Benchmarks for Alternative Investments

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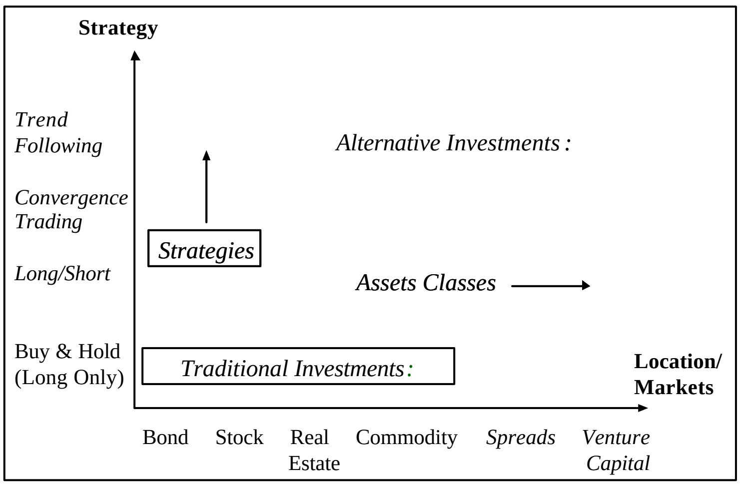
Introduction

This particular session is mainly on hedge funds, or more precisely, hedge fund strategies. Within the context of the seminar, let me begin by placing hedge funds within a broader context of other asset categories.

Typically, when we think of traditional investments, we think of asset classes --- familiar ones are bonds, stocks, real estate, and commodities. Often, real estate and commodities are placed into the alternative category. But these investments have been around so long, I prefer to leave them in the "conventional" category. As **Exhibit 1** illustrates, moving along the horizontal axis, the first addition I made beyond the traditional asset classes are— "spread". At the very end of non-traditional investment classes, we have venture capital. There is a reason why I ordered them in this way.

The logic is as follows. With traditional investments, we frequently assume that the strategy used is one of buy- and-hold and long only. By making that assumption, one is simply saying that only where those assets transact determines all the risk return characteristics. Whereas with hedge

Exhibit 1. Investment Landscape



This is the proceedings of a presentation delivered by William Fung to the 15th SAAJ-AIMR/JSIP Joint Seminar "Asset Management and Benchmarks", March 5-7, 2003, Tokyo. The content of the presentation represents co-study by William Fung and David A. Hsieh.

funds strategies it is not where these assets transact, it is how the risk is being managed that matters. In other words, hedge funds may hold a portfolio of conventional stocks and bonds, how hedge fund managers generate return and risk characteristics different form the underlying holdings is a function of how the underlying securities are managed. Put differently, hedge fund returns differs from conventional assets not because they invest in different assets but because of the way the underlying investments are managed.

This is a very important distinction— conventional asset classes are different from each other in terms of physical attributes--stocks versus bonds for example. What make hedge fund returns different are the differences between hedge fund strategies and the buy-and-hold strategy assumed in generating conventional asset class returns.

As shown in **Exhibit 1**, along the horizontal axis, the only substantive difference in terms of assets used by hedge funds from conventional asset categories is the emphasis on "spreads" or long/short combinations of conventional assets. In contrasts, there is a much more significant difference between hedge fund strategies and conventional asset management strategies as the vertical axis depicts.

In general, hedge fund strategies are long-short combinations of traditional assets. It is the management of these long-short positions, together with leverage, that generate interesting alternative risk-return characteristics.

The rest of the talk will be focused on "What are these strategies?", "How is it done?", and "How do we go about measuring it?"

My talk has three parts. The first part deals with the difficulties in measuring hedge fund return characteristics, and the second part deals with the different ways to simplify the wide range of hedge fund strategies to something more manageable. The third is a combination of the first two topics, where I analyze the different ways of creating benchmarks for hedge funds. The first and second part of my talk consists of extracts from two papers that David Hsieh and I have published in the Financial Analysts Journal. The third part is an extension of these earlier works.

Problems with Database Biases

If an investor wants to know something about alternative investments, the first difficulty that he or she comes across is "how are these returns generated?"

To answer this question, we begin by learning from past performance. Here we come across the first difficulty in analyzing hedge funds—namely data limitations. Over the decades of investment experience with traditional assets, we are spoiled with twenty, fifty and sometimes even a hundred years of data, spanning a broad range of economic cycles. In contrast, the hedge fund industry is still in its infancy compared to traditional investments. In addition, it has stayed pretty much unregulated to now. Therefore, data and information are not easy to obtain. When you do get them, they frequently come in non-standardized formats, which make comparison and analysis using conventional statistical tools very difficult. Let me begin by discussing these data difficulties researchers face.

Before going into analyzing the specifics of hedge fund performance, it is helpful to state the goals of such an exercise. One of the outputs of performance analysis is to help us construct effective investment benchmarks to judge past performance on a risk-adjusted basis or to compute risk-adjusted alphas. I will try to persuade you that not all "alternative alphas" are born equal, or that they can differ greatly in terms of risks. That is one concept I want to stress. Moreover, I would like to highlight the differences between alternative strategies in order to identify these risk differences. This is essential if we are to determine how hedge fund strategies fit into an overall asset allocation framework. Beyond identifying these risk differences, we also need to form reasonable expectations about future return and risk in order to manage investments going forward. To achieve this, we need to develop efficient benchmarks in a coherent, consistent framework for doing all three.

