Alpha Characteristics of Hedge Funds

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Introduction

Hedge Fund (HF) managers are expected to create excess investment returns (Alpha) through two primary skills based sources:

- **Security selection**: buying undervalued securities and selling overvalued securities.
- **Market timing**: entering markets in advance of, or when they are rising and exiting, or shorting them when they are declining.

In this paper we employ a Kalman Filtering approach to measure the skills based component of HF returns. We separately quantify value generated through market timing and security selection decisions over various market regimes and detail the characteristics of HF Alpha.

Key Takeaways

- HF managers have historically generated meaningful, excess, skill based returns (Alpha) through active management.
- These excess returns, whilst still very significant, have decayed over time as the industry has grown.
- The Alpha in HF returns has consistently come from security selection decisions.
- The Alpha in HF returns has been reduced by market timing decisions.
- The benefits of taking risks to generate active skill based returns outweigh their costs.
- In secular equity bear markets, HFs have significantly outperformed on both an absolute as well as on a risk adjusted basis.
- In secular equity bull markets, HFs have sacrificed some upside but have been less volatile and have outperformed on a risk adjusted basis.
- Quantification of time varying Alpha has important implications for manager selection, asset allocation and portfolio construction.

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Separating Sources of Manager Value Creation

HF manager returns are seen to be a combination of passive exposure to general market factors (referred to as Beta) and active investing decisions resulting in market outperformance (referred to as Alpha). Alpha, in other words, is the skills based return component accruing from (i) an ability to time the markets i.e. to directionally lever and de-lever positions, thus magnifying or diminishing levels of exposure to markets and (ii) from security selection (to go either long or short). While most practitioners agree that securities selection has the potential to generate Alpha in investing, not much is known about the value generated from market timing decisions alone.

Surprisingly, it is poorly understood how HFs produce meaningful Alpha over long term market cycles. Generally, when investors and analysts assess manager outperformance to the market —or Alpha— they combine market timing and security selection sources, rather than distinguish the unique contribution of each to a manager's risks and returns. Once one separates a manager's Alpha into market timing and security selection components, one can determine whether each component adds value on a stand-alone basis.

In this article, we outline a theoretically sound framework for measuring changing exposures to underlying markets. By identifying and measuring such changing market exposures — or dynamic Betas — of HF managers, we are able to break down a HF strategy's returns and risks into three distinct components:

- **Beta:** the portion created by the passive average long-run market exposure.
- **Market Timing Alpha:** the portion created by proactive variations in market exposure around the passive average exposure over time.
- **Security Selection Alpha**: the portion remaining, due to security selection and stock picking skills – both long and short.

We outline here a Kalman Filtering approach (described in detail later) for measuring value generated through market timing and security selection decisions.

Our analysis suggests that HF managers have historically generated Alpha across most strategies especially through security selection, but they have detracted value through their market timing decisions. This however does not necessarily indicate that all HF managers are bad market timers, for our study was done at an aggregate industry level by strategy type; when we tested selectively on proprietary data for a biased sample of manager returns, we did detect market timing Alpha, albeit on an inconsistent basis.

Our analysis also suggests that during bear markets, in particular September 2000 – September 2002 and November 2007 – February 2009, HF managers have significantly outperformed the broad equity index by protecting downside risk.

Changing Market Risk Exposure

HFs pursue absolute return strategies in an attempt to generate attractive returns in a variety of market conditions. Accomplishing this goal requires significant flexibility including the ability to increase or decrease exposure very quickly, short sell markets and securities, invest in illiquid securities, shift strategies as well as rotate across sectors or asset types. Skillful managers are expected to anticipate favorable market movements by increasing exposures in advance of, or with, rising markets or decreasing exposures in advance of declining markets – i.e. adjust their Betas in anticipation of broad market moves.

These short to medium term shifts to preempt markets are essentially market timing decisions. The question for investors, therefore, is to understand to what extent such market timing decisions add value. If a HF manager is good at market timing, investors may feel comfortable allowing them to change exposures to different markets as they see fit. On the other hand, if a manager is a poor market timer, such tactical bets could add significant risk without a commensurate increase in returns.

Active Management

Why do market exposures of HF strategies change over time?

In many cases, managers actively manage market exposures as an explicit way to create value. If a manager believes that a certain equity market is undervalued, then for a period of time, he will potentially increase exposure to those equities in that market as a means of creating value, or in other words generate market timing Alpha. In other cases, however, a change in market exposure is a by-product of a strategy to create value, say through security selection. In this case, changing exposures happens without regard to explicit market timing value-creation; the value-creating strategy is based on some other premise, often valuations based security selection. As an example, it may be the case that an equity long-short manager is changing her Beta over time simply as a result of changes in the attractiveness of valuations in high Beta (small cap) versus low Beta (large cap) stocks.

Measuring the Value of Timing Decisions

In this paper we have dispensed with most of the mathematics that we used in building our models, except for a few equations that are integral to the explanation. Most readers may however, skim these equations without loss of comprehension, or direct their attention to the results of our analysis on page 9.

In order to decompose the various aspects of HF Alpha, we first need a way to quantify the market timing component of returns. One conceptually simple approach is to examine a manager's exposure to the markets that he trades at every point in time. If on average the manager increases his exposure to markets when they go up, and decreases exposure to these markets when they go down, the manager will generate positive returns through market timing.

Comparing the returns from a manager's average market exposures to the returns from the manager's time varying market exposures can therefore help determine value added from market timing.

More formally, we can express a manager's returns as follows:

$$R_t = \alpha_t + \beta_{m,t} R_{m,t} + \varepsilon_t = \alpha_t + \bar{\beta}_m R_{m,t} + \left(\beta_{m,t} - \bar{\beta}_m\right) R_{m,t} + \varepsilon_t \quad (1)$$

where R_t is the manager's excess return over cash at time *t*, α_t is the expected Alpha at time *t*, $\beta_{m,t}$ is a vector of the manager's exposure to the market at time *t*, $R_{m,t}$ is the market's excess return over cash at time *t*, and ε_t is the residual variation in the manager's return.

The first equality term in the above equation is a fairly standard representation but things get more interesting when we examine the second equality term, which is in fact, a measure of Active Beta or market timing.

