Alternative Investment Analyst Review

Editor's Letter: Stock Market Myths: High P/E Ratio, Volatility Tsunami & Share Buybacks
Hossein Kazemi

Revisiting the Role of Alternatives in Asset Allocation
Harsh Parikh, *PGIM*, and Tully Cheng, *Neuberger Berman*

Factor Investing in South Africa
Emlyn Flint, *Peregrine Securities*, Anthony Seymour, *Peregrine Securities*, and Florence Chikurunhe, *Peregrine Securities*

Momentum: A Practitioners Guide
Hamish Preston, *S&P Dow Jones Indices*

More than Just a Second Risk Number: Understanding and Using Statistical Risk Models
Christopher Martin, *Axioma*, Anthony A. Renshaw, *Axioma*, and Chris Canova, *Axioma*

Ranges and Rebalancing
Frederic Methlow, *CAIA, Al Futtaim Group*, and Abdulaziz Alnuaimi, *CAIA, Harvard Business School*

Performance Attribution in Private Equity: A Case Study of Two North American Pension Funds
Rainer Ott, *Capital Dynamics*, and Mauro Pfister, *Capital Dynamics*

Applying an Enterprise Risk Management (ERM) Framework to Fund Governance
Masao Matsuda, *CAIA, Lainston International Management*

Including Investment Process Technologies within Operational Due Diligence
Dana Lambert, *CAIA*, and Rayne Gaisford, *Olive Street Advisers*

From Theory to Practice: The Collaborative Model for Investing in Innovation and Energy
Jagdeep Singh Bachher, *University of California Board of Regents*, Ashby Monk, *Stanford Global Projects Center, and* Rajiv Sharma, *Stanford Global Projects Center*

(R)Evolution of the Regulatory Landscape in the UK
Marianne Scordel, *Bougeville Consulting*

The CAIA Endowment Investable Index
Hossein Kazemi, *CAIA Association*, and Kathryn Wilkens, *CAIA, Pearl Quest LLC*

VC-PE Index: A View inside Private Equity's Latest Golden Age
Mike Roth, *Bison*

The MSCI Global Intel Report
Max Arkey, *MSCI Real Estate*

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Stock Market Myths: High P/E ratio, Volatility Tsunami & Share Buybacks

With the stock market's bull run celebrating its 8th anniversary, newspapers' headlines and pundits have been spreading a number of myths regarding the stock market, trying to convince the public that there is something unusual and unreal about this bull run. Here, I want to address three of these myths. First, that the current market valuations (e.g., measured by the price-earnings ratio) are too high and that they presage a 7- to 10-year negative return for the market. The most prominent supporter of this view is GMO's Jeremy Grantham who predicts an annual rate of return of -3.9% for large US stocks over the next seven years.

The second myth is that the current market volatility is too low and that sooner or later there will be a sharp increase in volatility. The most prominent proponent of this view is J.P. Morgan's Marko Kolanovic, who predicts a 50% rise in volatility and potentially a substantial decline in equity prices.

The third myth is that stock buybacks by US companies have artificially increased stock prices and therefore have contributed to the current bubble in US stock market. The latest person claiming that share buybacks are fueling the stock market bubble is Oaktree's Howard Marks.

As you can see, proponents of these myths are distinguished and successful members of the investment community. Therefore, there is a chance that my analysis could contain a few fatal flaws. However, I will attempt to make as few assumptions as possible in presenting rather parsimonious rational explanations to counter their arguments. Also, it is important to point out that several other factors affecting the stock market (e.g., central bank policies) that are ignored here.

The point of this note is that the current levels of equity markets and their volatility levels are where they are for real economic and structural reasons and using them as guide to do market timing and make drastic changes to asset allocation strategies may not be value added. Some academic and industry research show that market timing based on valuation metrics may add some value. However, these approaches work only when valuations are in the extreme and tend to produce many of false positives. For instance, the P/E ratio was above average for all of 1990s and the signal indicated that investors should be in cash or at least reduce their equity allocation significantly. However, investors would have given up on significant gains had they followed this advice. Even after the tech bubble burst, investors were left with 160% cumulative return from 1990-2002 (the bear market bottom was in 2002). A sound asset allocation strategy that diversifies across traditional as well as alternative asset classes is far more likely to add value than a strategy that attempts to time the market based on valuation metrics.

Is the Market's P/E Ratio Too High?

Are stocks overvalued? This is the other side of the same question because the most common and convenient way of arguing in favor of a stock market bubble is to point out that the current S&P 500 P/E, which is 24.7, is 58% above its long-term mean (since 1871) and 31% above its most recent average (since 1961). These are indeed eye-popping figures. A 58% or even 31% drop in the stock market is likely to lead to a deep recession and a financial crisis like the one we experienced in 2007-08.

The stock market is never clearly overvalued or undervalued. One can justify any stock market level by picking the "right" discount rate (i.e., expected future rate of return). The current annual earnings and dividends per share of S&P 500 are approximately $100 and $50, respectively. Let's assume a very modest growth rate of 3% per year in dividends per share going forward, which is half the growth rate in dividends since 1961. What expected rate of return would justify the S&P 500's current level of 2470? A simple constant growth rate model shows that the current level of S&P 500 is consistent with an expected rate of return of 5%. Therefore, the market is overvalued only if one assumes that investors should or will require higher rates of return in future. Stating that the current level of market P/E is too high compared to its historical average and should decline is no different than saying the speed of computer CPUs is too high by historical standards and therefore should decline. There is a reason for each of these occurrences, and both statements will be meaningless unless one is ready to show that the conditions leading to these observations will cease to exist.

Let's dig deeper into the P/E ratio and its determinants. Using the simple Gordon model, the current P/E ratio is given by

$$PE = \frac{(1+g)\times b}{y_{10} + \pi - g}$$

Here, g is the future growth rate in earnings and dividends, b is the payout ratio, y_{10} is the 10-year Treasury yield and π is the premium above the Treasury yield that stocks are required to earn. I will contend that a sensible argument regarding overvaluations of the stock market should focus on the risk premium, π, rather than the P/E ratio. There are other variables that affect the P/E ratio, and if their current levels are justified by economic conditions, then it will be difficult to argue that stock prices are overvalued because the P/E ratio is too high.

The following table displays these and some additional figures for various points in time.

Year	2017	1980	1995	Hypothetical Figures	
S&P500 Actual PE	24.70	7.39	14.80	18.93	Average since 1961
S&P500 Earnings Per Share	100.00	15.00	31.42	100.00	
S&P500 Dividend	49.40	5.06	10.42	49.40	
S&P500 Dividend Yield	2.00%	4.60%	2.24%	2.00%	Current Figures
S&P500 Payout Ratio	49%	34%	33%	49%	
S&P500 Level	2470	110	465	2470	
10-Year Treasury Yield	2.24%	12.70%	6.00%	*3.00%*	
Nominal GDP Growth	2.50%	12.40%	5.00%	*3.00%*	Projections
Premium above Treasury	2.3%	4.9%	1.4%	*2.7%*	
S&P500 Theoretical PE	24.76	7.31	14.64	18.85	

The primary lesson from this table is that the current level of S&P500 can be justified if one accepts that investors demand 2.3% premium per year above the 10-year Treasury yield. How unusual is this? In 1980, the market was extremely undervalued if one were to use the P/E ratio as the benchmark. We can see that the observed P/E ratio of 7.39 could have been justified if one were to assume that the required premium was 4.9% above the 1980 10-year Treasury yield. This is a very attractive premium and much higher than the current premium. However, let's think back to 1980s: The Cold War was going on, inflation was volatile and high, the Iranian revolution had just taken place, the Soviet Union had invaded Afghanistan a year earlier, and there were long lines for fuel at gas stations. No wonder investors demanded such a high premium.

Consider 1995 when the P/E ratio is slightly below historical average and stocks were considered fairly valued. The premium above the 10-year Treasury demanded by investors back then was only 1.4%, which under normal circumstances would signal a highly overvalued market. The Internet was not as widely spread as it is today, but there were far fewer references to a stock market bubble back in 1995. Alan Greenspan's famous speech about irrational exuberance took place almost two years later, in December 1996. Perhaps there were good reasons for investors to demand such a low premium. The US and its allies had won the Cold War, the first Persian Gulf War was over, oil prices were declining, Europe was about to launch the Euro and China was opening its economy.

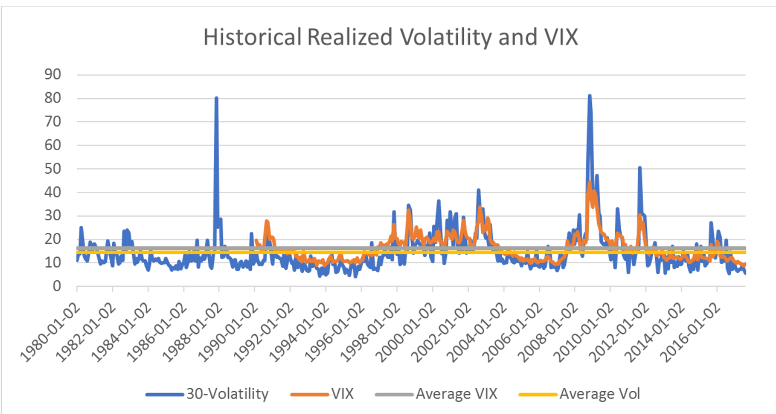
Finally, if we think that the average P/E since 1961 is the right benchmark, then given a 10-year Treasury yield of 3% and nominal GDP growth rate of 3%, a premium of 2.7% would be needed to bring the market back to the historical average (the historical average premium is about 2.7%). In other words, there is no obvious case for a stock market bubble and, by historical standards, investors are expecting a rather reasonable premium, which can easily justify the current P/E level of about 25.

The above analysis does not mean that there will be no pullback in stock prices or that the bull market will continue uninterrupted. Recessions will happen, central banks' policy makers will make mistakes, and national governments will make fiscal and political miscalculations. These would reduce the E in the P/E ratio and/or increase the premium such that it would require a decline in P to bring us to a new equilibrium in the stock market.

Is a Volatility Tsunami on the Way?

J.P. Morgan's Marko Kolanovic warned us in a July 2017 piece that there will be a sharp increase in volatility soon. This was not the first time that Marko Kolanovic has warned us of the incoming tsunami volatility. While there might be good economic reasons to believe that the current P/E ratio is too high (i.e., expected premium is too low) and that it must decline, there is absolutely no economic model or reason to believe that volatility is too low and therefore must increase. The only reason people say that volatility must increase is because it used to be much higher. Well, mortality rate used to be much higher, too. There are real reasons for the decline in mortality rate and volatility. It turns out that this is the easiest myth to debunk.

The following graph displays the historical realized volatility and VIX since 1980 (VIX data is available since 1990).



Clearly, by historical standards, the realized volatility and VIX are low but not unusually low. In any case, I would argue that there are fundamental reasons for volatility to be low and that these reasons are likely to be there going forward and therefore, in the absence some external shocks such as war or social unrest, volatility has permanently declined.

There are two fundamental reasons for the secular decline in volatility (as mentioned, I am ignoring Fed policies). First, creating and holding diversified portfolios has never been easier or less expensive. Investors are far more diversified than they used to be and therefore many idiosyncratic sources of information and volatility are ignored by them. To see this, suppose there are only two types of stocks in an economy: Sunny and Cloudy. Sunny pays dividends only on sunny days and Cloudy pays dividends only on cloudy days. The only relevant pieces of information in this economy will be changes in weather forecasts and interest rates. If investors are poorly diversified, then they would react to changes in weather forecasts as well as interest rates, creating volatility in prices of Sunny and Cloudy. In contrast, consider the case where everyone is holding both stocks. Weather forecasts will become fake news and prices would only react to changes in interest rates. We will have a much less volatile market.

The second reason, in my opinion, is that most of the global wealth is now managed on a fee-only basis. Pundits have largely ignored this fundamental change. Money managers are no longer incentivized to trade and to use buy/sell recommendations to generate trades and fees. Today, Morgan Stanley Wealth Management is the world's largest fee-based asset management company with over $2.2 trillion in clients' assets in such accounts. Morgan Stanley's inflows per quarter have averaged close to $20 billion. The same story is going on with other wealth management firms with the largest ones experiencing inflows of $10-$20 billion per quarter. These asset management firms have no incentive to trade. They want to put their clients' money to work quickly and inexpensively. This method of asset management has had two profound effects on financial markets. First, it has substantially reduced market volatility, and, second, it has made any stock market dip shallow and short-lived. There is another potential impact of fee-only and passive investment management. The market may experience more flash crashes than before. To the degree that herding is taking place among investors and money managers, the markets may experience long periods of calm followed by a flash crash.

Are Stock Buybacks Responsible for the Rising Stock Market?

Here is a headline from CNBC: "…corporate buybacks have become the chief source of buying in the market and the recent 21% decline in corporate buybacks is the alarm bell that the stock market bubble is about to burst." There are two problems with this statement. First, the headline is from 2 years ago. Second, it is nonsense.

Consider Apple Corporation, which is the largest public company in the world with a market capitalization of roughly $800 billion. It has about 5 billion shares outstanding with each share selling for about $160. Suppose Apple's CEO, Tim Cook, decides that 5 billion shares are simply too many and implements a 1-for-5 reserve split. That is, every five shares are converted into one new share. In the absence of any other news or transactions, each new share would sell for $800, representing a 400% increase in price. Since Apple's weight in the S&P500 index is 3.7%, this should have a meaningful impact on the index. Of course, it will not because the market capitalization of Apple has not changed. That is, the total market value of Apple is still $800 billion. The size of a pizza does not change if there are 4 large slices as opposed to 8 smaller ones.

One may argue that this example is irrelevant because in a stock buyback a company uses its cash to buy back its shares. Well, a buyback is identical to when a firm pays a one-time special dividend and institutes a reverse split. In fact, if Apple announces a special dividend of $80 billion along with a 9-for-10 reverse split, the impact on its earnings and capital structure would be identical to when it spends $80 billion buying back its shares. There is absolutely no difference between the two (I am ignoring the small tax effect on investors). Most commentators ignore this equivalence because it is hard to argue that special dividends plus reverse splits will cause a stock market bubble.

In the absence of any news, a stock buyback would cause Apple's stock price to increase, but the market capitalization of Apple should remain roughly the same, as its market capitalization is determined by its future total earnings, which are basically unaffected by the buyback or the reverse split. In practice, there is typically a small rise in the market capitalization because investors like the fact that the firm is returning its excess cash to shareholders rather than using it to make unwise acquisitions and investments. Also, the buyback may signal that the firm will have plenty of internally generated cash going forward, which should increase the firm's market capitalization. However, both effects will be present when the same firm announces an increase in dividends. The point is that share buybacks or special dividends plus reverse splits will not automatically increase the market capitalization of firms and the level of stock indices. Finally, assuming that markets are on average efficient, buybacks represent zero-NPV investments. However, corporations are not created to make zero-NPV investments. At the end of the day, positive-NPV projects are needed if a firm is to grow, prosper and reward its shareholders for their commitments.

Hossein Kazemi

Editor

Table of Contents

Revisiting the Role of Alternatives in Asset Allocation 7

Harsh Parikh, *PGIM*, and Tully Cheng, *Neuberger Berman*

ABSTRACT: From the US stock market's bottom in March 2009 through December 2015, US broad market equity indices returned more than 200%, far surpassing the gains made in most alternative strategies. As a result, many institutional investors are finding themselves faced with the question: Why invest in alternative assets if they underperformed equities and cost significantly more than traditional strategies? To address this question, this paper explores the role of alternatives in institutional portfolios by reviewing hedge funds, private equity, and real estate investment strategies. They analyze the role of these alternatives from the beginning of 2000 to Q1 2015 representing two full market cycles.

Factor Investing in South Africa 19

Emlyn Flint, *Peregrine Securities*, Anthony Seymour, *Peregrine Securities*, and Florence Chikurunhe, *Peregrine Securities*

ABSTRACT: Risk factors and systematic factor strategies are fast becoming an integral part of the global asset management landscape. In this paper, they provide an introduction to, and critique of, the factor investing paradigm in a South African setting. They initially discuss the general factor construction process at length and construct a comprehensive range of risk factors for the South African equity market according to international factor modelling standards. Lastly, in the portfolio management space, they discuss several approaches for creating multi-factor portfolios.

Momentum: A Practitioner's Guide 37

Hamish Preston, *S&P Dow Jones Indices*

ABSTRACT: This paper explores momentum as an investable concept and explains why over a 20-year period this particular factor has performed well relative to the S&P 500. With Mark Carhart's 1997 study adding momentum to the Fama-French Three Factor Model it brought it into the forefront of risk management and active management process and made it part of the mainstream financial discourse.

More than Just a Second Risk Number: Understanding and Using Statistical Risk Models 41

Christopher Martin, *Axioma*, Anthony A. Renshaw, *Axioma*, and Chris Canova, *Axioma*

ABSTRACT: Although fundamental factor risk models are more commonly used and understood by portfolio managers, statistical factor risk models provide an important alternative and adaptable view on risk. In times of unusual market movements and trends that are not well modelled or captured by traditional fundamental factors, statistical risk models can be leveraged to identify these unexpected sources of risk. This paper describes how a combination of fundamental and statistical factor risk models can be exploited in any investment process.

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Table of Contents

Ranges and Rebalancing 49

Frederic Methlow, *CAIA, Al Futtaim Group*, and Abdulaziz Alnuaimi, *CAIA, Harvard Business School*

ABSTRACT: This paper tries to examine whether there is evidence that periodic rebalancing would yield significant results than a 'buy and hold' strategy. Moreover, the paper also focuses on the setting of ranges around the 'neutral' weight of a portfolio. It advocates an optimization approach where different tracking error levels are used to arrive at the highest information ratio. The resulting 'efficient frontier' reveals that there are optimal tracking error levels, meaning that beyond a certain tracking error the corresponding information ratio declines.

Performance Attribution in Private Equity: A Case Study of Two North American Pension Funds 54

Rainer Ott, *Capital Dynamics*, and Mauro Pfister, *Capital Dynamics*

ABSTRACT: Evaluating and quantifying the strengths and weaknesses of the investment process is key to portfolio managers, senior management, consultants and investors; performance attribution addresses this challenging task. However, the nature of private equity makes it difficult to apply any of the well-established public equity performance attribution models. This paper approaches the problem by developing an innovative model for private equity, which dissects the private equity portfolio performance into a base factor and four premiums: Illiquidity Premium, Strategic Asset Allocation Premium, Tactical Asset Allocation Premium, and Manager Alpha.

Applying an Enterprise Risk Management (ERM) Framework to Fund Governance 65

Masao Matsuda, *CAIA, Lainston International Management*

ABSTRACT: This paper argues that an enterprise risk management (ERM) framework should be applied to the governance of investment funds. Investment funds are generally structured as corporations, and each fund has shareholders and the mission of each fund is to maximize shareholder values. Properly implemented, the objective of a fund and the goal of an ERM process converge into one. Therefore, in order for a fund director to effectively exercise his/her oversight responsibilities, it is essential to systematically apply appropriate elements of an ERM process. Such a process not only covers duties normally expected of a fund director, but helps foster a risk aware culture among entities involved in the management of the funds.

Including Investment Process Technologies within Operational Due Dilligence 73

Dana Lambert, *CAIA,* and Rayne Gaisford, *Olive Street Advisers*

ABSTRACT: Active managers can improve their investment process meaningfully, starting with an awareness of the best decision engines for security selection and portfolio construction – systems which offer data-driven, analytical perspectives on both an ex-ante and ex-poste basis. Implementing the tools and techniques discussed in this paper can potentially move the performance needle meaningfully by bringing a systematic approach to the equation. These elements provide PMs a much more comprehensive information set and feedback loop than the usual market data provider/excel combination most in the industry still rely on.

Table of Contents

From Theory to Practice: The Collaborative Model for Investing in Innovation and Energy . . .79

Jagdeep Singh Bachher, *University of California Board of Regents,* Ashby Monk, *Stanford Global Projects Center,* and Rajiv Sharma, *Stanford Global Projects Center*

ABSTRACT: Innovation and energy are likely to be two of the most attractive investment themes in the coming years. The world is moving to an increasingly technical and digital age, and the search for renewable sources of energy intensifies as the detrimental impacts of climate change increase in frequency and magnitude. Given that backdrop, the 'Collaborative Model' has emerged as a distinct model of institutional investment management that aims to re-orientate long-term investment capital more efficiently into long-term investments such as innovative companies and energy infrastructure. In this paper, they illustrate how beneficiary organizations can leverage their unique organizational competitive advantages for finding the most efficient access points for investments in innovation and energy.

(R)Evolution of the Regulatory Landscape in the UK 85

Marianne Scordel, *Bougeville Consulting*

ABSTRACT: Before the term Brexit became part of our vernacular, the UK regulatory system had been integrated into one single body looking after all aspects of regulation in 2001. Eleven years later, the systemic aspect of the financial crisis prompted the UK authorities to move in reverse, splitting up again various aspects of regulation that had previously been put together. This article discusses how the "new" system came about, how it applies to hedge funds and the extent to which Brexit may impact the way it works.

The CAIA Endowment Investable Index. 88

Hossein Kazemi, *CAIA Association, and* Kathryn Wilkens, *CAIA, Pearl Quest LLC*

VC-PE Index

A View inside Private Equity's Latest Golden Age 91

Mike Roth, *Bison*

MSCI Global Intel Report

Propery Income Risk & Performance 95

Max Arkey, *MSCI Real Estate*

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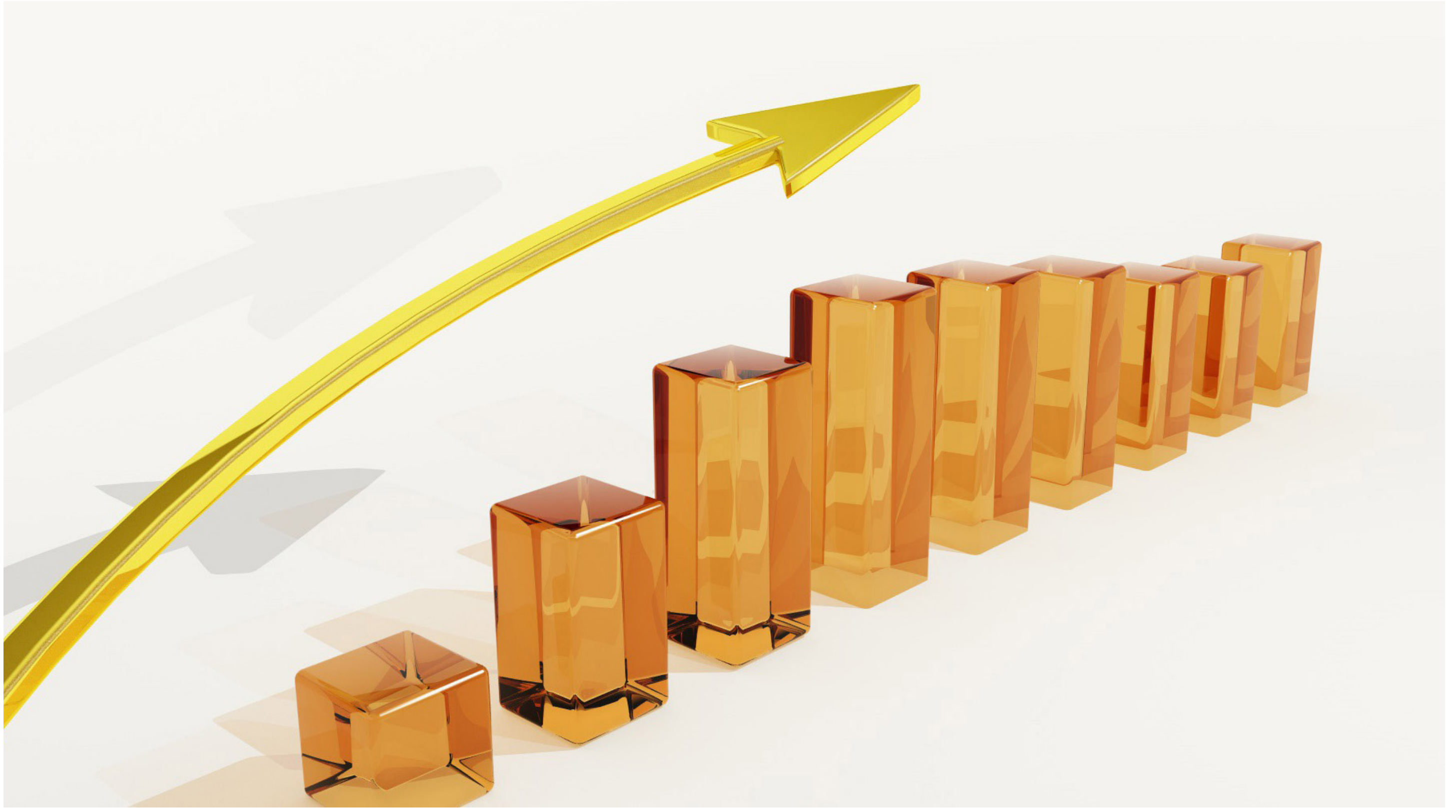

Revisiting the Role of Alternatives in Asset Allocation*

Harsh Parikh
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Tully Cheng,
Neuberger Berman

From the US stock market's bottom in March 2009 through December 2015, US broad market equity indices returned more than 200%, far surpassing the gains made in most alternative strategies. As a result, many institutional investors are finding themselves faced with the question: Why invest in alternative assets if they underperformed equities and cost significantly more than traditional strategies?

To address this question, we expand on previous practitioner research exploring the role of alternatives in institutional portfolios by reviewing hedge funds, private equity, and real estate investment strategies. We analyze the role of these alternatives from the beginning of 2000 to Q1 2015 representing two full market cycles. Our key conclusions:

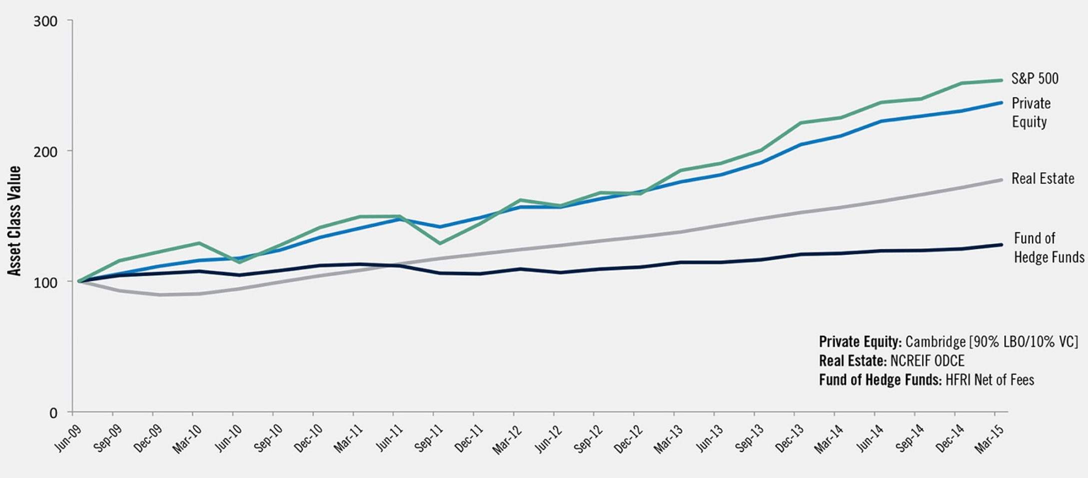
- Alternatives are far from homogenous; characteristics vary widely by strategy.
- Many alternative strategies have time-varying albeit significant embedded exposure to cheaply accessible market betas.
- Nevertheless, some strategies have historically provided "true" alpha and diversification benefits—including real estate, global macro, and relative value strategies.
- Investors should carefully evaluate the market exposures and other key characteristics associated with a range of alternatives in order to craft an allocation that serves their overall investment objectives.
- Manager selection is critical, given the wide performance dispersion observed across many types of alternatives.

Unpacking the Performance of Alternatives

In the late 1980s, David Swensen, Yale's Chief Investment Officer, pioneered the "endowment model." Through strong manager selection and reallocation from traditional assets to alternatives, Swensen successfully generated outsized returns, prompting others to follow

EXHIBIT 1

Post-Crisis Cumulative Performance by Asset Class, July 2009 - March 2015



Data sources: NCREIF, Cambridge Associates, HFR, FactSet, Datastream

suit. Minimal disclosure requirements and specialized investment mandates (that allow illiquid assets, leverage, short-selling, derivatives, and esoteric assets) provided the alternative managers a unique way to exploit market inefficiencies. Partially due to the success of the endowment model, investors have until recently perceived:

> Private equities to offer attractive risk-adjusted returns albeit with a high risk target and a long lock-up period.
>
> Real estate to provide meaningful diversification to a portfolio with the stipulation of possible cyclical returns.
>
> Hedge fund strategies, such as event-driven and relative value, to improve diversification and lower drawdown risk while generating robust alpha.

Despite these perceived advantages, alternatives have come under a fair amount of scrutiny in recent years. For instance, large public pension systems like California Public Employees' Retirement System and New York City Employees' Retirement System have recently been trimming their hedge fund exposure.[1,2] Indeed, performance at the broad asset class level suggests that alternatives have been underperforming equities since the financial crisis (Exhibit 1).

In reality, not all alternatives are created equal. Taking style differences into account, we disaggregate hedge funds into equity hedge, event-driven, macro, and relative value; private equity into leveraged buyouts and venture capital; and real estate into core, value-add, and opportunistic.[3] Large investors (those with more than $1 billion in hedge funds) are estimated to have an average of thirty hedge funds in their portfolio.[4] This implies that such investors hold a well diversified set of alternatives, and analysis at the subcategory level can be particularly relevant.

Institutions have long invested in certain kinds of alternatives, such as real estate. We conducted our analysis over the period from January 2000 to March 2015, in order to capture the wave of institutional interest and investment into hedge funds and other alternatives, as investors sought new ways to diversify their risks following the dramatic run up in equities that ended in 2000. This period is relatively short when compared with the histories for equities or for fixed income, and includes two of the most dramatically negative equity cycles in history—periods when investors would likely expect their alternative investments to provide distinct diversification relative to equities and to protect against downside risk. Of course, the choice of sample period would not only impact the performance metrics but also our derived results. For example, if we include 1995 to 1999 into our sample (the tech boom), equities would have had greater overall performance.

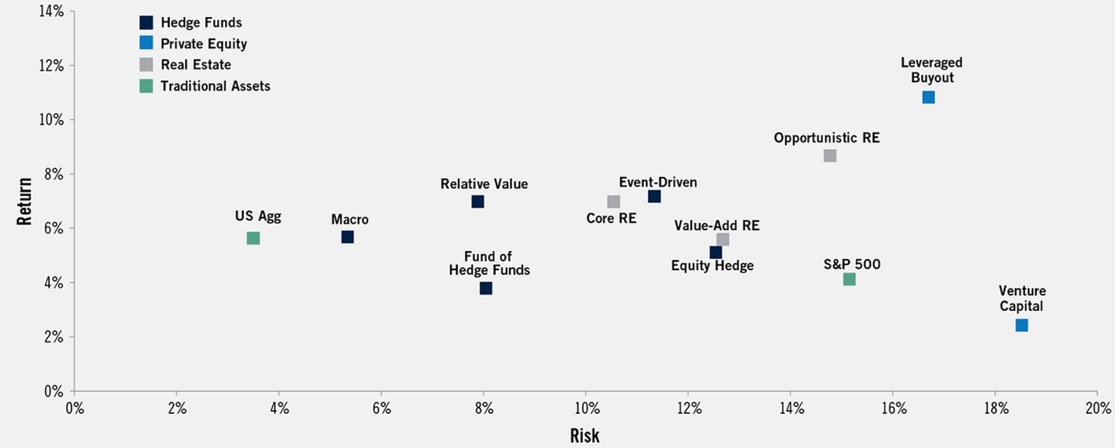
We conducted our analysis at the index level: hedge fund indices were based on the HFRI indices, private equity indices were based on indices from Cambridge Associates, and real estate indices were based on the NCREIF's ODCE and Townsend Fund Returns. The HFRI indices are monthly reported, equally-weighted hedge fund performance indices net of all fees. The Cambridge private equity and venture capital indices are based on quarterly and yearly financial statements produced by the fund managers for their limited partners and provided to Cambridge by the fund managers themselves. The NCREIF ODCE index is a capitalization-weighted, time-weighted index of investment returns based on the results of 33 open-end commingled funds pursuing a core investment strategy. The NCREIF Townsend Fund Returns index reports internal rates of return and multiples of invested capital by vintage or inception year for closed-end, value-added and opportunistic funds. Further data on these indices can be found in the Appendix.

We unsmoothed the data to account for infrequent pricing of the underlying assets which we believe understates realized volatility.[5] However, we note that some common biases such as self-reporting and survivorship remained due to constraints inherent in the data, possibly leading to somewhat more positive hedge fund and private equity results than investors actually experienced.

To begin our analysis, we present some performance metrics for the selected alternative strategies, as well as for traditional assets (equity and fixed income), over the full sample period. From this perspective, venture capital's poor performance and large volatility from the dot-com bust stands out. But most of the other alternative categories, except for fund of funds, outperformed equities over this period. Perhaps not surprisingly,

EXHIBIT 2

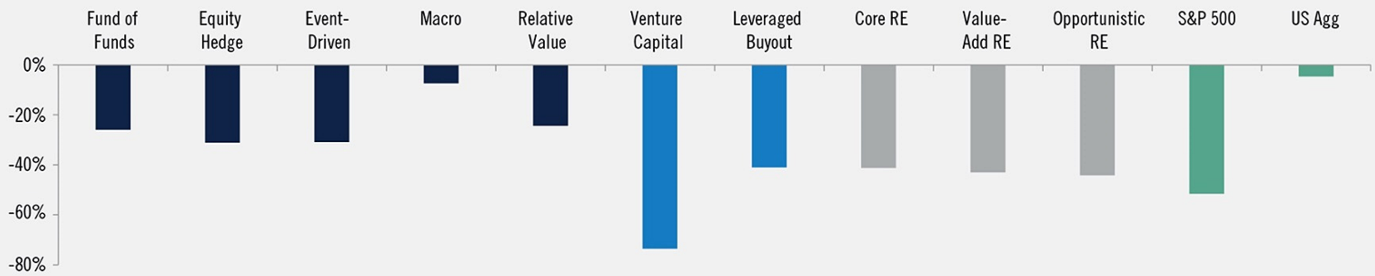
Risk/Return of Asset Subcategories, January 2000 - March 2015[6]



Data sources: NCREIF, Cambridge Associates, HFR, FactSet, Datastream

EXHIBIT 3

Maximum Drawdowns, January 2000 - March 2015



Data sources: NCREIF, Cambridge Associates, HFR, FactSet, Datastream

some hedge fund subcategories (equity hedge and fund of funds) underperformed fixed income, which enjoyed strong performance over this sustained declining rate environment.

Additionally, with the exception of venture capital, alternatives produced better risk-adjusted performance than equities over the period studied. In particular, core and opportunistic real estate, leveraged buyout private equity, and macro, event-driven, and relative value hedge fund strategies appear to perform better on a risk/return basis (Exhibit 2).

Since many institutional investors allocate to alternatives for downside protection, standard deviations may underestimate the risks associated with these subcategories. One of the selling points of certain hedge fund strategies is that they offer lower risk and downside protection as well. Indeed, macro and relative value had the lowest risk and drawdowns amongst alternatives over the period, and were second only to fixed income (Exhibit 3). Not surprisingly, private equity and real estate strategies had high volatility and much larger drawdowns.

Diversification Potential Varies

Beyond the performance metrics that alternatives are expected to generate, another key reason for the inclusion of alternatives in a portfolio is their power of diversification. Theoretically, alternatives should generate returns that are uncorrelated with traditional asset classes due to their unique drivers of returns.

As a starting point, a straightforward correlation of different alternative strategies versus traditional asset classes shows that many alternative strategies, on average, have significant exposures to market betas—as evidenced by the high correlations to equities for funds of funds, equity hedge and event-driven hedge funds, and leveraged buyout private equity. In contrast, real estate and macro hedge fund strategies offer better diversification against equities with correlations less than 0.50 (Exhibit 4). Relative value hedge funds and venture capital show some diversification advantages as well. With the exception of macro hedge funds, almost all of these strategies had negative correlations to fixed income. This is not surprising, given the overall positive correlations observed between alternatives and equities, and the strongly negative correlation between the US Aggregate and the S&P 500 (-0.36) over this same period.

Focusing in on hedge funds alone, an analysis of rolling correlations to the S&P 500 reveals that while there is variation through time, equity hedge and event-driven strategies demonstrate consistently elevated correlations to equity, while macro appears to provide distinct potential for diversification (Exhibit 5). Additionally, macro hedge funds exhibited low correlation to equities during periods of stress such as during the height of the financial crisis.

Alternative Strategies: Beta or Alpha?

Full Period

While correlations do a decent job in gauging asset diversification, we believe that it is helpful to understand the actual factors driving these alternative subcategories. Therefore, we use a factor approach to build a consistent set of risk characteristics for conventional and alternative asset classes. Extending the original approach by Fung & Hsieh, we implemented a ten factor model that attributes alternatives performance to alpha and exposures to investable market factors.[8] Included are both the traditional market factors (equity, bond, size, credit, and emerging markets) and trend-following factors (bond trend, currency trend and commodity trend) cited in that original piece, as well as REITs and mortgage factors to reflect the extension of this analysis to cover additional assets, such as aggregate bonds and real estate. In principle, the less one can replicate returns through factor exposures (suggested by low R-squared), the more the alternative subcategory delivers on its promise. Investors should be wary of paying the high fees that many alternatives managers charge if they can replicate the strategy through market factors.

Our analysis leads to some key insights (Exhibit 6). Over the historical time period analyzed, returns of fund of funds, equity hedge, and event-driven hedge funds can to a large extent be explained by market beta factors, based on relatively high and significant R-squared values. Macro hedge fund strategies, on the other hand, appeared to be less driven by market factors. Market factors appeared to have very low explanatory power for real estate returns—two of the three types of real estate had the lowest R-squared measures in the analysis. Private equity, as a whole, did not demonstrate particularly high R-squared values.

In addition, we analyzed the implied historical alpha (intercept) based on the factor model employed, for each asset class. Core real estate, value-add real estate, and opportunistic real estate, as well as leveraged buyout private equity, had the highest alpha among the strategies studied.[9] We believe that, for direct real estate, a combination of outperformance from active management and consistently high current income drove the large model alpha. On the other hand, for leveraged buyout private equity, which does not typically have a significant current income, alpha is more likely driven by outperformance from active management and

EXHIBIT 4

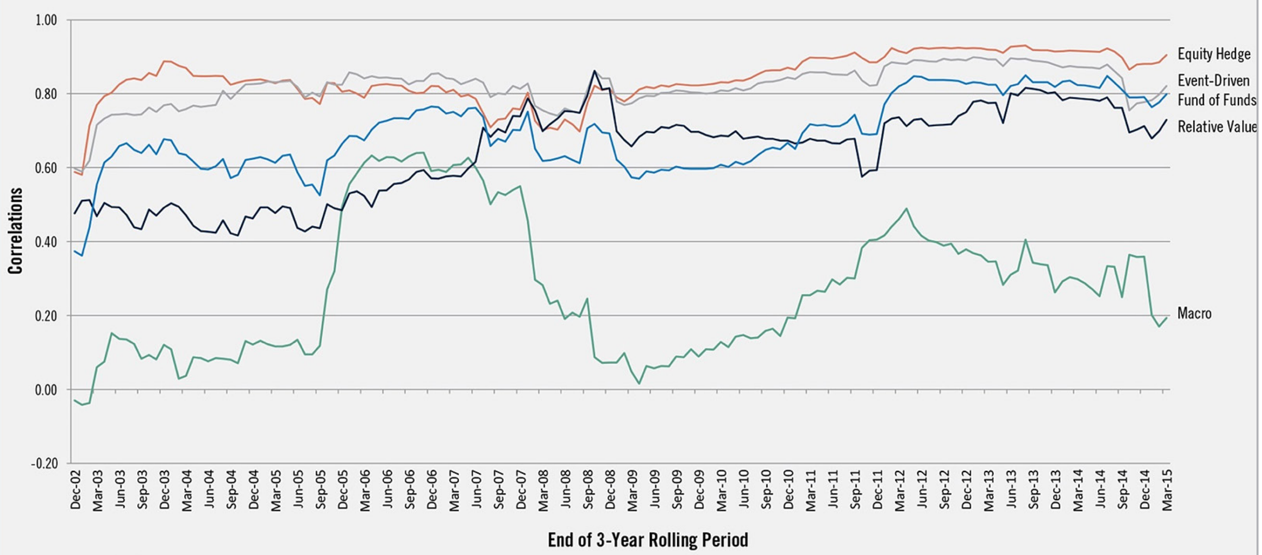
Correlations of Asset Subcategories to Traditional Equities and Fixed Income[7]

FULL PERIOD JANUARY 2000 - MARCH 2015	HEDGE FUND					PRIVATE EQUITY		REAL ESTATE		
	Fund of Funds	Equity Hedge	Event-Driven	Macro	Relative Value	Venture Capital	Leveraged Buyout	Core	Value-Add	Opportunistic
S&P 500	0.69	0.82	0.79	0.27	0.55	0.58	0.77	0.45	0.33	0.44
World Equities	0.77	0.88	0.84	0.38	0.63	0.52	0.78	0.43	0.33	0.46
US Aggregate	-0.22	-0.29	-0.30	0.13	-0.14	-0.30	-0.34	-0.16	-0.11	-0.13
Global Aggregate	0.04	0.02	0.01	0.40	0.02	-0.19	-0.03	-0.07	-0.04	0.03

Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

EXHIBIT 5

3-Year Rolling Correlations of Hedge Funds to the S&P 500, January 2000 - March 2015



Data sources: PGIM, HFR

EXHIBIT 6

Factor Analysis of Asset Subcategories[10]

FULL PERIOD JANUARY 2000 - MARCH 2015	ANNUALIZED STANDARD DEV.	HEDGE FUND					PRIVATE EQUITY		REAL ESTATE			TRADITIONAL	
		Fund of Funds	Equity Hedge	Event-Driven	Macro	Relative Value	Venture Capital	Leveraged Buyout	Core	Value-Add	Opportunistic	S&P 500	US Agg
Annualized Alpha		1.46%	1.58%	**3.46%**	**2.30%**	**4.46%**	0.64%	**7.72%**	**9.38%**	**7.42%**	**9.71%**	0.00%	0.02%
Bond Trend	67%	**-0.02**	-0.02	**-0.02**	-0.01	**-0.02**	-0.04	0.00	0.00	0.01	0.01	0.00	0.00
Currency Trend	70%	0.01	0.01	0.00	**0.03**	-0.01	-0.01	0.03	0.00	0.00	0.03	**0.00**	0.00
Commodity Trend	47%	**-0.03**	**-0.04**	**-0.03**	0.00	**-0.04**	0.07	**-0.08**	-0.03	**-0.08**	**-0.10**	**0.00**	**0.00**
Equity Market Factor	17%	**0.20**	**0.45**	**0.31**	**0.15**	0.02	**0.70**	**0.76**	0.13	0.24	**0.37**	**1.00**	0.00
Size Spread Factor	8%	0.14	**0.36**	**0.37**	**0.14**	0.00	0.09	0.16	**-0.41**	-0.33	**-0.66**	**0.00**	**-0.01**
Bond Market Factor	5%	-0.15	-0.23	**-0.40**	**0.31**	**-0.46**	0.25	-0.04	**-0.69**	-0.11	-0.38	**0.00**	**0.60**
Credit Spread Factor	5%	**0.49**	**0.68**	**0.70**	**0.27**	**0.65**	-0.32	-0.20	0.03	-0.50	-0.57	0.00	0.23
Emerging Market Factor	15%	**0.14**	**0.19**	**0.11**	**0.13**	**0.10**	0.03	**0.23**	0.01	0.06	0.18	0.00	0.00
REITS Index	16%	**-0.12**	-0.19	-0.11	**-0.10**	-0.04	-0.22	-0.15	**0.41**	**0.27**	**0.27**	0.00	**0.01**
Mortgage Factor	2%	-0.67	-0.58	-0.42	-0.41	-0.17	0.39	-0.22	**-1.73**	-1.03	0.52	**0.00**	**0.37**
R-squared		0.77	0.90	0.86	0.58	0.73	0.28	0.65	0.51	0.24	0.36	1.00	0.99

Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

Bold numbers indicate significance of t-statistic at the 90% confidence level

EXHIBIT 7

Segmented Factor Analysis of Asset Subcategories

	PRE-CRISIS (JANUARY 2000 - AUGUST 2007)						POST-CRISIS (JULY 2009 - MARCH 2015)					
	ANNUALIZED STANDARD DEV.	HEDGE FUND					ANNUALIZED STANDARD DEV.	HEDGE FUND				
		Fund of Funds	Equity Hedge	Event-Driven	Macro	Relative Value		Fund of Funds	Equity Hedge	Event-Driven	Macro	Relative Value
Annualized Alpha		-0.01%	0.67%	**1.35%**	0.77%	**1.11%**		-2.00%	**-2.49%**	0.06%	-1.47%	2.13%
Bond Trend	46%	0.00	0.00	0.00	0.01	0.01	57%	0.01	0.01	0.00	0.02	0.00
Currency Trend	59%	0.01	0.01	0.00	**0.03**	0.00	65%	**0.02**	0.01	0.00	**0.03**	0.00
Commodity Trend	45%	**0.02**	**0.02**	0.00	**0.03**	0.01	53%	-0.01	**-0.01**	**-0.02**	0.01	-0.01
Equity Market Factor	14%	0.26	0.53	0.40	0.17	0.13	13%	0.36	0.62	0.43	0.31	0.15
Size Spread Factor	14%	**0.23**	**0.46**	**0.31**	**0.14**	0.00	8%	0.03	**0.20**	0.08	-0.11	0.03
Bond Market Factor	5%	**0.30**	**0.39**	0.02	**0.37**	0.06	4%	0.05	-0.08	-0.22	**0.38**	-0.10
Credit Spread Factor	3%	0.07	-0.30	**0.72**	0.17	**0.26**	4%	0.49	**0.37**	**0.61**	0.13	**0.85**
Emerging Market Factor	14%	0.16	0.10	0.09	0.16	0.07	11%	**0.07**	**0.19**	**0.09**	**0.09**	0.06
REITS Index	16%	-0.08	-0.13	-0.05	-0.03	0.02	13%	**-0.09**	**-0.08**	-0.05	-0.02	-0.04
Mortgage Factor	1%	0.45	**0.77**	0.15	-0.37	0.34	1%	0.01	0.11	-0.04	-0.13	0.10
R-squared		0.75	0.87	0.82	0.64	0.43		0.78	0.94	0.86	0.49	0.79

Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

Bold numbers indicate significance of t-statistic at the 90% confidence level

management of distributions. We also observed significant alpha for event-driven, macro, and relative value hedge fund strategies. We did not, however, find significant alpha associated with funds of funds or equity hedge funds, nor with venture capital.

Not surprisingly, private equity demonstrated fairly high and positive factor exposures to the equity market (albeit with moderate R-squared levels). The significant factors associated with real estate included REITs (positive) as well as primarily negative exposure to bonds, mortgages, and size.

While macro hedge fund strategies had a positive exposure to the bond market factor, other hedge fund strategies (equity hedge,event-driven and relative value) had lower, or even negative, exposure to the bond market, but with greater exposure to the credit factor. For example, relative value strategies had about three times the credit spread exposure of fixed income itself.

The equity-oriented hedge fund strategies (fund of funds, equity hedge, and event-driven) carried significant equity, size (small cap), and emerging markets factor exposures, which may explain the drawdowns these categories experienced during the financial crisis. In contrast, the macro and relative value hedge fund strategies provided much lower betas to these factors, and macro additionally provided significant positive systematic exposure to the nonlinear payoffs associated with the currency trend-following factor, which almost none of the other hedge fund categories provided.

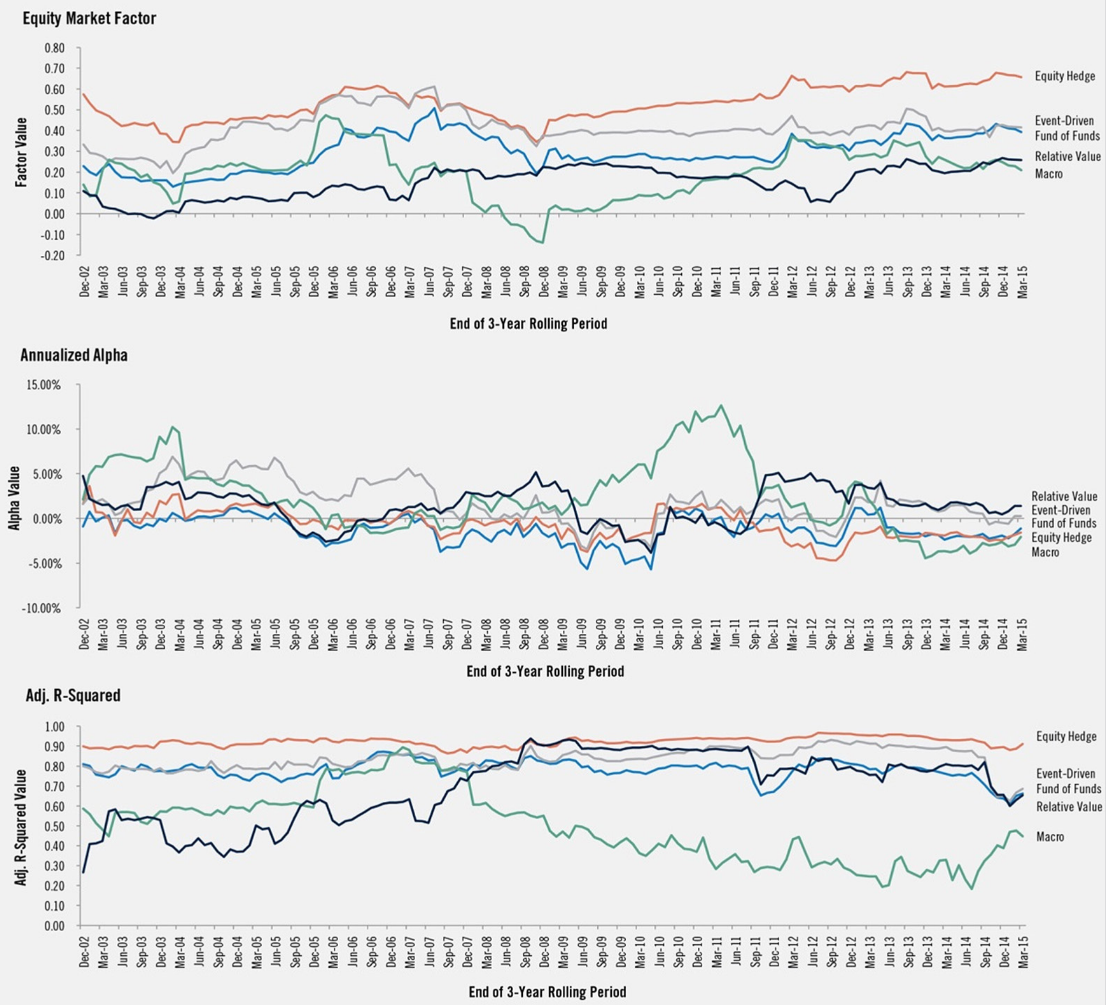
Pre- and Post-Crisis

While we based the above analysis over two complete market cycles, we recognize that a prolonged recovery from the global financial crisis may imply a regime change; thus, we also analyzed factor sensitivity of hedge funds before and after the crisis period(Exhibit 7). Since the segmented analysis periods were relatively short, we conducted the factor analysis on a monthly basis and centered our analyses on the hedge fund subcategories, as private equity and real estate data are generally reported on a quarterly basis.

