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Abstract

Numerous hedge funds stop reporting to commercial databases each year. An issue for hedge-fund performance estimation 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 maximum likelihood estimates for hedge-fund delisting returns. The estimated mean delisting return for all exiting funds is small, although statistically significantly different from the average observed returns for all reporting hedge funds. These findings are robust to relaxing several underlying assumptions.

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 8.1% in Morningstar's ALTVEST database for January 1994 – June 2006 (the data used in this paper).[1] If one is studying hedge-fund performance, this raises the issue of what return should be attributed to such funds for the period when they stop reporting. Typically, these funds are described as "dead funds"; but it is clear that not all of them have ceased to exist. The information in ALTVEST is self-reported by the funds, with only 20% of dead funds indicating they were being liquidated. Indeed, another 4% 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). Moreover, information for the remaining 76% of delisted funds either does not indicate why they ceased reporting or provides non-informative statements such as "requested by manager".

One possibility for addressing this issue 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 delisting return of -50% "outrageous". However, if a fund has suffered massive losses and is being liquidated, a large negative delisting return is definitely possible. This would be the case if the fund's mark-to-market valuation prior to delisting underestimated the extent of losses that would be incurred with liquidation, presumably under adverse circumstances. On the other hand, a highly successful fund that chooses to restrict further investment and focus on managing its current funds might well have a substantial positive (but unreported) delisting return. Moreover, for the vast majority of funds, we do not know why they stop reporting.

There is a literature which explores hedge-fund performance prior to delisting.[2] However, the only paper of which we are aware that makes any attempt to examine performance after delisting is Ackermann, McEnally, and Ravenscraft (1999). They used a combined data set with

[1] In what follows, we will use the term "delist" to indicate that the fund has stopped reporting its results to database providers while other authors have also used the term "exit" instead.

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 old (1993-1995), predating the boom in the hedge-fund industry; and it is based on a relatively small sample (at most 37 terminating funds). Also, they do not report delisting return estimates for funds that did not provide a clear reason for delisting or for what would correspond in the ALTVEST database to being closed to further investment.

In this paper, we propose a methodology for estimating delisting returns based on a fund-of-funds (FoF) being a portfolio of positions in individual hedge funds, some of which may stop reporting in any given period. If we had 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.

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.

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

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)."

An issue with the 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 different mean delisting returns for hedge funds that do not provide a clear reason for delisting as opposed to those that liquidate and those which state they are closed to further investment. However, none of these estimates are large. Across all delisting hedge funds, the estimated mean delisting return is -1.86%. This compares with a mean monthly return for all hedge funds in our sample of 1.01%. Thus, we find that the estimated average delisting return is fairly small and nowhere near values of -50%. Nevertheless, some funds have large negative exit returns, which results in substantial variability of our estimated delisting returns.

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 along with several robustness checks. Section IV provides concluding comments.

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 based on the concept of principle components. A somewhat similar problem has been encountered with empirical macroeconomic models in which a short time series needs to be explained by many potential predictors.[3] The macroeconometric approach of aggregating many predictors (hedge funds in our case) into principle components is not directly applicable to our setting of FoF returns. After all, each FoF invests into a relatively small number of individual hedge funds (the reported average for our data is 24) and not into principle components. However, we use a related idea which keeps the basic approach of principle components.

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[3] See e.g. Bai (2003), Bai and Ng (2002), Boivina and Ng (2006), plus Stock and Watson (2002).

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) that is described in the Appendix.

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 the robustness of our estimates 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 III below. As a general statement, our qualitative results are quite 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. 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. We provide a detailed description of the methodology in the next section.

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. 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 funds indexed by i and time periods (months) by t:

$$\begin{aligned} &R_{it} = [r_{Lt}]\beta_i + \varepsilon_{it}, \quad t = 1,...,T, \quad \varepsilon_{it} \sim N(0, \sigma^2_{\varepsilon i}) \\ &\text{s.t.:} \quad 0.25 \geq \beta_i \geq \beta_{\min}, \quad 1^{\perp}\beta_i = 1 \end{aligned} \tag{1}$$

In order to insure economically sensible portfolio positions, we restrict the loadings β_i (portfolio weights for FoF_i) on the matched hedge funds to be smaller than 0.25 and larger than some minimal value β_{min}. We further assume that each FoF is fully invested in its set of matched hedge funds.[4]

