Illuminating Hedge Fund Returns to Improve Portfolio Construction

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Hedge funds’ risk and return drivers can be opaque, difficult to identify, and dynamic through time. As multi-asset managers, hedge funds have the flexibility to select securities, time markets, employ leverage, and sell short across asset classes globally. Investors often struggle with finding appropriate performance and risk benchmarks, typically settling with index composites, Treasury bills plus a premium, or one of the hedge fund indices. But these benchmarks do not capture and explain the underlying risk exposures of individual hedge funds, nor do they inform the investor of the hedge fund’s unique risk and return contributions to the broader portfolio.

We present an applied portfolio factor model (PFM) that illuminates the risk and return drivers of broad strategies of hedge funds from the opportunity-cost perspective of a portfolio investor who owns traditional assets. We demonstrate how to interpret and use key information from the factor attribution to improve hedge fund manager selection and broader portfolio construction for investors who already own portfolios of long-only stocks, bonds, and cash. We find that diversification is the primary benefit of adding select hedge funds to a portfolio of traditional assets, but differentiating the truly diversifying managers from the crowd requires a portfolio opportunity-cost perspective and high manager selectivity aided by the ability to disentangle return premiums into traditional risk premiums, alternative risk premiums, and alpha. Portfolio diversification is improved when hedge fund manager selection is focused on adding alternative risk premiums and pure alpha to existing portfolios of traditional assets. High selectivity is required to maximize the diversification benefit; this can be achieved with the concepts, tools, and methods we present.

We build on the existing literature for hedge fund risk factors and factor-based investing, introducing certain concepts and adjustments for more pragmatic application. Our main contribution is to present applied tools and methods within an economically intuitive and implementable framework for investors who already own diversified, multi-asset portfolios—often with pre-determined policy allocations based on a conventional asset class framework.

COMPENSATED RISK FACTORS

Factor models attribute a portfolio’s return variation to one or more risk factors. The sensitivity or magnitude of exposure to each factor is quantified by the beta coefficients resulting from a regression. Alpha is the intercept of the regression; it represents the return premium above (or below) the return
variation explained by factor risk. Alpha (risk-adjusted excess return) is a primary measure of manager skill.


Investors consider many portfolio attributes, but only a limited number of compensated risk factors explain the cross-section of diversified portfolio returns empirically. This is where investors should focus. For purposes of an applied PFM, we define compensated risk factors—or systematic risk premiums—as satisfying three key criteria important to portfolio investors with an opportunity-cost perspective. First, portfolio factors should offer return premiums that are statistically significant. This indicates to a certain confidence level that the risk exposure and its associated return variation is compensated with a positive return, on average. A return premium is critical to considering factors as opportunity-cost investments for the broader portfolio. Return variation without a return premium is uncompensated and diversifiable idiosyncratic risk.

Second, factors should be relatively unique sources of return that are largely independent of each other. This does not necessarily mean they must be strictly orthogonal, but rather sufficiently different to disentangle returns into their underlying sources with statistical confidence, which improves the granularity and precision of hedge fund evaluation for portfolio construction purposes.

Third, factors should explain the return variation of a cross-section of diversified portfolios, and therefore explain compensated risk. Ultimately, investors experience and consume risky returns, so the factor premiums and correlation matrix that contribute to that experience are what count most.

In summary, a good portfolio factor model offers a parsimonious set (approximately 10 or fewer) of largely independent, compensated risk factors that explain diversified portfolio returns. Ideally, the regressions produce high adjusted values of R-squared, robust factor betas, and alphas that are close to zero.

PORTFOLIO FACTOR MODEL

We construct the PFM from the perspective of compensated risk factors available to the total portfolio. The aggregate of compensated risk factors should look similar to a highly diversified portfolio of true asset classes, where the marks of a true asset class are a positive average return premium and low correlations with other asset classes. In the spirit of an applied model for investment practitioners engaged in hedge fund evaluation for portfolio construction purposes, all factors in the PFM offer sufficiently long return histories for testing purposes, are readily accessible to investment practitioners from internet sources or common industry databases, and meet our three criteria that are important for portfolio investors.

To disentangle and identify global equity risk from hedge fund returns, we use Fama and French’s four global equity factors. These include a global market factor, global size factor, global value factor, and global momentum factor for equities. Global factor definitions are consistent with a global market for risk, where hedge funds operate. We find a meaningful premium in emerging-markets returns over the returns of global developed equities, so the PFM also includes an emerging-markets premium.

To disentangle and identify fixed-income risk from hedge fund returns, we use global versions of Lee’s [2009] term and default (credit) factors, which are slight modifications of Fama and French’s original term and default factors. These modifications better capture credit risk.