We find that hedge funds' association with the equity market factor was relatively similar across the pre- and post-crisis

EXHIBIT 8

3-Year Rolling Factor Analysis, January 2000 - March 2015



Data sources: PGIM, HFR

regression, suggesting a systematic exposure. But in most cases, there was a positive shift in exposure post-crisis, suggesting positioning meant to capitalize on an equity recovery. For example, the macro hedge fund strategy's equity market factor beta exposure increased from 0.17 to 0.31.

Additionally, while most of the hedge fund strategies (fund of funds, equity hedge, event-driven, and macro) had positive and significant exposure to size (small cap) pre-crisis, the size factor fell away for three of the four (fund of funds, event-driven, and macro) in the post-crisis period. This shift suggests that some hedge funds may have divested from the small cap premium—taking advantage of small cap equities' lagging performance post-crisis.

While macro maintained its bond market exposure both pre- and post-crisis, there were some significant bond exposures (in fund of funds and equity hedge) and even mortgage exposures (in equity hedge) pre-crisis that dissipated post-crisis. Credit subsequently emerged as a more significant factor for several of these strategies post-crisis (fund of funds, equity hedge, event-driven, and relative value).

We also note a change observed in the commodity trend factor exposure. In the pre-crisis period, fund of funds, equity hedge, and macro had significant and positive commodity trend factor exposures, which subsided post-crisis, possibly reflecting the end of the commodity super cycle.

Finally, while several of these hedge fund strategies continued to carry low R-squared values in the pre- and post-crisis analysis, none of the hedge fund strategies demonstrated statistically significant, positive alpha in the post-crisis period, raising questions as to the sustainability of alpha going forward.

Rolling Periods

Given the tumultuous markets since 2000, investors might expect many hedge funds to have exhibited more frequent, active shifts in their specific exposures. While the full period and pre/ post crisis period results are meant to provide investors with a grasp of these strategies' overall characteristics, we also consider whether these characteristics might shift more continuously over time. Thus, we also analyzed hedge funds' factor exposures on a rolling three-year basis (Exhibit 8).

We find the rolling equity market factor results to be generally consistent with the full period results, with equity hedge showing the strongest exposure to the equity factor over time, followed by event-driven. Relative value demonstrated relatively stable, low positive exposure to the equity market. Macro exhibited the most dramatic shifts, with both positive and negative exposures over time—yet never reached the levels associated with equity hedge or event-driven. These results were also consistent with the 3-year rolling correlations presented earlier

Most—but not all—of the hedge fund strategies were highly explainable by the given factor exposures—with generally high, stable R-squared values—even rolling through time. Equity hedge demonstrated the strongest, and most consistent, R-squared over time. The notable exception was macro, which was by far the most variable. At times, the strategy appeared to be relatively easy to characterize by this approach (note the high R-squared values over 2005-2007), but at most other times was much less so.

The rolling alpha analysis suggests that many of the hedge fund strategies generated stronger alphas in the earlier, as opposed to later, years. Equity hedge funds and funds of funds, in particular, appeared to fall into, and remained in, mostly negative alpha territory beginning in 2005. Overall, funds of funds appeared to provide very little alpha over time. In contrast, macro demonstrated very strong countercyclical surges in alpha following both equity market downturns, shifting to a period of negative alpha only over the most recent period. Relative value and event-driven appeared to provide more moderate, and frequently positive, alpha over time.

A given strategy's propensity to demonstrate stable factor weightings and/or R-squared values over time may bring some benefits, but also may raise some concerns. On the positive side, more stable results, which can provide a solid understanding of a strategy's characteristics, make it easier to model in the context of one's overall portfolio. However, a high level of explainability (high R-squared), with relatively stable factor weightings and low (if stable) alpha levels, can indicate that a given strategy might not bring much to the overall portfolio—and could be relatively straightforward to access in the public markets (with lower fees). Based on our analysis, it appears that both equity hedge funds and fund of funds strategies run this risk of "mediocrity." On the other hand, incorporating some of the more variable, and volatile, strategies would certainly require a thoughtful approach to portfolio diversification.

Portfolio Level Dynamics

It is clear that the alternatives choices available to investors come with a range of potential factor-related characteristics. Focusing in on the subcategories which demonstrated significant alpha relative to the factors identified over the study period, we analyze how these various strategies might be incorporated at the whole portfolio level and their potential impact on the nature of portfolio risk. For example, we may identify a "risk-off" (or lower-risk) alternatives bucket with a two-thirds allocation to lower-risk hedge funds (macro and relative value) and a third allocation to core real estate. Conversely, a "risk-on" (or higher-risk) alternatives bucket might be allocated with a third in event-driven hedge funds (with stronger ties to equity and credit factors), a third in opportunistic real estate, and a third in leveraged buyout private equity. Finally, we might consider a "broad" alternatives bucket that equally weights the three broad alternative categories (real estate, hedge funds, and private equity) and includes the outperforming alternatives within each of these broad alternative categories (Exhibit 9).

What effect might these differing approaches have on an investor's overall portfolio? We illustrate by considering a range of hypothetical portfolios over the study period (January 2000 to March 2015). Hypothetical portfolios are allocated to fixed income (proxied by the US aggregate bond index) and equity (proxied by S&P 500) and are compared with similar portfolios that have an allocation of 20% to alternatives (risk-off, risk-on, or broad). In the following examples, we can think of the 20% in alternatives as replacing equity, so one might compare "50% fixed/50% equity" with "50% fixed/30% equity/20% alternatives." This replacement could just as easily be viewed from the reverse perspective or as an equal subtraction from fixed and equity, but the current view might be particularly useful to those employing alternatives as a diversifier to equities.

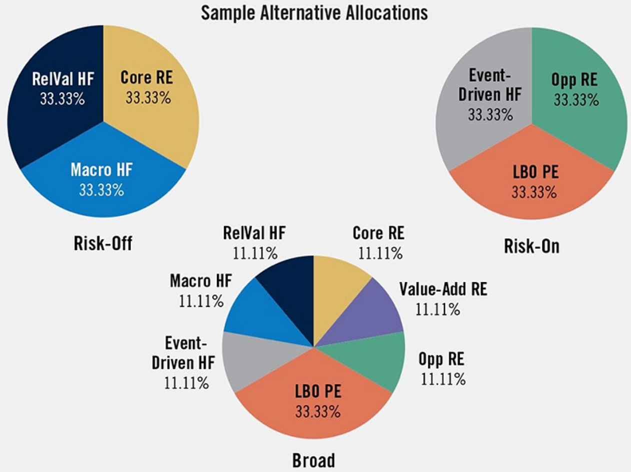
First, we note that the introduction of selected alternatives strategies reduces realized volatility and dampens the maximum realized drawdown, relative to a straight fixed income/equity approach (which naturally decreases in risk with greater allocations to fixed income)—compare the 50% fixed income

EXHIBIT 9

Alternative Bucket Factor Analysis

FULL PERIOD JANUARY 2000 - MARCH 2015	ANNUALIZED STANDARD DEV.	ALTERNATIVES ALLOCATIONS		
		Risk-Off	Risk-On	Broad
Annualized Alpha		**5.38%**	**6.93%**	**6.64%**
Bond Trend	67%	-0.01	0.00	0.00
Currency Trend	70%	0.01	0.02	0.02
Commodity Trend	47%	**-0.02**	-0.07	-0.06
Equity Market Factor	17%	**0.10**	**0.48**	**0.39**
Size Spread Factor	8%	-0.09	-0.04	-0.04
Bond Market Factor	5%	**-0.28**	-0.27	-0.21
Credit Spread Factor	5%	**0.32**	-0.03	0.00
Emerging Market Factor	15%	**0.08**	**0.18**	**0.15**
REITS Index	16%	**0.09**	0.01	0.03
Mortgage Factor	2%	**-0.77**	-0.04	-0.44
R-squared		0.69	0.70	0.71
Return		7.38%	10.53%	9.54%
Risk		5.43%	12.36%	9.89%
Maximum Drawdown		-17.98%	-32.75%	-26.74%

Sample Alternative Allocations

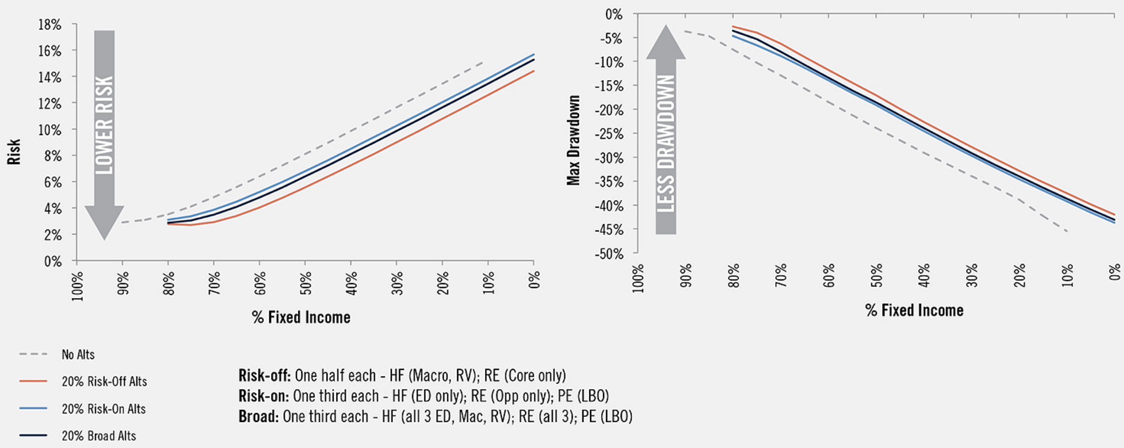


Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

Bold numbers indicate significance of t-statistic at the 90% confidence level

EXHIBIT 10

Risk and Maximum Drawdown of Illustrative Portfolios, January 2000 - March 2015

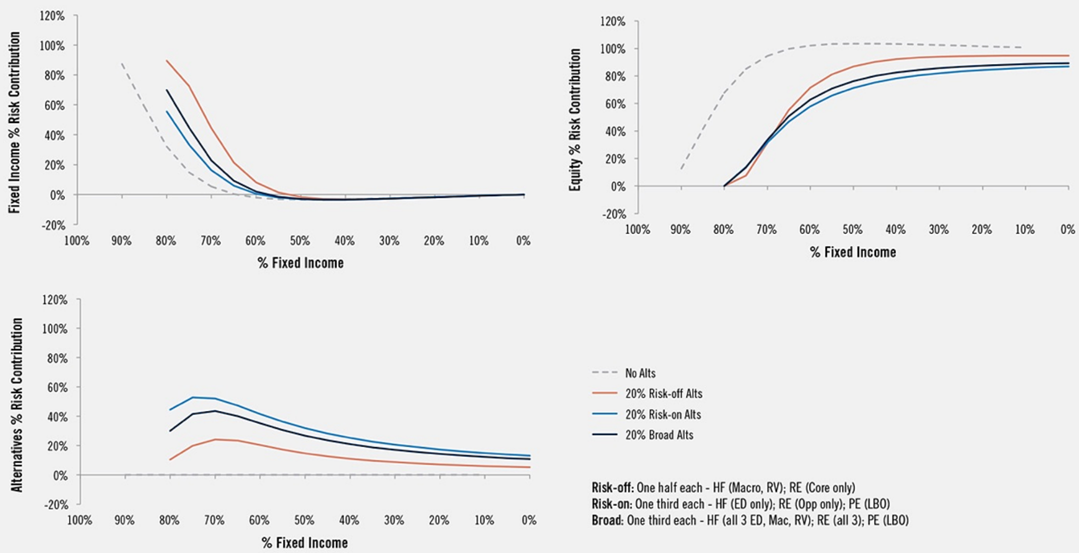


The charts above represent the risk characteristics associated with a range of hypothetical allocations to fixed income and equity, compared to similar portfolios with an additional allocation of 20% to alternatives (risk-off, risk-on, or broad). For the "No Alts" series, the portfolios represent a range from 90% fixed/10% equity, 80% fixed/20% equity, etc. down to 10% fixed/90% equity. For the "20% Alts" series, a steady allocation of 20% to a particular alternatives bucket is used in place of some of the equity allocation, while the fixed income allocation remains the same. Therefore, the portfolios in these series represent a range from 80% fixed/0% equity/20% alts, 70% fixed/10% equity/20% alts, etc. down to 0% fixed/80% equity/20% alts. Risk is calculated based on excess portfolio returns.

Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

EXHIBIT 11

Contribution to Risk in Illustrative Portfolios by Asset Class, January 2000 - March 2015



The charts above represent the risk characteristics associated with a range of hypothetical allocations to fixed income and equity, compared to similar portfolios with an additional allocation of 20% to alternatives (risk-off, risk-on, or broad). For the "No Alts" series, the portfolios represent a range from 90% fixed/10% equity, 80% fixed/20% equity, etc. down to 10% fixed/90% equity. For the "20% Alts" series, a steady allocation of 20% to a particular alternatives bucket is used in place of some of the equity allocation, while the fixed income allocation remains the same. Therefore, the portfolios in these series represent a range from 80% fixed/0% equity/20% alts, 70% fixed/10% equity/20% alts, etc. down to 0% fixed/80% equity/20% alts. Risk is calculated based on excess portfolio returns.

Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

portfolio with no alternatives to one with 20% in one of the selected alternatives buckets (Exhibit 10). Not surprisingly, the "risk-off" bucket is marginally more effective than "risk-on" or "broad" toward this end.

Next, we illustrate which asset categories dominate the portfolio-level volatility along the allocation spectrum (Exhibit 11). Fixed income's contribution to portfolio-level risk diminishes steeply with decreasing allocations to the asset class, such that even with a 60% allocation to fixed income, its contribution to risk becomes negligible. Of course, these results would vary considerably depending on the type of fixed income employed; longer duration investments would contribute more risk, which is often desired by specific kinds of investors to offset liability duration.

Equity's contribution to portfolio-level risk increases sharply as it is included in greater levels, to the point where it dominates the risk budget even as a minority holding in the portfolio. Interestingly, the alternatives considered (which might include hedge funds, real estate, and/or private equity), modeled as a static allocation of 20%, demonstrate a peak contribution to risk at around 70% fixed income (70% fixed/20% alternatives/10% equity). However, as the allocation to equity increases (with lower fixed income allocation), the impact on overall risk from equity allocation overtakes that from alternatives allocation.

How can we use our understanding of the factor sensitivities present in these various assets to describe the nature of portfolio-level risk observed? We know, for example, that private equity will

EXHIBIT 12

Factor Analysis of Illustrative Portfolios

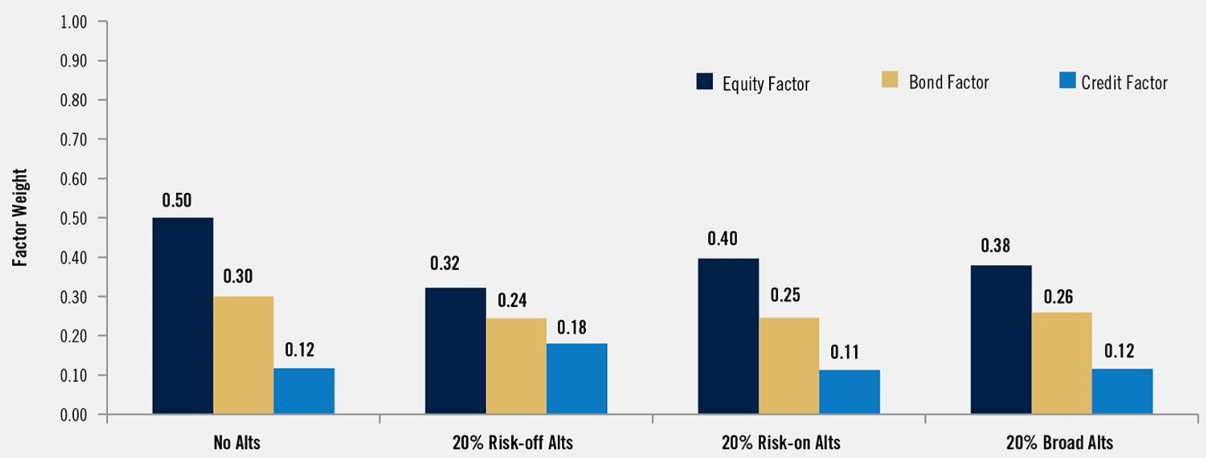
FULL PERIOD JANUARY 2000 - MARCH 2015	ANNUALIZED STANDARD DEV.	PORTFOLIOS			
		50FI/50E	50FI/30E/20A Risk-Off	50FI/30E/20A Risk-On	50FI/30E/20A Broad
Annualized Alpha		0.01%	**1.09%**	**1.40%**	**1.34%**
Bond Trend	67%	0.00	0.00	0.00	0.00
Currency Trend	70%	0.00	0.00	0.00	0.00
Commodity Trend	47%	**0.00**	**-0.01**	**-0.02**	**-0.01**
Equity Market Factor	17%	**0.50**	**0.32**	**0.40**	**0.38**
Size Spread Factor	8%	**0.00**	-0.02	-0.01	-0.01
Bond Market Factor	5%	**0.30**	**0.24**	**0.25**	**0.26**
Credit Spread Factor	5%	**0.12**	**0.18**	**0.11**	**0.12**
Emerging Market Factor	15%	0.00	**0.02**	**0.04**	**0.03**
REITS Index	16%	**0.01**	**0.02**	0.01	0.01
Mortgage Factor	2%	**0.19**	0.03	0.18	0.10
R-squared		1.00	0.98	0.96	0.97
Return		5.66%	6.14%	6.82%	6.59%
Risk		7.83%	5.32%	6.57%	6.15%
Maximum Drawdown		-21.39%	-15.22%	-17.36%	-16.82%

Alternative allocations in risk-off, risk-on, and broad portfolios refer to allocations detailed in Exhibit 9.

Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

EXHIBIT 13

Equity, Bond, and Credit Factor Exposures of 50% Fixed Income Portfolios, January 2000 - March 2015



Data sources: PGIM, NCREIF, Cambridge Associates, HFR, FactSet, Datastream

have a strong relationship to the equity market factor and that there are varying equity and credit sensitivities in hedge funds. These sensitivities naturally contribute to the individual asset-level volatility and cross-asset correlations that lead to portfolio risk.

We can make several observations by taking a closer look at the 50% fixed income portfolios as an example. First, while there was a statistically significant factor weighting to mortgages in the "no alternatives" (50% fixed/50% equity) portfolio, that factor falls away in the portfolios diversified with alternatives (Exhibit 12). The equity factor naturally falls nearly in proportion to its diminished weight, from 0.50 to 0.32, when comparing the "no alternatives" portfolio to the 20% "risk-off" alternatives version (50% fixed/30% equity/20% risk-off) (Exhibit 13). Both "risk-on" and "broad" versions, incorporating some private equity, push the equity factor back up. However, focusing on "risk-off" alternatives pushes the credit factor noticeably higher (from 0.12 to 0.18). This shift might be desirable for those investors that might, for example, be overweight Treasuries relative to credit instruments and wish to supplement their credit exposure. But for others, taken together with the dominance of equity risk, the additional credit weighting might be an unintended result. Investors should carefully consider the nature of the exposures that they are taking on, particularly within the context of their own objectives.

Additional Considerations

As investors continue to evaluate their alternatives manager program, they should consider a range of factors including dispersion, persistence, fees, transparency, and liquidity. We particularly focus on outsized dispersion in manager performance where outcomes may vary significantly even within a subcategory and fee structures where alternative fee structures might evolve to better align investor and manager interests.

Dispersion

The range of outcomes for alternatives greatly varies in comparison with traditional assets. While it is widely known that private equity returns are significantly manager specific, we find that hedge fund category outcomes are quite disperse as well (Exhibit 14).[11,12] Therefore, manager selection is essential when it comes to including alternatives in a portfolio. If an institution has access to a manager research program that is able to consistently select managers in the top 25% or even 40% of the peer group, then the appropriate alternatives strategies identified in the previous section are likely to add even more value to a portfolio.

Fees

The fees associated with many alternative investments have come under significant pressure, with a strong post-financial crisis focus on compensating alternatives managers for generating true alpha versus simply delivering market returns (beta). Many studies today challenge the "two percent-plus-performance" structure as excessive, and a number of US pension plans have publicly declared that they plan to rethink their fee structure for alternative assets.[13, 14, 15]

Alternative manager fees should compensate managers for skill, not for leveraging standard market returns. This will require investors to ensure a well-aligned and carefully designed incentive structure that might include consideration of tiered annual management fees, appropriate hurdle rates, high watermark provisions, potential clawback provisions in the event of large performance reversals or drawdowns, and a reasonableness test for pass-through expenses. In the case of private equity funds, investors will likely also include a discussion on the appropriate fee rates for committed versus invested capital, on whether the hurdle thresholds for carried interest are calculated on a deal-by-deal basis or at the aggregate fund level, and whether costs are being adequately shared between the primary fund and associated side-cars or co-investment vehicles.

Conclusion

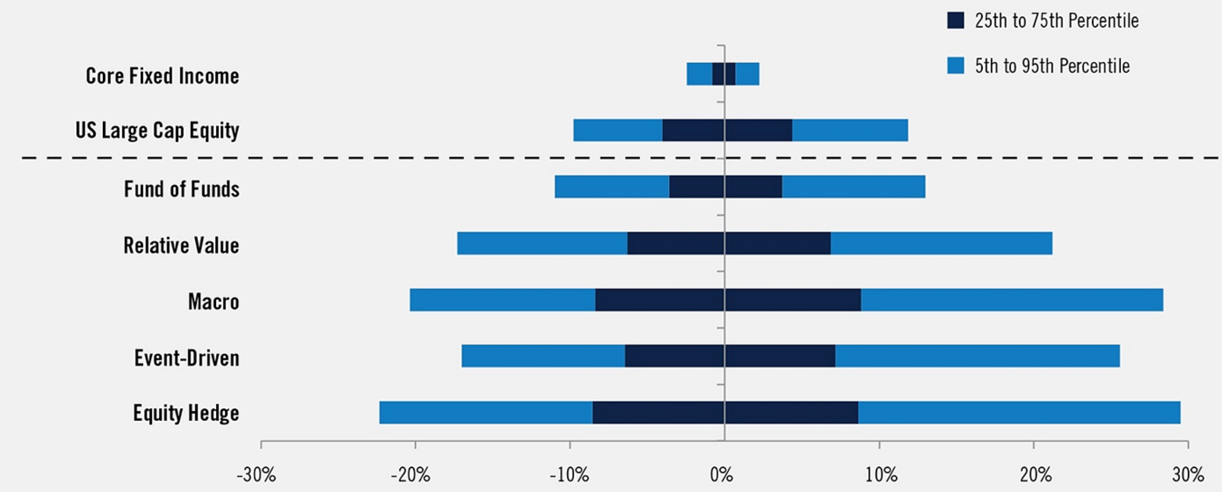
Alternatives are far from homogenous, and allocation decisions need to be made at a more granular level. By applying a factor model to the alternative subcategory level, we find that many alternatives are exposed to a variety of market betas. While some of these exposures may have a place within total portfolio construction, others might be more efficiently accessed, at more reasonable fees, elsewhere.

Based on our analysis, there are certain strategies that appear to have delivered significant alpha as well as attractive diversification characteristics—real estate strategies as well as macro and relative value hedge funds fared particularly well on this score. But others, such as fund of funds and equity hedge strategies, demonstrated a high level of explainability, relatively stable factor weightings, and lower alpha, and as such might not, on average, contribute much to one's overall portfolio.

Our analysis was conducted with a select set of market factors, over a specific time period, and at a certain level of granularity. We would encourage investors to consider the factors most relevant to their own manager universe, as well as to their overall investment strategy, when determining the diagnostic approach that would be most helpful to them. The characteristics associated with specific strategies might prove to be either desirable or inadvisable to a given investor, depending on their overall investment profile and objectives. With this knowledge in hand, investors can properly address the role of alternatives in the context of their total portfolio.

EXHIBIT 14

Annual Manager Dispersion from Median Performance by Asset Class Since 2000



Data source: eVestment

Appendix:

Factor Descriptions

PTFS Lookback Straddles: The bond trend, currency trend, and commodity trend series were developed by Fung and Hsieh using portfolio of straddles rolled every three months in order to proxy lookback straddles which are not exchange traded.[17] This concept of lookback option was developed to provide a payout profile equal to the difference between the maximum and minimum price achieved by the underlying asset from inception to expiration. Trend followers should deliver returns resembling the portfolio of bills and lookback straddles as described in Fung, W. and D. Hsieh, 2001, "The Risk in Hedge Fund Strategies: Theory and Evidence From Trend Followers."

The Primitive trend-following strategy (PTFS) "has the same payout as a structured option known as the "lookback straddle." The owner of a lookback call option has the right to buy the underlying asset at the lowest price over the life of the option. Similarly, a lookback put option allows the owner to sell at the highest price. The combination of these two options is the lookback straddle, which delivers the ex post maximum payout of any trend-following strategy. Within this context, trend followers should deliver returns resembling those of a portfolio of bills and lookback straddles."[18] These lookback straddles "can be replicated by dynamically rolling standard straddles over the life of the option."[19] As lookback straddles are not exchange-traded contracts, the price was replicated by rolling a pair of standard straddles. The PTFS used in the analysis are a long position based on three-month straddles.

Bond Trend: Return of PTFS Bond Lookback Straddle. This PTFS portfolio is an equally weighted portfolio of the US 30 yr, the UK Gilt, the German Bund, the French 10 yr, and the Australian 10 yr.

Currency Trend: Return of PTFS Currency Lookback Straddle. This PTFS portfolio is an equally weighted portfolio of the British Pound, the Deutsche Mark, the Japanese Yen, and the Swiss Franc.

Commodity Trend: Return of PTFS Commodity Lookback Straddle. This PTFS portfolio is an equally weighted portfolio of Corn, Wheat, Soybean, Crude Oil, Gold, and Silver.

Equity Market Factor: S&P 500 monthly excess return.

Size Spread Factor: Russell 2000 monthly excess return less beta adjusted S&P 500 monthly excess returns.

Bond Market Factor: (Barclays US Aggregate Government) less (Treasury monthly excess return).

Credit Spread Factor: (Barclays US Aggregate Credit - Corporate monthly excess return) less (beta adjusted Barclays US Aggregate Government - Treasury monthly excess return).

Emerging Market Factor: MSCI Emerging Market monthly excess return less beta adjusted S&P 500 monthly excess return.

REITs Factor: Dow Jones US Select Real Estate Securities monthly excess return less beta adjusted S&P 500 monthly excess return.

Mortgage Factor: (Barclays US Aggregate Securitized - MBS monthly excess returns) less (beta adjusted combination of Barclays US Aggregate Government - Treasury and Corporate spread returns).

Endnotes:

**This article was completed when Tully was employed by PGIM*

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2. Pensions&Investments, "NYCERS pulls the plug on hedge funds," April 2016. http://www.pionline.com/article/20160418/PRINT/304189975/nycers-pulls-the-plug-on-hedge-funds. Accessed June 2016.

3. Fung and Hsieh demonstrate that the broad-based indices of hedge funds are more likely to mask the style diversity of individual hedge funds. William Fung and David Hsieh, "Hedge Fund Benchmarks: Information Content and Biases," Financial Analysts Journal, 58(1), 22-34, January 2002.

4. Hedge Fund Spotlight, "The $1bn Club: Largest Investors in Hedge Funds," 5-7. May 2015.

5. Using an AR(1) for real estate, private equity, and hedge funds under the Geltner Approach. For real estate, Clayton, et al., uses a property index; since we use NCREIF ODCE for our analysis, we expect fund volatility to be higher based on the amount of leverage applied. We use scaling factors 1.25, 1.5, and 1.75 for Core, Value-Add, and Opportunistic, respectively. J. Clayton, D. Geltner, S. Hamilton, "Smoothing in Commercial Property Appraisals: Evidence from Individual Appraisals," Real Estate Economics, Fall 2001, 337-360.

6. S&P 500 and US Aggregate bonds are presented gross of fees. Hedge fund and private equity returns are net of fees. Real estate returns are presented net of hypothetical fees. We reduced the real estate indices' gross annualized return over the given period by hypothetical fee levels of 1% for core, 2% for value-add, and 3% for opportunistic. Hypothetical fee levels were derived by PGIM Institutional Advisory & Solutions based on a historical analysis of gross vs. net real estate index returns and are shown for illustrative purposes only.

7. US Aggregate is measured using Barclays US Aggregate Index; World Equity is measured using MSCI ACWI Gross Returns; Global Aggregate is measured using the Barclays Global Aggregate Index.

8. William Fung and David Hsieh, "Hedge Fund Benchmarks: A Risk Based Approach," Financial Analysts Journal, 60(5), September 2004, 65-80.

9. Significant at the 90% confidence level. Real estate returns were evaluated on a gross of fees basis due to data availability. Please see Note 10.

10. Hedge fund and private equity analyses are conducted net of fees and carried interest. Real estate and traditional assets are gross of fees. We estimate that fees would reduce the real estate model alpha by approximately 1%, 2%, and 3% for core, value-add, and opportunistic respectively. A detailed description of the factors can be found in the Appendix.

11. Deborah Kidd, "Manager Due Diligence: Searching for Alpha in Private Equity," Investment Risk and Performance Feature Articles—CFA Institute, Vol. 2013, No. 1.

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15. John Morris, Bloomberg Brief, "The Problem with Carry," March 2016.

16. Prudential Financial, Inc. (PFI), a company with corporate headquarters in the US, is not affiliated in any manner with Prudential plc, a company incorporated in the United Kingdom.

17. William Fung and David Hsieh, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," Review of Financial Studies, Vol. 14, No. 2, Summer, 2001, 313-341.

18. Ibid.

19. Ibid.

20. For complete disclosures and important information please refer to this PGIM whitepaper. https://www.pgim.com/insights/pgim-expertise/role-alternatives-asset-allocation

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Factor Investing In South Africa

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Introduction

Risk factors and the strategies based thereon are fast becoming an integral part of the global asset management landscape.[1] The financial industry has adopted the moniker smart beta to describe such strategies as the term is both highly marketable and sufficiently broad to cover a wide range of investment products. However, in this report we will rather make use of the terms risk factors and/or risk premia when referring to underlying market drivers, and systematic strategies when referring to the dynamic investment strategies followed in order to gain exposure to these underlying risk factors. We do this not only to be more rigorous but also to draw attention to the practical fact that identifying a risk factor and subsequently harvesting returns from such a factor are essentially separate problems and need to be approached as such.

The latest annual smart beta surveys from FTSE Russell, EDHEC and MSCI all show variations of the same two major trends. Firstly, there are already a number of large international institutional investors that have sizeable factor-based portfolios and secondly, that many more investors are either in the process of reviewing such strategies or are looking to do so in the near future. In order to understand why risk factor investing has shown such a remarkable growth in popularity, it is worth briefly considering the greater history of portfolio management and asset pricing.

Nearly 70 years ago, Markowitz (1952) introduced the efficient frontier approach to asset allocation, which is still the most popular framework for constructing portfolios of assets. Under this framework, an optimal portfolio is defined as the combination of assets that maximises the expected return of the portfolio at a given time horizon for a specified level of portfolio risk (Meucci, 2001). In theory then, the portfolio construction problem had been solved. One simply needed to input the expected returns and covariances of the assets into the framework and out would pop an optimal portfolio specific to one's risk preferences. When applied in practice though, the model was found to be incredibly sensitive to small changes in the estimated mean returns and the optimisation procedure would almost certainly output unreasonable allocations. This behaviour led to Michaud (1989) coining the infamous phrase "error maximiser".

As a result, academics and practitioners alike then focussed their efforts into two separate areas in order to address the framework's weaknesses. The first area was based on all things risk-related: risk-based portfolio construction, more efficient risk estimates, and new risk and diversification measures. The result of this work has culminated in a rich risk budgeting and diversification approach. Roncalli (2013) provides an excellent review of generalised risk budgeting and Flint et al. (2015) provides a comprehensive study of diversification in the South African market.

The second area is based on all aspects of creating better expected return estimates. In particular, academics and practitioners went on the hunt for the underlying building blocks of asset classes in a similar manner to the way that physicists have hunted for the increasingly small and elementary particles from which all matter is comprised. The result of this search in the financial industry has given rise to the current factor investing paradigm. Podkaminer (2013) describes risk factors as the "smallest systematic units that influence investment return and risk characteristics" and Cazalet and Roncalli (2014) describe risk factor investing simply as "an attempt to capture systematic risk premia". Homescu (2015) further adds that the aim of factor investing is to construct portfolios in a systematic manner in order to gain exposure to a range of underlying risk factors.

The objective of this report is to construct a comprehensive range of risk factors for the South African equity market, analyse the historical behaviour of these factors and provide an overview of how such factors can be used in risk management and portfolio management. In order to achieve this objective, this research draws heavily on the excellent reviews written by Ang (2014), Cazalet and Roncalli (2014), Amenc et al. (2014), Homescu (2015) and Meucci (2016). We also make reference to Mutswari's (2016) recent work on testing the validity of a number of recent factor models for South African stock returns.

The remainder of this report is set out as follows. Linear Factor Models in Finance reviews the set of linear factor models used in finance and discusses the Fama-French factor models at length. South African Equity Risk Factors discusses the general factor construction process and the Fama-French construction methodology in detail. South African risk factors are introduced and thoroughly analysed. Factor-Based Risk Management then considers the application of these factors in risk management, focussing on risk attribution and returns-based style analysis. Factor-based portfolio management is discussed in Factor-Based Portfolio Management, with emphasis on creating multi-factor portfolios, and then the report concludes.

Linear Factor Models in Finance

Almost all finance studies throughout history have shown that there is a trade-off between risk and return. A natural question for investors then is what level of return can one expect to obtain for exposing oneself to a given level of risk? Traditionally, questions of this nature have been answered by using Linear Factor Models, or LFM's, which posit a linear relationship between an asset's expected return and its covariance with the risk factors incorporated in the model.

Meucci (2016) states that LFM's are used in almost every step of the risk and portfolio management process, including asset pricing, risk attribution and modelling, alpha prediction, portfolio optimisation and asset allocation. LFM's are also the cornerstone of factor investing as they are the main quantitative tool used to create systematic factor strategies. In this section, we briefly review the key LFM's used in the asset pricing literature and discuss at length the commonly used Fama-French-type factor models.

CAPM & APT

The capital asset pricing model (CAPM) was introduced by Sharpe (1964) and serves as the basis for all other factor models of asset returns. Based on the framework defined by Markowitz (1952), Sharpe showed that the risk premium on an asset (or portfolio of assets) was a linear function of a single market risk premium, represented by the market-capitalisation index. Mathematically, the CAPM states that

$$\mathbb{E}\left[R_i\right] - R_f = \beta_i\left(\mathbb{E}\left[R_m\right] - R_f\right), \tag{1}$$

where R_i and R_m are the returns on the i^{th} asset and market portfolio respectively, R_f is the risk-free rate, $\mathbb{E}[\bullet]$ represents the expectation and β_i is the beta – or sensitivity – of the i^{th} asset to the market portfolio, calculated as the ratio of the covariance of the asset and the market portfolio to the variance of the market portfolio:

$$\beta_i = \frac{\mathbb{C}ov\left[R_i, R_m\right]}{\mathbb{V}ar\left[R_m\right]}. \tag{2}$$

Beta thus measures the level of non-diversifiable, systematic risk embedded within any asset. Given that there is only a single market risk factor, the CAPM states that the reward for taking on additional risk is directly proportional to the underlying market risk. Therefore, everyone should hold the market portfolio in equilibrium as it is the only risk that is truly rewarded. While extremely elegant, there have been countless studies since its introduction that have shown that the theoretical CAPM is not validated by empirical evidence.

Ross (1976) proposed an alternative model, known as arbitrage pricing theory (APT) based on the increasing evidence of multiple market risk premia. Ross posited that the return of an asset is driven by a combination of random market factors and that this can be modelled with an LFM:

$$R_i = \alpha_i + \sum_{j=1}^{m} \beta_i^j \mathcal{F}_j + \varepsilon_i, \tag{3}$$

where α_i is a constant, β_i^j is the sensitivity of asset i to factor j, $\mathcal{F}_j$ is the return on factor j, and ε_i is the iid error – or stock-specific risk – term, which is also independent from any of the risk factors. It can be shown from Equation 3 that under APT, the risk premium on an asset is given by

$$\mathbb{E}\left[R_i\right]-R_f=\sum_{j=1}^{m}\beta_i^j\left(\mathbb{E}\left[\mathcal{F}_j\right]-R_f\right), \quad (4)$$

Equations 3 and 4 form the basis of nearly all risk attribution systems and systematic factor strategies. One of the challenges in using the APT though is that it is left to the user to define what the underlying market risk factors really are. In this vein, Cazalet and Roncalli (2014) define three main risk factor categories. The first category comprises factors based purely on statistical asset data – e.g. Principal Components Analysis risk factors. The second category comprises factors based on macroeconomic data – e.g. inflation and GDP growth. The final category comprises factors based on market data. This can be further classified into those factors based on accounting data – e.g. size and value – and those based on price data – e.g. momentum and low volatility. In this work, we focus mostly on the third category of risk factors.

The Fama-French Model and its Extensions

Fama-French Three-Factor Model

Based on the prior empirical studies that analysed numerous potential risk factors, Fama and French (1993) proposed a three-factor model for equity stock returns, which has since become the industry standard. This model linearly combines accounting- and price-based factors in the form

$$R_i-R_f=\alpha_i+\beta_i^m\left(R_m-R_f\right)+\beta_i^{smb}R_{smb}+\beta_i^{hml}R_{hml}+\varepsilon_i. \quad (5)$$

R_{smb} is the return on a long/short portfolio of small/big market capitalisation stocks and R_{hml} is the return on a long/short portfolio of high/low book-to-market stocks.[2] These are known as the size factor and value factor respectively. Because market capitalization and value ratio indicators are correlated, Fama and French (1993) use a two-way sorting procedure to strip out any confounding factor effects. The value factor thus captures the value premium that is independent of the effect of size and the size factor captures the size premium that is independent of the effect of value.

There has been much literature aimed at assessing the appropriateness of the Fama-French three-factor model in equity markets worldwide. In the South African context, van Rensburg (2001) and van Rensburg and Robertson (2003) provide some of the earliest comprehensive assessments of Fama-French-based APT models on the Johannesburg Stock Exchange (JSE). Although not testing the exact Fama-French three-factor model, they show convincingly that one needs to incorporate several risk factors in order to accurately model the cross-section of equity returns on the JSE. More recent studies in the same vein include the works of Mutooni and Muller (2007), Basiewicz and Auret (2009, 2010), Strugnell et al. (2011) and Muller and Ward (2013), among others. Although these studies report differences in the magnitudes and significance levels of certain equity risk factors, they all conclude that a broader APT-based factor model is required to model South African equity markets correctly. The difference in study results is also to be expected, given the variations in data period and method across the various studies. As both Amenc et al. (2014) and Cazalet and Roncalli (2014) note, risk factors can be both cyclical and market-specific.

Carhart Four-Factor Model

Motivated by the evidence provided by Jegadeesh and Titman (1993) on the existence of significant medium-term price momentum trends, Carhart (1997) introduced a four-factor model based on Fama and French's work but including a momentum factor. This has since become the standard model used in fund performance and persistence literature. Mathematically, the Carhart four-factor model is given as:

$$R_i-R_f=\alpha_i+\beta_i^m\left(R_m-R_f\right)+\beta_i^{smb}R_{smb}+\beta_i^{hml}R_{hml}+\beta_i^{wml}R_{wml}+\varepsilon_i, \quad (6)$$

where R_{wml} represents the return on a long/short portfolio of winner/loser stocks, based on the previous 12-month's price performance. Although initially met with severe scepticism, the momentum factor is now referred to as the "premier market anomaly" (Fama and French, 2008). Studies have confirmed the presence of this anomaly across numerous geographies and asset classes, making it the most prevalent market factor to date (Moskowitz, Ooi and Pedersen (2012), Asness et al. (2013)). Perhaps the reason for this pervasiveness is because the momentum factor is in essence a behavioural artefact, driven by cognitive biases which are unlikely to disappear in the near future (Antonacci, 2013). The same is perhaps not true about the justifications of the size and value factors.

Fama-French Five-Factor Model

In the time since Fama and French's (1993) initial work, many authors have shown that the three-factor model and even the four-factor model may well not be sufficient to explain the variation in the cross section of asset returns. To this effect, Fama and French (2014) introduced a novel five-factor model which included factors relating to the profitability and level of investment made by a company. In contrast to their original model, which is based on APT and empirical market research, the justification for the five-factor model stems from the bottom-up dividend discount model. Specifically, Fama and French (2014) suggest that expected stock return, as modelled by the dividend discount model, is based on three variables, namely the book-to-market ratio, expected earnings and expected growth in book equity – what they dub 'investment'. From their investigations, they posit the following five-factor model:

$$R_i-R_f=\alpha_i+\beta_i^m\left(R_m-R_f\right)+\beta_i^{smb}R_{smb}+\beta_i^{hml}R_{hml}+\beta_i^{cma}R_{cma}+\beta_i^{rmw}R_{rmw}+\varepsilon_i \quad (7)$$

where R_{cma} represents the return on a long/short portfolio of conservatively/aggressively invested stocks, and R_{rmw} represents the return on a long/short portfolio of robust/weak profitability stocks. Apart from the dividend discount model, the inclusion of these two factors was also influenced by the work of Novy-Marx (2013) and others, who showed that high profitability (or quality) stocks are rewarded with a significant and consistent premium, even after accounting for the return stemming from the original risk factors. Asness et al. (2013b) have since refined Novy-Marx's proxy of profitability/quality and proposed a new long/short factor of quality/junk stocks, where quality is defined as a composite score based on the dividend discount model and comprising numerous single accounting values. For the remainder of this paper, we will focus only on Fama and French's (2014) version of the profitability (i.e. quality) factor.

Asness et al. Six-Factor Model

Given that the Fama-French five-factor model is motivated by the dividend discount model, which describes the long-term behaviour of expected stock returns, the absence of the shorter-term momentum factor becomes somewhat more understandable. However, its exclusion is still surprising given that these very same authors named momentum as the premier market anomaly. In addition to this observation, Asness et al. (2015) also suggest that value and momentum are complementary risk factors and should be placed together. As a result, they propose a six-factor model extension which includes the momentum factor and makes use of a slightly adjusted value factor:

$$R_i - R_f = \alpha_i + \beta_i^m \left(R_m - R_f\right) + \beta_i^{smb} R_{smb} + \beta_i^{hml} R_{hml}^* + \beta_i^{wml} R_{wml} + \beta_i^{cma} R_{cma} + \beta_i^{rmw} R_{rmw} + \varepsilon_i \quad (8)$$

According to their results, the six-factor model provides a more complete explanation of the variation in historical US stock returns than the five-factor model and the adjusted value factor, which was shown to be nearly redundant by Fama and French (2014) before adjustment, now remains a significant risk factor.

Other Risk Factors

In what has now become one of the classic empirical finance papers, Harvey et al. (2015) surveyed hundreds of asset pricing papers published over the last fifty years and tallied more than 300 factors that are purported to explain the variation in the cross-section of expected returns. This concerted exercise in data mining led to Cochrane (2011) coining the phrase "the factor zoo".

The proliferation of purported factors is also partly a consequence of the popularity of the factor investing paradigm: factors are now everywhere and everything has become a factor. Cazalet and Roncalli (2014) suggest that this is arguably the most pernicious fantasy in the factor investing literature. Instead, they state that there are only a handful of risk factors that represent true risk premia or market anomalies. Ang (2014) suggests four main criteria for determining whether an observed market phenomenon is actually a true risk factor:

1. It should have strong support in academic and practitioner research and strong economic justifications.
2. It should have exhibited significant premiums to date that are expected to persist.
3. It should have history available during both quiet and turbulent market regimes.
4. It should be implementable in liquid, traded instruments.

Although the final criterion is not strictly required if only using the factor model in a risk attribution setting, it is still vitally important for creating tradable systematic factor strategies.

The factors we have discussed so far are all considered to be true risk factors in the sense that they are prevalent across nearly all markets studied to date, have valid economic and/or behavioural justifications and have histories stretching back more than a hundred years in some cases. In addition to these well-established risk factors, there are also a handful of recently discovered factors that are fast becoming accepted as true risk factors.

Two such recent factors attempt to capture the observed empirical phenomena that low volatility stocks outperform high volatility stocks and, similarly, that low beta stocks outperform high beta stocks. Ang et al. (2006) and Blitz and van Vliet (2007) popularised the idea of the low volatility factor and showed significant premium levels attached to this factor across a range of markets. Baker et al. (2014) and Frazzini and Pedersen (2014) among others have since confirmed their results and refined the economic rationale, further justifying the observed risk premia.

The low beta factor can be traced all the way back to Black (1972) and the leverage effect. Despite this lengthy history, the factor has only come back into vogue in the last ten years. Interestingly, van Rensburg and Robertson (2003) showed early on that the low beta anomaly commanded a significant premium in the South African equity market and could be accessed by sorting portfolios into quintiles based on their CAPM betas.

Other common factors not considered in this work are the carry (i.e. dividend yield), liquidity and quality factors. The carry risk factor is perhaps the most easily accepted in South African markets, where both the FTSE/JSE Dividend Plus Index and dividend-based unit trusts have existed for many years already. The liquidity factor is also easily appreciated in South African markets given its extremely high levels of concentration and the constant problem of capacity that many of the larger fund managers are faced with. Even though the strategy is accessed by going long illiquid stocks and shorting liquid stocks, it is unlikely that one could ever easily trade a South African liquidity factor in any decent size. For this reason, we leave this factor for future consideration. Finally, we have the quality factor. As mentioned above, the Fama and French (2014) profitability factor is essentially equivalent to the Novy-Marx (2012) version of quality. Although the more involved definition by Asness et al. (2013b) is arguably a better proxy for the true quality factor, it is also considerably more complicated to manufacture. For the sake of simplicity then, we leave this more advanced quality factor for future consideration.

South African Equity Risk Factors

In Linear Factor Models in Finance, we outlined several of the most popular APT-based factor models used in practice which have become essential risk and portfolio management tools. Although the selection of an optimal model specification remains an open question, it is clear that the underlying risk factors used in these competing models will continue to remain relevant for the foreseeable future. To this end, there are several online, open-source risk factor databases for large international equity markets.[3] However, and despite the South African-based factor studies mentioned earlier, a similar database does not exist – or at least is not publically available – for the South African equity market.

One of the goals of this research is to create a growing database of South African equity risk factors – and underlying stock variables – constructed as per the international asset pricing literature. In particular, we construct seven Fama-French style factors: size, value, momentum, profitability, investment, low volatility and low beta. Our hope in doing so is to make available to market participants an independent factor database that enables one to run a number of important risk and portfolio management factor applications in line with international best practice. This online South African factor data library can be found at https://www.preregrine.co.za/Content/PeregrineSecuritiesResearch.

Generalised Factor and Signal Processing

The factors discussed in this work are based on the Fama-French portfolio sorting methodology, which we will outline shortly. However, it is important to realise this is simply a special case of a more general signal processing framework. Meucci (2016) outlines three steps in the general allocation policy for systematic strategies. Firstly, process the set of current information into one or more factor signals. Secondly, transform these signals into a single set of consistent characteristics (i.e. expected return estimates) on the underlying stocks. Thirdly, construct optimal portfolio weights as a function of the transformed signal characteristics.

The initial step can be broken further into data collection, signal generation and signal processing. Consider a momentum signal for example. After collecting the requisite price data and correcting for any corporate actions and dividend payments, one uses a defined function to create factor scores. This could be as simple as prior 12-month return or something more complicated like a Hull moving average filter. Finally, these scores are filtered over time and/or cross-sectionally in order to create factor signals. Common filtering techniques include smoothing over time, scoring to reduce volatility, ranking cross-sectionally, twisting ranks nonlinearly, and trimming or Winsoring outliers.

The second step is not usually carried out when constructing single factors but is vitally important when considering multiple factors. For example, consider a universe of stocks that have both momentum and value scores. One then needs to define a methodology for creating a single consistent characteristic value for each stock that is consistent with both sets of factor scores. Such methods can vary from basic portfolio sorts to complex nonlinear programming solutions. We revisit this point in the section on Factor Portfolio Mixing and Integrated Factor Scores.

Finally, create an optimal portfolio based the estimated stock characteristics, a given satisfaction index and a set of constraints. This implementation step is ultimately what separates systematic factor strategies from underlying risk factor portfolios. In special cases, one can directly trade the underlying risk factors but usually investors are faced with real-world constraints that make this impossible. For example, long-only investors wanting to gain exposure to the long/short Fama-French value factor need to use optimisation techniques in order to maximise targeted factor exposure while minimising unwanted factor exposures. See the section on Factor Risk Attribution and the Factor Efficiency Ratio for more on this.

Constructing South African Risk Factors

We now consider the Fama-French construction methodology in light of the general factor framework outlined above. The dataset consists of the 383 constituents of the FTSE/JSE All Share Index (ALSI) over the period January 1996 to August 2016. All available total return and fundamental stock data were obtained from Bloomberg and INet for the 20-year period. Due to severe limitations on available fundamental data, the initial starting date had to be moved forward to December 2002, thus yielding a final sample period of just less than 14 years.

