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Benchmarks of Hedge Fund Performance: Information Content and Measurement Biases

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Abstract

This paper discusses the information content and potential measurement biases in hedge fund benchmarks. Hedge fund indices built from databases of individual hedge funds will inherit their measurement biases. In addition, broad-based indices mask the diversity of individual hedge fund return characteristics. Consequently, these indices are less informative for investors seeking diversification from traditional asset classes through the use of hedge funds. This paper proposes a different approach to constructing hedge fund benchmarks. It is based on the simple idea that the most direct way of measuring hedge fund performance is to observe the investment experience of hedge fund investors themselves. In terms of measurement biases, returns of funds-of-hedge funds can deliver a cleaner estimate of the investment experience of hedge fund investors. In terms of risk characteristics, indices of funds-of-hedge funds is more indicative of the demand side dynamics driven by hedge fund investors' preferences. Therefore, indices of funds-of-hedge funds can provide additional valuable information to the assessment of the hedge fund industry's performance.

1. Introduction

This paper analyzes the problems that arise in creating benchmarks for assessing the performance characteristics of hedge funds. We begin by discussing potential measurement biases that are embedded in the historical returns of hedge funds. Organized as private investment vehicles, hedge funds generally do not disclose their activities to the public. A complete record of every single hedge fund simply does not exist. The incompleteness of hedge fund data arises from three reasons. First, hedge fund participation in any database is voluntary. Second, most commercially available hedge fund databases came into existence around the mid-1990s. Third, different databases have different inclusion criteria for funds.

It is well known in statistical sampling theory that voluntary participation can lead to sampling biases. Most database vendors began collecting hedge fund data in earnest when they came into existence around 1993 and 1994. It is inevitable that observable data on hedge funds pre-1994 inherit measurement biases as a natural consequence of the way in which the hedge fund industry evolved. Post-1994, hedge fund data is less susceptible to measurement biases. However, differences in the data collection methods among database vendors can lead to other forms of measurement biases. In Section Two, we focus on two main biases that arise in analyzing hedge fund data–survivorship bias and selection bias.

An important attribute of hedge fund investing is the diversity in their performance characteristics. Composites of hedge fund performance are available from a variety of sources. Of these, two organizations have made serious attempts to create hedge fund indices that are comprehensive and transparent. They are Hedge Fund Research (“HFR”) and CSFB/Tremont (“CT”). Both organizations attempt to rectify some of the measurement biases we discussed earlier. Nonetheless, some measurement biases are unavoidable. The balance of Section Two, therefore, is devoted to measurement biases that may arise in constructing hedge fund benchmarks based on historical returns.

It is natural for hedge fund managers to focus their effort on liquid markets where there are trading opportunities and leverage is readily available. As the dynamics in the global markets change, the supply of hedge funds will change over time depending on the birth and death rate of funds as well as changes in the trading styles of existing funds. Benchmarking such a dynamic process is in itself a difficult task. It is further compounded by the fact that the component of these benchmarks, the hedge funds, are drawn from a population of funds managed by nimble managers with very diverse investment styles. Section Three of the paper focuses on how well existing benchmarks reflect the risk characteristics of hedge funds.

In Section Four, we propose a new approach to assess the performance characteristics of hedge funds. It is based on the simple idea that if we are interested in the performance characteristics of hedge fund investing, why not look directly at the investment experience of the hedge fund investors themselves. We do this by analyzing the performance of funds-of-hedge funds. In addition, it is reasonable to assume that the performance characteristics of hedge funds are driven by the opportunities in the global markets and investor preferences. To stay in business, funds-of-hedge funds have to respond to investor preferences. Therefore, this latter approach to measuring performance characteristics of hedge funds supplements the analysis based on the hedge funds themselves. We argue that data from the demand side of hedge funds, the funds-of-hedge funds, are less susceptible to a number of measurement biases we noted in the earlier sections. This allows us to make the case for using funds-of-hedge funds, rather than individual hedge funds, to construct hedge fund indices. Conclusions of the paper are presented in Section Five.

2. Biases and Information Content in Hedge Fund Databases

Advances in information technology over the last decade have led to dramatic improvements in the investment arena. Nowadays, investors can readily access historical data on almost any security or mutual fund with unquestioned quality and consistency. However, the same cannot be said about hedge funds. Although database services on hedge funds have expanded dramatically since the 1990s, there has yet to emerge a generally accepted, standardized information provider on hedge funds due to the absence of a centralized depository of performance records like the Investment Company Institute. Both the scope and the quality of the data vary among hedge fund database vendors. Therefore, it is still very much a case of *caveat emptor* when it comes to users of available hedge fund performance data. In this section we consider some frequently encountered problems in assessing the information content of a sample of hedge fund returns.

Consider an investor interested in assessing the general performance characteristics of hedge funds. The natural way to go about this is to obtain a sufficiently broad "sample portfolio" of hedge funds and construct its pro forma return statistics. In assessing these pro forma return statistics, what kind of measurement errors should investors be aware of? The answer to this question is especially important to the benchmarking of hedge fund performance. In order to gain insight to this question, we begin by examining the way the hedge fund industry is organized and its impact on data collection.

Organized as private and frequently offshore investment vehicles, hedge funds generally do not disclose their activities to the public.[1] A complete record of every single hedge fund simply does not exist. Available information comes as samples of hedge funds in the form of "databases." To sharpen the discussion, we use the term "universe" (or "population") to denote the collection (or set) of all hedge funds that have operated, past or present, dead or alive. We use the term "database" to refer to a subset of the population of hedge funds collected by data vendors.[2]

The incompleteness of hedge fund data arises from several reasons. First, hedge fund participation in any database is voluntary. Only a portion of the universe of hedge funds is observable. Second, most commercially available hedge fund databases came into existence around the mid-1990s. Information of funds that ceased operation before they could be included into databases may have been lost forever. Third, different databases have different inclusion criteria for funds.

These three reasons can lead to important differences between the hedge funds in a database and those in the population. It is also well known in statistical sampling theory that voluntary participation can lead to sampling biases. Here, we focus on two main biases that arise in analyzing hedge fund data–"survivorship bias" and "selection bias." We further distinguish between biases that are consequences of sampling from an unobservable universe of hedge funds as "natural biases" and those that arise from the way data vendor collect hedge fund information as "spurious biases."

2.1. Survivorship Bias

Survivorship bias arises when a sample of hedge funds includes only surviving funds (i.e., funds that are operating at the end of the sampling period) and excludes dead funds (i.e., funds that have ceased operations during the sampling period). Presumably, funds cease operation because of poor performance. This implies that the historical performance of surviving funds are biased upwards in return and biased downwards in risk relative to the universe of all funds. The amount of bias is called survivorship bias and is a natural consequence of the way the hedge fund industry evolved.[3] Therefore, in the context of analyzing hedge fund data, survivorship is a natural bias and cannot be completely mitigated.