Logically, equation (1) should not include a constant term since we do not have an investable asset with a constant return. One might anticipate that a FoF would have an approximately constant component in its operation costs; however, we assume operating costs are effectively paid out of the Fund's management fee and hence do not appear in equation (1). Some 70% of FoF in our data report not using leverage on average. Apparently, most FoFs also attempt to remain close to fully invested. Hence, we do not include the riskless asset as one of the investments for our primary implementation of equation (1). However, we do include in our analysis FoFs which indicate average borrowing up to 100% (200%) of their equity. Those funds represent some 20% and 5%, respectively, of all FoFs in our data. For such FoFs, we allow investment into the riskless asset with $0 \geq \beta_{riskless} \geq -1$ (respectively ≥ -2). We use monthly returns based on 3-month T-bills from the Federal Reserve Statistical Release H.15 as a riskless rate. In those implementations, the upper limit on β_i changes then from 0.25 to 0.5 or to 0.75, respectively.

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 using the estimated portfolio weights from equation (1) 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 that period. 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 portfolios where there is a single

[4] There is an omitted variables problem in that a given FoF may be invested in one or more hedge funds that are not in our database. ALTVEST is not all-encompassing; and indeed, there are hedge funds that do not report to any of the publicly available databases. Our procedure assumes that we can implicitly approximate the omitted funds by a linear combination of hedge funds that are in our database. Simulation studies discussed in Section II below indicate our methodology works adequately, even with a large number of omitted funds. A similar argument can be used concerning turnover in the fund of funds. As long as there is a reasonably similar hedge fund which mimics the time-varying true holdings of the FoF, our method will adequately match the performance for that FoF.

delisting hedge fund. That situation represents approximately 88% of our matched sample. 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 are alive in period T+1. We model the unobserved delisting return $r_{E,T+1}$ as being normally distributed with mean μ_E and standard deviation σ_E. 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:

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

where we treat the FoF_i replication error ε_i as uncorrelated with estimated delisting returns.[5]

We approximate the true betas with the estimated betas and the variances of the residuals with their estimated values. For support of such assumptions, see the simulations and robustness checks in Section III below. The above approach leads to the following normally distributed quantity:

$$(R_{i,T+1} - r_{L,T+1}\hat{\beta}_{L,i}) \sim N(\hat{\beta}_{E,i}\mu_E, \hat{\beta}_{E,i}^2\sigma_E^2 + \hat{\sigma}_{\varepsilon i}^2), \tag{4}$$

where $\hat{\beta}_{L,i}$ and $\hat{\beta}_{E,i}$ are the estimated betas respectively for the hedge funds staying alive and those exiting in period T+1 in the matched portfolio of FoF_i.

When calculating the log-likelihood, we pay attention to the fact that several FoFs can invest into 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 portfolio. Thus, we add up the relevant equations (3) while keeping the $r_{E,T+1}$ constant in that case. Not doing so biased σ_E upward in unreported simulations.

The above procedure delivers an unbiased estimate of the mean exit return μ_E if all matched portfolios used for the analysis have the number of delisted funds correctly identified. That is, if a FoF truly invests into k delisted hedge funds, then the corresponding matching portfolio should also have exactly k delisted funds. 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. The estimate of μ_E stays unbiased as long as the number of identified delisted hedge funds coincides with the number of truly delisted funds. However, one cannot guarantee this correspondence while constructing the matching portfolios; and the resulting estimate of μ_E can be biased.

Since we use only matches that have exactly one delisted fund, the following biases can occur. First, consider a FoF that does not invest into any delisted fund, but the estimated matching portfolio erroneously has a delisted fund. Using this match, one would estimate not an unobserved delisting return (on average μ_E) but the return of a hedge fund that was still alive. The higher the share of matches of this type, the more the estimate of μ_E will be biased towards the average return of hedge funds that were reporting to the database during that period, which we denote by μ_{HF}. Second, if a FoF truly invests 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 μ_E. Third, consider a FoF that actually has investments in two or more hedge funds that delist but is matched with a portfolio having only one delisted fund. Trying to compensate for this mismatch would tend to impart an upward bias in the estimated absolute value of μ_E. For example, if the number of truly delisted funds is two, one would obtain an average estimate of $\mu_E + (\mu_E - \mu_{HF})$ instead of μ_E. Our adjustment procedure does not consider cases with three or more truly delisting hedge funds since the probability of such a situation is very low for a FoF portfolio invested in 15 hedge funds. According to our simulations described below, the probability that a FoF has 3 or more exiting hedge funds while being matched with only one exiting fund is less than one percent.

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 invests into 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 a hedge funds in the database μ_{HF}.[6] That is:

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[5] Changing the correlation coefficient to 0.5 or -0.5 does not qualitatively change the results, with only small changes in the estimated numerical values.