Diversified portfolios of long-only commodity futures do not offer meaningful excess return premiums. For example, the return premium of the Dow Jones UBS Commodity Index over Treasury bills is not statistically significant since the Index’s inception. However, long-short commodity momentum generates a robust return premium, and we include it in the PFM.

Lustig et al. [2011] found a slope factor in exchange rates formed on long-short currency interest rate dif-
It offers a positive average return premium and accounts for most of the cross-sectional variation of excess currency returns. This is a component of the currency premium we include in the PFM, which is constructed from a two-thirds value score (based on interest rate differentials and purchasing power parity) and a one-third momentum score. We use a composite currency factor for model parsimony, as exposure to the currency premium is less common across hedge fund strategies.

Investable insurance premiums are potential risk premium candidates for the PFM. These can range from equity tail risk insurance to more exotic catastrophe reinsurance. There is a strong negative correlation between the first difference of the CBOE Volatility Index (VIX) and the market factor, and we find sensitivity to the first difference of the VIX across different hedge fund strategy categories. However, the first difference of the VIX is not defined as a return per se, let alone a return that offers a robust average return premium. This is one of our three criteria for a compensated risk factor.

For portfolio investors with an opportunity-cost perspective, the beta is much less relevant as a driver of return contribution when its associated return premium is indistinguishable from zero. In contrast, the put premium rewards investors who provide insurance (by writing puts) to other investors who seek to hedge the downside risk of their equity investments. It relies on high implied volatility (VIX) versus realized volatility to generate a true excess return premium. The put premium has offered a statistically significant excess return premium, but is highly correlated with the existing market factor. We choose not to include it in the PFM, to maintain a parsimonious model of largely independent risk factors.

Exhibit 1 defines the nine global factors and displays their average return premiums since common PFM inception. We will show that all nine factors generally meet our three criteria.

Based on monthly returns since PFM inception, six of the nine factors offer statistically significant average return premiums at the conventional 95% confidence level ($t$-statistic > 1.96). Surprisingly, global equity does not. Because $t$-statistics ($t$-stats) are sensitive to variance and the number of observations, we test the much longer history of the U.S. market factor (1926 to 2012) and confirm a statistically significant return premium ($t$-stat = 3.71). Similarly, global size does not show a statistically significant premium either, so we run the same test over the longer U.S. history and find a $t$-stat of 2.28. Finally, when we backdate the emerging-markets premium to the inception of the MSCI Emerging Markets Index in 1988 and define the premium in excess of the MSCI World Index (inception of the global market factor is 1990), we also find a statistically significant emerging-markets premium ($t$-stat = 2.06). We are therefore satisfied that all nine factors show reasonable evidence of offering a true average return premium.

Exhibit 2 displays the correlation matrix of the nine factors. The average pairwise correlation is close to zero and the low correlation coefficients across the table show that the nine factors are largely independent, though not necessarily strictly orthogonal. For example, global market and global credit are not orthogonal, but they are sufficiently different to improve hedge fund evaluation for portfolio construction purposes.

We regress excess monthly hedge fund returns against the nine factors, per Equation (1). Each factor

### Exhibit 1

**Factor Definitions and Return Premiums**

<table>
<thead>
<tr>
<th>Nov/1990–Dec/2012</th>
<th>Definition</th>
<th>Premium (% Annualized)</th>
<th>$t$-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF Global Market</td>
<td>Global Developed Equity – Treasury Bills</td>
<td>5.10</td>
<td>1.58</td>
</tr>
<tr>
<td>FF Global Size</td>
<td>Global Small Cap – Global Large Cap</td>
<td>0.98</td>
<td>0.63</td>
</tr>
<tr>
<td>FF Global Value</td>
<td>Global Value – Global Growth</td>
<td>4.72</td>
<td>2.69</td>
</tr>
<tr>
<td>FF Global Momentum</td>
<td>Global Up Momentum – Global Down Momentum</td>
<td>7.24</td>
<td>2.40</td>
</tr>
<tr>
<td>Commodity Momentum</td>
<td>Morningstar Long – Short Commodity Momentum (excess)</td>
<td>5.87</td>
<td>2.55</td>
</tr>
<tr>
<td>Global Term</td>
<td>Barclays Global Treasury – Treasury Bills</td>
<td>3.65</td>
<td>2.60</td>
</tr>
<tr>
<td>Global Credit</td>
<td>Barclays Global High Yield – Barclays Global Treasury</td>
<td>4.80</td>
<td>2.01</td>
</tr>
<tr>
<td>Currency Premium</td>
<td>Deutsche Bank Currency Returns (funded) – Treasury Bills</td>
<td>3.26</td>
<td>3.17</td>
</tr>
</tbody>
</table>
is defined as a monthly premium in excess of the risk-free rate or as a long-short premium (see factor return definitions in Exhibit 1).