The effect of survivorship bias is well documented in the mutual fund literature.[4] The standard procedure, as in Malkiel (1995), is to obtain the population of all mutual funds that operated during a given time period. The average return of all funds is compared to that of the surviving funds at the end of the period. The return difference is survivorship bias.

Unlike mutual funds, survivorship bias in hedge funds cannot be measured directly as the universe of hedge funds is not observable. Survivorship bias can only be estimated using hedge funds in a database. This creates a new set of problems that do not arise in mutual funds.

The first problem concerns information on hedge funds that ceased to exist before database vendors started their data collection. Due to the lack of public disclosure, database vendors have only sketchy information on hedge funds that ceased operation (i.e., died) prior to the mid-1990s.[5] It is therefore impossible to assess survivorship bias prior to the mid-1990s. This leaves hedge fund databases, no matter how broad, vulnerable to survivorship bias, especially prior to the mid-1990s.

The second problem arises from the difference between funds that exited a database (which we term "defunct funds") and funds that ceased operation (termed "dead funds"). A "defunct" fund is a fund in a database that ceased to report information to the database vendor, whereas a dead fund is a fund that is known to have terminated operation. Of course, a "dead" fund in a database must be a "defunct" fund. However, a "defunct" fund need not be a "dead" fund.

For example, a fund delisted by the database vendor[6] is a "defunct" but not "dead" fund. Presumably, vendors delist funds that they believe are likely to harm their reputation for providing reliable information to their customers. In this case, delisted funds are likely to have less accurate, and in most cases worse, performance history than the typical hedge fund.

Another example of a fund being "defunct" but not "dead" is one that voluntarily stops reporting information to a database vendor because it has reached the optimal size given its style of trading. The preference for privacy coupled with a diminishing appetite for new capital often means that the fund no longer avails its performance statistics to database vendors.[7] This type of defunct fund may actually have a higher return and lower risk than the typical hedge fund in the universe or in the database.[8]

This discussion indicates that defunct funds in a database are not necessarily dead funds in the universe of hedge funds. Defunct funds may include dead funds, delisted funds (that may or may not be dead), and operating funds that reached capacity constraints. With this caveat in mind, we used both surviving and defunct funds from a database to estimate the survivorship bias as the difference between the returns of two portfolios – the "observable portfolio" and the "surviving portfolio."[9]

Given a set of hedge funds over a sampling period, the observable portfolio consists of an equally-weighted investment in **all funds** in the portfolio rolling forward from the beginning of the period. The portfolio is rebalanced when a new fund is added to the portfolio or when a fund becomes defunct.[10] The surviving portfolio consists of an equally-weighted investment **only in** those **funds that survived** until the end of the sampling period. Going forward in time, this portfolio is rebalanced only when a new fund is added to the sample but, by construction, it never has to be rebalanced when a fund becomes defunct. Malkiel (1995) estimated the survivorship bias in mutual funds to be 0.5% per year in return space. In comparison, Fung and Hsieh (2000b) estimated the survivorship bias in hedge funds in the TASS Asset Management (TASS) database to average roughly 3% per year. This is consistent with Brown, Goetzmann, and Ibbotson (1999) who studied offshore hedge funds. We refer to this 3% figure as an estimate because we use a sample instead of the population of hedge funds and because we use defunct funds in a database to proxy for dead funds in the population.

2.2. Selection Bias and Instant History Bias

The combination of the voluntary nature of hedge funds availing their information to databases and the different inclusion process of database vendors can lead to performance differences between funds in a database and funds in the universe of hedge funds. We call this difference "selection bias."

Selection bias manifests itself in two basic ways. Hedge funds that satisfy the inclusion criteria of a vendor may enter a database depending on their track record and assets under management. Presumably, only those funds that have "good" performance and are looking to attract new investors want to be included in a database. This implies that hedge funds in a database have better performance than those that were excluded. On the other hand, it is also possible that hedge funds do not participate in a database because they are not looking to attract new investors. These "self-excluded" funds may have better performance than the average hedge fund. Thus, the net effect of "self selection" biases on the returns of hedge funds in a database is ambiguous.

Beyond the voluntary nature of funds participating in a database, the database vendors themselves may introduce sampling biases in their inclusion criteria. For example, of the three major hedge fund database vendors, managed futures programs are excluded in Hedge Fund Research ("HFR" for short) but included in TASS and the Managed Account Review ("MAR" for short).

Empirically, it is difficult to determine the magnitude of the selection bias in a database, because it is not possible to compare the observed hedge funds in the database with the unobservable hedge funds in the population. However, differences in both the number and the identity of hedge funds across databases are indicative of selection bias. We will return to this issue in Section Four.

A related bias to "selection" was first analyzed in Park (1995) and has come to be referred to as the "instant history" bias. When a data vendor adds a fund into a database, the fund's historical returns are often backfilled. In the words of Park (1995), funds enter a database with instant history. This happens because hedge funds usually undergo an incubation period. The fund manager starts the fund with a small amount of seed capital.[11] When the track record is satisfactory, the fund manager markets the fund to investors, often by asking to be included in a hedge fund database. Given that the fund manager has the option to decide when to "reveal" his track record, it would be reasonable to presume that the returns from the incubation period would be higher than normal.

In order to estimate the magnitude of instant history bias, Fung and Hsieh (2000b) studied the hedge funds in the TASS database, which reported the inception date of each fund as well as the date the fund entered the database. On average, the incubation period (from a fund's inception to its entry into TASS) is one year. Fung and Hsieh (2000b) measured the instant history bias as the average difference between two portfolios. The first portfolio is the observable portfolio, as defined in the previous subsection on survivorship bias. The second portfolio is the "adjusted" observable portfolio, which is constructed in the same manner after dropping the first 12 monthly returns of every fund. On average, the second portfolio's return was lower by 1.4% per year.

In Fung and Hsieh (2000b), selection bias and instant history bias were referred to as "spurious biases" because both the causality and magnitude of these biases are inherent in the data collection process. With some careful and tedious data manipulation, most spurious biases can be remedied. Selection bias can be eliminated if hedge fund databases eventually converge to the universe of hedge funds. Instant history bias can be remedied by dropping the returns of a fund prior to its entry into a database. In contrast, natural biases (such as survivorship) generally cannot be rectified. In a later section, we propose a simple remedy to both types of performance measurement biases. Next we move on to examine the impact of measurement biases on an important application of hedge fund data–the benchmarking of hedge fund performance.

