The Risk in Hedge Fund Strategies: Alternative Alphas and Alternative Betas

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Introduction

Hedge fund managers typically transact in similar asset markets to those used by conventional fund managers. Yet, there is much documented evidence that hedge funds have different return characteristics than those of conventional asset class managers. Some authors have attributed this apparent dilemma to the skill-based nature of hedge fund performance. However, this proposition is inconsistent with the convergence to poor performance of the hedge fund industry and conventional asset classes during stressful market conditions. Clearly, a model of hedge fund strategies that captures return behavior under different market environments is needed. In the absence of such a model, the opaqueness and the limited operating history of hedge fund organizations inhibits institutional investors' confidence in the consistency of hedge fund performance.

Little can be done to eliminate the limitations of historical hedge fund data. Time remains the only solution for documenting hedge fund performance over a broader range of economic cycles. In order to overcome this problem, we develop rule-based models of hedge fund strategies to help us relate the sources of hedge fund returns to directly observable market prices. A key output of such models is the risk factors that drive hedge fund performance. We call these ABS (short for Asset-Based Style) factors. We show that simple models with only a limited number of ABS factors can capture both cross-sectional variations of hedge fund returns as well as the return dynamics of hedge fund portfolios over time. Similar conclusions were reached in Jaeger and Safvenbald (2003). Models of ABS factors can also be used to integrate the construction of hedge fund portfolios in a unifying framework consistent with conventional asset allocation models. Finally, ABS factors are key variables for assessing risk under stressful market conditions.

The chapter is organized as follows. Section one outlines the existing models of hedge fund risk and point out the inadequacies of these models. Section two is dedicated to the development of ABS factor models. Section three summarizes the empirical results on ABS factors and Section four is devoted to applications of ABS factors in portfolio analysis and risk management of hedge fund portfolios. Concluding remarks are in section five.

1. *Peer-Group-Based* style factors and *Return-Based* style factors

Strategy versus Style—A framework

Typically, conventional assets classes transact in different markets and can easily be distinguished by their physical attributes. An index of a conventional asset class is usually an average (equally weighted, price weighted or value weighted) of the underlying assets in that class—refer to these as *asset-class indices* for short. Therefore, an asset-class index resembles a broad-based index for the market in which the constituent assets are traded—for example, the S&P 500 index.

By construction, an asset-class index implicitly assumes a long-only, buy-and-hold strategy for investing in the underlying assets. As an investment portfolio, an investable asset-class index is *passive* and its constituent changes only according to *explicitly defined rules governing index rebalancing*. Consequently, a passive management strategy applied to a conventional asset class closely resembles an indexed fund of the relevant market. The return characteristics of such a strategy, by design, mirror a given asset class's returns.

Sharpe (1992) introduced the idea of a *style model* to capture active management strategies applied to conventional asset classes in a unifying framework. In Sharpe's model, an investment style is a linear combination of an expanded set of asset-class indices—expanded to allow for sector specialization. Refer to this expanded set of asset-class indices as the *conventional asset set*. *Investment styles* differ from each other by the choice of asset-class indices and the exposure (β) to each index—market leverage. In essence, active strategies are depicted as linear combinations of passive (long-only, buy-and-hold) strategies. Therefore, return characteristics of active strategies are driven by *tilts* from conventional, broad-based asset-class indices as well as the respective levels of exposure (βs)—the *conventional strategy set*. In this formulation, Sharpe's style model resembles that of an asset allocation model on an expanded set of asset-class indices. *Implicitly, it depicts style in two dimensions—the choice of asset class, and the level of b; or the choice of markets and the respective betas.*

Fung and Hsieh (1997) extended Sharpe's model to hedge fund styles. First, the notion of asset-class indices is extended to reflect hedge fund managers' ability to short sell securities. Second, the set of asset class indices are expanded further to include derivative securities and "Over-The-Counter" securities. Collectively, define this expanded set as the *hedge fund asset set*. Third, the strategy set is expanded to allow for the dynamic nature of hedge fund strategies. Define this as the *hedge fund strategy set*. Finally, the range of *asset-class betas* has to be broadened to allow for the use of financial leverage as well as market leverage—*financial betas versus market betas*. Although the first two points take us beyond conventional definitions of asset classes, nonetheless, the hedge fund asset class remains rule-based combinations of conventional assets and their derivatives. It is the dynamic expansion of the strategy set together with the opaqueness of hedge fund operations that represents the more challenging aspect of modeling hedge fund returns.

Consistent with the definition of conventional asset management style in Sharpe (1992), hedge fund styles can be defined as pair-wise combinations of hedge fund assets and hedge fund strategies. In contrast to conventional asset management styles where the emphasis is on the choice of asset-class indices, the emphasis of hedge fund style is on both dimensions—markets and strategies. Therefore a lack of correlation between hedge fund returns and asset-class indices can come from two sources.

Figure 1 contrasts the low correlation of hedge fund returns to asset-class indices to the high level of correlation between mutual fund returns and the same set of asset-class indices.

