# Recovering Delisting Returns of Hedge Funds

by

James E. Hodder

Jens Carsten Jackwerth

Olga Kolokolova

First draft: March 11, 2008

This version: April 29, 2011

Version 35

James E. Hodder, University of Wisconsin-Madison, jhodder@bus.wisc.edu
Jens Jackwerth, University of Konstanz, jens.jackwerth@uni-konstanz.de
Olga Kolokolova, Manchester Business School, olga.kolokolova@mbs.ac.uk

We would like to thank the following for helpful comments on earlier versions of the paper: Kostas Iordanidis, Veronika Krepely Pool, Ingmar Nolte, Winfried Pohlmeier, and seminar participants at the University of Cyprus, Nikosia, the University of Konstanz, the University of Zurich, and the Universitat Pompeu Fabra.

# Recovering Delisting Returns of Hedge Funds


## Abstract

Numerous hedge funds stop reporting each year to commercial databases. A performance estimation question is: what delisting return to attribute to such funds? This would be particularly problematic if delisting returns are typically very different from continuing funds' returns. In this paper, we use estimated portfolio holdings for funds-of-funds with reported returns to back out estimates for hedge-fund delisting returns. The estimated mean delisting return for all funds of 0.31% per month is not statistically significantly different from the average monthly return for all reporting hedge funds of 0.56%. Upon delisting, hedge fund value does not seem to deteriorate considerably.

# Recovering Delisting Returns of Hedge Funds

Each year, a substantial percentage of hedge funds stop reporting their results to publicly available databases. For example, the annual average "delisting" rate was 14.55% in the data used for this paper.[1] That data is a combined database created from six major commercial databases (ALTVEST, BarclayHedge, CISDM, Eurekahedge, HFR, and TASS) for January 1994 – June 2009.[2] Typically, delisting funds are described as "dead funds"; but it is clear that not all of them have ceased to exist. The information in the databases is self-reported by the funds, with only 23.59% of dead funds indicating they were being liquidated. Indeed, another 2.08% indicate that they stopped providing their returns because they closed to further investments (potentially due to stellar performance and large previous inflows of investment capital); and some 0.97% state that they were merged with another hedge fund. Moreover, the remaining 73.36% of delisted funds either did not indicate why they ceased reporting or provided non-informative statements such as "requested by manager".

If one is studying hedge-fund performance, delisting raises the issue of what return should be attributed to delisting funds for the period when they stop reporting. One possibility for addressing the missing delisting returns is to simply drop the last period from the analysis, but that ignores the fact that fund investors will actually experience the delisting return. In contrast, Posthuma and van der Sluis (2004) used 0%, -50%, and -100% to cover a wide range of possibilities for the unknown delisting return. This drew a strong response from two practitioners, Van and Song (2005, p.7), who call the assumption of a -50% delisting return "outrageous". However, if a fund has suffered massive losses and is being liquidated, a large negative delisting return is definitely possible. This would be particularly likely if the fund had large illiquid positions that would be difficult to value and sell. Such a fund's mark-to-market valuation prior to delisting could seriously underestimate the extent of losses that would be incurred with liquidation, presumably under adverse circumstances. Moreover, for the vast majority of funds, we do not know why they stopped reporting.

---

[1] In what follows, we will use the terms "delist" and "exit" to equivalently indicate that the fund has stopped reporting its performance to database providers.

[2] Our versions of the respective databases cover somewhat differing time periods; but in the aggregate, the combined data spans the January 1994 – June 2009 period. There is also overlapping coverage of some funds, and we adjust for that overlap.

In this paper, we develop a methodology for estimating delisting returns based on a FoF being a portfolio of positions in individual hedge funds, some of which may stop reporting in any given period.[3] If we had direct information on the actual FoF portfolio positions, it would be straightforward to back out returns for delisting funds using that information plus the FoF returns and the returns of live hedge funds for the delisting month. Unfortunately, we do not have that information on FoF portfolio positions. Instead, we estimate those portfolio holdings through a matching algorithm related to principal component analysis. Once we have inferred the portfolio holdings (positions in hedge funds) for each FoF in our sample, we can obtain delisting returns during the next period based on the difference between the observed next-period return for each FoF and that period's return from its estimated portfolio holdings in live (still reporting) hedge funds. An issue with our matching algorithm is the potential for mismatches where the estimated FoF portfolio contains a different number of delisted funds than truly occurred for that FoF during the period. We develop an adjustment to correct for this bias and report below estimates using that methodology.

We find that the estimated mean delisting return for all exiting funds is slightly smaller but not significantly different from the mean monthly return of 0.56% for all hedge funds in our sample during January 2000 - June 2009. Thus, we find that the estimated average delisting return is nowhere near large negative values of -50% or -100%. We document some persistence in the delisting returns. The sub-group of hedge funds that delist after having positive returns tend to have higher delisting returns than the average hedge fund, whereas hedge funds that delist after having negative average returns tend to have negative delisting returns, which are significantly smaller than the average hedge fund return of 0.56% per month.

There is a small group of funds, which delist after having positive mean return over six months prior to the delisting and which state that they are being liquidated. These funds seem to be rather profitable with a very high delisting return of 7.09% per month. However, they are about three times smaller than an average live hedge fund and experience fund outflow prior to

[3] Fung and Hsieh (2000) as well as Fung, Hsieh, Naik, and Ramadorai (2008) have also noticed that FoF returns implicitly incorporate the delisting returns of individual hedge funds; however, they do not use the portfolio connection to actually back out the delisting returns. Nevertheless, Fung, Hsieh, Naik, and Ramadorai (2008, page 1778) do point out that the absence of delisting returns leads to a situation where a "fund-of-fund's return more accurately reflects the losses experienced by investors in the underlying hedge fund (albeit indirectly)."

delisting. Such small funds might not be able to break even on their fixed costs and, thus, decide to liquidate despite their positive returns.