2.3. Potential Measurement Errors and Differences in Hedge Fund Indices

Two broad-based hedge fund indices have been created to benchmark the performance of the hedge fund industry. They are, respectively, the Hedge Fund Research Performance Index (referred to as "HFRI" by the vendor) and the CSFB/Tremont Hedge Fund Index (which we refer to as "CTI" for short)[12]. The HFRI is an equally-weighted index of over 1,000 hedge funds tracked by HFR, whereas the CTI is a value-weighted index (using the assets under management as "value" in the weighting scheme) based on a sample of approximately 300 funds extracted from the TASS database (created and maintained by TASS Asset Management). The CTI was constructed with the purpose of being an "investable" index whereas the HFRI is designed to be a broad-based proxy of the hedge fund industry's performance.[13] These two indices are typical applications of constructing hedge fund portfolios to proxy the universe of all hedge funds. It is, therefore, important to understand their potential measurement errors in order to asses their respective information content.

From our earlier discussions it is clear that hedge funds in any database, including HFR and TASS, will suffer from both natural biases and spurious biases. Here, we distinguish between data pre- and post-1994.

Pre 1994, HFR and TASS are likely to suffer from survivorship bias. According to Ackerman, McNally, and Ravenscraft (1999) and Liang (2000), both databases have very limited records of funds that became defunct before 1994. Hence both HFR and TASS suffer from survivorship bias before 1994. In addition, the absence of defunct funds before 1994 indicates that both HFR and TASS began their data collection around 1994. This implies that both databases suffer from selection bias with historical data pre-1994. This is because data prior to 1994 had to be compiled and backfilled.[14] For these reasons, we ignore the HFRI data prior to 1994.

Post 1994, both databases have information on operating as well as defunct funds. Therefore, *relative to their record of defunct funds,* the pro forma returns of the two hedge fund indices should not suffer from survivorship bias so long as proper adjustment procedures were adhered to when computing the respective time series of index returns. However, *relative to the universe of all hedge funds*, the indices may suffer from various forms of natural and spurious biases.

The reasons are fourfold. First, there is no realistic way of verifying that complete records of defunct funds were used to adjust the index returns for survivorship bias, especially prior to the mid-1990s. Second, differences in their data collection methodology could result in different degrees of selection bias and instant history bias. Put differently, "missing funds" could also be a consequence of the respective data collection methodology. Third, different approaches to index construction can result in performance differences despite the fact that both indices are meant to proxy the population of all hedge funds. Fourth, the CTI can be interpreted as a tracking portfolio of the TASS universe of hedge funds. It must naturally contain tracking errors, whereas the HFRI is supposed to be an average of *all* hedge funds tracked by HFR.

2.3.1. Benchmarks Inherit Survivorship Bias from a Database

The first point refers to a natural bias that arises from the private nature of hedge funds. Currently, observable hedge funds in databases do not fully reflect the universe of all hedge funds. In time, observable funds may converge to the universe of all hedge funds. From that point forward, survivorship bias can be remedied by analytical methods. Until that occurs, performance statistics derived from the observable funds remain biased estimators of the population statistics.[15] However, time series of returns prior to the "point of convergence" remain vulnerable to survivorship bias.[16] This in turn affects benchmark indices based solely on samples of observable funds.

It is important to note that the HFR and TASS databases yield different estimates of survivorship bias. Ackerman, McNally, and Ravenscraft (1999), Fung and Hsieh (2000b), and Liang (2000) found that the attrition rate (i.e., the percent of funds that become defunct in each year) is much higher in TASS. As a result, the measured survivorship bias (i.e., the performance difference between all funds and surviving funds) is also higher in TASS. Interestingly, TASS's attrition rate and survivorship bias is comparable to those in the Brown, Goetzmann, and Ibbotson (1999) study who used the *U.S. Offshore Hedge Funds Directory*. What is not clear is why the attrition rate is so low in HFR.

2.3.2. Benchmarks Inherit Selection Bias and Instant History Bias From a Database

The second point refers to the issue of selection bias and instant history bias. To begin with, both HFR and TASS backfill the return history of funds that enter their databases. Thus, they both suffer from instant history bias.

In addition, both HFR and TASS are likely to have selection bias, due to the idiosyncrasies in their respective data collection method. For the purposes of this paper, we shall focus only on those that are relevant to our analysis.[17] Most notably, HFR excludes funds that are generally referred to as commodity funds.[18] In contrast, “Managed Futures,” an important subset of commodity funds, is included in the CTI index.

Beyond differences in inclusion criteria, a large number of hedge funds appear to report to only one database vendor. For instance, Liang (2000) found that out of 1,162 funds in HFR and 1,627 funds in TASS, there were only 465 common funds.

Thus, the evidence indicates the potential for selection bias clearly exists across hedge fund databases. However, it is difficult to assess its impact on benchmark indices created from these databases directly.

2.3.3. Benchmark Returns Can Differ Depending on Their Weighting Schemes

The third point concerns the differences in benchmarks as a result of the weighting schemes used in their construction. Specifically, the HFR indices use equal weights while the CTI indices use value weights. We begin our analysis by comparing the annual returns of the two indices from 1994 to 1999,[19] as reported in Table 1.

There are significant differences between the HFRI and the CTI in the two lowest-return years of the CTI –1994 and 1998. The same holds true for the two highest-return years of the CTI–1997 and 1999. In the other years, the differences are small.

These sizable return differences can result from the different weighting schemes of the two indices. The HFRI represents the returns of a “contrarian” asset allocation strategy because an equally-weighted portfolio is rebalanced by “selling winners and buying losers” every month.[20] In order to maintain equal weighting, assets have to be diverted from performing funds to “underperforming” funds. This is an artifact of an equal weighting asset allocation strategy. In contrast the CTI represents the returns of a momentum-driven asset allocation strategy. A value-weighted portfolio allows “winners” to naturally increase their portfolio weights in the index and “losers” naturally reduce their portfolio weights. These two strategies can generate path-dependent divergence in their performances, especially in a diverse universe of assets like hedge-fund investments.

