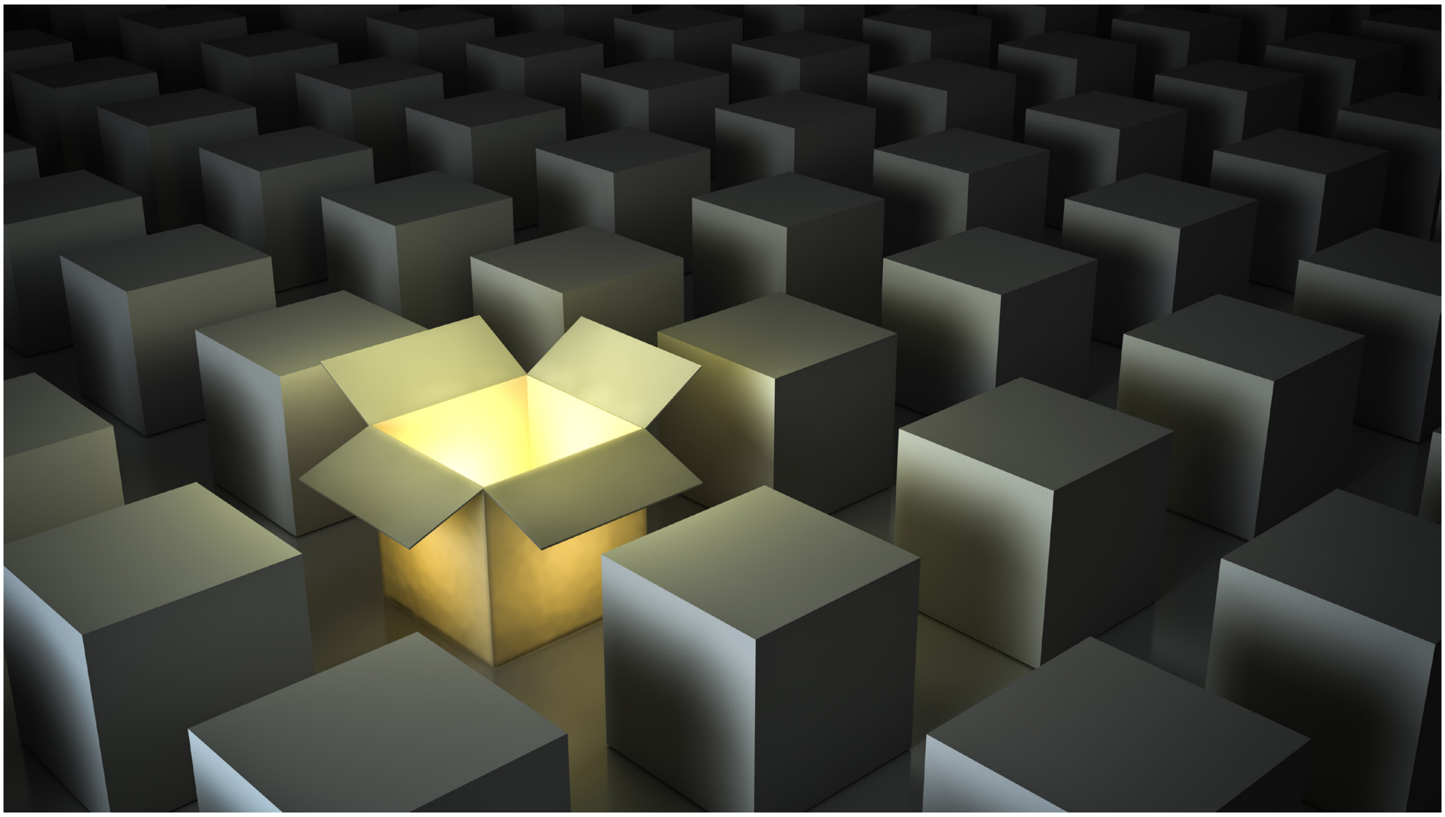

Exploring Dynamic Factor-Based Categorization of Alternative Returns

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The Investment Product Universe is Broad and Deep, Necessitating Some Form of Classification

The mutual fund universe is vast not only in the number of offerings it makes available to investors, but also in the asset class and strategy exposures that the individual funds provide. US mutual fund assets as of 2017 amounted to roughly $18.7 trillion dollars in assets.[1] This behemoth of a complex is difficult to navigate even with the existing fund category methodologies provided to the investor community by several investment research and consulting firms. In a universe of such complexity, a categorization or classification system is necessary to help distill these funds into common groups that share overwhelming asset class and risk exposures.

Various classification methodologies have been proposed by some of the biggest investment product research firms in the world, and over the years, the number of new fund categories have significantly increased with the aim of being more specific given the dynamically changing fund universe and its more sophisticated offerings, namely liquid alternatives.

Categories Serve Many Types of Industry Participants in Varying Ways

Fund categories allow investors to make assumptions about the performance characteristics of the product, help investors search for the right investment products, help to judge the performance of an investment product relative to a peer group, and allow for monitoring of category flows, among other things. Investment analysts create "recommended lists" of investment products within each category. Portfolio managers rely on asset class research at a category level but then apply that research by choosing a product within that category. For example, an analyst might produce research using the S&P 500 or Russell 1000 indices in order to describe U.S. large-cap stocks, but a portfolio may be implemented using a mutual fund or ETF that resides in a "US Large Cap Equity" category.

Discrete Categorization May Pose Challenges in a More Fluid Investment Product Landscape

Categorization has historically been discrete and mutually exclusive. Although firms employ rules defining categories, the rules can be diverse and can be somewhat subjective at times. A category can be appropriately descriptive for investment products that are strictly bound to an investment universe that accurately describes the strategy (i.e. a mutual fund in the US Large Cap Equity category only buys US large cap equities that are part of the Russell 1000 or S&P 500) but can be misleading for investment products that apply opportunistic strategies or own assets in multiple asset classes. In the case where a category does not accurately describe an investment product's performance, the categorization can become a significant barrier to accurate research by unfairly inflating or deflating perceived performance relative to a benchmark or peer group.

While this paper will focus its analysis on liquid alternative mutual funds, this product categorization problem runs beyond the liquid alternatives industry: Solutions-based or opportunistic strategies that may not be appropriately defined by categorization include not only liquid alternative funds, but also allocation funds, target-date funds, smartbetafunds, and other strategy-specific funds that may reach across asset classes (e.g. a multi-asset fund designed to provide exposure to inflationary assets). Finally, hedge funds suffer similar mis-classification challenges.

Categorization and Benchmarking of Liquid Alternatives

The Liquid Alternatives Industry Has Grown by Over 4x from Approximately $41 billion to Over $170 Billion in Total Assets Over the Last Decade[2]

Investors have sought mutual fund and ETF solutions designed to deliver differentiated risk and return from products that reside in traditional core asset class strategies (equities, and fixed income). The growth of liquid alternatives has been largely viewed as a democratization of hedge fund strategies via a '40-act wrapper. The impressive growth of the liquid alternative investment universe has brought with it categorization challenges, as investment product research firms have tried to apply their classification methodologies used on the traditional side to this new—and different—sector.