I begin with looking at past performance. Analyzing the hedge fund industry reminds me of trying to observe an eclipse-- you are never allowed to see the entire picture--there is always something missing. The industry has grown in the past from a very small size to approximately 6,000 funds and hundreds of billions of dollars under management. The more funds there are, the more we should be concerned about the size of that portion of the industry that we cannot see in judging the past.

Just how big is this problem? Look at existing databases of hedge funds. Typically, these databases have three main sources of biases inherent in their data. These are: "selection bias", or missing data or funds; "survivorship bias;" and the third "instant history bias".

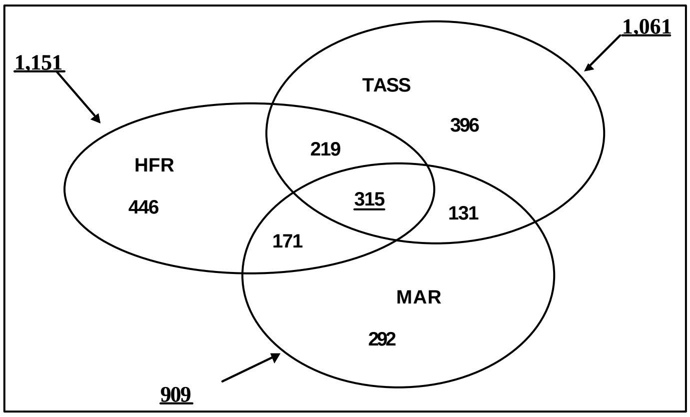
Selection Bias

Let me begin with selection bias. No database vendor has ever been able to capture all hedge funds ever existed at any point in time. That is just a consequence of an unregulated industry where hedge fund managers can choose to report to one database vendor but not to another. In fact, there is no obligation to report to database vendors at all. On the data collection side, different database vendors have different criteria for including a fund in their database. Given this, how different is one database from another? At the research center of London Business School, we have been trying to develop statistics that will help us determine the magnitude of these biases. Here are some of our findings, at the end of 2000, combining different commercially available databases together allows us to see the following picture:

First, you begin with a commonly-known database like Hedge Fund Research (HFR). Next, we added another well-known database like TASS. Finally, add an equally well-known database like MAR/Hedge.

As shown in **Exhibit 2**, at the end of 2000, HFR had approximately 1,151 funds in their database, TASS had 1,061 funds, and MAR had about 909 funds. Superficially, it is tempting to conclude that"they are not very different". But if you look closely at the data, you find that of the three databases, there are only have 315 funds in common. In other words, if you ask the question "What does the universe of hedge funds look like at the end of the millennium?" you may get very different answers depending on whom you ask. That is a little disturbing. For some reason, different database vendors managed to uncover a sizeable number of hedge fund managers that the other database vendor did not have. What I find amazing is that despite having only 315 funds common to all three, their respective indices of the industry are highly correlated!

Exhibit 2. December 2000: 1,970 Live Funds



Survivorship Bias

If you cannot see all the funds that are in business, then by implication, you are hardly likely to be able to see all the funds that died or went out of business. These missing funds are the primary cause of survivorship bias. Over time, funds come into the industry, and they go out of industry. Some funds survive, and others will not. It will be logical to expect that performance characteristics of those that went out of business to be inferior to those that managed to stay in business—or that there is a survivorship bias in their performance statistics.

However, there is another aspect to survivorship bias among hedge funds. This comes from managers who simply chose not to report to database vendors. Hedge funds tend to have finite capacity. When successful managers raised enough capital, they are no longer interested in disclosing their performance statistics--they will simply stop reporting. If successful managers are also among the missing funds in a database, this "missing funds bias" cannot be easily determined—in that it can run in opposite directions.

Clearly, funds that went out of business will bias your performance statistics upwards, in the sense that all those funds that died with poor performance are missing. Against this, successful managers with good performance characteristics may also be missing as they stopped reporting to databases. In the end, we have these two offsetting forces affecting historical returns making it hard for us to form definitive conclusions.

"How big a problem is this?" At the end of December 2000, there are all together 2,087 missing or dead funds. At the LBS Research Center, we purchased all the dead fund information from these major database vendors. Arranging the results in the same format as before, as illustrated in **Exhibit 3**, we see that HFR have 1,021 funds in their missing fund database. With TASS, there are 497. With MAR/Hedge, there are 885. The dead/missing funds that are common to all three databases only come to 39. With this, one arrives at the same uncomfortable conclusion. That is: no matter what type of hedge fund data you are interested in, dead or alive, you may get very different answers depending on whom you ask.

Not only does this problem exist with past data, we don't see the problem going away in a hurry. Consider this--if we track all the hedge funds that came into existence since 1977 (all those that we were able to collect) one arrives at this diagram as shown in **Exhibit 4**. From 1977 to the end of 2000, approximately 6,000+ funds entered the hedge fund industry. Of that, 2,087, as I pointed out, died or went missing. Each year, the ratio of new funds created to funds exiting known

Exhibit 3. December 2000: 2,087 Missing/Dead Funds (since 1987)

