Strategic Asset Allocation Model for Nonliquid Alternatives: Seeking Complementary Returns from Hedge Fund Exposure in Limited Partnerships

“It is a curious thing that God learned Greek when he wished to turn author—and that he did not learn it better.”

Friederich Nietzsche, Beyond Good and Evil

The Greek letter alpha (α) represents the idea of uncorrelated returns offered by hedge fund managers. This was the notion explored in our August 2009 Investment Strategy white paper The Science of Alternative Investments. The above quote from Nietzsche is a metaphor for alpha and beta: alpha (outperformance) is good and beta (market exposure) is evil.

If we carry the analogy further, the hedge fund manager is like the prime mover who uses Greek language, alpha and beta, to describe the world of investing. However, alpha is a nebulous term. Alpha could mean the excess return over some benchmark, such as the S&P 500; hedge fund return without any benchmark adjustment, since hedge fund returns are de facto devoid of any true benchmark; or the excess return over what would be predicted by some equilibrium model such as the capital asset pricing model (CAPM).

Variants of alpha exist, including smart alpha, idiosyncratic alpha, and systematic alpha. These are all very different quantities with sometimes multiple interpretations. With all of these alpha sources, an investor’s job should not be difficult; however, it is precisely this lack of pure alpha that typically makes the investment decision a challenging one.

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1 Section head quotes are from Friedrich Nietzsche, Beyond Good and Evil.
2 http://www.investopedia.com/terms/a/alpha.asp.
3 Capital asset pricing model, \( r_p = \alpha + \beta r_m + \epsilon \), with the usual meaning of the notation.
6 For help in distinguishing the various forms of alpha and beta, please refer to the alpha-beta spectrum mentioned in the November 2014 Investment Strategy Market Update, 40 Act Funds as Risk Diversifiers—Third Annual Liquid Alternatives Strategies Conference.
Accessing hedge fund exposures is part of diversification. It is a matter of philosophy whether a portfolio is built around sound expectations of diversification using beta or around the Herculean assumption of certainty of pure alpha. The ideal goal, although not a realistic one, is to achieve pure and positive alpha in all markets regardless of economic conditions.

We laid out some of the challenges of achieving pure alpha in the May 2013 Investment and Portfolio Strategy white paper Tactical Asset Model for Liquid Alternatives: Seeking Alternative Beta from Alternative Investments in Mutual or Exchange-Traded Funds. The challenge of alpha is persistence and the challenge of beta is consistency, neither of which seems likely for hedge fund managers using security selection, market timing, leverage, and other tools. Refocusing the discussion on diversification and not outsized returns is one way to avoid the endless search for the hedge fund manager with flawless return histories and to reframe the discussion toward exposure to so-called “different” risks, a tenet of diversification. Different can be a subjective determination, or one can use a more rigorous and mathematical definition, as we will do later. For our purposes, we are looking to hedge fund exposure to provide risks that are orthogonal to (or statistically independent of) those already contained in our portfolio.

The desire for alpha is the desire for uncorrelated returns or, more specifically, orthogonal returns. Diversification works best when the portfolio constituents behave as independently as possible. The exact meaning of this is that one would prefer two portfolio constituents whose returns are orthogonal or perpendicular. This is not perpendicular in two dimensions as we describe alpha and beta (forced projection onto a 1-D space) but perpendicular in T dimensions where T is the number of observations. This is harder to visualize for T > 3, but nevertheless is the exact description of the type of returns we seek for diversification.

This work, like any other portfolio construction methodology, is part science and part art. We want to avoid a point-by-point comparison with other techniques. At the end of the day, return and risk are important, and that notion drives the side-by-side comparison of techniques. What we are presenting here is a self-consistent approach with plausible data sources and without specific hedge fund returns. A side-by-side comparison might suffer from data mining, idiosyncratic behavior of a fund or group of funds, selection bias for the back test, and so forth. Any of these experiments will have most if not all of the problems associated with hedge fund indexes. Given that the optimization routine in portfolio construction includes an objective function and constraints, we will judge our methodology on out-of-sample results and stability of the solution with respect to the constraints.