"Style Boxes" Don't Exist in Liquid Alternatives

Because liquid alternative strategies tend to be "strategy-based" or "solution-based," rather than focused in a specific asset class, it is important to understand the risks in these investment strategies, as well as how risks may change over time. For example, an equity market neutral manager typically implements a non-directional view on broad equity markets and may carry a beta to equities of near-zero. Rather, its strategy is focused on building a long/short portfolio that may be positively skewed to certain risk factors like value or momentum factors within equity markets, or positively skewed toward more event-driven risks. The potential diversification benefits of liquid alternative mutual funds can be due to either different kinds of holdings (alternative asset classes), different investing strategies, or both. The key here is realizing that given these differentiated mandates, managers can deliver more nuanced sources of risk into an investor's portfolio. With that said, *more manager investment flexibility inherently means wider performance dispersion within sub-strategy peer groups.* It is this observation where allocators ought to address their attention and attempt to better understand where and how these various managers are sourcing their risks. Furthermore, the fact that there is wider dispersion amongst fund performance in this particular niche of the mutual fund complex means that manager outperformance becomes even more critical.

Large Amounts of Dispersion within Categories Makes Benchmarking Difficult

The alternative investment industry has been challenged with benchmarks in order to gauge investment performance and manager skill. The CFA Institute has issued guidance on benchmarks via the Global Investment Performance Standards: Benchmarks should be specified in advance, relevant, measurable, investable, unambiguous, reflective of investment options, accountable, and complete. While this guidance about benchmarks makes sense for asset classes, those investing across asset classes or in hedged strategies may not want a long-only asset class or index as a benchmark. As a result, benchmarks used tend to be "peer group" benchmarks. Peer group benchmarks do not meet GIPS standards because they are generally subject to survivorship bias and are not investable in the same way traditional asset class benchmarks are.

Quantitative Finance May Provide a Solution to Both Categorization and Benchmarking for Solutions-Based Strategies Like Liquid Alternatives

Whereas some research on alternative methods for categorization (Das, 2003;[3] Marathe/Shawky, 1999,[4] Bailey/Arnott, 1986[5]) have centered on unsupervised learning (e.g. k-means cluster analysis), the authors suggest there may be a way to combine supervised and unsupervised learning so that industry knowledge can be married with historical performance in a way that can benefit the analyst both in categorizing liquid alternatives as well as benchmarking them. This hybrid method of categorization and benchmarking can be an effective tool to explain performance characteristics, define peer groups, and judge relative performance. Furthermore, a better understanding a fund's true factor biases overtime will help better set and manage forward expectations.
The remainder of the paper will be divided into four sections, where the authors attempt to:

- Explore popular methods of categorization by large industry participants;
- Propose a dynamic factor-based method to classify alternative fund return streams;
- Compare the results of classic categorization with factor-based categorization; and
- Draw conclusions based upon the results.

Exploring Popular Methods of Liquid Alternatives Categorization

Fund categorization is largely a standardization exercise that is intended to help investors differentiate mutual funds according to a specific set of features (investment objectives, assets of the portfolio, and various other risk return objectives). As mentioned before, categorization provides a critical service to the broader investment community. Such a system clarifies how a fund may fit into a portfolio from an asset allocation and risk exposure perspective. With that said, let us explore the overall liquid alternatives categorization methodologies of three of the largest allocators/fund data providers in liquid alternatives space, highlight the similarities and differences in their processes, and lastly point out where conventional fund categorization may fall short when classifying more complex investment strategies such as liquid alternative strategies.

Morningstar

Morningstar is a well-known investment research firm that offers an extensive line of products and services to various investor groups. One of the firm's core businesses is the delivery of data and research insights on a wide range of investment offerings, including managed investment products, publicly listed companies, private capital markets, and real-time global market data. The Morningstar Category Fund Classification system today has over 120 categories, which aims to map nine category groups: U.S. equity, sector equity, allocation, international equity, alternative, commodities, taxable bond, municipal bond, and money market. There are eight primary categories inside the alternatives category group. In general, Morningstar is dependent on a holdings-based analysis and heavily reliant on an analyst-driven qualitative assessment. Morningstar's teams get together to review their formal category process twice a year—in May and November—while additional reviews for funds less than one year old are also conducted in February and August. According to Morningstar, funds are placed in a given category based on their average holdings statistics over the past three years. Morningstar's editorial team also reviews and approves all category assignments. If the portfolio is new and has no history, Morningstar estimates where it will fall before giving it a more permanent category assignment. When necessary, Morningstar may change a category assignment based on recent changes to the portfolio.

The following are the driving principles behind the Morningstar classification system:[6]

- Individual portfolios within a category invest in similar types of securities and therefore share the same risk factors (for example, style risk, prepayment risk).
- Individual portfolios within a category can, in general, be expected to behave more similarly to one another than to portfolios outside the category
- The aggregate performance of different categories differs materially over time.
- Categories have enough constituents to form the basis for reasonable peer group comparisons.
- The distinctions between categories are meaningful to investors and assist in their pursuit of investing goals.

The overall process makes sense for the vast majority of the mutual fund universe, which are long only, traditional asset-based strategies. However, there is still a considerable amount of subjectivity when this process is applied, which at times may be problematic as it relates to alternative strategies. Even Morningstar acknowledges that liquid alternatives bring a wide variety of exposures, and that those funds within the same Morningstar categorization that implement somewhat similar strategies can deliver very different diversification properties. Not only are liquid alternative strategies within their alternatives style box very different, but dispersion even within fund categories can vary widely.

Lipper

Lipper is a financial services firm that delivers data on more than 265,000 collective investments worldwide. According to Lipper, all funds have a prospectus-based classification. Only those funds that are considered "diversified," meaning they invest across economic sectors and/or countries, will also have a portfolio-based classification. When it comes to liquid alternatives, Lipper views alternative strategy funds as portfolios that generate low correlation to traditional, long-only-constructed funds, as well as portfolios that implement a hedge fund–like strategy often incorporating one or a combination of the following: leverage, derivatives, short positions and/or multiple asset classes.

Lipper offers a suite of alternative strategy classifications that for the most part attempts to bucket strategies via a hedge strategy lens. Categorization strongly depends upon the wording from the investment strategy in the fund's prospectus. Lipper expanded their alternative peer group choices in 2013. With the expansion of Lipper's alternative strategies peer groups, funds that state absolute returns as their investment objective are first measured versus the appropriate alternative classifications. Emphasis will be given to the specific strategies represented in the alternative categories, however, those strategies that do not necessarily fit the hedge fund strategy style box will be assigned to the catch all category of Absolute Return.

The Lipper Absolute Return category can range from multi-strategy to managed futures, long/short equity, or even short-biased funds. Within this peer group, many of these funds may rely on directional beta for their returns and may potentially experience steep drawdowns during a heightened volatility environment.