Figure 1. Distribution of R^2s Vs Asset Classes

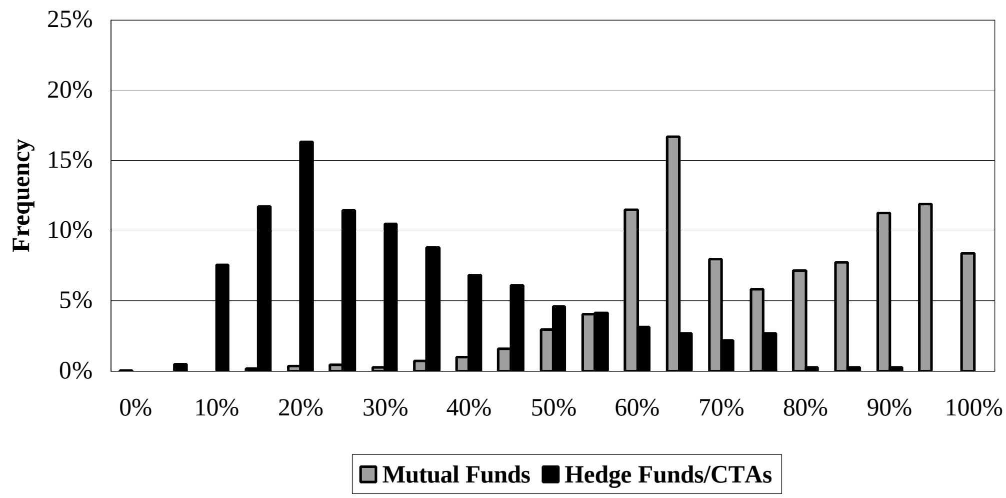

Figure 1 is reproduced from Fung and Hsieh (1997). It represents the distribution of R^2s of regressions of hedge fund returns and mutual fund returns on eight asset classes (US equities, non-US equities, emerging market equities, US government bonds, non-US government bonds, one-month Eurodollar deposit rate, gold, trade-weighted value of the Dollar). While 48% of hedge funds have R^2s below 0.25, 47% of mutual funds have R^2s above 0.75. This indicates that hedge fund returns have low correlation with standard asset returns, quite different from mutual fund returns.

Other studies have reported similar low correlation between hedge fund returns and conventional asset-class indices. All of these studies point to the conclusion that hedge funds are different from conventional asset classes historically. This lack of historical correlation is often cited as corroborating evidence that hedge funds offer an alternative source of return to conventional asset classes. However, to go beyond relying on historical hedge fund performance repeating itself, one needs to answer the key question about hedge fund performance: What is the wind behind this sail?

In order to answer this question, we need to identify the systematic factors that motivate hedge fund returns—the *hedge fund return generation process*. Ideally, one should establish a model similar to Sharpe (1992) that allows us to identify the factors that drive fund returns and to express these factors in terms of observable market prices—*establish explicit links between the hedge fund asset set and the conventional asset set*. In addition, a complete model of hedge fund styles should also *establish a set of transparent, rule-based strategies that mimics the hedge fund strategy set*. Defined this way, investors will be able to compare hedge fund styles to conventional asset classes in a systematic fashion as well as differentiate the quality of returns from different hedge funds on a risk-adjusted basis. The development of a complete model of hedge fund styles has followed a somewhat chaotic path.

Peer-group style factors

To help investors understand hedge funds, consultants and database vendors group the funds into categories based on managers' self-disclosed strategies—define this as the *qualitative approach* to hedge fund style construction. Averages of the returns of the funds in each group are reported as style factors (or style indices)—define these group averages as *peer-group-based style factors*. The objective of the peer-group approach is to identify hedge funds with similar return characteristics. The qualitative nature of the approach can lead to curious performance differences between similar-sounding style groups.[1] To an extent, these anomalies are to be expected. The desired for privacy of most hedge fund managers and the unregulated nature of the industry meant that no standard format for performance reporting existed for years (and arguable up to now other than industry conventions). Consequently, there is no single source where one can observe the entire universe of hedge fund performance with a high degree of certainty. There exist potentially large sampling differences between various hedge fund database vendors.[2] Although at the aggregated level, broad-based indices of hedge fund performance only exhibit small variations among alternate index providers, at the micro level of peer-group-based style specific sub-indices, significant discrepancies among index providers can occur. This, together with other difficult statistical measurement problems relating to hedge fund databases[3], greatly limit the insight offered by peer-group-based hedge fund style factors on the hedge fund return generation process. Put differently, peer-group-based hedge fund styles are helpful, but only as one of many inputs we need to properly identify hedge fund risk factors.

Return-based style factors

To add rigor to the qualitative approach to measuring hedge fund risk, Fung and Hsieh (1997) proposed a supplementary quantitative approach. Instead of relying on hedge fund managers' self-disclosed description of their strategies, one can construct groups of hedge funds that exhibit similar return characteristics. In other words, don't just rely on what they say they do, look also at what they actually do.

The Fung and Hsieh (1997) approach is predicated on the idea that managers with the same style should deliver higher correlated returns than those of different styles—define these as *return-based style factors*. To achieve this, we appealed to the statistical analysis of principal components. The choice of method is motivated by four reasons. First, statistical clustering of returns should approximate the common risk-return characteristics of the strategies they use and the markets they transact in. Second, to retain the elegance of Sharpe's (1992) linear style model, potential non-linearity in hedge fund returns can be largely absorbed by the returns of the estimated factors thus preserving the linear relationship between a fund's return and that of the factors. Third, it is likely that a principal component analysis will lead to a reduction in the myriad of peer-group-based style factors to a more manageable set. Finally, qualitative, self-

[1] For example, in early February 2001, the Hedge Fund Research index for equity market-neutral hedge funds reported a return of –1.81% for the month of January 2001, whereas the CSFB/Tremont index for equity market neutral hedge funds returned 2.13% for the same month. During the 1998/1999 period, the maximum drawdown for the Global Macro funds according to CSFB/Tremont was worse than 25% whereas HFR reported a maximum drawdown of less than 10% for their Macro funds .