[6] In our adjustment, we use the average monthly return of all hedge funds in the sample. This will include funds that were alive during a portion of the 1994 – June 2006 period but eventually died and are thus included in the dead funds portion of the database as of June 2006.

$$\mu_E^{Estimated} = p_0 \cdot \mu_{HF} + p_1 \cdot \mu_E^{Unbiased} + \left(1 - p_0 - p_1\right) \cdot \left(2\mu_E^{Unbiased} - \mu_{HF}\right) \tag{5}$$

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

$$\mu_E^{Unbiased} = \left[\mu_E^{Estimated} - (2p_0 + p_1 - 1) \cdot \mu_{HF}\right] \Big/ \left(2 - 2p_0 - p_1\right) \tag{6}$$

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

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. Finally, we describe our adjustment for the bias induced by potential mismatches regarding the number of delisting funds in a FoF portfolio.

A. The Data

We use the ALTVEST database which contains 6827 reporting funds during the January 1994 – June 2006 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 exclude 36 dead funds that were removed from the live database because of duplicate registration. This leaves us with 6169 total funds, of which 4873 are hedge funds and 1296 are FoFs. Panel A of Table 1 reports descriptive statistics for those funds. A fund being designated as live or dead in that table refers to its status as of June 2006. 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.

Table 1. Descriptive Statistics

The table reports descriptive statistics for funds reporting to the ALTVEST database. Panel A is based on all funds reporting in US dollars during January 1994 - June 2006. 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 funds that did not have at least 36 consecutive remaining observations. Return statistics are across funds and based on monthly returns. 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 statistics.

Panel A

	Hedge Funds, post-fee			Funds of Funds, post-fee		
	All	Live	Dead	All	Live	Dead
Number	4873	2130	2743	1296	886	410
Life Time in Years	4.67	5.60	3.94	4.80	5.12	4.10
Mean	1.05	1.13	1.00	0.66	0.68	0.61
Median	0.90	1.01	0.82	0.69	0.74	0.59
STD	4.36	3.58	4.98	2.12	1.75	2.92
Min	-9.65	-8.27	-10.72	-4.79	-3.90	-6.72
Max	13.05	11.93	13.92	6.16	5.10	8.45
Skewness	0.09	0.16	0.03	-0.11	-0.15	-0.04
Kurtosis	5.29	5.38	5.22	4.65	4.44	5.12
Sharpe Ratio	0.25	0.32	0.19	0.29	0.33	0.22

Panel B

	Hedge Funds, post-fee			Funds of Funds, pre-fee		
	All	Live	Dead	All	Live	Dead
Number	2496	1290	1206	759	540	219
Life Time in Years	6.40	7.08	5.67	6.79	7.12	5.98
Mean	1.01	1.05	0.97	0.84	0.85	0.80
Median	0.88	0.94	0.81	0.81	0.86	0.71
STD	4.32	3.83	4.85	2.17	1.81	3.06
Min	-11.21	-10.06	-12.45	-5.65	-4.70	-8.01
Max	14.65	13.56	15.81	7.56	6.34	10.55
Skewness	0.06	0.12	-0.01	-0.06	-0.13	0.10
Kurtosis	6.18	6.01	6.37	5.64	5.39	6.26
Sharpe Ratio	0.24	0.29	0.19	0.37	0.41	0.26

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 also exclude FoFs which indicate they are highly levered, defined as average borrowings exceeding 200% of their equity capital. This reduces our sample of FoFs by 5.12%. Panel B of Table 1 reports descriptive statistics of the remaining funds. We have 2496 hedge funds, of which 1206 delisted (stopped reporting) at some time prior to the end of June 2006 and are thus classified as dead funds. We are not focusing on hedge fund style; however, our data contains a good representation of several styles with equity long/short (43%), directional (20%), relative value (23%), and event driven (14%). Among the 759 FoFs, 540 are classified as live funds; however, we can still use the 219 dead FoFs for windows of time when they were alive. For the FoF statistics in Panel B, we now report pre-fee returns computed using the algorithm described in the Appendix. We use the reported fee structure with that algorithm; 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

Theoretical standard errors for our analysis would be problematic due to assumptions that the true beta is equal to the estimated beta and that the residuals are normally distributed. These assumptions might well be violated. 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 parameter estimates for μ_E and σ_E via maximum likelihood. Finally, we use our bias correction to obtain unbiased estimates for μ_E and σ_E. We repeat this exercise $1,000$ times to obtain bootstrapped standard errors which allow for estimation error in the portfolio weights, non-normal residuals, overlapping time series, and small sample effects.