There is a literature which explores hedge-fund performance prior to delisting.[4] However, there have been few attempts to examine performance after delisting. Ackermann, McEnally, and Ravenscraft (1999) used a combined data set with underlying data from two providers, Managed Account Reports, Inc. (MAR) and Hedge Fund Research, Inc. (HFR). During 1993-1995, their combined data included 37 "terminated" funds (liquidated, restructured, or merged into another fund) plus an additional 104 funds that stopped reporting without a clear indication as to why they ceased reporting. That is, a total of 141 delisting funds. Those authors were able to obtain information on returns for some fraction of the terminated funds (only) via a request to HFR regarding funds that had been listed in the HFR portion of the joint database. Thus, the information refers to only a subset of the 37 terminated funds rather than all 141 delisting funds. The response from HFR indicated an average return for the terminating funds after delisting of -0.7%, with a surprisingly rapid final redemption that occurred on average only 18 days after delisting. It would appear that some of the terminating funds were in the process of liquidating while still reporting returns. Unfortunately, that data is rather early (1993-1995), predating the boom in the hedge-fund industry; and it is based on a relatively small sample (at most 37 terminating funds).

Agarwal, Fos, and Jiang (2010) also perform some analysis of delisting returns, although the authors largely focus on an attempt to estimate "self-reporting bias" using information from 13F filings with the SEC which only covers US equity and some option positions with few exceptions. The analysis covers a longer period from 1980 to 2007; however, their reported number of delisting hedge funds is still rather limited - only 187 instances. Their estimated mean delisting return of -0.72% is quite similar to that reported by Ackermann, McEnally, and Ravenscraft (1999).[5] However, the 13F filings are quarterly and involve sizable management firms (AUM over $100 million) rather than individual hedge funds. This suggests their estimated returns are for management firms and may involve multiple funds.

---

[4] See for example, Brown, Goetzmann, and Ibbotson (1999), ter Horst and Verbeek (2007), as well as Liang (2000).

[5] The delisting funds in Agarwal, Fos, and Jiang are not liquidated or merged but continuing to operate in contrast to the funds used in the -0.7% estimate of Ackermann, McEnally, and Ravenscraft (1999).

There is also a recent paper by Aiken, Clifford, and Ellis (2010) that estimates hedge fund returns based on reported quarterly hedge fund holdings during 2004-2009 by each of 80 fund-of-funds (FoF) that were registered with the SEC. That paper focuses on self-reporting bias but also reports some results for delisting hedge funds. Those results indicate delisting funds underperform funds that remain listed by approximately 0.45% monthly during the quarter after delisting. That estimate is on a risk-adjusted basis using the Fung and Hsieh 7-factor model. However, the delisting funds in this paper (as in Agarwal, Fos, and Jiang (2010)) are not liquidated or merged but continuing to operate. Moreover, a potentially important issue with this paper is that it only checks for listing (delisting) in two databases (TASS, and BarclayHedge). Hence, there may be a rather large fraction of the non-listed firms that are actually listed and/or delisting from other commercial databases.

The next section provides details on the matching algorithm and the econometric model of FoF returns. In Section II, we describe our empirical design and basic characteristics of the data sample. Results are contained in Section III with several robustness checks collected in Section IV. Section V concludes.

## I. The Basic Model

Since we do not have precise information on portfolio holdings for each FoF in our sample, we need a procedure for estimating those holdings. We use a matching algorithm described below that is conceptual related to principle components. As a preliminary step, we need to “gross up” the reported FoF returns to a pre-fee level – that is, to the return level before management and incentive fees were extracted by the FoF. That pre-fee FoF return is the return on a portfolio of post-fee hedge fund returns (management and incentive fees having already been extracted by the respective hedge funds). As our FoF and hedge-fund return data is all post-fee, we transform the FoF returns to a pre-fee basis using an algorithm closely related to Brooks, Clare, and Motson (2007) and detailed in Kolokolova (forthcoming).

In our implementation, we use a 36-month rolling window and consider only FoFs and hedge funds which report returns for all months in the relevant window. As with many other implementation choices for our basic methodology, we have examined robustness to variations in the choice of a 36-month window. To avoid cluttering the exposition, we defer discussion of most such robustness checks until Section IV below. As a general statement, our qualitative results are robust; but there can be some variation in point estimates and significance tests.

For each FoF, we find the hedge fund whose (post-fee) returns are most highly correlated with the (pre-fee) returns of that FoF. Then, we regress the FoF returns on the chosen hedge fund and obtain the residual returns. In these regressions, we impose upper and lower limits on the estimated weights (more details below) to assure a reasonable level of portfolio diversification and avoid highly concentrated holdings that would be rather unlikely in FoF portfolios. Next, we find a second hedge fund that is now the most highly correlated with the residual returns for that FoF. We add that hedge fund to the portfolio, find new residual returns, and proceed in this fashion until we have 15 hedge funds in the portfolio.[6] Additionally, after having added the 10th hedge fund, we require the estimated portfolio weights in all subsequent portfolios to sum up to unity.

Once we work out the set of matched hedge funds for each FoF, we are ready to model the pre-fee returns of the FoF as a portfolio of the (post-fee) returns on the matched hedge funds. Hedge funds within each match are indexed by j. The (pre-fee) FoF returns are always indicated with an upper-case *R*, and the live hedge fund returns (post-fee) are denoted with a lower-case $r_L$. We use T = 36 consecutive returns to estimate the following regression model for each FoF, with those FoFs indexed by *i* and time periods (months) by *t*:

$$\begin{gathered} R_{it} = [r_{Lt}]\beta_i + \varepsilon_{it},\ t = 1,\dots,T,\ \text{and } i = 1,\dots,N_{FoF} \\ \text{s.t. } \beta_{min} \le \beta_i \le 0.10,\ \sum_j \beta_{ij} = 1 \end{gathered}, \tag{1}$$

where $N_{FoF}$ is the number of all possible subsamples of T consecutive returns for the FoFs reporting to our database. We do not make any assumptions concerning the distribution of the error term $\varepsilon_{it}$ except that it has a zero mean.

Logically, equation (1) should not include a constant term since we do not have an investable asset with a constant return.[7] Since equation (1) implicitly has unlevered returns for

[6] In the robustness section, we allow up to 26 hedge funds in each portfolio, which matches the reported average for FoFs in our data.
[7] We have also run the analysis allowing a constant term, and there is little effect on the results.

the FoFs, we limit ourselves to only those FoFs that report not using leverage. These FoFs attempt to remain close to fully invested, and we do not include the riskless asset as one of the potential investments.

