Out of the dark: Hedge fund reporting biases and commercial databases

Adam L. Aiken
Department of Finance
School of Business
Quinnipiac University

Christopher P. Clifford*
Department of Finance
Gatton College of Business and Economics
University of Kentucky

Jesse Ellis
Department of Economics, Finance, and Legal Studies
Culverhouse College of Commerce and Business Administration
University of Alabama

This draft: November 16th, 2011

Abstract

We examine the self-selection bias in voluntarily reported hedge fund performance data. Using data from a set of fund-of-funds, we construct a novel set of returns for hedge funds that otherwise have never reported to a commercial database. These returns allow, for the first time, a direct comparison of performance between funds that choose to report to commercial databases and funds that do not. We find evidence that most of the average fund's alpha can be explained by its decision to voluntarily report its performance to a database. Additionally, the nature of our data allows us to measure the performance of funds even after they exit the databases - the so-called "dead" funds. After delisting from databases funds have dramatically lower performance than funds that continue reporting to a database. However, even when controlling for dead funds we find a large and positive self-selection bias in voluntarily reported hedge fund performance data.

JEL Classification: G11, G23

*Contact author: chris.clifford@uky.edu. We thank Anup Agrawal, George Aragon, Jeffrey Coles, Joseph Gerakos, Michael Hertzel, Brad Jordan, Laura Lindsey, Shane Underwood, several hedge fund managers who wish to remain anonymous, and seminar participants at Arizona State University, the University of Kentucky, the Securities and Exchange Commission, the FIRS Finance Conference (2010) in Florence, Italy, the FMA Conference (2010) in New York, New York, and Quinnipiac University for their useful comments. We thank Monika Rabarison and Xin Hong for their research assistance.

Over the last decade, the hedge fund industry has become an increasingly important participant in the financial markets, managing over $1.97 trillion in assets and accounting for over one-third of equity trading volume in the United States.[1] One of the reasons for this growth is the apparent ability of hedge funds to deliver superior risk-adjusted performance for their investors. Many studies of hedge fund performance document significant alpha in hedge fund returns, with estimates ranging from 3-5% annually (e.g. Fung, Hsieh, Naik, and Ramadorai (2008), Ibbotson, Chen, Zhu (2011), Kosowski, Naik, and Teo (2007), Stulz (2007)). An important question in the literature is how hedge funds are able to consistently deliver alpha in a competitive financial market.

Proponents of hedge funds argue that the lack of regulation, unique organizational features, compensation arrangements, and manager skill are the primary reasons for their superior track record (e.g. Agarwal, Daniel, and Naik (2009), Bollen and Whaley (2009), Stulz (2007)). An alternative explanation, however, is that the empirical estimates of hedge fund performance are overstated and come from biased data sources. Hedge funds are not required to report their returns to any regulatory body, yet some funds voluntarily disclose their performance to data vendors, likely as a means of attracting capital. Funds with poor performance have a strong incentive to withhold their returns from these databases. Because studies of hedge fund performance only examine funds that choose to report, estimates of alpha are likely missing the worst performing hedge funds. As a result, it may be that the superior performance of hedge funds documented in the literature is an illusion stemming from the self-selection bias inherent in hedge fund performance data. Put differently, do hedge funds have superior performance or do researchers only study superior performing funds?

The academic literature has long acknowledged the possibility of self-selection bias in the most commonly-used hedge fund data, but due to data limitations, the direction and economic magnitude of this bias is unknown. The traditional approach to this issue has been to argue that hedge fund databases are also missing the best funds, as these funds are likely closed to new investment and have little to gain from further advertising their performance.[2] This line of reasoning suggests that the performance of good funds missing from the databases cancels out the missing performance of bad funds, leaving the resulting sample relatively unbiased. This argument is convenient, but due to data limitations, it lacks any empirical support. Thus, the direction and magnitude of the self-selection bias in hedge fund data is currently unknown.

[1]HFR Q3 2011.

[2]See Fung and Hsieh (2009) for a discussion of hedge fund databases and the biases inherent in this data.

In this paper, we use a novel data set of hedge fund returns which, for the first time, allows us to empirically study the self-selection bias. As a break from the previous literature, we do not obtain our returns from commercial databases; instead, we hand-collect returns from a sample of hedge fund investors, registered funds-of-funds (FoFs). In Section IV, we address any selection bias this may cause. Our sample captures the returns for 1,445 distinct hedge funds, yielding over 10,000 quarterly returns over the period 2004-2009. We employ a name matching procedure to determine which of these funds choose to list their returns in commercially available databases and which do not. By contrasting the returns for these two groups of funds, we are able to directly calculate the direction and magnitude of the self-selection bias.

We find that the self-selection bias in commercially available hedge fund data is severe. Funds that do *not* report their returns to commercial databases have significantly worse performance than funds that do. For example, using the Fung-Hsieh (2004) 7-factor model to control for sources of risk, we find that the alpha of funds that report to a commercial database in our sample is a statistically significant 92 bps/quarter, similar in magnitude to the 3-5% annual alpha commonly cited and mentioned above. After controlling for self-selection, however, the average fund's alpha falls to 5 bps/quarter (t-statistic = 0.39). In our sample, 95% of a typical fund manager's measured skill can be explained by whether they report to a database. We find similar results with alternative factor-pricing models. Thus, the managerial skill documented in previous studies is, in large part, overstated. Rather than fund managers having ability to consistently deliver superior risk-adjusted returns, it appears that much of the previously documented skill of hedge fund managers can be explained by the upwardly biased returns data employed by researchers.

We investigate whether the returns for the top performing funds are missing from commercial databases as well. Our results indicate that such funds make up only a small minority of our sample, and the superior performance of these "good" non-reporting funds does little to outweigh the poor performance of the "bad" non-reporting funds.

Funds that choose to disclose their return series to a database can also choose to stop reporting at any time. Funds that perform poorly may have an incentive to delist from the database in an effort to mitigate the loss of reputational capital to the manager. Conversely, funds that have performed well and raised sufficient capital may no longer see the benefit in publicly disclosing performance. This delisting decision is likely to impart bias on commercially available data (Posthuma and Van der Sluis (2003)). We identify 205 hedge funds that have delisted from the commercial databases and are subsequently present in our sample of returns (they continued to operate for some time after delisting). The returns for this group of "dead" funds allow us to address the size and nature of the delisting bias. Although other studies have attempted to estimate the delisting bias using returns prior to delisting, we know of no other study that has directly documented the returns of delisted funds.

On average the quarterly returns of dead funds are −16 bps, 184 bps lower than the returns of funds that continue to report to commercial databases. These returns are missing from the commercial databases and create a delisting bias that cannot be accounted for by merely analyzing the once "live" returns of now dead funds. We examine the pre-delisting performance of dead funds and find that funds with both good and bad performance delist from the databases, although funds with poor prior performance account for the majority of the overall delisting bias. Controlling for differences in factor exposures, the alpha of funds that delist from a database following poor performance is 181 bps/quarter worse than funds that delist following good performance. Delisted funds continue to operate for some time after the last database return is recorded, as 85% of the delisted funds have at least two quarters of returns subsequent to the delisting date (48% of the funds have at least eight quarters of returns following the delisting date).

In addition to contributing to the broad academic literature on the performance and risk characteristics of hedge funds, our results have important implications for hedge fund investors, the hedge fund industry, and financial market regulators. First, investors using observed historical performance and risk metrics may view hedge funds as a disproportionally attractive investment vehicle, potentially leading to an inefficient allocation of capital. Second, because investors commonly use indices of observable hedge fund performance as a means of gauging the relative performance of hedge fund managers, managers are being compared to an upwardly biased benchmark. This could cause even good managers to appear to trail their peers, when in fact they only trail the peers who report good returns.[3] Funds that trail their (upwardly biased) benchmarks may have an incentive to increase portfolio risk to the potential detriment of fund investors (e.g. see Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997)). Additionally, comparisons to an inflated benchmark could exacerbate the flight to quality problem during crises, as investors withdraw their money after observing what they mistakenly infer to be inferior relative fund performance. Finally, because available data does not accurately capture the size, performance, or risk of the hedge fund industry, regulators may be unable to properly gauge the potential systemic risks that the industry poses for the financial system.[4]

[3]We thank several hedge fund managers for calling this benchmarking problem to our attention.

[4]The Dodd-Frank Wall Street Reform and Consumer Protection Act is expected to increase disclosure in the hedge fund industry. The SEC has recently approved mandatory confidential reporting for certain private investors, such as large hedge funds. See http://www.sec.gov/news/press/2011/2011-226.htm.

The remainder of the paper is organized as follows. Section I reviews the relevant literature. Section II describes our data and return methodology. Section III reports our results. Section IV addresses selection bias in our data and tests for robustness. Section V presents our conclusions.

I Literature Review

A Hedge Fund Performance

Many studies have found evidence indicating that hedge funds on average deliver abnormal risk-adjusted returns and that their performance cannot be merely attributed to luck. Recent work by Ibbotson et al. (2011) finds an aggregate annual alpha for the hedge fund industry of roughly 3% when using the TASS database over a period from 1995 through 2009. Furthermore, this aggregate alpha was significant in every period. Using Bayesian and bootstrap analysis, Kosowski et al. (2007) determine that top hedge fund performance cannot be determined by luck. Certain alpha producing funds are also able to attract steadier capital inflows as the market rewards their talent (Fung et al. (2008)). Agarwal et al. (2009) find that funds with greater managerial incentives deliver better performance. Aragon and Martin (2011) find evidence that suggests that because hedge funds face fewer restrictions than mutual funds, they are able to deliver alpha through the use of more exotic trading strategies than those utilized by mutual funds.[5]

B Biases in Hedge Fund Databases

As private entities, hedge funds are not currently required to report to any regulatory agency with regards to most aspects of their business, including their performance.[6] As a marketing tool, however, hedge funds often voluntarily submit their returns to commercial database providers (e.g., Lipper TASS) in an effort to document their performance for potential investors. These commercial databases have been the primary

[5] While a great deal of research has found positive alpha, not all academic work is as kind. For example, Aragon (2007) attributes positive alpha to a liquidity premium earned by the funds limited partners. Asness, Krail, and Liew (2001) find that non-synchronous return data can lead to underestimating a funds market exposure. Whether or not you use buy-and-hold or dollar-weighted returns can also affect estimates of fund performance (Dichev and Yu (2011)). Finally, Griffin and Xu (2009) use the actual stocks held by hedge funds to measure performance and find no evidence of security selection ability.

[6] Though, as noted above, this requirement may soon change. The SEC has indicated that an initial Form PF, which will include position, leverage, and liquidity information, must be filed by December 15th, 2012. This information will remain confidential, however.

data source used to study hedge funds. Yet, the voluntarily nature of the disclosure decision creates a host of biases that affect inferences on hedge fund performance and risk.

In order to study the performance of hedge funds, the literature has spent considerable time addressing many of the biases present in hedge fund data and has developed a variety of tools to mitigate them when possible. To address survivorship bias, most commercial data providers now include an archive of dead funds to capture the previously reported returns of funds that no longer choose to report to the database. The inclusion of these funds in research may help to alleviate the survivorship bias, but does not help solve the problem of self-selection. For example, little is known about the funds that stop reporting.[7] A poorly performing fund may choose to delist in an effort to hide poor performance or simply for the fact that it is near liquidation. However, funds may choose to leave a database out of strength rather than weakness (Fung and Hsieh (2009)). Funds with strong performance that have increased their asset base beyond critical mass may choose to stop listing once the costs of disclosure outweigh the gains. Compounding the issue further, funds that raise a considerable amount of assets from inception may never see the need to disclose their returns at all.

Hedge funds often incubate a fund for some time before offering it to the market. These early stage funds are typically funded with capital from the general partner(s) and possibly a few limited partners. If the strategy works well, the fund is listed on a database and the fund's history of returns prior to listing is subsequently backfilled in the database. If the strategy does not work as planned, the fund is never listed. This backfilling of returns can generate a positive bias in observed hedge fund performance. Aggarwal and Jorion (2010) find that backfilling of returns imparts an upward bias of 5% over the first three years of a fund's life. Standard practices to reduce the backfill bias include eliminating all return observations before the date the fund was added to the database (e.g. Aragon (2007)), choosing funds that report an inception date close to the date the fund began reporting to the database (e.g. Aggarwal and Jorion (2010)), or simply throwing out the first year or two of return data for a fund (e.g. Bollen and Whaley (2009)). However, none of these methods is fully satisfactory. For example, some funds may report to one database, stop, and then start reporting to another. Using the date a fund is added to a database in order to correct for the backfill bias will introduce a spurious bias into data if this is the case (Fung and Hsieh (2009)). Further, the

[7] See Posthuma and Van der Sluis (2003) and Grecu, Malkiel, and Saha (2007) for a discussion regarding funds that leave a database.

inception date a fund chooses to list is in some sense arbitrary and provides the manager an ability to game the system.[8]

Ours is not the first paper to study the self-selection bias in hedge fund returns. Fung and Hsieh (2000) study the self-selection bias by using the returns of FoFs, rather than hedge fund returns.[9] The track records of FoFs retain the returns of hedge funds that stop reporting to a database for both good and bad performance, are typically unaffected by backfill bias, and may contain returns of both listed and non-listed funds. While their approach mitigates some data biases, issues still persist. Namely, FoF returns are indirect in that they do not fully control for the double layer of fees, leverage, or cash balances of the fund of funds. Also, because FoF portfolio returns are value weighted, the authors cannot identify the disparate performance of non-reporting funds from those that report. Further, it is unclear to what magnitude the self-selection bias affects the reporting decision of the FoFs themselves; FoFs must also make the decision whether to report their returns to a database. Our paper avoids these issues and provides for the first time a direct test of the size and direction of the self-selection bias using actual hedge fund returns that are not present in a database.

Likely because the data offer no easy remedy, the literature typically assumes that the process of self-selection does not impart a bias on empirical estimates of performance by invoking two offsetting incentives: the desire of poor funds to avoid databases and the ability of good funds to ignore them (Fung and Hsieh (2009)). A contemporaneous paper by Agarwal, Fos, and Jiang (2011) finds evidence consistent with this belief. Their study uses equity holdings from quarterly 13F filings to generate a proxy for hedge fund performance. The authors conclude that the desire to initiate reporting following good performance and the desire to delist from the database to hide bad performance "largely offset one another", further arguing that "the self-selection bias may not have a material impact when it comes to performance evaluation". This result differs markedly from ours largely due to differences in empirical design. Though the authors examine a wide cross section of hedge funds, their methodology allows for only an imprecise estimation of actual hedge fund performance.[10]

[8]The hedge fund literature is not alone in having an incubation bias, as Evans (2010) finds that incubated mutual funds outperform non-incubated funds during the start-up period.

