2000-2003	
Distributions	KSa statistic	p-value	KSa statistic	p-value
Observable funds	0.8829	0.4168	0.9650	0.3094
Liquidated and closed funds	0.8837	0.4156	1.0105	0.2589
All reporting funds	0.7041	0.7045	0.9187	0.3674
	1998-2001 - 2001-2004		1999-2002 - 2002-2005	
Distributions	KSa statistic	p-value	KSa statistic	p-value
Observable funds	1.0974	0.1797	1.4868	0.0240
Liquidated and closed funds	1.3483	0.0527	0.8328	0.4918
All reporting funds	0.8909	0.4055	1.3373	0.0559

Table 19: Kolmogorov-Smirnov tests for closeness of alpha 0 distributions. KSa statistic denotes the asymptotic Kolmogorov-Smirnov statistic, and the p-value is provided for the test of the null hypothesis that there is no difference between the two distributions. The non-reporting funds distribution is compared to the observable funds distribution, liquidated and closed funds distribution, and to the all reporting funds (i.e. observable, liquidated, and closed funds) distribution.

Cross-section	Portfolio	Funds at formation	Survived Funds	Past Alpha	Out-of-sample Alpha	Appraisal Ratio
1996-1999 - 1999-2002	Inferior	163	99	-0.1075	0.0960	0.0659
	Neutral	167	109	0.1995	0.0991	0.0736
	Superior	163	110	0.7497***	0.3292***	0.5083
1997-2000 - 2000-2003	Inferior	223	140	-0.0641	0.0202	0.0220
	Neutral	227	148	0.5016**	0.0074	0.0107
	Superior	223	170	0.9010***	0.0943	0.1666
1998-2001 - 2001-2004	Inferior	239	148	-0.1032	0.3116**	0.4341
	Neutral	245	172	0.4540**	0.2026**	0.3727
	Superior	239	187	0.8738***	0.2693***	0.6795
1999-2002 - 2002-2005	Inferior	252	156	-0.0921	-0.0138	-0.0219
	Neutral	259	172	0.5705***	0.1214	0.2158
	Superior	252	191	0.8685***	0.1768*	0.6494

Table 20: Out-of-sample performance of three relative performance ranked portfolios. Portfolios are formed and ranked according to the previous relative t-alpha performance in the evaluation period with the 33 percent cutoff. Then the Fung and Hsieh (2004) portfolio alphas and appraisal ratios are calculated for the prediction (i.e. out-of-sample) period, as well as past alphas for the evaluation period (i.e. in-sample alphas). Portfolio alphas marked with ***, **, and * are statistically significant at 1, 5, and 10 percent respectively.

Cross-section	Portfolio	Funds at formation	Survived Funds	Past Alpha	Out-of-sample Alpha	Appraisal Ratio
1996-1999 - 1999-2002	Inferior	50	34	-0.0857	0.1513	0.0749
	Neutral	394	252	0.3108	0.0174**	0.0155
	Superior	50	32	0.7460***	0.7883***	1.4514
1997-2000 - 2000-2003	Inferior	68	45	-0.3106	0.3758*	0.3537
	Neutral	537	361	0.4805**	-0.0159	-0.0257
	Superior	68	52	0.9348***	0.3213**	0.7923
1998-2001 - 2001-2004	Inferior	73	45	-0.5262	0.4722*	0.5329
	Neutral	577	405	0.4646**	0.2165**	0.4241
	Superior	73	57	1.1569***	0.2485***	0.8478
1999-2002 - 2002-2005	Inferior	77	43	-0.3503	0.1209	0.1453
	Neutral	609	415	0.5481***	0.1966**	0.3563
	Superior	77	61	1.0102***	0.3884***	0.8362

Table 21: Out-of-sample performance of three relative performance ranked portfolios. Portfolios are formed and ranked according to the previous relative t-alpha performance in the evaluation period with the 10 percent cutoff. Then the Fung and Hsieh (2004) portfolio alphas and appraisal ratios are calculated for the prediction (i.e. out-of-sample) period, as well as past alphas for the evaluation period (i.e. in-sample alphas). Portfolio alphas marked with ***, **, and * are statistically significant at 1, 5, and 10 percent respectively.

