CAIA ASSOCIATION®

Alternative Investment Analyst Review

Editor's Letter

Diversified Hedge Fund Portfolios

"Put all your eggs in one basket and then watch that basket." This quote, which is attributed to Mark Twain, appears to violate one of the most basic and least controversial aspects of the modern portfolio theory. Nobel Prize winner Harry Markowitz showed that risk-averse investors should always hold diversified portfolios of investments. Holding an undiversified portfolio exposes the investor to risks that are not rewarded by markets, and, therefore, on a risk-adjusted basis the portfolio will underperform an appropriate benchmark.

While there were no hedge funds when Mark Twain made this statement, his insight actually is quite applicable to the world of hedge fund investing, where diversification is costly. Creating a diversified portfolio of hedge funds costs money. Of course, having a concentrated portfolio of hedge funds costs money as well. The investor is exposed to strategy as well as manager risks. Thus, like many other financial decisions faced by investors, there is a trade-off.

Suppose an endowment decides to dedicate a portion of its portfolio to hedge funds. Here are a few important parameters that the investment manager should take into account.

The initial cost of finding and evaluating a hedge fund is around $100,000. The annual monitoring cost will be around $50,000 per year.[1] Of course, one may decide to cut some corners and spend less on due diligence. There will be cost associated with it. Studies have shown that more than 50% of fund failures are due to operational risks. In addition, if enough resources are not spent on evaluation of fund managers, then there is a greater chance that a poor performing fund is selected. Even if one spends the full amount on fund evaluation, there is a reasonable chance that the fund will underperform its peers. After all, alpha generation is close to a zero-sum game and not all active managers can be above average.

To create a diversified portfolio of hedge funds where the portfolio covers more than one strategy and each strategy has more than one manager, the endowment should consider a portfolio of about 15 managers. The total cost of creating this portfolio is about $1,500,000 in the first year and $750,000 annually going forward. What level of "alpha" should the portfolio provide to make this investment justifiable? If this were a one-year investment, then the calculation would be simple. Assuming a 2% annual alpha, the size of the portfolio must be $1,500,000/2% = $75,000,000. If we assume that 20% of the portfolio has to be turned over every 4 years, and the portfolio continues to produce 2% alpha each year, then the minimum allocation should be about $50,000,000, with each manager receiving around $3.5 million. Finally, if we assume that 10% of the entire portfolio is allocated to hedge funds, then the entire portfolio should be around $500 million.

Our endowment is likely to run into another problem. Large, reputable, and top-performing funds are difficult to find and, when you find them, the minimum investment is likely to exceed $3.5 million. The more likely figure is $10 million. Thus, the minimum size of the hedge allocation is about $150 million, with the size of the entire portfolio being about $1.5 billion. Of course, this is a relatively small figure for most institutional investors. However, it will be wise not to allocate more than a small percentage of a portfolio to a single hedge manager in order to reduce the manager risk. Therefore, as the size of the portfolio increases, the investment manager will need to find, evaluate, and monitor more managers. It is safe to assume that while the first 20 managers could be strong alpha generators, the last 20 managers may find it difficult to match the average performance of their peers. As a result, as the portfolio increases in size, the allocation to hedge funds may have to grow at an increasing rate to justify the costs of the investment.

The above calculations become more complex, and the minimum investment size may increase further if we add other risks or costs. For example, headline risk tends to be higher for hedge funds and other private placement products. In addition, cross-sectional variation among active managers is much higher than passive managers. Studies have shown that the difference between top 10% and bottom 10% active managers is 10 times greater than the difference between top and bottom passive managers. Finally, in recent years many hedge fund managers have failed to deliver significant alpha.

In this example, we have ignored a relatively simple solution to the above problem. Our hypothetical endowment could choose to invest in a fund of funds, which may provide access to a diversified portfolio of hedge funds in exchange for another layer of fee. With some modification, the above calculation can be applied to a fund of funds. That is, what is the minimum AUM for a fund of funds so that it can perform rigorous evaluation and monitoring of its managers and remain profitable? It appears that one should be extra careful before investing in a single fund of funds that has less than $1 billion in assets under management. It may be difficult for smaller funds of funds to create diversified portfolios of hedge funds while performing rigorous evaluation of their managers.

Hossein Kazemi, Editor

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[1]See "Testimony of Andrew K. Golden, President of the Princeton University Investment Company, presented to the Financial Services Committee, United States House of Representatives" (March 13, 2007). Available at: www.house.gov/apps/list/hearing/financialsvcs_dem/ht031307.shtml, and Brown, Stephen J. and Fraser, Thomas L. and Liang, Bing, Hedge Fund Due Diligence: A Source of Alpha in a Hedge Fund Portfolio Strategy (January 21, 2008). Available at SSRN: http://ssrn.com/abstract=1016904

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Article submissions for future issues of *Alternative Investment Analyst Review* are always welcome. Articles should cover a topic of interest to CAIA members and should be single-spaced. Additional information on submissions can be found at the end of this issue. Please email your submission or any questions to **AIAR@CAIA.org**.

Chosen pieces will be featured in future issues of *AIAR*, archived on **CAIA.org**, and promoted throughout the CAIA community.

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ABSTRACT: During the last decade, two deep bear markets (results of the high tech bubble and the subprime mortgage crisis) have challenged conventional wisdom in finance, including modern portfolio theory (MPT) and the efficient market hypothesis (EMH). As an alternative to these traditional viewpoints, the adaptive markets hypothesis (AMH) proposed by Professor Andrew Lo of MIT Sloan School of Management helps to explain the importance of macro factors and market sentiment in driving asset returns.

This article examines some of the shortcomings of MPT and the EMH and introduces the framework of the adaptive investment approach, under which investors can adjust their investments to reflect economic regimes, ongoing market returns, or market volatility. This approach has the potential to deliver consistent returns in any market environment by dynamically taking positions in the financial assets that are perceived as likely to have the best returns, given current market conditions.

ABSTRACT: *AIAR* interviews CAIA Member Kathryn Kaminski about her new book, *Trend Following with Managed Futures: The Search for Crisis Alpha* (co-authored with Alex Greyserman).

ABSTRACT: Increased investment in the commodity markets has challenged the reported diversification benefits of commodities and triggered investment firms to improve the methodology behind their indices. As a result, investors must consider three different generations of commodity indices; the question is, "Which index still provides diversification benefits?"

This article addresses this question for traditional U.S. investors by considering seven commodity indices from May 1991 to June 2013, covering all three generations. Using spanning tests, the research results show that the first generation indices no longer provide benefits in portfolio diversification. Evidence for the second generation indices is mixed, while the third generation indices still offer improvements with regard to portfolio diversification.

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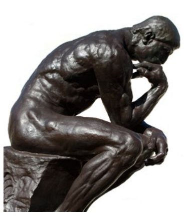
ABSTRACT: This article introduces assimilation funds as a new approach to invest capital in startups. Instead of funding startups and hoping for extraordinary returns, an assimilation strategy recommends diversifying early stage capital across the strategic value chain of selected portfolio companies. Such an asset allocation allows investors to reap rewards when investee companies perform strongly, while capping downside risk through diversification and collateral.

The article provides the underlying theory of these financial instruments, their asset allocation, and their return characteristics. It shows how the approach is helpful for venture capital firms and other investment firms. Finally, it compares the approach to traditional venture capital practices and points out its advantages and disadvantages from different viewpoints.

ABSTRACT: In this article, the authors study the procyclical behavior of hedge funds in relation to the portfolio manager and the investor—an often-neglected topic in hedge fund literature. Using spectral analysis, they show that hedge fund returns display fluctuations at the business cycle frequency and that these spectra are quite different from those of the market portfolio. This suggests that hedge fund returns are predictable to a certain degree.

The authors continue with a study of the cyclical behaviour of alpha and beta, finding that hedge fund managers tend to increase their beta, and thus their leverage, in expansionary periods and to deleverage during recessions. The study concludes with a cross-sectional measurement of diversification showing that good diversification opportunities in the hedge fund industry continue to exist, particularly during times of recession.



ABSTRACT: How is it that one day the headlines are filled with cautions over unmet expectations from hedge fund investments and the next day we hear about record inflows and proclamations of $3 trillion in AUM by year-end? Some institutions have been disappointed by the performance of hedge funds, while others are highly optimistic about

These articles reflect the views of their respective authors and do not represent the official views of AIAR or CAIA.

Adaptive Investment Approach

Henry Ma
Founder and Chief Investment Officer, Julex Capital

During the last decade, we have experienced two deep bear markets as results of the Internet bubble burst and the subprime mortgage crisis. Many investors lost significant amounts of their wealth, and as a result, some of them had to put their retirement plans on hold. The traditional investment theory such as mean-variance (MV) portfolio theory, the efficient market hypothesis (EMH), and associated practices such as buy-and-hold, or benchmark-centric investments have proven inadequate in helping investors to achieve their financial goals. Market participants are now questioning these broad theoretical frameworks and looking for alternative ways to make better investment decisions.

As an alternative, the adaptive markets hypothesis (AMH), proposed by Lo (2004, 2005, 2012), in which intelligent, but fallible investors constantly adapt to changing market conditions, helps to explain the importance of macro factors and market sentiment in driving asset returns. It allows for evolution towards market efficiency and a dynamic and adaptive approach to investing. It may serve investors well in the ever-changing financial markets.

In this article, I will address some of the shortcomings of modern portfolio theory and the efficient market hypothesis and the drawbacks in their application. More importantly, I will introduce a framework of adaptive investment, in which investors try to find the best investment opportunities by adapting constantly to changing economic and market conditions. In its simplest form, in a risk-seeking ("risk on") environment, investors allocate their portfolios to risky assets such as equities, commodities, real estate, and high yield bonds; in a risk-avoidance ("risk off") environment, investors flight to safety by allocating portfolios to Treasuries and cash. Although there are numerous ways to define and estimate market regimes, these types of strategies aim to deliver consistent returns by adapting portfolios to constantly changing market conditions. Instead of forecasting future returns under the traditional active investment framework, the adaptive approach focuses on identifying the market regimes and conditions and adjusting the investment strategies accordingly.

This approach differs from the absolute return strategy in that it generates returns through market betas rather than uncorrelated alpha, although it aims to provide consistent returns regardless of market conditions. It also differs from traditional beta investments, because it does not follow any particular benchmark. Adaptive investment is similar to tactical asset allocation (TAA) or global macro. TAA normally under/over-weights certain asset classes relative to its strategic targets. The TAA managers normally make tactical decision mainly based on their return forecasts. There is no need to forecast returns with the adaptive investment approach. A global macro strategy typically allocates capital to undervalued asset classes and shorts overvalued asset classes. In addition, it employs leverage to enhance returns based on the managers' views. The adaptive investment approach is a long-only strategy. In addition, given ETFs rapid development in recent years, they have become ideal instruments for the implementation of adaptive investment strategies due to their low cost and high liquidity.

I will introduce three different adaptive approaches. In the first approach, investors adapt their portfolios to the ongoing economic and business conditions. This has the flavor of regime-based investment. In the second approach, investors adapt to recent market performance. Momentum strategies and trend-following strategies fall into this category. In the third approach, investors adjust their portfolios based on recent volatility. Risk-parity and risk targeting are examples of this approach. In the end, I will discuss an integrated approach that incorporates all three elements into a robust investment process. In addition, I will show how this approach can help to enhance returns and diversify risks in the context of asset allocation.

The Shortcomings of Modern Portfolio Theory and Its Implementation

In the wake of the financial crisis of 2007–2009, modern portfolio theory and the efficient market hypothesis seem inadequate in explaining market behaviors. As Lo (2012) pointed out, most of the assumptions in the modern portfolio theory are only approximations of the real world. Those assumptions include:

- The risk/return relationship is static across time;
- The parameters such as expected return, expected standard deviation, and correlation, and CAPM beta can be accurately estimated;
- The return distributions are stationary, static, and can be accurately estimated;
- Market participants are rational and therefore markets are efficient.

These assumptions lead to many results, including the presence of a linear positive risk/return tradeoff across all financial assets. Although these assumptions may be good approximations in the long-run, most of them are hardly the case within reasonable investment horizons of most investors, e.g. 5–20 years. In a shorter horizon, all of the parameters are highly unstable. Moreover, when modern portfolio theory and the efficient market hypothesis were developed between the 1950s and 1970s, the majority of empirical research was done on the U.S. equity and bond markets. Nowadays, the asset classes and geographical regions are much broader, which makes these assumptions appear more problematic. In this section, I will examine some of shortcomings in the theory and its related practices.

The risk/return relationship breaks down when including international equities and other asset classes

After Harry Markowitz completed his pioneering work on the modern portfolio theory in the 1950s, many financial economists and practitioners have tested the theory empirically with data from the U.S. equity and bond markets. However, over the last few decades, as investors have become more sophisticated and the economy has become more globalized, the asset classes in an investor's asset allocation model are broader and geographically more diverse. The traditional linear relationship between risk and returns, which is approximately right if we are considering only equities and bonds, breaks down when more asset classes are introduced.

Exhibit 1 shows the return/risk relationship among five asset classes: U.S. Large Cap Equity, International Equity, REITs, Commodities, and Treasuries. I used monthly data including the S&P 500 Index, MSCI EAFE Index, S&P GSCI Commodity Index, FTSE All Equity REIT Index, and Barclays Treasury Index between January 1970 and September 2013 in the calculations. It is clear that international equities and commodities are inferior, offering lower returns with higher volatility. This may present a problem for an asset allocator. In a mean-variance efficient portfolio, it may be difficult to incorporate international equities or commodities because an unconstrained portfolio optimization does not favor asset classes with lower expected returns and higher risks.

Average returns are hardly static

To apply modern portfolio theory, practitioners need to estimate expected returns. The common practice is to use historical averages as starting points and then to adjust them, either through quantitative models or qualitative judgments. However, the average return estimates are so unstable that the estimation of expected returns has always resulted in unsatisfactory outcomes.

Exhibit 2 shows the S&P 500 Index's average annual returns for five-year, ten-year, and twenty-year horizons between January 1928 and September 2013. For a five-year investment horizon, an investor's average returns range from -20% to +30% annually; for a ten-year investment horizon, the average returns range from -10% to +15%; for a twenty-year horizon, the average investment returns go from -4% to +14%. Although with increasing investment horizons, the average returns be-

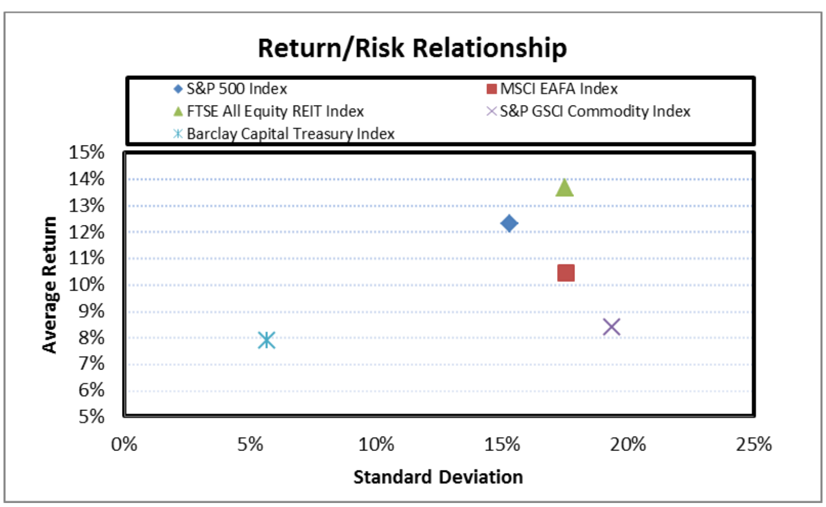


Exhibit 1 The Risk/Return Relationship Across Asset Classes

Source: Bloomberg

come more certain, the range of variation is substantial. Whether a person will end up on social welfare or living in an extravagant beach house after he retires will all depend on the timing of his investments.

Volatility and standard deviation are constantly changing

Another assumption under MPT is that the asset return distribution is stationary. In fact, neither the average returns nor the standard deviations, the second moment of a distribution, are stable over time.

Exhibit 3 illustrates the historical 12-month annualized standard deviation of the S&P 500 Index between January 1928 and September 2013. The volatility level ranges from a high of 75% to a low of 5%. The wide ranges of the standard deviation and volatility make it hard for any market participant to have confidence in their estimates.

Correlations are unstable and trending higher in the new millennium

One of the more important inputs in portfolio construction is correlation, which is assumed to be stationary and stable over time. Exhibit 4 shows the 12-month correlation between the S&P 500 Index and the MSCI EAFE Index between January 1971 and September 2013. The correlation ranges from -0.2 to 0.94, which is hardly stable over time. In the new millennium, the average correlation was 0.83 vs. 0.42 between January 1971 and December 1999. This may reflect the trend of

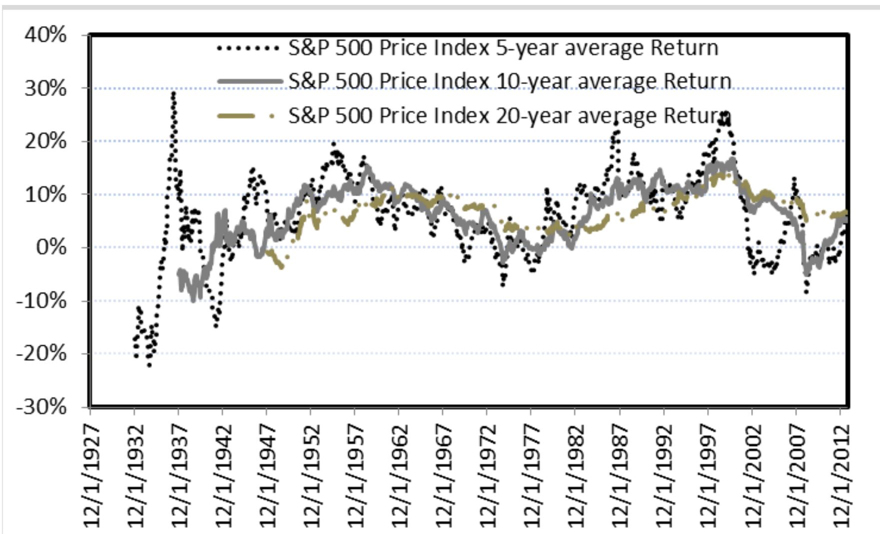


Exhibit 2 Historical Average Returns of the S&P 500 Price Index
Source: Bloomberg

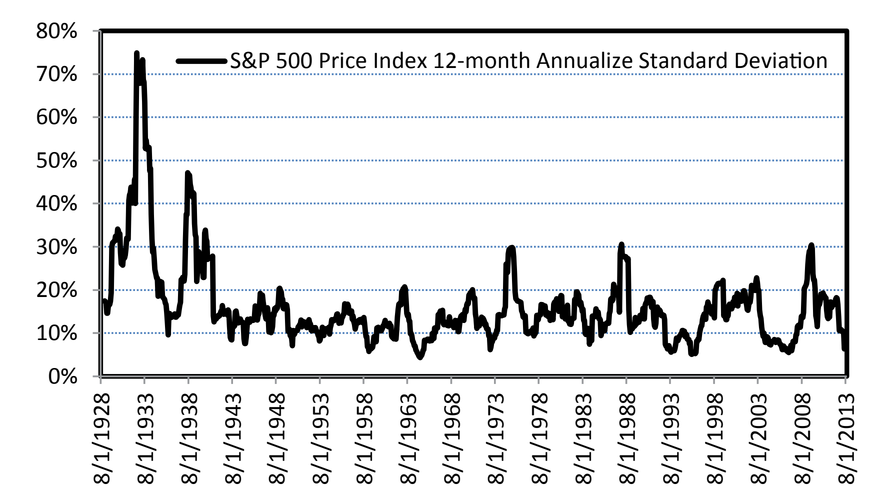


Exhibit 3 Historical 12-month Standard Deviation of the S&P 500 Index
Source: Bloomberg

economic integration and globalization.

In summary, although modern portfolio theory may be a good approximation of market reality over the long-run in developed markets, all of the parameters of mean-variance efficient frontier or portfolio optimization are hard to estimate accurately. The traditional implementation with historical averages will not give satisfactory results for a strategic asset allocation.

The Efficient Market Hypothesis (EMH) and Suboptimal Investment Practices

In finance, the efficient market hypothesis (EMH) asserts that financial markets are "informationally efficient." As a result, investors cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis, given the information available at the time that the investment is made. Normally, the excess returns come from two different sources: market-timing and security selection. Under EMH, both sources of excess returns are hard to generate. However, the finance industry tends to believe that it is easier to generate excess return – "alpha" – from security selection than it is from market timing. Thus, some of the common industry practices during last few decades have resulted in suboptimal outcomes for investors. For example,

- Investment advisors recommend buy and hold strategies to investors without much consideration of the ongoing market conditions. As a consequence, many investors suffered unbearable losses when the Internet and subprime housing bubbles burst.
- Money managers are obsessed with beating their benchmarks and managing tracking errors. As a result, the industry delivers negative aggregate alpha to investors as a whole. Moreover, the industry did not provide enough downside protection during market downturns.
- Hedge fund managers, who are supposed to generate alpha, are facing diminishing returns as the industry grows, and increasingly resort to repackaging beta as alpha.

Buy and Hold

Buy and hold is an investment strategy based on the view that, in the long-run, financial assets generate a good rate of return despite periods of volatility or decline. This viewpoint also holds that short-term market timing, i.e. the concept that one can enter the market on the lows and sell on the highs, does not work; attempting timing gives negative results. One of the strongest arguments for the buy and hold strategy is the efficient market hypothesis (EMH): If every security is fairly valued at all times, then there is really no point to trade.

The biggest drawback of the buy and hold strategy is that the occasional significant drawdowns in the markets destroy not only investors' wealth, but also investors' confidence in investing in the markets again after deep losses. Historically, major market drawdowns were deep and it took a long time to recover from the losses (see Exhibit 5). In the United States, the worst drawdown happened during the Great Depression. The

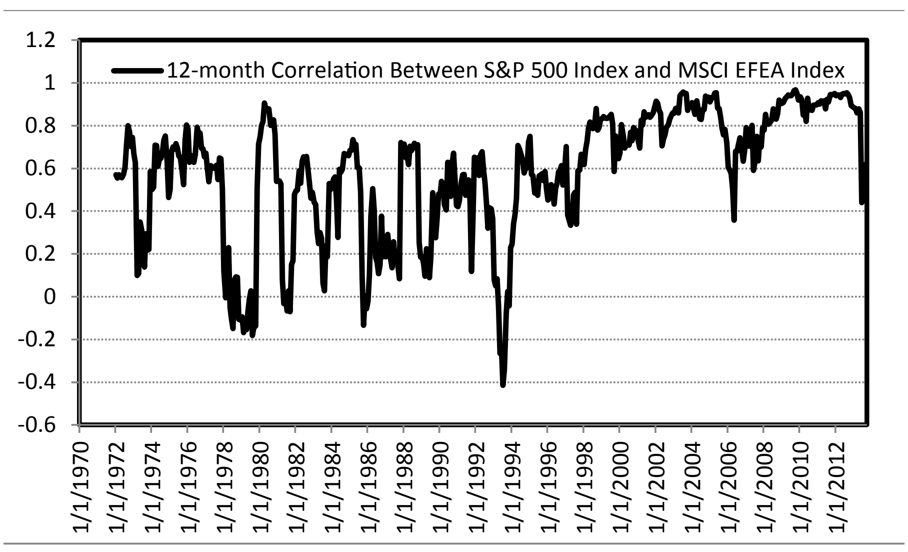


Exhibit 4 Historical 12-month Correlations between the S&P 500 Index and the MSCI EAFE Index

Source: Bloomberg

market declined by 86% and only recovered fully after 22 years. The second worst drawdown occurred during the financial crisis in 2007–2009. The market tumbled by 53% and has just recovered after four and a half years. The Japanese stock markets are still 62% below the highs reached in 1989, before the Japanese housing bubble burst.

The buy-and-hold investors suffered significant losses during those periods. Even worse, many investors became panic sellers who sold their stocks at the bottom of the markets and were afraid of getting back in when the new bull market began. The buy and hold strategy is only good for bull markets. It worked very well in the bull markets of the 1980s and 1990s, but did not work in the last decade, when we experienced two deep bear markets. It does not provide downside protection. One may argue that the market always recovers after losses. However, time may not always be on an investor's side, especially for a retiree who lives on his savings and does not have the luxury of waiting years for a recovery.

Benchmark-Centric Investment

Under EMH, no one can consistently outperform the markets, no matter whether he is market-timer or stock picker. However, the asset management industry tends to believe they can generate excess returns through security selection. It is possible that the examples of legendary stock pickers such as Warren Buffet or Peter Lynch, give everybody some hope. To prove the value-added or to measure the performance of asset managers, the industry adopts an approach of managing investment strategies against certain benchmarks. For example, managers in the Morningstar Large Cap Blend category normally use the S&P 500 Index as a benchmark. Although this approach serves many purposes, such as defining an asset manager's universe and measuring manager's performance, the approach has significant drawbacks as well:

- It puts constraints on what managers can do and limits their ability to generate returns;
- Managers are evaluated by relative performance. The risks are measured by tracking errors, rather potential losses or drawdowns. This approach implicitly does not intend to meet investors' goals of preserving capital or achieving stable returns. For example, during the financial crisis of 2007–2009, the S&P 500 Index lost 37%. If a large cap manager managed to outperform S&P 500 Index by 2%, he had beaten his benchmark, but still lost 35% of his investors' money.
- Fierce competition among managers to generate alpha leads to negative-sum-game in aggregate. As the asset management industry grows and institutional investors become more dominant players in the markets, the opportunities to generate excess returns tend to diminish. After the management fees, the net average alpha has become negative in many asset categories.

In an article published in *Journal of Finance*, Fama and French (2010) stated, "The aggregate portfolio of U.S. equity mutual funds is close to the market portfolio, but the high costs of active management show up intact as lower returns to investors. Bootstrap simulations suggest that few funds produce benchmark adjusted expected returns sufficient to cover their costs," after examining the performance during 1984–2006 of actively managed U.S. mutual funds that invest primarily in U.S. equities. It confirms the view that most of the active mutual funds underperformed their benchmarks, especially on an after-fee basis.

Selling Beta as Alpha

The efficient market hypothesis also takes its toll on hedge funds as the industry grows. Hedge funds, as a

Market Index	Event	Begin	End	Loss	Time to Recover
S&P 500 Index	Great Depression	Aug-1929	Jun-1932	-86%	22 years
S&P 500 Index	Oil Crisis	Dec-1972	Sep-1974	-46%	6 years
S&P 500 Index	Internet Bubble Burst	Mar-2000	Feb-2003	-44%	5 years
S&P 500 Index	Subprime Crisis	Oct-2007	Feb-2009	-53%	4 years
Nasdaq Index	Internet Bubble Burst	Mar-2007	Sep-2002	-81%	26% Below Peak
Nikkei Index	Housing Bubble Burst	Dec-1989	Apr-2003	-78%	62% Below Peak

Exhibit 5 Severe Market Downturns
Source: Bloomberg

pure alpha generator, have enjoyed spectacular growth over the past 15 years, climbing from about 120 billion dollars of assets under management (AUM) in 1997 to about 2 trillion dollars in assets in recent years, according to BarclayHedge. Despite a temporary outflow after the recent financial crisis, total AUM have almost clawed back to the peak of 2007. There are many reasons for this growth. But undoubtedly the most important one is hedge funds' ability to deliver superior uncorrelated returns accompanied by reduced volatility. Proponents of hedge funds point out that the out-sized performance is possible due to their lightly regulated status, flexible investment process, skilled managers, and the ability to use unconventional assets and strategies, such as investing in illiquid assets, taking short positions, using leverage or derivatives, and taking bets on event arbitrage.

However, hedge funds operate in extremely competitive markets, where information and trading advantages are unlikely to last for long. As the industry becomes bigger and assets under management grows, it has become harder and harder to deliver alpha. Many managers have found that markets inefficiencies disappear quickly. In addition, when managing a large amount of assets, the managers find it difficult to execute trades without moving the market. Even worse, many hedge funds are chasing the same opportunities. Meanwhile, attracted by the high fees and high incentive pay structure, many unskilled me-too managers have started to run hedge funds. As a result, hedge fund returns have declined steadily over the past two decades. The efficient market hypothesis and the law of diminishing returns are taking effect in the hedge fund industry.

To prove this point, I have calculated annualized five-year rolling returns of Hedge Fund Research Hedge Fund Weighted Index, as shown in Exhibit 6. There is a very clear downward trend in aggregate hedge fund returns, declining from 20% in 1994 to around 1% in 2012, although it rises slightly in 2013.

The other undesirable observation is that the correlations between hedge fund performance and equity markets are increasing over the years (see Exhibit 7 for details). This may imply that hedge fund managers are taking more beta risks, as it is getting harder to find alpha opportunities. Under the tremendous pressure from competition and investors, hedge fund managers may have engaged in the practice of "packaging beta as alpha," which undermines the original objective of hedge funds – the delivery of high uncorrelated returns.

The Adaptive Market Hypothesis

In the last two sections, I have examined some of the shortcomings of modern portfolio theory and its implementation as well as some of the suboptimal investment practices as the efficient market hypothesis (EMH) takes effect and markets become more efficient over time. Investors may wonder if there is a better way to

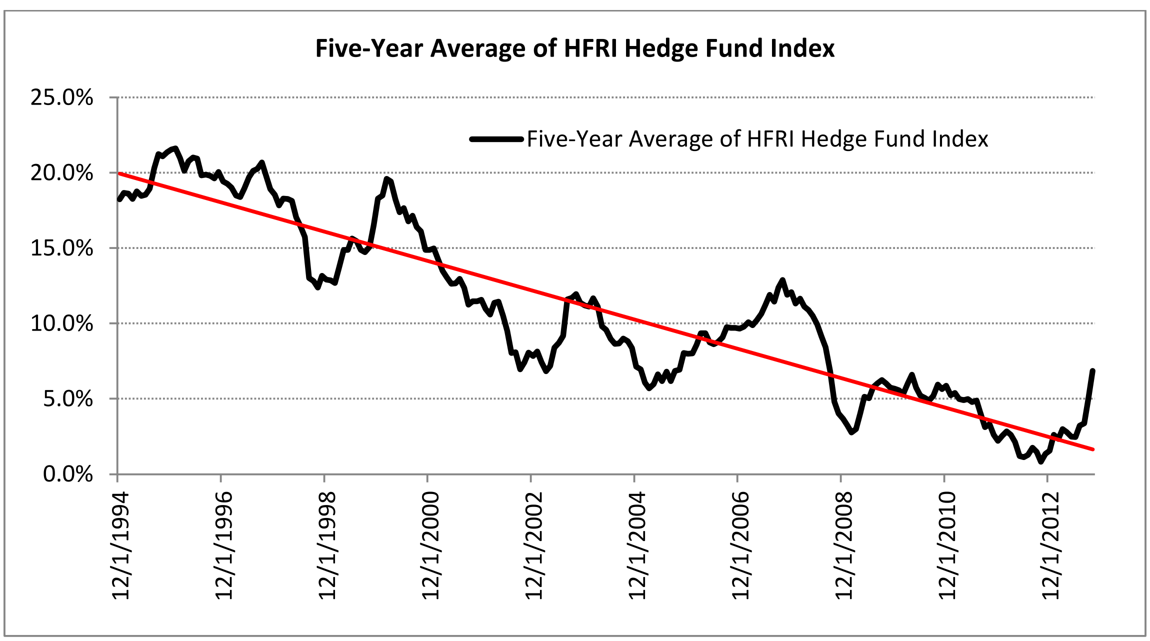


Exhibit 6 Historical 5-Year Average Hedge Fund Performance

Source: Hedge Fund Research

invest. To answer the question, I will show the adaptive investment approach could provide a good alternative to traditional methods. In this section, I will survey the theory of adaptive market hypothesis (AMH), which serves as a theoretical foundation of the adaptive investment approach.