[9]Fung et al. (2008) also uses FoFs to study the returns of the overall hedge fund industry.

[10]13F filings are quarterly snapshots of aggregate equity positions disclosed at the advisor level, not the fund level. Therefore, allocating the return of the advisor to individual funds becomes imprecise. More importantly, 13F filings contain only period-end snapshots of long equity-based positions. The 13F filing does not require the disclosure of short-selling (both equities and options), illiquid securities, and intra-quarter trading, all strategies likely to contribute significantly to the observed returns of hedge funds. This holdings-based return is likely to be measured with considerable imprecision.

In contrast, the returns used in this paper are the actual, net of fee, fund-level returns. For the subsample of our funds that also report to a database, our calculated return measure has a 0.98 correlation with the corresponding returns reported to the commercial databases.[11] For comparison, Agarwal et al. (2011) report a correlation of 0.54 between their set of implicit returns and the corresponding database returns. We feel that the greater precision of our return measure allows us to more carefully test (and reject) the null hypothesis that voluntarily reported returns are unbiased.

II Data

A Registered Funds of Funds

Here we describe the process for hand-collecting our set of hedge fund returns. Our data comes from a set of registered fund of funds (FoFs) that have received little, if any, attention from the literature. These funds register with the Securities and Exchange Commission (SEC) pursuant to the Investment Company Act of 1940 (40 Act). With similar filing requirements to that of a mutual fund, these registered funds allow the researcher the unique opportunity to use regulatory filings to study FoFs. In Section IV of the paper, we provide a detailed discussion of potential selection biases regarding the use of registered FoF data.

A registered FoF is organized as a closed-end investment company. Unlike the traditional closed-end fund, however, it is usually not listed on an exchange. Rather, the fund typically offers interests to investors on a periodic basis (usually monthly or quarterly). These funds have an average (median) minimum investment of $528,559 ($100,000). Similar to that of a typical FoF, the registered funds are marketed to qualified investors and typically charge both fixed and performance based fees. Additionally, investors often have their assets "locked-up" for periods of up to a year and receive liquidity when fund management agrees to redeem interests through a regular tender offer.

The primary benefit to the fund in registering with the SEC is to allow the manager access to greater distribution channels. Non-registered FoFs typically offer interests under Regulation D of the Securities Act of 1933. While this allows the fund to avoid registration and sell interests in its fund through private placements, it explicitly limits the fund's ability to market or advertise. A registered fund faces no such

[11] In section II.B, we discuss how name matching, as well as differences in taxes, fees, and highwater marks, may yield small discrepancies that account for less than perfect correlation.

restrictions. A registered fund files an offering prospectus with the SEC that allows them to actively advertise or market the fund to potential investors, including dedicated distribution platforms through investment advisers.[12]

According to the SEC, the first fund of fund to register with the SEC was PW After Tax Equity Partners. [13] They filed their first registration statement in 1998 and reported their first set of holdings in late 1999. The advantage of using registered FoFs is that SEC filing requirements mandate the fund disclose a detailed account of the hedge fund investments in their underlying portfolio. These portfolio snapshots enable us to construct the set of hedge fund returns we use in this paper. However, prior to 2004, funds only had to report semi-annual statements of financial position that included an analysis of their portfolio holdings. Beginning in 2004, funds were required to report portfolio holdings on a quarterly basis (in forms N-Q and NCSR). This allows for the estimation of quarterly returns. Thus, we restrict our analysis to the holdings of registered funds between 2004 and 2009 where quarterly holdings are available.

Unfortunately, the SEC does not provide a distinctive classification mechanism that allows for an easy identification of all registered FoFs. We employ a set of search algorithms that comb through SEC filings to identify registered FoFs. We use NSAR forms from the SEC to identify all funds that file as a closed-end fund, but do not list a closing price for the fund.[14] This results in a sample of 132 possible FoFs from 2004-2009. We believe this to be the universe of registered FoFs.[15] We eliminate 15 funds that either registered and never raised any funds or held primarily venture capital or private equity investments. We then eliminate funds that simply duplicate the holdings of another fund from the same management company (such as feeder funds or funds with special tax treatment that cross register). This screen eliminated 38 funds, which yields our final sample of 79 registered FoFs.

[12]Additionally, registered funds face less regulatory scrutiny under the Employee Retirement Income Security Act of 1974 (ERISA) and Section 4975 of the Internal Revenue Code. The ERISA act limits the amount of money a hedge fund can manage without becoming an ERISA fiduciary. This is often referred to as the "25% rule". Hedge funds that manage more than 25% of ERISA-regulated assets may be deemed an ERISA fiduciary. This designation can constrain the fund manager's use of leverage, diversification, and liquidity in its investments. By registering under the 40 Act, registered funds do not face this limitation and can accept ERISA money without concern of increasing their fiduciary responsibilities. Further, the registered FoFs are able to "pass along" this benefit to the hedge fund they select, as registered money managed by a hedge fund is also exempt from the ERISA limits.

[13]Implications of the Growth of Hedge Funds 2003 Staff report to the United States Securities and Exchange Commission. See http://www.sec.gov/news/studies/hedgefunds0903.pdf .

[14]Q76 on the NSAR lists the closing price for closed-end funds. Registered funds do not have a closing price, as they are not listed on any exchange. As such, they report "0.00" to this question. We further confirm that our sample is a registered fund of funds using additional regulatory filings (e.g., N-2).

[15]We confirm this by performing a text search of all N-CSR filings for words related to hedge funds, such as "Limited Partner and "L.P.".

Table 1, Panel A details the years our sample FoFs filed their initial registration statement with the SEC (Form N-2). A few funds existed prior to 2000, but the bulk of our sample began reporting in years 2001-2004. The funds typically register as *de novo* funds seeking startup capital from initial investors. However, established asset management companies operate most of the funds. The managers of our sample of FoFs represent some of the largest money managers and financial institutions, including Morgan Stanley, J.P. Morgan, Credit Suisse, UBS, and Blackrock. We have included a detailed case study of a representative fund from our sample of registered FoFs in the appendix (Exhibit A.1) describing the funds history, organizational form, and contract characteristics.

Table I, Panel B reports summary statistics for our set of FoFs and compares these funds to non-registered FoFs found in the Lipper TASS, HFR, and BarclayHedge databases. The average FoF in our sample earns a mean (median) net of fee return of 0.89% (1.71%) a quarter, while the mean (median) database FoF earns 0.82% (1.73%) a quarter. Differences in means and medians are not statistically significant. The average FoF in our sample is slightly older (4.2 vs. 3.5 years), manages more money ($273.0 vs. $208.0 million in assets), and requires a lower minimum investment ($528,559 vs. $727,619). Registered FoFs charge slightly lower management fees, but appear to offset this with higher performance fees. The average registered FoF holds over 23 unique hedge funds at any point in time, representing an average of 4.5 unique hedge fund styles (this data is not available for the database FoFs). Interestingly however, differences in contract features between registered and non-registered FoFs do not contribute to differences in performance on average.

B Sample Construction

Registered FoFs have similar filing requirements to those of a mutual fund. The funds disclose their quarterly holdings in N-CSRS, N-CSR, and N-Q filings. These are the same forms utilized to generate the Thomson mutual fund holdings database (s12). However, whereas the mutual fund holdings disclose the funds' positions in various publicly traded equities, the FoF holdings disclose the funds' positions in their underlying hedge fund investments. The filings disclose the name of the underlying hedge fund, the FoFs cost basis in the position, and the current value of the position.[16] The time-series combination of these forms allows us to utilize the underlying holdings to create a quarterly panel of hedge fund returns.

[16]In less than 5% of our filings, the FoF did not disclose the cost basis for the position. Because a return series cannot be generated without the cost basis, we remove these observations from our data.

One of the primary innovations in our paper is that our hedge fund returns are not supplied by a commercial data provider (e.g., Lipper TASS). While this data allows us to study returns for a set of hedge funds that have never been examined, the downside is that these returns have never been used in the literature either. As such, some effort must be spent explaining our methodology for generating the quarterly series of hedge fund returns and ensuring their accuracy.

We provide an example of our return calculation using data provided by the March 2007 and June 2007 filings of the UBS Equity Opportunity Fund II, LLC. UBS held a position in the Cobalt Partner, L.P. fund in March 2007. The cost basis of this holding was $29,000,000 while the value of the holding was $48,873,238. UBS maintained this position in June 2007, reporting an increased value of $51,754,258. The cost basis remains $29,000,000. We use the following formula to generate our quarterly return:

$$\text{Fund Return}_{i,t} = \frac{\text{Value}_{i,t} - \text{Change in Cost}_{i,(t-1,t)}}{\text{Value}_{i,t-1}} - 1 \tag{1}$$

In the case of the Cobalt Partner, L.P. fund, its second quarter return for 2007 is 5.89%. We repeat this process for each FoFs quarterly filings and generate a sample of quarterly hedge fund returns for 1,538 funds from 2004-2009.

For a small sample of our funds, we find discrepancies in how they report their changes in cost basis. While most funds report the actual dollar change in cost, some report the change as a percentage of the funds value.[17] Additionally, changes in cost require placing strong assumptions on the timing of cost changes throughout the quarter. Given our inability to be certain of the regime, the remainder of the paper focuses exclusively on those returns where cost basis does not change. Our results are robust to their inclusion and discussed more fully in Section IV.

Multiple FoFs may hold the same underlying hedge fund during the quarter. The DE Shaw Oculus fund, for example, was held by three distinct FoFs during the first quarter of 2008. Based on the timing of when the different FoFs acquired their respective interests, it is possible for differences in highwater marks or fees to exist, leading to small differences in quarterly returns for the same hedge fund. In the results that follow, we take the median return for any fund-quarter with multiple return observations. Our results are robust to using means as well. Additionally, we trim our returns at the 0.5% and 99.5% levels to reduce the

[17]Conversations with several managers at registered funds revealed this discrepancy. Mutual fund holdings largely avoid this issue as they list the number of shares they hold in a registered security, not their cost basis.

outliers that accompany hand-collected data. Our results are robust to the inclusion of the trimmed data. See Section IV for a discussion of these and additional robustness tests. After forming median returns across FoFs for every quarter, our final sample consists of 1,445 unique hedge funds and 10,126 unique fund-quarter returns.

Of these 10,126 fund-quarters, 4,925 fund-quarters (49%) have a corresponding fund-quarter in either the Lipper TASS, HFR, BarclayHedge, Morningstar, or Eureka Hedge databases.[18] The remaining 5,201 (51%) fund-quarter observations comprise the first large set of hedge fund returns from funds that did not choose to report to a commercial database.[19] The goal of this paper is to compare these two separate distributions of hedge fund returns to understand the nature and magnitude of the self-selection biases inherent in voluntarily reported hedge fund returns.[20]

We perform several robustness checks to ensure that our returns are calculated accurately. For the fund-quarters that also match to either Lipper TASS, HFR or BarclayHedge, we can compare the funds actual returns reported to the database to the returns we calculate from FoF holdings.[21] The average discrepancy between the samples is near zero: both the mean and median sample differences are less than 0.01 bp/quarter. Additionally, the correlations between our calculated returns and those of the reported database returns are over 98% across each of the three databases. Any discrepancies likely come from small differences in fees/highwater marks between the FoFs, differences in taxes, or errors in our name matching. Importantly, we note that for the 49% of our sample for which returns are available in a database, we instead use our calculated returns from equation (1) for our tests. This is done to ensure that our return methodology and/or data errors in the inputs to calculate returns do not drive our results. That is, any errors from our

[18]Morningstar has acquired both the CISDM and MSCI hedge fund databases and incorporated their funds into the Morningstar global hedge fund database. Thus we have matched our sample of funds across a grand total of seven of the most widely used hedge fund databases in the academic literature. For instance, we have matched across the same databases used in the comprehensive superset of databases analyzed in Agarwal, Fos, and Jiang (2011). We arrive at this sample by hand-matching the fund names found in our SEC filings to the names found in each of the five commercial databases. This process is inherently imperfect and adds an element of noise to our results. However, any errors from name matching are likely random and unlikely to bias our results as the difficulty of text matching should be unrelated to performance.

[19]Our final sample consists of 11,574 unique fund-quarter returns when we relax the cost change constraint. As before, 49% of these fund-quarters have a corresponding fund-quarter in one or more of the 5 commercial hedge fund databases, while 51% do not, indicating that the propensity for cost basis to change is of equal probability for both database and non-database funds.

[20]We note that these proportions should not be interpreted as 51% of the hedge fund universe is missing from a database. Hedge fund databases are comprised of many small funds. Because FoFs typically select from larger hedge funds, this skews our proportion of database funds downward. Finally, note that these are fund/quarter observations. At the fund level, roughly 53% of our funds report a live database return at some point in during our sample period. About 60% of the funds in our sample reported to a database at some point in their history.

[21]We were able to access the full monthly return series for Lipper Tass, BarclayHedge, and HFR databases. Morningstar and EurekaHedge were kind enough to provide us the names and dates for funds in their databases. This was sufficient for identification purposes. Thus, we are able to identify if and when a fund reported to either Morningstar or EurekaHedge but cannot examine the reported returns. Accordingly, we are unable to check return discrepancies across those two databases. However, we find no meaningful difference in return discrepancies across any of the 3 databases for which we have returns.

name matching or return generation procedure are equally likely to affect both reporting and non-reporting funds.

C Database and Non-Database Returns

–Table II HERE–

Table II details the distribution of quarterly returns in our sample and reports summary statistics for returns found in a database (*database returns*) and for those returns that were not reported to a database (*non-database returns*). The table reveals that the average quarterly return for a fund in our sample is 1.13%. However, returns reported to a database are larger than returns that were not. For example, the average return for a database fund is 1.68% a quarter, while the average return for a non-database fund is 0.60%. The inferences are similar when we evaluate the medians. The equality of both means and medians between the two groups is rejected at the 1% level. We also note that returns not reported to a database are more volatile than returns included in a database (a standard deviation of 8.58% vs. 6.85%). A variance ratio tests reveals these standard deviations are significantly different at the 1% level.

In addition to comparing the returns that are reported to a database to those that are not, we also explore the returns of funds that reported to a commercial database at some point in their life cycle, but subsequently chose to stop reporting. As mentioned previously, the nature of our data allows us to track the performance of these funds even after they stop reporting and, as noted, the average performance of dead funds is dramatically lower than their live counterparts. For funds that delist, their average quarterly return prior to delisting was 1.59%, however, following delisting their average quarterly return falls to −0.16%. Differences are similar when we examine the medians. Differences between means and medians are both statistically significant at the 1% level. This is consistent with the findings of Agarwal et al. (2011), who also show that fund performance after delisting is significantly lower than prior performance.