[2] At the Centre for Hedge Fund Research and Education of the London Business School, we have collected data from several database services. Preliminary research reveal significant sampling differences among them. For example, as of Dec. 2000, there are approximately 1,970 operating hedge funds collectively (adjusting for duplicated funds). Yet only 315 funds are common to the three main databases in the industry.

[3] See, for example, Fung and Hsieh (2000) for a review of these problems.

disclosed strategy information from hedge fund managers can be used as an additional step to identify the statistically constructed factors.

Following this process, Fung and Hsieh (1997) identified five return-based style factors. Since then Brown and Goetzmann (2003) extended that study using an updated data set applying different statistical techniques and found eight style factors. They interpreted these factors to be Global Macro (similar to Fung and Hsieh (1997)); Pure Leveraged Currency (similar to the trend-following factor of Fung and Hsieh (1997)); two equity factors—a US and a non-US factor (similar to the Value factor of Fung and Hsieh (1997)); an Event-Driven factor (similar to the Distressed Factor of Fung and Hsieh (1997)); and two sector specific factors—Emerging Markets and Pure Property (both excluded from the Fung and Hsieh (1997) study). Like Brown and Goetzmann (2003) other studies[4] on return-based style factors have generally identified additional factors that help to better explain hedge fund returns, it is satisfying to note that like the Brown and Goetzmann (2003) study, they have mostly concluded consistent findings to Fung and Hsieh (1997). This adds credence to the proposition that there are only a limited number of systematic hedge fund risk factors that persist over time. What remains is to design a more explicit method for identifying these factors and to link them to the hedge fund asset set using observable market prices. We do this in section two.

2. Asset-Based style factors

Asset-based style factors are rule-based replications of hedge fund strategies using conventional assets and their derivatives. Two simple examples help illustrate this concept.

Market-timing ABS factor

One of the better-known market timing strategies is trend following. Extending some path breaking work of Merton (1981), Fung and Hsieh (2001) modeled the performance of a generic trend-following strategy using *lookback* straddles. A lookback straddle pays the difference between the highest and lowest price of the reference asset realized over a given period of time (the maturity of the option). Clearly, this mimics the payout of a trend-follower with perfect foresight. The return of such a strategy has to account for the cost (option premium) of the lookback options used. The dynamic exposure to the reference asset during the life of a lookback straddle can be interpreted as reflecting the dynamic exposure to the reference asset of a trend-following manager. Based on this insight, Fung and Hsieh (2001) constructed a trend-following ABS factor by applying lookback options on a broad range of futures contracts on conventional assets. This is shown to have a much higher degree of explanatory power of trend-following funds than previously constructed indices such as the Commodity Research Bureau Index and the Mount Lucas/BARRA Trend-Following Index.

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[4] See for example *Lhabitant (2002).*

Table 1
Explaining Trend-Following Funds' Returns:
The $\bar{R}^2$s of Regressions On Ten Sets of Risk Factors

Sets of Risk Factors	Adjusted R^2 of Regression
Eight major asset classes in Fung and Hsieh (1997) (US equities, non-US equities, US bonds, Non-US bonds, gold, US Dollar index, Emerging market equities, 1-month Eurodollar)	1.0%
Five major stock indices (S&P 500, FTSE 100, DAX 30, Nikkei 225 Australian All Ordinary)	-2.1%
Five government bond markets (US 30-year, UK Gilt, German Bund, French 10-year, Australian 10-year)	7.5%
Six three-month interest rate markets (Eurodollar, 3m Sterling, Euro-DM, Euro-Yen, Australian Bankers Acceptance, Paris Interbank Rate)	1.5%
Four currency markets (British Pound, Deutsche Mark, Japanese Yen, Swiss Franc)	-1.1%
Six commodity markets (Corn, Wheat, Soybean, Crude Oil, Gold, Silver)	-3.2%
Goldman Sachs Commodity Index	-0.7%
Commodity Research Bureau Index	-0.8%
Mount Lucas/BARRA Trend-Following Index	7.5%
Five PTFS portfolios (Stock PTFS, Bond PTFS, Currency PTFS, 3-month interest rate PTFS, Commodity PTFS)	47.9%

Note:

Here, PTFS stands for Primitive Trend Following Strategy, which is an option-based replication of trend following strategies; see Fung and Hsieh (2001) for a more detailed explanation.

This table is reproduced from Fung and Hsieh (2001). It contains the adjusted-R^2s of the average trend-following fund's return on ten sets of risk factors. The first set is the eight asset class returns used to generate Figure 1. There are other sets of asset market indices underlying the lookback straddles we used to model trend-following strategies. The table shows that lookback straddles explain trend-following returns much better than the other sets of risk factors.

In a subsequent paper, Fung and Hsieh (2002) argued that the set of all market-timing strategies can be thought of as a union of the set of trend-following (momentum) strategies, and the set of trend-reversal (contrarian) strategies. These two complementary sets of market-timing strategies can both be modeled as lookback options--they differ only in the entry and exit points of the respective trades. This interpretation allows us to characterize the set of all market-timing strategies using a transparent, rule-based option formula. Applying this application to specific asset markets allows us to define the market-timing ABS factor.