\[
RH_t - RF_t = a + b_1 MKT_t + b_2 SMB_t + b_3 HML_t + b_4 WML_t + b_5 EMP_t + b_6 CMO_t + b_7 TERM_t + b_8 DEF_t + b_9 CP_t + \varepsilon_t
\]

where

- \( RH_t \) is the return of hedge funds,
- \( RF_t \) is the return of one-month Treasury bills,
- \( MKT_t \) is the return of the Fama-French global market factor,
- \( SMB_t \) is the return of the Fama-French global size factor,
- \( HML_t \) is the return of the Fama-French global value factor,
- \( WML_t \) is the return of the Fama-French global momentum factor,
- \( EMP_t \) is the return of the emerging-markets premium,
- \( CMO_t \) is the return of commodity momentum,
- \( TERM_t \) is the return of the global term factor,
- \( DEF_t \) is the return of the global credit factor, and
- \( CP_t \) is the return of the currency premium.

### HEDGE FUND RISK AND RETURN

We next use the PFM to illuminate the risk and return drivers of diversified categories of hedge funds, with manager selection and portfolio construction ultimately in mind. Our proxies for average hedge fund returns are the industry standard Hedge Fund Research HFRI Fund Weighted Composite and the four main HFRI strategy classification indices: equity hedge, event driven, relative value and macro. We test the five HFRI indices over the last 10 and 20 years to December 2012, as both of these time periods offer sufficiently long data samples for robust analysis of hedge fund returns with nine independent variables. The inception of our 20-year time period closely coincides with the establishment of Hedge Fund Research in 1992. The shorter 10-year period offers a more contemporary view that begins with an inflection point in alpha deterioration. In addition to being the industry standard, the benefit of using the HFRI indices in our tests is that they are highly diversified, which reduces the noise of idiosyncratic return variation common with individual hedge funds. If our tests prove fruitful on these diversified strategy categories, then the PFM can be used to test individual funds with a heightened awareness of idiosyncratic risk and the parameter uncertainty of shorter timeframes.

Exhibit 3 shows the \( t \)-stats of the factor betas and the adjusted R-squareds of the PFM regressions for each of the five HFRI indices over both the 10- and 20-year periods. We focus on beta \( t \)-stats in Exhibit 3 because we are interested in gauging whether the observed risk factor exposures are likely present and real, and not just a random result.

We begin with the HFRI Fund Weighted Composite over the 10-year period ending in December 2012. The HFRI Fund Weighted Composite is a good proxy for the average hedge fund. It is an equally weighted index of a broad universe of hedge funds. The 10-year period to 2012 is a contemporary view that still offers sufficient observations for our tests. The PFM explains 93% of the return variation of the HFRI Composite over the 10 years to 2012. We see statistically significant exposures (beta \( t \)-stats > 1.96 or < –1.96) in the HFRI
Composite to all factors except global term and the currency premium. Global momentum is on the threshold of significance over the 10-year period (at a 94% confidence level), and it is significant over 20 years. Both the 10- and 20-year periods offer nearly identical information with regard to the presence of risk factor exposures in the HFRI Fund Weighted Composite.

As we look across the table to view the other HFRI strategy categories, we find a similar overall presence of risk factor exposures, along with some differences. For example, global term and credit are present in relative value, and the currency premium is only present in macro. Over the 10-year period, the adjusted R-squareds are 96% for equity hedge, 87% for event driven, 83% for relative value, and 58% for macro. Although the PFM explains only 58% of the return variation of macro, we show in Exhibit 4 that the alpha is not statistically significant, which indicates that the unexplained return variation in macro is idiosyncratic and uncompensated on average. Overall, the nine factors largely explain the compensated return variation of diversified and different hedge fund strategies.

Exhibit 4 displays the risk and performance characteristics of the five HFRI indices over the 10-year and 20-year periods to December 2012. We first focus on the 10-year return panel.