Cross-section	Portfolio	Funds at formation	Survived Funds	Past Alpha	Out-of-sample Alpha	Appraisal Ratio
1996-1999 - 1999-2002	Inferior	163	89	-0.3711	-0.1755	-0.1050
	Neutral	167	111	0.7005*	0.1432	0.1174
	Superior	163	119	0.9401***	0.3739*	0.5302
1997-2000 - 2000-2003	Inferior	223	131	-0.5100	0.1172	0.1288
	Neutral	227	147	0.6617***	0.0237	0.0318
	Superior	223	176	1.2712***	-0.0451	-0.0604
1998-2001 - 2001-2004	Inferior	239	130	-0.4060	0.3581**	0.4332
	Neutral	245	183	0.6713***	0.0838	0.1684
	Superior	239	194	1.0676***	0.1900**	0.4187
1999-2002 - 2002-2005	Inferior	252	142	-0.3343	0.0364	0.0607
	Neutral	259	190	0.6134***	0.0055	0.0111
	Superior	252	188	1.0723***	0.3115***	0.6936

Table 22: Out-of-sample performance of three absolute performance ranked portfolios. Portfolios are formed and ranked according to the previous Fung and Hsieh (2004) t-alpha performance in the evaluation period with the 33 percent cutoff.Then the Fung and Hsieh (2004) portfolio alphas and appraisal ratios are calculated for the prediction (i.e. out-of-sample) period, as well as past alphas for the evaluation period (i.e. in-sample alphas). Portfolio alphas marked with ***, **, and * are statistically significant at 1, 5, and 10 percent respectively.

Cross-section	Portfolio	Funds at formation	Survived Funds	Past Alpha	Out-of-sample Alpha	Appraisal Ratio
1996-1999 - 1999-2002	Inferior	50	29	-0.8991***	-1.4539	-0.7838
	Neutral	394	253	0.4804*	0.2155	0.2003
	Superior	50	37	0..9819***	0.4339***	1.0363
1997-2000 - 2000-2003	Inferior	68	38	-1.1450***	0.1189	0.0868
	Neutral	537	360	0.5990**	0.0807	0.1119
	Superior	68	56	1.0182***	0.0890	0.2017
1998-2001 - 2001-2004	Inferior	73	32	-1.0481***	0.2763	0.2943
	Neutral	577	414	0.5276**	0.2506**	0.4962
	Superior	73	61	0.9858***	0.2518***	0.6268
1999-2002 - 2002-2005	Inferior	77	36	-0.8127***	0.0169	0.0258
	Neutral	609	424	0.5625***	0.2232**	0.3867
	Superior	77	60	0.9705***	0.3522***	0.8798

Table 23: Out-of-sample performance of three absolute performance ranked portfolios. Portfolios are formed and ranked according to the previous Fung and Hsieh (2004) t-alpha performance in the evaluation period with the 10 percent cutoff. Then the Fung and Hsieh (2004) portfolio alphas and appraisal ratios are calculated for the prediction (i.e. out-of-sample) period, as well as past alphas for the evaluation period (i.e. in-sample alphas). Portfolio alphas marked with ***, **, and * are statistically significant at 1, 5, and 10 percent respectively.

	Relative performance model			Fung and Hsieh (2004) model		
	Average alpha	Average appraisal ratio	Retained alpha	Average alpha	Average appraisal ratio	Retained alpha
33% cutoff	0.2174 (0.1033)	0.5010 (0.2351)	25.63%	0.2076 (0.1849)	0.3954 (0.3241)	19.08%
10% cutoff	0.4366 (0.2413)	0.9819 (0.3139)	45.39%	0.2817 (0.1485)	0.6862 (0.3644)	28.48%

Table 24: Average estimates of out-of-sample performance for the superior portfolio. Standard deviations are provided in parentheses. Retained alpha is measured as average percentage of the past alpha retained in the out-of-sample period.