–Figure 1 HERE–

Figure 1 shows kernel density estimations for the distributions of different return types. Panel A compares returns that are present in a database to those returns that are absent. Panel B compares dead returns (i.e. returns that are subsequent to a fund's last reporting date) to live returns (i.e. returns in our sample that are also in a database). Note that the distributions of non-database and dead returns have thicker left-hand tails, indicating a greater frequency of negative returns.

III Results

Our results focus on three different ways the database self-selection bias may affect inferences in hedge fund research. First, we estimate the association between a hedge fund's choice to be in a database and its abnormal returns using a pooled OLS regression. This allows us to test how selection bias affects estimates of the average hedge fund manager's skill. Second, we investigate the role dead funds play in the bias of database returns. Finally, we examine the tails of the return distribution in order to examine whether the selection bias is symmetric among the best and the worst performing funds.

A Self-Selection Bias and Estimating Manager Skill

We estimate abnormal returns using two common factor pricing models and a benchmark-based method, but include an indicator variable for whether or not the return was reported to any of the five commercial hedge fund databases (*database*):[22]

$$\mathrm{r}_{i,t} = \alpha + \beta_1 * \mathrm{database}_{i,t} + \sum_{j=2}^{J} \beta_j * \mathrm{factor}_{j,t} + \epsilon_{i,t} \tag{2}$$

$$\mathrm{r}_{i,t} = \alpha + \beta_1 * \mathrm{database}_{i,t} + \sum_{j=2}^{J} \beta_j * \mathrm{factor}_{j,t} + \sum_{j=2}^{J} \beta_j * \mathrm{factor}_{j,t} * \mathrm{database}_{i,t} + \epsilon_{i,t} \tag{3}$$

where $r_{i,t}$ is a fund's quarterly return in excess of the 3-month risk-free rate and the controls come from: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model[23], or a modified version of the Jagannathan, Malakhov, Novikov (2010) hedge fund (HF) benchmark model.[24] Our *database* indicator

[22] This pooled OLS method with additional fund characteristics is similar to the methodology used in Aragon (2007).

[23] The Fung and Hsieh (2004) model includes the following returns: the S&P 500 total return, a size spread return (Wilshire Small Cap 1750 - Wilshire Large Cap 750), a bond market factor (quarterly change in the 10-year constant maturity treasury yield), a credit spread factor (quarterly change in the Moody's Baa yield less the 10-year treasury constant maturity yield), and three trend-following factors for the bond market, the currency market, and the commodities market. See David Hsieh's web page at http://faculty.fuqua.duke.edu/%7Edah7/HFRFData.htm for a complete description.

[24] The Jagannathan et al. (2010) model includes the fund's style index return and a market factor. Unlike their version, we are not able to directly correct for smoothed returns due to the pooled nature of our analysis. However, the quarterly

variable will shift the intercept from the regression, allowing us to estimate how much the self-selection bias affects the alpha estimate from a pooled regression. Standard errors are robust to heteroskedasticity and are clustered at the fund-level. We report only our estimates of the intercept and the indicator variable for expositional ease.

–Table III HERE–

Table III reports the results from these regressions. In Panel A, the coefficient on the *database* indicator is positive and statistically different from zero for each of the models. In the case of the 7-factor model, the *database* variable indicates that abnormal returns found in a database are 87 bps/quarter larger than the set of returns that are not reported to a database. The results are similar with the 4-factor model and the hedge fund benchmark model.

In Panel B, we allow for the possibility of differences in risk exposures between the database and non-database funds by including a database interaction variable with each of the factors in the model (equation 3). With the exception of the market factor, sensitivities to the factors are similar between the database and non-database funds. Database funds have lower sensitivities to the market factor. In each of the models, the database indicator variable remains positive and statistically different than zero. In the case of the 7-factor model, estimates of alpha for the database funds are 133 bps/quarter (t-statistic of 6.09) higher than hedge funds that do not list in a database. For both the 4-factor and HF Benchmark model, estimates of alpha for the database funds are 88 bps/quarter higher than hedge funds that do not list in a database.

The interpretation of the alpha coefficient is the average managerial skill for all hedge funds in our sample after removing the database effect. Interestingly, in each of the factor models in both Panels A and B, the coefficient on alpha is not statistically different from zero, indicating non-database funds contribute little valued-added after fees. The implications of this result are large and no easy solutions exist to mitigate this bias. Much of what previous researchers and practitioners attribute to managerial skill likely stems from the self-selection bias in hedge fund returns. At a minimum, until performance reporting for hedge funds becomes mandatory, it will be difficult to draw strong conclusions about average managerial skill from hedge fund performance studies that use voluntarily reported data. Much like the vast mutual fund literature that

nature of our hand-collected returns mitigates the smoothing problem, as it is unlikely that quarterly returns exhibit as much autocorrelation (Bollen and Pool (2009)). We use the return on the S&P 500 and the return on the Credit Suisse/Tremont Hedge Fund Index associated with the fund (each less the risk-free rate) as our factors for this modified model.

finds little evidence of managerial skill (Fama and French (2010)), our results indicate that when voluntarily reported returns are excluded, the average excess return of hedge funds does not differ markedly from zero.

B How Does Delisting Affect Hedge Fund Returns?

Just as hedge funds can choose whether or not to report their returns to a database, they can just as easily choose to stop supplying returns to a commercial database. When a hedge fund stops reporting, it enters the graveyard portion of a database and is considered a dead fund. However, a dead fund has not necessarily stopped operating when it delists, the fund has merely stopped reporting its performance. Understanding the returns of dead funds is important because hedge fund investments are illiquid and the traditional investor cannot simply liquidate his position immediately after a fund goes dead. Thus, the true hedge fund investor experience necessarily comprises the returns of dead funds.

Although no study examines the returns of dead funds directly, there have been two primary explanations put forth explaining why a fund would stop reporting its returns to a database. Most researchers suggest that funds chose to stop reporting because they have been unsuccessful (Malkiel and Saha (2005)). Funds that underperform their peers do not have an incentive to continue advertising that fact in a commercial database. These funds may benefit from ceasing reporting and waiting until their track record improves before they advertise to new investors. Additionally, very poor performers may stop reporting because they have ceased operations and begun the liquidation process. In this case, dead funds should exhibit very poor returns on average.

A competing hypothesis suggests that funds may choose to stop reporting because they have been very successful (Ackermann, McEnally, and Ravenscraft (1999)). A successful fund may not need to advertise its performance in a database because it could either have strong word of mouth reputation or the fund could have simply reached critical mass and closed to new investors. As the marginal benefit from advertising falls for these funds, they may choose to stop reporting returns in fear that their competitors would replicate their investment strategy. If this were the case, dead funds would likely exhibit higher than average returns. Although some studies have attempted to estimate the reason a fund has stopped delisting by looking at returns prior to the delist date (Grecu, Malkiel, and Saha (2007)), no study has examined actual hedge fund returns after the delist date.[25]

[25] As mentioned before, Agarwal et al. (2011) estimate the returns of dead funds from equity positions. Hodder, Jackwerth, and Kolokolova (2009) document that 8.1% of hedge funds delist from a commercial database annually. The authors indirectly

Because of our unique sample, we have returns for hedge funds that have stopped reporting to a database but continue to operate and are held by a FoF in our data. This attribute allows us to study the performance of the dead funds. To do this, we identify the funds that matched to any commercial database and compare their last database return date to the return observation date generated from our sample. We classify return observations that occur after the last date the fund stopped reporting to all databases as dead returns.

$$\mathrm{r}_{i,t} = \alpha + \beta_1 * \mathrm{dead}_{i,t} + \sum_{j=2}^{J} \beta_j * \mathrm{factor}_{j,t} + \epsilon_{i,t} \tag{4}$$

$$\mathrm{r}_{i,t} = \alpha + \beta_1 * \mathrm{dead}_{i,t} + \sum_{j=2}^{J} \beta_j * \mathrm{factor}_{j,t} + \sum_{j=2}^{J} \beta_j * \mathrm{factor}_{j,t} * \mathrm{dead}_{i,t} + \epsilon_{i,t} \tag{5}$$

–Table IV HERE–

In Table IV, we report a series of tests using equations (4) & (5) above with the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and the modified version of the Jagannathan et al. (2010) benchmark model. The dead indicator variable in the models allows a test of how funds that have delisted from the database perform following their delisting decision. The first three columns of Panel A contain both funds that matched to a database and those that did not and provide a test of whether dead funds underperform the general population of hedge funds in our sample. In each of the models, our indicator variable for dead returns is negative and statistically significant. The coefficient in the 7-factor model is -109 bps/quarter (t-statistic = -3.65), indicating that the average fund that delists from a database has an economically large reduction in average performance. The results are similar with the 4-factor and hedge fund benchmark model.

In the second three columns of Panel A, we limit the sample to only those funds that reported to a commercial database at some point. As before, the indicator variable on dead returns is negative and statistically significant in each of the models. Using the 7-factor model, funds that delist from a database

estimate the delisting returns of hedge funds by using reported FoF returns. They find that delisting returns are statistically different from the average hedge fund return.

underperform the returns in a database by 146 bps/quarter (t-statistic = -4.85). In Panel B, we repeat the analysis while allowing for differences in risk exposure (equation 5). The results are similar when controlling for differences in risk between the two groups. The results in Table IV indicate that the average performance for funds following delisting is poor.

B.1 Do Dead Funds Fully Explain the Self-Selection Bias?

The negative returns of dead funds are likely to contribute to the upward bias in average hedge fund returns. By construction, these returns are missing from the *database* indicator in Table III. If it were the case that the delisting returns fully explained the self-selection bias, one could estimate an average delisting effect for these funds and include it to control for the reporting decision. We test this possibility in Table V by simultaneously controlling for both database returns and dead returns. That is, we add both the database and dead fund indicator variables from equations (2) through (5) above into a series of factor pricing models. In Panel A, we estimate the models without any interaction terms, while in Panel B, we allow for differences in risk for database and dead funds by including interaction terms with each of the model factors. The results are similar. Focusing on Panel B, the *database* indicator is positive and statistically different from zero for each of the models. The *database* indicator in the 7-factor model indicates that returns found in a database are 105 bps/quarter (t-statistic = 4.56) larger than the set of returns that are not reported to a database, even when controlling for the dead returns. The *dead* indicator remains negative (-113 bps/quarter). By comparing these results to Table III, one can see that while the returns of those funds that delist from a database contribute to the overall positive self-selection bias in database returns (the *database* coefficient drops from 133 bps/quarter to 105 bps/quarter), they do not fully capture the bias. Rather, the sample of funds that choose to report to a database are fundamentally different from those that do not, and adding a delisting return for these funds is unlikely to fully control for the self-selection bias.

–Table V HERE–

B.2 Dead Returns and Prior-Fund Performance

The results in Table IV show that dead funds underperform the universe of hedge funds on average. However, Ackerman et al. (1999) and others have argued that some funds might delist out of strength, suggesting that some dead funds may outperform. We test this possibility here. While the fund's stated intent for delisting is available in certain commercial databases, this variable is often labeled as "no reason given" and is in many ways arbitrary, as the fund manager has no reason to answer honestly, if at all. As such, we use a more objective measure to proxy for delisting out of strength by examining the fund's style-adjusted performance in the months leading up to delisting. In Table VI, we estimate the pooled factor models with the *database* indicator, while including two interactions on the *dead* fund variable. The first interaction takes a value of one if the funds style-adjusted performance prior to delisting was positive (*dead*positive*), while the second takes a value of one if the fund's style-adjusted performance was negative (*dead*negative*). Funds that perform worse (better) than their matched hedge fund style benchmark prior to delisting are considered negative (positive) delisters. We estimate the prior performance measure over different horizons (three, six, and twelve months) and find similar results. Funds with negative relative performance prior to delisting perform poorly after exiting the database, while funds with positive relative performance do not suffer as much.

The results in Panel A include all of the returns, while Panel B restricts the data to just those funds that report to a database at some point in their lives. Focusing on those funds that reported to a database (Panel B), we find that hedge funds with negative performance in the three months prior to delisting suffer a significant drop in alpha of between 235 bps and 243 bps compared to live funds. The *dead*positive* interaction is also negative and significant in all models, but the coefficient is always less than half the size of the *dead*negative* interaction. This indicates that dead funds with positive performance prior to delisting also suffer a decrease in performance, but their drop in performance is less severe.

On whole, our results from Table VI provide evidence that funds delisting out of weakness perform significantly worse following delisting than other hedge funds. This suggests that prior delisting performance can be a useful tool for inferring the future performance of delisted funds. However, we also find some evidence that though they outperform funds that delist following negative performance, funds that delist following positive performance underperform database funds in the full sample. This suggests that the delisting effect is detrimental across the population of dead funds. This result is important because, although an investor could potentially shield herself from the self-selection bias by maintaining a trading strategy that only invests in funds that report to databases, the illiquid nature of hedge fund investment leaves investors vulnerable to the poor returns of dead funds following delisting.[26]

[26]It is questionable that an investor could even actively select funds that report to databases, as funds report their performance with a lag ranging from 2 to 3 months. Thus, an investor cannot be sure that a fund will report its contemporaneous returns.

–Table VI HERE–

If the delisting bias does not fully account for the upward bias in hedge fund data, what does? In addition to fund managers having general discretion over whether they report their performance to databases in the first place, there are two institutional features of database reporting that could further contribute to self-selection bias in hedge fund returns.[27]

First, because funds have some discretion as to the timing of their reports to the databases there is potential for a timing/re-listing bias. In most cases the fund has up to 3 months to file its monthly return before being moved to the graveyard database. A fund with poor performance in a given month may have the incentive to delay reporting, increase the fund's risk, and hope for a better outcome in the next month. If the strategy works, both monthly returns are listed. If it does not work, the fund never reports either return to the database. A similar version of this bias occurs when a previously delisted fund is allowed to rejoin the live funds file. If a fund is willing to fill all gaps in its time-series of returns, it is allowed to rejoin the database. As it is likely that only funds that performed well during their delisting period will re-list, these features of the commercial data will impart a further upward bias on the return data.

Second, there is evidence that funds retroactively revise or completely remove returns from databases, creating scope for a deleted/revised history bias. For example, we downloaded the BarclayHedge database in both August 2008 and August 2010. Looking at both the live and graveyard sections of the 2010 data, we notice 67 hedge funds that were present in the 2008 data but have been completely deleted in 2010. We find deleted funds in Lipper TASS as well. Conversations with BarclayHedge revealed that funds may ask the databases to completely remove their return history from the database. If it were the case that poor return histories are more likely to be deleted, then the observed returns in a database are biased.[28]

[27] An additional bias that is largely ignored in the literature deals with side-pockets. In times of distress, hedge funds may carve out their most illiquid investments into stand-alone investment pools. It is unclear whether the funds subsequently include the performance of these side-pockets when they report their performance to the commercial databases. If side-pockets perform differently than the fund's main strategy, this option of whether to include side-pockets as part of the monthly return is likely to contribute additional bias in the data. We thank Joseph Gerakos for calling this to our attention.