The usefulness of any hedge fund portfolio construction methodology is limited without manager research and due diligence. To begin with subpar funds and to expect above-par results using only portfolio construction methodology is not good practice. (Please see the March 2014 Investment Advisor Research white paper, Selecting the Managers: Research and Due Diligence Process, for insight into the PNC viewpoint.)

**α: An Example of Orthogonal Returns in T Dimensions**

“Madness is something rare in individuals – but in groups, parties, peoples, ages it is the rule.”

Many of us think in terms of correlation when it comes to the dependency of one quantity on another. Pearson’s product-moment correlation coefficient is the most
familiar type of correlation. It is a staple of modern portfolio theory, given the inclusion of the covariance structure. Much work and augmentation have been conducted on the statistic, which we will not cover here. What is important to note is that there is a sensitivity to the data distribution. Calculating the correlation on non-normal data can be less meaningful than the user would like. (For a detailed discussion on the limitations of correlation and covariance in portfolio construction, please see the July 2014 Investment and Portfolio Strategy white paper, *Rethinking Portfolio Optimization*, which examines mean variance optimization and the sensitivity to inputs.)

Rather than dwell on this expression of group think, we move to the dot product$^7$ of two vectors, $\vec{A}$ and $\vec{B}$, which is expressed as $\vec{A} \cdot \vec{B} = |\vec{A}||\vec{B}| \cos \theta$, where $\theta$ is the angle between them. The dot product in mathematics describes projection of one vector onto another without regard to the structure of the returns distribution; if the dot product were zero that would imply $\theta = 90^\circ$. Recall that there are no assumptions in the calculation of this quantity.

The paradigm shift away from beta and alpha leads us to the discussion of benchmarks. $\beta \perp \beta$ is an obvious statement. We make the distinction because normally one expects a manager’s performance to stay within some neighborhood of a benchmark. Performance is interpreted as deviations from some expected benchmark or standard. What we are doing here is separating performance from the benchmark. The first reaction is that alpha should be the quantity that tells about performance different from a benchmark. However, for the reasons laid out in our liquid alternatives paper, the certainty in alpha builds from the certainty in beta and they are inseparable in that context. The discussion of hedge fund exposure is not about beta or alpha in the regression sense; rather, it is a discussion about risk exposures separate from traditional benchmarks and investment offerings. The risk exposures provided by hedge funds should have minimal overlap with the risk exposures provided by traditional investments, which now include liquid alternatives.

Why not build a portfolio around ordinary least squares $\alpha$ and $\beta$? Statistically, $\alpha$ has always been defined within the context of some benchmark, $\alpha = \alpha(\beta)$, or multiple benchmarks, $\alpha = \alpha(\beta_i)$. Identifying beta statistically can be an onerous task. It is accompanied by the missing variables problem if there are many benchmarks, that is, $\beta_i$ versus $\beta_j$, and it almost always involves dynamic loadings, $\beta_i = \beta_i(t)$, the obvious consequence of which is $\alpha = \alpha(\beta_i(t)) = \alpha(t)$. The different betas are sources of risk, and they can indicate whether an addition to the portfolio is piling more of the same type of risk into that portfolio. The caveat in all this is that the portfolio must be first spanned by these risks, and spanning has its own issues, such as colinearity ($\beta_i = \beta_i(\beta_j)$ ), incomplete basis set ($\vec{\beta} = \{\beta_1, \beta_2, \beta_4\}$ missing $\beta_3$), nonorthogonal factors ($\beta_1 \perp \beta_2 \perp \beta_3 \perp \beta_4$ is never true for an arbitrary set of factors), and so forth. The advantage of the dot product is that it already specifies the orthogonal risks by construction. Also, the dot product has the advantage of retaining the dimensionality of the problem. Whenever we say that a portfolio is spanned by a set of risk factors or benchmarks, say four of them, we are taking a T-dimensional problem (where T is the number of months, say 50) and forcibly reducing it down to a smaller number, four, for example. It is reasonable to try to scale down the