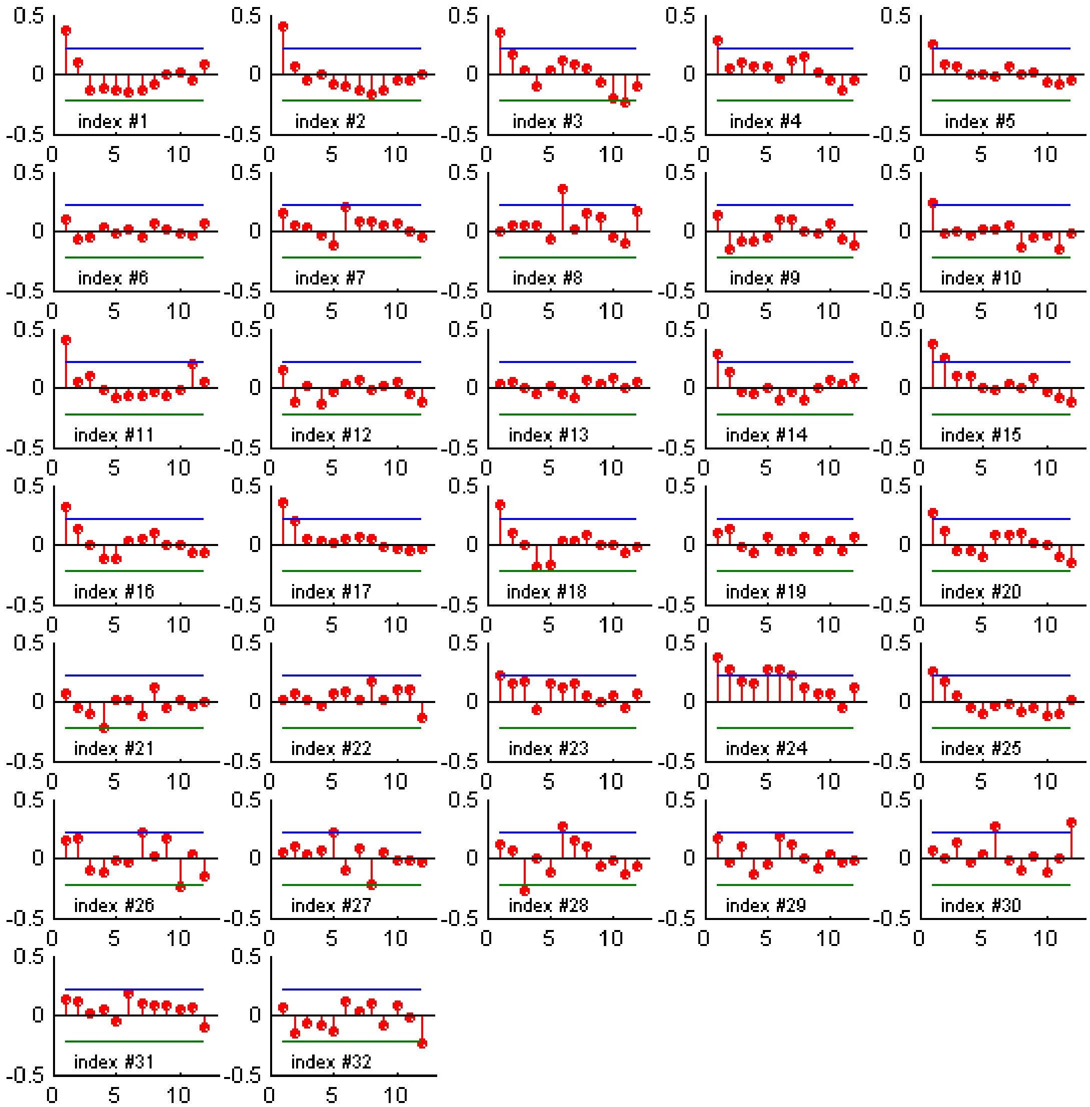

Figure 1: The autocorrelation functions for style indices are presented in this figure. The style indices used are *before* the adjustment for smoothing (i.e. as they were presented in the original database). The autocorrelations were computed for lags from 1 to 12. The thin horizontal lines around the horizontal axes represent 95% confidence intervals. Style index names can be retrived from table 1. For example, index #1 stands for Convertible Arbitrage index.