[28] A recent working paper by Patton, Ramadorai, and Streatfield (2011) examines revisions to historical returns in hedge fund databases. The authors find that nearly 40% of the hedge funds in their sample either deleted, revised, or added returns to their historical record. These revisions appear to be non-random and predict subsequent underperformance on the part of the revised funds.

C Does the Self-Selection Bias Affect the Best and Worst Funds Differently?

Though the choice of disclosure in a hedge fund database may alter estimates of average manager skill, there is a common assumption in the hedge fund literature that both the worst and the best funds are missing from the databases. If this is the case, then it is important to study returns in the tails of the distribution of hedge fund performance. For example, if the best funds choose not to report, then we expect that the portion of our hand-collected sample not in a database should outperform those funds in a database when returns are high. The opposite should hold true when returns are low.

–Table VII HERE–

Table VII tests this hypothesis in a univariate setting. Raw hedge fund returns are independently sorted into deciles based on their inclusion in, or exclusion from, a commercial database. We test whether the two means in each decile are different from one another. The returns reported to a database are significantly larger than the non-database returns for deciles one through six: funds that report to a database perform better than those funds not in a database. These differences are economically large. In the first decile, the non-database returns underperform the database returns by -648 bps/quarter, while the underperformance is still meaningful (43 bps/quarter) in the fifth decile. This underperformance shrinks monotonically from deciles 1 to 10. At the upper end of the distribution (deciles nine and ten), average returns are actually higher for non-database returns. In the tenth decile, hedge funds that do not report to a database outperform those that do by 53 bps/quarter. We perform a difference in means test for the bottom and top decile and reject the null (p-value < 0.01) that differences amongst the extreme deciles are equal. In a univariate setting, these findings support the hypothesis that databases are missing some of the best and worst performing funds. We now examine the distribution of returns while controlling for risk using a series of factor pricing models.

–Table VIII HERE–

In Table VIII, we use a simultaneous quantile regression framework (Koenker and Bassett (1978)) with a focus on the tails of the return distribution. The most common application of quantile regressions is a median regression whereby one minimizes the sum of the absolute deviations of the errors to estimate a median effect of the response variable. However, the same framework can be used to estimate the effect on any quantile in the distribution and proves particularly useful in estimating the impact of an explanatory variable, in our case the database indicator, at different points of the returns distribution.

We estimate five quantiles (10%, 25%, 50%, 75%, and 90%) using the 7-factor, 4-factor, and hedge fund benchmark models, in Panels A, B, and C respectively, of Table VIII. Standard errors are bootstrapped (400 repetitions). In each model our variable of interest is the *database* indicator.

–Table IX HERE–

If the bias from database inclusion were constant across the returns distribution, we would not expect the estimated coefficient on the *database* variable to vary. Rather, we would expect the coefficient on the indicator to remain constant and equal to that of our pooled OLS result from Table III. However, we find substantial variation in the estimate of self-selection bias. Similar to the univariate results of Table VII, the abnormal returns of reporting funds shrinks monotonically as returns increase. For example, turning to the Fung and Hsieh 7-factor model (Panel A), inclusion in a database leads to a 142 bps/quarter (t-statistic = 4.84) higher alpha when returns are low (in the 10th quantile), but an insignificant 3 bps/quarter higher alpha (t-statistic of 0.11) when returns are high (in the 90th quantile). An F-test of equality between the 10th quantile and 90th quantile is rejected (p-value < 0.01). This result is robust to each of the three factor models. In Table IX, we repeat the analysis by allowing for differences in risk as in Table III, Panel B. Our conclusions are similar.

–Figure 2 HERE–

These findings are perhaps best seen graphically. Figure 2 provides the estimated coefficients for the 5% quantile to the 95% quantile. For comparison, we provide the estimate from the OLS regression. Confidence intervals (5th and 95th) are also included for the coefficients estimated from the quantile regression. In Panels A, B, and C we estimate the 4-factor mode, 7-factor model and HF Benchmark model. In Panels C, D, and E we repeat the analysis, but allow for the possibility of differences in risk exposures between the database and non-database funds by including a database interaction variable with each of the factors in the model. Our conclusions are similar. When returns are low, the database indicator has a large, positive value; reported returns are greater than non-reported returns. The value of the coefficient falls conditional on higher returns and approaches zero for the better performing funds. The pattern is similar for each of the factor models.

Collectively, these results strongly suggest that the database self-selection bias can be severe, particularly affecting inferences of performance when returns are poor. This is the first paper to provide systematic evidence to this point and to attempt to quantify the bias. Additionally, we note the large economic magnitude of our coefficients, thereby indicating that hedge funds may be riskier than commonly thought. Further, we find little evidence that non-database funds in the right tail of the distribution perform better than database funds. The economic magnitude of this difference is modest when compared to the difference in the left tail of the distribution, indicating that good funds missing from databases do little to cancel out the poor performance from bad funds.

IV Robustness

Previous research acknowledges the self-selection bias in hedge fund data, but argues that both the best and worst funds are likely missing from the data (Ackerman et al. (1999)). If the missing performance of these two groups of funds cancels each other out, the observed performance in a database will be relatively unbiased. In this paper, we present results counter to that claim. We find convincing evidence that non-database funds perform significantly worse than funds in a database. In doing so, we collected a relatively unknown dataset of SEC registered FoFs and utilized their quarterly hedge fund holdings to generate a quarterly series of returns. Additionally, we made several restrictive data assumptions in an effort to generate a usable return series. In the following section, we test whether our conclusions are driven by self-selection in the data and ensure that they are robust to relaxing certain assumptions made when calculating our return series. We have included all tables for this section in two appendices. Appendix A is included with the paper, while Appendix B is available as an internet appendix.

A Sample Selection and Generalizability of Results

The hedge funds in our sample are all held by registered FoFs. As such, a potential concern is that the returns for this group of funds may introduce a different form of selection bias. Fortunately, for the 1,445 underlying hedge funds in our data, we have returns for both funds in a database and funds not in a database. We therefore control for selection bias by focusing only on the differences in performance between the reporting and non-reporting funds contained in our sample. That is, both the test and control group are drawn from the same sample of funds selected by a FoF. In doing so, we assume that fund characteristics of the database and non-database funds are similar, which ensures that any selection bias will net out in our analyses. Also, for our results to be generalizable, we assume that hedge funds selected by a FoF in our sample perform similarly to the population of hedge funds. We address the validity of these claims below.

A.1 Comparing Database Funds and Non-Database Funds

In Table A.1 in the appendix, we examine whether differences in non-performance characteristics of database funds and non-database funds could be driving the performance documented above. Other than returns, the only information available in the quarterly holdings data is style, fund size, and liquidity (withdrawal frequency).[29] Table A.1 compares the distribution of styles, size, and liquidity between the database and non-database funds in our sample. In Panel A, we find that the distributions of styles are economically similar. For example, long/short equity is the most common style in both samples, while the short-bias style is one of the least common. Using the HF Benchmark model will help mitigate any effect differences in style might have on our results, since the appropriate style benchmark is included in the regression.

In Panel B, we address the issue of fund size. Due to diseconomies of scale, fund size can have a negative effect on returns (Chen, Hong, Huang, and Kubrik (2004) and Berk and Green (2004)). If smaller hedge funds outperform larger funds, differences in size between the database and non-database funds may bias our findings. However, we find that database funds are larger than non-database funds. The mean (median) fund size is $751.6 million ($335.9 million) for database funds and $584.7 million ($267.1 million) for non-database funds. While these differences are both economically and statistically meaningful, they bias against our findings. We instead find that these smaller, non-database funds underperform their larger, database peers.

Finally, in Panel C we address liquidity. Liquidity can impact the expected returns of hedge funds. For instance, Aragon (2007) attributes positive alpha to a liquidity premium earned by the funds limited partners. If it were the case that database funds impose greater liquidity restrictions on their investors, then differences in liquidity may drive our results. Using withdrawal frequency to proxy for the liquidity of the underlying hedge funds, we find similar liquidity for both database and non-database funds. The median withdrawal frequency for both database and non-database funds is 90 days. Average liquidity is slightly

[29] Fund size and liquidity data are available for 21% and 68% of our sample, respectively

lower for database funds, predicting that database funds would actually have lower expected returns than non-database funds, the opposite of our findings.

A.2 Comparing Sample Database Funds to the Population of Database Funds

We find strong evidence that database funds outperform non-database funds within our sample of FoF holdings. Because FoF managers do not select hedge funds at random, it is likely the case that the funds differ from the population across certain dimensions such as size, age, or redemption frequency.[30] However, we argue that the self-selection bias we document in our sample of hedge funds is generalizable to the population if the *performance* characteristics of database funds in our sample do not markedly differ from those in the hedge fund population.

We explore this issue in Table A.2 in the appendix by comparing many of the characteristics of our sample of database funds to the universe of database funds found in the union of the Lipper-Tass, BarclayHedge, and HFR databases over our sample period 2004-2009. In Panel A, we compare the style distributions of funds selected by our sample FoFs to the universe of database funds. We find that they are very similar, with the exception of a preference for event driven managers (19.9% of sample vs. 8.7% of the overall universe).

Panel B compares the two samples across many fund-level characteristics. We find evidence that FoFs hire hedge funds that are older and have significantly greater assets under management than the average fund. The average investment size made by a FoF in our sample is $10.2 million, so these FoFs are seeking out hedge funds that are large enough to be both willing and able to accept relatively large allocations. Investing with many small funds would cause a FoF to spend more resources performing due diligence, while ending up a larger percentage of each individual hedge fund's total assets under management. We also find evidence that FoFs hire hedge funds that have higher minimum investments, longer lock-up periods, longer redemption notice periods, and less frequent redemptions than the average hedge fund. Perhaps FoFs create value as an intermediary by offering their investors exposure to funds with relatively more restrictions.

Importantly, however, we find no material differences in performance between our sample of database hedge funds and the population. We test for differences in performance between our sample and the population of hedge funds in three ways. First, we examine raw, monthly fund performance and find that the

[30] See Brown, Goetzmann, and Liang (2004), Ang, Rhodes-Kropf and Zhao (2008), and Brown, Gregoriou, and Pascalau (2012) among others for a discussion of the constraints and incentives faced by FoF managers.

mean and median monthly returns of our sample of funds are virtually identical to the population (less than 1 bp/month difference). Second, in order to adjust for risk we estimate fund-level alphas for every fund in the population (including those in our sample) using the monthly returns reported in the database over our sample period.[31] We report alphas at the fund level for the Fung and Hsieh (2004) 7-factor, Carhart (1997) 4-factor model, and the HF Benchmark model similar to Jagannathan, Malakhov, and Novikov (2010). Mean and median fund-level alphas are not statistically different between sample funds and population funds in any of the three factor models. Finally, we form calendar-time portfolios over our sample period at the monthly level and estimate aggregate alphas for our sample of funds as compared to the population using a long-short portfolio approach (Panel C). We find no significant differences in either the 4-factor or 7-factor calendar-time alphas.[32]

Taken together, the results indicate that the performance characteristics of our sample of database funds provide a similar representation of the performance characteristics of the population of funds reporting to a database over our sample period. Although our funds differ from the universe in many observable dimensions such as age, size, and redemption flexibility, we do not find evidence that they differ across the most important dimension for our study: risk adjusted (or unadjusted) performance. This supports our premise that the difference in performance between our sample of database funds and non-database funds is an unbiased estimate of the difference between non-database funds and the universe of hedge funds that choose to report to a commercial database.

B Robustness of Results

The following robustness tests relax various restrictions imposed in our main results. These additional results are available via an internet appendix.

B.1 Changing Cost Basis

Using equation (1), we generate our return series by comparing changes in the value of a hedge fund from two consecutive SEC filings. FoFs can of course add or subtract capital to their hedge fund investments over

[31] We require a fund to have a minimum of 24 months of returns in order to estimate alphas with greater precision. However our results are not affected by loosening this restriction to 12 months.

[32] Because calendar time portfolios aggregate funds across all styles we are unable to construct portfolio alphas that control for style returns analogous to the HF Benchmark model.

time. To capture the true return for the hedge fund holding, one must account for this change in cost basis. Unfortunately, FoFs in our sample appear to account for drawdowns of capital differently. While most funds appear to account for changes in cost basis in dollars, some appear to present percent changes in cost basis. For example, if a FoF invested $1 million in a hedge fund that subsequently doubled in value, its cost basis would be $1 million, while the value of its holdings would be $2 million. If the FoF then decided to drawn down half of the value of its investment ($1 million), it could account for its reduced cost basis using a total dollar value approach resulting in a new cost basis of $0. Alternatively, the fund could apply a proportion of initial capital approach whereby the fund reduces its cost basis in proportion to the total value of the fund. This would result in a new cost basis of $0.50 million. An inability to accurately capture the reporting regime of a FoF will create measurement error in our return variable. While this is unlikely to affect returns when FoFs add capital to a fund, we previously omitted these observations to exclude any bias this asymmetry may cause. This omission excluded 1,448 quarterly hedge fund returns (12.5% of the sample). Upon relaxing this constraint, the difference in performance between the database and non-database sample is similar to the one we document in Table II.

Additionally, we repeat the regression analysis of Table III, by using a series of common factor models and the addition of our database indicator variable, while including those observations where *additions* in capital occurred. Our conclusions are unchanged. As before, our database variable remains positive and significant in each of the pricing models. On whole, the conclusions for our tests appear unaffected by our cost change restriction.

B.2 Long-Short Equity Funds Only

We use a pooled OLS approach throughout the paper because of the short time-series and quarterly frequency of our data. The pooled nature of our analysis forces the average exposures of the factor model to be homogenous across different fund styles. To assess how this constraint affects the inferences from our tests, we restrict our analysis to a sub-sample of our most frequently observed style Long/Short Equity managers. These managers are potentially following similar strategies with similar risk characteristics, which means that our results will be less influenced by model error. This restriction leaves us with only 4,815 fund/quarter observations. However, the *database* indicator is still positive and statistically significant, ranging from 44 bps/quarter to 98 bps/quarter.

B.3 Return Outliers

As stated previously, our returns are generated from hand-collected data. To mitigate any data errors and reduce the impact of outliers, we trimmed our return observations at the 0.5% and 99.5% level. We recreate Table III and include these trimmed returns. Our results are similar, as the database variable remains positive and significant for all factor model regressions.

