Hedge Fund Performance: Are Stylized Facts Sensitive to Which Database One Uses?

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ABSTRACT

This paper proposes a novel database merging approach and re-examines the fundamental questions regarding hedge fund performance. Before drawing conclusions about fund performance, we form an aggregate database by exploiting all available information across and within seven commercial databases so that the widest possible data coverage is obtained and the effect of data biases is mitigated. Average performance is significantly lower but more persistent when these conclusions are inferred from the aggregate database than from some of the individual commercial databases. Although hedge funds deliver performance persistence, the average fund does not deliver significant risk-adjusted net-of-fee returns while the gross-of-fee returns remain significantly positive. Consistent with previous literature, we find a significant association between fund characteristics related to share restrictions as well as compensation structure and risk-adjusted returns.

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The decisions of investors and regulators in the multi-trillion-dollar hedge fund industry are informed by research that employs commercial hedge fund databases.[1] Investors are keen to understand whether hedge funds add value and whether performance persists. Regulators debate alternative investment fund rules whose soundness depends on whether liquidity and managerial incentives are actually related to fund performance.[2]

In this paper we examine hedge fund performance from 1994 to 2016 using five commonly used (BarclayHedge, EurekaHedge, Hedge Fund Research (HFR), Lipper TASS, and Morningstar) and two previously unused (eVestment and Preqin) commercial databases. Our focus is on the research questions that are of fundamental interest to investors, researchers, and regulators: is the average hedge fund generating alpha after fees; is there persistence in hedge fund returns; and which of the fund characteristics explain the future alphas of hedge funds? Although these questions have already been examined in previous hedge fund literature, it is important to address the robustness of those results using a wider cross-section of hedge funds and a longer sample period than has previously been used. As we later show, relatively few of the previous papers use a database combining multiple commercial vendor's data, and even if an aggregate database is used, the period studied is relatively short—ending most often before the financial crisis started.

To investigate whether the choice of commercial hedge fund database affects the conclusions drawn about hedge fund performance, we create an "aggregate database" by consolidating the seven aforementioned databases. The aggregate database allows us to exploit all available information across and within the individual commercial databases so that we obtain the widest possible data coverage,

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[1] The hedge fund industry has evolved in response to the U.S. Dodd-Frank Act and the EU AIFMD (both passed in 2010): assets under management grew to more than $5 trillion in end of 2016. During this period leading academic journals have featured an increasing number of papers on hedge funds.

[2] For example: Ellen Kelleher, "Managers look on as bonus cap begins," *Financial Times*, 10 March 2013; Steve Johnson, "Regulator puts REITs into turmoil," *Financial Times*, 21 April 2013.

while at the same time mitigating the effect of data biases. In contrast to the extant hedge fund literature, to eliminate duplicate share classes we do not simply select a "representative" share class, such as the one with the longest return series and the largest assets. Instead, as in mutual fund literature, we aggregate the fund-level information across all duplicates. We create a "master" share class by utilizing information across databases and different share classes (e.g., onshore, offshore, and currency classes). We demonstrate the increase in data coverage by showing that many incomplete fund data in individual databases can be augmented using the aggregate data. Our results reveal that three high-quality individual databases stand out, namely BarclayHedge, HFR, and Lipper TASS. To draw a reliable comparison between the databases, we compare databases after removing all backfilled data from each database. Therefore, in our between-database comparisons, we concentrate on these three high-quality individual databases, their aggregate, and our seven-database aggregate.

We start by examining the average performance differences between individual databases and the aggregate database. We find that the average return in individual databases is significantly higher than in the aggregate database, by 0.58% to 1.25% per year. In addition, the average return is monotonically increasing in the number of databases a fund reports to. These findings suggest that databases differ in their coverage of under-performing funds. Therefore, using any single database results in a positive selection bias, which is alleviated with database aggregation.

Having documented the benefits of database aggregation in terms of increased coverage and decreased biases, we next examine three aforementioned fundamental questions about hedge fund performance. To ensure that our results are not sensitive to the benchmark model selection, throughout the analysis we adjust for risk using two benchmarks: the Fung and Hsieh (2004) seven-factor model and the global Carhart (1997) model augmented with a time-series momentum factor (Moskowitz, Ooi, and

Pedersen 2012) as well as the Pastor-Stambaugh (2003) liquidity risk factor and betting-against-beta factor (Frazzini and Pedersen 2014).[3]

First, we examine average risk-adjusted performance. An evaluation of the aggregate database reveals that, on average, hedge funds do not deliver superior net-of-fees risk-adjusted performance over the sample period from 1995 to 2016. For the consolidated aggregate *equal*-weighted (EW) portfolio, we estimate an annualized average excess return of 3.68% per year (t = 2.51). However, after adjusting for risk either using the Fung-Hsieh or global benchmarks, the risk-adjusted returns are indistinguishable from zero, suggesting that a typical hedge fund does not deliver abnormal performance.

We next focus on the *value*-weighted (VW) average returns of the aggregate database. VW measures are disproportionately influenced by larger funds; therefore, the quality and coverage of assets under management (AUM) information provided by commercial databases is critical for obtaining accurate estimates about the average performance of the hedge fund industry as a whole. Larger institutional investors typically focus on value-weighted measures because they are not driven by small hedge funds that may not be investable. Our results reveal that the VW index of the aggregate database generates a mean excess return of 4.37% p.a. (t = 3.25), but again the alphas are indistinguishable from zero.

Having established that in net-of-fees terms a typical fund and the industry as a whole does not deliver abnormal performance, we next examine the gross-of-fees average performance. We find that the average alpha remains consistently positive and significant, and ranges from 3.11% to 4.50% per year. Hence, hedge funds produce positive alpha before but not after fees, suggesting that fund managers extract all the economic rents. Our conclusions are not sensitive to the choice of period, benchmark, or weighting scheme.

[3] In our robustness tests, we add the emerging market factor to the Fung-Hsieh (2004) seven factors. Our conclusions remain unchanged.

We next focus on the second fundamental question, namely performance persistence. Using quintile portfolios sorts on past performance, we find that the aggregate database delivers top portfolio alpha similar to that of individual research-quality databases (TASS, HFR, BarclayHedge). However, in terms of the portfolio of the worst performing funds, the aggregate database consistently delivers lower alpha than any individual database, consistent with the idea that the aggregate database contains the widest coverage of poor performing funds. Importantly, the *t*-statistics of the top–bottom alpha spread are consistently highest for the aggregate database. These findings reflect the wider coverage of funds—especially under-performing ones—in the aggregate database, which adds statistical power to persistence tests. However, when we measure performance persistence in terms of VW alphas the persistence almost vanishes, suggesting that performance persistence is driven by small funds as shown by Joenväärä, Kosowski, and Tolonen (2019).

We finally address the third fundamental question related to fund performance. Using both portfolio sorts and multivariate regressions, we examine which of the fund characteristics are important determinants of fund performance. Consistent with Aragon (2007) and Agarwal, Daniel, and Naik (2009), we find that tighter share restrictions are associated with greater risk-adjusted returns. Among the share restrictions, the notice period seems to be the most robust variable in determining risk-adjusted returns. Our evidence also reveals that the compensation variables are positively associated with risk-adjusted returns. The relationship is quite robust for both incentive fees and high-water mark provision. Our multivariate regressions also suggest that variables related to diseconomies of scale are important determinants of risk-adjusted returns. The coefficients on fund size, fund age, and capital flows are always negative and most often significant. This suggests that diseconomies of scale play an important role in the hedge fund industry.

Our paper is related to three streams of hedge fund literature. First, it is related to studies that show that database selection affects the conclusions of investment fund performance. Elton, Gruber, and

Blake (2001) find systematic differences in returns between the popular Morningstar and CRSP mutual fund databases that can alter conclusions regarding investment strategies which incorporate individual mutual funds or a group of such funds. Harris, Jenkinson, and Kaplan (2014) find that the venture capital funds in the Burgiss database outperform those funds in the Thomson Venture Economics. Although several hedge fund studies build and use a large consolidated database, recognize the role played by strategic advertising (Jorion and Schwarz 2014a), and compare the coverage of fund characteristics across commercial databases (Liang 2000), we are not aware of any study that rigorously examines the effect of database selection on conclusions about hedge fund performance and its persistence.

Second, we add to the existing literature by updating the stylized facts on average hedge fund performance (e.g., Brown, Goetzmann, and Ibbotson 1999 and Kosowski, Naik, and Teo 2007) and performance persistence (e.g., Brown, Goetzmann, and Ibbotson 1999; Liang 1999; Agarwal and Naik 2000; Baquero, ter Horst, and Verbeek 2005; and Jagannathan, Malakhov, and Novikov 2010). We confirm that there is short-term performance persistence but hedge funds are not able to deliver positive risk-adjusted net-of-fees returns, on average, even though the gross-of-fees risk-adjusted returns are significantly positive. Regarding fund characteristics and fund performance, our findings confirm that tighter share restrictions (Aragon 2007) and greater compensation structure variables (Agarwal, Daniel, and Naik 2009) are associated with higher risk-adjusted returns.

Third, this paper relates to the literature examining hedge fund data biases, misreporting, and strategic reporting behavior. Due to the voluntary nature of reporting, it is well known that hedge fund databases are associated with many data biases (e.g., Fung and Hsieh 2000, 2009; Liang 2000; and Getmansky, Lo, and Makarov 2004), while more recent studies (e.g., Bollen and Pool 2008, 2009; Patton, Ramadorai, and Streatfield 2015; and Aragon and Nanda 2017) show that hedge funds misreport, revisit, and strategically delay their returns when reporting to commercial databases. We add to this literature by showing that a database selection bias may arise when a study relies only on one of the hedge fund databases to draw conclusions about hedge fund performance. We emphasize that the focus of our paper is not to back-test previously published papers. We stress this point because our results may also be due to different download dates and to ongoing revisions in databases, an issue documented by Patton, Ramadorai, and Streatfield (2015).

Although we recommend that researchers should use an aggregate database consisting of all seven commercial databases, we find that our empirical results remain consistent when we use only three (BarclayHedge, HFR, and Lipper TASS) research-quality databases. Among the newer databases (EurekaHedge, eVestment, and Preqin), EurekaHedge is very comprehensive with respect to fund coverage and quality of return, AUM, and fund characteristics variables, but the respective quality of eVestment and Preqin is quite poor. The frequently used Lipper TASS and Morningstar databases could be described as high-quality databases in the past, but recently they have deteriorated in quality. Lipper TASS has one of the poorest fund coverages towards the end of our sample ends, whereas Morningstar has an increased pattern of missing AUM observations, for example. The only minor problem with BarclayHedge is that during the early periods, they did not gather share restriction variables consistently. If a researcher is interested in a single database for research purposes, then on balance our recommendation is to use the HFR database. It is survivorship bias-free from 1994 onwards, and exhibits a consistently high coverage of return, AUM, and fund characteristics information.

The rest of this paper is structured as follows: Section 1 describes the evolution of the databases' organizational structures; Section 2 describes the procedure used to merge individual databases; Section 3 examines average hedge fund performance; Section 4 focuses on performance persistence; and Section 5 concludes.

1. Institutional Development of Hedge Fund Databases

This paper addresses the effect of hedge fund database selection on conclusions drawn about performance and its persistence. Database selection bias is a type of sample selection bias which is known to have several drivers. It goes without saying that every existing database is incomplete, and most hedge fund databases require their constituent funds to meet some specific criteria (e.g., minimum asset base, audited track record, minimum number of years since inception). Database selection bias can lead to inter-database differences in other biases, including self-selection bias, survivorship bias, backfill bias, and illiquidity bias. Given that hedge funds report voluntarily to commercial databases, they may have strategic motives as Jorion and Schwarz (2014a) document. Hence, we would expect that poorly performing funds are reporting only to one or very few databases, while the best performing funds' track records are listed in several databases.

In order to appreciate the effect of database differences on hedge fund performance, it is helpful to understand how different databases evolved over time, how data vendors differ in terms of organizational structure, and how these factors can induce specific biases. Most hedge fund databases started within small independent data vendors that, over the years, were subsumed by larger organizations as part of a merger and acquisition process that in itself can cause survivorship bias (Aggarwal and Jorion 2010a). Moreover, it is plausible that the amount of resources allocated to maintaining databases depends on the size of the database company. A company's wider business interests may also affect the focus of —and incentives related to—the data gathering process.

One of the most commonly used databases in academic research is the Lipper TASS database. The London-based Trading Advisor Selection System (TASS) was founded in 1990. In March 2005, Lipper (now a subsidiary of the global giant Thomson Reuters) acquired TASS Research and the TASS database from Tremont Capital, which had purchased TASS in 1999. Aggarwal and Jorion (2010a) report that, pursuant to Tremont's purchase of TASS, the acquiring firm decided that its own hedge fund managers should contribute to the newly acquired database; in other words, the Tremont database was not absorbed directly into the TASS database. Hence a large number of Tremont funds were added to the TASS database between 1 April 1999 and 30 November 2001, a process that (according to Aggarwal and Jorion) induced a spurious survivorship bias. In an earlier paper, Fung and Hsieh (2009) had pointed out another bias stemming from this database merger. Because the field "date added to the database" refers to the date of entry into the TASS database and not the Tremont database, data before that date are not necessarily backfill-biased and so discarding such information unnecessarily reduces sample sizes.

Both the HFR and BarclayHedge are databases maintained by companies that are not part of a major financial organization. The HFR database is a production of Hedge Fund Research, Inc., which is part of the Chicago-based HFR Group LLC founded in 1993. Unlike some of the other databases, HFR excluded managed futures programs from earlier vintages of its database (Fung and Hsieh 2002).

BarclayHedge is a database widely used by practitioners; however, it is used relatively less often in academic research even though it features comprehensive coverage of the hedge fund sector, including Commodity Trading Advisors (CTAs). We group hedge funds into the nine broad investment strategies listed in SEC Form PF and show the numbers of hedge funds and their proportions in each strategy in Panel B of Table A2. We find that BarclayHedge has by far the largest CTA coverage at 2,944 funds (compared to between 650 and 1,449 funds in other databases). BarclayHedge was formerly known as The Barclay Group, which was founded in 1985; it is not related to Barclays Bank.

Morningstar's hedge fund database is the result of several mergers. In 2010, Morningstar took over the Center for International Securities and Derivatives Markets (CISDM) database, which was originally called the MAR database and focused on CTAs. Morningstar also bought the Altvest database in 2006, and in 2008 it took over the MSCI/Barra hedge fund database. In addition, Morningstar has gathered separate hedge fund data from the quarterly SEC holdings reports of funds of (hedge) funds (FOF) as in Aiken, Clifford, and Ellis (2013). Because the FOF holdings are not voluntarily reported, they may alleviate potential selection bias issues. However, Morningstar has not updated their holdings-based data, suggesting that their clients have not found it very useful. Recently, Morningstar has started to distribute other hedge fund vendors' (Hedge Fund Research and eVestment) data via their Direct platform. Although it was traditionally a provider of mutual fund data, these acquisitions have resulted in Morningstar becoming an important hedge fund data provider and distributor.

EurekaHedge, launched in 2001, is a relatively recent addition to the choice of hedge fund databases. In March 2011, Mizuho Corporate Bank Ltd., a subsidiary of the Japan-based Mizuho Financial Group, Inc., acquired a 95% stake in EurekaHedge. Their data has relatively high coverage of European and Asian funds. Hence, we would expect that EurekaHedge complements other databases that are domiciled in the U.S. or U.K.

We also use two newly formed databases, eVestment and Preqin, that are not frequently used by academics but are popular among practitioners. The eVestment database is a product of several mergers. In September 2011, eVestment acquired Channel Capital Group that owned HedgeFund.net[4], a hedge fund data provider since 1997. In November 2012, eVestment acquired PerTrac (a hedge fund analysis software provider) and Fundspire (a cloud-based technology that is used to analyze hedge funds). Although we used to have access to the PerTrac analytical platform, in this paper we only use the eVestment hedge fund database and do not use their other services. Although the PerTrac platform could be used to merge commercial databases, we opt to merge the databases by ourselves, because that allows us to transparently document each step and examine the impact of different merging assumptions on fundamental questions about hedge fund performance.

Preqin, owned by its directors and employees, has provided alternative investment data and solutions since 2003. Preqin's private equity data is heavily used by both academics and practitioners.

[4] We find that HedgeFund.net is only used in one published paper (Brav et al. 2008) in our 116-paper literature survey.

Since 2007 Preqin has also provided hedge fund data services, but academics have not often used their database for research purposes.[5] Like other commercial databases, both Preqin and eVestment obtain their data from hedge fund managers that report voluntarily to data vendors. Hence, these two databases are associated with a similar kind of selection bias to the other commercial databases. However, both of these databases claim to work closely with large institutional investors. It is plausible that large hedge funds voluntarily report to these databases in the hope that this helps them raise capital from large institutional investors. Finally, it is logical to suppose that the more recently established databases have less complete coverage of defunct funds, and indeed this is confirmed by our database analysis. Both eVestment and Preqin advertise that they provide a master-feeder structure for the funds belonging to their databases. This would be helpful because our aim is to aggregate hedge fund data in a way similar to how this has been done in the mutual fund literature. Indeed, a typical hedge fund database contains an identifier for a hedge fund management firm and all its share classes, but there is no identifier defining to which "fund" or "product" each of the share classes belong. Our principal aim is to aggregate our data so that all these three levels—firm, fund, and share class—are well defined.

To investigate how hedge fund researchers use different commercial databases, we examined 116 papers published in five frequently cited finance journals.[6] The most widely used database was TASS, used by the authors of 92 papers (about 79% of those we reviewed). HFR and Morningstar were also quite popular and were used in 46 (40%) and 44 (38%) papers respectively. Only a few authors constructed a comprehensive database containing information from several major data vendors. A total of 24 (21%) papers have used at least three of the databases, while none of the papers use the same combination of the seven databases that we use; indeed, the present maximum is five databases, used in

[5] In their study Agarwal, Nanda, and Ray (2013) have used the hedge fund investor type information provided by Preqin.

[6] Namely: *Journal of Finance*, *Journal of Financial Economics*, *Review of Financial Studies*, *Journal of Financial and Quantitative Analysis*, and *Financial Analysts Journal*. See the Appendix (Table A1) for the list of the papers as of May 2018.

4 (3%) papers. Although hedge fund researchers recognize that strategic advertising considerations influence which database a hedge fund chooses to report to (e.g., Jorion and Schwarz 2014a), we are not aware of any study that rigorously examines the effect of database selection on research findings.