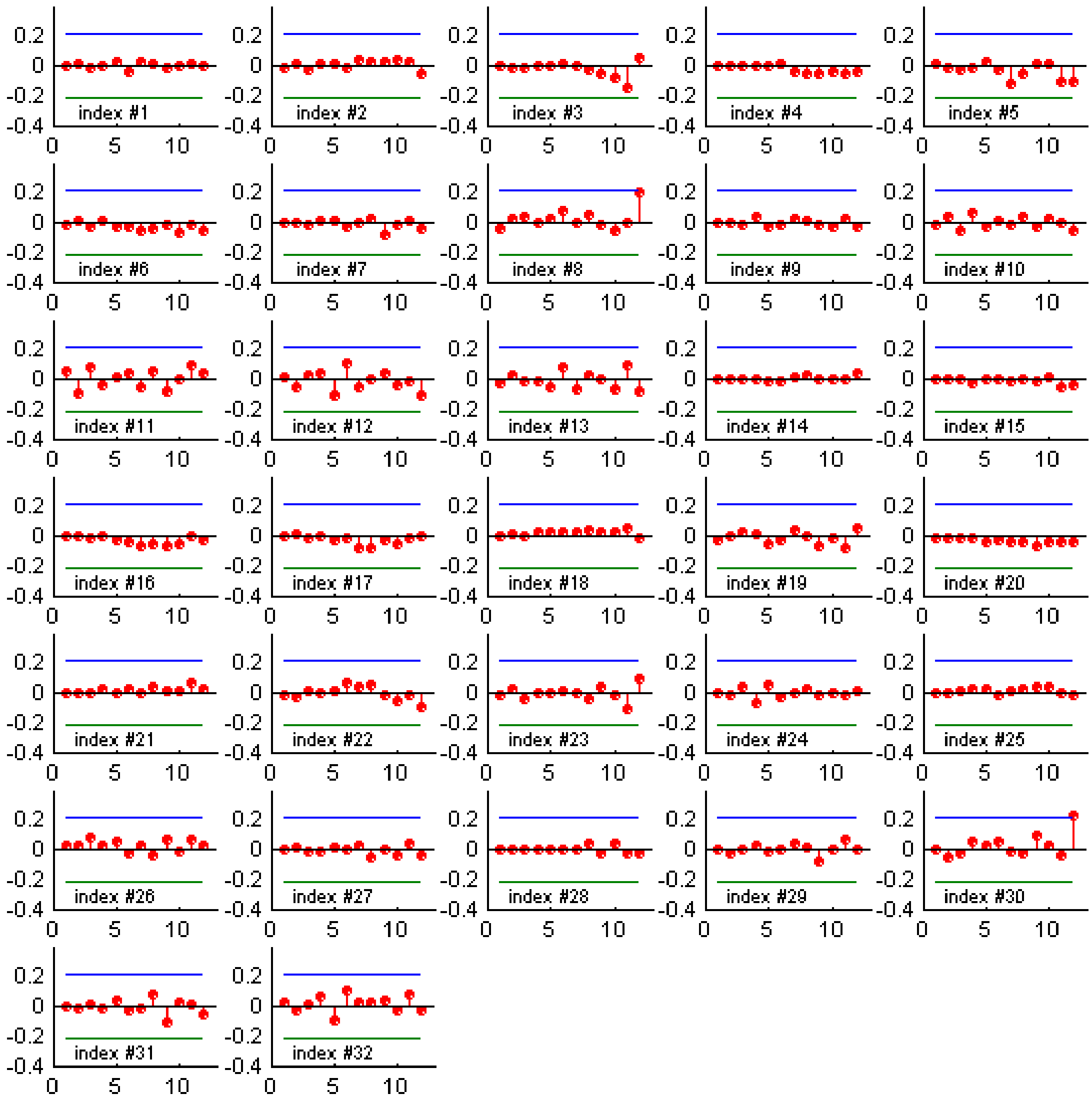

Figure 2: The autocorrelation functions for style indices are presented in this figure. The style indices used are *after* the adjustment for smoothing (η_t^J from (4)). The autocorrelations were computed for lags from 1 to 12. The thin horizontal lines around the horizontal axes represent 95% confidence intervals. Style index names can be retrived from table 1. For example, index #1 stands for Convertible Arbitrage index.

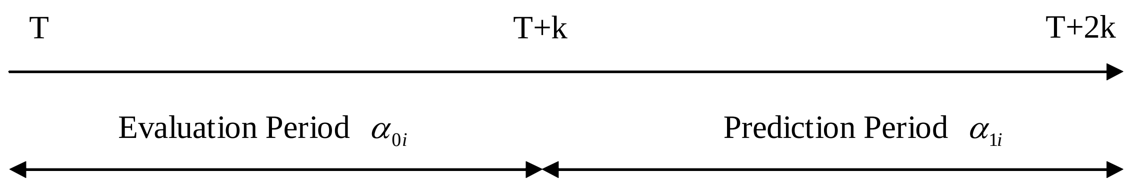

Figure 3: This diagram shows the timeline for the estimation of hedge fund alphas. In this paper k is equal to 36 months, i.e. evaluation and prediction periods are 3 years. The hypotheses is tested if alphas from the evaluation period can explain alphas from the prediction period.