Estimating Active Beta: If we define $\bar{\beta}_m$ as the manager's average Beta exposure, $\beta_{mt} - \bar{\beta}_m$ is the manager's Active Beta exposure based on the manager's timing decisions. Equation (1) therefore states that a manager's return at each point in time consists of four components:

1. Expected Alpha based on security selection decisions, α_t
2. A return based on the manager's average exposure to the market, $\bar{\beta}_m R_{m,t}$
3. A return based on the manager's market timing decisions, $\left(\beta_{mt} - \bar{\beta}_m\right) R_{m,t}$
4. A residual component with zero mean, corresponding to the risk generated from security selection decisions, ε_t

Computing $\left(\beta_{mt} - \bar{\beta}_m\right) R_{m,t}$, we generate a time series of the manager's market timing returns and estimate the expected return and standard deviation of market timing returns; i.e., the Alpha and Alpha volatility from market timing decisions.

Challenges in Measuring Changing Market Exposures

The challenge that investors face, and much of the literature on the subject ignores, is in measuring market exposures on a time varying basis. Standard factor models assume that market factor exposures are constant through time, as shown in the fairly popular equation (2).

$$R_t = \alpha_t + \beta_m R_{m,t} + \varepsilon_t \quad (2)$$

As a result, returns from market timing are captured in the α coefficient. If a manager has generated positive Alpha (α), investors have no way of knowing how much of this α comes from market timing versus security selection. However, this distinction is crucial to understanding *how* managers have generated returns, and to *what types of* risks (whether market timing or security selection) they have been exposed to.

As an example, a long short equity manager who is poor at market timing may have substantial exposure to the equity market during a downturn. Investors with significant equity positions in their portfolios may want to avoid this manager, or at the very least, actively manage their equity exposure in a way that offsets the manager's market timing decisions.

We tested multiple approaches to isolate the market timing component of manager returns and present our findings in Figure A and Figure B (page 7 and 8).

Approach 1: Ordinary Least Square Regression (OLS)

In calculating the historical Beta, or historical market exposure, a popular approach is to undertake a regression analysis of the HF returns series against one or more explanatory factors. These explanatory factors are usually tradable market factors such as the S&P 500 index returns; the presumption being that market factors can be used to model HF returns and any return above the market return is the manager's excess return, Alpha. Whilst intuitively appealing, this leads, as it did in our case, to spurious results. This is because underlying *factor sensitivities* (i.e. relationships between market factors and HF returns) *are never constant* over the estimation period but vary over time. This method measures an average Beta effect over the estimation data set, but at any given time, the expected value of market Beta is quite different from the true value. In other words the method estimates past *average* factor exposures over a long period of time. It does not explain how exposures have evolved over time and thus has very modest explanatory power for arriving at a manager's true Beta at any given point in time.

Approach 2: Rolling Regression

An improvement over the OLS method is the rolling regression. This method consists of applying the OLS regression model to a rolling window of observations.

In practice, when investors estimate Beta from monthly return series, a 36 to 60 month history is often used to achieve a good balance between bias and variance. In our study, we chose a window size of 36 months to yield better sensitivities to Beta changes. We did an OLS regression of a HF strategy's excess returns against market returns between time periods *t* – 35 months and the current time period *t* which yielded estimations of α_t and β_t at time *t*. The size of the rolling window reflected the trade-off between capturing the Beta variation over time and reducing sampling error. However, we found that if the data set was too large, stale data in distant history caused the model to be less responsive to Beta changes and introduced bias in the estimation. Conversely, in those cases when the data size was small, noises in the short history caused the regression model to fit the noises in the data and introduced variance in the estimation; in statistics, this is called bias/variance tradeoff.

A drawback in this widely used approach is that rolling regressions too are not suitable for time-varying sensitivity estimation. This is because the regression estimates an average sensitivity over each rolling window. We discovered that sensitivities computed from adjacent windows of time (i.e rolling periods) are highly correlated and if actual sensitivities vary over time, or follow a trend, they depart from their average.

We were also aware that another fallacy in this approach was that the regression ascribed all data between *t* – 35 months and *t* with the same weights instead of giving more recent data higher weights. We therefore modified our model by giving more importance to recent observations as described below.

Approach 3: Time Weighted Regression

This approach overcomes some of the limitations of the OLS and rolling methods described earlier by giving more importance to recent observations. In testing this, we used a decay rate to determine the speed at which the weight of an observation decreases with time. This popular procedure is known as weighted least squares (WLS) estimation. We used an exponentially weighted least-square regression to assign recent data higher weights: the data point at $t-i$ had weight λ^i ($0 < \lambda < 1$) , we choose λ = 35/37 and a half life of the exponential weighting ~12 months — i.e. a data point from 12 months ago had half of the weight as the most recent data point. To compare with the earlier approaches we stuck to a 36 month window size.

These Approaches Do Not Work

Our results suggest that although rolling window regressions and time weighted regressions are popular choices for estimating average Beta, they are inadequate at capturing dynamic Beta variation and providing clues about a manager's ability to time markets.

This was especially true where the time horizon was much smaller than the window size. For example, if a HF strategy's Beta was historically close to 0.5 and increased to 0.7 in a month, the Beta estimated using OLS with 36 months data, changed less than 0.2 (0.7 minus 0.5) since the most recent data point (0.7) was only one data point out of 36 data points in the regression. Further, if in a subsequent month, the Beta exposure decreased to 0.1 from 0.7, the regression yielded a Beta close to 0.5; since the previous data point with higher Beta (0.7) had far higher weight which reduced the information content in the newest data point that had a much lower Beta (0.1).

Also, in practice, HF managers make market timing decisions on time scales far shorter than 36 months, rendering traditional regression approaches ineffective for capturing market timing decisions. Moreover, these approaches did not provide any way to model the sensitivities of factor exposures in the returns time series. They measured past (weighted) average sensitivities. In addition, all sensitivity coefficients in the regression equation were identically affected by the weighting, regardless of their rate of change as the weights only depend on the position of the observation in the time series.

A Better Approach to Measuring Changing Beta – Kalman Filtering

We propose that measuring a manager's market timing ability requires a new estimation framework, one that adapts to and dynamically reflects the manager's actual exposures. After extensively testing, we discarded regression based approaches and chose to estimate HFs dynamic Betas using a filtering procedure. This approach, borrowed from engineering, treats Betas as state variables that follow an autoregressive process.

As is fairly well known in signal processing, when it comes to separating impurities from valuable information, a key feature of any high quality filter is to keep as much useful data as possible while eliminating less meaningful data. However, due to the difficulty in differentiating between the two, it is almost always impossible to obtain 100% pure information. The most acceptable compromise is to adopt an approach that establishes the *minimum estimation error* with respect to the true value. The Kalman Filter is an approach that has been shown not only to work well in practice, but proves to have smaller estimation error than most other techniques in a broad array of situations.