One can see that the methodology described above again, suffers from many of the same issues pointed out in the Morningstar categorization process. The process is heavily dependent on prospectus language and an analyst's qualitative judgement.

Wilshire

Wilshire Associates is a global investment management firm that provides consulting and analytical products to various institutional clients. The firm is widely known for its strong manager research capabilities and expertise in the liquid alternatives space. The firm is also famously known for the creation of the Wilshire 5000 index, which has also led to the creation of various other liquid alternative indices and sub-indices. Their liquid alternatives index construction process relies on their own liquid alternatives classification schema that more closely emulates the classification system of the hedge fund industry popularized by Hedge Fund Research, Inc. The Wilshire Liquid Alternatives universe is their pool of constituents that feeds the index construction process.

As mentioned before, Wilshire Liquid Alternatives Index and its sub-indices seeks to categorize liquid alternative mutual funds through the lens of long standing hedge fund strategies like long short equity, relative value, event-driven, global macro, and multi-strategy. However, there are some issues in the way their classification methodology will group certain funds together. For example, within Wilshire's Long Short Equity category, both market neutral and options-based strategies play meaningful weightings. Within its Global Macro category of funds, there are a mix of both systematic trend following strategies and discretionary global macro strategies. While their trading implementation may both make use of futures contracts, the risk return profiles look quite different, resulting in low correlation of near 0 (as measured by HFRX indices). According to the 2Q2018 Wilshire Liquid Alternatives Industry Monitor, the Global Macro category contains 70 funds, of which 36 are considered managed futures.[7] The vast majority of these managed futures strategies will largely rely on trend following strategies, whereas a discretionary macro strategy may be implementing more intrinsic valuation based trading strategies, or a number of different strategies that show a very different type of risk return profile from that of trend followers or traditional CTAs.

Alt Categorization	# of total alt mutual funds	$ AUM in alt mutual funds	# of alt mutual fund categories
Morningstar	504*	$173.6bn*	15 (8)[8]
Lipper	562	$369.0bn	11
Wilshire	492	$329.19bn	5

Exhibit 1: Summary of Categorization
Source: Morningstar, Thomson Reuters, Wilshire. As of 6/30/18

A comparison of the categorization methodologies applied to liquid alternatives using the table above reveals meaningful differences in terms of defining the size of the liquid alternatives universe. While fund count between Morningstar and Wilshire Associates is roughly similar, notice the large difference in terms of the size of each sponsors' liquid alternatives universe. This can be largely attributed to the fact that Morningstar's categorization system does not recognize its Nontraditional Bond group as an alternative category (it is today associated with its Global Broad Category of Fixed Income). On the other hand, Wilshire Associates recognizes many of Nontraditional bond funds in Morningstar's database as alternative mutual funds. The matrix below in Exhibit 2 published in Wilshire's 2Q2018 Liquid Alternatives Industry Monitor shows that 83 funds in Morningstar's Nontraditional Bond category are considered alternative within Wilshire's liquid alternatives universe, the majority of which are defined as relative value strategies by Wilshire Associates. If one were to include all of Morningstar's Nontraditional bond funds in its alternatives universe, the fund count jumps to 587 and adds approximately $128bn in AUM. Such a lack in classification overlap boils down to philosophical and qualitative differences. One can imagine that this type of classification gap amongst mega industry players has large implications in terms of guiding strategy flows.

Categories in Review

After reviewing the methodologies of various allocators and data providers, we can summarize today's conventional liquid alternatives fund categorization by highlighting the following observations:

- The overall processes across vendors is heavily reliant on holdings data, prospectus language, and an analyst's qualitative judgement.
    a. Many holdings snapshots fail to handle derivatives and short exposures.
- Large differences in terms of the size of each respective liquid alternative universe due to nuances in investment philosophy or categorization methodology across each vendor.
- Today's fund categorization systems implicitly impose mutual exclusivity, meaning that a fund's currently assigned categorization defines a strict set of peers only found within that category group.
- High levels of dispersion amongst alternative categories can be problematic.

Revisiting the topic of benchmarking within liquid alternative categories, tighter dispersion amongst peer groups could potentially alleviate some of today's performance measurement issues amongst liquid alternatives. Benchmarking is intended to help investors measure performance and determine the value add delivered by their active managers. Tighter benchmarks could help better set and manage return expectations for allocators, and furthermore, help fairly assess manager skill against a more disciplined set of comparable investment products.

Related to benchmarking performance, investors should be focused on fund flows and the implications that fund categorization methodologies have on product allocations. The broader investors base's understanding of mutual fund strategies is strongly guided by the fund categorization methodologies delivered by the industry's largest fund data providers and allocators. Allocators and consulting firms largely serve as the gatekeepers for investor flows across the fund complex, and while

		Wilshire Alternative Categories						
		Equity Hedge	Event Driven	Global Macro	Multi-Strategy	Relative Value	Not Liquid Alt	Grand Total
Morningstar Alternative Categories	US Fund Multialternative	4	6	22	86	3	1	122
	US Fund Long-Short Equity	107			2		3	112
	US Fund Nontraditional Bond		2	3	4	55	19	83
	US Fund Options-based	56			1	5	3	65
	US Fund Market Neutral	25	15	1		7	2	50
	US Fund Managed Futures			36	1			37
	US Fund Long-Short Credit		6			8	2	16
	US Fund Multicurrency			6			6	12
	US Fund Volatility					1	2	3
	US Fund Bear Market	3	1				3	7
	US Fund Large Blend	4						4
	US Fund World Allocation				3			3
	US Fund High Yield Bond		2				1	3
	US Fund Multisector Bond					2		2
	US Fund Tactical Allocation			2	1	1		4
	US Fund Mid-Cap Blend	2						2
	US Fund Mid-Cap Growth	1						1
	US Fund Preferred Stock					1	1	2
	US Fund Small Blend		2					2
	US Fund Allocation-50% - 70%	1						1
	US Fund Allocation-70%+				1			1
	US Fund Convertibles				1			1
	US Fund Corporate Bond					1		1
	US Fund Real Estate	1						1
	Grand Total	204	34	70	100	84	43	535

Exhibit 2: Matrix of Wilshire and Morningstar Classifications
Source: Wilshire, Morningstar, as of 6/30/18

hard to quantify, these firms likely have an incredible influence on the direction and magnitude of flows. In some instances, these firms may have full discretionary relationships with clients and allocate within their discretionary mandates. However, in many instances, these firms provide their clients with "recommended lists" or "focus lists" on a non-discretionary basis.

For all these reasons, many investment professionals recognize that a "fill-in-the-style-box" approach to portfolio management poses major challenges in the liquid alternatives universe. The current categorization methodologies leverage smart analysts at experienced companies and is good in many ways—but perhaps there is a method of categorization that can better capture the fluidity of investment products, strategies, and markets.

