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Editor's Letter

Best-Case Scenario for the Long-Term Expected Return on a 60/40 Portfolio

"Those who have knowledge, don't predict. Those who predict, don't have knowledge. " Lao Tzu, 6th Century BC Chinese Poet

"If you can look into the seeds of time, and say which grain will grow and which will not, speak then unto me. " William Shakespeare

Introduction

The 60/40 portfolio plays a central role in asset management. Many pension funds and endowments use a portfolio consisting of 60% in equities and 40% in bonds as the benchmark. There is no real theoretical reason as to why this allocation should serve as benchmark, and it not the purpose of this essay to argue its merits. Rather I will attempt to do something that Lao Tzu advised against it more than 2,500 years ago – develop an estimate of the best-case scenario for expected return on the 60/40 portfolio.

Note that I am not going to predict the expected or the most likely rate of return on this portfolio, rather I will give an estimate of its expected return if the economy remains the its current "goldilocks" state. Based on many common valuation metrics (e.g., PE ratio), many analysts claim that US equity markets are overvalued. For instance, the current PE ratio for S&P500 is about 40% above its long-term mean. Does this mean US equity markets will experience decades of negative or no returns as the PE ratio reverts to its normal level? It is hard to say.

Using valuation metrics from the past 100 years, US equity markets look overvalued currently, but it is also possible that US equity markets were grossly undervalued for most of the 20th century. Perhaps investors were demanding too high a risk premium because of their experiences with the Great Depression and WWII. It is hard to argue that investors are irrational and wrong now while they were rational and right in the past. In other words, current valuation metrics could be high for some fundamental reasons and they may never revert to their long-term means. It is a fact that financial theory has little to say about the right levels valuation metrics (e.g., the PE ratio) as they all depend on the risk premium demanded by investors, which depends on their degree of risk aversion. Maybe past investors were just too risk averse. We have no way of knowing it. So, one of the assumptions I make is that equity markets are neither undervalued nor overvalued, and, therefore, the current valuation metrics will neither expand nor shrink. I will make a few other assumptions that would make my estimates of expected returns the best-case scenario for the 60/40 portfolio.

I report that the best-case scenario for the 60/40 portfolio is an annual real return of 4.29% and an annual nominal return of 6.38% assuming 2% inflation. What are the implications of this simple analysis? A recent report by NASRA.ORG shows that the average rate of return assumed by public pension funds is 7.56%, more than a full percentage point higher than the best-case scenario presented here.[1] That is, these funds are counting on outperforming their benchmark by a full percentage point per year over the next 10 years. If they fail to achieve this level of performance, their underfunded statuses are likely to widen even further. The most viable path for these funds is to increase their allocations to global equity and fixed income markets and hope that they outperform their US counterparts. Also, they should consider increased allocations to alternatives if they have the knowledge to select and manage alternative asset classes.

The 60/40 Portfolio

Since I am going to provide an estimate of the best-case scenario for the 60/40 portfolio, it is useful to see how it has performed in the past and why, which is discussed later. I will be using S&P500 and Ibbotson Associates Indices to measure performances of equity and bond markets. I could use more global equity and fixed income indices, but then my data will have limited history, and more importantly, my data regarding dividends, earnings and buybacks will be even more limited. My bond index is an equally weighted average of 3 indices produced by Ibbotson Associates: Intermediate and long-term government bonds and long-term corporate bonds. For equity index I will use the S&P500 index, which ignores the small cap segment of the market. US small cap stocks have outperformed the large cap stocks since 1950. However, lack accurate historical estimates of earnings and dividends prevents me from including small cap and foreign markets in this analysis.

Using the above two indices and rebalancing annually, Exhibit 1 and Exhibit 2 (next page) display the performance of this portfolio since 1950. I could go back further to 1925, but I did not want to include the periods covering the Great Depression and WWII in my analysis. The analysis, therefore, covers almost 70 years of global economic growth and relative peace.

	Jan 1950-Dec 2017			Jan 1990-Dec 2017		
	Geometric Annual Total Return	Arithmetic Annual Total Return	Annualized Std	Geometric Annual Total Return	Arithmetic Annual Total Return	Annualized Std
S&P 500	11.31%	11.48%	11.90%	9.80%	10.12%	12.04%
Bonds	6.13%	6.21%	7.13%	7.22%	7.24%	7.10%
60/40 Portfolio	9.46%	9.37%	7.72%	9.04%	8.97%	7.47%
Inflation	3.51%	3.46%	1.25%	2.42%	2.40%	1.15%

Exhibit 1: Performance of the 60/40 Portfolio and its Constituents
Source: Morningstar

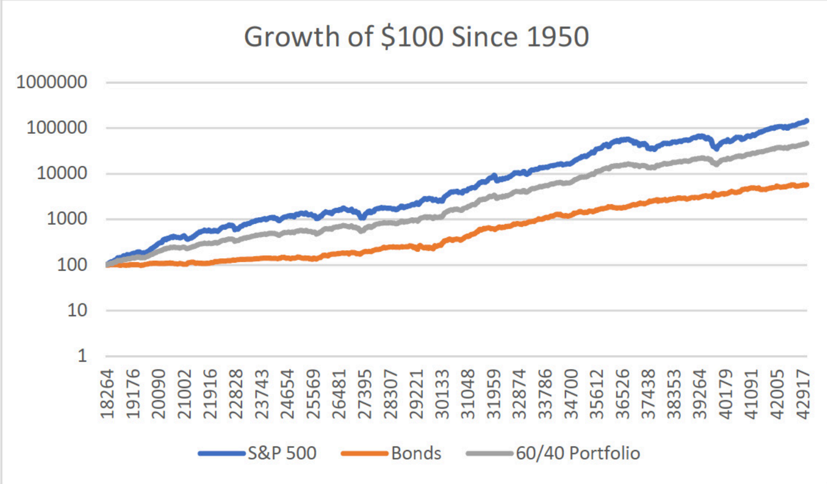

Exhibit 2: Growth of the 60/40 Portfolio and its Constituents
Source: Morningstar

It is important to note that the above figures represent total returns from these asset classes – i.e., dividends and coupons have been reinvested.

Current State of Markets

Before I present my estimate of the best-case scenario for the 60/40 portfolio, I will briefly review the current state of both equity and bond markets.

Equity Markets

By historical standards, US equity markets are rather expensive. Exhibit 3 displays the historical values of the S&P 500 PE and CAPE ratios. The PE ratio is calculated by dividing the current value of the index by its trailing 12-month nominal earnings. The Cyclically Adjusted PE (CAPE) Ratio is like regular PE ratio except that inflation-adjusted earnings from the previous 10 years are used to calculate the ratio. Exhibit 4 displays current and historical averages of these two measures.

Current levels of PE and CAPE ratios are significantly higher than their historical averages. If these ratios were to revert to their historical means, then the returns from US equities will be negative for the next several years in future. A number of other valuation metrics may be used to make the same point. For instance, the ratio of the equity markets capitalization is close to all time high and is higher by 108% compared to level we saw in 1950.

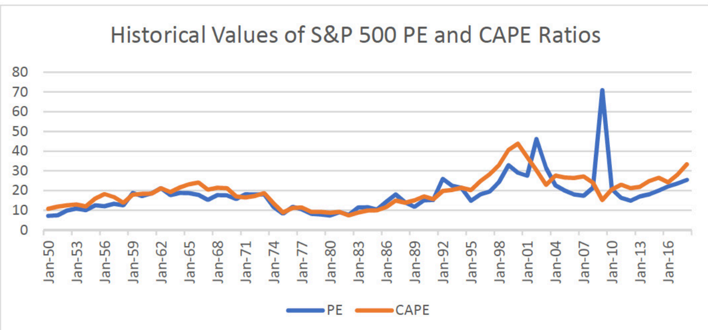

Exhibit 3: Historical Values of S&P500 PE and CAPE Ratios
Source: Robert Shiller's Website

1950-2017	Current Value	Historical Mean	Percentage Above Historical Mean
PE Ratio	25.39	17.86	42%
CAPE Ratio	33.31	19.43	71%

Exhibit 4: Historical and Current Values of S&P 500 PE and CAPE Ratios
Source: Robert Shiller's Website

Not only valuations are stretched but measures of corporate performance are also abnormally high. For instance, as reported by Standard and Poor's, the current profit and operation margins for S&P 500 companies are respectively 11.9% and 10.2%, nearly 100% higher than what we observed in 1994.

While for the past several years analysts have been predicting a decline in these margins, we have seen further increases in these margins. Several reasons have been put forward to support the current high valuations of equities.

- Structural changes in the economy support higher EPS growth. Technology companies, which dominate the US equities in terms of profitability and market cap could be able to maintain higher EPS growth rates because of their global reach.
- Moderation in the US business cycles makes equities less risky, reducing the risk premium demanded by investors. The PE ratio is inversely related to the risk premium demanded by investors and therefore a lower risk premium supports a higher PE ratio.

- Lower real interest rates support higher EPS. The PE ratio is inversely related to the discount rate (i.e., the required rate of return) applied by investors to corporate cash flows.
- Increased market and political powers of certain companies could lead to more stable EPS, leading to lower risk premium demanded by investors.

I am going to assume that for these and other reasons the current elevated valuation and profitability levels are sustainable going forward.

Bond Markets

There has been a strong secular decline in US interest rates since 1982, which has led to strong performance for all fixed income instruments. Despite the recent rise interest rates, they are still close to lowest levels we have seen since 1950s (see Figure 5)

Not only the levels of US rates are low by historical standards, the spreads between corporate and Treasury bonds are close to all-time lows as well. There are several reasons for the current state of fixed income markets. Low expected inflation, expansionary monetary policies practiced by most central banks, aging populations in advanced economies and changes in the structure of many economies from industrial to service economies.

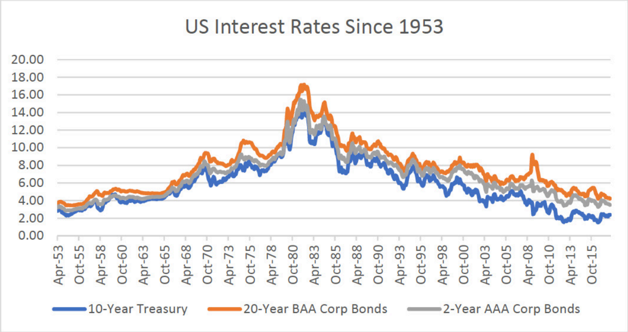

Exhibit 5: US Interest Rates

Source: Federal Reserve Bank of St. Louis

Similar to my assumption regarding equity markets, I will assume that the current real and nominal rates will prevail going forward. Of course, there is a possibility that interest could decline to lower levels improving the performance of bond portfolios. However, this scenario is most consistent with slowing economies and poor performance in equity markets. Therefore, the most optimistic scenario is for interest rates to remain at their current levels creating an environment conducive to further increase in equity market prices.

Sources of Returns on Equities and Bonds

Here I discuss components of annual returns to equities and bonds. The total annual rate of return on equities can be expressed as

Total Rate of Return = (1 + Growth of EPS)×(1 + Growth of PE Ratio) + Dividend Yield - 1

Since 1950, the figures for the above sources of returns have been

We can see that since 1950 the annual compounded total real return on S&P 500 has been 7.54%. This has come about because of 2.25% real growth rate in EPS, 1.82% growth rate in the PE ratio and 3.55% dividend yield.[2] The growth of the PE ratio shows how US equities have steadily become more expensive during the past 70 years. While it is possible that the PE ratio will continue to expand, it appears the path of least resistance is a decline in the PE ratio.

Contribution to Annual Total Return Since 1950				
S&P 500	Growth of EPS	Growth of PE ratio	Dividend Payments	Total Return
Nominal Values	5.84%	1.82%	3.55%	11.31%
Real Values	2.25%	1.82%	3.55%	7.54%

Exhibit 6: Components of Returns to S&P 500

Source: Robert Shiller's Website and Author's Calculations

The sources of returns on bonds are somewhat similar to those of equities. If we consider a par bond, then the total annual rate return on a constant maturity par bond will be

Total Rate of Return = - Change in Yield to Maturity × Duration + Yield to Maturity

Since 1950, the change in the yield maturity has contributed very little to the total return on bonds as interest rates increased from 1950 to 1982 and has since declined to their 1950s level. From 1950-1982, annual returns on bond portfolios were almost 1% less than the yields observed in 1950.

Best-Case Scenarios

In this section I will use the analysis of the previous sections to develop the best-case scenarios for equities, bonds and the 60/40 portfolio.

First, consider equities and return components in equation (1). What are the best-case scenarios for values of these components going forward?

- Real growth rate of EPS: The best-case scenario is to assume the same growth rate going forward. This represents the best-case scenario because during the last 68 years we saw a post WWII economic expansion, rapid increase in productivity, and a young expanding population. Important to note that in fact productivity growth has slowed in recent years and that the US population is growing a slower pace.
- Growth rate in PE ratio: The best-case scenario is that the current elevated PE ratio will persist and will not decline. It will be hard to argue that the PE ratio will expand further making US equity more expensive.
- Dividend yield. The dividend yield has steadily declined in recent years, standing at 1.836% currently. This decline in dividends has been accompanied by increased share buybacks. Since buybacks are identical to special dividends plus a reverse split, we can adjust the above dividend yield to reflect increased use of buybacks as a method of returning cash to shareholders. Last year's buyback rate was 2.2% of outstanding equity and this was close to all-time high. I am going to make the optimistic assumption that the sum of regular dividends and special dividends due to buybacks will equal its historical level of 3.55%.

The best-case scenario for bonds is somewhat easier to develop. We can assume that there will be no secular rise or decline in interest rates going forward. Average yield to maturity on an equally weighted portfolio of 10-year Treasuries, AAA and BAA long-term corporate bonds is approximately 4% per year. I am now prepared to develop the best-case scenario for a 60/40 portfolio with annual rebalancing

The best-case real and nominal returns are presented in blue colored cells while the more realistic real and nominal returns are presented in orange colored cells. We can see that the best-case scenario for the 60/40 offers 4.29% real return and 6.38% nominal return per year. This best-case scenario comes about because of 5.85% annual real return on equities and 1.96% annual real return on bonds. A more realistic scenario is the one involving a slightly lower PE ratio for stocks and slightly higher level of interest rates for bonds. In this case, the real annual return on the 60/40 portfolio is expected to be 2.70%, translating to 4.75% in annual nominal terms.

As mentioned in the introduction, the implications of these results for pension funds are enormous, which are counting on

	Real Values		Nominal Values at 2% Inflation	
	The 60/40 Portfolio			
	Average Yield Stays Equal to 4%	Average Yield Increases to 5%	Average Yield Stays Equal to 4%	Average Yield Increases to 5%
PE Stays Equal to 25.39	4.20%	4.09%	6.29%	6.17%
PE Declines to 20	2.76%	2.64%	4.82%	4.69%
	S&P 500			
PE Stays Equal to 25.39	5.70%		7.81%	
PE Declines to 20	3.29%		5.36%	
	Bonds			
PE Stays Equal to 25.39 PE Declines to 20	1.96%	1.67%	4.00%	3.71%

Exhibit 7: The Best-Case Scenario for the 60/40 Portfolio

Source: Author's Calculations

outperforming the best-case scenario of the 60/40 benchmark by more than a full percentage per year. Given their underfunded status, such an unrealistic assumption could result in sever financial difficulties for sponsors and beneficiaries. The most viable path for these funds is to increase their allocations to global equity and fixed income markets and hope that they outperform their US counterparts. Also, they should consider increased allocations to alternatives if they have the knowledge to select and manage alternative asset classes.

Hossein Kazemi,

Editor

Endnotes

1 See https://www.nasra.org/files/Issue%20Briefs/NASRAInvReturnAssumptBrief.pdf

2 Note that dividend yield is defined as the total dividend paid during the previous 12 months divided by the end of the year price.

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There is a new generation of investment managers which will disrupt asset management. These managers – which engage in Autonomous Learning Investment Strategies (ALIS) – use unstructured non-financial data, machine learning, and record-low computer processing and storage costs to run innovative investment strategies at lower costs vs. traditional fundamental and quantitative managers. ALIS managers typically don't originate from the traditional finance world of Wall Street and MBAs, but rather they are run by PhDs and have their roots in the counter-culture arena which include gamers and hackers (though benign ones).

Historically, private equity General Partners (GPs) and their Limited Partners (LPs) have not paid a great deal of attention to the area of compliance management. This was likely a function of the nature of private equity investing where the focus was on long-term profitability as compared to day-to-day operational considerations potentially impacting the funds, coupled with a less restrictive regulatory environment. In the forthcoming book Private Equity Compliance: Analyzing Conflicts, Fees, and Risks (Wiley Finance, September 2018), the author provides a perspective on how we arrived at the current compliance environment as well as an overview of the historical development of the modern private equity compliance environment and other key issues.

It is widely accepted that a categorization methodology is necessary in order to make sense of size of the investment product landscape, a categorization methodology is necessary to allow the investor to make performance-based assumptions about a group of products as well as appropriately judge any given product against a peer group and benchmark. But discrete categorization poses challenges in a fluid investment landscape. This paper explores the current classification system used by three large industry participants, proposes a dynamic factor-based categorization methodology that can be easily customized to any given product, tests various methods of exploring that quantitative method, and shows that using out-of-sample data and dynamic factor-based categorization methodology significantly improves the future correlation between an alternative fund and its peer group.

Illiquid asset classes have become a significant contributor to return and risk for institutional investment portfolios. However, the dynamics of how these asset classes behave within multi-asset portfolios are not captured very well by traditional portfolio modelling processes. This paper explores how multi-asset investors can incorporate the

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Young Potential ALIS Managers
Source: http://www.texasenterprise.utexas.edu/2015/05/13/workplace/how-strangers-unlock-our-creativity

Data De Groove

Michael Weinberg
MOV37

There is a new generation of investment managers which will disrupt asset management. These managers – which engage in Autonomous Learning Investment Strategies (ALIS) – use unstructured non-financial data, machine learning, and record-low computer processing and storage costs to run innovative investment strategies at lower costs vs. traditional fundamental and quantitative managers. ALIS managers typically don't originate from the traditional finance world of Wall Street and MBAs, but rather they are run by PhDs and have their roots in the counter-culture arena which include gamers and hackers (though benign ones).

It is therefore fitting that we've drawn the title of this paper from a Falco album, *Data De Groove.* The album was released nearly three decades ago, in 1990, and was dedicated to the computer era. At that time society was still in early innings in the 'computer era', and therefore we would state that Falco was decades ahead of its time, at least with *Data De Groove.* (Though the author notes that he personally was an early adopter of technology, having had an original IBM 8086 PC dual floppy disk drive PC with a monochromatic monitor, nearly a decade earlier.)

We have met more than 200 ALIS managers around the world over the past few years as well as other thought leading asset owners and investors, and one of the main things we speak to them about is data. In our view it's one of the most misunderstood ALIS topics. We will attempt to answer some important questions about data usage by ALIS managers, and hopefully clarify a few common misperceptions.

How do ALIS Managers Differ From Established Quantitative Managers?

We believe ALIS represents the proverbial "third wave" of investment management. The first wave was fundamental discretionary managers, which was disrupted by the second wave – quantitative managers. Autonomous Learning Investment Strategies – the third wave – are new managers forming due to the confluence of five unprecedented events.

First, data blew up. There are massive and exponentially increasing amounts of new data being created – much of which is untapped by investors. Second, data science caught up. New analysis and structuring platforms are arising to make all this new data usable. Third, machine learning is surpassing humans. As opposed to the old model of humans programming computers, computers are now learning from experience and "teaching" themselves at a lightening fast pace. Fourth, the cost of computer processing and storage has collapsed. Prohibitively expensive server rooms are now replaced with cheap cloud computing. And fifth, discretionary management is being left behind, as their information edge has been eroded by regulatory enforcement.

As a result of these five events, small teams that combine the power of human + machine can now effectively compete with discretionary managers as well as the large established quants. Quant strategies that used to take an army of PhDs and massive investments in servers can now be run by a couple of PhDs and the cloud, at a much lower cost.

Data is Expensive - Don't Managers Need Large AUM to be Able to Afford Expensive Data Sets?

We couldn't agree more. Some data is expensive. Credit card data is an example that falls in this category. We believe that almost all large hedge funds subscribe to this data. Similarly, the providers of this data typically are quite prevalent due to large marketing budgets to tout their offerings, which managers pay for through substantial subscription fees, resulting in a virtuous cycle. For precisely these reasons, we believe the value of some of this 'off-the-shelf' data has likely diminished to the point that it is commoditized and the residual alpha from this (and similar) sources has in many cases decayed to the point of being immaterial.

With These Expensive Data Sets – How Much Value is in Them?

Our sense is there may be some value in them, but not in and of itself. Marcos Lopez del Prado, a world leading machine learning expert, analogizes that a good way to find alpha sources is akin to using a sieve to strain gold out of substrate rather than searching for nuggets. In other words, the aggregation of many smaller particles will be greater than that found in nuggets. We believe this analog may hold with some of these more expensive and potentially commoditized data sets – that in conjunction with other data sets, there may be some residual value to them. Another analog that we would use is that it is akin to combining orthogonal low(er) Sharpe strategies that result in a higher Sharpe strategy.

	9	CUST_ID	CUST_CAT	MERCH_ID	MERCH_CAT	MERCH_SUBCAT	FRAUD	GROUP
1		Customer001	65andOver	Merchant0001	Retail	DrugStores	0	1
2		Customer001	65andOver	Merchant0002	Retail	FoodStores	0	1
3		Customer001	65andOver	Merchant0003	Services	Restaurants	1	1
4		Customer001	65andOver	Merchant0004	Services	Restaurants	0	1
5		Customer001	65andOver	Merchant0005	Services	OtherServices	0	1
6		Customer001	65andOver	Merchant0006	Services	OtherServices	0	1
7		Customer001	65andOver	Merchant0007	Retail	General	1	1
8		Customer002	35to44	Merchant0008	Services	OtherServices	0	1
9		Customer002	35to44	Merchant0009	Retail	GasStation	1	1
10		Customer002	35to44	Merchant0010	Retail	OtherRetail	0	1
11		Customer002	35to44	Merchant0011	Services	OtherServices	0	1
12		Customer002	35to44	Merchant0012	Retail	NonStore	1	1
13		Customer002	35to44	Merchant0013	Services	OtherServices	0	1
14		Customer002	35to44	Merchant0014	Retail	FoodStores	0	1

Credit Card Data: Credit card data is an example of an expensive data set that is marketed to investment firms, so much so that alpha from the 'off-the-shelf data' may have diminished since the data is becoming commoditized.
Source: http://morgan.dartmouth.edu/Docs/sas92/support.sas.com/documentation/cdl/en/grnvwug/61307/HT ML/default/ n0n6fnvllk0wwun1t38tds6cpl2y.htm

	Trading Days	NYSE Group Block Share Volume (Millions)	NYSE Group Block Trades (Thousands)	NYSE Group Block Dollar Volume (Billions)
January	20	5954	103.2	$224.80
February	19	5566.9	102.1	$212.60
March	23	7799	126.1	$304.90
April	19	5599.3	105.1	$202.50
May	22	6843.2	131.4	$244.10
June	22	9212.7	132.7	$326.20
July	20	6058.9	100.9	$233.70
August	23	6164.8	118.3	$237.50
September	20	7418	109.5	$296.60
October	22	6322.4	116.5	$249.90
November	21	6493.5	115.1	$260.00
December	20	7618	101.9	$333.50

NYSE Group Block Volume in NYSE Listed, 2017: Structured financial data often can be obtained for free online, like data available on the NYSE's website.
Source: https://www.nyse.com/data/transactions-statistics-data-library

How do ALIS Managers Procure Data Differently Than Large, Established Managers?

The short answer, in one word - Creatively!

The long answer, in more than one word....

As we previously stated, ALIS managers often originate from the counter-culture, including gamers and hackers. There are successful managers who see no need to subscribe to Bloomberg, Reuters, FactSet or Capital IQ. They procure their technical structured financial data gratis from open sources and avoid paying for the aforementioned data services.