The majority of Fama-French risk factors are based on fundamental stock variables, with the remainder based on price information variables. The definitions of each such variable were kept consistent with the relevant international literature. At any particular month in the analysis window, the factor variables are defined as follows:

- **Size** is defined as the market value of the stock as at the end of the previous month. The shares in issue are taken directly from the underlying FTSE/JSE index data and multiplied by the index-recorded share price to obtain the gross market capitalisation.
- **Value** is defined as the ratio of book value to market value (BtM). This ratio is computed by taking the most recent book value six months prior to the current month and dividing it by the market value as at the end of the previous month. This is slightly different to the original definition but is in line with the alteration proposed by Asness and Frazzini (2013).
- **Momentum** is defined as the prior twelve month total stock return, less the prior month's return to account for any short-term reversal effects.
- **Profitability** is defined as the ratio of operating profit (total annual revenue, net of sales and other expenses) to the most recent book value for the previous year.
- **Investment** is defined as the relative growth in total assets six months prior to the current month.
- **Low volatility** is defined as the standard deviation of weekly total stock returns measured over the three years prior to the current month. If three years of weekly return data are not available, a smaller history is used with the minimum period required being one year. This is the factor definition proposed by Blitz and van Vliet (2007).
- **Low beta** is defined as the CAPM beta estimated from weekly excess total stock returns and excess ALSI returns, measured over the three years prior to the current month. If three years of weekly return data are not available, a smaller sample is used with the minimum period required being one year. This is the factor definition proposed by Blitz and van Vliet (2007).

The stock universe available for factor construction at any given month is taken as the historical ALSI constituent basket for that month. In order to isolate the true premia of the underlying factors, Fama and French (1993) employ a basic two-way portfolio sorting methodology. We create long/short factor returns in a consistent manner:

1. First rank all stocks according to their size score. Using the 50th percentile as a break point, create two subsets

	Book-to-Market Value Portfolios		
	Growth	*Neutral*	*Value*
Small	SG	SN	SV
Big	BG	BN	BV

	12-1m Momentum Portfolios		
	Losers	*Neutral*	*Winners*
Small	SL	SN	SW
Big	BL	BN	BW

Table 1: Depiction of the two-way factor portfolio sorts for the Carhart four-factor model

of stocks, namely **Big** (all the stocks above the break point) and **Small** (stocks below the break point).

2. Independently rank all the stocks according to their value score. Taking the 30th and 70th percentiles as break points, construct three value subsets; namely, **High** value above the 70th percentile, **Neutral** value between the 30th and 70th, and **Low** value (i.e. growth) stocks below the 30th percentile.
3. Repeat the previous step to construct stock subsets on the basis of momentum, profitability, investment, low volatility and low beta scores respectively. Note that in the case of investment, low volatility and low beta, the portfolio below the 30th percentile is the one which is expected to render the positive return.
4. Use the two-way size/factor sort in order to create equally-weighted factor portfolios, as depicted in Table 1. For example, the size/value sorting procedure gives one six portfolios: namely, Small Value, Small Neutral and Small Growth, and Big Value, Big Neutral and Big Growth.
5. Construct long/short factor returns by averaging the returns on the Small High and Big High factor portfolios and subtracting the average of the returns on the Small Low and Big Low factor portfolios. Repeat this for each set of sorting tables to create the six size-agnostic factor portfolios.
6. Construct long/short size factor returns for each of the independent two-way sorting tables by averaging the returns on the Small High, Small Neutral and Small Low factor portfolios and subtracting the average of the returns on the Big High, Big Neutral and Big Low factor portfolios. The final long/short size factor return is then calculated as the average of the various size factor returns across all factors included in the model.

Following Step 5 above, the long/short value factor return is calculated as (9)

$$R_{hml} = \frac{1}{2}\big(R(SV)+R(BV)\big) - \frac{1}{2}\big(R(SG)+R(BG)\big)$$

$$= R_{hml}^{+} - R_{hml}^{-} \qquad (10)$$

$$= \frac{1}{2}\big(R(SV)-R(SG)\big) + \frac{1}{2}\big(R(BV)-R(BG)\big)$$

$$= \frac{1}{2}\big(R_{hml}^{s} + R_{hml}^{b}\big)$$

Equations 9 and 10 show how to decompose the long/short factor return into separate long and short components as well as into separate size components. These decompositions also represent perhaps the two most common constraints faced by investors in the risk factor space: namely, long-only and capacity constraints. We will revisit this in the section on Factor Analysis.

Following Step 6, the size factor return from the size/value portfolios is calculated as (11)

$$R_{smb}^{val} = \frac{1}{3}\big(R(SV)+R(SN)+R(SG)\big) - \frac{1}{3}\big(R(BV)+R(BN)+R(BG)\big).$$

A similar calculation is done for the size/momentum portfolios and the final size factor return is thus given as (12)

$$R_{smb} = \frac{1}{2}\left(R_{smb}^{val} + R_{smb}^{mom}\right).$$

One departure from the methodology of Fama and French is the continued use of two-way rather than n-way sorts for the larger factor models. We do this because of the discrepancy between the size of the SA stock universe, which ranges from 150 – 171 stocks over the 14 year period, and the size of the US stock universe, which numbers in the thousands. Even if one were to use only two portfolios per factor, a four-way sort would cause the average portfolio size to drop to only ten stocks. This is clearly not large enough to ensure a well-diversified portfolio free from stock-specific risk.

Rebalancing of the value, profitability and investment factors occurs annually at each December-end. The low volatility and low beta factors are rebalanced quarterly, beginning from December-end, and the momentum factor is rebalanced monthly. As noted in Step 4, the standard methodology is to create equally-weighted factor portfolios, although one can also consider value-weighted portfolios. If any constituents of the factor portfolios delist during the holding period, an appropriate portfolio rebalance is done as at the close on the day prior to delisting as per standard indexing rules.

In summary, the process outlined above ensures that we create realistic and tradable daily risk factor returns over the complete sample period. Finally, we use the ALSI total return less the three-month NCD rate as a proxy for the excess market factor.

Factor Analysis

Figure 1 displays the cumulative log-performance of the eight South African long/short risk factors over the full 14-year sample period. Equal-weighted factors are represented by the solid lines and cap-weighted factors by the dashed lines. The most striking observation is that the scale of the momentum factor is significantly larger than any of the other factors, including the (excess) market factor. Apart from the international evidence that suggests that momentum generally does command the largest risk premium (Antonacci, 2013), the strong performance is likely also due to the underlying equity market's strong performance over the

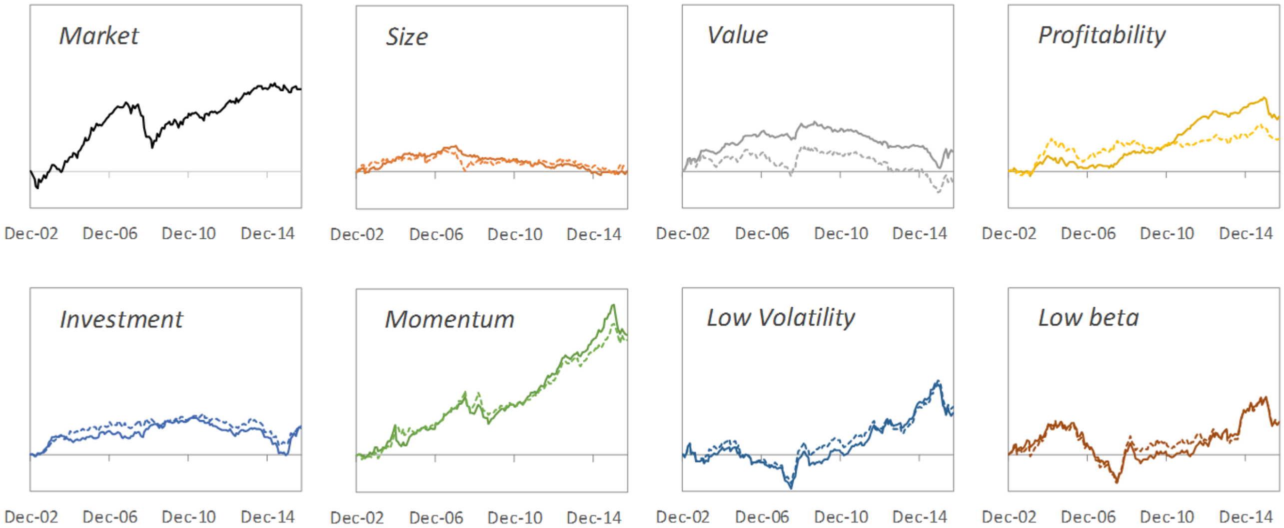

Figure 1: Cumulative log-performance of equal-weight (solid) and cap-weight (dashed) South African risk factors, Dec 2002 to Aug 2016

sample period, coupled with the extreme level of concentration. On average, the ten largest stocks in the ALSI have historically accounted for nearly 60% of the total index value (Flint et al., 2013). Therefore, any strong underlying equity market trend – positive or negative – is almost certainly driven by this handful of large counters. Such a feature is exactly what the momentum factor attempts to capture. Lastly, one must also remember that the momentum portfolio rebalances monthly and thus a large proportion of this return could be lost in practice due to high turnover costs.

Figure 1 also shows that the weighting scheme used in the Fama-French sorting procedure can impact the performance of the risk factor, although the magnitude of the effect is very factor-dependent. The discrepancy in equal- and cap-weighted factors is most obvious for the momentum factor but also affects value and profitability factors to some extent. Interestingly, we note almost no difference in either the trend or return magnitude for the low volatility and low beta factors.

Over the complete period, the size premium has remained consistently small and has in fact been slightly negative since the 2008 financial crisis; in line with the findings of Strugnell et al. (2011). As Table 2 shows, the expected return on the size factor is only 0.1%, a stark contrast to the 12.4% return on the momentum factor. The value factor, arguably the most well-known and accepted risk premium, has also struggled since the financial crisis, thus giving only a 2% annual return over the full period. This perhaps explains the poor performance of many South African value funds over the last decade.

We also note that the investment factor has not been particularly well rewarded over the last five years, showing a similar contraction as in the value premium. This is perhaps somewhat understandable as the level of annual asset growth and the book value of a company are surely somewhat connected on a fundamental level. This hypothesis is also supported by the fact that investment is the only factor to show a positive correlation 0.31 to value, even if small in absolute terms.

In contrast to the size, value and investment factors, profitability has shown strong performance over the last decade, particularly over the financial crisis and recovery period. This makes intuitive sense though as this factor essentially proxies the quality of a company's earning streams and one would expect high quality earnings streams to have been the least affected by the crisis and also to have participated strongly in the subsequent recovery rally. It also supports the recent industry trend in international markets of focussing on quality-sorted versions of the other factors (Gray (2014), Vogel and Gray (2015)).

	Market	*Size*	*Value*	*Profitability*	*Investment*	*Momentum*	*Low Volatility*	*Low Beta*
Exp. Return (CAGR)	8.66%	0.11%	1.98%	5.70%	2.68%	12.43%	4.25%	3.38%
Volatility	15.95%	7.21%	10.45%	9.21%	10.18%	14.86%	15.90%	18.04%
Kurtosis	0.55	0.36	1.66	3.14	5.66	2.11	1.67	0.22
Skewness	-0.12	-0.14	0.23	-0.93	1.01	-0.60	-0.22	-0.13
Return Range	27.31%	12.24%	20.54%	19.43%	24.35%	29.58%	33.23%	30.65%
Min Return	-14.25%	-7.63%	-11.08%	-12.90%	-7.68%	-17.63%	-17.11%	-13.71%
Max Return	13.05%	4.61%	9.46%	6.53%	16.68%	11.96%	16.13%	16.94%
Sharpe Ratio	0.54	-1.01	-0.52	-0.18	-0.46	0.34	-0.20	-0.22
Max Drawdown	-47.4%	-32.8%	-47.6%	-26.6%	-40.6%	-28.8%	-45.4%	-56.2%

Table 2: Equal-weight long/short factor summary statistics, Dec 2002 to Aug 2016

Equal-Weight	Market	Size	Value	Profitability	Investment	Momentum	Low Volatility	Low Beta
Mkt	1.00							
Size	-0.37	1.00						
Value	-0.20	0.09	1.00					
Profitability	-0.14	0.08	-0.26	1.00				
Investment	0.01	-0.04	0.31	-0.51	1.00			
Momentum	-0.01	-0.04	-0.45	0.42	-0.75	1.00		
Low Vol	-0.49	0.20	-0.03	0.62	-0.46	0.33	1.00	
Low Beta	-0.48	0.20	0.02	0.55	-0.33	0.35	0.78	1.00

EW vs CW	Market	Size	Value	Profitability	Investment	Momentum	Low Volatility	Low Beta
	0.94	0.73	0.84	0.68	0.70	0.74	0.95	0.92

Table 3: Equal-weight factor correlation matrix and correlations between equal-weight and cap-weight factor returns, Dec 2002 to Aug 2016

Tables 2 and 3 also highlight some interesting points about the low volatility and low beta factors. In contrast to what one might expect, Table 2 shows that these two factors have the second highest and highest return volatility respectively. However, this phenomenon actually confirms the rationale motivating these factors; namely that there is an inverse relationship between volatility or beta and the actual risk premium awarded to the stock. Whatever the economic reasoning though, we note that both factors have performed strongly since the financial crisis. The strong positive correlation of 0.78 between the returns of these two factors suggests that they are capturing overlapping parts of the same underlying factor, which one would expect. However, we do note a higher kurtosis, lower volatility and lower maximum drawdown attached to the low volatility factor. One final point of interest with these factors is their strong positive correlations of 0.62 and 0.55 respectively to the profitability factor. We leave this observation for future research.

As with all asset classes, risk factors also display varying degrees of cyclical behaviour. Although this is graphically evident in Figure 1, we provide more tangible evidence of this feature in Table 4, which presents factor statistics for three contiguous sub-periods of 4 1/2 years. In particular, we consider the bull market from December 2002 to June 2007, the crisis and recovery rally from June 2007 to December 2011, and the positive but slowing market from December 2011 to August 2016.

There are clear and meaningful differences in nearly all factors and statistics across the sub-periods. In particular, notice that the largest drawdown for most of the factors has actually occurred in the most recent sub-period and specifically over the last two years. Two of the main reasons for this – although certainly not the only ones – are that the proportion of SA-specific risk to global risk in the local market has been consistently increasingly since 2012 (Flint et al., 2015), and that some of the largest ALSI constituents have experience significant company-specific events in the recent past. This observation highlights the general need to ensure that one is effectively diversified against those risks which do not carry any discernible risk premia as well as being diversified across the risk factors that do carry a positive premium over the long-term. It is this last reason that has driven the rise of multi-factor portfolios, discussed further in in the section on Factor-Based Portfolio Management.

Statistic	Period	Market	Size	Value	Profitability	Investment	Momentum	Low Volatility	Low Beta
Exp. Return (CAGR)	1	21.64%	7.59%	11.40%	1.88%	6.86%	13.41%	-3.50%	-0.91%
	2	-2.52%	-4.47%	0.78%	11.57%	3.29%	7.25%	7.45%	2.27%
	3	8.26%	-2.29%	-5.24%	3.93%	-1.76%	18.38%	9.06%	8.81%
Volatility	1	16.13%	7.89%	9.50%	9.75%	7.70%	15.52%	13.49%	17.44%
	2	19.61%	6.68%	8.98%	7.18%	8.56%	12.30%	15.69%	16.64%
	3	10.67%	6.67%	12.16%	10.31%	13.29%	16.63%	18.13%	20.00%
Sharpe Ratio	1	1.34	0.02	0.42	-0.57	-0.07	0.39	-0.81	-0.48
	2	-0.13	-1.78	-0.74	0.58	-0.48	-0.01	0.00	-0.31
	3	0.77	-1.45	-1.04	-0.34	-0.69	0.66	0.09	0.07
Max. Drawdown	1	-21.3%	-8.0%	-8.0%	-16.4%	-9.8%	-24.9%	-26.8%	-39.3%
	2	-47.4%	-15.2%	-15.2%	-15.5%	-9.5%	-31.1%	-45.4%	-56.2%
	3	-15.4%	-32.8%	-47.6%	-26.6%	-40.6%	-34.2%	-35.5%	-38.1%

Table 4: Long/Short Factor performance across three sub-periods: Dec 2002 – Jun 2007, Jun 2007 – Dec 2011, Dec 2011 – Aug 2016

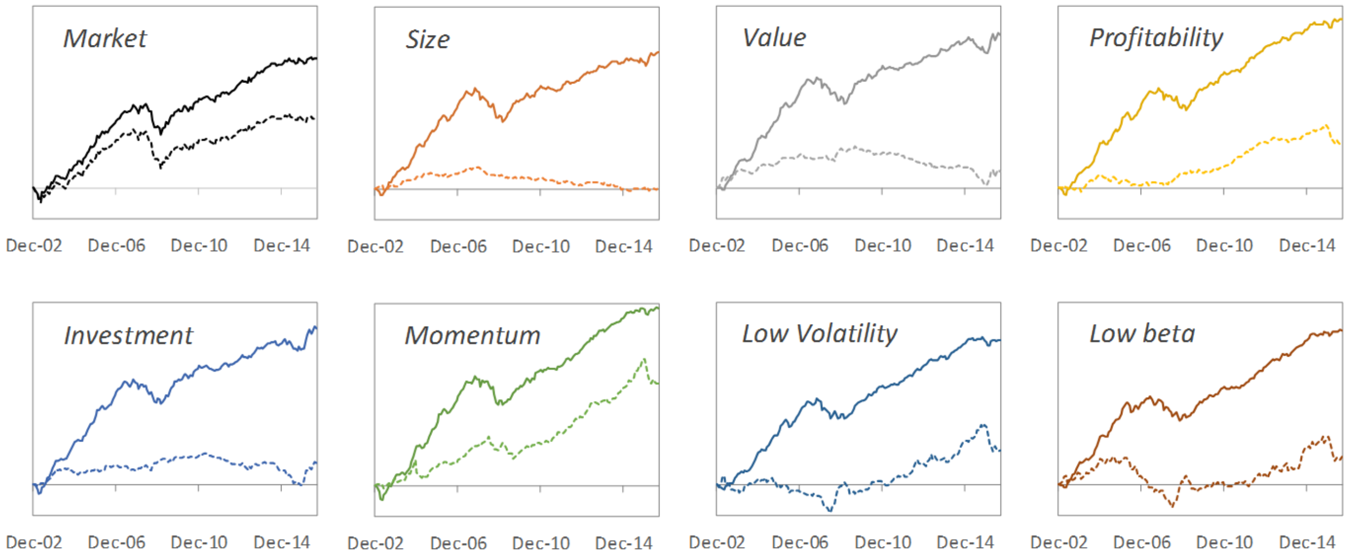

Figure 2: Cumulative log-performance of long-only (solid) and long/short (dashed) South African risk factors, Dec 2002 to Aug 2016

Table 5: Equal-weight long-only factor summary statistics, Dec 2002 to Aug 2016

	Market	*Size*	*Value*	*Profitability*	*Investment*	*Momentum*	*Low Volatility*	*Low Beta*
Exp. Return (CAGR)	16.92%	17.85%	20.22%	22.49%	20.66%	23.74%	18.97%	20.40%
Volatility	15.32%	13.62%	15.19%	13.51%	15.51%	15.32%	11.98%	12.74%
Kurtosis	0.34	1.31	0.60	0.53	0.14	1.41	1.47	1.35
Skewness	-0.18	-0.73	-0.20	-0.42	0.01	-0.58	-0.70	-0.59
Return Range	26.09%	22.33%	25.13%	21.94%	26.90%	26.74%	21.78%	21.86%
Min Return	-13.10%	-14.07%	-13.14%	-11.87%	-10.01%	-14.27%	-13.07%	-11.58%
Max Return	12.99%	8.26%	11.99%	10.07%	16.89%	12.47%	8.71%	10.28%
Sharpe Ratio	1.10	0.77	0.84	1.12	0.86	1.07	0.97	1.02
Max Drawdown	-40.4%	-42.2%	-35.1%	-30.8%	-33.3%	-37.5%	-27.5%	-32.5%

Factor Robustness

As with any empirical financial study, one needs to address the question of robustness. In particular, one should always be cognisant of the fact that the constructed factor portfolios will always only be noisy proxies of the true underlying risk factors. To this end, we consider the robustness of such factors to the choices made during the construction process. We have already highlighted one such choice in Figure 1 by showing the effect that weighting scheme can have. In this section we scrutinise a number of other important construction choices.

Long-only versus Long/Short Factors

One of the most pertinent constraints for many investors is the inability to short sell assets either at all or to the extent that they would wish. This raises the issue of whether long-only factor proxies are able to provide similar risk factor exposure in comparison to their long/short counterparts. A fundamental challenge in factor investing is the investability of the underlying factor portfolios. It is all well and good to create theoretically appealing long/short factor portfolios and use these for risk attribution – see the section on Factor Risk Attribution and the Factor Efficiency Ratio – but this may all for nought if one cannot effectively allocate capital to such portfolios. Hence the proposal of long-only factor portfolios. Although such portfolios will contain residual market risk by construction, we believe that their interpretation as risk factors still remains valid. Furthermore, given that all the factors will on average have similar levels of market risk exposure, this residual risk should largely cancel out in any risk attribution exercises.

Figure 2 compares the performance of the long-only component of each factor (solid lines) against the complete long/short portfolios (dashed lines), and Table 5 gives the long-only factor summary statistics. In the case of the market factor, we are comparing the absolute market return with its excess-to-cash counterpart. There is a stark contrast in performance between all the long-only and long/short portfolios. It is also clear that the long-only risk factors – barring size – comfortably outperform the absolute market return.

Table 6 gives the correlation matrix of the long-only factors as well as the correlations between the long-only and long/short versions of each factor. The supposition of contaminating latent market exposure is proven by the strong positive correlations with the market factor. Furthermore, the correlations between each risk factor are now also very high as a result. Considering the correlations between long-only and long/short factor versions, it is interesting to note that despite the similarity in trend between the two momentum factors, the correlation between these two factors is only mildly positive at 0.29. This serves as a

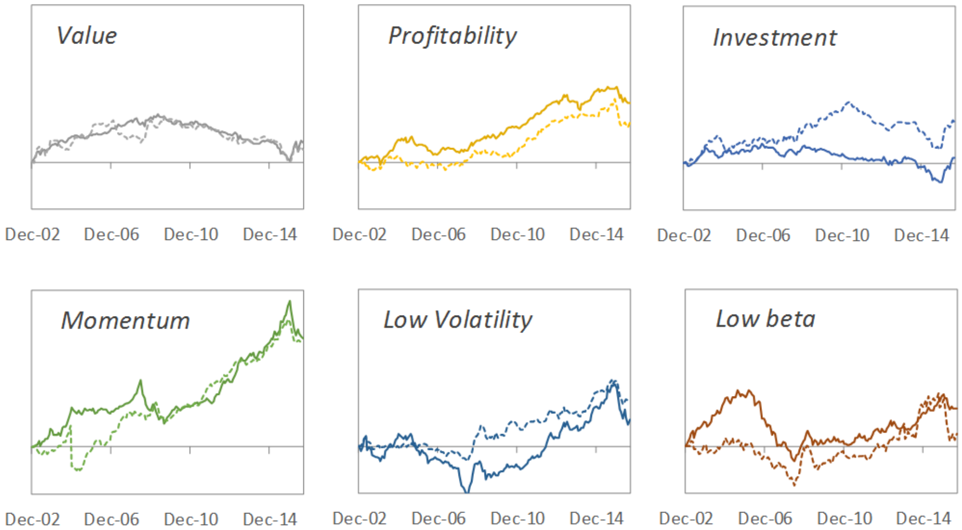

Figure 3: Cumulative log-performance of big (solid) and small (dashed) South African risk factors, Dec 2002 to Aug 2016

Long-Only	*Market*	*Size*	*Value*	*Profitability*	*Investment*	*Momentum*	*Low Volatility*	*Low Beta*
Market	1.00							
Size	0.71	1.00						
Value	0.66	0.90	1.00					
Profitability	0.76	0.91	0.84	1.00				
Investment	0.75	0.88	0.90	0.81	1.00			
Momentum	0.80	0.87	0.76	0.91	0.80	1.00		
Low Volatility	0.62	0.86	0.80	0.89	0.69	0.81	1.00	
Low Beta	0.55	0.81	0.74	0.83	0.66	0.78	0.85	1.00

L-O vs L/S	*Market*	*Size*	*Value*	*Profitability*	*Investment*	*Momentum*	*Low Volatility*	*Low Beta*
		0.18	0.41	0.17	0.42	0.29	0.07	0.16

Table 6: Long-only factor correlation matrix and correlations between long-only and long/short factor returns, Dec 2002 to Aug 2016

poignant reminder about the pitfalls of conflating price trend and correlations. What Figure 2 does suggest though is that the short component of the momentum factor provides only limited benefit across the period.

Factor Size Effects

Another constraint faced by many investors is that of capacity. Even if one has the ability to short, it may be that the majority of a factor's return stems from the Small sub-portfolios of the factor. Such a size bias would imply limited investment capacity owing to the small market capitalisation of the underlying stocks and potential illiquidity issues. Several authors have suggested that such factor size biases exist in many markets (Homescu, 2015). If present in the highly concentrated SA equity market, this bias would have serious ramifications on the prospect of large-scale SA factor investing. Figure 3 breaks down each factor return into its Big (solid line) and Small (dashed line) sub-portfolio as per Equation 10. Note that these sub-portfolios are still long/short combinations and hence are of similar magnitudes to the complete factor returns shown in Figure 1.

Momentum and value don't display any significant size bias. Of the remaining four, profitability displays a small, persistent bias towards large stocks, while investment displays a persistent bias towards small stocks. Low volatility and low beta display discrepancies between big and small long/short portfolios that vary over the sample period.

Rebalancing Frequency & Date

Value, profitability and investment portfolios are rebalanced annually at the beginning of each year. Low volatility and low beta portfolios are rebalanced quarterly with the first rebalance occurring at the beginning of the year, and momentum portfolios are rebalanced at the end of each month. The choice of rebalance frequency for each factor is driven by the time frame over which the factor signal decays. There is also the more practical issue that any benefit gained from more frequent rebalancing may be offset by the additional transaction costs. For the majority of our factors, the time frame of the risk premia is well established. However, given the relatively new 'discovery' of the low volatility and low beta factors, the effect of rebalance frequency is less well documented. To this end, we compared the returns from the low volatility and low beta factors when rebalancing monthly, quarterly, biannually and annually and found only minor differences.

Another rebalancing issue to consider for those factors with longer holding periods is the choice of month in which to enact the rebalance. As above, we test how much of an impact moving rebalance dates has by considering the returns from twelve value factors each rebalanced in different months of the year and again find no significant return differences. Although it may seem odd to include such a non-result in our research, it is an incredibly important one from a practical implementation perspective.

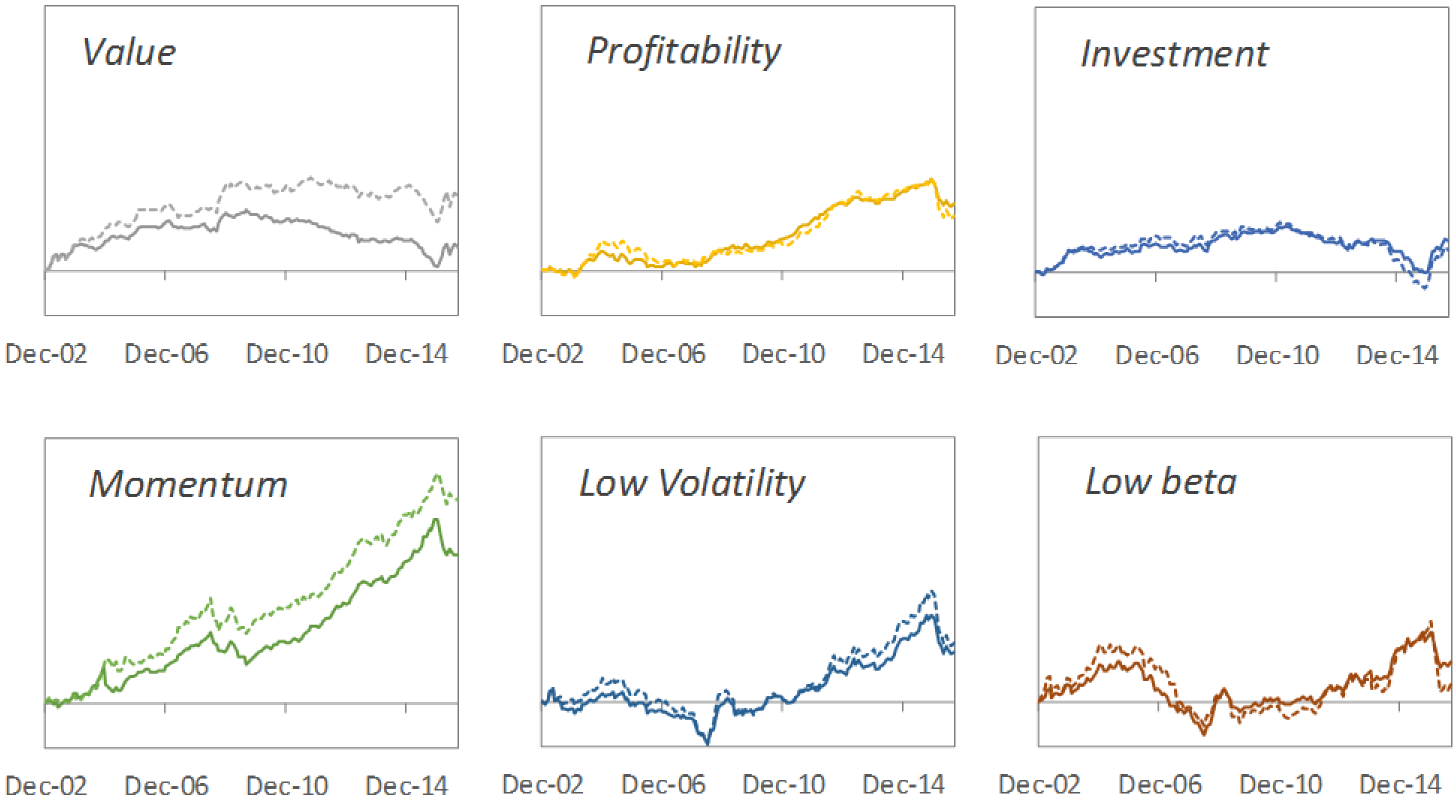

Figure 4: Cumulative log-performance of standard (solid) and extreme (dashed) South African risk factors, Dec 2002 to Aug 2016

Furthermore, it showcases the fact that the factor construction methodology outlined in in the section on Constructing South African Risk Factors is generally robust to rebalancing choices.

Portfolio Extremity

The standard Fama-French two-way sorting procedure uses the 50th percentile of the size score and the 30th and 70th percentiles of the factor scores as the relevant sorting break points. A natural question then is whether using more extreme percentile break points results in larger factor risk premia. The trade-off here is that one essentially creates 'purer' factor portfolios but at the cost of increasing the portfolio's idiosyncratic risk. This is particularly pressing in the South African equity market, which only contains around 160 counters.

To test the robustness of the factors to the sorting methodology, we create extreme factor portfolios using the 20th and 80th percentiles of the relevant factor scores as sorting break points. Figure 4 gives the comparison between the standard (solid line) and extreme (dashed line) factors. Somewhat surprisingly, only the extreme value and momentum factors show any significant difference to their standard counterparts. In both cases, the divergence of the extreme factor performance is most evident in the last ten years and seems to be linked to outperformance during periods of financial stress. We leave further investigation of this phenomenon for future research.

Alternative Factor Definitions

Although varying the choice of sorting percentile can in some respects be considered as using an alternative factor definition, the more obvious alternative is to use a different fundamental stock characteristic as a proxy for the underlying factor score. As an example, we have already discussed the multiple definitions of the quality factor in the section on The Fama-French Model and its Extensions. In a similar vein, a number of authors have considered alternative measures for value and for low volatility. Popular alternative value score candidates include earnings-to-price, cash flow-to-price and a composite scored based on these two metrics as well as the original book-to-market ratio (Amenc et al., 2014). In the low volatility literature, the alternatives are not different risk measures but rather different calculation methods for volatility; the main variables being the length of the historical estimation window and the frequency of return data.[4] Blitz and van Vliet (2007) suggest using three years of weekly data, Baker et al. (2014) suggests using either 60 monthly or 60 weekly return observations, local research considers three years of monthly data, while Frazzini and Pedersen (2014) suggest one year of daily return data.

Figure 5 gives the cumulative log-performance of long/short factors based on these alternative value and low volatility scores. The variant return range for both factors is fairly substantial and particularly so for the value factor. Furthermore, the behaviour of the variant value factors differs significantly throughout the period, which suggests that the selected stock characteristics capture different aspects of the true value risk factor. The relative outperformance of the composite value score supports this suggestion and also highlights the importance of reducing signal noise; in this case achieved by averaging out the characteristic-specific noise.

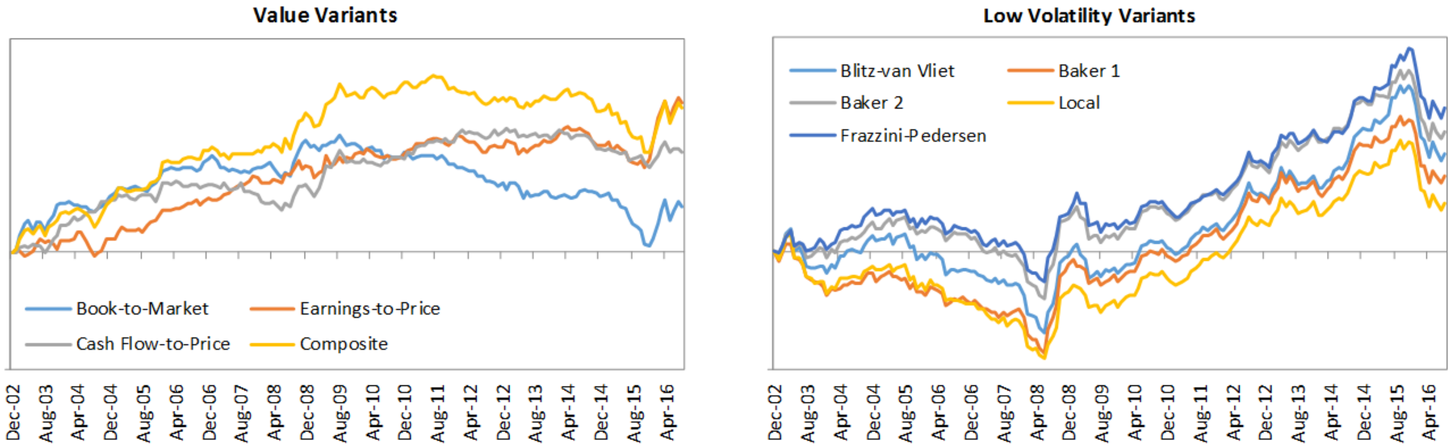

Figure 5: Cumulative log-performance of value factor variants (left) and low volatility factor variants (right), Dec 2002 to Aug 2016

For the low volatility factor, performance of the factors all show the same pattern, indicative of the fact that only the calculation method is changing, rather than the measure itself. Interestingly, both of the top performing variants are those that use the smallest estimation window – 1 year and 60 weeks respectively – as well as higher frequency data – daily and weekly respectively.

Factor-Based Risk Management

At its core, portfolio management is about making decisions: when to buy or sell any given asset and in what quantity. These decisions are made in order to add value to a passive benchmark, be it a nominated index or a cash-based rate.[5] In this setting, 'adding value' is usually defined in two ways. The first is by achieving a positive return, or alpha, over and above the nominated benchmark at an acceptable level of risk. The second is by achieving a specified target return at a lower level of risk than that of comparable passive market products.

In both cases, the strength of any portfolio decision should be measured by how much value it generates for the fund, conditional on the market and fund constraints faced by the manager over the performance period. In prior Peregrine Securities research, we showed how one could use the fundamental law of active management (FLOAM) framework of Clarke et al. (2002) in order to decompose a fund's relative return and risk into contributions from each of the underlying fund constituents (Flint et al., 2015).

We build on this work here but consider instead the idea of risk attribution rather than risk decomposition. In particular, we consider how to attribute a fund's risk – absolute or relative – to a given set of external risk factors. Such an attribution lets one identify what kinds of factor risk a fund is exposed to and furthermore calculate how large these factor bets are. Knowing this allows one to make informed and efficient investment decisions.

Factor Risk Attribution and the Factor Efficiency Ratio

Given a series of fund returns – absolute or relative – we can use one of the LFM's in The Fama-French Model and its Extensions to attribute risk to the underlying risk factors constructed in Constructing South African Risk Factors. Although more difficult than attributing risk to the fund's constituents, Meucci (2007, 2016) describes how one can still attribute fund risk to a set of external risk factors in an additive fashion. Furthermore, if one does have sight of the fund's holdings, it is possible to attribute risk similarly for each of the underlying constituents so that the fund's factor risk contributions can be written as a linear combination of the constituents' factor risk contributions (see also Roncalli and Weisang, 2012). This is perhaps the most important factor application in the risk management space. Consider the pedagogical example below.

We select the Carhart four-factor risk model and make use of long-only risk factors. Let us assume that there are four funds that are currently under investigation. We simulate monthly returns for these funds using the factor exposures given in Table 7. A small random alpha term (centred at 0.25%) and a larger random noise term (centred at zero) are added to each fund's monthly return.

	Fund1	Fund2	Fund3	Fund4	Benchmark
Market	0.5	0.1	0.1	0.2	0.25
Size	0.2	0.5	0.1	0.2	0.25
Value	0.2	0.2	0.5	0.1	0.25
Momentum	0.1	0.2	0.2	0.5	0.25

Table 7: Simulated fund risk factor exposures

Betas	Fund1	Fund2	Fund3	Fund4	Benchmark
Alpha	0.38%	0.10%	0.35%	0.18%	0.00%
Market	0.52	0.05	0.14	0.23	0.23
Size	0.29	0.48	0.11	0.24	0.26
Value	0.15	0.24	0.51	0.06	0.24
Momentum	0.05	0.22	0.15	0.49	0.25
R^2	94.2%	95.5%	94.6%	95.4%	95.9%
Risk (Volatility)	14.27%	13.88%	13.01%	14.68%	13.86%
Tracking Error	5.37%	4.71%	4.89%	4.48%	n.a.
	Risk Contributions				
Market	52.9%	4.0%	13.8%	21.3%	22.8%
Size	23.8%	44.9%	10.2%	20.2%	24.0%
Value	12.9%	24.3%	55.5%	5.4%	23.4%
Momentum	4.6%	22.3%	15.1%	48.4%	25.7%
Residual	5.8%	4.5%	5.4%	4.6%	4.1%
	Tracking Error Contributions				
Market	30.9%	26.9%	14.3%	-0.4%	n.a.
Size	-0.8%	9.5%	12.7%	-0.7%	n.a.
Value	3.9%	0.1%	-1.6%	4.7%	n.a.
Momentum	4.6%	0.8%	15.8%	29.5%	n.a.
Residual	61.3%	62.6%	58.8%	66.8%	n.a.

Table 8: Carhart risk factor attribution

Table 8 gives a comprehensive factor risk attribution for both the absolute and relative risk of each fund based on the Carhart four-factor model. By construction, the estimated betas are very similar to the input fund exposures and the R^2 of the risk model is very high. Table 8 also shows the risk contributions of each factor as well as the catch-all residual term. These values are also closely related to the estimated beta levels owing to the high correlation between the risk factors as well as their similar volatility levels. Finally, contributions to tracking error are also calculated across the funds for each risk factor. Because of the good fit of the risk model, most of the tracking error stems from the fund-specific noise term.

In the context of factor investing, where investors are actively seeking exposure to the underlying risk factors, risk and tracking error contributions become incredibly important as they provide a means of quantifying and thus evaluating such exposure. To this end, Hunstad and Dekhayser (2015) introduce the Factor Efficiency Ratio (FER) as a means of gauging the amount of intended versus unintended factor risk exposure in a given fund (or asset). Letting $\mathcal{F}_d$ represent the set of k desired factors, we can write

$$FER(\mathcal{F}_d) = \frac{\sum_{i=1}^{k} RC_i}{1 - \sum_{i=1}^{k} RC_i}, \tag{13}$$

where RC_i is the generic risk contribution stemming from the i^{th} desired risk factor. Hunstad and Dekhayser originally consider the contributions to active risk (i.e. tracking error) but one can just as easily use any convex risk measure to calculate risk contributions.[6] This FER is interpreted as follows: for every *X*% of risk stemming from the desired factor set, the fund takes on an additional 1% of risk from undesired factors. Therefore, the higher the FER, the more efficient the fund is at gaining desired factor exposure.

Consider the four fund example and further assume that all of these funds are marketed as composite value/momentum indices. Using this as our desired factor set, we calculate FER's of 0.21, 0.87, 2.40 and 1.17 for each of the funds respectively. Based on these scores, it is clear that Fund 3 provides one with the most efficient exposure to the desired value and momentum factors.

Return-Based Style Analysis & Fund Replication

Sharpe (1992) introduced the concept of returns-based style analysis (RBSA) used extensively in the fund management literature. In essence, RBSA is a form of constrained regression

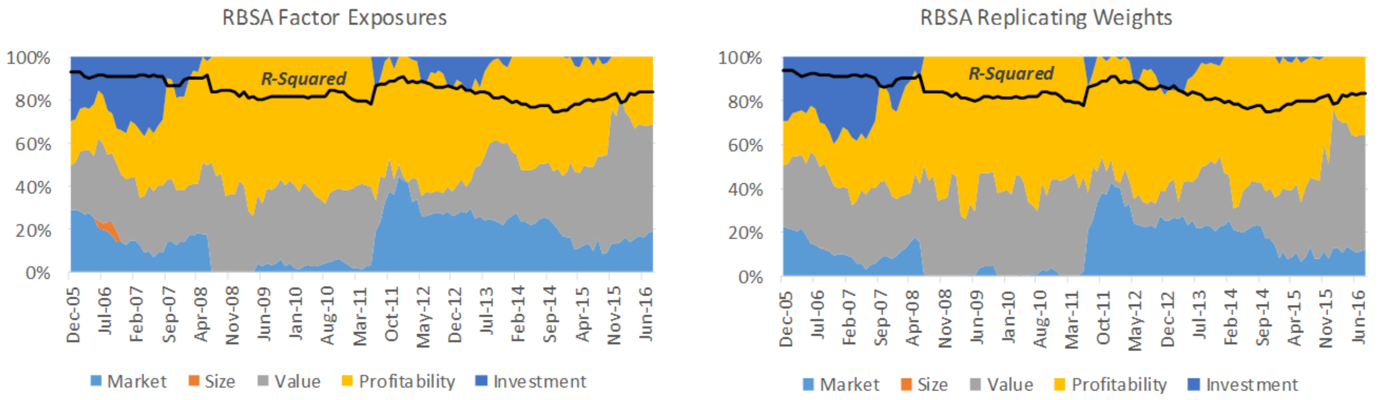

Figure 6: RBSA betas (left) and end-of-period weights (right) for the FTSE/JSE Dividend Plus Index and the long-only Fama-French five-factor model, Dec 2005 to Aug 2016

that allows one to draw inference on funds for which only historical return data is available. Sharpe suggested using factors based on asset classes and interpreted the model output as being indicative of a manager's style mix. Ultimately, given a set of historical fund returns, RBSA estimates the static mix of tradable market indices or factors that most closely replicates the fund's returns, R_{pt}. Letting β represent the vector of factor exposures, we can formulate the RBSA estimation problem as follows:

$$\begin{aligned} &\underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{T}\left(R_{pt}-\sum_{j=1}^{m}\beta_j \mathcal{F}_{jt}\right)^2 \\ &s.t. \qquad \beta_j \geq \\ &\sum \beta_j = 1. \end{aligned} \tag{14}$$

In a sense, the RBSA betas represent the long-only weights of the replicating style portfolio. However, this is not strictly true because the betas remain fixed across the estimation window whereas portfolio weights would change in line with the performance of the underlying factors. Several improvements to the initial RBSA methodology have been suggested to address this (and other) issues. These include the use of the Kalman filter, corrections for heteroscedasticity and the inclusion of structural break detection mechanisms. Another point which is common to all regression but generally not considered in RBSA is that of confidence intervals around the estimated betas.[7] For example, a style weight of 30% with a confidence interval of +/- 2% should be viewed very differently to a weight of 30% with a confidence interval of +/- 20%.

A variation of RBSA that is particularly relevant in the index tracking space is to solve for the initial number of 'shares' (rather than betas) of each factor that minimises the tracking error (rather than sum of squared errors) of the estimated style portfolio to the given fund returns. Therefore, one can not only use the RBSA framework to measure a given fund manager's style mix but also – after some adjustment – to create tradable replicating portfolios for a fund. This alternative usage has been explored at length in connection with hedge fund replication.

As in Factor Risk Attribution and the Factor Efficiency Ratio, we illustrate RBSA with an illustrative example. We attempt to uncover the style mix of the FTSE/JSE Dividend Plus Index by making use of the long-only Fama-French five-factor model. Figure 6 displays the RBSA factor exposures (left panel) and the adjusted-RBSA replicating weights (right panel) from December 2005 onwards. We fit both models using rolling 36-month windows and record the static betas and end-of-period weights respectively.

Although the exposures are similar to the replicating weights, one can still easily see the discrepancies in Figure 6. The R^2 of both models is consistently high, meaning that the majority of variation in the index is well-captured by the five-factor model. The style mix of the index varies considerably over the period, which suggests that the dividend yield measure is actually a composite signal for a number of underlying risk factors. The largest exposure over the period has been to the profitability factor – in line with the yield-driven nature of the index – with the remainder mostly split between the value and market factors. Investment exposure is sporadic and has been absent over the last three years. Size is irrelevant for the Dividend Plus index, which is to be expected given that the index is limited to large- and mid-cap stocks.

Table 9 gives the RBSA betas and end-of-period weights for the 36-month period ending at 31 August 2016. Although similar in nature, there is still an absolute difference of 13.7% across the factors. This difference is driven by the varying performance of the underlying factors and is directly related the level of factor dispersion over the period.

	Market	*Size*	*Value*	*Profitability*	*Investment*
RBSA Betas	19.0%	0.0%	50.0%	31.0%	0.0%
95% Conf. Interval	7.8% – 30.3%	-11.9% – 11.9%	40.3% – 59.7%	21.5% – 40.5%	-10.7% – 10.7%
RBSA Weights	12.2%	0.0%	52.6%	35.3%	0.0%
Weight-Beta Spread	-6.9%	0.0%	2.6%	4.3%	0.0%

Table 9: RBSA betas and replicating weights for the Dividend Plus Index as at 31 Aug 2016

Factor-Based Portfolio Management

In addition to the risk management applications given above, risk factors are also used extensively in portfolio management. And while the concept of factor investing is definitely not new, the rise of the smart beta phenomenon has attracted significant attention to this area.

In the last several years, the focus has started to move away from identifying additional risk factors and towards constructing optimal multi-factor portfolios. While some authors have said that there is no formal framework in place for combining systematic factor strategies (De Franco et al., 2016), the fact of the matter is that the majority of the existing optimisation frameworks – risk/return or risk-only – are fully capable of incorporating both factor portfolios and factor-based risk/return views. Furthermore, the allocation policy for systematic strategies outlined by Meucci (2016) provides one with a fully general framework for creating optimal multi-factor portfolios in the presence of transaction costs and fund constraints.

In this section we discuss several ideas on how to create such multi-factor portfolios, ranging from the very simple to the fairly complex. Note that most of these are based on concepts that we have already introduced and analysed in preceding sections.

Factor Portfolio Mixing and Integrated Factor Scores

According to Fitzgibbon et al. (2016), two of the most common approaches for creating multi-factor portfolios are the 'portfolio mix' and 'integrated score' methods. Portfolio mixing is simply the linear combination of factor portfolios constructed from single-variable sorting procedures. For example, consider a value portfolio based solely on the top quintile of book-to-market stocks and a momentum portfolio based solely on the top quintile of twelve month return stocks. These portfolios would then be taken as existing building blocks and the only challenge facing the investor would be to set an appropriate weight for each portfolio. Viewed in this light, portfolio mixing can be thought of in a similar manner to the decisions made in strategic asset allocation.

The integrated score approach goes one step further by mixing the underlying factor scores ex ante rather than mixing given factor portfolios ex post. The Fama-French two-way sorting methodology – whereby stocks are selected based on their respective factor score ranks relative to a set of constant percentile break points – is perhaps the simplest example of the integrated score approach. In general, the integrated score approach combines individual factor scores in some manner to create a single, unified score. Figure 7 displays this concept graphically and confirms that the field of (non)linear programming provides investors with a natural set of tools for creating optimal integrated multi-factor scores, and thus optimal multi-factor portfolios.

Lastly and very importantly, Hoffstein (2016) points out that one needs to consider the speed of factor decay when creating these integrated signals. This is particularly relevant when combining the fast-decaying momentum signal with slower signals like value or profitability, for example.

Constrained Risk Factor Optimisation

A more technically rigorous approach than those given above is to view the construction of an efficient multi-factor portfolio as a constrained optimisation problem. Although more complex, this approach allows an investor to construct a multi-factor portfolio that is as consistent with their return objectives and risk preferences as their constraint set will permit. There are a number of optimisation frameworks available to investors, including classical mean-variance and risk-based investing (Richard and Roncalli, 2015), among others.[8] Below we sketch out two candidate optimisation approaches that could be used to create constrained optimal multi-factor portfolios.

The first approach makes use of the risk attribution framework introduced in in the section Factor Risk Attribution and the Factor Efficiency Ratio. Assuming that one is given a risk factor model, the problem then becomes finding the underlying stock weights that provide the requisite exposure to the targeted risk factors, whilst minimising undesired factor exposures. If exposure is defined in terms of beta, then one needs to solve for the portfolio of assets that minimises the total distance between estimated and targeted betas, where the target levels for the undesired factors are set to zero. Alternatively, if exposure is defined in terms of risk contributions, then there two options available. The first option is similar to the beta optimisation but where one instead specifies target risk contribution levels. The second option is to solve for the portfolio of assets that maximises the FER for the set of desired factors. FER optimisation is arguably more intuitive and will likely provide more robust results due to the fact that it simultaneously accounts for the desired and undesired factor exposures in a single monotonic metric. Of the two approaches, we therefore favour FER maximisation.