In order to insure economically sensible portfolio positions, we restrict the loadings $\beta_i$ (portfolio weights for $FoF_i$) on the matched hedge funds to be smaller than 0.10 and larger than some minimal value $\beta_{min}$. For the main part of our analysis, $\beta_{min}$ is set at 0.02; however, we explore alternative values in our robustness tests discussed in Section IV. We further assume that each FoF is fully invested in its set of matched hedge funds.[8]

We now turn to the fitted return of the FoF in period T+1. If all the hedge funds in that particular FoF portfolio are still alive, then the fitted return is simply calculated with the portfolio weights that were estimated using equation (1) coupled with the observed returns of the matched hedge funds for period T+1:

$$\hat{R}_{i,T+1} = [r_{L,T+1}]\hat{\beta}_i \tag{2}$$

Now consider the situation where a hedge fund delists and does not report its return for period T+1. We denote that unreported return as $r_{E,T+1}$. The econometrics and computations turn out to be much simpler if we base our estimates on matched FoF portfolios where there is a single delisting hedge fund. That situation represents approximately 89% of our matched sample, and we drop matches with multiple delisting hedge funds from the estimation procedure. Note that with one delisting fund in the portfolio, the vector of live returns $r_{L,T+1}$ will be one shorter than in the above situation where all hedge funds for a given FoF portfolio remained alive. In period T+1, a FoF with a (single) delisting hedge fund in its portfolio will have an actual return that can be expressed as:

$$R_{i,T+1} = [r_{L,T+1}, r_{E,T+1}]\beta_i + \varepsilon_{i,T+1} \tag{3}$$

[8] There is a potential omitted variables problem in that a given FoF may be invested in one or more hedge funds that are not in our database. Our procedure implicitly approximates such missing funds by a linear combination of hedge funds that are in our database. Simulation studies discussed in Section IV below indicate our methodology works relatively well, even with a hypothetically large number of missing funds. As a practical matter, our combined

We approximate the true betas with the estimated betas from equation (1), and compute one realization of the delisting return as:

$$\hat{r}_{E,T+1} = \left(R_{i,T+1} - [r_{L,T+1}]\hat{\beta}_{L,i}\right) \Big/ \hat{\beta}_{E,i}\ ,\ t = 1,\ldots,T, \text{ and } i = 1,\ldots,N_{FoF}\ , \tag{4}$$

where $\hat{\beta}_{L,i}$ and $\hat{\beta}_{E,i}$ are the estimated betas respectively for the 14 hedge funds staying alive and the one delisting hedge fund in period T+1 for the matched portfolio of $\text{FoF}_i$. The numerator of equation (4) will contain estimation error which is amplified when dividing by a fractional $\hat{\beta}_{E,i}$ (which is also estimated with error). Particularly when $\hat{\beta}_{E,i}$ is low, this calculation can result in large errors which we mitigate by trimming (in each tail) the most extreme 1% of estimates from equation (4).

We also consider the fact that several FoFs might invest in the same hedge fund. If that hedge fund delists, then the associated delisting return $r_{E,T+1}$ will be the same for all FoFs with that hedge fund in their portfolios. To ensure that result, we add up the relevant equations (3) while keeping the $r_{E,T+1}$ constant. The estimated realization of the delisting return in this case is:

$$\hat{r}_{E,T+1} = \sum_i \left(R_{i,T+1} - [r_{L,T+1}]\hat{\beta}_{L,i}\right) \Big/ \sum_i \hat{\beta}_{E,i}\ ,\ t = 1,\ldots,T, , \tag{5}$$

where the sum is taken across all FoF matches i that include the delisted hedge fund of interest.

We estimate the mean delisting return by averaging the individual realizations calculated above. Our procedure does not require precise hedge fund identification, and the returns of the truly delisted funds can be proxied by returns of different (but correlated) funds in the matching portfolio. Nevertheless, the estimate of $\mu_E$ is unbiased only if a FoF truly invests into $k$ delisted hedge funds and the corresponding matched portfolio also has exactly $k$ delisted funds. One cannot guarantee that exact correspondence regarding the number of delisted funds while

database is large and should have a substantial portion of the relevant hedge funds, further mitigating the potential omitted variables problem.

constructing the matching portfolios; and hence, we need to adjust the estimated $\mu_E$ for potential bias.

Since we use only matches that have exactly one delisted fund, the following biases can occur. First, consider a FoF that did not actually invest in any delisted fund; but the estimated matching portfolio erroneously contained a single delisted fund. Using this match, one would estimate not an unobserved delisting return (on average $\mu_E$) but the return of a hedge fund that was still alive. The higher the share of such matches, the more the estimated $\mu_E$ will be biased towards the average return of hedge funds that were reporting to the database, which we denote by $\mu_{HF}$. Second, if a FoF truly invested into one delisted hedge fund and the estimated matching portfolio also has one delisted fund, then the match has perfect correspondence and does not bias the estimate of $\mu_E$. Third, consider a FoF that actually had investments in two or more hedge funds that delisted; but that FoF was matched with a portfolio having only one delisted fund. If the number of truly delisted funds was two, one would obtain an average estimate of $\mu_E + (\mu_E - \mu_{HF})$ instead of $\mu_E$. Simulation results described below indicate the probability is only 0.04% that a FoF with 3 or more truly delisting hedge funds is matched with a single delisting fund. Consequently, our adjustment procedure does not consider cases with three or more truly delisting hedge funds in a single FoF portfolio.

The biases due to such mismatches can be corrected, if one knows the share of matches for each type. Let us denote by $p_k$ the probability that a FoF truly invested in $k$ delisted funds, and the estimated matching portfolio indicates the existence of only one delisted fund. Then the estimated biased delisting return $\mu_E^{Estimated}$ is a weighted average of the unbiased estimate $\mu_E^{Unbiased}$ and the average return of hedge funds in the database $\mu_{HF}$.[9] That is:

$$\mu_E^{Estimated} = p_0 \cdot \mu_{HF} + p_1 \cdot \mu_E^{Unbiased} + (1 - p_0 - p_1) \cdot \left(2\mu_E^{Unbiased} - \mu_{HF}\right) \qquad (6)$$

and we can solve for $\mu_E^{Unbiased}$ :

[9] In our adjustment, we use the average monthly return of all hedge funds in the sample. This will also include funds that were alive during a portion of the January 2000 – June 2009 period but eventually died.

$$\mu_E^{Unbiased} = \left[ \mu_E^{Estimated} - (2p_0 + p_1 - 1) \cdot \mu_{HF} \right] \Big/ \left( 2 - 2p_0 - p_1 \right). \tag{7}$$

The probabilities $p_k$ are not known but can be estimated using a simulation procedure which is described in the appendix.