We used the Kalman Filter to generate estimates of a time series of hidden true information using observable data that was accompanied by a lot of noise. By combining this filtering technique with statistical estimation methodology, we were able to obtain the hidden true information – HF market risk exposure and time varying Beta - with a fair degree of precision.

The basic structure of the Kalman Filter has two parts: (i) a measurement module, and (ii) a process module. While the measurement module connects the unobservable information (HF market risk exposure) to the observable data (monthly returns data of the HF index), the process module describes a model that allows the unobservable data to evolve through time. Once we started with a "good" estimate of market risk exposure with some degree of confidence in that estimate, we could predict a "better" estimate of future market risk exposure - through the process and measurement module by using only expectations and not the variance associated with the predicted values.

After this, the next step was to compare the predicted value with the realized value and minimize the error to improve the predicted value iteratively for the next period.

Technical Description

Our filter can be expressed using an observation equation and measurement equation, as shown below:

Observation Equation

$$R_t = \alpha_t + \beta_{m,t} X_t + \varepsilon_t \qquad (3)$$

where $\varepsilon_t \sim N(0, R)$

Process Equation

$$\begin{pmatrix} \alpha_t \\ \beta_{m,t} \end{pmatrix} = M \begin{pmatrix} \alpha_{t-1} \\ \beta_{m,t-1} \end{pmatrix} + \xi_t \qquad (4)$$

where M is a 2 × 2 state transition matrix that models the dynamics of expected Alpha and market Beta over time, ξ_t is a vector of serially uncorrelated disturbance with mean zero and covariance matrix Q, $\xi_t \sim N(0, Q)$.

Estimates for β_t are derived using the following equation:

$$\hat{\beta}_{t|t} = \hat{\beta}_{t|t-1} + K_t (R_t - \hat{R}_{t|t-1}) \qquad (5)$$

where $\hat{\beta}_{t|t}$ is the estimate of the manager's time t market exposures at time t, $\hat{\beta}_{t|t-1}$ is the estimate of the manager's time t market exposures at time t – 1, R_t is the manager's actual return at time t, $\hat{R}_{t|t-1}$ is the manager's time t predicted return at time t – 1, and K_t is the Kalman Gain.

Conceptually, the time *t* Beta estimate depends on the previous Beta estimate, the difference between the predicted and actual return, and the Kalman Gain. The Kalman Gain, in turn, is a function of the observation noise (ε_t) and the process variation (ξ_t). If the observation noise is high relative to the process variation, the Beta estimates will be relatively stable. On the other hand, if the process variation dominates the observation noise, the Beta estimates will fluctuate substantially.

Kalman Filter Provided Superior Results

We established that the Kalman Filter approach outperformed both time weighted and rolling regressions, for it optimally used all information about a manager's returns. Exponentially weighted regressions or rolling regressions, by contrast, made arbitrary judgments about how much importance to attach to each observation, and lead to less reliable estimates.

However, one of the drawbacks in using Kalman Filtering, was that it required a significant amount of data. While an OLS regression may be reliably estimated with as few as 30 data points, Kalman Filtering requires an order of magnitude more data, depending on the number of factors. Fortunately, we were able to limit this drawback to some extent by adding more structure to our model. For example, we assumed that Alpha and Beta is not correlated – i.e while both Alpha and Beta have their own variance the covariance between Alpha and Beta- i.e. the off-diagonal elements in the Q matrix are zero - and were able to reduce the amount of data required to properly estimate the Kalman model.

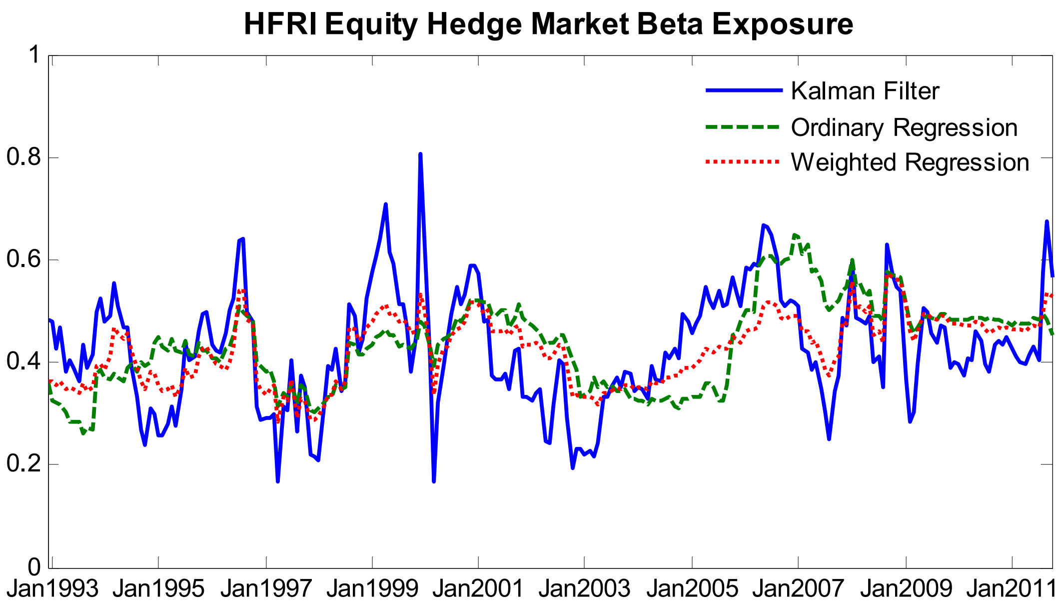
Kalman Filter Results

One of the practical advantages of the Kalman Filter was that due to the filtering property, information from the previous steps was accumulated in the variance of "best" estimate, and the variance of "best" estimate was reduced relative to the variance of "better" estimate. In essence this filter recursively minimizes estimation error without observing the hidden (market factor exposure) information.

In Figures A and B, we provide empirical evidence of the minimum error property by filtering the HFRI Equity Hedge index's excess returns into US market excess returns for the S&P 500.

Kalman Filter Results (continued)

Figure A: HFRI Equity Hedge Beta Exposure



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While normal regressions show a relatively flatter and smoother pattern of Beta changes- as seen in the green and red lines- , the filtering technique produces much more dynamic picture – as seen by the more volatile blue line - of change in market exposures. When we compared the mean square error, the statistical measure of how much the forecasted value differed from the realized value, the filtering technique turned out:

(i) to have 27% lesser error than from normal regression and

(ii) to have 18% lesser error than from the weighted regression technique.