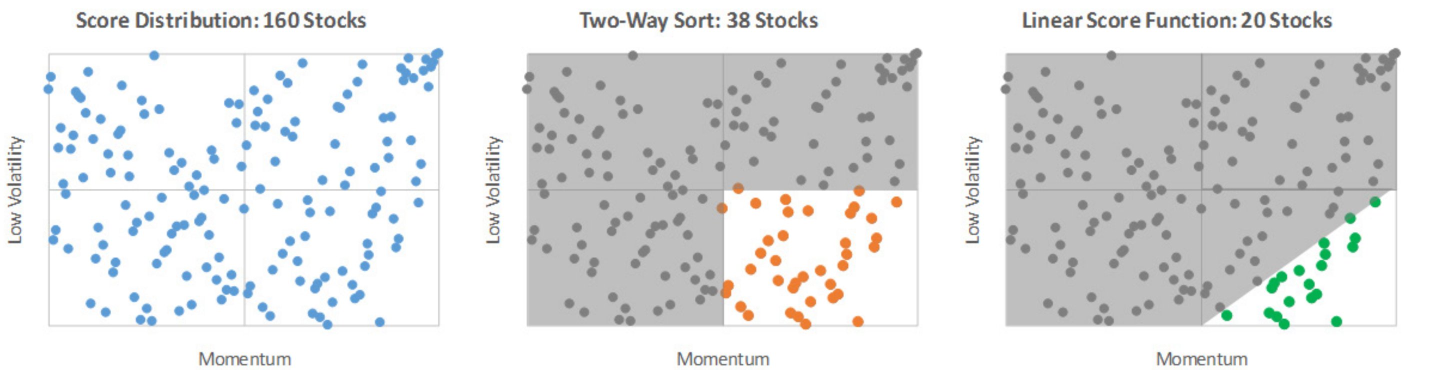

Figure 7: Integrated scoring examples for momentum and low volatility

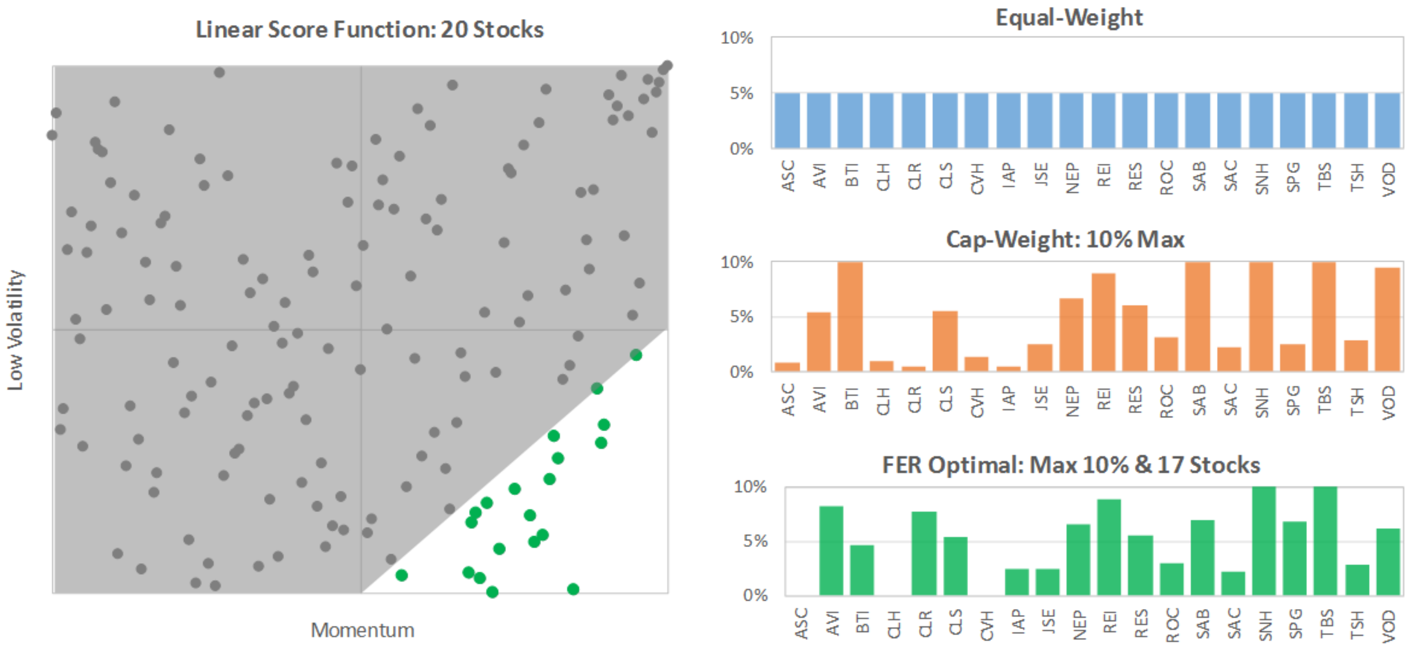

Figure 8: Creating a multi-factor portfolio by combining an Integrated Scoring screen with an MILP optimisation of the portfolio's Factor Efficiency Ratio

The second optimisation approach makes use of mixed integer programming (MIP). A mixed integer program is one in which some variables are continuous and some are integers. Such a setting is ideal for problems in which one has to first select a subset of assets from the available universe – the integer variables – and subsequently search for the set of weights – the continuous variables – that minimises an objective function under a set of constraints. In general, mixed integer programs can be quite hard to solve unless one can formulate the problem in a very particular way. Thankfully, we are able to set up both linear (MILP) and quadratic (MIQP) mixed integer programs for most portfolio construction problems which can be solved fairly easily – albeit slowly – with freely available optimisation toolboxes and heuristic solvers. In prior Peregrine Securities research, we have successfully used the MIQP approach to replicate the Top40 index with only a small number of stocks and also construct optimal hedging baskets for active funds (Flint et al., 2015).

One of the main issues with multi-factor investing is smoothly transitioning between risk and return preferences in the factor space to risk and return preferences in the asset space. This is not a trivial exercise. One way of linking the factor and asset spaces in a manner which does not add additional estimation error would be to combine the integrated score approach with the risk attribution optimisation by means of an MILP. Figure 8 presents an example of this combined approach for a low volatility and momentum multi-factor portfolio using scoring data as at August 2016.

One uses the integrated score as a screening tool to find the subset of assets that display the fundamental factor characteristics most in line with the desired factor set. Taking this subset of factor-screened assets as an input, one then solves the MILP problem for the maximum FER portfolio under the given constraints, where the choice of assets included in the portfolio and the subsequent weights attached to the chosen assets are both variables in the optimisation. Introducing the integrated score screen and subsequently maximising the portfolio's FER obviates the need to explicitly assign factor-consistent expected return estimates to each asset – a difficult task – and thus also reduces the potential for estimation error in the optimisation.

Conclusion

Risk factors and systematic factor strategies are fast becoming an integral part of the global asset management landscape. In this report, we have attempted to provide an introduction to, and critique of, the factor investing paradigm in a South African setting.

We created a range of long/short and long-only risk factors for the South African equity market according to the standard Fama-French factor construction methodology: size, value, momentum, profitability, investment, low volatility and low beta. Historical risk and return characteristics varied significantly across the factors as well as across market regimes. Momentum has been the most rewarded factor historically. Low volatility, profitability and low beta have also shown positive risk premia, while the size factor seems to be non-existent in South Africa. We then tested factor robustness at length and showed the effect that each of the major decisions taken in the factor construction process can have. The largest such effect stems naturally from the choice of long-only or long/short factors. Interestingly, we found that, barring size, all long-only factors handily outperformed the market.

In addition to constructing this factor database, we also showcased several risk factor applications. In the risk management space, we considered risk attribution to factors and introduced the Factor Efficiency Ratio as a measure of how efficiently a fund gained exposure to a set of desired risk factors. We also considered returns-based style analysis with long-only risk factors and showed how this could be used to estimate a manager's style mix or to create a replicating factor portfolio for an index.

In the portfolio management space, we considered the issue of creating multi-factor portfolios. We discussed simple approaches such as portfolio mixing and integrated scoring, and more complex approaches based on solving for target risk contributions or optimising the factor efficiency ratio for the desired factors. Finally, we introduced the mixed integer programming framework as a means of combining the integrated scoring approach with the risk attribution optimisation approach in a robust manner, thus allowing one to smoothly transition between preferences and constraints in the non-tradable factor space and the tradable asset space.

Endnotes

1. The factors and strategies are known by many names. Some of these include: risk factors, risk premia, smart beta, alternative beta, systematic strategies, quantitative strategies and rule-based strategies.

2. Factor construction is discussed at length in Section 3.

3. For example, see the comprehensive risk factor databases maintained by Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and Andrea Frazzini (http://www.econ.yale.edu/~af227/data_library.htm).

4. Similar calculation method alternatives apply to the beta factor score.

5. All portfolio management should be considered benchmark-relative, even if the selected benchmark is a constant value of zero.

6. Note that one has to treat negative risk contributions with caution when calculating the FER as they can materially change its interpretation. The simplest solution is to take absolute values of all risk contributions and replace the '1' in the denominator with the sum of the absolute risk contributions.

7. See Lobosco and diBartolomeo (1997) for an approximation formula for constructing confidence intervals around the constrained betas.

8. Please see Homescu (2014) for a comprehensive review of the available portfolio construction frameworks.

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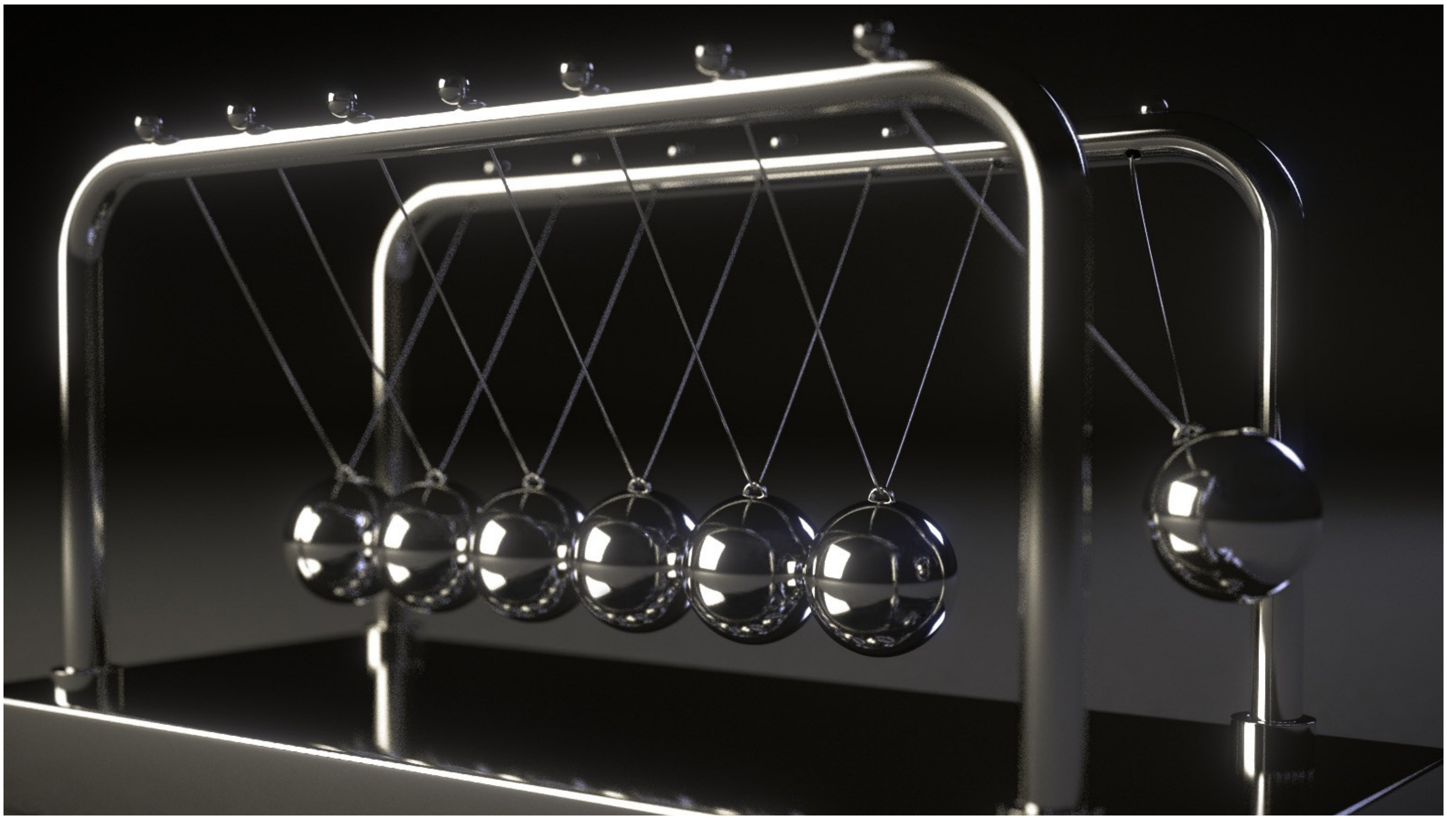

Momentum: A Practitioner's Guide

Hamish Preston
S&P Dow Jones Indices

What is Momentum?

As an investable concept, momentum is straightforward—purchase (avoid) stocks that have performed relatively well (poorly) recently. The period over which returns are evaluated is important for momentum; for example, there is evidence of a one-month reversal effect in stock prices.

The most influential paper on momentum is arguably Mark Carhart's 1997 study; adding momentum to the Fama-French Three Factor Model increased the model's explanatory power and showed momentum was a key factor in describing cross-sectional returns.[1] After momentum had first been formalized into a systematic investment strategy as part of Dow Theory and following a period in the latter half of the 20th century where there was much debate over its existence and potential origins[2], Carhart's study meant momentum was incorporated into risk management and active management processes.

The S&P Momentum Indices are rebalanced semiannually after the close of the third Friday of March and September; the reference dates are the last business day of February and August, respectively. As of the rebalance reference dates, momentum is calculated using 12 months of data beginning 13 months prior, ensuring the one-month reversal effect is avoided. The momentum scores for each security are adjusted for risk to account for the standard deviation of daily price returns over the period that is used to calculate the unadjusted momentum values. For more information regarding the calculation of the S&P Momentum Indices, please see the S&P Momentum Indices Methodology.

How Has Momentum Performed?

One of the first questions to ask about momentum is: how has it performed? To analyze this, we turn to the S&P 500® Momentum, which was launched on Nov. 18, 2014.[3] Exhibit 1 shows the total return performance of the S&P 500 Momentum

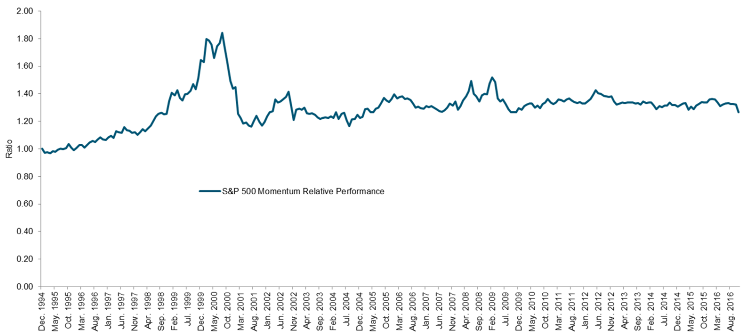

Exhibit 1: Relative Performance of the S&P 500 Momentum to the S&P 500
Source see Appendix

compared to the S&P 500. As the ratio was routinely above one, we can see that momentum performed better than the S&P 500 over the period studied. Additionally, the biggest upward movements in the ratio appear to have preceded the most sizeable falls—namely in the late 1990s, early 2000, and the period around 2008. This should not be too surprising; momentum did relatively better when strong trends emerged and many market participants bought into these trends. However, if such a trend becomes a bubble that subsequently bursts—as was the case for the technology bubble—it is not difficult to imagine momentum being relatively more affected than the broader market, which has exposure to other factors in addition to momentum.

Interestingly, although the relative performance of momentum was fairly constant since early 2010, the annualized risk and return statistics paint quite a different picture. Indeed, the risk-adjusted return of the S&P 500 Momentum lagged the S&P 500 over the five-year period ending November 2016. Only over longer horizons did momentum do as well—if not slightly better—than the benchmark. The similarity in risk profiles means that the smaller returns for momentum in the short-run explain the sizeable differences in the risk-adjusted returns.

Exhibit 3 shows that the S&P 500 Momentum likely lagged the S&P 500 over shorter horizons because of a relatively low capture in upward market movements. This may indicate a recent lack of persistently strong trends in the S&P 500; therefore, even though momentum may recognize new trends, the market environment was not conducive to momentum outperforming over the five-year period. This is exactly what we see in Exhibit 4, which shows the relative over- or under-weighting of each sector in the S&P 500 Momentum compared with the S&P 500. The relative weights changed much more quickly in the five-year period than they did 15 years prior—thus, any recent trends, even if strong, have been fleeting.

As a result, the S&P 500 Momentum tended to perform relatively well compared to the S&P 500 when strong, persistent trends have emerged in the market. The smaller maximum drawdowns show that momentum has been successful at identifying new trends, although when these trends have not been strong or persistent, momentum is much more likely to be have been a laggard.

Possible Uses of Momentum

Another key question for any factor—momentum included—is: how might market participants use it? One possibility would be to combine value and momentum. Exhibit 5 shows the total

PERIOD	S&P 500	S&P 500 MOMENTUM
ANNUALIZED RETURN (%)		
1-Year	8.06	2.50
3-Year	9.07	6.94
5-Year	14.45	13.19
10-Year	6.89	6.64
15-Year	6.62	7.18
20-Year	7.47	8.38
ANNUALIZED RISK (%)		
3-Year	10.77	10.62
5-Year	10.36	10.23
10-Year	15.28	15.05
15-Year	14.35	14.11
20-Year	15.30	17.55
RISK-ADJUSTED RETURN		
3-Year	0.84	0.65
5-Year	1.39	1.29
10-Year	0.45	0.44
15-Year	0.46	0.51
20-Year	0.49	0.48
MAXIMUM 12-MONTH DRAWDOWNS (%)		
3-Year	8.36	6.86
5-Year	8.36	8.28
10-Year	46.41	42.73
15-Year	46.41	42.73

Exhibit 2: Risk/Return Comparison
Source see Appendix

PERIOD	3-YEAR	5-YEAR	10-YEAR	15-YEAR	20-YEAR
DOWN CAPTURE (%)					
S&P 500 Momentum	77	85	93	94	104
UP CAPTURE (%)					
S&P 500 Momentum	84	81	94	91%	100

Exhibit 3: Percentage of Up and Down Movements in the S&P 500 Captured by the S&P 500 Momentum
Source see Appendix

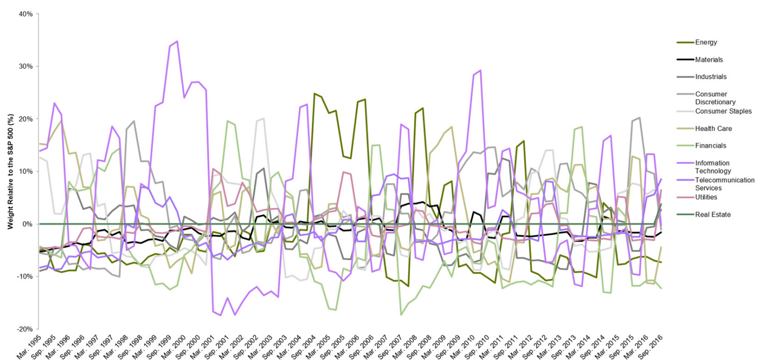

Exhibit 4: Relative Sector Weights Compared to the S&P 500
Source see Appendix

return ratio between the S&P 500 and a hypothetical 50%-50% blend of the S&P 500 Enhanced Value Index[4] and S&P 500 Momentum. From this, we can see the benefit of combining the factors; not only did the blend improve on the relative performance of either enhanced value or momentum (and at times both), but its relative performance compared to the S&P 500 was less volatile than for either individual factor. The benefits of diversification can be seen in the higher risk-adjusted returns; despite the annualized risk sometimes being greater for the blend than for momentum, the increase in annualized returns more than compensates for this (see Exhibit 6).

This is not too surprising, because momentum should perform well when persistently strong trends emerge. In

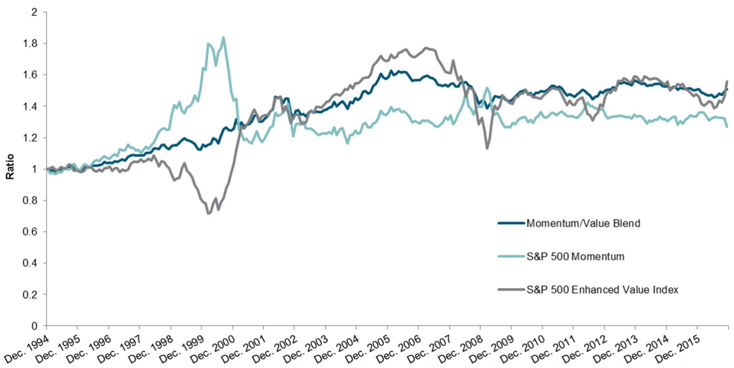

Exhibit 5: Relative Total Return Compared to the S&P 500
Source see Appendix

PERIOD	MOMENTUM/VALUE BLEND	S&P 500	S&P 500 MOMENTUM	S&P 500 ENHANCED VALUE INDEX
ANNUALIZED RETURN (%)				
1	8.46	8.06	2.50	14.23
3	7.77	9.07	6.94	8.34
5	15.10	14.45	13.19	16.75
10	6.52	6.89	6.64	5.83
15	7.69	6.62	7.18	7.73
20	9.50	7.47	8.38	9.85
ANNUALIZED RISK (%)				
3	11.12	10.77	10.62	13.74
5	11.23	10.36	10.23	14.15
10	17.21	15.28	15.05	21.72
15	15.80	14.35	14.11	19.65
20	16.53	15.30	17.55	19.39
RISK-ADJUSTED RETURN				
3-Year	0.70	0.84	0.65	0.61
5-Year	1.34	1.39	1.29	1.18
10-Year	0.38	0.45	0.44	0.27
15-Year	0.49	0.46	0.51	0.39
20-Year	0.57	0.49	0.48	0.51
MAXIMUM 12-MONTH DRAWDOWNS (%)				
3-Year	9.00	8.36	6.86	14.65
5-Year	10.93	8.36	8.28	14.65
10-Year	51.98	46.41	42.73	61.29
15-Year	51.98	46.41	42.73	61.29
20-Year	51.98	46.41	49.10	61.29

Exhibit 6: Risk/Return Characteristics – Comparison of Benchmark, Momentum, and Value Indices With Hypothetical Blended Portfolio
Source see Appendix

these environments, value may suffer if bubbles emerge and valuations become removed from fundamentals. Conversely, in the absence of strong, persistent trends—when momentum is likely to underperform the market—value may be able to negate any such underperformance. This is exactly what we see from the information ratios; the blend's information ratio almost always exceeded at least one of the corresponding ratios for the individual factors during the period studied. In short, the benefit to combining value and momentum is that these factors have tended to work well in different market environments, and so there have been advantages to diversification.

Momentum: A Global Reach

For those concerned that this analysis focuses solely on the U.S., it is worth noting that momentum has a global reach—it has been shown to work in many different markets. For example, Fama and French (2012) showed the presence of momentum in North America, Europe, and Asia Pacific (the notable exception where momentum did not work was Japan).[5] To further illustrate momentum working in many markets, we consider the S&P Momentum Developed LargeMidCap, which is designed to measure the performance of securities in the developed markets that exhibit persistence in their relative performance (see Exhibit 8). Since the pattern of risk, returns, and drawdowns for this index seem to have been similar to the S&P 500 Momentum over the period in question, it appears that converting various currencies into U.S. dollars when calculating the index on a daily basis does not change the results substantially. This is not too surprising, because the momentum scores are calculated using returns denominated in each stock's local currency, and many exchange rates have a tendency to behave as though they are following a random walk.[6] Such behavior may help to ensure that the returns to momentum (denominated in U.S. dollars) have not been driven, or subsumed, by currency movements in general.

Conclusion

In general, momentum is straightforward as an investable concept: purchase (avoid) stocks that have performed relatively well (poorly) recently. Over the 20-year period ending in November 2016, the S&P 500 Momentum performed well relative to the S&P 500. Its risk-adjusted return was similar to—if not slightly higher than—that of the S&P 500 over longer horizons when strong, persistent trends emerged in the market. Over shorter horizons, when market trends were more fleeting and the relative sector weights changed more quickly, the S&P 500 Momentum lagged the S&P 500. The momentum strategy provided lower participation in market gains, despite having a similar risk profile to the benchmark.

The hypothetical 50%-50% blend of momentum and value demonstrated the potential benefits of diversification. Over the period studied, the blend's risk-adjusted return was always higher than the risk-adjusted returns of at least one of the individual factors and the information ratio almost always exceeded at least one of the corresponding ratios for the individual factors. The similarity in risk, returns, and 12-month drawdowns between the S&P 500 Momentum and the S&P Momentum Developed LargeMidCap illustrates that the momentum factor has been present in many different markets, and the factor returns have not been driven, or subsumed, by currency movements in general.

PERIOD	MOMENTUM/VALUE BLEND	S&P 500 MOMENTUM	S&P 500 ENHANCED VALUE INDEX
TRACKING ERROR			
3-Year	2.52%	5.01%	6.46%
5-Year	2.99%	4.65%	6.98%
10-Year	3.49%	6.59%	9.31%
15-Year	4.66%	7.57%	8.46%
20-Year	4.96%	9.32%	10.02%
INFORMATION RATIO			
3-Year	-0.5142	-0.4253	-0.1133
5-Year	0.2194	-0.2701	0.3296
10-Year	-0.1061	-0.0375	-0.1135
15-Year	0.2301	0.0748	0.1316
20-Year	0.4093	0.0980	0.2382

Exhibit 7: Tracking Error and Information Ratio Comparisons
Source see Appendix

PERIOD	ANNUALIZED RETURN (%)	ANNUALIZED RISK (%)	RISK-ADJUSTED RETURN	MAXIMUM 12-MONTH DRAWDOWNS (%)
3-Year	2.18	10.54	0.21	9.12
5-Year	10.17	10.45	0.97	11.61
10-Year	5.19	16.27	0.32	48.01
15-Year	7.86	14.86	0.53	48.01
20-Year	7.55	17.47	0.43	48.01

Exhibit 8: Risk/Return Characteristics of S&P Momentum Developed LargeMidCap
Source see Appendix

Endnotes

1. Carhart, Mark, “On Persistence in Mutual Fund Performance”, Journal of Finance, 52:1, 57-82 (March 1997) https://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/Carhart_funds_jf.pdf.

2. For an overview, see Swinkels, Laurens. "Momentum investing: A survey." Journal of Asset Management 5.2 (2004): 120-143.

3. All S&P 500 Momentum data used in this document prior to this date is based on back-tested data.

4. The S&P 500 Enhanced Value Index was launched on April 27, 2015. All data for this index prior to this date is back-tested. The hypothetical 50%-50% blend of Momentum and Enhanced Value is rebalanced on a monthly basis.

5. Fama, Eugene and Kenneth French, “Size, value, and momentum in international stock markets,” Journal of Financial Economics, 105:3, 457-472 (2012) https://ideas.repec.org/a/eee/jfinec/v105y2012i3p457-472.html#biblio. For earlier evidence of momentum please see, among others, Rouwenhorst (1998); Chan, Jegadeesh, and Lakonishok (1996); and Jegadeesh and Titman (1993).

6. For evidence on this random walk phenomenon, see Meese and Rogoff (1983); Taylor (1995); and Kilian and Taylor (2001).

Appendix

Source: S&P Dow Jones Indices LLC. Data from December 1994 to November 2016. Past performance is no guarantee of future results. Table is provided for illustrative purposes and reflects hypothetical historical performance. Please see the Performance Disclosure at the end of this document for more information regarding the inherent limitations associated with back-tested performance.

Author Bio

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More than Just a Second Risk Number: Understanding and Using Statistical Risk Models

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Introduction

There are strategic benefits to incorporating different kinds of risk models – fundamental, statistical, and macroeconomic factor risk models – into an investment process.

Fundamental factor risk models decompose risk using well-understood and intuitive factors. The factors have been heavily researched and are known to give highly reliable risk predictions. However, the factors used by a fundamental factor risk model are fixed[1]. As a result, such models may have trouble modeling unusual market trends. When such trends are not well modeled by a fundamental model's fixed set of factors, the risk associated with those trends is modeled as asset-specific, idiosyncratic risk.

In contrast, statistical factor risk models do not impose or assume a fixed factor structure but instead use asset returns directly to mathematically construct an optimal set of factors explaining the current risk environment, regardless of whether the factors represent short- or long-term phenomena or are associated with intuitive, well- known factors. The factors of a statistical risk model evolve to fit the current market conditions. This adaptability means that statistical factors model risk extremely well. However, the lack of intuitive meaning to these evolving factors makes risk decomposition and performance attribution difficult.

Macroeconomic factor risk models constitute a third kind of factor risk model. In these risk models, estimates are computed for the sensitivity (beta) of an asset's time series of returns to historical changes in a set of broad macroeconomic variables such as economic growth and interest rates. These factors are intuitive and are particularly helpful for stress-testing a portfolio for market events and surprises. In fact, stress testing normally motivates the choice of macroeconomic factors. However, macroeconomic factors generally have less explanatory power than either fundamental or statistical factors. If they were as predictive,

	Fundamental Risk Models	Statistical Risk Models	Macroeconomic Risk Models
Assumed Inputs	Factor exposures	None	Factor returns
Estimated Outputs	Factor returns	Factor exposures and returns	Factor exposures
Strengths	Intuitive & widely used Consistent framework for: - Risk Decomposition - Perf. Attribution - Portfolio Construction	Factors are not fixed Responsive Captures short term phenomena Effective Portfolio Construction	Stress testing of macro events & surprises
Weaknesses	May miss short term trends	Lacks intuition Difficult to interpret - Risk Decomp. - Perf. Attribution	Broader, less predictive factors Less explanatory power

Table 1: A summary comparison of fundamental, statistical, and macroeconomic factor risk models.

they would be included in fundamental factor models. As a result, fundamental and statistical risk models are generally considered more reliable than macroeconomic risk models.

A comparison of assumptions, strengths, and weaknesses of these three kinds of factor risk models is shown in Table 1.

In the present paper, we describe how a statistical factor risk model can be used in conjunction with a fundamental factor risk model to improve an investment process. Even though statistical factors have no predefined meaning, there are a number of techniques that leverage the information in these models to help manage risk, construct portfolios, and explain performance. While fundamental factor risk models may be better understood and widely used in investment processes, statistical risk models uniquely capture and quantify unexpected market trends as well as aid in portfolio construction to account for these trends.

The outline of the paper is as follows. First, we provide an overview of statistical factor risk models, review how they are constructed, and contrast them with fundamental factor risk models. Next, we describe a number of approaches for comparing fundamental and statistical risk model predictions on a side-by-side basis. We use a detailed analysis of a case-study portfolio for illustrating these approaches. Finally, we offer suggestions for how these approaches can be applied in risk management, portfolio analysis, and portfolio construction.

An Overview of Statistical Factor Risk Models

A statistical factor risk model is a risk model whose factors are constructed by mathematically processing asset return time series, so that the set of factors chosen has the maximum possible explanatory power. The mathematical technique used is Principal Components Analysis (PCA), Asymptotic Principal Components Analysis (Asymptotic PCA), or a variant of these.

Because these mathematical techniques maximize the commonality among the asset returns, the techniques are free to find factors not found in fundamental factor risk models. Statistical factors frequently capture short- term market trends that are important over short periods of time even if they do not persist. Identifying and reacting to relevant market trends is, of course, an essential part of any investment process even if the trends do not last long enough to be included in a fundamental factor risk model.

Mathematically, both fundamental and statistical risk models begin with the same linear factor model of asset returns:

$$R = Bf + u$$

R is a vector of asset returns, B is a matrix of factor exposures or factor loadings, f is a vector of factor returns, and u is a vector of asset-specific, idiosyncratic returns.

While R is known, fundamental and statistical risk models approach the solution of the rest of the terms in this equation differently.

With fundamental models, the factors and their exposures, B, are given, and the equation is solved for the factor return, f, using regression. This permits risk modelers to select factors that are intuitive, well researched, and predictive. The factors used in a fundamental factor risk model on one day are the same factors used on the next day, although the factor exposures are updated daily.

For statistical risk models, both the matrix of factor exposures, B, and the vector of factor returns, f, are solved for simultaneously so as to maximize the predictive power of the above equation. Statistical factors, factor exposures and returns are re-estimated independently for each risk model update. As a result, the factors and factor exposures may change substantially from one day to the next as they adapt to market conditions.

When compared with fundamental factor risk models, the adaptability of statistical factor risk models has two key drawbacks. First, the factors have no obvious economic or investment meaning. They are simply numerical exposures that best explain the observed asset returns. Second, the factors change from one day to the next. This makes statistical factor exposures difficult to incorporate into a portfolio construction strategy or use in creating a meaningful performance attribution over time.

The advantage of the statistical approach, however, is precisely the adaptability of the factors. During time periods when the factors in a fundamental risk model include all the key factors driving risks in the market, fundamental risk models work well. However, suppose that the market starts to be driven by a new and unexpected factor that is not included or well represented by the fixed set of fundamental factors. In this situation, the explanatory power of the fundamental risk model decreases.

A statistical factor risk model, however, adapts to the changing market, and the factors and the risks associated with them would be properly reported by the statistical risk model. In other words, the chances of being hurt by an unintentional exposure to new market forces are significantly less when using a statistical factor risk model because its factors are able to change and adapt over time.

Case Study: Using Statistical Models For An Additional Risk Perspective

Next, we present a case study on a representative quantamental portfolio, in order to illustrate some of the most useful and insightful practices that have emerged since Axioma first introduced its suite of fundamental and statistical risk models.

The case study portfolio is an actual, real-world Large Cap Core strategy benchmarked to the Russell 1000 and typically aims to target around 3% to 4% annualized realized active risk while holding 50-100 names. We use Axioma's latest US Risk Model suite, US4, for analysis.

Risk Differences

Figure 1 shows a time series plot of the predicted active risk using Axioma's US4 Fundamental Medium Horizon risk model. The portfolio had an active risk of more than 4%, starting in January 2010, but the tracking error quickly dropped to almost 2% by January 2011. Since then, the tracking error of the portfolio has been steadily rising, with tracking error hovering around 3.5% since mid-2014.

Figure 1 gives only one risk model's prediction – that is, only one view on risk. However, Axioma's risk model suite includes four different risk models:

- A fundamental, medium horizon risk model (MH – already shown in Fig. 1)
- A fundamental, short horizon risk model (SH)
- A statistical, medium horizon risk model (MH-S)
- A statistical, short horizon risk model (SH-S)

Figure 2 shows the tracking error of the same portfolio for all four risk models. Overall, the trends are similar, and the four different predictions of tracking error are consistent. However, there are

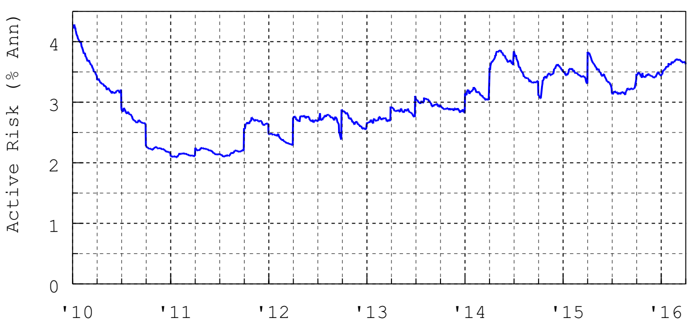

Figure 1: The predicted active risk of the Large Cap Core portfolio using Axioma's US4 Fundamental Medium Horizon risk model. The quarterly spikes indicate portfolio rebalancing, not an abrupt change in predicted risk.

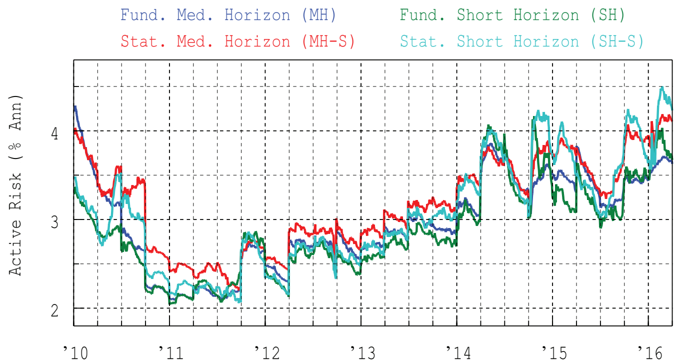

Figure 2: The predicted active risk of the Large Cap Core portfolio using all four of Axioma's risk models. Models colors are shown above.

trends in Fig. 2 that suggest whether or not the statistical risk model is picking up a factor that is missing from the fundamental model.

In January 2010, the two medium horizon models (MH (blue) and MH-S (red)) predict almost identical tracking error, while the two short horizon models (SH (green) and SH-S (turquoise)) also agree with each other, although they both predict somewhat smaller tracking error than the medium horizon models. The agreement between fundamental and statistical risk models with the same horizon suggests that there are no missing factors in the fundamental risk model.

However, starting in 2015, there have been three time periods during which both statistical predictions were significantly larger than both fundamental predictions. The first period started in January 2015 and lasted about three months. The second period starting in Q4 2015 and lasted three months. At the close of 2015, the risk predictions briefly came together, but as 2016 started, both statistical risk predictions shot up again. This is illustrated in closer detail in Fig. 3 which shows all four active risk predictions for just the last nine months. Interestingly, these last two time periods – September 2015 to January 2016, and February to April 2016 – coincide with two relatively challenging periods for active and long-short managers.

These changes can be conveniently captured by two different risk spreads:

- Factor Risk Spread = Highest predicted factor risk minus the lowest predicted factor risk across all risk models.
- Stat Minus Fund Risk Spread = Predicted risk from the statistical model minus the predicted risk from the fundamental model with the same estimation horizon.

Figure 4 shows these two spreads since June 2015. Starting in August 2015, there was a notable increase in the spread that peaked near early October 2015 at nearly 100 bps of difference between the risk models. This spread contracted through year end, and then surged again in February of 2016. As of April 2016, both spreads were at historically large values.

Factor vs. Specific Risk

In addition to considering risk differences, as was done in the previous section, it is also important to recognize the changing proportions of risk coming from common factor risk and specific

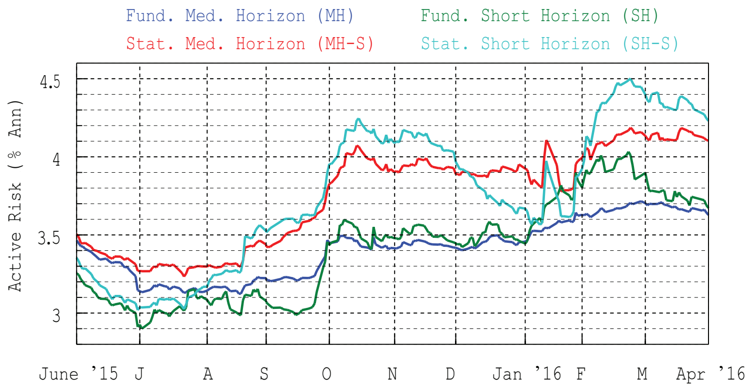

Figure 3: The predicted active risk of the Large Cap Core portfolio over the last nine months using all four of Axioma's risk models.

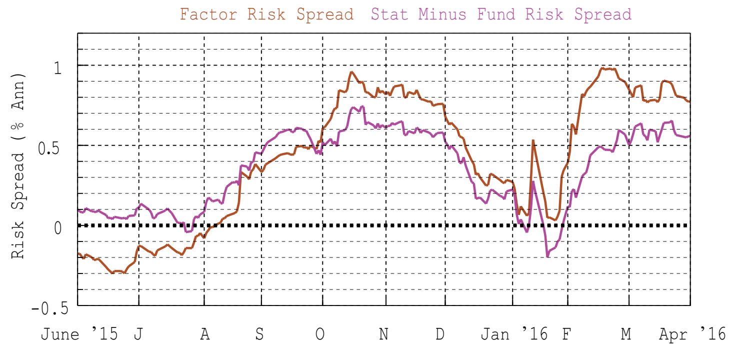

Figure 4: The Factor Risk Spread and the Stat Minus Fund Risk Spread

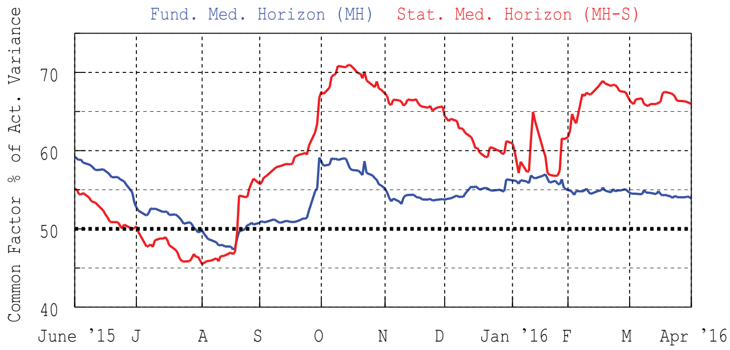

Figure 5: The Proportion of active common factor variance for the statistical and fundamental risk models.

risk. As a general rule of thumb, stock pickers would expect more specific risk than factor risk, since their skill is picking individual stocks. Market timers would expect more factor risk than specific risk, since the factors of any risk model represent market trends.

Figure 5 shows the common factor percentage of the total active variance (e.g., the proportion of risk associated with the risk model factors) for the medium horizon fundamental and statistical risk models since Q3 2015. The percentage predicted by the fundamental risk model varies between 48% and 60%, but has been steady at 55% since November 2015. The percentage predicted by the statistical risk model tracked the fundamental prediction until mid-August 2015, and then surged to more than 70%. Since then, this has remained greater than 60% except for January 2016. The implication is, of course, that the statistical risk model has found a factor (or set of factors) that is missing from the fundamental factor risk model, and that this missing factor impacts the portfolio and drives higher predicted factor risk. This corroborates what was observed in the previous section on risk differences.

Risk Decomposition Using Projection

We can corroborate this observation in yet a third way by using the Risk Decomposition features in Axioma Portfolio. In particular, we can take advantage of Axioma Portfolio's ability to project a first risk model's predictions onto the factors of a second risk model. The factor risk that can be explained by the second set of factors will be reported in terms of those factors. Any risk that cannot be explained by the second set of factors will be reported as "unexplained" risk.

Table 2 shows the risk of the portfolio as of 3/31/2016 decomposed using the fundamental, medium horizon risk model. The predicted active risk is 3.63% annual volatility. Of the total active variance, 39% is specific risk, while factor risk accounts for the other 61%, which, using US4, can be further decomposed into Style, Industry, and Market factors.

Table 3 shows the decomposition of the same 3/31/2016 portfolio using the statistical, short horizon risk model. Two decompositions are shown. On the left, the decomposition is done directly on the statistical risk factors. On the right, the decomposition is done using the fundamental factors, with the missing risk reported as unexplained.

Clearly, the first five lines are identical. The statistical risk model predicted 4.42% annual volatility (higher than the fundamental risk model): 31% specific risk and 69% common factor risk. However, when the common factor risk of the statistical risk model is projected onto the fundamental factors (Style, Industry, Market), a full 15% of the risk is unexplained. This 15% corresponds to an annual volatility of 1.27% — a substantial fraction of the overall risk budget.

At this stage, after having compared the active risk predictions using different models, various risk spreads, the proportion of factor risk, and performed high level risk decompositions, the typical next step – at least for a fundamental factor risk model – would be to drill down into each of the factors, identify meaningful active exposures, and the active risk associated with them. This was partially performed already shown in Table 2, where the factors were separated into Style, Industry, and Market factors.

For statistical risk models, we recommend skipping this step, as it is difficult to interpret the results and even harder to take action based on them. Table 4 shows this decomposition. The first five lives are the same as in Table 3, but an additional column has been added for the factor exposures, which are blank for these first five lines.

The additional information is shown in the last 16 lines, which lists the active exposure, percent annual volatility, and proportion of variance for each of the 15 statistical factors and then the covariance among the factors. For this particular decomposition, the largest contributions are Factors 2, 1, and 6. However, this information is not helpful. Knowing the portfolio is underweight -0.00128% to Statistical Factor 6 does not provide immediate insight, at least not without substantial analysis of which other interpretable factors may be similar to Statistical Factor 6.

	Pred Risk (% Ann)	% of Variance
Total Risk	18.02%	100%
Benchmark Risk	17.13%	100%
Total Active Risk	3.63%	100%
Specific Active Risk	2.25%	39%
Factor Active Risk (Fund)	2.84%	61%
Style (Fund)	1.95%	34%
Industry (Fund)	1.77%	29%
Market (Fund)	0.25%	-1%

Table 2: The risk decomposition of the portfolio as of 3/31/2016 using the fundamental, medium horizon risk model.

	Pred Risk (% Ann)	% of Variance
Total Risk	20.23%	100%
Benchmark Risk	18.29%	100%
Total Active Risk	4.42%	100%
Specific Active Risk	2.48%	31%
Factor Active Risk (Stat)	3.66%	69%

	Pred Risk (% Ann)	% of Variance
Total Risk	20.23%	100%
Benchmark Risk	18.29%	100%
Total Active Risk	4.42%	100%
Specific Active Risk	2.48%	31%
Factor Active Risk (Stat)	3.66%	69%
Unexplained (Stat)	1.27%	15%
Common Factors (Fund)	3.04%	54%

Table 3: The risk decomposition of the portfolio as of 3/31/2016 using the statistical, short horizon risk model. On the right, the risk has been projected onto the fundamental factors: 15% of the active variance is unexplained by the fundamental factors.

	Active Exposure	Pred Risk (% Ann)	% of Variance
Total Risk		20.23%	100%
Benchmark Risk		18.29%	100%
Total Active Risk		4.42%	100%
Specific Active Risk		2.48%	31%
Factor Active Risk		3.66%	69%
Statistical Factor 2	0.0191%	2.30%	27.0%
Statistical Factor 1	-0.0132%	1.55%	12.3%
Statistical Factor 6	-0.0128%	1.42%	10.3%
Statistical Factor 10	0.0096%	1.08%	5.91%
Statistical Factor 8	-0.0091%	1.07%	5.91%
Statistical Factor 13	0.0070%	0.80%	3.30%
Statistical Factor 15	0.0049%	0.51%	1.31%
Statistical Factor 14	0.0045%	0.47%	1.15%
Statistical Factor 7	-0.0041%	0.39%	0.76%
Statistical Factor 11	-0.0029%	0.31%	0.51%
Statistical Factor 9	-0.0025%	0.29%	0.43%
Statistical Factor 12	-0.0023%	0.29%	0.43%
Statistical Factor 3	-0.0027%	0.27%	0.38%
Statistical Factor 4	0.0006%	0.06%	0.02%
Statistical Factor 5	-0.0004%	0.05%	0.01%
Covariance			-1.22%

Table 4: The risk decomposition of the portfolio as of 3/31/2016, using the statistical, short horizon risk model, drilling down into individual factors.

Ticker	Company Name	Active Weight (%)	% of Active Risk
DAL	DELTA AIR LINES INC DEL	2.14%	5.61%
SWKS	SKYWORKS SOLUTIONS INC	2.00%	7.56%
LNC	LINCOLN NATL CORP IND	2.05%	3.07%
MGA	MAGNA INTL INC	2.18%	4.60%
FL	FOOT LOCKER INC	2.35%	3.88%
		SUM	24.71%

Table 5: The active weight and % of Active Risk for five portfolio names. The sum of just these five names – out of 1,000 in the portfolio and benchmark – uses almost 25% of the full active risk budget.

Asset Level Decomposition — % of Active Risk

Instead of decomposing the portfolio along factors, we recommend decomposing risk at the asset level contribution to risk, termed "% of Active Risk" in Axioma Portfolio. This is a decomposition of the total tracking error into separate contributions from each asset, based on analyzing the asset's active weight and its riskiness (as quantified by the marginal contribution to active risk, MCAR). This metric is intuitive, sums to 100% for all the assets in the portfolio and the benchmark, and spans all sources of risk present in any risk model (e.g., style, industry, statistical and specific).

Table 5 shows five select names from the portfolio, their active weight, and their % of Active Risk as computed with the fundamental, medium horizon risk model. This table is taken directly from Axioma Portfolio, which automatically computes the % of Active Risk. The sum of % of Active Risk of just these five names – out of the 1,000 in the portfolio and benchmark – is 24.71%. That is, these five positions take up almost a quarter of the full tracking error budget for this portfolio. Since these five over-weights are so risky, a portfolio manager should be highly confident in these particular positions. If not, he or she should consider down-weighing the ones in which he or she has less confidence. This is exactly analogous to managing Style and Industry factor exposures – they should not be large unless the portfolio manager intends them to be large. Notice also that the ordering of Active Weight and % of Active Risk is not the same. The largest active weight shown – 2.35% for Foot Locker – does not have the largest % of Active Risk.

In Table 6, we extend the previous analysis to include the statistical, medium horizon risk model.[2] We also include five more names, each of which has a negative % of Active Risk; that is, these positions, all underweights, are diversifying positions that reduce the total tracking error of the portfolio. Also included in the Table is a column labeled DELTA with the difference between the statistical % of Active Risk and the fundamental % of Active Risk. We have sorted each set of names using this difference.

Of the 1,000 names in the portfolio and benchmark, these 10 names represent the names with the largest differences in % of Active Risk.

Whereas the five overweight names consume almost 25% of the risk budget according to the fundamental risk model, they consume almost 40% of the risk budget according to the statistical risk model. This is a large difference and is expected, in that these are the five names with the largest difference in % of Active Risk (e.g., the differences for all the other names will be considerably less). Similarly, for the five names with the most diversifying (negative) % of Active Risk, the fundamental risk model predicts that these positions reduce the risk by 3.05%, whereas the statistical risk model predicts that they reduce risk by 10.68%.

For the top five names, we see that these names are both inherently risky (they consume a disproportionate fraction of the risk budget) and that the prediction of just how risky they are is uncertain. If a portfolio manager does not have confidence in these positions, he should consider reducing them.

Similarly, the five diversifying names also have uncertainty about how much they diversify the risk.

This kind of analysis can be performed across other risk models as well as using % of Active Factor Risk instead of % of Active Risk.

This procedure identifies individual assets that have the largest contributions (positive and negative) to the risk budget as well as the largest differences (positive and negative) between the various models. Both of these characteristics are potential warning signals coming from the risk models.

How Reliable Are These Signals?

We have described a number of techniques using a statistical risk model in conjunction with a fundamental risk model to identify missing factor risk and asset level differences in risk and risk contribution. It is reasonable to ask how reliable this information is.

The graphs in Figure 6 give results indicating that the differences in risk between a statistical and fundamental risk model are meaningful and reliable. In both charts in Fig. 6, the horizontal axis is the asset total risk predicted by the statistical, medium horizon risk model minus the asset total risk predicted by the fundamental, medium horizon risk model. We compute these asset-level differences for all assets in the Russell 1000 index, on each trading day since January 2000. Then for each trading day in each year (Q1 only for 2016), we group the asset differences into 10 deciles. These correspond to the diamond points on the graphs. For each decile of differences, we compute the average predicted asset risk (average of the statistical and fundamental risk models). This data is shown in the top chart. We also computed the realized risk for the decile over the year, which is reported in the bottom chart.