## II. Data Characteristics and Implementation

We begin this section with a description of the data before proceeding to a discussion of our bootstrap procedure for estimating standard errors.

### A. The Data

We have constructed a joint database using a union of six major databases (ALTVEST, BarclayHedge, CISDM, Eurekahedge, HFR, and TASS) from which we deleted duplicates and different share classes of the same fund. That joint database is large, containing more than 20,000 hedge funds and about 6,000 FoFs that reported sometime during the January 1994 – June 2009 period. Those funds are classified into dead and live hedge funds plus dead and live FoFs. We only use funds that report in US dollars and have any performance record after January 2000. This leaves us with 16,398 individual hedge funds and 5,031 FoFs. Panel A of Table 1 reports descriptive statistics for those funds for the period from January 2000 to June 2009, which we will later use as the main reference period. A fund being designated as live or dead in that table refers to its status as of June 2009. Note that the monthly returns are post-fee for both hedge funds and FoF in Panel A, just as they are reported in the database.

We eliminate the first 12 returns for each hedge fund in order to mitigate backfill bias. Our matching procedure requires funds which report returns for at least 36 consecutive months, and we eliminate all funds which do not satisfy that requirement (after deleting the first 12 monthly returns for hedge funds). We only keep FoFs which indicate they never use leverage.

When one looks carefully at delisting events before January 2000, nearly half are reported as occurring at year end; however in many cases, the last months (sometimes several) of reported returns were all zeros. Thus, we believe that monthly delisting dates before January 2000 are not reliable. Consequently, we use only funds that report at least 36 returns after January 1997, such that their reported delisting occurs no earlier than January 2000. Panel B in Table 1 reports descriptive statistics for those funds; and we have 7,910 hedge funds, of which 3,194 delisted (died) at some time prior to the end of June 2009. Among the 1,348 FoFs in our restricted sample, 921 are classified as live funds; however, we can still use the 427 dead FoFs for windows of time when they were alive. For the FoF statistics in Panel B, we report pre-fee returns computed using the algorithm mentioned previously. When implementing that algorithm, we use the reported fee structure for each FoF; however, as a point of information, the typical FoF in our data charges a management fee of 1% and an incentive fee of 10% per year.

### B. Bootstrapped Standard Errors

Calculating standard errors for our analysis is potentially problematic due to the multiple-layer estimation procedure and the consequent accumulation of errors from the potential mismatch of FoF portfolios and estimation of betas. Moreover, the different FoF matches will typically have overlapping time series. Because of these issues, we use a bootstrap approach to estimate standard errors. In particular, we utilize a two-stage procedure that bootstraps over the matches and also over the returns in each match. For the first stage, we use our matched portfolios where each match is a sequence of 37 returns for the relevant FoF complete with the respective matched portfolio of hedge funds. We randomly draw with replacement the same number of matched portfolios to constitute a bootstrapped set. For the second stage, we also bootstrap from the monthly return vectors within each match. That is, we resample by time-slice (keeping the actual returns aligned by month) the 36 months of FoF and matched hedge fund returns. This allows re-estimated portfolio weights to differ in the bootstrap procedure. We obtain a new estimate for $\mu_E$ using this bootstrapped set of matches and beta estimates. Finally, we use our bias correction described in the appendix to adjust for a mismatched number of delisting funds and obtain unbiased estimates for $\mu_E$. We repeat this exercise 1,000 times to obtain bootstrapped standard errors which allow for potential mismatch of FoF portfolios, estimation error in the portfolio weights, overlapping time series, and small sample effects.

### Table 1: Descriptive Statistics

The table reports descriptive statistics for funds from the union of six databases (ALTVEST, BarclayHedge, CISDM, Eurekahedge, HFR, and TASS). Panel A is based on all unique funds reporting in US dollars during January 2000 - June 2009. Panel B is based on the funds used in our analysis, after we dropped the first 12 observations for all hedge funds and eliminated any hedge fund and FoF that did not have at least 36 consecutive remaining observations between January 1997 and June 2009. The performance of these funds is reported between January 2000 and June 2009. We also eliminate FoFs that report using leverage. Return statistics are based on monthly returns in percent. Note that all returns in Panel A are post-fee. In Panel B, the FoF returns are grossed up to a pre-fee basis, while the hedge-fund returns remain post-fee. All values except Number of Funds are averages of the corresponding statistics for the individual funds.

**Panel A: All Funds Jan. 2000 – Jun. 2009**

| | Hedge Funds, post-fee | | | Funds of Funds, post-fee | | |
|---|---|---|---|---|---|---|
| | All | Live | Dead | All | Live | Dead |
| Number | 16398 | 8847 | 7551 | 5031 | 3625 | 1406 |
| Life Time in Years | 3.27 | 4.72 | 2.00 | 4.12 | 4.82 | 2.53 |
| Mean Return | 0.55 | 0.70 | 0.37 | 0.25 | 0.22 | 0.31 |
| Median Return | 0.50 | 0.79 | 0.16 | 0.46 | 0.51 | 0.34 |
| STD | 4.60 | 4.33 | 4.92 | 2.45 | 2.48 | 2.37 |
| Min Return | -10.18 | -11.01 | -9.21 | -6.71 | -7.34 | -5.09 |
| Max Return | 11.68 | 11.78 | 11.56 | 5.32 | 5.27 | 5.45 |
| Skewness | -0.07 | -0.22 | 0.11 | -0.63 | -0.81 | -0.18 |
| Kurtosis | 5.04 | 5.71 | 4.25 | 5.56 | 5.97 | 4.47 |
| Sharpe Ratio | 0.14 | 0.22 | 0.05 | 0.13 | 0.12 | 0.16 |

