



To Hedge or Not to Hedge: Factor Dependence and Skill among Hedge Funds

Abstract

Do you know how your hedge fund generates returns? As average hedge fund performance continues to wane, investors are increasingly seeking objective criteria to distinguish talented managers from the herd. Differentiating the contributions of systematic and idiosyncratic factors in a fund's return stream is one way to accomplish this goal. In this paper, we combine two related, but distinct, methods of measuring these variables. Using the Fama-French-Carhart 4-factor approach, we find that hedge funds with the highest 4-factor alpha (a proxy for skill) and lowest r-squared to the four factors (a proxy for factor dependence) produce the strongest subsequent returns. We also find that those managers with high trailing 4-factor alpha have lower exposure to systematic risk factors in general.

Investment returns, whether on individual stocks or entire portfolios, are widely considered the payoffs to systematic and security-specific risks. When hedge funds posted impressive returns in the late 1990s and early 2000s, investors lacked many of the tools to differentiate between the two types of risk. More recently, however, competitive pressures and regulatory changes¹ have eroded hedge fund returns, and investors now seek informative methods to identify the small percentage of managers with true talent. Fundamental to this process is determining to what extent systematic risks are responsible for generating returns.

The Capital Asset Pricing Model (CAPM) was the first model to assume that expected returns are not entirely specific to an individual stock. According to CAPM, part of a stock's expected return is due to its systematic covariance with the market's return (the stock's beta). Since CAPM was developed, research has uncovered additional systematic factors that influence expected returns beyond the market's movements. Specifically, researchers identified systematic excess returns to value companies over growth companies,² small stocks over large stocks,³ and recent "winners" (as measured by price change over the last 3, 6, or 12 months) over recent "losers."⁴ But the excess expected returns to these factors arise from taking additional risks. Generally speaking, smaller companies tend to be riskier than larger companies, undervalued stocks tend to be unpopular investments, and momentum stocks with recent steep price climbs are prone to reversals.

In decomposing hedge fund portfolio returns, a portion will be explained by exposure to these systematic sources, but successful managers should also contribute skill in the form of unique alpha sources. By isolating the effects of these systematic factors – equity beta, value, size, and momentum – when analyzing a fund's returns, an investor can more effectively distinguish the

¹ Though difficult to prove empirically, we observe that Regulation Fair Disclosure (2000), Decimalization (2001), the Global Settlement (2002), and the "Late Trading" scandal and subsequent regulation (2003) were coincidental with the largest decline in equity hedge fund 4-factor alpha in the last 15 years.

² Shiller (1984), Fama and French (1992), Lakonishok, Shleifer, and Vishny (1994).

³ Banz (1981), Reinganum (1981), Fama and French (1992).

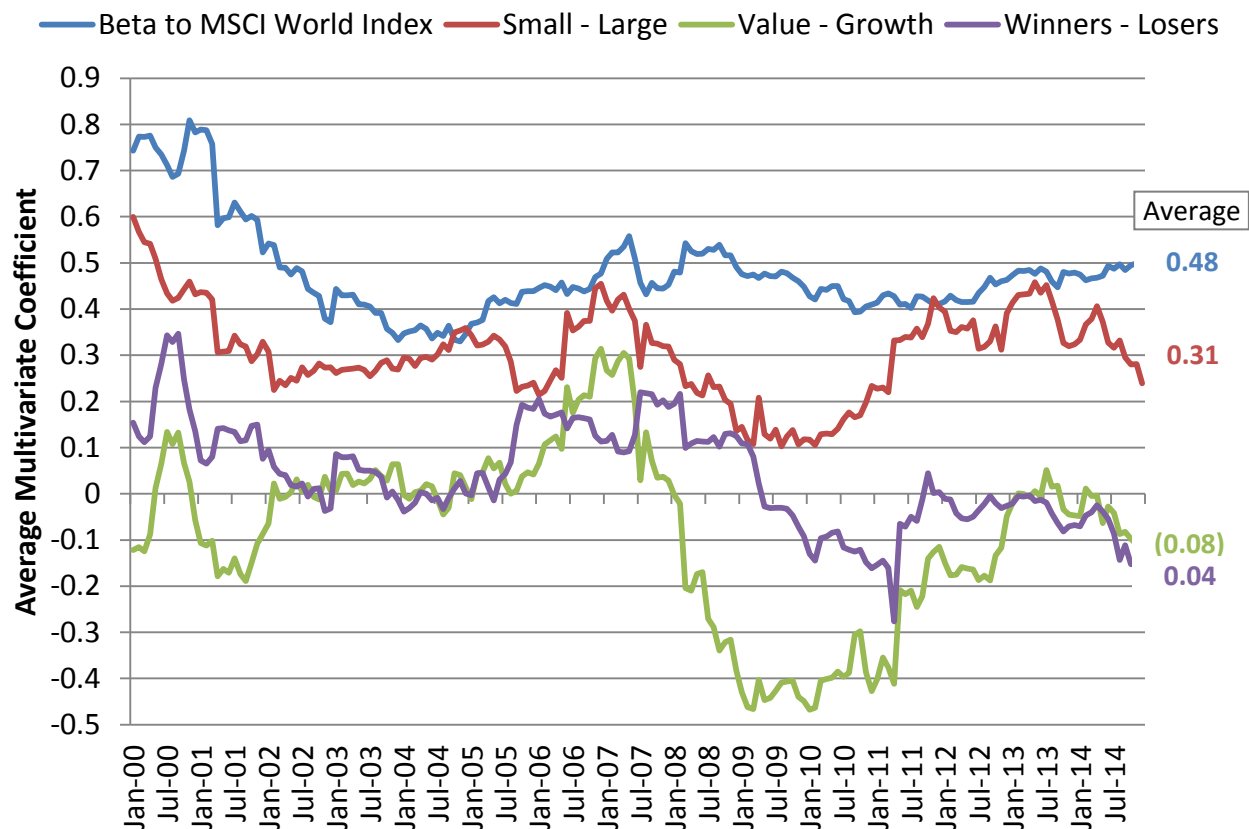
⁴ Jegadeesh and Titman (1993), Carhart (1997).