A New Factor-Based Categorization Framework

A potential solution to address today's shortcomings in fund categorization may be to introduce a new framework entirely. This framework leverages well-documented research in the field of factor-based investing as well as some well-tested machine learning approaches and applies these well-known fields to the categorization and benchmarking process in a previously-unseen way.

Any good categorization process should consider the way categories are used by investment professionals

As a reminder, the authors believe the primary uses for categorization are:

- To make assumptions about the performance characteristics of the category members
- To aid in a product search
- To judge the performance of an investment product relative to a benchmark and peer group
- To monitor industry flows

Any categorization process should attempt to solve for those four use-cases. While discrete categorization can help with some of these, mis-categorization can have a compound impact on one of or all these use cases. There is more than one story about a fund that was mis-categorized, raised a significant amount in assets, attracted attention, and was then re-categorized or disappointed investors after returns weren't what investors thought they would be. As shown in Barber, Huang and Odean (2016),[9] Investors buy and sell funds based on their performance relative to their category. Further, Agarwal, Green and Ren (2017)[10] show that although most investors chase returns in hedge funds based on a simple beta to equities, investors would be better served by adjusting for alternative factors and exotic risks.

This paper attempts to propose a quantitative factor-based framework that has the potential to work well in categorizing and benchmarking traditional strategies and alternative strategies. Specifically, evaluating alternative strategies using a multi-factor model assist the investor to not only better categorize investments but also to better judge performance relative to a benchmark or peer group.

The categorization process begins by calculating factor loadings for all assets in the investment universe using a multi-factor returns-based regression model. Weekly returns for the funds are used to calculate the factor loadings. Additionally, regularization is applied to help with feature selection and out of sample data is used to test efficacy of the factor loadings. Finally, while this paper does not dive into detail on the underlying factors or on their creation, it should be noted that this kind of analysis can be performed with another group of factors to similar effect, provided the factors are diverse enough to cover a large portion of a multi-asset universe and techniques to combat collinearity are applied.

The factors in this analysis are shown on Table 1 in the appendix.

Through iterative testing and leveraging the analysis from many global investment banks, the authors have established that these factors represent a strong subset of the investment universe. Further, most investment products (including liquid alternatives) carry persistent factor exposures, meaning these factors not only help to explain past performance but may help to explain some of future performance as well.

Both Holdings-Based Factor Analysis and Returns-Based Factor Analysis Have Their Advantages and Disadvantages. On the one hand, returns-based analysis can be performed on any asset with returns—even when holdings information is unavailable. On the other hand, returns-based analysis requires a length of time (preferably at least 18 months, but potentially as little as 6 months) whereas holdings-based analysis needs no historical data—only a single point in time. Returns-based analysis is also effective when analyzing multi-asset portfolios relative to holdings-based analysis because it is ambivalent to asset class. On the other hand, holdings-based analysis tends to be more stable than returns-based analysis. Of course, returns-based analysis is backward-looking in nature, and although "past performance cannot guarantee future results," past factor exposures have demonstrated to be effective predictors of future factor exposures.[11] As previously mentioned, this factor-based framework uses returns-based analysis.

This paper is focused on providing a framework for categorization rather than weighing the merits of returns-based analysis and holdings-based analysis. That said, there may be advantages to returns-based analysis over holdings-based analysis specifically when attempting to understand liquid alternatives. First, derivatives data and data on short positions can be difficult to model in holdings-based factor models or may not be available. Second, many managers—particularly in the hedge fund space—are reluctant to provide holdings on a regular basis but are more willing to provide return streams, so there may be a practical advantage to applying a returns-based approach over a holdings-based one. Finally, variability in factor loadings can help to explain "model risk" inherent in tactical managers.

	Holdings-Based	Returns-Based
Effectiveness in single-asset portfolios	Very effective	Effective
Effectiveness in multi-asset portfolios	Somewhat effective	Effective
Handles shorting	Less effective	Effective
Handles tactical managers	Not effective	Effective
Frequency of data points	Not frequent	Very frequent
Stability of factors	More stable	Less stable

Exhibit 3: A Brief Comparison of Holdings - Based and Returns - Based Factor Analysis

The factor loadings from this analysis are used as feature sets that form the basis for the creation of peer groups, categories and benchmarks. For example, if a fund has a beta to equities of 0.61, a beta to emerging markets of -0.22, a beta to inflation of 0.18, and a beta to value of -0.1, one might characterize it as "similar to" another fund with an equity beta of 0.58, a beta to emerging markets of 0.09, a beta to inflation of 0, and a beta to value of -0.05.

An Illustrative Example of Two Similar Funds

Factor	Fund 1	Fund 2
Equity	0.61	0.58
Emerging Markets	-0.22	0.09
Inflation	0.18	0
Value	-0.10	-0.05

Below is an image the authors use to help describe similarities and differences between the factor loadings of two different funds or portfolios. The two portfolios shown below are illustrative portfolios.

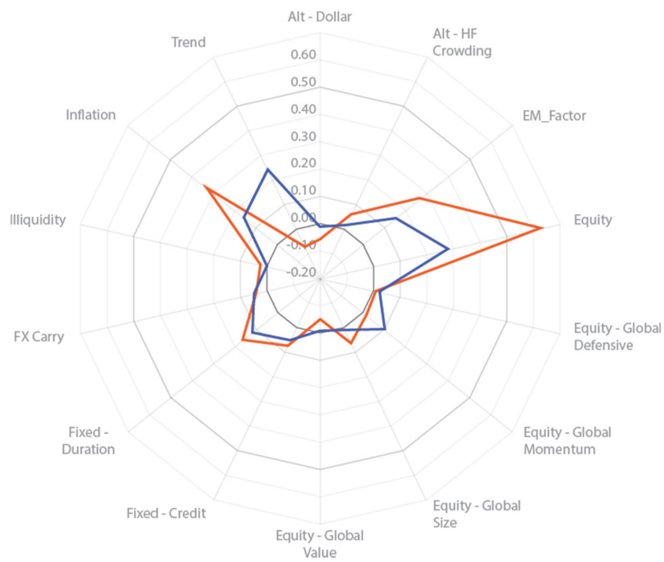

Exhibit 4: A "Factor Radar" Displaying Factor Loadings From Two Portfolios
Source: myfactore.com

Distance can be measured in order to understand similarities and differences between funds. A distance measure can be represented as a Euclidean distance matrix:

$$distance(x_i,\ x_q) = \sqrt{(x_i[1] - x_q[1])^2\ + \cdots + (x_i[d] - x_q[d])^2}$$

Distance is being measured between fund x_i and x_q, where [1]… [d] represent the factor loadings for each respective fund (equity, emerging markets, etc). Using a Euclidean distance measure for the two example funds above, the distance would be calculated as:

$$\sqrt{(0.58 - 0.61)^2\ + (-0.22 - 0.09)^2 + (0.18 - 0)^2 + (-0.1 - \ -0.05)^2}\ \cong 0.36$$