C. Adjusting for the Potential Mismatch Bias

Since the probabilities p_k are not known, we estimate them using simulation. First, we construct hypothetical FoFs from existing hedge funds. 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. We construct 500 FoFs each consisting of 15 such randomly drawn hedge funds and flag which funds in a simulated FoF actually delisted. The portfolio weights are uniformly and randomly selected in the interval 0.02 to 0.07 and normalized to sum to one. We then move forward six months 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 exits 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 2 below reports the characteristics of the estimated probabilities.

Table 2: Estimated Probabilities for 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 (%)	63.48	29.67	5.94	0.91
STD Probability (%)	1.02	1.00	0.45	0.19

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

We investigate the quality of our matching algorithm by constructing hypothetical FoFs returns from live hedge fund returns. The procedure here is almost identical to that employed for estimating the probability of a mismatch regarding the number of exiting hedge funds in a FoF portfolio. The only difference is, that for delisting hedge funds, we introduce a fictitious delisting return drawn from a Normal distribution with mean -50% or -10% and a respective standard deviation of 10% or 3%. We again construct 500 FoFs and repeat this exercise for another eighteen sets of 500 FoFs, each time moving forward by six months and then drawing hedge fund return vectors. We finally employ our usual estimation procedure to back out the mean delisting returns.

In implementing this test, we also explore 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 with this approach are reported in Table 3 both with and without the bias correction for mismatches. The simulations indicate the bias correction is not perfect but has an important impact, moving the estimated delisting return from -20.30% to -48.13% in the case of a true -50% delisting return with all hedge funds in the visible set. Similarly in the case of a true mean delisting return of -10%, our bias correction moves the estimated mean from -4.17% to -10.92%.

Table 3: Simulated Performance Results

The table reports the average delisting return 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 (μ_E) and standard deviation (σ_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 two possible delisting return distributions for hedge funds, characterized by pairs (μ_E, σ_E) of (-50, 10) and (-10, 3). Values are in % per month for the unbiased results and in parentheses for the biased, estimated results.

Number of Visible Funds	Number of Matches	Mean Delisting Return	Bootstrapped STD of Mean Delisting Return	STD of Delisting Return
		(μ_E, σ_E) = (-50,10)		
15	176	-48.13 (-20.30)	4.57 (1.98)	23.70
10	175	-47.20 (-19.87)	4.29 (1.86)	21.70
5	171	-35.74 (-14.93)	3.87 (1.68)	20.10
		(μ_E, σ_E) = (-10,3)		
15	172	-10.92 (-4.17)	1.60 (0.69)	6.90
10	174	-9.50 (-3.55)	1.38 (0.60)	6.10
5	172	-7.09 (-2.50)	1.71 (0.74)	6.30

In situations where some of the hedge funds held by the simulated FoFs are not in the visible data, our methodology underestimates 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 including a live fund in the match. This is analogous to the mismatch problem described above and again biases the estimated mean delisting return toward the average monthly return for all hedge funds. Since we do not know the extent of delisting funds that are not in the ALTVEST database but are nonetheless held by our FoFs, we cannot adjust for that bias. Nevertheless, the results in Table 3 indicate that our procedure does recover most of the simulated mean delisting return (-50% or -10% respectively in the upper and lower panels) even under the worst case scenario when only 33% of hedge funds in which 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.

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 over a three-year period). As with invisible funds, this leads to our methodology underestimating the magnitude of the true simulated delisting return. Nevertheless, we recovered between 70% and 84% of the correct value. This suggests that our results reported below may be modest underestimates if FoF turnover is that substantial. If actual turnover across all FoFs is less than the simulated 20% annual rate, then the effect of this estimation issue will be lessened. In any case, even if the described problem changed the magnitude of our estimates by as much as 30%, it would not change the qualitative results.

III. Results

In this section, we first describe our main results and then discuss several robustness tests conducted to validate our results.