The difference in weighting scheme can account for the 7.4% difference between the HFRI and the CTI in 1999. During the 1998 turmoil, emerging market hedge funds lost well over 30% according to both data sources. This is followed by a dramatic rebound in 1999 where the returns were in the region of 50%. To illustrate the effect of the weighting schemes, Panel A in Table 2 provides the portfolio weights of emerging market hedge funds in an equally-weighted portfolio versus a value-weighted portfolio based on figures reported by HFRI.[21] After the August 1998 debacle, the HFRI would have diverted assets towards emerging market hedge funds (thereby holding their weight in the index to be 11.9%).[22] During their rebound in 1999, these funds contributed a gain of 6.57% (= 55.22% × 11.9%) towards the overall HFRI. In contrast, the CTI approach would have allowed the weight of emerging market hedge funds to fall as their assets shrank (from 9.50% in 1998 to 7.10% in 1999), so these funds only contributed 3.18% (= 44.82% × 7.10%) in 1999 towards the overall CTI. The differential contribution of emerging market hedge funds accounted for nearly half of the 7.4% difference in 1999 between the two overall indices.[23]

One other worthy note is the substantial return difference between the HFR and CT subindices of emerging market hedge funds over this 1994-1999 period. This is consistent with the existence of selection bias: that different databases can contain different samples of the universe of hedge funds.

In another instance, the different weights of “Global/Macro” funds may explain the 9.1% performance discrepancy between the HFRI and CTI in 1997. The relevant figures are reported in Panel B of Table 2. The Global/Macro subindex contributed a small gain of 1.13% (=6.0%× 18.82%) in 1997 towards the overall HFRI. In contrast, it contributed a large gain of 8.83% (=23.8% × 37.11%) in 1997 towards the overall CTI, due to its higher value-weight and the fact that CT Macro/Global subindex recorded a much higher return than its counterpart in the HFRI. The difference of 7.7% accounts for much of the 9.1% difference between the two overall indices in 1997.

As proxies of the same universe of hedge funds, the above examples point to spurious biases generated by the different index construction methods as well as selection biases in the respective databases. At this point we need to analyze the risk characteristics of these two indices prior to reaching our conclusions on their respective information content. This is done in Section Three.

3. Broad-Based Benchmarks Can Mask Interesting Performance Characteristics of Hedge Funds

An important issue for a hedge fund benchmark is whether it captures the key performance characteristics of individual hedge funds. Performance characteristics that would attract institutional investors looking for "alternative investments" to traditional asset classes as well as those who are simply looking for good performance on a risk-adjusted basis. An important attribute of hedge fund investing is the diversity of styles employed by hedge fund managers. However, diversity comes at a cost. It may be quite difficult to construct a benchmark that reflects the overall performance characteristics of the hedge fund industry as well as its diversity. In order to address this question, we analyze the risk characteristics of the HFRI and CTI.

3.1. Hedge Fund Indices Have High Correlation to Standard Asset Classes

We begin by tabulating the correlation coefficients between the HFRI and CTI and some standard asset class indices over the sample period of 1994-1999. Panel A in Table 3 reports their correlation with the returns of nine broad-based market indices: one-month Eurodollar deposits, the Goldman Sachs Commodity Index (GSCI), Morgan Stanley US and World Ex-US equities, J.P. Morgan US and World Ex-US government bonds, the Federal Reserve's US Dollar index against major currencies, the International Finance Corporation's Emerging Market equities, and the Merrill Lynch High Yield bond index. Both the HFRI and CTI are strongly positively correlated to US equities, non-US equities, Emerging Market equities, and High Yield bonds.

The high degree of correlation between the hedge fund indices and several of standard asset indices is in contrast to earlier empirical findings in Fung and Hsieh (1997a), Schneeweis and Spurgin (1998), Brown, Goetzmann, and Ibbotson (1999) and Ackerman, McNally and Ravenscraft (1999). All of these earlier studies reported low correlations between standard asset indices and individual hedge funds.

3.2. Individual Hedge Funds Have Low Correlation to Standard Asset Classes

In order to standardize the results from the individual hedge funds and the two hedge fund indices, we employed the methodology in Fung and Hsieh (1997a). We use a sample consisting of 1,129 hedge funds in the TASS database that had at least 36 monthly returns between 1994 and 1999. We regress their monthly returns on the nine broad-based market indices. Panel C of Table 3 reports the distribution of the adjusted-R^2 from these regressions. More than 50% of these funds have adjusted-R^2 below 0.3. This is very similar to the result in Fung and Hsieh (1997a).

In contrast, the HFRI and CTI have much higher R^2s to the standard asset indices. Panel B in Table 3 reports the results of the regressions for the period 1994-98. For the HFRI, the adjusted-R^2 of the regression is quite high, at 0.76. The HFRI is positively related to the US stock market, Emerging Market Equities, High Yield US Bonds, and the GSCI. For the CTI, the adjusted-R^2 of the regression is somewhat lower, at 0.55 but still substantially higher than the average hedge fund in the sample. It is difficult to directly compare the regression coefficients in Panel A of Table 2 to the simple correlation coefficients reported in Panel B. There is clearly colinearity among the regressors. However, scatter plots of the indices[24] against each of the standard asset indices reveal that the relationship is basically linear.

The evidence indicates that hedge fund benchmarks have much greater exposure to traditional asset categories than the typical hedge fund. This leaves us with a puzzle: *By diversifying among hedge funds, is an investor exchanging idiosyncratic hedge fund risk for systematic exposure to traditional risk factors?* This would be a most uncomfortable implication for investors looking to hedge fund investments as a mean to diversify a portfolio of traditional asset classes.

3.3. Individual Hedge Funds Have Significant Common Risks

There is a natural explanation that apparently reconciles the low correlation of individual hedge funds and the high correlation of broad-based hedge fund indices to traditional asset markets. With traditional equities, returns of individual equities contain a large component of idiosyncratic (or nonsystematic) risk. Modern portfolio theory posits that a sufficiently large portfolio of equities can diversify away theses idiosyncratic risks, leaving only systematic risks as the dominant risk in the portfolio. It would be tempting to apply the same argument to portfolios of hedge funds to explain the emergence of traditional risk factors at the index level. However, a closer examination of the evidence on individual hedge fund returns does not favor this explanation.

Fung and Hsieh (1997a) showed that there is substantial style diversity in hedge funds. They found five principal components, or common risks, in 409 hedge funds and commodity funds. These principal components themselves have low correlation to standard asset indices. This evidence is not consistent with the view that individual hedge funds have substantial idiosyncratic risk. It is, on the other hand, consistent with the conjecture that hedge funds have common risk characteristics that are not "systematic" in the traditional sense of being highly correlated to standard asset indices. Unlike idiosyncratic risks commonly found in traditional equities, these risk characteristics are common among groups of hedge funds[25] and cannot be easily diversified away. We demonstrate this assertion empirically as follows.

A standard method to determine a portfolio's ability to diversify away idiosyncratic risks is to examine how the standard deviation of a portfolio changes with the number of assets in the portfolio. If the portfolio standard deviation drops quickly when more assets are added, then there is substantial amount of idiosyncratic risk.