The adaptive market hypothesis, as first proposed by Andrew Lo in 2004, is an attempt to combine the rational principles based on the efficient market hypothesis with the irrational principles of behavioral finance, by applying the theory of evolution to the interactions of financial market participants: competition, mutation, adaptation, and natural selection.

Under this theory, the traditional theories of modern financial economics such as EMH can coexist with behavioral models. According to Lo, much of the "irrational" investor behavior — loss aversion, overconfidence, and under/overreaction—are, in fact, consistent with an evolutionary model of individuals adapting to a changing environment using simple heuristics derived from human instincts such as fight or flight, greed, and fear. Lo argued that the adaptive market hypothesis can be viewed as a complement to the efficient market hypothesis, derived from evolutionary principles: "**Prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of 'species' in the economy**." By species, he means distinct groups of market participants, such as retail investors, pension fund managers, mutual fund managers, hedge fund managers, and market makers, each behaving in a common manner.

If a large number of market participants are competing for scarce resources within a single market, then that market is likely to be highly efficient. On the other hand, if a small number of participants are competing for abundant resources, then that market will be less efficient. Market efficiency cannot be evaluated in a vacuum, but is highly context-dependent and dynamic. Simply stated, the degree of market efficiency is related to environmental factors characterizing market ecology, such as the number of competitors in the market, the magnitude of profit opportunities available, and the adaptability of the market participants.

According to Lo, the adaptive market hypothesis has several important implications that differentiate it from the efficient market hypothesis:

- A relation between risk and return may exist, but it is unlikely to be stable over time.
- The market efficiency is not an all-or-nothing condition, but a continuum. As a result, there are opportunities for arbitrage.
- Investment strategies, including quantitatively, fundamentally, and technically based methods, will perform well in certain environments and poorly in others. Therefore, investment policies must be

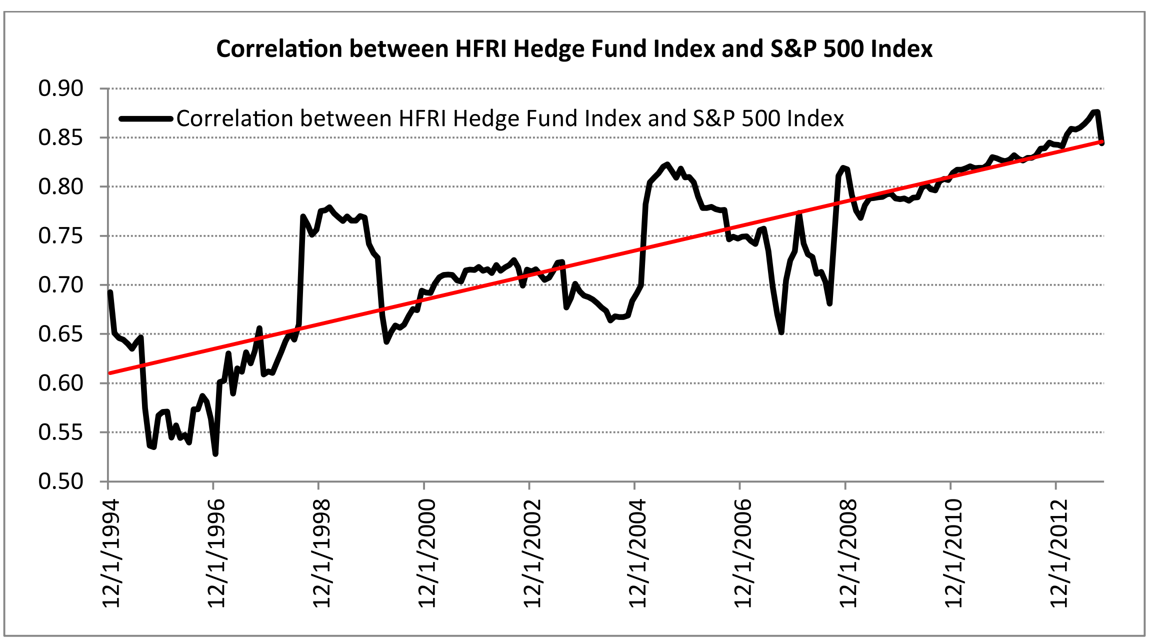


Exhibit 7 Historical Correlations between the Hedge Fund Index and the S&P 500 Index

Sources: Hedge Fund Research & Bloomberg formulated with market condition changes in mind, and should adapt accordingly.

- The primary objective of risk-taking is survival; profit and utility maximization are secondary. The key to survival is adaption. As the risk/reward relationship varies, a better way of achieving a consistent investment returns is to adapt to changing market conditions.

Lo (2012) further pointed out, "The AMH has several implications, including the possibility of negative risk premia, alpha converging to beta, and the importance of macro factors and risk-budgeting in asset-allocation policies."

Adaptive Investment Approach

The most important implication of the adaptive market hypothesis (AMH) is that any investment strategies aiming for a long-term success must have the ability of adapting to the ever-changing market conditions. In this section, I will introduce three different ways to develop investment strategies with the ability of adapting to economic regimes, market returns, or market volatility. In the end, I will discuss an integrated approach, which incorporates all three elements to deliver more robust results and better risk-adjusted returns.

Adaptive Regime Approach

There is a well-established relationship between financial market returns and business cycles. Normally, equity markets tend to perform well during economic expansion and underperform during business contraction. Exhibit 8 shows the stock market performance between January 1957 and October 2013. During recessions indicated in the shaded areas in the graph, the S&P 500 Index was likely to perform poorly.

Many economists have developed complex indicators or sophisticated models to identify the business cycle or economic growth regimes. For example, Stock and Watson (2002) proposed a diffusion index approach to forecasting macroeconomic variables. Hamilton (2005) summarized how a regime-switching model can be used to forecast business cycles. Here I will use a simple and popular indicator – the Weekly Leading Index (WLI) published by Economic Cycle Research Institute (ECRI), to identify economic regimes and to show how an adaptive regime approach can help to improve risk-adjusted returns. How to best forecast or identify the economic regimes is out of the scope of this paper.

The ECRI publishes the WLI and WLI Growth weekly. The components of the index are considered proprietary. ECRI says that it uses some proprietary components in addition to the ten components that the Conference Board uses. These ten components include:

- Average weekly hours, manufacturing;

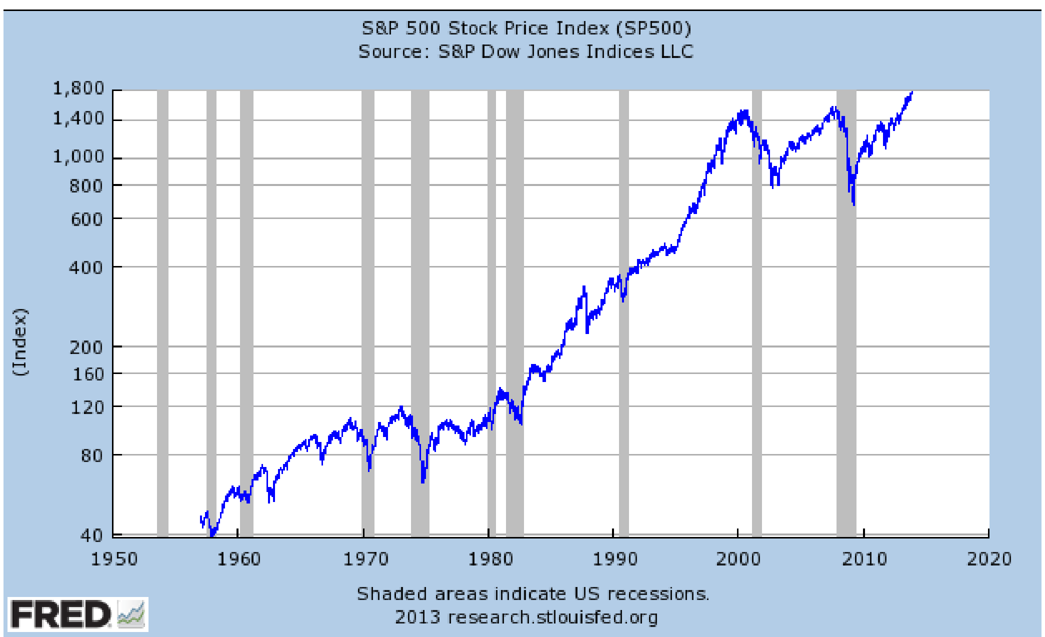


Exhibit 8 Stock Market Performance and the Business Cycle

Source: Federal Reserve Bank of St. Louis

- Average weekly initial claims for unemployment insurance;
- Manufacturers' new orders for consumer goods and materials;
- ISM Index of New Orders;
- Manufacturers' new orders for non-defense capital goods excluding aircraft orders;
- Building permits, new private housing units;
- Stock prices of 500 common stocks;
- Leading Credit Index™;
- Interest rate spread of 10-year Treasury bonds less federal funds;
- % average consumer expectations for business conditions.

Exhibit 9 shows the relationship between WLI growth and the S&P 500 Index performance. The stock markets seemed to have a positive correlation with WLI growth. The positive WLI growth indicates the regime of economic expansion and a bull market while the negative WLI growth indicates the regime of economic contraction and a bear market. For this reason, the adaptive regime approach here follows a simple rule:

Invest in S&P 500 Index,	if WLI growth >0
Invest in Barclays Capital US Aggregate Bond Index,	otherwise

Exhibit 10 summarizes the performance of the investment rule with the monthly data between January 1970 and September 2013. The portfolio is rebalanced monthly following the rule. Transaction costs are ignored for illustration purpose only. Compared to a buy-and-hold strategy involving the S&P 500 Index, the simple adaptive regime approach dramatically reduces the drawdown risk from 51% to 23%. In addition, the risk-adjusted return, measured by Sharpe ratio, also improves from 0.38 to 0.51. Of course, we can always find a more sophisticated rule to get better performance, but the objective of this article is only to show how the adaptive investment rule works, rather than propose optimal trading rules.

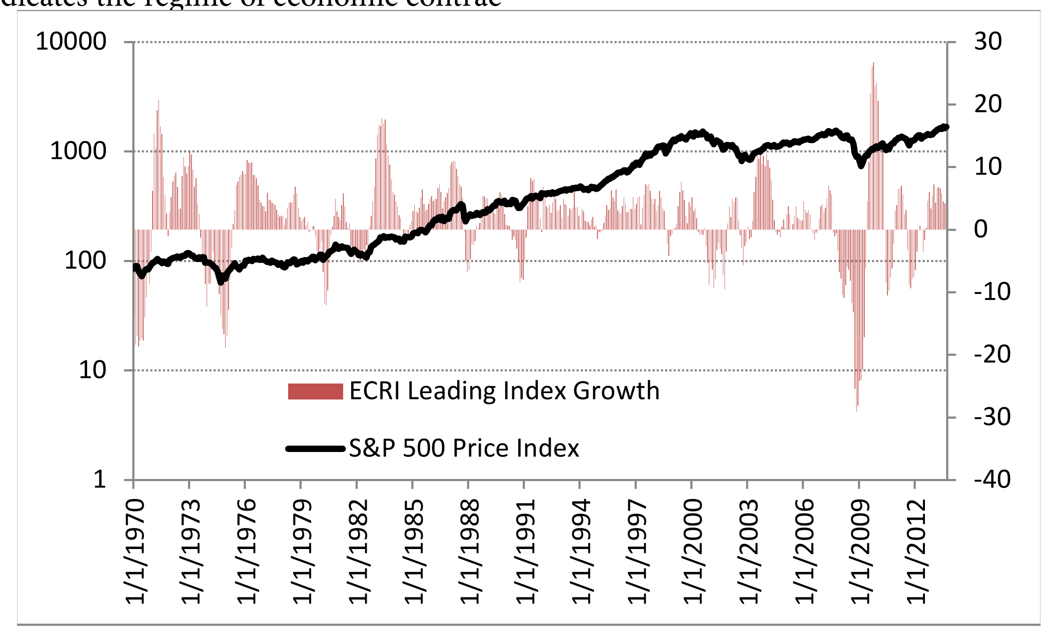


Exhibit 9 Stock Market Performance and WLI Growth
Source: ECRI & Bloomberg

Performance Metrics	Adaptive Regime Approach	S&P 500 Index
Average Monthly Return	0.9%	0.9%
Monthly Standard Deviation	3.4%	4.5%
Annualized Return	11.0%	11.0%
Annualized Standard Deviation	11.7%	15.5%
Sharpe Ratio (risk-free rate = 5%)	0.51	0.38
Maximum Drawdown	-23.3%	-50.9%
Expected Years to Recover	2.1	4.6

Exhibit 10 Performance Statistics of the Adaptive Regime Approach
Source: Author's calculations & Bloomberg

Adaptive Return Approach

Another adaptive approach is to adapt investment strategies to ongoing market performance such as market returns. Momentum strategies, which buy securities with the highest past returns and sell securities with lowest past returns, can be classified as an example of the adaptive return approach. It was shown that stocks with strong past performance continue to outperform stocks with poor past performance in the next period, with an average excess return of about 1% per month (Jegadeesh and Titman, 1993). Although it is hard to explain under EMH, the momentum strategy can be readily explained under the adaptive market hypothesis and behavioral finance theory. Human beings are normally slow to adapt at beginning when things start to change. As more and more people adapt to the changes, human beings tend to overreact to the changes at a later time. This adaption process creates long-lasting trends, which momentum strategies can take advantage of.

Trend-following strategy is another example of adaptive return approach. Trend-following is an investment strategy based on the technical analysis of price actions. Traders and investors using a trend-following strategy believe that prices tend to move upwards or downwards over time and that the price trends will last for a while. They try to take advantage of these trends by observing the current direction and using it to decide whether and when to take a long or short position. There are a number of different techniques and time frames that may be used to determine the general direction of the market to generate a trading signal, these including the moving averages and channel breakouts. Traders who use these strategies do not aim to forecast specific price levels; they simply follow the trend and ride it. Due to the different techniques and time frames employed by trend-followers, trend-following traders as a group are not always correlated to one another. Basically, trend-following strategy aims to adapt to ever-changing price trends in the markets.

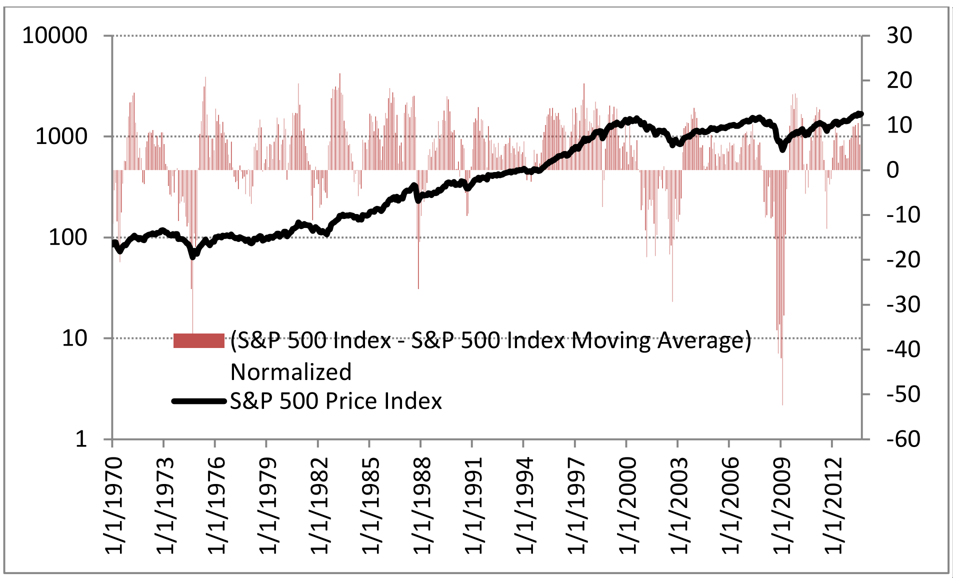


Exhibit 11 Stock Market Performance and Market Moving Average

Source: Bloomberg

Performance Metrics	Trend Following	S&P 500 Index
Average Monthly Return	1.1%	0.9%
Monthly Standard Deviation	3.5%	4.5%
Annualized Average Return	12.8%	11.0%
Annualized Standard Deviation	12.0%	15.5%
Sharpe Ratio (risk-free rate =5%)	0.65	0.38
Maximum Drawdown	-23.3%	-50.9%
Expected Years to Recover	1.8	4.6

Exhibit 12 Performance Statistics of the Adaptive Regime Approach - Trend Following

Source: Author's calculations & Bloomberg

In this section, I will introduce two examples to show how the adaptive return strategies work. In the first example, I will apply a trend-following approach to the two asset cases we have discussed previously. In the second example, I will apply a momentum strategy in a multi-asset setting.

Example One: Trend Following Strategy

In this section, I define a market trend with 9-month moving average. Exhibit 11 shows the relationship between the S&P 500 index and the 9-month moving average of the S&P 500 Index. When the S&P 500 Index is trading above its moving average, the market tends to rise and verse versa. For this reason, the trend-following strategy here follows a simple rule:

Invest in S&P 500 Index, if S&P 500 is above its 9-month simple moving average;
Invest in Barclays Capital US Aggregate Bond Index, otherwise.

Exhibit 12 summarizes the performance of the investment rule with the monthly data between January 1970 and September 2013. The portfolio is rebalanced monthly following the rule and transaction costs are ignored in the results for illustration purpose only. It is shown that the simple adaptive return approach not only improves the average annual return by 1.8%, but also dramatically reduces the drawdown risk from 51% to 23%. In addition, the Sharpe ratio increases from 0.38 to 0.65, compared to a buy-and-hold strategy of the S&P 500 Index.

Example Two: Momentum Strategy

Momentum is normally defined by the past performance over a given time horizon. Because there is no theory to pick the best horizon for momentum calculation, I use 3-month past returns to capture the medium term trend. Then I select four of the assets with the strongest momentum to create an equally-weighted portfolio. The portfolio includes 4 of the 14 asset classes listed in Exhibit 13. For all of the indexes in the table, there are corresponding ETFs traded in the markets. It is easy to create a portfolio with those ETFs to implement this strategy.

Exhibit 14 summarizes the performance of the momentum strategy with the monthly data between January 1970 and September 2013. The portfolio is rebalanced monthly. It is shown that the momentum strategy not only improves the average annualized return by 3.3%, but also dramatically reduces the drawdown risk from 51% to 21%. In addition, the Sharpe ratio goes up from 0.38 to 0.91. Figure 15 shows the cumulative value of an initial investment of $100 in 1970. It is clear that the momentum strategy has outperformed both the S&P 500 Index and a balanced portfolio of 60% S&P 500 and 40% Barclays Aggregate with lower volatility and drawdown.

Adaptive Risk Approach

In addition to adapting to economic regimes or market returns, investment strategies can be adapted to chang-

Asset ID	Category	Index	ETF
1	US Large Cap	S&P 500 Index	SPY
2	US Small Cap	Russell 2000 Index	IWM
3	International	MSCI EAFE Index	EFA
4	Emerging Markets	MSCI EM Index	EEM
5	US REITs	MSCI US REIT Index	VNQ
6	Infrastructure	Alerian MLP Index	MLPI
7	Gold	London Gold Fixing	GLD
8	Commodities	SPGC Commodity Index	GSG
9	High Yield	Barclays US HY Index	JNK
10	US Bond	Barclays US Aggregate Bond	AGG
11	Inflation	Barclays US TIPs	TIP
12	Medium-Term Treasuries	Barclays US 7-10 Year Treasuries	IEF
13	Long-Term Treasuries	Barclays US 20+ Year Treasuries	TLT
14	T-Bill		

Exhibit 13 Asset Classes

ing market volatility. In this section, I will show that some of the portfolio construction methods such as risk-parity, volatility-weighted portfolio, and risk-targeting fall into the adaptive risk framework. In practice, volatility and correlations are estimated with data from the recent past. This practice makes a portfolio adaptive to changing risk environment. In the period of rising volatility, the above methods can reduce exposures, and automatically lower risks and limit drawdown.

Example One: Risk-Parity Portfolio

Risk-parity is a portfolio management approach that focuses on the allocation of risk, usually defined as volatility, rather than the allocation of capital. The term "risk-parity" was first used by Qian (2005). The method attempts to equalize risk by allocating funds to a wider range of categories such as stocks, government bonds, credit-related securities, and inflation hedges, while maximizing gains through financial leveraging if necessary. The risk-parity approach asserts that when asset allocations are adjusted to the same risk level, the risk-parity portfolio can achieve higher Sharpe ratios, in addition to being more resistant to market downturns than traditional portfolios. Interests in the risk-parity approach have increased since the 2007–2009 financial crisis, as the risk-parity approach fared better than traditionally constructed portfolios.

Mathematically, suppose there are N assets with weights $W = \{w_1, w_2, ..., w_i, ..., w_N\}$ in a portfolio, then the standard deviation of the portfolio can be written as

$$\sigma_P = \sqrt{W^T \Sigma W}$$

where Σ is the covariance matrix of the N risky asset returns. Under risk-parity, every asset contributes the same amount of risk to the portfolio. Thus, the portfolio weights can be found by solving the following equation:

$$w_1 \times \frac{(\Sigma W)_1}{\sigma_P} = w_2 \times \frac{(\Sigma W)_2}{\sigma_P} = \cdots = w_i \times \frac{(\Sigma W)_i}{\sigma_P} = \cdots = w_N \times \frac{(\Sigma W)_N}{\sigma_P} = \frac{\sigma_P}{N}$$

under which the risk contributions are equal across all

Performance Metrics	**Momentum**	**S&P 500 Index**
Average Monthly Return	1.3%	0.9%
Monthly Standard Deviation	3.3%	4.4%
Annualized Average Return	15.4%	11.1%
Annualized Standard Deviation	11.4%	15.4%
Sharpe Ratio (risk free rate = 5%)	0.91	0.40
Maximum Drawdown	-21.1%	-50.9%
Years to Recover	1.4	4.6

Exhibit 14 Performance Statistics of the Adaptive Return Approach

Source: Author's calculations & Bloomberg

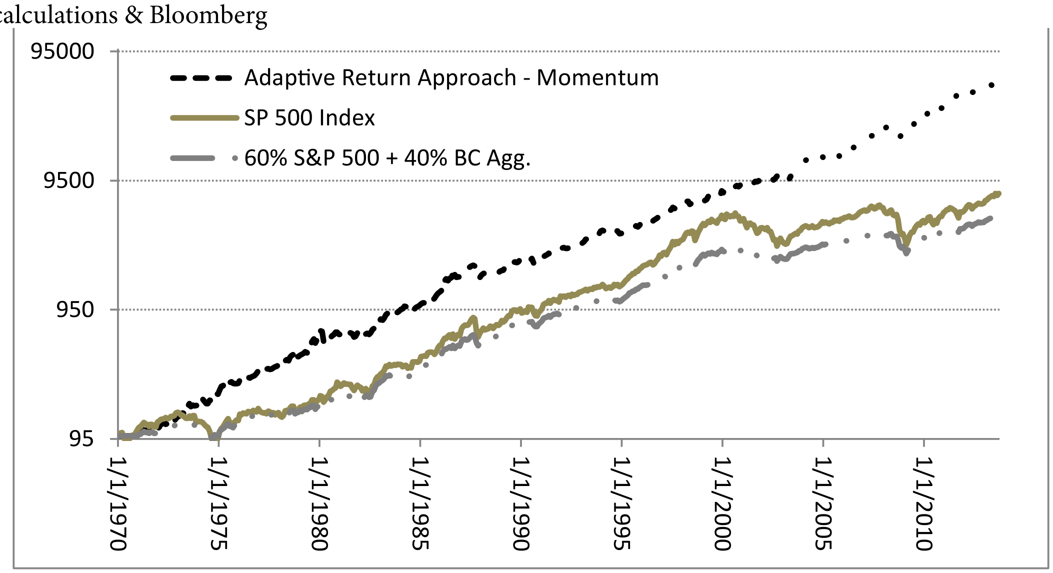


Exhibit 15 Cumulative Value of Initial Investment of $100

Source: Bloomberg

the assets. $(\Sigma W)_i$ is the ith row of the $N \times 1$ matrix ΣW.

Example Two: Volatility-Weighted Portfolio

The volatility-weighted portfolio is constructed with portfolio weights that are inversely related to the volatility, which is measured by standard deviation. The approach is a special (naive) form of the risk-parity approach, which intends to create more diversified and balanced portfolios. Under a special condition where correlations are all equal, each position contributes the same amount of risk to a volatility-weighted portfolio. This method has been widely used by commodity trading advisors (CTAs) for decades to construct the portfolios consisting of futures positions.

Mathematically, suppose there are N assets with weights $W = \{w_1, w_2, \ldots, w_i, \ldots, w_N\}$ in a portfolio, the weight of ith asset can be expressed as

$$w_i = \frac{1/\sigma_i}{\sum_1^N 1/\sigma_i}$$

where σ_i is the standard deviation of ith asset.

Exhibit 16 summarizes the performance statistics of both risk-parity and volatility-weighted portfolios compared with equally weighted portfolios. I use monthly data between January 1975 and September 2013 in the analysis. The thirteen asset classes (excluding T-Bills) used are shown in Exhibit 13 and standard deviation and correlation are calculated with 12 months of data points each month. All the portfolios are constructed without any leverage. There are two interesting observations here:

- There is not much difference between the risk-parity and volatility-weighted portfolios in terms of overall performance. This is not surprising because volatility plays a bigger role in determining the portfolio positions than correlation.
- The risk-adjusted return of the volatility-weighted portfolio is better than that of the equally weighted portfolio. More importantly, the portfolio drawdowns of both volatility-weighted and risk-parity portfolios are much smaller. This is not surprising either, because more weights have been allocated to bonds under risk-parity and volatility-weighted portfolios.

Integrated Approach

So far, I have discussed three possible approaches to create dynamic and adaptive investment strategies. All of these approaches have the potential to improve risk-adjusted returns. In this section, I will introduce a holistic approach that integrates all three components, which can further improve investment results. The integrated approach follows three steps:

1. Identify economic/market/risk regimes with economic and market indicators using the *Adaptive Regime Approach*;
2. Select the best assets in the economic regime identified in step (1) with the *Adaptive Return Approach*, such as momentum;
3. Construct portfolios with the assets selected in step (2) with the *Adaptive Risk Approach*, such as risk parity.

Exhibit 17 shows the summary performance statistics of the integrated approach. I use monthly data between January 1975 and September 2013 in the analysis. The overall performance looks better than either the momentum strategy or regime-based strategy alone. Ex-

Performance Metrics	**Volatility-Weighted Portfolio**	**Risk-Parity**	**Equally Weighted**
Average Monthly Return	0.8%	0.8%	0.9%
Monthly Standard Deviation	1.8%	1.8%	2.4%
Annualized Average Return	9.6%	9.2%	10.7%
Annualized Standard Deviation	6.3%	6.2%	8.4%
Sharpe Ratio (risk-free rate = 5%)	0.73	0.68	0.68
Maximum Drawdown	-15.1%	-14.1%	-31.4%
Expected Years to Recover	1.6	1.5	2.9

Exhibit 16 Performance Statistics of the Adaptive Risk Approach

Source: Author's calculations

hibit 18 illustrates the cumulative return over time. The integrated approach generates higher returns with less volatility and drawdown than the S&P 500 Index.

Adaptive Return in a Portfolio

Since the adaptive investment approach offers consistent returns in any market environment, it should serve as a valuable alternative strategy to enhance return/risk profile in the context of asset allocation. Exhibit 19 shows the 12-month correlation between adaptive return and the S&P 500 Index from January 1975 to September 2013. The overall correlation is 0.39, but the correlations range from -0.41 to 0.95 over time. It is especially beneficial from the standpoint of asset allocation that the correlations were negative during market downturns. In Exhibit 20, by adding adaptive return to the traditional asset mix of stocks and bonds (represented by the S&P 500 Index and Barclays Capital US Bond Aggregate Index), the efficient frontier has improved significantly. Therefore, the adaptive strategy can play a significant role in a portfolio either as a replacement of core holdings, or as a satellite return enhancer or risk diversifier.

Concluding Remarks

This article has addressed some of the shortcomings of traditional modern portfolio theory and the drawbacks in its application to asset allocation and portfolio management. For example, the linear risk/return relationship may break down once more asset classes are introduced. The estimates of parameters in the model are inherently unstable and proved less useful in a strategic asset allocation framework. In addition, the paper has examined the efficient market hypothesis (EMH) and its implication to investment industry. Some common practices such as buy and hold, tracing benchmarks, and packaging beta to alpha, result in sub-optimal outcomes from the investors' standpoint. As an alternative, the adaptive market hypothesis (AMH) allows for evolution towards market efficiency and a dynamic and adaptive approach to investing. This article introduced an adaptive investment framework, under which investors can adapt their investment strategies to economic

Performance Metrics	Integrated Approach	S&P 500 Index
Average Monthly Return	1.4%	1.0%
Monthly Standard Deviation	3.2%	4.4%
Annualized Average Return	16.6%	12.5%
Annualized Standard Deviation	11.2%	15.3%
Sharpe Ratio (risk-free rate =5%)	1.03	0.49
Maximum Drawdown	-17.6%	-50.9%
Expected Years to Recover	1.1	4.1

Exhibit 17 Performance Statistics of the Integrated Approach

Source: Author's calculations & Bloomberg

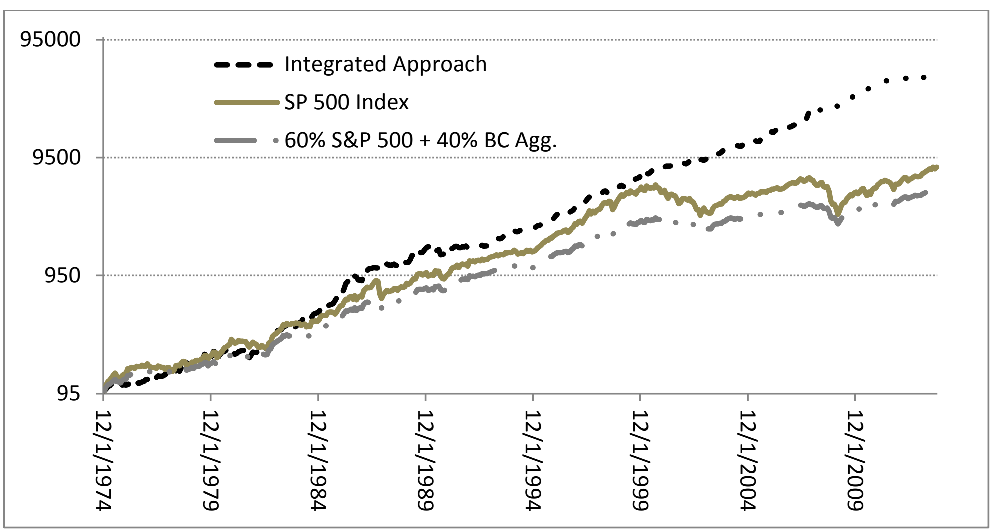


Exhibit 18 Cumulative Value of Initial Investment of $100 - Integrated Approach

Source: Bloomberg

regimes, market performance, or market risks. Some of the investment methods such as regime-based investing, momentum strategies, trend-following, risk-parity, volatility-weighted portfolio, and risk targeting, fall into this framework.