Furthermore, if certain factors are more important than others in the creation of a peer group, category, or benchmark, weightings can be applied to these features to emphasize their importance—in the equation below, A is a diagonal matrix with feature weightings across the diagonals and $\mathbf{x}_i$ and $\mathbf{x}_q$ are the matrices that represent the factor loadings for each respective fund:

$$distance(\mathbf{x}_\mathrm{i},\ \mathbf{x}_\mathrm{q}) = \sqrt{(\mathbf{x}_\mathrm{i} - \mathbf{x}_\mathrm{q})^T\mathbf{A}(\mathbf{x}_\mathrm{i} - \mathbf{x}_\mathrm{q})}$$

Using this method for categorization, a practitioner can create a customized peer group based on any set of risk factors he/she thinks are most important. This dynamic categorization represents a drastic departure from traditional means of categorization. While categorization of an entire universe has historically been necessary when performing discrete categorization, it is not common practice for most kinds of analysis to involve using the entire universe into discrete categories and working with that dataset. As a result, the ability to dynamically categorize using a factor-based framework is a distinct advantage over traditional categorization.

A practitioner can create his/her own benchmark by simply choosing factors and betas for those factors. For example, a practitioner looking for a hedged equity product with positive value exposure along with a bias toward smaller capitalization stocks can generate a search using a global equity beta of 0.3, a beta to value of 0.3, along with a beta to size of 0.4 (numbers chosen arbitrarily). He/she can weight those factors if one or more of the factors carry more importance than others in the search. Euclidean distances for the entire universe are then calculated on the fly and the practitioner has a customized peer group and benchmark where:

- Performance can be assumed to be similar for all members of the peer group;
- A search can then be applied within that peer group;
- Performance can be judged against both the benchmark (0.3 equity beta, 0.3 value beta, 0.4 size beta) as well as against each member of the peer group; and
- Product flows can be classified using this same factor-based framework.

It goes without saying that this kind of information can also help an analyst to ask more pointed qualitative questions as well as better understand how one investment within a category may fit within a portfolio.

Testing Categorization Methods

To test the efficacy of the traditional categorization and the factor-based categorization approaches, dispersion in returns for both traditional and factor-based categories were measured. In addition, the robustness of the factor-based categorization model was tested by comparing pairwise Euclidean distances between a training set and a test set using out of sample returns data. Finally, testing was performed in order to demonstrate the effectiveness of dynamic categorization by comparing out of sample correlations between factor-based dynamic categories and traditional categories.

Testing Period

- In-sample period: 1/5/2014 – 12/31/2016, weekly data
- Out-of-sample period: 1/1/2017 – 6/30/2018, weekly data
- Source: Morningstar

The Sample Set

The data used included a total of 238 liquid alternative mutual funds with continuous performance history between January 2014 until June 2018. Morningstar classification was used to represent traditional methods of classification (Lipper and Wilshire categories were unavailable). The total universe of alternative funds as measured by Morningstar was 348 funds as of 12/31/2016.

The Morningstar Categories assigned to the funds as of 12/31/2016 represented traditional categorization techniques used in both in-sample and out-of-sample tests. Funds where Morningstar instituted a category change between January 2014 and December 2016 were then excluded to create a "pure" list of categories, with exceptions being the Long/Short Credit and Option Writing Categories, which were created in 2014. Because these categories did not exist prior to their creation, the authors believed it was reasonable to include funds that were moved into that category under the assumption that had the categories existed prior to 2014, the funds would have already been part of those categories.

These traditional category assignments were formed in an effort to reduce hindsight bias, although it could not be entirely eliminated. Additionally, that same categorization as of 12/31/2016 is applied to test dispersion during the period 12/31/2016 – 6/30/2018. A summary of the list of funds is provided in the Appendix as Table 2.

Testing Performance Dispersion

3-year performance dispersion was measured for each Morningstar category. Then, that same categorization from December 2016 was used to calculate dispersion in the out-of-sample period. There is admittedly some survivorship bias, as not all funds that existed in 2016 were around for the next 18 months. Additionally, Morningstar likely used data from before January 2014 in order to conduct its categorization so there is some bias that cannot be prevented in this test. The results from both the in-sample and out-of-sample category dispersion tests are shown on Table 3.

Performance dispersion representing a factor-based classification was measured using both a k-means cluster analysis as well as using individual dynamic factor-based analysis. For k-means cluster analysis, multiple analyses were generated using both five and eight clusters using factor loadings from the January 2014 – January 2016 timeframe in order to measure performance dispersion both during the in-sample period as well as the out-of-sample period. Both five and eight clusters were chosen for two reasons: 1) There were eight categories used in the traditional classification, and 2) While an elbow in the cluster analysis exists at three clusters, an elbow could be interpreted as being at five clusters as well. In fact, the rounded area between the 5-8 cluster mark suggests having between 5-8 categories is probably the right choice. A chart that shows average centroid distances is shown on Chart 1 in the Appendix.

Average factor loadings for the traditional categories as well as for the clusters are shown in Tables 6-8.

Testing Dynamic Categorization

While cluster analysis is somewhat instructive in demonstrating the validity of returns-based analysis, the real power in dynamic benchmarks and peer groups comes from the idea that an investment product does not need to belong to a category at all! Or, conversely, the same fund can belong to multiple peer groups.

The basis for dynamic categorization is that current factor loadings have some predictive ability toward future factor loadings. In other words, factor exposures tend to be autocorrelated. We measure predictability over the in-sample and out-of-sample periods by comparing pairwise Euclidean distances between the two periods. That analysis is shown on Chart 2 in the Appendix.

Testing dynamic categorization is performed by taking every ticker from each category and comparing the average correlation between each fund and its category during the out-of-sample period and the correlation between the fund and its dynamic factor-based category in the out-of-sample period. The analysis is shown on Table 9.

70% of the 238 funds surveyed had a higher correlation to their factor-based categories than to their traditional categories using out of sample data. The average increase in correlation from using a factor-based category was 0.080, whereas the average decrease in correlation from using a factor-based category was only 0.036. The factor-based categorization performed better than traditional categorization in every category.

Conclusion

The categorization performed by Morningstar does a good job of separating out some of the asset classes. For example, factor analysis points out that long/short equity carries a reasonably high factor loading to large, developed equities (0.54 to equity; -0.34 to EM, -0.13 to size). Further, long-short credit and non-traditional bond carry an appropriate weighting to credit (0.25 and 0.21, respectively). Managed Futures carries a 1.26 beta to trend, which again makes sense. These high level statistics suggest that many of these classifications are congruent with their underlying risk factors. Other classifications, though, may not be congruent. For example, the average fund in the Option Writing category carries a 0.49 beta to equities and 0.17 beta to illiquidity, but that factor loading varies, as the highest loading to illiquidity in the Category is 0.61, while the lowest is -0.12. Illiquidity helps to assess risk if there is a shock to volatility or liquidity, such as the sharp swing in early February 2018. In fact, the fund with the highest loading to illiquidity was not in the Option Writing Category but was in Managed Futures (with a five-star rating) until 2017.