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skilled-based, active returns (what we call “4-factor alpha”) from the systematic, passive returns. Since most hedge funds have no benchmark (an effective 0% hurdle), they earn performance fees for any positive return – regardless of the attribution between passive and active sources. Despite this fact, many investors seem comfortable with high exposure to systematic factors (chiefly equity beta and exposure to small caps) in their hedge fund portfolios. Figure 1 tracks the average exposure to the four Fama-French-Carhart style factors (equity beta, value, size, momentum) over time across all equity hedge funds in Hedge Fund Research’s HFRI returns database. These numbers represent the average month-to-month multivariate coefficient using a 24-month rolling regression window.

Equity hedge funds exhibit persistent exposure to market beta and small caps.

Figure 1. Average cross-sectional rolling 24-month multivariate coefficients to four style-based factors



Note: Values represent the universe average monthly rolling 24-month coefficients from January 2000 to December 2014 when hedge fund net returns less monthly risk-free rate (interpolated 1-month return on BofA ML 3-month Treasury Index) are regressed against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in MSCI World Index from previous 12 months). Includes all funds designated as “Equity Hedge” funds by Hedge Fund Research’s HFRI database with at least 24 months of continuous returns between February 1998 and December 2014. Source: HFRI, MSCI, FactSet.

Review of Past Research

Previous research has explored similar issues of factor dependence and skill among mutual funds and hedge funds. Professors Sheridan Titman and Cristian Tiu hypothesized that specific “hedge

funds...will choose greater exposure to priced factors if they have less confidence in their abilities to generate abnormal returns from the active component of their portfolios.”⁵ In other words, those that lack skill will seek to hide this fact by relying mostly on standard factors to produce returns. To test this, the authors sorted hedge funds by r-squared to standard risk factors, and they found that funds with lower r-squareds have higher alphas, attract more capital, and charge higher fees. Zheng Sun, Ashley Wang, and Lu Zheng used an alternate measure of strategy distinctiveness – a fund’s past correlation to its peer average – to sort hedge funds, and found that funds with lower correlation to their peers had better subsequent performance.⁶

Most recently, Professors Yakov Amihud and Ruslan Goyenko sorted the mutual fund universe by two variables/characteristics. They not only sorted mutual funds based on trailing r-squared but also by trailing 4-factor alpha, and found that funds that sorted into the lowest quintile of r-squared and the highest quintile of 4-factor alpha went on to produce the highest subsequent alphas.⁷ Additionally, they found that those funds with high r-squared measures were larger, were run by managers with shorter tenures, and had lower fees.

Our Approach

Assessing funds using both 4-factor alpha and r-squared is more revealing than focusing on one dimension alone. Therefore, we sought to apply the same methodology used by Amihud/Goyenko to hedge funds rather than mutual funds. Conveniently, both of these dimensional measures – r-squared and 4-factor alpha – are outputs of the same regression. When we regress hedge fund returns against returns to these four factors (equity beta, value, size, and momentum), we can derive the r-squared (or “coefficient of determination”) of the regression, which will tell us the percentage of variation in fund returns that is attributable to variation in the factor returns. Additionally, the regression output will include an alpha term, which is the return over and above (or under and below) what would be expected from a fund’s average factor exposures alone. This “4-factor alpha” will measure the alpha relative to a benchmark tailored specifically for that fund’s recent exposures. It’s also worth noting that 4-factor alpha, in addition to capturing stock selection skill, will capture factor timing skill provided that factor exposures are adjusted more frequently than the window size (24 months in our analysis).

The r-squared highlights a fund’s factor dependence (the higher the r-squared, the more a fund is relying on factors to produce returns), while the 4-factor alpha is a proxy for skill, which, in this case, will capture stock selection skill and higher-frequency factor timing skill. There exists a misguided notion that hedge funds with demonstrated skill also come with high levels of systematic factor exposures – that skill and factor dependence come as a “package deal.” The relatively steady run-up in equities over the past six years has supported this notion, since many of the funds with the highest recent returns (and therefore perceived skill) have also had high exposure to equity beta. But while recent experience might suggest otherwise, skill is

⁵ Sheridan Titman and Cristian Tiu, “Do the Best Hedge Funds Hedge?” *Review of Financial Studies* 24 (2011): 123-168.