To determine this relationship, we estimated the average monthly standard deviation of 1,000 randomly created portfolios of hedge funds in the TASS database. Take, for example, a portfolio of 20 funds. We randomly draw (without replacement) 20 funds from the sample of TASS funds that had returns at any time during a given time period, say, from 1994 to 1998. We then formed an equally-weighted portfolio of these funds and computed the monthly standard deviation of the portfolio. This procedure is repeated 1,000 times, and the average monthly standard deviation of these 1,000 portfolios recorded.[26]

Figure 1 shows how the standard deviation of hedge fund portfolios changes with the number of funds in the portfolio. While the standard deviation declines rapidly, it continues to decline without stabilizing to a fixed number. Specifically, it takes a portfolio of at least 120 hedge funds to have a standard deviation within 10% of an equally-weighted that of the portfolio of all TASS hedge funds. This is quite different from equities, where only a few dozen funds are needed in a portfolio to achieve the standard deviation of the market portfolio .

This evidence is consistent with the presence of significant, common, but not easily diversifiable risk factors[27] among the hedge funds. On average, a large number of funds are needed before a portfolio converges to a stable standard deviation.

This evidence is consistent with the findings in Fung and Hsieh (1997) that groups of hedge funds have strong correlations, but as groups of hedge funds, they have low correlation with standard benchmark returns. A single hedge fund benchmark will not be able to reflect this heterogeneity in hedge funds. This leaves us with the question as to what risk characteristics does a broad-based index of hedge funds reflect?

To answer this question, we need to reference the interaction between global market dynamics and the growth of the hedge fund industry. It is natural for hedge fund managers to focus their effort on liquid markets where there are trading opportunities and leverage is readily available. Over the last few years, the global equity markets certainly have been most conducive to this tendency. Therefore, it is hardly surprising that both the number and amount of capital managed by "equity oriented" funds have increased dramatically. This is shown in

Table 4. A broad-based index of hedge funds is likely to reflect this trend.

Consequently, broad-based indices of hedge funds are more likely to reflect the risk characteristics inherent in the more recent "popular bets" among hedge fund managers. The evidence here shows that these popular bets have a significant degree of equity content. Because of this, these indices will understate the diversity of hedge fund trading styles in general and overstate the risk of style convergence. Style convergence in the sense that when a large number of hedge funds in a portfolio converge onto a similar set of bets, portfolio diversification implodes. This happened when a large number of hedge fund managers took big bets on bonds during 1993 and was caught in the market turmoil of 1994 when the Federal Reserve unexpectedly raised interest rates; see Fung and Hsieh (2000a). Therefore, for investors seeking diversification from traditional asset classes, subindices of specific hedge fund trading styles that are properly constructed are more informative in terms of risk than a broad-based index.

4. Hedge Fund Benchmarks Based on the Investment Experience of Hedge Fund Investors

The previous two sections were devoted to discussions on potential biases that may arise when measuring hedge fund performance using pro forma returns based on a portfolio of individual hedge funds extracted from a database. We alerted the readers to natural biases that are consequences of the way the hedge fund industry is organized. These natural biases cannot be easily remedied. In this section, we examine potential solutions that also emanate from idiosyncrasies of the hedge fund industry.

Here we introduce a simple idea. If we want to estimate the investment experience of hedge funds, why not look directly at the experience of the hedge fund investors themselves.

4.1. Funds-of-Hedge Funds as Proxies for Hedge Fund Investment Experience

Unlike mutual funds where the concept of funds-of-mutual funds never gained popularity, the structure of the hedge fund industry has led to the demand for and the existence of funds-of-hedge funds ("FOFs" for short)[28]. There are 224 FOFs in the HFR database and 322 FOFs in the TASS database. Of the three major database vendors we referred to -- HFR, TASS, and MAR -- two regularly report a FOF composite performance. These are the HFR fund-of-hedge funds index ("FOFHFR" for short) and the MAR fund-of-hedge funds benchmark ("FOFMAR" for short). The FOFHFR index is an equally-weighted index of funds-of-hedge funds for 112 FOFs in 1994 and 224 FOFs in 1999. The FOFMAR is a historical series of the median FOF's returns. For completeness, we constructed an equally-weighted index for the FOFs in the TASS database ("FOFTASS" for short).

What do the FOF data tell us about the experience of hedge fund investing over the last five years? Following the format of the earlier sections, we begin by discussing potential measurement biases in the FOF returns.

4.2. Returns From Funds-of-Hedge Funds Are Less Susceptible to Measurement Biases

The track records of FOFs avoid many of the idiosyncratic biases that are embedded in pro forma returns based on individual hedge funds extracted from databases. First, the majority of FOFs report audited performance to their investors where successful investments as well as "mistakes" are recorded. For example, a successful investment in a hedge fund that reached capacity constraint and stopped reporting to database vendors will remain in the history of the FOF. This investment experience will continue to be a part of the FOF's performance as long as the FOF stays invested in that hedge fund. Similarly, past investments in funds that ceased operation will also remain in the track record of the FOF. Consequently, there is no survivorship bias in the actual track record of a FOF. In addition, the question of selection bias does not arise. While an individual hedge fund may choose not to participate in a database, its return would be fully embodied in the performance of any FOF that invests in it.[29] When a FOF adds a hedge fund to its portfolio, the portfolio's history is not affected so there is no question of instant-history bias.

Finally, as noted in Fung and Hsieh (2000b), survivorship bias in FOFs' returns is less severe than that in individual hedge funds. This is because FOFs, through the natural process of diversification, have inadvertently minimized the measurement errors that may arise.[30]

As the returns of each individual FOF reflect the actual decisions of the FOF manager, we can compare the return behavior of the FOFHFR and the HFRI during extreme market conditions to see if the spurious bias generated by the weighting scheme of the HFRI exists in the FOFHFR. Figure 2 tells the story during 1998. Prior to Aug. 1998, both indices moved in tandem to each other. The "rapid" recovery of the HFRI from the Aug. 1998 debacle can be largely attributed to the artifact of the overall index's equal weighting methodology where "losers were bought and winners were sold." Such a strategy, when applied to a very diverse hedge fund universe under extreme market conditions, leads to unrealistic return patterns. The recovery of the FOFHFR, on the other hand, was much more gradual, despite the fact that the FOFHFR is also an equally-weighted index.[31] What this implies is that few, if any, actual portfolio managers followed the "contrarian" asset allocation strategy implicit in the HFRI. In addition, it is almost impossible to effect such a quick asset reallocation on over 1,000 funds within the space of a month.

Based on this evidence, it appears that the FOF indices do not suffer from spurious biases arising from unrealistic asset allocation schemes.