2. Data

A. Data Construction Process

We gather net-of-fees returns as well as assets under management (AUM) and accompanying information from a combination of seven commercial databases: Lipper TASS, Hedge Fund Research (HFR), BarclayHedge, EurekaHedge, Morningstar, Preqin, and eVestment. In total, these databases consist of more than 110,000 share classes. This number does not constitute a true count of unique hedge funds because much of the information is duplicated: the same fund is covered by multiple database vendors and each database contains multiple share classes for the same fund investment program. In these situations, we identify duplicate share classes manually, and use correlation-based algorithms to refine the manual matches. We merge the characteristics and time series of the duplicate share classes to produce the most comprehensive per-fund coverage. We convert monthly returns and AUMs into U.S. dollars using end-of-month spot rates downloaded from Thomson Reuters Datastream. We document the details of the merging approach in the Data Appendix.

In contrast to the extant hedge fund literature, to eliminate duplicate share classes we do not simply select a "representative" share class, such as the one with longest return series. Instead, as in the mutual fund literature, we utilize and aggregate the fund return, AUM, and characteristics information across all duplicates. This results in a "master" share class with comprehensive per-fund coverage gathered across databases and different share classes (e.g., onshore, offshore, and currency classes). To demonstrate the increase in data coverage, we show that a lot of incomplete fund data in individual databases can be augmented using the aggregate data.

In the hedge fund literature there exist two methods that are extensively used to correct for backfill bias: (1) an *ad-hoc* cut-off method (e.g., Kosowski, Naik, and Teo 2007 and Joenväärä, Kosowski, and Tolonen 2019), where a fixed amount of months (typically 12, 24, or 36) of initial fund returns are removed; and (2) the listing date method (e.g., Jagannathan, Malakhov, and Novikov 2010 and Bhardwaj, Gorton, and Rouwenhorst 2014), where all returns before the listing date (that is, the day the fund was added to the database) are removed. The listing date method is generally superior, because no cut-off threshold can handle the highly skewed distribution of backfill periods. Furthermore, using a too large cut-off threshold will disregard too much non-biased data. The drawback of the listing date method is that the listing date variable is included only in the TASS, HFR, EurekaHedge, and eVestment databases. However, a recent algorithm by Jorion and Schwarz (2017) allows the imputation of listing dates for other databases as well.

To address backfill bias, we use the listing date method. We utilize all available database-level information on a fund's listing dates to produce a fund-level listing date, and remove all return observations prior to that date as backfilled. If available, we select the earliest reported listing date from TASS, HFR, EurekaHedge, and eVestment as the fund-level listing date. Otherwise, we use the algorithm of Jorion and Schwarz (2017) to impute the listing dates for the share class duplicates, and again select the earliest date. This imputation algorithm cannot be run for Morningstar because Morningstar Direct downloads do not provide numeric fund identifiers (which the algorithm assumes to be correlated with the listing date). Therefore, all funds unique to Morningstar are removed in our backfill bias-free sample. Intuitively, our fund-level listing date reflects the date that a fund first chose to disclose its returns.

B. Fund Coverage

Prior to backfill correction, our consolidated aggregate database consists of 12,308 unique management firms and 26,432 unique hedge funds obtained from the union of seven databases, excluding funds of funds. This database tracks returns and AUM data for the period from January 1974 through February

2017. However, we focus on the January 1994 through December 2016 period because few data vendors kept records of defunct funds prior to 1994 (e.g., Ackermann, McEnally, and Ravenscraft 1999; Brown, Goetzmann, and Ibbotson 1999; Fung and Hsieh 2000, 2009; and Liang 2000), and because the early 2017 returns may be subject to reporting lags, including strategic delays (Aragon and Nanda 2017).

[[INSERT TABLE 1 ABOUT HERE]]

Table 1 illustrates the limited overlap among the commercial databases, and thus the importance of database aggregation. The Venn diagram in Panel A shows that 12,774—that is, nearly half (48.3%)—of the funds are covered by only one database (minimum 1,034 in Preqin to maximum 2,776 in BarclayHedge). Panels B and C show the number and fraction of funds in all possible 2^7=128 database aggregations. From Panel C, we can deduce the optimal order of adding individual databases to produce N-database aggregates with most coverage (N=1,...7), which is BarclayHedge (44.74%), HFR (62.56%), eVestment (74.04%), TASS (82.07%), EurekaHedge (89.26%), Morningstar (96.06%), and Preqin (100.0%). This order gives a first-order approximation of the relative importance of each database, although the quality of each database must still be studied more carefully.

[[INSERT TABLE 2 ABOUT HERE]]

The annual reporting and attrition rates of each database in Table 2 show two important findings. Most notably, except for TASS, HFR, and BarclayHedge, all databases contain suspiciously low (including zero) attrition rates for the early sample, which indicates survivorship bias. The attrition rates normalize (to levels in other databases) in 2000 for eVestment, 2004 for EurekaHedge, 2006 for Morningstar, and 2013 for Preqin. Before these years, the low yet positive attrition rates most likely reflect database return revisions documented by Patton, Ramadorai, and Streatfield (2015). The other interesting finding in Table 2 is that while all databases increase in coverage until 2008 (reaching 3,650 to 5,068 funds with the exception of still-survivorship-biased Preqin), three databases (TASS, Morningstar, eVestment) subsequently decrease in coverage until 2016, finishing at only 1,578 to 2,884 funds. The four remaining databases (HFR, BarclayHedge, EurekaHedge, Preqin) maintain good coverage until 2016 (3,476 to 3,864 funds). Such time-varying database coverage again highlights the importance of database aggregation.

Finally, although we can mitigate the impact of backfill bias and survivorship bias on our empirical results, we would like to note that our data is likely to suffer from a "graveyard bias" documented by Bhardwaj, Gorton, and Rouwenhorst (2014). Using CTA funds obtained from Lipper TASS, they show that CTA funds are often dropped from the graveyard file and those removed CTA funds tend to have even worse performance than the average dead fund has. Unfortunately, we do not have access to vintage year data, which is required for correcting the graveyard bias.

C. AUM Coverage

Figure 1 studies the assets under management (AUM) as contained in each of the individual databases and the seven-database aggregate (AGG7). We also consider a three-database aggregate (AGG3) consisting of TASS, HFR, and BarclayHedge. As seen before, these three databases alone do not suffer from post-1994 survivorship bias, and except for TASS they are still thriving as of 2016. In addition, these databases cover 71.88% of the funds in AGG7 (Panel C, Table 1).

[[INSERT FIGURE 1 ABOUT HERE]]

Panel A of Figure 1 plots the aggregate hedge fund industry AUM, which includes backfilled AUM for completeness. The general trends roughly reflect the reporting frequencies in Table 2. At the end of 2016, the largest individual database is BarclayHedge with about \$1.3T, whereas AGG3 has \$1.8T, and AGG7 has \$2.5T. Panel B shows what percentage of industry AUM is due to backfilled observations. For AGG7, the backfill percentage is < 40 % in 1996 to 2004, < 30% in 2005 to 2010, and then converges towards 0% until 2016. That is, as the industry AUM grew, the percentage of backfilled AUM decreased. Therefore, even after a conservative listing date-based backfill correction, our sample still covers the majority of database AUM. On one hand this is to be expected, because funds tend to be smaller during their backfilled incubation periods. More importantly, it ensures that our later value-weighted performance results are economically significant.

Panel C of Figure 1 shows what percentage of AUM observations are missing. There is wide discrepancy between databases, with three databases (pre-2005 EurekaHedge, pre-2014 Preqin, and pre-2014 eVestment) having > 50% missing AUM observations. There are also numerous hard-to-correct outliers in the AUM reporting of eVestment from November 2011 through June 2012, even for long-liquidated funds, which we correct by removing all eVestment AUMs in this period, resulting in a 100% missing AUM rate. Surprisingly, the coverage of AUM in the more complete hedge fund databases is comparable to that in mutual fund databases. Berk and van Binsbergen (2015) and Pastor, Stambaugh, and Taylor (2015) find that around 18% of mutual fund AUM data are missing in a commonly used mutual fund database, which is close to our AGG3 database (time-series average 16.8%), and not far off from our AGG7 database (25.2%). In other words, after careful aggregation, hedge fund data have similar rates of missing AUM as mutual fund data.

Panels D and E of Figure 1 plot the monthly cross-sectional mean and median of fund AUM. At the end of 2016, the mean in both AGG3 and AGG7 is around \$400M, and the median around \$50M. The median is more stable over time, suggesting an increasing skewness in fund size. The average fund in eVestment and Preqin, and especially the median fund in eVestment, are much larger compared to the rest of the databases. However, combined with Panel C, this suggests that these databases lack the AUM information for smaller funds, especially pre-2014 where the size differences are most pronounced. Importantly, the means and medians of AGG7 funds are still close to most individual databases and AGG3. Therefore, while the AUM coverages of Preqin and eVestment are biased towards large funds, they are unlikely to contain *unique* large funds, because their inclusion would also positively skew the distribution of AGG7 fund size.

D. *Return Coverage*

Figure 2 illustrates the fund life-cycle as it relates to voluntary database reporting. To correct for backfill bias, we remove the observed returns from the incubation period (i.e., prior to listing date). The post-delisting returns are unavailable by definition. In addition, the real-time reporting period between listing and delisting dates can suffer from missing returns, or "holes." However, our database aggregation effectively widens the real-time reporting period, and can also fill return holes.

[[INSERT FIGURE 2 ABOUT HERE]]

Table 3 shows how much bias-free return data can be augmented relative to individual databases. Exceptionally for this analysis, we correct backfill bias in each database by using only its own (imputed) listing dates; this provides the best measure of the value added by aggregating the listing dates as well. Panel A shows that our aggregation can augment at least one incubation return to 46.2% of funds (average across databases), with an average of 26.8 incubation return months added within these funds (i.e., 26.8 × 46.2% = 12.4 months across all funds). Similarly, Panel B shows that an average of 11.7 months of return holes can be augmented within 1.0% of funds (0.1 months across all funds). Panel C shows that an average of 15.6 months of delisting returns can be augmented within 25.1% of funds (3.9 months across all funds). As expected, the abnormal (above-index) augmented incubation return per fund (5.14% p.a.) is on average positive, and the augmented hole return per fund (−3.77% p.a.) and delisting return per fund (−11.00% p.a.) are on average negative. The returns are similar, although of smaller magnitude, when measured per month (that is, as portfolios).

[[INSERT TABLE 3 ABOUT HERE]]

Panels A, B, and C of Table 3 also show the same results for AGG3. As expected, the percentage of funds with augmentable returns is lower than for individual databases (18.32% vs. 46.2% for incubation returns; 0.3% vs. 1.0% for return holes; and 8.6% vs. 25.1% for delisting returns), yet remains sizable, suggesting an added benefit to aggregating more than three databases.

[[INSERT TABLE 4 ABOUT HERE]]

A natural question to ask at this point is what the fraction of *true* returns covered is (for funds that chose to report to a database). TASS, Eureka, and eVestment report both inception and liquidation dates of funds, from which we can calculate the true lifespan, incubation period, and liquidation period. We can then compare these periods against our bias-free return coverage, before and after aggregation. Table 4 shows that the average (across funds) true lifespan is between 66.01 and 76.97 months. The bias-free return coverage is between 38.36% and 60.37% before aggregation, and between 65.66% and 71.65% after aggregation. That is, our aggregation procedure can get us between 11.3 and 27.3 percentage points closer to the true lifespan coverage. Most of the remaining gap is due to missing incubation returns, not delisting returns.[7]

[[INSERT TABLE 5 ABOUT HERE]]

Finally, our aggregation can also detect and correct reporting errors in individual databases by using majority voting (e.g., a median of returns across databases). Table 5 shows that an average (first across funds, then across databases) of 1.8% of funds have returns with accidentally reversed signs, and this reduces to 0.5% in the AGG3 database. Similarly, 27.0% and 51.9% of funds have return differentials above 1% and 1bp, which reduce to 12.17% and 40.22% in the AGG3 database.

E. Characteristics Coverage

We next study the coverage of six fund characteristics: three characteristics related to fund liquidity (lockup, notice, and redemption periods), and three characteristics related to managerial compensation (management fee, incentive fee, and use of high-water mark). To aggregate characteristics at the fund level, we use the median value across database duplicates for continuous variables (lockup, notice, and

[7] Upon listing to a database, the fund generally backfills its whole return history until inception. Therefore, allowing for backfill-biased returns would trivially bring us close to 100% coverage (minus a small gap due to missing delisting returns), with bias resulting from omitted funds that never choose to report. For this reason, we concentrate on bias-free return coverage.

redemption periods; management and incentive fees), and most common value across database duplicates for categorical variables (high-water mark dummy).

[[INSERT TABLE 6 ABOUT HERE]]

Panel A of Table 6 shows the characteristics coverage in all seven individual databases plus AGG3, and how much the coverage can be improved by augmenting missing data from the other databases. Averaging over all six characteristics and seven individual databases, the average pre-augmentation coverage is 82.7%, which increases to 93.5% post-augmentation, for an improvement of 10.8%. However, there is wide discrepancy across databases: in Morningstar, Preqin, and eVestment, the average improvements are 11.0%, 25.1%, and 33.1%, whereas in the remaining four databases the average improvement is merely 1.6%. As expected, the improvement is even lower in the AGG3 database; 0.6%, or from 95.3% to 95.9%, because it already aggregates the characteristics of three high-quality databases (TASS, HFR, BarclayHedge).

Panel B of Table 6 shows the mean and median of (pre-augmented) characteristics in all databases including AGG7, and the percentage of missing data. Most of the characteristic distributions are similar between well-covered databases, and especially between AGG3 and AGG7. The only exception is average redemption period, which is somewhat lower in AGG7 compared to AGG3 (1.66 vs. 1.81). However, as expected, the average missing rate is higher in AGG7 (12.6% vs. 4.7%), because it adds the individual databases with least characteristic coverage (Morningstar, Preqin, eVestment).

Finally, while the requirement of non-missing characteristics will obviously reduce the number of funds used, it may also introduce subtle survivorship bias if the data vendor has started collecting the characteristics at different times. To understand whether this is the case, in Panel C of Table 6, for each database-characteristic pair we restrict the sample to funds with a non-missing characteristic, and calculate the first year that the attrition rate normalizes (to levels in other databases). For most database-characteristic pairs, these initial regular attrition years follow Table 2: 1995 for TASS, HFR, and

BarclayHedge; 2004 for EurekaHedge; 2006 for Morningstar; 2013 for Preqin; and 2000 for eVestment. A notable exception is that in the otherwise high-quality BarclayHedge, the initial regular attrition year for the lockup and redemption period characteristics is 2000—that is, requiring these characteristics will introduce survivorship bias for the pre-2000 period. In the eVestment database, the initial regular attrition year for notice period is 2013, introducing a massive survivorship bias. Of course, our listing date-based backfill correction trivially fixes such survivorship biases, but at the cost of a shortened bias-free return period. However, as seen in Panel A, the coverage of these three characteristics within their respective databases can be greatly improved via database aggregation from between 22.5% and 83.5% to between 83.6% and 90.7%, thus preserving fund coverage during the survivorship-bias-corrected periods.

3. Average Performance of Hedge Fund Databases

In this section we first investigate performance differences between individual and aggregate databases, and then we study the risk-adjusted performance of the aggregate database in detail. To draw reliable comparisons between the databases, we compare databases after removing all potentially contaminated data from each database. Hence, we only look at bias-free returns before making a comparison.

A. Average Performance Between Databases

In our between-database comparisons, we concentrate on the three research-quality individual databases TASS, HFR, and BarclayHedge; their aggregate (AGG3); and our seven-database aggregate (AGG7). Panel A of Table 7 shows the year-by-year EW returns of each database from 1994 through 2016, plus their full sample averages. The primary finding is that the average return in individual databases is higher (6.40% to 7.32% p.a.) than in aggregate databases (5.84% to 5.91% p.a.). Panel B confirms this idea by testing the 1995 to 2016 mean returns against the AGG7 equivalent.[8] The mean returns of the individual databases are 0.58% to 1.25% p.a. above AGG7 (t from 2.80 to 4.05), whereas the AGG3 is indistinguishable from AGG7 with a difference of 0.07% p.a. (t = 1.28). Overall, these findings suggest that databases differ in their coverage of under-performing funds. Aggregating these unique under-performing funds across databases naturally results in a lower average.

[[INSERT TABLE 7 ABOUT HERE]]

To test this idea further, we form $k = 1,...,7$ portfolios of funds from AGG7, where each portfolio contains the monthly returns of funds reporting to exactly k databases. We restrict the period to 1997 to 2016 to ensure enough coverage in all seven portfolios. Figure 3 shows that the average abnormal return over all-funds index is monotonically increasing in k, from −2.46% per year (k = 1) to 5.62% per year (k = 7). All abnormal returns except for k = 3 are significant at the 5% level. Incidentally, the pooled average of k is 3.07. Our analysis extends the Jorion and Schwarz (2014a) results based only on HFR and TASS. They find that funds reporting to both databases have higher returns than funds reporting to only one database.

[[INSERT FIGURE 3 ABOUT HERE]]

In conclusion, we find that funds reporting to a fewer (resp. more) than average number of databases have lower (resp. higher) returns. Therefore, using any single database results in a positive selection bias, which is alleviated by database aggregation. However, we find that the three-database aggregate of TASS, HFR, and BarclayHedge is already indistinguishable from the seven-database aggregate.

[8] Throughout the paper, we omit the 1994 returns in performance tests for two reasons. First, HFR has no bias-free returns before January 1995, which precludes testing intra-database differences in 1994. Second, we cannot calculate value-weighted January 1994 returns due to lack of December 1993 AUMs, so January 1995 serves as a simpler starting date.

B. Risk-Adjusted Performance

Having shown the benefits of database aggregation in terms of increased coverage and decreased biases, we now concentrate on the net-of-fees and gross-of-fees risk-adjusted performance of the aggregate database. In addition to EW portfolios, we now also form VW portfolios weighted by one-month-lagged AUM, which helps us to understand the economic significance of the hedge fund industry's performance.

To adjust for risk, we use two benchmarks given the lack of consensus regarding an appropriate factor model.[9] The first is the seven-factor benchmark of Fung and Hsieh (2004), hereafter referred to as the FH benchmark.[10] The second is the global Carhart (1997) model augmented with a time-series momentum factor (Moskowitz, Ooi, and Pedersen 2012) as well as the Pastor-Stambaugh (2003) liquidity risk factor and a betting-against-beta factor (Frazzini and Pedersen 2014), hereafter referred to as the global benchmark. The Carhart model's global market, size, and value factors are from Fama and French (2012), and the global momentum factor is from Asness, Moskowitz, and Pedersen (2013). We admit that the choice of the benchmark models is *ad-hoc*. However, as we show below our conclusions are not sensitive to benchmark model selection.