⁶ Zheng Sun, Ashley Wang, and Lu Zheng, “The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance,” *Review of Financial Studies* 25 (2012): 96-143.

⁷ Yakov Amihud and Ruslan Goyenko, “Mutual Fund’s R^2 as Predictor of Performance,” *Review of Financial Studies* 26 (2013) 667-694.

independent of factor exposure. An individual manager has a fixed level of skill (or lack of skill), but factor exposure and timing are within a manager’s control. In other words, a manager has the choice to layer factor exposures on top of the skill-based returns. In Figure 2, we propose a high-level classification framework for hedge funds based on the relative measures of these two variables.

4-factor alpha is a proxy for skill while the R-squared to the 4 factors is a proxy for factor dependence.

Figure 2. Hedge fund classification framework

		R ² to 4 Factors (Factor Dependence)	
		Low	High
4-Factor Alpha (Skill)	Low	<i>“Honest Loser”</i>	<i>“Smoke and Mirrors”</i>
	High	<i>“Pure Skill”</i>	<i>“Polluted Skill”</i>

We assume that all fund managers seek to deploy their maximum level of skill (and, by extension, 4-factor alpha since this is a good proxy) regardless of their view on factor exposure. When it comes to factor dependence (we use r-squared to the 4 factors as a proxy), managers may have high factor exposures for a variety of reasons including:

1. They may simply be unaware of their factor exposures in which case any dependence / bias is unintentional.
2. They may believe that there are long-term, systematic returns to equity risk, smaller capitalization stocks, value equities, and recent “winners” (momentum).
3. They may believe that they can time these factors (in which case a point-in-time measurement may mischaracterize a variable exposure as static).
4. They may be seeking to offset their (lack of) skill by assuming sizable factor exposures in order to deliver acceptable return levels (which may otherwise be unachievable).

However, none of these reasons aligns with investor interests:

1. Most managers have an idea, even if imprecise, as to their equity beta exposure, but many managers are unaware of their exposure to other style factors. Returns to these factors ebb and flow just like equity market returns, so not monitoring exposure to them puts the portfolio at risk of underperforming when specific factors are out of favor.
2. Incorporating factor exposures will add an additional source of volatility, and the precise degree of exposure to each factor will be unknown to the investor ahead of time, making it practically impossible for them to hedge out these exposures. Relatedly, an investor can achieve exposure to these return drivers separately through passive ETFs or other “smart beta” products, typically offered at a fraction of the hedge fund fee structure.
3. Our analysis captures the value added (or lost) from higher-frequency changes in factor exposures (any repositioning on a timeframe shorter than two years). We are less concerned about lower-frequency factor timing; given the length of equity and style

factor cycles (usually many years), skill would be much harder to prove to investors since it would involve multiple correct calls over the course of decades.

4. If indeed the high factor dependence is intentional, the last explanation is the one that is likely most probable. Managers without skill choose significant factor exposure to offset their lack of talent. Perhaps they correctly reason that with enough factor exposure, factor performance will dominate their returns making “skill” very difficult to isolate and analyze by investors.

This line of reasoning prompts the question: For managers that *do* have skill, why would they choose to layer in factor returns that are presumably outside their control? It’s possible that some skilled managers simply don’t want to fight the current trend, and may choose a beta similar to that of their peers. However, in this case, systematic factor performance will potentially overwhelm any skill-based returns since factor volatility and returns are usually higher than expected alpha generation.⁸ Targeting mid- or high-single digit annual alpha production, for instance, the skill-based portion of the return stream will be hidden beneath the much more dominant factor returns. So is it true that the combination of high skill and low factor exposure is preferable? And are the two measure related (i.e. how does factor dependence vary with changes in skill levels)? These are two central questions we seek to answer.

Before we report the results of our analysis, we want to mention a couple caveats to our approach. First, the factors used in this analysis must be relevant to the underlying asset class or the results will suffer from model misspecification. R-squared and 4-factor alpha provide two powerful and distinct measures of factor dependence and skill, and they are conveniently derived from the same regression. Because our analysis focused on equity hedge funds, we used equity-based indices to represent factor returns, and we included the four most prominent systematic factors, each supported by decades of academic research. However, if we applied this framework to a credit-focused hedge fund, for instance, the results would likely not be informative or predictive of subsequent performance. Credit risk, duration risk, interest rate risk, and call risk are factors that may be more pertinent to describing the performance of individual bonds or a bond portfolio. Correctly defining the systematic risk factors underlying different investment strategies or assets classes is therefore critical to producing meaningful results.