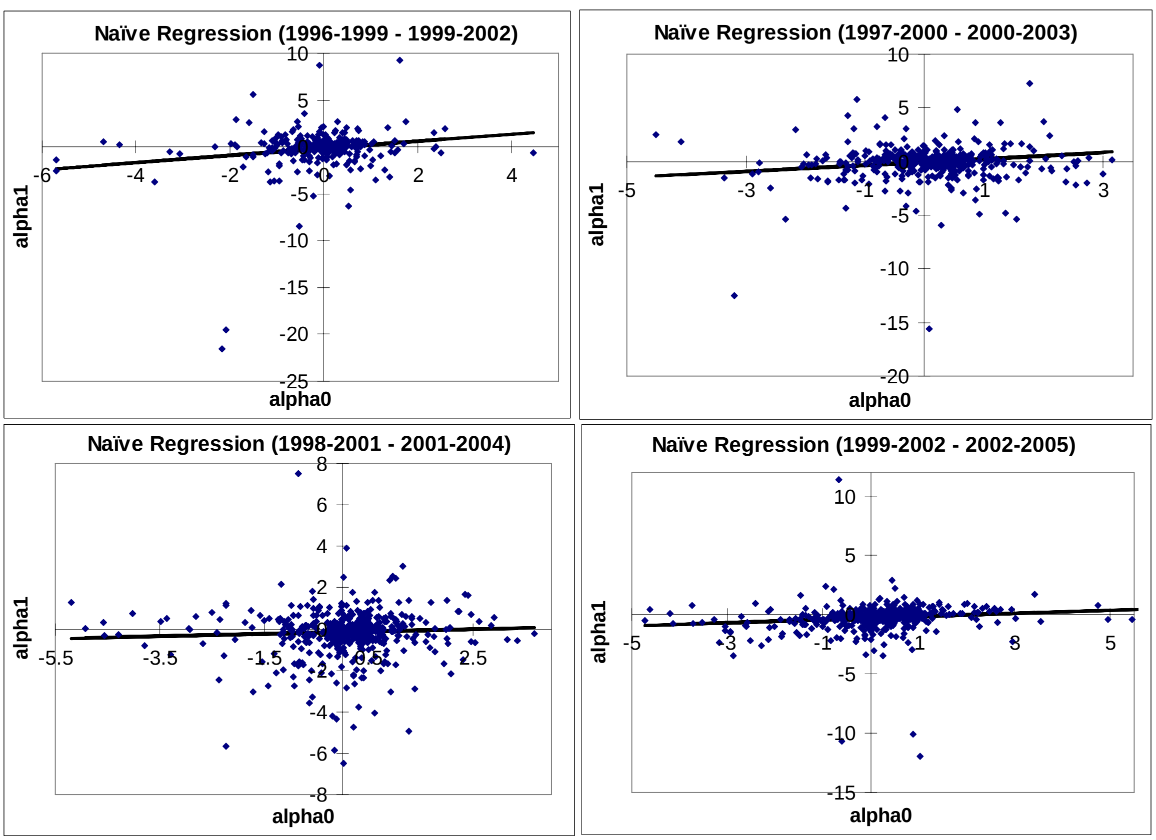

Figure 4: Scatter plots from the naive regression.