The adaptive approach may offer an alternative to traditional active investment. Financial economists and practitioners have spent a lot of time forecasting market returns and risks without much success. Instead of forecasting, the adaptive approach focuses more on identifying the market regimes and conditions and adjusting the investment strategies accordingly. In the examples of this article, I have shown the possibility and potential of improving investment performance with this approach.

In the article, I have used some simple examples to show how adaptive investment strategies can be built and how investment performance can be improved with this type of strategy. However, the examples should only serve as starting points for further research and may not be con-

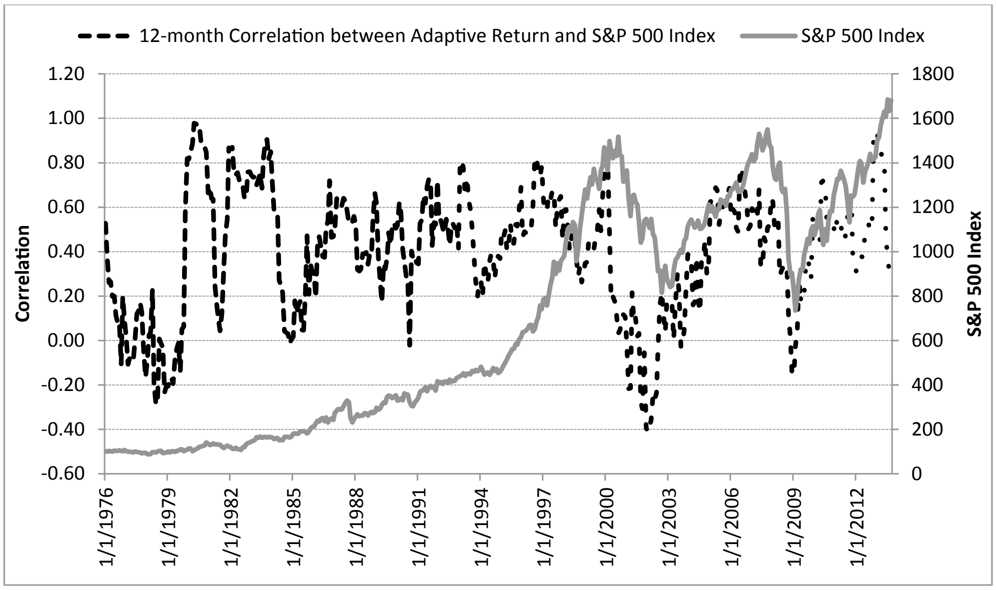


Exhibit 19 Correlation between Adaptive Return and the S&P 500 Index
Source: ECRI, Bloomberg

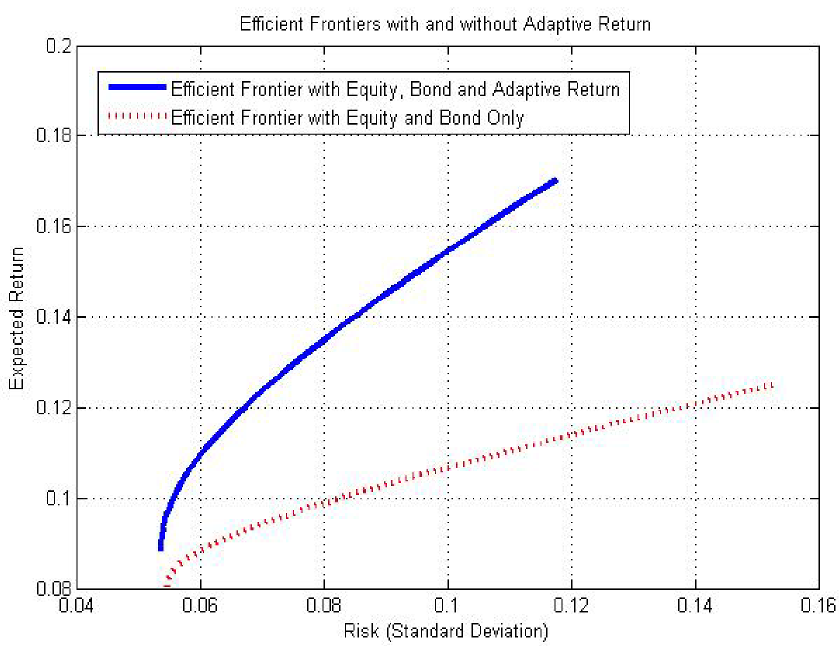


Exhibit 20 Efficient Frontier with Adaptive Return
Source: Author's calculations

sidered optimal trading rules for investments. There are four different areas worth further research:

- Regime identification with more sophisticated methods or techniques. There are numerous papers on forecasting business cycles or market cycles, but still more work need to be done on identification of market regimes.
- Optimal momentum and trend-following rules. I have shown that some simple momentum and trend-following rules can improve performance significantly. However, finding better or optimal trading rules has always been and will continue to be an interesting research area. For example, Dai, Zhang, and Zhu (2011) have found that the optimal trend following rule can be obtained by solving a Hamilton–Jacobi–Bellman partial differential equation in a bull-bear Markov-switching model.
- Other adaptive behaviors and adaptive investment rules. In my examples, I have discussed momentum and trend-following strategies. Sharpe (2010) proposed an asset allocation policy that adapts to outstanding market values of major asset classes. Other rules such as anti-trend or contrarian strategies might also be of interest.
- Higher frequency data. I have used monthly data in the examples. It is possible to get better results with weekly, daily, or even higher frequency data.

Data Description

In this paper, I used the index data between January 1970 and September 2013 for my study. For some of the indices that do not have data dated back to the start of testing period, I used proxies, approximation, or just left them incomplete. The following are the details:

- SP 500 Index: 1/1970-9/2013
- Russell 2000 Index: 1/1979- 9/2013, proxy 1/1970-12/1978 SP500 Index
- EAFE Index: 1/1970-9/2013
- MSCI Emerging Market Index: 1/1988-9/2013, proxy 1/1970-12/1987 MSCI EAFE Index
- FTSE Equity REIT: 1/1972-9/2013
- JP Morgan Alerian MLP Index: 1/1996- 9/2013, proxy 1/1972-12/1995 REIT Index
- London Gold Price: 1/1970-9/2013
- SPGC Commodity Index: 1/1970-9/2013
- Barclays Capital HY index: 07/1983- 9/2013, approximation: 01/1970-06/1983 0.5*Russell 2000+0.5*Barclays Aggregate Bond
- Barclays Capital US Aggregate Index: 1/1976 - 9/2013, proxy 1/1973-12/1975 Barclays Treasury Index
- Barclays Capital US TIPS Index: 3/1997-9/2013, proxy 1/1973-2/1997 Barclays Treasury Index
- Barclays Capital US Treasury Index: 1/1973-9/2013
- Barclays Capital US Treasury 20YR+ Index: 2/1992-9/2013, approximation: 1/1973-1/1992 3*Barclays Treasury Index – 2*3-Month Treasury Bill
- US Three-Month Bill: 1/1970-9/2013

References

Min Dai, Qing Zhang and Qiji Jim Zhu, "Optimal Trend Following Trading Rules." Working paper, 2011. http://papers.ssrn.com/abstract_id=1762118.

Eugene Fama and Kenneth French, "Luck Versus Skill in the Cross Section of Mutual Fund Returns." Journal of Finance, October 2010.

James Hamilton, Regime-Switching Models. Palgrave Dictionary of Economics, 2005.

Jegadeesh, N., and S. Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." Journal of Finance, 48, 1993.

Andrew Lo, "The Adaptive Market Hypothesis: Market Efficiency from an Evolutionary Perspective." The Journal of Portfolio Management 30, (2004), pp. 15-29.

Andrew Lo, "Reconciling Efficient Markets with Behavioral Finance: The Adaptive Market Hypothesis." Journal of Investment Consulting 7, (2005), pp. 21-44.

Andrew Lo, "Perspectives: Adaptive Markets and the New World Order." Financial Analyst Journal, Vol. 68, No. 2, 2012.

Henry Ma, "A Multi-Asset Investment Strategy for Individual Investors." Seeking Alpha, 2010.
Available at http://seekingalpha.com/article/240688-a-multi-asset-investment-strategy-for-individual-investors.

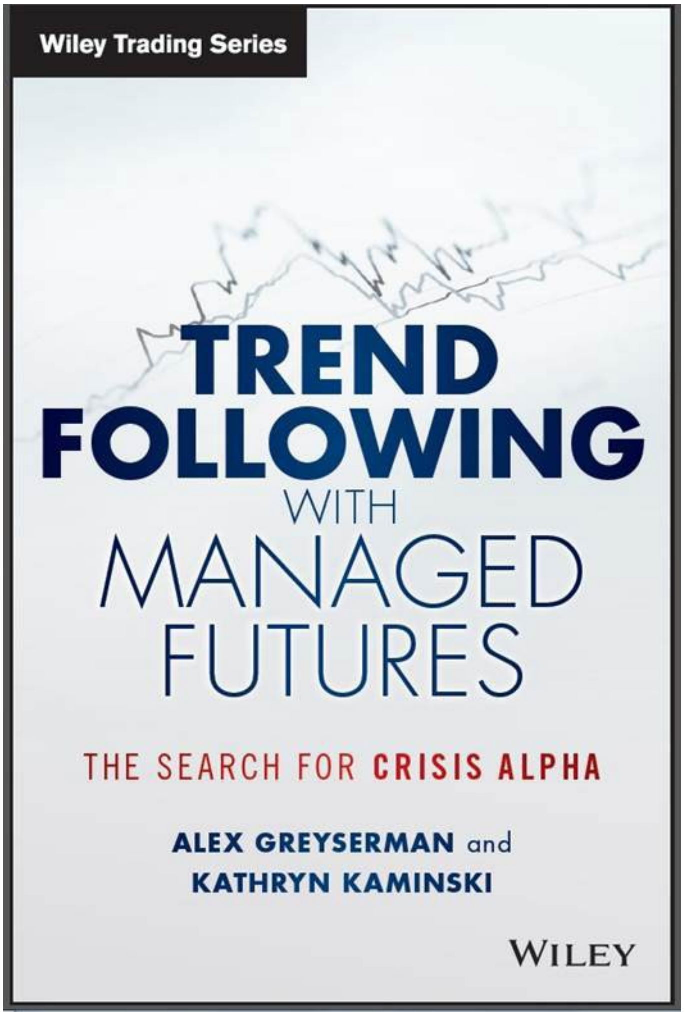
Edward Qian, "Risk Parity Portfolios: Efficient Portfolios Through True Diversification." Panagora Asset Management, White paper, 2005.

William F. Sharpe, "Adaptive Asset Allocation Policies." Financial Analyst Journal, Vol. 66, May/June 2010.

James Stock and Mark Watson, "Macroeconomics Forecasting Using Diffusion Indexes." Journal of Business & Economic Statistics, Vol. 20, April 2002.

Author Bio

Dr. Henry Ma is the founder and Chief Investment Officer at Julex Capital Management, a tactical investment management firm in Boston. Prior to founding Julex, he managed a global macro hedge fund strategy with Geode Capital Management (a Fidelity affiliate). Earlier, he served as Director of Quantitative Research and Financial Engineering with Loomis Sayles & Co., and Director of Quantitative Research and Risk Management with Fortis Investments, where he led quantitative research and risk management efforts. Dr. Ma also worked as Senior Vice President and Director of Fixed Income Strategies at Sun Life Financial, where he helped manage $30 billion in fixed income assets. His investment career began with John Hancock Financial Services as a Senior Associate Investment Officer. Dr. Ma is a published author and an industry speaker on the topics of quantitative investing, risk management, and structured finance. He earned both a bachelor's degree and a master's degree in Economics and Management from Peking University, and a Ph.D. in Economics from Boston University.



Kathryn Kaminski, CAIA On Her New Book, *Trend Following with Managed Futures: The Search for Crisis Alpha*

A View to the Futures: Following Trends with Kathryn Kaminski

In the late fall, Barbara J. Mack, AIAR Content Director, spoke with author Kathryn Kaminski, Ph.D., CAIA about her new book, ***Trend-Following with Managed Futures: The Search for Crisis Alpha.***

BJM: You completed a Ph.D. at MIT Sloan and have done a wide variety of interesting things since then. You also have the CAIA designation. How did you discover CAIA and why did you decide to complete the program?

KK: I found out about the CAIA designation through 100 Women in Hedge Funds – I had been working for RPM, a CTA fund of funds in Stockholm. At that time, I joined 100 Women in Hedge Funds and saw an advertisement for a CAIA scholarship for women. Since I teach courses on derivatives and hedge funds, it was an obvious choice for me. I found the materials to be very interesting, and I am a great advocate of CAIA. I like the fact that it is pretty broad; if I take the perspective of most academics, we tend to stick to our regime and don't always learn about things like REITs and infrastructure investing. As it turned out, I enjoyed some of those topics the most – they were outside of my field and learning about them helped me to become more versatile, with a view on the whole industry. That is an important thing to do in finance; especially if you teach, you need to know about many things, and it never hurts to learn more.

BJM: So you have been hard at work and your new book, *Trend-Following with Managed Futures*, came out late last summer. What can you tell us about the motivation behind the book and how did you find your co-author, Alex Greyserman?

KK: My Ph.D. thesis at MIT was on stopping rules and investment heuristics. I later became interested in CTAs and was working as an allocator. A couple of years ago, I started writing white papers on trend-following and wrote a paper for the CME Group called "In Search of Crisis Alpha," which became quite popular. This particular piece is often used by managers and allocators to help educate investors and launched a friendly relationship with the CME. We shared a mutual goal of providing education on managed futures and promoting the managed futures industry. Randy Warsager, who is in charge of hedge fund relationships, sent me articles that he knew would interest me and informed me about key topics of discussion. Alex Greyserman, chief scientist at ISAM (a systematic CTA), had similar interests and also had a relationship with the CME. Randy introduced me to Alex's work with ISAM, and we decided to meet. I went in with the intention of writing a research paper together and the meeting ended with the challenge of writing a book.

As it turned out, Alex and I have very similar backgrounds – we both come from a signal processing background and turned to quant finance. I'm more on the behavioral finance and investment side and Alex has been building systems for trend-following funds for 25 years, which means that he knows all the ins and outs of how to design and construct the systems. Writing the book was an educational mission – Alex teaches courses at Columbia on how to build trading systems and develop trading strategies, and I teach courses on derivatives and hedge funds. We wanted to present the subject as objectively as possible; so, for example, there are no names of funds in the book - we have lists of funds, but they are called "CTA 1", "CTA 2", and so forth. We did not want to highlight one fund or another - the book was produced independent of any marketing objective. Our goal is that any investor can read the book and gain a detailed understanding of what trend-following is about and why it should work.

In part, our mission stemmed from the fact that a number of questions about trend-following have never been answered in an adequate way. There are some great trend-following books out there, but most of them have different goals – some are very fantastical and intriguing, but they can be quite anecdotal. Other books are very sales-oriented. We treated the creation of this book as if we were teaching a course. In fact, while I was writing the book, I had CAIA in mind because this is an area where there needs to be more education for financial professionals. The academic community basically disregarded trend-following and momentum in futures trading until the paper by Moskowitz, Pedersen, and Ooi was published in 2012. However, I had been a big fan of trend-following long before that time. In the asset management industry, a lot of people know that it works and the academics are finally coming around.

BJM: The book was released in the summer of 2014. Can you describe how you covered the topics and what the points of emphasis are?

KK: There are five parts to the book. The first part begins with a historical perspective including an 800-year analysis of trend-following. In chapter two, we talk about futures markets in general - futures trading, the managed futures industry, and the futurization of the OTC derivatives markets. The third chapter covers the basics of building a systematic trend-following system. Here we introduce one equation that is used for the entire book. This is important, because there are so many ways that you can design a systematic trend-following system. Our goal was to have a general equation that gives a single frame of reference for the book and includes an analysis of how to build a trend-following system: from entry to exit, and through position sizing, adjusting for dollar risk per position, and so forth.

The second part of the book covers the theoretical foundations of managed futures markets. In chapter four, we discuss the adaptive market hypothesis, speculative risk premiums, and crisis alpha. This chapter talks about Andrew Lo's work and how to think about markets as ecologies and provides connections with behavioral finance, so it's fun. Chapter five explains the act of divergent risk taking, risk and uncertainty, and the philosophy behind trend-following strategies. At the end of this chapter, we address the question – "Is the strategy actual tradable?" and look at the importance of exit and entry. Chapter six is on the role of interest rates in futures trading, including earned interest and roll yield. The third part of the book is focused on trend-following as an alternative asset class. Chapter seven focuses on statistical properties – crisis alpha, conditional correlation, skewness, the higher order moments - these are the basics. Chapter eight is on drawdowns, volatility, and correlation and we talk about the relationship between strategy volatility and market volatility and how that works, because it is a bit complicated. Chapter nine is on the hidden and unhidden risk in alternative investments, particularly related to trend-following and we cover credit risk, liquidity risk, price risk, and leverage risk. We explain these risks and examine how trend-following systems fall into those different categories. At the end of the chapter, we touch on margin, leveraging, and how dynamic leveraging works. Chapter ten provides a more general discussion of the macro environment and the impact of government intervention and regulatory change.

The fourth section of the book is on indexing and benchmarking. Chapter eleven discusses return dispersion in the CTA space and how different choices of parameters for trading systems can create return dispersion from one systematic fund to another. This discussion leads to chapters twelve and thirteen, which are on style analysis and benchmarking. Here, similar to the Fama and French three-factor model, we design a model for benchmarking CTA returns as a function of their construction style. We show how you can create a market size factor, an equity bias factor, and a trading speed factor to supplement an underlying trend-following strategy. Using this model, different CTA indices and individual CTAs can be examined to perform style analysis and performance attribution. This is one the most exciting parts of the book and has been very well-received by CTA investors.

Finally, the last section of the book covers a series of more advanced portfolio level topics from the investor perspective. Chapter fourteen discusses equity bias, dynamic leveraging, and the importance of mark-to-market. Chapter fifteen discuses size, capacity, and liquidity. Here, we take a closer look at how important commodity or small markets are with regard to the different strategies. Chapter sixteen addresses the move from pure trend-following to a multi-strategy approach and is intended to prompt a discussion from both individual and global portfolio perspectives on the pros and cons of the multi-strategy approach. Chapter seventeen evaluates dynamic allocation to trend-following strategies. This chapter focuses on when to invest or divest, answering the questions – "Should I buy when the strategy is in a drawdown, or should I buy when the strategy has done well? Is return chasing a good way to invest in CTAs, yes or no? "

BJM: With the book published and out in the world, how does that feel and what are your plans now?

KK: It takes quite a long time to finish a book and I had no idea how satisfying it would be. My immediate focus is on continuing to publicize and promote the book. I spoke at Quant Invest in London in September, Battle of the Quants in London in November, and several other events are planned. We are always considering which conferences will be best for reaching out and hopefully talking about this book will keep the momentum going. Our main audience is the institutional investor but also fund managers, students, and the CTAs themselves.

The CTA space seems to be on the upswing now and, if that is the case, this is a good time to be talking about these issues. This is why I am delighted to be able to announce that I have joined a well-respected and forward looking systematic manager, Campbell & Company. Their focus on innovation and education will provide a great opportunity for me to continue to expand on my past work.

To learn more about Trend-Following and Managed Futures: The Search for Crisis Alpha, visit: http://www.wiley.com/WileyCDA/WileyTitle/productCd-1118890973.html

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Comparing Three Generations of Commodity Indices: New Evidence for Portfolio Diversification

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Finding assets that reduce portfolio risk without sacrificing returns can be seen as the holy grail in portfolio diversification [Galvani and Plourde, 2009]. With one of the first studies concerning diversification benefits of commodity futures, Bodie and Rosansky [1980] demonstrate that commodities can be considered as an asset class that provides exactly this characteristic to investors. Evaluating the performance of individual commodities from 1950 to 1976, they report that adding these securities to a U.S. stock portfolio reduces overall risk without sacrificing returns. Gorton and Rouwenhorst [2006] attribute this to the fact that commodities are prone to a number of factors, such as weather, environmental developments, or unexpected supply and demand shocks which affect traditional asset classes to a lesser degree [Jensen and Mercer, 2011]. With the launch of the S&P Goldman Sachs Commodity Index (GSCI) in November 1991, investors were able to invest in a broad selection of commodity futures for the first time, without interacting in the complicated process of closing or rolling future contract positions [Georgiev, 2001]. This new possibility incited a stream of research that questions the performance of such indices in portfolios.

Satyanarayan and Varangis [1996] analyze the shift of the efficient frontier in a mean-variance framework and conclude that an investment of only 3% into the GSCI leads to a reduction in portfolio risk of over 3.6%. Georgiev [2001] reports that adding the GSCI to a global stock/bond portfolio, also including hedge funds, reduces overall risk and improves the Sharpe ratio (SR). Using a regression-based approach, evidence in favor of commodities is further reported by Belousova and Dorfleitner [2012] and Galvani and Plourde [2009]. The former study performs mean-variance (MV) spanning tests including individual futures. Focusing only on energy futures, the latter study shows that portfolio risk is reduced when commodities were held in the period from 1980 to 2008.

While in-sample properties of commodities are exhaustively studied, the literature with regard to the out-of-sample (OOS) performance is limited. The only studies considering commodities in an OOS setting are Daskalaki and Skiadopoulos [2011], You and Daigler [2012], and Bessler and Wolf [2014]. Daskalaki and Skiadopoulos [2011] show that while commodities provide gains in-sample, the reported benefits vanish out-of-sample. Using a rolling window approach and various risk coefficients, they report no diversification benefits for the GSCI and the Dow Jones-UBS Commodity Index (DJUBSCI) over the period from 1989 to 2009 and 1991 to 2009, respectively. They also challenge the diversification benefits from later generation indices. Including two second generation indices and, using significance tests in their analysis, they show that these benchmarks do not provide benefits when added to the investment universe. However, You and Daigler [2012] contradict the findings of Daskalaki and Skiadopoulos [2011]. The authors report that a MV portfolio improves when future contracts are included. Finally, Bessler and Wolf [2014] agree on the OOS risk return improvements by analyzing Sharpe ratios of different portfolio strategies and different commodity classes for a traditional U.S. investor. Using the GSCI, as well as Energy-, Metal-, Livestock- and Agriculture-futures contracts, they show that the risk-return performance improves.

Moreover, the increasing investments in the commodity markets in the early 2000s started to cast doubts on the benefits available to investors [Domanski and Heath, 2007]. Domanski and Heath [2007], Tang and Xiong [2012], and Silvennoinen and Thorp [2012] provide evidence for the financialization of this asset class. Domanski and Heath [2007], for example, argue that increased commodity investment leads to more integrated markets. Commodity markets are no longer only driven by fundamental factors, but are also prone to financial market factors. Moreover, Tang and Xiong [2012] state that rising commodity investment leads to volatility spillovers and excess correlation among commodity prices, which have a tremendous effect on investors' hedging and investment strategies. Finally, Silvennoinen and Thorp [2012] investigate the correlation of commodity and equity markets. Their results show that the increased correlation among these markets has led to weakened diversification benefits for investors. The reported evidence against the diversification benefits and the increased financialization should nevertheless be interpreted with caution. Growing research in the field of investment strategies and weighting methodologies has triggered investment companies to further improve their indices [Louie and Bourton, 2013]. Today, investors face three different generations of commodity benchmarks - furnishing them with various weighting and selection methodologies - and must address the question of whether or not diversification benefits still exist in the commodity markets [Miffre, 2012].

Since later generation indices are relatively new, research often focuses on first generation indices. Exceptions are Chong and Miffre [2010], Rallis, Miffre, and Fuertes [2012], and Miffre [2012]. Chong and Miffre [2010] consider commodity investment from a tactical asset allocation point-of-view. Comparing long-only and long-short strategies, they show that the latter outperforms the former. As a result, first generation indices that represent long-only strategies used by Daskalaki and Skiadopoulos [2011] might be considered weak diversifiers. Later generation indices, on the other hand, following different allocation strategies, also including long-short allocations, may still be beneficial. Further support for this argument is provided by Miffre and Rallis [2007] and Erb and Harvey [2006], and is validated by Fuertes, Miffre, and Rallis [2008]. Miffre and Rallis [2007] use momentum strategies, while Erb and Harvey [2006] use the futures term structure to improve roll returns. Miffre [2012] provides a classification into different generations for several indices. In total, she evaluates 38 benchmarks, classifying them into three generations. Reporting SRs over the period from 2008 to 2012, she outlines the advantage of second and third generation indices over their first generation counterparts. However, she does not address their diversification benefits in a portfolio setting, nor does she provide significance tests for the obtained results.

This article aims to fill the gap by evaluating the diversification benefits of seven different commodity indices - covering all three index generations - for a traditional U.S. investor from June 1991 to May 2013. The article extends the existing body of literature in various ways: first of all, to the best of my knowledge, it is the only study that considers third generation indices in a portfolio setting for a traditional U.S. investor and analyzes their benefits in an OOS setting. While earlier generation indices are exhaustingly analyzed, evidence for later generations is lacking. Moreover, by using a time span of 22 years, the study extends prior surveys like those of Miffre [2012] or Rallis, Miffre, and Fuertes [2012]. Finally, evaluating the risk-return performance of the commodities in an OOS setting provides further insights on the potential diversification benefits.

To evaluate the impact of the commodity indices, Lagrange Multiplier- (LM), Likelihood Ratio- (LR) and Wald-Tests (W) are performed to test statistically for mean-variance spanning, including a spanning test based on the Generalized Method of Moment (GMM) to account for conditional heteroskedasticity [Erb and Harvey, 2006]. Additionally, a step-down approach is used to characterize the source of a possible rejection. To test the commodity index performance in an OOS setting, a fixed rolling window approach is considered and significance tests according to Jobson and Korkie [1989] and Gibbson, Ross, and Shanken [1989] are performed.

Using spanning tests, the results show that after accounting for non-normality, first generation indices do not provide any benefits in terms of portfolio diversification, or in providing an improved tangency portfolio. The evidence for second generation indices is mixed, while third generation indices exhibit benefits in terms of both higher returns and lower volatility. The OOS analysis confirms these results. Later generation indices, clearly increase the OOS Sharpe ratios and reduce the expected shortfall for all considered window sizes. On the other hand, first generation benchmarks show non-persistent performance with some improved and some degraded portfolios. Overall, the investor should consider indices with trading strategies rather than simple long-only benchmarks. Companies should possibly follow multidimensional weighting and allocation schemes to improve their benchmark's performance.

Methodology and Hypothesis Building

The increasing doubts of the recent past challenge the reported diversification benefits of commodities and make it fair to ask whether those benefits still exist in today's financial markets. As already stated above, commodities are said to be influenced by factors different from those of equity or bond markets. Additionally, firms that use commodities as an input factor face increased costs and uncertainty when input prices rise [Chong and Miffre, 2010]. This adverse behavior leads to the often-reported low or even negative correlation values [see e.g. Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006]. Nevertheless, this benefit is under attack by increased derivative market activity [Domanski and Heath, 2007]. The resulting financialization describes an environment where the equity and commodity markets becomes more integrated. Commodities are no longer only prone to their market-specific factors, but also to investors' behavior and equity market fundamentals. This leads to higher correlation values with other asset classes and to a time-varying volatility. In short, these volatility spillovers could result in reduced diversification benefits [Silvennoinen and Thorp, 2012]. The investor is thus left with the question: "Do diversification benefits in commodity markets still exist?"

Trying to answer this question, some studies have incorporated first generation indices such as the GSCI or the DJUBSCI into portfolios. Since these benchmarks are the most widely traded indices, a possible financialization caused by index investors may be more present in these benchmarks [Yau et al., 2007]. It is thus reasonable to include later generation indices in the analysis. However, evidence for these benchmarks is lacking. The only study evaluating enhanced benchmarks is the one by Miffre [2012], who does not analyze them within a portfolio environment. Yet, the performance in a portfolio setting is closer to the reality, since investors see commodities as an additional asset class for diversification, rather than as a standalone investment [Gorton and Rouwenhorst, 2006].

The analysis above raises the following questions: "Which generation of commodity indices still provides diversification benefits for a traditional U.S. investor?" and "What is the source of potential portfolio improvements?" The reported evidence with regard to trading strategies, provided by Erb and Harvey [2006], Miffre [2011], Miffre and Rallis [2007] and Fuertes, Miffre, and Rallis [2008] expects later generation indices, which follow momentum, term structure, or fundamental rules, to outperform their first generation counterparts and to provide benefits where the earlier indices may be lacking. Using these enhanced strategies, it is possible to weight the index away from poorly performing futures contracts. Finally, it is necessary to evaluate the performance of the commodities also in an OOS setting. While the commodities may show a superior performance in-sample (IS), practitioners are more concerned about the ex-ante setting. The question is thus: "Does the IS performance of the commodity indices also hold in an OOS setting?"

To evaluate the performance of the different commodity indices, first of all, the method of mean-variance spanning is used. Mean-variance spanning was introduced by Huberman and Kandel in 1987 [DeRoon and Nijman, 2001] and analyzes whether adding a set of N test assets significantly improves the initial efficient frontier, consisting of only K benchmark assets. If the new frontier, represented by the set of N+K assets, and the initial frontier coincide, there is spanning. In this case, no mean-variance optimizer can improve its portfolio by including the test assets in its investment universe [DeRoon and Nijman, 2001].

Formally, spanning tests are based on the idea of regressing the test assets on the benchmark assets. Given that the test asset only consists of one index at a time, the final regression equation is given by:

$$R_{com} = \propto + \beta_{U.S.Equity} R_{U.S.Equity} + \beta_{U.S.Bond} R_{U.S.Bond} + \epsilon \quad (1)$$

where R_{com}, $R_{(U.S.Equity)}$ and $R_{(U.S.Bond)}$ are (T×1) vectors of excess returns and ε represents the error term. Kan and Zhou [2012] state that the regression for the statistical tests can be performed using both total and excess returns. Since the investment universe also includes a risk-free asset, using total return data would mean including this rate as an independent regressor. Daskalaki and Skiadopoulos [2011], however, stress that this is undesirable, because the asset tends to exhibit persistency. Thus, excess returns over the risk-free rate are constructed. Hubermann and Kandel [1987] state the null hypothesis for spanning as:

$$H_0: \alpha = 0, \delta = 1 - \beta = 1 - \beta_{U.S.Equity} - \beta_{U.S.Bond} = 0 \quad (2)$$

Economically, this means that failing to reject the null, the universe of (K+1) assets does not improve the tangency portfolio $\propto = 0$, nor does it have a positive effect on the Global Minimum Variance Portfolio (GMVP) (δ=0). Since (2) is a joint hypothesis, the null states that both frontiers coincide and that including additional assets into the investment universe does not shift the efficient frontier [Belousova and Dorfleitner, 2012].

Assuming a normal distribution of returns, the critical values of the LM-, LR- and W-statistics are computed. All tests are asymptotically chi-squared distributed with two degrees of freedom. For finite samples, Berndt and Savin [1977] and Breusch [1979] show that $W \geq LR \geq LM$ holds. As a consequence, the W test favors rejections, while the opposite is true for the LM test. Hence, to obtain reliable results, all three tests should be performed [Belousova and Dorfleitner, 2012].

Since the academic literature reports a presence of non-normality in commodity future returns [see e.g. Erb and Harvey, 2006; Jensen and Mercer, 2011], but the three tests are based on the assumption of a normal distribution, the presence of conditional heteroskedasticity leads to invalid results for the three test statistics. In this case, the tests are no longer asymptotically chi-squared distributed [Belousova and Dorfleitner, 2012; Kan and Zhou, 2012].