A. Main Results

In Table 4, we present results based on FoF matches where the adjusted R-squared in implementing equation (1) is at least 50%.[7] We also provide the estimated standard deviation σ_E of the delisting returns as well as bootstrapped standard errors for our estimated mean delisting returns. For the set of all delisting hedge funds, we find an estimated average monthly delisting return (bias-corrected) of -1.86%. Based on the self-reported reason for delisting, we

[7] Using cut-off values of 25% or 75% does not qualitatively change the results, with only small changes in the estimated numerical values.

find that funds stating they were liquidated had a delisting return of 2.34%.[8] Funds that stopped reporting due to being closed for further investment had a delisting return of 1.99%. Finally, funds that did not clearly state a reason for no longer reporting had a mean delisting return of -3.27%. Using p-values based on the bootstrapped distribution for delisting returns indicates that the estimated mean delisting returns for the categories All and No Reason are significantly different from the average return for all funds of 1.01% (see Panel B of Table 1).[9] Both Liquidated and Closed categories have estimated mean delisting returns that are not significantly different from the 1.01% average return for all funds in the database.[10]

This provides rather strong evidence that on average, delisting returns are far from disaster scenarios with exit returns of -50% or worse. Since the average delisting return is significantly different from all funds, it would be reasonable to base performance estimates on a small negative assumed delisting return like -1,86%. Note that simply ignoring the delisting fund would over-weight the remaining live funds and bias the performance estimate slightly upward. Nevertheless, that bias is not likely to be serious in most applications.

The maximum likelihood estimate for the standard deviation of all delisting returns, 7.70%, is considerably higher than the average standard deviation of 3.83% for all hedge fund returns (in Table 1, Panel B). This difference is due to the maximum likelihood estimate also capturing possible portfolio mismatches and estimation errors.

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8 This is broadly in line with the findings of Ackermann, McEnally, and Ravenscraft (1999) who report a small, albeit negative, mean delisting return of -0.7% for terminated funds (which corresponds approximately to our liquidated funds category).

9 Recall that the categorization of live versus dead in Table 1 refers to a fund's status as of June 2006. Hence it seems appropriate to make a comparison with the mean return for all funds (1.01%) which refers to monthly returns when funds were alive. Using the average return on live funds (1.05%) or on dead funds (0.97%) hardly changes the results, as the average return differences are very minor.

10 We explored whether partitioning the sample based on reported style or fee structure had an economically important effect on estimated mean delisting returns. However, the reduced sample size in each category led to inconclusive results.

Table 4: Mean Delisting Returns

We report the monthly delisting returns (bias-corrected) for FoFs where the adjusted R-squared of the main regression model is at least 50%. Values are in % per month.

	Number of Matches	Mean Delisting Return	Bootstrapped STD of Mean Delisting Return	Non-parametric p-value for difference with 1.01	STD of Delisting Return
All	986	-1.86	1.06	0.00	7.70
Liquidated	160	2.34	1.76	0.20	5.20
Closed	36	1.99	4.03	0.29	4.40
No Reason	790	-3.27	1.28	0.00	8.60

B. Robustness Tests

To assess the stability of our results, we implement our procedure using variations on our basic methodology. Most resulting changes relative to the estimated mean delisting returns in Table 4 are within one bootstrapped standard deviation (using the Table 4 values) of the original estimate. We interpret such changes as minor and discuss more substantial changes below.

To begin, we examine accuracy for the matching algorithm and estimated portfolio weights by comparing the forecast 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 0.054%.

We conduct a set of runs which test for potential problems with the residuals of our main regression model in equation (1). First, we use only FoFs where a Jarque-Bera test for normality of the residuals cannot be rejected. Second, we use only those FoF returns where a Breusch-Pagan test for no heteroscedasticity cannot be rejected. Third, we use only FoF returns where a Ljung-Box test for no first order serial correlation cannot be rejected. Fourth, we use only FoF returns where the average residuals $\varepsilon_{i,t}$ are not significantly different from zero. In Table 5, we report the results for matched portfolios that satisfy the joint restriction that no rejection at the 10% significance level is allowed for any of the four tests regarding that particular match. The general picture remains much the same as in our main results from Table 4; however, bootstrapped standard deviations are larger due to reduced sample sizes. Note that the mean delisting returns for both the Liquidated and the Closed categories declined by more than one bootstrapped standard deviation. However, these mean estimates are not significantly different in either table from the average monthly return for all hedge funds. Moreover, we are following the relatively conservative approach of using the Table 4 bootstrapped standard errors which are substantially smaller than those in Table 5.

Table 5: Mean Delisting Returns for Well-Behaved Residuals

We report the monthly mean delisting returns (bias-corrected) for FoFs where the adjusted R-squared of the main regression model is at least 50%. We also only use those FoFs where the residuals from regressions on the model in equation (1) do not reject the following four restrictions at the 10% significance level: normally distributed, homoskedastic, no first-order autocorrelation, and zero average residuals. Values are in % per month.