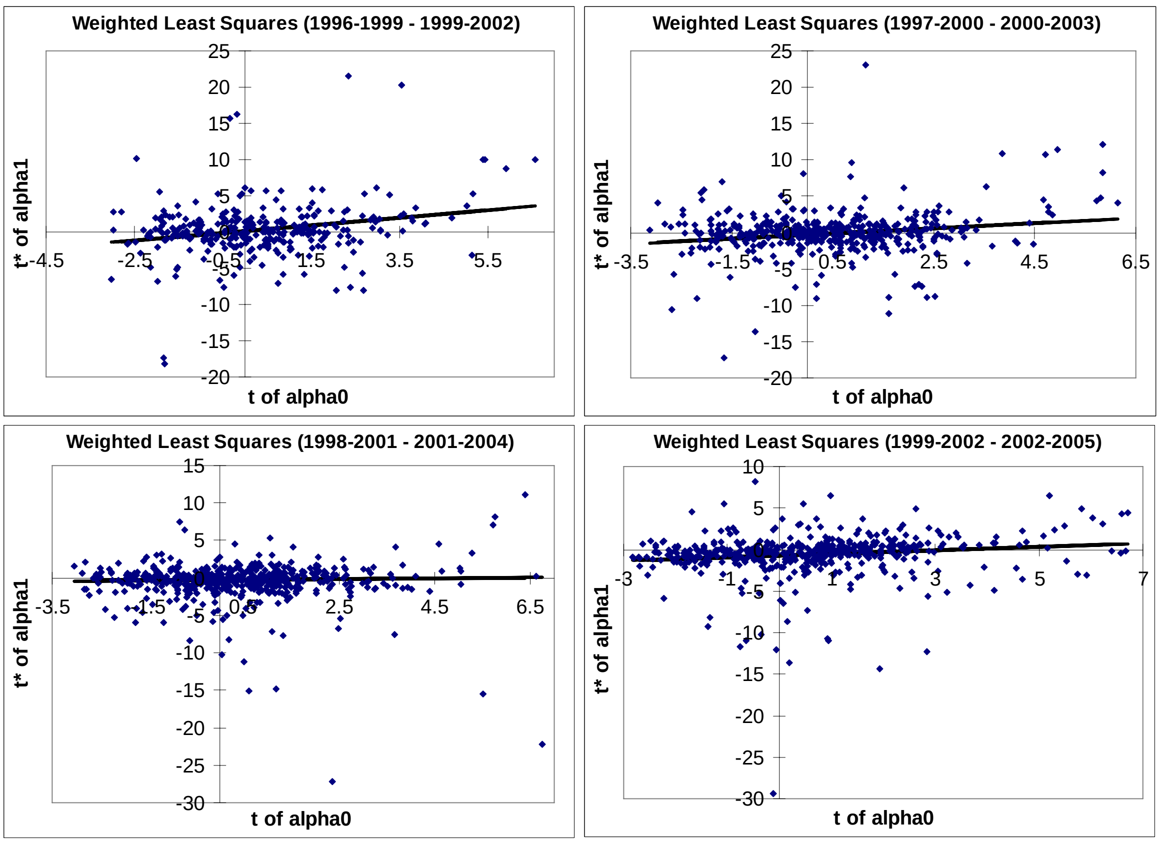

Figure 5: Scatter plots from the weighted least squares approach.