The top section of the 10-year return panel shows the beta coefficients (with corresponding t-stats shown in Exhibit 3). Global market and global size are the most prevalent and economically meaningful betas across the strategies, with large term and credit betas in relative value and the currency premium in macro. The pattern is the same with regard to the components of return contribution, which is a function of factor betas multiplied by their respective factor premiums. (More on return contribution later.) The betas are low across the table, which is the result of counteracting short posi-
The middle section of the 10-year return panel compares the standard deviation and conditional value at risk (CVaR, 5% monthly) of the factor benchmark to the HFRI indices. The factor benchmark is a pure systematic risk benchmark of monthly returns, where each month’s return is calculated from Equation (2) and \( RB_t \) is the return of the factor benchmark. Equation (2) adds back the risk-free rate and removes alpha from Equation (1) to create a directly comparable factor risk benchmark.

\[
RB_t = RF_t + b_1 \times MKT_t + b_2 \times SMB_t + b_3 \times HML_t + b_4 \times WML_t + b_5 \times EMP_t + b_6 \times CMO_t + b_7 \times TERM_t + b_8 \times DEF_t + b_9 \times CP_t
\]  

Critically, the PFM captures the risk of the different HFRI strategy categories almost perfectly. The standard deviation of the factor risk benchmarks and their respective HFRI indices are nearly identical (which is a manifestation of the high adjusted R-squareds). The one possible exception is the slightly higher standard deviation of macro, where we have already documented...
higher idiosyncratic risk. Similarly, when we investigate CVaR, we find that the factor risk benchmarks and their respective HFRI indices offer nearly identical tail risk.

Exhibit 5 compares the monthly returns for each HFRI index to the monthly returns of its respective factor benchmark. These graphs are visual representations through time of the summary risk and return metrics in the 10-year return panel of Exhibit 4. The factors explain return variation through time for each strategy category, whether viewed as interim volatility, upside/downside capture, or peak and trough returns.

The bottom section of the 10-year return panel in Exhibit 4 shows the alphas, or risk-adjusted excess

E X H I B I T  5
HFRI Indices vs. Factor Benchmarks

![Graphs comparing monthly returns for each HFRI index to monthly returns of its respective factor benchmark.](image-url)
return. The alpha \( t \)-stats indicate the alphas are statistically indistinguishable from zero for all categories except event driven and relative value. Mitchell and Pulvino [2001] find that returns from merger arbitrage (common in event driven) are analogous to writing uncovered index put options (a form of insurance premium). From this perspective, some of our observed alphas for event driven may be a compensated risk premium. Interestingly, however, we do not find exposure to the put premium in event driven. We will show in the next section that our observed 10-year alpha for relative value becomes insignificant when we adjust for serial correlation of illiquid assets.

The 20-year return panel in Exhibit 4 displays much larger alphas and alpha \( t \)-stats. Looking back to Exhibit 3, we also find lower adjusted R-squareds across all HFRI strategy categories over the longer 20-year period than over the more contemporary 10-year period. Alpha persistence and time-varying risk factor exposures are important considerations for manager selection and portfolio construction. One way to test persistence is to view alpha and factor betas over rolling windows of PFM regressions. Exhibit 6 shows annualized rolling 36-month PFM alphas (left graph) and global market betas (right graph) over the 20 years to 2012 for the HFRI Fund Weighted Composite.

Consistent with the comparative results of the 10-year versus 20-year return panels in Exhibit 4, the rolling 36-month alphas have deteriorated over the more recent 10 years (to 2012) relative to the earlier time periods. The main inflection point is around the bursting and aftermath of the technology bubble. In contrast, exposure to global equity—the most significant factor beta in the HFRI Fund Weighted Composite—has been relatively persistent, though we also observe a dip around the bursting and aftermath of the technology bubble. Among the nine portfolio factors, visual inspections of rolling 36-month betas show that global market and global size have been the most persistent betas for the HFRI Composite, followed by global credit and the emerging-markets premium, while the other factor betas have been more time-varying.

Alpha deterioration over the more contemporary 10-year period is likely due to some combination of increased market efficiency, the more recent entry of less-skilled hedge fund managers and less reporting bias. It is well documented that historical hedge fund return data are biased upward.\(^4\) This reporting bias should affect alphas more than betas, as it results from favoring funds with better risk-adjusted performance. Our results confirm significant differences in alpha, but less meaningful differences in betas when we compare 20- and 10-year test periods. In addition to lower alphas, we also view the higher R-squareds over the more contemporary 10-year period as indicative of improved hedge fund reporting. We believe today’s environment is better represented by the results in the more recent 10-year period than the full 20-year period.

The overall results show that hedge funds as a group can be characterized as diversified portfolios of compensated risk factors. Risk and return across the

**Exhibit 6**
Persistence in Alpha and Global Market Beta

![Alpha](image1.png)

![Global Market Beta](image2.png)
different HFRI strategies are almost fully explained by the mix of systematic risk premiums.