These managers subscribe to the philosophy that data is like air. It is no less available than air is when one exists and should be the same price, free. They employ complex web scraping techniques to systematically obtain data from the internet to generate alphas. Sources range from search engines, to social media, to news to other third-party websites. These managers then systematically use Convolutional and Recurring Neural Networks, CNN and RNNs, to analyze and process the data, which is in turn used in its models to make investment (or divestment) decisions.

ALIS managers also may train their neural nets to work better than 'off the shelf' products or approaches used by more traditional quantitative or computational finance funds. For example, sentiment analysis of text is quite common, and also possibly commoditized. However, we believe that these managers have a better mouse trap that is effectively more nuanced in ascertaining the meaning of words, phrases and sentences, resulting in material and accretive alpha, where competitors may only find commoditization.

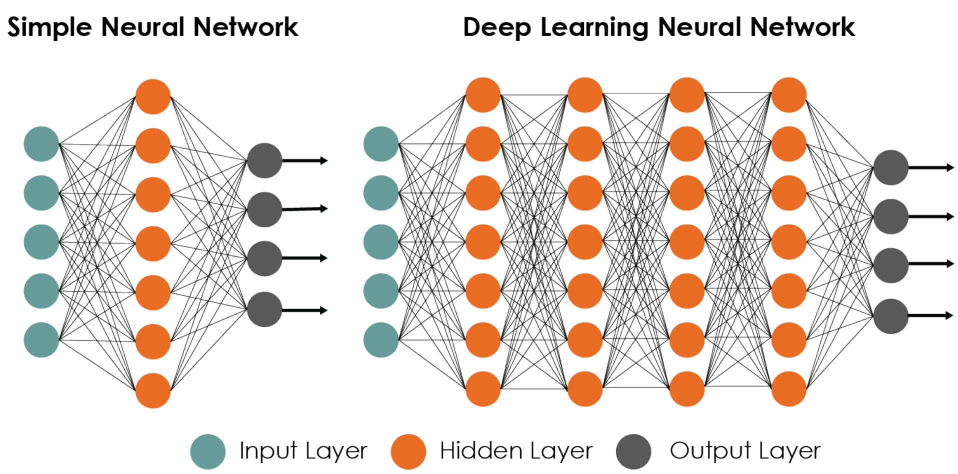
This is not to say that ALIS managers don't pay for data; some better ones certainly do. And what they have found is that the data market, like the security markets, is similarly inefficient. There are the expensive, well marketed data sets, as described above, that typically provide low returns and/or alpha per cost, and there are under or un-marketed data sets that may provide high returns and/or alpha per cost. These valuable, alpha and return rich data sets often are procured in a one-off way as they are inherently under-marketed.

How do ALIS Managers Approach Charging Data Costs to Their Investors?

We've found that most ALIS managers, having come from outside the Wall Street world of MBAs, view fees differently. ALIS managers believe fees should be reasonable and that high fees should only be earned when there is high performance. This differs from some established managers who earn high fees on large asset bases, even during years of mediocre performance.

One place we see a difference is in the much lower prevalence of "pass-through" expense structures among ALIS managers. These pass-through expenses for data and related costs are relatively common among larger quantitative managers and can range from 0.5% to multiple percentage points and are on top of fees of 2 and 20 or 3 and 30 or even higher.

Another difference between ALIS managers and established quants is ALIS managers are more open to fee structures that incentivize performance over asset gathering. We published an article in *Pensions & Investments* called "Hedge fund fees – a perfect solution", describing a 1/10/20 fee structure that we created and some ALIS managers have adopted. Investors pay a fixed 1% management fee, a 10% incentive fee for net returns below 10%, and a 20% incentive fee for net returns above 10%. Investor interests are better aligned



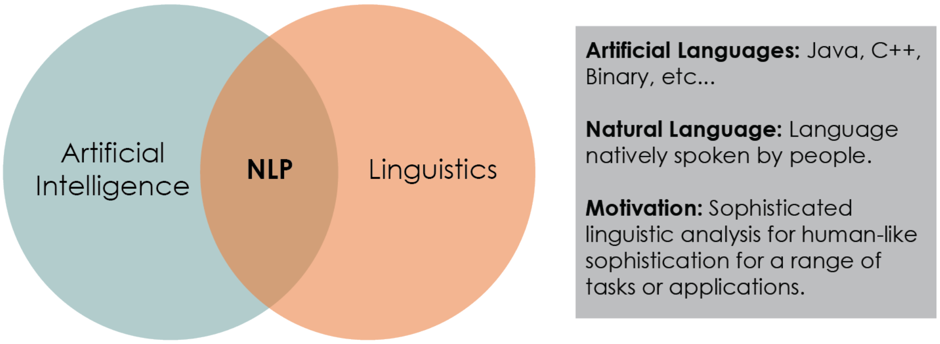
Neural networks, used to analyze unstructured data such as text scraped from websites, can vary in effectiveness, meaning that data which may be commoditized to a manager using a simple off-the-shelf Neural Network may be valuable to a manager using a more complicated Neural Network that may uncover more relationships.

because there are more incentives to produce high returns (and earn a 20% incentive fee), and less of an incentive to stick investors with large pass-through expenses and management fees. ALIS managers can offer these investor friendly fee structures because they are not tied to expensive legacy systems and processes and can tap cheap computing power and machine learning to run their strategies with fewer staff.

In summary, ALIS managers who typically are small, emerging and often from the counter- culture, can be more creative in data acquisition and spending for multiple reasons. These managers don't feel compelled to use traditional Wall Street vendors, and may philosophically believe that content should be gratis. They also may have fee structures that incentivize them to minimize data and other expenditures.

Concomitant with what we believe is a vastly inefficient data market, where expensive data can be commoditized, while off-the-run, free, web-scraped or inexpensive data may be very valuable. We believe Falco nailed it nearly three decades ago, with the prescience of naming his album *Data de Groove.*

What is Natural Language Processing?



Goal: Have computers understand natural language in order to perform useful tasks.

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Author Bio

Michael Weinberg
MOV37

For 25 years Michael has invested directly at the security level and indirectly as an asset allocator in traditional and alternative asset classes. He is the Chief Investment Officer at MOV37 and Protege Partners, and on the investment, management and risk committees. MOV37 invests in ALIS, systematic strategies that deploy machine learning/artificial intelligence and data science. Michael is also an Adjunct Professor of Economics and Finance at Columbia Business School, where he teaches Institutional Investing, an advanced MBA course that he created.

He also testifies as an expert witness in financial and technology litigation. He was a portfolio manager and global head of equities at FRM, a multi-strategy investment solutions provider. Prior to that, Michael was a portfolio manager at Soros, the macro fund and family office, and at Credit Suisse. Before that he was a real estate analyst at Dean Witter.

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Compliance

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Historically, private equity General Partners (GPs) and their Limited Partners (LPs) have not paid a great deal of attention to the area of compliance management. This was likely a function of the nature of private equity investing where the focus was on long-term profitability as compared to day-to-day operational considerations potentially impacting the funds, coupled with a less restrictive regulatory environment. Today perspectives on this matter have reversed, and compliance has become one of the fastest growing areas in the private equity space. Mirroring trends from the hedge fund industry, surveys indicate that private equity managers consistently rank compliance as one of the most challenging aspects of their business. Recent studies also indicate that private equity compliance spending has rapidly outpaced other GP operating costs, with estimates indicating that private equity funds increasingly spend larger portions of their operating budgets on this area.

In the forthcoming book Private Equity Compliance: Analyzing Conflicts, Fees, and Risks (Wiley Finance, September 2018) to provide perspective on how we arrived at the current compliance environment an overview of the historical development of the modern private equity compliance environment is discussed. Other key compliance topics covered in the book include:

- Overview of key GP compliance and obligations
- Analysis of GP global regulatory reporting requirements and associated venture capital fund obligations
- Analysis of the impact of emerging regulations on the private equity industry including the General Data Protection Regulation (GDPR), Senior Managers and Certification

Regime (SM&CR), Markets in Financial Instruments Directive II (MiFID II), and the Packaged Retail and Insurance-based Investment Products (PRIIPs)

- Perspectives on the ways in which GPs approach conflicts of interest management
- Analysis of the compliance implications of common private equity practices such as the use of management fee offsets and the compensation of operating partners and advisors
- Examination of the approaches to manage compliance with valuation policies and procedures
- Analysis of the impact of technology on GP compliance management including data management and cybersecurity considerations
- Regulatory case studies in private equity compliance failures

Private Equity Compliance also addresses the ways in which LPs are becoming active participants in engaging with GPs on a variety of investment and operational matters including compliance management. An increasingly popular mechanism to facilitate these conversations between LPs and a GP is through a Limited Partner Advisory Committee (LPAC). The following excerpt from Private Equity Compliance provides background on several of the common duties of LPACs, as well as provides an overview of the importance of GP disclosures to LPACs, and discusses options for LPAC formation:

LPAC's serve as an oversight and governance mechanism on the operations of the fund. They are meant to represent the interest of LPs and provide them with a voice in the management of the fund. While the specific duties of LPAC may differ across private equity funds, traditionally the core duties of an LPAC are often centered around the areas which present may present the greatest risks to LPs. Specifically, key areas LPACs focus on include:

- Conflict of interest oversight -the LPAC may be responsible for overseeing a number of situations in which different conflicts of interest may arise between the actions of the GP, its employees, and the LP. Two of the more common conflicts that LPACs review include:

  (i) Related party transactions oversight – These are investments where a fund may seek to enter into transaction with individuals or entities related to the GP. Two common related party transactions are for which LPAC provide oversight are:

    a. Approval of concurrent investments- A concurrent investment generally refers to a situation in which a fund purchases the securities of a portfolio company concurrently with another fund. In practice, the timing of the investments may not be simultaneous, and the two purchases could occur at slightly different times. In these situations, inherent conflicts may arise across a variety of areas including the allocation of securities among the two affiliated funds. Therefore, most funds are structured to submit concurrent investments to the LPAC for review and approval.

    b. Approval of cross investments – a cross investment refers to a situation where a fund purchases the securities of a company that is a portfolio company of another fund managed by the GP. Due to the dual ownership of both affiliated funds of the investment, the potential for conflicts related to items such as the valuation of the investment may arise either at the time of the initial purchase, throughout the life of the investment or upon sale. In order to provide additional oversight of such conflicts, LPACs typically are required to grant approval on any cross investments.

  (ii) LP transaction oversight – A fund may also seek to enter into a transaction directly with an LP in addition to their capital commitment to the fund. To oversee these conflicts, the LPAC therefore represents LPs in reviewing and ultimately deciding whether to approve or prevent such transactions.

- Valuation oversight – When disagreements arise between LPs and GPs over the valuation of an asset or group of assets held by a fund, the LPAC typically plays a role in working with the GP, and in some cases third-party appraisers, to determine a valuation.

The duties of LPACs are typically outlined specifically in the fund formation documents. Common LPAC duties include:

- Approving capital calls from investors in certain situations - Approving the issuing of capital calls by the GP in certain instances where they would not otherwise normally be permitted is one common LPAC role. An example of a situation where this could occur, would be if the commitment period for a fund had ended and the GP wanted to issue a special capital call to raise more funds for the purpose of enabling the fund to make additional opportunistic investments in portfolio companies. Typically, since the commitment period had already ended the fund formation documents would outline that LPAC approval was required to issue these new capital calls.
- Approving tax distributions amounts to GPs – Tax distributions are distributions of capital typically made to LPs in order to offset each individual LP's deemed tax liability with respect to their investment in the fund. To be clear the purpose of these

distributions is to provide the LP with money to pay taxes related to their investment in a fund, not to provide them with any sort of profits related to their investment in the fund. These tax distributions are typically paid by funds within 90 days after the end of the fiscal year of a fund. In some instances, a fund's formation documents may set a ceiling limit on the amount of total aggregate tax distributions the fund can pay out to LPs, such as $500,000 USD. If the aggregate contributions were to exceed this ceiling amount, then approval from the LPAC would typically be required to payout a greater amount of tax distributions.

- Override investment limitations – At the time of formation of a private equity fund, there may be a variety of investment limitations placed on a fund. These are also sometimes referred to as investment restrictions. A common example of such a restriction would be a cap on the total investment that may be placed into a single portfolio company. For a variety of reasons, such as a shifting market conditions, a GP may wish to override this cap once the fund actually starts investing capital. In order to breach this cap, LPAC approval would typically be required.

- Approving the advance of GP litigation defense costs – Under certain circumstances a fund may advance an LP money to fund their defense in litigation related to their duties on the LPAC. Similarly, in some cases a fund may advance the GP capital to fund their defense in a lawsuit brought from other LPs. The advance of capital in these situations typically requires LPAC approval prior to disbursement.

- Restricting fund principal's activities and new fund launches – Typically when a private equity fund is in the process of allocating capital, a restriction exists with regards to the principals of the fund (i.e. -the portfolio managers) from working on the management of other funds. Similarly, in order to not cannibalize the opportunity set of the current fund, restrictions also exist on the launching and subsequent closing of new funds by the GP. Any decision to violate these restrictions would require approval from either the LPAC or the majority of interest holders of the fund in most instances.

- Ceasing limited operations mode related to key person events – A key person event refers to a situation that is triggered when a single individual, or multiple persons as the case may be, that are critical to the management of a fund are no longer able to perform their duties. Historically, these provisions were also referred to as key man events. An example of such an individual would be a portfolio manager of a fund. Specifically, the common occurrences that trigger a key person clause include the death of a key person, their incapacitation, if they take bad actions that are determined to constitute items such as fraud or gross negligence, or if they are simply no longer involved in the day-to-day management of the fund for an extended period of time.

While the specifics of key person clauses vary across private equity funds, once a key person clause is triggered, many private equity funds formation documents contain a provision that the LPs that hold that majority of the fund's interest can vote to place the fund into what is known as a limited operations mode. In this mode, the fund will not make any new investments and will generally only fulfil the funding of previous investment obligations and make follow-on investments into portfolio companies. Depending on the circumstances of the key persons involved in the fund, and the specific investment situation of the fund, its LPs may decide to pull the fund out of limited operations mode and continue normal investment activities. An example of such a situation would be if a portfolio manager of a fund suffered an illness that forced the fund in limited operations mode but had since recovered from the sickness, and the LPs wanted to resume the normal fund operations. Typically, most funds are structured in such a way so that in order to resume normal operations of the fund out of limited operations mode, either a majority-in-interest of the LPs of the fund or the LPAC must approve this transition back to normal fund operations.

- Service provider oversight – In certain instance the fund formation documents may outline that changes to material service providers relationships, such as the auditor of a fund, would require LPAC approval.

- Extensions of a funds term – The term, of a private equity fund refers to the entire period of the fund's existence through to the winding-up and liquidation of the fund. The term of a fund is also sometimes referred to as the life of a fund. A common fund term would be 10 years from the date of the initial fund closing however, they may be longer or shorter. Generally, extensions of a fund's term require approval by the LPAC.

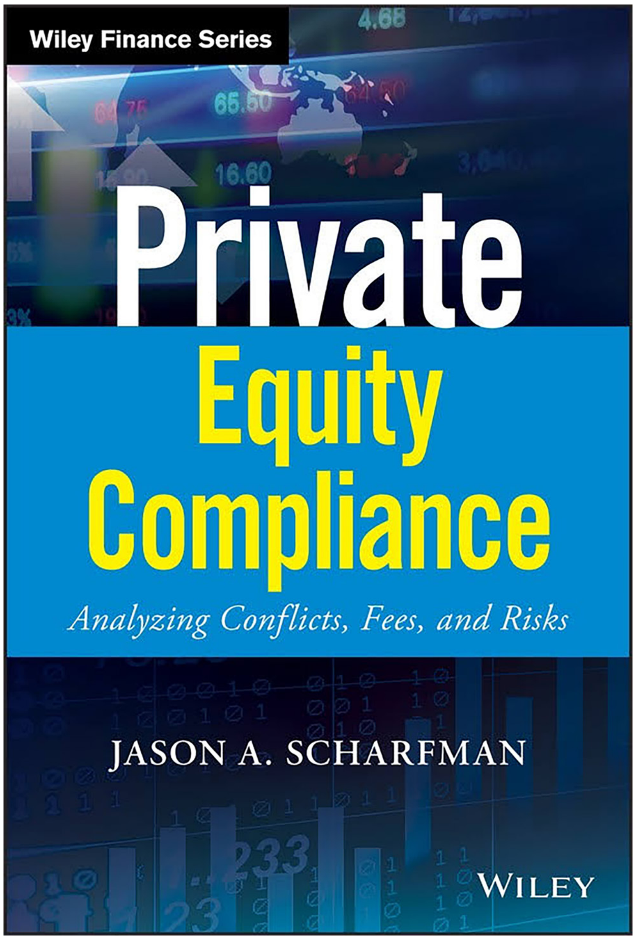
- Other matters the GP deems important – Many fund formation documents contain a provision such as this, "The General Partner may consult with, or seek the approval of the LPAC regarding any other matter determined by the GP for any other matter as determined by the GP in its sole and absolute discretion." This means that there may be other situations or potential investments that were not specifically contemplated at the time the original fund formation documents were drafted that have subsequently arisen that the GP feels is a good idea to run past the LPAC.

However, as these clauses are typically written the other types of items the GP brings to the LPAC is in the GP's complete discretion. So how should a GP, or an LPAC for that matter, determine what other items that should be raised to the LPACs attention? This determination is typically related to a concept known as a good faith effort. The general standard outlined in fund formation documents is that the GP makes what is known as a good faith effort to bring items to the LPACs attention and provide them with enough material facts so that they can make an informed determination of the merits of the proposed GP action. This good faith effort is also related to the issue of GP disclosures.

GP Disclosures to LPACs

When capital is first committed by LPs to a private equity fund the issue of disclosures by the GP is one that has come under increased scrutiny by private equity regulators. In particular, one of the key areas of focus relates to disclosures, is their completeness. In some cases, a GP may make disclosures of relevant information that are too limited in nature, or on the other hand a GP that makes very broad disclosures that do not specifically address important information material to LPs at the time capital is being committed. Once the initial capital commitments have been made by LPs, similar issues related to GP disclosures to LPs arise in the context of ongoing disclosures that should be made throughout a fund's term.

Disclosures of material information cannot be made by General Partners selectively, especially to LPACs who may be tasked with reviewing potential conflicts. Representatives of private equity regulators including the US SEC have highlighted that LPAC's decision making ability has been impaired in many cases by GP's failure to provide the LPACs with sufficient disclosures to make informed determinations over areas such as conflicts of interest, which are particularly important based on the nature of private equity investing. Regulators have observed the incompleteness of these disclosures was particularly noteworthy, as it related to the disclosures centered around the potential conflicts surrounding the practice of GP representatives taking board seats on underlying portfolio companies.



LPAC Formation Considerations

Although not a technical requirement, due to the increased input and oversight it affords LPs, today most private equity funds maintain an LPAC. Once a decision has been made to implement an LPAC, there are a number of initial questions facing GPs regarding the structure, membership and duties of the LPAC.

Determining Which LPs Can Serve on an LPAC?

After a determination has been made as to how many seats there will be on the LPAC, often the next question facing a GP is which investors will be invited to sit on the committee. Often to keep their larger investors happy, a GP will invite the larger investors in a fund to serve on an LPAC. These larger investors are sometimes referred to as seed investors or anchor investors.

It should be noted that certain seed investors may require a seat on the LPAC as part of their own investing process. In these cases, therefore, their committing of capital to the fund is predicated on their receiving a seat on the LPAC. From a legal perspective, this agreement between the GP and LP is often outlined in a supplemental document to the fund formation documents known as a side letter. A side letter is a separate agreement applicable to a specific LP, as opposed to the entire pool of LPs. Side letters typically outline certain specific rights available to LPs and unique obligations the GP has to a specific LP, such as a requirement to offer them a seat on the LPAC.

How Many LPs Can Serve on an LPAC?

One of the first questions a GP must determine is how many LP members the LPAC will have. There are no bright line legislative or regulatory rules with regards to specific minimum or maximum requirements. In practice, many GPs decide to keep the number of LPs to a manageable size. The actual number of LP seats on the committee may vary according to a number of factors including the actual size (i.e. – assets committed) of the specific fund, and the total number of investors in the fund.

For example, a larger private equity fund would likely have a greater number of large investors and therefore, the GP may feel obligated to create an LPAC board with more investors represented as compared to a smaller fund. In general, the minimum size for most LPACs is three LPs.

In order to provide further current advice on the applications of private equity compliance in practice the book also features interviews with private equity compliance practitioners. Additionally, the book features examples of key private equity compliance documentation including a compliance manual, code of ethics and relevant sections of private equity offering memorandums. Private Equity Compliance: Analyzing Conflicts, Fees, and Risks is currently available for pre-order from booksellers worldwide including Amazon.

Author Bio

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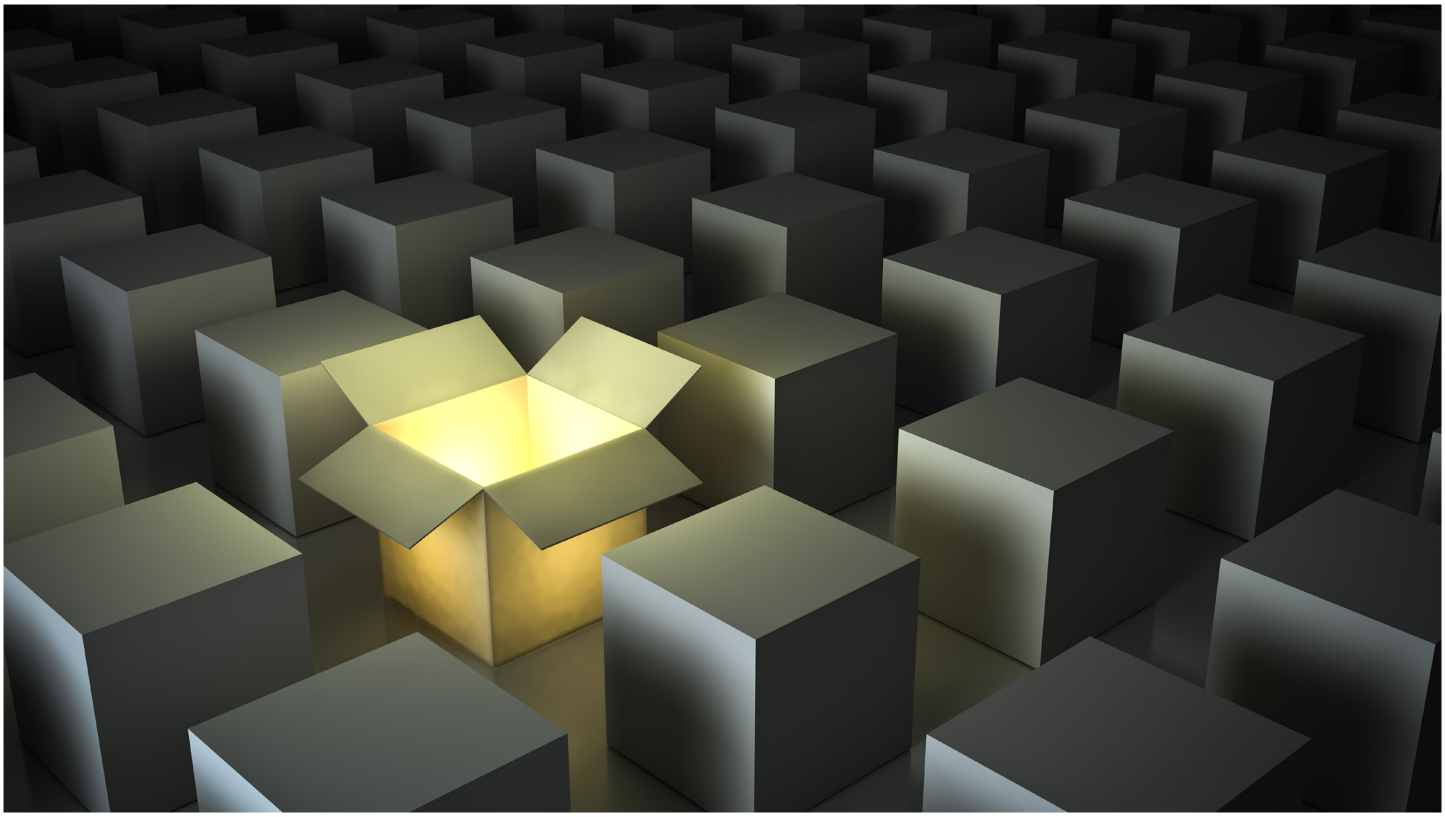
Jason Scharfman is the Managing Partner of Corgentum Consulting, a specialist consulting firm that performs operational due diligence reviews and background investigations of fund managers of all types, including hedge funds, private equity, real estate, and long-only funds on behalf of institutional investors, including pensions, endowments, foundations, fund of funds, family offices, and high-net-worth individuals.