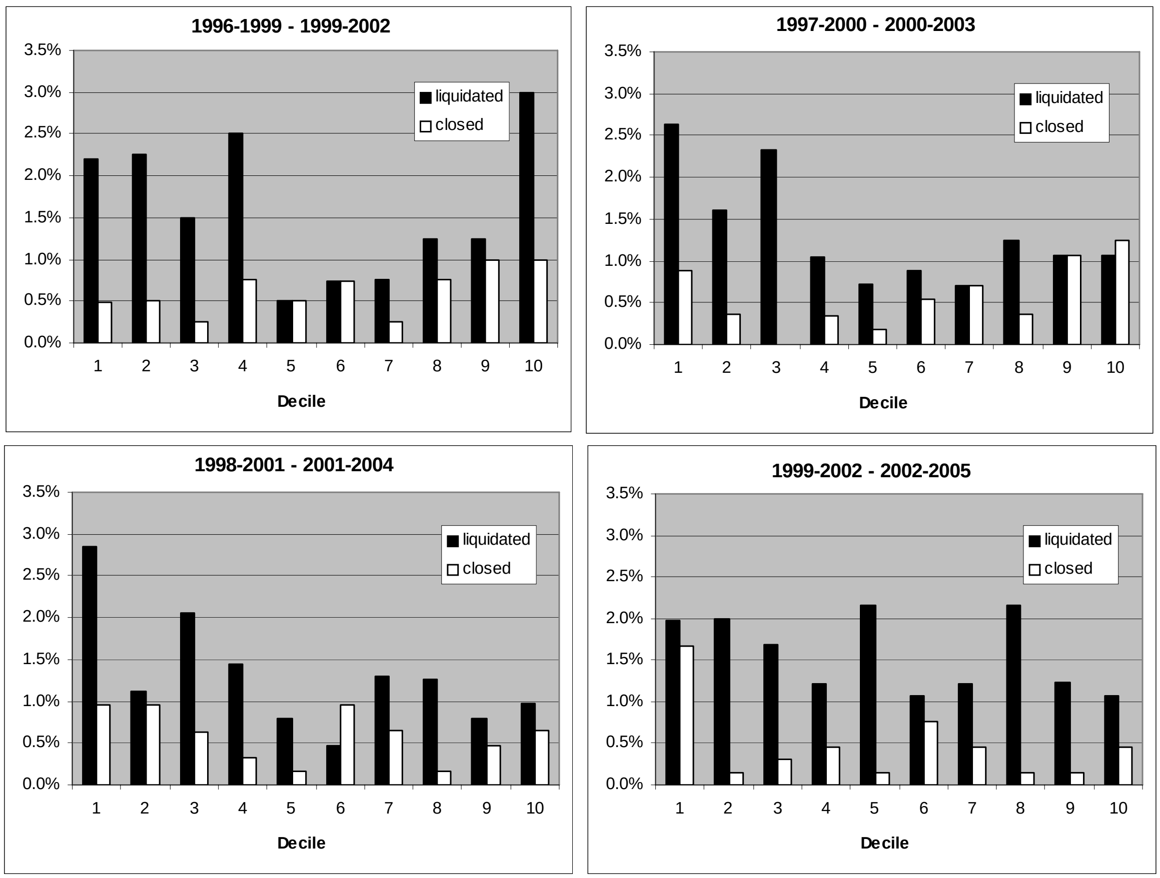

Figure 6: Histograms of distributions of liquidated and closed funds by deciles of α_0.