$^7$ The notion of the dot product in portfolio construction was explored by Maxim Golts and Gregory Jones in the unpublished work “A Sharper Angle on Optimization,” available at SSRN. See also Geraldine Bailey’s University of Cape Town master’s thesis, “Robust Portfolio Construction: Controlling the Alpha-Weight Angle” (2013).
strategic complexity of a problem, but, if there is no need to do it, then it might serve to retain
the original dimensionality.

Portfolio Construction

“He who fights with monsters might take care lest he thereby become a monster. And when you gaze long enough into an abyss the abyss also gazes into you.”

Portfolio construction can involve many highly advanced mathematical techniques, and it is tempting to use some of the more exotic methodologies. There is always a tradeoff to doing more mathematics for the sake of academics versus doing less mathematics for the sake of transparency. Again, this is a matter of preference in model building, but a model with a parsimonious set of assumptions generally has fewer opportunities for deviation from reality, and all financial models deviate sooner or later. Also, a model without strong returns distribution assumptions has a better chance of being more robust to an unpredictable market where tail events seem to happen more frequently than they should. (Tail refers to the tail of the distribution. Tail is further discussed beginning at the bottom of page 10.)

There are a set of benchmark exposures away from which we can orient our portfolio because those exposures can be found more cheaply. The overall equity market, represented by the S&P 500, is one, and the bond market, represented by the Barclays Capital U.S. Aggregate, is another. We can add liquid alternative exposures to that set. Liquid alternatives are new, and there is no well-defined product or benchmark that represents them all. To this end, we can fall back on the primary classifications offered by Hedge Fund Research in the form of the HFRX Equity Hedge (HFRXEH), HFRX Event Driven (HFRXED), HFRX Relative Value Arbitrage (HFRXRVA), and HFRX Macro/CTA (HFRXM) indexes. We repeat the exercise with the Credit Suisse Alternative Beta indexes, Managed Futures (CSLABMFN), Merger Arbitrage (CSLABMN), Event Driven (CSLABEN), and Long/Short (CSLABLN). It is an open-ended question that these indexes positively and absolutely capture the liquid alternative premiums in the market. In the previous section, we detailed how a select group of risk factors might not adequately span returns. The crux of the argument is that we are not counting on these factors to span the space of returns that we do need; we are counting on these factors to span the range of returns that we do not need. That is why we tilt the resulting portfolio away from this range.

Constraint: \( \text{Risk}_{\text{Portf}} \leq \text{Risk}_{\text{Benchmark}} \)

Constraint: \( \text{Return}_{\text{Portf}} \geq \text{Return}_{\text{Benchmark}} \)

Objective Function: \( \min \sum (\vec{R}_{\text{Portf}} \cdot \vec{R}_{\text{Risk Factor},i})^2 \)

The objective function is quadratic with respect to the weights because of the following:

\[ \min \sum_i (\text{Dot Product})^2 \]

\[ \min \sum_i w^T R_{\text{ALT}}^T R(i)_{BM} R_{BM}^T R_{\text{ALT}} w \]

\[ \min w^T R_{\text{ALT}}^T \left( \sum_i [R(i)_{BM} R_{BM}^T (i)] \right) R_{\text{ALT}} w \]
This quadratic optimization is also accompanied by a quadratic constraint. This is the Chebyshev\(^8\) Value-at-Risk (VaR). VaR alone is accompanied by a host of issues\(^9\) complicated by its application to non-normal distributions. Non-normality may be handled with the use of Chebyshev VaR. We choose Chebyshev VaR (also known as nonparametric VaR) to represent portfolio risk because hedge fund returns are non-normal.