Second, most hedge fund returns databases depend on self-reporting and suffer from backfill bias. Managers that choose to report their returns are more likely to have a successful track record, and when they begin reporting they will likely “backfill” this past performance into the database. Conversely, managers with poor performance may simply choose not to report to a database. The decision to begin reporting probably hinges principally on absolute performance in recent periods. Since most of our database analysis adjusts returns for systematic factor exposures, statistics which fewer managers track, our results probably suffer less from this bias.

⁸ Over the past 15 years (January 2000 – December 2014), the volatility of the equity market premium (MSCI World Index – risk free rate) has been 16%, that of the small-cap premium (MSCI World Small Cap Index – MSCI Large Cap Index) has been 8%, that of the value premium (MSCI World Value Index – MSCI World Growth Index) has been 7%, and that of the momentum premium (float-weighted return of top half of price performers in the MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in the MSCI World Index from previous 12 months) has been 12%.

After all, a fund that derives all of its returns from systematic factor exposures may have high returns, but unimpressive 4-factor alpha.

Our Analysis

In our analysis, we first sought to apply the Amihud/Goyenko (2013) methodology to hedge fund returns instead of mutual fund returns, while expanding it to answer the questions we just raised. We drew from Hedge Fund Research's HFRI database of over 8,000 "Equity Hedge" funds, current and closed (to avoid survivorship bias), and observed their monthly net returns since 1997. Because the traditional single-metric portfolio returns used for Fama-French-Carhart factors place a disproportionate weight on small value stocks, which have done relatively well recently, Cremers et al. (2012) suggest using "common and tradable benchmark indices" instead.⁹ Therefore, to track specific factor returns, we use MSCI World indices. We use the MSCI World Index for equity market returns, the MSCI World Value Index - MSCI World Growth Index return spread for returns to value, the MSCI World Small Cap Index - MSCI World Large Cap Index return spread for returns to size, and the float-weighted return of the top half of price performers in the MSCI World Index from previous 12 months – the float-weighted return of the bottom half of price performers in the MSCI World Index from the previous 12 months return spread for returns to momentum.

For each fund, on a rolling 24-month basis, we regress net monthly returns (less the risk-free rate " r_f ") against returns to the equity market (less r_f), value, size, and momentum. Following the Amihud/Goyenko methodology, we sort funds into quintile baskets based on r-squared to these four factors. Then, within each r-squared quintile, we sort again based on 4-factor alpha. For each month, every fund will be a member of 1 out of a possible 25 baskets based on its r-squared and 4-factor alpha quintile combination. Because of the dependent sorting, all baskets will contain the same number of funds. Then, for each basket, we take the average return of the portfolio of funds for the 25th month (the month immediately following the 24-month estimation window). We then have a time series of 25th-month returns for each of the 25 quintile combination baskets from January 2000 to December 2014 (180 months = 15 years). We regress each of those time series on the historical 4-factor return streams, and multiply the alpha term by 12 to get an annualized 4-factor alpha term. Figure 3 displays this alpha term and the related t-statistic for each basket.

⁹ Martijn Cremers, Antti Petajisto, and Eric Zitzewitz, "Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation," *Critical Finance Review* 2 (2012): 1-48.

Funds with higher skill (4-factor alpha) and lower R-squared (to the 4 factors) produce higher subsequent alpha.

Figure 3. Subsequent 4-factor alphas and t-statistics (Dependent Sort)

		R^2_{t-1}						
		Low	2	3	4	High	All	Low-High
4-Factor Alpha _{t-1}	Low	1.350% 1.23	-0.540% (0.34)	-2.008% (1.10)	-2.257% (1.36)	-3.755% (2.31)	-1.462% (1.12)	5.105% 2.69
	2	2.191% 3.26	1.096% 1.26	0.648% 0.70	0.764% 0.75	-0.089% (0.09)	1.074% 1.54	2.280% 1.71
	3	3.020% 5.06	2.867% 3.38	2.121% 2.35	2.663% 2.83	0.257% 0.29	2.204% 3.56	2.762% 2.28
	4	5.555% 7.89	4.645% 4.87	2.957% 3.12	2.430% 2.02	1.287% 1.13	2.781% 3.76	4.268% 2.78
	High	7.302% 4.84	6.875% 4.35	7.174% 3.97	4.144% 2.49	3.243% 1.79	6.312% 4.30	4.060% 1.73
	All	3.940% 5.83	3.033% 3.42	2.202% 2.35	1.558% 1.58	0.201% 0.21	2.190% 2.92	3.738% 3.27
	High-Low	5.952% 3.11	7.414% 3.48	9.182% 3.48	6.400% 2.76	6.997% 2.87	7.773% 3.84	

Note: On a rolling monthly basis, funds are sorted into r-squared quintiles, and then 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in MSCI World Index from previous 12 months). 25th month returns are then averaged across all funds in the basket, and the time series for each basket is then regressed against the same four factors and annualized (monthly alpha * 12). The t-statistic for each regression is reported below the annualized 25th month returns. Sample period includes test months from 1/2000 to 12/2014 (180 months). All hedge funds, open or closed, included are classified as “Equity Hedge” funds by HFRI and have at least 25 months of continuous returns. Source: HFRI, MSCI, FactSet.