For both the top and bottom chart, each color line is nominally U-shaped with its minimum value occurring at approximately no difference between the statistical and fundamental asset risk

			% of Active Risk		
Ticker	Company Name	Active Weight	Fund	Stat	DELTA
DAL	DELTA AIR LINES INC DEL	2.14%	5.61%	9.56%	3.96%
SWKS	SKYWORKS SOLUTIONS INC	2.00%	7.56%	10.54%	2.98%
LNC	LINCOLN NATL CORP IND	2.05%	3.07%	5.53%	2.46%
MGA	MAGNA INTL INC	2.18%	4.60%	6.94%	2.35%
FL	FOOT LOCKER INC	2.35%	3.88%	6.11%	2.23%
		SUM	24.71%	38.69%	

			% of Active Risk		
Ticker	Company Name	Active Weight	Fund	Stat	DELTA
BRK/B	BERKSHIRE HATHAWAY INC DEL	-1.44%	-0.16%	-1.45%	-1.29%
AAPL	APPLE INC	-1.33%	-0.73%	-2.19%	-1.46%
BAC	BANK AMER CORP	-0.96%	-0.59%	-2.12%	-1.53%
WFC	WELLS FARGO & CO NEW	-1.42%	-0.69%	-2.23%	-1.54%
FB	FACEBOOK INC	-1.20%	-0.88%	-2.70%	-1.82%
		SUM	-3.05%	-10.68%	

Table 6: The active weight and % of Active Risk computed with the fundamental and statistical risk models for 10 portfolio names.

predictions. That is, assets with large positive or negative risk differences are riskier, both in predicted risk as well as realized risk. While the overall level of risk varies from year to year, the pattern of increased risk with increased difference in the risk models persists.

Implementation

Different investment processes have different priorities. Here we list some of the possible steps investment managers may consider using to exploit having both fundamental and statistical factor risk models available.

Quantitative Active Managers

- Introduce a second risk constraint or objective term that penalizes risk coming from the statistical model (in general, or when spreads suggest it necessary)
- Adjust asset-level constraints to reduce exposure to assets with high stat/fund differences
- Prescreen for risk differences

Fundamental/Quantamental Active Managers

- Adjust position sizes for problematic assets to ensure conviction is properly implemented

Long-Short Managers

- Explicitly hedge systematic risk as estimated by the statistical model in addition to the fundamental model
- You are not factor neutral if you are optimizing with only fundamental models
    - There is a better "best hedge"
    - Constrain assets with increased risk coming from the statistical model
- Early warning signal on potential problem areas

Passive/ETF/Tax-Efficient Managers

- Constrain tracking error using multiple risk models
- Tighten asset bounds for assets with larger differences in risk estimates

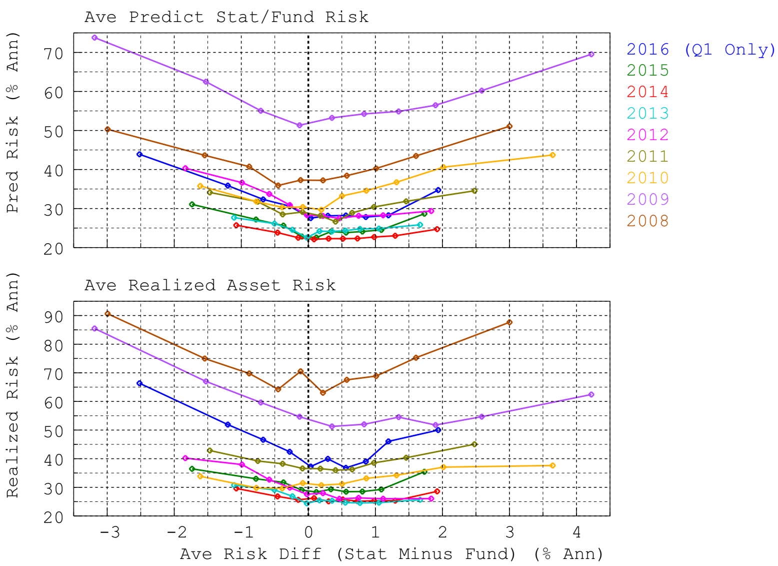

Figure 6: The predicted (top) and realized (bottom) risk of assets as a function of the difference in asset risk (statistical asset risk minus fundamental asset risk). Results are averaged over the years indicated by each color and across deciles of the asset risk difference (e.g., the horizontal axis).

Conclusions

No risk model is perfect – fundamental models and statistical models each have their pros and cons. Given their intuitive factors, fundamental models are generally used for factor exposure management and performance attribution, neither of which can be done well with statistical risk models because of their adaptive factor structure. However, statistical risk models are useful precisely because their factors adapt and pick up 'hidden' or transitional risks in the market that are missed by fundamental factor risk models.

Different risk models will have different risk predictions, and it is useful to understand which model is predicting higher risk and whether that risk is factor or specific. The high level tracking error comparisons, differences in % of factor and specific tracking error, and asset level % of tracking error analytics help explain where differences in risk may arise.

Endnotes

1. The exposures change from day to day, but the factor itself and underlying descriptors – Value, Industry, etc. – are fixed and do not change.

2. We could, of course, do the analysis for all four risk models. We use two risk models solely to make the results more legible.

Authors' Bios

Anthony Renshaw, *Ph.D.*
Axioma

As Director of Applied Research, Dr. Anthony Renshaw is responsible for advanced applications of Axioma's portfolio optimization solutions and risk model content, fundamental portfolio management research, and advanced client consulting. He also plays a leading role in client training, software development and testing, and providing expert client-specific consulting services. From 1994 to 2003, Renshaw worked as an Associate Professor of Mechanical Engineering at Columbia University, and prior to that, he worked at General Electric's Corporate Research and Development Center. Renshaw received his Ph.D. in Mechanical Engineering from U.C. Berkeley, a Master of Engineering degree with a Business minor from U.C. Berkeley, and a bachelor's degree in Applied Mathematics from Harvard in 1985.

Chris Canova, *CFA*
Axioma

Chris Canova oversees the efforts of the client-facing organization including pre-sales, consulting, and implementation services. Chris has over fifteen years of experience in business development, client consulting, theoretical best practices and relationship management in the portfolio construction and analytics space. Chris has extensive experience working with quantitative equity and multi-asset class solutions. Prior to joining Axioma in 2006, Chris held a number of positions in the client support and sales organizations of Barra, subsequently MSCI Barra, from 2000 through 2006. Chris earned a BA in Finance from California Polytechnic State University with a minor in Economics and was awarded the CFA charter in 2003. He is a member of the Chicago Quantitative Alliance.

Chris Martin, *CAIA, CIPM*
Axioma

Chris Martin has worked at Axioma for more than eight years in a variety of positions. Internally, he works closely with all members of the Axioma team, including: Product, Research, Content, Sales, and Support. This range of experience allows Chris to support the needs of Axioma's clients, whether it be training new users or helping existing users get the most out of Axioma's Risk Models, Optimizer, and Analytics software. Chris received his Masters in Financial Engineering, a joint degree from the Drucker School of Management and Mathematical Sciences at Claremont Graduate University. He received his bachelor's degree in General Engineering with a concentration in Aeronautical and Mechanical Engineering and a Minor in Physics from California Polytechnic State University, San Luis Obispo. Chris is a certified Engineer-in-Training in California and is a *CAIA* and CIPM charterholder.

Ranges and Rebalancing

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Al Futtaim Group

Abdulaziz Alnuaimi, *CAIA*
Harvard Business School

Institutional money managers develop asset allocation strategies which should represent their optimal risk tolerance. This asset allocation is expressed as a composite benchmark of a variety of underlying asset classes which is in usually rebalanced monthly. Monthly rebalancing in this regards means that the monthly returns are weighted each month by the initial asset allocation weights (neutral weights). The resulting time-series is then the basis of any return and risk calculation.

The literature of 'smart beta' or 'alternative beta' discusses a variety of rebalancing mechanism which are superior of capital weighted indices – mostly equity indices – and periodic rebalancing – mostly fixed income indices. We will abstain from this discussion but acknowledge that periodic rebalancing of asset allocation strategies has its advantages and disadvantages.

The advantages are

- Ease of calculation
- Lack of path-dependency which is often the case with more elaborate mechanism
- Ease of entry for new mandates due to frequent recalibration of asset weights

The disadvantage is

- Calendar based re-balancing does not take into account any underlying capital market characteristics such as valuations et cet. That makes this rebalancing mechanism 'inefficient' from a capital market perspective.

Asset class rebalancing aims to stay close the relative neutral weights of an asset allocation, which are the calculation basis of monthly rebalanced indices. The reason for the deviation is that asset classes perform differently over time. It is therefore interesting to see how a monthly rebalanced portfolio behaves in contrast to a portfolio where no rebalancing takes place (buy & hold portfolio).

Rebalancing versus 'buy and hold'

The starting point is the construction of an equally weighted portfolio of 4 asset classes, of which 2 are global equity indices (MSCI developed and MSCI emerging) and 2 are global fixed income indices (High Yield & Government Bonds). All 4 indices are total return indices which are unhedged. 15 years of monthly data are being used, starting in 2001. We are aware that the equal weights applied are not the result of an optimisation exercise. We address this point later in the analysis and concentrate for now on the aspect of periodic rebalancing versus no re-balancing ('buy & hold').

The chosen constituents of this asset allocation have the following risk return profiles over the 15 years horizon:

2001 - 2016	MSCI World Developed	MSCI World Emerging	Barclays Global High Yield	Barclays Global Government
Ann Return	4.15%	7.87%	8.34%	4.33%
Ann Volatility	15.54%	22.32%	10.15%	6.78%

Exhibit 1

We now construct 2 time series: one where the initial weights are applied every month and one where no adjustment to the initial weight is being applied. For both time series we calculate the annualised return and volatility. The result shows that the difference between the 2 portfolios is relatively small in terms of return but also in terms of volatility. Moreover, the return data do not take into account any rebalancing costs which would weigh

2001 - 2016	with monthly rebalancing	without monthly rebalancing
Ann Return	6.61%	6.43%
Ann Volatility	11.79%	12.44%

Exhibit 2

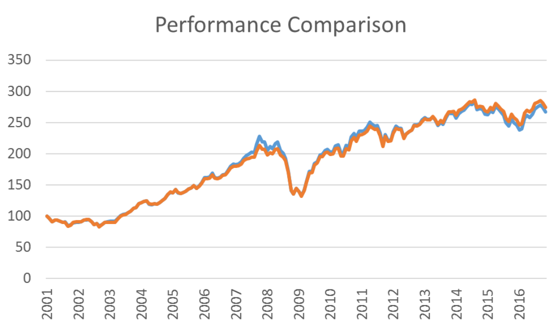

Exhibit 3

on the results of the monthly rebalancing portfolio.

Looking at the monthly return differences between the 2 portfolios one can easily see that the biggest differences occur in times of stress, like in the GFC of 2008. The tracking error

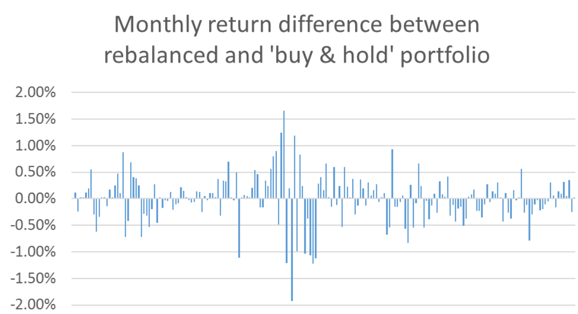

Exhibit 4

between the 2 portfolios is an annualised 1.5% over the last 15 years.

The fluctuations around the neutral asset class weights have been substantial. In the case of emerging markets equities it was 20% before the 2008 crisis hit, while development market equities deviated a maximum of 12.8% from its neutral weight.

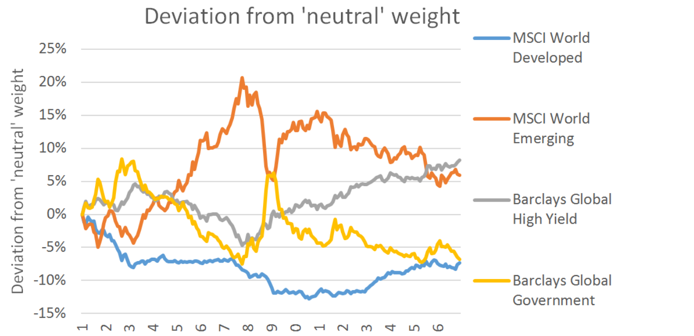

Exhibit 5

We have started this analysis with allocating an equal weight to each of the 4 asset classes for simplicity sake. In a next step we allocate randomly weights to these four asset classes and compare the annualised return and volatility of the monthly rebalanced one with the buy & hold strategy. We repeat this procedure 1000 times. With this step we want to avoid any bias in the analysis due to the allocation weights.

If we plot the results in terms of return on a scatter chart, we obtain the following results for two time periods, i.e. 2001 – 2016 and 2007 - 2009. Similar to the initial result where monthly rebalancing outperformed the 'buy & hold' strategy by a small margin, the performance difference between the 2 strategies over the 1000 iterations ranges between 0.1% to 0.4% on average.[1] As it can be seen from exhibit 6, the dispersion in terms of annualised return is also relatively contained for the entire period from 2001 – 2016 but three times less dispersed when looking at the time period between 2007 – 2009, the time of the GFC.

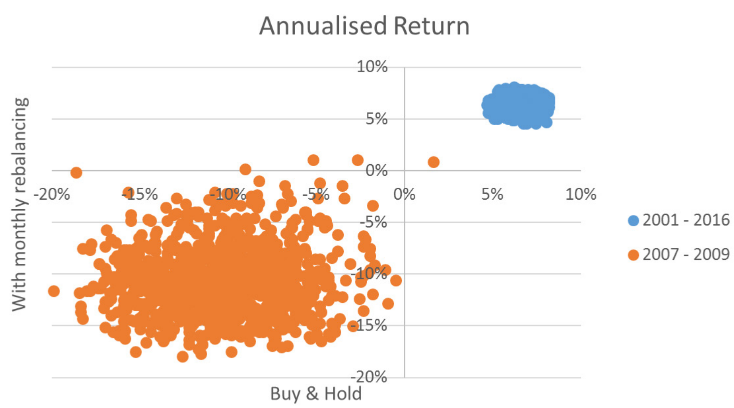

Exhibit 6

The picture is also in line with initial findings when comparing the annualised volatility between the 2 portfolios. The dispersion is first of all higher and the balanced portfolio displays between 30 and 50bp less annualised volatility on average over the 1000 iterations. The dispersion between the entire period 2001 – 2016 is slightly lower than the dispersion of the annualised volatility over the crisis period 2007 – 2009.

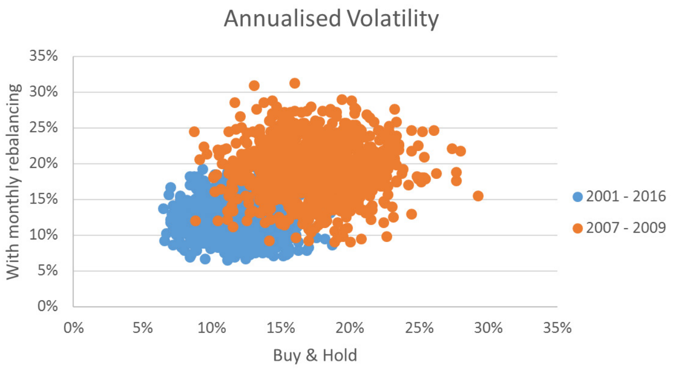

Exhibit 7

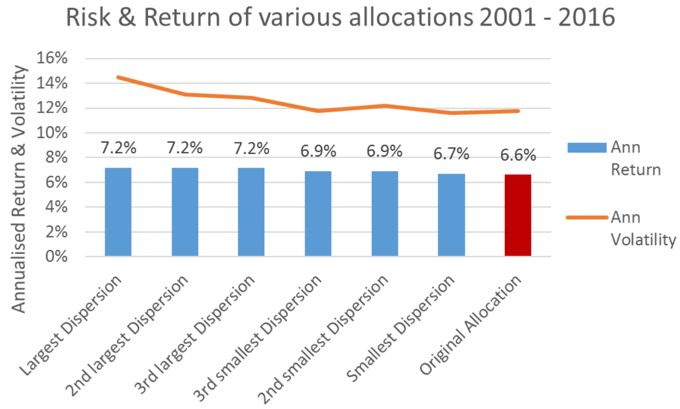

Exhibit 9

Does this imply that re-balancing does not matter? From Perold & Sharpe we know that 'buy & hold' pays off in times of trending markets, while in times of directionless markets, rebalancing makes more sense. In other words 'buy & hold' favours momentum, while rebalancing favours mean-reversion.[2] This would explain the results above that over a longer period where momentum and mean-reversion follow each other, the difference between 'buy & hold' and rebalancing converge. However, A Dayanandan and M Lam also showed in their analysis that the difference between 'buy& hold' and rebalancing is insignificant.[3] However one has to carefully distinguish between the merits of rebalancing and active portfolio management. Other studies are in favour of rebalancing and see value in certain times.[4] We can conclude that rebalancing is good for risk reduction but matter less for return enhancement. In this context one may argue that the lower risk budget could be used for increasing the return by adding leverage.

Why not 'buy & hold' then?

Investors have difficulties tolerating a 'buy & hold' approach as the underlying asset allocation of the portfolio changes substantially.

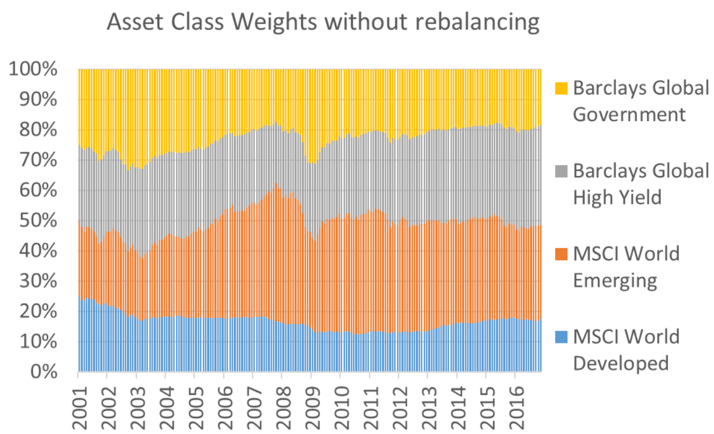

Exhibit 8

The problem is that each allocation point taken in isolation and used as a basis for a long-term allocation calculation would result in substantial differences vis-à-vis the neutral allocation. In order to illustrate that point we take 6 different allocation weights of the 'buy & hold' approach and use them as a basis for calculating risk and return numbers. The calculation is again based on a monthly rebalancing.

Range Settings

While we have discussed periodic rebalancing, a different approach would be to rebalance the portfolio if certain asset class thresholds are being met. Ranges are therefore set to trigger rebalancing. We leave aside the question whether it is preferred to re-establish the neutral weight if one of the ranges are met or if it is sufficient to get the allocation back within the ranges.

Range setting is often done by practitioners on a rule-of-thumb basis. We will argue that range setting is as much an optimisation exercise as it is the strategic asset allocation in itself. For this reason the first step is to identify the risk contribution of each asset class.

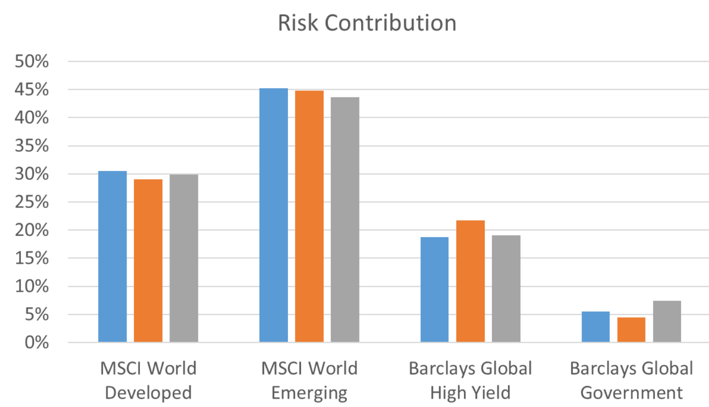

Exhibit 10

The risk contribution analysis compares a variety of time periods in order to see whether there are material differences. At this point it is obvious that emerging market equity dominate the risk contribution with a value close to 45%, while global government added only 5% to the overall risk of this portfolio. This result is consistent in each of the three time periods chosen. Again the calculation is based on time series which have been monthly rebalanced.

The setting of ranges around the 'neutral' weights is seen as pivotal when establishing a tracking error target. The tracking error provides then an indication of the information ratio, which is the outperformance of the portfolio versus the 'neutral' composite benchmark, divided by the tracking error. Assuming a manager wants to outperform the benchmark by 2% per annum, a 4% tracking error would be sufficient if the manager assumes that he is able to achieve an information ratio of 0.5. This analysis assumes that only asset allocation decisions are the source of outperformance and no security selection within the various asset classes.

Therefore ranges which are too tight would jeopardise the ability of the manager to achieve his outperformance target. Opposite ranges which would be too wide, would allow the manager to divert too far from the 'neutral' weights without being necessarily being compensated by a sufficient outperformance. As a consequence the exercise of setting asset class ranges warrants full analytical attention as tracking error targets combined with asset class ranges often represent a crucial element of investment management agreements (IMA).

We are now going to offer a variety of optimisation techniques each of them designed to gauge the deviation from the 'neutral' weight of each asset class.

Maximum Information Ratio

The first optimisation maximises the information ratio while increasing the tracking error at each step by 25bp. The optimisation exercise should provide us with a sort of optimal portfolio indicating at which tracking error the highest information ratio can be achieved. We perform this optimisation again over three time periods, one covering the period from 2001 – 2016, the next one from 2007 – 2009 (March) and finally from 2009 – 2016. The reason is to see whether the 'optimal' tracking error is substantially differs among these three periods.

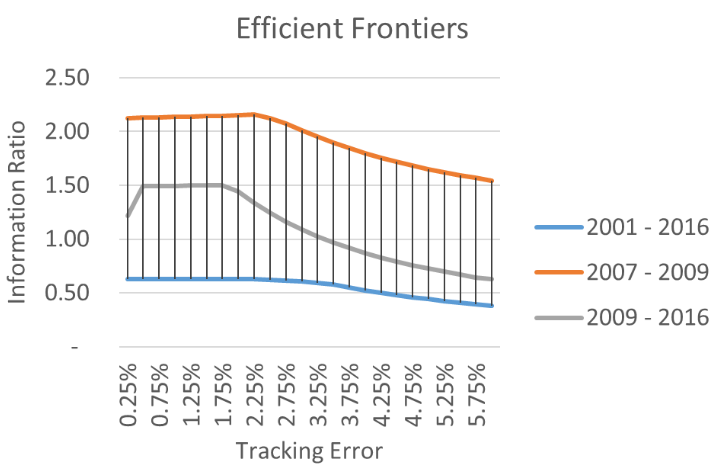

Exhibit 11

Over the longest time period, the information ratio starts to decline when the tracking error is around 3%. Based on a time period between 2007 and 2009, the point where the efficiency of the portfolio expressed in terms of information ratio declines already when the tracking error is around 2.5%. The 'optimal' tracking error is around 2% when looking at monthly data over the last 7 years. This very simple analysis vividly shows how sensitive any optimisation results are vis-à-vis changes in the underlying time periods.

Obviously the composition of the portfolio changes also dramatically with the choice of different time periods.

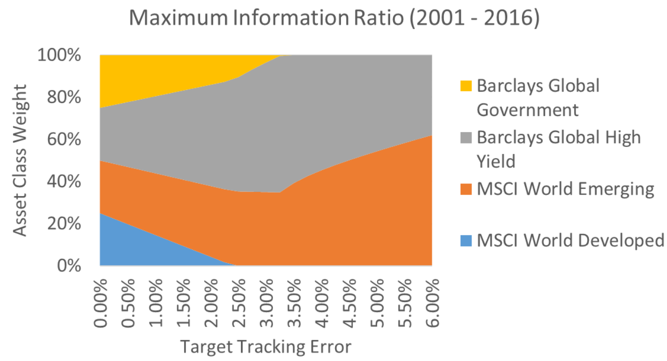

Exhibit 12

Looking at the asset weight development based on a calculation period of the last 15 years, the portfolio becomes a 2 asset class portfolio when the tracking error is higher than 3.5%, with emerging market equities and high yield bonds, both the asset classes with the highest returns over this period in almost 50/50 split when the tracking error reaches 6%.

For the next period (2007 – 2009 March) the allocation development is completely different. As this period is dominated by the events of the Great Financial Crisis (GFC), where risky assets underperformed, government bonds are becoming fast the most dominant asset class as it has performed by far best during these months. Due to its correlation behaviour emerging market equities maintain a 40% weight when the tracking error is higher than 2%.

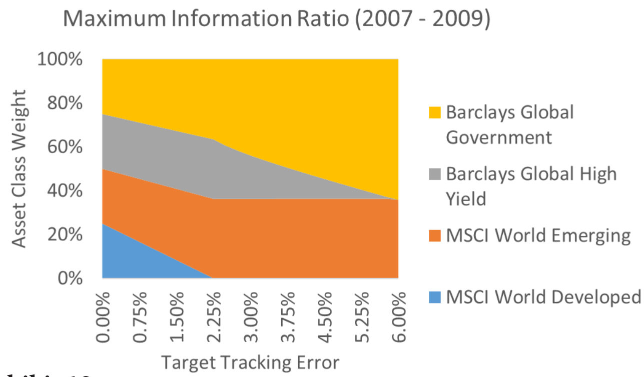

Exhibit 13

Finally when looking at the time period over the last 6 years, where global high yield and developed markets gained the most, these two asset classes are quickly dominating the portfolio, when the tracking error becomes greater than 2%.

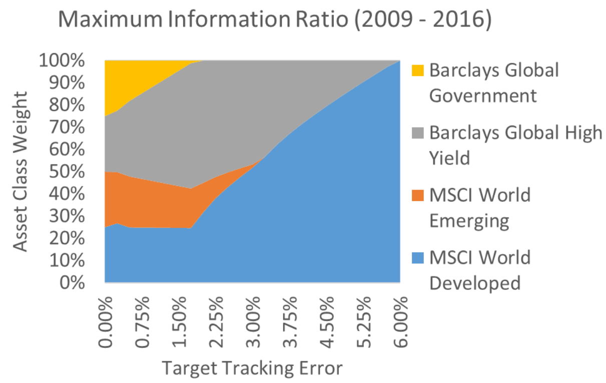

Exhibit 14

All three examples show that a tracking error in excess of 1.5% to 2% will result in asset weights which range from 0 to 100%, which is partly a result of the quadratic nature of the tracking error calculation. However, as also indicated this threshold is also more or less the frontier where the information ratio of any additional increase in tracking error starts to decline. In summary it means that the setting of tracking error in conjunction with the setting of ranges should be done prudently and being seen as an optimisation exercise.

Conclusion

We have shown that the fact that most strategic asset allocation calculations are based on an implicit rebalancing assumption in terms of periodic rebalancing – we have focussed on monthly rebalancing – is not capital market efficient. However the obvious practical advantages of this approach outweighs the deficiencies. Furthermore an entire industry around the 'smart beta' tries to identify smarter and more capital market efficient ways. We also showed that rebalancing is best suited for risk reduction purposes rather than return enhancements when a 'buy &n hold' is confronted with rebalanced portfolio.

We have further concluded that the setting of ranges around the neutral weight – which should represent the optimal allocation weight – should be seen as an optimisation exercise rather than just a rule-of-thumb practice. This makes intuitively sense as it is difficult to explain why so much effort goes into the definition of the neutral weight and so little in the definition of any deviation from it.

One way of approaching this optimisation exercise in a useful manner is to optimise the portfolio vis-à-vis predefined tracking errors. The most important conclusion out of our analysis is that there is an optimal tracking error level when the optimisation has to identify an optimal balance between tracking error and information ratio, which is the outperformance divided by the tracking error. Due to its quadratic nature the deviation from the neutral weights becomes exponentially higher with a higher degree of tracking error. We compare the optimisation result under various regimes in order to identify an 'optimal' region of tracking errors

Endnotes

1. We have run the iterations several times over a variety of time horizons.

2. A Perold and W Sharpe, Dynamic Strategies for Asset Allocation, Financial Analyst Journal (1995).

3. A Dayanandan and M Lam, Portfolio Rebalancing – hype or hope?, Journal of Business Inquiry (2015).

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Authors' Bios

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Frederic started his career as a Rating Analyst at Standard & Poor's in London. Later he became the Chief Investment Strategist for Commerz International Capital Management, the institutional asset manager arm of Commerzbank/ Germany. In 1996 he joined Credit Suisse, working as an asset allocation analyst. He built up the fund research department for Credit Suisse and became head of investment strategy for Credit Suisse Private Banking in 2002. In 2006 he moved to Geneva to become the Chief Investment Officer at the Swiss Social Security Fund. In 2012 he started as the Chief Investment Officer with Emirates Investment Authority in Abu Dhabi, the federal sovereign wealth fund of the UAE. In 2016 he became Chief Investment Director for Al Futtaim Group with the task to build up the investment office for the group. He holds a PhD in Economics from the Economics University in Vienna and is a CAIA charterholder.

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Performance Attribution in Private Equity: A Case Study of Two North American Pension Funds

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Introduction

Evaluating and quantifying the strengths and weaknesses of the investment process is key to portfolio managers, senior management, consultants and investors. Performance attribution is the tool to address this challenging task. The aim of performance attribution is the dissection of the portfolio performance into several components, where each component is associated with a particular decision in the investment process. Basically, performance attribution is conducted through chaining several benchmarking calculations, resulting in a separation of the asset allocation and fund selection component.

Any benchmarking methodology leads to meaningful insights only if the selected benchmark is appropriate. It is accepted that a valid benchmark should exhibit the following characteristics: investable, measureable, specified in advance, unambiguous and reflective of the portfolio manager's investment options. However, in practice it is often difficult to identify a benchmark satisfying all of these properties.

For public equity investments the benchmark is generally defined in the investment policy statement and typically consists of a public equity index or a combination of various such indices. The availability of passive funds tracking the performance of public equity indices guarantees the investability of the benchmark. While such a benchmark is valid at the time of specification, sometimes the investment mandate changes and the benchmark is no longer reflective of the portfolio manager's investment options. On the other side, no investable index exists for private equity. In fact, the situation is even worse as there is no widely accepted private equity index. The family of private equity and venture capital indices compiled by Cambridge Associates[1], which are used by some investors, provide quarterly returns and include all funds irrespective of their vintage year. Such a benchmark is representative of the private equity industry but should not be used to benchmark an investor's private equity portfolio, as the vintage year is an important driver of the portfolio performance.

The lack of a widely accepted and valid private equity benchmark makes it difficult to apply public equity performance models to the private equity world. More importantly, applying public performance attribution models to the private world is meaningless when different performance measures are used. In the public world, the time-weighted rate of return (TWRR) is the prominent measure to track performance while private equity uses the internal rate of return (IRR), which is also called the money-weighted rate of return (MWRR). The IRR measure is more reflective of private equity performance because it incorporates the timing of cash flows. A key characteristic of the TWRR, which is used in most performance attribution models, is its additivity property. The IRR, however, cannot be deconstructed easily.

The difference in performance measures and the difficulty to define a valid benchmark for private equity render it difficult to put public equity performance attribution models into the private equity world. Long (2008)[2] overcomes these two issues by introducing a private equity-specific performance attribution model. The model does not depend on an external benchmark and is based solely on the IRR measure – the preferred private equity performance measure. Long dissects the performance into a Base Performance, Timing Premium and Selection Premium. These three factors are derived from different IRRs obtained by modifying the weighting and/or shifting the timing of the private equity fund cash flows constituting the portfolio:

- Base Performance = IRR of equally weighted[3] funds with all funds anchored to time zero[4]
- Timing Premium = Actual Portfolio IRR - IRR of all fund anchored to time zero
- Selection Premium = Actual Portfolio IRR - IRR of equal weighted funds

The simplicity of these formulas is clearly an advantage. Additionally, these three factors do not depend on an external benchmark. Instead, modified versions of the portfolio cash flows are used to construct a benchmark. The "IRR of all funds anchored to time zero" is used as a benchmark to determine the Timing Premium and the "IRR of equal weighted funds" is used as a benchmark to determine the Selection Premium. In other words, bootstrapped portfolio cash flows determine the benchmark.

However, the methodology to calculate the Selection Premium can easily produce misleading results: Consider a portfolio manager who has only committed to top quartile funds. Furthermore, assume that the commitment sizes to the weaker top quartile funds are larger than the stronger top quartile funds. In this scenario, the Selection Premium will be negative in most cases despite all investments being top quartile. This is because the Selection Premium only addresses the question of whether the relatively stronger performing funds of the portfolio are overweighted - the absolute performance of the funds is disregarded. Another shortcoming of the model is that the performance attribution consists of only two premiums, which does not adequately address the multiple steps within the private equity investment process. Last but not least, it is difficult to provide a practical interpretation of the Base Performance.

Our new model dissects the portfolio performance into five premiums, which are: Illiquidity Premium, Strategic Asset Allocation Premium, Commitment Timing Premium, Strategy Timing Premium and Manager Alpha. An interpretable base factor called Passive Public Equity Performance is also introduced. This level of granularity in premiums enables quantification of the strengths and weaknesses of an investment process. The issue of the Selection Premium in the approach of Long is overcome by constructing a customized index based on private equity market data.

In the coming section, the model is explained in detail; each premium is described and put in relation to the investment process. Moreover, the mathematics of each premium is depicted. In the Case Study, the model is applied and illustrated on the portfolios of two North American pension funds.

Model description

The investment process in private equity

Private and public equity share many characteristics and risks. Even though some of the fundamentals differ, private equity is ultimately still equity. As such, various sophisticated investors[5] treat private equity as part of the equity allocation. Once the equity allocation has been identified, the initial question to pose is how to split the equity allocation between private and public equity. Subsequently, a long-term strategic asset allocation (SAA) within private equity needs to be established. The SAA defines the annual target commitment volume to private equity and how this commitment volume is spread over the various private equity strategies. Specific views on the short-term market development will occasionally result in deliberate deviations from the SAA. Such deviations are called Tactical Asset Allocation (TAA) decisions. Finally, the portfolio manager is tasked to allocate the available commitment volume to private equity fund managers; it is his responsibility to select the individual funds and to determine the commitment amount to each fund. The green arrows in Figure 1 summarize the investment process in private equity.

In the following sections, each step of the investment process is examined in detail and quantified with one or more premiums. The blue boxes in Figure 1 provide an overview of the premiums

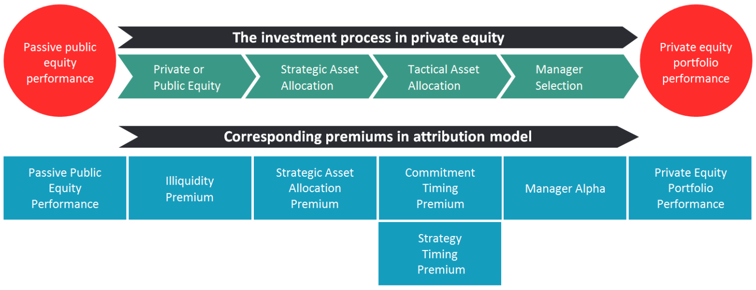

Figure 1: Investment process into private equity and premiums of the performance attribution model

Table 1: Definition of the Premiums

Illiquidity Premium	Private Equity Market IRR - Passive Public Equity Performance
Strategic Asset Allocation Premium	SAA IRR - Private Equity Market IRR
Commitment Timing Premium	Commitment Timing IRR - SAA IRR
Strategy Timing Premium	Strategy Timing IRR - Commitment Timing IRR
Manager Alpha	Private Equity Portfolio IRR - Strategy Timing IRR

Table 2: Definition of the IRRs

Passive Public Equity Performance	PME+ of the PE market over the investment horizon of the PE portfolio
Private Equity Market IRR	IRR of the PE market over the investment horizon of the PE portfolio
Strategic Asset Allocation (SAA) IRR	IRR of the PE market at the SAA weights of the PE portfolio
Commitment Timing IRR	IRR of the PE market at the strategy weights of the SAA but at the actual annual commitment volumes of the PE portfolio
Strategy Timing IRR	IRR of the PE market at the actual annual commitment volumes and at the actual strategy allocation of the PE portfolio
Private Equity Portfolio IRR	Private Equity Portfolio IRR

related to the different steps in the investment process. Basically, a premium is defined as the difference between two IRRs that are based on cash flows differing in only one characteristic – the characteristic measured by the premium. Table 1 provides an overview of the calculation of each premium, while Table 2 depicts the calculation of the various IRRs.

Private or public equity

Once the overall target allocation to equity has been identified, the next issue is how to split the equity allocation between private and public equity. The opportunity cost of investing in private equity can be viewed as the return of investing passively in public equity. This opportunity cost is quantified in the performance attribution model by the Passive Public Equity Performance. As opposed to the other factors in the model, the Passive Public Equity Performance cannot be interpreted as a premium, but should be regarded as the passive return of investing in the public index at the private equity market cash flows.

Mathematically, the Passive Public Equity Performance[6] is derived by a PME+ calculation with private equity market data, which is collected and published by various private equity data vendors such as Cambridge Associates. The PME+ of quarterly private equity cash flows and NAVs covering the same time horizon as the private equity portfolio is defined as the Passive Public Equity Performance. The time horizon starts at the year of first investment of the private equity portfolio and ends at the year of the last investment. Even if the portfolio did not invest in certain vintage years, those vintage years are still included in the Passive Public Market Performance. The portfolio manager's decision to skip certain vintage years will be quantified later in the Commitment Timing Premium. The Passive Public Equity Performance should be interpreted as investing in the public market at the cash flows dictated by the private equity market and with the time horizon defined by the private equity portfolio.

As pointed out in the previous Section, neither the private equity market nor even the corresponding PME+ are investable. Nevertheless, both PME+ and the relevant private equity market performance are often used to benchmark private equity investments. PME+ benchmarks a private equity investment against a select public equity index. Ideally, the public index matches the characteristics of private equity market as closely as possible. To guarantee a fair comparison, the public equity index should be a total return index ensuring that dividend payouts are reinvested.

Private equity investors want to be compensated for the illiquid nature of private equity. Illiquidity risk refers to the fact that private equity investments cannot generally be immediately sold at NAV but only at a discount to NAV. Private equity investors want to be compensated for this risk in the form of the Illiquidity Premium. The Illiquidity Premium is modelled by subtracting the Passive Public Equity Performance from the Private Equity Market IRR. The Private Equity Market IRR is the IRR of the private equity market cash flows and NAVs covering the same time horizon as the private equity portfolio. Therefore, the Illiquidity Premium is simply the outperformance (or underperformance) of the private equity market over a public equity market index as measured by the PME+ methodology. Comparing the public and private equity market with the PME+ methodology is proposed by Rouvinez (2003).[7]

Strategic Asset Allocation

Once a private equity allocation is on the agenda, a long-term strategic asset allocation (SAA) within private equity needs to be established. For private equity, the SAA involves three components: vintage year, sector and geography, where the combination of the latter two will be often summarized as strategy. The vintage year component defines the annual future target commitment volume. Sector and geography determine how the annual commitment volume is spread over the various sectors (i.e. buyout and venture capital) and geographies (i.e. US and EU). The SAA is likely to differ from the asset allocation of the private equity market. For instance, in a given vintage year the private equity market may exhibit a sector allocation of 80% to buyout and 20% to venture capital, while the SAA of the investor prescribes only a 10% allocation to venture capital and the remaining 90% to buyout. Similarly, the allocation could also differ with respect to the geographic focus.

Whether investing based on the SAA or based on the private equity market, allocation results in a higher performance when measured by the Strategic Asset Allocation Premium. For instance, if the buyout sector of the market outperforms the venture sector then the Strategic Asset Allocation Premium would be positive in the previous example, since the SAA to buyout is 10% higher than the private equity market allocation to buyout. It is important to note that the performance of the private equity portfolio itself is not relevant at this stage - what matters is only whether the SAA of the investor was able to identify and overweight the long-term outperforming strategies and vintage years.

In practice, the SAA of a private equity investor is often defined in terms of a target private equity NAV as percentage of total asset value. However, private equity funds build up the NAV over time, which makes it difficult to reach a precise target NAV within a short period of time. Typically, a long-term commitment plan to reach the strategic allocation is set up. Such a long-term plan can be achieved by applying the model from Jost and Herger (2013).[8] In essence, the plan specifies the annual strategic commitment volumes for the next couple of years. The plan is reviewed and revised annually to incorporate any fluctuations in the private equity NAV or in the total asset value.

Mathematically, the Strategic Asset Allocation Premium is obtained by subtracting the Private Equity Market IRR from the SAA IRR. The SAA IRR is the IRR achieved by investing the amounts prescribed by the SAA into the private equity market. Any of the major private equity data vendors provide pooled quarterly private equity cash flows segregated by vintage year and strategy, which can be used to calculate the SAA IRR. The cash flows and NAV used for the SAA IRR and for the Private Equity Market IRR differ only in the weighting factor applied to each vintage year and strategy.

Tactical Asset Allocation

Views on short-term market developments will occasionally result in deviations for the SAA. Short-term deviations from the long-term SAA are called Tactical Asset Allocation (TAA) decisions. In the case of private equity, tactical deviations from the SAA can be observed in two ways: deviations from the strategic commitment volume and deviations from the strategic strategy allocation. The model captures the former by the Commitment Timing Premium, while the latter is measured by the Strategy Timing Premium. A current over- or under-allocation to private equity or changes in the general private equity market outlook might justify deviations from the strategic commitment volume. Deviations from the strategic strategy allocation might be explained by a lack of strong managers in certain strategies or a perceived (un)attractiveness of certain private equity strategies.

As stated, the TAA is broken down into two premiums. The order in which the two premiums are calculated matters. In the case of private equity it seems natural that an investor first determines the tactical commitment volume and only thereafter the tactical strategy allocation; therefore the model first measures the Commitment Timing Premium. Another possibility would be to treat the two premiums independently and introduce a residual (or interaction) premium representing the joint/combined effects. However, since there is a natural order in private equity they are treated sequentially and no residual is necessary.

The Commitment Timing IRR is derived from investing in the private market at the actual private equity portfolio commitment amounts and at the strategy defined by the SAA. Mathematically, the Commitment Timing Premium is obtained by subtracting the SAA IRR from the Commitment Timing IRR. The difference between these two IRRs lies solely in the annual commitment amounts; the strategy allocation is the same for both. If the short-term view of a portfolio manager constitutes a strong private equity market outlook then an increase in the private equity allocation, above the levels prescribed by the SAA, increases the Commitment Timing Premium - assuming the short-term view actually materializes.

The Commitment Timing Premium quantifies the tactical decision to deviate from the strategic commitment amounts. However, deviations from the SAA can not only occur by under- or overcommitting but also by adjusting the strategy allocation. These deviations are captured by the Strategy Timing Premium. Mathematically, this premium is calculated by subtracting the Commitment Timing IRR from the Strategy Timing IRR. The Strategy Timing IRR is derived from investing in the private equity market at the actual commitment amounts and the actual strategy allocation. Note that the Strategy Timing IRR has the same allocation as the actual portfolio. The only difference is that the Strategy Timing IRR is based on the private equity market cash flows, while the actual portfolio is based on the cash flows of the actual funds being selected.

Manager selection

Finally, the portfolio manager is tasked with allocating the available commitment volume to private equity fund managers. It is his responsibility to select individual funds and the corresponding commitment size. The portfolio manager is accountable for the number of selected funds, the commitment amount to each fund and the ultimate performance of each fund. The Manager Alpha bundles the success of these three interrelated decisions into a single number. It is important to note that the overall portfolio performance is driven by both the performance of the selected funds and the commitment amount to each fund. For instance, a portfolio may perform poorly if several but small commitments are made to top quartile funds together with a large commitment to a bottom quartile fund.

Mathematically, the Manager Alpha is calculated by subtracting the Strategy Timing IRR from the Private Equity Portfolio IRR. Both of these IRRs are based on the same annual commitment amounts and strategy allocation. The only difference is that the Strategy Timing IRR is derived from investing the private equity market whereas the Private Equity Portfolio IRR is based on the actual funds selected by the portfolio managers. Hence, the Manager Alpha quantifies the success of deploying the available commitment capacity.

A Case Study on Portfolios of two North American Pension funds

The data sets

To demonstrate the performance attribution model on real world examples, data of two North American pension funds have been collected from public sources such as annual and quarterly pension fund reports or the Preqin database. Finding complete cash flow data for all private equity holdings of an investor is challenging. For each of the two pension funds, it was possible to identify complete cash flow data for more than 90% of the funds with vintage years ranging from 2003 to 2012. Due to the lack of reliable private benchmarks, both data sets had to be pruned. The portfolio for the first case study is restricted to US/EU focused buyout funds and venture capital funds. In the second case study, energy funds were included as well. The second portfolio is invested into approximately a dozen funds of funds and secondary funds which are benchmarked against buyout funds invested over three consecutive vintage years. In both case studies, funds with incomplete cash flow history were dropped from the analysis. For both portfolios, we have to make assumptions about the strategic asset allocation based on publicly disclosed investment policies. The lack of complete data may have had a meaningful impact on the following results. It is therefore important to note that we see the two case studies as illustrative, as a truly fair analysis would have to be based on better input data.

First case study

Figure 2 depicts the commitment volumes by strategy of the first North American pension fund ("Portfolio 1"). Over the 10-year period, Portfolio 1 committed more than USD 21bn to 95 private equity funds. The annual commitment volume successively increased until the maximum of approximately USD 5bn was reached in 2006. Subsequently, the commitment volume fell to a minimum of below USD 0.5bn after the height of the global financial crisis in 2010 and recovered thereafter. The allocation to US and EU buyout was roughly constant with a bias towards US buyout. Before 2008, the Portfolio committed to venture capital funds. Thereafter, only a single venture capital commitment was made in 2011.

Figure 3 shows the performance attribution model applied to Portfolio 1. By December 31, 2014, the 10-year investment program returned a 9.3% IRR which corresponds to an outperformance of 2.7% over the Passive Public Equity Performance of 6.7% IRR. The Illiquidity Premium and Strategic Asset Allocation Premium generated a combined value of 5.9% IRR while the Tactical Asset Allocation Premiums and the Manager Alpha diminished the performance by 3.2% IRR resulting in a total 2.7% IRR increase compared to passively investing the public market at the private equity portfolio cash flows.

In the following paragraphs, each premium in Figure 3 is investigated in more detail. By examining and comparing the private equity market allocation and performance together with the private equity portfolio allocation and performance the magnitude of each of the premiums becomes clear and intuitive.

The Passive Public Equity Performance and the Illiquidity Premium

The Passive Public Equity Performance is the PME+ of private equity market cash flows over the investment horizon of Portfolio 1. Only US/EU buyout and venture capital have been included in the private equity market, which reflects the investment universe of Portfolio 1. As a proxy of the private equity market, the Cambridge Associates database[9] is used. Cambridge Associates provides quarterly cash flows and NAVs together with the corresponding commitments (so-called market capitalization) by vintage year and strategy. Figure 4 shows these market capitalizations for the time period under consideration. The PME+ of the private equity market results in a 6.7% IRR which is the Passive Public Equity Performance. The IRR of the private equity market data yields an 11.0% IRR. Therefore, the Illiquidity Premium is 4.3% (=11.0% - 6.7%). The PME+ is based the MSCI World Total Return Index, which captures over 1,600 mid and large cap companies from 23 developed countries.

The Strategic Asset Allocation Premium

The strategic asset allocation to private equity is often specified in terms of a target private equity NAV as a percentage of total plan assets. However, for private equity such a target alone does not directly imply the annual required commitments (the strategic commitments) since the private equity NAV builds up over time and not instantaneously as in public equity investment. Therefore, to meet a target private equity NAV, a long-term commitment plan containing the strategic commitments must be established and regularly reviewed.