[[INSERT TABLE 8 ABOUT HERE]]

Panel A of Table 8 risk-adjusts the net-of-fees returns for the full period 1995 to 2016, as well as the two subperiods 1995 to 2005 and 2006 to 2016. While the full period EW and VW excess returns are positive at 3.68% per year ($t = 2.51$) and 4.37% per year ($t = 3.25$) respectively, the alphas are consistently insignificant under both benchmark models and in all periods. Panel B of Table 8 repeats the risk adjustment for gross-of-fees returns imputed using the algorithm of Feng, Getmanky, and Kapadia

[9] For example, Bollen (2013) provides evidence that unidentified systematic risk is still present after controlling for the Fung and Hsieh (2004) seven factors, and even after an additional seven factors are included in the regression. Moreover, according to Bhardwaj, Gorton, and Rouwenhorst (2014), the Fung and Hsieh alphas are biased upwards because of inefficient factor replications.

[10] In our robustness tests, we extend Fung-Hsieh seven-factor model with the emerging market factor. Our conclusions are robust for this extension.

(2011). Here the alpha remains consistently positive in all specifications, e.g., with a full sample seven-factor EW alpha of 4.47% per year (t = 4.66) for the FH benchmark, and 3.61% per year (t = 4.72) for the global benchmark. In conclusion, we find that the hedge fund industry produces positive alpha before but not after fees, and this result is not sensitive to the choice of period, benchmark, or weighting scheme.

[[INSERT TABLE 9 ABOUT HERE]]

Table 9 shows the factor loadings for the net-of-fees returns over 1995 to 2016. To elucidate which factors result in the insignificant net-of-fees alpha over this period, we first regress the EW (Panel A) and VW (Panel B) return indices on each individual factor (always including the market factor), and finally on the full set of factors. For the FH benchmark, using just the market factor (S&P 500) results in a statistically insignificant EW alpha. However, no individual FH benchmark factor (combined with the market factor) eliminates the statistical significance of the VW alpha (t from 1.91 to 2.23). Only the full seven-factor FH model (t = 1.11) results in a statistically insignificant VW alpha. For the global benchmark, only the cross-sectional momentum, time-series momentum, and betting-against-beta factors (combined with global market factor) are individually able to eliminate the statistical significance of both the EW and VW alpha. Hence, the global market factor on its own is not sufficient for making alpha statistically indistinguishable from zero.

An interesting pattern is seen in the adjusted R-squared in Table 9. In Panel A, for example, the R-squared ranges from 0.52 to 0.67 for the FH benchmark, but from 0.72 to 0.82 for the global benchmark. The global market factor alone has a better time-series explanatory power than the entire FH benchmark model. Another consistent finding is that in Table 9, the level of alpha is consistently higher for the FH benchmark, consistent with the notion of Bhardwaj, Gorton, and Rouwenhorst (2014) that the trend-following FH factors are inefficient and thus bias alphas upwards. These findings confirm the need for an updated benchmark model that reflects the post-2004 literature.

C. Determinants of Risk-Adjusted Return

Finally, we want to ask how average performance varies along fund characteristics. We divide funds along four characteristics: lockup provision (dummy), notice period (six levels), incentive fee (three levels), and high-water mark provision (dummy). Table 10 confirms that, consistent with the earlier literature (e.g., Aragon 2007 and Agarwal, Daniel, and Naik 2009), all four characteristics are generally associated with higher risk-adjusted performance in terms of top–bottom alpha spread, and the alphas are also monotonic along the six notice period levels and three incentive fee levels.

[[INSERT TABLE 10 ABOUT HERE]]

The results are most robust for the AGG7 database. Using BarclayHedge alone often leads to a wrong conclusion (i.e., lack of significance), especially with VW returns (Panel B) whose alpha spreads are generally smaller compared to EW returns (Panel A). This is likely because BarclayHedge didn't collect all characteristics in its early years (Section 2E). In addition, the results are stronger against the global benchmark compared to the FH benchmark. This highlights another benefit of the global benchmark: explaining more time-series variation (i.e., having a higher adjusted R-squared) adds statistical power to inferences about the remaining "true" alpha.

4. Performance Persistence

In Section 3 we showed that, controlling for database selection bias against under-performing funds via database aggregation, in addition to the well-known backfill bias, the average hedge fund delivers positive risk-adjusted performance only before fees, but not after fees. Yet rather than employing a buy-and-hold strategy, investors may choose to rebalance their portfolio in an attempt to "chase" winning funds. Of course, such an investment strategy will be successful only if performance persists. In this section we investigate whether the performance persistence results are sensitive to database selection and their associated, previously documented biases.

A. Portfolio Sorts

We first investigate performance persistence by means of a commonly used portfolio sorting methodology (see Carhart 1997). We sort hedge funds into quintile portfolios based on their past FH alpha *t*-statistics estimated using the prior two years of data.[11] The portfolios are initially either equal-weighted (EW) or value-weighted (VW). We use three different portfolio rebalancing periods: quarterly, semi-annual, and annual. Across rebalancing horizons, we calculate buy-and-hold returns for each of the decile portfolios. To gauge the economic magnitude of persistence, we estimate the alpha of top and bottom quintile portfolios, and the *t*-statistic of their spread.

[[INSERT FIGURE 4 ABOUT HERE]]

Panel A of Figure 4 shows the EW alphas against the FH benchmark. In terms of top portfolio, our aggregate database (AGG7) delivers about the average alpha of individual databases (TASS, HFR, BarclayHedge). However, in terms of bottom portfolio, AGG7 consistently delivers lower alpha than any individual database. In addition, the *t*-statistics of the top–bottom alpha spread are consistently highest for AGG7. These findings reflect the wider coverage of funds—especially under-performing ones—in the aggregate database, which adds statistical power to persistence tests.

Panel B shows the same EW alphas for the global benchmark. The results are similar to the FH benchmark, although the bottom portfolio alphas of AGG7 and TASS are tied. Here the increased statistical power of AGG7 has a concrete effect on inference: it is the only database whose top–bottom

[11] Although in hedge fund literature almost 30 predictors are proposed to predict hedge fund performance, Bollen, Joenväärä, and Kauppila (2018) document that three alphas (OLS alpha, Bayesian alpha, and Relative alpha) are the most robust predictors. For simplicity, we opt to use OLS alpha *t*-statistic.

alpha spread has $p < 0.01$ at annual horizon, whereas TASS and BarclayHedge have $p < 0.05$, and HFR has $p > 0.10$.

Panels C and D show the VW alphas against both benchmarks. Here the persistence practically vanishes ($p > 0.10$), except for quarterly rebalanced portfolios in BarclayHedge and AGG7 plus semi-annually rebalanced portfolios in BarclayHedge. Consistent with Joenväärä, Kosowski, and Tolonen (2019), small funds seem to drive performance persistence. In addition, the vanishing persistence is driven by the bottom portfolios, whose VW alphas are much higher compared to EW alphas, and thus closer to top portfolios. This may reflect the capability of larger funds to survive bad performance better than smaller funds, resulting in mean reversion rather than forced liquidation. However, the bottom portfolio VW alphas are still usually lowest for the AGG7 database, suggesting that the aggregation of badly performing funds across databases may still be economically important even in VW terms.

B. Regressions

We next examine whether historical FH alphas of hedge funds predict their future FH alphas while simultaneously controlling for the role of other fund characteristics, which previous literature found to explain future FH alphas, and whose univariate role we explored in Section 3C.

The cross-sectional regression analysis of performance persistence provides several advantages. First, the methodology allows us to directly control for fund-level characteristics that may affect future returns. Second, we can control for the serial correlation, which is evident in hedge fund returns and may affect the predictability of returns (Getmansky, Lo, and Makarov 2004). Third, we can account for style and domicile fixed effects. Controlling for the effects of fund domicile is important, because the impact of share restrictions on hedge fund performance varies across domiciles, as described in Aragon, Liang, and Park (2013).[12] Controlling for fund style is essential given that differences in investment style have been shown to contribute a significant portion of the cross-sectional variability in hedge fund performance (Brown and Goetzmann 2003).[13]

We apply the methodology proposed by Brennan, Chordia, and Subrahmanyam (1998), and applied by Busse, Goyal, and Wahal (2010) in the investment fund context. To do so, we estimate the FH alphas and beta coefficients by means of the time-series regression using the full sample of fund returns for each fund having at least 24 return observations. From monthly FH alphas (i.e., intercept plus residual) we geometrically compound the annual FH alphas, requiring 12 monthly observations. Table 11 studies the annual performance persistence in terms of a Fama-MacBeth (1973) regression, where the following year's alpha is regressed on the past year's alpha plus standard controls. The coefficient on past alpha is positive and highly significant for all databases (t from 3.14 to 5.10), confirming the persistence of performance observed in portfolio sorts.

[[INSERT TABLE 11 ABOUT HERE]]

We next focus on the role of share restrictions, which consist of lockup, redemption, and notice periods. Whereas in earlier portfolio sorts the association between tighter share restrictions and greater risk-adjusted returns was most robust for AGG7, in regressions the association is entirely confined to AGG7. The coefficient on notice period is highly significant (t = 3.08) in AGG7, while the coefficients on redemption and lockup periods are insignificant. This finding is consistent with Joenväärä and Tolonen (2009), who argue that notice period gives fund managers accurate information about the level and time of investors' redemptions, while lockup period applies only for initial investments, and may not thereby be informative for fund managers.

[12] Our database contains eight standard domiciles listed in Panel B of Table A2. In regressions, we simplify these into four broad domiciles: (1) North America; (2) Europe; (3) Caribbean; and (4) Rest of the world, which includes the remaining domiciles (Asia, Pacific, Central America, South America, Others).

[13] We use the eight SEC Form PF broad strategies (other than funds of funds) listed in Panel A of Table A2.

As in portfolio sorts reported earlier, the compensation structure variables are positively associated with risk-adjusted returns, but not always significantly. The results differ between individual databases and AGG7. Most notably, the coefficient on high-water mark is highly significant in AGG7 (t = 3.71) but insignificant in individual databases (t from 0.23 to 1.52). On the other hand, the coefficient on incentive fee is significant in individual databases (t from 1.72 to 2.51) but not in AGG7 (t = 1.34).[14] Coefficient on management fee is significant in all databases (t from 1.67 to 2.04) except HFR (t = 0.90). Although the regression-based evidence is a bit weaker than earlier reported portfolio sort-based evidence, we can conclude that our results are consistent with the earlier literature (e.g., Agarwal, Daniel, and Naik 2009), suggesting that managerial incentives are important for hedge funds, although the conclusions are somewhat sensitive to database selection.

The hedge fund literature suggests that fund size, age, and flow have a negative association with future returns, indicating decreasing returns-to-scale for hedge funds (e.g., Aggarwal and Jorion 2010b and Teo 2010, 2011). Our regression-based evidence supports this idea. All relevant coefficients are negative but not always significant. Across variables, only the past flow is consistently significant (t from −3.33 to −1.66). Across databases, only AGG7 is consistently significant (t from −3.33 to −1.67). Consistent with the extant theoretical literature (e.g., Berk and Green 2004), our regression results support the idea that diseconomies of scale play an important role in the hedge fund industry.[15]

One of the reasons why our results may differ from those documented in previous papers is that there are changes in cross-sectional variables such as share restrictions and compensation structure as documented by Getmansky et al. (2015) and Agarwal and Ray (2013), and ongoing revisions in fund

[14] Agarwal, Daniel, and Naik (2009) construct a proxy for hedge fund manager's performance-based compensation. Their "total delta" proxy measures the total expected dollar change in the hedge fund manager's compensation for a 1% change in NAV for a given fund. In order to keep our analysis simple, we use the time-invariant incentive fee in our regressions. In undocumented tests, we find that the total deltas are positively related to the future returns of hedge funds.
[15] One potential caveat of our analysis is related to Pastor and Stambaugh (2012) who develop a model in which active managers face decreasing returns to scale when the aggregate assets under management increase. However, testing this idea in the context of hedge funds is not trivial because hedge fund strategies are heterogeneous and they trade in various markets.

returns documented by Patton, Ramadorai, and Streatfield (2015). Unfortunately, we do not have access to vintage snapshots of cross-sectional variables.

C. Delisting Returns

Our consolidated aggregate database is constructed using hedge funds that report to at least some of the seven commercial databases. One caveat in our analysis is the fact that the databases may suffer from self-selection bias because some hedge funds do not report to any commercial database. Edelman, Fung, and Hsieh (2013) show that the inclusion of such non-reporting funds does not qualitatively change most insights that are based on research findings about hedge fund performance, whereas Aiken, Clifford, and Ellis (2013) find that hedge funds that report to commercial databases deliver higher returns than those that do not report. Although our data is not particularly well suited for addressing self-section bias, we are able to study the impact of delisting bias on the conclusions of performance persistence tests.[16] To mitigate delisting biases, hedge fund papers often apply a delisting adjustment suggested by Titman and Tiu (2011) to reverse the censoring of unreported poor returns of failing funds, where the fund's return series is appended with a large terminal loss.

As we have shown in our data section, our data aggregation method mitigates the delisting bias. Next, we merge the aggregate database with a sample of hedge funds that do not report to any of the commercial databases, and ask whether performance persists after a fund has stopped reporting to the databases. We can infer returns not reported to databases using the methodology of Aiken, Clifford, and Ellis (2013). In short, we download the quarterly holdings of funds of (hedge) funds (FOF), and match them with our commercial database funds. The quarterly fund returns can be imputed from the FOFs' successive quarter-end valuations. The details on this procedure are available in the Data Appendix. Our final FOF holdings database contains holdings of 1,989 funds, of which 1,137 (57.2%) can be matched

[16] Jorion and Schwarz (2014b) study delisting bias using HFR and TASS databases. We extend their analysis by using the non-voluntarily reported data as well as seven commercial databases.

with our database funds. Out of the 1,137 matched funds, we can impute quarterly returns for 928 (81.6%) funds.

We define a fund's *attrition quarter* as its last return-reporting quarter in our aggregate database. We measure pre-attrition performance by the 24-month FH7 alpha *t*-statistic calculated in the quarter *before* the attrition quarter; and post-attrition performance by the FOF-based fund return on the quarter *following* the attrition quarter. We identify only 37 funds where both data are available, which is a small percentage (4.0%) of the total 928 holdings-matched funds with imputable returns.

[[INSERT TABLE 12 ABOUT HERE]]

Panel A of Table 12 shows that just around half of these funds (18 / 37) are in the top alpha quintile of all funds. The propensity of FOFs to hold funds post-attrition quickly diminishes with pre-attrition performance. This pattern seems to reverse in the very bottom quintile, with 7 / 37 funds held; however, 5 / 7 of these funds impose discretionary liquidity restrictions (DLRs)[17], which means that the FOFs are unable to liquidate these positions immediately (DLRs are rare in non-bottom quintiles). Although these findings are consistent with the well-known flow-performance relation, the very small number of funds with post-attrition holdings indicates that the magnitude of possible delisting bias should be low.

Panel A also suggests that funds in higher pre-attrition alpha quintiles have better post-attrition performance. Indeed, the results are monotonic except for the bottom quintile, which mostly contains funds that impose DLRs. However, due to the very limited amount of data, we test these results only within a regression framework in Panel B, which shows that the fractional pre-attrition performance rank is consistently associated with higher post-attrition returns (*t* from 2.70 to 2.85).

[17] Following Aiken, Clifford, and Ellis (2015) classification, we define that the underlying fund has imposed a DLR when any FOF reports a position for the underlying hedge fund that is (1) in a side pocket (either completely or partially), (2) subject to investor-level gates, (3) liquidating, (4) organized as a special purpose vehicle or special liquidating vehicle, or (5) explicitly said to be illiquid or having its liquidity restricted.

In conclusion, performance persists even after funds stop reporting to databases. However, the occurrence of such post-attrition returns is very rare—especially for poorly performing, and thus likely liquidated funds. This should limit the delisting bias in average fund performance suggesting that the delisting bias may not be an issue for our aggregate database.

5. Concluding Remarks

This paper proposes a novel and replicable methodology to aggregate hedge fund databases, and then re-examines three fundamental questions about fund performance. We document several findings. First, hedge fund average returns are upward biased if a researcher uses only one of the commercial databases, because databases differ in their coverage of under-performing funds. Second, after correcting for data biases—including the aforementioned positive database selection bias—a typical hedge fund or the industry as a whole delivers significant abnormal returns before fees but not after fees, suggesting that fund managers extract the majority of the rents. Third, although the average hedge fund does not deliver abnormal performance for their investors, our evidence suggests that performance persists. Persistence is more significant in the aggregate database, because the distinct under-performing funds are combined across databases. Fourth, consistent with the previous literature, we find that variables related to share restrictions, compensation structure, and diseconomies of scale are important determinants of risk-adjusted returns. These associations are more robust in the aggregate database, due to its increased coverage of funds and their characteristics.

Although our aggregate database is comprehensive and can be used to conduct reliable inference, even our aggregate database may still suffer from self-selection bias. Indeed, some of the hedge funds may not choose to list in any of the commercial databases. Since 2013, certain rules require that large hedge funds must report with SEC. An important avenue for future research would be to combine these two sources of data in order to examine potential self-selection bias in the hedge fund industry.