He is recognized as one of the leading experts in the field of due diligence and is the author of several publications including Hedge Fund Compliance: Risks, Regulation and Management (Wiley Finance, 2016), Hedge Fund Governance: Evaluating Oversight, Independence, and Conflicts (Academic Press, 2014) Private Equity Operational Due Diligence: Tools to Evaluate Liquidity, Valuation, and Documentation (Wiley Finance, 2012), and Hedge Fund Operational Due Diligence: Understanding the Risks and (Wiley Finance, 2008). Mr. Scharfman has also contributed to the Chartered Alternative Investment Analyst (CAIA) curriculum on due diligence, has served on the organization's Due Diligence, Risk Management and Regulation Committee and is a CAIA charterholder.

Before founding Corgentum, he previously oversaw the operational due diligence function for a $6 billion alternative investment allocation group called Graystone Research at Morgan Stanley. While at Morgan Stanley, Mr. Scharfman was also a senior member of a team which oversaw all of Morgan Stanley's hedge fund operational due diligence efforts allocating in excess of $13 billion to a firm-wide platform of over 300 hedge fund managers across multiple investment strategies. Prior to joining Morgan Stanley, he held positions which primarily focused on due diligence and risk management within the alternative investment sector at Lazard Asset Management, SPARX Investments and Research and Thomson Financial.

Mr. Scharfman received a B.S. in Finance with an additional major in Japanese from Carnegie Mellon University, an MBA in finance from Baruch College's Zicklin School of Business, and a JD from St. John's University School of Law. He is admitted to the practice of law in New York and New Jersey. Additionally, he holds the Certified Fraud Examiner (CFE), and Certified in Risk and Information Systems Control (CRISC) credentials.

Mr. Scharfman's additional experience includes consulting with the U.S. House of Representatives Judiciary Committee on the subject of hedge fund regulation. and providing training to financial regulators on the subject of hedge fund due diligence. He has also served as a consultant and testifying expert on hedge funds and due diligence practices in litigation and arbitration proceedings. Additionally, he has lectured on the subject of hedge fund operations and operational risk as an adjunct professor at New York University. Mr. Scharfman is a member of several industry organizations including the Information Systems Audit and Control Association (ISACA), the American Bar Association, the New York State Bar Association and the New Jersey State Bar Association. He has written extensively on the subject of due diligence and travels and speaks worldwide on due diligence and operational risks.



Exploring Dynamic Factor-Based Categorization of Alternative Returns

Jonathan Belanger
AlphaCore Capital

Johann Lee
AlphaCore Capital

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.

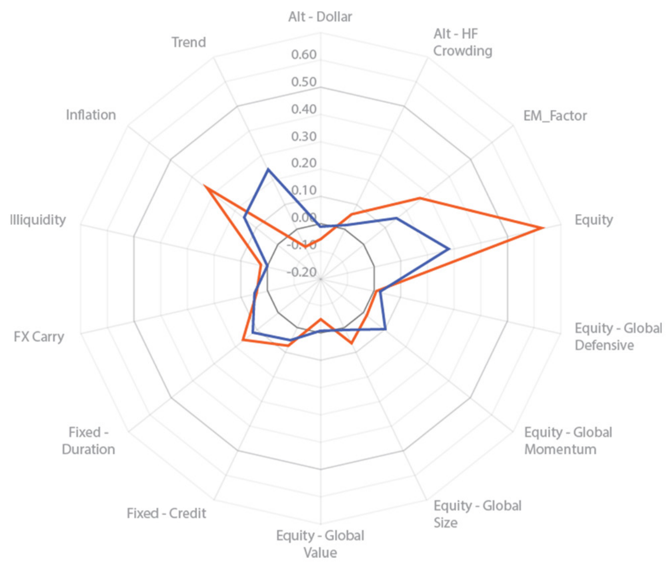


Exhibit 4: A "Factor Radar" Displaying Factor Loadings From Two Portfolios
Source: myfactore.com

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 Multialter-native	58	1.3%	2.1%	-4.3%	6.8%	11.1%	2.7%	3.4%	-6.1%	14.6%	20.7%
US Fund Multicur-rency	11	0.7%	7.1%	-9.5%	15.1%	24.6%	-0.1%	4.6%	-8.5%	5.8%	14.3%
US Fund Nontradi-tional 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

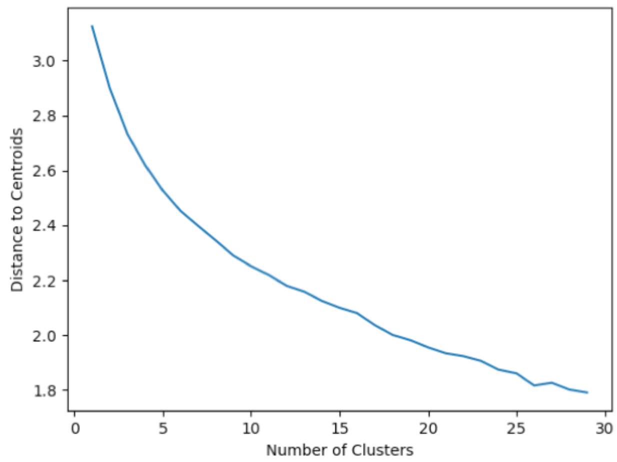


Chart 1: K- Means Cluster Interpretation

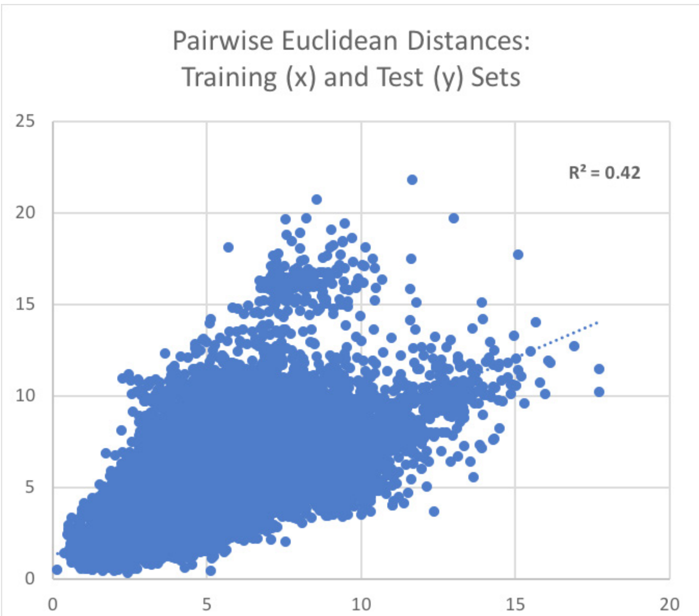


Chart 2: Comparison of pairwise Eucldean Distances

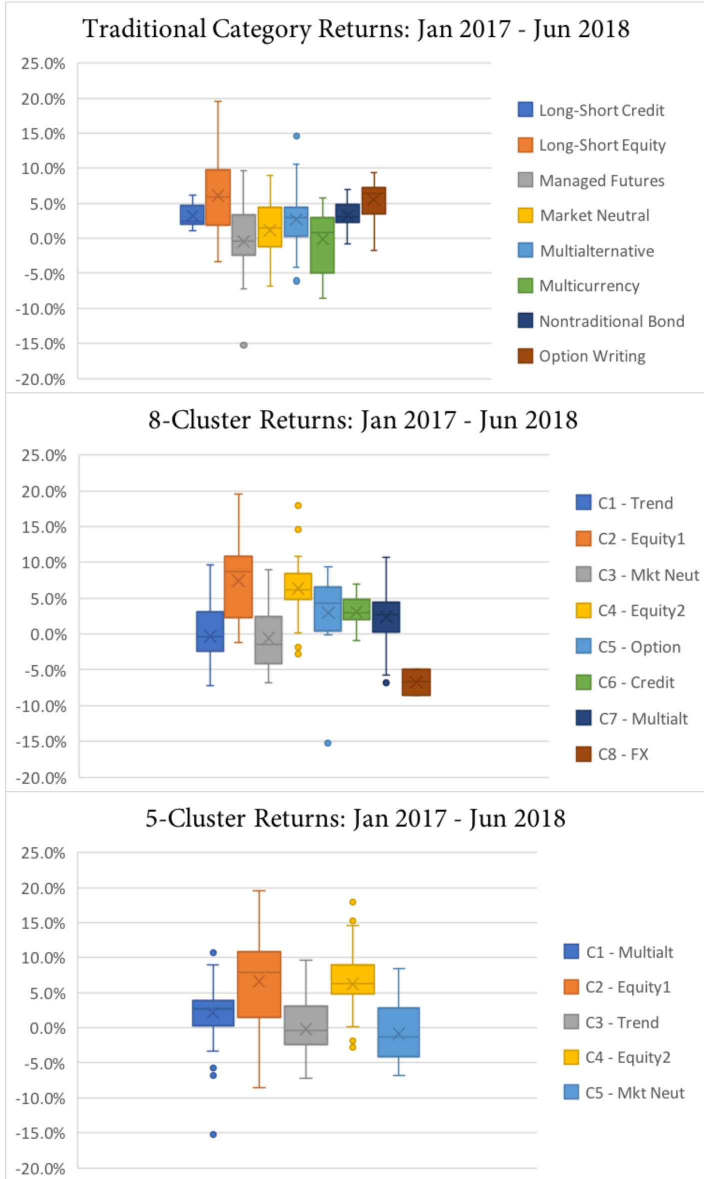


Chart 3: Comparison of Category Returns in Out of Sample Period

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

10. "Alpha or Beta in the Eye of the Beholder: What Drives Hedge Fund Flows?" Vikas Agarwal, T. Clifton Green, and Honglin Ren. March 2017

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The authors would like to acknowledge the following people who contributed to the research:

Jason Knapp, PhD, Cornerstone Software

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In addition to performing as a pianist in both the US and Europe, Jonathan was the lead singer, guitarist and pianist in a band, and recorded with 12-time Grammy-award winning producer, T-Bone Burnett. He still writes and performs occasionally.

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Modelling Illiquid Assets within Multi-Asset Portfolios

Daniel Baxter
Jacobi

A Common (But Flawed) Approach to Incorporating Illiquid Asset Classes

It is common practice for investors and consultants to establish return, volatility and covariance assumptions for all their asset classes, and to use these to produce a raft of portfolio return and risk statistics. A key assumption underpinning this kind of analysis is that portfolios can be rebalanced to target, even after large market drawdowns. One of the key benefits of diversification comes from the idea that we can rebalance from assets that have performed well into those that have not, and then reap the benefits as they mean revert to their long-run returns.

But certain characteristics of illiquid asset classes can invalidate this key assumption. To illustrate this, you simply need to recall the situation that some funds found themselves in during the Financial Crisis. After years of strong returns and expanding fund balances, these funds found themselves underweight private market asset classes and made unfunded commitments to get back to target. When equity markets collapsed the size of the funds shrank, but their unfunded commitments remained. To retain liquidity to meet potential capital calls, some funds were forced to reduce distributions, sell equities at depressed prices, or even borrow, while elsewhere in the market many asset classes offered valuations at generational lows.

Lessons From the Financial Crisis

The introduction of illiquid asset classes into a portfolio brings with it several features that investors need to incorporate into their portfolio modelling if they are to gain a more complete picture of their risks and opportunities. The experience of the Financial Crisis highlights that investors should consider the following when modelling illiquid asset classes:

- Breaking the nexus between the fund size and the percentage allocation to illiquid asset classes.
- Incorporating cash flows: Capital calls and distributions, along with growth and income, need to be factored into portfolio modelling.
- Incorporating unfunded commitments into portfolio modelling and stress testing.

Breaking the Nexus Between Fund Size and Percentage Allocations

Assuming an illiquid asset class's weight is fixed as x% of total fund size does not always make sense, as the overall portfolio value can change day-by-day with market moves or cashflows, while illiquid asset values may only be updated once per quarter and can take months or years to rebalance.

Instead, investors should be able to identify which of their asset classes are illiquid and allow their portfolio weights to be determined by how the value of those asset classes move relative to the overall portfolio. This is particularly useful for stress-testing applications as shown in Exhibit 1.

The top panel of Exhibit 1 shows a forecast for fund size and the relative allocation to illiquid asset classes assuming no new investments are made. The bottom panel shows the same charts assuming a market drawdown event in year one. By breaking the nexus between fund size and illiquid asset class weights we can see that overall illiquidity spikes after the fund drawdown in year one. This analysis can also be extended to include the impact of recurring or one-off cash flows into or out of the fund.

Incorporating Cash Flows

An existing portfolio of illiquid asset class investments will have cash inflows (capital calls) and outflows (income or capital distributions) that need to be considered, especially when stress testing. To demonstrate the importance of cash flows in this paper, we use results based on an example multi-asset portfolio from the Jacobi platform that includes four illiquid asset classes – private equity, real estate, debt, and infrastructure.

In the early years of our analysis, both the private debt and infrastructure asset classes are drawing capital from pre-existing commitments, while private equity and private real estate are returning capital. Later in the simulation the private debt portfolio begins returning capital also. These assumptions are easily visualized in the platform as shown in Exhibit 2.

Exhibit 2: Cash Flow
Source: Jacobi. Simulated results only

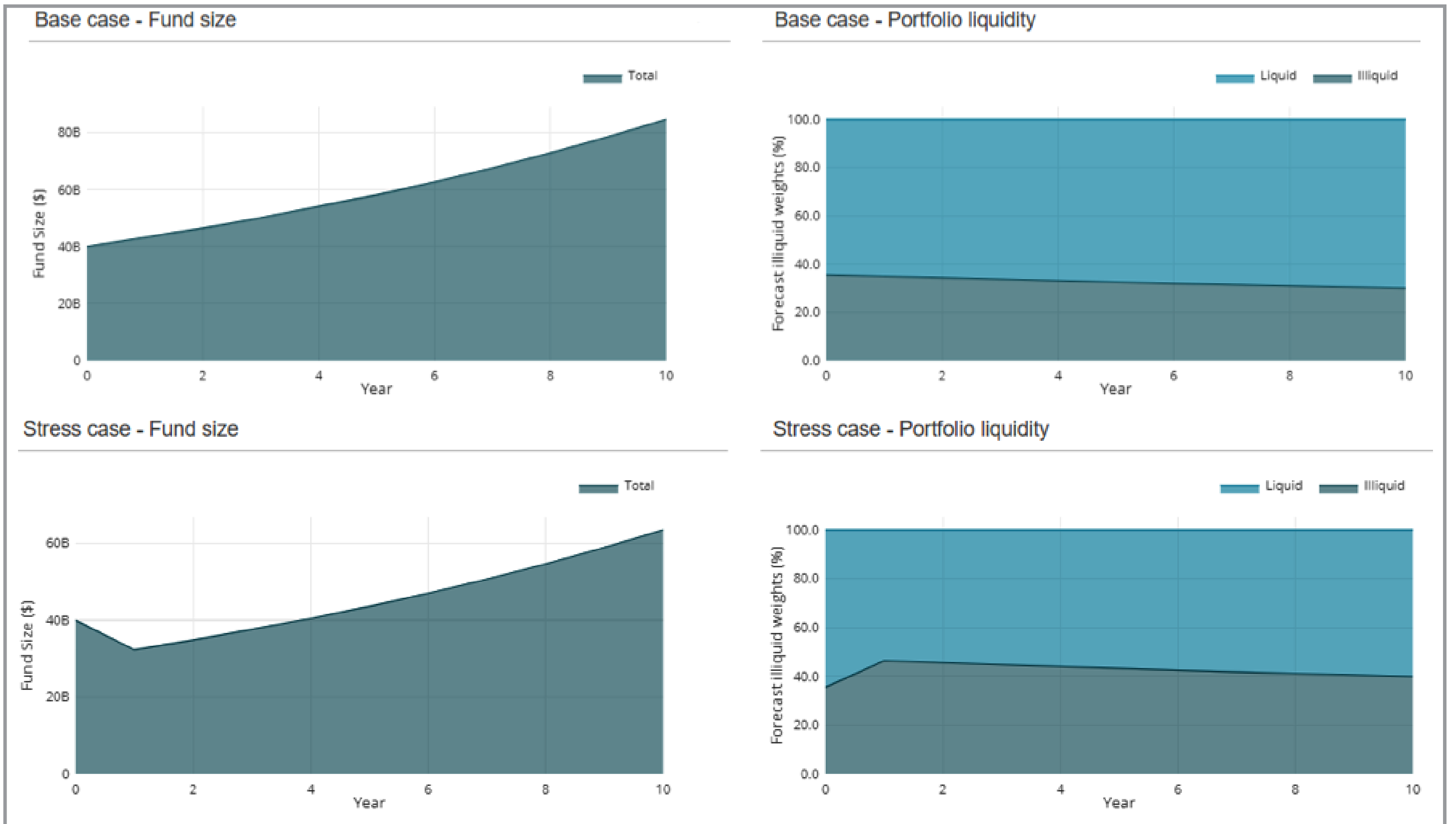

Exhibit 1: Breaking the nexus between fund size and illiquid asset percentage
Source: Jacobi. Simulated results only

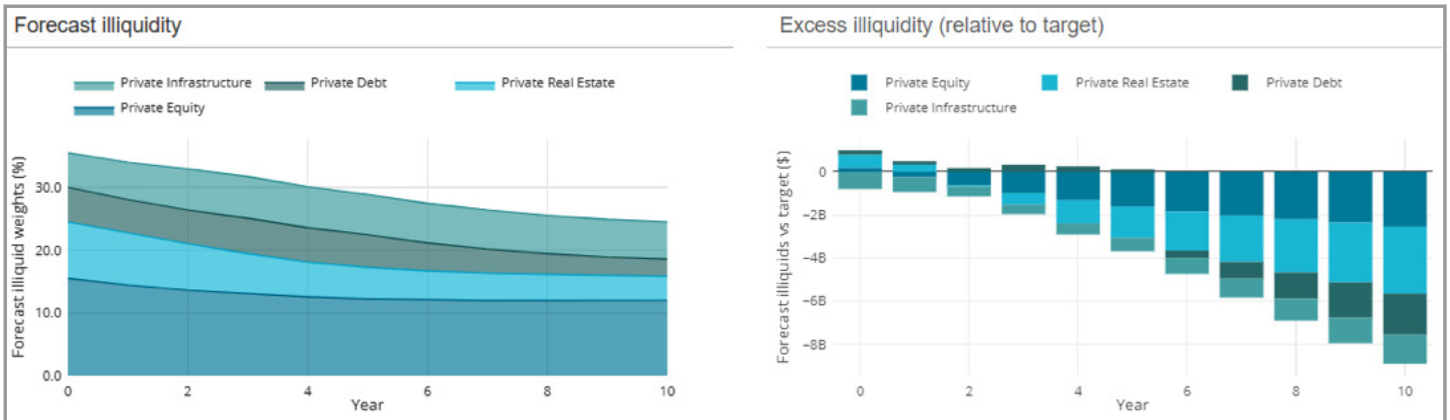

Exhibit 3: Illiquid asset class forecasts with cash flows
Source: Jacobi. Simulated results only

With these assumptions, and splits between growth and income for returns, the investor could forecast their total portfolio volatility as shown in Exhibit 3. The left panel of Exhibit 3 shows the total level of illiquid assets in the portfolio, while the right panel shows the value of illiquid assets relative to the target level.

In this example the weight to illiquid assets falls through time, leading to the portfolio becoming significantly underweight the portfolio targets. Without the ability to incorporate cash flows the modelling would not reflect the extent to which the portfolio was becoming underweight illiquid asset classes. This in turn could result in the portfolio failing to achieve the expected returns and diversification objectives that went in to setting the target weights.

While some investors naturally anticipate the direction of these results, they don't have tools to accurately forecast how much they need to commit/redeem to remain at target weights. This point leads us to the next lesson from the Financial Crisis, the need to forecast and incorporate unfunded commitments.

Incorporating Commitments

Existing commitments can be incorporated into portfolio modelling using the cash flow approach described above. For stress testing and liquidity management purposes the Jacobi platform allows users to have multiple cash flow profiles that can reflect different drawdown rates.

A more interesting application of commitment modelling involves estimating the correct size and pace of future commitments. To maintain illiquid asset classes at their target weights investors continually need to be thinking about the right amount to commit or redeem from their illiquid asset classes. For any given set of circumstances and constraints, Jacobi allows users to solve for the value of commitments or redemptions that best achieves their desired portfolio targets.

Consider again the results shown in Exhibit 3, where the portfolio becomes materially underweight to illiquid asset classes over time. Given a set of target illiquid asset class weights and constraints on what can realistically be committed, Jacobi identifies the commitments shown in Exhibit 4 to minimize variation from target levels of liquidity.

Exhibit 4: Forecast commitments
Source: Jacobi. Simulated results only

Incorporating those commitments gives the total portfolio liquidity and excess liquidity (relative to target) shown in Exhibit 5, next page. Clearly, this framework for incorporating cash flows and commitments can be helpful for identifying the size and pace of commitments that are required to help the fund achieve its illiquidity targets.

No Two Investors and No Two Portfolios Alike

The examples used in this paper are relatively simple to clearly illustrate the concepts being discussed. Behind the scenes, there are a wide range of practical questions that investors need to address for their own circumstances to properly model illiquidity within their portfolios. These include:

- How many illiquid asset classes and sub-asset classes do you invest in? What are your assumptions for return and risk?
- From where are capital calls into illiquid asset classes funded?
- What type of rebalancing occurs within liquid asset classes if illiquid weights deviate from target?
- How are fund commitments in foreign currencies handled?
- What pace of drawdowns/capital return should be assumed across asset classes?
- What is the maximum amount the fund can reliably commit in any given year?

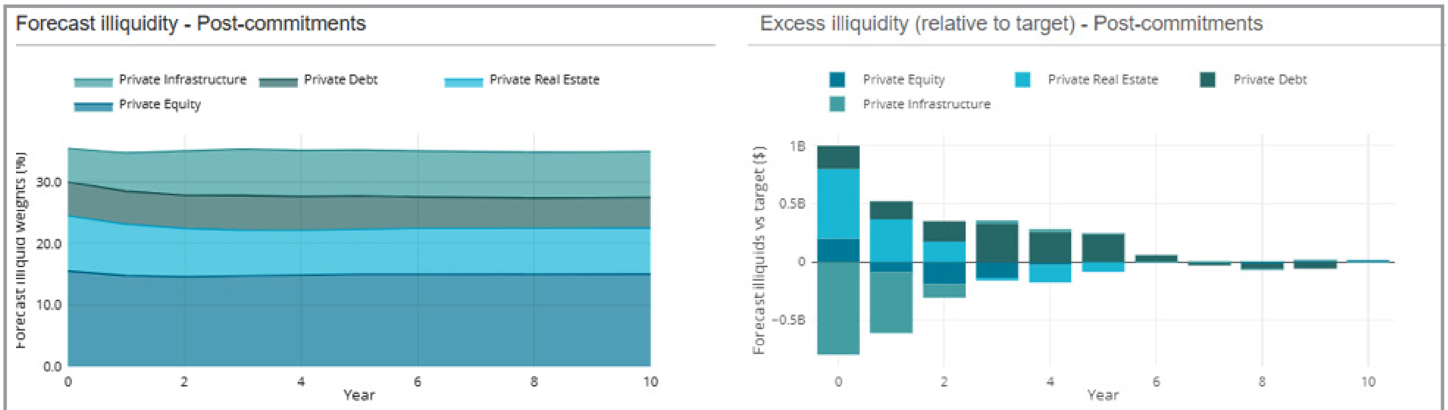

Exhibit 5: Illiquid asset class forecasts with cash flows and commitments

Source: Jacobi. Simulated results only

We believe that investors need to think very clearly about these questions as they relate to their own portfolios, and be wary of generic, one-size-fits-all solutions or industry "short cut" assumptions.