\[
VaR_{c, \Delta t}^{Mean} \leq \frac{\sigma}{2c}
\]

which comes from:

\[
c = \text{Prob}(V - E(V) \leq -VaR_{c, \Delta t}^{Mean})
\leq \frac{1}{2} \left(\frac{\sigma^2}{VaR_{c, \Delta t}^{Mean}}\right)^2
\]

Apart from full investment and non-negativity, the only linear constraint concerns the returns. It requires that the resultant portfolio’s return be no worse than the benchmark. An astute reader might argue that there is no difference between the average of logarithmic returns and the sum up to a multiplicative constant. While this might be semantics to some, this is part of the portfolio construction thesis that the collection of hedge funds should have returns that are different from returns that could more readily be found in the market (S&P 500, Barclays Capital U.S. Aggregate, liquid alternatives represented by the HFRX indexes) without affecting the overall risk or impacting the overall return. In our view, that is what investors should be seeking when adding hedge funds to an overall allocation.

The portfolio construction algorithm is formulaic if taken in an obvious context. With most optimizations, there is a statement about:

- **return**—whether it is active return, average return, Bayesian return, robust return, and so forth;
- **risk**—it could be VaR, CVaR, tail risk, covariance, robust covariance, Bayesian covariance, and so forth;
- **some dependence structure**—it could be correlation, robust correlation, copula based, Bayesian based, and so forth.

In PNC’s case:

- the return statement is about the sum of the logarithmic returns;
- the risk statement is about Chebyshev VaR; and
- the dependence structure is about the dot product.

The advantage of defining the portfolio construction methodology in this way is that one does not have to make assumptions about the exact form of the distributions of the underlying managers.

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\(^8\) Chebyshev’s theorem gives an upper bound to the probability that a certain random variable \(X\) falls far away from its mean without any assumption on the shape of the probability distribution. The only requirement is that the variance of the distribution is finite.

The appeal of using the dot product as the dependence structure is that it allows the algorithm to select portfolios that are different from traditional investments and liquid alternatives. This is desirable because the exposures can be attained through more cost-effective vehicles. Hedge funds traditionally have been viewed as absolute return providers, that is, pure alpha plays. Over the years, hedge fund strategies have become more well-known to more traders. If alpha denotes skills and everyone has the same skill, then it is no longer alpha; it metamorphoses into beta. This set of risk exposures become more accessible to investors. We want to avoid paying for managers with high loadings to the market, which can be acquired through more cost-effective vehicles. With the advent of liquid alternatives, this becomes even more important as alternative beta is available through exchange-traded funds (ETFs) and mutual funds.

Another useful aspect of the portfolio construction algorithm is that it is independent of distributional assumptions. This aspect ventures into the philosophy of model building. Financial models of any kind are built on certain assumptions because there are no laws on which to base financial modeling (some practitioners will point to the CAPM, efficient markets hypothesis, the law of one price, and so on, as laws, but we do not agree).

### Hedge Fund Alpha

“Truth and the search for truth are no trivial matter.”

Evaluation of the effectiveness of the portfolio construction is not insignificant. Because portfolio construction is part art, there is no definitive way to judge the effectiveness of a portfolio construction algorithm. Also, we cannot show actual hedge fund data due to the proprietary nature of the returns. So, the algorithm has no proof, and the raw data are restricted.

There are a couple of things we can do. For one we can find proxy data to make our point—and we can find a lot of it. We can also make sure that we offer an allocation that is well-diversified with as few constraints as possible but that still offers a diversified allocation. Recall that in our liquid alternatives paper, apart from non-negativity and full investment, there were no additional constraints on the weights; we will demand the same thing here. This is where the art of portfolio construction comes into play. Instead of actual hedge fund data, we use the HFRI indexes and the Credit Suisse Hedge Fund indexes, two sets of data with enough history and dissimilar index construction methodology. In our favor is the fact that if the technique does work in some of the years after the financial crisis, then there is some reassurance of its validity, since most hedge fund indexes have lagged the S&P 500.