K-means classification helps to sort through the different risk factors. For example, in the 8-cluster classification, there was a very clear assignment to large-capitalization value investing. Further, the illiquidity factor appropriately captured those strategies prone to larger losses (reflected in the variability of performance in 2017-2018, including the large loss to the fund with the high loading to illiquidity).

Although the algorithm can be run from a chosen group of centroids, the analysis for this paper was performed using a random start. The 8th cluster (with two members) is a function of that random loading. Although it did appropriately sort out those funds with large exposure to a rising US Dollar, that category would not necessarily be useful to most practitioners. A major advantage traditional classification has over k-means cluster analysis in this experiment is that Morningstar had the entire universe to choose from when creating these categories, whereas the algorithm only had those funds that Morningstar had already deemed to be alternative funds. Having a larger universe would most likely improve the classification, especially given the large disagreements already inherent in the alternative classification universe. That said, naïve k-means classification did some things better than traditional categorization. In addition to capturing certain factor betas, the weighted average dispersion in returns was lower in the out-of-sample data for the clusters than it was for the traditional categories. That said, many readers may still believe that quantitative analysis is still best served in the hands of a decision-maker.

Although k-means clusters carried only slightly lower dispersion than traditional categorization, the real power in classification is not in a full classification system—which is what k-means classification attempts to do—**but rather smart classification is the ability to find what the user performing the categorization wants to find.** A full classification system is incongruent with the way most practitioners use and apply categorizations. Most practitioners care about only a handful of categories at a time, which is exactly where a dynamic factor-based categorization becomes incredibly powerful.

This method of categorization has all the positives of k-means classification (strong pull to risk factors, an attempt to minimize subjectivity) while giving control of the classification to the user or analyst. Pearson's correlation was used to test the efficacy of the factor-based categorization relative to a traditional categorization. In addition, the category size was the same for both category types. The dynamic factor-based approach to categorization saw improvements in the correlation coefficients—on average, correlation between the fund and the dynamic category was a meaningful 0.08 higher than the traditional category. Finally, using correlation as a measurement of efficacy, dynamic factor-based categories were more effective than traditional categories in every Morningstar category.

Furthermore, it is almost certain that using a universe outside of Morningstar's alternative universe would cause factor-based categorization to perform even better than it did with this constrained universe of funds. Finally, while the dynamic categories took on the same size as their respective Morningstar category counterparts in order to control for peer group size, using the dynamic categorization process, the size of the category can be customized to reflect the intentions of the user. For example, smaller peer groups can reflect a more constrained opportunity set.

While creating customized peer groups has historically been a time-consuming exercise, with the appropriate tool, technology has now made it possible to create a customized peer group and benchmark with a tap or click. User-directed dynamic factor-based classification is patent pending and the authors believe it will have wide applicability across the universe:

- The ability for consultants to create peer groups and benchmarks that match their clients' needs
- The ability for analysts to appropriately benchmark and categorize funds
- The ability to measure alpha against not only a multi-factor benchmark

The need to classify investment products is clear: Investors must be able to make assumptions about the products they are buying; they want help in searching for funds that meet a certain criteria; they want to be able to judge the performance to a fair peer group and a fair benchmark; and they want to be able to understand flows linked to their categories and peer groups.

While traditional categorization may have historically been the only option for practitioners, technology is opening up the landscape of possibility for those interested in using empirical data to support their categorization process. The shift to factor-based investing has captured almost $1 trillion in assets over the last five years—this analysis hopefully sheds some light on the potential to reclassify investments in light of this dynamic investment paradigm.

Appendix

Factor	Brief Description
Equity	Global equity markets
Credit	Additional premium for corporate credit risk over US Treasuries
Duration	Premium for interest rate risk
Emerging Markets	Additional return for owning stocks or bonds in emerging markets
Inflation	Premium for inflationary assets
Equity - Global Value	Premium for equities that exhibit value characteristics
Equity - Global Momentum	Premium for equities that exhibit momentum characteristics
Equity - Global Size	Premium for equities with smaller market capitalizations
Equity - Global Defensive	Premium for equities with quality and low volatility characteristics
Alt – Dollar	Exposure to the US dollar
Illiquidity	Premium for taking illiquidity risk, proxied using options markets
Trend	Premium for multi-asset trend-following
FX Carry	Premium to own higher-yielding currencies relative to lower-yielding

Table 1: The Multi - Asset Risk Factor Model Used

Category	Number of Funds (n)
US Fund Long-Short Credit	7
US Fund Long-Short Equity	51
US Fund Managed Futures	23
US Fund Market Neutral	31
US Fund Multialternative	58
US Fund Multicurrency	11
US Fund Nontraditional Bond	34
US Fund Option Writing	23

Table 2: Summary of Liquid Alternatives Universe Used
Source: Morningstar

		Performance: January 2014 - December 2016					Performance: January 2017 - June 2018				
Category	n	Average	StDev	Min	Max	Range	Average	StDev	Min	Max	Range
US Fund Long-Short Credit	7	2.1%	1.4%	0.6%	4.8%	4.2%	3.3%	1.8%	1.1%	6.2%	5.1%
US Fund Long-Short Equity	51	2.3%	4.0%	-8.0%	14.4%	22.4%	6.1%	5.5%	-3.4%	19.5%	22.9%
US Fund Managed Futures	23	3.5%	4.3%	-3.7%	14.3%	18.0%	-0.4%	5.4%	-15.2%	9.7%	24.9%
US Fund Market Neutral	31	1.3%	3.1%	-9.5%	6.6%	16.1%	1.2%	4.2%	-6.8%	9.0%	15.8%
US Fund Multialternative	58	1.3%	2.1%	-4.3%	6.8%	11.1%	2.7%	3.4%	-6.1%	14.6%	20.7%
US Fund Multicurrency	11	0.7%	7.1%	-9.5%	15.1%	24.6%	-0.1%	4.6%	-8.5%	5.8%	14.3%
US Fund Nontraditional Bond	34	2.3%	1.9%	-3.5%	6.4%	9.9%	3.3%	1.9%	-0.8%	6.9%	7.7%
US Fund Option Writing	23	3.1%	2.2%	-1.7%	6.3%	8.0%	5.5%	3.1%	-1.7%	9.4%	11.1%
		Weighted Average Range				14.8%	Weighted Average Range				17.4%

Table 3: Category Dispersion Using Traditional Classification
Source: Morningstar, AlphaCore, as of 6/30/18