4.3. Tracking Errors in Hedge Fund Indices

We conclude this section with a discussion on the construction of tracking portfolios to a given benchmark. In the case of the HFRI, the large number of funds (in excess of 1,000) makes it virtually impossible to replicate without significant tracking errors. In the case of the CTI, which has roughly 300 funds, tracking error may still be quite large, for a different set of reasons. Firstly, the CTI may contain funds that are closed to new investments (and/or investors). This is clearly noted in the "Frequently Asked Questions" section in the CSFB/Tremont website. Secondly, and more interestingly, the liquidity and redemption policies of hedge funds make it impossible to define an unambiguous rebalancing scheme. Hedge funds frequently require advance notification prior to redemption. This can range from 10 days to six months. Redemption intervals also vary from fund to fund between 30 days to one year. In order to rebalance an index based on "known" values of it's constituents, the rebalancing date has to coincide with the component hedge fund that requires the longest notification period and redemption interval. If this turns out to be a quarter or longer, then it will fail the monthly rebalancing rule of the CTI, but more importantly, it imposes a buy-and-hold strategy on an index in-between rebalance dates. This "rebalancing" bias is a natural consequence of the way the hedge fund industry operates.

If the inherent level of "natural" tracking error arising from the way the hedge fund indstury is organized is high, then the property of being an investable index is no longer relevant. It follows that a broad-based index is purely a synthetic hedge fund portfolio whose objective is to deliver the risk return characteristics of the "popular bets" among hedge fund managers. To this end, we would argue that using FOFs as building blocks for hedge fund performance benchmarks is a better alternative to individual funds. It takes fewer FOFs to deliver the same diversification benefit as individual hedge funds as illustrated in Figure 1, and FOFs are likely to have a more uniform redemption policy than individual funds. Both of these observations suggest that portfolios of FOFs are likely to have a lower rebalancing bias than portfolios of individual funds. In addition, FOFs have smaller measurement biases than individual funds. However, in interpreting the risk return characteristics of FOFs, it is important to make adjustments for the portfolio management costs of FOFs. A procedure for approximating these costs can be found in Fung and Hsieh (2000b). Finally, neither a broad-based index of FOFs nor a broad-based index of individual hedge funds can capture the diverse risk characteristics of different hedge fund trading styles. However, as FOFs reflect the actual portfolio decisions of the FOF managers, it is reasonable to assume that their return characteristics better reflect hedge fund investors preferences than portfolios of hedge funds defined by arbitrary index rules.

5. Summary and Conclusions

Due to the lack of public disclosure, database vendors have only sketchy information on hedge funds that ceased operation (i.e., died) prior to the mid-1990s. It is therefore impossible to fully adjust historical returns from hedge fund portfolios for survivorship bias prior to the mid-1990s. Since the emergence of the major hedge fund database vendors in the mid-1990s, survivorship bias can be partially rectified in pro forma returns depending on the completeness of the respective database vendor's record on defunct funds. Consequently, pro forma portfolio returns from hedge fund databases suffer from *survivorship bias* that is natural to the way the hedge fund industry is organized. Based on available information on defunct funds, Fung and Hsieh (2000b) estimated the survivorship bias in hedge-fund returns from the TASS Asset Management (TASS) database to average roughly 3% per year since 1994. In other words, pro forma returns from a portfolio of surviving hedge funds are biased upwards by approximately 3% per year. The caveat in using this estimate is that there is no way to assess the impact of unobserved defunct funds.

The combination of the voluntary nature of hedge funds availing their information to databases and the respective inclusion process of database vendors leads to differences between the funds in a database and funds in the universe of hedge funds. Coupled with the fact that most commercial hedge fund databases came into existence around the mid-1990's, hedge fund data pre-1994 will also suffer from a natural form of *selection bias*. However, it is not possible to determine the size of the selection bias, because we cannot compare the performance of the observed hedge funds in databases with the performance of unobserved hedge funds in the population.

When a hedge fund enters into a vendor's database, the fund's history is generally "backfilled." This gives rise to an "instant history" bias. Fung and Hsieh (2000b) estimated to have an upward bias on the average pro forma return by 1.4% per annum.

Post-1994, natural biases can be partially rectified as the difference between databases and the unobservable population data converged over time. The extent to which survivorship bias can be mitigated depends on the completeness of database vendors' collection of defunct funds information. Earlier studies by Ackerman, McNally, and Ravenscraft (1999) and Liang (2000) indicated significant differences exist between records on defunct funds among database vendors. This casts doubt that a complete record of post-94 defunct funds exists. It is reasonable to conclude that survivorship bias continues to exist in pro forma return series based on hedge fund databases, albeit to a smaller extent than pre-1994 returns series. These earlier studies also reported differences in the composition of the HFR database and the TASS database. These differences support the conclusion that a spurious selection bias exists in pro forma returns series from these databases.

There are significant differences between the returns of the two broad-based hedge fund indices – the HFRI and the CTI. Most of the return differences came from the way the respective indices are constructed. The HFRI is an equally-weighted index on over 1,000 hedge funds whereas the CTI is a value-weighted index on a sample of around 280 hedge funds. The impact of alternative index construction method on returns is magnified by the diversity in the trading styles and performance among the underlying hedge funds.

In terms of risk characteristics, broad-based indices like the HFRI and CTI mask the diversity of individual hedge fund return characteristics. This sentiment is reflected by MAR in their stated reason for publishing median hedge fund return for individual styles without one for all hedge funds. A broad-based index is helpful for investors wishing to gain exposure to the **current** growth trend of the hedge fund industry. It allows investors to have similar exposures to "popular bets" among hedge fund managers. However, this exposes investors to potential "style convergence risk" in the sense that, when a large number of hedge fund managers converge onto a similar set of bets, portfolio diversification implodes. For those investors seeking diversification from traditional asset classes, a broad-based index like the HFRI and, to a lesser extent, the CTI have limited information content.

In Section Four of the paper, we introduced a simple solution to mitigate some of these biases. It is based on the idea that we can estimate hedge fund investment experience by looking at the records of funds-of-hedge funds ("FOFs"). The FOFs' investment records avoid many of the idiosyncratic biases that are embedded in pro forma returns based on individual hedge funds extracted from databases.

Survivorship bias in FOFs' returns relative to the universe of all hedge fund investors is less severe than using individual hedge funds. This is because FOFs, through the natural process of diversification, have inadvertently minimized the measurement errors that may arise. Also, the question of selection bias is much more muted in the case of FOFs due to the fact that all individual hedge funds are likely to have some FOF investors irrespective of whether they report performance to any hedge fund database. The question of instant history bias does not arise with FOFs. Also, empirical evidence suggests that indices of FOFs do not suffer from spurious biases arising from unrealistic asset allocation schemes. .