Finally, we compare the PFM to the Fung-Hsieh seven-factor hedge fund model [2004] and the betas of Carhart et al. [2014] over the longest common data period available to us (January 1995 to December 2012) using the HFRI Composite. One issue with the Fung-Hsieh model for investors considering a portfolio opportunity-cost perspective is that not all Fung-Hsieh factors offer true return premiums. Indeed, some of the factors are not even directly defined as returns. Although these factors were developed to explain hedge fund risk, they complicate the interpretation of alpha as an intuitive, economic measure of risk-adjusted excess return for portfolio investors. The Fung-Hsieh model produces an adjusted R-squared of 72%, with three of the seven factors offering statistically significant betas. The betas of Carhart et al. are more closely related to the PFM factors. Although they were not developed for hedge fund evaluation per se, they produce an adjusted R-squared of 73%, with five of the ten factors offering statistically significant betas. The PFM produces an 87% adjusted R-squared, with seven of the nine factors offering statistically significant betas.

**ILLIQUID ASSETS**

U.S. fair-value accounting rules were not in force until 2009, which represents the majority of our 10- and 20-year test periods. Some hedge funds invest in illiquid level 2 and level 3 securities, which are not market priced. The reported returns on these assets are appraisal-based and subject to the manager's opinion and judgment. Getmansky et al. [2004] show that returns from illiquid assets can display serial correlation and artificially low volatility. These smoothed returns are imperfectly explained by market-priced factors.

To mitigate the potential effect of serial correlation of illiquid hedge fund assets on the PFM, we can include lagged factors in the regression. We find meaningful exposure to the first lags of global market and global credit factors. Equation 3 adds these lags to Equation (1).

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**EXHIBIT 7**

**Regression Summary with Lagged Market and Credit Factors**

<table>
<thead>
<tr>
<th>HFRI Indices - 10 Years to Dec/2012</th>
<th>Fund Weighted Composite</th>
<th>Equity Hedge</th>
<th>Event Driven</th>
<th>Relative Value</th>
<th>Macro</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted R-Squared</td>
<td>0.94</td>
<td>0.96</td>
<td>0.89</td>
<td>0.86</td>
<td>0.59</td>
</tr>
<tr>
<td>Alpha t-Stat</td>
<td>0.81</td>
<td>-1.74</td>
<td>2.19</td>
<td>1.63</td>
<td>1.11</td>
</tr>
<tr>
<td>Global Market Beta (t)</td>
<td>0.30</td>
<td>0.45</td>
<td>0.28</td>
<td>0.07</td>
<td>0.12</td>
</tr>
<tr>
<td>Global Market Beta (t-1)</td>
<td>0.02</td>
<td>0.02</td>
<td>0.05</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Global Market Beta t-Stat (t-1)</td>
<td>2.13</td>
<td>1.26</td>
<td>2.85</td>
<td>1.39</td>
<td>1.00</td>
</tr>
<tr>
<td>Global Credit Beta (t)</td>
<td>0.05</td>
<td>0.03</td>
<td>0.12</td>
<td>0.31</td>
<td>-0.17</td>
</tr>
<tr>
<td>Global Credit Beta (t-1)</td>
<td>0.04</td>
<td>0.04</td>
<td>0.05</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>Global Credit Beta t-Stat (t-1)</td>
<td>2.45</td>
<td>2.32</td>
<td>2.26</td>
<td>3.62</td>
<td>0.65</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>HFRI Indices - 20 Years to Dec/2012</th>
<th>Fund Weighted Composite</th>
<th>Equity Hedge</th>
<th>Event Driven</th>
<th>Relative Value</th>
<th>Macro</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted R-Squared</td>
<td>0.87</td>
<td>0.83</td>
<td>0.81</td>
<td>0.67</td>
<td>0.39</td>
</tr>
<tr>
<td>Alpha t-Stat</td>
<td>5.26</td>
<td>4.29</td>
<td>5.61</td>
<td>6.00</td>
<td>1.53</td>
</tr>
<tr>
<td>Global Market Beta (t)</td>
<td>0.31</td>
<td>0.46</td>
<td>0.25</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Global Market Beta (t-1)</td>
<td>0.02</td>
<td>0.01</td>
<td>0.03</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Global Market Beta t-Stat (t-1)</td>
<td>1.34</td>
<td>0.59</td>
<td>2.05</td>
<td>2.30</td>
<td>-0.02</td>
</tr>
<tr>
<td>Global Credit Beta (t)</td>
<td>0.11</td>
<td>0.08</td>
<td>0.21</td>
<td>0.24</td>
<td>0.03</td>
</tr>
<tr>
<td>Global Credit Beta (t-1)</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Global Credit Beta t-Stat (t-1)</td>
<td>2.57</td>
<td>1.69</td>
<td>2.45</td>
<td>1.73</td>
<td>1.01</td>
</tr>
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</table>
\[ RH_t - RF_t = a + b_1 \text{MKT}_t + b_2 \text{SMB}_t + b_3 \text{HML}_t \]
\[ + b_4 \text{WML}_t + b_5 \text{EMP}_t + b_6 \text{CMO}_t \]
\[ + b_7 \text{TERM}_t + b_8 \text{DEF}_t + b_9 \text{CP}_t \]
\[ + b_{10} \text{MKT}_{t-1} + b_{11} \text{DEF}_{t-1} + \epsilon_t \]  