By making the error component as small as possible the Kalman filter was able to pick up changing Beta exposures faster which, as described earlier helped us determine Active Beta, and market timing Alpha.

Kalman Filter Results (continued)

Figure B: HFRI Equity Hedge Annualized Alpha

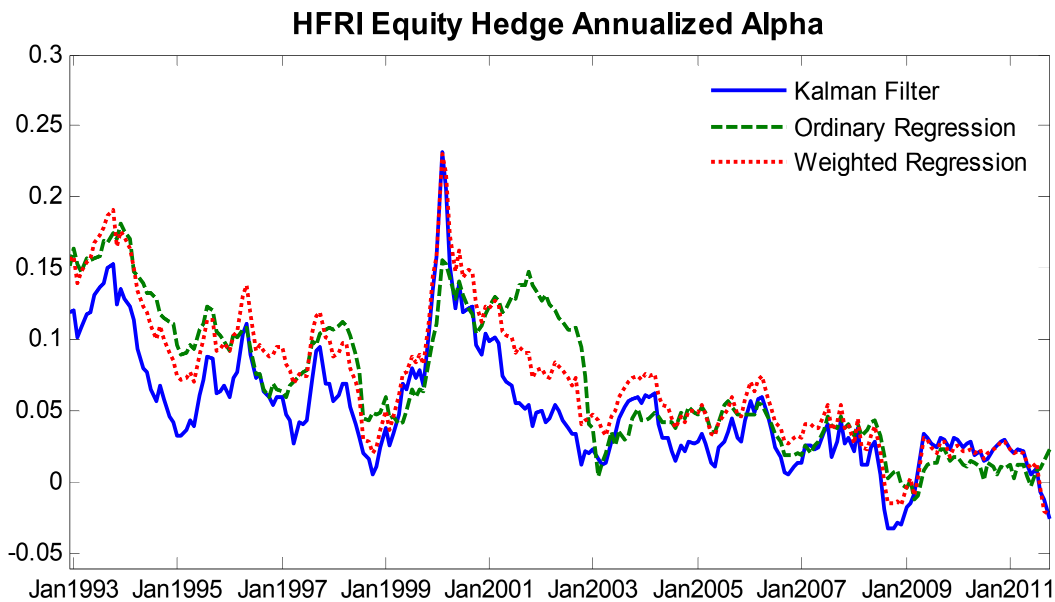

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Figure B plots expected Alpha over time. It suggests that, except for a brief time period in 2008, over nearly all other time periods HF managers have generated Alpha. The skills based component of returns generation has been of particular value to investors, as we will later demonstrate.

Figure B also suggests a discernable trend in diminished Alpha over time, though. Our calculations suggest that after 2003 the average Alpha in the Equity Hedge strategy has been around 3% to 4 % while for the six years following 1993 the average Alpha was around 9%. Despite the decay, our analysis suggests that HFs have significant and persistent excess returns that are from security selection based, rather than market timing based. We do not know the reasons for Alpha decay. It is entirely possible, that as HFs have proliferated over the years, the underlying markets for their securities may have become more efficient. Also, growth in assets under management may have curtailed their ability to uncover arbitrage opportunities or have reduced their capacity for implementation. Another reason could be that the greater institutionalization of the industry, as well as risk from outflows/ investor redemptions, may have reduced their propensity for risk-taking.

Another point, which bears with intuition is that, one would not expect long term expected Alpha to fluctuate as much as Beta (as compared with Figure A), and indeed our results bear that out.

We further conducted this exercise for HFRI Event Driven, HFRI Macro, HFRI Market Neutral, HFRI Quantitative Directional and HFRI Short Bias indices and found results that were not too different.

Results of Our Analysis

Figure 1 and 2: Alpha Return by Strategy

Figure 1: Alpha Return by Strategy (1993-2011)

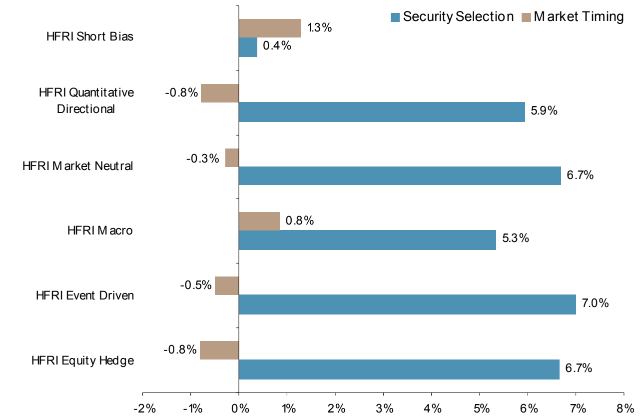

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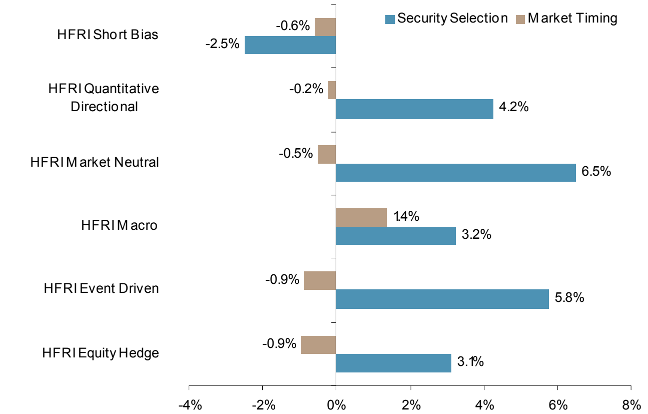
Figure 2: Alpha Return by Strategy (2003-2011)



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We analyzed Alpha characteristics for three major HF strategy groupings — equity hedge, event driven, macro — as well as three sub-strategies in the Equity Hedge index. Those being, market neutral, quantitative directional, and short bias strategies.

Figures 1 through 6 compare the level of Alpha return, Alpha volatility or risk, as well as the Information Ratio from security selection versus market timing for these six strategies.

- With the exception of global macro and short biased, all other strategies had negative market timing returns. We conclude that in aggregate, HF managers have not been able to produce positive Alpha return through market timing over the long run. This result is not particularly surprising as very few managers, both in the traditional active long-only space, or in mutual funds too, have been successful at persistently timing markets correctly over different market cycles.