**Panel B: Funds with at least 36 Returns Jan. 2000 – Jun. 2009**

| | Hedge Funds, post-fee | | | Funds of Funds, pre-fee, no leverage | | |
|---|---|---|---|---|---|---|
| | All | Live | Dead | All | Live | Dead |
| Number | 7910 | 4716 | 3194 | 1348 | 921 | 427 |
| Life Time in Years | 5.37 | 6.44 | 3.81 | 5.56 | 6.33 | 3.91 |
| Mean Return | 0.56 | 0.75 | 0.26 | 0.56 | 0.62 | 0.45 |
| Median Return | 0.51 | 0.84 | 0.02 | 0.71 | 0.84 | 0.41 |
| STD | 4.55 | 4.17 | 5.11 | 2.54 | 2.46 | 2.72 |
| Min Return | -11.66 | -12.19 | -10.87 | -7.51 | -8.06 | -6.32 |
| Max Return | 13.34 | 13.06 | 13.74 | 6.92 | 6.71 | 7.38 |
| Skewness | -0.08 | -0.26 | 0.18 | -0.54 | -0.77 | -0.04 |
| Kurtosis | 6.00 | 6.67 | 4.99 | 6.65 | 7.17 | 5.52 |
| Sharpe Ratio | 0.11 | 0.17 | 0.04 | 0.20 | 0.20 | 0.20 |

## III. Results

The results discussed in this section are based on those FoF matches where the adjusted R-squared in implementing equation (1) is at least 25%.[10] In those matches, the average holdings of individual hedge fund ($\beta_i$) are estimated to be 0.067, with the standard deviation across matches of 0.033. The average loadings on the delisting funds are estimated to be 0.062, which is significantly smaller than the average loading on the surviving funds due to the very large number of beta estimates across all matches.

In Table 2, we report estimated mean delisting returns for "All" matches as well as for funds that stated they were being "Liquidated" or provided "No Reason" that was informative regarding their reason for delisting.[11] For the set of All delisting hedge funds, we find an estimated average monthly delisting return (bias-corrected) of 0.31% that is not significantly different from the average return for all hedge funds of 0.56% reported in Panel B of Table 1. Moreover, this result is very different from a large negative delisting return such as -50%; and the bootstrapped STD is such that we can be quite confident the average delisting firm does not have such a large negative exit return. That conclusion is further supported by a simulation test reported in Section IV that indicates our procedure (albeit noisy) would reliably find a mean delisting return that was large and negative if the process generating the data had such a large negative mean.

**Table 2: Mean Delisting Returns**

We report the monthly delisting returns (bias-corrected) based on matched portfolios of FoFs where the adjusted R-squared of the main regression model is at least 25%. We use 1% tail trimming. Mean delisting returns and their standard deviations are in % per month.

| | Number of Matches | Mean Delisting Return | Bootstrapped STD of Mean Delisting Return | Non-parametric p-value for difference with average HF return |
|---|---|---|---|---|
| All | 1873 | 0.31 | 1.41 | 0.43 |
| Liquidated | 464 | 1.27 | 2.75 | 0.29 |
| No Reason | 1364 | 0.18 | 1.70 | 0.34 |

[10] Using cut-off values of 15%, 30%, or 50% does not qualitatively change the results, with only small changes in the estimated numerical values.

[11] Other self-reported categories such as "merged" and "closed to further investment" were too small to have reliable mean estimates.

Considering the No Reason and Liquidated categories of funds separately, we find that in none of the categories hedge funds had mean delisting return significantly different from 0.56%. However, funds that state they were being Liquidated had slightly higher point estimate of a mean delisting return of 1.27%. This is somewhat surprising because one tends to think that funds being liquidated were presumably poor performers. Poor past performance, however, might not indicate a negative exit return if the fund's assets have been properly marked-to-market.

On the other hand, it seems plausible that the mean delisting return of hedge funds, especially funds stating no reason for delisting, could be similar to the average monthly return of all (live) hedge funds. It might be that a substantial fraction of delisting funds were doing fairly well and delisted for other (unstated) reasons. Perhaps they merged or even were closed to further investment but did not bother to state a clear reason. Reporting to a database can be characterized as a form of advertising, and there could be a variety of reasons to stop advertising.

To investigate this issue further, we sorted the Liquidated and No Reason hedge funds into Top and Bottom groups, such that Top funds exhibit positive average returns over the six months prior to delisting, whereas Bottom funds exhibit negative average returns.[12] Mean delisting returns for these sub-categories are reported in Table 3. There is evidence of return persistence, with the Top Funds having higher mean delisting returns than the Bottom set of funds. The p-value of that difference for all funds is 0.02. Top funds have a higher delisting return of 3.63%, and Bottom funds have a negative delisting return of -3.99%. Both estimates are different from the average return of the live hedge funds at the 10% significance level. Such return persistence is consistent with Getmansky, Lo, and Makarov (2004), who found persistence among live funds. Also, it is probable that some funds are exiting because their strategy and/or implementation is performing poorly in the then current economic environment. Most such funds would presumably be in the Bottom set; and assuming the environment continued to be unfavorable as they exited, return persistence seems reasonable. The negative mean delisting returns of the Bottom set of funds is consistent with that story; however, the result for Top Liquidated funds is

[12] We also tried other benchmarks to separate Top and Bottom funds. This included basing the Top category on whether the fund's return exceeded the mean hedge fund return over the six months prior to delisting. We also tried a

somewhat counterintuitive. The return persistence is not surprising; but if a fund is apparently doing well, why is it being liquidated?

Addressing this question for the Top set of funds, we find positive average returns over the last half-year prior to delisting of 1.25% per month for the Liquidated sub-group and 1.45% per month for the No Reason sub-group. However, funds in both subgroups were smaller than average funds and experienced fund outflow. Thus, they might have difficulties to break even on their fixed costs, which could explain their delisting decision.