(3)

The 10-year return panel in Exhibit 7 shows that the lagged global market beta is positive and statistically significant for the HFRI Composite and Event Driven, while the lagged global credit beta is positive and statistically significant for all indices except HFRI Macro. The 20-year return panel shows evidence of serial correlation from illiquid assets for the HFRI Fund Weighted Composite, Event Driven, and Relative Value. Relative to Exhibits 3 and 4, adjusted R-squareds increase and alpha t-stats decrease slightly overall, indicating that we are detecting and explaining some additional return from illiquid assets when we employ the lagged betas. The low-alpha t-stats in the 10-year return panel in Exhibit 7 show the alphas are indistinguishable from zero for all categories except event driven. The lagged betas are meaningful and persistent for event driven in particular, suggesting the possibility that some of the observed alpha may be due to an illiquidity premium the lagged betas do not capture. Consistent with our previous results, alphas remain high over the 20-year period, when there was likely more upward return bias. The addition of lagged factors to the PFM also provides a better estimate of total market and credit betas, which are slightly higher than when estimated without the lags.

**IMPLICATIONS FOR MANAGER SELECTION AND PORTFOLIO CONSTRUCTION**

The previous sections focused on diversified strategy sorts of average hedge fund returns to develop an applied PFM that can improve hedge fund evaluation for portfolio construction purposes. A good factor model for portfolio construction purposes defines factors by our three criteria and produces high adjusted R-squareds and near-zero average alphas across diversified strategy sorts, which the PFM accomplishes. However, factor models will evolve as researchers continue to identify and more deeply understand the risk premiums that drive diversified portfolio returns, so model specification is flexible. More critical for investment practitioners is how to use the information from the PFM and its variants to improve hedge fund manager selection and ultimately broader portfolio construction.

It is clear from the many different factor exposures we document that hedge funds are not a discrete and transparent asset class. Rather, they capture a myriad of systematic risk premiums and skill-based returns, some of which are more beneficial to traditional portfolios of stocks, bonds, and cash than others. For purposes of forthcoming discussions, we define traditional risk premiums as factors investors commonly own in their traditional portfolios of long-only stocks, bonds, and cash. This category includes the global market factor, emerging-markets premium, global term, and credit factors. We define the other five long-short factors in the PFM as alternative risk premiums. In general, traditional and alternative risk premiums are systematic to capital markets, while alpha is idiosyncratic to the manager. However, exotic risk premiums are a hybrid. We characterize them as systematic to capital markets, but they can require manager skill that goes beyond implementing mechanical trading rules. Examples include illiquidity premiums and certain insurance premiums.

High selectivity is the key to successful hedge fund investing. Titman and Tiu [2011] found that hedge funds in the lowest quartile of adjusted R-squareds (sorted using step-down risk factor regressions) produced higher alphas and Sharpe ratios than did hedge funds in the highest quartile of adjusted R-squareds. Furthermore, low past R-squared predicted strong future performance. Similarly, Sun et al. [2012] found that the quintile of hedge funds with the highest strategy distinctiveness (relative to their closest statistical peer group) generated more alpha than did the least strategy distinct quintile. Strategy distinctiveness at the fund level persisted for many years into the future. These important performance studies concluded that the best-performing hedge funds offer unique and uncorrelated sources of return. In other words, the best-performing hedge funds are also the best diversifiers of traditional portfolios.

High selectivity requires a portfolio opportunity cost perspective and transparency into the different sources of hedge fund returns. Most investors already own broadly diversified portfolios of traditional risk premiums. From the perspective of this traditional long-only portfolio of stocks, bonds, and cash, the important consideration is what hedge funds can contribute to enhance the risk/return profile of the total portfolio. Classic Markowitz diversification is the main benefit
of adding select hedge funds to portfolios of traditional assets. By adding unique and uncorrelated sources of return to an existing portfolio of stocks, bonds, and cash, the investor pushes up the efficient frontier of traditional risk premiums. These unique and uncorrelated sources of return include alternative risk premiums and skill-based returns (pure alpha), which increase the Sharpe ratios of diversified portfolios of traditional risk premiums, boosting return per unit of risk (or conversely, reducing risk per unit of return).