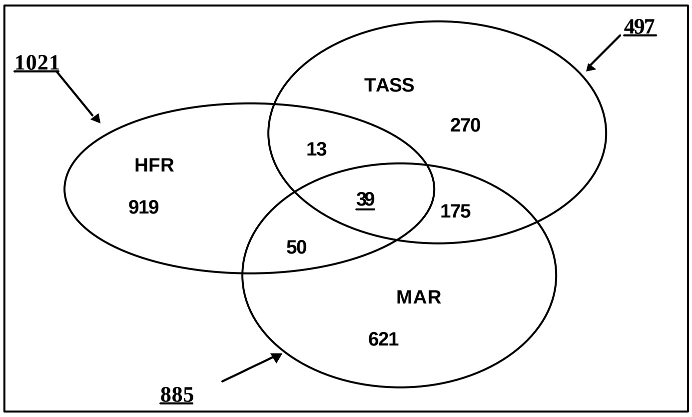
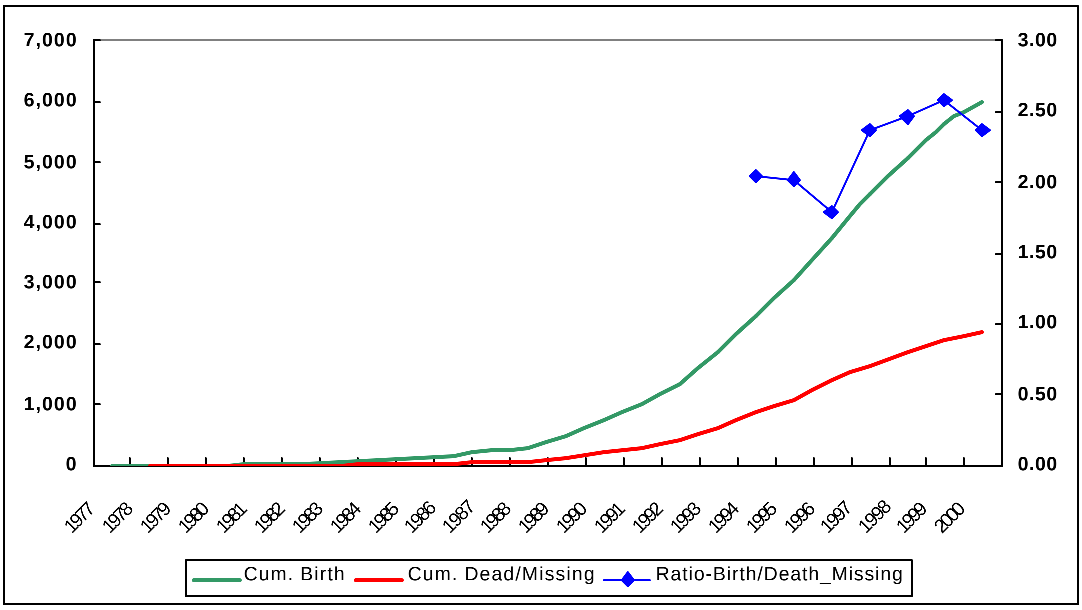


Exhibit 4. Hedge Funds Entry/Exit Trend: 1977 to 2000



Source: HFR, TASS, MAR and others

databases has been remarkably stable. It varied between1.75 to 2.50 in favor of new funds. That tells us that the missing fund problem is not likely to go away anytime soon.

What are the practical implications? It turns out that these biases can impact pro forma returns of given samples of hedge funds. Omitting the impact of "dead funds," from pro forma returns is similar to simulating historical performance free of investment errors. This is clearly unrealistic.

How big is survivorship bias? The range of estimates from existing research falls within the range of 0% to 3%. In other words, if you had measured the performance using only live available funds, you can be making errors of up to 3% per annum in performance. However, since we can never see the entire universe of hedge funds, this range remains an estimate. That said, I would take some of the work that concluded a zero percent bias with caution.

Instant History Bias

Next I come to "Instant History" bias. "Instant History" bias is something peculiar to hedge funds. In the hedge fund industry, it is quite often that new funds get started with friends' and relatives' money as well as the manager's own capital. Over the initial trading period (or an incubation period) success will lead them to grow by raising more capital. Failures will simply disappear unnoticed. Therefore, by the time we see a new hedge fund appearing in any database, almost by definition, the incubation experiment has succeeded. Typically, when a fund gets started, the fund manager works much harder running a small business. Quire often, there is a tendency to see better performance in the first 12 months of a fund's operation. Generally when they grow bigger, with few exceptions, performance tends to decline. Database vendors generally do not distinguish performance during the incubation period from the subsequent periods. This is known as the "Instant History" bias, which affects estimates of historical mean returns. We estimated this number in one of our earlier papers in the Journal of Financial and Quantitative Analysis, to be approximately 1.4% per annum (too high) on average.

What can be done to mitigate some of those problems? For instance, we can consider the question "Are these measurement errors diversifiable?" Generally, if a fund is missing, no matter how big a sample you use from "live funds," it will remain missing. Bear in mind that the survivorship bias figures I mentioned earlier are derived from using "entire" databases, it is unlikely that most simulated portfolios are sampled from larger universes. Until the true universe of hedge funds, past and present, can be observed, there is no way to determine whether broadening a sample of hedge funds necessarily reduces measurement errors.

Other Problems: Peer-Group Averages

Another tricky problem arises in the construction of hedge fund portfolios. Take for example, an equally weighted portfolio of hedge funds. Over time, an investor of an equally weighted portfolio is actually following a contrarian strategy.

How does that happen? Every time a fund does better than its peer (a winning fund relative to its peer), in order to maintain equal-weighting, you will have to reduce exposure to the winner and increase the exposure on the losing funds (relative losers) to restore equally weighting among all funds in the portfolio. I do not know of too many portfolio managers who are very comfortable selling winners and buying losers in a consistent manner. It is possible that this strategy suits certain specific investment mandates but one should be aware that a seemingly passive, simple weighting scheme implies an active contrarian portfolio strategy.