Portfolio construction involves constraints and an objective function. The constraints in-sample speak for themselves. The other aspects are the objective function and the output, that is, weights. The objective function is arguably the most important part of the portfolio construction. Choosing what to optimize is the most crucial part of the optimization, which is why we focus on that for presenting the results. The other part is the set of weights that are produced. Minimizing the dot product implies maximizing the angle between the portfolio and the respective benchmark and liquid alternative indexes. Ideally, this angle should be $90^\circ$; this is practically impossible, but we can see how close we get. The expectation regarding the weights is that they be nonzero for some subset. We feel this is a judgment call, but we are trying to

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10 We acknowledge all the peccadillos that these families of indexes possess. In the absence of a better alternative, this is how we proceed.
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Avoid the situation where one asset gets all the weights all the time. Diversification is important and, if we have asked the right question in the optimization, there is no need to artificially enforce it with maximum/minimum constraints on the individual weights. For the optimization, we used an in-sample period of 48 months and a rolling out-of-sample period of 12 months. The benchmark is 50% stocks/50% bonds. Post-2014 results for the Credit Suisse indexes and post-2013 results are not presented for the HFR indexes due to violation of the return constraint owing to the strong bull market. Selection of the relevant Credit Suisse Alternative Beta indexes employed some judgment. In general, the chosen indexes allowed for a longer backtest or made the comparison between the two index families more effectively.

Results for the weights are presented in Chart 1 and Chart 2 (page 8). The Credit Suisse family of indexes has a longer history than the HFR family. This is not a question of quality. Credit Suisse back-filled its indexes for the alternative beta components further back than HFR did for the HFRX indexes. Again, this was a matter of using all the available data from both providers in a consistent manner. It is clear to us that no one index dominates the asset allocation. Even for HFR, where there are only three out-of-sample periods, there is some oscillation of the weights among the members. This is exactly what we wanted to see, because a hallmark of a

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**Chart 1**

_weights of the various credit suisse hedge fund indexes for different one-year periods_

Source: Bloomberg L.P., PNC
questionable optimization is the domination of the asset allocation by one and only one constituent, the so called “corner solution.”

It is also important not to extrapolate these results to individual hedge fund managers that an investor believes are representative of the one of these indexes. Hedge funds fit less well than traditional managers into specific styles. Whereas we might be concerned if a traditional manager deviated too much from its traditional benchmark, we are less concerned if a hedge fund manager deviated from its hedge fund benchmark—it is indeed the case that this framework rewards the hedge fund manager for idiosyncratic risk. This is why investors pay hedge fund managers for their unique skills. If all a hedge fund manager did was follow a benchmark, even an alternative benchmark, then an investor would have to question whether that exposure was cheaper to obtain in liquid alternative form. This portfolio construction methodology specifically allocates away from such cases.

The reader might expect that there would be some comment around indexes that tend to show up more frequently than others and indexes that show up in the allocation less frequently. This is not the aim of the exercise. A discussion on that topic would delve into index construction methodology and we are by no means advocating one family over another for that reason. HEDGNEUT might be one such case in the
Credit Suisse family and HFRIFIMB in the HFR family might be another case. Again, we do not want to have a discussion on the index, we would rather discuss the portfolio construction algorithm. The main thing to take away from both of these sets of data for the allocation is that they change over time and do not result in a corner solution. This is seen even with a parsimonious set of constraints. We achieve diversification through the objective function and not through minimum/maximum constraints.