- Global macro managers have produced Alpha return through market timing over both the long and short run. This is perhaps because macro managers are given a wider mandate enabling them to participate across all asset classes including equities, fixed income, interest rates, currencies and commodities. Macro strategies are primarily centered on directional Beta timing investments which may explain their ability to generate market timing Alpha returns.

- However, all HF manager strategies have generated significant excess return through security selection.

- While there has been some Alpha return decay through security selection in the past decade, most HF managers still produce meaningful Alpha return.

- Market Neutral is the largest Alpha return producer through security selection at approximately 6.5%, suggesting that HF managers have unique skills in going both long and selling short.

- Equity Hedge strategies have seen the most decline in Alpha return across time. This could be attributed to the fact that it is the most popular strategy by number of firms, funds and largest AUM which may have resulted in a drag from underperforming managers.

- The analysis suggests that over the past 20 years, HF managers destroy value through market timing, very similar to findings from active long-only managers. However, due to HFs ability to participate in a wider range of investment instruments and markets, ability to short, and hedge, HF managers have delivered Alpha return over the long run.

Results of Our Analysis (continued)

Figure 3 and 4: Alpha Volatility by Strategy

Figure 3: Alpha Volatility by Strategy (1993-2011)

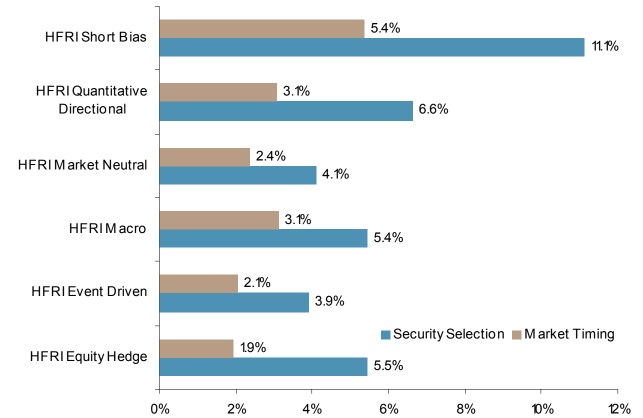

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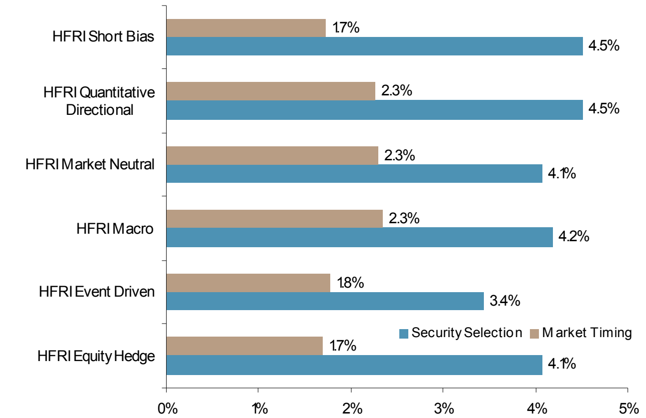
Figure 4: Alpha Volatility by Strategy (2003-2011)



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- Security selection, across all strategies, contributed more volatility to the funds when compared to market timing.

- Alpha volatility from market timing has ranged approximately between 2-4% while security selection has had a higher Alpha volatility between 4-7%. Even though both Alpha volatility components added additional risk to overall returns, returns derived from taking security selection risks outweigh the negatives as explained by an increase in the Information Ratios.

- It appears, as seen in Figure 3 and Figure 4, that almost all HF strategies have reduced their risk profiles since 2003. This may explain why most HF strategies have generated lower returns. Due to the recent market environment uncertainty and posture favored towards capital preservation, HFs appear to be taking less risk resulting in lower returns.

- Historically, quantitative directional strategies have produced the most Alpha volatility while event driven strategies have added the least. More recently, risk appears to be more evenly distributed. Because of this, we next examine the Information Ratio to determine Alpha per unit of risk taken. Ostensibly, if an investor is strategy agnostic, the strategy with the highest Information Ratio, is the one that ought to be chosen.

Results of Our Analysis (continued)

Figure 5 and 6: Information Ratio by Strategy

Figure 5: Information Ratio (1993-2011)

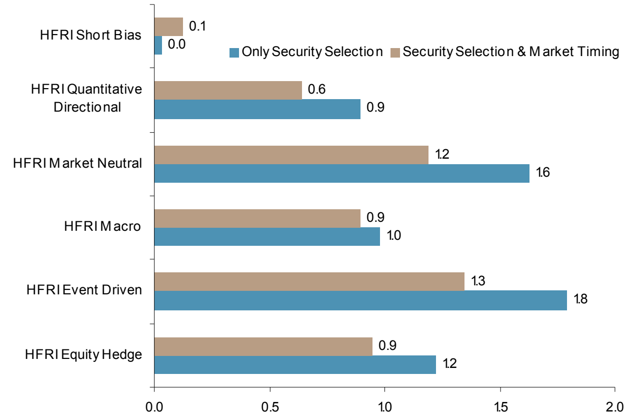

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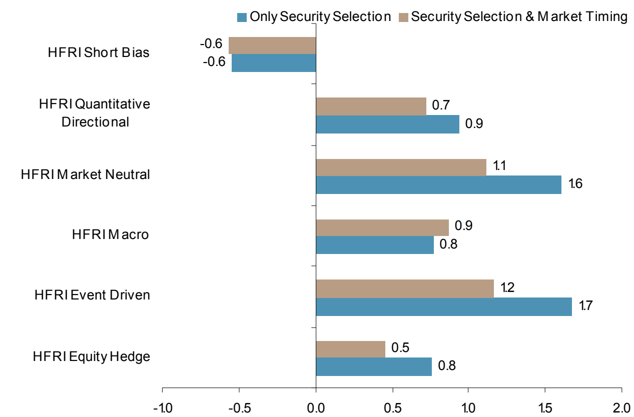
Figure 6: Information Ratio (2003-2011)



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The Information Ratio here is a measure of Alpha return per unit of Alpha risk undertaken to generate that excess skill based return. It removes Beta or market risk and isolates just the active risk – the risk that HF managers are paid to take. Similar to the Sharpe ratio, the higher the value, the more attractive the strategy is on a risk adjusted basis.

- Our analysis theorizes that the Information Ratio of security selection alone is higher than that of combined returns from security selection and market timing. In other words, market timing actually destroys efficiency, even after taking into account that it provided diversification against security selection.