Conclusion

Investing in illiquid asset classes is not a simple endeavour, yet many investors adopt overly simplistic approaches to modelling them and incorporating them into multi-asset portfolios. Key elements that investors should consider for illiquid assets include breaking the nexus between fund size and portfolio allocation, cash flows, and how commitments/redemptions will impact future asset allocation and liquidity.

Incorporating these three elements into a multi-asset portfolio model, especially in conjunction with the ability to stress factors such as fund returns and cash flows, provides a much more robust way to estimate portfolio risk. As simple as this sounds, there are an infinite number of ways in which this type of analysis could be customized for a given investor's situation. Investors therefore need a solution that is highly customizable.

Authors' Bio

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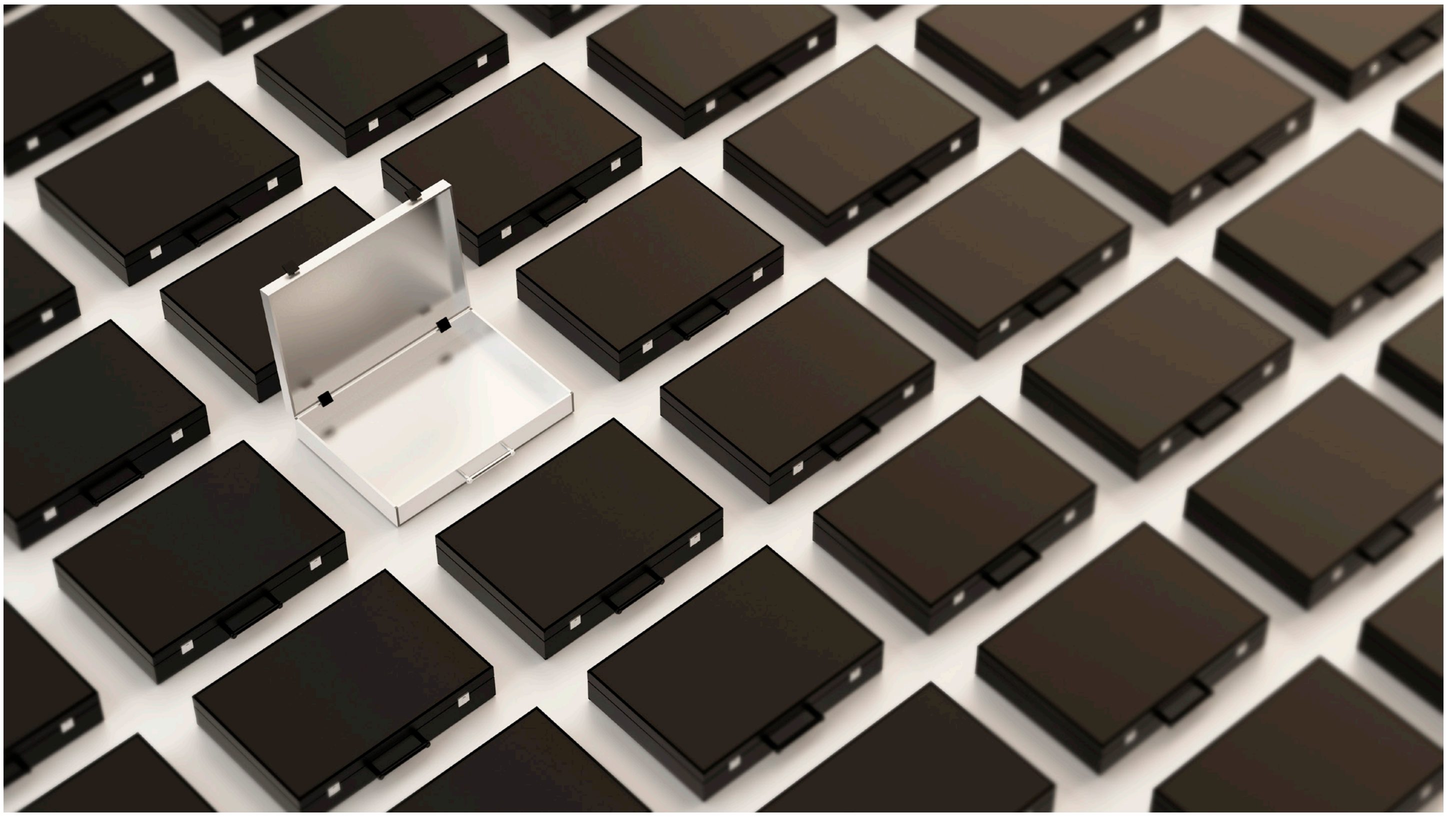
Daniel is a seasoned investment professional with international experience in portfolio construction, risk management and capital markets assumptions. Before joining Jacobi, Daniel was a Senior Strategist at QIC.



Why Should Investors Consider Credit Factors in Fixed Income?

Jay Raol
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A substantial body of academic research and a long track record of use in portfolios has led to a growing acceptance of factor investing within the investment community. Most of the academic research and practical implementation of factors has been done in the equity asset class, where factors have been used to explain equity risk and return. In more than 50 years of research, three general reasons have been given for why factors earn excess returns.

First, factors can earn higher returns given higher risk levels. Second, factors address the collective behavioral biases of investors that result in sub-optimal investing. And third, structural impediments to the efficient use of capital can lead to excess returns. For example, companies downgraded to below investment grade — so-called "fallen angels" — may be off-limits to certain investors but offer opportunities to others. Often, a single factor's return pattern encompasses all three explanations.

Factors Should Exist in All Asset Classes

While factor investing is quite established within equities, there is much less academic research and a much shorter track record when it comes to fixed income portfolios. However, we believe the underlying reasons for factors are not asset class-specific.

Factors simply connect investor behavior to investment returns. As such, there is no reason to believe they cannot be applied to other asset classes, such as fixed income.

However, factors are only recently being harvested in fixed income portfolios. What are the reasons for this lag in adoption? First, fixed income securities are inherently more complex than equities, causing fixed income factor research to be slower to evolve. For example, while equities of one issuer are interchangeable, bonds are typically not. Bonds of the same issuer can have different

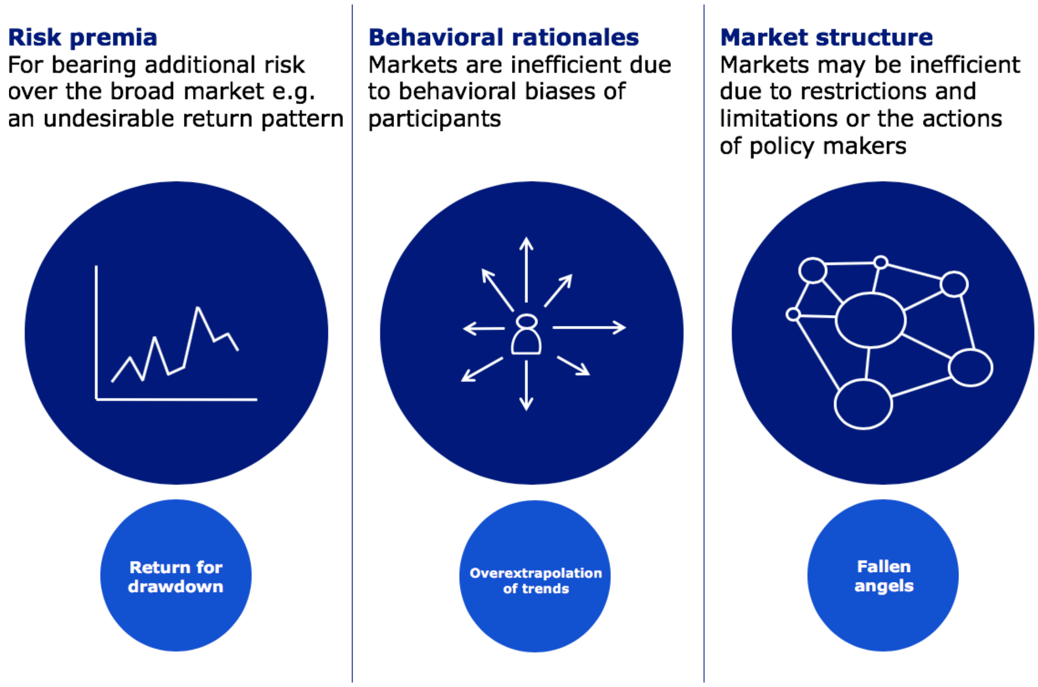

Exhibit 1: Three major reasons for excess returns associated with factors
Source: Invesco.

maturities, levels of liquidity, embedded optionality and can represent different parts of the capital structure.

Second, when interest rates were high, many investors were content to earn returns from coupons, without giving much thought to price appreciation. However, as yields have fallen, factors have become viewed as more valuable in helping to generate returns from prices, and not just from coupons.

Risk Premia Definitions Matter

Many investors have concerns about using factors in fixed income investing. We believe choosing the right factor definitions can improve reliability and comfort around the concept of factors. In our view, risk premia definitions are favorable since they are the most likely to provide attractive long-term outcomes to investors.

Risk premia definitions are based on the rationale that excess returns can be generated by assuming unwanted risks. We believe this fits into an efficient market framework and offers a compelling and consistent approach to understanding asset performance.

A recent review of academic literature confirms this view. Two new studies utilizing robust techniques to guard against data mining confirm that only a few factor definitions have a high likelihood of existence — these definitions are based largely on risk premia.[1] Several authors have also identified a striking relationship between factor strategies with high tail risk and higher Sharpe ratios.[2]

Another advantage of risk premia definitions is gaining more certainty around risk. By pre-identifying the risks inherent in strategies, and not mistaking them for pure alpha, investors can better size these factors in portfolios. For a conservative investor, we believe risk premia-based factors are likely to entail fewer unidentified risks.

Fixed Income Factor Definitions Must Be Carefully Designed to Allow Practical Implementation

There are major differences between equity and fixed income factor investing. The spread of electronic trading, dedicated pools of factor investors and deeper shorting liquidity among equities relative to bonds are among the reasons that equity and fixed income factor implementations differ. Fixed income, generally, has higher transaction costs, lower liquidity and lacks a deep short market, apart from a few types of government bonds.

Higher transaction costs mean that factor returns need to be heavily scrutinized to ensure that their returns are positive and not just trading frictions.

In addition, less liquidity at the bond level means that factor definitions must be robustly designed so that their risk and return characteristics are relatively independent of the number or types of bonds used. Often, only 60% of the bonds desired for a factor portfolio are available for trading. There needs to be some confidence that factor portfolios can be formed given the available liquidity underlying the market. Finally, it is generally difficult to short bonds. Therefore, practically speaking, long-only portfolios are the principal way to gain fixed income factor exposure.

Fixed Income Investors May Wish to Consider Credit Factors First

While we strongly believe that factors can be found in all asset classes, we believe credit offers the best place to start fixed income factor investing. Corporate bonds offer a larger cross-sectional universe from which to build portfolios than government bonds or currencies, facilitating larger, more diversified portfolios that retain mostly factor exposures. Second, given the long-only constraint, we would expect credit beta exposure to be a large driver of returns — credit beta has one of the most consistent Sharpe ratios among all asset classes and clear risk-return characteristics, which build confidence in the likelihood of future excess returns.

Factors in Action — Liquidity, Quality, Value, Momentum and the Multi-Factor Approach

Our research has focused on creating credit factor definitions consistent with traditional equity factors and applying them to corporate bonds. While corporate bonds have traditionally been classified by maturity, rating and industry, we have created a four-factor model that includes liquidity, quality, value and momentum. We briefly describe these factors below. In keeping with our factor philosophy, we describe the fundamental rationale, regime dependency of each factor and consistency of performance across investment grade, high yield and equities, which we believe indicates robustness. Our definitions build on studies found in academic literature, although some key details differ.[3,4,5] Finally, we provide an example of the potential excess return generated by a multi-factor credit model.[6]

Table 1

a. Investment grade

	Index	Liquidity	Quality	Value	Momentum	Multi-factor
Beta	1.00	0.82	0.48	1.17	0.67	0.63
Alpha (bps)	0.00	4.10	2.47	5.96	-0.09	5.02
Turnover (annual %)	19	39	57	269	295	209
Tracking error bps (ER)	0	129	244	126	246	188
Sharpe ratio (ER)	0.18	0.31	0.29	0.34	0.14	0.38
Drawdown (%) (ER)	24	22	14	24	15	14

b. High yield

	Index	Liquidity	Quality	Value	Momentum	Multi-factor
Beta	1.00	0.80	0.64	1.40	0.68	0.71
Alpha (bps)	0.00-	23.28	11.27	3.51	21.27	8.10
Turnover (annual %)	31	85	65	255	276	192
Tracking error bps (ER)	0-	296	386	561	433	324
Sharpe ratio (ER)	0.31	0.54	0.51	0.32	0.61	0.72
Drawdown (%) (ER)	45	38	34	51	33	33

Exhibit 2:
Source: Bloomberg Barclays US Corporate Investment Grade Index (IG Index) and Bloomberg Barclays US Corporate High Yield Index (HY Index), Invesco calculations. Summary statistics are shown for investment grade and high yield factors over the period Jan. 1, 1994 to March 31, 2017. "bps" is basis points. All statistics are in excess returns (ER), or duration-hedged returns. Turnover is calculated as half of the percentage of portfolio buys and sells. The drawdown is calculated from peak to trough over the period. Past performance is not a guarantee of future results. An investment cannot be made directly into an index

Summary of Factor Risks and Returns

Exhibit 2 summarizes the risk and return characteristics of the four factors relative to the Bloomberg Barclays US Corporate Investment Grade and High Yield Indices (IG and HY indices). All the Sharpe ratios, except investment grade momentum, exceed those of the benchmark issue-weighted indices.

Credit Factor Descriptions

Liquidity

We start with liquidity and treat it separately because it is somewhat unique to the fixed income space. The liquidity factor explains the excess risk and return associated with holding illiquid bonds. The liquidity factor is defined by those older bonds that are small in issue size relative to large, newly issued bonds. This factor definition has been well researched.[7]

- In fixed income, illiquid bonds are often not marked to market accurately. As a result, they tend to have higher yields relative to comparable liquid bonds. Historically, they seem to have higher Sharpe ratios (Exhibit 2) without any additional drawdown.
- Exhibit 3 shows the average return of the liquidity factor for both high yield and investment grade bonds in different risk environments, i.e. five different VIX scenarios.[8] Bucket one represents the periods with the largest decreases in the VIX and represents periods when risk sentiment was the best (risk-on). Bucket five represents the periods with the largest increases in the VIX and represents periods when risk sentiment was the worst (risk-off).
- The returns are plotted in terms of duration-hedged excess returns versus the benchmark returns. The benchmarks used were the Bloomberg Barclays US Corporate Investment Grade and High Yield Indices for the investment grade and high yield liquidity factors, respectively.

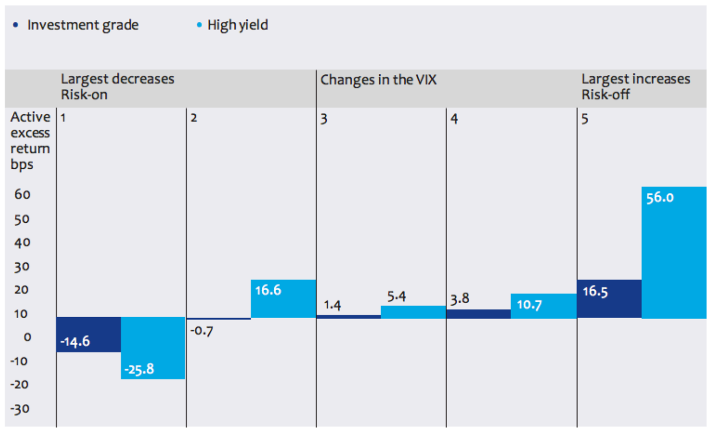

Exhibit 3: Liquidity factor excess returns in different VIX Scenarios:
Source: Bloomberg Barclays US Corporate Investment Grade and High Yield indices, Invesco calculations. The scenarios were during the period January 1, 1994–March 31, 2017. The average return of the liquidity factor in both high yield and investment grade is plotted for five different scenarios of VIX changes. Bucket 1 represents the periods when the VIX decreased the most and, therefore, represents periods of very positive risk sentiment (risk-on). Bucket 5 represents the periods when the VIX increased the most and, therefore, represents periods of very negative risk sentiment (risk-off). The returns are duration-hedged returns (excess returns), relative to the respective benchmark returns (active returns). The benchmarks used were the Bloomberg Barclays US Corporate Investment Grade and Bloomberg Barclays US Corporate High Yield Indices.

Contrary to the idea of a higher "risk premium" driving higher returns, the liquidity factor outperformed during periods of extreme market stress (bucket five). However, in reality the risk is significant, in that it is extremely likely that selling an illiquid bond during times of market stress would result in a significant loss. The scenario analysis returns only accrue to buy-and-hold investors. Therefore, only investors who can hold illiquid bonds through market turmoil would be able to harvest higher Sharpe ratios.

Quality

The quality factor explains the higher risk-adjusted returns associated with holding low volatility, bonds, as is widely observed in the academic literature.[9] These are typically shorter-maturity bonds with low default risk, as measured by their credit ratings. The quality factor is a characteristic of securities that tend to be good stores of value during times of market stress since they demonstrate low volatility. Exhibit 4, (a-c) shows that the quality factor consistently outperformed during periods of market stress across the three asset classes. Conversely, quality underperformed during market rallies. in Exhibit 2 shows that the quality factor earned risk-adjusted alpha and had a higher Sharpe ratio than the market index of each asset class. Since the quality factor typically underperforms during market rallies, it must offer a higher Sharpe ratio to compensate investors for this trade-off.

Value

The value factor explains the excess return obtained by holding assets that are priced at a discount relative to other similar securities. Since a bond's price is a function of its default risk, it makes sense to look for those bonds that are priced at a discount relative to their implied default rates. Exhibit 2 shows that the value factor earned risk-adjusted alpha and had a higher Sharpe ratio than the market index. Exhibit 4 shows that the value factor provided strong Sharpe ratios in compensation for the materially larger tail risk during times of market stress.

Momentum

The momentum factor explains the return of past winners versus past losers. Momentum produced the weakest Sharpe ratios in investment grade (Exhibit 2), especially using definitions most consistent with traditional equity momentum factors. This is partly because bonds can only appreciate by so much, especially investment grade bonds with prices already close to par. As a result, bonds have a different time horizon and structure than equities. More speculative bonds have the strongest Sharpe ratios using the equity-based definition due to the role of price appreciation in their returns.[10] Our analysis indicates that momentum offers diversification benefits,[*] which can lead to improved Sharpe ratios in the case of multi-factor portfolios.

Comparing Quality, Value and Momentum Factors in Different Risk Environments

Exhibit 4 (a-c) shows the performance of the quality, value and momentum factors across five different VIX scenarios for high yield, investment grade and equities. There is a striking similarity

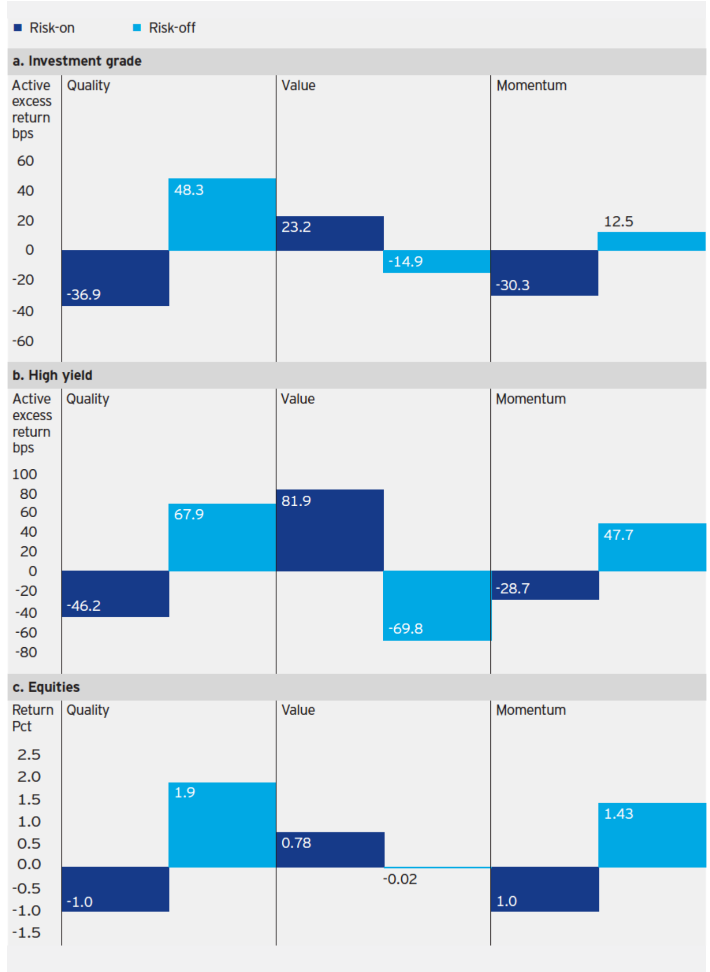

Exhibit 4 (a-c): Average excess returns of quality, value and momentum factors in high yield, investment grade and equities, corresponding to historical changes in the VIX
Source: Bloomberg Barclays US Corporate Investment Grade and High Yield indices, CRSP US Stock Databases, Invesco calculations. Scenario returns were calculated from January 1, 1994–March 31, 2017. "bps" is basis points. For the equity factor returns, "Quality" is taken from Frazzini, Andrea and Lasse H Pedersen, "Betting Against Beta", Journal of Financial Economics, 111, 1–25, 2014. The value factors taken from Asness and Frazzini, "The Devil in HML's Details," Journal of Portfolio Management, 29, 29–68, 2013. The momentum factor is based on Fama and French, "Multifactor Explanations of Asset Pricing Anomalies," Journal of Finance, 51, 55–84, 1996. The returns are duration-hedged returns (excess returns), relative to the respective benchmark returns (active returns). Indices utilized are the Bloomberg Barclays US Corporate High Yield Index and the Bloomberg Barclays US Corporate Investment Grade Index. The dark blue bars represent periods when the VIX decreased the most and represents periods of very positive risk sentiment (risk-on). The light blue bars represent the periods when the VIX increased the most and represents periods of very negative risk sentiment (risk-off).

in the conditional correlations, or return patterns, of the factors across the VIX scenarios and the three asset classes. Quality and momentum were positively correlated to each other but negatively correlated to risk sentiment — they had the highest return periods when risk sentiment was the lowest (risk-off).

Value was negatively correlated with quality and momentum and negatively correlated with risk sentiment — value tended to have its highest return periods when the VIX was decreasing the most (risk-on). We believe this consistency suggests that our definitions reflect the generation of a common value risk premium across all three asset classes.

Benefits of a Multi-Factor Portfolio

Exhibit 2 shows that our factors helped generate higher Sharpe ratios over the period shown, underscoring their diversification benefit. However, single factors can experience long periods of underperformance or outperformance. Therefore, we believe it is valuable to take a balanced, multi-factor approach to help ensure consistent outperformance. For simplicity, we show the return profile and attribution of an equally weighted multi-factor portfolio.

Exhibit 2 shows that, in both high yield and investment grade, the multi-factor portfolio produced higher Sharpe ratios without adding a significant amount of downside risk.

Factors are Always Evolving and Require Continuous Research and Active Management

We end our discussion of factors with a word of caution and stress the need for continuous research. It is very likely that factor investing will change the landscape of more fundamentally based investment strategies. As more players adapt to factor-based investing and asset markets evolve, we believe factor definitions and their risks and rewards must be continuously updated to ensure their appropriate use in portfolios. This is particularly true for non-risk premia-based factors, i.e. factors based on behavioral or market structure rationales.

To illustrate, we offer the example of the "fallen angels" factor. A fallen angel is a bond that has been downgraded from investment grade to speculative grade. Because many investors are prohibited from investing in speculative bonds, there can be short-term excess selling pressure around the time of a downgrade, which has historically allowed eligible buyers to realize excess returns. But this pattern may be coming to an end. Exhibit 5 shows the average performance of fallen angel bonds before and after a downgrade, relative to the performance of similar bonds. As shown in Exhibit 5, since 2010, there has been a meaningful reduction in relative returns earned following a downgrade announcement. At the same time, the market value of fallen angel bonds has shrunk from an average of 8% of the speculative market in 1990–2009 to an average of around 2% since 2010.[10] This illustrates one of the challenges of depending on market structure-based factors, which can decrease in effectiveness over time.