Focusing on the “All” column and row, we can see that subsequent alphas are higher for funds with lower trailing r-squared and higher trailing 4-factor alphas. In other words, funds with less factor dependence and higher factor-adjusted returns go on to perform better than those with opposing characteristics. These relationships are nearly monotonic across all rows and columns, and the majority of the alphas in extreme cells are statistically significant. Looking at the quintile spreads (“Low – High” column and “High – Low” row), we also see a consistent story with uniformly positive return spreads along both dimensions.

One potential weakness of this analysis is that we sorted the funds into quintiles using a dependent (two-stage sort) following Amihud/Goyenko: first by r-squared, and then by 4-factor alpha within each r-squared quintile. The rationale was to create an equal number of funds/observations underlying each cell. However, any correlation between the two variables may impact the results using this method. Our suspicion that there *is* a relationship prompted us to re-run the analysis using an independent sort. Below in Figure 4, we demonstrate the same analysis as above, but utilizing an independent sort and thus allowing for an uneven distribution of funds across cells.

An independent sorting of funds along both dimensions does not affect the general outcome.

Figure 4. Subsequent 4-factor alphas and t-statistics using an independent sort

		R^2_{t-1}						
		Low	2	3	4	High	All	Low-High
4-Factor Alpha _{t-1}	Low	1.194% 0.75	-0.686% (0.40)	-1.439% (0.81)	-1.959% (1.31)	-3.370% (2.13)	-1.462% (1.12)	4.564% 2.00
	2	1.951% 2.58	0.542% 0.58	0.810% 0.89	1.512% 1.54	0.481% 0.54	1.074% 1.54	1.469% 0.84
	3	2.444% 3.98	2.332% 2.87	1.863% 2.11	2.869% 3.12	1.614% 1.82	2.204% 3.56	0.830% 0.19
	4	4.405% 6.33	4.001% 4.87	2.555% 3.02	2.454% 2.09	1.501% 1.30	2.781% 3.76	2.904% 1.78
	High	7.315% 5.07	6.624% 4.41	7.141% 4.15	4.272% 2.46	4.396% 1.86	6.312% 4.30	2.918% 0.97
	All	3.940% 5.83	3.033% 3.42	2.202% 2.35	1.558% 1.58	0.201% 0.21	2.190% 2.92	3.738% 3.27
	High-Low	6.121% 2.70	7.310% 3.47	8.580% 3.38	6.230% 2.80	7.766% 2.57	7.773% 3.84	

Note: On a rolling monthly basis, funds are sorted simultaneously into r-squared quintiles and 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in the MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in the MSCI World Index from previous 12 months). 25th month returns are then averaged across all funds in the basket, and the time series for each basket is then regressed against the same four factors and annualized (monthly alpha * 12). The t-statistic for each regression is reported below the annualized 25th month returns. Sample period includes test months from 1/2000 to 12/2014 (180 months). All hedge funds, open or closed, included are classified as “Equity Hedge” funds by HFRI and have at least 25 months of continuous returns. Source: HFRI, MSCI, FactSet.

As you can see from the table above, the results largely stay the same. Subsequent alphas are higher for those with lower r-squared figures and higher trailing 4-factor alphas. All quintile spreads (“Low – High” column and “High – Low” row) are also positive, indicating persistence of these relationships across all quintiles. And similar to Figure 3, we find that the trailing 4-factor alpha is perhaps more determinative than trailing r-squared since the quintile spread from low to high 4-factor alpha (across all quintiles of r-squared) is 7.773% vs. 3.738% for r-squared.

Thus far, we have explored the relationship between trailing r-squared and subsequent 4-factor alpha, in addition to that between trailing 4-factor alpha to subsequent 4-factor alpha. The latter is essentially testing the persistence of skill. Do managers who have exhibited skill in the past continue to exhibit skill in the future? We have found that indeed, there is a strong relationship, consistent with our hypothesis that skill is largely fixed – either a manager has it or doesn’t.

But what about predictiveness of actual returns, because isn’t that the first concern of hedge fund investors? As we pointed out earlier, there is reason to doubt that the managers with the lowest factor exposure in the recent past will deliver the highest returns going forward. With most developed markets in rally mode since the financial crisis, the best-performing hedge funds have undoubtedly had positive exposure to equity market beta. But what happens across market

cycles? To avoid the potential of timing bias, we look at the last 180 months (15 years) in an attempt to capture a cross-cycle representation. We perform the same independent sort that we did for Figure 4 based on trailing 24-month 4-factor alpha and r-squared, then observe performance in the 25th month. This time, we record 25th-month returns relative to the universe median hedge fund return for that month. We take a cross-sectional average for each month, then average this number across all months and annualize it. These are the returns that appear in Figure 5.

Relative measures of 4-factor alpha and R-squared have significant implications for subsequent returns.