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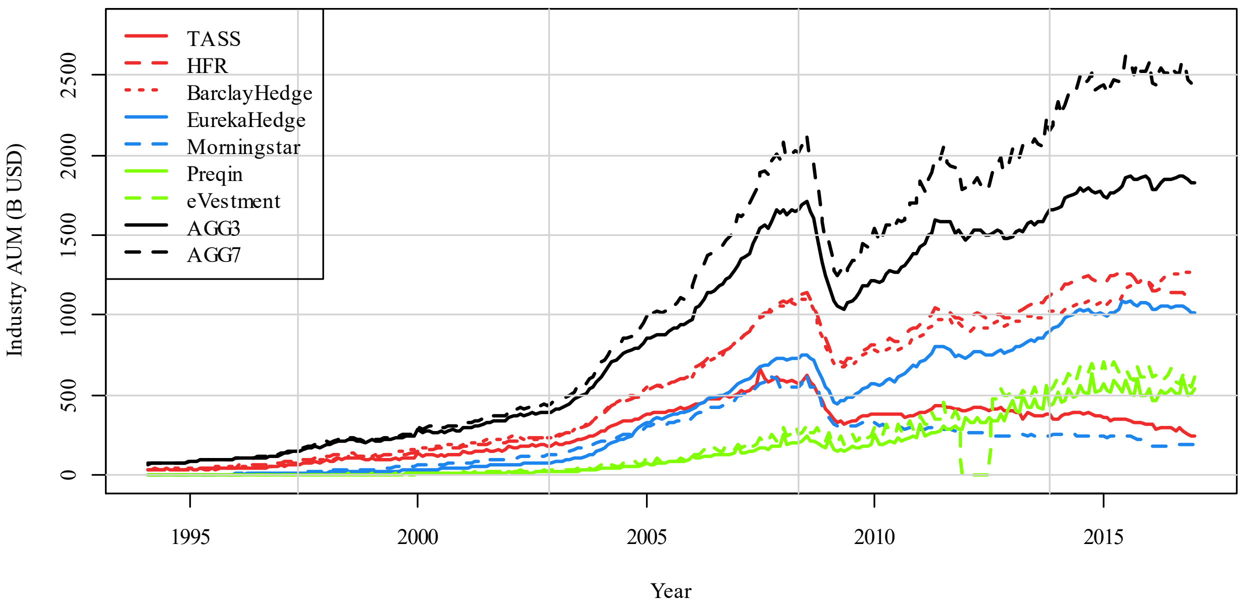
Figure 1: Assets under management

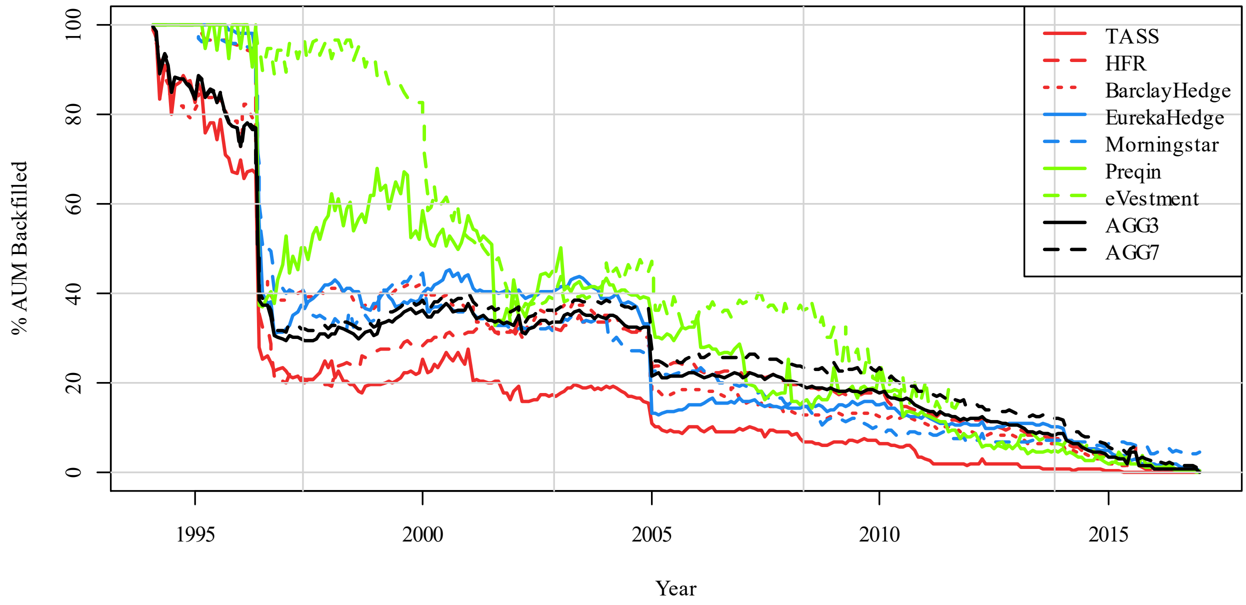
Description: This figure shows the assets under management (AUM) from 1994 through 2016 for each of the seven individual databases, their three-database aggregate (AGG3, containing Lipper TASS, HFR, and BarclayHedge), and their seven-database aggregate (AGG7). Backfilled observations are not removed. Panel A shows the monthly total database AUM. Panel B shows the percentage of AUM that is backfilled. Panel C shows the percentage of missing AUM observations. Panels D and E show the monthly cross-sectional mean and median AUM. We remove all eVestment (dashed green line) AUM observations from November 2011 through June 2012 due to numerous hard-to-correct outliers which are likely attributable to the database's merger history.

Interpretation: Database aggregation captures a larger cross-section of hedge fund industry AUM than any individual database. The majority of AUM are not subject to backfill bias, and the proportion of missing AUMs is comparable to similar mutual fund data (e.g., Berk and van Binsbergen 2015). These findings help ensure that the performance estimates of our bias-free aggregate database are economically significant, especially in value-weighted terms.

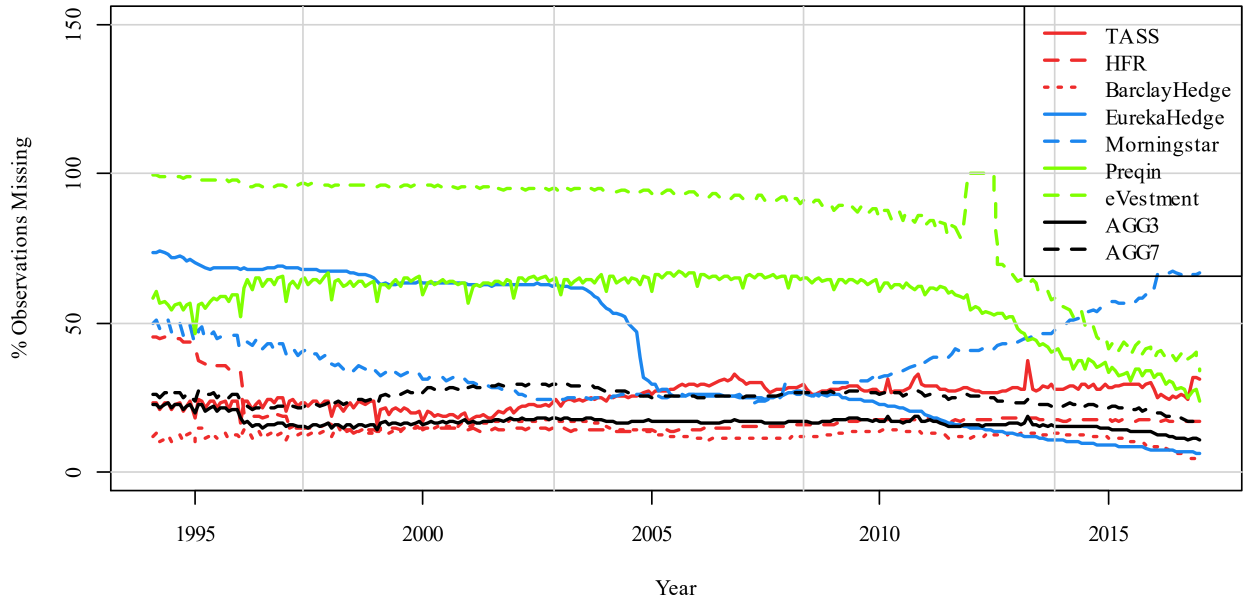
Panel A: Total database AUM



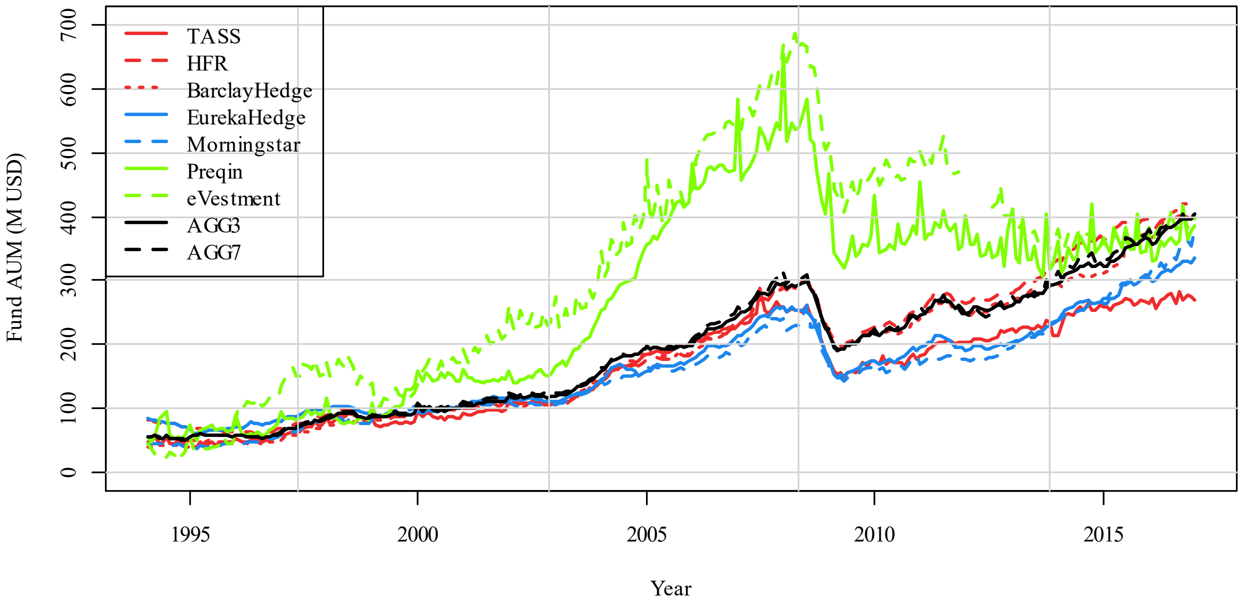
Panel B: Percentage of total database AUM that is backfilled



Panel C: Percentage of missing AUM observations



Panel D: Cross-sectional mean AUM



Panel E: Cross-sectional median AUM

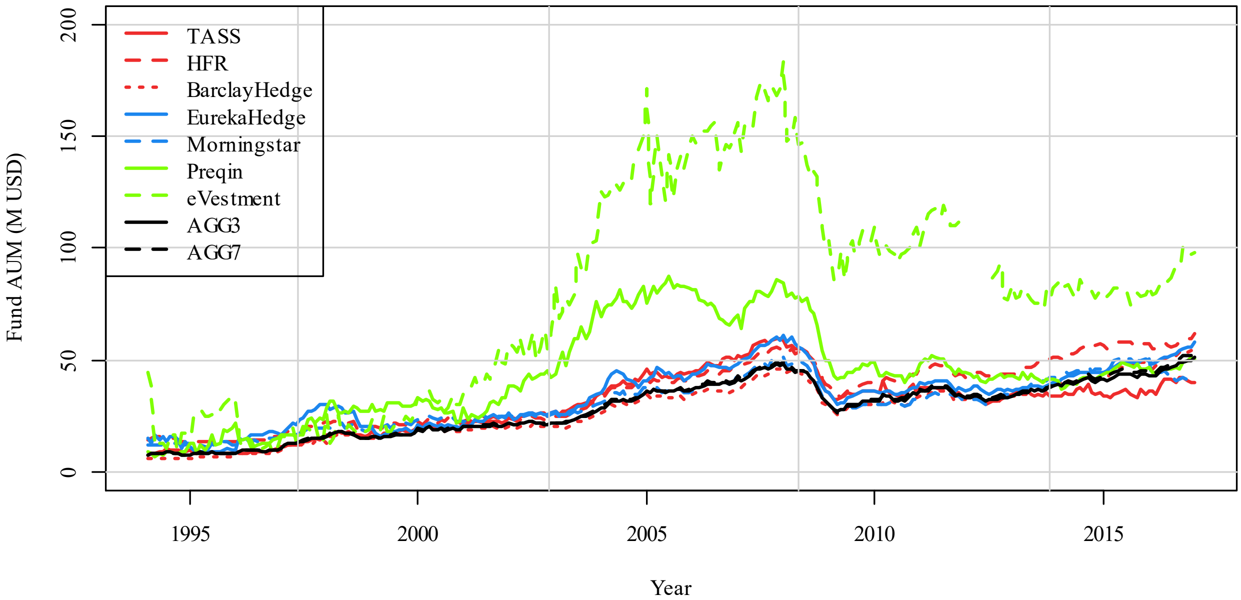


Figure 2: Reporting life-cycle

Description: This figure illustrates the major events of the hedge fund life-cycle that relate to voluntary reporting to commercial databases. *Inception date* and *Liquidation date* denote when the fund begins and ceases its operations; together, they define the fund lifespan. Within fund lifespan, *Listing date* and *Delisting date* occur when the fund starts and stops reporting into a database; these dates may vary across databases, but can be aggregated. Upon listing to a database, the fund generally backfills its incubation period returns from its inception date to listing date, and then reports real-time monthly returns until the delisting date.

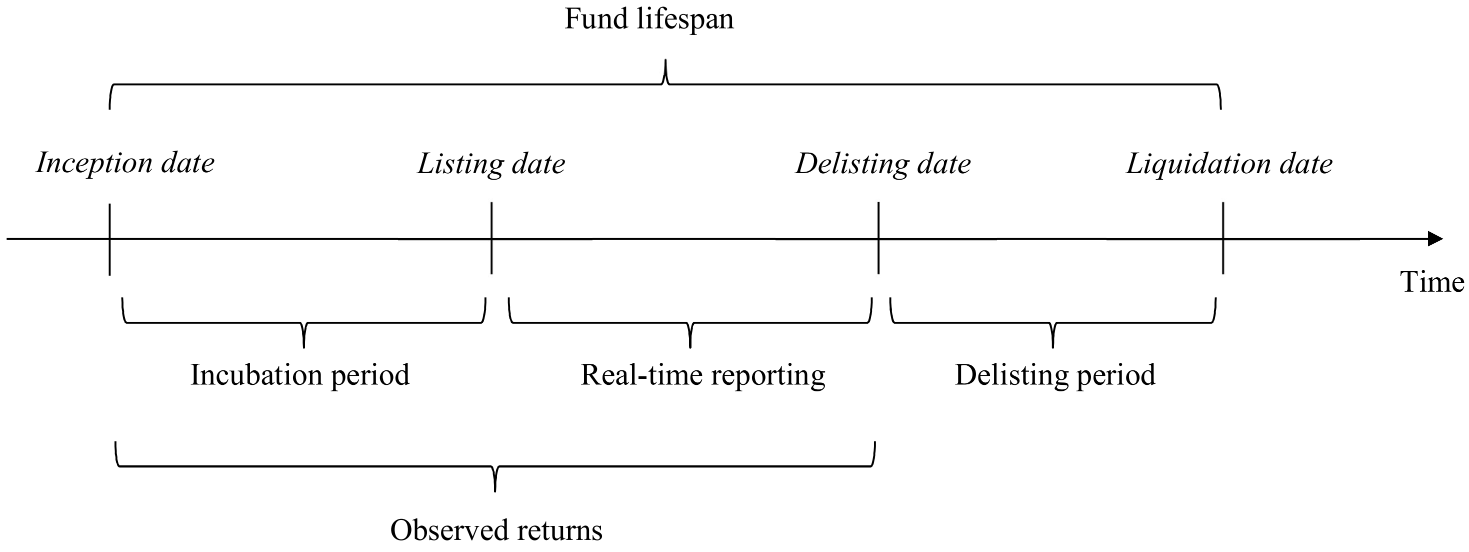


Figure 3: Average return vs. number of databases reported to

Description: This figure shows how the number of databases a fund reports to affects the average return. Within the bias-free AGG7 database, we form seven equal-weighted (EW) portfolios ($k = 1,\ldots,7$), each of which contains the monthly net-of-fees returns that were reported to exactly k databases. We restrict the period to 1997 to 2016 to ensure enough coverage in all seven portfolios. To calculate the abnormal return of each portfolio, we subtract the return of the all-fund portfolio. The solid line shows the average abnormal return for $k = 1,\ldots,7$, and the dashed line shows the 95% confidence interval.

Interpretation: Funds reporting to fewer databases have worse average performance. Performance estimates derived from any single database are therefore subject to upward bias, which is mitigated by database aggregation.

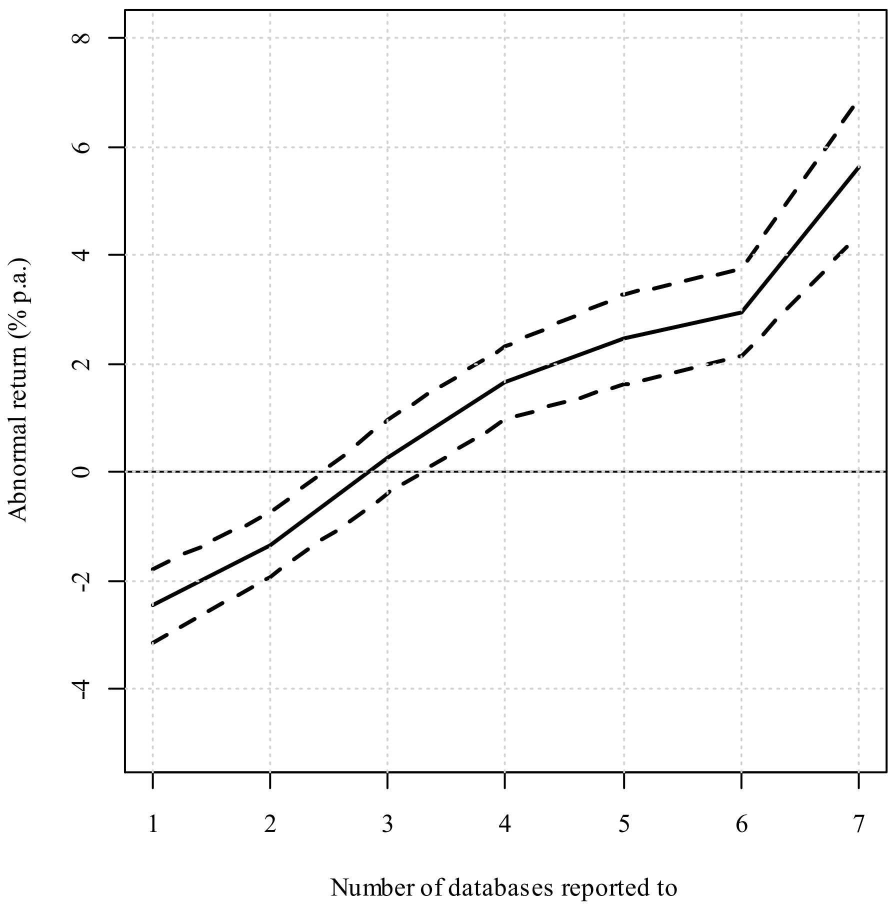


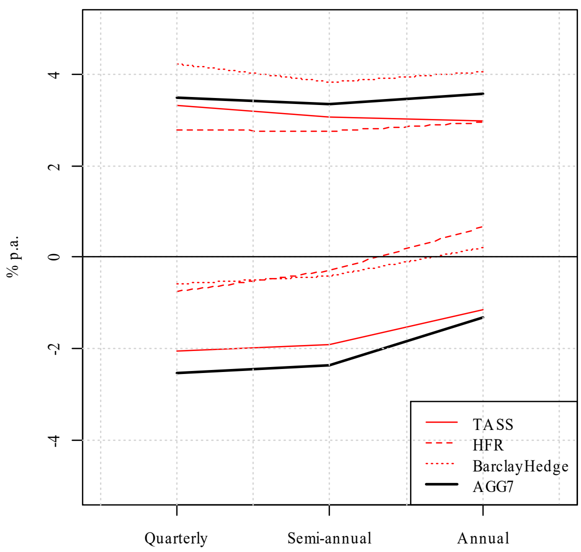
Figure 4: Performance persistence

Description: This figure shows how performance persists in three individual databases (TASS, HFR, BarclayHedge) and our seven-database aggregate (AGG7). Starting in December 1996, we sort funds into five portfolios based on their past performance measured by the *t*-statistic of the seven-factor Fung-Hsieh (2004) alpha over 24 months. These buy-and-hold portfolios are initially either equal-weighted (EW) or value-weighted (VW), and rebalanced either quarterly, semi-annually, or annually. Proceedings from funds liquidated during the holding period are reinvested at the risk-free rate. Panel A shows the Fung-Hsieh alpha of the top and bottom EW quintile portfolios for each database, and *t*-statistic of the top–bottom alpha spread. Panel B repeats these EW results for the global seven-factor benchmark. Panels C and D repeat the benchmark analyses for VW portfolios. The factors are explained in detail in Table 9.