Alternative risk premiums, particularly those related to value and momentum, are pervasive across capital markets. The $t$-stats in Exhibit 1 show that these premiums can be as robust as traditional risk premiums, which suggests relatively high confidence that they will persist. As unique and uncorrelated sources of return, they are accretive to the total portfolio and can be captured through a careful selection of hedge funds and/or quantitative alternative managers. Investors should look for PFM performance attribution that shows economically meaningful and statistically significant exposures to alternative risk premiums. Tests of factor return contribution ensure that alternative risk premiums contribute a meaningful proportion of a hedge fund’s total return. Equations (4) and (5) define alpha and factor return contributions (in excess of the risk-free rate), respectively.

$$C_a = a / (R - RF)$$  \hspace{1cm} (4)

$$C_k = b_k R_k / (R - RF)$$  \hspace{1cm} (5)

where

- $C_a$ is the return contribution of alpha,
- $C_k$ is the return contribution of factor $k$, and
- $R_k$ is the return of factor $k$.

Another test is to perform a step-down regression that employs only the four traditional risk premiums to confirm whether the alternative risk premiums contribute unique return. An economically meaningful and statistically significant four-factor alpha will confirm this. Indeed, if an investor desires exposures to alternative risk premiums and select managers capture intentional and persistent exposures, then portfolio optimization or risk parity techniques can be employed to target exposures, either within a predetermined hedge fund policy allocation, or more holistically across the broader portfolio by using factor-based asset allocation, as in Ilmanen and Kizer [2012].

Manager skill can also be a unique and uncorrelated source of return, particularly when it comes in the form of pure alpha representing a large proportion of the hedge fund’s total return. Hedge funds have the tools to isolate and magnify alpha by counteracting long-short positions and leverage. There are a number of potential sources of factor-adjusted alpha: skilled security selection and market timing, unique ideas and time-varying opportunities, and exotic risk premiums not represented in the PFM. All of these sources of additional return are accretive to the total portfolio. However, the 10-year panel in Exhibit 4 shows that alpha is uncommon, so high selectivity is critical. Security selection and market timing are more characteristic of capturing traditional risk premiums, where the performance evidence is weaker. On the other hand, there are a number of unique ideas and time-varying opportunities less commonly available from traditional stock and bond managers. Their identification and exploitation is idiosyncratic to the hedge fund manager who has a broader mandate, investment universe, and tool set than traditional stock and bond managers. Unique ideas and time-varying opportunities can often intersect with exotic risk premiums. For example, distressed debt and the specialty corners of the credit markets can offer illiquidity premiums, and are often better suited for financial intermediation by hedge funds than are regulated mutual funds.

Investors should consider PFM performance attribution that shows economically large, statistically significant and persistent alpha, ideally with low R-squared. These managers are capturing unique and uncorrelated skill-based returns that are not available from either traditional or alternative risk premiums. The low R-squared suggests that the return variation is diversifying because it is driven by the uncorrelated alpha. Tests of alpha return contribution (Equation (4)) should show that alpha represents a large proportion of the hedge fund’s total return. Low R-squared managers in particular require deep qualitative due diligence, because the source of their returns is less transparent. Investors can detect evidence of illiquid assets and a potential illiquidity premium by employing lagged market and credit factors in PFM regressions, which also provide a better estimate of total betas. An evaluation of the investment process and holdings through time should determine whether idiosyncratic manager skill, exotic risk premiums, or some combination of the two are driving the observed alpha.
Individual hedge funds often display lower R-squareds than do portfolios formed from the same individual hedge funds. This is due to the idiosyncratic return variation that is diversified away with the addition of managers. It is the reason our tests in previous sections focused on diversified strategy categories of hedge funds (as did Fung and Hsieh, who also focused their work on hedge funds of funds). A key question when evaluating individual skill-based hedge funds is whether or not the idiosyncratic return variation is compensated with alpha. Without alpha, the idiosyncratic risk is uncompensated and diversifiable. With meaningful alpha, the idiosyncratic risk is compensated and helps diversify the broader portfolio. This is why there remains significant information in the interpretation of alpha for individual funds, even if the PFM R-squared is low.