Fung and Hsieh (2000b) estimated the portfolio management costs from FOFs returns to be approximately 2% per annum. After adjusting for these costs and for instant history bias, the broad-based indices deliver roughly the same returns as the FOF indices with comparable standard deviations. Investors interested in "popular bets," however, may prefer equally-weighted broad-based indices as they are more responsive to newer, smaller hedge funds. In contrast, investors interested in more established, larger hedge funds would prefer using indices using FOFs. This is similar to the distinction between small cap and large cap stock indices. However, for investors looking for diversifying alternatives to traditional asset classes, neither the broad-based indices nor the subindices of hedge fund styles are suitable building blocks for customized indices that reflect these investment objectives.

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Table 1
Annual Returns of Hedge Fund Indices

Year	HFR Index (HFRI)	CFSB/Tremont Index (CTI)	Difference HFRI-CTI
1994	4.1%	-4.4%	9.5%
1995	21.5%	21.7%	-0.2%
1996	21.1%	22.2%	-1.1%
1997	16.8%	25.9%	-9.1%
1998	2.6%	-0.4%	2.2%
1999	30.8%	23.4%	7.4%
Mean 94-99	16.2%	14.7%	1.5%

Table 2
Statistics on Subindices of Hedge Funds

A. Emerging Market Hedge Fund Subindices

Year	Weighting Scheme In Overall Index		Annual Return	
	Equal	Value	HFR Subindex	CT Subindex
1994	12.5%	16.3%	3.38%	12.51%
1995	13.9%	18.0%	0.69%	-16.91%
1996	14.5%	14.7%	27.14%	34.50%
1997	12.7%	12.1%	16.57%	26.59%
1998	11.8%	9.5%	-32.96%	-37.66%
1999	11.9%	7.1%	55.22%	44.82%

B. Global/Macro Hedge Fund Subindices

Year	Weighting Scheme In Overall Index		Annual Return	
	Equal	Value	HFR Subindex	CT Subindex
1994	4.9%	38.2%	-4.30%	-5.72%
1995	4.9%	34.3%	29.32%	30.67%
1996	4.7%	24.8%	9.32%	25.58%
1997	6.0%	23.8%	18.82%	37.11%
1998	5.4%	13.7%	6.19%	-3.64%
1999	4.8%	13.2%	17.62%	5.81%

Table 3
Correlation Between Benchmark Hedge Fund Indices and Market Indices

A. Correlation Coefficients

	Hedge Fund Indices	
Market Indices	**HFRI**	**CTI**
Euro$ one-month Return	0.14	0.29
GSCI	0.26	0.15
US Equities	0.73	0.55
Non-US Equities	0.66	0.42
US Bonds	-0.05	0.17
Non-US Bonds	-0.14	-0.36
US Dollar	0.01	0.40
Emerging Market Equities	0.76	0.47
High Yield US Bonds	0.56	0.51

B. Regression of HFRI and CTI on Market Indices

	Hedge Fund Indices	
Market Indices	**HFRI**	**CTI**
Constant	-0.02	0.02
Euro$ one-month Return	6.77 *	5.14 *
GSCI	0.08 *	0.05
US Equities	0.15 *	0.10
Non-US Equities	0.04	0.10
US Bonds	-0.35	0.30
Non-US Bonds	-0.25	0.29
US Dollar	-0.24	0.37
Emerging Market Equities	0.11 *	0.06
High Yield US Bonds	0.51 *	0.24
Adjusted-R^2	0.76	0.55

C. Frequency Distribution of Adjusted-R^2
For Individual Hedge Funds on Nine Market Indices

Adjusted-R^2 From	To	% of Individual Hedge Funds
-0.2	-0.1	0.9%
-0.1	0.0	8.1%
0.0	0.1	15.3%
0.1	0.2	14.5%
0.2	0.3	15.5%
0.3	0.4	11.9%
0.4	0.5	11.2%
0.5	0.6	11.8%
0.6	0.7	5.4%
0.7	0.8	3.2%
0.8	0.9	1.9%
0.9	1.0	0.4%

Table 4
The Size of HFR Equity Hedge Subindex Relative to the Overall HFRI

	% of Overall HFRI	
Year	By Number of Funds	By Assets of Funds
1994	16.8%	7.1%
1995	14.7%	7.4%
1996	14.1%	12.8%
1997	15.4%	10.2%
1998	17.9%	14.2%
1999	27.3%	30.4%

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Footnotes:

1. See Fung and Hsieh (1999) for an overview of how hedge funds are organized and their economic rationale.

2. This distinction does not arise in the mutual fund industry where public disclosure enforces the convergence of the universe and the database of all mutual funds. However, with the hedge fund industry, the very fact that the population is not observable means that a single database (or for that matter, the set of all databases) need not coincide with the universe.

3. Technically, over any sample period, if a complete record of defunct funds is available, survivorship bias can be mitigated through some tedious data manipulations. The problem is in verifying the completeness of historical records on defunct hedge funds.

4. See Grinblatt and Titman (1989), Brown, Goetzmann, Ibbotson, and Ross (1992), and Malkiel (1995).

5. This is because these funds predated the existence of most hedge fund databases.

6. Generally, database vendors have "listing requirements" that a hedge fund must meet in order to be included in their databases. Such listing requirements typically involve a minimum amount of assets under management, timely reporting of information, as well as the ability of the database vendor to verify performance record.

7. Fung and Hsieh (1997a) cited anecdotal evidence that some managers with superior performance have refused to participate in databases because they have reached capacity constraints and are no longer looking for investors.

8. Of course if the database from which a sample of hedge funds is extracted has survivorship bias, then, *a fortiori*, the smaller "sample portfolio" is likely to exhibit survivorship bias.

9. Here we follow a methodology first used in Malkiel (1995).

10. This calculation requires data vendors to retain records of defunct funds.

11. Often from friends and relatives in addition to the manager's personal capital.

12. Of the three most widely known hedge fund database vendors, HFR, TASS and The Managed Account Review (MAR), MAR elected not to report a performance index on their database of hedge funds. They cite the diversity of trading styles as the reason for not compiling an index of all funds. In the next section we analyze this question.

13. At the time of writing, a new value-weighted index of hedge funds has been added to the family of HFR indices. However, historical returns prior to 2000 have not been released.

14. Although the MAR existed much before 1994, historically their focus was on Commodity Trading Advisors.

15. This is notwithstanding the questions on the stationarity of the return time series.

16. In much the same way, historical returns on mutual funds before the sixties are vulnerable to survivorship bias as records of defunct mutual funds became sketchy.