Another popular passive portfolio strategy is the standard value-weighted method. Value-weighted method can be problematic with hedge fund portfolios. It effectively assumes a buy-and-hold strategy where "the rich gets richer." The better performing funds have a tendency to increase in their portfolio weighting reducing diversification. Unfortunately, the hedge fund industry is a finite capacity industry. So, ultimately you will run out of capacity with the good performing funds. Value weighting is a popular method among conventional asset indices but is naturally unsuitable for the hedge fund industry.

Another problem with peer-group averages is that it is frequently based on qualitative information from the hedge fund managers themselves. Because there is no standardization in the hedge fund industry what one database vendor means by a particular description could be very different from what another database vendor despite (almost) identical sounding strategies. For example, in what is described by the CSFB/Tremont family of indices as "Equity Market Neutral Funds", there are 27 funds in that category at the first quarter of 2001. Out of these 27--18 are in Hedge Fund Research's database. According to HFR, these very same funds were classified into different groups. (6 in Equity Market Neutral, 7 in Statistical Arbitrage, 3 in Equity Hedge, 2 in Other Sub-indices). It is hard to tell if different database vendors describing these funds by similar "words" actually result in funds with similar risk and return characteristics. How then do investors extract "forward looking" risk-return characteristics based on qualitative descriptions of funds? One needs to go a step further, and ask the question: "What are the risk and return characteristics behind these words? What makes a fund market-neutral?"

Style Categorization

With all these caveats regarding the interpretation of past hedge fund performance, what can we learn from historical data?

Funds of Hedge Funds Performance

If you are interested in the past performance of hedge funds, why not look at the actual experience of hedge fund investors. That--translates to looking at the funds of hedge funds. These are actual portfolios of hedge funds. Their returns are usually audited, compiled by independent administrators, and if any investment a fund of fund made ended poorly (say the underlying fund went out of business) the impact remains in their track record. In other words, you cannot erase it from the past returns like simulated pro forma returns out of a database. In addition, we do not have to make artificial assumption on the portfolio's weighting scheme like equal weighting or value weighting. The historical pattern of asset allocation is kept in the track record of funds of hedge funds.

A negative for using funds-of-hedge funds to assess past performance is the lack of transparency. Rarely are the historical portfolio compositions of funds-of-hedge funds kept (or for that matter, disclosed). A positive for using funds-of-hedge funds is that they are investable. Something to be careful about using data from funds-of-hedge funds is the extra layer of fees over and above the underlying hedge funds.

Although an index of funds-of-hedge funds is helpful in giving us almost bias-free historical performance characteristics of a typical portfolio of hedge funds, more work is needed to explicitly identify the current asset allocation of such a portfolio. This is so because asset allocation decisions of funds-of-hedge funds do change over time. To explore this question we need to draw from some of the research on estimating the aggregate risk characteristics of the hedge fund industry and how they evolved over time.

This takes me to the second part of the talk – Return-Based Style Models.

Return-Based Style Factors

Qualitative style categorization of a hedge fund's strategy typically depends on the fund manager's self-descriptions of what the strategy does. Like historical hedge fund performance, there is no standard format in which the information is reported. At best, this source of information is too imprecise and open to interpretation and at it's worst, it can be confusing and unreliable. An alternative to relying on what managers tell us what they do, why not look at the actual return patterns to see what managers actually do.

It turns out that we can achieve this by running statistical analyses on historical performance using techniques such as cluster analysis or principal component analysis to group funds with similar return characteristics together. We call these groupings of funds "return-based style factors". In our first paper in 1997, David Hsieh and I did this analysis and found five major principal components, or return-based style factors. More recently, Steve Brown (NYU) and Will Goetzmann (Yale) extended our work and found up to eight return-based style factors. Whether there are five or eight return-based style factors is unimportant. What is important is that these results tell us that the problem of having so many different qualitative style groups can be reduced by way of actual performance characteristics from funds.

How does this help us in making decisions? Where it helps us is to reduce the dimensions of the manager-selection to more manageable proportions. It also helps us to reduce the missing funds data problems. This is so because if return characteristics are being grouped into homogeneous groups, there is a good chance that the missing funds will have return characteristics that can be capture by these return-based style factors.

Where return-based factor analysis cannot help us are in the following areas:
1. Some database biases still remain when it comes to measuring average returns.
2. Return-based style factors do not give us any further insight into the strategies other than the fact that groups of funds perform like each other statistically. But no further clue is provided as to how and why.
3. These return-based style factors may not be stable over time and can be sample-dependent.
4. Return-based style factors are mathematical constructs that are not investable. There is no unique qualitative interpretation of the factors.
5. Finally, it is hard to deal with the multi-strategy funds within a return-based style factor framework.

These are difficult problems to resolve. Over the last four years, David Hsieh and I have tried to find an alternative to return-based style factors that are less vulnerable to these problems.