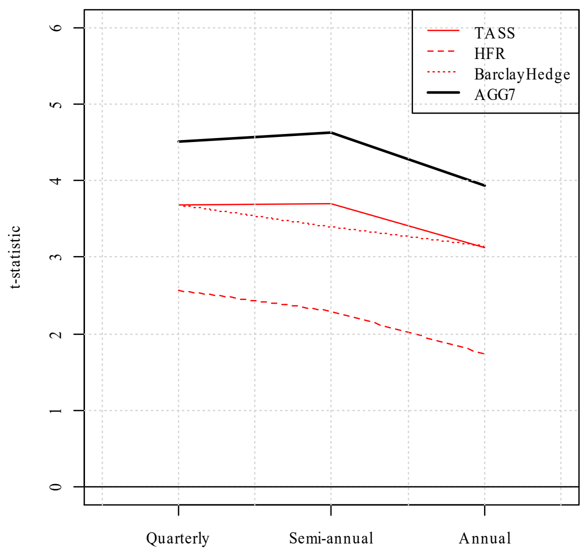
Interpretation: EW persistence (*t*-statistic of the alpha spread) is consistently highest for AGG7. This result is driven by the bottom portfolio, which suggests that aggregation widens the coverage of under-performing funds. Results are weaker in terms of VW persistence.

Panel A: Fung-Hsieh seven-factor benchmark (EW)

Top and bottom portfolio alpha

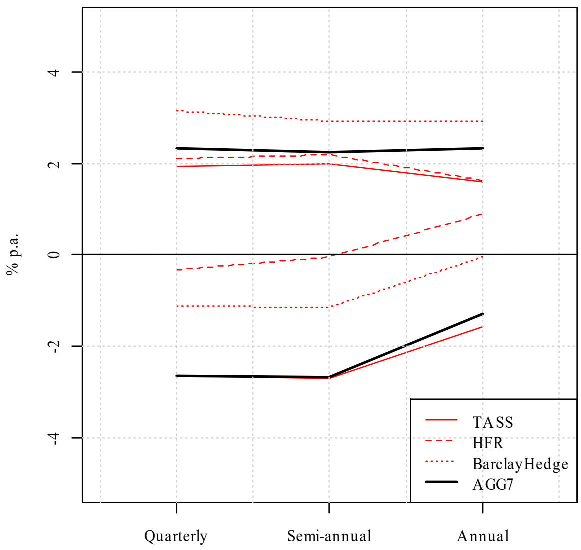


Alpha spread *t*-statistic

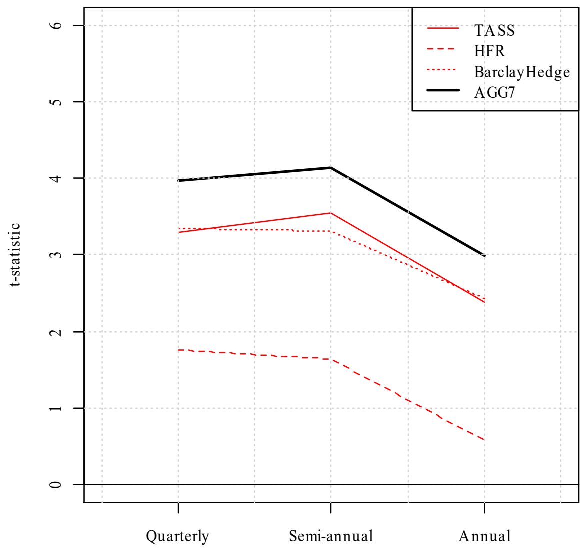


Panel B: Global seven-factor benchmark (EW)

Top and bottom portfolio alpha

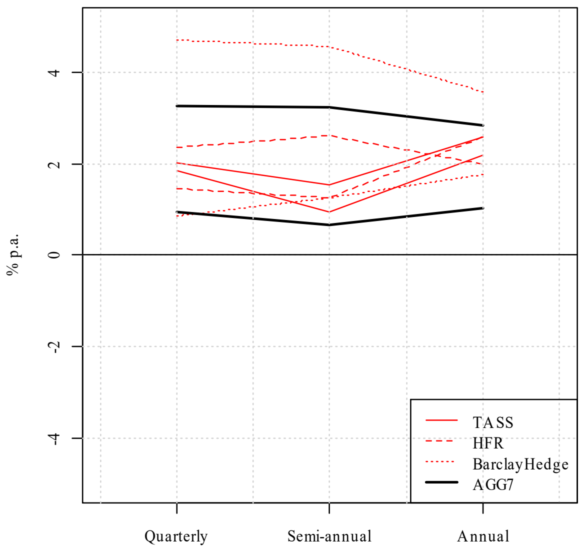


Alpha spread *t*-statistic

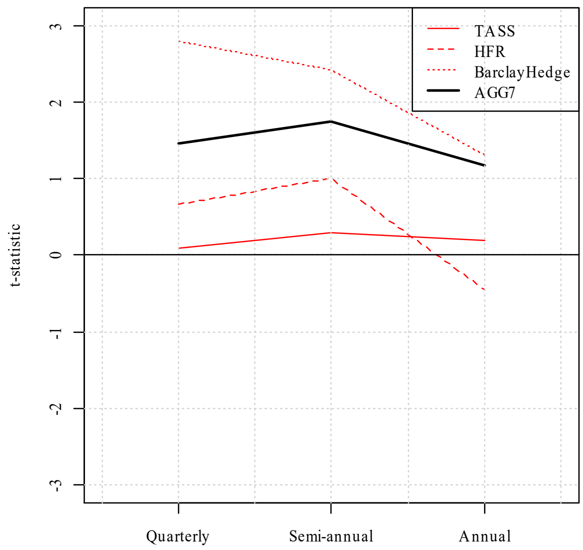


Panel C: Fung-Hsieh seven-factor benchmark (VW)

Top and bottom portfolio alpha

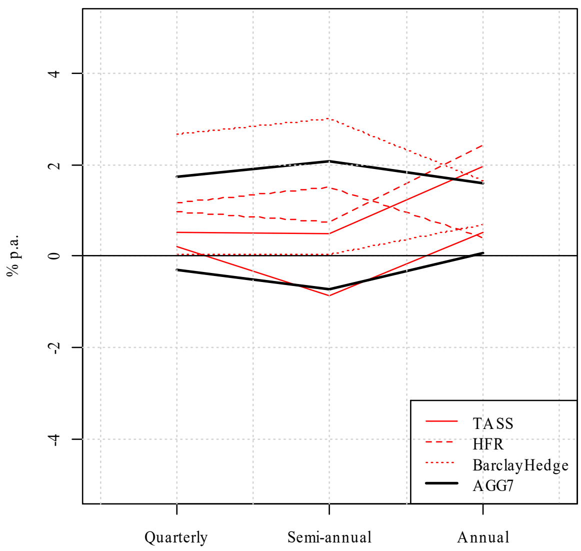


Alpha spread *t*-statistic



Panel D: Global seven-factor benchmark (VW)

Top and bottom portfolio alpha



Alpha spread *t*-statistic

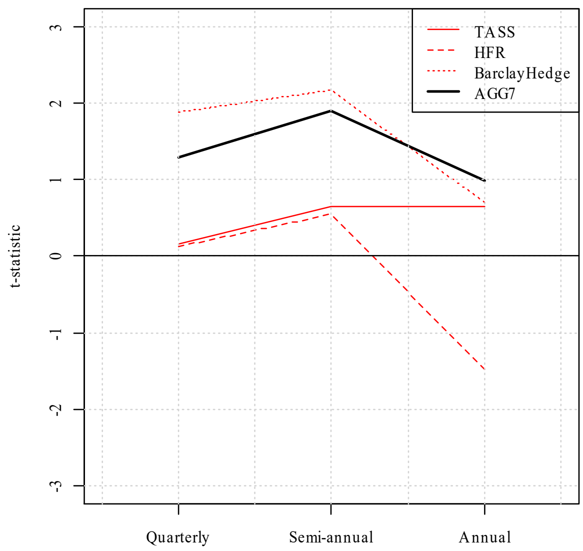


Table 1: Database overlap

Description: This table shows the amount of overlap between databases. Panel A tabulates the Venn diagram, whose entries show the number of funds that are unique to the given intersection of databases. The entries of Panel A sum up to 26,432, which is the total number of funds in the seven-database aggregation. More generally, Panel B shows the number of funds in each of the 2^7=128 possible database aggregations, and Panel C shows the same results as a percentage of the maximum 26,432 funds. In all Panels, different colors show the order of intersection or aggregation, i.e., the number of databases (1,…,7) under inspection. The smallest and largest entry within each order are shown in boldface. For compactness, we use some shorthands for the individual database names: Barclay for BarclayHedge, Eureka for EurekaHedge, Mstar for Morningstar, and eVest for eVestment.

Interpretation: Nearly half (48.3%) of funds are covered by only one database. The optimal order of adding individual databases to produce N-database aggregates with most coverage (N=1,…,7) is: BarclayHedge (44.74%), HFR (62.56%), eVestment (74.04%), TASS (82.07%), EurekaHedge (89.26%), Morningstar (96.06%), and Preqin (100.0%).

Panel A: Venn diagram (∑ = 26,432)

					TASS	HFR	Barclay	TASS HFR	TASS Barclay	HFR Barclay	TASS HFR Barclay
					1 775	1 913	**2 776**	323	**464**	453	267
Eureka				1 541	105	268	300	42	61	217	105
	Mstar			1 782	87	89	111	37	33	91	83
		Preqin		**1 034**	57	123	159	5	**4**	96	19
			eVest	1 953	140	442	367	155	119	**366**	345
Eureka	Mstar			74	37	34	47	35	29	91	151
Eureka		Preqin		272	41	130	148	29	20	202	45
Eureka			eVest	338	64	213	136	123	55	**312**	**374**
	Mstar	Preqin		**22**	8	10	9	4	4	14	14
	Mstar		eVest	98	32	81	66	66	39	189	242
		Preqin	eVest	151	10	95	57	10	**3**	106	31
Eureka	Mstar	Preqin		13	13	18	22	14	17	56	72
Eureka	Mstar		eVest	45	37	48	48	104	67	227	**879**
Eureka		Preqin	eVest	92	33	142	100	54	37	317	220
	Mstar	Preqin	eVest	15	11	7	9	11	**9**	35	52
Eureka	Mstar	Preqin	eVest	4	11	29	37	57	**18**	166	**618**

	Order
	1
	2
	3
	4
	5
	6
	7

Panel B: Number of combined funds

					TASS	HFR	Barclay	TASS HFR	TASS Barclay	HFR Barclay	TASS HFR Barclay
					8 026	11 166	**11 826**	14 606	15 356	**16 537**	18 998
Eureka				9 254	13 713	15 028	15 886	17 823	18 617	19 257	21 377
	MStar			6 478	11 613	14 020	14 759	17 008	17 725	18 826	21 051
		Preqin		**5 241**	11 716	13 606	14 351	16 750	17 513	18 324	20 601
			eVest	10 317	14 317	15 367	16 497	18 122	19 109	**19 571**	**21 694**
Eureka	MStar			12 614	16 341	17 363	18 246	19 935	20 721	21 312	23 294
Eureka		Preqin		11 448	15 655	16 590	17 459	19 279	20 074	20 565	22 599
Eureka			eVest	14 566	17 750	18 107	19 163	20 539	21 459	21 667	**23 594**
	MStar	Preqin		**10 320**	14 837	16 238	17 037	19 021	19 764	20 516	22 600
	MStar		eVest	13 438	16 800	17 675	18 774	20 202	21 151	21 607	23 585
		Preqin	eVest	13 011	16 645	17 210	18 290	19 801	20 731	21 031	23 035
Eureka	MStar	Preqin		**14 574**	**18 162**	18 838	19 731	21 336	22 124	22 564	24 479
Eureka	MStar		eVest	16 964	19 878	20 163	21 202	22 463	23 362	23 566	**25 398**
Eureka		Preqin	eVest	16 148	19 217	19 404	20 426	21 763	22 648	22 788	24 650
	MStar	Preqin	eVest	15 822	18 964	19 410	20 465	21 815	22 710	23 011	24 891
Eureka	MStar	Preqin	eVest	18 461	**21 290**	21 417	22 421	**23 656**	24 519	24 657	**26 432**

	Order
	1
	2
	3
	4
	5
	6
	7

Panel C: Number of combined funds (% of maximum)

					TASS			TASS	TASS		TASS
						HFR		HFR		HFR	HFR
							Barclay		Barclay	Barclay	Barclay
					30.36	42.24	**44.74**	55.26	58.10	**62.56**	71.88
Eureka				35.01	51.88	56.86	60.10	67.43	70.43	72.85	80.88
	MStar			24.51	43.94	53.04	55.84	64.35	67.06	71.22	79.64
		Preqin		**19.83**	44.33	51.48	54.29	63.37	66.26	69.33	77.94
			eVest	39.03	54.17	58.14	62.41	68.56	72.29	**74.04**	**82.07**
Eureka	MStar			47.72	61.82	65.69	69.03	75.42	78.39	80.63	88.13
Eureka		Preqin		43.31	59.23	62.76	66.05	72.94	75.95	77.80	85.50
Eureka			eVest	55.11	67.15	68.50	72.50	77.71	81.19	81.97	**89.26**
	MStar	Preqin		**39.04**	56.13	61.43	64.46	71.96	74.77	77.62	85.50
	MStar		eVest	50.84	63.56	66.87	71.03	76.43	80.02	81.75	89.23
		Preqin	eVest	49.22	62.97	65.11	69.20	74.91	78.43	79.57	87.15
Eureka	MStar	Preqin		**55.14**	**68.71**	71.27	74.65	80.72	83.70	85.37	92.61
Eureka	MStar		eVest	64.18	75.20	76.28	80.21	84.98	88.39	89.16	**96.09**
Eureka		Preqin	eVest	61.09	72.70	73.41	77.28	82.34	85.68	86.21	93.26
	MStar	Preqin	eVest	59.86	71.75	73.43	77.43	82.53	85.92	87.06	94.17
Eureka	MStar	Preqin	eVest	69.84	**80.55**	81.03	84.83	**89.50**	92.76	93.28	**100.00**

Order
1
2
3
4
5
6
7

Table 2: Reporting and attrition rates

Description: This table shows the number of reporting funds at each year-end from 1994 through 2016. We calculate the attrition rate ("% Stop") as the fraction of previous year's funds that stopped reporting during the current year.

Interpretation: The very low (including zero) attrition rates for the early sample indicate survivorship bias. Only TASS, HFR, and BarclayHedge are free from such bias. The fund coverage in TASS, Morningstar, and eVestment decreases towards sample end. Such time-varying database coverage highlights the importance of database aggregation.