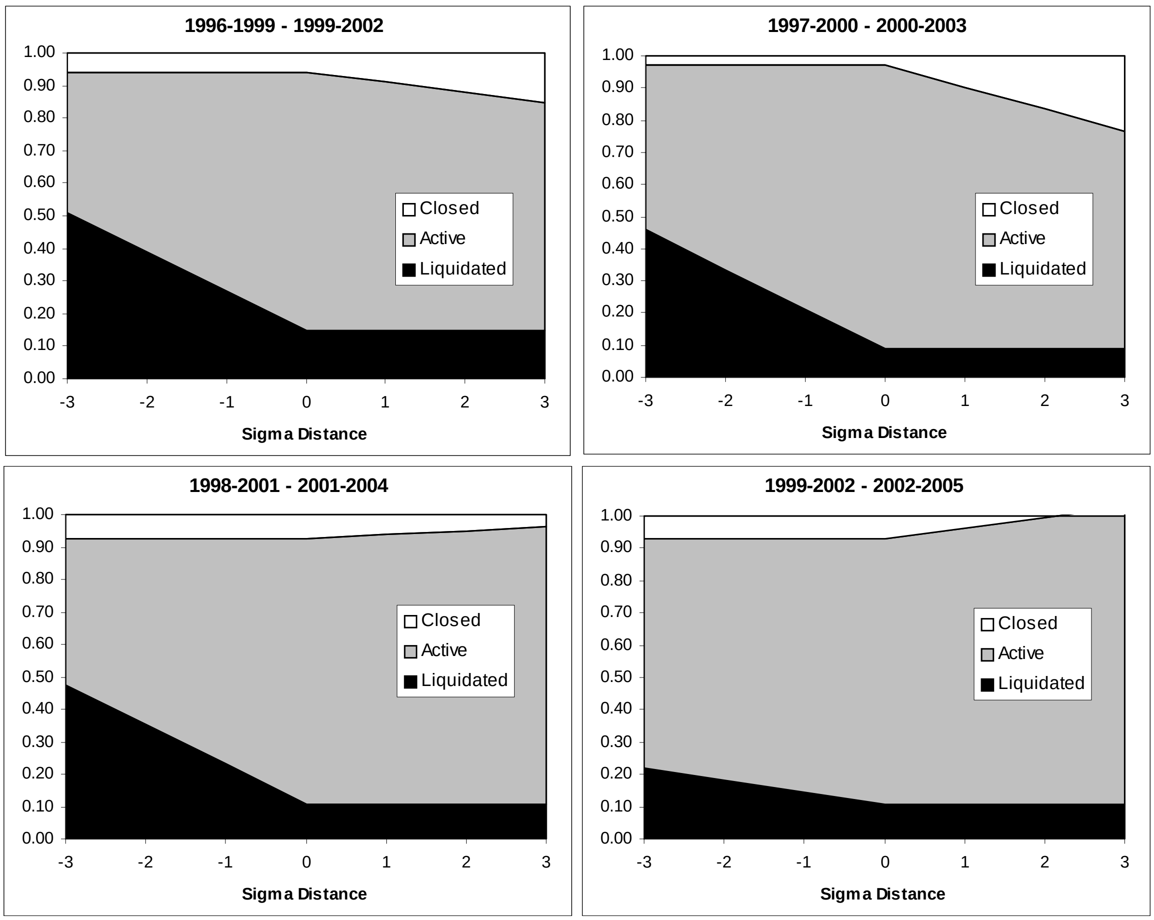

Figure 7: GMM estimated conditional probabilities of liquidation and closure with respect to α_0^*.