Exhibit 1 reports the p-values for the Engle [1988] test for conditional heteroskedasticity of the residuals. Since the dataset rejects the null of "no conditional heteroskedasticity" for some variables, the analysis is complemented by the Wald test introduced by Ferson, Foerster, and Keim [1993]. The three authors developed the test by using the GMM approach introduced by Hansen [1982]. The only difference is that the GMM Estimator is used instead of the MLE [Belousova and Dorfleitner, 2012].

Furthermore, Kan and Zhou [2012] outlined that particular attention has to be paid when using the joint hypothesis in (2). Since the GMVP can be estimated more accurately than the tangency portfolio, the test is biased towards (δ=0). This gives rise to potential divergence discrepancy between economic and statistical significance. Given that a small change in the GMVP is statistically easy to detect, it is not necessarily important in economic terms. Furthermore, a difference in the tangency portfolio might be economically very important, yet will be difficult to detect statistically [Kan and Zhou, 2012]. Kan and Zhou [2012] proposed a step-down procedure that aims to resolve these problems. They created two distinct F-tests with the following hypotheses:

$$H_{0,F1}: \alpha = 0 \qquad (3)$$

$$H_{0,F2|\alpha=0}: \delta = 0 \qquad (4)$$

Failing to reject (3) states that the two tangency portfolios are statistically similar, while (4), conditional that (3) holds, shows that the two GMVP are statistically not dissimilar. The two F-tests are given by:

$$F_1 = (T - K - 1)\left(\frac{\bar{\Sigma}}{\hat{\Sigma}-1}\right) \qquad (5)$$

$$F_2 = (T - K)\left(\frac{\tilde{\Sigma}}{\bar{\Sigma}-1}\right) \qquad (6)$$

where $\hat{\Sigma}$ is the unconstrained and $\bar{\Sigma}$ is the constrained, when α=0, MLE of Σ. Further $\tilde{\Sigma}$ is the constrained estimator when both α=0 and δ=0 hold. Under H_0, the F-test in (5) follows a F-distribution with 1 and (*T-K-1*) degrees of freedom. The test in (6) follows the same distribution, but with 1 and (*T-K*) degrees of freedom.

Complementing the analysis with the step-down approach leads to a higher degree of information, regarding the impact commodities have on a traditional portfolio. First of all, it is possible to determine the source of a possible rejection in (2). This is either due to the change in the GMVP or because of an improved tangency portfolio. Second, it is possible to solve the problem of divergence in economic and statistical significance by setting different significance levels for the two tests [Kan and Zhou, 2012].

Finally, since practitioners are mostly concerned with the out-of-sample performance of their investments, the analysis is contemplated with a fixed rolling window approach. Given a time series of length *T*, a rolling window of size Z, where *Z*≥*T*, and any point in time *t*, we use the last *Z* return observations to compute the mean-variance efficient portfolio weights. These weights are then used to construct optimal portfolios and to extract the resulting OOS returns for the time interval [*t*,*t*+1]. This process is repeated, by incorporating the observation from *t*+1 and ignoring the earliest one. In total, this approach allows to compute (*T-Z*) optimal mean-variance OOS portfolio returns, which are then used to construct performance measures including Sharpe ratios, total turnover, expected shortfall, as well as general descriptive measures. First, these steps are taken for the base portfolio and then for the seven other portfolios, always including one commodity index at a time. To ensure robust results, different window sizes are used, including: *Z* = 36,48,60,and 72. To account for significance, I further incorporate the approach by Jobson and Korkie [1989] and Gibbson, Ross, and Shanken [1989], who test the null hypothesis of whether or not there is a difference between the SRs of two portfolios.

Data

Monthly return data are obtained from Bloomberg covering a 22-year period from June 1991 to May 2013 (264 observations). Exhibit 1 provides summary statistics of the indices, including an overview of their individual construction methodologies. The data cover the S&P 500, representing the U.S. Stock Market, a 3-month U.S. Treasury (T-Bill) serving as an indicator for the risk-free rate and the Barclays Capital U.S. Aggregate Bond Index (BARC), representing fixed income securities. The BARC was created in 1986 and includes Treasuries, Government and Corporate Bonds, as well as mortgage-backed securities. It also includes high yield and emerging market bonds traded in the United States [Barclays, 2012]. With regard to the commodities, data on seven indices from the different generations were obtained. All indices represent total return indices, classified according to Miffre [2012].

The GSCI and the Dow Jones-UBS Commodity Index (DJUBSCI) are two of the most widely used commodity indices in the academic literature and do not include any trading strategies [Yau et al., 2007]. Both are long-only indices. The GSCI was launched in 1991 and currently invests in twenty-four futures from five commodity classes including Energy, Industrial Metals, Precious Metals, Agriculture and Livestock. The main criterion to be included in the GSCI is the average world production over the last five years. To prevent unimportant commodities being included in the index, a minimum contribution to world production is necessary.

While the GSCI has a higher exposure to the Energy sector (around 70%), the DJUBSCI is more diversified across the different commodity sectors. Created in 1998 and backfilled with data until 1990, it currently covers twenty future contracts from various commodity sectors. The DJUBSCI uses both world production and liquidity to classify investable commodities. Moreover, special weight requirements apply: no sector should exceed 33% of the index weights, and the weight for individual futures is a minimum of 2% and a maximum of 15%. The DJUBSCI is reweighted on an annual basis, while the GSCI remains fixed [GSCI, 2013; DJUBSCI, 2013a; DJUBSCI, 2013b; Daskalaki and Skiadopoulos, 2011; Erb and Harvey, 2006].

Later generation indices are characterized by specialized rolling, selecting, or reweighing methodologies. Both the GSCI and the DJUBSCI hold liquid contracts that lie on the front end of the term structure. They roll from the front to the second nearest contract. The problem is that first generation indices always assume a backwardated market. In markets characterized by high inventory costs and an upward sloping term structure (a market in contango), these indices perform poorly. Second generation indices try to solve this problem

Asset	Construction Methodology	Annual Mean (%)	Annual Volatility (%)	Sharpe Ratio	Skewness	Excess Kurtosis	Min. Return	Max. Return	Jarque-Bera p-Values	Engle p-Values
Base Portfolio										
S&P 500	Market Cap	10.13	14.83	0.48	-0.63	1.27	-16.79	11.44	0.001	---
Barclays	Market Cap	6.62	3.70	0.98	-0.28	0.86	-3.36	3.87	0.0118	---
1st Generation										
GSCI	Long Only	5.38	21.00	0.11	-0.37	1.84	-28.19	19.67	0.001	0.0026
DJUBS	Long Only	5.84	15.03	0.19	-0.57	2.61	-21.28	13.00	0.001	0.0029
2nd Generation										
ML	Semi Continuous Rolling	11.50	20.01	0.43	-0.27	2.13	-26.57	21.71	0.001	0.0659
MSLF	Momentum Long/Flat	9.30	10.66	0.59	0.07	2.54	-10.12	11.42	0.001	0.0002
3rd Generation										
CYD	Term Structure	7.55	8.33	0.55	-0.24	1.79	-11.20	7.90	0.001	0.7928
MSLS	Momentum Long/Short	7.33	10.93	0.40	0.21	1.91	-10.89	11.62	0.001	0.0039
SH	Fundamental/Rule Based	14.96	14.06	0.85	-0.81	4.73	-22.60	13.96	0.001	0.0014
T-Bill	-	2.99	0.5	---	-0.23	-1.47	0.000	0.005	0.001	---

The exhibit reports the descriptive statistics on total return data over the period June 1991–May 2013 for each individual asset. From column 2 to 10: constructing methodology, annual mean, annual volatility, Sharpe ratio, skewness, excess kurtosis, minimum return, maximum return, and the p-values for the Jaruqe-Bera Test and the Engle Test. Sharpe ratios are computed using annual mean, annual volatility and the annual mean of the 3-month U.S. Treasury Bill as the risk free rate. To test for normality of the returns, Jarque-Bera p-values are reported. Engle p-values, capture whether the residuals from the regression specified in (1) are prone to conditional heteroskedasticity. The null of the former states that the series follows a normal distribution and the null of the latter assumes no conditional heteroskedasticitv of the residuals.

Exhibit 1 Descriptive Statistics for the Period May 1991–June 2013

Source: Bloomberg

by considering the whole term structure of the future contract Miffre [2012]. With regard to this family, the article focuses on the Merrill Lynch Commodity Index eXtra (MLCX) and the Morningstar Commodity Index Long/Flat (MSLF).

The MLCX follows a semi-continuous roll scheme, meaning that it rolls from the second to the third month future contract. As of today, the MLCX invests in more downstream commodities, such as gasoline or live cattle. All commodities are selected based on liquidity and importance for the global economy [Lynch, 2006].

The MSLF follows a momentum-long-flat strategy. Next to rolling into future contracts that lie further apart on the term structure, the index also considers the past performance of the future contracts. If a commodity exceeds its 12-month moving average, the index takes the long position. The flat positions are equal to holding cash. These investments are implicitly derived from the short positions of the Morningstar Long/Short Commodity Index (MSLS), which are also determined on the basis of the 12-month moving average. Thus, while the MSLS takes both investment sides, the MSLF replaces the short positions with flat positions. The MSLS also follows a momentum strategy.

With its long and short positions, the MSLS characterizes the third generation of commodity indices. These benchmarks try to enhance their performance by going long into commodities currently facing a backwarded market and going short in future contracts with contangoed markets. As a result, they are said to perform well in good and bad market environments Miffre [2012]. The MSLS currently consists of Energy (39.30%), Metals (13.90%), Agriculture (38.40%), and Livestock (8.40%) futures. The maximum load of a futures contract is 10%, with monthly rebalancing, dependent on the moving average [Morningstar, 2013]. The CYD Long/Short Commodity Index (CYD) is a Term Structure Index, meaning that long and short positions are determined by the shape of the term structure, whereby long positions are taken for the most backwarded commodities and short positions for the most contangoed futures. The CYD currently consists of Cereals (21.74%), Meat and Livestock (13.04%), Energy (26.09%), Metals (21.74%), and Exotics (17.39%), including Cocoa, Coffee, or Sugar [CYD, 2013].

Finally the Summerhaven Dynamic Commodity Index (SDCI) is a fundamental rule-based index. The benchmark includes forecasts of fundamental factors, as well as technical signals or price signals to determine the optimal commodity weights. As of 2013, the SDCI consisted of 14 out of 27 eligible commodity futures, including sectors like Industrial Metals, Precious Metals, Energy, and Agriculture, that are rebalanced every month [Miffre, 2012; Summerheaven, 2013].

Analyzing the reported annual means and standard deviations from Exhibit 1, no clear picture emerges. While first generation indices show both a lower mean and a higher standard deviation, the results for second and third generation indices are inconsistent. Both higher means with lower volatility and lower means with higher volatility co-exist.

Asset	S&P 500	Barclays	GSCI	DJUBS	ML	MSLF	CYD	MSLS	SH	T-Bill
S&P 500	1	-	-	-	-	-	-	-	-	-
Barclays	0.0714	1	-	-	-	-	-	-	-	-
GSCI	0.2468*	0.0155	1	-	-	-	-	-	-	-
DJUBS	0.3119*	0.0391	0.8972*	1	-	-	-	-	-	-
ML	0.2489*	-0.0002	0.9745*	0.9231*	1	-	-	-	-	-
MSLF	0.0792	-0.0253	0.7443*	0.7838*	0.7488*	1	-	-	-	-
CYD	-0.2087*	0.0119	0.0752	-0.0206	0.0375	0.3107*	1	-	-	-
MSLS	-0.1054	-0.0641	0.5269*	0.4838*	0.5160*	0.8715*	0.4568*	1	-	-
SH	0.2933*	0.0068	0.7569*	0.8762*	0.7810*	0.7788*	0.0733	0.4892*	1	-
T-Bill	0.0497	0.0841	0.0473	0.0631	0.0682	0.0747	0.1362**	0.1103	0.0875	1

The table reports Pearson's correlation coefficients for each asset. Significance tests were performed using a standard t-test.

* Significant at 1%; ** Significant at 5%.

Exhibit 2 Correlation Matrix for the Period May 1991–June 2013

Source: Author's calculations & Bloomberg

Comparing SRs, it can be seen that the fixed income securities exhibit the highest value with 0.98. First generation indices are dominated by both equity and bond indices. Again, the evidence for later generation indices is mixed. For the second generation, only the MSLF shows superior performance over equities, while in the third generation only the CYD and the SDCI exhibit higher risk-return performance compared to the S&P 500. Comparing SRs across the different commodity indices, first generation indices are dominated by second and third generation indices. This observation is in line with reported evidence by Miffre [2012]. Contradictory results are found for second and third generation indices. The latter does not necessarily outperform the former: The SR for the MLCX (0.43) and MSLF (0.59) are both higher than for the CYD (0.55) and the MSLS (0.40). Finally, the highest SR is reported for the SDCI (0.85), indicating the benchmark as the best standalone investment in comparison to the other commodity indices.

Looking at the return distributions, all indices exhibit positive excess kurtosis. This implies a leptokurtic return distribution, meaning the curve shows fatter tails and a higher probability for extreme events compared to a normal distribution [Belousova and Dorfleitner, 2012]. Furthermore, the majority of indices report negatively skewed return distributions. Exceptions are the MSLF and the MSLS. This contradicts findings from Jensen and Mercer [2011] and Erb and Harvey [2006], but is in line with the mixed evidence reported by Miffre [2012]. The two exceptions (MSLF and MSLS) go in hand with the same rebalancing methodology. Both select their commodities on the basis of the 12-month moving average. Thus futures are only included if they exceed this average, or will be otherwise considered as short or flat positions. This could explain the positive skewness. Also reported are the p-values of the Jarque-Bera test for normality. All assets reject the null of a normal distribution at the 5% significance level. Exhibit 2 shows the Correlation Matrix for the entities in Exhibit 1, a subject to which we will return later.

Empirical Analysis

Commodity Index Performance from 1991–2013

Exhibit 3 reports the results of the mean-variance spanning tests, including the GMM-Wald and the step-down procedure. As noted earlier, Kan and Zhou [2012] state that it is statistically more difficult to detect a change in the tangency portfolio. To accurately interpret the results of the F1-Test, p-values that slightly exceed the 10% significance level will still be considered as a rejection of the null hypothesis.

Concerning first generation indices, the GSCI fails to reject the joint hypothesis of mean-variance spanning at the 5% and 10% significance level. Also, after accounting for non-normality, no diversification benefits are reported. On the other hand, the DJUBSCI rejects the null of mean-variance spanning at the 5% significance level. Accounting for non-normality, this result becomes insignificant.

Evidence for second generation indices show that the MLCX fails to reject the null hypothesis of mean-variance spanning at the 5% significance level. This result is underlined when accounted for non-normality. On the other hand, the MSLF shows a significant improvement in the efficient frontier, which also holds under non-normality of returns. The step-down procedure states that this positive change is due to both an improvement in the tangency portfolio and the GMVP.

Considering the third generation, all indices reject the null of mean-variance spanning, even when accounting for non-normality. Additionally, the step-down procedure shows that including third generation indices in an otherwise diversified portfolio will lead to an improved tangency and GMVP at the 5% significance level.

Out-of-Sample Performance of Commodity Indices

Exhibit 4 shows the results of the OOS performance tests for the different portfolios over the various windows sizes. Comparing the SRs of the base portfolio and those including first generation indices, no clear picture emerges. For the different window sizes, some portfolios show an increased SR, while others show inferior performance. Evidence is clearer for later generation indices. Here, benchmarks from both families improve the SRs, for all considered window sizes. The largest increase of all benchmarks is always reported for the CYD, and accounts for an improvement of approx. 13%. For the second generation, the MSLS performs best and accounts for an increase of around 9%.

The same pattern is also reflected in the values of the expected shortfall. Here, second and third generation indices lead to a reduction in the measure of maximal loss that the investor encounters. Again, for the first generation, these values vary, depending on the third and fourth moment of the return distribution.

While the overall picture shows an improvement due to commodity indices, especially when considering later generations, only some of the results are statistically significant. Exhibit 4 shows that of the 32 portfolio SRs analyzed, only 12 are significantly different from the base portfolio. Nearly half of the ones that are significant belong to the first generation. Since this includes SRs that are higher and lower than the base portfolio, we can conclude on the varying benefits of these benchmarks. With regard to the second generation, only the MLCX shows a significant improvement for Z=72. Thus, one has to be careful in concluding on the diversification benefits of second generation indices. The rest of the significant measures belong to the third generation, which supports their diversification benefits.

Discussion

The empirical results provide room for interpretation and fund allocation recommendations for a traditional U.S. investor. Over the whole period from May 1991 to June 2013, first generation indices will no longer provide the investor with benefits. The two benchmarks employed fail to reduce the portfolio volatility, or only exhibit varying OOS-SRs. This lack in performance is in line with the research of Daskalaki and Skiadopoulos [2011], and contrasts the findings of Belousova and Dorfleitner [2012] and Galvani and Plourde [2009], who rely on individual future contracts. Looking at Exhibits 1 and 3, the GSCI rejects the null at a higher significance level than the DJUBSCI. This might be due to the much higher volatility, given the nearly equal level of return for both indices. In the end, the investor is better off not to allocate his funds towards these benchmarks. With regard to second generation indices, the investor should consider momentum strategy indices to improve its investment universe. The results can be explained by the high SR and the low correlation values. Looking at Exhibits 1 and 2, the MSLF reports one of the highest SRs among the indices. The low and even negative correlation values, especially with the fixed income index, marks the source of the diversification benefits. Furthermore, it can be seen that benchmarks like the MLCX, which just rolls into the second nearest future contracts rather than front end contracts, will not reduce the overall volatility, nor enhance portfolio return. Obviously, indices need to provide more enhanced construction methodologies.

This argument is supported when looking at the third generation. All three indices provide benefits for the in-

Commodities		LM	LR	Wald	GMM-Wald	F1	F2
1st Generation	GSCI	3.9645	3.9946	4.0249	2.8540	0.0000	3.9944
		(0.1388)	(0.1388)	(0.1388)	(0.2458)	(0.9933)	(0.0467)
	DJUBS	6.7324	6.8197	6.9085	5.6842	0.0124	6.8435
		(0.0344)	(0.0344)	(0.0344)	(0.0620)	(0.9115)	(0.0094)
2nd Generation	ML	5.9019	5.9689	6.0369	3.8737	1.9419	4.0119
		(0.0523)	(0.0523)	(0.0523)	(0.1494)	(0.1646)	(0.0462)
	MSLF	30.0814	31.9377	33.9498	51.8200	6.1158	26.9225
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0140)	(0.0000)
3rd Generation	CYD	48.5552	53.6565	59.4982	59.2415	7.2785	50.3372
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0074)	(0.0000)
	MSLS	40.0690	43.4574	47.2388	63.9214	8.5804	37.0496
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0037)	(0.0000)
	SH	15.9220	16.4223	16.9439	8.6864	9.7537	6.7714
		(0.0003)	(0.0003)	(0.0003)	(0.0146)	(0.0020)	(0.0098)

The table reports the test statistics and p-values (in brackets) for the Lagrange Multiplier (LM)-, the Likelihood Ratio (LR)-, and the Wald-Test, as well as for the Wald Test using the generalized Method of Moments Approach (GMM-Wald). Under the null the test asset spans the same universe as the benchmark assets. Also included are the results for the two F-Tests of the Step-Down Procedure. Here F1 evaluates the ability of the test assets to increase the overall return, while F2 tests for an overall reduction of risk. For all computation monthly excess return data over the 3-month U.S. Treasury Bill was used covering the period from June 1991 to May 2013.

Exhibit 3 Results of Spanning Tests for Commodity Indices (1991–2013)

Source: Author's calculations

vestor and should have been included in the portfolio. Again, they all report very high SR together, with low or negative correlation values. The beneficial strategies include fundamental, momentum, and term-structure methodologies. This result is in line with Erb and Harvey [2006], Miffre [2011], Miffre and Rallis [2007], and Fuertes, Miffre, and Rallis [2008], who utilize these strategies with individual future contracts.

The same conclusion can be drawn when looking at the results of the OOS performance. The reported evidence is in line with the studies from You and Daigler [2012] and Bessler and Wolf [2014] and partly contradicts the findings of Daskalaki and Skiadopoulos [2011]. While Daskalaki and Skiadopoulos [2011] report reduced SRs when commodity indices are included, our analysis shows the opposite. Nevertheless, only some of the reported SRs are also statistically significant, which should be treated with caution.

How can the observed differences between the three index families be explained? Obviously all indices that fail to reject the null of mean-variance spanning do not follow a rolling technique that includes the whole term structure of future prices, nor do they take short positions. As already noted, first generation indices suffer from the fact that they assume the market is always in backwardation. The MLCX tries to solve this problem by considering future contracts that lie further apart on the term structure curve, but only rolls from the second to the third month contract, as opposed to considering the whole curve. The problem of contracts closer to maturity is that they tend to be more in contango than more distant contracts [Miffre, 2012]. This would subsequently lead to lower returns for these indices.

Moreover, the considered dataset covers bullish and bearish market periods. The commodity boom from 2005 to 2008 is included, but the recent financial crisis from 2007 to 2009 is as well. In particular, the last period was characterized by one of the largest economic recessions since the Great Depression of the late 1920s. Today, agriculture prices still remain below their previous peaks in the 1970s [Dwyer, Gardner, and Williams, 2011]. Oil as a major part of the energy sector was in contango from late 2004 to 2009 [Domanski and Heath, 2007]. For long-only indices, like the DJUBSCI, the GSCI, or the MLCX, this time was associated with negative roll returns. Later generation commodity indices may have improved their returns during these contangoed markets by weighting towards better performing future contracts, or by going short. This explanation would be in line with reported evidence from Miffre [2012], Erb and Harvey [2006] and Rallis, Miffre, and Fuertes [2012], who show that long-short, momentum, or enhanced rolling techniques improve the overall return when compared to long-only strategies. Furthermore, indices that roll into mid- to far-end future contracts may incur a liquidity risk premium, since these futures are less liquid than front contracts [Rallis, Miffre, and Fuertes 2012]. The DJUBSCI and the MLCX, on the other hand, select futures on the basis of liquidity. Thus they may not have earned this source of return.

With regard to a possible diversification benefit, futures close to expiration are more volatile because they are more prone to supply and demand shocks [Miffre, 2012]. This would explain the high standard deviations, reported for the three indices in Exhibit 1. Additionally, Miffre [2011] reports that during phases of economic turmoil long-short strategies tend to provide lower correlations than long-only indices. Indeed, when looking at Exhibit 2, all three indices show significantly high correlation values compared to the other indices. Yet the same level of correlation is also reported for the SDCI, which reports benefits. An explanation could be that for a commodity index to be beneficial in terms of the joint hypothesis in (2), it not only has to provide diversification benefits, but also must have a high return. Truly, when looking at the SR, the SDCI reports the highest value among the commodity indices. Having a look at the associated means and standard deviations from Exhibit 4, we can see that the reported gains mostly stem from a reduction in risk, rather than from improved returns. This underlines the diversification character of the commodity indices.

Finally, it can be asked whether the obtained results are a sign for an increased financialization of the commodity markets. The answer to this question is: “Maybe.” One has to be careful in linking the obtained results to the effects of financialization. This article does not cover the analysis to conclude whether there are increased cross-sectional correlations or volatility spillovers from traditional asset markets or not. Nevertheless, Tang and Xiong [2012] argue that the increased index investment since the early 2000s has led to rising correlations among commodity futures, especially in indices like the GSCI and the DJUBSCI. This in turn has diminished the diversification benefits of these benchmarks. Indeed, the results show that first generation indices no longer provide any benefits IS and mixed results OOS. Additionally, when looking at Exhibit 1, the correlation among the commodity indices is mixed, but is mostly high and positive. However, these values are also reported for later generation indices, which still yield benefits to investors. It might be tempting to assume that financialization is an explanation for the observed results, but as the debate of whether it is a cause of increased correlation and volatility is still going on, it only

	Portfolio		Sharpe Ratio	Average Return	Standard Deviation	Skewness	Kurtosis	Expected Shortfall(5%)	Total Turnover
Z= 36	*Base Portfolio*		*0.4814*	*0.0644*	*0.1338*	*-0.1845*	*35.810*	*-0.2355*	*0.0089*
	+ 1st Generation	GSCI	0.4729	0.0630	0.1333	-0.3185	39.342	-0.2399	0.0139
		DJUBS	0.4813	0.0625	0.1300	-0.2305	37.905	-0.2309	0.0169
	+ 2nd Generation	ML	0.4874	0.0648	0.1329	-0.2764	38.220	-0.2343	0.0144
		MSLF	0.5329	0.0638	0.1198	-0.1615	34.188	-0.1994	0.0192
	+ 3rd Generation	CYD	0.5580*	0.0673	0.1207	-0.1091	33.536	-0.1951	0.0220
		MSLS	0.5446*	0.0661	0.1214	-0.1194	29.887	-0.1921	0.0210
		SH	0.5391*	0.0683	0.1267	-0.2910	38.391	-0.2178	0.0168
Z=48	*Base Portfolio*		*0.4877*	*0.0650*	*0.1332*	*-0.1855*	*36.006*	*-0.2349*	*0.0092*
	+ 1st Generation	GSCI	0.4779*	0.0636	0.1332	-0.3169	39.362	-0.2395	0.0150
		DJUBS	0.4866	0.0630	0.1295	-0.2374	38.246	-0.2297	0.0177
	+ 2nd Generation	ML	0.4921	0.0653	0.1326	-0.2761	38.417	-0.2336	0.0154
		MSLF	0.5370	0.0640	0.1192	-0.1512	34.405	-0.1980	0.0201
	+ 3rd Generation	CYD	0.5599	0.0673	0.1203	-0.0995	33.890	-0.1950	0.0237
		MSLS	0.5432*	0.0657	0.1209	-0.0923	30.496	-0.1911	0.0218
		SH	0.5478*	0.0692	0.1263	-0.3008	38.838	-0.2166	0.0174
Z=60	*Base Portfolio*		*0.5161*	*0.0659*	*0.1276*	*-0.2006*	*34.239*	*-0.2216*	*0.0069*
	+ 1st Generation	GSCI	0.5202**	0.0656	0.1261	-0.2047	33.252	-0.2164	0.0108
		DJUBS	0.5179**	0.0636	0.1228	-0.2118	34.209	-0.2158	0.0137
	+ 2nd Generation	ML	0.5306	0.0668	0.1259	-0.1882	32.909	-0.2149	0.0113
		MSLF	0.5842	0.0665	0.1138	-0.2224	33.033	-0.1817	0.0147
	+ 3rd Generation	CYD	0.5973	0.0694	0.1162	-0.2305	33.837	-0.1898	0.0181
		MSLS	0.5878	0.0686	0.1168	-0.2196	31.530	-0.1906	0.0158
		SH	0.5795*	0.0689	0.1189	-0.2798	34.755	-0.1998	0.0124
Z=72	*Base Portfolio*		*0.5023*	*0.0655*	*0.1304*	*-0.2753*	*37.082*	*-0.2286*	*0.0050*
	+ 1st Generation	GSCI	0.5018*	0.0651	0.1298	-0.2771	36.137	-0.2256	0.0088
		DJUBS	0.5115*	0.0643	0.1258	-0.3087	38.059	-0.2238	0.0107
	+ 2nd Generation	ML	0.5185*	0.0669	0.1291	-0.2755	36.105	-0.2236	0.0092
		MSLF	0.5522	0.0650	0.1177	-0.2775	36.977	-0.1915	0.0122
	+ 3rd Generation	CYD	0.5839	0.0697	0.1194	-0.2347	35.853	-0.1935	0.0143
		MSLS	0.5596	0.0668	0.1194	-0.2365	33.893	-0.1942	0.0129
		SH	0.5653	0.0687	0.1215	-0.3718	39.451	-0.2086	0.0104

The table shows the out of sample performance measures for the different portfolios using a window size of K= 36, 48, 60, and 72, respectively. Included are the Sharpe ratio, the average annual Return and Standard Deviation, the Skewness, the Kurtosis, the Expected Shortfall, and the Total Turnover. Significance of the Sharpe ratio was tested according to Jobson and Korkie [1989] and Gibbson, Ross, and Shanken [1989]. The null hypothesis is whether there is no difference between the SR of the base portfolio and one that includes a commodity index. *Significant at 1%. ** Significant at 5%.

Exhibit 4 Out-of-Sample Performance of Commodity Indices (1991–2013)

Source: Author's calculations

provides a possible explanation for the observed results, rather than a final conclusion.

Conclusion

With commodity indices, the investor is able to gain exposure to a broad basket of commodity sectors. Since the launch of the GSCI, constant developments in the area of trading strategies, weighting, and rolling techniques have led to the development of a contemporaneous third generation of commodity indices. This increasing number of investment possibilities and the ever-increasing doubts about possible financialization make it more difficult for investors to choose among these benchmarks. To shed light on the issues, this article extends the prior research by formally comparing the three currently existing index families.

Using mean-variance spanning and including the first generation indices separately into a traditional U.S. portfolio over the period from May 1991 to June 2013, it can be seen that these indices no longer provide benefits to investors. The evidence for second generation indices is mixed: while long-only indices fail to improve the efficient frontier, momentum strategy indices should be considered as an investment, contributing to lower risk and higher returns. The latter point is also true for the third generation indices. Here, momentum, term-structure, and fundamental-based weighting strategies improve the efficient frontier. The same conclusion can be drawn in an OOS setting. While first generation indices show mixed results, later generation indices improve the SRs and reduce the expected shortfall. Although only some of the results are significant, the various window sizes all lead to the same picture.

These results challenge the existing literature and search for explanations in the different construction methodologies and the growing financialization of the commodity market. They show that trading strategies are an integral part for commodity indices. An investor should allocate his funds towards later generation indices to make use of their diversifying ability. Issuing companies should consider a multidimensional selection and weighting methodology in order to improve the performance of their indices and attract more investors.

With its active weighting and allocating characteristics, third generation indices also challenge commodity traders, public funds, and commodity pools. A comparison between these groups might provide further insights. In the situation where later generation indices perform equally well, investors could have an investment opportunity that provides active allocation at lower costs. That analysis is beyond the scope of this article and is left to future research.

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References

Barclays Capital. "US Aggegate Index." (2014), https://index.barcap.com/Home/Guides_and_Factsheets.

Belousova, J. and G. Dorfleitner. "On the Diversification Benefits of Commodities from the Perspective of Euro Investors." Journal of Banking and Finance 36, (2012), pp. 2455-2472.

Berndt, E. R. and N.E. Savin. "Conflict Among Criteria for Testing Hypotheses in the Multivariate Linear Regression Model." Econometrica 45, (1977), pp. 1263-1278.

Bessler, W. and D. Wolf. "Do Commodities add Value in Multi-Asset-Portfolios? An Out-of-Sample Analysis for Different Commodity Groups." Working paper, 2014.

Bodie, Z. and V.I. Rosansky. "Risk and Return in Commodity Futures." Financial Analysts Journal, May-June 1980.

Breusch, T. S. "Conflict Among Criteria for Testing Hypotheses: Extensions and Comments." Econometrica 47, (1979), pp. 203-207.

Chong, J. and J. Miffre. "Conditional Correlation and Volatility in Commodity Futures and Tradtitional Asset Markets." The The Journal of Alternative Investments, Winter 2010, 12:3, pp. 61-75.

CYD. "CYD LongShort TR Index." (2013), http://www.cyd-research.com/en/indices/longshort_tr_index.php.