B.4 Multiple Hedge Fund Observations

It is possible for multiple FoFs to hold the same hedge fund in a given quarter. Based on differences of when the FoF invested in the hedge fund, it is possible for each of these FoFs to have slightly different highwater marks, fees, or tax status that could lead to slight discrepancies in the hedge funds return. Previously, we took the median quarterly return for any hedge fund held by multiple FoFs in an effort to reduce any outliers. For robustness, we instead take the mean return and again replicate Table III. Our results are similar. We also examine the subset of hedge funds that are held by two or more FoFs. The potential advantage of this subset is that the funds may be more homogenous in terms of size since a hedge fund held by multiple FoFs is likely to be larger. The disadvantage is that we are reducing the power of our tests to identify performance differences because it is likely that non-database funds held by multiple FoFs at the same time represent the best performing non-database funds. Despite this issue we find that the self-selection bias persists even in the more restricted sample.

B.5 Backfill Bias

Another important database bias that has been documented in the hedge fund literature is the backfill bias.[33] This bias is caused by successful managers choosing to enter a database and include their past returns. Accordingly, some of the hand-collected returns that we are matching to a database could be backfilled returns, which could potentially cause our positive results. We separate the backfill bias from the self-selection bias by marking a return as *backfilled* if it appeared during the first two years that a fund reported to a database. We then treat these *backfilled* returns as missing from the database (i.e. non-database returns). We recreate Table III using this backfilled-corrected data and find similar results.

[33] See our discussion in Section I.B

C Calendar-Time Regressions

While the pooled regression approach exhausts the time-variation of fund returns and characteristics in the full sample of hedge funds, it imposes restrictions on individual fund loadings on the factor indices. Throughout the paper, we have included a database interaction term for each of the factor exposures to allow risk to vary between groups, yet the pooled approach restricts factor sensitivities within groups. As a robustness check, we form portfolios of funds and utilize a calendar-time approach to test for differences in database and non-database funds. We separately form portfolios for database funds and non-database funds. To test for differences in portfolio alphas between the groups, we form a long-short portfolio that buys database funds and shorts non-database funds. For the 7-factor model, the alpha for the database portfolio is 123 bps/quarter, while the alpha for the non-database portfolio is -10 bps/quarter. The long-short portfolio has an alpha of 133 bps/quarter (t-statistic of 4.29).[34]

V Conclusion

This paper uses a new data set of hedge fund returns from SEC filings in order to test for a self-selection bias in commercial hedge fund databases. Comparing voluntarily reported returns to those returns not found in a database enables us to test a host of issues stemming from self-selection bias, including manager skill and delisting bias. We conclude that, on average, there is a positive self-selection bias in voluntarily reported hedge fund performance data and that estimates of average managerial skill using this data are likely overstated. We show that funds that stop reporting to a database have dramatically lower performance after they delist. However, delisting returns do not solely drive the positive self-selection bias that we document. Even after controlling for dead funds, the observed performance of voluntarily reported returns has a positive bias.

The implications of this result are large. Much of what previous researchers and practitioners attribute to managerial skill likely stems from the self-selection bias in hedge fund returns. At a minimum, until performance reporting for hedge funds becomes mandatory, it will likely be difficult to draw strong conclusions from hedge fund performance studies that use voluntarily reported data. Similar to the mutual fund literature that finds little evidence that mutual fund managers add value (Fama and French (2010)), our

[34] Because calendar time portfolios aggregate funds across all styles we are unable to construct portfolio alphas that control for style returns analogous to the HF Benchmark model.

results indicate that when we exclude self-selected database funds, the average excess returns of hedge funds does not differ markedly from zero.

The results of our study inform the debate over hedge fund disclosure. If the tail-risk for the entire hedge fund universe is greater than the risk estimated from returns from commercial databases, then some degree of mandatory disclosure to regulatory bodies could be warranted. Leverage and riskier positions could be driving the poor returns of non-reporting hedge funds, which could affect the level of systemic risk present in the financial system. Using only voluntarily reported performance data might lead regulatory bodies to underestimate the degree to which hedge funds may contribute to financial instability.

References

[1] Ackermann, C., R. McEnally, and D. Ravenscraft (1999), The Performance of Hedge Funds: Risk, Return and Incentives, *Journal of Finance* 54, 833-874.

[2] Agarwal, V., N.D. Daniel, and N. Y. Naik (2009), Role of Managerial Incentives and Discretion in Hedge Fund Performance, *Journal of Finance* 64, 2221-2256.

[3] Agarwal, V., V. Fos, and W. Jiang (2011), Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings, Working Paper.

[4] Aggarwal, R. and P. Jorion (2010), The Performance of Emerging Hedge Fund Managers*Journal of Financial Economics* 96, 238-256.

[5] Ang A., Rhodes-Kropf M., and Zhao R. (2008), Do Funds-of-Funds Deserve Their Extra Fees?, *Journal of Investment Management* 6 no.4.

[6] Aragon, G. (2007), Share Restrictions and Asset Pricing: Evidence from the Hedge Fund Industry, *Journal of Financial Economics* 83, 33-58.

[7] Aragon, G. and J. S. Martin (2011), A Unique View of Hedge Fund Derivative Usage: Safeguard or Speculation?, *Journal of Financial Economics*, Forthcoming.

[8] Asness, C., R. Krail, and J. Liew (2001), Do Hedge Funds Hedge?, *Journal of Portfolio Management* 28, 6-19.

[9] Berk, J. and R. Green (2004), Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.

[10] Bollen, N. and V. Pool (2009), Do Hedge Fund Managers Misreport Returns? Evidence from the Pooled Distribution, *Journal of Finance* 64, 2257-2288.

[11] Bollen, N. and R. Whaley (2009), Hedge Fund Risk Dynamics: Implications for Performance Appraisal, *Journal of Finance* 64, 985-1035.

[12] Brown, Goetzmann, and Liang (2004), Fees on fees in funds of funds, *Journal of Investment Management* 3, 39-56.

[13] Brown, S., Gregoriou, G., and Pascalau, R. (2012), Is it Possible to Overdiversify? The Case of Funds of Hedge Funds, *Review of Asset Pricing Studies*, Forthcoming.

[14] Brown, K., W. V. Harlow, and L.T. Starks (1996), Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry, *The Journal of Finance* 51, 85-110.

[15] Carhart, M. (1997), On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57-82.

[16] Chen, J., H. Hong, M. Huang, and J. Kubik (2004), Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization, *American Economic Review* 94, 1276-1302

[17] Chevalier, J. and G. Ellison (1997), Career Concerns of Mutual Fund Managers, *Quarterly Journal of Economics* 114, 389-432.

[18] Dichev, I. and G. Yu (2011), Higher risk, lower returns: What Hedge Fund Investors Really Earn, *Journal of Financial Economics* 100, 248-263.

[19] Evans, R. (2010), Mutual Fund Incubation, *Journal of Finance* 65, 1581-1611.

[20] Fama, E. and K. French (2010), Luck versus Skill in the Cross-Section of Mutual Fund Returns, *Journal of Finance* 65, 1915-1947

[21] Fung, W. and D. Hsieh (2000), Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases, *Journal of Financial and Quantitative Analysis* 35, 291-307.

[22] Fung, W. and D. Hsieh (2004), Hedge Fund Benchmarks: A Risk Based Approach, *Financial Analysts Journal* 60, 65-80.

[23] Fung, W. and D. Hsieh (2009), Measurement Biases in Hedge Fund Performance Data: An Update, *Financial Analysts Journal* 65, 36-38.

[24] Fung, W., D. Hsieh, N. Naik, and T. Ramadorai (2008), Hedge Funds: Performance, Risk and Capital formation, *Journal of Finance* 63, 1777-1803.

[25] Grecu, A., B. Malkiel, and A. Saha (2007) Why do hedge funds stop reporting performance? *Journal of Portfolio Management* 34, 119-136.

[26] Griffin, J. and J. Xu (2009), How Smart are the Smart Guys? A Unique View of Hedge Fund Stock Holdings, *Review of Financial Studies* 22, 2531-2570.

[27] Hodder, J., J. Jackwerth, and O. Kolokolova (2009), Recovering Delisting Returns of Hedge Funds, Working Paper.

[28] Ibbotson, R., P. Chen, and K. Zhu (2011), The ABCs of Hedge Funds: Alphas, Betas, and Costs, *Financial Analysts Journal* 67, 1525

[29] Jagannathan, R., A. Malakhov, and D. Novikov (2010), Do Hot Hands Exist Among Hedge Fund Managers? An Empirical Examination, *Journal of Finance* 65, 217-255.

[30] Koenker, R. and Bassett, Jr. G. (1978). Regression Quantiles, *Econometrica* 46, 33-50

[31] Kosowski, R., N. Naik, and M. Teo (2007), Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis, *Journal of Financial Economics* 84, 229-264.

[32] Malkiel, B., and A. Saha (2005), Hedge Funds: Risk and Return, *Financial Analysts Journal* 61, 80-88.

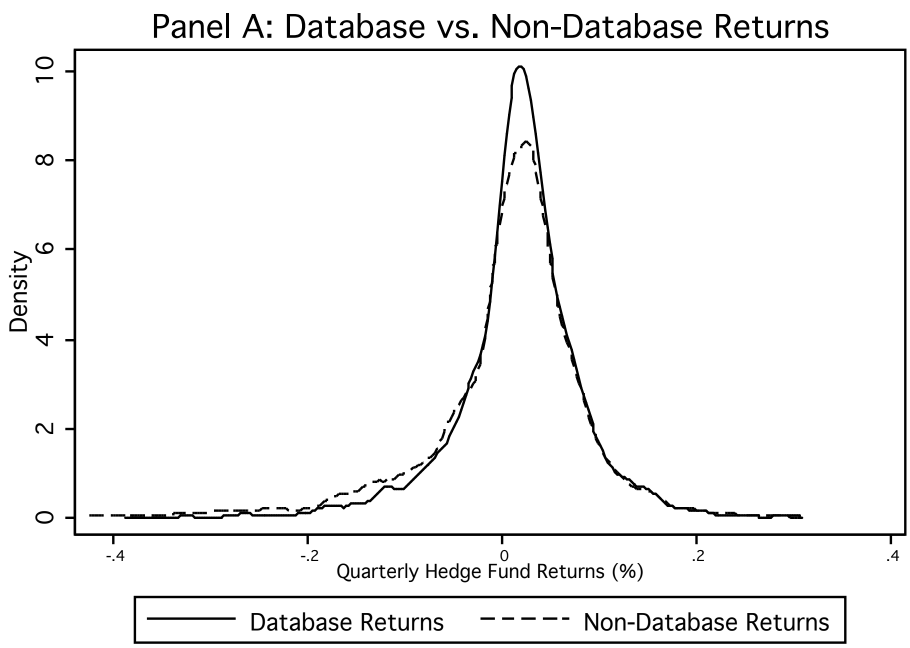
[33] Patton, A., T. Ramadorai, and M. Streatfield (2011), The Reliability of Voluntary Disclosures: Evidence from Hedge Funds, Working Paper.

[34] Posthuma, N. and P. Van der Sluis (2003), A Reality Check on Hedge Fund Returns, Working Paper.

[35] Shumway, T. (1997), The Delisting Bias in CRSP Data, *Journal of Finance* 52, 327-340.

[36] Stulz, T. (2007), Hedge Funds: Past, Present, and Future, *Journal of Economic Perspectives* 21, 175-194.