Asset-Based Style Factors

We came up with an idea that in order to solve all these problems, we need another way of measuring hedge fund risk beyond just looking at past hedge fund returns. It turns out that the most direct approach is to explicitly model hedge fund strategies using a rule-based model and observable market prices. We call these Asset-Based Style Factors (ABS factors for short). The first model we build was an option-based replication of trend-following strategies (Fung and Hsieh, Review of Financial Studies, 2001). Since then Mitchell and Pulvino (respectively of Harvard and Northwestern) have created a similar factor for merger arbitrager strategies (Mitchell and Pulvino, Journal of Finance, 2002). We have also created models that mimic the return characteristics of fixed income arbitrage (Fung and Hsieh, Journal of Fixed Income, 2002) and we are now finishing some work mimicking the equity long-short strategies extending some of the work of (Agarwal and Naik, Review of Financial Studies, forthcoming). A summary of ABS factors can be found in our article in the Financial Analysts Journal, 2002.

How do ABS factors work? From return-based style factors we can identify groups of hedge funds with similar return characteristics. The question is how to interpret these groups and how do we know if they are stable over time? ABS factors are rule-based models of hedge fund strategies. They are easy to interpret since they are constructed with a specific strategy in mind. ABS factors are computed based on market prices. Therefore, we can now compare the return series of ABS factors to the return-based style factors without risk of over fitting the data.

Whenever a return-based style factor's return matches with that of an ABS factor (or a linear combination of ABS factors), we now have an explicit identification of that group of hedge funds belonging to the return-based style factors. In other words, we have associated the return behavior of a group of hedge funds with that of a pre-determined rule-based model.

How would these things help us? These "asset based style-factors" have very interesting characteristics. They are bias-free because only market prices are used in the modeling process. We do not use hedge fund returns in constructing ABS factor returns.

They are transparent because the models are rule-based. It translates hedge fund risk into a conventional setting. In other words, we can take hedge fund risk, and directly relate it to stocks, bonds, and interest rates—conventional asset classes that you are familiar with. Through this process it is bringing hedge fund risk factors much closer to conventional risk factors.

In terms of performance evaluation, with ABS factors, we are now able to answer the following questions. Let us suppose that hedge fund returns are not risk-free. Few, if any of us, are willing to believe that alternative alpha is risk-free. What then are the risks inside these alternative alphas? The answer to this question tells us about the systematic risk factors inherent in the hedge fund strategies. Put differently, it tells us about hedge-fund betas.

In terms of risk management, through these ABS factors, we can relate hedge fund risks to conventional assets. Because of this association, we can infer from the performance of the ABS factors (which has data going back much further in history spanning many more economic cycles) and will no longer be constrained by the short history of the hedge fund industry itself.

Finally, in terms of measuring the expected risk and return, we can now directly relate the assessment of risk and return on hedge funds in a consistent framework with our opinions on traditional stocks, bonds and interest rates.

That-- is a lot of new ideas to digest. But I have to ask for your patience to go over one more slide on the limitations of ABS factors before showing examples of how ABS factors work. Like every theory, ABS factors have limitations. So far, we have only been able to identify ABS factors for a broad-based category of strategies. We cannot, at this point, model very specific strategies. That's one big limitation.

More work needs to be done but it will take time. Right now, there are researchers working on creating ABS factors for convertible arbitrage. I am looking forward to seeing outputs, because it will help us achieve the following.

Benchmarks for Hedge Funds

Recall from earlier discussions that, if you use traditional asset categories, stocks, bonds, emerging markets, currencies, gold---these are standard indices; assuming a long-only and buy-and-hold strategy--to explain the hedge fund returns, you won't do well. You will have very low R-squares, very low explanatory power. Unlike mutual funds, which are typically buy-and-hold strategies, the hedge fund return is distributed toward the zero-R-squared side to the left of the graph as shown in **Exhibit 5**.

Whereas applying the same standard indices to mutual funds, you will have the explanatory powers in the order of 70 to 90%. That is not terribly surprising, because mutual funds naturally buy and hold those types of assets.