Results for the angles are presented in Chart 3 and Chart 4 (page 10). Ideally, these values should be close to 90. What value is the right threshold? There is no easy answer. It happens that the angle between the S&P 500 and the Barclays Capital U.S. Aggregate is about 90. One might easily conclude that this makes for a great pairing in portfolios. It does, but the angle says something only about the dependence and ignores an explicit average return consideration. For instance, in the HFR case, the S&P 500 angle is close to 90, so one might think that this portfolio allocation is superior. As we expressed earlier, we could not present results for the recent year because any combination of the HFRI indexes did not keep pace with the S&P 500 unless it violated the non-negativity or risk constraint. This result is an artifact of the
index construction methodology. In the plots, all the angles for the benchmark liquid alternative indexes are greater than 45.

That is probably the best rule of thumb for any allocation, in our opinion. This technique emphasizes minimal overlap with the alternative beta indexes simultaneously. If we did it only for one, we might be tilting a portfolio away from a particular liquid alternative exposure but directly on top of another. Taking them collectively is probably a safer way to construct the portfolio. Which set of liquid alternative indexes is superior? This probably is more a function of art than science. Clearly the HFRX are more popular. The Credit Suisse Alternative Beta indexes do go further back, but they are back-filled, which may introduce a bias. To complicate matters, HFR is introducing an explicit set of liquid alternative indexes; we are using the HFRX as proxy because of the daily pricing. The problem with those indexes is the short (less than a year) history. It is a matter of choice, but the HFRX might serve better.

Why not do portfolio construction solely on the tail of the distribution? The various crises of the past 20 years have affected many investors in negative ways. A common reaction has been to focus on portfolio losses and blindly mitigate them, even at the expense of portfolio gains. Tail engineering refers to the practice of emphasizing the
lower end of the portfolio distribution (or lower partial moments) with the aim of limiting drawdown, conditional value at risk (CVaR), VaR, and so forth. That is, tail engineers wish to identify the tail and manage the outcomes of the portfolio construction process according to it. The largest challenge might be to identify the actual tail. To give scope to that challenge, we note that there is no unique statistical definition of the tail of the distribution. At best one might say the upper bound is everything to the left of the mean, but that is still not a rigorous definition. It is exactly this conundrum that practitioners of tail engineering must confront if there were to be a more scientific approach to the portfolio construction process.

A straightforward calculation will demonstrate how the propagation of errors makes the tail hard to identify. Let us assume a normal distribution with known population standard deviation, $\sigma$ (not sample population standard deviation, $s$) to infinite precision. A known statistical fact is that the standard deviation of the mean is $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$. The situation is idealized for convenience and tractability. We use the usual scaling, $z = \frac{x-\mu}{\sigma}$. For the 5% tail, we take $z = 1.96$ and the resultant tail area is 
\[\text{Area} = 1 - (0.5 + 0.475) = 0.025,\]
which is a familiar outcome. Let’s look at the propagation of errors of the mean. Let’s say that we are off by 5%11. Instead of $\mu$ we have some $\bar{R}x$ where $1 - \bar{R} = 0.05$. With rearrangement, we have 
\[z' = \frac{x-k\bar{x}}{\sigma} = 1.96 + \frac{(1-k)x}{\sigma} = 2.21\]
for $\frac{k}{\sigma} = 5$. The error in the mean has propagated to give us an error in the scaled variable, $z$. The new area is now 
\[\text{Area} = 1 - (0.5 + 0.4861) = 0.0139,\]
which is different by 44.4%! A 5% uncertainty in the mean can change the tail weight by almost half for an ideal normal distribution with known parameters. For non-normal distributions with unknown parameters, the situation quickly degenerates into much larger error bars for the tail weight.

## Alpha-Beta Separation Anxiety

“Vanity is atavism.”

Divorcing alpha returns from beta returns is an endless pursuit—practitioners have been doing it since the inception of the CAPM and present-day practitioners continue the search. Those of us conditioned to believe that the CAPM describes an actual law will probably accept the notion less readily that alpha and beta might be inseparable.12 The equation for the CAPM represents a model, not a fact or law, for a stock. Imbedded in that are the assumptions that the parameters are knowable and observable. A simple example borrowed from Emanuel Derman should dispel any notion left within the reader that the CAPM holds for a single stock let alone a limited partnership.