	TASS		HFR		BarclayHedge		EurekaHedge		Morningstar		Preqin		eVestment	
Year	N	% Stop	N	% Stop	N	% Stop	N	% Stop	N	% Stop	N	% Stop	N	% Stop
1994	1 083		913		1 175		250		231		65		400	
1995	1 250	10.3	1 183	4.0	1 299	11.8	320	0.0	320	0.0	83	0.0	542	0.0
1996	1 415	13.1	1 447	9.8	1 455	10.9	426	0.0	416	0.0	112	0.0	733	0.0
1997	1 546	8.9	1 616	9.1	1 633	8.7	550	0.0	522	0.0	152	0.0	960	0.1
1998	1 694	9.7	1 808	14.1	1 833	7.0	715	0.0	661	0.0	204	0.0	1 275	0.2
1999	1 884	10.7	1 963	8.5	2 166	6.0	961	0.0	843	0.0	260	0.0	1 702	2.9
2000	2 052	12.3	2 236	11.1	2 463	10.6	1 228	0.0	1 056	0.0	332	0.0	2 107	10.7
2001	2 206	10.5	2 439	7.8	2 710	7.5	1 532	0.0	1 280	0.0	405	0.0	2 385	10.9
2002	2 438	9.5	2 800	7.6	3 086	18.7	1 977	0.8	1 587	0.0	503	0.0	2 752	10.2
2003	2 690	8.2	3 214	7.9	3 224	8.8	2 526	1.7	1 978	0.0	629	0.0	3 157	8.3
2004	2 990	9.4	3 685	7.5	3 619	10.1	3 047	6.7	2 445	1.1	770	0.0	3 621	8.7
2005	3 285	10.9	4 218	9.6	4 044	11.0	3 463	12.0	2 982	3.4	974	0.0	4 157	11.3
2006	3 499	11.7	4 624	10.1	4 397	12.1	3 770	9.1	3 431	8.4	1 210	0.3	4 604	10.3
2007	3 641	15.0	4 892	12.1	4 600	13.3	4 135	9.5	3 645	13.8	1 518	0.2	4 933	13.0
2008	3 650	20.5	5 011	18.5	4 717	20.2	4 476	14.0	3 650	22.7	1 862	0.2	5 068	18.2
2009	3 381	12.6	4 829	12.4	4 536	12.4	4 597	9.7	3 318	17.7	2 243	0.5	4 833	12.6
2010	3 359	13.6	4 859	11.1	4 619	12.7	4 838	10.4	3 167	20.0	2 683	1.2	4 775	15.0
2011	3 209	15.6	4 925	12.3	4 652	13.9	4 959	11.5	2 941	17.6	3 179	2.8	4 567	15.3
2012	2 958	18.9	4 872	13.9	4 638	15.9	4 978	13.7	2 696	21.5	3 660	7.7	4 321	19.1
2013	2 605	16.1	4 708	12.7	4 503	14.7	4 852	13.0	2 443	17.8	3 924	10.1	3 961	12.7
2014	2 304	16.9	4 493	12.2	4 326	13.6	4 661	13.6	2 334	17.4	4 031	14.6	3 802	17.5
2015	1 955	19.7	4 195	14.6	4 078	15.9	4 334	14.7	2 070	18.0	3 814	15.4	3 367	17.8
2016	1 578		3 740		3 642		3 864		1 790		3 476		2 884	

Table 3: Augmenting missing returns

Description: This table shows how our database aggregation procedure adds value by augmenting missing returns in individual databases. We consider only bias-free returns, i.e., we remove backfilled returns. To remove backfill bias in each individual database, in this analysis we exceptionally use only the listing dates in that database. We also show results for the AGG3 database defined as the aggregation of TASS, HFR, and BarclayHedge. Panel A shows statistics of funds whose incubation returns (i.e., returns prior to listing date) can be augmented. Panel B shows the same statistics for return holes (i.e., missing returns between listing and delisting dates). Panel C shows the same statistics for delisting returns (i.e., returns after the delisting date). In each Panel, "Mean augmented months" is the number of return months augmented *within* the augmentable funds. To gauge the performance of these augmented returns, we measure their abnormal returns above the bias-free VW seven-database aggregate index. "Mean fund abnormal return" first averages within, then across funds. "Portfolio abnormal return" first averages within, then across months (assuming zero abnormal return for months with no augmented returns).

Interpretation: A large proportion of fund returns not found in individual databases can be augmented from the remaining databases, suggesting a benefit to database aggregation.

Panel A: Augmentable incubation returns

	TASS	HFR	Barclay	Eureka	Preqin	eVest	AGG3
Total funds	7,821	10,839	11,730	8,922	3,112	7,038	18,536
Funds with incubation returns	3,408	3,416	5,085	3,376	2,074	3,840	3,396
% of total	43.57	31.52	43.35	37.84	66.65	54.56	18.32
Mean augmented months	16.54	18.22	15.90	27.71	43.88	38.36	15.20
Mean fund abnormal return (% p.a.)	6.22	5.69	6.40	4.70	3.75	4.07	5.40
Portfolio abnormal return (% p.a.)	5.07	3.74	4.72	4.94	4.09	4.78	1.86

Panel B: Augmentable return holes

	TASS	HFR	Barclay	Eureka	Preqin	eVest	AGG3
Total funds	7,821	10,839	11,730	8,922	3,112	7,038	18,536
Funds with return holes	149	42	32	33	81	14	57
% of total	1.91	0.39	0.27	0.37	2.60	0.20	0.31
Mean augmented months	3.84	15.02	22.22	6.97	6.30	16.14	10.40
Mean fund abnormal return (% p.a.)	−6.01	−7.51	−1.03	−8.24	2.35	−2.20	−3.25
Portfolio abnormal return (% p.a.)	−1.64	−0.86	−7.59	−3.00	−0.11	3.17	−1.94

Panel C: Augmentable delisting returns

	TASS	HFR	Barclay	Eureka	Preqin	eVest	AGG3
Total funds	7,821	10,839	11,730	8,922	3,112	7,038	18,536
Funds with delisting returns	2,599	2,527	2,355	2,192	641	2,027	1,598
% of total	33.23	23.31	20.08	24.57	20.60	28.80	8.62
Mean augmented months	20.59	14.47	20.94	11.72	11.09	14.53	16.47
Mean fund abnormal return (% p.a.)	−12.35	−13.14	−9.76	−12.99	−8.74	−9.00	−9.05
Portfolio abnormal return (% p.a.)	−2.45	−2.40	−4.10	−2.49	−1.78	−2.07	0.06

Table 4: Fund lifespan coverage

Description: This table shows how much closer to the *true* average fund lifespan our coverage of bias-free returns gets when using our database aggregation procedure. For three individual databases (TASS, EurekaHedge, eVestment) we collect funds that have both inception and liquidation dates available. "True fund lifespan" is the difference between liquidation and inception dates; "true incubation period" is the difference between listing and inception dates; and "true delisting period" is the difference between liquidation and delisting dates. All periods are measured as average months per fund. Augmented incubation, hole, and delisting periods are the average number of bias-free return months per fund that can be augmented using our seven-database aggregate (measured across all funds). Table 3 defines these periods more precisely. Pre- and post-augmented reporting periods are the average number of reported bias-free returns per fund, before and after augmenting the incubation, hole, and delisting returns. We require the inception and liquidation dates to be within 1994 to 2016, and drop all funds where liquidation date exceeds inception date.

Interpretation: For the average fund, our aggregation procedure can get us 11.28 (TASS), 15.33 (HFR), and 27.30 (eVestment) percentage points closer to the true lifespan coverage of bias-free returns. Most of the remaining unobserved returns are incubation returns, not delisting returns.

	TASS	Eureka	eVestment
Total funds	4,618	3,506	3,792
True fund lifespan	65.09	66.01	76.97
True incubation period	24.03	28.66	43.61
True delisting period	2.69	2.32	4.85
Augmented incubation period	6.30	9.28	19.38
Augmented hole period	0.05	0.01	0.03
Augmented delisting period	0.99	0.82	1.61
Pre-augmented reporting period	39.29	36.00	29.52
% of true lifespan	60.37	54.54	38.36
Post-augmented reporting period	46.64	46.12	50.54
% of true lifespan	71.65	69.87	65.66

Table 5: Correcting reporting errors

Description: This table shows how our database aggregation procedure adds value by correcting reporting errors in individual databases. The fund data are as in Table 3. The table shows how many (and what percentage of) funds contain each of three types of reporting errors. "Wrong sign" is triggered if a return observation is the exact negation of the respective return in the AGG7 database (i.e., our seven-database aggregation), after rounding to basis points, and after removing zero returns post-rounding. "Diff > 1%" is triggered if a return differs from its respective AGG7 return by more than 1% p.m. "Diff > 1bp" is triggered if a return differs from its respective AGG7 return after rounding to basis points.

Interpretation: Individual databases contain return deviations, including accidentally reversed return signs. These problems are mitigated in the AGG3 database, suggesting that our median-based return aggregation rule can correct reporting errors.

	TASS	HFR	Barclay	Eureka	Preqin	eVest	AGG3
Total funds	7,821	10,839	11,730	8,922	3,112	7,038	18,536
Wrong sign (funds)	216	185	174	127	54	127	98
% of total	2.76	1.71	1.48	1.42	1.74	1.80	0.53
Diff > 1% (funds)	2,167	2,173	1,974	5,426	501	1,460	2,256
% of total	27.71	20.05	16.83	60.82	16.10	20.74	12.17
Diff > 1bp (funds)	4,851	6,616	6,161	1,769	1,756	4,186	7455
% of total	62.03	61.04	52.52	19.83	56.43	59.48	40.22

Table 6: Augmenting fund characteristics

Description: This table shows how our database aggregation procedure adds value by augmenting missing fund characteristics in individual databases. We also show results for the AGG3 database defined as the aggregation of TASS, HFR, and BarclayHedge. To aggregate fund characteristics at the fund level, we use the median across database duplicates for continuous variables (lockup, notice, and redemption periods; management and incentive fees), and most common value across database duplicates for categorical variables (high-water mark dummy). In Panel A, "Pre-augmentation" shows what percentage of the characteristic is covered in the original database; "Augmentable" the percentage that is missing in the original database but can be augmented using database aggregation; and "Post-augmentation" is the sum of "Pre-augmentation" and "Augmentable". Panel B shows the summary statistics *before* augmentation, including percentage missing ("% Miss"). Panel C shows the first year that the attrition rate normalizes (to levels in other databases) for each database-characteristic pair, restricted to funds with a non-missing characteristic. "Reference year" gives the first regular attrition year deduced from Table 2, where funds are not restricted.

Interpretation: A large proportion of fund characteristics not found in individual databases can be augmented from the remaining databases. The characteristic distributions are similar between well-covered databases. BarclayHedge and eVestment did not collect all characteristics in their early years, but the resulting survivorship bias is mitigated by database aggregation, and the remainder is eliminated via our listing date-based backfill correction.

Panel A: Characteristics coverage before and after augmentation

Characteristic	Coverage (%)	TASS N=8,026	HFR N=11,166	Barclay N=11,826	Eureka N = 9,254	Morningstar N = 6,478	Preqin N=5,241	eVestment N=10,317	AGG3 N=18,998
	Pre-augmentation	100.0	95.5	83.5	98.0	59.2	16.9	26.3	92.5
Lockup (years)	Augmentable	0.0	2.6	7.2	1.4	21.9	64.0	57.6	0.6
	Post-augmentation	100.0	98.1	90.7	99.3	81.0	80.8	83.9	93.2
	Pre-augmentation	100.0	95.6	100.0	93.3	61.9	59.5	22.5	98.7
Notice (months)	Augmentable	0.0	2.5	0.0	4.5	15.7	28.1	61.1	0.1
	Post-augmentation	100.0	98.1	100.0	97.8	77.6	87.6	83.6	98.9
	Pre-augmentation	81.9	97.8	75.4	97.6	67.3	73.3	89.5	84.2
Redemption (months)	Augmentable	4.6	0.6	10.2	1.2	12.4	18.5	6.4	2.4
	Post-augmentation	86.4	98.4	85.6	98.8	79.7	91.8	95.9	86.6
	Pre-augmentation	99.0	99.1	100.0	99.0	88.7	88.0	93.7	99.3
Management fee (%)	Augmentable	0.2	0.3	0.0	0.6	4.3	8.6	3.7	0.0
	Post-augmentation	99.3	99.4	100.0	99.7	93.0	96.6	97.4	99.3
	Pre-augmentation	95.3	98.4	100.0	99.0	84.2	85.2	91.6	97.6
Incentive fee (%)	Augmentable	0.9	0.6	0.0	0.6	3.2	9.6	5.2	0.2
	Post-augmentation	96.2	99.0	100.0	99.5	87.4	94.8	96.8	97.8
	Pre-augmentation	99.0	100.0	99.9	98.4	74.1	68.0	19.5	99.6
High-water mark (?)	Augmentable	0.2	0.0	0.0	0.9	8.4	21.8	64.7	0.0
	Post-augmentation	99.2	100.0	100.0	99.2	82.5	89.8	84.1	99.7

Panel B: Summary statistics before augmentation

	Lockup (years)			Notice (months)			Redemption (months)			Management fee (%)			Incentive fee (%)			High-water mark?	
Database	Mean	Median	% Miss	Mean	Median	% Miss	Mean	Median	% Miss	Mean	Median	% Miss	Mean	Median	% Miss	Mean	% Miss
TASS	0.22	0.00	0.0	0.85	0.69	0.0	1.92	1.00	18.1	1.55	1.50	1.0	17.4	20.0	4.7	0.57	1.0
HFR	0.27	0.00	4.5	1.08	0.99	4.4	1.83	1.00	2.2	1.51	1.50	0.9	18.0	20.0	1.6	0.87	0.0
BarclayHedge	0.26	0.00	16.5	0.81	0.46	0.0	1.99	1.00	24.6	1.56	1.50	0.0	18.0	20.0	0.0	0.60	0.1
EurekaHedge	0.17	0.00	2.0	1.03	0.99	6.7	1.35	1.00	2.4	1.53	1.50	1.0	17.7	20.0	1.0	0.83	1.6
Morningstar	0.44	0.00	40.8	1.24	0.99	38.1	1.94	1.00	32.7	1.51	1.50	11.3	18.7	20.0	15.8	0.87	25.9
Preqin	1.01	1.00	83.1	1.13	0.99	40.5	1.35	1.00	26.7	1.52	1.50	12.0	18.5	20.0	14.8	0.96	32.0
eVestment	0.71	1.00	73.7	1.34	1.00	77.5	1.92	1.00	10.5	1.52	1.50	6.3	18.6	20.0	8.4	0.69	80.5
AGG3	0.23	0.00	7.5	0.82	0.49	1.3	1.81	1.00	15.8	1.53	1.50	0.7	17.2	20.0	2.4	0.64	0.4
AGG7	0.25	0.00	19.1	0.85	0.51	15.4	1.66	1.00	17.5	1.51	1.50	3.9	17.2	20.0	7.0	0.68	12.8

Panel C: Year of first regular attrition for funds with a non-missing characteristic

Characteristic	TASS	HFR	Barclay	Eureka	Morningstar	Preqin	eVestment
Lockup (years)	1995	1995	2000	2004	2006	2013	2000
Notice (months)	1995	1995	1995	2004	2006	2013	2013
Redemption (months)	1995	1995	2000	2004	2006	2013	2000
Management fee (%)	1995	1995	1995	2004	2006	2013	2000
Incentive fee (%)	1995	1995	1995	2004	2006	2013	2000
High-water mark (?)	1995	1995	1995	2004	2006	2013	2000
Reference year	1995	1995	1995	2004	2006	2013	2000

Table 7: Average performance between databases

Description: This table shows the average performance between databases. We remove backfilled returns and form an equal-weighted (EW) portfolio of monthly net-of-fees returns for each database, including aggregates (AGG3, AGG7). Panel A arithmetically averages the monthly returns for each year 1994 to 2016, and finally shows the average of the annual returns. Panel B calculates the average of monthly returns for the 1995 to 2016 period and tests them against AGG7.

Interpretation: The average return in individual databases is higher than in aggregate databases, suggesting that databases differ in their coverage of under-performing funds.

Panel A: Annual average returns 1994 to 2016

	Individual databases							Aggregate databases			
	TASS		HFR		BarclayHedge			AGG3		AGG7	
Year	Funds	Return	Funds	Return	Funds	Return	Year	Funds	Return	Funds	Return
1994	259	0.98			435	1.47	1994	538	0.73	538	0.73
1995	366	10.14	76	10.69	461	7.73	1995	662	8.58	662	8.59
1996	787	10.91	838	15.70	830	10.22	1996	1,441	9.72	1,442	9.74
1997	887	13.07	921	14.06	872	13.44	1997	1,512	11.78	1,515	11.75
1998	986	2.46	956	3.41	966	5.59	1998	1,584	2.54	1,590	2.61
1999	1,026	18.24	991	25.03	997	19.76	1999	1,547	18.55	1,560	18.64
2000	1,054	4.84	1,019	3.90	1,101	7.00	2000	1,549	3.61	1,572	3.56
2001	1,254	3.26	1,198	4.04	1,365	3.98	2001	1,815	2.81	1,840	2.82
2002	1,381	2.99	1,439	0.68	1,387	3.42	2002	2,011	2.12	2,045	1.98
2003	1,561	18.57	1,632	19.20	1,600	17.87	2003	2,302	17.60	2,349	17.66
2004	2,073	8.74	2,343	8.49	2,259	8.62	2004	3,204	8.21	3,623	8.18
2005	2,172	7.10	2,639	7.46	2,451	7.30	2005	3,513	6.87	3,890	7.20
2006	2,288	13.51	2,939	12.61	2,634	12.42	2006	3,869	12.53	4,294	12.42
2007	2,323	12.76	3,176	11.66	2,810	11.75	2007	4,172	11.64	4,784	11.57
2008	2,316	−20.30	3,013	−20.78	2,655	−17.85	2008	4,193	−20.83	4,996	−22.22
2009	2,351	21.83	3,097	21.22	2,849	19.86	2009	4,362	20.42	5,310	21.21
2010	2,611	10.53	3,327	10.32	3,078	10.31	2010	4,981	9.90	6,030	10.00
2011	2,483	−5.11	3,414	−5.33	3,123	−5.10	2011	5,127	−5.42	6,309	−5.84
2012	2,260	6.10	3,427	7.00	3,118	6.62	2012	5,201	6.22	6,435	6.36
2013	2,011	5.74	3,488	8.82	3,137	8.16	2013	5,208	7.14	6,615	6.83
2014	1,858	−0.90	3,567	0.85	3,239	0.96	2014	5,334	0.01	6,943	−0.42
2015	1,626	−6.72	3,449	−2.89	3,193	−2.14	2015	5,328	−4.34	7,054	−4.60
2016	1,306	8.59	3,198	4.87	3,054	4.41	2016	5,027	5.49	6,746	5.49
Average		6.40		7.32		6.77	Average		5.91		5.84

Panel B: Average returns 1995 to 2016

	TASS		HFR		BarclayHedge		AGG3		AGG7	
	% p.a.	*t*-stat.	% p.a.	*t*-stat.	% p.a.	*t*-stat.	% p.a.	*t*-stat.	% p.a.	*t*-stat.
Average return	6.65		7.32		7.01		6.14		6.07	
vs. AGG7	0.58	(2.80)	1.25	(3.03)	0.94	(4.05)	0.07	(1.28)		

Table 8: Risk-adjusted performance

Description: This table shows the risk-adjusted performance in our bias-free seven-database aggregate over the full 1995 to 2016 period as well as the two subperiods 1995 to 2005 and 2006 to 2016. Panel A shows results for net-of-fees returns, and Panel B for gross-of-fees returns imputed using the algorithm of Feng (2011). We calculate both equal-weighted (EW) and value-weighted (VW) returns, where VW returns are weighted by one-month-lagged assets under management (AUM). We regress each return index on a number of factors, and present the intercept (i.e., alpha) in annualized percentage terms. We use two sets of factors: the seven-factor Fung-Hsieh (2004) benchmark ("FH7"), and an alternative seven-factor global Carhart (1997) benchmark ("GLOB7") augmented with a time-series momentum factor (Moskowitz, Ooi, and Pedersen 2012) as well as the Pastor-Stambaugh (2003) liquidity risk factor and betting-against-beta factor (Frazzini and Pedersen 2014). The factors are explained in detail in Table 9, which presents the factor loadings.