Daskalaki, C. and G. Skiadopoulos. "Should Investors Include Commodities in Their Portfolios After All?

New Evidence" Journal of Banking and Finance 35, (2011), pp. 2606-2626.

DeRoon, F. A. and T. E. Nijman. "Testing for Mean-Variance Spanning." Journal of Empirical Finance 8, (2001), pp. 111-155.

DJUBSCI "Dow-Jones UBS Commodity Index Fact Sheet." (2013), http://www.djindexes.com/mdsidx/downloads/fact_info/Dow_Jones-UBS_Commodity_Index_Fact_Sheet.pdf.¬¬---- ,"Dow-Jones UBS Commodity Index Methodology 2013." (2013) http://www.djindexes.com/mdsidx/downloads/ubs/DJ_UBS_Commodity_Index_Methodology_2013.pdf.

Domanski, D. and A. Heath. "Financial Investors and Commodity Markets." BIS Quarterly Review, (March 2007), pp. 53-67.

Dwyer, A., Gardner, G., and T. Williams. "Global Commodity Markets – Price Volatility and Financialisation." Reserve Bank of Australia, June Quarter 2011, pp. 49-58.

Engle, R. "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation." Econometrica, (1988), Vol. 96, pp. 893–920.

Erb, C. B. and C. R. Harvey. "The Strategic and Tactical Value of Commodity Futures." Financial Analysts Journal, (2006), Vol. 62, No. 2, pp. 69-94.

Ferson, W., Foerster, S. R., and D.B. Keim. "General Tests of Latent Variable Models and Mean-Variance Spanning." Journal of Finance 48, (1993), pp. 131-156.

Fuertes, A.-M., Miffre, J., and Rallis, G. "Tactical Allocation in Commodity Futures Markets: Combining Momentum and Term Structure Signals." EDHEC Business School, (2008), pp. 1-30.

Galvani, P. and A. Plourde. "Portfolio Diversification in Energy Markets." Energy Economics 32, (2009), pp. 257-268.

Georgiev, G. "Benefits of Commodity Investment." CISDM Working Paper, (2001), University of Massachusetts, pp. 1-13.

Gibbson, M., Ross, S., and J. Shanken. "A Test of Efficiency of a Given Portfolio." Econometrica 57 (1989), pp. 1121-1152.

Gorton, G. and G. Rouwenhorst "Facts and Fantasies about Commodity Futures." Financial Analysts Journal, Vol. 62.2, (2006), pp. 47-68.

GSCI "S&P GSCI Commodity Index Fact Sheet." (2013), http://www.spindices.com/documents/factsheets/fs-sp-gsci-ltr.pdf.

Hansen, L. P. "Large Sample Properties of the Generalized Method of Moments Estimator." Econometrica 50 (1982), pp. 1029-1054.

Huberman, G. and S. Kandel "Mean-Variance Spanning." Journal of Finance 42 (1987), pp. 873-888.

Jensen, G. and J. Mercer. "Commodities as an Investment." The Research Foundation of CFA Institute (2011), Literature Review, pp. 1-33.

Jobson, J.D. and B. Korkie. "A Performance Interpretation of Multivariate Tests of Asset Set Intersection, Spanning, and Mean-Variance Efficiency." Journal of Financial and Quantitative Analysis 24 (1989).

Kan, R. and G. Zhou. "Tests of Mean-Variance Spanning." Annals of Economics and Finance 13-1, (2012), pp. 139-187.

Louie, N. and C. Burton. "Uncovering Hidden Risks in Active Commodity Indices." Credit Suisse Asset Management Brochure (2013).

Merrill Lynch "The Merrill Lynch Commodity Index eXtra." (2006), http://www.ml.com/media/67354.pdf.

Miffre, J. "Comparing First Second and Third Generation Commodity Indices." EDHEC Business School (2012), pp. 1-13.

Miffre, J. "Long-Short Commodity Investing: Implications for Portfolio Risk and Market Regulation." EDHEC-Risk Institute (2011), pp. 1-70.

Miffre, J. and G. Rallis. "Momentum Strategies in Commodity Futures Markets." Journal of Banking and Finance (2007), Vol. 31.6, pp. 1863-1886.

Morningstar “Commodity Index Comparison” (2013), http://corporate.morningstar.com/US/documents/Indexes/CommodityIndexComparison.pdf.

Rallis, G., Miffre, J., and A.-M. Fuertes “Strategic and Tactical Roles of Enhanced Commodity Indices.” Journal of Futures Markets (2012), Available at SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1648816.

Satyanarayan, S. and P. Varangis. “Diversification Benefits of Commodity Assets in Global Portfolios.” The Journal of Investing 5.1, (1996), 69-78.

Silvennoinen, A. and S. Thorp. “Financialization, Crisis, and Commodity Correlation Dynamics.” Journal of International Financial Markets, Institutions & Money 24 (2012), pp. 42-65.

Summerheaven “SummerHeaven Synamic Commodity Index: Index Methodology.” (2013), https://www.summerhavenindex.com/guest/sdci.html.

Tang, K. and W. Xiong. “Index Investment and the Financialization of Commodities.” Financial Analysts Journal (2012), Vol. 68.6, pp. 54-74.

Till, H. “Structural Sources of Return and Risk in Commodity Futures Investment.” EDHEC Business School (2006), pp. 1-19.

Yau, J. K., T. Schneeweis, T.R. Robinson, and L.R. Weiss “Chapter 8: Alternative Investments Portfolio Management.” In: Managing Investment Portfolios: A Dynamic Process, by Maginn, J. L./ Tuttle, D. L./ McLeavey, D. W./ Pinto, J. E., 3rd Edition (2007), John Wiley & Sons, Inc.

You, L. and R. T. Daigler “A Markowitz Optimization of Commodity Futures Portfolios.“ The Journal of Futures Markets 33.4, (2011), pp. 343-368.

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Beyond Venture Capital: An Innovative Approach for Investment in New Ventures and Projects

Manuel Stagars, CAIA
Entrepreneur and Economist

How Venture Capital Works

To prototype his vision and receive feedback from the market, an entrepreneur raises seed capital from a business angel or venture capital firm. When the market confirms that the idea has room to grow, the startup raises further rounds of capital, scaling the business up from round to round. At some point, the early-stage venture capitalists start selling their shares in the second market to realize a profit. Finally, in an initial public offering (IPO), founders and later stage investment firms sell shares to the public to realize their profits.

Venture capital firms usually strive for at least a 10X multiple (1,000 percent return) over the investment period. The desired average lies somewhere around a 30X multiple. The investment capital is concentrated and dependent on the success of a single venture. To hedge their bets, venture capitalists invest funds in more than one startup at the same time, hoping that roughly one in ten will end up in a lucrative exit and more than cover the costs for those that did not work out as well. See Exhibit 1.

In this article, the term "investors" describes the investors in the venture capital fund, not the venture capital firm itself. Most venture capitalists co-invest their own money, but they draw the bulk of their invested capital from venture funds, which hold money raised from high-net-worth individuals and institutional investors. The size of these venture funds is usually around $200 million. Investments funds are locked up for 7-10 years and the investors receive their principal plus (presumably) a profit upon liquidation of the portfolio. The venture capital firm manages the venture fund by allocating it across several portfolio investments.

Assimilation Funds Enable Network Effects

This article introduces the concept of *assimilation funds* as a fresh perspective on venture capital funding. Instead of concentrating on single companies and their management, the approach allows investors to buy strategic building blocks of a growth story right from the beginning. By investing in both the startup and its value chain partners, assimilation funds "assimilate" strategic investments early on. Not only does this diversify risk and cap the downside of the project, it also enables synergies that may accelerate profits if investee companies take off. If unexpected tail events happen, such as total failure of a business or an unexpected windfall, the strategy may achieve superior returns compared to traditional venture capital investment. This is possible because the portfolio contains several tangible assets in addition to startup equity. Their value may decrease, but it is not likely that it will go to zero. Conversely, when one asset in the basket takes off, it may lift the others as well.

While venture capital firms commonly diversify across several investments, they do not always consider the potential network effects they create. If one startup in a portfolio becomes successful, it could boost other assets as well. This may occur if it lowers the cost of certain components that other companies use, or if the companies share innovations rapidly and freely. In reality, successful startups use every advantage to beat the competition, not to support it. However, if one investor controls large parts of the value chain that several startups depend on, the situation changes. Advantages can spread to other companies more easily. Further, control of supply and distribution channels keeps competitors out and gives portfolio companies an added boost. Venture capital investors can do this with an assimilation fund.

Comparison to Conventional Venture Capital

Assimilation funds run differently from venture capital funds. Taking into account the strategic value chain of a small group of portfolio companies gives them a better chance at becoming successful. Such an approach takes a more sustainable view on startup investments. It veri-

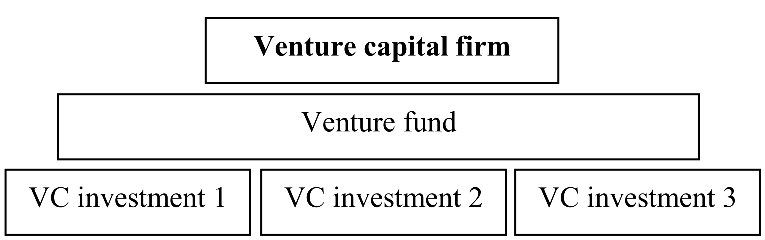

Exhibit 1 Conventional venture fund

Source: Author

fies that they have enough potential to scale well into the future. It also introduces hard assets as collateral earlier into the investment portfolio, reducing the risk for financial investors. Exhibit 2 outlines the main differences between the two approaches.

Introducing a Long-Term View

Spreading investment over strategically linked assets and asset classes moves the focus away from chasing a 10-30X return with a startup relatively quickly. Instead of trying to identify the next "big thing," an assimilation strategy realizes profits from the entire supply chain over the longer term. This shift in focus serves as an additional filter when evaluating portfolio assets. It goes one step beyond the obvious market that startups may play in. The bigger picture becomes more important.

Just as venture capital firms hedge their bets with investments in several startups, assimilation funds spread their capital across more than one core company. If the venture capital firm selects its portfolio companies wisely, there will be overlap in the strategic partners. The stronger this overlap is, the stronger the potential for network effects. When selecting investments, the fund manager should seek out complementary assets. Exhibit 3 shows how clusters of portfolio companies and their value chains overlap.

Investment Style and Characteristics

In terms of portfolio companies, assimilation funds have a narrower focus than venture capital funds. They follow a solid investment thesis and purchase stakes in partners in the value chain of the startups, often established companies in their own right. The fund achieves this through convertible debt, private equity invest-

	Venture capital	**Assimilation funds**
Use of funds	Purchasing a stake in a startup (investment size depends on stage)	Purchasing a stake in complementary startups and their upstream and downstream partners in the value chain
Term of investment	Short/medium-term view, exit pre-IPO or at IPO	10+ year horizon, long-term view, exit at IPO, or later
Size of the capital pool	Up to US$ 200 million for the entire venture fund	Up to US$200 million per assimilation fund, several are possible per VC firm
Objective	Realizing 10-30X return fast	Realizing 100X return over the long term
Investment thesis	"The startup quickly exploits a highly lucrative market opportunity, profit through IPO"	"The startup addresses a long-term need, which will take time to monetize. When that happens, large profits come from the startup and its partners in the value chain"
Investment theme	None, other than a sector focus, based on expertise of the firm	Strong themes, such as impact investment, sustainability, clean air, etc.
Fund manager	Venture capital firm	Venture capital firm together with dedicated fund manager
Business model for fund manager	Annual management fee, performance fee ("carry") at liquidation	Annual management fee, performance fee ("carry") at liquidation – but on a larger capital base than conventional VC funds
Return characteristics for investors	Option-like returns	Blended: Fixed income and equity from value chain investments; option-like on the upside, capped on the downside for startups

Exhibit 2 Comparison between venture capital and assimilation funds

Source: Author

ment, or purchases of publicly traded equity. Currency and interest rate hedges are also included in assimilation funds. This blend of asset classes diversifies risk and transforms venture capital into a less risky asset class. Compared to conventional venture capital, assimilation funds outperform as soon as investee companies deviate from normal performance. See Exhibit 4.

The dashed line in the figure represents classical venture-style returns. They have the characteristics of a call option. If investee companies do well and their share price exceeds the cost of the options premium, investors will realize a return. Otherwise, their entire investment is lost. The option expires worthless when investee companies are shut down or go bankrupt.

Investment performance in an assimilation fund follows a different pattern. It has the combined return characteristics of equity, a put option, and a call option. The strong line in the figure represents the return from a blended strategy. If investee startups perform poorly, collateral from value chain investments and hedges pad the loss. When startups are successful, network effects potentiate their benefits and boost not only the direct investment in those companies, but also the value chain assets. In these events, assimilation funds outperform conventional venture capital funds. However, diversification comes at a price. When startups perform as ex-

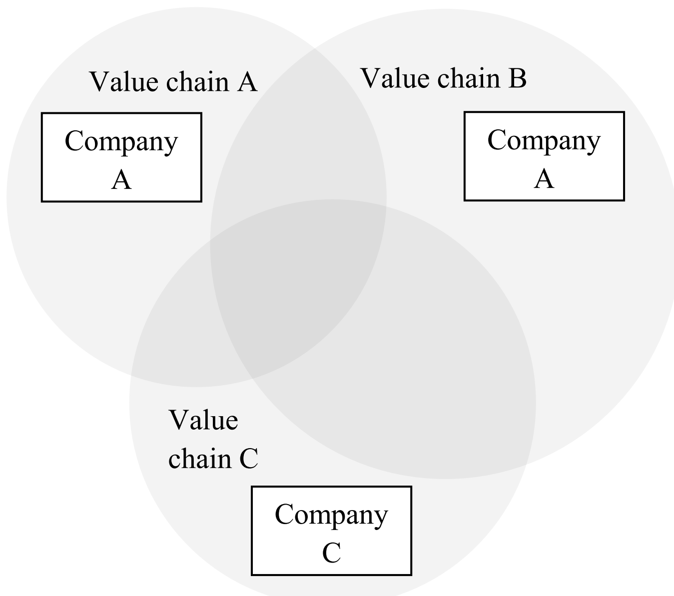

Exhibit 3 Synergies through overlapping value chains
Source: Author

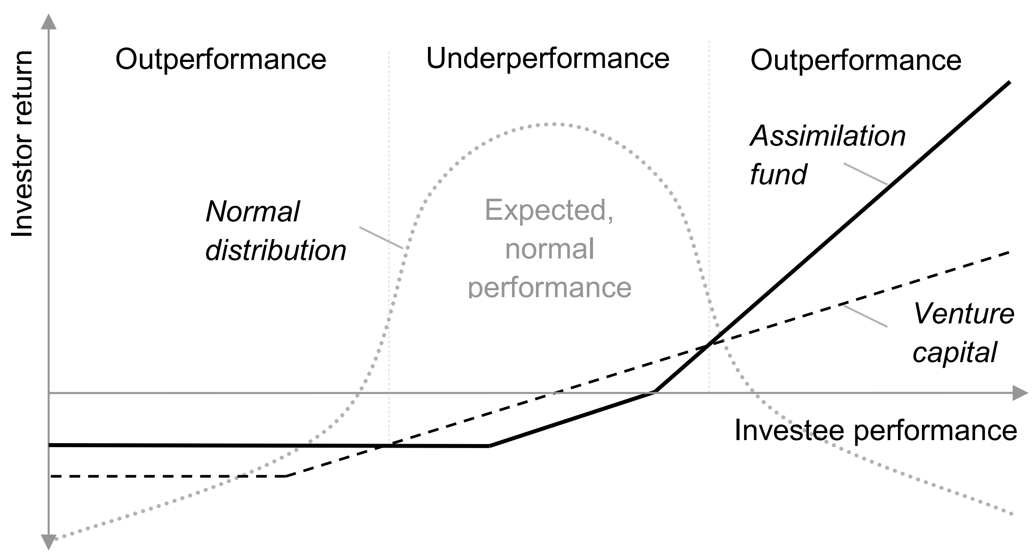

Exhibit 4 Investor return with conventional venture capital and assimilation funds
Source: Author

pected by achieving medium returns, the costs of the put and the call option outweigh these returns. With normal performance, the strategy underperforms traditional venture capital investment.

Venture Funds Become Hedge Funds
Venture capital firms enjoy an additional benefit when using assimilation funds to capitalize startups. As the total assets under management in these funds are larger than those of traditional venture funds, they generate higher annual management fees. Venture capital firms may do better with assimilation funds than funds operated under the old model, both in the event of success, and in the event of failure. Their business model becomes more like that of a hedge fund.

Application
Similar to traditional venture funds, assimilation funds allow venture capital firms to allocate capital from third parties to promising investments. However, these funds impose some additional constraints on investment selection that conventional venture capitalists may not be familiar with.

- Startups must follow a certain thesis and theme, e.g. SRI, sustainable transport, etc.;
- Startups must allow for scale and must involve an investible value chain;
- Startups must benefit from synergies by using the same value chain companies;
- Asset allocation.

Necessary Skills
Venture capital firms must carry out the assimilation approach consistently to take full advantage of the assimilation strategy. It is essential that interested venture capital firms familiarize themselves with the intricacies of these financial instruments and understand their implications. In particular, identifying complementary value chain assets may not be intuitive to conventional venture capital firms right away.

Since assimilation funds are blended funds and not pure venture funds, the fund manager has a dual role. On one hand, he is responsible for directing the venture capital investments in the portfolio. This is the expertise already native to venture capital firms. Additionally, he must also oversee the value chain assets and other financial instruments in the portfolio, such as private equity stakes in supply partners, publicly traded equity,

	Investment	Size (US$ millions) and % AUM	Stake
Venture capital (45%)	Electric car company	60 (30%)	60%
	Traffic flow software	20 (10%)	30%
	Regenerative breaking technology	10 (5%)	50%
Private equity (30%)	Electronic motor manufacturer	20 (10%)	5%
	Assembly plant	20 (10%)	5%
	Windshield projector manufacturer	20 (10%)	10%
Public equity (20%)	Manufacturer of charging stations	5 (2.5%)	
	Battery manufacturers	10 (5%)	
	Motor manufacturers	5 (2.5%)	
	Component manufacturers	20 (10%)	
Hedging instruments (5%)	Currency USD/CNY	5 (2.5%)	
	Put options on public equity	5 (2.5%)	

Exhibit 5 Asset allocation in an assimilation fund
Source: Author

and hedging instruments.

Asset Allocation
In addition to venture capital, assimilation funds include several other asset classes. Imagine a hypothetical assimilation fund of US$200 million with the theme "sustainable transport." It may consist of the following investments and asset classes, as seen in Exhibit 5.

Allocating the raised capital over about twenty investments in different asset classes helps to reduce the risk. The collateral of the hard assets in the value chain serves as a cap on the downside. At the same time, when the venture allocations outperform, their success may stimulate network effects that make the value chain companies more valuable. Their strategic ownership may help position the startups even more strongly in the market. Alternatively, when network effects kick in, investors may wish to realize capital gains.

Fund Structure
A venture capital firm can (and should) have several assimilation funds to increase its assets under management and benefit from larger scale in its operations. To do that, it will have to integrate new skills into its operations to manage the funds, comply with regulations, and regularly report to investors. A support structure and stronger banking relationships will be crucial in order to attract a more potent investor base and achieve scale. Just as other investment funds, assimilation funds are domiciled in a designated fund jurisdiction. The paper Themed Investment Funds (Stagars, 2014) explains their setup in more detail.

Exhibit 6 shows an example of a fund structure and its most important stakeholders.

Performance Modeling
Since assimilation funds are not pure venture capital funds, their returns have different characteristics from conventional venture capital funds. According to portfolio composition, fund managers need to find adequate benchmarks against which they compare their performance. Comparability is equally important when investors and their advisors evaluate assimilation funds against other investments.

When investments have a long performance history and trade on public exchanges, data is often freely available. However, in the case of startup investments and unproven investment theses, fund managers must construct a hypothetical portfolio and calculate model performance. They should back-test this portfolio over a certain time horizon, perhaps three to five years, and project returns into the future with several scenarios. Of course, accredited investors know that model performance does not ensure actual performance. Nevertheless, extra care to follow disclosure guidelines is important, perhaps more so than in a conventional venture fund. The CFA Institute recommends the following best practices when disclosing model performance.

- Clearly label all theoretical results as such (e.g.,

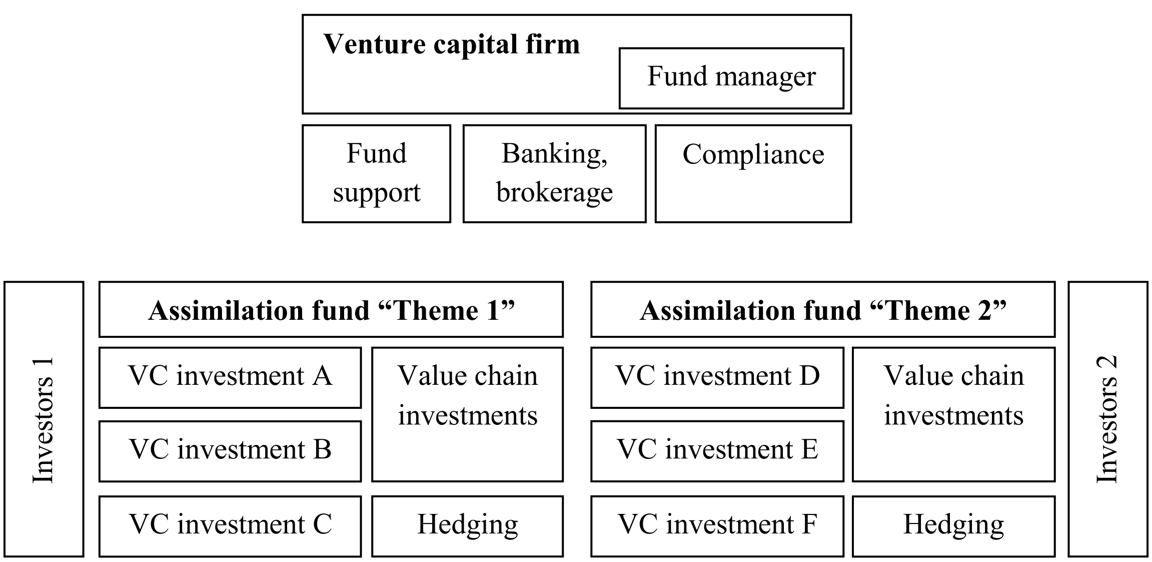

Exhibit 6 Structure of an assimilation fund funds
Source: Author

Backtested Global 130/30 Strategy).

- Do not link theoretical performance with actual performance in any way. This means more than just not linking the returns geometrically. If you must include theoretical and actual performance in the same presentation, then show them on separate pages, and label them clearly.
- Do not state that "past performance is not indicative of future results." Even though we are accustomed to this language, in the context of model performance, it implies that what is being shown is actual performance.
- Provide clear and prominent disclosure that the returns are theoretical, and describe all of the assumptions that have been made and their limits.
- Theoretical results should be shown only to consultants and sophisticated clients or prospects that have sufficient experience and knowledge to assess the product, presentation, and risks.
- Maintain sufficient records to support calculations and presentations.
- Consult with attorneys and your compliance department regarding applicable laws and regulations.

Such disclosures are more common in investment banking and private banking than in venture capital. To implement assimilation funds, venture capitalists need to adjust their approach to disclosures and compliance slightly, in order to include new practices and vocabulary.

Advantages and Disadvantages

Assimilation funds offer many advantages for investors, investment companies, family offices, foundations, and asset owners. The main benefit for venture capital firms lies in the larger pool of assets they manage. This may give them access to bigger deals, which results in larger revenues from management and performance fees. However, assimilation funds are more complex to manage than conventional venture funds.

Investors profit from blended exposure to venture-style returns. As venture capital is still the dominant asset class in assimilation funds, they may fulfill their allocation requirements with less downside risk and a stronger thematic investment thesis. However, if they wish pure exposure to venture capital, including its well-known risk-return profile, they may wish to allocate capital to more conventional funds instead.

Exhibit 7 summarizes some of the most important advantages and disadvantages from both perspectives.

Conclusion

This article gives an overview of assimilation funds and assimilation strategy. It introduces them as an innovative approach to financing new ventures and projects. This technique goes beyond venture capital investment, as it considers not only startups by themselves, but their strategic value chain as well. Investments follow a theme and have a longer-term investment horizon. This approach has the potential to offer superior risk-return characteristics to investors, especially lower downside risk. Blending several asset classes may attract more risk-averse investors, such as large institutions and endowments.

Venture capital firms benefit from assimilation funds as well. They gain access to larger pools of capital that

	Venture capital firm	Assimilation fund investors
Advantages	• Access to larger investor group • More assets under management (AUM) • High management /performance fee • Higher profile	• Blended venture capital exposure • Leveraged investment with capped downside risk • Larger secondary market, better liquidity during the investment term
Disadvantages	• More complex to set up and administer • Fund requires detailed reporting, compliance • Venture capital firm needs to find agreement with the board of the fund/fund manager	• Not "pure" venture capital exposure, if that is desired • Boundary to entry, as funds may impose higher investment minimums

Exhibit 7 Advantages and disadvantages for venture capital firms and assimilation fund investors

Source: Author

would otherwise not find their way into venture capital. The larger account size generates higher management fees, which allow venture capitalists to source new assets more aggressively.

Assimilation funds are new territory for both venture capitalists and financial investors. Because of their more complex structure, investors should familiarize themselves thoroughly with the risk-return characteristics of the approach. When venture capital firms introduce these financial products, they may find them complementary to conventional venture capital. However, it is possible that a new breed of venture firms will emerge that uses structured finance more audaciously. This may reinvent the traditional business model and make venture capital more palatable for a larger investor base.

Important note: This article contains information on portfolio management and wealth management principles and is for informational purposes only. It should not be construed as investment advice. In particular, it is not intended as a recommendation that any investor pursue investment strategies involving listed options, high-yield bonds, venture capital, or other alternative investments.

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Procyclical Behavior of Hedge Funds: A Portfolio Manager and Investor's Perspective

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Procyclical risk analysis is one of the main concerns for researchers working in the field of financial institutions, especially in banking research and macro-prudential analysis (Shin 2009; Adrian and Shin 2010; Jacques 2010). Procyclicality may be defined in two ways. First, a time series is procyclical if it tends to co-move positively with the business cycle. Thus, it increases in expansionary periods and decreases during recessionary periods. Second, a time series is procyclical if it tends to increase the amplitude of the business cycle. Similarly, a financial institution generates procyclicality if the credit it grants gives rise to an amplification of the business cycle. In this scenario, procyclicality generates systemic risk or risk related to contagion. The term "procyclicality" is somewhat ambiguous in the economic and financial literature, so we will retain both definitions of procyclicality in this article.

According to many studies, the main drivers of procyclicality are the big banks, which are very involved in off-balance-sheet activities, investment bankers, and more globally, the actors in the shadow banking business. However, the cyclical behavior of hedge funds, which are a constituent of shadow banking, is often neglected in the financial literature. However, it is well known that the recent financial crisis was attributable to the procyclicality of credit. The role of hedge funds in this procyclicality must not be minimized. According to Adrian and Shin (2010), the share of hedge funds in the origination of U.S. subprime mortgages by the leveraged financial sector was as high as 32% before the crisis, which suggests that hedge funds may originate important financial shocks that have repercussions throughout the entire economy.

To study the procyclical behavior of hedge funds, we place our analysis in a dynamic setting (Racicot and Théoret, 2013). We first show that the spectra of hedge fund returns classified by strategies highlight fluctuations in the business cycle frequency, which provides evidence of procyclicality in the hedge fund industry. Since the spectrum is a way of capturing the autocorrelation of returns, we can conclude that there is persistence in the series of the strategy returns at the business cycle frequency. This result is useful because it means that hedge fund returns are not pure random walks and can thus be forecasted. Importantly, the spectra of hedge fund strategy returns are quite different from one strategy to the next, which suggests that strategies may be a way for the investor to diversify his or her portfolio. We then conduct an empirical study on the procyclicality of two key financial parameters in portfolio management: the alpha and the beta of hedge fund strategies. Traditionally, these parameters are analyzed in a static way, in the sense that they are not time-varying. We make them time-varying by relying on two empirical methods applied to the Fama and French model (1992, 1993, 1997): the conditional regression and the Kalman Filter. We find that when classified by strategy, hedge fund portfolio managers tend to manage the risk of their portfolio, as measured by the time-varying beta, in a procyclical fashion. That is, the portfolio manager bears more risk (or leverages his portfolio) during expansion and bears less risk (or deleverages his portfolio) during recession. Importantly, strategies focusing on arbitrage, e.g., futures and distressed strategies, follow a different cyclical behavior. In this respect, it is interesting to note that the spectra of strategies based on arbitrage are different from those of the other strategies. Arbitrage strategies are also the ones whose returns are less easily captured by the Fama and French model (1992, 1993, 1997). The cyclical behavior of the alpha of arbitrage strategies is also dissimilar. Indeed, some strategies display a countercyclical behavior, which suggests that an absolute positive return may be obtained even in bad times. These results also indicate that hedge fund strategies may provide good diversification benefits. We complete our analysis of the diversification benefits provided by hedge fund strategies by studying the cyclical behavior of the cross-sectional dispersion of hedge fund strategy returns.

Data and Stylized Facts

Data

This study is based on a sample of the indices of U.S. Greenwich Alternative Investment (GAI) hedge fund strategies, a leader in hedge fund databases and collects data on the broad universe of hedge funds. Note that we compare hedge fund databases in some previous studies (Racicot and Théoret 2007a,b) and the empirical results are very close, especially with respect to the Hedge Fund Research (HFR) database. Descriptive statistics on this sample are reported in Exhibit 1. Our observation period for the monthly returns of these hedge fund indices runs from January 1995 to March 2010, for a total of 183 observations for each index (strategy). The risk factors that appear in the Fama and French equation (1992, 1993, 1997) - the market risk premium and the two mimicking portfolios: SMB and HML - are drawn from French's website. The interest rate used to test the models is the U.S. three-month Treasury bill rate and the selected market portfolio index is the S&P 500. The period we analyze was plagued by four major financial crises: (i) the Asian financial crisis (1997-1998); (ii) the Russian/LTCM crisis (1998); (iii) the bursting of the high-tech market bubble (2000); and (iv) the 2007-2009 subprime market crisis, related to high risk mortgages. Our period of analysis is, therefore, rich in major stock market corrections. Despite these market collapses, Exhibit 1 reveals that the GAI hedge funds performed quite well during this period. The mean monthly return of these indices is 0.71% over this period, for an annual rate of 8.5%. This rate is higher than the annual mean return of the S&P 500 over the same period, which amounted to 5.5%. The low performers over this period are the short-sellers, convertible arbitrage, and macro strategies while the high performers are the long-short, growth, and market-neutral strategies. In addition, the standard deviation of returns differs greatly from one index to the next. The standard deviations of the strategy returns are generally below those of the S&P 500.

Several researchers argue that the strategies followed by hedge funds are similar to option-based strategies (Fung and Hsieh, 1997, 2004; Weisman, 2002; Agarwal and Naik, 2000, 2004). And effectively, Exhibit 1 reveals that some hedge fund strategies are similar to hedged option strategies, like the covered call and protective put strategies. These option-based strategies have a beta that is quite low, in the order of 0.6 for at-the-money options, and yet may offer high returns that approximate those shown in Exhibit 1. The following strategies - equity market-neutral, arbitrage, futures, and distressed securities - have a very low beta compared to other funds. These strategies are more involved in arbitrage activities than the others. Their returns are also less tractable in the Fama and French model. Other risk factors are at play to explain the returns of these low-beta strategies.