Figure 5. Annualized average 25th month peer-relative subsequent return

		R^2_{t-1}						
		Low	2	3	4	High	All	Low-High
4-Factor Alpha _{t-1}	Low	-2.27%	-3.45%	-2.85%	-2.41%	-4.63%	-2.94%	2.36%
	2	-2.35%	-2.79%	-1.79%	-0.44%	-1.22%	-1.51%	-1.13%
	3	-1.84%	-1.17%	-0.92%	0.43%	-0.24%	-0.74%	-1.60%
	4	0.22%	0.47%	-0.11%	0.72%	0.68%	0.09%	-0.46%
	High	4.81%	4.46%	6.37%	4.46%	4.41%	4.95%	0.39%
	All	0.20%	0.04%	0.29%	0.31%	-0.92%	0.00%	1.12%
	High-Low	7.08%	7.92%	9.23%	6.87%	9.04%	7.89%	

Note: On a rolling monthly basis, funds are sorted simultaneously into r-squared quintiles and 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in MSCI World Index from previous 12 months). 25th month returns are then adjusted by subtracting out the universe-wide peer median monthly return, and then a cross-fund, cross-time average is taken across all data points in the basket and annualized (monthly average return * 12). Sample period includes test months from 1/2000 to 12/2014 (180 months). All hedge funds, open or closed, included are classified as “Equity Hedge” funds by HFRI and have at least 25 months of continuous returns. Source: HFRI, MSCI, FactSet.

You can see that returns increase as 4-factor alphas increase and as r-squared decreases. 9.4% in annualized return separates the high-r-squared, low-4-factor-alpha cell from the opposite corner (the two cells highlighted in yellow). The trend is much more monotonic in terms of 4-factor alpha (in the “All” column): The funds that have demonstrated skill in the past consistently earn better returns going forward. Focusing on the bottom row of 4-factor alpha quintile spreads (“High – Low”), you can see that all spreads are positive. The r-squared trend is also apparent, though admittedly less monotonic (see “All” row). The r-squared quintile spreads (“Low – High” column) are positive for the highest and lowest 4-alpha quintiles. But as we discussed, the r-squared results are still susceptible to cyclical bias. When the equity market is rising and small cap, value, and momentum stocks are performing well, a high r-squared will naturally lead to higher returns. Nevertheless, the general trend remains: Funds with higher skill and lower factor dependence subsequently outperform their peers.

These results hold up when we risk adjust hedge fund returns by volatility. Using each fund’s annualized 25th month return, we then divide by the annualized volatility over the previous 25 months. The results in Figure 6 then represent the average subsequent Sharpe ratio of fund peers sorted along the two dimensions. Although not separately shown, fund volatilities generally

increase as r-squared increases. This stands to reason since factor returns, as they are layered in, contribute additional volatility above and beyond the volatility of 4-factor alpha itself. Focusing on the “All” column and row, we observe that Sharpe ratios monotonically increase as 4-factor alpha increases and as r-squared decreases. Further, the quintile spreads (“Low – High” column and High – Low” row) are positive in all but one instance. Comparing the extreme cells in Figure 6 (shaded in yellow), we observe a +0.88 increase in Sharpe Ratio moving from the top right cell to the bottom left.

The results hold true if we adjust subsequent returns for volatility.