Merger arbitrage ABS factor

Mitchell and Pulvino (2001) constructed the historical performance of a rule-based merger arbitrage strategy—invest in all *stock for stock* and *cash* deals (long acquiree and short acquirer) with a prespecified entry and exit strategy. The experiment was conducted for 4,750 merger transactions from 1963 to 1998. The resulting simulated return for merger arbitrage has similar characteristics to returns of merger arbitrage hedge funds-- strongly correlated to each other. One notable characteristic is the strong correlation with the S&P during large down markets (but low correlation during normal market conditions). This *tail phenomenon* is true of both the simulated as well as the actual merger arbitrage hedge fund returns.

The hedge fund style model: Alternative alphas and alternative betas

The market-timing and merger arbitrage ABS factors are two examples of hedge fund style factors. Armed with a sufficient number of ABS factors to describe the main hedge fund styles, we can complete the extension of Sharpe's (1992) style model to hedge funds. Simply replace the conventional asset-class indices in Sharpe's style model by ABS factors and we can arrive at the hedge fund style model. Refer to the equation from such a model as the ABS factor equation. With such an equation, a hedge fund manager's return is expressed as a linear combination of the appropriate ABS factors. The concept of alternative alphas and alternative betas applied to hedge funds now follows naturally from these ABS equations.

Similar to Sharpe's (1992) model, a style-adjusted alpha can be identified by using the ABS factor equation—*define this as the alternative alpha*.

At the present time, we have identified four sets of ABS factors. The Fung and Hsieh trend-following factor was constructed using 26 futures contracts (and the corresponding options) covering nearly all liquid financial and commodity futures contracts worldwide. The trend-following factor of Fung and Hsieh (2001) resembles a passive, unlevered portfolio of trend-following factors applied to a broad range of conventional asset classes. Recall that hedge-fund (βs) encompass both financial as well as market leverage. Although the option replication technique used by Fung and Hsieh (2001) already absorbed most of the market-driven variation in (β)[5], the performance impact from the dynamic use of financial leverage by trend-following managers are reflected in the alpha term of the ABS equation. This is because a static, linear ABS factor equation can only reflect the "average" level of (β) with respect to the ABS factor. Therefore, a *trend-following alpha* will reflect the *skill in leveraging the right bets and deleveraging the bad ones as well as using superior entry/exit strategies.* Negative alphas will be

[5] This is because option deltas naturally adjust to both market levels and volatility changes. Therefore the periodic return from option positions already reflect market-driven time varying exposures.

accorded to those managers that failed to lever the right bets and showed no ability in avoiding losing bets irrespective of the level of overall portfolio return—luck should not be rewarded.

The Mitchell and Pulvino merger arbitrage factor is constructed using all stock and cash mergers in the US market over the period *1963 to 1998.* It can be interpreted as the unlevered, diversification limit of all stock and cash merger arbitrage deals in the US. Applying an ABS equation to this merger arbitrage factor, investors can decompose a merger arbitrage manager's return into a skill component (merger-arbitrage alpha) and a systematic component (passive return earned by being in the merger arbitrage space). Since different deals carry different degrees of deal risk, the use of financial leverage on any specific deal depends solely on the judgment of the manager. The incremental performance from financial leverage (good or bad) now impacts the manager's alpha. Another source of alpha is the manager's ability in timing the entry and exit points of individual deals. The final source of alpha comes from the limitation to the data set used by Mitchell and Pulvino (2001). Their study is based on cash deals only. Exposure to non-cash deals will also impact a manager's alpha.

By expanding the merger arbitrate asset set to include more complex deals one can obtain a more broad-based merger arbitrage factor with a (potentially) different ABS equation. It also follows that the interpretation of the alpha term from this expanded ABS equation will be affected. There is no absolute definition of a uniquely correct merger arbitrage factor. Different factors will lead to variations to the ABS equation. The choice depends on the investment mandate of the manager. Likewise, the trend-following ABS factor of Fung and Hsieh (2001) can be adjusted to reflect specific investment mandates.

In Fung and Hsieh (2002), a set of ABS factors was identified for a broad range of fixed-income oriented hedge fund strategies. These fixed-income ABS factors are designed to reflect fixed-income hedge fund styles from mortgaged-back securities specialists to multi-strategy fixed-income hedge funds.

More recently, Agarwal and Naik (2003, forthcoming) reported other ABS factors relating to equity-oriented hedge fund strategies. Fung and Hsieh (2003, working paper) summarized these earlier results and constructed ABS factors for equity-oriented hedge fund strategies in a format similar to those reported in Fung and Hsieh (2002) for fixed-income related hedge fund strategies.

ABS factors as diversification limits

By design, an ABS factor is constructed to capture the systematic performance characteristics of a particular class of hedge fund strategy. It is well known from classic portfolio theory that the limit to diversification in equity securities is the systematic risk of the equity market. It is perhaps not surprising that an ABS factor closely approximate the diversification limit of that class of strategy it attempts to mimic. This can be seen from the Fung and Hsieh (2002) model of fixed-income ABS factors.