In addition, plain vanilla puts, to which the short-seller strategy is linked, have a negative expected return. That might explain the low mean return of the short-seller index over the period of analysis. At a monthly 0.18%, it is well below the mean return of the whole set of strategies. Incidentally, the CAPM beta of the short-seller index, equal to -1.01, is negative and quite high in absolute value over the sample period. According to the CAPM, the excess return of a portfolio having a negative beta should be low and even negative: this is the case of the short-seller index.

	Mean	Median	Max	Min	sd	Skew	Kurtosis	CAPM-beta
Distressed Securities	0.68	1.04	4.79	-7.44	2.06	-1.47	6.86	0.22
Equity Market-Neutral	0.87	0.80	8.10	-2.53	1.41	1.33	8.95	0.08
Futures	0.67	0.21	7.71	-6.80	3.10	0.18	2.72	-0.08
Macro Index	0.55	0.66	4.00	-2.95	1.45	0.29	3.06	0.27
Market-Neutral Group	0.93	0.92	7.20	-6.06	1.48	-0.61	8.99	0.20
Short-Sellers	0.18	-0.10	11.41	-6.88	3.61	0.56	3.46	-1.01
Value Index	0.61	1.11	5.68	-9.65	2.54	-1.21	5.94	0.56
Arbitrage Index	0.87	0.90	4.10	-8.58	1.38	-2.40	17.99	0.16
Convertible Arbitrage Index	0.31	0.60	6.55	-19.31	2.98	-3.78	26.43	0.40
Growth Index	1.04	1.19	20.10	-12.99	4.53	0.43	5.50	0.76
Long-Short	1.09	1.31	13.20	-9.24	3.02	0.04	5.20	0.52
Mean of indices	*0.71*	*0.78*	*8.44*	*-8.40*	*2.51*	*-0.60*	*8.65*	*0.19*
Weighted composite	0.56	0.90	4.75	-5.96	1.86	-1.01	5.18	0.37
S&P500	0.46	1.29	11.06	-18.47	4.62	-1.13	5.99	1.00

Notes: The statistics reported in this Exhibit are computed on the monthly returns of the GAI indices over the period running from January 1995 to March 2010. The weighted composite index is computed over the whole set of the GAI indices (strategies). The CAPM beta is estimated using the simple market model, that is: $R_{it} - R_{ft} = \alpha + \beta_i\left(R_{mt} - R_{ft}\right) + \varepsilon_{it}$, where R_i is the return of the index i, R_m is the S&P500 return. R_f is the riskless rate and ε_i is the innovation.

Exhibit 1 Descriptive statistics of the GAI indices returns, 1995–2010

Source: GAI & Bloomberg

Furthermore, according to Exhibit 1, the composite index of hedge funds has lower kurtosis than the market index given by the S&P 500. However, this characteristic is not shared by all hedge fund strategies, the convertible arbitrage index having a kurtosis as high as 26.43. A high kurtosis means that rare or extreme events are more frequent than for the normal distribution, which suggests that the payoffs of strategies displaying high kurtosis in their returns are very nonlinear. Once more, we may relate these statistics to those associated with the cash-flows of option-based strategies. Their payoffs have a relatively low standard deviation, but a high degree of kurtosis compared to the returns of the stock market index, which is priced in their returns.

Stylized facts

The spectrum of a time series is a device to depict its persistence at different frequencies, the business cycle frequency being the most important . In other words, the spectrum detects persistence or autocorrelation in the time series over the frequencies varying on a time scale running from 0 to π. When there is persistence over a time frequency, returns are predictable over this frequency. In this respect, the spectrum of a pure random variable—which by nature is not predictable—is flat (Exhibit 3). This kind of variable displays no persistence. Exhibit 4 shows the plot of the spectrum of a standard macroeconomic variable expressed in logarithm, like the logarithm of GDP or the logarithm of aggregate consumption. This kind of variable displays high persistence at very low frequencies, i.e., the trend

	r_{t-1}	$(Rm\text{-}Rf)_{t-1}$	VIX_{t-1}
Distressed Securities	-0.0014	0.0000	0.0043
	0.9172	*0.7714*	*0.0016*
Market-Neutral	-0.0145	0.0001	0.0027
	0.2183	*0.3054*	*0.0114*
Long-Short	-0.015	0.0001	0.0041
	0.030	*0.0484*	*0.0001*
Value Index	0.0072	0.0025	-0.0002
	0.5283	*0.0321*	*0.2502*
Growth Index	-0.0591	0.0055	0.0007
	0.0007	*0.0014*	*0.0014*
Futures Index	-0.1540	0.0108	0.0019
	0.000	*0.0001*	*0.000*
Weighted Composite	-0.0216	0.004	0.0002
	0.000	*0.000*	*0.000*

Notes: The Kalman Filter model used to estimate these coefficients is explained in the article. For each strategy, the first line of numbers provides the estimated coefficients of the variables and the second line gives the corresponding p-values (reported in italics).

Exhibit 2 Time-varying betas of some strategies estimated by the Kalman Filter

Source: Author's calculations

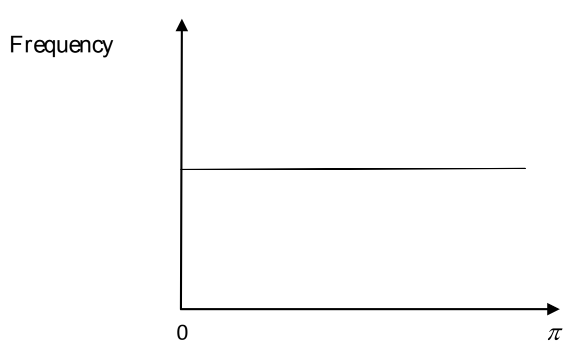

Exhibit 3 Spectrum of a random variable

Source: Author

of the variable is very pronounced. But it shows no fluctuation at higher frequencies, i.e., the trend dominates this time series. In Exhibit 4, the shaded area represents the business cycle frequency. As we see, a standard macroeconomic variable expressed in logarithm shows no fluctuation at this frequency. It must be transformed in order to study its cycle.

Exhibit 5 plots the spectrum of the hedge fund composite return. Since the spectrum has a peak at the business cycle frequency—always represented in the shaded area, it is the first indication that the return of a representative hedge fund is procyclical. It is thus persistent at the business cycle frequency. This result is not covered in the hedge fund literature. Note that the spectrum of the stock market return (S&P 500) is different (Exhibit 5). It shows fluctuations at a higher frequency than the business cycle one. This suggests that the stock market return is more unstable than the hedge fund composite return.

As mentioned previously, the behavior of hedge funds included in strategies focusing on arbitrage activities differs from the behavior of hedge funds mainly involved in other strategies. Exhibit 6 supports this hypothesis. Except for the futures strategy, strategies based on arbitrage show high fluctuations at low frequencies but much less fluctuation at higher frequencies. In this respect, the equity market-neutral spectrum is very similar to the one of a standard macroeconomic variable (Exhibit 4). It displays no fluctuation at the business cycle frequency, suggesting that the returns of this strategy are not procyclical. The spectrum of the futures strategy is quite different from the other three since it displays significant peaks at the business cycle frequency and at higher frequencies. Note that this strategy is sometimes classified in directional strategies although it has low beta, which might explain why the return delivered by the futures strategy displays fluctuations at the business cycle frequency.

We expect higher beta strategies to be more procyclical. Exhibit 7 plots the spectra of three of these strategies. Among all hedge fund strategies, the most conventional one is the long-short strategy. Its spectrum displays two peaks: one at low frequency and one at the business cycle frequency. Consequently, even if the returns of this strategy are partly procyclical, they are also related to the behavior of returns of arbitrage strategies. Therefore, a strategy may belong to many categories, which rep-

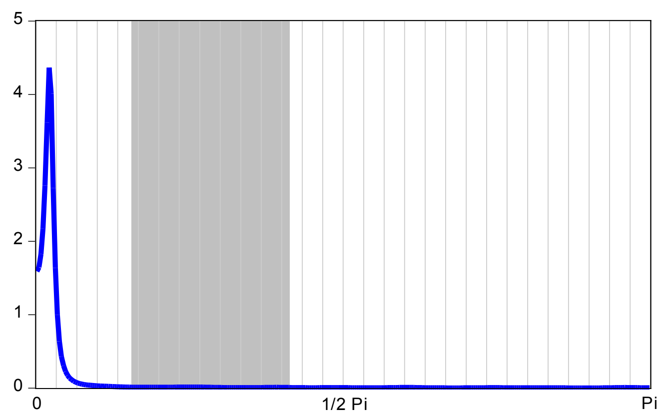

Exhibit 4 Spectrum of a standard macroeconomic variable

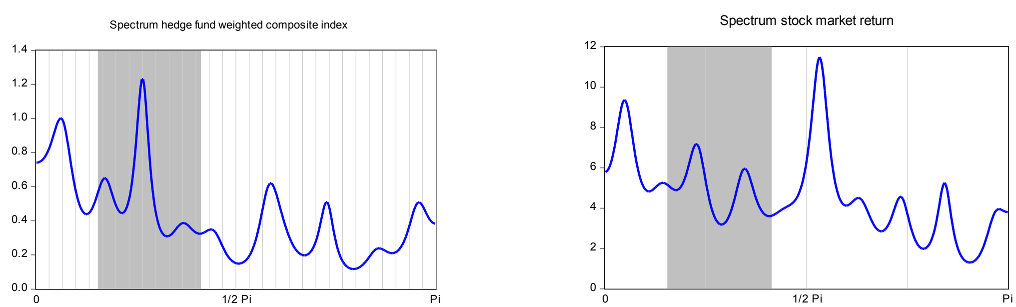

Exhibit 5 Spectra of the hedge fund composite return and the stock market return (S&P 500)

resents a good opportunity to diversify a portfolio. The spectrum of growth funds is quite similar to the one of the long-short strategy while the spectrum of the value index is more procyclical. From the investor's point of view, the growth strategy would be more appropriate in expansion than the other two strategies, although they may be beneficial in recession since they embed an arbitrage dimension. We know that the value strategy is associated with one market anomaly. Indeed, stocks related to this strategy incorporate a high dividend yield: these stocks tend to be undervalued. According to the spectrum, this dimension would be more valuable in expansion than in recession. The cyclical behavior of this anomaly is similar to the small firm anomaly. In this respect, Exhibit 7 shows that the spectrum of the SMB portfolio as computed by French - a portfolio long in firms with low capitalization and short in firms with high capitalization - is quite similar to the spectrum of the value index, even if it shows more fluctuations at higher frequencies. The SMB anomaly would thus be a better opportunity during an expansion than during a recession.

Overall, the analysis of the spectra shows that each strategy may embed many dimensions, even if it is classified as an arbitrage strategy or as a strategy more sensitive to the business cycle. These strategies may offer good diversification benefits to the investor. We examine this aspect more thoroughly in the following sections.

Return Models: The Conditional Model and the Kalman Filter Model

To further study the procyclicality of hedge fund behavior, we must simulate the time profile of strategies' alphas and betas. To do so, we rely on the standard conventional Fama and French model (1992, 1993, 1997), which reads as follows:

$$\left(R_{pi}-R_f\right)_t = \alpha_{it} + \beta_{1i,t}\left(R_m-R_f\right)_t + \beta_{2i,t}SMB_t + \beta_{3i,t}HML_t + \varepsilon_{it} \quad (1)$$

where $\left(R_{pi}-R_f\right)_t$ is the excess return of the portfolio of strategy i over the risk-free rate R_f ; $\left(R_m-R_f\right)_t$ is the market risk premium; SMB_t is the "small firm anomaly"; HML is the "value stock anomaly"; α_{it} is the time-varying alpha; $\beta_{1i,t}$ is the time-varying beta, and ε_{it} is the innovation.

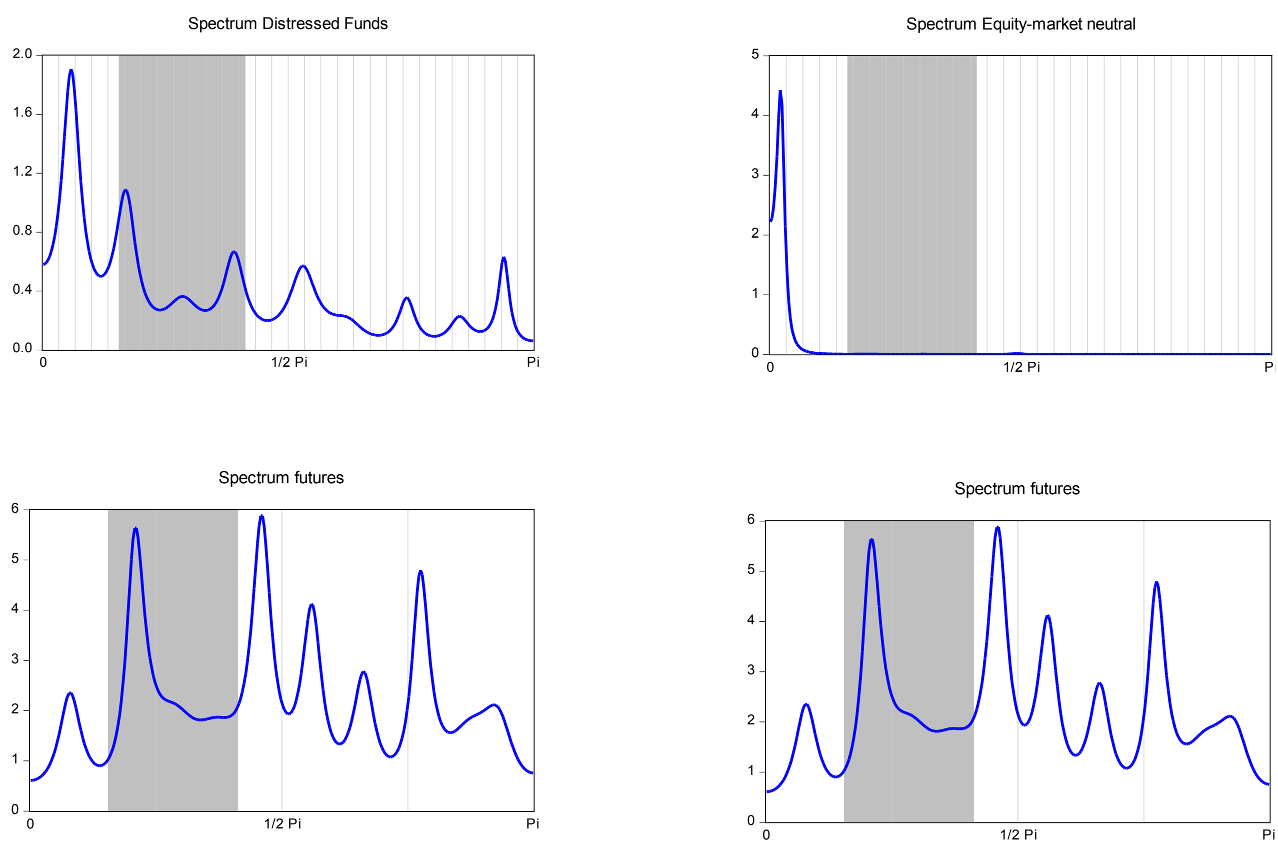

Exhibit 6 Spectra of some strategies focusing on arbitrage

We rely on two ways to compute the time-varying alpha and beta in equation (1). One way is to resort to the conditional model (Ferson and Schadt, 1996; Christopherson, Ferson and Glassman, 1998; Ferson and Qian, 2004). In line with this model, we express the conditional alpha and beta as follows:

$$\alpha_{it} = \alpha_{0i} + \phi_{1i} r_{t-1} + \phi_{2i} \left(R_m - R_f \right)_{t-1} \quad (2)$$

$$\beta_{1i,t} = \beta_{0i} + \phi_{3i} r_{t-1} + \phi_{4i} \left(R_m - R_f \right)_{t-1} + \phi_{5i} VIX_{t-1} \quad (3)$$

with r, the level of short-term interest, and VIX, the impliedvolatility of the S&P 500 index. The conditioning variables are lagged one period, our aim being to track the reaction of the time-varying coefficients to the conditioning market information. The selected financial variables are thus known at time t.

We thus postulate that the alpha and beta are under the control of the portfolio manager to a certain degree. Equation (3) indicates that the manager is involved in market timing, as he adjusts the beta of his portfolio according to the market risk premium. We may postulate that he bears more risk, or increases the beta of his portfolio, when the market risk premium increases. Conversely, he takes less risk, or decreases the beta, when the market risk premium decreases. Note that market-timing is usually studied by introducing the squared market risk premium in the return model (Treynor and Masuy, 1966; Henriksson and Merton, 1981). But we can easily verify that this is the case in our model by substituting equations (2) and (3) in equation (1). Aside the market risk premium, we also postulate that the beta is also sensitive to the short-term interest rate, which is viewed as an indicator of market conditions. The beta is also conditioned by the stock market volatility (VIX). The alpha responds to the risk market premium and the short-term interest rate.

To estimate the conditional model, we substitute equations (2) and (3) in equation (1). We can then rely on OLS (ordinary least-squares) to estimate the coefficients of equation (1). The coefficients of equations (2) and (3) are then exactly identified.

The Kalman filter is another method to estimate the time-varying alpha and beta. In this setting, equations (2) and (3) are transformed as follows:

$$\alpha_{it} = \alpha_{t-1,i} + \phi_{1i} r_{t-1} + \phi_{2i} \left(R_m - R_f \right)_{t-1} \quad (4)$$

$$\beta_{1i,t} = \beta_{t-1,i} + \phi_{3i} r_{t-1} + \phi_{4i} \left(R_m - R_f \right)_{t-1} + \phi_{5i} VIX_{t-1} \quad (5)$$

Compared to equations (2) and (3), the conditional al-

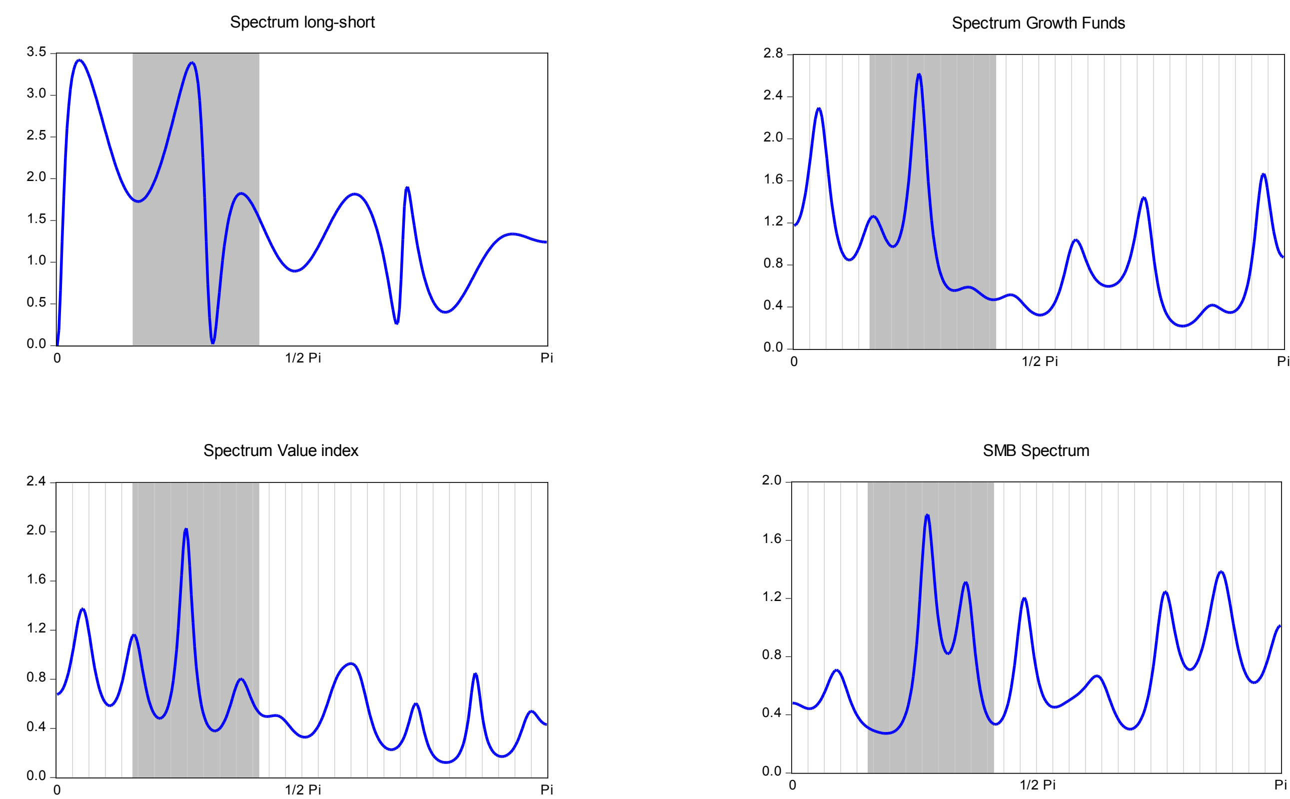

Exhibit 7 Spectra of some strategies having higher betas

pha and beta take a recursive form in the Kalman Filter model—i.e., the conditional alpha and beta are functions of their lagged values. In this model, the estimated alpha and beta ought to be smoother.

In the Kalman Filter model, equation (1) is the signal equation and equations (4) and (5) are the state equations. In this kind of model, these three equations are estimated simultaneously with a routine using the maximum likelihood method.

Empirical Results

Hedge fund portfolio managers and market timing

In this section, we focus on the time variability of the strategies' betas since it is the most important aspect of our article. In Exhibit 2, we note that the interest rate (r_f) has a negative impact on hedge funds betas, i.e., an increase in interest rate signals a market deterioration, which leads hedge funds to take less risk. Note however that this variable is not significant for strategies focusing on arbitrage, such as the distressed securities and market-neutral strategies. In other respects, according to the market variable (R_m - R_f), hedge funds take more risk when the market return, as measured by the S&P 500 index, increases. This result also indicates that hedge funds are good market-timers. However, as in the case of the interest rate conditioning variable, this effect is quite low and not significant for the distressed securities and market-neutral strategies.

Finally, financial market volatility, as measured by VIX, impacts positively and significantly on the market returns of all strategies except the value index strategy, for which the exposure to volatility is negative and insignificant. Hedge funds seem conditioned by the payoffs related to forward market volatility, the value of an option being dominated by its volatility.

Overall, the behavior of portfolio managers associated with arbitrage strategies seems different from that of managers associated with directional strategies. In the following section, we examine the time-varying behavior of the alphas and the betas of some representative strategies involved respectively in arbitrage activity and

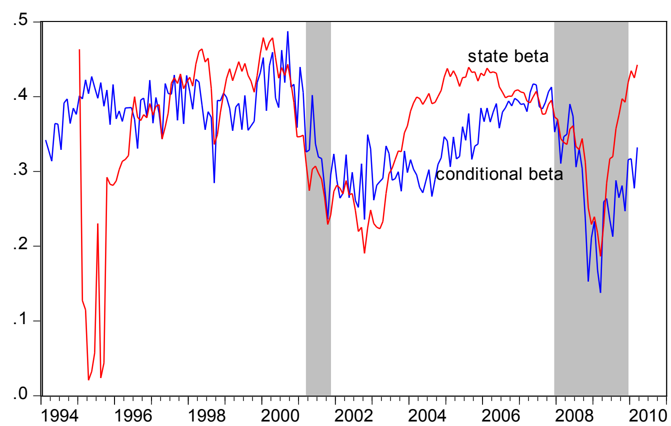

Exhibit 8 State beta and conditional beta for the GAI weighted composite index

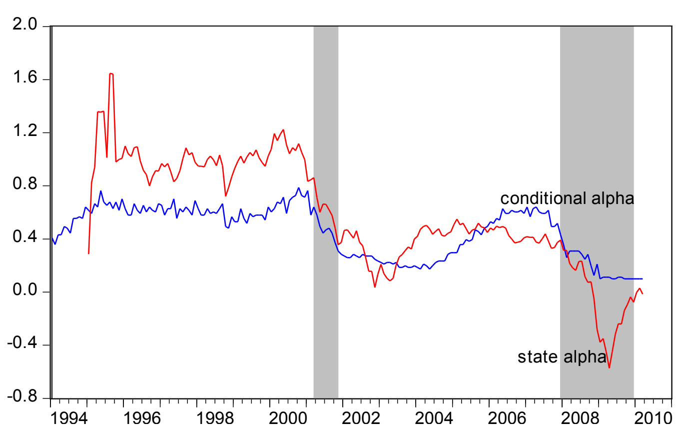

Exhibit 9 State alpha and conditional alpha for the GAI weighted composite index

market-oriented business lines in more detail.

The cyclicality of representative strategies' alphas and betas.

The plots of the betas indicate that they are far from being constant, as suggested by the conventional CAPM, and that many strategies exhibit a procyclical behavior with respect to the beta. As shown in Exhibit 8, the state beta of the weighted composite index decreased during the 1997 Asian crisis before resuming its rise in 1998. Thereafter, following the first U.S. recession of the millennium, the beta decreased from the beginning of 2000 until the end of 2002, which paved the way for a market recovery. The beta almost doubled from 2003 to the middle of 2005. It decreased progressively thereafter in expectation of an economic slowdown and in reaction to the corporate accounting scandals. This beta dynamics is comparable to the one obtained by McGuire et al. (2005) during the period from 1997-2004 with respect to hedge fund risk exposure, whereby funds lever their positions during the upward trend of the stock market or in economic expansions, and delever their positions during crises. Note that the profiles of the time-varying beta obtained by our two models—the conditional model and the Kalman Filter model—are quite close (Exhibit 8). Since the profiles of the strategy's conditional alpha and beta are also similar to the ones obtained with the Kalman filter, we only report the Kalman filter results in the ensuing discussion.

The state alpha related to the weighted composite index has a profile similar to the beta but is more volatile (Exhibit 9). The alpha decreased after the Asian crisis, the decrease gaining momentum during the technological bubble. During this episode, the estimated alpha dropped from a high of 1% (monthly) to a low close to 0%, which suggests that the alpha puzzle must be studied in a dynamic setting and might not be a puzzle after all. Our procyclical approach thus seems more relevant to track the alpha process than the one based on a static framework. As in the case of beta, the alpha profile is particularly interesting during the 2007–2009 subprime crisis. According to Exhibit 9, it decreases to a low of -0.5% in the middle of the crisis, before recovering thereafter—profile similar to the beta. In summary, alpha and beta co-move positively, a result in line with the common factors that drive these two performance measures.

We reproduced the same plots for four representative strategies: two arbitrage strategies—the distressed securities and equity market-neutral strategies—and two

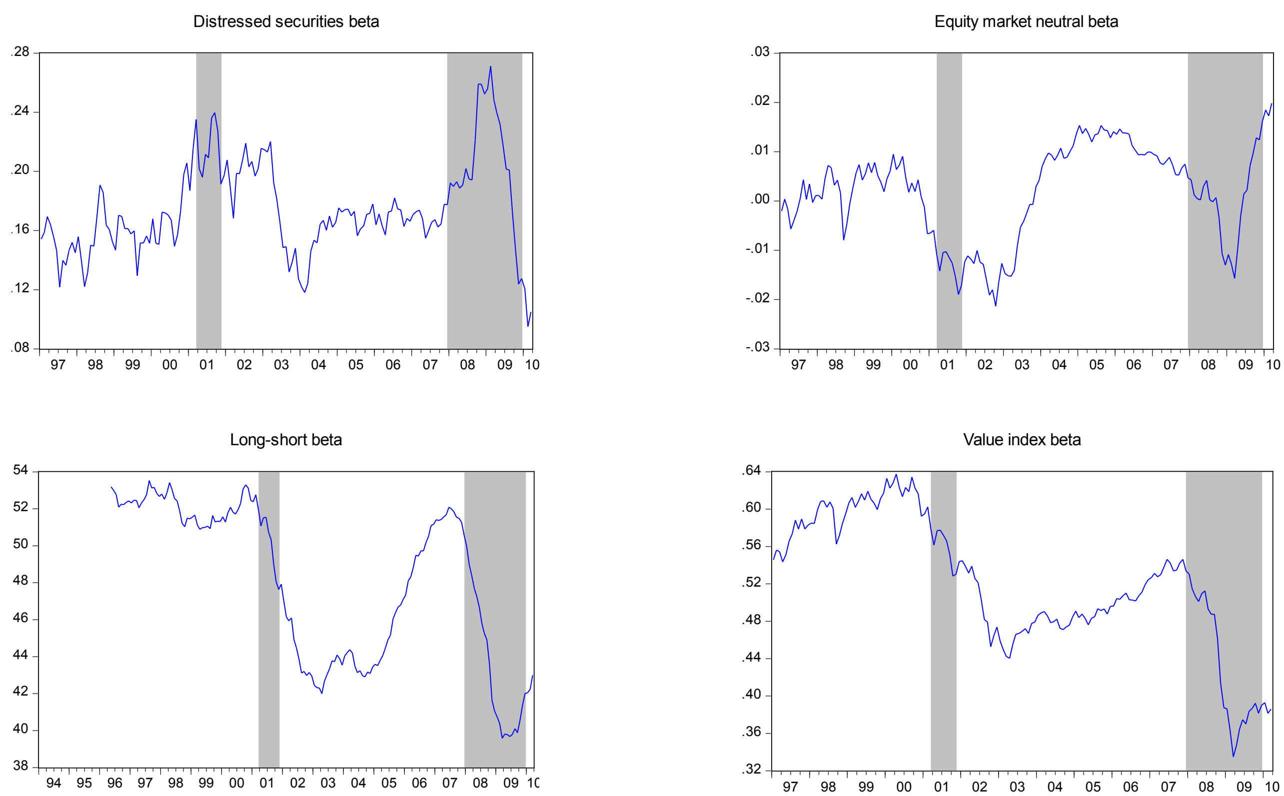

Exhibit 10 State betas for some strategies

directional strategies—the long-short and value index strategies. In Exhibits 10 and 11, we note that the cyclical behavior of the alphas and betas of these two groups of strategies is quite different. Exhibit 10 shows that the managers involved in the distressed securities strategy take more risk during periods of recession or financial turmoil. The jump of the beta of this strategy is particularly high during the subprime crisis. This result was expected since the managers of these funds are confronted with better opportunities, i.e., more businesses in bad shape, during these periods. However, the beta of the market-neutral strategy displays some procyclicality, even if it tends to remain close to zero. Indeed, it fluctuates in a very narrow range, comprised between
-0.02 to 0.02.

The cyclical behavior of the beta of the two representative market-oriented hedge funds differs markedly. The beta of these two strategies collapses during episodes of crises. In this respect, the drop is very sharp during the subprime crisis. Interestingly, these betas seem forward-looking since their decrease tends to lead the crises, and they resume their increase before the start of an economic recovery. In times of expansion, the betas of the long-short and value index strategies tend to increase. In line with the conventional behavior of portfolio managers, the managers of these strategies use leverage to increase risk in periods of expansion and deleverage to reduce risk in periods of recession.

Exhibit 11 provides the corresponding plots of the time-varying alphas of our four strategies. In terms of alpha, the distressed securities strategy seems to benefit from periods of crises, when business opportunities are greater for this strategy. We also note a great compression of this strategy alpha during expansion. The distressed securities strategy is definitively more valuable to the investor in crisis episodes. The pattern of the alpha of the equity market neutral strategy is similar. However, the alpha of this strategy remains above 0.6 over the entire sample period, which seems to suggest an alpha puzzle for this strategy.