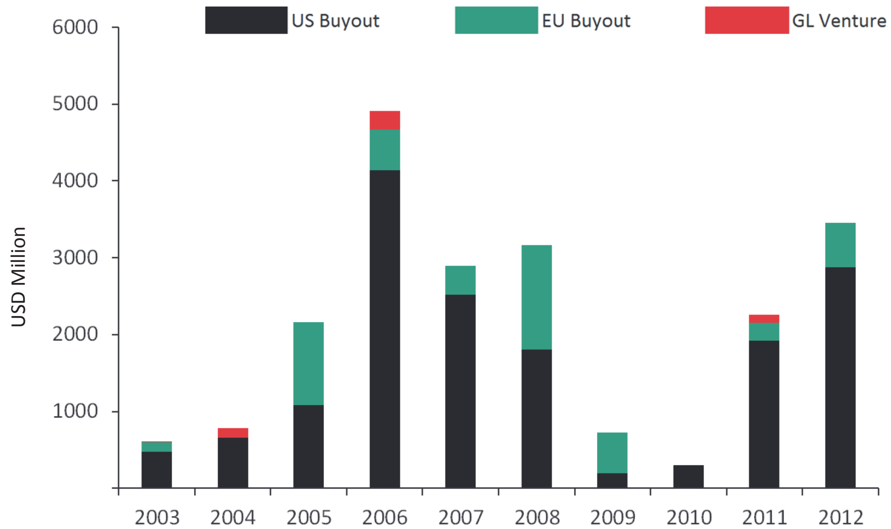

Figure 2: Commitments of Portfolio 1 by vintage year and strategy

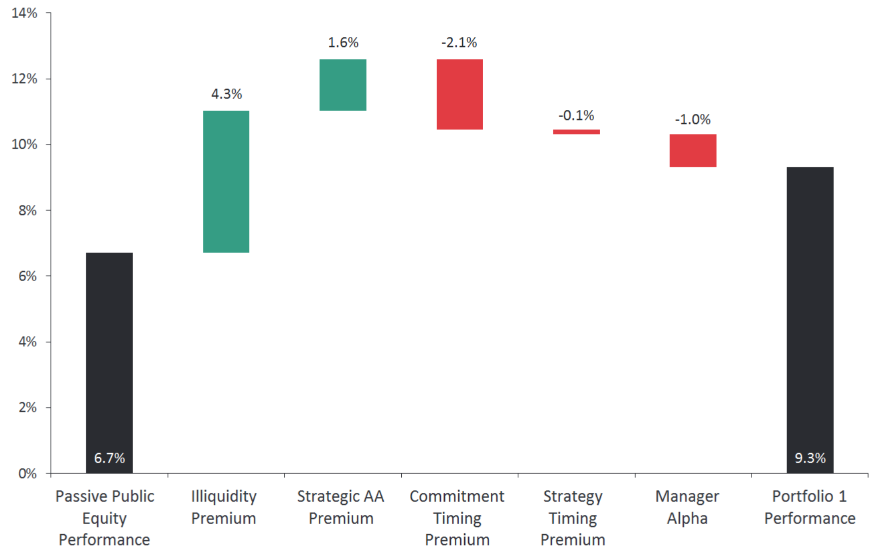

Figure 3: Performance attribution of Portfolio 1

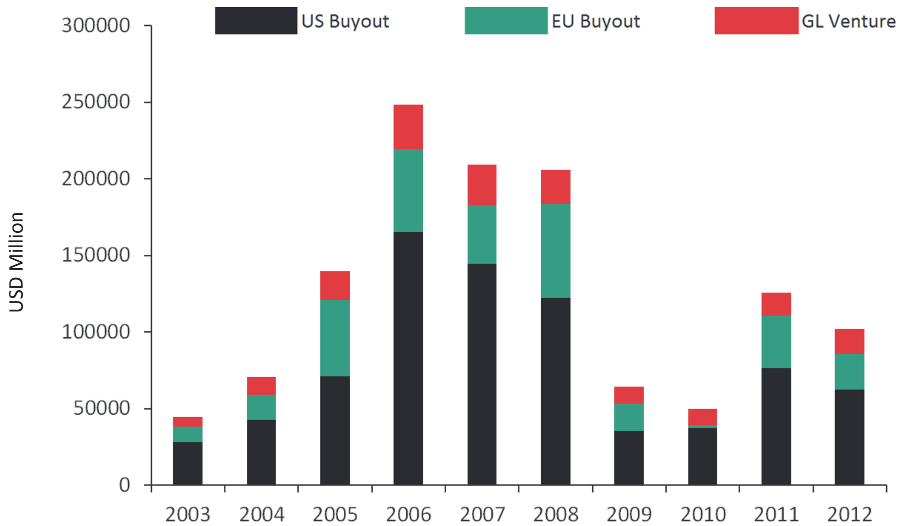

Figure 4: Market capitalization by vintage year and strategy

The pension fund in this case study does not provide a publicly available commitment plan and therefore the following approach is implemented to estimate the strategic commitments; Historical simulations suggest that to smoothly reach and maintain a *constant* target NAV exposure of x (dollars) in the future, annual commitments of approximately x divided by 6.5 are required. However, if the target exposure of x_t at time t is growing at a constant rate g then the required strategic commitment in year t to reach the *growing* target NAV exposure can be approximated by

$$\textit{strategic commitment in year } t = \frac{x_t\,(1+g)^r}{6.5} \tag{1}$$

where r is the number of years it takes for a fund to reach its maximum NAV. Historically, the maximum NAV of a fund is reached after 4.5 years in the median case. Figure 5 shows the annual strategic commitment amounts calculated according to this methodology. The jump in 2007/2008 is due to the pension fund increasing its private equity allocation. The remaining fluctuations are due to total plan assets varying from year to year.

At this stage, the strategic commitment amounts are determined. The breakdown of the strategic commitments into the different strategies (i.e. sector and geographic) needs to be established as well. This strategy breakdown of the strategic asset allocation will be called *strategic strategy allocation*. The pension fund increased the private equity allocation in 2008, suggesting that the periods before and after 2008 should be treated separately. For the periods 2003-2007 and 2008-2012, the strategic strategy allocation is defined as the average of actual allocation to each strategy over each of the two time periods. For instance, the USD 11.4bn commitments during 2003-2007 are made up of commitments of USD 8.9bn to US buyout, USD 2.1bn to EU buyout and USD 0.4bn to venture capital. Therefore, the strategic strategy allocation for these three strategies are 78%, 19% and 3% respectively for the 2003-2007 period. For the 2008-2012 period we apply the same methodology, but disregard the single venture capital commitment in 2011. The pension fund had made statements that it would not invest into venture capital any longer and hence this single commitment is part of the tactical and not the strategic asset allocation.

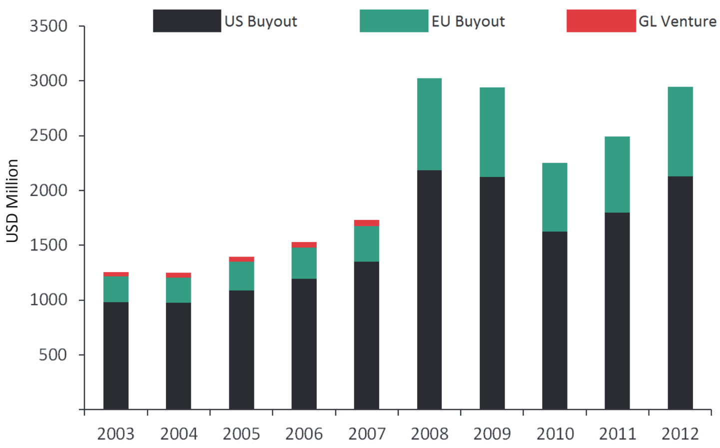

Figure 5: Strategic asset allocation of Portfolio 1

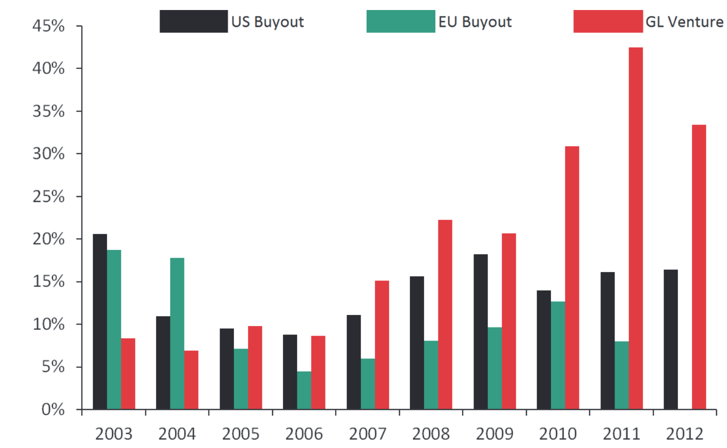

Figure 6: Market IRRs

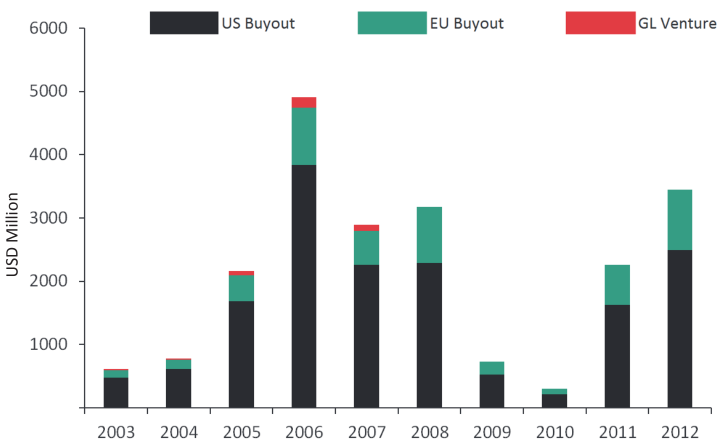

Figure 7: Actual commitment volumes but strategy allocation from SAA of Portfolio 1

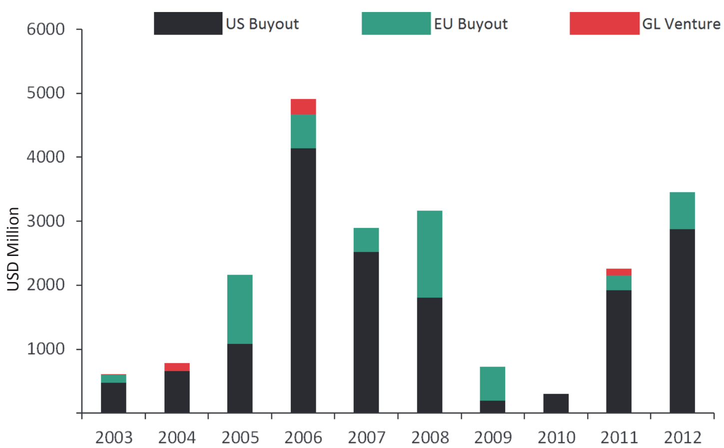

Figure 8: Actual allocation in terms of commitments and strategy allocation of Portfolio 1

The fact that the Strategic Asset Allocation Premium is positive for Portfolio 1 becomes evident when comparing the market commitment volumes in Figure 4 with the market performance depicted in Figure 6. The market capitalization is largest when the market IRRs are lowest (i.e. 2005-2007). On the other hand the strategic asset allocation of Portfolio 1 prescribes relatively lower commitment amounts to the underperforming vintages 2005-2007 which contributes to the positive Strategic Asset Allocation Premium. In addition, in nine out of ten years US buyout outperforms EU buyout; coupled with Portfolio 1's strategic overweight of US buyout compared to EU buyout, this leads to a positive Strategic Asset Allocation Premium. Only in 2004 did EU buyout outperform US buyout.

The Commitment Timing Premium

The Commitment Timing Premium of the Portfolio 1 is -2.1%. As previously discussed, this premium measures the tactical decisions to deviate from commitments specified by the strategic asset allocation. Figure 7 depicts the actual (tactical) commitment amounts. The pattern of tactical commitments resembles the market capitalization from Figure 4. The tactical commitments are large during 2005-2008. During that time fund raising was very strong. It is likely that various managers appealing to the investor were in the market at that time and the investor did not want to miss them. In hindsight, too much capital was chasing deals and the hit caused by global financial crisis leads to weak performance of those vintage years. Investing into the private equity market along the allocation from Figure 7 yields a Commitment Timing IRR of 10.5% which is subtracted from the SAA IRR of 12.6% resulting in the -2.1% Commitment Timing Premium.

The Strategy Timing Premium

The Strategy Timing Premium captures tactical deviations from the strategy allocation defined in the SAA. Figure 8 shows Portfolio 1's tactical strategy allocation together with the tactical commitment amounts. This allocation is the same as the actual allocation of Portfolio 1, as previously shown in Figure 2. The tactical decision to make a single venture capital commitment in 2011 is included in Figure 8. Portfolio 1's tactical strategy allocation does not significantly differ from the strategy allocation of the SAA, resulting in a Strategy Timing Premium of only -0.1%. Mathematically, the Strategy Timing Premium is the difference between the Strategy Timing IRR and the Commitment Timing IRR.

The Manager Alpha

The allocation used in deriving Portfolio 1's IRR (9.3%) and the allocation used in calculating the Strategy Timing IRR (10.3%)

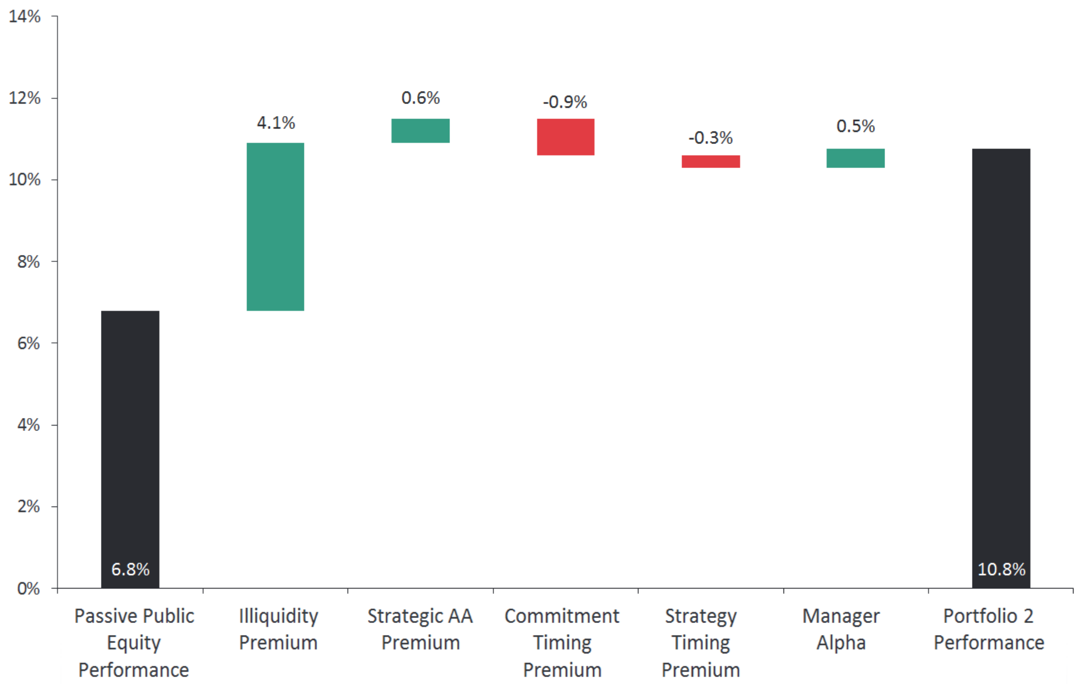

Figure 10: Performance attribution of Portfolio 2

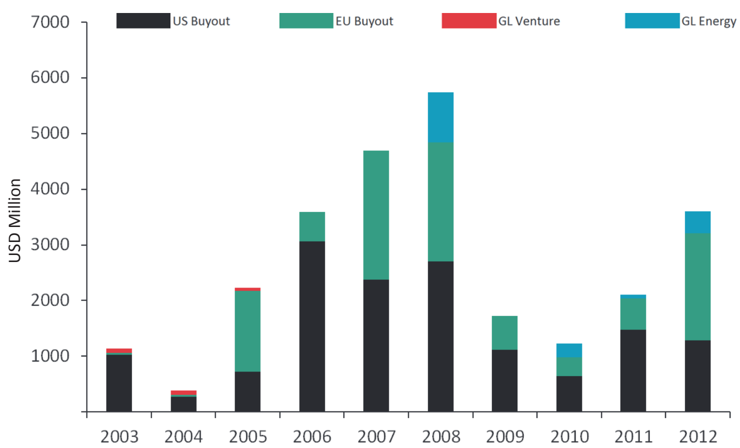

Figure 9: Commitments of Portfolio 2 by vintage year and strategy

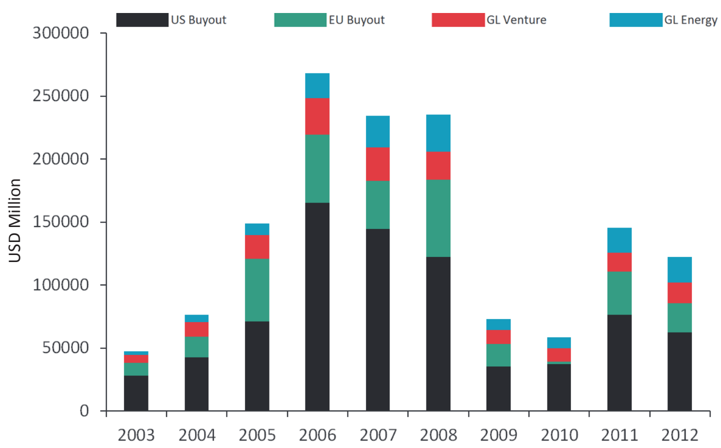

Figure 11: Market capitalization by vintage year and strategy

coincide in terms of timing and strategy; the only difference is that Portfolio 1's IRR is based on the cash flows of the actual funds selected by the portfolio managers and not the private equity market cash flows as used in the Strategy Timing IRR. The portfolio managers decide on the fund selection, but also the commitment amount to each fund and the number of funds being committed to. These decisions are summarized in the Manager Alpha, which turns out to be -1.0% for Portfolio 1. The portfolio managers selected below-market average managers. From a statistical point of view, it is very difficult to generate a positive alpha for portfolios with a large number of funds. More concentrated portfolios have a higher probability of generating a positive alpha, but are also riskier.

Second case study

Figure 9 depicts the commitment volumes by strategy and by vintage year of a second North American pension fund ("Portfolio 2"). Over the 10-year period, Portfolio 2 made commitments of over USD 26bn to 104 private equity funds. The annual commitment volume increased until the maximum of about USD 6bn is reached in 2008. Subsequently, the commitment volume fell below USD 2bn and recovered thereafter. Portfolio 2 only made commitments to venture capital up until 2005 and invested into energy thereafter. The pension fund made its first energy commitment in 2006, but since no cash flow data was available for that fund, the commitment had to be removed from Portfolio 2.

The result of the performance attribution for Portfolio 2 is displayed in Figure 10. Portfolio 2 had an IRR of 10.8% as of December 31, 2014. The Passive Public Equity Performance and the Illiquidity Premium are similar to Portfolio 1 and would be identical if the energy sector was to be excluded from the private equity market. The Strategic Asset Allocation Premium is 0.6%. The Tactical Asset Allocation Premiums decreased the performance by 1.2% while the Manager Alpha contributed 0.5%.

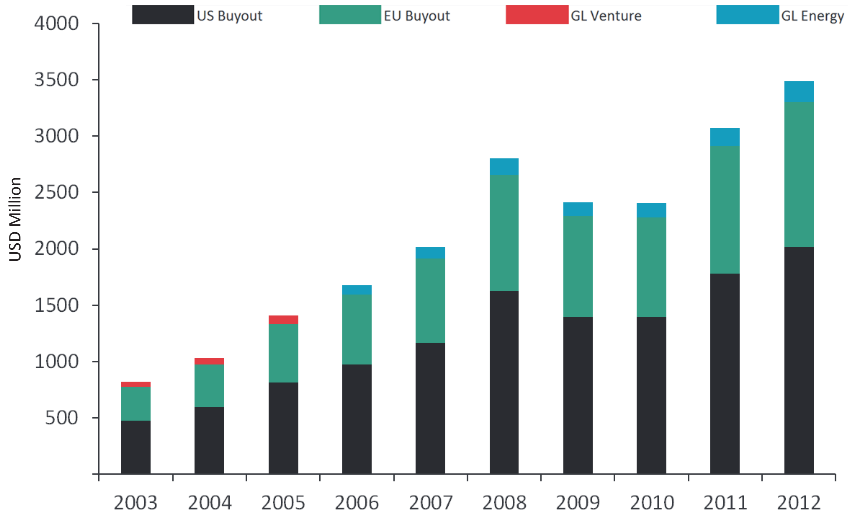

Figure 12: Strategic asset allocation of Portfolio 2

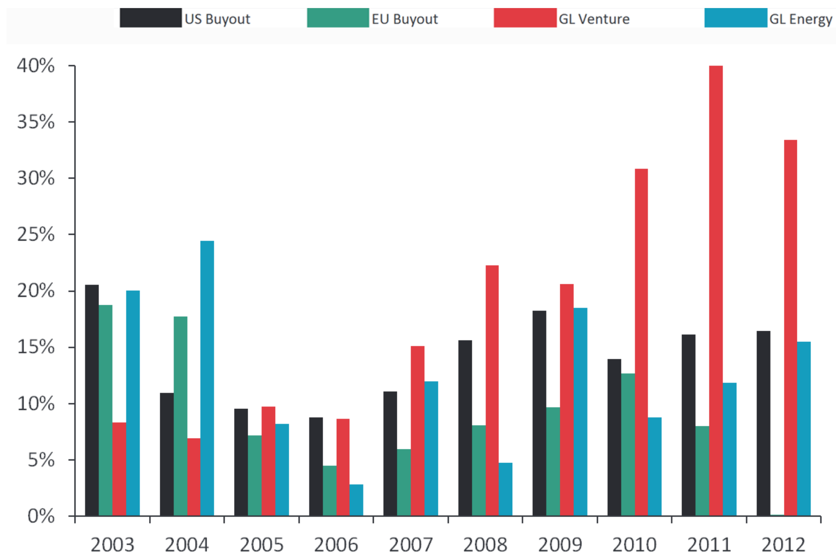

Figure 13: Market IRRs

The Passive Public Equity Performance and the Illiquidity Premium

Besides buyout and venture capital commitments, Portfolio 2 has made several considerable energy commitments. In order to reflect this additional investment choice, the energy sector has been included in the private equity market universe. Figure 11 shows the private market universe used to derive the Passive Public Equity Performance of 6.8% and the Illiquidity Premium of 4.1% in this second case study. The addition of the energy sector to the market universe results in the Passive Public Equity Performance and the Illiquidity Premium of Portfolio 1 and 2 being slightly different.

The Strategic Asset Allocation Premium

The strategic asset allocation depicted in Figure 12 has been determined in the same way as described in the methodology surrounding equation (1) of the first case study. As opposed to the first case study, where the private equity target allocation changed from 2007 to 2008, this pension fund exhibits a constant private equity allocation target over the 10-year horizon. Therefore, the fluctuations of the strategic commitments are solely due to the fluctuations of the total plan assets.

The Strategic Asset Allocation Premium of Portfolio 2 is only 0.6%, which is 1% smaller than for Portfolio 1. A key driver for this reduction is the different strategy allocation of the two portfolios: Portfolio 1 has a larger allocation to EU buyout and a smaller allocation to US buyout in comparison to Portfolio 2. The market performance in Figure 13 shows that EU buyout underperformed US buyout in all but one vintage year. Therefore an increase in the strategic asset allocation to EU buyout will decrease the Strategic Asset Allocation Premium.

The Commitment Timing Premium

The actual commitment amounts, together with the strategy allocation implied by the strategic asset allocation, are shown in Figure 14. Investing in the private equity market according to the allocation from this figure results in a Commitment Timing IRR of 12.6%. Note that the SAA IRR is 11.5% resulting in a Commitment Timing Premium of -0.9% for Portfolio 2. This negative premium can be explained by the considerable

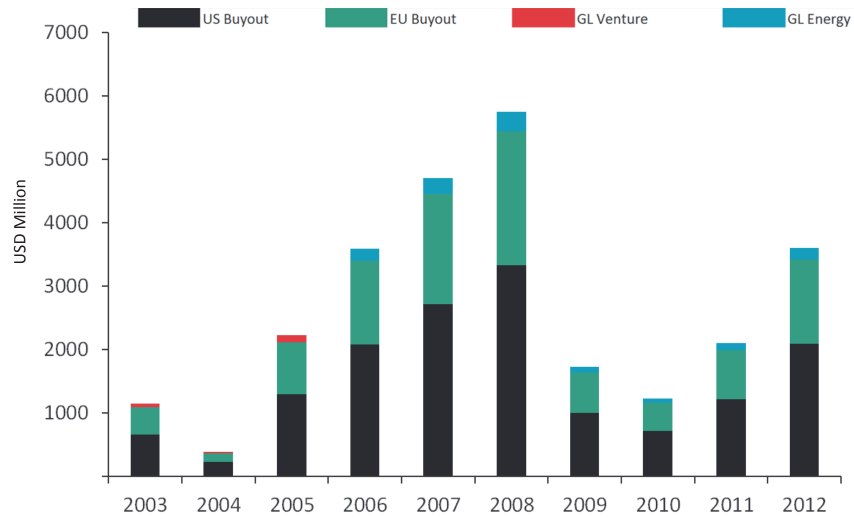

Figure 14: Actual commitment volumes but strategy allocation from SAA of Portfolio 2

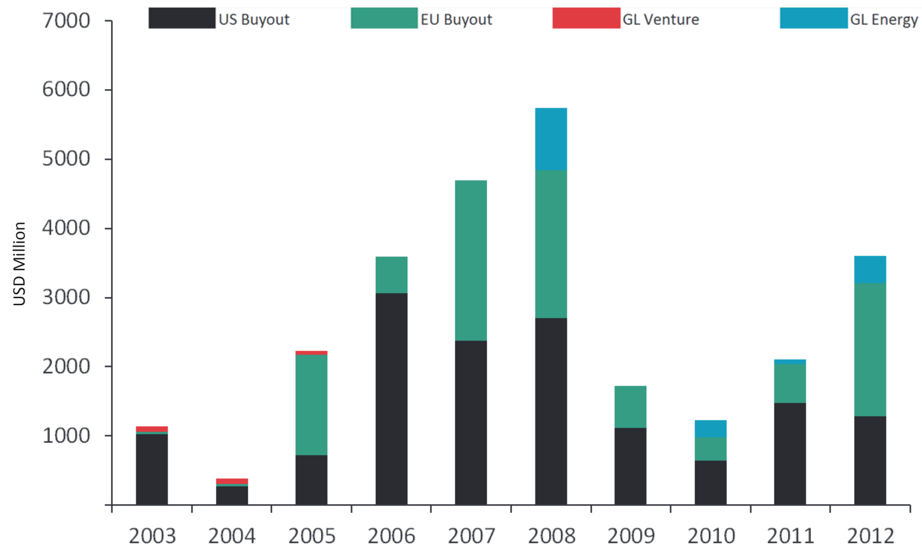

Figure 15: Actual allocation in terms of commitments and strategy allocation of Portfolio 2

commitment amounts in the weaker performing vintage years 2006 and 2007. By contrast, the strategic asset allocation prescribed commitment amounts of less than half of the actual amounts for these two vintage years. The Commitment Timing Premium of Portfolio 1 is -2.2% below Portfolio 2. Investigating the vintage year exposure of each portfolio sheds some light on this difference; the single largest vintage year exposure of Portfolio 1 is 2006, which is also the weakest performing vintage year hampering the Commitment Timing IRR. Even though Portfolio 2 also has a significant exposure to 2006 its largest exposure is to 2008, which in terms of performance shows a considerable recovery compared to 2006.

The Strategy Timing Premium

The actual strategy allocation in Figure 15 and the strategic strategy allocation in Figure 14 are similar and therefore the Strategy Timing Premium is -0.3%. An important factor contributing to this negative premium is the under-allocation (compared to the strategic asset allocation) of EU buyout in vintage year 2004. This is the only vintage year for which EU buyout actually outperformed US buyout and hence an under-allocation of EU buyout in this year was a sub-optimal tactical asset allocation decision. In addition, the significant over-allocation to EU buyout in 2012 decreased the Strategy Timing IRR, since 2012 EU buyout is particularly weak. Another factor contributing to the negative premium is the energy allocation in 2008, which is the weakest vintage year for energy funds. The over-allocation to US buyout in 2006 (in which US buyout performance is almost twice as high as EU buyout performance) is positively contributing to the Strategy Timing Premium.

The Manager Alpha

Investing in the market according to Portfolio 2's actual allocation as shown in Figure 15 leads to an IRR of 10.3%. By allocating capital to superior managers, Portfolio 2 was able to generate a 10.8% IRR leaving a Manager Alpha of 0.5%. In both case studies the Manager Alpha is a relatively small driver of the overall portfolio performance. The portfolio performance is dominated by asset allocation decisions. The importance of asset allocation is already pointed out by Brinson et al (1986)[10] by asserting that more than 90% of the variation in quarterly portfolio returns is explained by the asset allocation.

Conclusion

Achieving a positive Manager Alpha is challenging. Even more so, if an investor is required to deploy several hundred millions of dollars every year. This forces him to build highly diversified portfolios or portfolios focusing primarily on large to mega cap funds. With respect to asset allocation, the two case studies illustrate that staying the course of a predefined strategic asset allocation is a wise decision. In both case studies tactical decisions were market cyclical and diminished value. However, investors of the size considered in the case studies inevitably move with the market to some degree as the market might not offer sufficient investment opportunities at all times. The result is that during recessions when fewer suitable funds are in the market, the deployed capital decreases and during booms the committed capital increases. It is in the hands of the portfolio managers to resist the temptation of over-allocating during bull years and try hard to find suitable investments in a bearish environment.

In the search of market alpha, various large pension funds and insurance companies recently accessed the direct private equity market through active ownership of companies or co-investing along other funds. They hope that these more concentrated portfolios have higher potential to generate outperformance. Tapping the direct market increases the investable universe significantly and might facilitate the deployment of capital during a bearish environment when too few suitable funds are in the market. However, the challenges of direct investing should not be underestimated as the skillset required is clearly different from that of a private equity fund investor.

Endnotes

1. See Global Private Equity & Venture Capital Index and Benchmarking Statistics from Cambridge Associates LLC for instance.

2. Long, Austin, 2008, Performance Attribution in Private Equity, The Journal of Performance Measurement, Fall 2008.

3. The equal weighting is based on capital called, i.e. all cash flows and NAVs of each fund in the portfolio are scaled in such a way that each fund has the same amount of total called capital. Note that whether all funds are scaled to have total called capital of 100 million or 1 million is irrelevant for the IRR, what counts is only that all funds are scaled to the same amount.

4. With the expression "anchored to time zero" it is meant that all cash flows and NAVs of each fund are shifted in time so that the all funds have the first cash flow at the exact same date.

5. Teacher Retirement System of Texas follow this approach, but also La Caisse de Dépôt et Placement du Québec as published on their website in April 2016.

6. The PME+ methodology is an established method to benchmarking private equity against public equity. Essentially the method works as follows: Shares of a public market index are bought whenever a private equity capital called occurs and shares are sold whenever a distribution happens. PME+ scales the cash flows in a way that the index is not being shorted. For more details see Rouvinez, Christophe, 2003, Private Equity Benchmarking with PME+, Venture Capital Journal, August, 34-38.

7. Rouvinez, Christophe, 2003, Private Equity Benchmarking with PME+, Venture Capital Journal, August, 34-38.

Jost, Philippe and Herger, Ivan (2013), Private Equity Asset Allocation: Robust but adaptable.

9. Quarterly private equity cash flows and NAV from the Cambridge Associates LLC as of December 31, 2014. Cambridge Associates LLC obtains data from LPs and from GPs who have raised or are trying to raise capital. Therefore, it might have a bias toward well performing funds. However, given the large coverage of the database, this bias is likely to be relatively low.

10. Gary P. Brinson, L. Randolph Hood, and Gilbert L. Beebower (1986) Determinants of Portfolio Performance, The Financial Analysts Journal.

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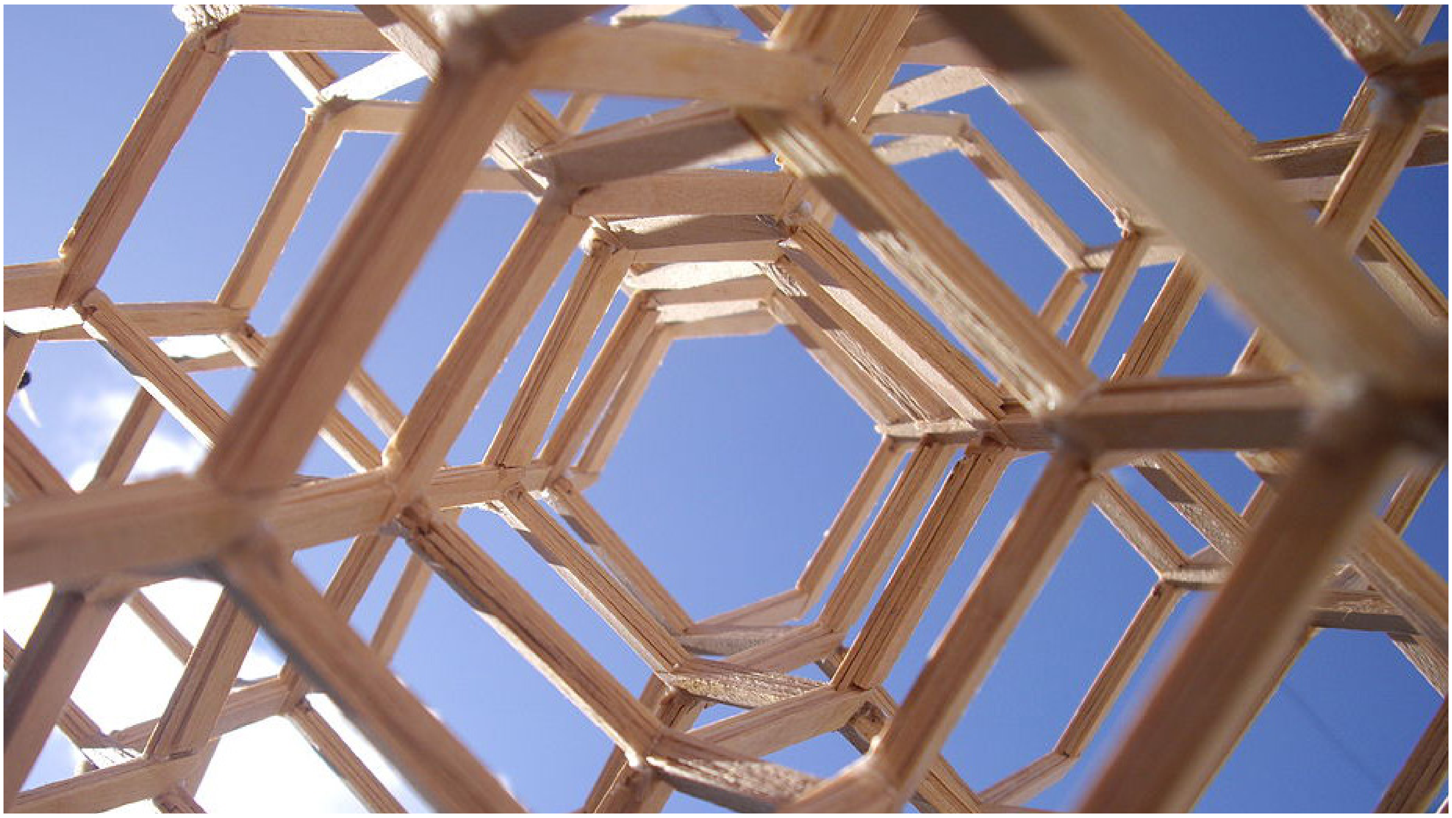

Applying an Enterprise Risk Management (ERM) Framework to Fund Governance*

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Introduction

It is not yet common practice to apply an Enterprise Risk Management (ERM) framework to the governance of investment funds.[1] Upon reflection, however, one realizes that funds are generally structured as corporations, and each fund has shareholders (fund investors), and the mission of each fund is to maximize shareholder values. Even if a fund is of a contractual type, a fund still can be viewed as an enterprise, and also faces similar corporate governance issues. Overlaying fund governance then with ERM processes can be beneficial.

Contrary to what some may assume, risk management is not a means of risk avoidance. Rather it is a means of implementing proper risk taking and, hence, contributing to value creation. ERM's goal is value-creation through enterprise-wide integrated and holistic risk management. Thus, an investment fund can be viewed as an enterprise that creates value through calculated risk taking. In this sense, there is no reason that an ERM framework cannot be suitably applied to fund governance in a way that helps maximize values for fund investors.

Top management of a corporation/ enterprise and its board of directors bear oversight responsibility for ERM processes in their organizations. Similarly, directors of investment funds owe fiduciary duties to investors, and they need to ensure that an integrated risk management process be in place and the process be monitored. In the paragraphs below, this paper discusses how an ERM framework can be applied profitably to the governance of investment funds. The author argues that applying an ERM framework is not only desirable, but also critical in order for a fund director to fulfill his/her responsibilities.

At the same time, applying an ERM framework to fund governance should not create an undue burden on fund directors. Fortunately, fulfilling duties normally expected of fund directors in a conscientious and systematic fashion coincides with satisfying most of the key components of ERM processes. Helping to foster a risk-aware culture among the stakeholders of a fund is arguably the only new ERM oriented task that a fund director needs to perform in addition to fulfilling other commonly expected responsibilities of a director.

What is ERM?

An often cited definition of enterprise risk management (ERM) is given by the Committee of Sponsoring Organizations of the Treadway Commission (COSO):

[ERM] is a process effected by an entity's board of directors, management, and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risk to be within its risk appetite, to provide reasonable assurance regarding the achievement of an entity's objectives.[2]

While this definition presumes that ERM is applied to regular enterprises, most of the expressions are also relevant to investment funds. The only exception might be "strategy setting" mentioned in the second line, as the "corporate strategy" or "objective" of an investment fund is made explicit prior to launch of the fund. Even then, to the degree that a fund's strategic objective can drift or formally change under certain circumstances, the issue of strategy setting may be relevant.

This definition highlights several important points that have relevance in the application of an ERM framework to investment funds.

- The board of directors and management of an investment fund are responsible for "effecting" the fund's ERM process.
- The ERM process needs to identify potential events that may affect the fund.
- The ERM process needs to manage risk within the fund's risk appetite.
- The ERM process helps provide reasonable assurance regarding the achievement of fund objectives.

Absent an effective ERM process, risk management tends to occur at division or business unit levels, each often referred to as a "silo." The problem with the silo approach is that there is no coordination among different silos and there is no way to form an assessment of the total risk which the enterprise faces. This is true, even if diligent risk management is implemented in each silo. Another key expression in the COSO definition of ERM is "across the enterprise." It is not difficult to deduce that without a risk management process which is applied across the enterprise, board members and top management cannot pursue integrated risk management.

It is true that, unlike a business enterprise, an investment fund has typically no, or virtually no, employees or departments that may form silos. However, this does not diminish the importance of the ERM process. Instead of internal silos, a fund has a different set of stakeholders such as an investment advisory firm, a fund administrator, an accounting firm, and investors (sometimes different classes of investors). These stakeholders often have diverging interests as do various silos or business units within an enterprise or corporation.

Fund Directors and ERM

In effecting the enterprise's ERM process, board members and top management must foster risk aware culture throughout the enterprise. Moreover, they are expected to set the tone of risk culture at the enterprise.[3] It is of paramount importance to note that "culture is not merely an intangible concept—its elements can be defined and progress in moving toward a desired culture can be measured."[4] Douglas Brooks cites the following three issues when a strong risk-aware culture is absent:

- Not all relevant risks may be identified and assessed.
- Decision makers may not be aware of some risks as decisions are being made.
- Decisions may be made ignoring certain risks.

Thus, board members, including independent fund directors, must exercise leadership in fostering a risk-aware culture for a fund, as should be done at an enterprise.

Despite sharing common objectives, the roles of the board and senior management are not identical. For instance, unlike senior management, boards "cannot and should not be involved in the actual day-to-day management of risks." Instead, the role of the board is "to ensure that the risk management process designed and implemented by senior executives and risk management professionals employed by the company act in concert with the organization's strategic vision, as articulated by the board and executed by senior management."[5]

The Independent Directors Council and Investment Company Institute jointly published a paper titled *Fund Board Oversight of Risk Management* in 2011. In the paper, the board's fundamental responsibilities are delineated as follows:

- Director's responsibilities to oversee risk management are derived from their general fiduciary duties of care and loyalty and are part of their overall responsibility to oversee the management and operation of the fund.[6]
- A fund's board is not responsible for overseeing the management of the [investment] adviser's risks or those of its parent or affiliates. …Nevertheless, the fund board's focus on the fund's risks will necessarily entail an understanding of the adviser's risk that may impact the fund as well as the associated risk management process.[7]
- A board does not manage [a] fund's investments or its business operations, nor does it manage the risks associated with these activities.[8]

Similarly, the Cayman Islands Monetary Authority (CIMA) issued a *Statement of Guidance for Regulated Mutual Funds — Corporate Governance*, in December 2013. The guidance lists the key responsibilities of the governing body of a fund, along with those of operators (fund directors). Among other duties, the guidance describes the risk management oversight role of the directors in Paragraph 9.9 as follows:

The Operator should ensure it provides suitable oversight of risk management of the Regulated Mutual Fund, ensuring the Regulated Mutual Fund's risks are always appropriately managed and mitigated, with material risks being discussed at the Governing Body meeting and the Governing Body taking appropriate action where necessary.[9]

Thus, for funds domiciled in the Cayman Islands, operators (fund directors) are mandated to oversee the risk management of the fund they serve; in this case it is equivalent to serving as a board member of an enterprise and facilitating its ERM process, including overseeing a more narrowly defined "risk management process."

The board of a corporate entity faces an array of strategic issues such as defining corporate missions, setting strategic objectives and responding to changing competitive landscapes. The board also oversees the operational aspects of its entity. While ERM is usually not directly involved in the strategic aspects of an entity,[10] it plays a key role in helping the board to meet the objectives of an entity.

By contrast, in the case of an investment fund, strategic decisions such as mergers and acquisitions usually are not the purview of the fund board. Nevertheless, as is the case for a corporate entity, the responsibility of overseeing operational aspects of the fund lies on the shoulders of the fund board and its directors. As ERM addresses and integrates all the key aspects of fund operations, it is clear that applying an ERM framework is a *necessary* condition for fund directors to fulfill their responsibilities. Once this is understood, the logical question becomes whether applying an ERM framework then constitutes a *sufficient* condition for a fund's directors to meet their responsibilities. The aforementioned *Statement of Guidance for Regulated Mutual Funds* by CIMA has 9 sections and only in the last and very brief section does the guidance address risk management. Other sections deal with responsibilities of directors including: Oversight Function, Conflicts of Interest, Governing Body Meetings, Operational Duties, Documentation, and Relations with the Authority. On the surface, it may appear that risk management constitutes a small part of director responsibilities. However, as will be discussed later, an ERM framework does address all of these responsibilities. Indeed, applying an ERM framework and diligently implementing the framework covers all of the fundamental responsibilities that are expected of fund directors by CIMA.

Key Risks of Investment Funds

Investment advisers are in the business of taking and managing investment risks. Therefore, it should come as no surprise that an investment fund faces an array of investment related risks. Addressing these risks constitutes the core competency of investment advisers, and fund directors need to abstain from "managing" these risks. However, there clearly exist other types of important risks that the directors ought to monitor and help mitigate, if appropriate. In the paragraphs below, market risk (investment risk), operational risk, liquidity risk, counter-party risk, and cyber-security risk will be discussed *from the perspective of fund directors.* Please note that these paragraphs are not a general description of each type of risk.

Market Risk (Investment Risk)

Unlike other types of enterprises, the role of investment funds is to take proper market risk[11] or more generally speaking, investment risk, so that risk exposure will translate into investment returns. For this reason, it is nonsensical to try to eliminate or mitigate market risk; when no market risk is taken, there will be no investment returns.

With respect to market risk, "[the] board should be especially sensitive to so-called 'red-flags,' or violations of existing risk limits established by the risk management team."[12] These days, most funds make use of risk management software. This type of software typically calculates value-at-risk (VaR) and/or other risk parameters on a daily basis. When a pre-determined risk limit threshold is violated, a red-flag is raised. It is the responsibility of the management team to take remedial action or, at minimum, take note of red-flag exceptions, and report the exceptions to the board.

Statistically speaking, exceptions are designed to occur with a certain probability. One may be inclined to believe that the fewer the exceptions the better. However, the reality is not that straightforward: if no exception is reported, it may be because the risk limits are set too high, rendering the risk monitoring process useless. On the other hand, if exceptions occur too frequently, it can be either because the fund's investment management team continues to take undue bets, or because the risk limits are set too stringently.

How the management team of investment advisers handles these exceptions is a good indicator of their depth of knowledge, skills in risk management, and the level of their risk appetite. Thus, monitoring and discussing exceptions provides fund directors with (1) valuable opportunities to gauge the level of commitment of the team to risk management, as well as, (2) insight into the firm's risk management culture.

This does not mean that focusing on the exceptions is sufficient for fund directors. Needless to say, a variety of risks related to markets, as well as how the investment manager reacts to these risks, need to be monitored, and potential and actual deficiencies addressed. Moreover, there may exist "unknown risks" at the time of fund inception, and exceptions reports, by nature, cannot handle previously unknown risks. Similarly, it is often the case that an investment portfolio has exposure to risk factors that its portfolio manager does not intend to take. Market risk of this type often causes significant drawdowns as the portfolio manager may be utterly unprepared for the adverse impacts of such factors.

Operational Risk

The failures of hedge funds are often attributed to operational risk rather than market risk. This has been the case since before, as well as during and after, the global financial crisis of the last decade. For instance, in 2003 CAPCO, a financial service consultancy, reported "50 per cent of hedge funds fail[ed] due to operational risk alone rather than bad investment decisions."[13] Moreover, "85% of these failures were due to: (1) misrepresentation (reports and valuations with false or misleading information); (2) misappropriation of funds (fraud); and unauthorized trading."[14]

Another study conducted by Castle Hall Alternatives indicates that up to the middle of 2009, "the total financial impact of hedge fund operational failure was estimated to be $80 billion."[15] The study also indicates "the most common causes of operational failure are theft and misappropriation, followed by [non-] existence of assets (the manager claimed to own fake securities or operated a Ponzi scheme where reported assets did not exist)."[16]

It is interesting that among different hedge fund strategies, long/short equity and managed futures were found to be more vulnerable to operational failures. This finding seems to be counterintuitive, as "these funds trade only exchange traded instruments, typically with little pricing risk and straightforward custody and brokerage relationships."[17] The study points out two potential reasons for this result: (1) "cooking the books is easier when dealing with more straightforward strategies which do not involve complex securities, high volumes of trades and multiple brokers and counterparties;" and (2) "a long/short equity manager or CTA can plausibly operate with a much smaller team than a more complex hedge fund. In general, the smaller the number of people involved, the easier it is to conduct a fraud."[18]

In March 2016, Skybridge Capital compared four studies of business and operational hedge fund failures. The studies by CAPCO and Castle Hall Alternatives were included in the four studies. Skybridge defines "operational risk" to be "the risk of loss stemming from issues related to middle and back office functions,"[19] and "these issues range from the misevaluation of a fund's investment portfolio; poor controls on the movement of cash; sloppy trade processing; or even the loss of trading capabilities from a power outage."[20]

In addition, Skybridge Capital defines "business risk" as "the possibility of loss stemming from issues related to the hedge fund management firm that are not directly associated with market movements."[21] The company claims that one can mitigate these operational risks by conducting thorough due diligence on the operational process of the fund, as well as the third parties involved. Importantly, Skybridge Capital also notes the benefits of having independent directors on the fund's board.

While the above examples have focused on the more notable failures of hedge funds, it is clear that operational risk extends to any fund. Other types of funds such as private equity funds and real estate funds are not without operational risk. As a matter of fact, to the extent that these funds typically require longer time frames to harvest risk premia from investments, the importance of operational risk cannot be over-emphasized.

Liquidity Risk

For an investment fund, two types of liquidity are relevant: market liquidity and funding liquidity. In the midst of the last global financial crisis, Lasse Pedersen gave a talk at the International Monetary Fund and the Federal Reserve Board, and defined each liquidity in simple terms: market liquidity risk is "the risk that the market liquidity worsens when you need to trade [and] funding liquidity risk is the risk that a trader cannot fund his position and is forced to unwind."[22]

An extreme form of market liquidity risk occurred around the time of Pedersen's talk in 2008, and dealers in some markets such as asset-backed securities and convertible bonds shut down and there were no bids for these securities. In addition, an extreme form of funding liquidity risk was observed "since banks [were] short on capital …and need[ed] to scale back their trading that require[d] capital."[23] Importantly, the two types of liquidity can "reinforce each other in liquidity spirals where poor funding leads to less trading," which "reduces market trading," thereby "increasing margins and tightening risk management," and "further worsening funding." Moreover, the crisis in certain asset classes spread to other asset classes and other markets globally.[24]

Liquidity risk affects fund investors in a number of ways. To provide several obvious examples: first, the performance of a fund is severely and adversely affected as security prices tend to fall sharply when liquidity dries up. This cost of illiquidity can be extremely significant and needs to be measured properly *ex ante*.[25] Second, gates may be imposed, and investors may not be able to withdraw the full amount normally allowed during a redemption period. Third, the policy of side-pockets may be instituted and illiquid assets may be separated from liquid assets. Unless investors remain in the fund, the investors cannot benefit from the sale of side-pocketed assets.

While a greater number of investors face liquidity risk under market stresses, it is possible for investors of a given fund to run into such risk due to solely idiosyncratic causes. For instance, the outright fraud or operational issues discussed previously can trigger a liquidity crisis for a fund. While fund directors cannot prevent market crises from affecting the performance of funds they oversee, imposing redemption restrictions such as gates or side-pockets on investors is a purview of fund directors. When decisions of these types are considered, a conflict of interest between an investment adviser and investors may become acute, and a fund director who is a member of the investment adviser may face conflicting objectives. With the goal of maximizing the value of the fund in the long run, "independent" fund directors should exercise their best judgement in a way consistent with the fund's ERM framework.

Counter-party Risk

Until the global financial crisis of the last decade, investment funds such as hedge funds were not particularly concerned about the counter-party risk of its service providers. Failures of large financial service organizations, such as Lehman Brothers and Bear Sterns, changed this picture completely. Prior to the crisis, investment advisory firms were content with relying on a single prime broker clearing and safe-keeping securities and cash. Nowadays, investment advisory firms seek to diversify counter-party risk by multiple means, including appointment of an additional prime broker and/or a separate custodian.

Spectacular failures of financial services organizations are not necessarily caused by a world-wide systemic event. A few years before the global financial crisis, Refco, a large commodities and futures brokerage firm, filed for bankruptcy two months after the firm went public. This failure was largely due to an accounting manipulation that hid their mounting debts[26] while some client assets were put into an unregulated entity and comingled with the firm's assets.[27] Another noteworthy bankruptcy of a financial services organization that involved comingling of assets occurred in 2007. Sentinel Management Group fraudulently "transferred at least $460 million of its client assets to its proprietary house account. …[Sentinel] also used "securities from client accounts as collateral to obtain a $321 million line of credit as well as additional leverage financing."[28] Thus, it is critical to go beyond ascertaining and monitoring the credit worthiness of one's counter-party and to examine how securely client assets are segregated from other assets.

Counter-party risk also occurs when a fund has exposure to derivative instruments such as swaps. This type of risk materializes when one of the parties in the derivative contract defaults. Many types of instruments such as interest rate derivatives, foreign exchange derivatives, and credit derivatives are exposed to counter-party risk. Derivatives are a double-edged sword. Judicious use of derivatives can be an effective means of risk management, but its misuse can lead to significant and, at times, insurmountable losses to a fund.

Fund directors are in a position to closely monitor a fund's exposure to counter-party risk. Just as with market risk, while it is not their responsibility to "manage" this type of risk, overseeing and monitoring how investment advisory firms handle this risk contributes to the goal of value-maximization for investors.

Cybersecurity Risk

According to the Securities and Exchange Commission (SEC), between 2013 and 2014, eighty eight percent (88%) of broker-dealers and seventy four percent (74%) of investment advisory firms experienced cyber attacks. The SEC clearly deems cybersecurity risk as significant and announced in early 2016 that cybersecurity was going to be a priority issue for the year.[29]

In 2015, RT Jones Capital Equities, a St. Louis-based investment advisory firm, was censured for its failure "to establish the required cybersecurity policies and procedures in advance of a breach that compromised the personally identifiable information (PII) of approximately 100,000 individuals, including thousands of the firm's clients."[30] According to the SEC,

The firm failed entirely to adopt written policies and procedures reasonably designed to safeguard customer information. For example, [the firm] failed to conduct periodic risk assessments, implement a firewall, encrypt PII stored on its server, or maintain a response plan for cybersecurity incidents.[31]

This case was significant in light of the fact that the firm received no indication from its clients that they suffered financial harm. Investment advisory firms are at minimum deemed to be responsible for the "defensive activities" listed in the above paragraph.