In Fung and Hsieh (2002), ABS factors are derived from rule-based models of various fixed-income hedge fund strategies. The returns of these ABS factors are highly correlated to the principal components of hedge fund returns drawn from qualitative style groupings.[6] Since principal components are designed to identify funds with similar return statistics, it is clear that there is limited diversification benefit by forming portfolios of funds that are highly correlated to the same principal component. Principal components are statistical constructs and there is no

[6] Frequently, qualitative groupings of hedge funds can have more than one significant principal component.

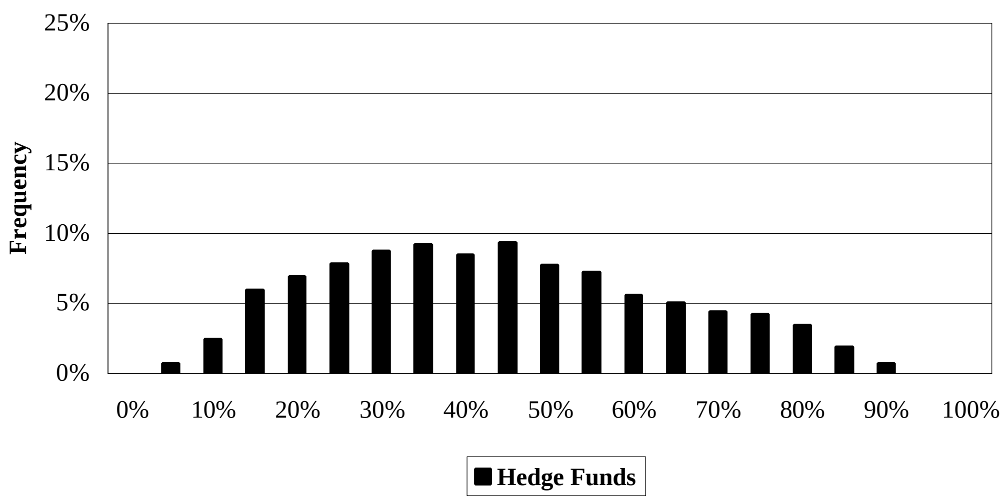
unique way of interpreting them qualitatively. The conventional way of interpreting these components is to think of them as uncorrelated factors (across components) each representing a source of systemic risk. Relating the ABS factors to these principal components thus help us identify the systematic risk factors common to funds in the same component.

3. Empirical results

ABS factors better capture hedge fund return characteristics

A simple way of assessing how ABS factors contribute to our understanding of hedge fund returns is to look at how well they explain hedge fund returns. Recall from Figure 1 that conventional asset class indices have low correlations to hedge fund returns. Another way of describing this observation is that a hedge fund style equation using conventional asset class indices will have low explanatory power when applied to hedge fund returns. Figure 2 illustrates how much improvement can be achieved when we replace the conventional asset class indices by ten ABS factors.

Figure 2. Distribution of R^2s Vs ABS Factors



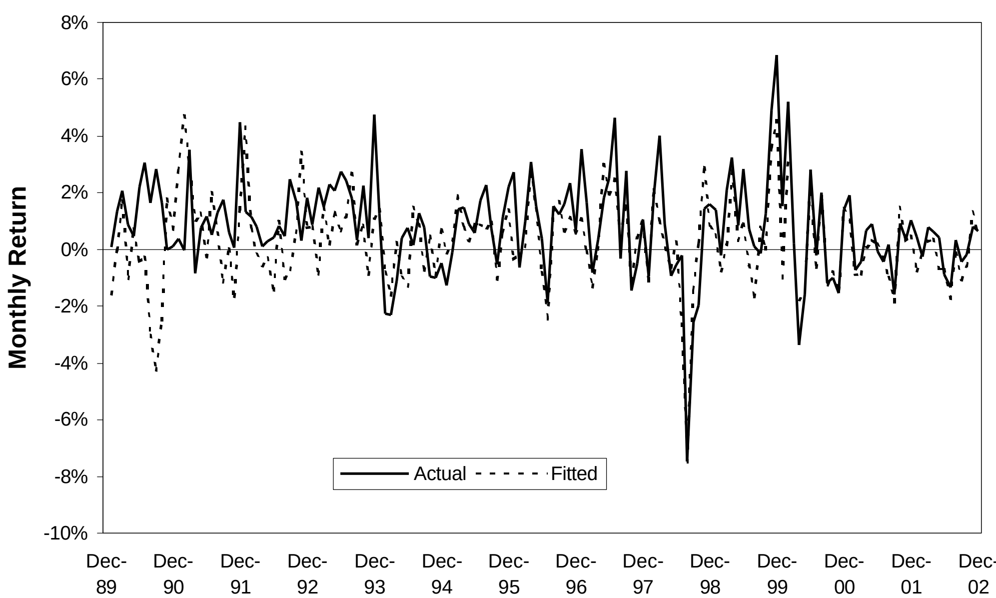
This figure updates Figure 1 in two aspects. Firstly, it uses individual hedge fund data from the TASS database ending April 2001. Secondly, it uses ten ABS factors that are related to the main hedge fund styles we have analyzed thus far. There are four ABS factors for equity hedge funds: the S&P, Small Cap-Large Cap stocks, Value-Growth stocks, Emerging Market equities. There are 3 ABS factors for fixed income hedge funds: High Yield bonds minus 10Y Treasury, Convertible bonds minus 10Y Treasury, Mortgage bonds minus 10Y Treasury. There are also 3 ABS factors for trend-following strategies: lookback straddles on bonds, currencies, and commodities. Comparing Figures 1 and 2, we see that the rightward shift of the 'black' bars , which indicates that the ABS factors can explain hedge fund returns better than standard asset-class indices.