The time profile of the directional strategies' betas is quite similar since their sensitivity to common factors is comparable. As expected, the alphas of these strategies decrease in the first phase of a recession but resume their increase before the start of the following recovery. The alphas of these two strategies tend to trend downward during our sample period, suggesting an attenuation of the alpha puzzle.

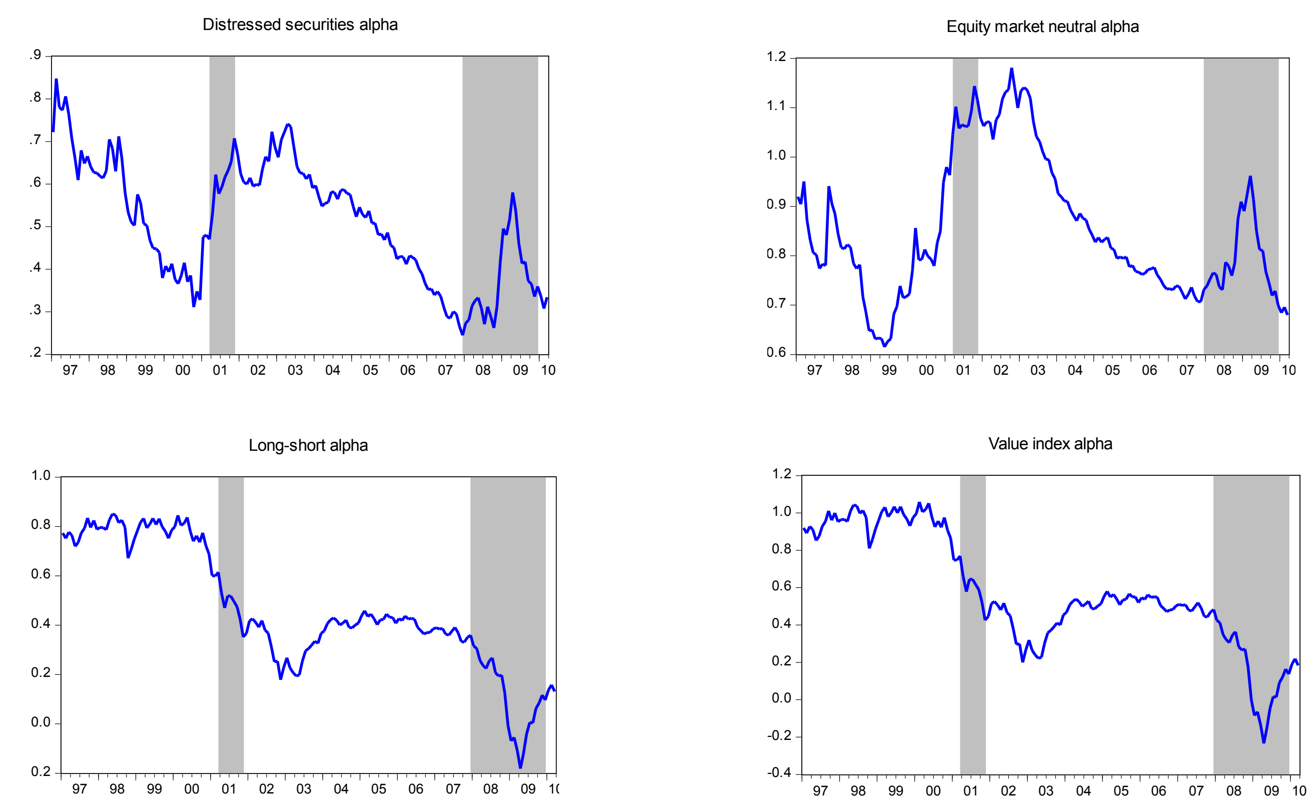

Exhibit 11 State alphas for some strategies

In summary, there are obvious differences in the behavior of hedge fund strategies' alphas and betas, especially between funds that focus more on arbitrage activity and funds that focus more on the direction of the stock market. This is good news for investors in search of yield and diversification opportunities.

Portfolio diversification across strategies

To track the co-movement of strategy returns, we rely on the cross-sectional standard deviation of strategy returns. Beaudry et al. (2001) rely on this indicator to study the co-movement of firm returns on investment. Solnik and Roulet (2000) also employ the cross-sectional dispersion to track the co-movement of the stock market returns. Sabbaghi (2012) transpose this indicator to the study of the co-movements of the returns of hedge fund indexes. The cross-sectional standard deviation, also labeled the cross-sectional dispersion, is defined as:

$$\forall t, \quad cs\_sd_t = \sqrt{\frac{1}{N}\mathbf{R}_{it}'\mathbf{R}_{it}} \qquad (6)$$

Where N is the number of strategies, and $\mathbf{R}_{it}$ is the cross-sectional vector of the strategies' returns observed at time t. The cross-sectional standard deviation of returns is thus the square-root of their cross-sectional realized variance. When the cross-sectional standard deviation of returns increases, the dispersion of returns increases. Thus, there is a rise in the heterogeneity of the hedge fund strategies in this case. This is good news with respect to portfolio diversification. And when the cross-sectional standard deviation decreases, there is an increase in the homogeneity of the strategies. This is bad news with respect to portfolio diversification, because strategy returns move closer in this case.

Exhibit 12 plots the cross-sectional dispersion of our strategies' returns from 1997 to 2010. Since this indicator is quite unstable, we also plot a twelve-month moving average of the series. We note that the cross-sectional dispersion jumps in times of crises. The investor can thus diversify his portfolio across hedge fund strategies when diversification is needed the most. Surprisingly, the cross-sectional dispersion jumped less during the subprime crisis than during the tech bubble burst. This may be an indication that hedge fund strategies become more homogeneous through time. Hedge funds may also have relied on more hedging operations during the subprime crisis than in the past. This is a kind of learning-by-doing or maturation process at play in the hedge fund industry that is beneficial to the hedge fund investor, since it signals a decrease in systemic risk in the hedge fund industry.

Conclusion

The returns behavior over the business cycle of standard financial instruments like stocks and bonds is well known. However, papers on the cyclical dimensions of hedge fund returns are scarce. Contrary to many other

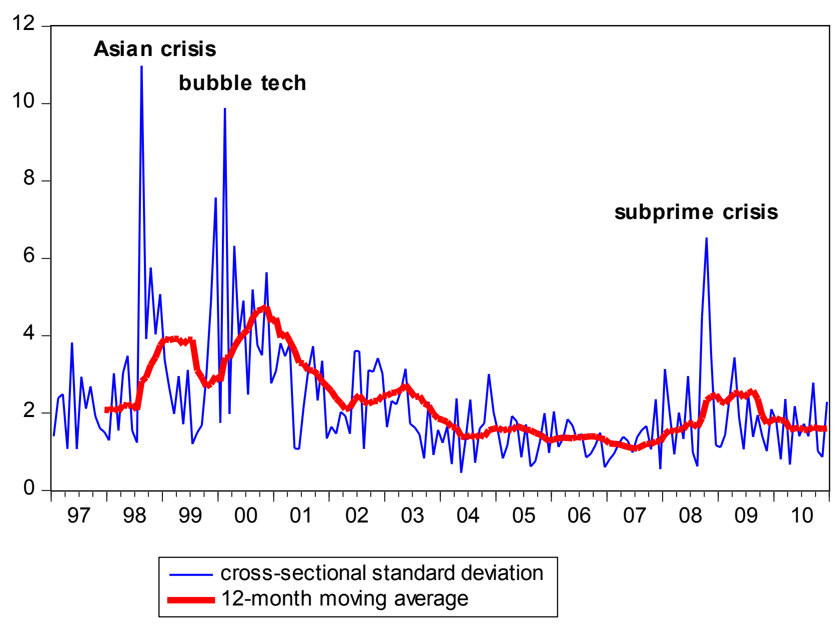

Exhibit 12 Cross-sectional standard deviation of strategies' returns

Source: GAI & author's calculations

financial institutions for which short-selling is restricted by the law, hedge funds may adopt investment strategies that deliver positive payoffs during crises. Some strategies, such as investment in distressed securities, short selling, and equity market-neutral, even benefit from a decline in stock markets. It is important to model the behavior of hedge fund strategies over the business cycle in order to pin down the dynamics of their risk-return trade-off.

Our study provides important insights regarding the hedge fund portfolio managers and investors. Regarding portfolio managers, we find that the manager of a representative hedge-fund modifies his beta in line with the trend and the volatility of financial markets. While managers of hedge fund strategies tend to increase their beta when volatility increases, funds differ regarding their market-timing activities. In this respect, there is a sharp contrast between funds focusing on arbitrage activities and funds that are more market-oriented. The beta of the distressed securities strategy even increases in times of financial turmoil, while the portfolio manager of a representative hedge fund tends to decrease his beta during such periods.

Turning to the investor's point of view, the results of our study indicate that hedge fund strategies continue to provide good diversification benefits over the business cycle. First, hedge fund strategies differ in terms of the profile of their systematic risk over the business cycle. Second, in spite of the subprime crisis, the alpha of most strategies remains positive. In addition, some strategies benefit from this crisis, which suggests good opportunities for hedge fund investors, even in bad times. Finally, our diversification index, as measured by the cross-sectional dispersion of hedge fund returns, indicates that diversification opportunities seem to increase in times of crisis, when they are needed the most.

References

Adrian, T., and Shin, H.S., 2010. "Financial Intermediaries and Monetary Economics." Staff Report, Federal Reserve Bank of New York.

Agarwal, V., and Naik, N.Y., 2004. "Risk and Portfolio Decisions Involving Hedge Funds." Review of Financial Studies 17, pp. 63-98.

Beaudry, P., Caglayan, M., and Schiantarelli, F., 2001. "Monetary Instability, the Predictability of Prices, and the Allocation of Investment: An Empirical Investigation Using Panel Data." American Economic Review 91, pp. 648-662.

Calmès, C., and Théoret, R., 2014. "Bank Systemic Risk and Macroeconomic Shocks: Canadian and U.S. Evidence." Journal of Banking and Finance 40, pp. 388-402.

Fama, E.F., and French, K.R., 1992. "The Cross-Section of Expected Stock Returns.“ Journal of Finance 47, pp. 427-465.

Fama, E.F., and French, K.R., 1993. "Common Risk Factors in the Returns on Stocks and Bonds.“ Journal of Financial Economics 33, pp. 3-56.

Fama, E.F., and French, K.R., 1997. "Industry Costs of Equity.“ Journal of Financial Economics 43, 153-193.

Fung, W., and Hsieh, D.A., 1997. "Empirical Characreristics of Dynamic Trading Strategies: The Case of Hedge Funds." Review of Financial Studies 10, pp. 275-303.

Fung, W., and Hsieh, D.A., 2004. "Hedge Fund Benchmarks: A Risk Based Approach." Financial Analyst Journal 60, pp. 65-80.

Henriksson, R., and Merton, R.C., 1981. "On Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills." Journal of Business 41, pp. 867-887.

Jacques, K., 2010. "Procyclicality, Bank Lending, and the Macroeconomic Implications of a Revised Basle Accord." The Financial Review 45, pp. 915-930.

McGuire, P., Remolona, E. and Tsatsaronis, K., 2005. "Time-Varying Exposures and Leverage in Hedge Funds." BIS Quarterly Review, pp. 59-72.

Racicot, F.E., and Théoret, R., 2007a. "A Study of Dynamic Market Strategies of Hedge Funds Using the Kalman Filter." The Journal of Wealth Management 10, pp. 94-106.

Racicot, F.E., and Théoret, R., 2007b. "The Beta Puzzle Revisited: A Panel Study of Hedge Fund Returns." Journal of Derivatives and Hedge Funds 13, pp. 125-146.

Racicot, F.E., 2011. “Low-Frequency Components and the Weekend Effect Revisited: Evidence from Spectral Analysis.” Aestimatio, the IEB International Journal of Finance, 3, pp. 8-26.

Racicot, F.E. Racicot, F.É., and Théoret, R., 2013. “The Procyclicality of Hedge Fund Alpha and Beta.” Journal of Derivatives & Hedge Funds 19 (2), pp. 109-128.

Sabbaghi, O., 2012. “Hedge Fund Return Volatility and Comovement: Recent Evidence.” Managerial Finance 38, pp. 101-119.

Shin, H.S., 2009. “Securitization and Financial Stability.” Economic Journal 119, pp. 309-332.

Solnik, B., and Roulet, J., 2000. “Dispersion as Cross-Sectional Correlation.” Financial Analysts Journal 56, pp. 54-61.

Treynor, J., and Mazuy, K., 1966. “Can Mutual Funds Outguess the Market? Harvard Business Review 44, pp. 131-136.

Weisman, A., 2002. “Informationless Investing and Hedge Fund Performance Measurement Bias.“ The Journal of Portfolio Management 28, pp.80-91.

Whaley, R.E., 2006. Derivatives: Markets, Valuation and Risk Management, Wiley & Sons, Inc..

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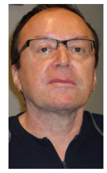

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The Hedge Fund Conundrum: Are Funds Meeting Investor Expectations Or Not?

Kevin Mirabile
Clinical Assistant Professor of Finance,
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How is it that one day the headlines are filled with cautions over unmet expectations from hedge fund investments and the very next day we hear about record inflows and proclamations of $3 trillion in AUM by year end?

Clearly, some institutions, (think private funds and CALPERS), have been disappointed by the performance, fees, and impact of hedge funds on their overall business. Still others, (think liquid alternatives, hedged mutual funds, retail investors, and 401(k)s), are euphoric about the prospects of adding hedge fund strategies to their existing portfolios. While each of these views may represent the extreme end of the investor spectrum in terms of sophistication, product access, and experience with alternatives, understanding this potential contradiction is useful for investors who lie somewhere in the middle, between the biggest of the big and smallest of the small hedge fund investors.

What accounts for such different levels of satisfaction with hedge fund programs is the way in which investor expectations have been set for this type of investment.

One reason some institutional investors been disappointed may be that those investors set their expectations for future returns based on an overreliance of historical data obtained from commercial databases. Databases are filled with statistical bias and risk. Unlike the returns from the S&P 500, it is impossible to observe or predict returns from hedge fund investing. Not all managers report to the databases and there are anomalies like survivorship and other biases that tend to inflate hedge fund performance to the upside. Although the degree of disappointment may vary, setting your course or using a model to allocate capital based on inputs that are biased will almost always result in your arrival at a destination that is different from the one that you had intended.

Another reason for disappointment is that some investors believe that hedge funds should be compared to the S&P 500. When they fail to beat this benchmark they assume something is wrong. This expectation may have developed due to the fact that, for many years, the long-term performance of hedge funds did exceed the S&P 500 and delivered lower volatility at the same time, but hedge funds are designed to provide equity-like returns with bond-like volatility over a market cycle. They should not be expected to beat the equity market consistently, or during any single period of time. An additional problem is that hedge funds are not a homogenous investment or asset class, so comparing a hedge fund composite to a single equity index is like comparing apples to oranges.

A third factor leading to unmet expectations is the pursuit of funds that are charging the lowest fees. Some hedge fund investors want their equity-like return and bond-like volatility, but at the lowest possible price. That is not how things work. Premium returns, risk adjusted returns, or returns that meet or exceed expectations often come at a premium price. Seeking out managers who charge the least will likely lead to the poorest performance. Incentives matter. Since performance is measured net of manager fees, the price paid to managers should not really be a factor. Obtaining a net return of 7% should meet most pension plan targets. So why complain that the managers who generated the return were overpaid at, say, 1.5% and 15% in management and performance fees? This seems to be more political than economical. Is it better to reallocate to other investments at a lower net return, or with more risk, or greater volatility because they charge lower fees? Remember, the best hedge funds, those that charge the highest fees, have often been associated with outperformance on a net of fee basis!

Why do so many other investors appear to be less disappointed with hedge fund returns, at least based on capital inflows to the category? Why are they piling into the asset class just when some of the biggest names are retreating, or taking a pause? Well, perhaps these investors are more interested in absolute returns and still look favorably on hedge funds and their promise of generating a T-bill plus 500 return or 5%-7% per annum, with 6% volatility or less. After all, this return and risk profile is very attractive relative to the expectation of a zero return on cash, negative return on bonds, and the fear of a 10%-20% equity market correction. Many high-net-worth individuals and even retail investors and their advisors are more focused on downside risk protection than Sharpe ratios or beating the S&P 500. Hedge funds traditionally lose less in falling markets. The worst-case drawdown and other downside measures of risk make hedge funds look very attractive relative to equities in almost all time frames and certainly relative to the forward outlook for bonds in a rising rate environment.

If you step away from the hype on both sides of the market, you will see that hedge funds are growing at a very healthy pace. Transparency is improving and performance is meeting expectations more often than not. Many, if not most investors are satisfied with the products they have purchased and the choices they are making. Even Bill Gross has changed from managing money to a traditional benchmark to a hedge fund-like unconstrained style of investing. Certainly things can get better and old expectations and beliefs need to be challenged, and certainly there is room for improvement, but it is not all doom and gloom.

Many investors believe that hedge funds are integral pieces of the portfolio construction process. They are neither disappointed, nor euphoric. Perhaps, they are just practical, thoughtfully examining individual managers and making choices on how any one manager or group of managers can help them to meet their objectives. They are fee-conscious, but focused more on value than headline manager compensation. They use funds of funds to gain diversified exposure where it makes sense, or hedged mutual funds to get some additional transparency, liquidity, and regulatory oversight. They enjoy it when hedge funds outperform the S&P 500, but they don't expect it.

For me, the outlook and process related to hedge fund investing is changing and they way in which investors form expectations needs to evolve. The world of finance rarely stands still, and the expectations and the tools used to formulate them need to evolve as well. I have no doubt that they will, but only time will tell. Are hedge funds meeting investor expectations – I guess it depends on whom you ask!

Author Bio

Kevin Mirabile is currently a Clinical Assistant Professor of Finance at Fordham University where he teaches courses on the principles of finance, alternative investing and hedge funds. Mr. Mirabile has over 30 years of business development, regulatory, financing, accounting, trading and sales experience in financial services dating back to 1983. He is an author of a book on hedge fund investing entitled, "Hedge Fund Investing: A practical guide to investor motivation, manager profits and fund performance" published by Wiley Press, January 2013 and is an active industry consultant on the topics of hedge fund investing, operational and business model risk assessment. Mr. Mirabile is a C.P.A., a member of the A.I.C.P.A., and a member of the Greenwich Roundtable's Founders Council as well as a contributor to its "Best Practices" series. Mr. Mirabile received his B.S. in Accounting from S.U.N.Y Albany in 1983, his M.S. in Banking and Finance from Boston University in 2008 and completed his doctoral studies with a D.P.S. degree in Finance and Economics from PACE University in May 2013.

IR&M Momentum Monitor

Alexander Ineichen, CAIA
Ineichen Research & Management AG

IR&M Momentum Monitor

By Alexander Ineichen, CFA, CAIA, FRM; www.ineichen-rm.com

	Price Momentum								Earnings Momentum							
	Medium-term				Long-term				Medium-term				Long-term			
Calendar Week:	2	3	4	5	2	3	4	5	2	3	4	5	2	3	4	5
Equities by region																
MSCI World	-1	-2	-3	-4	3	4	5	-1	-18	-19	-20	-21	-8	-9	-10	-11
Europe (STOXX 600)	9	10	11	12	3	4	5	6	1	2	3	4	27	28	29	30
MSCI Emerging Markets	-17	-18	1	-1	-10	-11	-12	-13	-18	-19	-20	-21	-15	-16	-17	-18
MSCI Asia Pacific ex Japan	-17	-18	1	2	-10	-11	-12	-13	-17	-18	-19	-20	-10	-11	-12	-13
Equities by country																
USA (S&P 500)	11	-1	1	-1	147	148	149	150	-12	-13	-14	-15	149	-1	-2	-3
Canada (SPTSX 60)	-1	-2	1	2	-7	-8	-9	-10	-12	-13	-14	-15	-2	-3	-4	-5
Brazil (Bovespa)	-15	-16	-17	-18	-5	-6	-7	-8	-19	-20	-21	-22	-19	-20	-21	-22
France (CAC 40)	-2	1	2	3	-21	-22	-23	1	1	2	-1	-2	17	18	19	20
Germany (DAX 30)	8	9	10	11	3	4	5	6	49	50	51	52	90	91	92	93
Italy (FTSE MIB)	-5	-6	1	2	-19	-20	-21	-22	-11	-12	-13	-14	-2	-3	-4	-5
Switzerland (SMI)	11	-1	-2	-3	130	131	132	133	35	-1	-2	-3	21	22	23	24
UK (FTSE100)	-5	-6	1	2	-15	-16	-17	-18	-13	-14	-15	-16	-8	-9	-10	-11
Australia (S&P/ASX)	2	-1	1	2	-11	-12	-13	-14	-12	-13	-14	-15	-7	-8	-9	-10
China (Shanghai Composite)	28	29	30	31	23	24	25	26	-12	-13	-14	1	-6	-7	-8	-9
Hong Kong (Hang Seng)	1	2	3	4	28	29	30	31	-11	-12	-13	-14	-1	-2	-3	-4
India (Nifty)	2	3	4	5	64	65	66	67	47	48	49	-1	59	60	61	62
Japan (Nikkei 225)	11	-1	1	2	26	27	28	29	61	62	63	64	98	99	100	101
South Korea (Kospi)	-5	-6	-7	1	-13	-14	-15	-16	6	7	8	9	-84	-85	-86	-87
Bonds																
Barclays Global Aggregate	-19	-20	-21	-22	-13	-14	-15	-16								
Barclays Global HY	-19	-20	-21	-22	-12	-13	-14	-15								
Barclays Euro Aggregate	68	69	70	71	63	64	65	66								
Barclays Asia Pacific Aggregate	70	71	72	73	66	67	68	69								
Barclays Global Emerging Markets	-10	-11	-12	-13	-5	-6	-7	-8								
Barclays US Aggregate	15	16	17	18	52	53	54	55								
Barclays US Corporate HY	-8	-9	-10	1	-8	-9	-10	-11								
Hedge Funds																
HFRX Global Hedge Funds	-15	-16	-17	-18	-11	-12	-13	-14								
HFRX Macro/CTA	21	22	23	24	26	27	28	29								
HFRX Equity Hedge	10	-1	1	2	4	5	6	7								
HFRX Event Driven	-17	-18	-19	-20	-13	-14	-15	-16								
HFRX Relative Value Arbitrage	-26	-27	-28	-29	-18	-19	-20	-21								
HFRX Fixed Income - Credit	-17	-18	-19	-20	-13	-14	-15	-16								
Commodities																
Thomson Reuters/Jefferies CRB	-27	-28	-29	-30	-19	-20	-21	-22								
Gold (Comex)	1	2	3	4	-17	-18	-19	-20								
Copper (Comex)	-20	-21	-22	-23	-17	-18	-19	-20								
Oil (WTI)	-27	-28	-29	-30	-20	-21	-22	-23								
FX																
USD (trade-weighted, DXY)	34	35	36	37	26	27	28	29								
EURUSD	-35	-36	-37	-38	-28	-29	-30	-31								
JPYUSD	-24	-25	-26	-27	-19	-20	-21	-22								
Central banks' balance sheets																
Fed balance sheet	117	118	119	120	109	110	111	112								
ECB balance sheet	7	8	9	10	1	2	3	4								
BoJ balance sheet	140	141	142	143	147	148	149	150								
BoE balance sheet	16	17	18	19	41	42	43	44								

Commentary

Long-term price momentum for the MSCI World turned negative at the end of January.

Long-term momentum in some broad bond indices remains negative.

Long-term momentum of earnings estimates for the MSCI World turned in November and has been negative ever since.

The USD has positive momentum.

The balance sheet of the main central banks are expanding.

Tutorial

The momentum numbers count the weeks of a trend based on moving averages. Green marks a positive trend, red a negative one. Example: In week 22, the S&P has been in a long-term bullish trend for 123 weeks. See www.ineichen-rm.com for more information and/or trial issue.

Purpose

The momentum monitor was designed to help investors with risk management, asset allocation, and position sizing. Tail events do not always happen out of the blue. They often occur when momentum is negative. Negative momentum makes hedging more important and suggests position sizing should be more conservative. In a bull market one ought to be long or flat but not short. In a bear market one ought to be short or flat but not long.

Source: IR&M, Bloomberg. Notes: Medium-term based on exponentially weighted average over 3 and 10 weeks. Long-term based on simply weighted average over 10 and 40 weeks. Earnings momentum is based on 12-month forward consesus EPS estimates.

Alexander Ineichen is founder of Ineichen Research and Management AG, a research firm founded in October 2009 focusing on risk management, absolute returns, and thematic investing.

Alexander started his financial career in derivatives brokerage and origination of risk management products at Swiss Bank Corporation in 1988. From 1991 to 2005 he had various research functions within UBS Investment Bank in Zurich and London relating to equity derivatives, indices, capital flows, and alternative investments, since 2002 in the role of a Managing Director. From 2005 to 2008, he was a Senior Investment Officer with Alternative Investment Solutions, a fund of hedge funds within UBS Global Asset Management. In 2009, he was Head of Industry Research for the hedge fund platform at UBS Global Asset Management.

Alexander is the author of the two publications "In Search of Alpha: Investing in Hedge Funds" (October 2000) and "The Search for Alpha Continues: Do Fund of Hedge Funds Add Value?" (September 2001). These two documents were the most-often printed research publications in the documented history of UBS. He is also author of "Absolute Returns: The Risk and Opportunities of Hedge Fund Investing" (Wiley Finance, October 2002) and "Asymmetric Returns: The Future of Active Asset Management" (Wiley Finance, November 2006). Alexander has also written several research pieces pertaining to equity derivatives and hedge funds including AIMA's Roadmap to Hedge Funds (2008 and 2012), which has been translated into Chinese and was the most-often downloaded document from their website at the time.

Alexander holds a Bachelor of Science in Business Administration with a Major in General Management from the University of Applied Sciences in Business Administration Zürich (HWZ) in Switzerland. Alexander also holds the Chartered Financial Analyst (CFA) and Chartered Alternative Investment Analyst (CAIA) designations and is a certified Financial Risk Manager (FRM). He is on the Board of Directors of the CAIA Association and is a member of the AIMA Research Committee.

VC-PE Index: A Look at Private Equity and Venture Capital as of Q2 2014

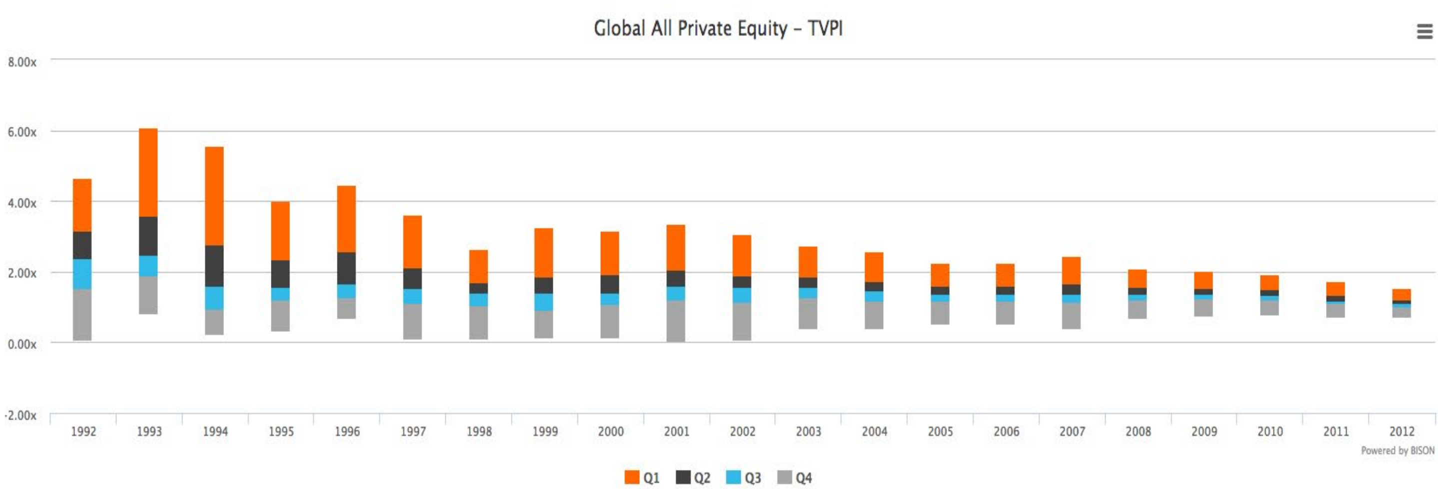
Mike Nugent
CEO/Co-Founder, Bison

Mike Roth
Research Manager, Bison

Looking at the Global All PE category for 2002 - 2012, the median TVPI, DPI and IRR figures have drifted up slightly quarter over quarter for most vintage years. The median Momentum (year-over-year valuation change) averaged 7.8% for the 2002 – 2012 vintage years. This is slightly below Q1's median Momentum, which averaged 7.9%.

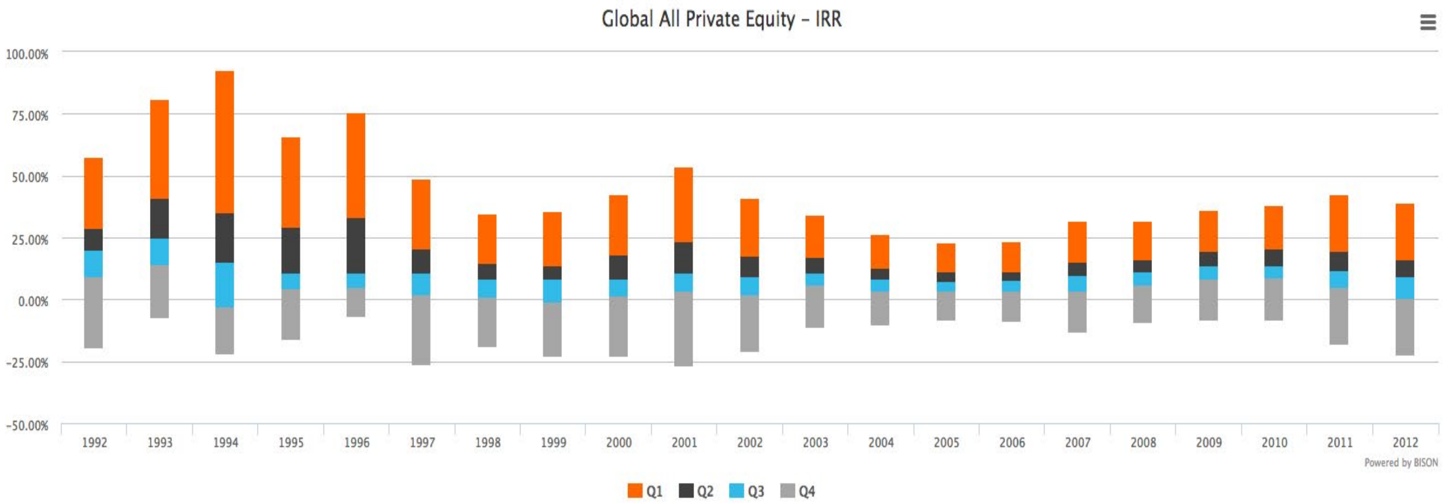
Honing in on IRRs briefly, funds that are in their value creation stage (2008 – 2011 vintage years) are producing noticeably better returns than the bubble years (2004 – 2007). The gap between the first and second quartile boundaries has also widened, highlighting the importance of picking first quartile managers. For 2004 through 2007, the difference between first and second quartile is averaging 396 basis points. By contrast, that difference for the 2008 through 2011 vintage years is averaging 626 basis points.