Unfortunately for investment advisers, the SEC has become more aggressive in requiring adaption of cybersecurity policies and procedures. For instance, in June 2016, Morgan Stanley was fined $1,000,000 for violating Rule 30(a) of Regulation S-P, known as the "Safeguards Rule."[32] Specifically, the company's "policies and procedures were not reasonable for two internal web applications or 'portals' [which] allowed its employees to access customers' confidential account information."[33] An employee downloaded customer information on his server, and the server was later hacked.

In light of the fact that cybersecurity risk is growing in its frequency and magnitude, the process of fund governance and an ERM framework should include steps and procedures intended to minimize such risk as one of their primary goals.[34] It is worth remembering that a mere occurrence of a cybersecurity breach, even if no actual damage is sustained, can make investors withdraw assets from a fund, as they become wary of an investment advisor's lack of preparedness for cyber attacks. Furthermore, cyber attacks can be aimed at any point in the chain of relationships surrounding a fund's operation, such as a fund's law firm or its accounting firm. A fund's cybersecurity policies and procedures should include monitoring of its third parties' preparedness

An ERM Framework as Applied to Fund Governance.

An investment fund generates returns by having exposure to investment risks. This means that investment advisers are in the business of harvesting risk premia by managing investment risks. Successful risk exposure is expected to result in positive changes in the net asset value (NAV) of a fund. A unique aspect of ERM as applied to investment funds is that the most important objective of the funds and the primary goal of the ERM process converge into one: maximization of fund value given the fund's investment objective and risk appetite.[35] Thus, proper implementation of ERM becomes *sine qua non* of successful fund management and governance.

Viewed differently, value maximization is the common thread that ties the top management of investment advisers and fund directors together in pursuing the shareholder (fund investor) objective. In this sense, there should be no resistance in implementing fund ERM. While conflicts of interest at times may occur among different groups of stakeholders, an ERM framework should provide an important guiding principle.

According to John Shortreed, a successful ERM framework should have the following components:

- Mandate and commitment to the ERM framework
- Risk management policy
- Integration of ERM in the organization
- Risk Management Process (RMP)
- Communications and Reporting
- Accountability
- Monitoring, review, and continuous improvement.[36]

Most of these components are self-explanatory, but others may require some elaboration. The first component "mandate and commitment to the ERM framework" requires agreement in principle to proceed with ERM. The related tasks are: gap analysis, context for framework,[37] design of framework and implementation of plan. The second component is risk management policy. Here one should clearly delineate "policies for the ERM framework, its process and procedure," as well as, "policies for risk management decisions such as risk appetite, risk criteria and internal risk reporting. The fourth component, Risk Management Process (RMP) is considered to be the core component of ERM, and consists of: context[38]; risk assessment (identification, analyses, and evaluation); risk treatment[39]; monitoring, review, and actions; and communications and consultation.[40]

Exhibit 1 combines (1) a list of duties that a regulator such as CIMA expects a fund director to perform, and (2) the components of an ERM framework described above. Director duties are indicated in the left column inside the circle. The ERM components that correspond to each of the director duties are listed on the right column inside the circle. Other components, in addition to the "risk aware culture" which was discussed earlier in this paper, are indicated within the outer band of the circle.

First, the *mandate and commitment to the ERM framework* becomes a precondition to successfully perform the "oversight" duty of a fund director. CIMA expects a fund director to satisfy him/herself that "the Regulated Mutual Fund is conducting its affairs in accordance with all applicable laws, regulations, rules, statement of principles, statements of guidance and anti-money laundering, …"[41]

Second, the "risk management" duty is expanded into *risk management policy* and *risk management process (RMP)* in the ERM framework. As descried earlier, each of risk management policy and RMP has distinct elements. However, these can be viewed as one seamless process for practical purposes.

Third, "operational duties" constitute the central part of CIMA's guidance, and cover the various aspects of a fund director's (operator's) duties.[42] Thus, from the perspective of CIMA, the accountability rests with the fund director. The fund director in turn holds service providers to the fund accountable for their duties.

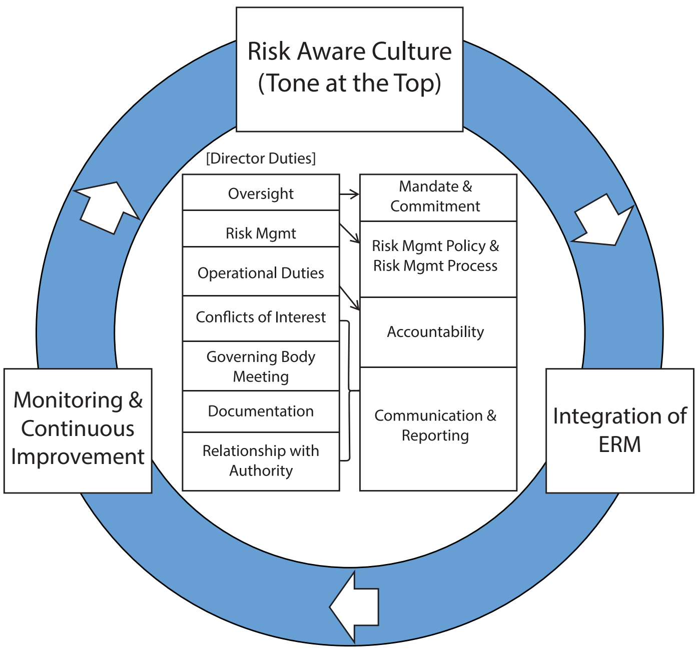

Exhibit 1: Director Duties and ERM Process

Fourth, CIMA requires that "conflicts of interest" be identified, disclosed, monitored, and managed.[43] While it refers to "managing all its conflicts of interest," eliminating the conflicts of interest is not expected. Rather its central focus lies in proper disclosure, and in the ERM framework it is a part of the communication and reporting process. Similarly, the rest of director duties, i.e., "governing body meeting," "documentation," and "relationship with authority" can be successfully fulfilled as a part of the communication and reporting process of ERM.

Fifth, the components that jointly comprise the outer band of the circle in Exhibit 1, are also a part of the ERM processes. Among these, a *risk-aware culture* is developed by fund directors setting the tone at the top. The well-known failures of the hedge funds described earlier clearly lacked, among other control issues, the appropriate tone at the top.

Last, another component, *integration of ERM*, by definition, is accomplished when one judiciously and systematically integrates the principle of ERM into fund governance. Moreover, it is no surprise that fund directors need to *continue monitoring and reviewing for continuous improvement*. In this manner these components noted in Figure 1's outer circle complete the application of an ERM framework to fund governance.

Thus, using the example of duties expected of a fund director by CIMA, Exhibit 1 has illustrated that these duties can be successfully performed by applying the ERM framework to fund governance. In other words, systematically implementing the ERM framework will create the necessary and sufficient conditions to fulfill these duties.

Conclusion

When applied to fund governance, it is clear that an Enterprise Risk Management process becomes more effective when several conditions are met. First, the fund's board must make its commitment to ERM known to the fund's investment adviser and relevant third party organizations such as a fund administrator. To the degree that the fund needs to have a solid risk management procedure in place, irrespective of its adaptation of ERM, this should not be a difficult commitment. Through the ERM process, the fund's board and top management of the investment adviser can help to develop the risk culture of the fund they serve.

Second, the fund's risk management policy should be articulated in a way consistent with the goal of ERM. Depending on the fund's objective, the fund's risk criteria and risk appetite differ. Appropriate risk parameters such as VaR (Value-at-Risk), position limit, and leverage limit should be documented and the mechanism for conveying and reviewing "red-flag exceptions" should be delineated. Just like the first condition, this should not pose a challenge, as an investment adviser should have a solid risk management policy in place in any case. In some cases, the adviser merely needs to include the board in the chain of communication for critical and potentially critical matters.

Third, each element of the Risk Management Process (RMP) must be followed judiciously. This means that the context is established, risks are assessed (identified, analyzed and evaluated), and risks are treated in accordance with the risk assessment. There should also be a mechanism for direct information transfer in place, between the fund's board and the fund's third party. Direct access to critical information sources such as fund accounting and portfolio risk reports will enable fund directors to monitor the effectiveness of the RMP.

Fourth, in addition to periodic board meetings, fund directors need to maintain open communication with the key personnel of the investment adviser. Mitigation of non-priced and unrewarded risk, e.g., operational risk and cybersecurity risk, is most effective when the risk is detected prior to its materialization. In addition, when an extreme market event occurs, it may become necessary to discuss imposition of redemption restrictions with the investment adviser. The importance of fund directors lies in their protecting the interests of investors in a way consistent with the goal of the ERM process for the fund.

In conclusion, assuming that the above conditions are met, applying and implementing an ERM framework will go demonstrably beyond the fundamental responsibilities of a fund director, such as those required by CIMA. Doing so will also contribute to maximizing shareholder value, in other words, maximizing the fund's net asset value in line with the fund's risk appetite. An ERM framework provides guiding principles so that a fund director can perform his/her duties in a systematic and conscientious fashion. A fund's directors are responsible for setting the tone for risk-aware culture for the fund, and while the ultimate beneficiaries of an ERM framework are investors, the service providers including a fund's investment advisory firm also gain from mitigation of unrewarded risks.

Endnotes

**The author would like to thank David M. Modest and Andrew B. Wesiman for their valuable comments.*

1. Interestingly, Norm Champ, Deputy Director, Office of Compliance Inspections and Examinations at U.S. Securities and Exchange Commissions in his speech in 2012 indicated that the advisers of hedge funds should ask themselves if "senior managers [are] effectively exercise[ing] oversight of enterprise risk management." Speech by SEC Staff: What SEC Registration Means for Hedge Fund Advisers, https://www.sec.gov/News/Speech/Detail/Speech/1365171490432.

2. This definition is cited a number of times by different authors. See, for instance, Branson (2010), p.56.

3. Branson (2010), p. 51.

4. Brooks (2010), p. 87.

5. Branson (2010), p. 52.

6. Independent Directors Council and Investment Company Institute (2011), p. 9.

7. Op. cit.

8. Independent Directors Council and Investment Company Institute (2011), p. 10

9. Cayman Islands Monetary Authority (2013), p.8.

10. However, ERM can provide valuable inputs into the strategy formulation.

11. In risk management terminology, "market risk" generally refers to risk related to exposure to financial securities and derivative instruments. By contrast, in modern finance literature, "market risk" refers to systematic or non-diversifiable risk. In this paper, "market risk" is considered to be the equivalent of "investment risk."

12. Branson, p. 53,

13. CAPCO (March 10, 2003). This press release caused controversy in the hedge fund industry, but some claim that their categorization of operational risk was inaccurate and the case for the operational risk was overstated.

14. Other causes of operational risk citied by CAPCP were staff processing error, technology failure, and poor data. Op.cit.

15. Castle Hall Alternatives (2009), p. 5.

16. Op. cit.

17. Op. cit.

18. Castle Hall Alternatives (2009), p. 9.

19. Skybridge Capital (March 2016), p.1.

20. Op. cit.

21. Op. cit.

22. See Pedersen (November 15, 2008).

23. Op. cit.

24. Op. cit.

25. A recent article by Lindsey and Weisman (2016) proposes the use of a barrier option-pricing methodology to measure the true cost of illiquidity.

26. See, for instance, Washington Post (October 15, 2005).

27. This is sometimes referred as "custody risk."

28. United States Securities and Exchange Commission v. Sentinel Management Group, August 27, 2007.

29. Financial Times (January 23, 2016).

30. US Securities and Exchange Commission (September 22, 2015).

31. Op. cit. SEC also noted the following:

- R.T. Jones stored sensitive PII of clients and others on its third party-hosted web server from September 2009 to July 2013.
- The firm's web server was attacked in July 2013 by an unknown hacker who gained access and copy rights to the data on the server, rendering the PII of more than 100,000 individuals, including thousands of R.T. Jones's clients, vulnerable to theft.
- After R.T. Jones discovered the breach, the firm promptly retained more than one cybersecurity consulting firm to confirm the attack, which was traced to China, and determine the scope.
- Shortly after the incident, R.T. Jones provided notice of the breach to every individual whose PII may have been compromised and offered free identity theft monitoring through a third-party provider.
- To date, the firm has not received any indications of a client suffering financial harm as a result of the cyber attack.

32. ThinkAdvisor (June 8, 2016).

33. Op. cit.

34. In designing an ERM framework, metrics such as key risk indicators (KRI) are utilized. It is beyond the scope of this paper to discuss the details of such metrics.

35. In most cases, maximizing fund value means maximizing net asset value given the fund's risk appetite. However, there are some funds, whose objective differs from pursing higher risk-return ratio.

36. Shortreed (2010), p. 101.

37. The external context includes "market conditions, competition, technology trends, legislative requirements,…" etc. The internal context includes "the complexity of organization …, key internal drivers of organization, the objective of organization, stakeholders and their perceptions …" etc. Shortreed (2010), p. 112.

38. “The context looks at the law, market, economy, culture, regulations, natural environment, stakeholders' needs, issues, and concerns.” Shortreed (2010), p. 105.

39. “Risk treatment includes the identification of a control option and implementation of the selected control. Shortreed (2010), p.109.

40. Shortreed (2010), p. 101.

41. CIMA, p. 2.

42. To illustrate, the Paragraph 6.7 of the CIMA guidance (page 5) indicates that “the Operator is responsible for:

6.7.1 Ensuring or receiving confirmation that the constitutional and offering documents of the Regulated Mutual Fund comply with Cayman Islands law, and for licensed funds, the Rule on Contents of Offering Documents.

6.7.2 Ensuring the investment strategy and conflicts of interests policy of the Regulated Mutual Fund are clearly described in the offering documents; and

6.7.3 Ensuring that the offering documents describe the equity interest in all material respects and contains such other information as is necessary to enable a prospective investor to make an informed decision as to whether or not to subscribe for or purchase the equity interest.

43. CIMA, p.3.

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Including Investment Process Technologies within Operational Due Diligence

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Rayne Gaisford
Olive Street Advisors

The Chartered Alternative Investment Analyst (CAIA) curriculum outlines operational due diligence steps that allocators should take to ensure that equity asset managers in whom they invest have the necessary processes and infrastructure in place to run their funds appropriately and effectively. Although not specified by CAIA, critical technology infrastructure has traditionally included (1) an accounting system, (2) an order management or trading platform, and ideally (3) a data warehouse. (The latter can maintain a comprehensive database of a firm's past and present securities, trades, prices, values, exposures and research for portfolio assets as well as potential trade ideas.) These infrastructure tools represent basic structural requirements for a fund manager to avoid the unrewarded and unintended risks that can result from sub-optimal record-keeping and related operational oversights or errors.

While most fundamental active equity managers have seen moderate enhancements to this key infrastructure, they have not changed the investment process itself meaningfully in decades, beyond leveraging more research sources, primary data sets, and occasional new features and functions in Bloomberg and Microsoft Excel. Portfolio managers and analysts generally (1) establish an addressable research universe or sector, (2) engage in fundamental due diligence, and (3) size positions on a stock-by-stock basis according to expected reward, level of conviction, and/or valuation metrics. They then measure results at a high level via P&L performance that fund administrators and accountants often help compute for them.

In recent years, an increasing number of technology vendors have introduced purpose-built, front-end solutions for portfolio managers to bring more versatile, efficient, precise, and information-rich methodologies to the investment process itself. These systems help provide a scalable framework to filter more precisely an appropriate addressable research universe, engage in intellectually rigorous security selection, establish optimal position sizes in relation to the overall portfolio, and measure risk exposures within that portfolio. These approaches to security selection, portfolio construction, analytics, and risk measurement – and the behaviors tied to them – enable much more data-centric and evidence-based practices, in many cases providing a "quantamental" overlay to a fundamental investing technique. This overlay can create the much sought-after "edge" or marginal information advantage that so many in the investment management business seek.

Importantly, unlike Microsoft Excel, these applications are buttressed by time-series databases coupled with refined informational dashboards, making key outputs measurable – and in turn providing a feedback loop for investment managers to continually refine their process. These tools apply intelligence and evidence-based inputs (i.e., data science) to security selection and portfolio construction – and as such have been shown to be alpha-enhancing relative to approaches that lack their comprehensive ex-ante and ex-post portfolio insights.

Investment allocators should become aware of these process enhancements and determine whether their current and prospective managers are making active use of such decision engines, analytics frameworks, and feedback mechanisms to bring systematic, rules-based logic to all their investment and trading choices.

The appropriate analogues for many of these systems are flight computers or chess programs, which take an enormous number of input variables and calculate as outputs optimal decisions for the user to make. However, these financial technology (or "fin-tech") portfolio management platforms indeed go further, by providing reports and dashboards that enable (and emphasize in some cases) learning from one's mistakes as well as successes. The systems provide investment teams comprehensive data sets geared toward reinforcing what PMs and analysts do well while also suggesting avoidance of what they do poorly.

As asset flows continue to swing towards passive investment vehicles, pressure will mount on active managers to leverage more process-centric methodologies to improve their alpha generation and resulting returns. A few investment savants may still use a "finger-in-the-wind" or back-of-envelope approach, and outperform their peers and/or relevant indices, but such individuals are likely to remain a tiny minority. It is important to recognize that, indeed, no human brain can compute key actionable outputs from thousands of inputs – and fluctuating ones in many cases – to reach an optimal decision. Nor is it common that instinct alone leads to a truly optimal determination.

All this said, a caveat or two are appropriate. No single silver bullet – technology- or data-wise – exists to enhance manager performance in perfect form. Accurate and appropriate fundamental research and due diligence are still required. The platforms we discuss in some cases have a "garbage-in, garbage-out" element to them, for instance, necessitating appropriate price targets or a trading pattern that proves repeatable.

Additionally, the fact that the data sets the systems generate are often substantial implies that someone on a PM's team other than the PM – possibly an outside consultant – may have more time and mental capacity to distill the most actionable information from the large volume of data output available. And of course, the PM will have to apply that actionable information to his or her process in a regular, repeatable, and systematic manner. Not all managers prove behaviorally adept at this. But none of this means that CIOs and PMs should let the "perfect" be the enemy of the "substantially better." These process improvement solutions have, in fact, moved the performance needle for hundreds of firms.

We estimate that between 500 and 600 managers use at least one of the investment process systems outlined. Given a universe of more than 8,000 equity asset managers globally, this implies that only a minority leverages any of these applications currently.

As noted above, the platforms we cover in depth by no means comprise a complete list of fin-tech solutions for the buy side. However, our emphasis here is on the primary front-end, PM-centric tools that directly enable enhancing a fund's investment approach. They are focused and refined technologies targeted at alpha generation, as opposed to (1) the all-encompassing market data platforms provided by the likes of Bloomberg, FactSet, Thomson Financial, and S&P/Capital-IQ (the "Big 4", so to speak), or (2) the infrastructure tools that address accounting/P&L analysis, order management, data warehouse development, and portfolio monitoring.

To be fair, the Big 4 offer some of the investment process functionality described below, but fall short of a comprehensive feature set. For their part, the aforementioned basic infrastructure systems one might regard as necessary "plumbing" to run an equity fund business comprehensively. Examples are: Barra/MSCI for factor risks and analytics, MiK for data warehouse/reporting/portfolio monitoring, EzeCastle or MiK for order management (OMS), and Advent Geneva for accounting. Each is an example of a best-of-breed product for the noted function, but other vendors such as Indus Valley Partners and BlackRock's Aladdin are seeking to develop more all-encompassing solutions that speak to a wider range of infrastructure "check-boxes."

The tools and processes below help enable more process-centric techniques for a manager's fundamental investment program. These approaches complement a comprehensive and repeatable due diligence methodology effectively, and therefore help enhance alpha generation when weaved effectively into a firm's behavior.

Stock Screening

While a fundamental manager may have a deep expertise in understanding the value of a specific company or theme, often the challenge is in finding which subset of companies to investigate more deeply. Screening frameworks comprise the tool to assist. Once managers have identified a tradable universe (i.e., region, sector, market cap, CEO type, etc.) they can further focus their efforts by screening within that universe for ideas with a higher probability of success.

There are tools the "Big 4" data vendors offer that represent an initial layer to this type of screening, but often they lack the ease or dimensions needed to give this process repeatability and scale. This is where platforms like Equity Data Science (EDS) can play an appropriate role, in assuring all historical and projected valuation, fundamental, trading, and other relationships make for the most compelling "outlier" research ideas. EDS's "quantamental" platform has helped its users identify the increasingly rare inefficiencies in the broader universe where, as a starting point, favorable data point to the greatest ROIs on one's research time. Only then can a PM start his due diligence on individual companies/securities most confidently and productively.

The notion is to present instances where there is a statistical alignment of stars, so to speak. This might imply for a particular stock an analyst is evaluating for the long side of the book, for example:

- A low relative valuation (and versus companies with similar financial profiles outside the specific sector in question);
- Improving fundamentals (sales, EPS, ROIC, etc);
- Upside revisions in earnings estimates;
- Margins with upside potential relative to historical levels;
- Declining short interest;
- Low relative crowdedness;
- The beginning of a shift from value holders to growth investors;
- Improving sector fundamentals;
- Positive correlation to a market-based factor that is coming into favor, such as a certain market cap levels or interest rate sensitivity, etc.;
- Sell-side ratings that imply room for numerous upgrades;

EDS can show all of these kinds of measures on one screen, with graphical illustrations and color-coded and Z-score-derived quintiles for appropriate quantifications. In so doing, the platform provides an abundantly clear picture that helps users identify the increasingly rare inefficiencies in the broader universe. This means users can quickly see where as a starting point, favorable data point to the greatest ROIs on one's research time. Only then can an analyst or PM start his or her due diligence on individual companies/securities most confidently and productively.

The EDS platform has been in development since 2013, and currently has multiple customers. Having such a comprehensive, efficient, and versatile screening and portfolio ranking tool brings data science capabilities to fundamental managers, helping them significantly increase productivity and generate alpha. The key is being able to assess and integrate a variety of information quickly in order to make critical investment decisions. Where the system is in use at its current clients, it effectively replaces a dedicated data analyst and rudimentary, non-database-linked screening tools (most often Bloomberg data pumped into Excel).

While all the fundamental and market-centric data that analysts and PMs need exists in a Bloomberg or a FactSet, it is the optimal presentation of this data, coupled with critical calculations (e.g., regression and correlation analysis), that allows for substantial time savings and efficient information digestion on the part of a user. Showing all critical elements and calculations in one dashboard makes EDS a much more elegant approach to leveraging such an overlay. Unlike other fin-tech platforms, EDS has no manual data input requirement and encourages ever-increasing usage, because more time with it equates to limitless comparative, precise, and profound insights into one's portfolio and wider idea universe.

Key attributes and use cases include:

- Offering rapid and complete data perspectives based on both historical and projected data, including predictive, cross-sectional valuation analysis and regressions, ownership and liquidity trends, sensitivity analyses, correlation screens, and key information for event monitoring and preparedness (cross-sectional analysis implies a PM can look at metrics across multiple sectors, comparing a company in one sector to all other companies that share similar valuation and market-based measures regardless of sector).
- Saving substantial analyst time and effort that might otherwise be spent manipulating, regressing, and/or rank-ordering valuation, attribution, correlation, performance and risk metrics in Excel, all to get the same answer a dedicated platform like EDS provides with a single mouse-click or pre-loaded view.
- Ranking a fund's active portfolio by assets demanding the greatest attention or actionability, providing an organized daily workflow whose main purpose is to create immediate responsiveness and thereby maximize alpha generation.
- Determining the most appropriate price targets and projected valuations, so that PMs can increase their conviction using evidence- or historically-based data constructs to pinpoint the most likely future valuation parameters.
- Providing an overall technical and fundamental score that is statistically appropriate and unbiased – for both the entire portfolio or an individual idea – and at a higher level a perspective highlighting whether the exposures the PM has are consistent with the fund's strategy or positioning.
- Measuring potential event risk, by enabling clients to understand quickly and visually the current trend in analyst revisions or surprises, as well as performance going into events such as earnings or analyst days.
- Engaging in correlation analysis, so users can understand factor relationships (such as stock movements vs. interest rates), which can provide both the raw material for idea generation, and a clearer picture of the market environment.

Portfolio Optimization

Once a PM recognizes a new idea as a valuable addition to the portfolio, he or she needs to incorporate it into the context of the larger book. In so doing, there are numerous variables to take into account, such as risk impacts, timing, and concentrations within the portfolio. Perhaps the most consistently underappreciated task is to assess the "value" of each position relative to its peers – that is, the position size decision.

Too few portfolio managers take more than a "finger-in-wind" approach to position sizing, but where the mean industry batting average from security selection resides in the 50% range, it is only overweighting winners, or improvement of slugging percentage, that leads to outperformance.

However, analysts that "grow up" as stock pickers do not readily develop the knowledge for appropriate portfolio construction, and most firms take an overly simplistic approach to position sizing based purely on relative conviction in their funds' assets. An optimal portfolio maximizes returns while minimizing risk, and realizes the efficient frontier from a risk/reward perspective. If a portfolio manager has rank-ordered the book appropriately, he or she will have enhanced alpha generation to the greatest degree possible.

An appropriate rules engine would give a precise rank-order for active and potential assets that maximizes the transfer coefficient between idea quality and position size. Such a platform would optimize portfolio construction by synthesizing expected returns, self-determined portfolio rules, and qualitative asset-specific factors to generate an "optimal position size" for each asset in the book, such that return is maximized and risk is minimized.

The reason to optimize the sizing of positions in a portfolio is to reduce "slippage", or the gap between potential portfolio returns based on expected risk/reward ratios and other key criteria at the portfolio and individual stock level, and the portfolio returns generated from having sub-optimal position sizes that fail to account for the projected varying stock-to-stock opportunities ex-ante. Notably, as security prices fluctuate, so do their expected returns (assuming static price target and probability inputs), and in turn their optimal position sizes. Indeed, as wind direction or speed changes, a flight computer re-calculates the appropriate altitude and direction for an airplane, so that analogy serves well for a rules engine for volatile asset markets.

By making such adjustments, portfolio managers are, in effect, on an ex-ante basis, maximizing their returns and minimizing risk – and doing so using their own assumptions. The key idea is to rank order all sources of alpha in terms of maximizing alpha generation for the overall portfolio – in short, align asset quality (or risk-adjusted upside) with its rank in the roster of assets. Ideally the system would even permit this ranking against a broader idea universe. Alpha Theory is one such platform that more than 70 fundamental-oriented hedge funds and mutual funds with aggregate AUM > $125B use and which has generated statistically significant available performance gain.

These type of systems have found several interesting conclusions from its data studies that analyze the aggregation of its clients' performance records. First, portfolio optimizations have outperformed the HFRI Equity Hedge Index every year since they've started collecting historical data. Of course, it helps that those willing to optimize in a systematic manner also tend to represent fund managers that believe in process and discipline. These firms' process orientation goes hand-in-hand with software that serves as a disciplining mechanism to align best risk/reward ideas with rankings in the portfolio.

Second, they found that price targeting improved forecast accuracy. Some investors chafe at price targets because they smack of "false precision." However, these investors may be missing the point. The key to price targets is not their absolute validity but their explicit nature – which allows for objective conversation about the assumptions that goes into them. Said another way, the act of writing down the targets/scenarios forces self-evaluation and more contemplative reflection.

Further, they have found that disciplined usage of portfolio optimization indeed reduces portfolio slippage. The vendor's research suggests not only that adoption of the application by itself led to improved performance, but actual usage intensity further enhanced results. (Usage intensity in the company's study was determined by [1] recency of price targets, [2] percentage of assets with price targets, and [3] login frequency. In short, higher usage scores resulted in higher return on invested capital.) Finally, comparing users' optimal versus actual returns showed improved batting average, better size-based slugging percentage, and higher total returns.

Allocators for their part like to see approaches that are systematic, scalable, logical, and repeatable – and this method of portfolio optimization checks all of those boxes.

Post-trade Reflection via Attribution and Analytic

Many investment professionals fail to understand with a meaningful level of depth what they do well versus what they do poorly. Attribution and analytics tools can offer comprehensive feedback loops to confirm perceptions about past performance successes and mistakes, as well as highlight new learnings. Asset managers can also see what their basic risk profiles may be, by highlighting beta, sector, country, and other exposures – and/or "mismatches" on each side of their books in cases of long/short equity funds. (Mismatches for a long/short portfolio imply that the portfolio is not positioned neutrally across key exposure criteria. A beta mismatch, for example, implies that the beta on the long or short side of the portfolio is meaningfully higher or lower than the opposite side.)

Vendors such as LightKeeper, Novus, or Essentia Analytics – which between them have roughly 300 clients – can reveal most findings a PM or analyst might want to know, as well as basic risk exposures. For instance, is one's fund better/more accurate in this sector or that, this region or that, the short side or the long side, with this analyst or that one, over shorter or longer time frames, with different trading patterns, factor exposures, etc.? Most PMs who dig in will see layers of actionable output they had not appreciated before, and clearly such learnings can be valuable if the managers apply them on a go-forward basis in practice, in an effort to improve batting average and slugging percentage.

The three vendors noted offer elegant portfolio analytics and reporting systems that take all of a fund's historical trading or P&L data and build a data warehouse via a process known as "extraction, translation, and loading" (ETL). The ETL process creates a versatile and flexible time-series database from which the platforms can present comprehensive attribution analysis via reports and/or dashboards. As is the case with many tools in this universe, ETL goes a significant step beyond Excel, as a purpose-built application is synthesizing and packaging structured data (versus unstructured) to present key dynamic, actionable insights. From these insights, both portfolio managers and investor relations/marketing staff can understand the factors that have driven risk and return – or alpha generation.

With all the permutations of reporting output, investment professionals at a fund (or investors in it) can readily answer thousands of possible questions. But at a basic level, these may include what performance was by sector, market cap, analyst, liquidity, time frame, long positioning, short positioning, individual position, geography, etc. Users can evaluate and compare batting average and slugging percentage, top winners versus losers, various performance periods, drawdowns, and any variety of rank-orders appropriate for analytical purposes. Basic factor/scenario analyses and risk assessments are also possible, where a PM can see exposures in the portfolio to different common thematic macro or micro risks as well as price reversions. Evaluating "what if" scenarios can be an important part of a manager's risk mitigation approach – although not all PMs make use of this either because they do not know how or they do not have time.

Charts and graphs are available for most permutations of data output, and the output can usually also be displayed across a variety of device types. Additionally, the vendors can generate reports (via email and as PDFs or spreadsheets) at any time interval for users to digest all relevant information.

The ROI case for an analytics and attribution system is based on a few obvious foundations. First, anyone at a fund would need to spend a substantial quantity of time working with spreadsheets to populate the same information offered in ready point-and-click form by LightKeeper, Novus, or Essentia. Having time series data offers much more functionality and ease-of-use versus spreadsheet aggregation and data manipulation. Second, having comprehensive awareness of exposure levels to different factors or potential price movements can be helpful on an ex-ante basis. Third, the lessons any PM can draw from the limitless permutations of data are valuable on an ex-post basis, as clearly a fund wants to keep doing more of what it does well and do less (or none) of what it does poorly. Fourth, having ready data sets to present to fund investors and prospective investors is important, and many elements from attribution and analytics systems go logically into a fund's standard PowerPoint pitch for allocators.

A few factors that differentiate the vendors in this group are worth noting. Novus is differentiated in the service it provides to allocators, which comprise roughly half the company's client base. Because the company is providing attribution analysis to individual managers on the other side of its business, it can readily offer narrower or tailored versions of the same data sets to the investors in its fund clients. Allocators can obtain via their Novus dashboard a detailed sense for the degree to which their managers overlap or correlate with one another, and the risks inherent in the portfolios or styles of the managers. Many endowment, foundation, and pension clients leverage the Novus dashboard to obtain a cross-sectional view of many of their managers.

For its part, Essentia Analytics takes a heavily consultative approach to a PM's investment process, by walking PMs through presentations that make clear the most actionable information culled from the volume of data the platform offers. Essentia highlights these signals on a quarterly basis, and offers to "nudge" its clients when they are following what was shown to be an inappropriate or poor-performing pattern in the past. This could mean the software flags a manager making a trade in a sector in which they have had a sub-optimal past performance, or suggests exiting a position over a shorter versus a longer time frame when that has proven successful in the past.

Finally, LightKeeper and Essentia both make use of trade-level data, while Novus uses P&L-based data to analyze key patterns and attribution.

A Note on 'Big Data'

There are a number of vendors offering substantial, marketplace-centric data sets and even outsourced analytics services to the buy side. These include but are not limited to: Yodlee, Second Measure, Discern Analytics, Thinknum, AlphaSense, Dataminr, Kensho, Indico, 1010data, M|Science. We could write an entirely separate and lengthy article on these so-called "Big Data" providers, but it is fair to say that none of these data sets represent a singular foundation for a rigorous and repeatable security selection or portfolio construction process. Our view is that fund managers can harvest the lowest-hanging fruit on these fronts from the aforementioned approaches for screening, attribution, and optimization – and this is appropriate to do as a first step in enhancing a firm's fundamental investment process.

This said, some of these vendors' data sets may offer alpha-enhancing opportunities on regular enough occasion when used with complementary due diligence activities, so as to form a potentially optimal mosaic. However, this can require context, experience, and often a human overlay to make the data truly actionable. The right unique or insightful information can be alpha-enhancing, although the validity of each data set depends heavily on the investment sector, the accuracy of the data, the specific methods being applied, and sometimes even the computational power of the firm buying the data in cases where it is "raw" or unstructured. (And this is before even noting the specific predictive power of information with regards to asset values.)

These solutions are therefore often best assessed by sector specialists with a technical or quantitative aptitude to determine how much 'signal' the data provide and the duration that signal is available.

Conclusion

Most active managers can improve their investment methodology – and resulting alpha generation and returns – meaningfully by taking a more process-centric approach. This starts with an awareness of the best-of-breed data/technology platforms, many of which we addressed in this review. But it truly culminates with the active integration of such tools to provide investment professionals with "intellectual leverage", as this lets them maximize impact from their fundamental research skills on the portfolio's final return, and in turn that of their investors.

**All views presented in this article are of the author's, and should not be considered an endorsement by the CAIA association.*

Authors' Bios

Dana Lambert, *CAIA, CFA*

Dana Lambert, has had a 23-year career in the institutional equities business, with five years in sell-side equity research and more than 15 years as a portfolio manager at hedge fund and mutual fund firms.

Dana spent his sell-side years at Schroders and Lazard, and spent ten years helping manage small-cap funds for value firm Royce & Associates.

Most recently, Dana headed client relations at Alpha Theory, where he helped more than 100 equity long/short and long-only managers re-construct their funds using the most logical, systematic, and repeatable approach to position sizing and portfolio optimization available. In surveying the landscape, he found too few active managers making use of the investment process tools and techniques that can most help their performance.

Rayne Gaisford
Olive Street Advisors

Rayne Gaisford founded Olive Street Advisers after more than a decade of experience in hedge fund management, including tenure with Balyasny Asset Management, Plural Investments, Folger Hill Asset Management and Pequot Capital.

Rayne is a strategic and systems-oriented thinker. He has designed, managed and overseen the build-out and ongoing improvement of multiple data, trading, risk and portfolio management infrastructures, providing information delivery solutions for fund principals, investment teams, IR teams and middle/back-office functions.

Rayne is a regular speaker at industry events and conferences; including events coordinated by: MSCI/Barra, Citibank, Bloomberg, BattleFin, RiskMinds and Risk.net to name a few.

From Theory to Practice: The Collaborative Model for Investing in Innovation and Energy

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Introduction

In response to a number of inefficiencies with traditional methods of investing, we argue that an increasing number of beneficiary organizations, such as pension funds, sovereign wealth funds, endowments and foundations, are adopting a new model of long-term investment management. The existing models that have been used by asset owners have included the Norwegian model, which focuses on investing primarily in traditional public markets; the Endowment model, which is based on adding risk into the portfolio by using external managers to invest in alternative assets such as real estate and private equity; and the Canadian model, which is based on investors employing resources in house to invest in real assets such as infrastructure and real estate directly. Each of these models has their own strengths and weaknesses and has been adopted in various amounts by investors around the world. In many ways these models dictate the types of assets that investors buy. Both the Endowment and Canadian models are premised on the idea that while being more risky, investments in illiquid, private assets enable investors to more accurately take advantage of key trends in the global economy. For example, the greatest performing asset class for the Yale endowment, which has been able to achieve 12.6% per annum over the last two decades, has been investing in innovation through venture capital. Similarly energy infrastructure has been a strong performer for direct investors.

As a global community, it is in our collective interest to cultivate an appetite for investing in innovation and energy to offset the extreme global challenges associated with rapid urbanization and population growth over the next 30 years. Radical resource innovation – across energy, agriculture, water, and waste – is required to prepare the world for this future. Finding a way to invest in the unpredictable is a crucial part of investing in innovation; in 2005, nobody could have conceived that in a decade's time, iPhones would be ubiquitous, YouTube would become a household name, and Uber would represent a global behemoth. Technology now plays a crucial role in all major developments of the future, and the savvy long-term investor should want to be invested in tomorrow's technologies.

While existing models provide an option for accessing these types of assets, there are drawbacks. The endowment model has worked very well for certain investors but the model is premised on investors getting access to the top performing managers, which can be difficult and comes with the very high fees usually associated with this access point. Direct Investing has proven to be a much more cost effective way of accessing long-term private market assets, but it is very difficult for many investors to fully replicate the required investment management function in house.

As a result, the collaborative model has emerged over the last few years as a fourth model of institutional investment, and we have been working over the last few years to understand, analyze, validate, and even implement it. The motivation for such a model has been a renewed focus, since the Financial Crisis, among institutional investors on long-term investing in long-term private market assets in the most efficient and innovative way possible. As detailed below, the collaborative model is all about leveraging an asset owner's competitive advantage of scale and time horizon to form long-term relationships with trusted investment partners. The collaborative model of investment essentially combines a number of the existing models, recognizing that:

1. *Private market investing is consistent with a long-term investment strategy.*
2. *The direct method of investing is a more cost effective means of accessing private market investments, but requires significant in-house resources.*
3. *Alternative external investment managers are required but the governance needs to be redefined for more alignment.*

Against this background, the collaborative model focuses on how innovative platforms can be developed directly with other peer investors and investment partners. The platforms/vehicles can help a group of peers invest more efficiently in long-term assets, get closer to either a direct investment method for real assets or an endowment method for innovation but on far more aligned terms. To be clear, these include co-investment platforms/vehicles, joint ventures, and seeding managers. We'd also suggest that the Collaborative model should extend to the new ways in which investors are engaging with their intermediaries and how new intermediaries are being formed to accommodate the unique long-term characteristics of these asset owners.

The key component of the Collaborative Model is an asset owner's own social capital, which is as asset than many institutional investors have failed to proactively develop. It is well understood that an asset owner must diligently cultivate financial and human capital, the value of an asset owner's social capital – such as the ability to build organizational capacity, share knowledge and ultimately find aligned co-investment partners – is less well understood. In most cases, it is in fact the network of an asset manager that is the biggest value-adding element of these actors in the investment management process, which means the asset managers can impose asymmetric and misaligned terms on the asset owner. We believe that an institutional investor that develops its social capital can reverse this trend and reap significant benefits for executing its investment management function. Furthermore, understanding in more detail, the unique organizational advantages of asset owner entities (whether they be sovereign funds, endowments, pension funds or foundations) can help the process of building social capital and subsequently enhance organizational capacity and investment performance.

While some of the concepts and vehicles that characterize the collaborative model (joint ventures, platform companies, co-investment platforms, seeded funds) have been around in some capacity for many years, our research has shown that the majority of these initiatives designed for long-term investment have been instigated over the last five years. This paper thus tries to further crystallize for readers how long-term investment communities can deploy them. Specifically, we provide an example of how the University of California Office of the CIO has adopted the Collaborative model in rolling out a number of new initiatives over the last two years.

The University of California Implementation

Organizational Mindset Change

The Regents of the University of California are the central governing body for the UC system, with the UC investment funds being managed by the Office of the CIO. The investment funds amount to about $100 billion and are made up of university endowment (with an annual spending rate of 4.75%) and defined benefit pension plan, which has annual net outflows with funded ratio of about 80%. The organizational mindset of the UC Office of the CIO over the years has reflected that of a classical US defined-benefit pension fund.

While the Office of the CIO has performed credibly over the last 20 years, a key motivation for implementing aspects of the collaborative model into the UC strategy has been the need to search for new sources of value and opportunities that are uncorrelated with traditional sources such as US public stocks (which are unlikely to continue appreciating in the same way they have over the last five years). At the core, was the realization that the UC investment funds needed to move away from responding to every bump in the road in the quest for short-term returns and instead adopt a long-run perspective that braces for the radical uncertainty that comes with the future. The looming impacts of climate change fueled the positive steps taken by UC towards investing in resource innovation, cleantech and renewable energy sources. Given the impact that technology has had on our lives in the last twenty years, the UC has also made a conscious effort to not only understand how technologies will affect their own function, but capitalize on the innovations that will change our lives over the next twenty years.

The motivation behind the collaborative model is the need for beneficiary organisations to focus more diligently on long-term performance and risks. In this section, we highlight some of the key organizational mindset changes that illustrate how the collaborative model has been implemented at the UC.

Re-Intermediation

The collaborative model recognizes that many institutional investors will still need to use asset managers for much of their investment management function. Institutional investors will however need to re-intermediate with their service providers in a way that creates more alignment. Re-intermediation is all about creating governance structures based on trust and co-operation over the long-term as opposed to short-term discrete transaction based contracts where the parties to the transaction are irrelevant. For large investors, this means negotiating co-investment rights which are free from adverse selection by managers and setting up separate managed accounts, given the ability of these investors to deploy significant amounts of capital at a time. For smaller investors that need to use intermediated products, an emphasis needs to be placed on transparency. The true costs of financial intermediation have been difficult to identify, rationalize and minimize. Investors should demand a detailed breakdown from their managers of how they make their money from using investors' money, and if not, investors should be prepared to walk away. If alignment is the key ingredient in long-term returns, transparency around fees and costs is one of the few ways to ensure that you can achieve it. This may require having fewer and deeper relationships with service providers. While it might be difficult to have a purely 'relational' form of governance with all asset managers, constructing portfolios from a concentrated set of assets that are deeply understood will hopefully reduce unwanted risks, costs and increase desired returns.

The UC has implemented such strategies in their roadmap for investing in the future – The 10 pillars of centennial investing. Since December 2013 to June 2016, the number of private equity managers used by the firm has reduced from about 130 to 50 while the number of co-investments made during this time period increased from about 20 to 25. The performance of the private equity co-investment program since inception (January 2010) has been an annualized return of 28% and provided estimated savings of $130 million ($30 million in management fees and $100 million in carried interest). Negotiating co-investment rights has been important for the UC and the strong record will be built upon moving forward.

Considerable attention has been focused on fee and cost transparency. Notwithstanding the disclosure required of all California public pension plans as per Assembly Bill No. 2833 that was passed in the summer of 2016, the UC will be providing full transparency on all fees paid to its managers for new investments in 2017. On top of the existing disclosure about fund gross and net performance, the enhanced disclosure will include management fees, fee offsets, portfolio company fees, and carried interest.

Build Knowledge by Building Social Capital

While a key component of the collaborative model is to develop social capital in order to ultimately co-invest via aligned vehicles into long-term investment opportunities, we also argue that investing time and resources into building social capital can help expand organizational capacity through knowledge sharing and staff secondments. For many investors that do not have the resources in house or are subject to structural and other long-term investing barriers, participating in the collaborative investment vehicles may not be possible. However, as indicated above, the collaborative model is just as much about a shift in mindset and thinking innovatively as it is about formally developing efficient investment vehicles. This firstly can be achieved by creating a collaborative environment within an investment organization, breaking down silos and facilitating information sharing across teams. As indicated in our case study research, internal collaboration is almost a pre-requisite before an organization carries out external collaboration.[1] It doesn't make sense to have an individual travel the world developing relationships with smart, aligned peers if that individual does not have the ability to translate that into some action via internal relationships with his or her investment team at home. Also, as mentioned above, much of the knowledge and value creating power of investment intermediaries is the rich, diverse network that they are able to tap into when they are executing their investment management function. One of the benefits of the Endowment model has been the access to top performing managers through the alumni networks of the university endowments. We believe (based on theoretical and empirical evidence) that an investment in time and resources into developing an investor's network, can lead to a number of knowledge creating and capacity building benefits for investor organizations.[2]

The UC has made a conscious effort to build its social capital through deepening its relationships with other peer investors locally and globally with other pension funds, sovereign funds and endowments. It has been able to do this through the personal relationships of individuals that have come into the organization. It is well in tune with the major global forums for long-term investing including the Institutional Investor Roundtable, Sovereign Investor Institute, Pacific Pensions Institute and World Economic Forum. It is also partly through these social capital avenues that the UC has been able to attract high quality senior talent to the organization in the key areas of public/private investing and risk management. Through this evolutionary process of building social and subsequently human capital, the UC has been able to grow into a reputed investment organization

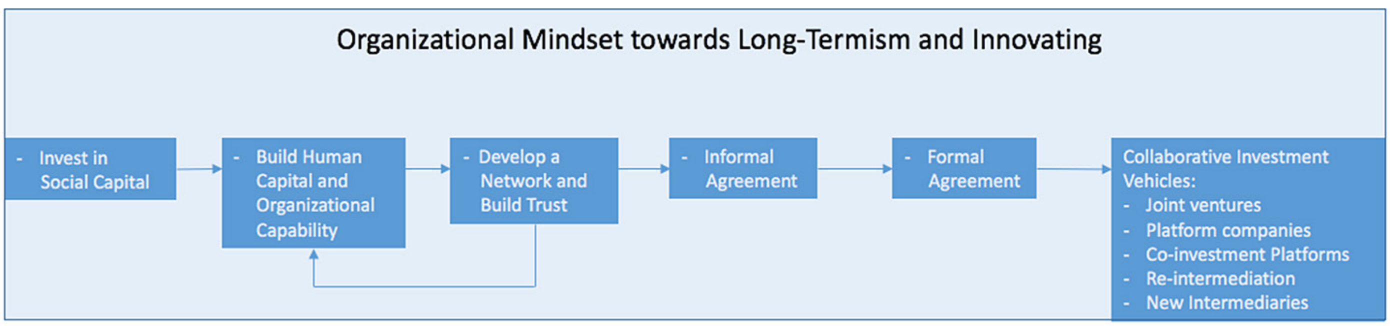

Figure 1: Collaborative Investment Process

on both the local and global stage, which helps to perpetuate an effective network building process.[3]

Many of the initiatives outlined in this short white paper follow a similar evolutionary process, indicative of the collaborative investing process, as illustrated by figure 1.

The UC Collaborative Investment Vehicles

Collaborative Vehicle 1: Aligned Intermediary for Climate Infrastructure

Part of the Collaborative model, is the need for new intermediaries to be formed to help channel long-term investor capital into long-term private market assets. One sector that is particularly suitable to long-term investors is Cleantech and Climate Infrastructure. Many investors in cleantech venture capital firms lost a lot of money because the scale of investments required and time horizon of clean energy companies did not fit within the fund structures of VC firms. This phenomenon is commonly referred to as the Valley of Death. There is an innovation valley of death at the early stage level of product development as well as a commercialization valley of death at the growth stage or project finance level of development for cleantech, renewable energy companies and ultimately climate infrastructure. Thus the Aligned intermediary was formed by the University of California as an investment advisory vehicle to originate, analyze and syndicate climate infrastructure opportunities on behalf of a membership base of long-term investors.

After a decision was made by the team at the Office of the CIO to commit about $1 billion to investments in the Clean Energy space, the team had to strategize how this investment program could be most effectively managed. It was soon evident that a large set of viable and attractive new ventures and sustainable infrastructure projects were being left behind due to a misalignment with traditional asset classes. The University of California thus went about finding an innovative solution to this problem.

The Aligned Intermediary (AI) was created as a University of California initiative to pool like-minded investors and provide a mechanism for helping these long-term investors invest in the most promising resource innovation assets. The initiative was developed into a new organization with the following objectives:

- *Reducing transaction costs by sourcing, measuring, screening and introducing companies that have as a primary function, resource innovation that reduce climate change effects.*

- *Providing buy-side advisory services to reduce the internal costs required by the member LTIs.*

- *Providing syndication services for member LTIs for deals that are of interest.*

- *Bringing standards, norms and benchmarks to the sector for LTI's.*

- *Collecting and anonymizing data on capital flows and returns to improve the understanding of investment activity in the sector.*

The AI has been developed into an independent organization with the UC Regents playing an integral role in setting up the governance structure, hiring a CEO and collating other LTI members into the initiative. The initiative has evolved over time to develop the right structure that fits in with how long-term investors operate. While these new initiatives in theory do sound like a good idea, there are a number of challenges that need to be overcome in order for them to come to fruition. This was evident in many of the cases that were studied in validating the Collaborative model. In the case of AI, there were challenges in co-ordinating the efforts of each of the LTI members (each LTI works very differently) towards the common purpose. This has been overcome and AI (as at November 2016) is in the process of completing three transactions for its long-term investor members.

A key ingredient to setting up the AI, interestingly, was the backing of four charities that allowed the AI to operate, from the investors' perspective, for free for the first 18 months. These charities were part of the UC's social capital and they recognized that new financial intermediaries would be required if we were going to get the private capital flowing into clean infrastructure. As such, they underwrote the launch of the AI. Indeed, these four foundations –Planet Heritage through it's multi million commitment but also Hewlett, MacArthur and Climate Works - represent new patrons of the coming 'aligned financial services sector'.

The AI is an example of how the UC Office of the CIO has put the collaborative investing process into practice to invest innovatively and solve some existing structural market deficiencies. Its network was been drawn on multiple times in bespoke ways, both pulling in peers but also in engaging charitable foundations and even the White House to get behind the initiative.

Collaborative Vehicle 2: UC Ventures for Innovation Investments

Platform companies and seeding management teams for attractive private market asset classes are core examples of the new vehicles that characterize the collaborative model. UC Ventures is an example of such a vehicle. It was set up by the Regents of UC Office of the CIO as a $250m Venture Capital fund with the idea of overcoming some of the traditional shortcomings of LP-style VC investing. UC Ventures aims to exploit its organizational comparative advantage by accessing the large pipeline of research, ideas and inventions originating from within the university network.

One of the main motivations for conceiving the UC Ventures program was the attraction of investing in innovation and generally, as these are the technologies that will shape and define the future. While investing in innovation can be difficult and arguably more risky, it launches businesses that can potentially disrupt and challenge pre-existing systems. UC Ventures would allow the organization to participate in the innovation economy and to invest in ideas, inventions and companies yet to be conceived.