Due to such challenges, we believe it is important to constantly re-evaluate risk premia-based factors. Doing so can detect shifts in investor attitudes toward risk and return to determine a factor's likely persistence. We believe such continuous research and active management are necessary to ensure that investors earn the returns they expect from their factor portfolios.

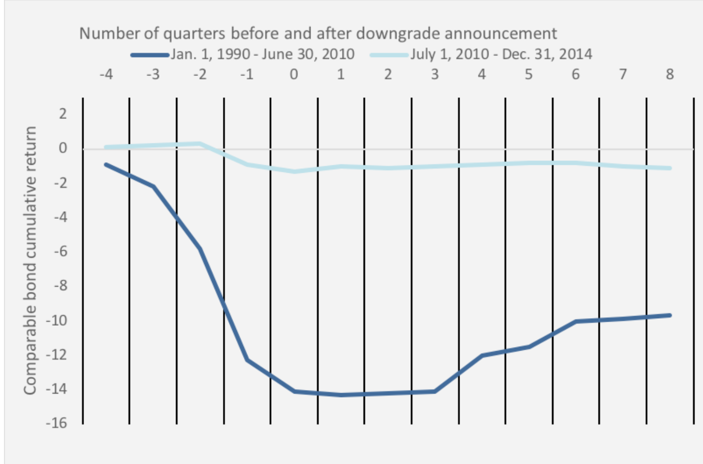

Exhibit 5: Cumulative Returns of Fallen Angel Bonds Compared to Returns of Similar Bonds Before and After Downgrade Announcement

Source: Ben Dor, Arik and Xu, Zhe, "Revisiting the Performance Dynamics of Fallen Angels," Quantitative Portfolio Strategy, Barclays Capital, 2015. The exhibit reports the performance of issuers by quarter relative to the downgrade month (defined as quarter zero). The return of each issuer is compared to the contemporaneous return of a peer group with similar characteristics ("relative returns") based on industry (financials, industrials, and utilities), credit quality (A and higher, Baa, Ba, B, and Caa and lower), and maturity (less than 10 years and greater than 10 years). Cumulative relative returns were calculated by averaging issuers' relative returns by month and then cumulating them from the beginning of the analysis window. Cumulative relative returns are reported as of the end of each quarter

Conclusion

We believe the adoption of fixed income factors allows investors to better decide which risks and returns are appropriate for their portfolios. However, by altering investor behavior, factor-based investing may also alter the risk-return landscape. At IFI, we are constantly adapting our factor framework and investment processes in order to stay ahead of these trends to help clients achieve their financial goals. In future discussions, we will demonstrate practical applications of credit factors in portfolio construction and risk mitigation.

Disclaimer

* Diversification does not guarantee a profit or eliminate the risk of loss.

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Endnotes

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4. Houweling and van Zundert (2014), "Factor Investing in the Corporate Bond Market," Working Paper.

5. Bai, Bali and Wen (2016), "Common Risk Factors in the Cross-Section of Corporate Bond Returns," Working Paper.

6. We constructed factor portfolios by market value weighting the top quintile of portfolios ranked by factor score (for example ranked by value score). The constituents of the Bloomberg Barclays US Corporate Investment Grade and High Yield Indices were used in factor construction from the period January 1, 1994 to March 31, 2017. For the construction of factors excluding liquidity, bonds were first screened for liquidity by keeping only the top 60% and 30% in bond size each month for investment grade and high yield, respectively.

7. Bao, Pan and Wang (2011), "Liquidity in Corporate Bonds," *Journal of Finance,* 66, 911–946.

8. The VIX is an index calculated by the Chicago Board Options Exchange, often referred to as the "fear" index. It represents one measure of the market's expectation of future stock market volatility.

9. For example: Frazzini, Andrea and Pedersen (2014), "Betting Against Beta," *Journal of Financial Economics*, 111, 1–25. Low volatility bonds are typically characterized as bonds with short maturities and low default risk.

10. Lin, Wu, and Zhou (2016), "Does Momentum Exist in Bonds of Different Ratings?" Working Paper.

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Jay Raol is the Director of Quantitative Research for Invesco Fixed Income (IFI). His team leads the research that underpins IFI's quantitative factor-based strategies across fixed income asset classes. In addition, he also leads the development of the quantitative tools that support the macro research process and factor-based portfolio construction process across the IFI platform. Mr. Raol has been in the industry since 2010. His experience has spanned across functions including quantitative macroeconomic analysis, portfolio construction and risk management. Prior to joining IFI in 2013, Mr. Raol worked within Invesco's risk management group for three years, where he ran the risk analytics function for several large equity funds. Mr. Raol earned a BA degree and a PhD in computational and applied mathematics from Rice University in Houston, Texas. Jay is a CFA Charter holder.

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Mr. Pope joined Invesco in 2013 as a fixed income risk analyst. He previously served as an analyst at Cambridge Systematics. Mr. Pope earned BS and MS degrees in civil engineering from the Georgia Institute of Technology. In addition, he earned an MS degree in quantitative and computational finance from the Georgia Institute of Technology. Shawn is a CFA charter holder.

Enhancing Private Equity Manager Selection with Deeper Data

Cameron Nicol
eVestment

While all institutional investors strive to predict and select top quartile private equity funds, there is a significant cost of missing out on these funds. According to various research studies, the difference between being invested in a top quartile and bottom quartile private equity fund has a significant impact on fund returns,[1] reported at as much as 16.9 percentage points in one study.[2]

What's more, is that achieving top quartile returns is crucial for investors' private equity portfolios to justify their place as a return enhancer relative to other asset classes. From 1980 through 2012, only those funds in the top quartile have produced returns clearly over and above those of public markets when a three-percent illiquidity premium is applied to an index (Exhibit 1, on next page).

The Myths of Gaining Top Quartile Returns

Preferential access to brand name managers is often cited as a common driver in private equity portfolio returns. Investors that have missed out on debut funds, or investors with smaller allocations, often perceive that they are unable to get into these funds and thus capture those returns. However, a recent study by Daniel Cavagnaro, Berk Senoy, Yingdi Wang and Michael Weisbach has busted those myths.[3]

Cavagnaro et al. analyzed a data sample of over 12,000 fund investments made by 630 limited partners (LPs), looking at the distribution of the returns. Their findings suggest that an investor's skill level in fund selection is a more important driver of their returns, than luck or access to managers. An increase of "one standard deviation in skill" leads to a three percentage point increase in

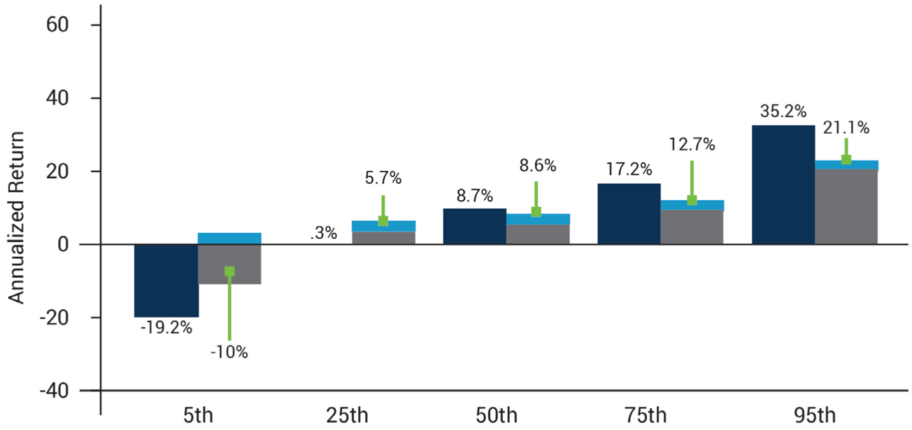


Exhibit 1: Private Equity Results are Highly Dependent on Quality of Manager-Selection Decisions-Jan. 1, 1980 Through Dec. 31, 2012
Source: The Allure of the Outlier, Vanguard, 2015

annual internal rate of returns (IRRs) according to the findings. Simply put, the ability to boost private equity portfolio returns is in the LP's hands.

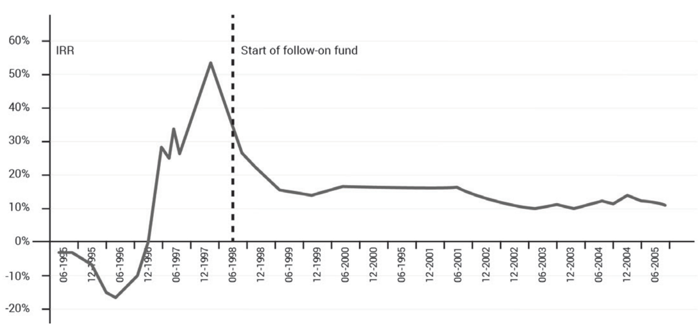
With this finding in mind, eVestment has compiled research, analysis and insights from the institutional investment community to provide valuable information on some of the key factors contributing to a truly skillful private equity manager selection process.

What Can You Do to be More Skillful in Fund Selection?

Realize the Importance of the Unrealized

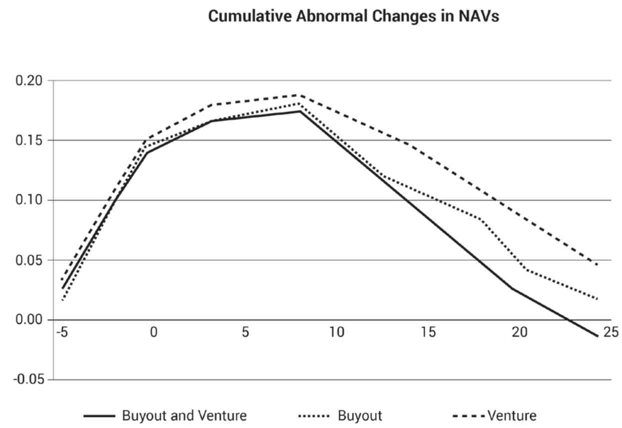
When private equity firms come back to market with a new fund, their track record will be comprised of a combination of realized and unrealized returns. With investors having to make investment decisions based on unrealized performance, investors must assess managers' NAVs with a level of scrutiny.

Figure 1 = IRR Development of an Exemplary US Buyout Fund



This figure shows the development of a U.S. buyout fund's IRR over its lifetime. The fund itself started investing in 1995. Its follow-on fund had its first close in the second quarter of 1998.

Exhibit 2: IRR Development of an Exemplary US Buyout Fund
Source:: How Fair are the Valuations of Private Equity funds? Jenkinson et al., 2013



This figure follows the cumulative abnormal annual changes in the sample fund's valuations around the first close of the follow-on fund for all corporate private equity funds, as well as buyout and venture funds separately.

Exhibit 3: Cumulative Abnormal Changes in NAVs
Source: Jenkinson et al., 2013

Research by Jenkinson, Sousa, and Stucke[4] in 2013 found that while private equity valuations are generally conservative and understate subsequent distributions over the life of a fund, this does not hold true when follow-on funds are being raised. Their research suggests that there is no statistically significant relationship between IRRs reported on fund n – 1 at both four and two quarters before a manager holds a first close on fund n, and the final performance of fund n – 1.

While Jenkinson et al. highlight this using what they even deem to be an extreme example (Exhibit 2) their results suggest that it is "by no means an isolated case" as displayed in the cumulative NAV data (Exhibit 3).

This may not be intentional or artificial NAV inflation by the managers, but could simply be a result of managers choosing to return to market when they can point to a strong track record. Jenkinson, Sousa, and Stucke suggest LPs should carefully consider the weight they put on IRRs reported by managers during fundraising that contain portions of unrealized investments. They suggest using public market equivalent analysis instead of IRR in this evaluation, as their research showed that this increases predictability of future performance significantly. To combat the potential inaccuracies of NAVs at fundraising, eVestment's limited partner clients are increasingly using eVestment Private Markets' What-if Analysis module to model the unrealized element of the portfolio under different scenarios to quantify the potential final performance. More sophisticated clients are also analyzing the NAVs of the unrealized deals at the time of the last fundraising compared with their eventual realized proceeds to gauge the level of NAV realism produced by a manager.

Reconsider Your Re-Ups

Even if a private equity manager can sustain top quartile NAVs through to exit, LPs should consider putting as much scrutiny on a re-investment with this manager as when considering a GP in the second or third quartile with their latest fund: only 19% of buyout funds raised after 2001 that were a successor to a top quartile performer have repeated this level of performance, showing a lack of persistent returns.[5]

This research has also been carried out separately by other groups including McKinsey.[6] Their analysis shows similar results – that top quartile persistence is low and has been steadily decreasing in more recent vintages (Exhibit 4). Interestingly, the only place where performance is persistent is for those producing bottom quartile funds.

It seems many investors understand the importance of thorough due diligence no matter the past relationship. In eVestment's 2018 survey of leading investors and consultants, the average number of days spent on due diligence of a re-up was 21 days, compared with 40 days on a new manager relationship.[7] While a difference is present, part of the shorter time frame may be explainable by the readily-available access to data for an existing relationship as opposed to the process of requesting and preparing data from a new manager relationship.

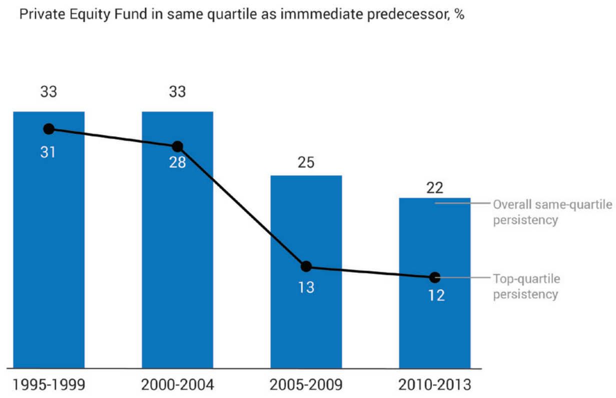
Trust but Verify Performance Numbers

Not all IRRs are created equal, and the majority of investors find this to be a challenge. In a 2018 survey, eVestment found that 61% of investors believe it is difficult to compare one manager's performance to another's on a fair and consistent basis.[8]

The best practice for investors is to use deal-level cash flow data to recalculate manager performance to address this challenge. According to eVestment's survey results, 75% of LPs recalculate manager performance more often than not. This is done in an attempt to ensure performance is calculated on a consistent basis for more accurate comparison, more informed decision making and compliance with fiduciary responsibility.

Determine the Impact of Credit Facilities

The increased use of credit facilities is also having a major impact on the industry's view of manager-reported IRRs. Credit facilities, also referred to as subscription lines, can be perfectly valid as an efficient fund management tool to ease the burden on LPs in



Note: Persistency is measured with immediate successor fund (eg. Asia Buyout Partners IV would be successor to Asia Buyout Partners III.

Exhibit 4: Persistency of Performance is Still Falling

Source: Global Private Markets Review, McKinsey, 2017

responding to short drawdown notices and allowing the manager to move quickly on deals.
That said, it is imperative to strip out the impact of credit facilities by recalculating managers' performance using their gross level cash flow data to ensure that comparisons are being made on a truly like-for-like basis.

This also highlights the importance of not just looking at IRR in isolation, but considering many other metrics to determine the real value produced by the manager. The caveat to this is that recalculating performance can be a very time-consuming process, which is why so many investors are switching to using dedicated private equity performance analytics software.

Perspectives From Leading Investors And Consultants

Q: Why do you recalculate private markets fund manager performance?

"I don't trust the hyperbole – 'top quartile.' I always test that against benchmarks."
>$3B Investment Consultant

"We recalculate as often as we can, and have found numbers almost always materially identical. However, managers will certainly cherry pick elements of their track record. So the issue isn't as much inaccuracy or misrepresentation as it is selective representation. Getting the entire attributable track record is key."
>$2B North American State Pension

"To independently verify the manager's performance figures, perform cross-sectional analyses, etc."
>$3.5B Consultant

"Little differences in timing and qualification of cash flows add up to meaningfully influence the performance figures."
>$12B Insurance Company

"By recalculating, you can determine the impact that bridge loans or credit facilities can have on the numbers."
>$1.5B North American State Pension

Find the Value Drivers

Looking just at IRRs, multiples and other headline numbers tells investors very little about the manager, their performance and their ability to repeat this – a point highlighted by the research around persistence of performance, credit facilities and more. Along with recalculating headline performance metrics to ensure consistency and standardization, LPs must gather granular data from managers in order to validate future strategy and make truly informed decisions.
In fact, Korteweg and Sorensen suggest that the reported drop in persistence of GP performance explains why LPs have increased their focus on looking beyond just high level returns and are now collecting more detailed information,[9] including performance at the deal and partner level to fully evaluate the repeatability of a GP's past fund returns.

Breaking down the key drivers of past success is one of the first ports of calls for sophisticated investors: a quarter of investors and consultants cited factors relating to this area as extremely important during their track record analysis.[10] (Exhibit 5).

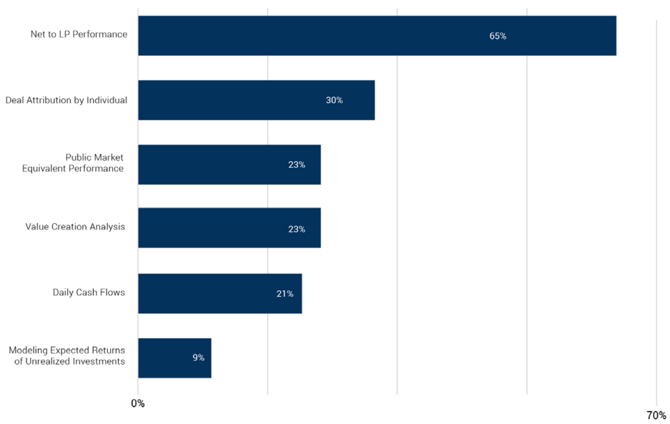


Exhibit 5: Factors Extremely Important to Investors and Consultants in Track Record Analysis
Source: Private Markets Due Diligence Survey, 2018

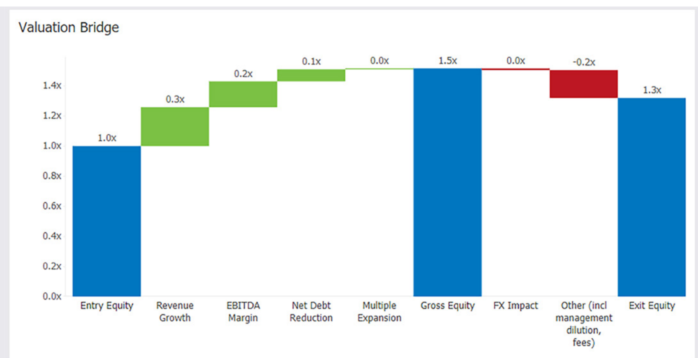


Exhibit 6: Valuation Bridge Analysis
Source: : eVestment Private Markets

	Smallest Market Cap	Median Market Cap
S&P 500	$2.7B	$20.0B
MSCI World	$1.2B	$9.4B
Russell 3000	$144M	$1.6B

Key Value Creation Analysis Techniques

Valuation Bridges: Valuation Bridges attempt to quantify the drivers of value and attribute them to certain key areas. From analyzing this at a fund level and individual deal level it is possible to gauge whether value was delivered through operational improvement, market dynamics, financial engineering and/or M&A activity. Investors then seek to evaluate how this compares to the future or current strategy of the manager. (See Exhibit 6, below)

Sensitivity Analysis: Another key area to focus on is understanding what deals have driven a fund manager's performance and how sensitive the fund level performance is to them.
This can be done through simple exclusion of specific deals based on IRR, TVPI, size etc. More sophisticated approaches include the use of box plots, return curves and impact charts to determine what proportion of deals have had a positive or negative impact on performance. (See Exhibit 7, next page)

Public Market Equivalent Analysis: While valuation bridges can help identify market dynamics such as multiple expansion, it can be difficult to identify if this is down to buying cheaply or a rising market. Public Market Equivalent (PME) analysis helps identify whether the manager has benefited from a general uptick in markets or has truly outperformed through skill in deal selection and/or operational improvements.
Market timing is not necessarily a bad strategy, and could be part of a manager's skill set, but it is crucial to understand how it has influenced returns. (See Exhibit 8, next page)

Identify Alpha Through Public Market Equivalent Analysis

Public market equivalent (PME) analysis is becoming standard practice in LP's due diligence and portfolio monitoring: eVestment's 2018 survey found that 72% of respondents carried out PME analysis and 52% were expecting to increase their use of it.[11]

While it is undoubtedly a useful tool to overcome some of the pitfalls of traditional benchmarking (such as the opaqueness of IRRs) and gain an understanding of a manager's value creation skills, the effectiveness of this analysis can depend heavily on the PME calculation methodology used and also the index it is benchmarked against.

Impact of Index Selection

Often, private equity's performance is compared to returns of the S&P 500 or MSCI World – most benchmarking reports reference this. However, the median market cap of the S&P 500 is $20B, and $9.4B for the MSCI World,[12] yet 95% of buyouts from 1993 to 2010 were below $1.08B in value.[13]

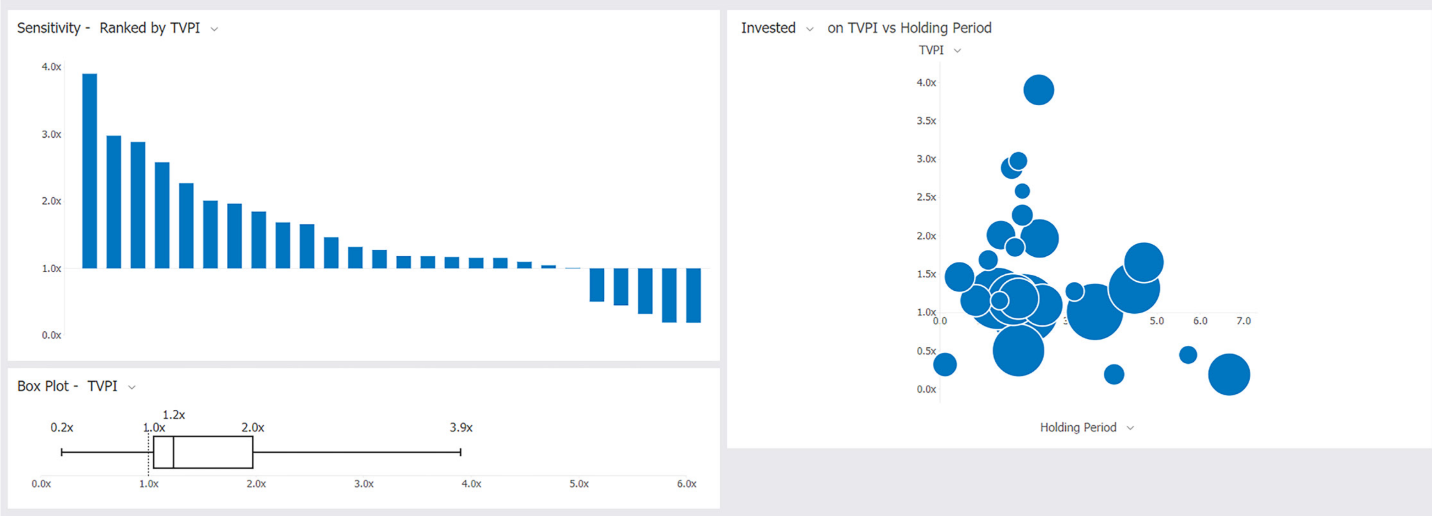


Exhibit 7: Sensitvity Analysis
Source: : eVestment Private Markets

TVPI 4.4x / IRR 36.0% (Net Cash Flows)	Time Weighted Return (Absolute Outperformance)		Modified IRR (Absolute Outperformance)		PME (Absolute Outperformance)		PME+ (Absolute Outperformance)		Direct Alpha	
S&P 500 COMPOSITE RI	3.6%	▲ +32.4%	11.8%	▲ +8.2%	2.3%	▲ +33.7%	9.3%	▲ +26.7%	31.5%	▲
RUSSELL 3000 RI	4.3%	▲ +31.8%	12.4%	▲ +8.1%	2.7%	▲ +33.3%	9.7%	▲ +26.3%	30.9%	▲
NASDAQ COMPOSITE RI	6.8%	▲ +29.2%	14.5%	▲ +7.7%	6.6%	▲ +29.4%	11.1%	▲ +24.9%	27.1%	▲
S&P Listed Private Equity $ RI	5.2%	▲ +30.8%	13.7%	▲ +8.5%	0.8%	▲ +35.2%	8.9%	▲ +27.2%	29.7%	▲

Exhibit 8: Public Market Equivalent Analysis
Source: : eVestment Private Markets

When trying to assess opportunity cost of private equity, are these indices most appropriate? The Russell 3000 is perhaps closer to the size of a PE deal given the median market cap. Those carrying out PME analysis should also consider if a sector-focused index is appropriate if the manager is a specialist.