	Number of Matches	Mean Delisting Return	Bootstrapped STD of Mean Delisting Return	Non-parametric p-value for difference with 1.01	STD of Delisting Return
All	694	-2.98	1.71	0.01	11.10
Liquidated	122	-0.10	2.74	0.44	6.20
Closed	28	-4.58	7.60	0.26	10.70
No Reason	544	-3.56	2.06	0.01	12.50

In Table 6, we report estimates which allow FoFs that report having no average leverage to have borrowing or lending positions of up to 10% of their portfolio value. Several of the estimated mean delisting returns in Panel A of Table 6 are substantially higher than their counterparts in Table 4. The largest move using bootstrapped standard deviations (from Table 4) is the Liquidated category which increased by 2.15 bootstrapped standard deviations. Note than when we switch to estimates with well-behaved residuals in Panel B, Table 6, the extent of increase for these estimated means is reduced. Table 6 illustrates one of the few robustness checks where we have relatively large changes in estimated mean delisting returns, on the order of two bootstrapped standard deviations. Nevertheless, the resulting estimates remain relatively small in the sense of being far from -50% or even -10%.

Table 6: Mean Delisting Returns with Investment in the Riskless Asset

In Panel A, we report the monthly mean delisting returns (bias-corrected) when an investment in the riskless asset of up to 0.1 in absolute terms is allowed. We only use FoFs where the adjusted R-squared of the main regression model is at least 50%. Values are in % per month. In Panel B, we only use those FoFs where the residuals from regressions on the model in equation (1) do not reject the following four restrictions at the 10% significance level: normally distributed, homoskedastic, no first-order autocorrelation, and zero average residuals.

	Number of Matches	Mean Delisting Return	Bootstrapped STD of Mean Delisting Return	Non-parametric p-value for difference with 1.01	STD of Delisting Return
			Panel A: All Matches		
All	**1001**	**0.20**	**0.91**	**0.12**	**8.10**
Liquidated	**165**	**6.12**	**1.58**	**0.00**	**6.10**
Closed	**35**	**-1.05**	**4.25**	**0.33**	**10.20**
No Reason	**801**	**-1.41**	**1.09**	**0.01**	**8.50**
			Panel B: Matches with Well-Behaved Residuals		
All	**726**	**-0.96**	**1.29**	**0.10**	**9.90**
Liquidated	**118**	**4.62**	**2.07**	**0.01**	**6.50**
Closed	**28**	**-2.19**	**6.63**	**0.40**	**13.20**
No Reason	**580**	**-2.53**	**1.56**	**0.04**	**10.60**

Table 7 provides results obtained when we run our estimation procedure excluding FOFs that report having non-zero average leverage positions. Again we have several estimated mean delisting returns in panel A of that table which have increased by somewhat more than one standard deviation relative to their counterparts in Table 4. However, once again, the situation with well-behaved residuals is much less pronounced. Moreover, the estimated means remain relatively small. In an additional robustness test, we allowed for a constant in Equation (1) and obtained mean delisting return estimates similar to those in Table 4.

Table 7: Mean Delisting Returns without Leverage

In Panel A, we report the monthly mean delisting returns (bias-corrected) for FoFs that report no average leverage. We only use FoFs where the adjusted R-squared of the main regression model is at least 50%. Values are in % per month. In Panel B, we only use those FoFs where the residuals from regressions on the model in equation (1) do not reject the following four restrictions at the 10% significance level: normally distributed, homoskedastic, no first-order autocorrelation, and zero average residuals.

	Number of Matches	Mean Delisting Return	Bootstrapped STD of Mean Delisting Return	Non-parametric p-value for difference with 1.01	STD of Delisting Return
			Panel A: All Matches		
All	**900**	**-0.32**	**1.22**	**0.20**	**9.30**
Liquidated	**144**	**5.52**	**2.45**	**0.04**	**6.40**
Closed	**31**	**1.03**	**4.88**	**0.50**	**4.90**
No Reason	**725**	**-1.65**	**1.43**	**0.07**	**10.10**
			Panel B: Matches with Well-Behaved Residuals		
All	**613**	**-1.93**	**1.78**	**0.03**	**11.70**
Liquidated	**106**	**3.32**	**2.96**	**0.14**	**6.80**
Closed	**21**	**3.17**	**6.48**	**0.50**	**8.10**
No Reason	**486**	**-3.48**	**2.09**	**0.01**	**13.10**

We further ran estimates using a rolling window of 24 months, which generated larger mean delisting returns than in Table 4; the largest (Closed category) was 5.73%. However, estimating 15 portfolio weights using only 24 months of data caused us to have little confidence in these particular results. There is a potential issue that hedge funds can revise their reported returns when they later find errors (e.g. due to an audit). We re-ran our analysis after eliminating the last 6 months of the overall sample and found a mean delisting return for Closed funds of -4.02%; however, that estimate was based on only 23 matches.