The main route to technology or innovation investing has traditionally been through the VC channel. Venture Capital as an asset class has generally not performed as well as many investors thought it would. It is true that the top tier firms have performed a lot better, mainly due to a limited number of 'home runs', but a large proportion of VCs have performed very badly. UC was fortunate to get early access to some of the better performing VC firms. This performance however, did not outperform public market benchmarks significantly enough to account for the greater illiquidity and asset risks of VC funds.

By internalizing the investment strategy, focusing the team on the main objective of long-term value creation, and exploiting its immediate and established network, the OCIO hopes to create a VC program with a longer horizon and more closely aligned with its endowment portfolio's objectives. It also aims for UC Ventures to be more scalable than traditional VC vehicles. The current allocation of $250 million is already larger than most VC fund commitments, and members of the OCIO want the UC Ventures portfolio to grow as the program achieves good results.

UC Ventures is designed to be a team of independent investment professionals operating at arm's length from the university, and will pursue investments in UC-affiliated companies within a clearly defined investment mandate. The team will be supported by operational staff managing the business's accounting, administration, finance and operations. UC Ventures will report to the UC Office of the CIO, which will hold approval and veto rights over critical governance issues.

Once fully operational, the team at UC Ventures expect that the unique channels of deal flow from the UC eco system will present them with over 200 investment opportunities every year. These opportunities will then be subject to rounds of reviews, due diligence and exploratory analyses until the pipeline is narrowed to about three to six seed-stage investments and three to five post-seed-stage investments. These investments are expected to translate into an annual capital deployment of $30 million-50 million over the investment period. So far, investments have been made into three companies by UC Ventures.

The UC Ventures Fund is an example of a long-term investor that has identified an attractive area that could provide outperformance if structured in the right way. In order to help achieve its objectives in technology and innovation investing, it has seeded a new vehicle that will operate independently from the Office of the CIO, to take advantage not only of its unique long-term characteristics but also the relative organizational advantages of being at the heart of one of the most innovative university and entrepreneurship ecosystems in the world.

Key Lessons and Takeaways

There are a number of lessons that can be drawn from the UC's implementation of the collaborative model. Firstly, the collaborative model might be perceived as restricted to only the most sophisticated investors to implement. The UC, while being large in size by assets under management, has many challenges. It is a large, public organization with a diverse stakeholder base and complex governance structure. It is nothing like a typical asset manager in the private sector let alone other sophisticated asset owner organizations. The implementation of the initiatives above has shown that even the less sophisticated, constrained organizations can execute the model by adopting a transparent, disciplined and understandable decision-making process, not controlled by one person. Getting stakeholders across the finish line was the result of smart and talented professionals working together to the highest standard.

One of the key takeaways from UC's implementation is the importance of leveraging the competitive advantages that a long-term investor organization possesses. For a lot of these investors, it is their long-time horizon and size of capital that provides them with significant negotiating power when choosing more efficient access points for long-term investments. Investors need to exercise this power but also understand the responsibility and duty of care that goes with this.

UC has also emphasized the importance of utilizing unique organizational advantages for long-term investing. In implementing the collaborative model, UC has tried to make the most of the constituents that the investment office represents, one of the largest and well-ranked public university systems in the world. This was particularly important in setting up the collaborative UC Ventures vehicle. But we've also established other platforms with name-brand people on the basis that we represent the UC. While the UC system is distinct, other LTI's will also have unique organizational advantages that they will need to consider leveraging, particularly when they are forming relationships with potential investment partners.

It must be noted that a number of the initiatives outlined above are at an early stage of development and time will tell how effective (or successful) they will be. The foundations for these strategies have been well researched and planned and so the signs are that the organization is well positioned to not only stomach the challenges moving forward but take advantage of the attractive opportunities that come up. In our previous research, the benefits of the collaborative model have been theoretically validated and empirically verified by a number of sophisticated long-term investors around the world. The UC implementation provides useful insights and lessons for other like-minded investors that might not be as sophisticated as the large Canadian direct investors but who share similar values and long-term objectives.

Endnotes

1. Monk, Ashby H. B. and Sharma, Rajiv. (2015) *Capitalising on Institutional Co-Investment Platforms*. Available at: http://dx.doi.org/10.2139/ssrn.2641898.

2. Monk, Ashby H. B. and Sharma, Rajiv and Feng, Wen. (2015) Social Capital and Building an Institutional Investor's Collaborative Network. Available at: https://ssrn.com/abstract=2698178.

3. Please see http://www.ai-cio.com/2015-industry-innovation-awards/?page=3. Also please see paper in footnote 2, for a discussion around power, reputation and centrality effects for the network building process.

Authors' Bios

Jagdeep Singh Bachher, *Ph.D.*
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Jagdeep Singh Bachher, Chief Investment Officer and Vice President of Investments, is responsible for managing approximately $103 billion across the UC Endowment, Pension, Retirement Savings, and Working Capital programs. He reports directly to the Board of Regents on investment matters and the Chief Financial Officer on administrative issues related to managing a group of more than 50 investment professionals and staff.
Before joining the UC system, Bachher was an Executive Vice President of Venture and Innovation for Alberta Investment Management Corp. (AIMCo), one of Canada's largest and most diversified investment fund managers. In addition, he served as the corporation's Deputy Chief Investment Officer and Chief Operating Officer.
Prior to his position at AIMCo, Bachher served as president at JH Investments (Delaware) LLC and worked in the U.S. Wealth Management, Canadian, and Investments divisions of Manulife Financial. Before joining Manulife, he was an entrepreneur. He is a visiting scholar in the Global Projects Center at Stanford University and chairman emeritus of the Institutional Investors Roundtable, a leading financial think tank. He is also a member of Young Presidents' Organization (YPO) and the Institute of Corporate Directors. Bachher received his Ph.D. and M.A.Sc. degrees in management sciences and B.A.Sc. degree in mechanical engineering from University of Waterloo. He has been a champion for change in the investment business and gained an international reputation as an innovator.

Ashby Monk, *Ph.D.*
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Dr. Ashby Monk is the Executive and Research Director of the Stanford Global Projects Center. He is also a Senior Research Associate at the University of Oxford. Dr. Monk has a strong track record of academic and industry publications. He was named by aiCIO magazine as one of the most influential academics in the institutional investing world. His research and writing has been featured in The Economist, New York Times, Wall Street Journal, Financial Times, Institutional Investor, Reuters, Forbes, and on National Public Radio among a variety of other media. His current research focus is on the design and governance of institutional investors, with particular specialization on pension and sovereign wealth funds. He received his Doctorate in Economic Geography at Oxford University and holds a Master's in International Economics from the Universite de Paris I - Pantheon Sorbonne and a Bachelor's in Economics from Princeton University.

Rajiv Sharma, *Ph.D.*
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Rajiv Sharma is a Research Manager at Stanford University's Global Projects Center and an honorary research associate at the Oxford University Smith School of Enterprise and the Environment. He received his Doctorate from Oxford University in the field of Pensions, Sovereign Wealth Funds and Infrastructure Investment. Rajiv has worked as an economist for the Organisation for Economic Cooperation and Development (OECD) in Paris and as a research fellow for the United Nations Environment Program Finance Initiative. While at the OECD, he worked at the International Transport Forum and he was also part of the OECD-G20 Long Term Investment Project. Promoting long-term investment by institutional investors is a focus of his current work at Stanford and through this, he has worked with a number of global institutional investors and governments. He has also worked for venture capital private equity firm Oxford Capital Partners and London-based Infrastructure/Private Equity Advisory firm, Campbell Lutyens.

(R)Evolution of the Regulatory Landscape in the UK

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Once upon a time in the UK, a long time before Brexit was voted – not that long, in fact, after the UK opted to come in to the group of European states that would later become the European Union (EU) – it was decided the existing regulatory landscape ought to change in order better to supervise a financial sector that had been evolving.

Back at the turn of the century, it was a question of consolidating a regulatory system, lest the ever expanding – and diversifying – financial institutions might escape supervision, or fall into gaps created as a result of the regulatory landscape being atomized. The Barings Bank had recently collapsed; it was time to reform a system that had not performed in the way it had been expected to.

In 2012, a reverse course of action was taken, as it was then decided that the Financial Services Authority – the UK single regulatory entity that had come together in 2001 – ought to be dismantled to some extent. The Financial Conduct Authority (FCA) was created instead, in 2012.

The following seeks to provide further details about the "new" regulatory system in the UK, and to discuss how it fits in with the hedge fund industry, especially in the context of the recently-voted Brexit.

Before the FCA

The first element to mention is that it seems customary for regulatory bodies to be created following major failures of their predecessors to prevent crisis, scandals, or bankruptcies, often of a systemic nature, or with a potentially systemic impact.

It was the collapse of the Barings Bank in 1995 that had prompted the reshuffling of the regulatory landscape in the UK a few years later: as a result of the creation of the Financial Services Authority (FSA), the Bank of England – the country's central bank – lost its regulatory powers in favor of the newly-created body;

other existing bodies (known as “self-regulatory organizations”) also merged into the FSA.

In addition to the fraud at Barings that had led to the bank going bankrupt (over 300 years after its creation), financial product innovation had been such that a new regulatory system had become necessary: while Barings was the trigger, the evolution of financial services firms was the underlying cause for the change. Previously, each firm could neatly fit into a well-defined bucket: for instance, a firm could be either a bank or an insurance company – not both. There no longer was any such clear delineation. The idea of the FSA was therefore to integrate, and to reform, the existing rules, and to make them applicable across all firm types, fine tuning them depending on risk and “topic” – not on the way the firms themselves were called.

Rules on capital requirements for all firm types, for instance, would be integrated with those applicable to banks. (Those rules applicable to banks themselves had come in application of the international Basel Accord on Capital, which, on top of it all, was also being re-negotiated at the same time as those national changes were going on in the UK.) A new “Integrated Prudential Sourcebook” would be created, in which all firm types (banks, insurance companies, asset managers) could look up rules applicable to their specific risk profiles or to the products it was dealing with.

The 2008 crisis

Not so long after all that had taken place, the global financial crisis emerged, raising questions about “who to blame” for what had gone on. Two culprits were found, at two ends of the “risk” (and freedom) spectrum:

- Regulators (worldwide) were seen as not having done their jobs properly. In the UK, and elsewhere, questions were asked about how structured products (i.e. mortgage-backed securities) had been treated in the light, precisely, of capital requirements: the risk inherent to those products had been underestimated, included by the FSA, which had approved many such structures without probing much further or seeking banks to set aside more capital given the level of risk. Formally as a result of yet another scandal – this time: the run against mortgage lender Northern Rock in 2007 – the head of the Prudential Standard Division at the FSA lost his job, the beginning of some of the changes that would ultimately result in the FCA being created in 2012.
- Hedge funds had until then not been regulated much in the UK. The FSA had been toying the question of “what to do” with hedge funds pre-crisis, notably in a Discussion Paper it published in 2005. It had not, however, made a decision about a way forward, two reasons for this being the lack of obvious problem / emergency and the difficulty to define what a hedge fund was. The FSA essentially gathered data via prime-brokers at the time – usually not directly from the hedge fund themselves. It is only post-crisis – starting, in fact, in 2009, when the EU issued a proposal for a new Directive on alternative investment products – that the UK started to take steps to regulate hedge funds the shorting techniques of which they suddenly seemed to be re-discovering.

The FCA, the regulation of hedge funds in the UK – and thereafter

Paradoxically, the creation of the FCA meant the Bank of England got back some of the regulatory powers it had lost at the beginning of the preceding decade. It did not get back banking supervision since the cross-sectoral approach the FSA had taken was kept. However, everything concerning prudential regulation did go back to the Bank of England (via the Prudential Regulation Authority, or PRI), which started to cover for that topic various types of financial services firms across the industry.

The FCA authorizes and regulates hedge funds, in-keeping with the Alternative Investment Fund Managers Directive (AIFMD) published in 2011 and coming into force in 2013, thus coinciding with the creation of the FCA.

In the pre-Brexit era, many hedge fund managers resented the new European Directive, which made it more onerous to run a hedge fund business than before. As one of the member states of the EU, the UK had no choice but to integrate the AIFMD rules into its regulatory framework. Among other features, the new rules require hedge fund managers to increase their minimum capital requirements and to separate its reporting lines in order to keep the risk function “separate” from portfolio management. (Managers have to show that the separation is both “functional and hierarchical”.) All this – and much more – can be costly for smaller managers, and hence create barriers to entry.

It is not certain whether those new requirements will disappear as a result of Brexit: while the FCA may no longer be under the obligation to have a similar regulatory framework to that of its European neighbors once it moves out of the EU, it may well choose to keep AIFMD-like requirements. This is because a discrepancy between the UK regulatory regime and that applicable in the rest of Europe may result in the UK attracting managers with lower compliance standards; conversely, such a discrepancy might also make it difficult for EU countries to accept the local distribution of UK managers as they may be seen as being of lower operational quality.

At the moment, the AIFMD makes it possible for managers authorized in one EU country to raise capital throughout the rest of Europe. That possibility is, to some extent, available to non-European managers also. Obviously, the UK leaving the EU, and throwing the AIFMD out of the window, would put that possibility into question, especially if the remaining EU member states decide a revamped UK regulatory regime for hedge funds is of inferior quality to that applicable in the rest of Europe.

While the current regime has advantages and disadvantages, for hedge funds and the rest of the financial services industry, the following points can objectively be made:

- Whether one decides to look at the creation of the FCA or the coming about of the AIFMD, the fact is that both constitute reactions to what happened within the industry – and beyond. The extent to which that may be deemed to be an over-reaction is obviously a matter of opinion: many in the hedge fund industry argue that the AIFMD was a political stance, aiming to find a culprit in the context of the financial crisis. In any event, one can wonder whether the “catch up game” between the regulators and the industry – with the latter taking advantage of loopholes of an existing framework, and then regulators changing their ways of doing things as a result of negative events – constitutes an optimum policymaking process.

- Looking at the situation from a market perspective, the recently-created UK regulatory framework can also be assessed as far as its impact is concerned. The point about the creation of barriers to entry has already been made. In addition, one can also look at it in terms of demand and supply: the objective of the AIFMD was to protect hedge fund investors (even though they are in principle institutional, or otherwise sophisticated, investors); with the increased cost of running a hedge fund, it is possible that investors may end up having less, not more, choice, with a consequential impact on the quality of the offering. The FCA has several objectives, one of which – like its predecessor the FSA – is to enhance competition; one can legitimately question whether the AIFMD meets, or contradicts, that objective.
- Finally, a hedge fund manager interested to do business in Europe, or to seek regulatory authorization in one of the European countries, may want to know whether any European jurisdiction might be more business friendly than the next. In spite of the fact the AIFMD exists across the EU, some margin of interpretation is left for each European state. In addition, "super-equivalence" may apply in certain cases, which means EU states are allowed (for any Directive) to make their national rules stricter than the Directive requires in certain specific areas. Obviously the regulatory practice overall – and other factors outside purely regulatory concerns – is also something to take into consideration: speed of authorization process, business friendliness and "approachability" of the regulators are all important points.

What happens to the regulatory framework once the UK is out of the EU is still highly uncertain at this stage.

Author Bio

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"Marianne Scordel set up Bougeville Consulting in 2012. She assists hedge fund managers in establishing their businesses or in moving across jurisdictions. In doing so, she has interacted with various regulators across borders. Bougeville Consulting won five awards in the past five years, including from Financial News, a national publication in the UK. In 2017 Marianne Scordel relocated her business from the UK to the US and has spent the past few months supporting US hedge funds doing business in Europe. She is French and graduated from the University of Oxford.

The CAIA Endowment Investable Index

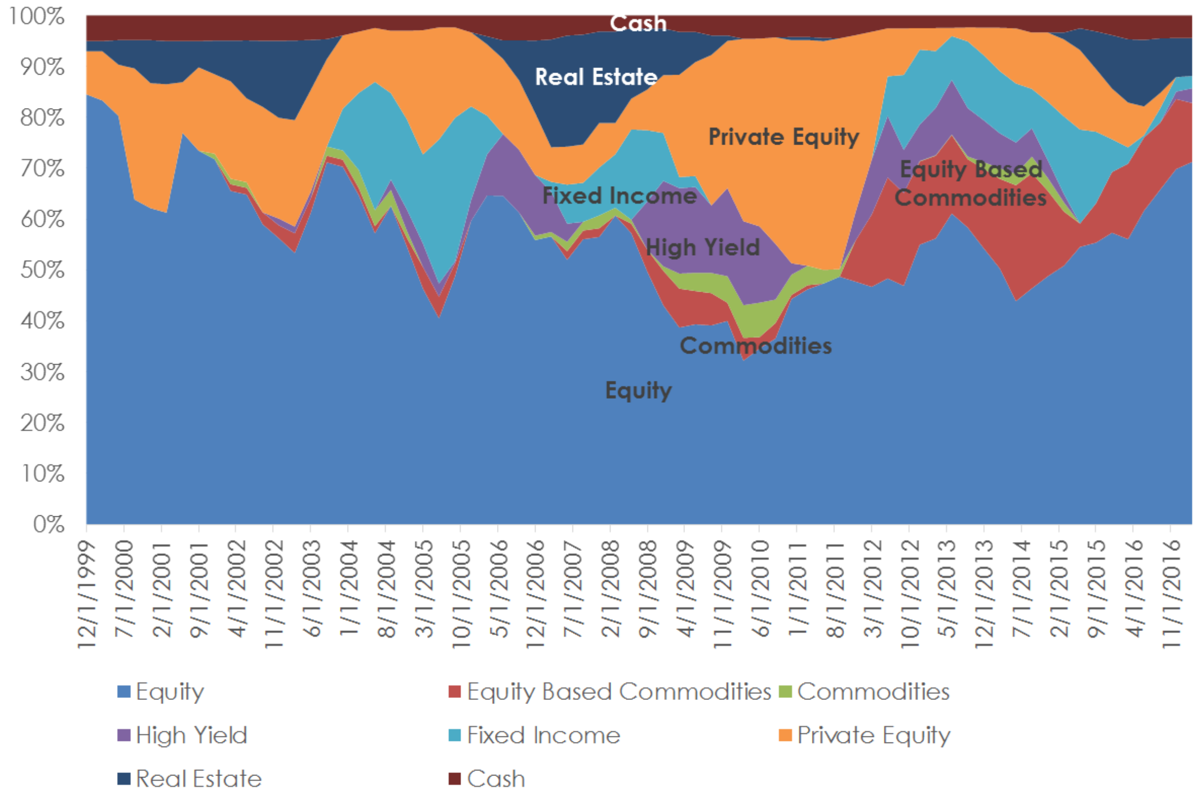
Hossein Kazemi
CAIA Association

Kathryn Wilkens, *CAIA*
Pearl Quest LLC

We present the weights, current allocation, 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.

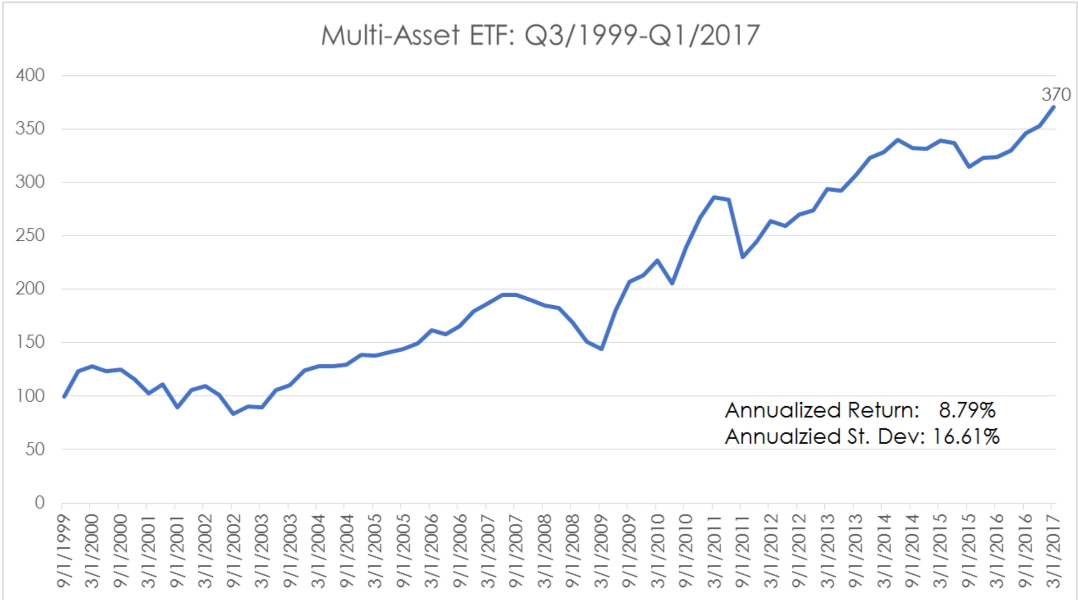
Endowment Index Weights



Allocation as of March 2017

RUSSELL 2000 ETF	PowerShares QQQ ETF	MSCI World Free	Vanguard FTSE Emerging Markets ETF	Materials Select Sector SPDR® ETF	Energy Select Sector SPDR® ETF	Health Care Select Sector SPDR® ETF	BBgBarc US Corporate High Yield	SPDR® Dow Jones Global Real Estate	Treasuries + Cash
24.61%	6.88%	30.48%	4.28%	7.45%	4.12%	5.00%	2.93%	7.49%	6.77%

Historical Performance



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Dr. Hossein Kazemi is the Senior Advisor to the CAIA Association's Program. Dr. Kazemi has been involved with the CAIA Association since its inception as a senior advisor and a managing director. In his current role, he helps with the development of the CAIA program's curriculum and directs the CAIA Association's academic partnership program. In addition, he serves as the editor of Alternative Investment Analyst Review, which is published by the Association. He has worked with universities and industry organizations to introduce them to the CAIA program. Dr. Kazemi is Michael and Cheryl Philipp Distinguished Professor of Finance at the Isenberg School of Management, the University of Massachusetts - Amherst. He is the Director of the Center for International Securities & Derivatives Markets, a nonprofit organization devoted to research in the area of alternative investments, a co-founder of the CAIA Association, and home to CISDM Hedge Fund/CTA Database and the Journal of Alternative Investments, the official research publication of the CAIA Association. He has over 25 years of experience in the financial industry and has served as consultant to major financial institutions. His research has been in the areas of valuations of equity and fixed income securities, asset allocation for traditional and alternative asset classes, and evaluation and replication of active management investment products. He has a Ph.D. in finance from the University of Michigan.

Kathryn Wilkens, *Ph.D., CAIA*
Pearl Quest LLC

Kathryn Wilkens is the president and founder of Pearl Quest LLC, a consulting company currently focused on tracking and replication products, and educational services in the alternative investments space. She is also an RIA with S Capital Wealth Advisors and assistant editor for the Journal of Alternative Investments.

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.

VC-PE Index
Are LPs Really Consolidating Relationships?

Mike Roth
Bison

"We are seeing LPs increasingly wanting to consolidate their providers... And so we're seeing definitely a trend towards the big providers—the big LPs—wanting to consolidate capital with the big managers like us."

- TONY JAMES, APRIL 20, 2017, Q1, 2017, EARNINGS CALL

We have seen and heard different variations of Tony James' anecdote from a number of clients and large LPs like Hamilton Lane. To help GPs better understand the breadth of this trend across the LP landscape, we dug into our dataset to get an in-depth understanding of the actual numbers.

What we found confirmed that consolidation is happening. One of the consequences of this trend has been that LPs have gravitated towards larger managers while being more selective when it comes to emerging managers.

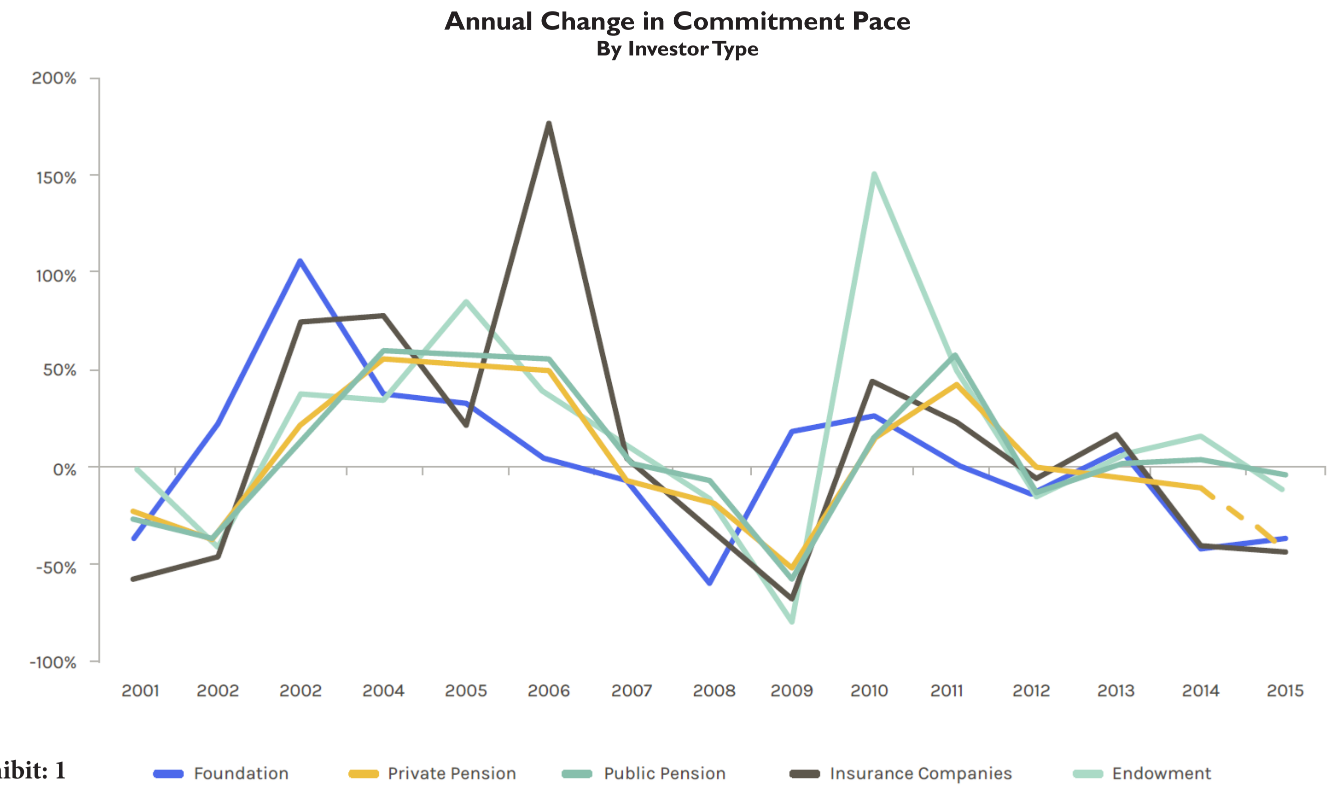

Exhibit: 1

LPs are Investing with Fewer Managers

We started by looking at the pace of commitments to see if the trend of consolidation was reflected in the numbers. As we described in our last thought piece,* fundraising markets are in the midst of a six year hot streak. In spite of this, the chart below illustrates that major segments of the LP market have been taking a slow and steady approach.

The final tally is not in yet for 2016 but we anticipate it will be the third consecutive year where we see a year-over-year decline in the number of commitments. To dig deeper and understand whether fewer commitments has meant these LPs are committing less to private equity, we analyzed how much public pensions have been committing annually.

The number of commitments made by public pensions was slightly positive in 2013 and 2014 before dipping in 2015. Despite the modest peaks and valleys in the commitment pace, the amount being committed to private equity has steadily increased since the market's recoil in 2009. What the chart above highlights, however, is that their steady increase has not kept pace with overall market's growth.

This confirms that, at least among public pensions, LPs are investing more capital with fewer managers. Knowing that a sizeable segment of the LP universe is investing more dollars with fewer managers, we wanted to understand who were the winners and losers in this consolidation trend.

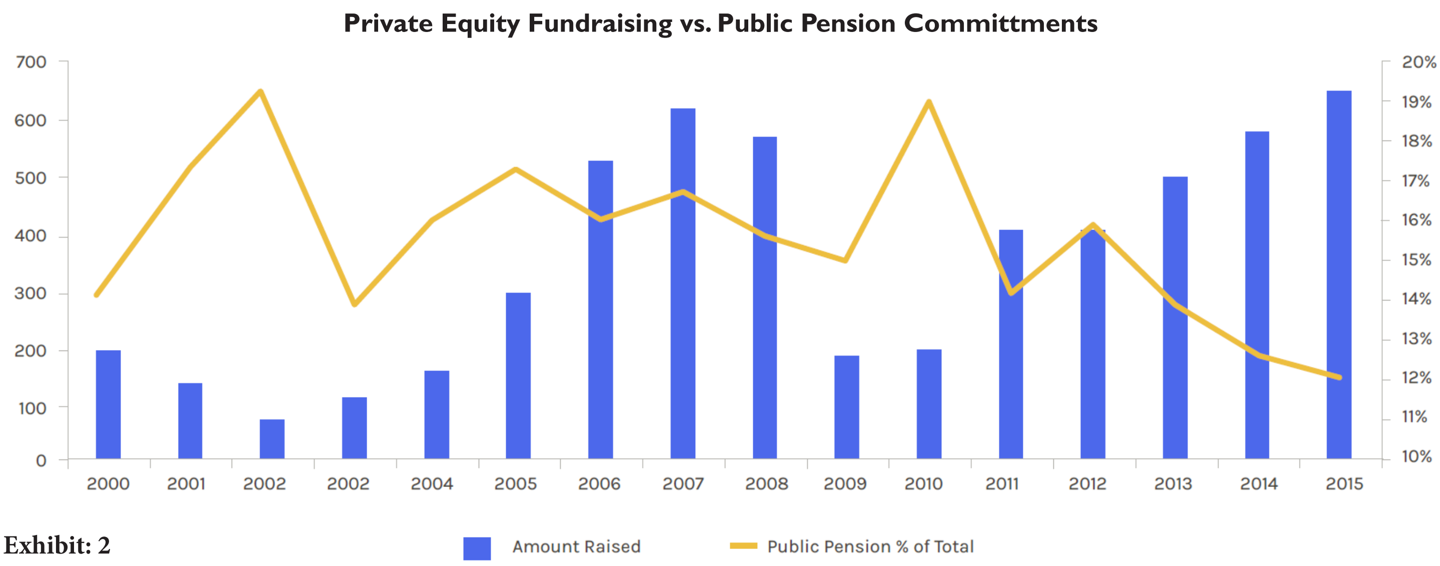

Exhibit: 2

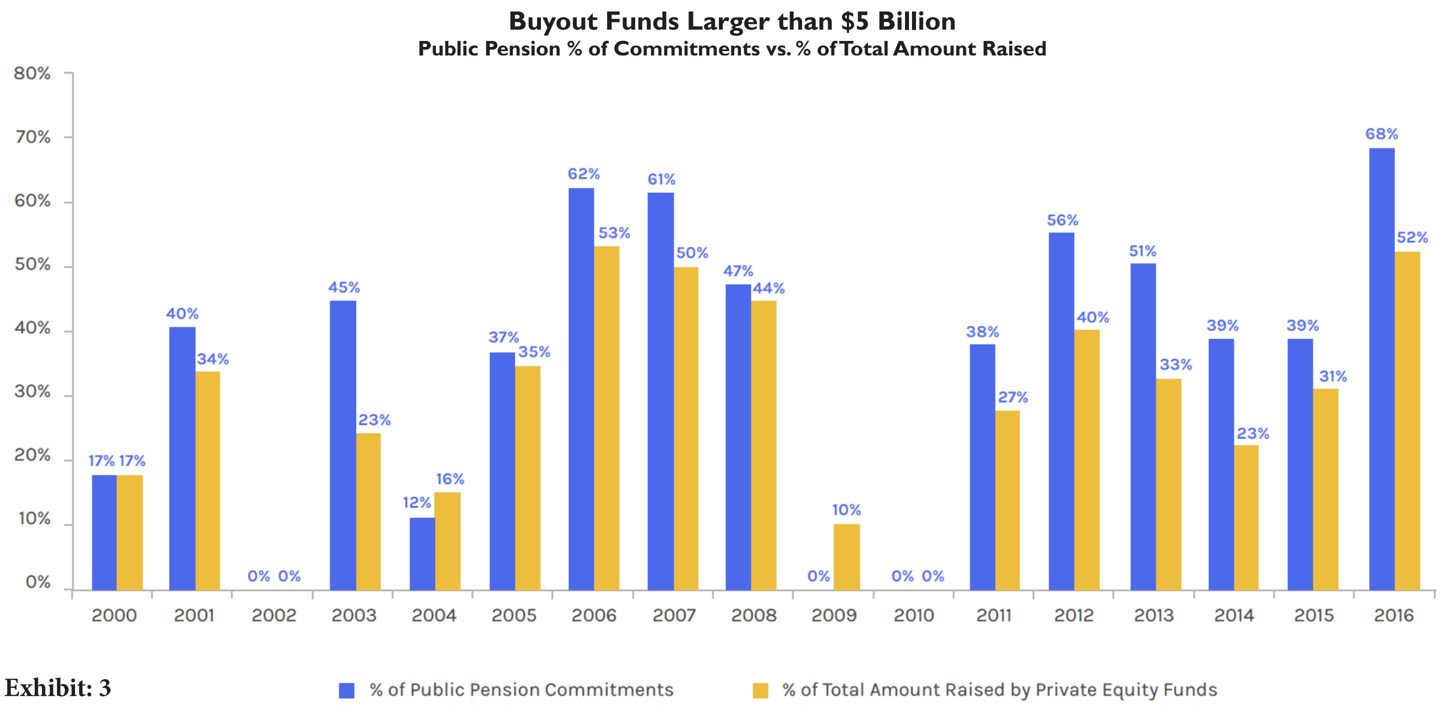

Exhibit: 3

Larger GPs Are Benefitting from the Consolidation Trend

The number of record-breaking fundraises is something that gets well documented during periods of fundraising strength. The news of Apollo IX's record-breaking $23.5 billion, CVC's record-breaking (for a European-based manager) €16 billion, and KKR Asia's record-breaking $9.3 billion fundraises proves that this period is no different.

Looking at commitment information for public pension funds underscores the degree to which large buyout funds dominated the market in 2016. As the chart below indicates, public pension funds have generally trended towards being overweight in larger funds in comparison to the larger funds' representation of the entire market.

However, the level to which large firms crowded out the rest of the market in 2016 reached new heights. Just 13 funds (10% of funds) represented 52% of the approximately $230 billion raised by buyout funds. Meanwhile, public pensions invested more than $42 billion into buyout funds in 2016, 68% of which went to managers

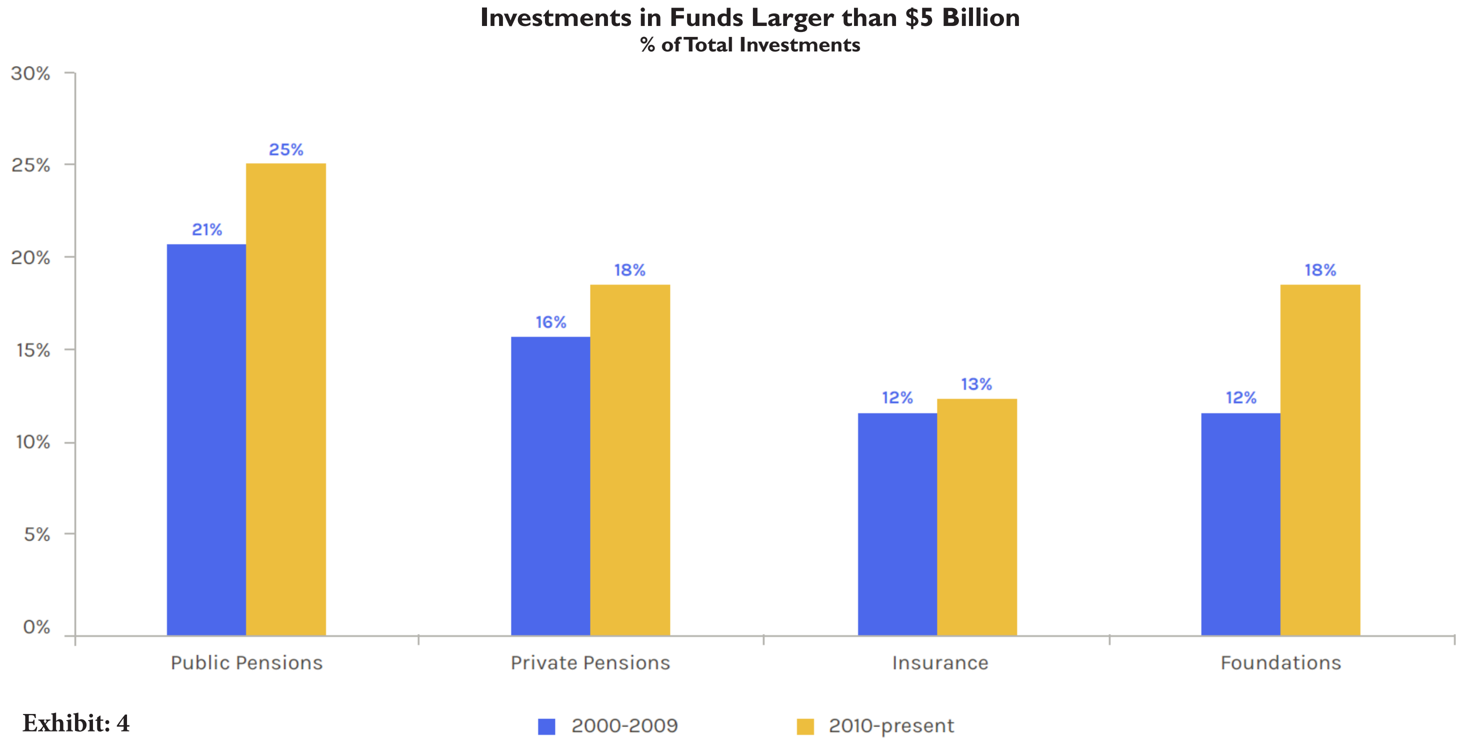

Exhibit: 4

As the chart above illustrates, larger managers appear to be having success increasing allocation across all the major LP types.

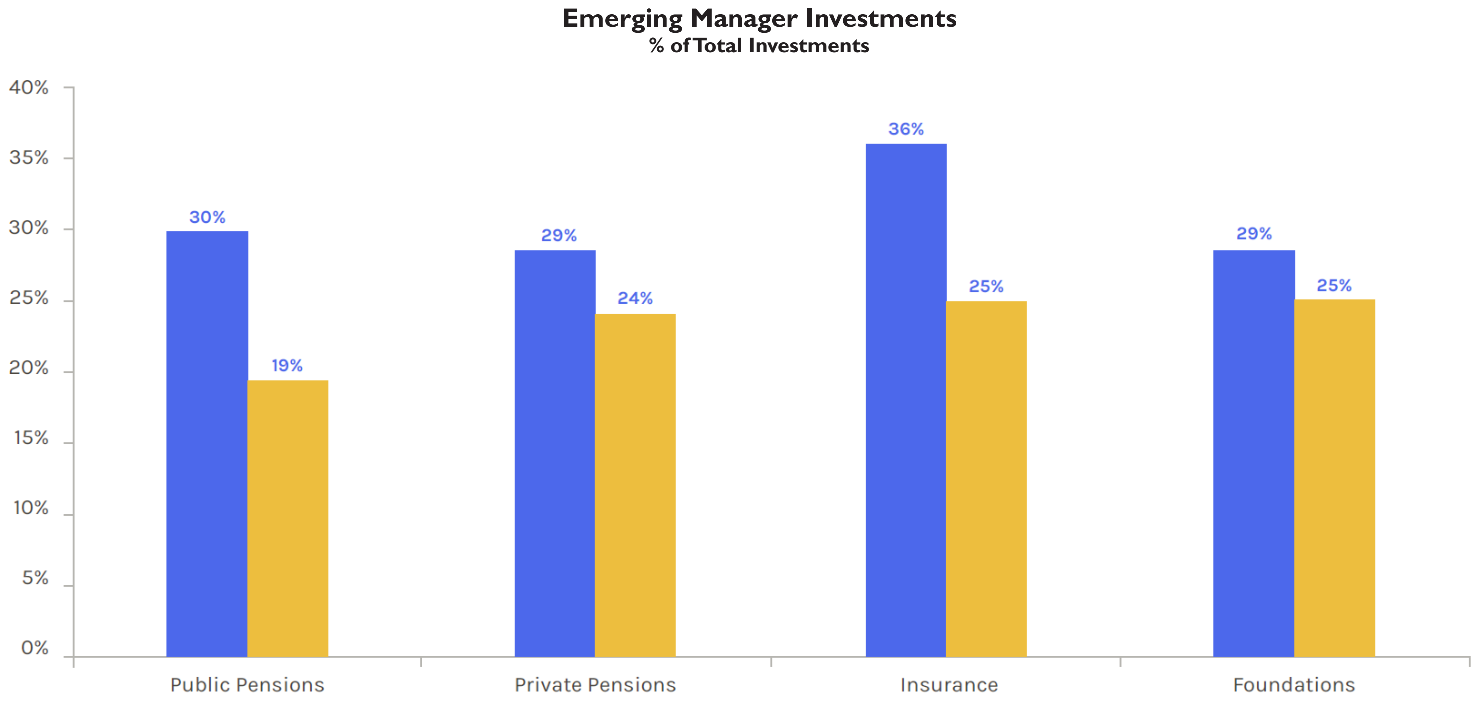

Exhibit: 5

that raised a fund larger than $5 billion. This easily surpassed the allocation percentages to larger funds last seen in 2006 and 2007.

If we cut the data by number of investments, we see that the positive trend in the amount committed by public pensions to larger funds does carry over to the number of investments as well.

Emerging Managers Are Faced With More Selective LPs

Private equity is a constantly evolving industry filled with highly-motivated, entrepreneurial- minded professionals that dream of charting their own course and putting out their own shingle. Their success at starting their own firms will depend heavily on finding a few cornerstone investors willing to take a chance on a new, highly motivated team. Based on what the data shows for large funds, one could anticipate what the emerging manager data would show.

As the chart above indicates, emerging managers had an easier time securing commitments in the previous decade than they are having in the current decade. From 2000 - 2009, the average LP invested in emerging managers 30% of the time. From 2010 to now, that average has fallen to 22% across the entire LP universe. As LPs shifted towards a model of allocating more money to fewer managers, LPs started to be more selective about whom among the next generation of firms they want to support.

Wrapping Up

When we looked at the market from the LP perspective, we saw an overly crowded market but more GPs were raising more money. While a rising tide generally lifts all boats, we wanted to dig into what LPs in our dataset were doing and understand who were the winners and losers of this era. What we found confirmed many of the anecdotes that we have heard from GPs and LPs that we work with. Namely, that a large portion of the LP market is being much more selective about how they allocate capital. Larger GPs have done a good job over the last few years absorbing these fewer, but larger, commitments. On the other hand, this has meant that newer GPs have had to work harder to separate themselves from the crowded field seeking LP attention. These GPs need to make sure they truly understand what makes them unique and how that value proposition matches up to what each LP is looking for.

*https://www.cobaltgp.com/private-markets-bubble-golden-age/

Author Bio

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Mike Roth is the Research Manager at Bison and oversees the data collection and content production. Before Bison, Mike spent six years on the investment team at SVG Advisers. There, he conducted research and due diligence on buyout and venture capital funds in the Americas. Mike received his BA in Economics from Boston College and is a CFA Level III candidate.

MSCI Global Intel Report
Have big-ticket properties performed better than lower-value properties?

Max Arkey
MSCI Real Estate

Some real estate investors assume that higher-value (big ticket) real estate assets outperform lower-value assets, partly because there are fewer of them and they are harder to buy. But is this just speculation? Using MSCI global real estate dataset, we find that higher-value assets were more likely to outperform other assets in the same country and sector than lower-priced assets.

One of the defining characteristics of directly owned real estate is its lumpy and indivisible nature. Real estate assets can range in size and value from small warehouses worth a few thousand dollars to downtown office towers worth billions. But buyers are limited by size and capacity constraints. For direct investments, smaller investors are generally limited to lower-value assets (though they can access higher-value properties via pooled vehicles), while larger investors typically prefer larger properties for efficiency purposes. The resulting stratification of investment markets could lead to differences in performance within the broader real-estate market.

Since 1999, for example, U.S. office assets worth more than USD 200 million have outperformed smaller U.S. office assets in every year except 2016.[1]

But has there been a systematic difference in performance across capital value bands at a global level? To answer this question, we used 487,152 annual return observations from 87,723 assets across 24 national markets over a five-year period in the retail, office and industrial sectors. The analysis controls for difference in

Large U.S. office assets have outperformed smaller office assets in 17 of the past 18 years

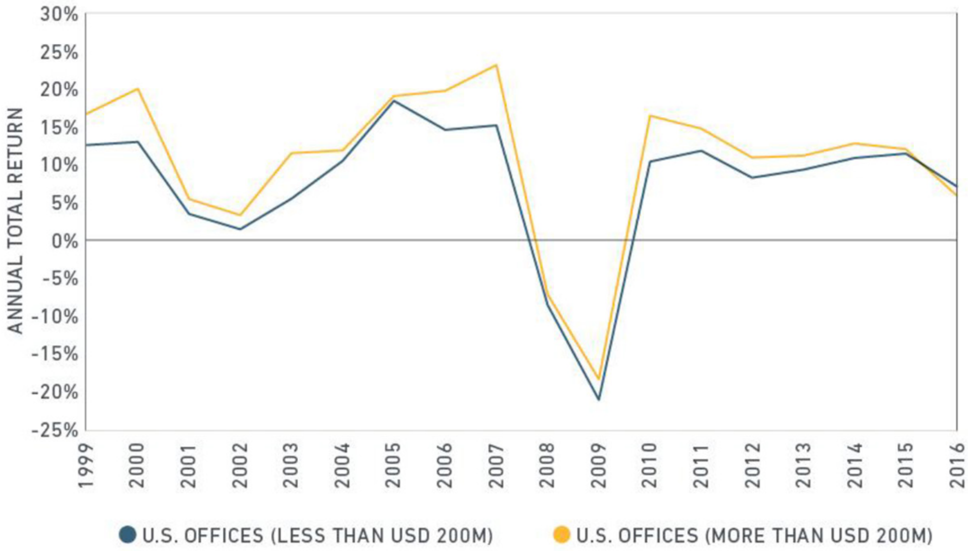

Exhibit 1

location and property type by comparing assets only within in the same country and sector.

The exhibit below, while not indicative of future probability or performance, shows that higher-value assets had a higher chance than lower-value assets of outperforming other assets in the same country and sector between 2012 and 2016. For instance, a fully owned asset in the top capital value quarter for its sector and country had a 53.2% chance of outperforming its country and sector peers overall, compared with 43.5% for a fully owned asset in the bottom quarter.

In addition, part ownership slightly reduced the chances of outperformance during this time, though this effect appeared to be relatively small compared with the impact of asset size. To illustrate, a part-owned asset in the top capital value quarter still had a higher chance of outperforming than a fully owned asset in the first or second quarters.

Notwithstanding these results, institutional investors may want to consider the wider implications for portfolio performance. Adding larger assets to a direct portfolio can increase concentration risk and leave the portfolio more exposed to asset-specific performance. Outside of direct ownership, investors can consider indirect investment via fund structures to increase their exposure across the value spectrum. They can also use market data to understand how assets of various sizes have performed historically and to track the performance of individual assets relative to their peers.

High-value assets were more likely to outperform low-value in the same country and sector

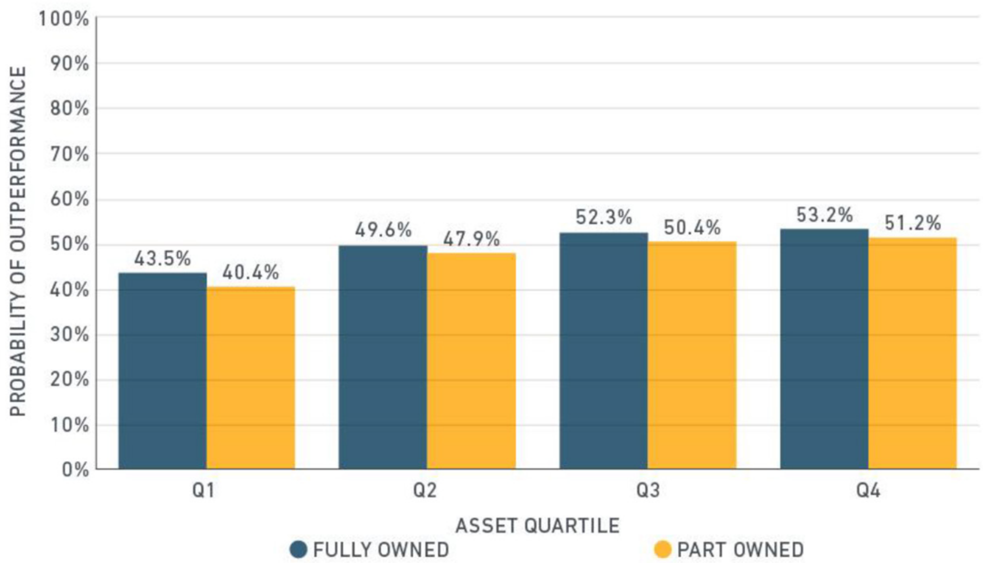

Exhibit 2

Source: MSCI Note: Probabilities are estimated using a probit model, in which the dependent variable can take only two values, in this case "outperform" or "underperform."

Endnotes

1. Past performance is not necessarily an indicator of future performance.

Author Bio

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Max Arkey works in product management at MSCI Real Estate where he heads up indexes and market information products. These analytics are mission critical to the investment process for 19 of the top 20 largest global asset managers, all the way through to specialized domestic investors.

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About MSCI

For more than 40 years, MSCI's research-based indexes and analytics have helped the world's leading investors build and manage better portfolios. Clients rely on our offerings for deeper insights into the drivers of performance and risk in their portfolios, broad asset class coverage and innovative research. Our line of products and services includes indexes, analytical models, data, real estate benchmarks and ESG research. MSCI serves 98 of the top 100 largest money managers, according to the most recent P&I ranking.

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File Format: Word Documents are preferred, with any images embedded as objects into the document prior to submission.

Abstract: On the page following the title page, please provide a brief summary or abstract of the article.

Exhibits: Please put tables and graphs on separate individual pages at the end of the paper. Do not integrate them with the text; do not call them Table 1 and Figure 1. Please refer to any tabular or graphical materials as Exhibits, and number them using Arabic numerals, consecutively in order of appearance in the text. We reserve the right to return to an author for reformatting any paper accepted for publication that does not conform to this style.

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