Capturing the dynamic style allocation of hedge fund portfolios using ABS factors

While the results in Figure 2 can be repeated using different sampling techniques to demonstrate the robustness of the results, the approach is not designed to capturing the time varying style allocation of diversified hedge fund portfolios.[7] The next example illustrates how a simple model with only a handful of ABS factors can capture most of the return variations of large hedge fund portfolios. To demonstrate the concept, we use the Hedge Fund Research's (HFR for short) fund-of-hedge funds (FOF for short) index to proxy the typical performance of a diversified hedge fund portfolio. In terms of risk factors, we use two ABS factors for equity hedge funds (S&P, Small Cap minus Large Cap stocks), two for fixed income hedge funds (changes in the 10Y government bond yield, and changes in the Baa-10Y bond yields), and three for trend-following funds (lookback straddles on bonds, currencies, and commodities). These choices are meant to represent risk factors in the most likely hedge fund styles. We test for coefficient stability using one-period ahead recursive residuals. Under the null hypothesis of no parameter change, the recursive residuals are normal, with mean 0 and variance 1. The cumulative recursive residuals have mean 0 and variance T, where T is the number of periods over which the residuals are cumulated. The null of parameter constancy is rejected in March 2000. Thus we ran the HFR FOF regression in two samples: Jan 1994-Feb 2000, and Apr 2000-Dec 2002.

Figure 3 graphs the actual and fitted monthly returns of the HFR FOF index. It shows that the small number of risk factors can reliably model the returns of large hedge fund portfolios.

Figure 3. Actual vs Fitted HFR FOF Index



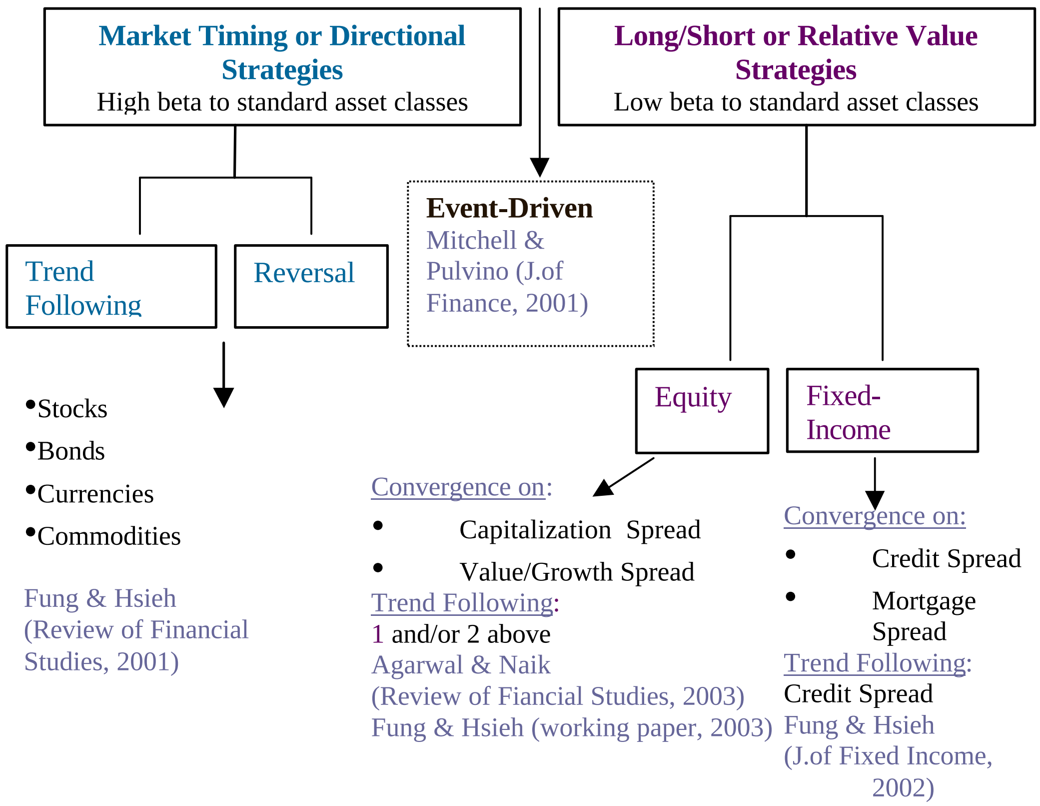
[7] A frequency plot of the explanatory power from a multiple regression across individual hedge funds is designed to capture the cross-sectional characteristics of the regression equation. Although it is possible to repeat the exercise over different sampling periods, the results remain specific to the reference sample period. It will not capture the process that governs the time variation of the multiple regression statistics. In addition, it is unlikely that such a process will work for all funds individually. A better starting point to analyze time varying behavior of the factor coefficients is to look at portfolios of hedge funds.

4. *Applications of ABS factors in portfolio and risk management*

A unifying model of hedge fund risk factors

The empirical results using a simple four (or five) ABS factor equation to capture the return characteristics of the HFR FOF index point to possibility of a simply unifying structure of hedge fund styles. This structure encapsulates the major hedge fund risk factors and can be directly linked to market prices by way of ABS factors. An example is the following diagram, which is an extension of the BIS (1999) paper.