**Table 3: Mean Delisting Returns**

We report the monthly delisting returns (bias-corrected) based on matched portfolios of FoFs where the adjusted R-squared of the main regression model is at least 25%. We use 1% tail trimming. Mean delisting returns and their standard deviations are in % per month.

| | Number of Matches | Mean Delisting Return | Bootstrapped STD of Mean Delisting Return | Non-parametric p-value for difference with average HF return | Non-parametric p-value for the difference between Top and Bottom Funds |
|---|---|---|---|---|---|
| **Top** | | | | | |
| **All** | **1056** | **3.63** | **1.70** | **0.08** | **0.02** |
| **Liquidated** | **242** | **7.09** | **3.70** | **0.04** | **0.03** |
| **No Reason** | **790** | **2.55** | **2.00** | **0.32** | **0.14** |
| **Bottom** | | | | | |
| **All** | **817** | **-3.99** | **2.34** | **0.06** | **--** |
| **Liquidated** | **222** | **-5.07** | **3.80** | **0.17** | **--** |
| **No Reason** | **574** | **-3.10** | **2.99** | **0.15** | **--** |

The size of the Top Liquidated funds was on average 60 million USD, compared to 150 million USD for Top No Reason fund and 172 million USD for live funds with positive average returns over half-year periods. In addition to their small size, both sub-groups suffer from fund outflow; on average -0.37 million USD per month for Liquidated funds and -0.44 million USD per month for No Reason funds. As a result, Top Liquidated funds might have delisted because of their inability to attract enough capital, despite their large delisting return of 7.09% which is achieved on a too small asset base.

similar approach using the median hedge fund return. The different benchmarks do not qualitatively change the results. There are only minor changes in the point estimates.

We also looked at alternative characteristics of Liquidated and No Reason funds beyond their Top and Bottom classification according to funds having positive or negative returns prior to delisting. We found that Liquidated funds have lower prior returns than No Reason funds during the past 12 and 36 months (p-values of 0.08 and 0.00, respectively). Volatility of the prior returns is significantly lower for Liquidated funds at all horizons (6, 12, and 36 months). Finally, alpha within the Fung and Hsieh (2004) model is significantly lower for Liquidated funds which might be attributable to their low skill, possibly contributing to their inability to attract capital and their final liquidation.

## IV Robustness Tests

In this section we first evaluate the general quality of our matching algorithm, and then proceed by checking the stability of the results with respect to various changes in the methodology.

### A. Quality of the matching algorithm

We investigate the quality of our matching algorithm by constructing hypothetical FoF returns from reported hedge fund returns. The purpose of this exercise is to confirm that our procedure would find a large negative mean return if, in fact, that was the true situation. In other words, if the true mean delisting return were say -50%, our estimation procedure would deliver a similarly large negative mean estimate despite generating noisy return estimates. The simulation procedure we use here is almost identical to that described in the appendix for estimating the probability of a mismatch regarding the number of delisting hedge funds in a FoF portfolio. The only difference is for delisting hedge funds, where we introduce a fictitious delisting return drawn from a Normal distribution with known mean and standard deviation. In order to test if the proposed methodology performs well for different scenarios, we cover a wide range of possible delisting return distributions within the simulation exercise. We first consider a case, in which hedge fund delisting returns are rather similar to the returns of reporting funds. We simulate delisting returns with mean value of 1% and standard deviation of 5%, which is roughly consistent with the mean of 0.56% and standard deviation of 4.55% of all hedge funds (Table

1, Panel B). Second, we simulate a case in which hedge funds incur moderately large losses upon delisting. The mean delisting return is shifted to -10% while we keep the standard deviation unchanged at the 5% level. Last, we investigate a possible scenario of a dramatic mean delisting return of -50% with a 10% standard deviation. We construct synthetic FoFs and repeat this exercise for as many sets of 36 consecutive FoF returns as we find in the actual data, each time moving forward by one month and then drawing hedge fund return vectors. Finally, we employ our usual estimation procedure to back out the mean delisting returns.

In implementing this test, we also consider the issue that our database does not contain all hedge funds. We do this by separating the hedge funds in our database into a "visible" set and an "invisible" set before generating the hypothetical FoF returns. That is, we split the database so that only a fraction (100%, 67%, or just 33%) of the total hedge funds will later be visible to our matching algorithm. For example, suppose we split the total so that 67% of the hedge funds are in the visible set and another 33% are invisible. We then generate each hypothetical FoF return by randomly drawing 10 hedge funds from the visible set and 5 funds from the invisible set. However when we implement the matching algorithm, it is only allowed to search for matches within the visible set.

The estimated mean delisting returns based on the simulated FoFs are reported in Table 4. Those results indicate that our procedure does a relatively good job of recovering large negative mean delisting returns of -10% and -50%, and does not mistakenly find large negative mean returns when true mean delisting return is 1%. This is true even when only 33% of hedge funds in which the simulated FoFs invest are visible. Thus, we are rather confident that our procedure would not miss a large and negative mean delisting return even if the database only contained a modest fraction of the hedge fund universe.

**Table 4: Simulated Performance Results**

The table reports mean delisting returns and their standard deviations as well as the bootstrapped standard deviations of the mean delisting return for simulated samples of FoF returns. Each FoF is modeled as a portfolio of 15 individual hedge funds. For simulated delisting funds, the hypothetical delisting return is drawn from a normal distribution with given mean ($\mu_E$) and standard deviation ($\sigma_E$), expressed in percent per month. The reported estimates are obtained using our standard procedure with a subset of the hedge funds used to generate the FoF returns being visible to our matching algorithm. We vary the fraction of visible funds using 100%, 67%, and 33% of the total generating set. We consider three possible delisting return distributions for hedge funds, characterized by pairs ($\mu_E$, $\sigma_E$) of (1, 5), (-10, 5), and (-50, 10). Values are in % per month.

| Number of Visible Funds | Number of Matches | Mean Delisting Return | Bootstrapped STD of Mean Delisting Return |
|---|---|---|---|
| | **($\mu_E$, $\sigma_E$) = (1,5)** | | |
| 15 | 2821 | -0.02 | 0.60 |
| 10 | 2025 | 1.48 | 0.61 |
| 5 | 1056 | -1.60 | 0.62 |
| | **($\mu_E$, $\sigma_E$) = (-10,5)** | | |
| 15 | 2809 | -10.27 | 0.61 |
| 10 | 2014 | -10.90 | 0.59 |
| 5 | 1021 | -8.26 | 0.68 |
| | **($\mu_E$, $\sigma_E$) = (-50,10)** | | |
| 15 | 2811 | -50.65 | 1.08 |
| 10 | 1987 | -49.84 | 1.15 |
| 5 | 1047 | -42.34 | 1.08 |

In situations (such as -50%) where the delisting return is very different from the average hedge fund results and some of the hedge funds held by the simulated FoFs are not in the visible data, our methodology tends to underestimate the absolute value of the delisting return. This is due to the algorithm not finding delisting hedge funds that are invisible (hidden) and instead erroneously includes a live fund in the match. This is analogous to the mismatch problem described earlier and again biases the estimated mean delisting return toward the average monthly return for all hedge funds. Our combined database of 6 widely used commercial databases is large, and it should contain a substantial portion of the total hedge fund universe. Thus, we believe that the problem of seriously underestimating delisting returns because hedge funds are missing from the data is relatively minor in our study.