		Performance: January 2014 - December 2016					Performance: January 2017 - June 2018				
Cluster	n	Average	StDev	Min	Max	Range	Average	StDev	Min	Max	Range
Cluster 1 (Trend)	19	3.1%	3.8%	-3.7%	9.5%	13.2%	-0.3%	4.3%	-7.3%	9.7%	17.0%
Cluster 2 (Equity1)	19	1.9%	3.1%	-2.1%	12.0%	14.1%	7.4%	5.8%	-1.2%	19.5%	20.7%
Cluster 3 (Value)	15	4.0%	4.4%	-3.5%	14.4%	17.9%	-0.6%	4.8%	-6.8%	9.0%	15.8%
Cluster 4 (Equity2)	41	3.1%	2.5%	-5.7%	7.8%	13.5%	6.4%	4.1%	-2.8%	18.0%	20.8%
Cluster 5 (Option)	12	2.0%	3.2%	-3.9%	6.1%	10.0%	2.9%	6.6%	-15.2%	9.4%	24.6%
Cluster 6 (Credit)	47	1.5%	1.9%	-3.5%	6.4%	9.9%	3.1%	2.1%	-1.0%	6.9%	7.9%
Cluster 7 (Multialt)	83	1.1%	3.5%	-9.5%	14.3%	23.8%	2.4%	3.3%	-6.8%	10.7%	17.5%
Cluster 8 (FX)	2	10.6%	6.3%	6.1%	15.1%	9.0%	-6.7%	2.5%	-8.5%	-5.0%	3.5%
		Weighted Average Range				16.5%	Weighted Average Range				16.5%

Table 4: Category Dispersion Using 8 Clusters
Source: Morningstar, AlphaCore, as of 6/30/18

		Performance: January 2014 - December 2016					Performance: January 2017 - June 2018				
Cluster	n	Average	StDev	Min	Max	Range	Average	StDev	Min	Max	Range
Cluster 1 (Multialt)	135	1.2%	3.1%	-9.5%	14.3%	23.8%	2.4%	3.3%	-15.2%	10.7%	25.9%
Cluster 2 (Equity1)	20	2.5%	4.2%	-2.1%	15.1%	17.2%	6.6%	6.7%	-8.5%	19.5%	28.0%
Cluster 3 (Trend)	19	2.9%	3.8%	-3.7%	9.5%	13.2%	-0.2%	4.4%	-7.3%	9.7%	17.0%
Cluster 4 (Equity2)	50	3.0%	2.7%	-5.7%	8.5%	14.2%	6.2%	4.1%	-2.8%	18.0%	20.8%
Cluster 5 (EMN)	14	4.4%	4.0%	-0.5%	14.4%	14.9%	-0.8%	4.4%	-6.8%	8.4%	15.2%
		Weighted Average Range				14.8%	Weighted Average Range				17.4%

Table 5: Category Dispersion using 5 Clusters
Source: Morningstar, AlphaCore, as of 6/30/18

Category	Equity	Credit	Duration	Emerging Markets	Inflation	Value	Momentum	Size	Dollar	Illiquidity	Trend	FX Carry
US Fund Long-Short Credit	0.06	0.25	-0.03	0.03	0.00	0.00	0.01	0.01	0.00	0.04	0.04	0.00
US Fund Long-Short Equity	0.54	-0.01	-0.04	-0.34	-0.02	0.01	0.03	-0.12	0.02	-0.03	0.15	0.02
US Fund Managed Futures	0.00	-0.05	0.14	0.06	-0.11	-0.01	0.13	-0.04	0.12	0.10	1.24	0.08
US Fund Market Neutral	0.06	-0.01	-0.01	-0.06	0.01	0.09	0.07	-0.10	0.00	-0.03	0.02	0.01
US Fund Multialternative	0.28	0.09	0.06	-0.04	0.01	0.01	0.06	-0.03	0.08	0.03	0.13	0.03
US Fund Multicurrency	0.09	0.07	0.08	0.08	0.03	0.01	-0.02	0.01	0.21	-0.04	-0.06	0.09
US Fund Nontraditional Bond	0.10	0.21	-0.03	0.03	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.00
US Fund Option Writing	0.48	0.00	0.03	-0.20	0.04	-0.02	-0.04	-0.07	0.03	0.17	-0.03	0.02

Table 6: Average Factor Loadings for Traditiongal Categories
Source: Morningstar, AlphaCore, as of 6/30/18

Category	Equity	Credit	Duration	Emerging Markets	Inflation	Value	Momentum	Size	Dollar	Illiquidity	Trend	FX Carry
Cluster 1 (Trend)	0.01	-0.07	0.21	0.03	-0.10	0.02	0.08	-0.02	0.10	0.01	1.50	0.11
Cluster 2 (Equity1)	0.65	0.11	-0.05	-0.38	-0.15	-0.20	0.06	0.10	0.05	0.01	0.07	-0.04
Cluster 3 (Value)	0.13	-0.08	-0.05	-0.20	-0.02	0.32	0.20	-0.45	-0.05	-0.01	0.19	0.13
Cluster 4 (Equity2)	0.58	-0.04	-0.04	-0.33	0.04	0.00	-0.06	-0.17	0.02	-0.01	0.14	0.03
Cluster 5 (Option)	0.27	-0.02	-0.01	-0.04	0.11	-0.06	0.03	-0.08	0.02	0.44	0.01	0.03
Cluster 6 (Credit)	0.16	0.24	-0.06	0.04	0.00	0.00	0.03	0.02	0.04	0.02	0.04	0.00
Cluster 7 (Multialt)	0.14	0.03	0.07	-0.01	0.03	0.02	0.03	0.00	-0.01	-0.01	0.07	0.03
Cluster 8 (FX)	0.04	-0.01	0.10	-0.12	0.00	-0.06	-0.07	-0.03	2.33	0.05	-0.06	0.00

Table 7: Average Factor Loadings for 8-Cluster Classification
Source: Morningstar, AlphaCore, as of 6/30/18

Category	Equity	Credit	Duration	Emerging Markets	Inflation	Value	Momentum	Size	Dollar	Illiquidity	Trend	FX Carry
Cluster 1 (Multialt)	0.14	0.11	0.02	0.01	0.02	0.01	0.04	0.00	0.02	0.02	0.06	0.02
Cluster 2 (Equity1)	0.62	0.11	-0.04	-0.37	-0.14	-0.20	0.05	0.09	0.21	0.01	0.07	-0.04
Cluster 3 (Trend)	0.02	-0.05	0.23	0.05	-0.09	0.01	0.05	-0.01	0.08	0.01	1.45	0.09
Cluster 4 (Equity2)	0.55	-0.04	-0.03	-0.30	0.05	0.01	-0.06	-0.17	0.01	0.05	0.12	0.03
Cluster 5 (EMN)	0.10	-0.11	-0.02	-0.20	-0.05	0.30	0.29	-0.45	-0.01	-0.03	0.31	0.12

Table 8: Average Factor Loadings for 5 - Cluster Classification
Source: Morningstar, AlphaCore, as of 6/30/18