Figure 4



This simple structure divides all hedge fund styles into three major categories—*Directional* strategies, *Long/Short or Relative Value* strategies, and *Event-Driven* strategies.

Directional strategies are defined as those strategies with a significant (ex-ante) beta exposure to conventional asset class indices. The ABS factors associated with this category of hedge fund strategies are lookback factors applied to various conventional asset markets.

Long/Short or *Relative Value* strategies can be divided into equity-oriented and fixed-income oriented. ABS factors for these two strategy categories have been documented in the previous section.

Event-Driven strategies. Under this heading, only a merger arbitrage ABS factor has been developed. More work is needed to fill the gap in this strategy category to cover other hedge fund strategies such as Distressed Securities investing.

This simple scheme allows us to specify a near-complete extension of Sharpe's (1992) style model—define this as *the ABS factor equation*.

The ABS factor equation allows us to decompose hedge fund return as:

$$\text{Alternative alpha} + \Sigma\,(\beta_i * \text{ABS factor}_i\,).$$

Put differently, a bet on a hedge fund manager can be decomposed into an alternative alpha bet plus systematic alternative beta bets.[8] Viewed this way, we can decompose the return from a hedge fund investment into an *idiosyncratic (alternative alpha)* and *a systematic (alternative beta)* component.

Hedge fund return = *manager's alpha + risk premium from systematic exposure to ABS factors*

The alternative alpha part of a hedge fund's return can be attributed to the manager's skill relative to his peers of comparable styles. The systematic part of a hedge fund's return depends on two things. The manager's choice of alternative beta and the impact of prevailing market conditions on the manager's style. For example, if a hedge fund follows a merger arbitrage strategy in the US market, then an abundance of merger activities will boost the beta part of the manager's return, while the lack of merger activities will lead to poor absolute returns. The ABS factor equation provides a framework to answer the key questions in hedge fund investments: *How do they make their money?* And: *What are the risks?* Jaeger and Safvenblad (2003) provided a qualitative approach to answering these questions, while we provide quantitative solutions to a subset of the hedge fund styles they discussed.

Applications to portfolio management

In terms of forming hedge fund portfolios, decomposing a hedge fund's return into its components allows for explicit recognition of common, systematic risk factors in different hedge fund strategies. Common ABS factors between two hedge funds will be indicative of converging risk profile whereas the absence of common ABS factors can be interpreted as having diversifying risk profiles.

By observing the link between ABS factors and conventional asset class indices, one can integrate hedge fund selection into part of the overall asset allocation process. Quite often, expectations on the future performance of conventional assets will have an impact on the expected return from ABS factors. This will in turn impact the expected return from hedge funds of particular styles.

[8] Note that multi-strategy managers can be accommodated easily in this framework as natural linear combinations of the component strategies (ABS factors).

An immediate application of this concept is the refinement on the *portability of hedge-fund alphas*. It is commonly accepted that hedge fund returns are portable alphas given the low historical correlation between hedge fund returns and conventional asset class indices. What the above decomposition shows is that not all hedge fund alphas are born equal. Some are more portable than others and the ABS factors help us measure the ex-ante correlation between the systematic component of hedge fund style returns and conventional asset class indices. We can represent the portability of hedge fund alphas via the ABS equation as follows:

$$\text{Alternative alpha} + \Sigma\,(\beta_i * \text{ABS factor}_i)$$

Completely portable

Partially portable depending on correlation of ABS factors and conventional asset class indices

Application to Risk Management

An important advantage of linking the systematic component of hedge fund returns to observable market prices via the ABS factors is the ability to simulate the risk of hedge fund strategies over long economic cycles. Consider the following example:

During the second quarter of 1997, one can establish the following ABS equation for fixed-income arbitrage hedge funds:

(HER) Fixed-Income Arbitrage Hedge Fund Index Returns= 0.96%-5.37(Change in credit spread)*

Define the credit-spread variable in the same way as in the four-factor model of hedge fund portfolio (Baa yield –ten year Treasury.

We can see from this equation that a +/- 1% change in credit spread will impact the monthly return of fixed-income arbitrage funds by –4.41%/+6.33%. From the risk management perspective, it is important to know the likelihood of a 1% adverse move in credit spread. Figure 5 plots the movement of the credit-spread variable over the ten-year period from July 1987 to July 1997. The maximum range over this ten-year period is 1.1%. One may conclude from this that a 1% adverse move is a low probability event. However, if one extends the plot in figure 5a to the beginning of 1970, a different picture emerges. Here, a 1% adverse move in the credit-spread variable is a much more likely event. The point here is that the ability to extend stress tests over a wider range of economic cycles using the ABS factors helps to refine one's assessment of risk during extreme markets. Over the period June 30th to October 16th, credit spread widened by 110bp. A highly leveraged fund using fixed-income arbitrage strategies, like Long-Term Capital Management (LTCM), would have experienced substantial loss over that period.[9]

[9] Prior to the fall of 1998, LTCM's returns were easily 4 times more volatile than the HFR fixed-income arbitrage index. Using this as a crude approximation, the credit spread expansion during the July to October period in 1998 would have cost LTCM in the region of –15.3%. The actual loss of LTCM over this period was –44.8%. Thus this single variable would have accounted for approximately one-third of LTCM's losses.