- We submit that if HF managers remove the market timing component and increase the risk exposure of security selection decision, one can achieve higher expected Alpha. In this context, therefore, our analysis provides a clear guide on whether the time variations in market exposures should be hedged—in case where value is being destroyed, our answer is unreservedly yes.

- Historically, as seen in Figure 5 and Figure 6, almost all strategies have produced a positive Information Ratio; this advances our thesis that HFs, in the long term through multiple market regimes, outperform traditional investing strategies.

Do Hedge Funds create Alpha in Bear Markets?

Figure 7: Bear Market Returns (09/00-09-02)

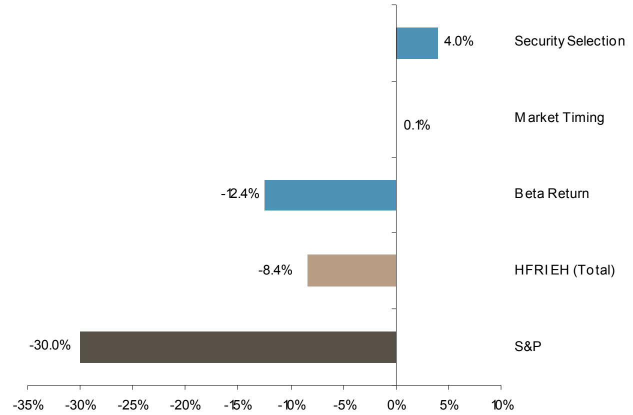

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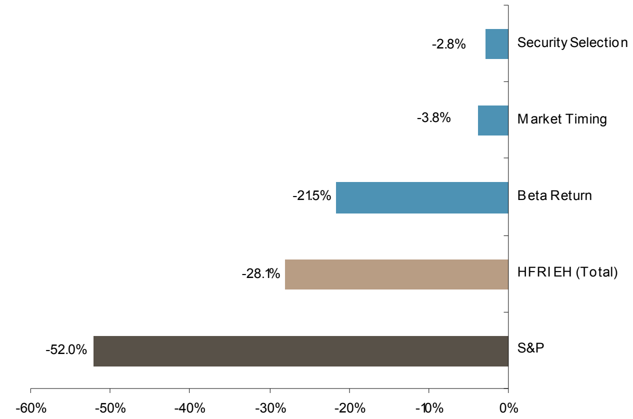
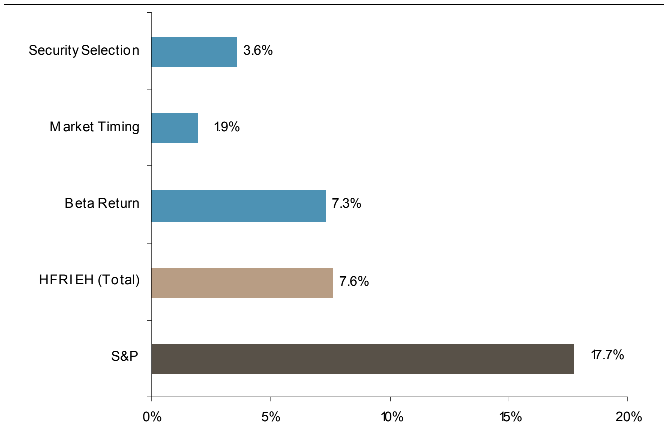
Figure 8: Bear Market Returns (11/07-02/09)



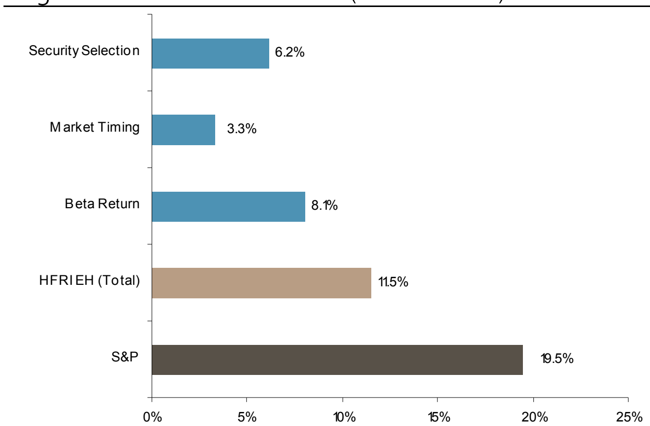
Source: UBS AI, HFR Industry Reports, © HFR, Inc., www.hedgefundresearch.com

Figure 9: Bear Market Risks (09/00-09-02)



Source: UBS AI, HFR Industry Reports, © HFR, Inc., www.hedgefundresearch.com

Figure 10: Bear Market Risks (11/07-02/09)



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Now that we have established that HFs, in aggregate, have demonstrated an ability to create Alpha, we explore their performance in falling markets. We select Equity Hedge strategies as an example due to their large sample size and commercial popularity.

As shown in Figure 7 and Figure 8, we tested for two periods of falling returns, September 2000 – September 2002 and November 2007 - February 2009.

- During periods of falling markets, Equity Hedge protected up to 50% in 2008/2009 and almost 72% in 2000/2002 of downside risk; we posit that these are not insignificant numbers. When comparing the different return drivers, Beta exposure in swift falling markets is the largest detractor of returns. HFs, for they are by definition hedged to Beta (a long term average of 0.41 for Equity Hedge) protect investors.
- One would expect that HF managers who cut net exposure to the equity markets when they are falling would outperform the markets still further. We however do not see this happening, as seen in Figure 7 and Figure 8; market timing has not created Alpha. Rather the Alpha of around 4% comes from security selection decisions in 2000/2002.

- In 2008/2009 security selection decisions was not a positive contributor as correlations peaked, and individual securities moved inline with the markets irrespective of sector, industry or geography. Prices deeply diverged from fundamentals as markets were largely driven by fear and panic. Stock pickers were rewarded for their fundamental analysis in the earlier bull market but failed to provide any meaningful return in the most recent crisis – this was not unexpected, for when markets stop functioning as they did in 2008/2009 price discovery broke down.

- By hedging on the downside, HF managers are able to lower their overall risk profile leading to lower volatility and greater diversification for investor portfolios. When comparing Equity Hedge risk to equity market risk, they appeared to be almost 45% less.

- These results reiterate the important role of having a low Beta and the potential for Alpha generation, when compared to passive long only equity index replication.