Category	Number in Cat.	Average Correlation to Morningstar Category	Average Correlation to Factor-Based Category	Difference in Correlation
US Fund Long-Short Credit	7	0.59	0.71	+0.12
US Fund Long-Short Equity	51	0.79	0.81	+0.02
US Fund Managed Futures	23	0.80	0.82	+0.02
US Fund Market Neutral	31	0.35	0.41	+0.07
US Fund Multialternative	58	0.70	0.73	+0.03
US Fund Multicurrency	11	0.23	0.53	+0.30
US Fund Nontraditional Bond	34	0.53	0.55	+0.02
US Fund Option Writing	23	0.83	0.86	+0.03
			Avg Difference	+0.08

Table 9: Comparison Between Category as Benchmark and Factor-Based Category as Benchmark
Source: Morningstar, AlphaCore, as of 6/30/18

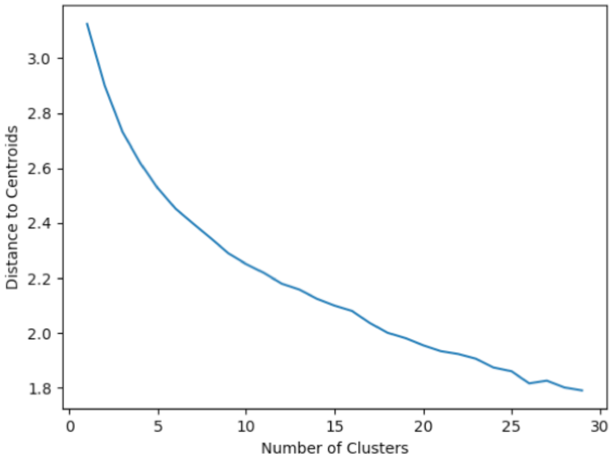

Chart 1: K- Means Cluster Interpretation

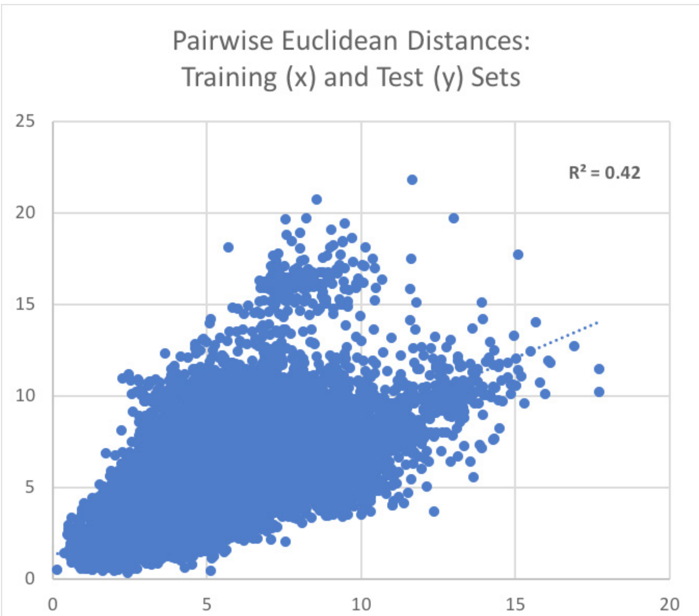

Chart 2: Comparison of pairwise Eucldean Distances

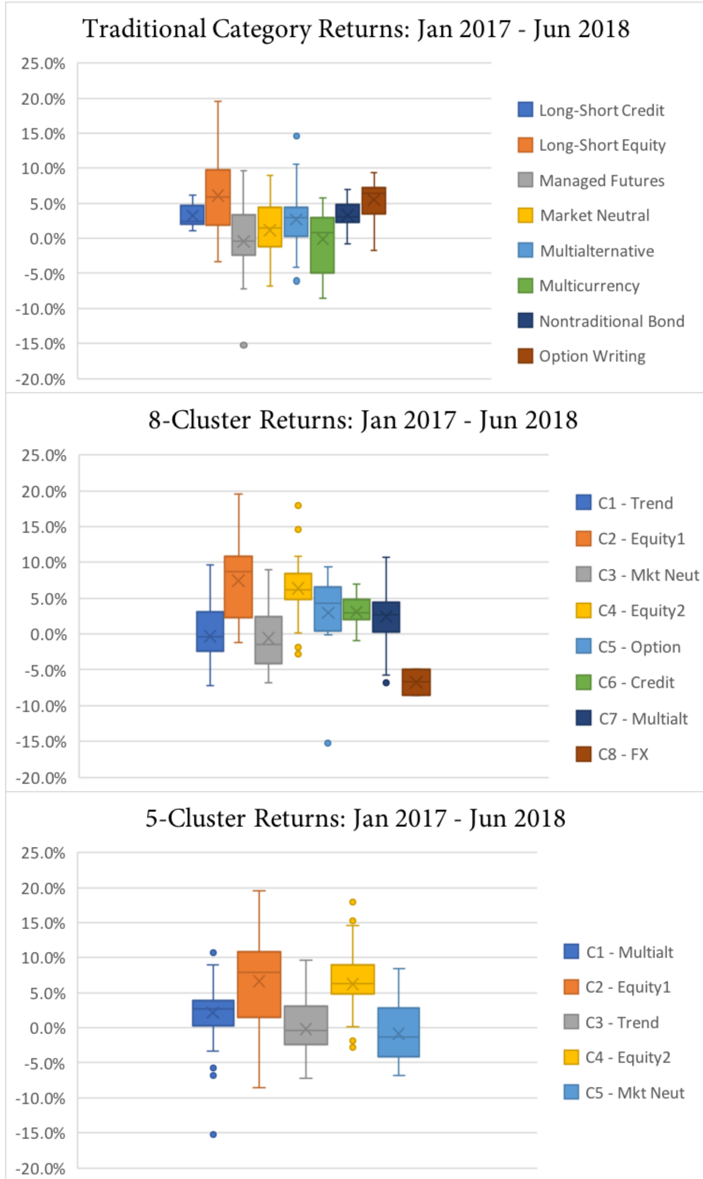

Chart 3: Comparison of Category Returns in Out of Sample Period

Endnotes

1. 2018 Investment Company Fact Book, Investment Company Institute

2. Source: Morningstar, from June 30, 2008 to June 30, 2018.

3. Hedge Fund Classification Using K-means Clustering Method; Das, 2003

4. Categorizing Mutual Funds Using Clusters; Marathe/Shawky, 1999

5. Cluster Analysis and Manager Selection; Bailey/Arnott, 1986

6. The Morningstar Category Classifications, Morningstar, 2016

7. Wilshire Associates Liquid Alternatives Industry Monitor, Wilshire Associates, 2018

8. Seven of Morningstar's alternative categories were small or were inverse or leveraged funds. These categories are considered "trading" categories and were excluded from this analysis.

9. "Which Factors Matter to Investors? Evidence from Mutual Fund Flows," Brad M Barber, Xing Huang, Terrance Odean. The Review of Financial Studies, Volume 29, Issue 10, October 1, 2016

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11. "On Persistence in Mutual Fund Performance" Carhart, 1997

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