17. See Liang (2000) for a more detailed comparison of the two databases.

18. See Fung and Hsieh (1999) for a description on the difference, or lack of, between commodity funds and hedge funds.

19. Monthly performance data on the CTI are available through the CFSB/Tremont web site from Jan. 1994 to date.

20. We shall leave aside the practical question of being able to implement this given the contribution and redemption polices of most hedge funds, which include advanced notification period prior to redemption and/or limited periodic exits ranging from monthly to annually.

21. In other words, the columns highlight the difference in portfolio composition had HFRI used a value weighting scheme.

22. Technically, the weights are adjusted on a monthly basis. Here we use the annual figures to illustrate our point.

23. A value weighting method in the CTI would have implied less exposure in emerging market funds and the emerging market funds in the CTI also returned less than their counterparts in the HFRI. A crude estimate of this is 7.1% x 44.82% = 3.18% compared to the 6.57% of the HFRI, which is almost half the difference between the performance of the two indices.

24. This is available from the authors upon request.

25. Fung and Hsieh (1997a) refer to these as Style Groups.

26. Since we did not require each fund to have performance information for the entire sample, we adjusted the portfolio weights to allow for entry and exit.

27. We choose the term “common risk factors” in order to avoid the confusing usage of the term “systematic risks.”

28. There are many reasons why constructing a passively diversified portfolio of hedge funds is not a practical proposition for individual investors. For instance, the minimum investment in a single hedge fund runs anywhere from US$100,000 (for very small funds) to several million dollars for the bigger Macro funds. Unless different hedge funds are efficiently blended together, Figure 1 tells us that it may take over 100 funds to passively reach the limit of diversification. Even if we assume a modest minimum investment of one million dollars per fund, the empirical evidence suggests that a substantial amount of capital is required to passively diversify away idiosyncratic hedge fund risk. This is not to mention the daunting task of administering such a large portfolio of essentially private investment vehicles. Therefore, in contrast to mutual funds where passive diversification leads investors to “low cost” indexed funds, the reverse is true of hedge fund investing. Funds-of-hedge funds offer investors a simple way of accessing a diversified portfolio of hedge funds.

29. It is reasonable to assume that even for hedge funds that do not report performance to database vendors, there must be some funds-of-hedge funds among its investor base.

30. There is, however, a peculiar form of self-selection bias that may arise with FOFs. Large institutional portfolios managed by FOF managers are generally kept confidential. In this case, there may be a downward bias in the recorded amount of assets managed by a FOF manager in databases. The impact of this bias on performance statistics is small as the FOF indices are generally not weighted by assets under management. In addition, the management style of the unreported programs is likely to be similar to those programs disclosed to database vendors.

31. Similar return behavior are also observed with FOFMAR and FOFTASS.

Figure 1. Portfolio Standard Deviation and Number of Funds: 1,000 Samples Without Replacement

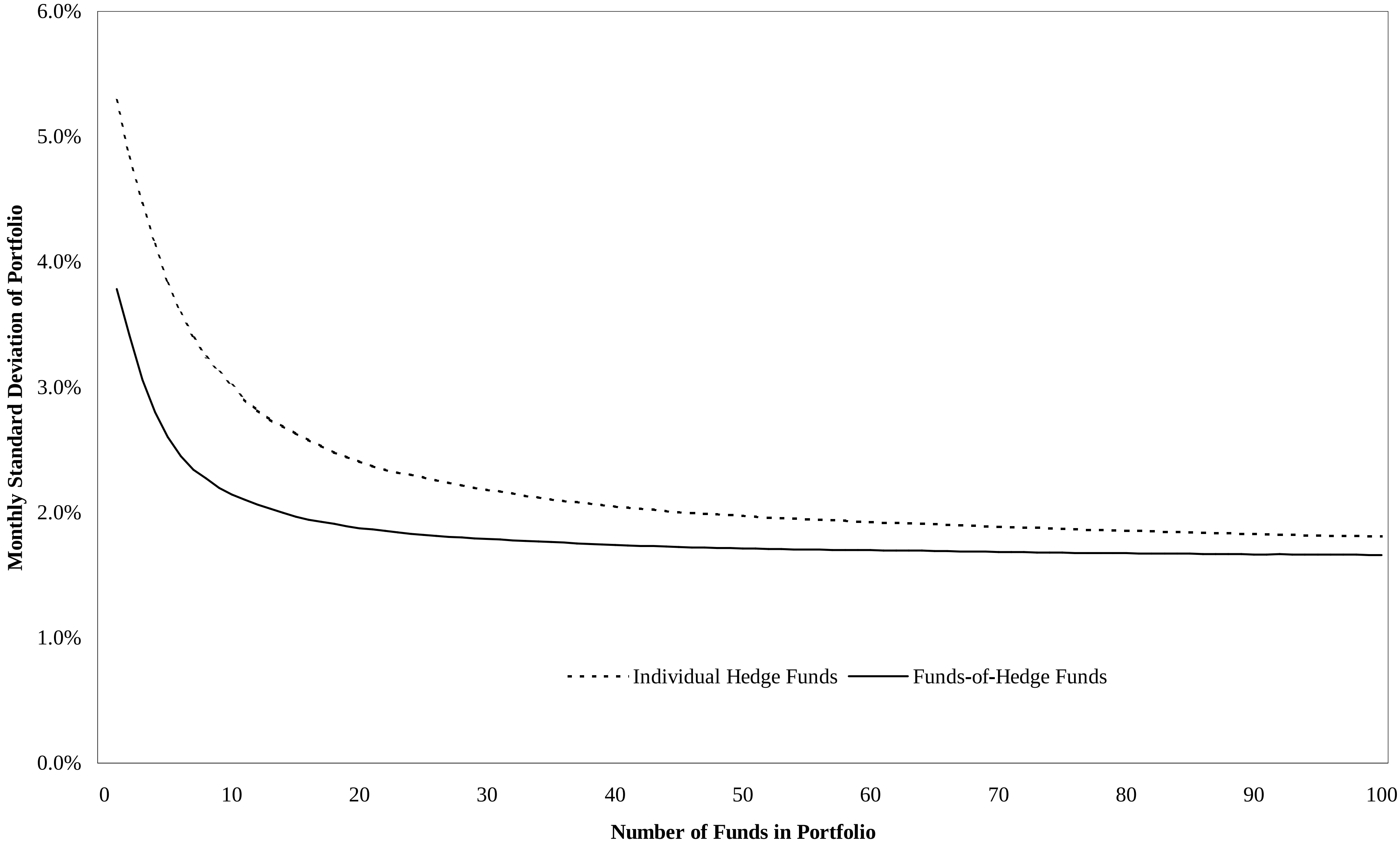

Figure 2. Monthly Returns of HFR's Overall Index & Funds-of-Hedge Fund Index