Figure 1: Kernel Density Estimations



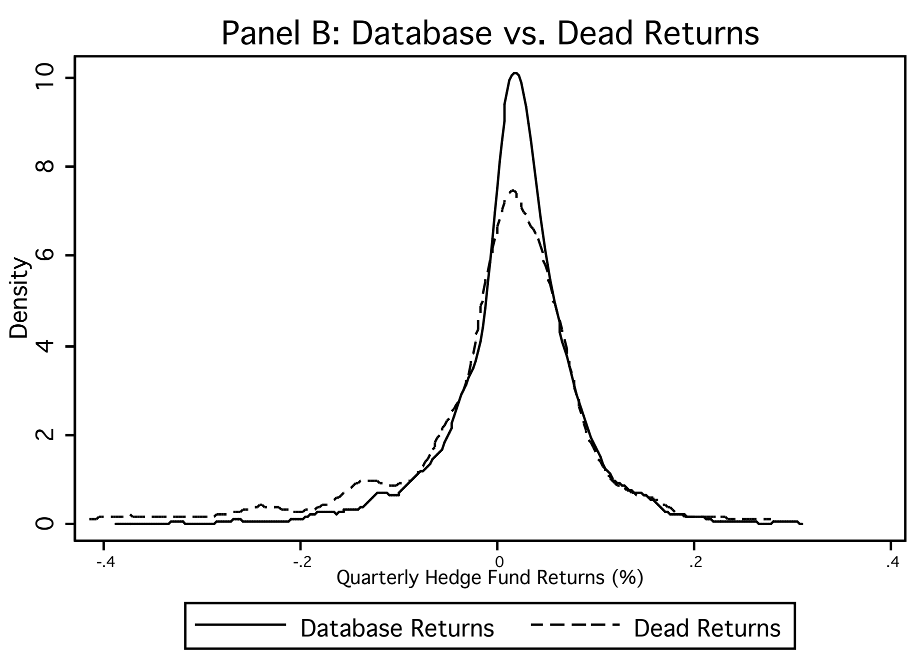


Figure 2: Estimates of Database Indicator by Return Quantile

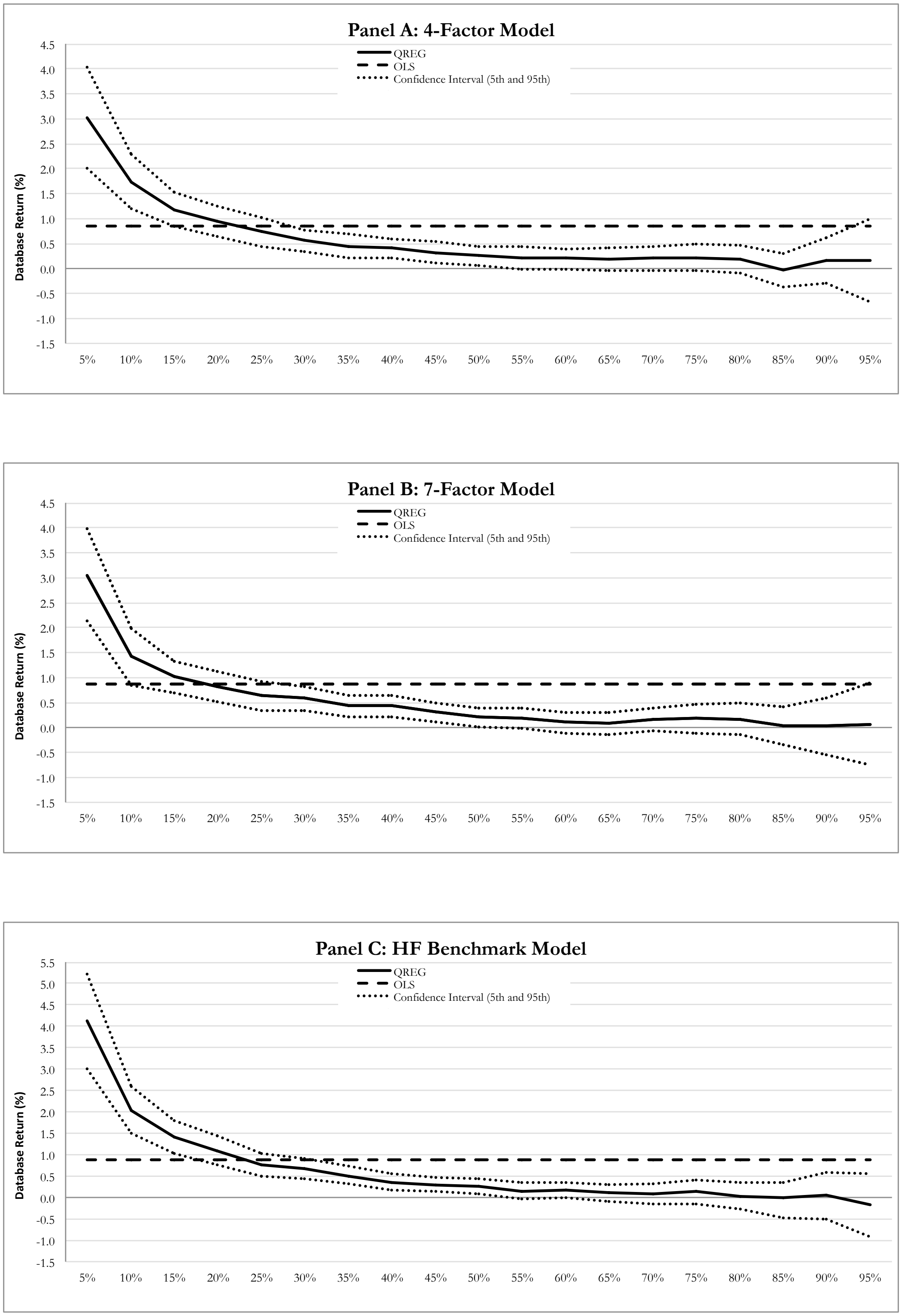
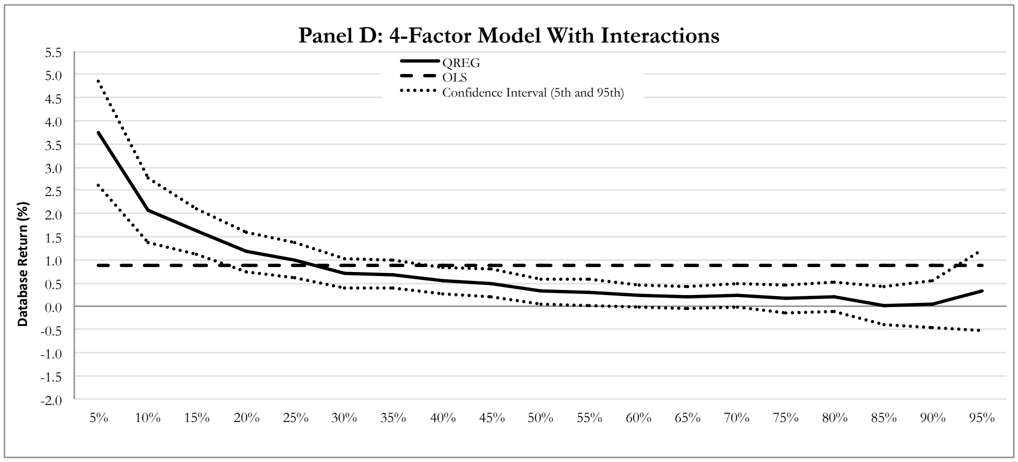
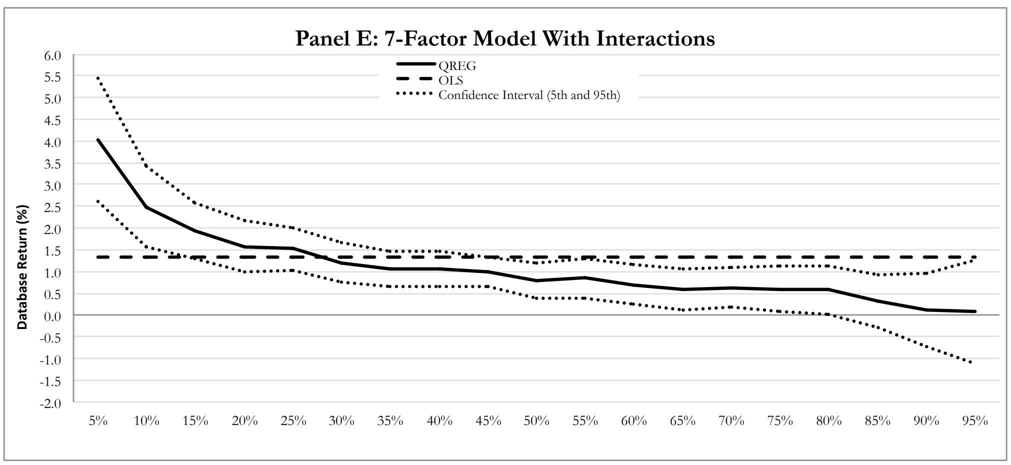


Figure 2 (continued)





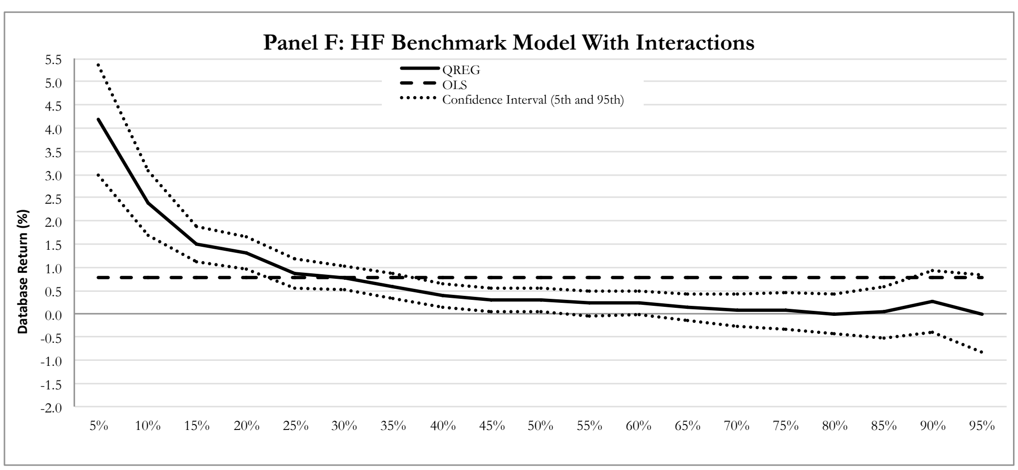


Table I: SEC Registered Funds-of-Funds

Panel A gives the number of registered fund-of-funds (FoF) that began reporting in a given calendar year. We define initial reporting as the year the initial N-2 registration was filed with the SEC. Panel B compares our sample of registered FoFs to the universe of FoFs that report to the union of commercial databases. All observations are at the FoF/Quarter level. Information about the registered FoFs has been collected from their registration filings. Registered FoF quarterly returns are calculated using the underlying hedge fund positions reported in their SEC filings. We only use individual hedge fund returns where the *cost* field has not changed from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. *Number of holdings* is the average number of underlying hedge funds that a registered FoF holds in a particular quarter.

Panel A: First Reporting Year for Sample of Registered FoFs

Year	Number of Funds Initiating Reporting
1998	1
1999	1
2000	2
2001	11
2002	23
2003	11
2004	17
2005	8
2006	4
2007	1

Table I (continued)

Panel B: Comparing Registered FoFs to Database FoFs (FoF/Qtr)

	Registered FoF			Database FoF			Differences	
	N	Mean	Median	N	Mean	Median	Means	Medians
Quarterly Net Return (%)	996	0.89	1.71	84,698	0.82	1.73	0.08	-0.01%
AUM ($MM)	1,008	273.0	113.0	84,698	208.0	54.4	65.0**	58.6***
Age (years)	1,008	4.2	4.0	84,698	3.5	2.0	0.6***	2.0***
Min. Invest.($)	992	528,559	100,000	83,327	727,619	149,690	−199,060***	−49,960***
Management Fees (%)	992	1.31	1.25	84,349	1.35	1.50	−0.04**	−0.25***
Incentive Fees (%)	420	8.45	10.00	84,943	7.48	10.00	0.97***	0.00***
Number of Holdings	1,008	23.2	21.0	-	-	-	-	-
Number of Styles	1,008	4.5	5.0	-	-	-	-	-

*** p<0.01, ** p<0.05, * p<0.1

Table II: Hedge Fund Quarterly Returns Calculated Using Fund-of-Fund Holdings

Table II gives descriptives for the quarterly hedge fund returns used in this study. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database Returns* describes all fund-quarter returns that are also found in the union of hedge fund databases. *Database Returns of Funds that Leave* are fund-quarter returns that are also found in a database, but only includes those funds that subsequently leave the databases. *Dead Returns* are returns that appear after a fund last reports to the databases. Quarterly underlying fund returns are calculated using the *value* and *cost* fields from hand-collected FoF SEC filings (see Equation 1). The *value* of FoF's investments used to calculate returns are net of all fees. We report returns calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. Different FoFs may hold the same underlying hedge fund, so multiple reported returns for the same hedge fund are possible in a given quarter. We report the median return across all FoFs that report a given hedge fund in a quarter. Returns have been trimmed at the 0.5% and 99.5% levels. We test for differences in means using a two-sample t-test with unequal variances and for differences in medians using a Wilcoxon rank-sum test.

	N	Mean	σ	Median	5th	95th
All Returns	10,126	1.13%	7.80%	1.91%	-12.96%	11.93%
Database Returns	4,925	1.68	6.85	2.03	-10.11	11.90
Non-Database Returns	5,201	0.60	8.58	1.76	-15.22	11.98
	Differences	1.07***		0.27***		
Database Returns of Funds that Leave	829	1.59	7.09	2.16	-11.74	11.59
Dead Returns	1,083	-0.16	9.84	1.43	-20.66	12.42
	Differences	1.75***		0.73***		

*** p<0.01, ** p<0.05, * p<0.1

Table III: Pooled OLS Results - Database Returns vs. Non-Database Returns

Table III describes the results from a pooled OLS regression of quarterly hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. The fund values used to calculate returns are net of all fees. Fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Benchmark
database	0.0085***	0.0087***	0.0087***
	(5.65)	(5.75)	(5.73)
α	-0.0002	0.0005	-0.0017
	(-0.14)	(0.39)	(-1.33)
Obs.	10,126	10,126	10,126
Adj. R^2	0.21	0.21	0.22

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Benchmark
database	0.0088***	0.0133***	0.0088***
	(5.65)	(6.09)	(5.21)
α	-0.0001	-0.0013	-0.0017
	(-0.08)	(-0.84)	(-1.30)
Obs.	10,126	10,126	10,126
Adj. R^2	0.22	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table IV: Pooled OLS Results - Dead Returns

Table IV describes the performance of dead funds from pooled OLS regressions of quarterly hedge fund returns using three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Dead* is an indicator that equals one if a fund's hand-collected return that quarter appears *after* the fund has last reported to the union of databases, i.e is no longer in a database. The regression specifications in Panel B include interaction terms between the *dead* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Each set of factor model regressions is run twice: first using all hedge fund returns from the hand-collected sample and then only using returns from funds that reported to a database at some point during their life. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	All Funds			Reporting Funds Only		
	4-Factor	7-Factor	HF Bench	4-Factor	7-Factor	HF Bench
dead	−0.0108***	−0.0109***	−0.0111***	−0.0141***	−0.0146***	−0.0144***
	(-3.73)	(-3.65)	(-3.81)	(-4.89)	(-4.85)	(-4.90)
α	0.0051***	0.0059***	0.0038***	0.0082***	0.0098***	0.0074***
	(6.08)	(5.12)	(4.16)	(8.02)	(6.63)	(6.71)
Obs.	10,126	10,126	10,126	6,026	6,026	6,026
Adj. R^2	0.21	0.21	0.21	0.22	0.21	0.21

Panel B: Include Interactions Between *Dead* Indicator and Factor Returns

	All Funds			Reporting Funds Only		
	4-Factor	7-Factor	HF Bench	4-Factor	7-Factor	HF Bench
dead	−0.0103***	−0.0166***	−0.0087***	−0.0137***	−0.0217***	−0.0134***
	(-3.86)	(-4.67)	(-3.13)	(-5.06)	(-5.88)	(-4.79)
α	0.0053***	0.0068***	0.0035***	0.0087***	0.0120***	0.0062***
	(6.28)	(5.87)	(3.87)	(8.54)	(7.80)	(2.76)
Obs.	10,126	10,126	10,126	6,026	6,026	6,026
Adj. R^2	0.22	0.22	0.22	0.23	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table V: Pooled OLS Results - Database and Dead Indicators Together

Table V describes the results from a pooled OLS regression of quarterly hedge fund returns on two different indicators (*database* and *dead*) using three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. *Dead* is an indicator that equals one if a fund's hand-collected return appears *after* the fund has last reported to the union of databases, i.e is no longer in a database. The regression specifications in Panel B include interaction terms between both the *database* and *dead* indicators and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0071***	0.0072***	0.0072***
	(4.35)	(4.49)	(4.43)
dead	−0.0069**	−0.0070**	−0.0071**
	(-2.24)	(-2.20)	(-2.29)
α	0.0013	0.0021	−0.0002
	(0.96)	(1.37)	(-0.12)
Obs.	10,126	10,126	10,126
Adj. R^2	0.21	0.21	0.22

Panel B: Include Interactions Between Both Indicators and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0072***	0.0105***	0.0078***
	(4.29)	(4.56)	(4.23)
dead	−0.0065**	−0.0113***	−0.0045
	(-2.23)	(-2.99)	(-1.50)
α	0.0015	0.0015	−0.0006
	(1.08)	(0.89)	(-0.44)
Obs.	10,126	10,126	10,126
Adj. R^2	0.22	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table VI: Pooled OLS Results - Prior and Post Reporting Performance of Dead Funds

Table VI describes how the performance of dead funds after they stop reporting to a database is related to their performance prior to leaving the database. We use pooled OLS and the three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used.*Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. *Dead* is an indicator that equals one if a fund's hand-collected return appears *after* the fund has last reported to the union of databases, i.e is no longer in a database. *Dead*negative3* is the interaction between the *dead* indicator and an indicator that equals one if a fund underperformed its Credit Suisse Tremont style index over the three-month period prior to leaving a database. The other interactions are defined similarly, but for positive performance and different periods. In Panel A, we use all hedge fund returns from the hand-collected sample, while, in Panel B, we use only returns from funds that reported to a database at some point during their life. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: All Funds