When estimating matched portfolios, we allowed the algorithm to stop with fewer than 15 funds as long as any fund would have an estimated weight of less than 0.02. The resulting estimated mean delisting returns were similar to Table 4 except for the Closed category, which increased by 1.28 bootstrapped standard deviations to 7.16%. Altering the constraint on the minimum portfolio weight from 0.02 to 0.04 did not change the estimated means by more than one standard deviation from the means in Table 4. Reducing that minimum beta constraint to 0.01 had a similar effect, except that the estimated mean delisting return for the Closed category increased by 1.28 bootstrapped standards deviations to 6.88%.

To address the concern that small funds might not be realistic targets for FoFs, we eliminated all funds with assets under management of less than $20 million at the beginning of relevant 36-month estimation period and obtained similar mean delisting returns to those in Table 4.

IV. Concluding Comments

Relatively little has been known about returns after hedge funds delist from a database. Only Ackermann, McEnally, and Ravenscraft (1999) provided an estimate which even partially addressed this issue. We examine the situation by modeling the econometric relationship between FoFs and the portfolios of hedge funds into which they invest. This structure allows us to estimate the average delisting return which turns out to be -1.86% per month for all delisting hedge funds. That figure is significantly smaller than the average hedge fund return of 1.01% but much higher than disaster scenarios with large negative returns such as -50%. When we condition on the self-reported reason for delisting, we find average delisting returns of 2.34% for liquidated hedge funds, 1.99% for hedge funds that indicate that they are closed to further investments, and -3.27% for the remaining 76% of delisting funds that did not provide an informative reason for delisting. Overall, our results indicate that average delisting returns are economically small. Moreover, this finding is robust with respect to several tests concerning the methodology and the selection of funds.

Appendix: Pre-fee Return Calculation

FoFs report their returns net of all fees. In order to reconstruct the pre-fee returns for FoFs, we use a slightly modified version of the algorithm developed by Brooks, Clare, and Motson (2007). The incentive fee is normally paid annually, but the reported monthly returns are adjusted for the accrued incentive fee during the year. In other words, the accrued incentive fee is deducted when calculating a hedge fund's reported Net Asset Value (NAV); but that accrued fee stays invested with the fund until year end. In most cases, the management fee is paid at the end of each month at 1/12 of the yearly rate. The management fee calculation uses NAV on the last day of each month before deduction of that month's accrued incentive fee. The modification we made relative to Brooks, Clare, and Motson (2007) involves using the end of month (rather than beginning of month) NAV to calculate the management fee. That change was based on our review of several hedge-fund prospectuses that indicated this was the typical procedure.

The figure below illustrates the transition from the pre-fee to post-fee NAV, where NAV(t) denotes the reported post-fee NAV at the end of period t. NAV(t)* denotes the associated pre-fee NAV at the end of the period t.

The reported post-fee return captures the change of the reported NAV from NAV(1) to NAV(2), indicated by the dash-dot line. The pre-fee return changes from the pre-fee NAV(1)* less the management fee (that is, equivalent to the reported NAV(1) plus the incentive fee at time 1) to NAV(2)*. The reconstructed NAV(2)* is the sum of the reported NAV(2), the accrued incentive fee at time 2, denoted as IF(2), and the management fee MF(2). The incentive fee base at each time is the difference between the NAV less the management fee and the high-water-mark (HWM).