Figure 6. Average Sharpe Ratio

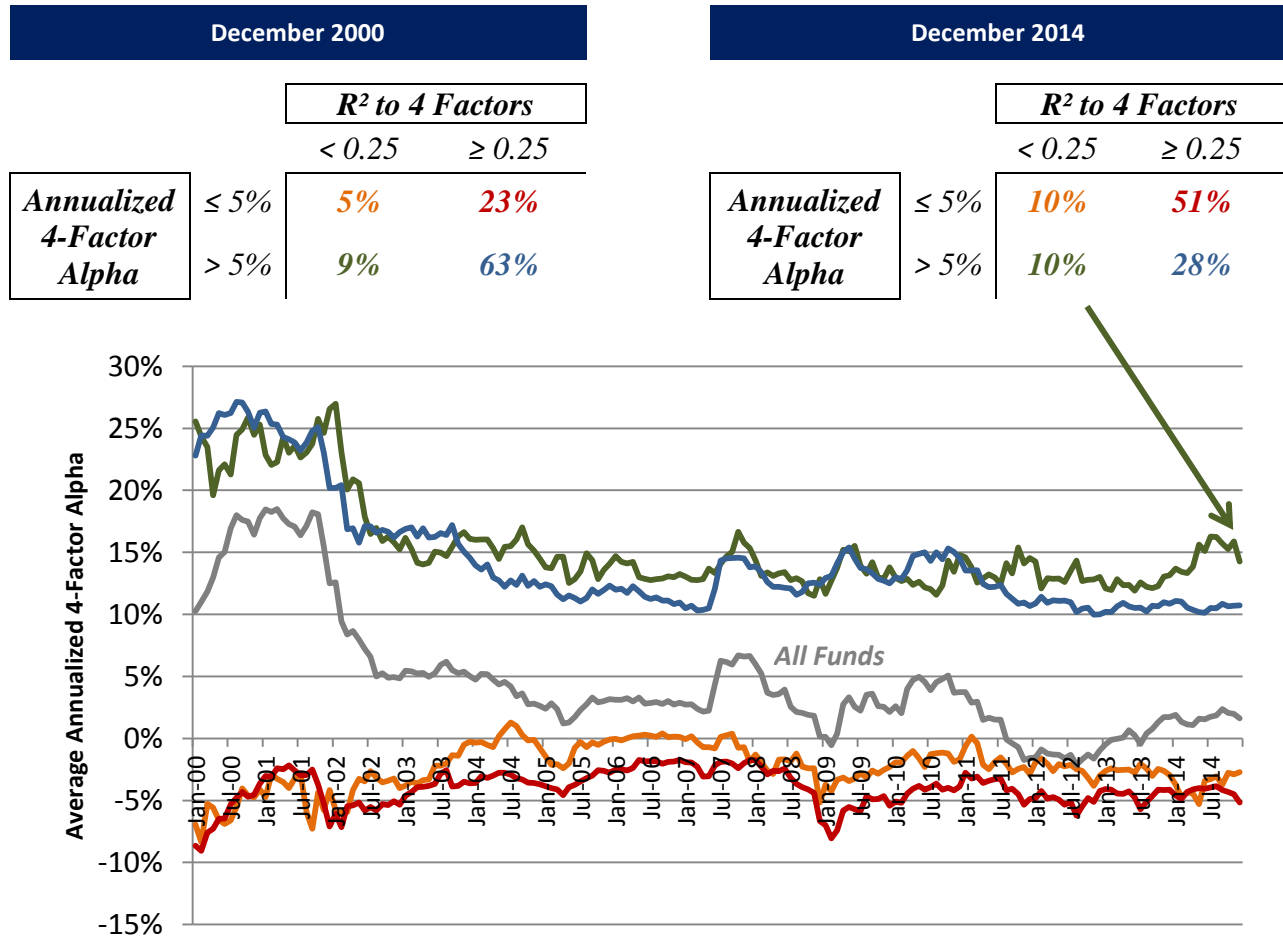
		R^2_{t-1}						
		Low	2	3	4	High	All	Low-High
4-Factor Alpha _{t-1}	Low	0.15	0.21	0.24	0.25	0.18	0.23	(0.03)
	2	0.66	0.49	0.52	0.49	0.42	0.53	0.23
	3	0.93	0.82	0.69	0.69	0.58	0.75	0.34
	4	1.13	0.93	0.78	0.72	0.63	0.85	0.50
	High	1.06	0.92	0.93	0.80	0.80	0.90	0.27
	All	0.90	0.72	0.63	0.56	0.44	0.65	0.46
	High-Low	0.92	0.71	0.69	0.55	0.62	0.68	

Note: On a rolling monthly basis, funds are sorted simultaneously into r-squared quintiles and 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in MSCI World Index from previous 12 months). 25th month returns are annualized (multiplied by 12) and divided by annualized standardized deviation of returns (volatility) over the previous 25 months, and then a cross-fund, cross-time average is taken across all data points in the basket and annualized. Sample period includes test months from 1/2000 to 12/2014 (180 months). All hedge funds, open or closed, included are classified as “Equity Hedge” funds by HFRI and have at least 25 months of continuous returns. Source: HFRI, MSCI, FactSet.

Now that we have relaxed the dependent sort assumption and moved to an independent sort in Figures 4-6, it’s worth examining the actual distribution of equity hedge funds by r-squared and 4-factor alpha. To add some specificity, let’s assume cutoffs of 0.25 for r-squared and 5.0% for annual 4-factor alpha. The distributions as of December 2014 and December 2000 appear in Figure 7. While over half of hedge funds in 2000 fell into the bottom right quadrant (high skill / high factor dependence), this large percentage of funds appears to have migrated into the top right quadrant (low skill / high factor dependence) today. Funds depended on factors to produce returns in 2000, but they supplemented that with meaningful factor-adjusted alpha; today, the majority of funds still have significant factor exposure with much less non-factor-dependent alpha. Interestingly, the percentage of funds in the preferred bottom-left quadrant (high skill / low factor dependence) has stayed roughly constant over the past 14 years. It remains as difficult as ever to find this rare combination of high skill and low factor dependence. Yet, as the line graph in Figure 7 illustrates, this is the quadrant (in green) that has consistently produced the highest factor-adjusted returns. Conversely, the low skill / high factor dependence quadrant (in red) has produced the lowest factor-adjusted returns.

4-factor alpha generation has deteriorated significantly since the year 2000 while most hedge funds remain dependent on factor performance.