In addition to diversification, leverage is the other potential benefit of hedge funds. In practice, most investors construct diversified portfolios from unleveraged efficient frontiers. Hedge funds leverage diversified portfolios of low-beta risk premiums, which is consistent with the modern portfolio theory concept of leveraging the maximum Sharpe portfolio up the capital market line. This leveraging of diversified portfolios of low-beta risk premiums results in higher Sharpe ratios than those of similar risk portfolios along the unleveraged efficient frontier. This is a different effect than pushing up the unleveraged frontier of traditional risk premiums by adding alternative risk premiums or pure alpha. Of course, investors can leverage the maximum Sharpe portfolio themselves at costs lower than hedge fund fees, but emerging literature on leverage constraints (or leverage aversion) is consistent with investors preferring to silo that leverage in the alternatives allocations of their broader portfolios.10

On the other hand, the lower volatility feature of hedge funds is not by itself accretive to an optimized portfolio of traditional stocks, bonds, and cash. When viewed in isolation, hedge funds have indeed offered lower volatility than have stocks and higher volatility than have investment-grade bonds. The standard deviations of the MSCI ACWI (All Country World Index) over the 10- and 20-year periods to 2012 are 16.79% and 15.77%, respectively, while the respective standard deviations of the Barclays U.S. Aggregate Bond Index are 3.55% and 3.65%. This compares to the HFRI Index standard deviations in Exhibit 4, which range from 4.34% to 9.26%. But hedge funds are not a discrete and transparent asset class like stocks and bonds; they largely represent different mixes of systematic risk premiums. As we showed in Exhibit 4, the standard deviations and CVaRs of the factor risk benchmarks are nearly identical to their respective HFRI indices. Equation (2), which defines the factor risk benchmark, includes both the risk-free rate and factor return contributions. This means that hedge fund volatility and tail risk are almost totally explained by cash and the mix of risk-premium betas. Therefore, it is the diversification benefit of adding uncorrelated sources of return that is contributory to an optimized portfolio of traditional stocks, bonds, and cash, not the lower volatility feature of hedge funds per se. The benefit of reduced volatility accrues at the portfolio level, and is due to classic Markowitz diversification. The investor can always add cash to the maximum Sharpe portfolio to reduce volatility, if that is the objective.

CONCLUSION

We presented an applied PFM that illuminates the underlying risk and return drivers of broad strategies of hedge funds from the opportunity-cost perspective of a portfolio investor who owns traditional assets. We demonstrated how to interpret and use key information from the factor attribution to improve hedge fund manager selection, and ultimately broader portfolio construction. Many investors own hedge funds due to their higher Sharpe ratios and lower volatility profile. But we have shown that the risk and return profile of hedge funds as group is almost totally explained by the mix of systematic risk premiums. Armed with this information and the tools and methods presented, hedge fund manager selection and broader portfolio construction can focus on identifying and capturing diversifying sources of return in the form of alternative risk premiums, exotic risk premiums, and skill-based returns, with each perhaps offering different confidence levels relative to traditional risk premiums for forward-looking investors.

Factor models will evolve as researchers continue to identify and understand the systematic risk premiums that drive capital market returns. With these innovations, the mystery of alpha is often illuminated as alternative beta, requiring a more discerning approach to hedge fund manager selection and broader portfolio construction. Model specification must remain flexible to keep pace, and to remain useful for investor decision-making.
ENDNOTES

1See Ken French’s online data library for factor definitions and data.

2We use the CBOE S&P 500 PutWrite Index as a proxy for the put premium. It has a 0.84 correlation with the S&P 500. When we regress the put premium (excess of the risk-free rate) against excess S&P 500 returns, the 0.56 market beta is robust, but there remains statistically significant alpha. The alpha is the unique component of the insurance premium, though Kelly and Jiang [2014] find it is explained by a novel approach to measuring equity tail risk. We find some negative exposure to the put premium in certain hedge fund strategy categories, depending upon the timeframe, suggesting the presence of tail risk hedging that has detracted from hedge fund returns on average.

3Common inception is November 1990. Average monthly premiums are multiplied by 12 to annualize them in Exhibit 1.

4See Fung and Hsieh [2004] for a summary of documented reporting biases.

5See David Hsieh’s Hedge Fund Data Library for factor definitions. The trend-following factors can be accessed at http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls and were originally published in Fung and Hsieh [2001].

6We exclude the ACWI lagged variable in our count.

7See US GAAP FAS 157 (FASB Accounting Standards Codification Topic 820) on fair-value accounting.

8We thank an anonymous reviewer for suggesting lagged betas over lagged dependent variables. Both methods mitigate serial correlation, but lagged betas provide a better estimate of total betas and total factor return contribution.

9See Asness et al. [2013].

10For example, see Frazzini and Pedersen [2013].

REFERENCES


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