In summary, we conclude that HFs have performed better than the equity market in drawdown periods. This outperformance however has little to do with superior market timing abilities; we were not able to conclusively establish that they increased their Beta exposures ahead of market rises or decrease their Beta before market falls. Rather, their outperformance is a function of their hedged characteristic – being hedged; they do not rely on market exposure to create returns, which protects them in falling markets.

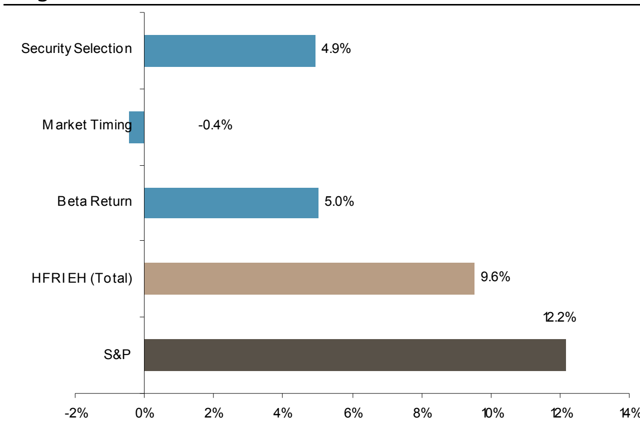
Do Hedge Funds create Alpha in Bull Markets?

We isolated three periods of rising returns, these being from January 1993 – August 2000, October 2002 – October 2007, and March 2009 – October 2011. The first and the most recent period data can be viewed in the appendix. We believe it is too premature to analyze the returns from the most recent 2 years as an indication of long term performance.

- From the data in Figure 11, we can see significant upside appreciation during rising equity markets. As noted in the commentary earlier, security selection and not market timing is the main Alpha generator during these successful times. Market timing actually reduced performance during these rallies while security selection provided an equal amount of return as Beta exposure. This demonstrates that there is skill generating the excess returns opposed to solely Beta exposure.

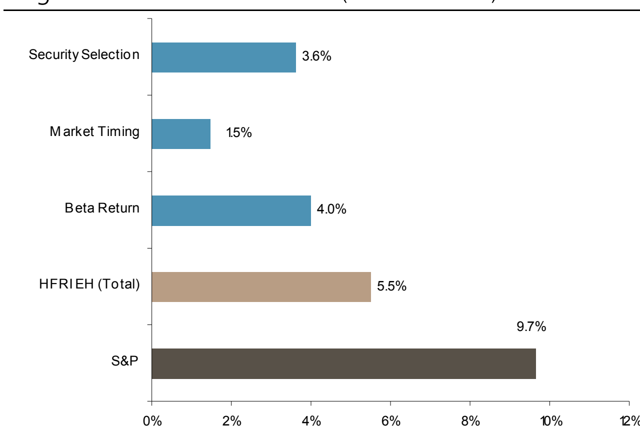
- HFRI Equity Hedge index captured 78% of the upside with 56% of the equity market risk. By analyzing the Information Ratio, or the Alpha risk adjusted return, the HFRI EH Index outperformed the broader markets. The results establish that even if the upside is only capturing a portion of the rally, EH is a superior investment option due to its decreased risk profile.

Figure 11: Bull Market Returns (10/02-10-07)



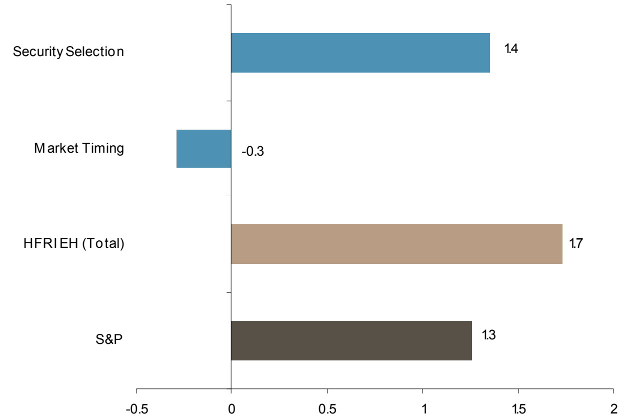
Source: UBS AI, HFR Industry Reports, © HFR, Inc., www.hedgefundresearch.com

Figure 12: Bull Market Risks (10/02-10-07)



Source: UBS AI, HFR Industry Reports, © HFR, Inc., www.hedgefundresearch.com

Figure 13: Bull Market Information Ratio (10/02-10-07)



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Conclusion

With reduced long-term return expectations for traditional assets, HFs, often perceived as a pure form of active management, have drawn increasing investor attention. HF managers have a great deal of freedom in exploiting trading approaches and utilize that freedom to change their strategy in order to capitalize on opportunities as they see them. It is precisely this freedom to actively manage their portfolio that has been viewed by many as the primary advantage HFs have over more traditional styles of active management; indeed, investors often want their managers to access opportunities where they see them. That said, this freer form of active management is not without its costs. To the extent that HF managers can employ dynamic trading strategies, and have more flexibility to execute market timing, it is important for both managers and investors to understand the risks they are exposed to; and whether those risks are ones that generate returns.

In this paper we provided a Kalman Filter based framework to better understand and measure Active Beta - the changing exposures that HFs have to underlying market factors in a more rigorous manner. We compared the returns from a manager's average market exposures to the returns from the manager's time varying market exposures to separately determine Alpha or value added from market timing and security selection. We explored the properties of HF Alpha and highlight implications.

We conclude that HF managers, as an industry, have demonstrated near persistent ability to create skills based returns in almost all market environments through security selection.

Implications of Absence of Market Timing Alpha

Conventional wisdom views market timing ability with a healthy dose of skepticism, and our analysis supports this view. However in some ways, this result may seem surprising. After all, why should timing markets be harder than selecting securities? There might be at least two reasons for this result.

First, HFs in general may be focused much more on security selection than on market timing. To the extent that market timing decisions are implicit, or unrelated to a manager's views about a particular market, we would expect market timing to increase risk without a commensurate increase in return.

Second, even managers who have some market timing ability will have difficulty demonstrating this ability across just one or two markets, when the market timing component of their strategies may lack sufficient breadth. The fundamental law of active management states that a manager's Information Ratio depends on the quality of his forecasts, as well as on the breadth of the investment strategy (i.e., the number of independent investment decisions he makes). Even a highly skilled manager will have trouble generating a high Information Ratio if he only makes timing decisions across one or two markets. This becomes more obvious when analyzing global macro strategies, which seemingly generates excess returns through market timing, as they focus on multiple markets and underlying instruments.