Figure 7. Distribution of equity hedge funds in December 2000 vs. 2014 and Average 4-factor Alpha by Quadrant over Time



*Note: All data based on the trailing 24 months as of each respective month. Funds are sorted simultaneously into r-squared and 4-factor alpha baskets based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in MSCI World Index from previous 12 months). 4-factor alpha is annualized (monthly average return * 12). All hedge funds, open or closed, included are classified as “Equity Hedge” funds by HFRI and have at least 24 months of continuous returns as of each respective month. Source: HFRI, MSCI, FactSet*

One question we have largely ignored until now is the actual relationship between 4-factor alpha and r-squared (to the four factors). We know the relative distribution of funds. The majority of funds today fall into the least desirable quadrant of both low skill and high factor dependence. But how does factor dependence vary with changes in skill levels? We raise the question again: Would a manager with true stock selection skill choose to layer on factor exposures that are beyond his or her control? We think not, and if we are correct, we would observe declining factor exposures as skill increases. The median characteristics of funds sorted by 4-factor alpha quintiles appear in Figure 8 as of December 2014.

As skill (measured by 4-factor alpha) decreases, factor exposure (as measured by r-squared and individual factor coefficients) increases.

Figure 8. Median characteristics of 4-factor alpha quintiles as of December 2014

4-Factor Alpha Quintile	Median Annualized 4-Factor Alpha	Median R ²	Median Multivariate Coefficient			
			Beta to MSCI World Index	Small - Large	Value - Growth	Winners - Losers
(Highest 4F Alpha) 5	9.14%	0.31	0.30	0.19	0.02	0.05
4	4.44%	0.35	0.29	0.16	0.02	0.04
3	2.07%	0.48	0.34	0.16	-0.08	0.01
2	-0.80%	0.54	0.50	0.25	-0.09	-0.02
(Lowest 4F Alpha) 1	-7.10%	0.54	0.72	0.49	-0.32	-0.28

Note: All data based on the trailing 60 months as of December 2014. Funds are sorted into 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in the MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in the MSCI World Index from previous 12 months). Median statistics are then calculated for all funds in each quintile over the same time period (trailing 60 months as of December 2014). All hedge funds included are classified as “Equity Hedge” funds by HFRI and have continuous returns for the 60 months ended December 2014. Source: HFRI, MSCI, FactSet.

As suspected, we see that the highest-skill quintile of 4-factor alpha also has the lowest factor exposures, whether represented by r-squared (to the 4 factors) or individual factor coefficients. These managers derive the majority of their returns from true alpha sources, and therefore do not hide behind the major style factors. As skill declines, median r-squared increases and factor exposures – specifically beta and small cap, growth, and negative momentum exposures – increase. The value and momentum coefficients are perhaps less informative (both cross the neutral zero line as skill declines), but as Figure 1 illustrated, beta and size bias are much more pervasive across all hedge funds and are the factors that primarily drive r-squared. In the lowest quintile of skill – significantly negative 4-factor alpha – the median beta is high, at 0.72, and the small cap coefficient is 0.49. These funds are not only producing negative alpha, but their performance will track that of the market and small cap stocks, and they are unlikely to provide the “absolute returns” that many hedge fund investors seek.

Conclusion

It remains more difficult than ever to distinguish skilled hedge fund managers from the growing pool of funds. However, we propose using two tools to decompose returns into factor-dependent and skill-dependent sources. We combine 4-factor alpha, a proxy for skill, with r-squared, a proxy for factor dependence, and we find that the highest-skilled, lowest-factor-dependent funds have the best subsequent performance. We also show that the highest skilled managers have the lowest factor exposures.

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"Alpha" is a measurement of performance return in excess of a benchmark index.

"Beta" is a measurement of sensitivity to the benchmark index. A beta of 1 indicates that a portfolio's value will move in line with the index. A beta of less than 1 means that the portfolio will be less volatile than the index; a beta of greater than 1 indicates that the security's price will be more volatile than the index.

"Correlation" ranges between -1 and +1. Perfect positive correlation (+1) implies that as the index moves up or down, the strategy will move in the same direction. Perfect negative correlation (-1) means the strategy will move in the opposite direction. A correlation of 0 means the index and strategy have no correlation.

"Covariance" is a measure of the degree to which returns on two risky assets move in tandem. Covariance is equal to the mean value of the product of the deviations of two variables from their respective means. A positive covariance means that asset returns move together. A negative covariance means returns move inversely.

"Sharpe ratio" is a measure of risk-adjusted performance that divides the average return minus the risk-free return by the standard deviation of those excess returns (returns above the risk-free return).

"T-statistic" is a measure of statistical significance. It is the ratio of the departure of an estimated parameter from its notional value and its standard error.

"Volatility" is the standard deviation of returns.

The HFRI Monthly Indices ("HFRI") are a series of benchmarks designed to reflect hedge fund industry performance by constructing equally weighted composites of constituent funds, as reported by the hedge fund managers listed within HFR Database. HFRI Equity Hedge strategies maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. Equity Hedge managers would typically maintain at least 50% exposure to, and may in some cases be entirely invested in, equities - both long and short.

The MSCI World Index is a free float-adjusted market capitalization index, designed to measure developed market equity performance, consisting of 23 developed country indices, including the U.S. The Index is gross of withholding taxes, assumes reinvestment of dividends and capital gains, and assumes no management, custody, transaction or other expenses. It is not possible to invest directly in an Index.

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