	4-Factor	4-Factor	4-Factor	7-Factor	7-Factor	7-Factor	HF Bench	HF Bench	HF Bench
database	0.0071***	0.0071***	0.0073***	0.0073***	0.0073***	0.0075***	0.0073***	0.0073***	0.0075***
	(4.50)	(4.54)	(4.63)	(4.64)	(4.69)	(4.78)	(4.61)	(4.66)	(4.72)
*dead*negative3*	−0.0160***			−0.0164***			−0.0158***		
	(-3.23)			(-3.24)			(-3.19)		
*dead*positive3*	−0.0021			−0.0012			−0.0026		
	(-0.67)			(-0.36)			(-0.81)		
*dead*negative6*		−0.0159***			−0.0163***			−0.0155***	
		(-2.93)			(-2.91)			(-2.83)	
*dead*positive6*		−0.0028			−0.0019			−0.0033	
		(-0.90)			(-0.59)			(-1.06)	
*dead*negative12*			−0.0118***			−0.0117***			−0.0118***
			(-2.71)			(-2.61)			(-2.70)
*dead*positive12*			−0.0036			−0.0029			−0.0041
			(-1.08)			(-0.83)			(-1.19)
α	0.0014	0.0013	0.0012	0.0021	0.0021	0.0019	−0.0001	−0.0001	−0.0002
	(1.05)	(1.03)	(0.92)	(1.42)	(1.41)	(1.29)	(-0.07)	(-0.09)	(-0.19)
Obs.	10,126	10,126	10,126	10,126	10,126	10,126	10,126	10,126	10,126
Adj. R^2	0.21	0.21	0.21	0.21	0.21	0.21	0.22	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table VI (continued)

Panel B: Reporting Funds Only

	4-Factor	4-Factor	4-Factor	7-Factor	7-Factor	7-Factor	HF Bench	HF Bench	HF Bench
*dead*negative3*	−0.0235***			−0.0243***			−0.0235***		
	(-4.92)			(-4.93)			(-4.86)		
*dead*positive3*	−0.0067**			−0.0062*			−0.0072**		
	(-2.14)			(-1.91)			(-2.26)		
*dead*negative6*		−0.0236***			−0.0245***			−0.0234***	
		(-4.52)			(-4.50)			(-4.38)	
*dead*positive6*		−0.0075**			−0.0070**			−0.0080**	
		(-2.43)			(-2.20)			(-2.58)	
*dead*negative12*			−0.0192***			−0.0195***			−0.0193***
			(-4.66)			(-4.55)			(-4.61)
*dead*positive12*			−0.0082**			−0.0078**			−0.0086**
			(-2.43)			(-2.26)			(-2.53)
α	0.0082***	0.0082***	0.0081***	0.0097***	0.0097***	0.0096***	0.0074***	0.0074***	0.0073***
	(7.89)	(7.79)	(7.67)	(6.36)	(6.41)	(6.29)	(6.55)	(6.56)	(6.46)
Obs.	6,026	6,026	6,026	6,026	6,026	6,026	6,026	6,026	6,026
Adj. R^2	0.22	0.22	0.22	0.21	0.21	0.21	0.22	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table VII: Hedge Fund Returns By Deciles

Table VII reports the hand-collected quarterly hedge fund returns for each sample (*non-database* and *database*) sorted into deciles. We create deciles for each sample separately and then compare the means of each decile. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database Returns* describes all fund-quarter returns that are also found in the union of hedge fund databases. Hand-collected returns are calculated using the *value* and *cost* fields collected from hand-collected FoF filings. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. The fund values used to calculate returns are net of all fees. Fund returns are defined as the median hedge fund return across all FoF advisors who report that underlying hedge fund in that quarter and have been trimmed at the 0.5% and 99.5% levels. For each decile, we perform a t-test for differences in means between the two samples.

	Non-Database Returns	Database Returns	Difference
1 (worst)	−18.73%	−12.25%	−6.48%***
2	−6.41	−3.66	−2.75***
3	−2.30	−0.89	−1.41***
4	−0.20	0.52	−0.71***
5	1.11	1.54	−0.43***
6	2.34	2.50	−0.16***
7	3.52	3.59	−0.07***
8	5.00	5.04	−0.04
9	7.32	7.23	0.09*
10 (best)	13.79	13.26	0.53*

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table VIII: Quantile Regression Results - Database Returns vs. Non-Database Returns

Table VIII describes the results from a quantile regression of quarterly hedge fund returns on the *database* indicator and three different factor models: the Fung and Hsieh (2004) 7-factor model, the Carhart (1997) 4-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. We suppress the individual factor loadings. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. The fund values used to calculate returns are net of all fees. Fund returns are defined as the median hedge fund return across all FoF advisors who report that underlying hedge fund in that quarter and are net of the risk-free rate. Returns have been trimmed at the 0.5% and 99.5% levels. Standard errors are bootstrapped (400 repetitions). We report t-statistics in parentheses.

Panel A: Seven-Factor Model

	Return Quantile				
	10th	25th	50th	75th	90th
database	0.0142***	0.0063***	0.0020**	0.0018	0.0003
	(4.84)	(3.92)	(1.98)	(1.21)	(0.11)
α	−0.0777***	−0.0326***	0.0044***	0.0402***	0.0803***
	(-24.86)	(-19.26)	(3.62)	(26.31)	(31.51)
Pseudo R^2	0.23	0.17	0.10	0.08	0.07

Panel B: Four-Factor Model

	Return Quantile				
	10th	25th	50th	75th	90th
database	0.0173***	0.0074***	0.0025**	0.0022*	0.0016
	(6.07)	(4.78)	(2.53)	(1.74)	(0.65)
α	−0.0768***	−0.0301***	0.0049***	0.0364***	0.0732***
	(-27.83)	(-22.74)	(6.29)	(33.46)	(48.97)
Pseudo R^2	0.22	0.17	0.10	0.08	0.07

Panel C: HF Benchmark Model

	Return Quantile				
	10th	25th	50th	75th	90th
database	0.0204***	0.0076***	0.0026***	0.0013	0.0004
	(7.65)	(5.88)	(2.77)	(0.98)	(0.16)
α	−0.0775***	−0.0316***	0.0012	0.0320***	0.0731***
	(-29.82)	(-27.80)	(1.39)	(31.40)	(38.22)
Pseudo R^2	0.22	0.19	0.13	0.09	0.05

*** p<0.01, ** p<0.05, * p<0.1

Table IX: Quantile Regression Results Including Factor Interactions

Table IX describes the results from a quantile regression of quarterly hedge fund returns on the *database* indicator and three different factor models with the indicator interacted with the appropriate factor returns: the Fung and Hsieh (2004) 7-factor model, the Carhart (1997) 4-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. The fund values used to calculate returns are net of all fees. Fund returns are defined as the median hedge fund return across all FoF advisors who report that underlying hedge fund in that quarter and are net of the risk-free rate. Returns have been trimmed at the 0.5% and 99.5% levels. Standard errors are bootstrapped (400 repetitions). We report t-statistics in parentheses.

Panel A: Seven-Factor Model With Interactions

	Return Quantile				
	10th	25th	50th	75th	90th
database	0.0249***	0.0152***	0.0080***	0.0059**	0.0011
	(5.52)	(6.17)	(3.99)	(2.43)	(0.26)
α	−0.0809***	−0.0366***	0.0012	0.0384***	0.0792***
	(-20.70)	(-16.89)	(0.83)	(24.88)	(29.07)
Pseudo R^2	0.23	0.17	0.11	0.08	0.07

Panel B: Four-Factor Model With Interactions

	Return Quantile				
	10th	25th	50th	75th	90th
database	0.0207***	0.0099***	0.0032***	0.0017	0.0005
	(6.03)	(5.54)	(2.85)	(1.15)	(0.22)
α	−0.0786***	−0.0308***	0.0046***	0.0366***	0.0737***
	(-28.62)	(-21.79)	(5.20)	(36.20)	(50.77)
Pseudo R^2	0.22	0.17	0.10	0.08	0.07

Panel C: HF Benchmark Model With Interactions

	Return Quantile				
	10th	25th	50th	75th	90th
database	0.0238***	0.0087***	0.0030**	0.0007	0.0027
	(6.54)	(4.74)	(2.15)	(0.31)	(0.80)
α	−0.0802***	−0.0321***	0.0010	0.0323***	0.0722***
	(-25.37)	(-21.45)	(1.06)	(26.24)	(35.90)
Pseudo R^2	0.22	0.19	0.13	0.09	0.05

*** p<0.01, ** p<0.05, * p<0.1

Appendix A

Exhibit A.1: Example of the Organization and Structure of a Registered Fund of Funds

Exhibit A.1 examines one particular registered fund-of-funds (FoF): Morgan Stanley Institutional Fund of Hedge Funds LP (CIK: 0001161973). On December 12, 2001 The Morgan Stanley Institutional Fund of Hedge Funds (MS) filed an N-2 with the SEC which registered the company as a closed-end investment company under Section 8(a) of the Investment Company Act of 1940. This statement detailed the terms and conditions of the newly formed limited partnership, whereby they would accept investments from qualified and accredited investors in the newly formed FoF. In the FoF's initial registration statement, the firm explained one of their reasons for registering with the SEC: "Unlike many private investment funds, the Partnership has registered under the 1940 Act to be able to offer the Interests without limiting the number of investors who may participate in its investment program." The FoF was operated as a limited partnership that accepted restricted investments from limited partners called "subscriptions". The assets were then managed by an Adviser called Morgan Stanley AIP. These assets were to be deployed into a diversified portfolio of hedge fund investments. The structure of the FoF is shown below in Figure A.1.

The FoF initially required a minimum investment of $250,000 and would accept follow on investments of $100,000. The FoF had a 1.3% management fee and had a performance fee of 15% of profits that exceeded a pre-defined hurdle rate of 5% plus the three month T-bill rate. This performance fee was subject to a high-water mark provision. These management and performance fees were at the FoF level and were in addition to the typical management and performance fees (1.5% and 20% respectively) paid to the underlying portfolio funds. MS accepted initial and follow-on investments the first of every month, but only allowed redemptions on a quarterly basis. The FoF redemption mechanism was through tender offers whereby the fund would file a Schedule TO-I offering to redeem up to a certain capped proportion of fund assets (typically 15% of NAV). If an investor wanted to redeem their interests, they typically have to provide notice 45 days prior to the end of the quarter. Although MS offered these quarterly redemptions, they did not offer initial redemptions until March 31, 2003, roughly one year following the initial accumulation of capital. This served as an additional one year lockup for initial investors. These features are very similar to the typical hedge fund or FoF.

MS attracted initial capital for seven months before commencing operations in July 2002. They filed their first semi-annual holdings statement in early 2003 for their holdings as of December 2002. At this point, the fund had assets of $667 million invested with 38 different funds from six different Lipper-Tass hedge fund strategies. Due to both capital appreciation from underlying investments and investor inflows into the fund, the fund grew in size to over $1.8 billion by early 2005. At this point, the fund increased its minimum investment to $25 million for new subscribers. In late 2005, MS began to disclose its performance and contract characteristics to the HFR commercial hedge fund database. Throughout our sample period of 2004-2009, MS closely tracked the performance of its peers, delivering a total net of fee return of 20.83% compared to the Lipper-Tass FoF index return of 20.80% over the same period. During our sample period, 38% of MSs portfolio hedge funds actively reported to one of the five commercial hedge fund databases used in our study and another 10% of their holdings had once reported to a database but subsequently de-listed (i.e. were "dead" funds). MS reached a maximum size of $3.3 billion in February 2008, but, like other hedge funds, was hit hard by the financial crisis of 2008-2009 and suffered both losses in investment value and investor redemptions. The fund ended 2009 with hedge fund assets of just over $1.5 billion, representing investments in 46 different hedge funds from six different Lipper Tass Strategies. The MS fund is still operating today under the same closed-end registered structure that it originated under in 2002.

Figure A.1: Morgan Stanley Institutional Fund of Hedge Funds Structure

(Source: N-2 Filing with the SEC)

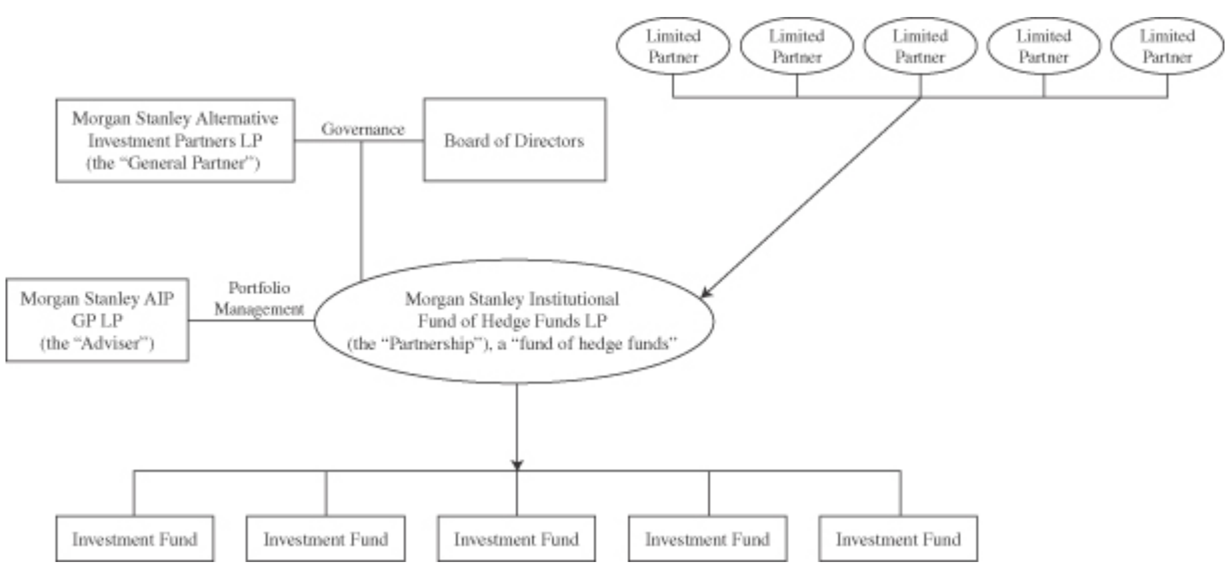


Table A.1: Differences Between Database and Non-Database Hedge Funds

Table A.1 tests for differences between the database and non-database hedge funds in our sample using only information from our hand-collected data. Panel A reports the percentage of quarterly hedge fund return observations in the reporting and non-reporting samples by category. The *database* sample consists of return observations (i.e. fund-quarter return pairs) from the hand-collected sample that appear in the union of databases. Fund strategies are taken from Fund-of-Fund (FoF) SEC filings and mapped to a Lipper TASS category. In Panel B, we examine differences in assets under management ($millions) based on whether the fund is in a database or not. In Panel C, we test for differences in liquidity between the two samples. We use withdrawal frequency (in days) as a proxy for liquidity. Only observations where cost did not change are included. We test for differences in means using a two-sample t-test with unequal variances and for differences in medians using a Wilcoxon rank-sum test.