We recognize the possibility that a FoF alters its portfolio over time rather than holding it constant for 36 months. Such turnover behavior has implications for our methodology that are similar to a hedge fund not being included in the database. That is, our algorithm will tend to include spurious hedge funds in the estimated matches in an attempt to mimic the true time-varying holdings of the FoF. To examine potential implications of this problem, we implemented a simulation using a monthly turnover rate for all FoFs of 1.8% (equivalent to 20% annually, which would correspond to roughly half of each FoF portfolio turning over in a three-year period). We create simulated FoF portfolios as previously (each with 15 hedge funds) except that none of the hedge funds will be treated as invisible. Then, each month with the probability 1.8% we substitute a randomly chosen new hedge fund for one in the current portfolio. For month 37, one of the remaining hedge funds is designated as the delisting fund and its return is replaced by a randomly generated delisting return. We then implement our standard procedure to estimate the mean delisting return. If the delisting return was from a distribution with a mean of 1% and a standard deviation of 5%, our procedure finds a mean return of 1.18%. Even if the delisting return was from a distribution with a -10% monthly mean return and a standard deviation of 5%, or with a mean return of -50% and a standard deviation of 10%, the estimated mean delisting returns are also relatively accurate at -10.19% and -51.46% respectively. This suggests that the estimated mean delisting returns reported earlier in Table 2 are not very sensitive to the possibility of turnover in the FoF portfolios.

We examine the accuracy of the matching algorithm and estimated portfolio weights by comparing the forecasted FoF portfolio return in the $37^{th}$ month with the actual FoF return in those matches where we have no delisting funds (consequently, having a full set of returns for the $37^{th}$ month). Our average forecast error is only 0.052% with a standard error of 1.76 for matches with R-squared above 25%.

B. Stability of the empirical results

To assess result stability, we also implemented our procedure using variations on the basic methodology. This included allowing a constant term when estimating equation (1), using rolling windows of 30 and 42 months, altering the minimum beta limit to 0.01 and to 0.04, and employing different trimming levels for excluding outliers from the set of estimated delisting returns. We also reran the analysis after excluding FoFs that exhibited serially correlated returns as well as employing a procedure that allowed up to 26 hedge funds in a match. Most resulting changes relative to the estimated mean delisting returns reported in Table 2 are substantially less than a bootstrapped standard deviation of the original estimate, and we interpret them as minor differences.

One of the potentially more interesting variations on our approach was a matching procedure that allowed up to 26 possible hedge funds in a FoF portfolio instead of requiring exactly 15. The algorithm proceeded in much the same way as our basic procedure but stopped adding funds to the portfolio when any fund would have an estimated weight of less than 0.02. We increased the maximum possible number of funds in the portfolio to 26 in this case. Using this procedure, the average number of hedge funds in a matching portfolio was 12.51. As one can see in Table 5, we have fewer matches with an R-squared above 25%. The bootstrapped STD and mean delisting return estimates have changed somewhat, but those changes are minor.

**Table 5: Mean Delisting Returns With up to 26 Funds in the Matching Portfolio**

We report the monthly delisting returns (bias-corrected) based on matched portfolios of FoFs where the adjusted R-squared of the main regression model is at least 25%. We use 1% tail trimming. Mean delisting returns and their standard deviations are in % per month. The estimation is conducted based on 36 returns. The algorithm stops as soon as any of the betas takes a value of 0.02.

| | Number of Matches | Mean Delisting Return | Bootstrapped STD of Mean Delisting Return | Non-parametric p-value for difference with average HF return | # of std away from the main results |
|---|---|---|---|---|---|
| All | 1578 | 0.75 | 1.29 | 0.38 | 0.31 |
| Liquidated | 380 | 2.61 | 2.47 | 0.08 | 0.48 |
| No Reason | 1163 | 0.09 | 1.50 | 0.35 | 0.05 |

We re-estimated delisting returns using only matches where we can reject first-order serial correlation for FoF returns at the 1% significance level. The largest change was a 0.16 STD increase in the Liquidated mean delisting return to 1.73%. Altering the minimum beta constraint to 0.01 or to 0.04 had similarly minor effects. The largest change was a 1.27 STD decrease in the mean delisting return for No Reason funds to -1.98% when we set the minimum beta constraint at 0.04. Using a 30- or 42-month rolling window also had minor effects. The largest change was a 0.87 STD increase in the Liquidated mean delisting return to 3.71% when 42-month window was used. The estimated delisting return remained, however, not significantly different from the average hedge fund return of 0.56%.

The effect of outliers is also an issue, and we re-estimated the mean delisting returns using different trimming percentages. Increasing the trimming level to 2% or even further to 5% has only a minor effect. The largest change was a 0.92 STD increase in the Liquidated mean delisting return to 3.81%. However, eliminating trimming entirely has more of an impact. It results in higher bootstrapped STD values. The mean delisting return for No Reason funds drops by 2.10 STD to -3.39%, but it remains not significantly different from the 0.56% monthly average return of all hedge funds.