Exhibit 5. R^2 to Standard Benchmarks: Fung and Hsieh, *RFS*, 1997

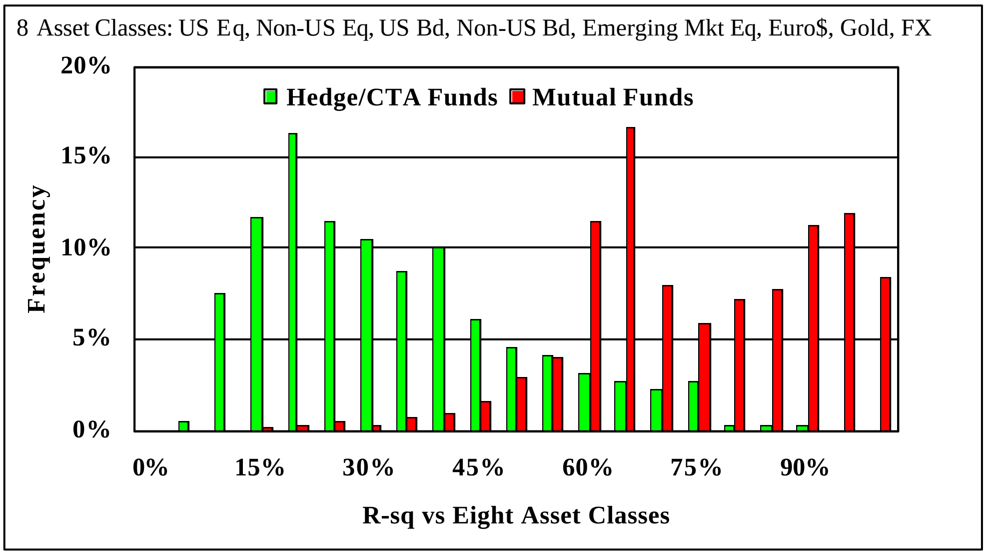
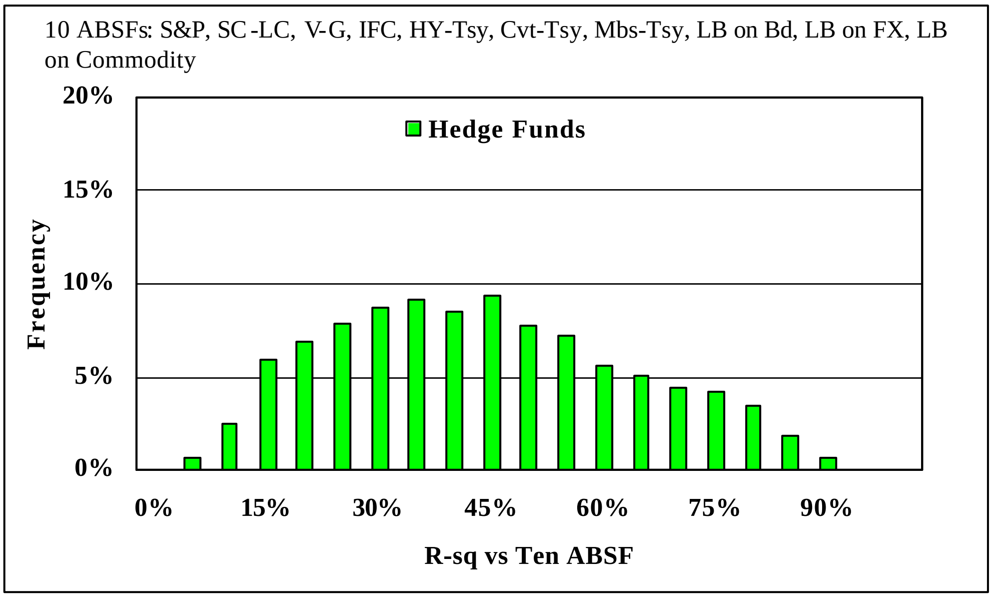


Exhibit 6. R^2 to Asset-Based Factors: Fung and Hsieh, 2001

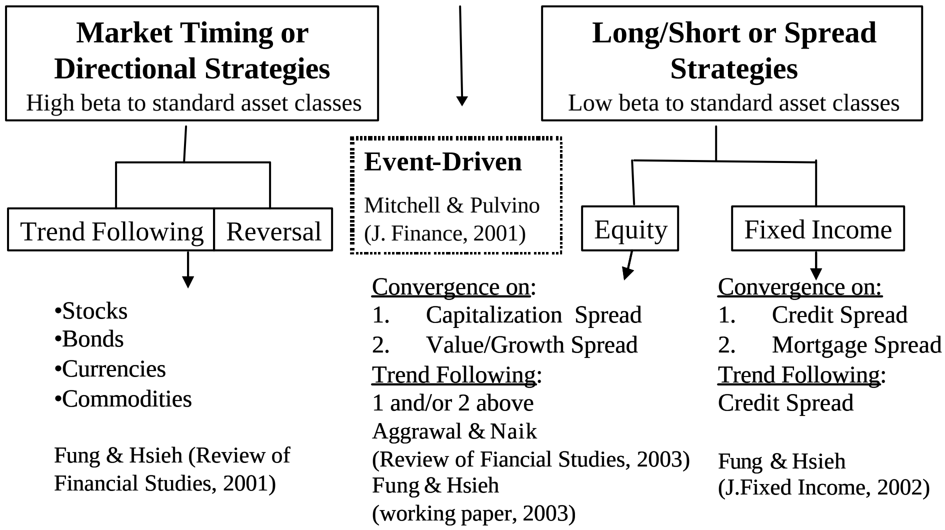


Cross-Sectional Differences of Hedge Fund Strategies

If we replace these conventional asset-class indices by ABS factors in the regression model, we can get it up to 40 to 50% R-squared as shown in **Exhibit 6**. I think that is pretty close to the limit in terms of explanatory power for most models because hedge fund strategies are dynamic cannot be easily capture by a stationary linear model like this. The details of those factors can be found in our second Financial Analyst Journal paper in 2002. There is also a reference section at the end of this presentation.

Exhibit 7 shows how these ABS factors fit into a single, unifying scheme of hedge-fund strategies. Soon after the Long-Term Capital disaster, the Bank for International Settlement, concerned about the impact on the banking system, produced a position paper attempting to categorize different hedge fund strategies into a single simplified framework. We extended that framework, to arrive at the following.

Exhibit 7. What we know about ABS Factors
BIS 1999, and Fung & Hsieh 2001 (NBER, Seminar)



In the original BIS framework, they simply have market-timing or directional strategies in one category, and the long-short or spread strategies in other category. They actually called "macro-trading" for directional, and "relative value" for the non-directional strategies. By "directional" they mean very high beta to the standard asset classes, by "relative value strategies" they mean low beta to standard asset classes. What's missing is, of course, the group of event-driven strategies. The challenge is to take this picture and create a single, unifying framework of risk factors that captures the characteristics all the hedge fund strategies?

Well, this is what we have got. For directional strategies--it really has two major components, trend following and reversals. In general, market-timing strategies are primarily momentum-driven (trend following) or contrarian-driven (reversal).