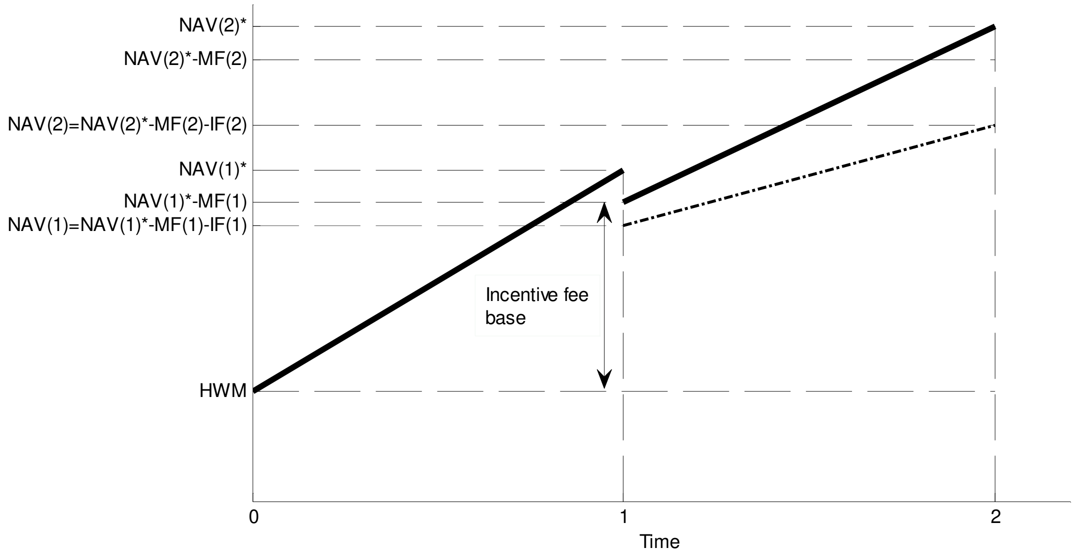
Thus, the total gross return for the period ($1 + R_{GROSS_t}$) can be expressed as follows:

$$1 + R_{GROSS_t} = \frac{NAV(t) + IF(t) + MF(t)}{NAV(t-1) + IF(t-1)} \tag{A1}$$

$$R_{GROSS_t} = \frac{NAV(t) - NAV(t-1) + MF(t) + IF(t) - IF(t-1)}{NAV(t-1) + IF(t-1)} \tag{A2}$$

Figure A1. Pre-Fee vs. Post-fee Net Asset Value

The figure illustrates the transformation of the pre-fee returns to the post-fee returns. The horizontal axis indicates time periods during which returns are accumulated. At the end of each period, a new net asset value (NAV) is computed. The NAVs are marked on the vertical axis. NAV(t) stands for the reported post-fee NAV at the end of period t. NAV(t)* stands for the associated pre-fee NAV at the same time. Solid black lines indicate the pre-fee NAV change within a given period. The dash-dotted line indicates the change in reported post-fee NAV within the same period. Reported NAV at the end of a period is obtain by subtracting from the pre-fee NAV the management fee MF(t) and the incentive fee IF(t). The incentive fee is zero, if the pre-fee NAV less the management fee is below the high-water mark HWM. Otherwise it is computed as a share of a difference between the pre-fee NAV less the management fee and the HWM.



If a hedge fund is above HWM at time t based on its post management fee NAV, it will stay above HWM after paying the percentage incentive fee. Denoting the percentage incentive fee by *IncentiveFee%*, we obtain:

$$\max(0, NAV(t) - HWM) = (1 - IncentiveFee\%) \cdot \left(\max(0, NAV(t) - HWM) + IF(t)\right), \qquad \text{(A3)}$$

This leads to the following expression for the accrued incentive fee at time t:

$$IF(t) = \max(0, NAV(t) - HWM) \cdot \left(\frac{1}{1 - IncentiveFee\%} - 1 \right) \quad \text{(A4)}$$

Similarly, the reported NAV plus the accrued incentive fee (if any) is a fraction of the total NAV^* equal to the total NAV^* minus the management fee. Thus, if the yearly management fee expressed in percentage terms is *MgmtFee%*, we obtain:

$$\left(NAV(t) + MF(t) + IF(t) \right) \cdot \left(1 - \frac{MgmtFee\%}{12} \right) = NAV(t) + IF(t),$$

The management fee actually paid can be expressed as:

$$MF(t) = \left(NAV(t) + IF(t) \right) \cdot \left(\frac{1}{1 - \frac{MgmtFee\%}{12}} - 1 \right) \quad \text{(A5)}$$

If at year's end, NAV exceeds HWM, the new HWM for the next year is reset to the level of the post-fee NAV; and the accrued incentive fee is reset to zero.

Under different assumptions on the exact timing of computing and paying the management fee, one can obtain a slightly different specification of equation (A5). For example, Brooks, Clare, and Motson (2007) seem to assume that the management fee, although paid at the end of the month, is computed based on the NAV at the beginning of the month. Thus, they obtain the following expression for the management fee, which introduces only negligible differences in the resulting pre-fee returns:[11]

$$MF(t) = NAV(t-1) \cdot \left(\frac{1}{1 - \frac{MgmtFee\%}{12}} - 1 \right) \quad \text{(A5')}$$

[11] Equation (A5') corresponds to equation (7) in Brooks, Clare, and Motson (2007), where they denote management fee paid at time t (*MF(t)* in our version) by $MgtFee_t$.

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