Methodologies

Since the PME methodology was first proposed by Austin Long and Craig Nickels in 1996, various iterations have been developed to counter some issues with this methodology. Read the full description of each methodology in the Appendix.

While many methodologies exist, there is not one industry standard. In an eVestment survey, it was discovered that that 54% of respondents use more than one methodology.[14]

As shown in Exhibit 9, the most popular PME methodology used by respondents to the 2017 eVestment survey was Kaplan-Schoar, with 48% using it. Direct Alpha, the newest of the methodologies, was used by 35% of respondents.

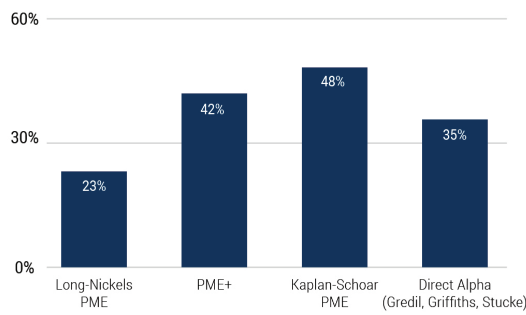


Exhibit 9: Most Popular PME Methodologies Used by Investors and Consultants
Source: : eVestment, 2018 Private Markets Due Diligence Survey

So Which Methodology Should LPs Use?

There is no "right" answer and so it highly depends on why PME is being used – is it to evaluate opportunity cost of an existing private equity portfolio? Is it to benchmark prospective managers? Is it to evaluate if PE investments are worth the PE-level fees?

LPs should consider these questions and evaluate the nuances of each methodology in depth to decide which methodology, or methodologies, are most appropriate.

Understand the People

Even though the industry has changed dramatically since its genesis, one of the old adages about it still rings true: private equity is a people business. eVestment's 2018 Private Markets Due Diligence survey found 79% of investors believe assessing a GP's team to be an extremely important aspect of their due diligence,[15] and understandably so. At the end of the day, investors are investing in a blind pool and entrusting a group of investment professionals to make good decisions on their behalf. During a webinar hosted by eVestment and Privcap that included representatives from StepStone and HarbourVest, industry practitioners shared key tips and best practices for how to carry out a comprehensive evaluation of a team.[16]

Leverage Quantitative Data for Better Qualitative Processes

The track record is never the end of due diligence – it won't answer all the questions, but it does provide the questions you need to ask in qualitative assessments, especially about the team.

Integrate Your Data

Data is important – it is the integration of the quantitative assessment and qualitative work that get you to the end conclusion.

Investing in PE is a mosaic. You've got lots of little tiles, lots of little pieces that you're trying to assemble together to get an overall picture of what the investment opportunity looks like, and that quantitative data helps you to assemble a lot of those little pieces to the puzzle.

Be Thorough, but be Efficient

Data really helps us ignore the "known knowns", so that we can truly focus on the list of questions from a qualitative perspective that the quantitative side have just eliminated. The trick is to make sure that you don't spend too much time on data risking the loss of too much qualitative time on the team itself.

As with all aspects of due diligence, it can be time consuming without the right tools, which is why more and more LPs are utilizing dedicated performance analytics tools to make quantitative due diligence more efficient, allowing them to spend more time on qualitative aspects.

Attributing Performance

Like looking at the effect of certain deals on overall performance, it is imperative to attribute fund performance back to the individuals within the team. If they are the ones managing the fund going forward, you must ensure you validate their skill set. What's more is that while fund structures last over a decade, team tenure may not always be as long-term, so understanding the history of the current team is important.

Key Questions to Ask PE Fund Managers About Performance

- Is the performance generated by the team balanced across the team?
- Is it skewed to certain individuals?
- How does this look across geographies and sectors?
- Are the current partners really the ones that are responsible for that track record, or is it people who have retired or left the organization?
- Has strong performance in early funds by retired professionals propped up an overall track record?

Team Dynamics

Understanding how a team works together is a crucial factor, but not always easy to uncover. Investors need to know the set of questions they are going to ask ahead of time, as well as the methods of getting the answers. Tapping multiple sources of information is crucial in this stage to get well-rounded and accurate information on the area of the team you're investigating. Sources can include interviews with the team, but also reference calls to other limited partners, portfolio companies and previous firms, of which the importance was highlighted by one panelist: *It's amazing some GPs put CEOs on their reference list, and when you actually talk to them, they give a reference on something completely different.*

Key Questions to Ask PE Fund Managers About Team

- What is the length and the quality of experience of the team?
- How is the team cohesiveness?
- How are they structured to share information with each other? How do they leverage the knowledge of the entire team.
- How do they source deals – what is their network like?
- How do they evaluate if investment opportunities in one of their target geographies or sectors are as good as those in another?
- Do they have bandwidth? What kind of capacity do they have when they're raising a new fund, to invest that fund?
- What are the assets under management per partner?
- How many board responsibilities do they have?
- What are the succession plans? Are there mentoring programs to develop leaders and investors?

Conclusion

The importance of selecting top quartile private equity funds has never been more clear – there is a significant cost of not being in these funds and historically those below the top quartile have not materially outperformed public markets. To justify the increases in allocations, its place as a return enhancer, and the fees, a private equity portfolio must materially outperform relative to public markets.

However, investors are faced with substantial challenges in fund selection: persistence of managers' top quartile performance is low and headline metrics are increasingly opaque, which means metrics such as IRRs and multiples can't be taken at face value or solely relied upon as accurate indicators of future performance.

Fortunately for investors, the power to build a leading private equity portfolio is in their hands and achievable through a more skillful due diligence process, not merely luck or preferential access to managers as is commonly cited.

Investors need to leverage quantitative data as a foundation to their due diligence process. Importantly, they need to look beyond headline numbers and into a variety of metrics and performance statistics across a manager's track record to understand how they created value, what their skillset is, and how this aligns with the strategy of the fund they are evaluating. They also need to collect detailed cash flow data to enable them to recalculate and standardize manager performance for truly like-for-like comparisons.
Yet this level of due diligence be challenging if relying on spreadsheet-based processes for track record analysis.

It can make a process prone-to-error, inefficient and not effective, with quantitative due diligence hindering the full due diligence process rather than helping it.

By using dedicated private equity performance analytics tools, such as eVestment Private Markets, investors can make track record analysis much more efficient and more valuable by being able to easily extract important insights for more informed fund selection.

Appendix

PME

First proposed by Austin M. Long and Carig J. Nickels in 1996 (A Private Investment Benchmark). They called it the ICM method (Index Comparison Method). Also known as the Long Nickels PME or LN-PME.

Creates a theoretical investment into the selected benchmark using the actual cash flows. Each Contribution is invested in the index and each distribution is treated as a sale out of the index. This results in a theoretical NAV, which is substituted in place of the actual NAV in order to calculate an IRR.

The PME result is directly comparable to an IRR and so outperformance is measured against the IRR. Where the fund significantly outperforms the selected benchmark it can result in a short in the index and a negative value, which is not appropriate for calculating a PME result.

Modified IRR

The MIRR (Modified Internal Rate of Return) is a modification of the IRR with the intention of resolving the associated issues of the finance rate and re-investment rate.

All contributions are discounted back to the initial cash flow date by the growth in the selected benchmark. All distributions are discounted forward to the final cash flow date by the growth in the selected benchmark.

The annualized performance can then be calculated using these two values as you would a Time Weighted Return (TWR). The MIRR is directly comparable to TWR of the selected benchmark over the same time period.

PME Ratio

First proposed by Steve Kaplan and Antoinette Schoar in 2005 (Private Equity Performance: Returns, Persistence and Capital Flows). Also known as the Kaplan Schoar PME or KS-PME.

Both the contributions and distributions are discounted back to the initial cash flow date by the growth in the selected benchmark. The resultant PV of all distributions is then divided the PV of all contributions.

The PME Ratio is not directly comparable to an IRR or other measure. Instead, if the ratio is in excess of 1.0 then the fund is deemed to have outperformed the selected benchmark and where the ratio is below 1.0 the fund is deemed to have underperformed the selected benchmark.

PME+

First proposed by Thomas Kubr and Christophe Rouvinez at Capital Dynamics in 2003, it was patented in 2010. In order to avoid the issue where PME results in a short position in the index and therefore a negative NAV, PME+ maintains the actual NAV and instead scales the distributions by a factor lambda. An IRR is then calculated on the revised cash flows.

The PME result is directly comparable to an IRR and so outperformance is measured against the IRR.

Direct Alpha

The Direct Alpha was introduced in March 6, 2014 in a paper by Gredil, Oleg and Griffiths. Both the contributions and distributions are discounted back to the intial cash flow date by the growth in the selected benchmark.

An IRR is calculated on the PV of all cash flows. The Direct Alpha result is an absolute measure of alpha and not a relative comparable.

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In Free Fall and Yet Attractive? Short Volatility ETFs

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In the twelve days between January 26th and February 6th in 2018, the S&P500 temporarily lost almost -10%. In the same period, a type of Exchange Traded Fund (ETF), so-called "Short Volatility ETFs" or "Inverse Volatility ETFs" lost more than -80% of their value. The main focus was on the two products "ProShares Short VIX Short-Term Futures (SVXY)" and "VelocityShares Daily Inverse VIX Short-Term ETN (XIV)". On the two business days from February 2nd to February 6th, SVXY corrected by -88% (see Exhibit 1). How can an ETF, which is also accessible to retail investors, suffer almost total loss in such a short time?

Short volatility products rely on the underlying volatility measure, such as VIX, to decrease or remain constant. The VIX is an index calculated from options on the S&P500 index with a maturity of 30 days. It is not directly tradable, but there are futures contracts with the underlying VIX. These futures contracts are offered with maturities of up to nine months in the future. It is very important that SVXY and XIV are based on DAILY percentage changes in the VIX futures: The maximum gain of SVXY through a daily price movement occurs when the VIX drops by -100%, i.e., the unrealistic case it falls to a value of 0. Then the value of the ETF would double within one day. A "killer", on the other hand, is a fast, violent upward rash. If, for example, the VIX futures explode from 10 to 20 in just one day, a price change of +100%, this means a loss of -100% of the inverse ETFs. On the other hand, if the VIX futures increases by 1 to 20 on 10 consecutive days, there is a loss of "only" -52.6%, see Exhibit 2. In Exhibit 2, on the next page, an investment of USD 100 is assumed whose value (NAV) is only USD 47.4 ten days later after a gradual increase in the VIX from 10 to 20.

The maximum loss of short volatility ETFs is theoretically infinite. With the VIX's low price levels of 10, the probability of a movement

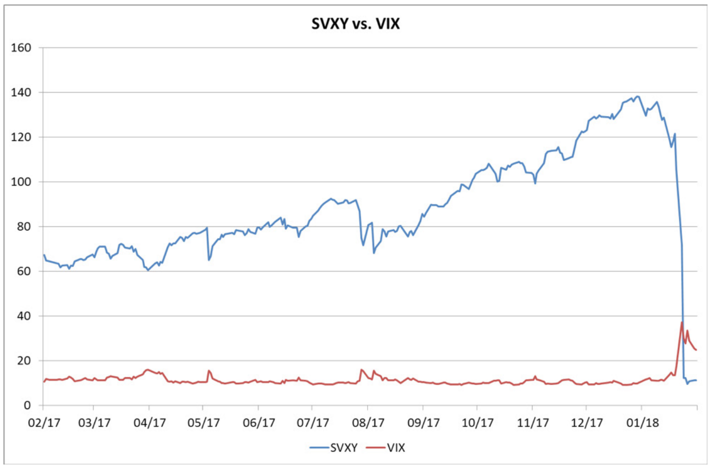

Exhibit 1: Price history of VIX and SVXY
Source: Yahoo Finance

Day	VIX-Fut.	Absolute change VIX-fut.	Percentage change VIX-fut.	NAV
0	10	n/a	n/a	100.0
1	11	1	10%	90.0
2	12	1	9%	81.8
3	13	1	8%	75.0
4	14	1	8%	69.2
5	15	1	7%	64.3
6	16	1	7%	60.0
7	17	1	6%	56.3
8	18	1	6%	52.9
9	19	1	6%	50.0
10	20	1	5%	47.4

Exhibit 2: Increase in VIX over ten days from 10 to 20

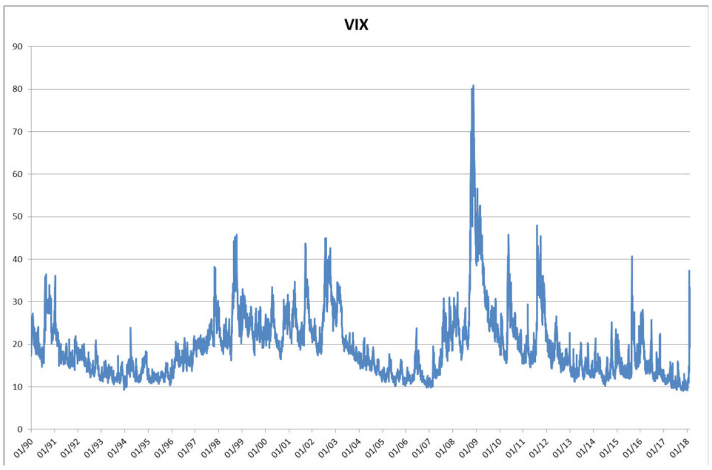

Exhibit 3: History of VIX from January 1990 to February 2018
Source: Yahoo Finance

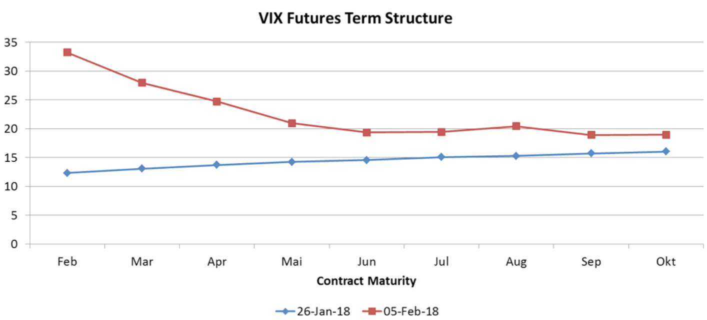

Exhibit 4: Term structure of the VIX futures
Source: CBOE website

from +100% to 20 or even +200% to 30 is significantly higher than in the upper regions above 25, such as from 30 to 60. In January 2018, the VIX was between 9.2 and 14.8. In a similar range, the VIX stayed for the entire year 2017, see Exhibit 3.

At VIX around 10 short volatility ETFs can therefore be said to have an unfavourable asymmetric risk profile, while a favourable asymmetric risk profile can be seen for VIX above 35. However, the latter does not mean that losses can be excluded if you buy inverse volatility products from a VIX over 35. There were times in the past when the VIX was already higher than 50 and still increased by 20% and more (e.g., October 2008).

How do Short Volatility products make money in times of low volatility?

Exhibit 4 shows the term structures of the nine VIX futures with maturities from February to October on two days: January 26, 2018 (blue) and February 5, 2018 (red). The blue curve follows a normal course: the short end, i.e., the maturities February and March, are recorded under the longer maturities such as August and September. If the VIX would remain constant, you can earn money by rolling down the futures. The difference between the March contract (13.075) and the February contract (12.325) on January 26th was 12.325 – 13.075 = -0.75. Assuming that an inverse volatility ETF enters a short position in the March contract at 13.075 and holds it for one month, the position rolls to a value of 12.325, which corresponds to a gain of +0.75 or 0.75 / 13.075 = +5.7%. In reality, financing and management costs have to be deducted from this, but there is still a considerable return on investment for a holding period of one month. If the VIX falls, the corresponding price movement of the VIX futures contract is added.

From 2012 to 2017, SVXY has achieved returns of 156%, 104%, -9%, -17%, 80% and 179%. The results of XIV were at a similar level. Those who invested at the end of 2011 could look forward to a return of 1870% until the end of 2017, which is a nineteen-fold increase in invested capital! However, the volatility was 66%. That is still some distance away from Bitcoin spheres - where volatility was 170% in the same period of time - but still with gusto. By way of comparison: The volatility of the S&P500 was 12%.

The goal of SVXY is to reflect the inverse change in the short-term volatility measure VIX. "Short-term" means that the ETF enters short positions in the two futures contracts with the next two maturities. On 5 February, the VIX jumped 116%, the futures contracts for February by 113% and for March by 87%. On this day, SVXY lost nearly -100% of its value (source: ProShares website). If the leap in the VIX or futures contracts had been even higher, the investor's entire invested capital would have been lost and the issuer of the ETF would have had to bear any additional losses. Credit Suisse, the issuer of XIV, has terminated its ETF and will repay the remaining capital to investors. According to media reports, it has not suffered any losses from the price activity of the XIV (Kilburn (2018)). It is not known how the issuer of the SVXY, ProShares, fared.

The market power of the short volatility products manifests itself in the open interest, i.e., the number of outstanding contracts, of

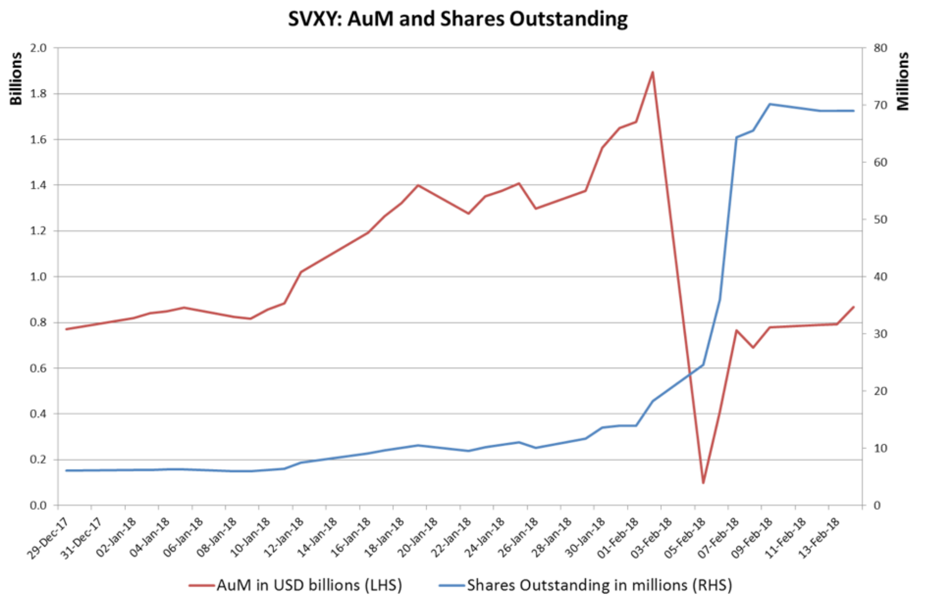

Exhibit 5: Assets under Management of SVXY and shares outstanding
Source: ProShares website

VIX threshold	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85
#days > threshold	7019	4653	2653	1241	582	293	168	89	56	41	27	18	6	3	2	0
%days > threshold	99.0%	65.7%	37.4%	17.5%	8.2%	4.1%	2.4%	1.3%	0.8%	0.6%	0.4%	0.3%	0.1%	0.0%	0.0%	0.0%

Exhibit 6: Proportion of days on which the VIX was above different thresholds (January 1990 to January 2018; a total of 7087 days)

the VIX futures. On January 26th, just under 630,000 VIX futures contracts were outstanding for all maturities (data source: CBOE website). Of these, SVXY alone held short positions in about 103,000 contracts, or 16.4% of all outstanding contracts! On February 5th, i.e., after the fall in the ETF's price, SVXY held only about 3,400 contracts or 0.5% of the outstanding contracts.

Why Do Investors Buy a Product That Has Suffered Such Ruinous Price Losses?

SVXY was launched at the end of 2011 and reached the peak of its managed capital shortly before its collapse: on February 2, 2018, it had almost USD 1.9 billion, which had shrunk to just under USD 0.1 billion by the end of February 5, 2018, see Exhibit 5.

Interestingly, the outstanding shares rose sharply shortly after the sharp price losses. Obviously, some investors have taken massive action. The outstanding shares peaked on February 9, 2018. Since then, their number has stabilised at just under 70 million. Why did investors enter this market? The answer lies in the VIX's ability to keep returning from levels above 20 to values below 20 ("mean reversion"), see Exhibit 3. The long-term average from early 1990 to February 2018 is 19.4; the average in the last few years since 2013 is significantly lower at 14.4. Fears flaring up every now and then are expressed in a rising VIX. When the situation calms down, life returns to normality and the VIX sinks again.

After the sharp rise of the VIX to a value of 37 at the beginning of February, the probability that the VIX will register another strong increase (e.g., by a further +50% to 55.5) is lower than a significant decrease (e.g., by -50% to 18.5). Exhibit 6 shows, for example, that the VIX traded above 35 on 293 days in the period from January 1990 to January 2018, or in 4.1% of all cases above 35, or in approximately 96% of all cases below. It is therefore likely that it will fall back below 35.

Exhibit 7 shows the number of days since 1990 on which VIX has increased by various percentage amounts. For example, it climbed by 20% or more on 79 days. This corresponds to 1.1% of all daily movements. It increased by 70% or more on only one day, on February 5, 2018 by 116%.

This brings us closer to the reason why investors are once again accessing the market immediately after the devastating price losses of short volatility products: the combination of a bet on falling volatility, the VIX close to the summit and the “Mean Reversion” property of the VIX transforms the unfavourable asymmetric risk

Change VIX% > X%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	110%	120%
# days > X%	420	79	31	13	5	2	1	1	1	1	1	0
%days > X%	5.9%	1.1%	0.4%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Exhibit 7: Number of days with increase in VIX by various thresholds from January 1990 to January 2018

profile of the SVXY with a VIX close to its historical lows into a favourable asymmetric risk profile. However, the window of opportunity for the favourable risk profile is extremely short (at best a few days) and only very risk-tolerant experts will be able to react so quickly.

Are Short Volatility Products Suitable Investment Modules for Me?

Short volatility ETFs securitise an investment strategy that delivers a fairly high return in a quiet market environment. However, there are always market phases in which they realise catastrophic losses that can reach as far as total loss - as we have seen. As a rule, these phases of loss occur when the stock markets incur heavy losses and thus at a point in time that cannot be more unfavourable. They are therefore completely unsuitable as building blocks in a long-term oriented portfolio. However, for investors who are willing to take risks and focus on short-term trading, a temporary position can make sense if the VIX reaches higher levels of 35 or more. Then the asymmetric risk profile turns from unfavourable to favourable. In the worst case scenario, assuming a total loss of the Short Volatility ETF, an investment of 1% of the portfolio in this ETF results in a return of -1% at portfolio level. A short-term oriented and risk-tolerant investor could opportunistically invest in such a short volatility ETF on a VIX over 35. However, the investment decision must be made in a very short time frame of at best a few days, in which many other parts of his portfolio will also suffer from high price losses. Once the VIX falls well below the 35 mark, e.g., close to 15, the Short Volatility ETF should be sold again.