Figure 5. Moody's Baa - 10Y Treasury Spread: Jul 1987 to Jul 1997

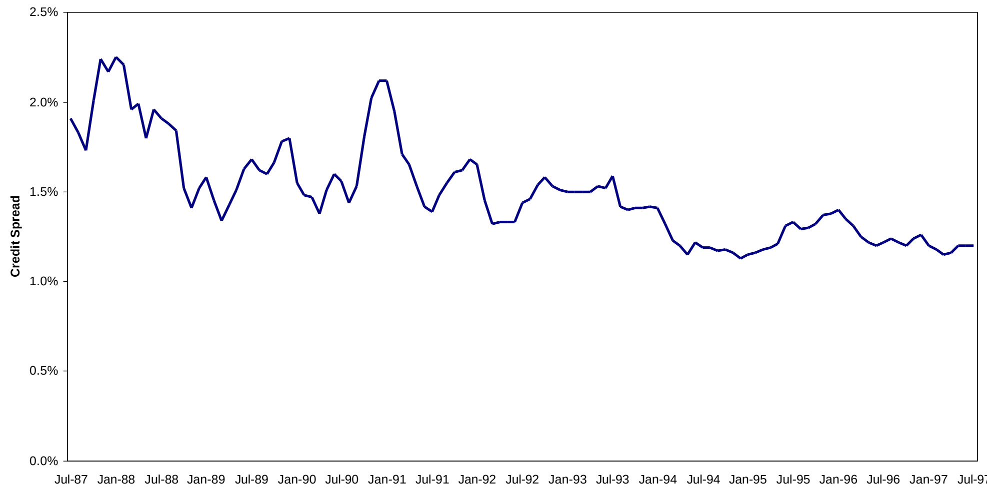


Figure 5a. Moody's Baa - 10Y Treasury Spread: Jan 1970 to Jul 1997

Just as ABS factors can be applied to refine investor's stress test estimates, it can also be used to identify diversifying styles during stressful markets. Fung and Hsieh (1997) noted the inverse performance characteristics of trend-following funds to global equity markets. Subsequently, this empirical regularity was modeled and verified in Fung and Hsieh (2002). Table 2 provides *out-of-sample* (in the sense that these are data points not used in the construction of the model) comparisons of the Fung and Hsieh (2001) model to Zurich/MAR trend following index during large down moves of the S&P 500 index.

Table 2.
Returns During Extreme Declines in the Stock Market

Periods of Large Decline	S&P 500	Zurich Trend Followers	Asset-Based Style Factor
Sep-Nov of 1987	-29.6%	11.7%	12.9%
Jun-Oct 1990	-14.7%	23.5%	28.5%
Jul-Aug of 1998*	-15.4%	9.4%	5.6%
Sep-Nov 2000*	-13.1%	6.5%	-5.0%
Feb-Mar 2001*	-14.9%	9.3%	3.6%
Aug-Sep 2001*	-13.8%	9.2%	3.9%

This table is extracted from Fung and Hsieh (2002). It shows how the trend-following factor can be used to generate large positive returns during periods of large equity market declines. The periods marked with an astride represent out-of-sample forecasts of our original model (Review of Financial Studies, 2001). During all large equity market declines, trend-followers (as proxy by the Zurich Trend Followers Index) did well delivering large positive returns (consistent with the ABS Factor returns except for one period in 2000 where the ABS factor incorrectly predicted a negative performance for trend-following funds). The same pattern persisted into 2002, where during the period April to September 2002, the S&P 500 index declined by 31.9%, the trend-following ABS Factor predicted a return of 11.1% versus a return of 28.2% from the Zurich Trend Followers index.[10]

These results illustrate how the trend-following ABS factor can be used to provide large, positive returns during periods when conventional equity markets are under stress.

5. Concluding remarks

Overall, ABS factors help us to decompose hedge fund returns into systematic and idiosyncratic components. This in turn helps investors differentiate between diversifying versus correlated hedge fund styles in an ex-ante setting. Ex-post, ABS factors help investors identify alphas adjusted for systematic style risks. ABS factors help enhance the integration of hedge funds into the conventional asset allocation process in a consistent manner. By linking hedge fund returns to market prices, ABS factors help to overcome the data limitation of hedge fund returns in conducting stress tests.

In time, more ABS factors will be identified as the body of research on this approach grows. The following list of ABS factors extracted from Figure 4 illustrates how far we have come over the last three years.

[10] There is often a scale difference between the trend-following ABS factor's return versus the actual trend-following funds. This is due to the fact that no financial leverage is assumed in the construction of the ABS factor.

Market Timing ABS factors—Option-based models on Stocks, Bonds, Currencies, and Commodities from Fung and Hsieh (2001);
Event-Driven ABS factors—Merger Arbitrage from Mitchell and Pulvino (2001)
Fixed-Income ABS factors—Credit Spread, Mortgage Spread, Convertible Bond Spread from Fung and Hsieh (2002)
Equity ABS factors—Capitalization Spread, Value/Growth Spread, VIX (Volatiity Implied Index) from Agarwal and Naik (2003), and Fung and Hsieh (2003).

What is perhaps even more encouraging is the fact that most of these ABS factors are variations of familiar risk factors in the finance literature. At this rate, it looks promising that a simple unifying model linking hedge fund risks factors to conventional economic risk factors is within our grasp.

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