Panel A: Differences in Style Distribution Between Samples

Style	Database Funds	Non-Database Funds
Convertible Arbitrage	1.7%	0.6%
Emerging Markets	2.2	0.2
Event Driven	19.3	17.8
Fixed Income Arbitrage	6.8	5.3
Long/Short Equity	45.7	49.3
Macro	6.0	3.7
Managed Futures	0.7	0.5
Market Neutral	12.0	11.5
Multi-Strategy	5.5	9.8
Short Bias	0.1	1.3

Panel B: Differences in Fund Size (AUM $millions)

	N	Mean	σ	Median	5th	95th
Database Funds	1,014	751.6	1,193.2	335.9	84.3	2,689.1
Non-Database Funds	1,068	584.7	1,291.2	267.1	13.7	1,809.3
	Differences	166.9***		68.8***		

Panel C: Differences in Withdrawal Frequency (Days)

	N	Mean	σ	Median	5th	95th
Database Funds	5,349	96.7	62.4	90.0	1.0	180.0
Non-Database Funds	5,469	103.6	71.4	90.0	30.0	360.0
	Differences	−7.0***		0.0***		

*** p<0.01, ** p<0.05, * p<0.1

Table A.2: Differences Between Database Funds in our Sample and the Universe of Database Funds

Table A.2 compares the hedge funds in our hand-collected sample that match to a database to the hedge funds found in the union of the commercial databases. Panel A compares the strategies used by the hedge funds selected by the FoFs in our sample to the universe of hedge funds. Fund strategies are taken from FoF SEC filings and mapped to a Lipper TASS category. We report the percentage of returns in each sample by category. Panel B examines univariate differences in performance and contract characteristics between sample database funds and the database universe. *7-Factor α* are the alphas across individual funds using the Fung and Hsieh (2004) 7-factor model. We also calculate alphas using a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model and the Carhart (1997) 4-factor model. Alphas are calculated using all of a fund's monthly database returns and the fund must have 24 months of continuous returns in order to be included. *Return (%)* is monthly return (net-of-fees). *AUM ($mm)* is the monthly assets under management, while *Fund Age (years)* is the number of years since fund inception. The remaining variables are time-invariant based on limitations in the commercially available data and are given as means and medians across all fund/month observations. *Management Fee (%)* and *Incentive Fee (%)* are the fund's fees charged to investors. *Highwater Mark (%)* is an indicator variable for that contract feature. *Lock-Up*, *Redemption Notice*, and *Redemption Frequency* are given in days and represent the illiquidity of the funds' shares. *Minimum Investment ($mm)*is the minimum dollar amount required for initial entry into the hedge fund. *Big Four* is an indicator variable for the use of a big four accounting firm. We test for differences in means using a two-sample t-test with unequal variances and for differences in medians using a Wilcoxon rank-sum test. Panel C compares the monthly calendar-time portfolio performance of the hedge funds selected by the FoFs in our sample to the hedge funds in the union of commercial databases. We use both the Fung and Hsieh (2004) 7-factor model and the Carhart (1997) 4-factor model.

Panel A: Differences in Style Distribution Between Samples

Style	Sample Database Funds	Database Universe
Convertible Arbitrage	2.6%	2.6%
Emerging Markets	1.4	4.7
Event Driven	19.9	8.7
Fixed Income Arbitrage	9.2	7.4
Long/Short Equity	44.7	43.3
Macro	6.7	10.9
Managed Futures	1.5	4.2
Market Neutral	3.6	6.5
Multi-Strategy	10.3	11.1
Short Bias	0.2	0.5

Table A.2 (continued)

Panel B: Differences in Returns and Contract Characteristics Sample Database Funds and the Database Universe

	Sample Database Funds			Database Universe			Differences	
	Mean	Median	σ	Mean	Median	σ	Means	Medians
7-Factor α (%)	0.46	0.44	0.69	0.48	0.41	0.80	-0.01	0.03
HF Bench α (%)	-0.07	0.00	0.72	-0.03	-0.02	0.80	-0.04	0.01
4-Factor α (%)	0.36	0.35	0.63	0.34	0.30	0.79	0.01	0.05
Return (%)	0.64	0.78	3.34	0.64	0.70	4.49	0.00	0.08*
AUM ($mm)	670	365	717	164	43	353	506***	322***
Fund Age (years)	6.7	5.6	4.5	4.5	3.2	4.4	2.3***	2.3***
Management Fee (%)	1.51	1.50	0.45	1.51	1.50	0.59	-0.004	0.00**
Incentive Fee (%)	19.8	20	2.3	17.8	20	6.1	1.9***	0.0***
Highwater Mark (%)	0.95	1.00	0.23	0.84	1.00	0.37	0.11***	0.00***
Lock-Up (days)	196	30	214	105	30	184	91***	0***
Minimum Investment ($mm)	2.27	1.00	5.13	0.93	0.5	2.69	1.34***	0.50***
Redemption Notice (days)	53	45	31	35	30	31	18***	15***
Redemption Frequency (days)	108	90	100	57	30	64	51***	60***
Big Four (%)	0.70	1.00	0.46	0.65	1.00	0.48	0.05***	0.00***

*** p<0.01, ** p<0.05, * p<0.1

Table A.2 (continued)

Panel C: Calendar Time Portfolio Comparison Between Samples

	4-Factor	7-Factor	Obs
sample database fund α	0.0039***	0.0035***	67
	(3.06)	(2.35)	
database universe α	0.0042***	0.0046***	67
	(2.78)	(2.42)	
long/short portfolio α	−0.0003	−0.0011	67
	(-0.36)	(-1.23)	

*** p<0.01, ** p<0.05, * p<0.1

Table B.1: Descriptives Where Cost Additions Are Allowed

Table B.1 gives descriptives for the quarterly hedge fund returns used in this study. In this table, we report returns calculated from a sample where the *cost* field either stays the same or has a positive change from quarter-to-quarter, i.e. capital may have been added to the underlying fund by the FoF. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database Returns* describes all fund-quarter returns that are also found in the union of hedge fund databases. *Database Returns of Funds that Leave* are fund-quarter returns that are also found in a database, but only includes those funds that subsequently leave the databases. *Dead Returns* are returns that appear after a fund last reports to the databases. Quarterly underlying fund returns are calculated using the *value* and *cost* fields from hand-collected FoF SEC filings (see Equation 1). The *value* of FoF's investments used to calculate returns are net of all fees. Different FoFs may hold the same underlying hedge fund, so multiple reported returns for the same hedge fund are possible in a given quarter. We report the median return across all FoFs that report a given hedge fund in a quarter. Returns have been trimmed at the 0.5% and 99.5% levels. We test for differences in means using a two-sample t-test with unequal variances and for differences in medians using a Wilcoxon rank-sum test.

	N	Mean	σ	Median	5th	95th
All Returns	11,574	1.21%	8.51%	1.98%	−13.46%	12.66%
Database Returns	5,687	1.81	7.53	2.11	−10.65	12.63
Non-Database Returns	5,887	0.63	9.32	1.81	−16.32	12.68
	Differences	1.18***		0.30***		
Database Returns of Funds that Leave	945	1.81	7.78	2.31	−12.39	12.33
Dead Returns	1,208	-0.01	10.70	1.62	−22.44	13.40
	Differences	1.84***		0.69***		

Table B.2: Pooled OLS Results Using Only Long/Short Equity Funds

Table B.2 describes the results from a pooled OLS regression of quarterly long/short equity hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field either stays the same or has a positive change from quarter-to-quarter, i.e. capital may have been added from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0046**	0.0046**	0.0044**
	(2.23)	(2.23)	(2.14)
α	0.0036**	0.0031	−0.0055***
	(2.35)	(1.63)	(-3.53)
Obs.	4,815	4,815	4,815
Adj. R^2	0.26	0.23	0.29

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0047**	0.0098***	0.0045*
	(2.18)	(2.90)	(1.92)
α	0.0037**	0.0011	−0.0055***
	(2.36)	(0.51)	(-3.84)
Obs.	4,815	4,815	4,815
Adj. R^2	0.26	0.24	0.29

*** p<0.01, ** p<0.05, * p<0.1

Table B.3: Pooled OLS Results With Cost Additions Allowed Returns

Table B.3 describes the results from a pooled OLS regression of quarterly hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field either stays the same or has a positive change from quarter-to-quarter, i.e. capital may have been added from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0092***	0.0095***	0.0097***
	(5.85)	(6.06)	(6.08)
α	−0.0001	−0.0003	−0.0022*
	(-0.08)	(-0.19)	(-1.69)
Obs.	11,574	11,574	11,574
Adj. R^2	0.19	0.19	0.20

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0093***	0.0148***	0.0103***
	(5.62)	(6.57)	(5.84)
α	0.0000	−0.0024	−0.0024*
	(0.02)	(-1.48)	(-1.81)
Obs.	11,574	11,574	11,574
Adj. R^2	0.20	0.20	0.21

*** p<0.01, ** p<0.05, * p<0.1

Table B.4: Pooled OLS Results With No Return Trimming

Table B.4 describes the results from a pooled OLS regression of quarterly hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. capital is not added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter and are net of the risk-free rate. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0095***	0.0096***	0.0098***
	(4.76)	(4.84)	(4.90)
α	−0.0009	−0.0015	−0.0021
	(-0.53)	(-0.74)	(-1.21)
Obs.	10,229	10,229	10,229
$Adj.R^2$	0.17	0.17	0.17

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0096***	0.0150***	0.0095***
	(4.80)	(4.94)	(4.23)
α	−0.0007	−0.0034	−0.0019
	(-0.40)	(-1.51)	(-1.08)
Obs.	10,229	10,229	10,229
Adj. R^2	0.17	0.17	0.17

*** p<0.01, ** p<0.05, * p<0.1

Table B.5: Pooled OLS Results Using Mean Returns

Table B.5 describes the results from a pooled OLS regression of quarterly hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. capital is not added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the mean return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0086***	0.0088***	0.0088***
	(5.70)	(5.80)	(5.78)
α	−0.0003	0.0004	−0.0018
	(-0.22)	(0.29)	(-1.43)
Obs.	10,126	10,126	10,126
Adj. R^2	0.21	0.21	0.21

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0089***	0.0136***	0.0089***
	(5.71)	(6.17)	(5.25)
α	−0.0002	−0.0015	−0.0018
	(-0.17)	(-0.95)	(-1.38)
Obs.	10,126	10,126	10,126
Adj. R^2	0.21	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table B.6: Pooled OLS Results - Only Hedge Funds Held by Two or More Fund-of-Funds

Table B.6 describes the results from a pooled OLS regression of quarterly hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. Furthermore, a hedge fund had to be held by two or more FoFs in order to be included in the sample. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0049**	0.0044*	0.0045*
	(2.02)	(1.81)	(1.79)
α	−0.0000	0.0002	−0.0027
	(-0.01)	(0.11)	(-1.29)
Obs.	3,669	3,669	3,669
Adj. R^2	0.21	0.21	0.24

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0048*	0.0063*	0.0051*
	(1.96)	(1.94)	(1.83)
α	0.0000	−0.0006	−0.0029
	(0.02)	(-0.26)	(-1.35)
Obs.	3,669	3,669	3,669
Adj. R^2	0.21	0.22	0.24

*** p<0.01, ** p<0.05, * p<0.1

Table B.7: Pooled OLS Results With Backfill Correction

Table B.7 describes the results from a pooled OLS regression of quarterly hedge fund returns on the *database* indicator included in three different factor models: the Carhart (1997) 4-factor model, the Fung and Hsieh (2004) 7-factor model, and a modified version of the Jagannathan, Malakhov, and Novikov (2010) hedge fund style benchmark model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. The regression specifications in Panel B include interaction terms between the *database* indicator and the appropriate factor returns. We suppress the individual factor loadings and interaction terms. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. capital is not added to or subtracted from the underlying fund by the FoF. Hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Returns defined as *backfilled* are treated as missing from the database. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

Panel A: Factor Model Regressions

	4-Factor	7-Factor	HF Bench
database	0.0082***	0.0083***	0.0084***
	(5.45)	(5.58)	(5.53)
α	0.0001	0.0008	-0.0014
	(0.07)	(0.55)	(-1.14)
Obs.	10,126	10,126	10,126
$Adj.R^2$	0.21	0.21	0.22

Panel B: Include Interactions Between *Database* Indicator and Factor Returns

	4-Factor	7-Factor	HF Bench
database	0.0085***	0.0132***	0.0085***
	(5.48)	(6.03)	(5.06)
α	0.0001	-0.0012	-0.0014
	(0.11)	(-0.76)	(-1.13)
Obs.	10,126	10,126	10,126
$Adj.R^2$	0.22	0.22	0.22

*** p<0.01, ** p<0.05, * p<0.1

Table B.8: Calendar-Time Portfolios

Table B.8 presents the results from a calendar-time regression of quarterly hedge fund returns for both database and non-database funds using two different factor models: the Carhart (1997) 4-factor model and the Fung and Hsieh (2004) 7-factor model. Only returns calculated from the underlying holdings of Funds-of-Funds (FoF) collected from SEC filings are used. *Database* is an indicator that equals one if a fund-quarter return from the hand-collected sample matches to a fund-quarter return in the union of hedge fund databases. *Non-Database* indicates that a fund-quarter return from the hand-collected sample does not match to the union of databases. We omit non-calendar quarters from this analysis as they represent only 5% of our quarterly returns and result in calendar-time portfolios with few observations. Finally, we present the results of a long/short portfolio that is long *database* funds and short *non-database* funds. Returns are calculated from a sample where the *cost* field is not allowed to change from quarter-to-quarter, i.e. no capital was added to or subtracted from the underlying fund by the FoF. Prior to constructing the portfolios, our hedge fund returns are defined as the median return across all FoF advisors who report that underlying fund in that quarter, are net of the risk-free rate, and have been trimmed at the 0.5% and 99.5% levels. Standard errors are robust to heteroskedasticity and are clustered at the hedge fund level. We report t-statistics in parentheses.

	4-Factor	7-Factor	Obs
database α	0.0097***	0.0123**	22
	(2.38)	(2.43)	
non-database α	0.0012	−0.0010	22
	(0.25)	(-0.20)	
long/short portfolio α	0.0084***	0.0133***	22
	(3.30)	(4.29)	

*** p<0.01, ** p<0.05, * p<0.1