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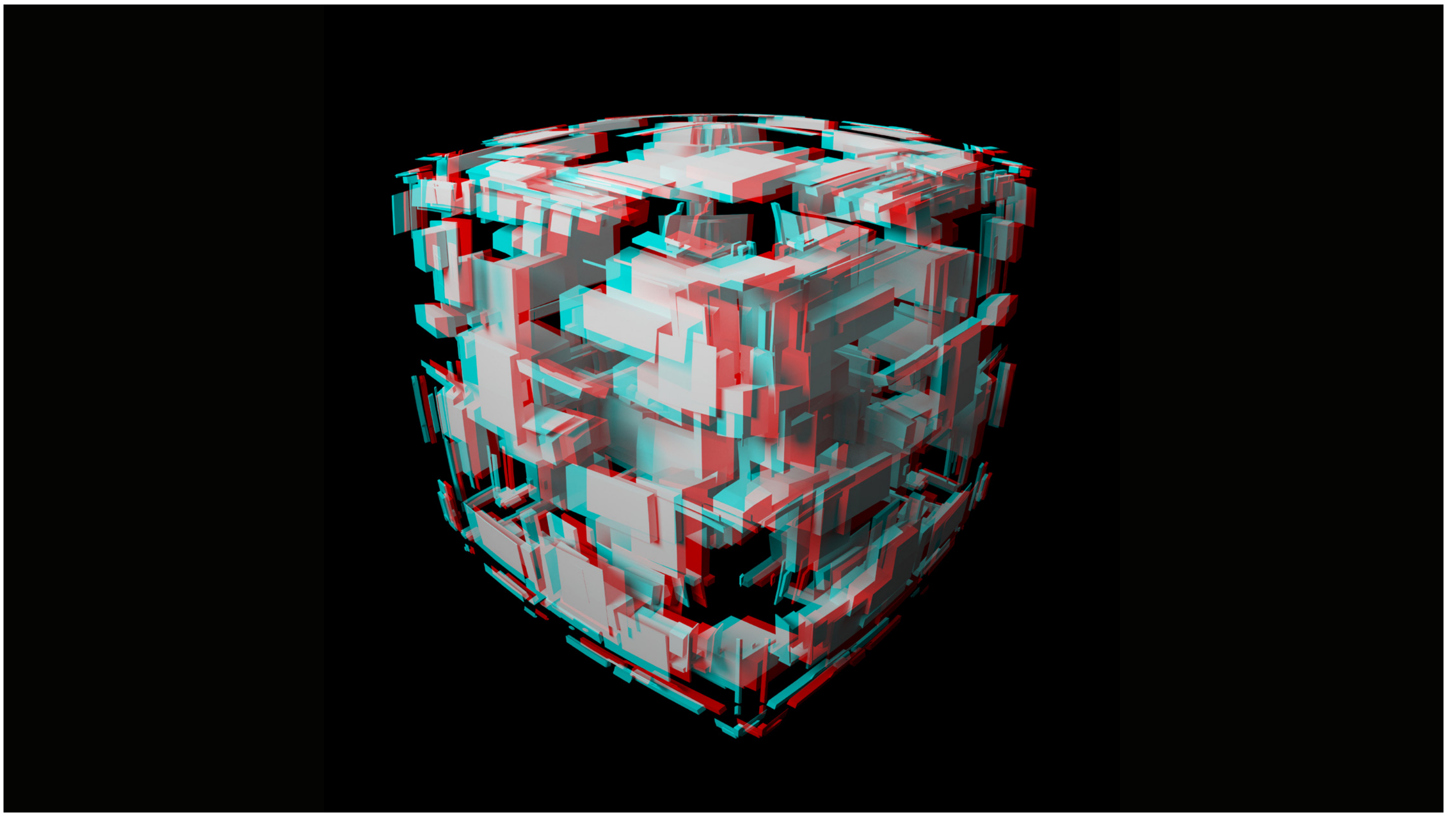

Hypercube in the Kitchen: Reading a Menu of Active Investment Strategies

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Introduction

The importance of skill in active investment management cannot be overestimated.[1] Investors' belief in their managers' skills is the only justification for the existence of the multi-trillion industry. Some skills are unique, i.e. only possessed by one manager. It is a set of independent unique skills that helps a fund manager to deliver long-term outperformance over his benchmark, be it an index or a peer universe. Moreover, unique skills that constitute the firm's investment edge are not easy to migrate from another firm. While more commoditized skills are readily available through the job market, core competences are likely to remain in scarce supply. Therefore, investment skill appears to be the most natural candidate for segregation of types of investment processes and of managers implementing them.

Indeed, classifying fund styles[2] based on skills ensures that respective segmentation is pretty stable: changing style in such coordinates is hard and expensive as it usually means acquiring new skills and only rarely abandoning those not required anymore. Different types of funds already possess well-established classifications.[3] Hedge funds are commonly classified by a strategy type. Though several competing classifications exist, they all closely resemble each other, differing predominantly by depth of granulation.[4]

The skill-based classification we propose below provides an extra dimension for diversification between active investment strategies. It is by no means a substitute for the traditional fund classifications. On the contrary, the two approaches are supposed to complement each other in a similar fashion as industry and style classifications work together in the equity space.

In some way, unique investment skills play the same role for hedge funds as factors do for traded assets. Much like returns of any asset may be attributed to returns of its basic ingredients – factors, one can attribute returns of an arbitrary hedge fund to a mix of its unique skills.

An investor may want to diversify her portfolio by allocating to managers possessing different unique skills. This creates a conceptual link to the Grinold-Kahn's fundamental law of asset management, only applied to skills. Thinking of unique investment skills akin to independent bets in the traditional formulation of the law, one can conjecture that the breadth of a unique skill set is a determinant of a fund manager's performance.

This article is deliberately non-technical and should be regarded as an invitation to further discussion on the subject. In particular, we do not go into quantitative aspects of the problem such as introducing a systematic methodology for measuring unique skills of hedge fund managers. Admittedly, inventing such a methodology for measuring uniqueness of skills is not a problem that only has one solution. While measuring the "unusualness" of a manager may be done by analyzing his correlations with peers or a R-squared from a regression on his benchmark, these and other similar approaches do not allow decomposition of the final product back into ingredients, i.e. individual skills, which are our focus in this paper. Instead of delving into technical details, our aim was to introduce the concept of skill based classification of fund managers and provide an intuitive justification for it.

Properties of a viable fund classification

Classifications built upon skills generally satisfy a number of properties pertinent to a good classification:

- **Stable**- Stability is guaranteed by the funds' need to maintain focus around their major investment edge.
- **Informative**- Funds that leverage on essentially different investment skills are supposed to have distinct performance: their decision-making processes should be rather uncorrelated.
- **Universal**- Unique investment skills developed in one asset class can often be transferred to other asset classes. Note that an absence of asset-class specific implementation skills will not present a hurdle for this universality because such skills are already commoditized to a high degree and should not be treated as unique.
- **Identifiable**- A strategy is identifiable as soon as its major edge is known. A clearly stated investment philosophy and description of investment process are examples of clues a potential investor may use to draw his conclusions about such positioning.
- **Exhaustive**- Each strategy can find its place within such classification.

Skill Scales

Combining several skill scales we would construct a viable skill-based classification. But first, given the fact that we aim at classifying fund managers based on their unique skills, we can list several examples of scales that are unsuitable for such a fund style classification:

- Absolute vs. Relative - based on a benchmark type;
- Long-only vs. Long-short - based on portfolio constraints;
- Leveraged vs. Unleveraged - based on amount of leverage used;
- Offshore vs. Onshore - based on a fund's jurisdiction.

None of the above dichotomies are based on unique skills: one does not need an essentially different investment edge to move along the spectrum of possible strategies for each of the above dimensions.

Skill-Based Classification of Investment Processes

As was already stressed, what we are going to classify is in essence the universe of distinct investment processes. We start from a description of an arbitrary investment process as an information processing system (IPS). An abstract IPS consists of three major parts: Input, Output and Processor in between, see Exhibit 1.[5]

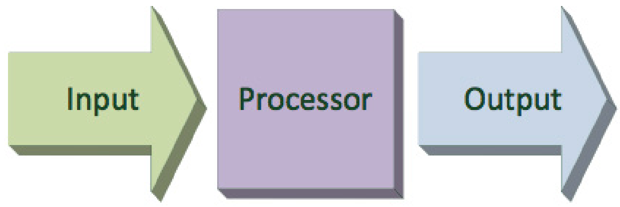

Exhibit 1: Information Processing System

Input is information received by Processor, Output is information produced by Processor based on Input. Processor itself can be imagined as a standard computer processor running a certain set of applications - decision making rules. Such a trivial representation of any informational processing including an investment process can be surprisingly beneficial for our purposes. To be more specific, we are going to associate appropriate scales of investment skills with each of the three IPS elements. These scales are depicted in Exhibit 2.

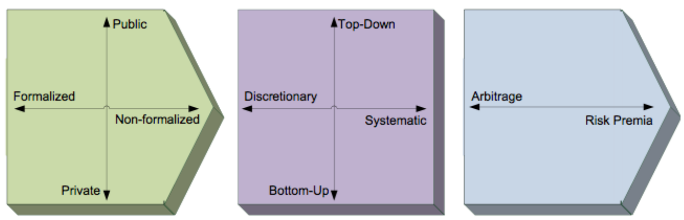

Exhibit 2: Investment skill dimensions projected on IPS parts

As is evident from Exhibit 2, we propose using five scales to classify investment processes: two for Input, two for Processor and one for Output. Below we discuss each of them in detail.

Output

We start with the Output scale because we believe that its role in classifying investment strategies is the most fundamental one. In fact, we would like to present two alternatives for the output scale. While one such scale shown in exhibit 3, is more important from the theoretical standpoint, the other is intended to be more useful in applications.

Alternative 1. Arbitrage vs. Risk Premia Performance Driver

Arbitrage Hybrid Risk Premia

Exhibit 3: Output: Performance driver scale

This dimension depicts the nature of major performance drivers of a fund.

The original CAPM only recognizes the market risk factor whose expected return is the market risk premium. According to a typical practical approach building upon this model, a part of a manager's return in excess of the market risk premium is considered to be driven by the manager's skill and is commonly referred to as alpha.

Loosely speaking, our performance driver scale can be seen as a variation of this alpha-beta dichotomy, only brought into a world of many systematic risk factors.

By systematic risk factors we mean a set of uncorrelated portfolios which serve investors as insurance against their bad times (times when consumption growth decreases or, equivalently, utility value of one extra dollar increases). Risk premia are expected returns of systematic risk factors.

We distinguish between two extremes: pure arbitrage (i.e. risk-free) and pure risk premia. An example of the former is a geographical arbitrage, i.e. arbitrage between prices of the same instrument quoted on different exchanges. Such strategies are critically dependent on the technological infrastructure, as they require ultra-fast market access and information processing. In contrast, strategies that only exploit risk premia can exist even in fully efficient rational markets since the existence of risk premia does not premise on any mispricing in assets. Put differently, pure arbitrage strategies exploit market informational inefficiencies on increasingly short time frames, while pure risk premia strategies aim at collecting profits that are left on the table after all available information has already been incorporated in prices. In reality, the performance of risk premia strategies is usually enhanced by persistent heterogeneities among market participants (heterogeneity in utility functions including investment horizons, presence of different types of costs and investment constraints), which can lead to stable market segmentation not easily arbitraged away.[6]

In general, the more one moves to the right along the performance driver scale, the more uncertainty is associated with performance. This is a reflection of the inevitable risks that one has to bear when collecting risk premia as opposed to arbitraging away market imperfections. Importantly, transition from arbitrage strategies to risk premia collection is rather smooth: even such "risk-free" strategies as a geographic arbitrage still bear some risk related to asynchronicity of order fills on two exchanges, FX movement or simply connectivity risk.

Performance driver	**Arbitrage**	**Risk Premia**
Use of market imperfections (inefficiency, irrationality, segmentation)	Based solely on the imperfections	Do not rely on imperfections
Time scale [7]	Short-term	Long-term
Risk	No risk	Systematic risk only
Uncertainty	Certainty: outcome is known	Uncertainty: probabilities are unknown
Critical skills	Recognition of arbitrage opportunities Speed	Factor capture Factor allocation Risk management

Exhibit 4: Characteristics of performance drivers

Exhibit 4 brings together various archetype features of the two performance drivers above.

Though determining exactly the major performance driver for a given strategy is not always easy, to say the least, the above discussion provides two indirect ways to approach this task:

> Risk premia strategies generally spend significantly longer time in trades as they do not aim at getting an informational advantage.[8] As a consequence, the Output scale also provides indirect information about a fund's investment horizon and capacity. The reverse is also true in most cases.
>
> For example, a high frequency trading (HFT) fund is more likely to exploit various degrees of arbitrage than risk premia;[9]
>
> Risk premia strategies usually have an upper limit on their risk-adjusted returns. Information ratios around 2-3 are extremely hard if even possible to accomplish in the long term. Pure arbitrage strategies, in contrast, can reach double-digit ex-post information ratios due to their near "risk-free" nature.[10] However, such strategies have relatively low capacity. Their expected performance is more uncertain because of the costly technology race among competitors. Therefore, such strategies' high historical risk-adjusted returns are less likely to be repeatable.

In theory, arbitrage strategies should be insensitive to bad times. Assuming that some arbitrage strategies are run alongside risk-premium type portfolios (e.g. equity portfolios) the overall allocation of capital to arbitrage strategies may suffer during the general market bad times, thus widening spreads and giving rise to richer arbitrage opportunities. Conversely, it may be expected that good general market conditions may lead to an increased competition between arbitragers and poorer arbitrage opportunities. However, real-life arbitrage strategies where profits are almost guaranteed may suffer during the transition periods of capital exhaustion as spreads widen and segmentation unimagined before becomes reality. Without pretending to explain when and why these bad times come, we only attempt to show that an inevitable exposure to a systemic risk provides another evidence of a risk premium component necessarily present in real-life arbitrage strategies.

A reader must have noticed that we did not mention a manager's alpha as a performance source in its own right. Jarrow and Protter (2013) provide theoretical justification for such omission. They show that in the absence of arbitrage positive alpha is always illusory: it is an artifact of a miss-specified factor model used to obtain alpha, or an incomplete information set.[11]

Hence, what people label as a market anomaly, in fact usually manifests some hidden systematic risk: the only way a positive alpha can be achieved is by exploiting (rare) arbitrage opportunities. This does not mean that active managers should only be compensated for arbitrage profits. Indeed, systematic risk factors are unobservable in the real world, and the respective risk premia are unknown. Moreover, the set of prevalent systematic factors can change with time and respective risk premia can also be dynamic. Therefore, identifying the most essential systematic risk factors and correctly estimating their current risk premia represents a special skill. This skill, crucial to risk premia strategies, is not covered by the notion of alpha but it would be reckless to underestimate its importance when choosing between active managers.

Needless to say, such a view is in sharp contrast with the conventional academic approach, where a risk model driving asset returns is assumed to be fully specified and known. In a common industry parlance, returns in excess of a well-defined and easy-to-capture set of risk factors are often referred to as alpha. In most cases, such a fixed risk model is misspecified, however, it may be very convenient for practical purposes. From a perspective of an investor whose starting point is such model, the difference between pure arbitrage and factors lying outside his model is blurred as both produce alpha, in his terms.

Alternative 2. Diversity of Risk Premia

Single — Multiple

Exhibit 5: Output: Risk Premia diversity scale

Looking at the performance driver scale, we notice that the majority of existing funds would be positioned near its right edge. Indeed, as we have already discussed, arbitrage opportunities are rare, so large enough funds usually exploit various risk premia, even if they declare to deliver alpha. This leads to a natural desire for a specific classification of risk premia funds. This can easily be accomplished within our framework by replacing the performance driver scale in Output with a scale distinguishing between risk premia strategies only. Thus we introduce a premia diversity scale that differentiates between single and multiple risk premia exploited within a strategy.

The left edge of this scale is occupied by single premium funds, which invest in one clearly defined systematic risk factor. For example, most CTAs would be located here due to their overwhelming exposure to a momentum factor.[12] Funds that attempt to identify and trade as many systematic risk factors as possible, ideally spanning the whole factor space, would reside on the opposite edge of the scale. Funds trading a multiple, but apparently incomplete set of risk factors would then be located between the two extremes. Global macro funds, both discretionary and systematic, would tend to lie closer to the right edge of the scale.

A skill critical for single premium funds is efficient exploitation of the respective risk factor. In our CTA example this mostly reduces to identifying an optimal definition of such a blurred notion as trend. In this respect, enhanced index funds are likely to belong to this point as well, since they are supposed to capture market premia better than cap-weighted index funds do. In contrast, distinctive skills of a fund positioned on the opposite edge of the scale would be factor allocation and risk management.

Should We Consider Factor Timing as a Unique Skill?

One could wonder whether dynamically managing factor exposure(s) represents a separate skill. At first glance, it may seem that some strategies skillfully provide a time varying exposure to a single risk factor. Consider, for example, a dynamic beta (market timing) strategy that takes a full long position in an equity market except in times of elevated volatility when the position reduces. Whatever it says on the tin, in reality this strategy provides constant exposure to an equity market risk factor (by always maintaining a full long position in the market) and a low volatility factor (by taking a short position in the market from time to time).[13] Thus, a time varying exposure to a risk factor is often equivalent to a combination of constant exposures to several risk factors.

One may reduce a dynamic allocation to a static one by following Brandt and Santa-Clara (2006). Their approach makes use of signals that are supposed to predict risk premia, or expected returns of factor portfolios. They suggest that the set of factors can be expanded by adding pairwise products of original factor portfolios and the predictive signals, thus marrying "factors for assets" to "factors for factors" and reducing the task to solving a conventional static portfolio choice problem.

Hence, a dynamic allocation to risk factors (factor timing) is not necessarily a skill per se because in reality it may be managed as a static allocation to an expanded set of risk factors.

Of course, in reality a set of factors that a manager is able to capture and trade is never exhaustive. Respective risk premia may be dependent on other, more fundamental forces driving investors' risk preferences. For example, an equity market risk premium being time varying may be further decomposed on underlying risk premia. A manager could try to identify these forces and exploit them to dynamically manage factor exposures, or, equivalently, to allocate statically across an expanded set of factors. At the same time, for all practical intents and purposes, this factor expansion process must stop at some level acceptable to a manager or to an investor. Therefore, this level of detail, or the choice of risk premia that one considers the most fundamental, has a strong bearing on whether allocation to the respective risk factors should be treated as static or dynamic.

This leads us to an analogy between traded instruments and risk factors – expected returns of both may consist of more fundamental building blocks. If we accept this view then portfolios of risk factors may be managed based on the same principles as portfolios of assets.

To summarise, identification and selection of risk factors and managing exposures to them by taking positions in tradable financial instruments represents a special skill. Note, however, that even in conjunction with the other edges of our hypercube, the number of risk premia exploited does not provide enough information to guarantee that similarly classified strategies would always display high correlation. Two strategies may use an equal number of risk premia but those premia may be qualitatively different. For example, a single-premium strategy exploiting value will provide very different characteristics when compared with a strategy exploiting momentum.

For any practical use, this scale should be complemented with risk premia actually used in the strategy. We are deliberately avoiding classifying risk premia in this paper: at the current level of perception of various risk premia it would be difficult to offer a non-controversial, theoretically justified and complete classification that would stand a chance of wide adoption by the industry. Even the best researched concepts like an equity risk premium still cause discussions about their interpretation and decomposition. Classification of less researched premia would risk facing a more heated opposition that could divert attention from our point, namely that even though the skill based classification does not aim to provide a complete risk premia classification it helps investor to better understand investment strategies.

We believe that each investor may use his own classification of risk premia to be used alongside our hypercube. Better constructed classifications of risk premia may help the investor to stand out from his competition and represent his own competitive edge.

Input

Input determines the type(s) of information used in investment decision-making. It has two scales that differentiate between formalized vs non-formalized and private vs public information.

Formalized vs. Non-Formalized Information

Formalized Hybrid Non-formalized

Exhibit 6: Input: Information formalization scale

Examples of formalized information are historical prices of financial instruments, fundamental and macro data. Non-formalized information would be mostly represented by news stories presented in various formats. Of course, non-formalized information can often be converted into formalized in many ways, but we leave this job for Processor as it is a part of interpretation of the information.

A hidden assumption behind introducing this scale is that hard-to-formalize data such as news or sentiment data derived from web mining might contain information not fully present in prices or fundamental data. Looking at this phenomenon from a different perspective, we can describe the whole financial market itself as an IPS representing a full set of IPS's active in the market. Such a combined market IPS processes all new information available to market participants into prices of financial instruments. Updates in fundamentals usually arrive at discrete moments, while historical prices reflect previous output of the same IPS, which could decrease their value. What is left, and presents a continuous information flow, is non-formalized information contained in news.

Crucially, gathering and processing these two types of information requires essentially different skills. Formalized information is relatively cheap to access and interpret. However, exactly because of this reason the universe of market participants utilizing it is extremely competitive. On the other hand, non-formalized data is hard to comprehend and apply and if implemented on a large scale, it requires extensive text mining and processing skills.

Private vs. Public Information

Private Hybrid Public

Exhibit 7: Input: Information accessibility scale

The second Input scale distinguishes between private and public information. Public information, in our terms, is information which is acquired relatively cheaply and often comes down to data vendor subscription fees. In contrast, obtaining private information, i.e. information not readily available through public information channels, is often associated with significant ongoing expenses, be they explicit or implicit. Leaving aside insider information (whose use is generally illegal), examples of legitimate private information gathering include detailed analysis of underlying companies or economies or commodities, all the way through to maintaining ultra-fast fibre-optic lines and co-located servers.

As with the formalized/non-formalized scale, the reliance of the decision-making process upon private and public information requires different skills. Private information gathering is an expensive and often technologically advanced process, so we class it as a skill. In contrast, the ability to avoid such expenses, i.e. make investment decisions based on information already disseminated in the marketplace is a skill that we position on the other side of the scale.

Development of computer technologies has been continuously pushing the boundaries: the same information may be classified in a more formalized and public manner now than only a few years ago, and there is no end to this push in sight.

It is worth noting that the input axes answer two fundamentally different questions - how difficult is it to obtain information (public/private) and how difficult is it to make the information usable (formalized/non-formalized). One can have private formalized info (e.g. an exclusive weather forecast) or public non-formalized info (e.g. a central banker hinting at something in her speech). Two other quadrants are obvious. Undoubtedly, one can digitize newspaper articles or apply artificial intelligence to interpret the central banker's speech. However, that would still be transformation of information not a part of decision making. For example, if the artificial intelligence suggests that the central banker has hinted at the possibility of a monetary expansion next year, what should one do about it? The processor will produce an answer.

Another thing to remember is that we are dealing with edges of a hypercube which are not binary, in the general case. Therefore a digitized newspaper is a bit farther from a formalized vertex than a price time series. The central banker's speech is closer to the non-formalized vertex.

Still, if one wishes to have fewer axes in his classification, he can combine the two input axes into one complex/simple axis at the expense of losing some information.

Processor

Unique investment skills relevant for Processor also form a two-dimensional plane. One dimension partitions investment processes into bottom-up vs top-down. The other - into systematic vs. discretionary.

Bottom-Up vs. Top-Down Analysis

Bottom-Up Hybrid Top-Down

Exhibit 8: Process: Analysis scale

The bottom-up and top-down approaches, so familiar to investment professionals, are in fact two alternative approaches to information processing in abstract systems.

In the case of an investment process the bottom-up approach usually means concentrating on the analysis of information relevant to particular securities and largely ignoring the information related to the whole environment. A good example would be an equity market-neutral fund that maintains neutrality to a wide variety of factors, such as market, region, sector, interest rates, size and possibly others. Such fund may focus on analyzing companies' fundamentals and build its portfolio bottom-up because its neutrality would arguably insulate it against macro risk.

Adepts of the top-down approach, in contrast, usually start with the big picture reflected in macro data, and only then descend to more granular levels to form positions in specific securities. A typical discretionary global macro fund would have a view on the economy and select individual trading ideas that should not contravene with it.

Obviously, the two types of analysis require very different types of skills. In reality, however, the two are often combined in some proportions, so one can rarely see their pure realizations. But still, one of them, where the firm has more expertise, would be dominant.