Interpretation: In all periods and under both benchmarks, the hedge fund industry produces positive alpha only before fees, but not after fees. Compared to the Fung-Hsieh benchmark, the alternative global benchmark consistently yields a lower level of alpha.

Panel A: Net-of-fees returns

		Excess return		FH7		GLOB7	
		EW	VW	EW	VW	EW	VW
1995–2016	Return (% p.a.)	3.678	4.367	−0.016	1.072	−0.799	−0.370
	t-statistic	(2.51)	(3.25)	(−0.02)	(1.11)	(−1.14)	(−0.47)
1995–2005	Return (% p.a.)	4.680	5.553	1.182	1.769	−0.506	−0.932
	t-statistic	(2.69)	(2.87)	(1.24)	(1.33)	(−0.46)	(−0.66)
2006–2016	Return (% p.a.)	2.675	3.182	−1.041	0.442	−1.109	−0.862
	t-statistic	(1.13)	(1.70)	(−0.78)	(0.34)	(−1.39)	(−1.04)

Panel B: Gross-of-fees returns

		Excess return		FH7		GLOB7	
		EW	VW	EW	VW	EW	VW
1995–2016	Return (% p.a.)	8.394	7.865	4.470	4.493	3.605	3.109
	t-statistic	(5.29)	(5.48)	(4.66)	(4.31)	(4.72)	(3.71)
1995–2005	Return (% p.a.)	10.520	9.459	6.612	5.521	5.002	2.918
	t-statistic	(5.34)	(4.44)	(6.15)	(3.90)	(3.97)	(1.96)
2006–2016	Return (% p.a.)	6.268	6.270	2.413	3.522	2.169	1.995
	t-statistic	(2.52)	(3.26)	(1.68)	(2.51)	(2.56)	(2.21)

Table 9: Factor loadings

Description: This table presents benchmark model coefficients in our bias-free seven-database aggregate from 1995 through 2016. Following the methodology of Table 8, we construct equal-weighted (EW) and value-weighted (VW) net-of-fees return indices. To gauge the relative importance of each factor, we first regress the return indices on each individual factor (plus market factor), and finally on the full set of factors. We present the intercept (i.e., alpha) in annualized percentage terms, and the factor loadings as-is. We use two sets of factors. The first set is the seven-factor Fung-Hsieh (2004) benchmark consisting of: the excess return on the S&P 500 index (SP); the return spread between the Russell 2000 index and the S&P 500 index (SCLC); the excess return on ten-year Treasuries (CGS10); the return on Moody's BAA corporate bonds minus 10-year Treasuries (CREDSPR); and the excess returns of look-back straddles on bonds (PTFSBD), currencies (PTFSFX), and commodities (PTFSCOM).[18] The second set is a global seven-factor benchmark consisting of: global equity market excess return (Market), size factor (SMB), and value factor (HML) of Fama and French (2012); global cross-sectional momentum (MOM) of Asness, Moskowitz, and Pedersen (2013); global time-series momentum (TSMOM) of Moskowitz, Ooi, and Pedersen (2012); global betting-against-beta (BAB) of Frazzini and Pedersen (2014); and liquidity risk (P-S Liq.) of Pastor and Stambaugh (2003).[19] As a risk-free rate we use the return on 1-month T-bills.[20] The coefficient *t*-statistics are shown in parentheses.

Interpretation: For the FH benchmark, the simple CAPM results in a statistically insignificant EW alpha, but no individual factor eliminates the statistical significance of the VW alpha. For the global benchmark, only the cross-sectional momentum, time-series momentum, and betting-against-beta factors individually eliminate the statistical significance of both the EW and VW alpha. Compared to the Fung-Hsieh benchmark, the alternative global benchmark consistently yields a higher adjusted R-squared.

[18] We obtain data for equity and bond oriented factors from Datastream, and trend-following factors from David Hsieh's website.
[19] We download the factor returns from their authors' websites.
[20] Provided by Ibbotson and Associates Inc., downloaded from Kenneth French's website.

Panel A: Net-of-fees EW returns

Alpha	1.045	1.010	1.023	0.652	0.951	1.012	1.013	−0.016	Alpha	1.379	1.343	1.431	0.678	0.245	0.082	1.179	−0.799
(% p.a.)	(1.02)	(1.07)	(0.98)	(0.69)	(0.92)	(0.99)	(0.99)	(−0.02)	(% p.a.)	(1.77)	(1.94)	(1.81)	(0.90)	(0.31)	(0.10)	(1.51)	(−1.14)
SP	0.334	0.323	0.335	0.276	0.329	0.343	0.338	0.285	Market	0.387	0.384	0.386	0.404	0.395	0.409	0.380	0.404
	(16.91)	(17.73)	(16.46)	(13.64)	(16.19)	(17.05)	(16.87)	(15.32)		(26.04)	(29.09)	(25.56)	(27.90)	(27.34)	(27.61)	(25.14)	(30.55)
SCLC		0.166						0.147	SMB		0.229						0.222
		(7.02)						(6.66)			(8.38)						(8.42)
CGS10			0.005					0.093	HML			−0.011					0.018
			(0.12)					(2.61)				(−0.41)					(0.65)
CREDSPR				0.294				0.293	MOM				0.147				0.029
				(6.76)				(7.16)					(5.37)				(0.85)
PTFSBD					−0.006			−0.010	TSMOM					0.078			0.068
					(−1.10)			(−1.82)						(4.51)			(3.54)
PTFSFX						0.009		0.013	BAB						0.114		0.070
						(2.00)		(3.19)							(5.14)		(3.08)
PTFSCOM							0.007	0.007	P-S Liq.							0.040	0.029
							(1.20)	(1.26)								(2.22)	(1.96)
Adj R2	0.520	0.595	0.518	0.590	0.520	0.525	0.521	0.668	Adj R2	0.720	0.779	0.719	0.747	0.740	0.745	0.724	0.816

Panel B: Net-of-fees VW returns

Alpha	2.246	2.217	2.041	1.980	2.113	2.212	2.203	1.072	Alpha	2.500	2.471	2.757	1.266	0.395	1.105	2.324	−0.370
(% p.a.)	(2.13)	(2.23)	(1.91)	(1.94)	(2.01)	(2.11)	(2.10)	(1.11)	(% p.a.)	(2.80)	(2.93)	(3.06)	(1.60)	(0.47)	(1.22)	(2.60)	(−0.47)
SP	0.269	0.260	0.275	0.230	0.262	0.278	0.275	0.239	Market	0.314	0.312	0.309	0.344	0.329	0.338	0.308	0.344
	(13.31)	(13.54)	(13.21)	(10.59)	(12.61)	(13.50)	(13.42)	(11.70)		(18.51)	(19.44)	(18.01)	(22.56)	(21.35)	(19.85)	(17.77)	(23.18)
SCLC		0.141						0.132	SMB		0.188						0.164
		(5.65)						(5.47)			(5.65)						(5.57)
CGS10			0.045					0.127	HML			−0.055					−0.008
			(1.09)					(3.22)				(−1.78)					(−0.26)
CREDSPR				0.199				0.203	MOM				0.259				0.110
				(4.26)				(4.52)					(8.96)				(2.92)
PTFSBD					−0.009			−0.015	TSMOM					0.145			0.099
					(−1.53)			(−2.61)						(7.85)			(4.61)
PTFSFX						0.009		0.012	BAB						0.123		0.071
						(1.99)		(2.60)							(4.81)		(2.80)
PTFSCOM							0.010	0.009	P-S Liq.							0.035	0.023
							(1.59)	(1.62)								(1.70)	(1.37)
Adj R2	0.401	0.464	0.401	0.438	0.404	0.408	0.405	0.525	Adj R2	0.565	0.611	0.569	0.666	0.647	0.599	0.568	0.725

Table 10: Univariate determinants of performance

Description: This table shows how risk-adjusted performance varies along fund characteristics. The risk-adjustment procedure follows Table 8. To ensure enough coverage in all portfolios, the sample ranges from 1997 through 2016. Panels A and B show the equal-weighted (EW) and value-weighted (VW) net-of-fees returns. FH7 and GLOB7 refer to the Fung-Hsieh and global benchmarks. To aggregate characteristics at the fund level, we use the median value across database duplicates for continuous variables (notice period, incentive fee), and most common value across database duplicates for dummy variables (lockup and high-water mark). "Funds" shows the number of funds in the AGG7 database.

Interpretation: Consistent with literature, all four characteristics are generally associated with higher risk-adjusted performance. The results are most robust for AGG7, and stronger against the global benchmark.

Panel A: Net-of-fees EW returns

Lockup period

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
No lockup used	16,241	0.27	1.03	2.27	0.04	−1.10	0.11	1.04	−1.35
Lockup used	5,185	3.60	2.62	2.88	2.22	3.22	3.35	3.36	2.97
Spread		3.33	1.59	0.61	2.18	4.32	3.24	2.32	4.32
t-statistic		(4.64)	(2.88)	(1.19)	(2.85)	(5.29)	(5.63)	(4.02)	(5.64)

Notice period

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
One day or less	6,825	−1.54	−0.02	0.48	−1.35	−3.90	−2.65	−2.51	−4.33
From 2 to 20 days	4,981	0.14	0.51	1.58	−0.65	−2.43	−1.16	0.50	−2.20
30 days	5,075	2.05	1.22	2.28	1.07	1.72	1.39	1.73	1.07
From 31 to 60 days	2,023	3.27	2.72	3.54	2.67	3.03	3.30	4.20	2.99
60 days	1,558	2.79	2.17	3.17	1.63	2.64	2.46	3.54	1.77
More than 60 days	1,908	4.42	3.70	4.56	3.45	3.24	3.17	4.19	2.87
Spread		5.95	3.72	4.08	4.81	7.13	5.82	6.71	7.20
t-statistic		(4.35)	(3.88)	(3.47)	(3.92)	(4.72)	(5.87)	(5.19)	(5.56)

Incentive fee

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
No incentive fee	2,690	−1.81	−1.39	−1.31	−2.35	−2.58	−1.58	−1.92	−3.31
Less than 20%	3,665	−0.28	0.45	0.55	−1.00	−1.52	−0.06	−1.07	−2.16
20% or more	18,214	1.72	1.65	2.22	0.98	0.38	1.13	0.88	−0.09
Spread		3.54	3.04	3.53	3.33	2.95	2.71	2.80	3.22
t-statistic		(2.95)	(5.08)	(4.39)	(4.42)	(2.46)	(4.55)	(3.75)	(4.57)

High-water mark

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
HWM not used	7,492	−0.96	−0.73	0.73	−1.67	−2.09	−1.40	−0.88	−3.12
HWM used	15,567	3.12	1.58	2.93	1.58	1.84	1.13	2.23	0.94
Spread		4.08	2.31	2.19	3.25	3.93	2.53	3.10	4.06
t-statistic		(4.43)	(5.34)	(2.84)	(4.31)	(3.92)	(5.86)	(3.49)	(4.95)

Panel B: Net-of-fees VW returns

Lockup period

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
No lockup used	16,241	1.30	1.52	2.41	1.00	−1.04	−0.06	−0.07	−1.02
Lockup used	5,185	2.73	2.33	1.65	2.07	2.45	2.93	1.37	2.35
Spread		1.42	0.81	−0.76	1.07	3.49	2.99	1.45	3.37
t-statistic		(1.47)	(1.18)	(−0.81)	(1.30)	(3.59)	(4.52)	(1.50)	(4.25)

Notice period

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
One day or less	6,825	−0.50	−0.48	2.00	−0.26	−4.93	−3.17	−1.32	−3.31
From 2 to 20 days	4,981	1.03	1.40	1.58	1.10	−2.25	−0.52	−2.16	−1.73
30 days	5,075	1.52	1.54	0.76	0.90	0.59	0.64	−1.11	0.13
From 31 to 60 days	2,023	3.18	1.52	2.86	2.67	2.27	1.93	2.90	2.50
60 days	1,558	3.14	1.68	2.90	1.28	3.93	1.73	1.94	0.62
More than 60 days	1,908	4.54	4.19	4.05	3.75	2.85	2.90	2.63	2.28
Spread		5.05	4.67	2.05	4.01	7.78	6.06	3.95	5.59
t-statistic		(3.29)	(4.56)	(1.71)	(3.54)	(4.88)	(5.98)	(3.01)	(4.88)

Incentive fee

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
No incentive fee	2,690	−0.87	−0.87	−0.86	−1.43	−3.67	−1.51	−3.45	−3.47
Less than 20%	3,665	0.66	0.83	0.11	0.01	−0.61	−1.40	−1.46	−1.58
20% or more	18,214	2.08	2.06	2.42	1.70	0.22	0.94	0.10	0.16
Spread		2.95	2.92	3.28	3.13	3.89	2.45	3.55	3.63
t-statistic		(1.70)	(2.84)	(2.74)	(2.76)	(2.19)	(2.21)	(3.10)	(3.29)

High-water mark

		FH7				GLOB7			
	Funds	TASS	HFR	Barclay	AGG7	TASS	HFR	Barclay	AGG7
HWM not used	7,492	−1.17	−0.21	1.56	−1.01	−3.05	−0.63	−0.17	−2.42
HWM used	15,567	2.79	2.01	2.18	1.71	1.16	0.83	0.15	0.35
Spread		3.96	2.22	0.62	2.71	4.20	1.46	0.32	2.77
t-statistic		(3.47)	(2.93)	(0.77)	(2.99)	(3.47)	(1.79)	(0.36)	(3.04)

Table 11: Persistence regressions

Description: This table shows Fama-MacBeth (1973) regressions of annual performance persistence in three individual databases (TASS, HFR, BarclayHedge) and our seven-database aggregate (AGG7). For each fund with minimum 24 months of bias-free returns we estimate its full-sample Fung-Hsieh regression, and aggregate the resulting monthly alphas (i.e., intercept plus residual) into annual alphas using geometric compounding (requiring full 12 non-missing monthly alphas). These annual alphas serve as our main dependent and independent variables. We winsorize annual fund flow at 5% and 95% levels within each year. We measure fund age as years since inception. Each regression (t = 1996,...,2015) includes domicile and style fixed effects, and standard errors (t-statistics shown in parentheses) are adjusted for heteroskedasticity and autocorrelation. To aggregate control variables at the fund level, we use the median value across database duplicates for continuous variables (inception date; lockup, notice, and redemption periods; management and incentive fees), and most common value across database duplicates for categorical variables (high-water mark dummy, domicile, and style).

Interpretation: The coefficient on past alpha is consistently positive and highly significant, confirming the persistence of performance observed in portfolio sorts. The coefficients on fund characteristics are most consistent in the aggregate database.

	Dependent variable: Alpha(t+1) (%)			
	TASS	HFR	BarclayHedge	AGG7
Alpha(t) (%)	0.161	0.190	0.167	0.189
	(5.00)	(5.10)	(3.14)	(4.74)
log(AUM(t))	−0.000	−0.004	−0.010	−0.002
	(−0.18)	(−2.66)	(−1.95)	(−1.71)
Flow(t) (%)	−0.009	−0.006	−0.007	−0.009
	(−2.56)	(−1.66)	(−2.32)	(−3.33)
Age(t) (years)	−0.001	−0.001	−0.000	−0.001
	(−1.91)	(−2.26)	(−0.27)	(−1.67)
Lockup (years)	0.007	0.003	−0.001	0.002
	(1.22)	(0.62)	(−0.39)	(0.49)
Notice (months)	0.082	0.042	0.038	0.099
	(1.52)	(1.02)	(0.81)	(3.08)
Redemption (months)	−0.004	0.009	−0.010	0.001
	(−0.73)	(1.48)	(−0.76)	(0.14)
Management fee (%)	0.865	0.376	1.791	0.540
	(1.98)	(0.90)	(1.67)	(2.04)
Incentive fee (%)	0.130	0.104	0.126	0.044
	(2.51)	(2.00)	(1.72)	(1.34)
High-water mark?	0.013	0.002	0.005	0.021
	(1.52)	(0.23)	(0.83)	(3.71)
Adjusted R-squared	0.128	0.117	0.139	0.129
Number of observations	15,944	26,764	21,167	42,900

Table 12: Post-attrition persistence

Description: This table shows the connection between pre-attrition performance rank and post-attrition performance. To gauge post-attrition performance, we use the approach of Aiken, Clifford, and Ellis (2013) to impute fund returns from fund of funds (FOF) holdings. For each fund, we identify its last return-reporting quarter in our aggregate database, termed attrition quarter. We measure pre-attrition performance rank by the 24-month FH7 alpha *t*-statistic quantile calculated in the quarter before the attrition quarter, using bias-free net-of-fees returns. We measure post-attrition performance as the FOF-based fund return on the quarter following the attrition quarter. We identify 37 funds where both data are available. Panel A sorts funds into quintiles based on their pre-attrition performance quantile, and shows the subsequent post-attrition performance. It also shows what percentage of funds impose discretionary liquidity restrictions (DLRs) on the subsequent quarter. Panel B regresses post-attrition return and DLR indicator on the pre-attrition performance quintile (fractional rank), using heteroskedasticity-robust standard errors (White). To control for industry, we subtract the equal-weighted average FOF-based return (or DLR). To control for style, we subtract this average within the same fund style.

Interpretation: Performance persists even after funds stop reporting to databases. However, observing such post-attrition returns is very rare, especially for poorly performing (and thus likely liquidated) funds. This suggests that delisting bias may not be a significant issue for our aggregate database.