In terms of long-short or spread strategies, we can break it down into stocks and bonds to keep it in line with conventional asset classifications. In the equity area, hedge fund strategies can be categorized into either following a "convergence" type of approach to trading capitalization spread (small cap vs. large cap), or value-growth spread (long value short growth stocks, or vice versa). As convergence strategies are primarily following a contrarian approach, the flip side to this will be a momentum approach to trading these spread variables (either capitalization and/or value-growth). References can be found at the end of the presentation.

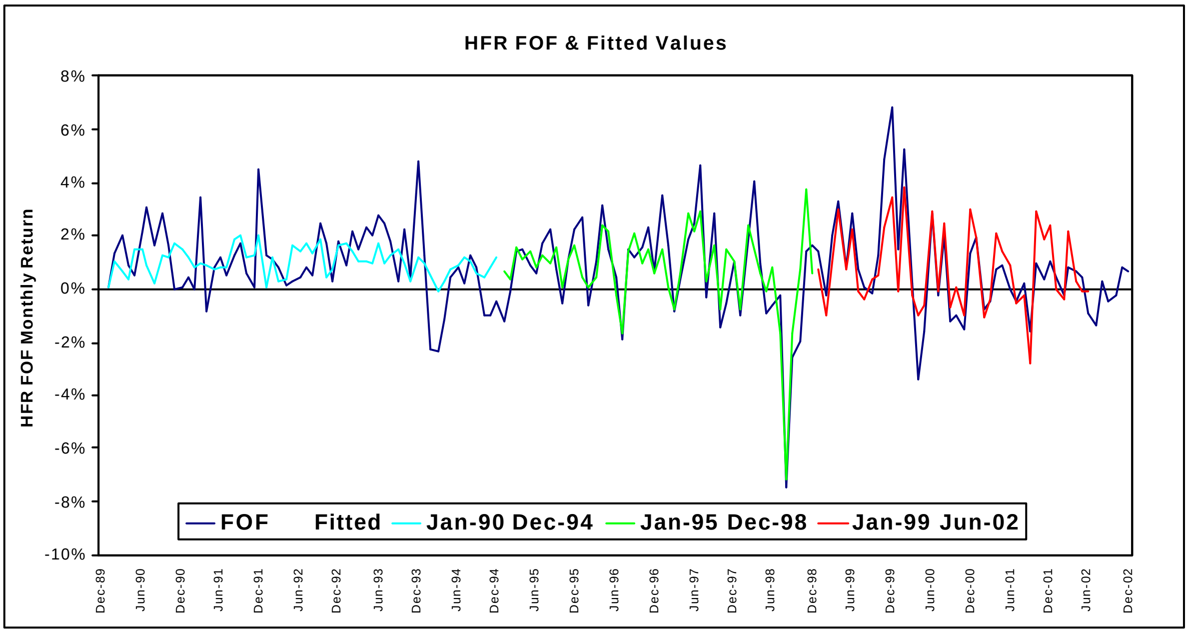
In fixed-income area, we see a similar picture. You are either following a convergence strategy on fixed-income related spreads variables (e.g. credit spread or mortgage spread), or you are following a momentum-driven approach to trading credit. You can find the details of this analysis in a paper I published with David in Journal of Fixed Income (2002).

Here we have a simplified picture of nearly all hedge fund strategies with their attendant ABS factors. It perhaps will not surprise you that index producers are beginning to follow a similar structure to this for index construction.

Dynamic Behavior of Hedge Fund Investing

All of the above deals with the cross-sectional differences of hedge fund strategies. The question remains, can ABS factors capture the dynamic behavior of hedge fund investing over time? Put

Exhibit 8. HFR Fund-of-Funds Index Returns (1990-June, 2002)



differently, can ABS factors tell us, "What are the major bets that large hedge fund portfolios have placed over the years?"

It turns out that using just four ABS factors--stocks (using S&P500), bonds (using constant maturity 10 years Treasury yield), and two spread variables equity capitalization spreads (here we used the Wilshire Small Cap minus Large Cap) and credit spread (Moody's BAA minus 10 year constant maturity Treasury) can do a reasonable job in explaining fund-of-hedge funds return over time (all of these variables are publicly available).

Exhibit 8 is the output of such a model--using the performance of fund-of-hedge funds index to proxy large hedge fund portfolios (the dark blue line is the monthly return series of fund-of-funds index from HFR) we see the prediction of the four-factor model (the light blue line is the prediction of the four-factor model from 90-94) over different time periods. And you can see, during the earlier period where there are relatively few funds-of-hedge funds and the model is still in learning mode, the predictions are not very good. When we get to the second period 1995 to 1998 (in the green line) you can see that the model has picked up most of the monthly return variations of the fund-of-hedge funds index.

There was a regime change in the last period, 1998-2002 and in that final period, the predictions continued to track closely (red line). More specifically, bets on narrowing credit spread by funds-of-hedge funds dropped dramatically (by over ten-fold) soon after the LTCM crisis. The R-squared of the fit between forecast and actual in the second and final periods stayed mostly in the 0.6 to 0.7 range. It is surprising that only a few systematic risk factors can explain this much

Exhibit 9 shows more recent predictions. This is the four-factor model based on the last update through June 2002. There is, and I am happily to report, an alpha term. Hedge funds do add value beyond systematic risk – it is approximately 60 basis points per month. The ABS beta --- stocks, equity spread, 10-year treasury for bonds, and credit spread --- are these four numbers.