Chart 5 displays the data and the line of best fit for Apple (AAPL) versus the S&P 500. CAPM tells us that the excess returns of the stock versus the market should be $(\mu - r) = \beta(\mu_M - r)$ . Using parameters from the fit

11 For $\sigma = 25\%$ and $n = 25$, this error in the mean is 5%.
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and $r = 1\%$, we have $44.7\% - 1\% = 1.02 (7.6\% - 1\%)$ as determined by CAPM, which denies the existence of any alpha term over the long run (in our case, $\alpha \approx 20\%$); “A kind way (to look at the CAPM)...is to say that CAPM holds over the long run, on average...An unkind way to look at CAPM is to say that it’s not very good. Newton’s law it ain’t.” Allowing for the existence of nonzero alpha, we are left with the industry interpretation: alpha connotes something about the skill of the manager. The uncomfortable sequitur of this is that a manager with 100% of AAPL over the period of study in the example generate 20% of alpha for the year. Is that really right, and is that what we want alpha to mean as investors? These issues arise out of language borrowed from a framework, that is, the CAPM, that was indeed universally accepted by modelers and universally excepted by actual data at the same time. Frameworks are useful for understanding, but they are less useful when taken out of context.

This discussion may seem like faint praise for the CAPM, but that is not our intent. The emphasis on the matter is that neither CAPM nor our descriptions of alpha and beta is law. They are constructs for understanding investments. In our white paper on liquid alternatives, the limitations of alpha-beta were examined in detail. There we gave specific conditions under which the alpha-beta decomposition of an investment were acceptable. The language was borrowed from the CAPM, which itself does not represent physical law. If alpha and beta are hard to identify in an investment, we do not think that should immediately preclude the investment as undesirable. That could just mean that a different framework might be more applicable, in our view. Alpha and beta are not immutable traits of an investment; they are merely lenses through which an investor may evaluate an investment, in this case, hedge funds.

A casual investor might believe that parsing the industry jargon of alpha and beta is nuanced at best. We are taking the extra step to define what we mean and what we do not mean in the hope that it will guide the portfolio construction process to a more meaningful result. In a perfect world, alpha and beta would be separable and that would facilitate the investment process. In the real world, the delineation is not so clear and the language tied to alpha-beta (such as correlation and covariance) gets murkier in practice.

**Conclusion**

*“You Can’t Unscramble Eggs.”*

Reliably separating alpha from beta for each and every hedge fund is a difficult task. For most investment strategies, alpha and beta are inseparable. The mathematical summary of this paper regarding the expectations of traditional, liquid alternative, and hedge fund exposures is the following:

$$\begin{align*}
\beta &: \text{Traditional Investments} \\
(\beta + \alpha) &: \text{Liquid Alternatives} \\
\bar{\beta} &: \text{Hedge Funds}
\end{align*}$$

The language of hedge funds can be convoluted owing to industry jargon and casual syntax, but if we keep to the rigor of the mathematical definitions of these terms, then this is clearly what is being sought from hedge fund exposure. The technique that we have presented builds a hedge fund portfolio explicitly around these considerations.

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13 Definitely not said by Nietzsche.
Seeking Complementary Returns from Hedge Fund Exposure in Limited Partnerships

We want to be careful not to pay for exposures that we can more cheaply access through alternatives, and we want to reward managers with superior idiosyncratic risk. This technique avoids questions of non-normality and is free of any assumptions regarding the exact structure of the returns distribution or assumptions about the exact form of the dependence structure among the individual hedge fund managers.

Simply put, this paper provides ample evidence that PNC’s portfolio construction process is robust and sound and provides the intended exposure to different factors than typical stocks, bonds, and liquid alternatives in order to improve diversification while providing competitive returns.