Panel A: Post-attrition performance sorts

		Return (% p.q.)			DLR (%)		
Rank	Funds	Excess of risk-free	Excess of industry	Excess of style	Raw	Excess of industry	Excess of style
5	18	2.7	1.8	1.7	5.6	−10.2	−9.6
4	6	2.1	−0.1	0.5	16.7	−3.2	4.9
3	3	−4.8	−3.2	−1.2	0.0	−16.8	−19.0
2	3	−11.8	−9.2	−7.4	0.0	−15.2	−17.5
1	7	−3.0	−2.4	−1.2	71.4	51.7	37.2
5−1		−5.8	−2.3	−1.7	54.8	54.9	32.3

Panel B: Post-attrition performance regressions

	Return (p.q.)			DLR (indicator)		
	Excess of risk-free	Excess of industry	Excess of style	Raw	Excess of industry	Excess of style
Fractional rank	0.094	0.070	0.053	−0.593	−0.551	−0.391
	(2.82)	(2.85)	(2.70)	(−2.68)	(−2.66)	(−2.42)
Intercept	−0.063	−0.051	−0.034	0.570	0.371	0.253
	(−2.16)	(−2.48)	(−2.20)	(3.18)	(2.23)	(2.02)
Adj R2	0.203	0.190	0.171	0.245	0.227	0.139
Observations	37	37	37	37	37	37

Table A1: Usage of commercial databases

Description: This table lists the academic research papers that use commercial hedge fund databases. Our list includes 116 papers. We consider five important financial economics journals: *Journal of Finance* (JF); *Journal of Financial Economics* (JFE); *Review of Financial Studies* (RFS); *Journal of Financial & Quantitative Analysis* (JFQA); and *Financial Analysts Journal* (FAJ). The letters in the fifth "Database" column indicate the following databases, which are used in the papers: B = BarclayHedge; Bg = Bloomberg; E = EurekaHedge; H = Hedge Fund Research (HFR); M = Morningstar (or some of the databases which were acquired by Morningstar including CISDM, MAR, Altvest, and MSCI Barra's hedge fund database); T = Lipper TASS (including its earlier versions like Tremont TASS); and eV = eVestment (including its earlier versions like HedgeFund.net).

Interpretation: The databases are used at different frequencies: 79% of papers use TASS; 40% use HFR; 38% use Morningstar; 10% use BarclayHedge; and 7% use EurekaHedge. Bloomberg and eVestment are both used in just a single paper, and Preqin is not used in any paper. A combination of at least three databases is used in 21% of papers. The maximum number of combined databases is five, used in 3% of papers.

Authors	Title	Journal	Year	Database
Ackermann C, McEnally R & Ravenscraft D	The performance of hedge funds: Risk, return, and incentives	JF	1999	T
Agarwal V, Arisoy E & Naik NY	Volatility of aggregate volatility and hedge fund returns	JFE	2017	E,H,M,T
Agarwal V, Boyson N & Naik NY	Multi-period performance persistence analysis of hedge funds	JFQA	2000	H
Agarwal V, Daniel ND & Naik NY	Do hedge funds manage their reported returns?	RFS	2011	E,H,M,T
Agarwal V, Daniel ND & Naik NY	Role of managerial incentives and discretion in hedge fund performance	JF	2009	H,M,T
Agarwal V, Green C & Ren H	Alpha or beta in the eye of the beholder: What drives hedge fund flows?	JFE	2018	E,H,M,T
Agarwal V & Naik NY	Hedge funds for retail investors? An examination of hedged mutual funds	JFQA	2009	M,T
Agarwal V & Naik NY	Risk and portfolio decisions involving hedge funds	RFS	2004	H,T
Agarwal V, Ruenzi S & Weigert F	Tail risk in hedge funds: A unique view from portfolio holdings	JFE	2017	E,H,M,T
Aggarwal RK & Jorion P	Hidden survivorship bias in hedge fund returns	FAJ	2010	T
Aggarwal RK & Jorion P	The performance of emerging hedge funds and managers	JFE	2010	T
Ahoniemi K & Jylhä P	Flows, price pressure, and hedge fund returns	FAJ	2014	T
Aiken AL, Clifford CP & Ellis JA	Out of the dark: hedge fund reporting biases and commercial databases	RFS	2013	B,H,T
Aiken AL, Clifford CP & Ellis JA	Hedge funds and discretionary liquidity restrictions	JFE	2015	B,E,H,M,T
Amenc N, El Bied S & Martellini L	Predictability in hedge fund returns	FAJ	2003	H
Amin GS & Kat HM	Hedge fund performance 1990-2000: Do the "money machines" really add value?	JFQA	2003	M

Ang A, Gorovyy S & van Inwegen GB	Hedge fund leverage	JFE	2011	B,H,M,T
Aragon GO	Share restrictions and asset pricing: Evidence from the hedge fund industry	JFE	2007	T
Aragon GO, Hertzel M & Shi Z	Why do hedge funds avoid disclosure? Evidence from confidential 13F filings	JFQA	2012	T
Aragon GO & Nanda V	Strategic delays and clustering in hedge fund reported returns	JFQA	2014	T
Aragon GO & Martin JS	A unique view of hedge fund derivatives usage: Safeguard or speculation?	JFE	2012	T
Aragon GO & Strahan PE	Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy	JFE	2012	T
Avramov D, Barras L & Kosowski R	Hedge fund return predictability under the magnifying glass	JFQA	2013	B,H,T
Avramov D, Kosowski R, Naik NY & Teo M	Hedge funds, managerial skill, and macroeconomic variables	JFE	2011	H,M,T
Bali TG, Brown SJ & Caglayan MO	Do hedge funds' exposures to risk factors predict their future returns?	JFE	2011	T
Bali TG, Brown SJ & Caglayan MO	Systematic risk and the cross section of hedge fund returns	JFE	2012	T
Bali TG, Brown SJ & Caglayan MO	Macroeconomic risk and hedge fund returns	JFE	2014	T
Baquero G, ter Horst J & Verbeek M	Survival, look-ahead bias, and the persistence in hedge fund performance	JFQA	2005	T
Ben-David I, Franzoni F, Landier A & Moussawi R	Do hedge funds manipulate stock prices?	JF	2013	T
Ben-David I, Franzoni F & Moussawi R	Hedge fund stock trading in the financial crisis of 2007–2009	RFS	2012	T
Bhardwaj G, Gorton G & Rouwenhorst K	Fooling some of the people all of the time: The inefficient performance and persistence of commodity trading advisors	RFS	2014	T
Bollen NPB	Zero-R2 hedge funds and market neutrality	JFQA	2013	M,T
Bollen NPB & Pool VK	Suspicious patterns in hedge fund returns and the risk of fraud	RFS	2012	M,T
Bollen NPB & Pool VK	Conditional return smoothing in the hedge fund industry	JFQA	2008	M
Bollen NPB & Pool VK	Do hedge fund managers misreport returns? Evidence from the pooled distribution	JF	2009	M
Bollen NPB & Whaley RE	Hedge fund risk dynamics: Implications for performance appraisal	JF	2009	M,T
Boyson NM	Hedge fund performance persistence: A new approach	FAJ	2008	T
Boyson NM, Stahel CW & Stulz RM	Hedge fund contagion and liquidity shocks	JF	2010	H
Buraschi A, Kosowski R & Sritrakul W	Incentives and endogenous risk taking: A structural view on hedge fund alphas	JF	2014	B
Buraschi A, Kosowski R & Trojani F	When there is no place to hide: Correlation risk and the cross-section of hedge fund returns	RFS	2013	B
Brandon R & Wang S	Liquidity risk, return predictability, and hedge funds' performance: An empirical study	JFQA	2013	T
Brav A, Jiang W, Partnoy F & Thomas RS	The returns to hedge fund activism	FAJ	2008	M,eV
Brown SJ, Goetzmann WN, Liang B & Schwarz C	Estimating operational risk for hedge funds: The ω-score	FAJ	2009	T
Brown SJ, Goetzmann WN, Liang B & Schwarz C	Trust and delegation	JFE	2012	M,T
Brown SJ, Goetzmann WN, Liang B & Schwarz C	Mandatory disclosure and operational risk: Evidence from hedge fund registration	JF	2008	T
Brown SJ, Goetzmann WN & Park J	Careers and survival: Competition and risk in the hedge fund and CTA industry	JF	2001	M,T
Brown SJ, Grundy BD, Lewis CM & Verwijmeren P	Convertibles and hedge funds as distributors of equity exposure	RFS	2012	T
Brunnermeier MK & Nagel S	Hedge funds and the technology bubble	JF	2004	H
Cao C, Chen Y, Goetzmann W & Liang B	Hedge fund and stock price formation	FAJ	2018	H
Cao C, Chen Y, Liang B & Lo A	Can hedge funds time market liquidity?	JFE	2013	T
Cao C, Goldie B, Liang B & Petrasek L	What is the nature of hedge fund manager skills? Evidence from the risk-arbitrage strategy	JFQA	2016	B,Bg,H,M,T
Carhart M, Cheah U & Santis G	Exotic beta revisited	FAJ	2014	H
Cassar G & Gerakos J	Hedge funds: Pricing controls and the smoothing of self-reported returns	RFS	2011	H,M,T
Chen Y	Derivatives use and risk taking: Evidence from the hedge fund industry	JFQA	2011	H

Chen Y, Cliff M & Zhao H	Hedge funds: The good, the bad and the lucky	JFQA	2017	H,T
Chen Y & Liang B	Do market timing hedge funds time the market?	JFQA	2007	H,M,T
Chung J & Kang B	Prime broker-level comovement in hedge fund returns: Information or contagion	RFS	2013	T
Choi D, Getmansky M, Henderson B & Tookes H	Convertible bond arbitrageurs as suppliers of capital	RFS	2010	M,T
Cici G, Kempf A & Puetz A	The valuation of hedge funds' equity positions	JFQA	2016	M,T
Deuskar P, Pollet JM, Wang ZJ & Zheng L	The good or the bad? Which mutual fund managers join hedge funds?	RFS	2011	M,T
Dichev ID & Yu G	Higher risk, lower returns: What investors really earn	JFE	2011	M
Duarte J, Longstaff FA & Yu F	Risk and return in fixed-income arbitrage: Nickels in front of a steamroller?	RFS	2007	T
Dudley E & Nimalendran M	Margins and hedge fund contagion	JFQA	2011	M
Edelman D, Fung W & Hsieh DA	Exploring uncharted territories of the hedge fund industry: Empirical characteristics of mega hedge fund firms	JFE	2013	H,M,T
Elaut G, Frömmel M & Sjödin J	Crystallization: A hidden dimension of CTA fees	FAJ	2015	T
Eling M	Does the measure matter in the mutual fund industry?	FAJ	2008	M
Fung W & Hsieh DA	Empirical characteristics of dynamic trading strategies: The case of hedge funds	RFS	1997	M
Fung W & Hsieh DA	Measurement biases in hedge fund performance data: An update	FAJ	2009	M
Fung W & Hsieh DA	Hedge fund benchmarks: A risk-based approach	FAJ	2004	H,M,T
Fung W & Hsieh DA	Asset-based style factors for hedge funds	FAJ	2002	H,T
Fung W & Hsieh DA	Hedge fund benchmarks: Information content and biases	FAJ	2002	H,T
Fung W & Hsieh DA	Performance characteristics of hedge funds and CTA funds: Natural versus spurious biases	JFQA	2000	T
Fung W, Hsieh DA, Naik NY & Ramadorai T	Hedge funds: Performance, risk, and capital formation	JF	2008	H,M,T
Fung H-G, Xu XE & Yau J	Global hedge funds: Risk, return, and market timing	FAJ	2002	M
Gao G, Gao P & Song Z	Do hedge funds exploit rare disaster concerns?	RFS	2018	T
Greenwood R & Schor M	Investor activism and takeovers	JFE	2009	M
Griffin JM & Xu J	How smart are the smart guys? A unique view from hedge fund stock holdings	RFS	2009	M,T
Hodder J, Jackwerth J & Kolokolova O	Recovering delisting returns of hedge funds	JFQA	2014	B,E,H,M,T
Ibbotson RG, Chen P & Zhu KX	The ABCs of hedge funds: Alphas, betas, and costs	FAJ	2011	T
Jagannathan R, Malakhov A & Novikov D	Do hot hands exist among hedge fund managers? An empirical evaluation	JF	2010	T
Joenväärä J, Kosowski R & Tolonen P	The effect of investment constraints on hedge fund investor returns	JFQA	2018	B,E,H,M,T
Jorion P & Schwarz C	Are hedge fund managers systematically misreporting? Or not?	JFE	2014	T
Jorion P & Schwarz C	The strategic listing decisions of hedge funds	JFQA	2014	H,T
Jurek J & Stafford E	The cost of capital for alternative investments	JF	2015	H
Jylhä P & Suominen M	Speculative capital and currency carry trades	JFE	2011	H,T
Kang BU, In F, Kim G & Kim TS	A longer look at the asymmetric dependence between hedge funds and the equity market	JFQA	2010	T
Kang N, Kondor P & Sadka R	Do hedge funds reduce idiosyncratic risk?	JFQA	2014	T
Kao DL	Battle for alphas: Hedge funds versus long-only portfolios	FAJ	2002	T
Kosowski R, Naik NY & Teo M	Do hedge funds deliver alpha? A Bayesian and bootstrap analysis	JFE	2007	H,M,T
Li H, Xu Y & Zhang X	Hedge fund performance evaluation under the stochastic discount factor framework	JFQA	2016	T
Li H, Zhang X & Zhao R	Investing in talents: Manager characteristics and hedge fund performances	JFQA	2011	T
Liang B	On the performance of hedge funds	FAJ	1999	H

Liang B	Hedge fund performance: 1990–1999	FAJ	2001	T
Liang B	Hedge funds: The living and the dead	JFQA	2000	H,T
Liang B & Park H	Predicting hedge fund failure: A comparison of risk measures	JFQA	2010	T
Lim J, Sensoy B & Weisbach M	Indirect incentives of hedge fund managers	JF	2015	T
Malkiel BG & Saha A	Hedge funds: Risk and return	FAJ	2005	H,T
Massoud N, Nandy D, Saunders A & Song K	Do hedge funds trade on private information? Evidence from syndicated lending and short-selling	JFE	2011	H,M,T
Nohel T, Wang ZJ & Zheng L	Side-by-side management of hedge funds and mutual funds	RFS	2010	H,T
Ozik G & Sadka R	Media coverage and hedge fund returns	FAJ	2013	T
Patton AJ & Ramadorai T	On the high-frequency dynamics of hedge fund risk exposures	JF	2013	B,H,M,T
Patton A, Ramadorai T & Streatfield M	Change you can believe in? Hedge fund data revisions	JF	2014	B,H,M,T
Patton AJ	Are “market neutral” hedge funds really market neutral?	RFS	2009	H,T
Ramadorai T	The secondary market for hedge funds and the closed hedge fund premium	JF	2012	M,T
Ramadorai T	Capacity constraints, investor information, and hedge fund returns	JFE	2013	H,M,T
Sadka R	Liquidity risk and the cross-section of hedge-fund returns	JFE	2010	T
Shi Z	The impact of portfolio disclosure on hedge fund performance	JFE	2017	T
Shive S & Yun H	Are mutual funds sitting ducks?	JFE	2013	T
Sias R, Turtle H & Zykaj B	Hedge fund return dependence: Model misspecification or liquidity spirals	JFQA	2017	H
Smith DM, Wang N, Wang Y & Zychowicz EJ	Sentiment and the effectiveness of technical analysis: Evidence from the hedge fund industry	JFQA	2016	T
Sun Z, Wang A & Zheng L	The road less traveled: Strategy distinctiveness and hedge fund performance	RFS	2012	T
Teo M	The liquidity risk of liquid hedge funds	JFE	2011	H,T
Teo M	The geography of hedge funds	RFS	2009	E
Titman S & Tiu C	Do the best hedge funds hedge?	RFS	2011	H,T
Yan L, Ray S & Melvyn T	Limited attention, marital events and hedge funds	JFE	2016	B,H,M,T
Yin C	The optimal size of hedge funds: Conflict between investors and fund managers	JF	2016	T

Table A2: Number of funds by style and domicile

Description: This table shows the number (N) and percentage (%) of funds in each style and domicile category for each individual database, a three-database aggregate consisting of TASS, HFR, and BarclayHedge (AGG3), and a seven-database aggregate (AGG7). The style categories follow the broad hedge fund strategies listed in SEC Form PF.

Panel A: Number of funds by style (including funds of funds)

	TASS		HFR		BarclayHedge		EurekaHedge		Morningstar		Preqin		eVestment		AGG3		AGG7	
Style	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Fund of funds	3,185	28	3,008	21	2,853	19	2,539	22	2,599	29	1,290	20	489	5	5,096	21	6,279	19
Credit	358	3	666	5	821	6	780	7	453	5	506	8	825	8	1,063	4	1,805	6
Equity	3,465	31	5,728	40	4,778	33	4,530	38	3,810	42	2,350	36	5,072	47	8,014	33	11,711	36
Event Driven	516	5	849	6	640	4	500	4	348	4	319	5	708	7	1,096	5	1,342	4
Macro	714	6	1,517	11	1,153	8	945	8	460	5	582	9	954	9	2,225	9	2,887	9
Managed Futures / CTA	1,449	13	1,019	7	2,944	20	1,435	12	650	7	884	14	1,120	10	3,488	14	4,121	13
Multi-Strategy	628	6	323	2	381	3	497	4	332	4	294	5	547	5	916	4	1,530	5
Relative Value	460	4	978	7	488	3	449	4	270	3	215	3	530	5	1,167	5	1,370	4
Other	145	1	86	1	330	2	118	1	41	0	48	1	389	4	452	2	782	2
Missing	291	3	0	0	291	2	0	0	114	1	43	1	172	2	577	2	884	3
All funds	11,211		14,174		14,679		11,793		9,077		6,531		10,806		24,094		32,711	

Panel B: Number of funds by domicile (excluding funds of funds)

	TASS		HFR		BarclayHedge		EurekaHedge		Morningstar		Preqin		eVestment		AGG3		AGG7	
Domicile	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Asia	30	0	21	0	67	1	135	1	914	14	31	1	25	0	98	1	1,114	4
Caribbean	3,177	40	4,178	37	3,353	28	3,419	37	2,216	34	1,557	30	3,303	32	5,932	31	7,410	28
Europe	1,203	15	1,617	14	1,852	16	2,062	22	692	11	1,291	25	1,265	12	3,341	18	5,053	19
Pacific	112	1	85	1	127	1	194	2	41	1	119	2	89	1	220	1	366	1
North America	2,988	37	4,955	44	6,265	53	3,104	34	2,525	39	1,799	34	5,066	49	8,524	45	10,638	40
Central America	1	0	5	0	12	0	5	0	2	0	2	0	4	0	15	0	15	0
South America	453	6	37	0	21	0	158	2	9	0	88	2	46	0	485	3	607	2
Others	58	1	90	1	76	1	168	2	79	1	105	2	94	1	151	1	331	1
Missing	4	0	178	2	53	0	9	0	0	0	249	5	425	4	232	1	898	3
All funds	8,026		11,166		11,826		9,254		6,478		5,241		10,317		18,998		26,432	