## V. Concluding Comments

Relatively little has been known about returns after hedge funds delist from a database. We examine the situation by modeling the econometric relationship between funds of funds and the portfolios of hedge funds into which they invest. This structure allows us to estimate the average delisting return of 0.31% for all delisting hedge funds which is not significantly different from the average return of live hedge funds of 0.56% per month. Delisting returns are somewhat persistent. Hedge funds delisting after having positive average returns over the last half-year have positive delisting returns of 3.63%, whereas hedge funds delisting after negative performance have negative delisting returns of returns of -3.99% per month. These returns are significantly different from 0.56% at the 10% significance level. Funds that state they were being liquidated but have positive pre-liquidation returns have an estimated mean delisting return of 7.09%, which is significantly greater than the 0.56% average monthly return for all live hedge funds. The estimated mean delisting return for liquidated funds might seem puzzling. The reason for such good performance is that those funds seem to be small funds with average assets under management of 60 million USD and a fund outflow of -0.37 million USD per month. They seem to be able to implement profitable investment strategies on only a small scale, but had never managed to increase in size substantially to sustain their business. Thus, they are being liquidated.

Our procedure for inferring FoF portfolio holdings is noisy; but with a large number of matches (more than 1000 in our case) we obtain enough precision to have confidence in our average estimates.

## Appendix: Adjusting for the Potential Mismatch Bias

To correct a potential bias from a mismatch indicating the wrong number of delisting funds in a FoF portfolio, we need an estimate of $p_k$ (the probability that there were truly k delisting funds in that portfolio when the estimated match indicates one delisting fund). We estimate those $p_k$ probabilities using simulation. First, we construct hypothetical FoFs from existing hedge funds. For each FoF portfolio, we randomly draw without replacement a hedge fund and its vector of consecutive returns from the hedge fund database. If that hedge fund remains alive, it will have a vector of 37 consecutive returns. If it is a delisting fund, the vector will have 36 consecutive returns with delisting occurring in month 37. Repeating this procedure, we construct the same number of FoFs for each consecutive 36 months as the true number of FoFs reporting to our database during this period. Each constructed FoF consists of 15 such randomly drawn hedge funds, and we flag which hedge funds in a simulated FoF actually delisted. The portfolio weights are uniformly and randomly selected in the interval 0.02 to 0.10 and are required to sum up to one.[13]

We then move forward by one month in time and repeat this exercise, continuing in this manner until we cover the complete time frame of available data. We next employ our usual matching procedure. Based on those estimated matches, we compute the frequencies for matches in which one estimated delisting fund (using our matching procedure) corresponds to 0, 1, 2, and 3 or more true delistings in the simulated FoFs. We repeat the complete simulation 100 times and compute the estimated probabilities $p_k$ as averages of the corresponding frequencies. Table A.1 below reports the characteristics of the estimated probabilities.

[13] We use a classical acceptance-rejection algorithm here, in which we uniformly and randomly select 14 portfolio weights from a closed interval [0.02, 0.10] and compute the 15th portfolio weight as a difference between unity and the sum of the previously obtained 14 weights. We accept this vector of portfolio weights if the last computed weight also lies between 0.02 and 0.10, and reject it otherwise.

**Table A.1: Estimated Probabilities for Delisting Mismatches of Different Types**

The table reports the estimated probabilities, via simulation, that the true FoF invests into 0, 1, 2, and 3 or more delisting hedge funds when the estimated matching portfolio includes exactly one delisting hedge fund.

| Number of delisted funds in true FoF (k) | 0 | 1 | 2 | 3 or more |
|---|---|---|---|---|
| Mean Probability (%) | 65.12 | 33.97 | 0.87 | 0.04 |
| STD Probability (%) | 0.68 | 0.70 | 0.19 | 0.04 |

The standard deviations of the simulated probabilities are rather small, and we use the mean probability values for the bias correction.

**References**


Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The Performance of Hedge Funds, *Journal of Finance* 54, No. 1, 833-874.

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance* 64, No. 5, 2221-2256.

Agarwal, Vikas, Vyacheslav Fos, and Wei Jiang, 2010, Inferring Reporting Biases in Hedge Fund Databases from Hedge Fund Equity Holdings, Working Paper, Georgia State University, SSRN=1536886.

Aiken, Adam L., Christopher P. Clifford, and Jesse Ellis, 2010, Out of the dark: Hedge fund reporting biases and commercial databases, Working Paper, University of Kentucky, SSRN=1519914.

Brooks, Chris, Andrew Clare, and Nick Motson, 2007, The Gross Truth about Hedge Fund Performance and Risk: The Impact of Incentive Fees, Working Paper, University of Reading, SSRN=1031096.

Brown, S. J., W. N. Goetzmann, and R. G. Ibbotson, 1999, Offshore Hedge Funds: Survival and Performance, 1989-95, *Journal of Business* 72, No. 1, 91-117.

Fung, William, and David A. Hsieh, 2000, Performance Characteristics of Hedge Funds and CTA Funds: Natural Versus Spurious Biases, *Journal of Financial and Quantitative Analysis* 35, No. 3, 291-307.

Fung, William, and David A. Hsieh, 2004, Hedge Fund Benchmarks: A Risk Based Approach, *Financial Analyst Journal* 60, 65-80.

Fung, William, David A. Hsieh, Narayan Y. Naik, and Tarun Ramadorai, 2008, Hedge Funds: Performance, Risk, and Capital Formation, *Journal of Finance* 63, No. 4, 1777-1803.

Getmansky, Mila, Andrew W. Lo, and Igor Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics* 74, 529-610.

ter Horst, Jenke, and Marno Verbeek, 2007, Fund liquidation, Self-selection and Look-ahead Bias in the Hedge Fund Industry, *Review of Finance* 11, No. 4, 605-632.

Kolokolova, Olga, forthcoming, "Strategic Behavior within Families of Hedge Funds," *Journal of Banking and Finance.*

Liang, Bing, 2000, Hedge Funds: The Living and the Dead, *Journal of Financial and Quantitative Analysis* 35, No. 3, 309-326.

Liang, Bing, and Hyuna Park, 2010, Predicting Hedge Fund Failure: A Comparison of Risk Measures, *Journal of Financial and Quantitative Analysis* 45, 199-222.

Posthuma, Nolke, and Pieter Jelle van der Sluis, 2004, A Critical Examination of Historical Hedge Fund Returns, Chapter 13 in Intelligent Hedge Fund Investing: Successfully Avoiding Pitfalls through Better Risk Evaluation. Edited by Barry Schachter. Risk Books.

Van, George P., and Zhiyi Song, 2005, Hedge Fund Commentary from VAN, Working Paper, Van Hedge Fund Advisors International, www.edge-fund.com/VanSong2005.pdf