Discretionary vs. Systematic Architecture

Discretionary Hybrid Systematic

Exhibit 9: Process: Architecture scale

Discretionary and systematic information processing architectures are self-descriptive. The former are based on discretionary decisions of portfolio managers and the latter are meant to be purely algorithmic. Each architecture type has its pros and cons. Discretionary processes are supposed to be far more adaptive to changing markets and are better suited to processing hardly quantifiable information. However, since their indispensable components are the black boxes of human brains, the whole process is on average less transparent and replicable. The latter means that it is harder to rely on past performance generated by discretionary managers. Not only because their portfolio managers are always at risk of losing their feel for the market, but also because such firms are more dependent on their key people. On the contrary, systematic managers are supposed to have more reliable processes, but at the same time their investment processes are in general less adaptive and not so suitable for processing qualitative information.

A fundamental but often overlooked distinction between discretionary and systematic architectures lies in a notion of trade. A discretionary manager's trade is a one-time activity in buying/selling financial instruments. A systematic manager's "trade" is a modification to the trading algorithm. Indeed, introducing occasional changes in their algorithms is in fact the only way that systematic managers can affect their performance. Buying/selling financial instruments is the algorithm's trade, not really the systematic manager's.

Hypercube in the Kitchen

The above classification (to be precise, there are two classifications corresponding to the two different output scales introduced) of investment processes based on the five scales can be represented as a 5-dimensional hypercube. Vertexes of this hypercube correspond to $2^5 = 32$ "pure" investment styles, where each pure style is associated with a set of five investment skills. All other points correspond to intermediate states. One can argue that some combinations of skills are more common in real life than others. For example, one would expect to see more funds that are [Formalized & Systematic] than [Non-formalised & Systematic], more [Systematic & Arbitrage] than [Discretionary & Arbitrage] or more [Formalized & Public & Systematic & Single risk premium] than [Formalized & Public & Systematic & Multiple risk premia] .

When cooking an investment strategy, a manager selects (or sometimes is pushed to) a point on each of the edges of the hypercube which eventually determine his position in the managers' universe or, in other words, his investment edge (the authors apologize for the pun). The menu of investment strategies visible to an investor may be split by these five categories and analyzed accordingly.

Note. It is natural to associate an interval [0,1] with each of the five hypercube dimensions and define the Euclidean distance between any two funds:

$$\|F_1, F_2\| = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2 + (c_2 - c_1)^2 + (d_2 - d_1)^2 + (e_2 - e_1)^2}$$

where $(a_i, b_i, c_i, d_i, e_i)\,|_{i=\overline{1,2}}$ are coordinates of the two funds on the five scales.

At the same time, the five hypercube dimensions are not born equal. When a customer comes to a restaurant, he first looks for a type of food that he wants (answering the question "what?"), and only afterwards chooses between competitive products based on how they were cooked or priced. In the same vein, while the first four scales answer the question "How?", the question "What?" is answered by the last one, nested in Output. Hence, one could consider modifying the above formula in the following way:

$$\left\|F_1, F_2\right\|_{\mathbf{w}} = \sqrt{w_1\left(a_2 - a_1\right)^2 + w_2\left(b_2 - b_1\right)^2 + w_3\left(c_2 - c_1\right)^2 + w_4\left(d_2 - d_1\right)^2 + w_5\left(e_2 - e_1\right)^2}$$

where $w = (w_1,w_2,w_3,w_4,w_5)$ is a vector of non-negative dimension weights.

The basis proposed in this paper is not the only skill based basis imaginable. We mentioned some alternative possibilities, and did not mention even more that we had thought of but rejected. The reader may and is indeed very welcome to come up with his own hypercube that better fits into his kitchen and helps produce a better investment product.

Another important question left unanswered is how exactly should one determine the coordinates on all scales? While the answer may be obvious when a strategy clearly lies at an edge (like a price-based, i.e. a formalized-input strategy) it is trickier in the general case. The scales we propose are quantifiable but we have not approached the task of introducing specific measures for each of them. We believe that at this initial stage, discretionary approaches may work reasonably well while the quantification may present a subject for future research. The coordinates and the weights of scales may represent a unique investor's view and help him interpret the menu of investment strategies in his own way.

Concluding Remarks

Summing it up, this paper proposes a new classification of active investment styles based on characteristics of underlying investment processes. The latter are usually determined by unique investment skills that firms possess. Hence we distinguish investment processes by suggesting five skill scales (dimensions), such that an arbitrary investment process can be characterized by five coordinates corresponding to its positions on these scales. Thus, the direct geometrical analogy with a 5-dimensional hypercube.

Importantly, the hypercube dimensions are well-structured as they correspond to different functional parts of an investment process represented in the form of an abstract information processing system consisting of Input, Processor and Output. With regards to Input, we distinguish between Formalized vs Non-formalized information and Private vs Public access to it. For Processor the two scales are Systematic vs Discretionary architectures and Top-down vs Bottom-up analyses. Within Output we suggest segregating Arbitrage and Risk premia performance drivers, but for practical purposes we prefer to distinguish between the use of Single and Multiple risk premia. Apparently, our choice of skill dimensions within each part is rather subjective, but we believe it serves as a good starting point for further discussion.

Each scale represents an interplay of two opposing skill sets, which are hard or expensive to combine within one investment process. Among the scales above, the most fundamental is the performance driver scale, which distinguishes between arbitrage and risk premia as the only two sources of active returns that exist. Crucially, not only arbitrage, but also risk premia strategies require special skills. Since we live in a world where true systematic factors are unobservable and their risk premia are unknown, extracting such factors, estimating their expected returns and managing exposures to them is a skill critical for all non-arbitrage investment strategies. This skill is not covered by the notion of alpha and is, in fact, orthogonal to it. The classification constructed has a direct application in asset allocation and risk management, especially for funds of hedge funds and pension funds. It could also serve as a basis for a new family of hedge fund indices. Though it is not clear how to measure quantitatively an exact location of a fund on each of the scales, their qualitative estimates made by the investor should not represent a problem.

It is interesting to speculate how the active investment industry is going to develop in the years to come. We would expect an increase in specialization, i.e. investment styles of successful hedge funds gradually drifting towards the hypercube vertexes. This is a manifestation of a natural trend towards separation of skills, the one we already witnessed during times when the idea of alpha-beta separation was so popular. We suggest that some form of skill separation similar to the one provided by the hypercube above will eventually replace the increasingly obsolete alpha-beta separation paradigm.

Endnotes

1. We define active investment as any type of investment whose value materially depends on the investment manager's decision-making. This definition is very general and covers a broad class of investment vehicles: hedge funds, mutual funds and ETFs with active investment policies, personal and professionally managed investment accounts. Since managing real estate or private businesses also means participating in investment decision-making, real estate funds, private equity and venture funds do fall into the category of active investments according to the definition above. Moreover, since the value of public and private companies is critically dependent on management decisions and corporate governance, they present examples of active investments as well. However, we won't reach that far and will concentrate on vehicles that invest in financial instruments, where a logical reasoning that we adopt seems the most fruitful. Further such vehicles are denoted in this paper as "active funds" or simply "funds", even if they are implemented via different legal structures such as institutional managed accounts. Hedge funds in this respect represent by far the purest form of active investments since their internal decision making (investment process) plays the most critical role in their performance and survival.

2. We use terms "active investment style", "fund style" and "fund manager style" interchangeably, always referring to an investment process that stands behind the scenes. Of course, some fund managers, especially the largest ones, implement dozens of investment processes simultaneously, so we treat them in our classification as baskets of different active investment styles.

3. Cazalet and Zheng (2014) compare hedge fund classifications employed by different data vendors and propose one of their own based on a role in an investor's portfolio. See also Fung and Hsieh (1997) who first introduced style analysis into the hedge fund world as well as Connor and Woo (2004) for a description of major hedge fund strategies and an overview of several classification principles.

4. For instance, the Credit Suisse index family uses the TASS database classification, breaking the hedge fund universe into 10 major groups (Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity, Managed Futures, Multi-Strategy).

5. Here we omit Storage (Memory), a part of a system responsible for storing information, because it does not play an essential role in our model.

6. As Cochrane (2007) puts it: "If a piece of information is not correctly incorporated in market prices, we only need a few arbitrageurs or "marginal investors" to trade. They don't have to take very large positions or bear much risk. In fact, the no-trade theorem studies the puzzle that in theory their private information should be revealed in prices with no trading at all! However, if some "systematic" factor (momentum, carry trade, put option writing) has an unwarranted risk premium, the only cure is for that risk to be more widely shared. The average investor must change his demands. This is much harder, so markets can maintain "segmented" risk premia for a long time, even while trading within each market quickly removes any informational "inefficiencies"."

7. The time scale uses relative rather than absolute measures of time. We are only interested, loosely speaking, in the strategy's trade cycle vs a frequency of news. For example, in the real estate market days or even weeks is almost unimaginably short term while in the geographical equity arbitrage moving ahead in a few seconds may be unaffordably long term.

8. As above, we are using the relative notion of time. For instance, to collect the earnings announcement premium a fund manager can buy several days before and sell immediately after the respective event (for further details see Barber et al. (2013)). Even though such a holding period may not seem too long at first sight, in comparison with the relevant news flow it is.

9. As a counter-example, many HFT funds play the role of liquidity providers. In other words, they accept a transfer of risk from a liquidity taker who is likely possessing an informational advantage. Therefore, one can speculate that such funds collect a risk premium associated with their market-making activity.

10. The "peso problem" teaches us that historical track record alone cannot serve as a sufficient evidence of skill. Often high historical information ratio is originated by an extremely skewed distribution of returns, where negative events are very rare but are disastrous for the strategy. The fact that such an event did not occur in the past can create an illusion of an exceptional performance. A good example of such a strategy is writing far out-of-the-money options.

11. The reasoning is based on the fundamental theorem of asset pricing which suggests an equivalence between absence of arbitrage and an existence of a strictly positive stochastic discount factor (SDF), which has an intuitive meaning of an index of bad times. In other words, the absence of arbitrage opportunities is equivalent to the existence of a universal way to discount future cash flows of all assets that makes the present value of each asset equal to its current price. An SDF is a set of random variables determining such discounting for each moment in the future. Hence, it incorporates the risk preferences of all market participants. For instance, if each investor's consumption growth depends on market return only, then SDF is a linear function of future market returns and CAPM holds (see Cochrane and Christopher L. Culp (2003)). The SDF plays so fundamental role in modern finance, that it is also known under many other names such as marginal rate of substitution, state price density, pricing kernel, change of measure and risk-neutral density. Back (2010) showed that when an SDF exists, assets' expected returns are fully determined by their covariances with it. Since an SDF does not in general represent a traded asset or a portfolio, a finite number of uncorrelated factor portfolios are considered instead. One may say that factor portfolios represent different dimensions of an unobservable SDF. Importantly, Jarrow and Protter (2013) show that an expected return of any asset is fully determined by its covariances with these systematic factors. Expected returns of such factor portfolios are called systematic risk premia. Hence, an expected return of any traded instrument or portfolio can be decomposed into a sum of systematic risk premia.

12. See Baltas and Kosowski (2012).

13. This exemplifies, by the way, that exploiting multiple risk premia does not necessarily mean trading many assets.

14. As an extreme example imagine that one is able to count all bottles of Coca-Cola being sold in every store worldwide in real time. Having such an infrastructure would allow a fund manager to see Coca-Cola sales figures well before they are announced by the company in a quarterly report. Another example would be a commodity manager having a network of their own meteorological stations and/or satellites.

15. The latter example highlights a subtle difference between private and public information with respect to market data available from exchanges. A speed advantage over commercial data vendors measured in milliseconds allows an HFT fund manager with an appropriate infrastructure to access what is effectively private information. The fact that such information will stay private for an extremely short time period only does not preclude its potential for profits.

16. The best general definition of top-down and bottom-up approaches that we came across is the one given in Wikipedia (http://en.wikipedia.org/wiki/Top-down_and_bottom-up_design):

"A top-down approach... is essentially the breaking down of a system to gain insight into its compositional sub-systems. In a top-down approach an overview of the system is formulated, specifying but not detailing any first-level subsystems. Each subsystem is then refined in yet greater detail, sometimes in many additional subsystem levels, until the entire specification is reduced to base elements. ...Top down approach starts with the big picture. It breaks down from there into smaller segments.

A bottom-up approach is the piecing together of systems to give rise to more complex systems, thus making the original systems sub-systems of the emergent system. ...In a bottom-up approach the individual base elements of the system are first specified in great detail. These elements are then linked together to form larger subsystems, which then in turn are linked, sometimes in many levels, until a complete top-level system is formed."

17. The term "systematic" used in this section has nothing in common with systematic risk factors discussed earlier.

18. Interestingly, the systematic manager's activity of changing trading algorithms (including conscious decisions of leaving them unchanged, as a special case) inevitably introduces a discretionary component into the whole decision-making process. Therefore, a pure systematic process may hardly exist in real life because it is a process that is guaranteed to stay unchanged and be allocated a certain amount of risk regardless of any exogenous events.

19. The latter pair would describe a typical CTA and a systematic macro, e.g. GTAA strategies. These two types of strategies may also take different positions along the Analysis scale where we would place the CTA closer to the bottom-up side and the systematic macro closer to the top-down side.

20. For example, it may seem natural to consider adding another scale to Processor, fast vs slow, to reflect its information processing speed. However, while being intuitively appealing this concept is closely related to the discretionary vs systematic dimension, which is why we decided to keep it out of our classification.

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Authors' Bio

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The CAIA Endowment Investable Index

Hossein Kazemi

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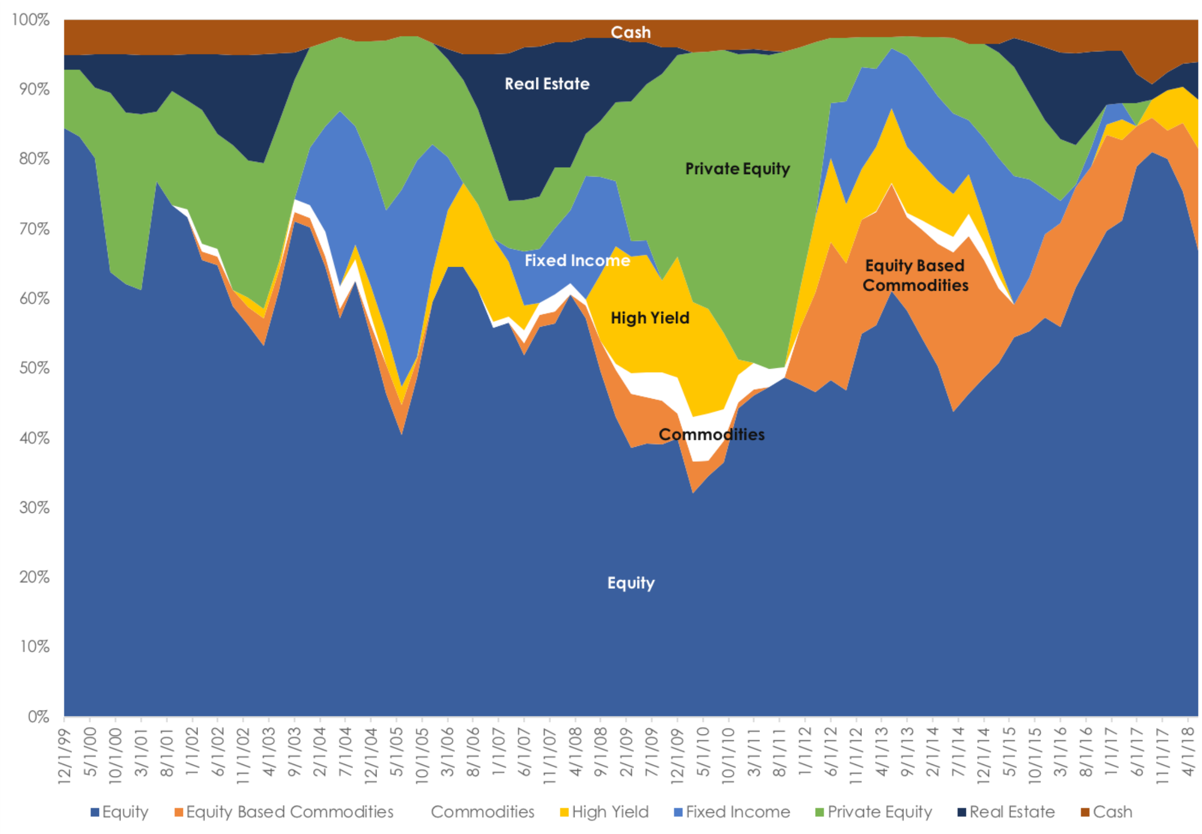
We present the historical weights, allocation as of month-end June 2018, and historical performance to the replication portfolio that was introduced in our AIAR publication Volume 6 Issue 1.

The below graph shows the exposures of the Multi-Asset ETF portfolio through time. It is important to note that the volatility displayed by these exposures does not imply that endowments alter their asset allocations as frequently as the Multi-Asset ETF portfolio. While an endowment may hold a fixed allocation to various asset classes, the underlying assets/manager may display time-varying exposures to different sources of risk. For instance, a hedge fund manager may decide to increase her fund's exposure to energy stocks while reducing the fund's exposure to healthcare stocks. Though the endowment's allocation to that manager has remained unchanged, its exposures to energy and healthcare sectors have changed. Also, if returns on two asset classes are highly correlated, then the algorithm will pick the one that is less volatile. For instance, if returns on venture capital and small cap stocks are highly correlated, then the program will pick the small cap index if it turns out to be less volatile.

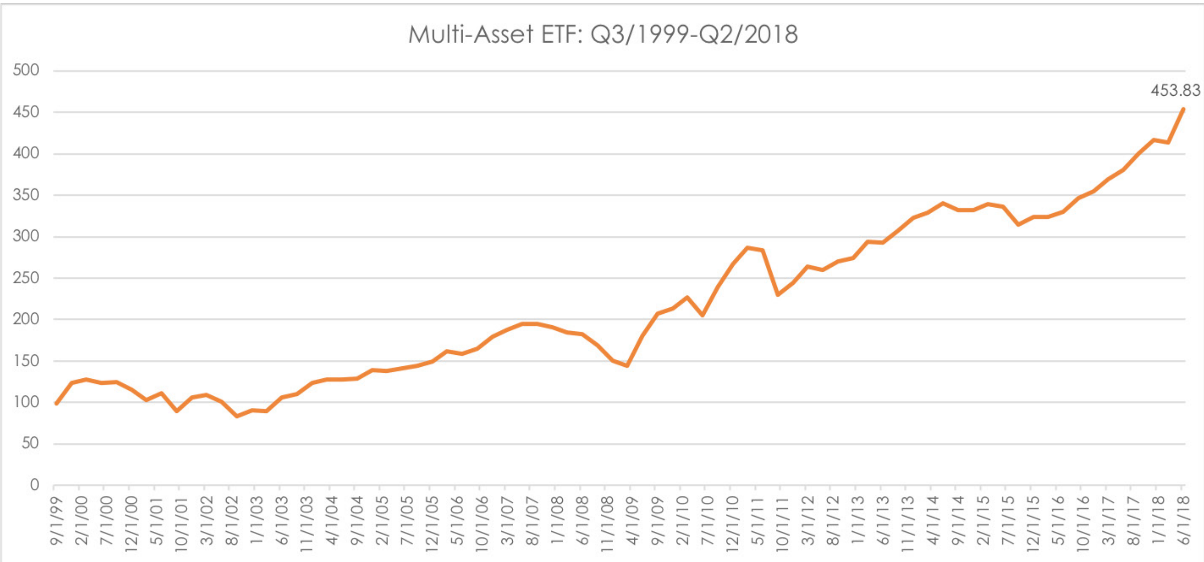
Endowment Index Weights



Allocation Suggested by Algorithm

Russell 2000 ETF	Power Shares QQQ ETF	MSCI World Free ETF	Vanguard FTSE Emerging Markets ETF	Materials Select Sector SPDR® ETF	Technology Select Sector SPDR® ETF	Consumer Staples Select Sector SPDR® ETF	Health Care Select Sector SPDR® ETF	BBgBarc US Corporate High Yield TR USD	SPDR® Dow Jones Global Real Estate ETF	Cash & Short-Term Treasuries
16.06%	17.19%	21.18%	4.36%	14.56%	2.29%	1.96%	3.97%	6.99%	5.46%	5.98%

Historical Performance



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About CAIA

Founded in 2002, the CAIA Association is the world leader and authority in alternative investment education. The CAIA Association is best known for the CAIA Charter (www.caia.org), an internationally-recognized credential granted upon successful completion of a rigorous two-level exam series, combined with relevant work experience. Earning the CAIA Charter is the gateway to becoming a Member of the CAIA Association, a global network of more than 9,000 alternative investment leaders located in 90+ countries who have demonstrated a deep and thorough understanding of alternative investing. The CAIA Association now supports 30 vibrant chapters located in financial centers around the world and sponsors more than 150 educational and networking events each year.

The List:
Alternative Indices

The performance table below is a collection of both traditional and alternative indices for the 1, 5, and 10-year period annualized through June 2018. Both the annualized volatility and draw-down figures are calculated using a 10 year quarterly return series.

Alternative investments have been growing markedly over the past few years, creating a multitude of opportunities for owners and allocators alike. As the number and type of alternative asset classes continue to proliferate, we believe they are playing a more unique role in assisting investors achieve their desired investment outcomes. As we expect this trend to continue, we found it necessary to structure a pure alternative assets portfolio to have visibility in this exciting marketplace.

We set out to strike a balance between available assets in proportion to their market value, and to reflect the average "alternative investor". We defined the investment opportunity to simply be the following three assets classes: Real Asset, Private Equity/Venture Capital, and Hedge Funds. Real assets are comprised of real estate, commodities, timberland, farmland, infrastructure, bank loans, and cat bonds; within real asset the weights were structured to reflect the market portfolio[1] within that universe. To arrive at our weight's, we researched various endowments and foundations, as well as surveys conducted by Willis Towers Watson and Russell Investments. Based on our research, alternative historical allocations have not had material deviation and therefore we decided to implement a market weight of 1/3 across each of those asset classes. A few of the constituents are not investable, and some may be reported gross or net of fee.

	Ending June 2018				
	1 Yr	**5 Yr**	**10 Yr**	**Ann. Vol**	**Draw-down**
MSCI World Free	11.70%	10.55%	6.86%	17.37%	-41.35%
Barclays Global Agg	1.93%	1.12%	2.11%	7.26%	-10.20%
MSCI Emerging Markets	8.59%	5.39%	2.60%	23.73%	-47.01%
Barclays Global High Yield	1.11%	5.15%	7.90%	13.00%	-26.20%
HFRI Fund Weighted Composite	5.69%	4.44%	3.45%	7.38%	-17.91%
CISDM EW Hedge Fund	6.52%	5.45%	4.54%	7.97%	-17.95%
CISDM CTA EW	3.37%	4.58%	3.65%	6.96%	-7.93%
CISDM Distressed Securities	5.27%	4.50%	5.38%	7.54%	-17.97%
CISDM Equity Long/Short	7.31%	6.30%	5.19%	7.03%	-11.90%
CA US Private Equity	18.58%	13.72%	10.85%	8.62%	-24.12%
CA US Venture Capital	18.27%	15.44%	10.21%	8.26%	-17.07%
LPX Mezzanine Listed Private Eqty	-1.45%	6.57%	4.39%	32.89%	-70.95%
FTSE NAREIT All Equity REITs	4.93%	8.88%	8.30%	24.86%	-58.31%
NCREIF Property	7.20%	9.77%	6.09%	5.74%	-23.88%
S&P Global Property	6.57%	6.87%	6.22%	22.10%	-50.90%
S&P Global Infrastructure	1.82%	8.04%	4.06%	17.27%	-43.75%
Bloomberg Commodities	7.35%	-6.40%	-9.04%	19.29%	-65.91%
NCREIF Timberland	3.56%	6.00%	4.00%	3.61%	-5.69%
NCREIF Farmland	6.54%	10.25%	11.73%	4.83%	0.00%
Alternative Assets Portfolio	**10.02%**	**9.31%**	**6.99%**	**6.92%**	**-21.34%**
Global 60/40	**7.78%**	**6.83%**	**5.37%**	**11.09%**	**-26.22%**
60% Portfolio/40% Global 60/40	**8.70%**	**7.85%**	**6.07%**	**9.04%**	**-24.24%**

Source: CAIA, CISDM, HFRI, Cambridge Associates and Bloomberg.

1. Global Invested Capital Market by Hewitt EnnisKnupp, an Aon Company

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