Although the reason why HFs have historically detracted value through market timing is unclear, the implications for investors are relatively straightforward. Either HF managers are poor market timers, or they do not actively manage their exposures to different markets. In either case, investors cannot rely on HF managers to avoid large corrections in the markets that they trade. Investors may also want to consider more actively managing their market exposures to offset the risks that HF managers generate by changing their Betas over time.

Appendix: Hedge Fund Alpha in Bull Markets

Figure A1: Bull Market Returns (01/93-08/00)

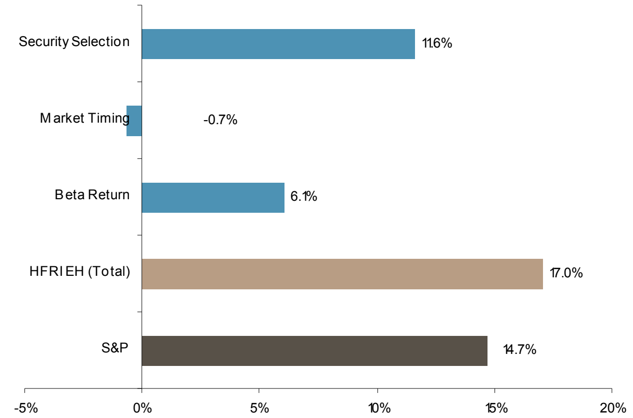

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Figure A2: Bull Market Returns (03/09-10/11)

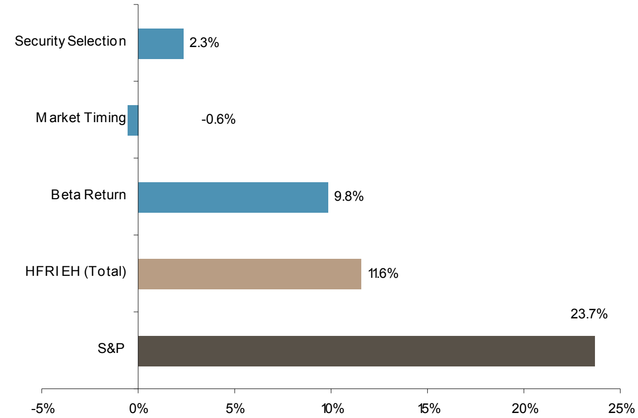

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Figure A3: Bull Market Risks (01/93-08/00)

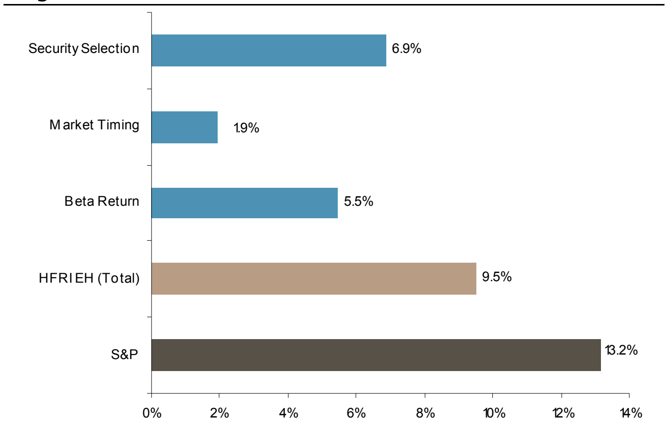

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Figure A4: Bull Market Risks (03/09-10/11)

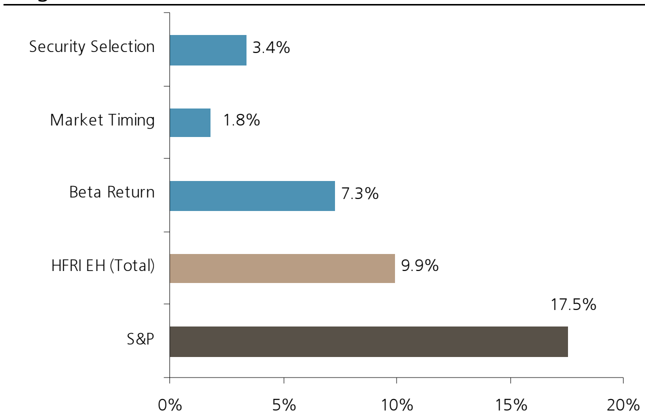

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Figure A5: Bull Market Information Ratio (01/93-08/00)

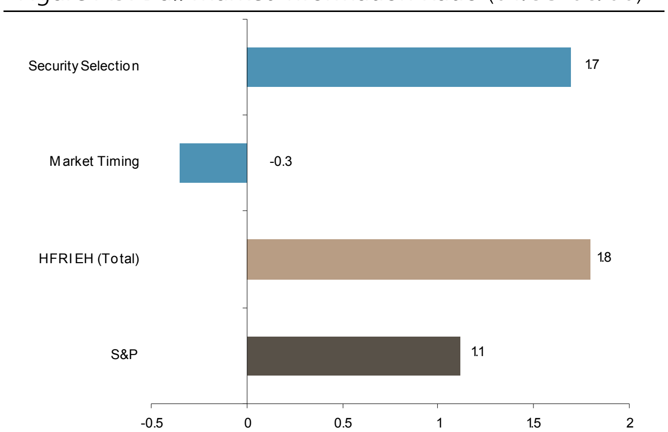

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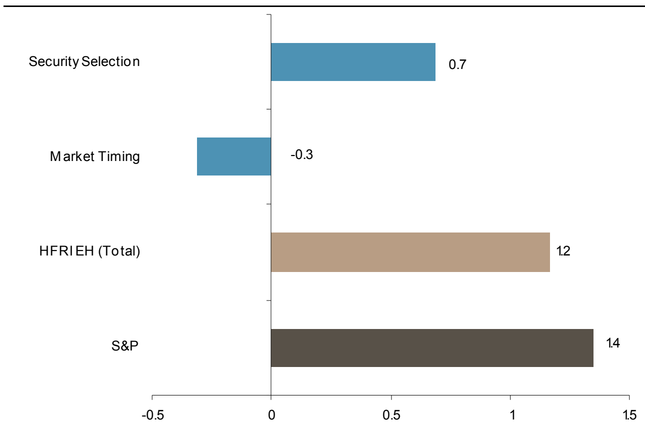
Figure A6: Bull Market Information Ratio (03/09-10/11)



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