Exhibit 9. Out of Sample Forecast: July 2002 to December 2002

	Four-Factor Model	{last update=6/2002}					
Alpha	*0.60%*					**HFR**	
Beta	*0.23*	*0.24*	*-0.71*	*-0.62*		**Composite**	
	S&P500	**SC-LC**	**10-yr UST**	**Credit Spd**	Forecast	**Actual**	Error
July	-7.80%	-6.19%	-0.35%	0.12%	*-2.55%*	-2.86%	0.31%
August	0.66%	-0.24%	-0.37%	0.07%	*0.91%*	0.53%	0.38%
September	-10.87%	2.50%	-0.51%	0.44%	*-1.26%*	-1.58%	0.32%
October	8.80%	-4.51%	0.30%	0.06%	*1.32%*	0.57%	0.75%
November	5.89%	3.14%	0.29%	-0.44%	*2.80%*	2.06%	0.74%
December	-5.88%	0.40%	-0.39%	0.10%	-0.47%	0.17%	-0.64%

Now against the 10-year yield, the number or beta is negative telling us that hedge funds tend to make money when yields go down or when the bond markets are behaving better. Similarly, when the credit spread narrows. It also tells us that hedge funds tends to perform better in markets with better economic conditions ---- falling interest rates, compressing or narrowing credit spread, and rising stock market. Less well, but not necessarily lose money, during bad economic conditions. There also appears to be a market timing components to this.

This simple four-factor model only uses static variables. It is done this way for simplicity. In general, we have found that adding dynamic, trend following variables can improve the explanatory power of the model (as we found in the ABS factor work we did on fixed-income strategies). In addition, the model is time varying, in the sense that you do need to update regularly.

The column of "Forecast" and "HFR Composite Actual" shows you the forecast of our model, and as an indicator of how the average of industry is doing—using the FoF index as the proxy for the hedge fund industry. Comparing the model's forecasts to the returns of HFR composite index of all hedge funds we can see the forecast errors of the model. The errors are not big --- in the region of 20 – 30 basis points per month with the occasional outlier (but bear in mind that this is a static example, in actual application, we would update the model monthly). The big advantage here is that we can update the prediction daily using market prices and have an estimate of how well the hedge fund industry is doing intra-month.

Organizing Hedge Fund Strategies by Risk Factors

What we have just looked at is how a simple four-factor risk-based approach can capture the general risk characteristics of large hedge fund portfolio's performance. The next logical step is to construct benchmarks along the lines of risk factors. In other words, we can imagine organizing the myriad of hedge fund strategies by ABS factors—which are based on directly observable market prices. We call this risk-based approach to benchmarking hedge funds.

How does a risk-based approach compare to existing hedge fund benchmarks? In a risk-based framework, we can describe the HFR index or HFR family of indices as having its focus on pure coverage--having as large a database as possible. The implicit assumption here is that when the database approaches the complete universe of hedge funds, all risk characteristics will be included.

The way HFR communicate risk differences of various funds is by a qualitative style description. With a focus on database size, there isn't much due-diligence done to funds that are included in the database—and perhaps intentionally so. The price one pays for such an approach is the cost in processing the vast amount of data and the array of measurement errors that I mentioned at the beginning of the seminar. Of course, it would be impractical to invest in a large index like the HFR composite.

In terms of Credit Suisse/Tremont index, their focus is to be investable hence their smaller database. And in terms of strategies, it is dependent on qualitative styles according to managers' descriptions and the index supplier's judgment. The way they include managers into their database is a little more selective than HFR, and because it is a smaller index, they can afford to be more selective. However, to go from several thousand funds (in the case of the HFR database) to less than a hundred funds (in the case of the CSFB/Tremont) one would need a comprehensive analysis of how this reduction process is achieved. It is unclear to me precisely how this is done.

Next, the more interesting index product that were introduced lately. The S&P HF index also focuses on investability but their approach has a distinctive risk dimension to it. In order to reduce the unobservable hedge fund universe into a manageable, investable size, they employed a stratified sample technique. This method is similar to what I described earlier as "return-based style" factors. Like all other statistical methods, there are strength and weakness to the approach (some of which have been covered earlier in this presentation).

The key point here is the careful reference to the risk dimension of hedge fund strategies in the index construction method. The main strength of the S&P approach is the extensive, careful due-diligence on each manager in the index. Because of the managed account structure of their investable index, continuing due diligence and index rebalancing should benefit from the greater transparency from the underlying hedge fund manages.

In terms of Morgan Stanley Capital International (MSCI), they too have added risk dimensions to the way their index construction method. They too have grouped and sorted hedge funds by the conventional asset classes each manager invests. The emphasis on creating a platform where customized indices can be easily constructed makes their approach in many ways similar to the ABS factors I described. Without the constraint of investability, the MSCI indices are based on a broader database of hedge funds. But against that, the sheer size of data also limits the level of detail the due diligence process on each manager in the database when compared to the S&P hedge fund index.

So, there is a gradual convergence of approaches in the market place for developing hedge fund benchmarks, and it is becoming more and more risk oriented with clear emphasis on being practical and investable.

In terms of portfolio construction, our model suggests that the way we should look at hedge fund returns is to adjust expected hedge fund returns for the appropriate systematic risk exposure to ABS factors. The HFR index is simply not designed to do that, and neither is the CSFB/Tremont index. The S&P Index, on the other hand, is much more closer to using this type of framework. The MSCI hedge fund index is even closer to a completely risk-based approach because of their focus on flexibility and customized indices designed along the risk dimension.