For a more in depth look at the buyout and venture capital benchmarks, please visit www.bison.co.



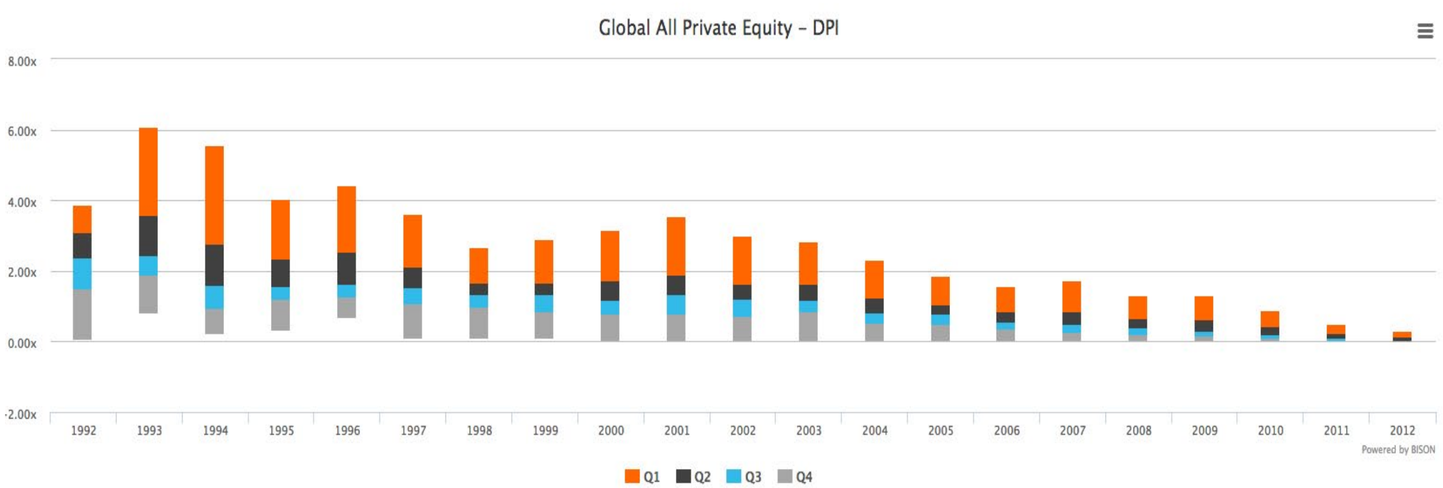
Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Upper Fence	4.60x	6.04x	5.50x	3.97x	4.41x	3.56x	2.61x	3.20x	3.12x	3.32x	3.01x	2.70x	2.55x	2.21x	2.20x	2.38x	2.03x	1.98x	1.87x	1.69x	1.48x
Q1	3.11x	3.53x	2.74x	2.29x	2.51x	2.06x	1.65x	1.80x	1.86x	2.03x	1.86x	1.82x	1.69x	1.56x	1.55x	1.62x	1.51x	1.50x	1.45x	1.31x	1.18x
Q2	2.36x	2.43x	1.59x	1.55x	1.64x	1.52x	1.37x	1.37x	1.38x	1.57x	1.53x	1.53x	1.44x	1.35x	1.34x	1.35x	1.34x	1.33x	1.31x	1.16x	1.08x
Q3	1.47x	1.86x	0.89x	1.17x	1.25x	1.06x	1.00x	0.87x	1.03x	1.17x	1.09x	1.23x	1.12x	1.13x	1.12x	1.12x	1.16x	1.18x	1.17x	1.05x	0.98x
Lower Fence	0.04x	0.77x	0.20x	0.28x	0.65x	0.06x	0.07x	0.11x	0.09x	0.01x	0.01x	0.35x	0.36x	0.47x	0.47x	0.36x	0.64x	0.71x	0.75x	0.67x	0.68x
Funds	23	42	26	44	51	67	92	113	159	107	80	78	118	190	237	280	277	104	170	172	181
Commitments	32	63	36	74	84	122	172	222	345	204	163	166	232	410	615	725	544	287	388	319	416

Exhibit 1 Global All Private Equity TVPI Benchmark



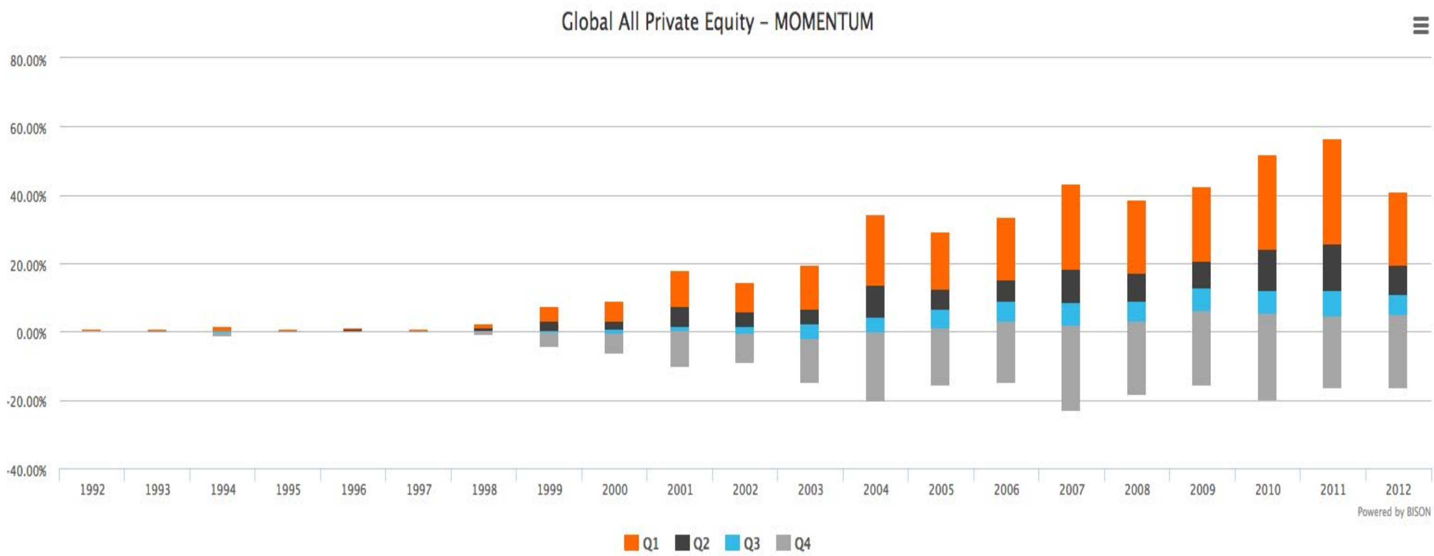
Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Upper Fence	56.88%	80.04%	91.88%	65.29%	75.14%	48.24%	33.97%	34.80%	41.78%	53.05%	40.13%	33.45%	25.58%	22.33%	22.81%	31.25%	31.13%	35.40%	37.26%	41.60%	38.46%
Q1	27.96%	40.13%	34.57%	28.42%	32.67%	20.00%	13.83%	12.99%	17.29%	22.82%	17.00%	16.50%	12.02%	10.58%	10.71%	14.35%	15.70%	18.82%	19.95%	19.10%	15.38%
Q2	19.86%	24.57%	14.80%	10.60%	10.30%	10.28%	7.82%	7.99%	7.80%	10.50%	9.09%	10.24%	7.82%	6.94%	7.55%	9.52%	10.74%	13.09%	13.19%	11.53%	8.81%
Q3	8.67%	13.52%	-3.63%	3.84%	4.36%	1.18%	0.41%	-1.55%	0.97%	2.67%	1.58%	5.20%	2.97%	2.75%	2.65%	3.08%	5.41%	7.77%	8.40%	4.10%	0.00%
Lower Fence	-20.24%	-8.10%	-22.56%	-16.78%	-7.38%	-27.06%	-19.73%	-23.36%	-23.53%	-27.56%	-21.55%	-11.75%	-10.60%	-9.00%	-9.44%	-13.83%	-10.02%	-8.81%	-8.92%	-18.40%	-23.08%
Funds	22	40	25	43	51	63	89	106	151	104	80	77	118	188	229	276	270	103	165	153	162
Commitments	31	61	35	72	83	111	165	211	333	198	161	160	227	404	593	717	527	271	355	267	330

Exhibit 2 Global All Private Equity IRR Benchmark



Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Upper Fence	3.82x	6.05x	5.50x	3.99x	4.39x	3.57x	2.64x	2.85x	3.13x	3.49x	2.94x	2.80x	2.27x	1.83x	1.52x	1.69x	1.26x	1.27x	0.85x	0.45x	0.26x
Q1	3.05x	3.53x	2.74x	2.30x	2.50x	2.06x	1.62x	1.63x	1.69x	1.84x	1.59x	1.60x	1.19x	1.01x	0.80x	0.82x	0.60x	0.58x	0.37x	0.18x	0.11x
Q2	2.35x	2.43x	1.58x	1.54x	1.61x	1.51x	1.32x	1.32x	1.16x	1.31x	1.17x	1.14x	0.78x	0.75x	0.54x	0.46x	0.37x	0.28x	0.19x	0.06x	0.02x
Q3	1.47x	1.86x	0.89x	1.17x	1.24x	1.05x	0.95x	0.82x	0.74x	0.74x	0.68x	0.80x	0.47x	0.46x	0.31x	0.23x	0.16x	0.13x	0.05x	0.00x	0.00x
Lower Fence	0.04x	0.77x	0.20x	0.28x	0.65x	0.06x	0.07x	0.05x	0.00x	0.01x	0.01x	0.00x	0.00x	0.00x	0.00x	0.00x	0.00x	-0.00x	-0.02x	-0.00x	-0.05x
Funds	23	42	26	44	51	67	92	112	159	107	80	78	118	185	232	272	272	102	166	167	178
Commitments	32	63	36	74	84	122	172	221	345	204	163	165	231	403	607	704	527	274	375	304	402

Exhibit 3 Global All Private Equity DPI Benchmark



Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Upper Fence	0.16%	0.20%	1.01%	0.34%	0.68%	0.52%	1.70%	6.85%	8.34%	17.61%	14.06%	19.09%	33.68%	28.84%	32.94%	42.79%	38.06%	41.90%	51.33%	56.21%	40.33%
Q1	0.04%	0.02%	0.09%	0.03%	0.20%	0.12%	0.59%	2.50%	2.74%	7.08%	5.23%	6.15%	13.24%	11.99%	14.86%	17.92%	16.76%	20.24%	23.53%	25.07%	18.86%
Q2	0.00%	-0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.24%	0.54%	1.36%	1.41%	2.04%	3.88%	6.21%	8.73%	8.25%	8.78%	12.67%	11.73%	11.68%	10.48%
Q3	-0.04%	-0.10%	-0.53%	-0.17%	-0.12%	-0.14%	-0.15%	-0.40%	-0.99%	0.06%	-0.67%	-2.47%	-0.38%	0.75%	2.80%	1.35%	2.57%	5.80%	5.00%	4.32%	4.55%
Lower Fence	-0.17%	-0.29%	-1.44%	-0.47%	-0.60%	-0.54%	-1.27%	-4.75%	-6.59%	-10.47%	-9.50%	-15.41%	-20.82%	-16.10%	-15.29%	-23.52%	-18.72%	-15.87%	-20.40%	-16.90%	-16.93%
Funds	21	34	23	38	43	57	81	100	144	96	76	62	99	158	199	248	245	95	137	139	135
Commitments	30	49	29	59	67	100	146	191	296	184	147	138	194	360	535	646	476	258	319	258	315

Exhibit 4 Global All Private Equity Momentum Benchmark

Author Bios

Prior to founding Bison, **Mike Nugent** held senior roles at SVG Advisers, LP Capital Advisors and HarbourVest Partners, and has more than $3B in private market commitments to his credit. Mike started his career in the public markets with the NASDAQ Stock Market, and also gained significant operating experience while running operations for a textiles manufacturer. He received his MBA from Boston College, and his BA from St. Bonaventure University. Mike lives on the North Shore of Massachusetts with his wife and two sons.

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.

The IPD Global Intel Report

Max Arkey
Vice President, Product Management
MSCI Real Estate

The UK real estate market picked up swift momentum in 2014, with returns of 18.3% up to Q3 2014. This was nearly double the average of 9.2% over the previous four years. The uptick in performance was seen across most major cities and property types, but it raises questions about the longevity of peak cyclical performance. Drawing from the Global Intel dataset, this report provides insights into four key areas of the investment process: performance, risk, strategy, and asset management.

NATIONAL DASHBOARD

2014 Q3
Annualized Total Return (%)
All property quarterly series in GBP to 2014 Q3

⊠ peak ⊠ trough	Latest	Trend 1-yr*	 Since 2001
UK	18.3	⊠	
Retail	14.6	⊠	
Office	22.9	⊠	
Industrial	23.0	⊠	
Residential	8.4	⊠	
Hotel	15.8	⊠	
London	22.4	⊠	
Birmingham	17.1	⊠	
Manchester	13.6	⊠	
Glasgow	11.2	⊠	
Bristol	17.4	⊠	
Edinburgh	13.8	⊠	
Reading	17.3	⊠	
Sheffield	13.6	⊠	
Cambridge	20.4	⊠	
Liverpool	10.0	⊠	
Leeds	16.3	⊠	
Aberdeen	18.5	⊠	
Guildford	14.7	⊠	
Cardiff	15.3	⊠	
Oxford	15.2	⊠	
Newcastle u Tyne	14.8	⊠	

* at least 100 bps above (⊠) or below (⊠) year ago

Performance

A strong wave of capital has flowed toward UK real estate over the past year, attracted in part by the cyclical opportunity of attractive spreads in bond yields and financing costs. Investors, pension funds, sovereign wealth funds, and high-net-worth individuals have sought out real estate in the United Kingdom as a way to support performance and diversify risks. These capital inflows led to more yield compression over the past year and a return to double-digit capital growth. Like the United States, the United Kingdom has been one of the better performing global markets in recent years, after being one of the worst through the financial crisis of 2007-2009. Significant variations exist within the UK domestic market, especially in terms of income return. The spread between the 25th and 75th percentiles of income return has averaged 340 basis points over the past four years, roughly double the 170 bps seen in 2007. Among cities and property sectors, industrial and office space experienced annualized total returns exceeding 20% in Q3 2014, as did London and Cambridge. This was more than double the returns in Liverpool, Glasgow, and the residential sector.

Risk

The UK property market's historical volatility reinforces the need to monitor market risks, avoid style drift, and focus on the movement of markets through their cycles. The IPD Pricing Indicator for the United Kingdom still shows attractive current pricing based on spreads, but with a relatively low income yield. The indicator's position hints at a potential shift as bond yields ultimately rise. The relatively low level of current UK liquidity also parallels aggressive pricing. These indicators are countered by a falling vacancy rate that is occurring amid a recovering economy and relatively low deliveries of new supply.

Strategy
Top-down choices of asset allocation and selection impact performance and risk through market cycles. Investors spurned the office sector and Greater London during the financial crisis, but have since returned. Retail continues to be a preferred investment sector, although it has consistently held overall UK performance back during the past decade. The residential sector has diverged the most from the overall market, lagging other sectors significantly over the past year, although it has boosted performance over the longer 10-year period. Among all cities, London—and to a lesser extent, its satellites across the Southeast, including Cambridge and Guildford—continue to dominate UK performance. Outside Southeast England, the only major city to outpace overall UK performance during the past decade has been Aberdeen, with an economy strongly tied to oil prices.

Asset Management
The Global Intel dataset provides asset managers with insight across a range of operating and investment data. Gross and net incomes lag their pre-financial crisis levels, thus leading to elevated operating cost ratios over the past five years. Improvement expenditures (as a share of capital value) have averaged below 100 bps over the past five years in most sectors (residential is an exception). In this improving market, UK funds have generally underperformed direct returns. Unlike their more leveraged U.S. and Continental European counterparts, UK funds have been slower to maximize on current low interest rates.

GLOBAL INTEL CALENDAR

Recently Added. Asset level indexes for Canada, Ireland, the Netherlands, New Zealand, the UK, and the US (to 2014 Q3), and for the UK (to October 2014) and Japan (to July 2014). Fund level indexes for the UK and the US (to 2014 Q3), and for Australia and Germany (to October 2014).

Scheduled. Asset level indexes for Australia, Nordic, Pan-Europe, and Portugal (to 2014 Q3), and for Japan (to August 2014). Fund level indexes for Global (to 2014 Q3) and for Australia, Germany, and the UK (to November 2014).

Important Note: The charts and metrics in this report are illustrative of the material within Global Intel. For further details and any feedback, please contact Max Arkey at +1.312.461.4371 or max.arkey@msci.com.

Author Bio

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 special ized domestic investors. For further details contact: max.arkey@msci.com

IPD Global Intel

December 2014

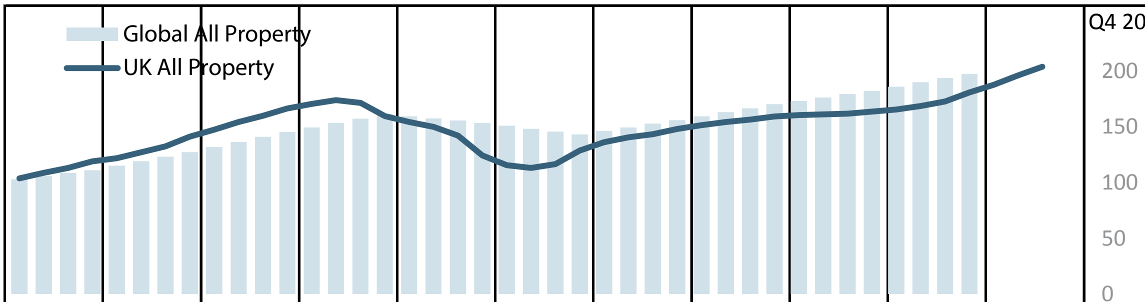
An MSCI Brand

MSCI – real estate market insights

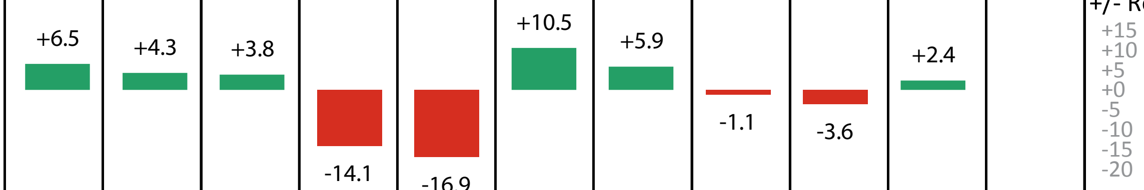
UK

1 PERFORMANCE

HISTORY

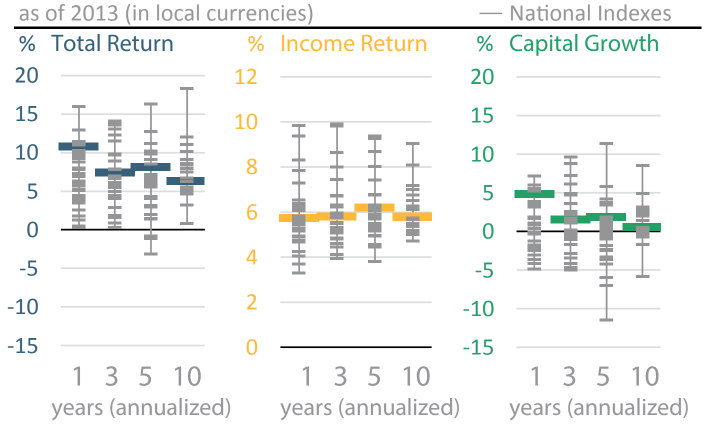


	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014 Q3
Performance (UK)											
Total Return %	17.5	18.9	18.0	-3.2	-21.7	3.7	14.9	8.0	3.5	10.7	18.3
Best/Worst Year											-
Quartile Rank Among Peers	1	1	1	4	4	2	1	2	4	1	-
+/- Relative to Global	+6.5	+4.3	+3.8	-14.1	-16.9	+10.5	+5.9	-1.1	-3.6	+2.4	
Components (UK)											
Income Return %	6.1	5.6	4.9	4.7	5.5	7.2	6.3	5.9	5.8	5.7	5.6
Capital Growth %	10.7	12.6	12.5	-7.5	-25.9	-3.3	8.2	2.0	-2.1	4.8	12.0



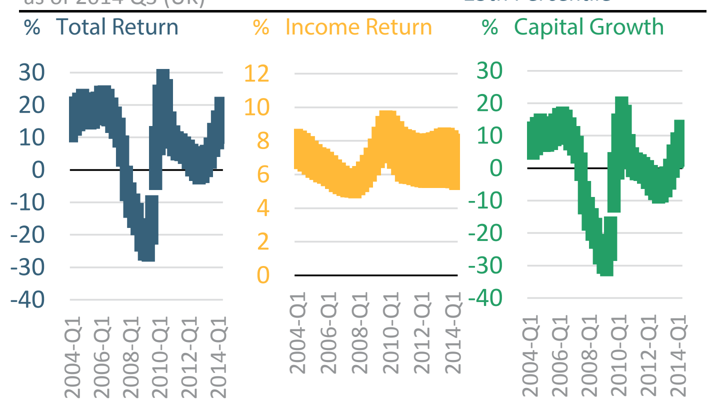
MARKET COMPARISONS

as of 2013 (in local currencies)



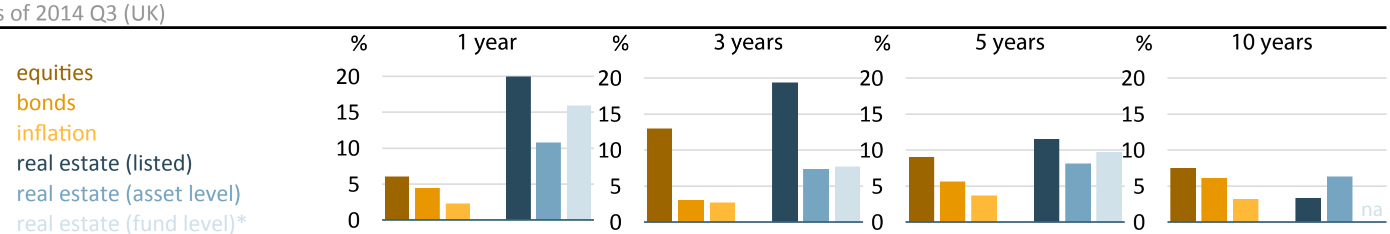
PERFORMANCE RANGES

as of 2014 Q3 (UK)



ASSET CLASS COMPARISONS

as of 2014 Q3 (UK)



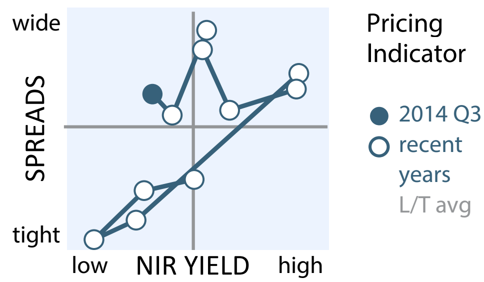
*Fund level real estate performance is calculated from a different sample than asset level real estate in Global Intel (see page 5).

RISK METRICS

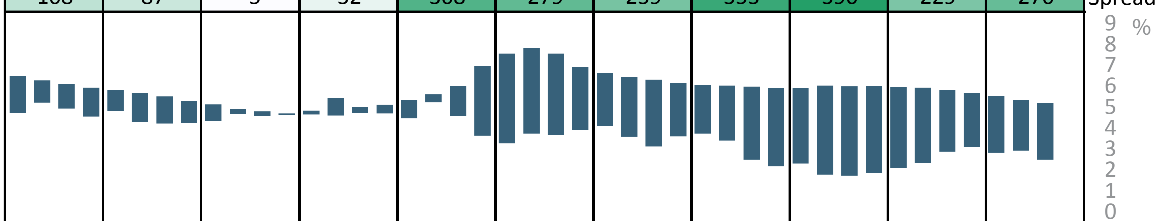
as of 2013

Asset Class Indicators		10-Year* Total Return	10-Year* Std Dev	10-Year* Sharpe Ratio	5-Year* Total Return	5-Year* Std Dev	5-Year* Sharpe Ratio
Global	Property (direct)	7.0	7.3	0.57	5.2	6.9	0.36
UK	Property (direct)	6.3	12.5	0.28	8.1	4.9	1.13
	Property (listed)	4.0	30.7	0.16	8.7	15.1	0.43
	Equities	8.0	15.4	0.36	12.9	10.9	1.02
	Bonds	5.8	6.9	0.33	4.5	8.4	0.21

*calculations on annual data for comparability to global real estate series



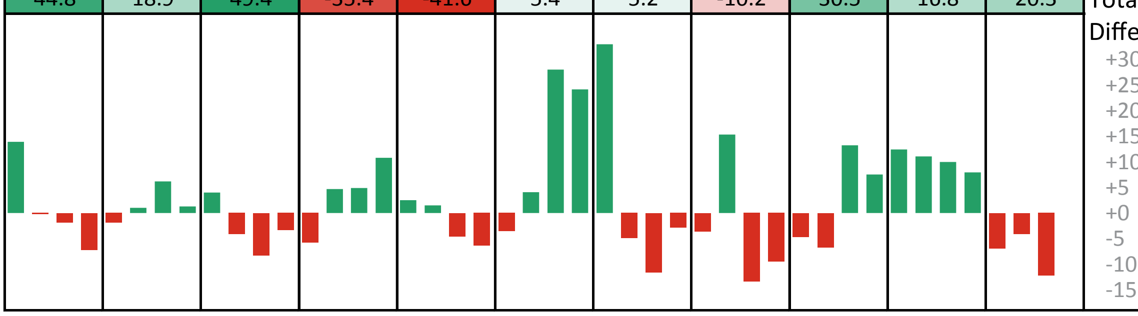
2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014 Q3	Market Indicators
9.7	10.4	6.9	7.7	14.1	10.9	5.6	4.8	5.9	8.7	5.5	Liquidity (%) SALES / CV
5.6	5.1	4.6	5.0	6.7	6.7	6.0	5.7	5.7	5.4	5.2	Yield (%) NIR YIELD
-	-	-	-	-	10.1	8.7	9.0	9.9	8.9	8.7	Vacancy % OF MARKET RENT
108	87	-5	32	308	279	239	353	390	229	270	Spreads BASIS POINTS



(difference between net income receivable yield and long-term national bond rate)

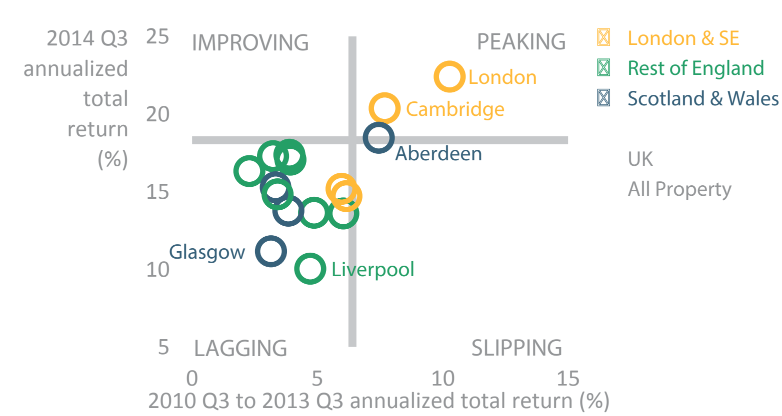
2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014 Q3	Cyclical Indicators
17.5	18.9	18.0	-3.2	-21.7	3.7	14.9	8.0	3.5	10.7	18.3	Total return DIRECT R.E.
44.8	18.9	49.4	-35.4	-41.6	5.4	5.2	-10.2	30.5	16.8	20.3	Total return PROP. EQUITIES

Difference from direct (+/-)



CYCLICAL PERFORMANCE

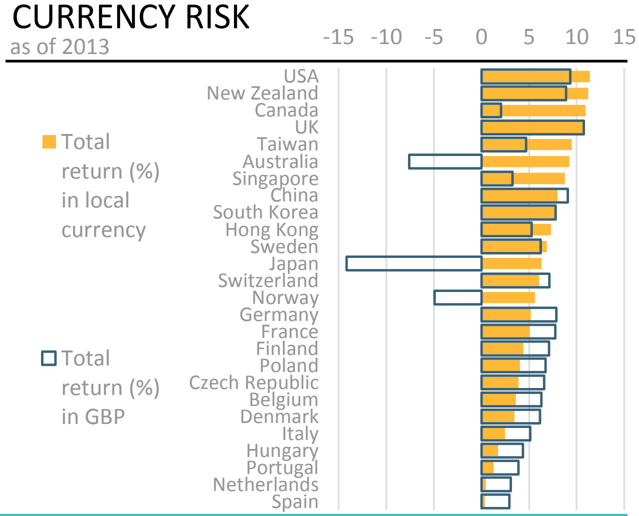
as of 2014 Q3 (UK cities)



Note: SE is Southeast England

CURRENCY RISK

as of 2013



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December 2014

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3 STRATEGY

WEIGHT OF CAPITAL

All property net investment in local currency, national average 2004-2013, indexed to 100

Property sectors and cities relative to national average net investment, 2004-2013 (index = 100)

2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014 Q3*	by Sector
124.8	68.8	45.6	-6.8	-49.6	9.9	110.6	138.4	81.4	41.0	111.1	Retail
22.9	39.0	187.8	50.4	-155.3	-157.8	38.7	31.1	-43.7	-24.1	76.8	Office
53.4	64.3	53.4	4.3	-37.4	-13.5	19.4	8.6	15.2	26.4	54.6	Industrial
-8.8	-1.7	5.4	14.5	5.1	-0.6	8.0	5.9	-2.3	7.1	13.7	Residential
1.0	1.2	3.6	0.9	-2.3	0.9	12.2	13.0	9.8	6.8	9.4	Hotel

2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014 Q3*	by Region
13.4	26.6	46.6	-21.8	-2.4	-31.9	5.2	10.6	-6.0	3.4	7.5	Greater London
10.4	23.9	40.3	-20.1	-17.6	0.1	13.5	13.4	6.4	-5.0	15.7	South East
7.8	27.5	40.9	-10.8	-5.2	3.5	16.3	12.1	8.6	-2.8	23.0	North West
7.3	8.3	30.3	-2.7	-13.6	11.5	12.9	11.4	19.0	11.7	21.7	Eastern
10.9	-0.6	25.9	-1.4	-14.8	11.1	6.2	5.6	18.4	13.0	17.6	West Midlands
9.3	-5.3	32.0	-3.2	-15.2	10.1	3.6	2.8	11.7	13.6	16.8	South West
6.1	7.1	29.7	-8.7	-4.5	10.4	9.9	4.9	4.2	13.0	15.2	Scotland
7.3	4.6	29.2	-7.5	0.5	18.0	7.4	3.6	0.5	8.1	13.1	Yorks & Humber
-0.1	4.3	21.0	-5.0	0.6	15.6	8.7	7.1	0.1	7.6	14.0	East Midlands
3.3	6.8	13.9	-5.7	-0.5	14.8	5.8	7.4	3.6	9.4	16.0	Wales
5.8	3.0	10.6	-5.2	-2.6	8.7	4.6	4.9	3.3	6.6	10.4	North East
7.1	4.3	5.4	-3.0	-0.9	8.4	2.2	4.1	2.9	4.4	10.2	Northern Ireland

*calculated on the four-quarter total ending in the quarter shown.

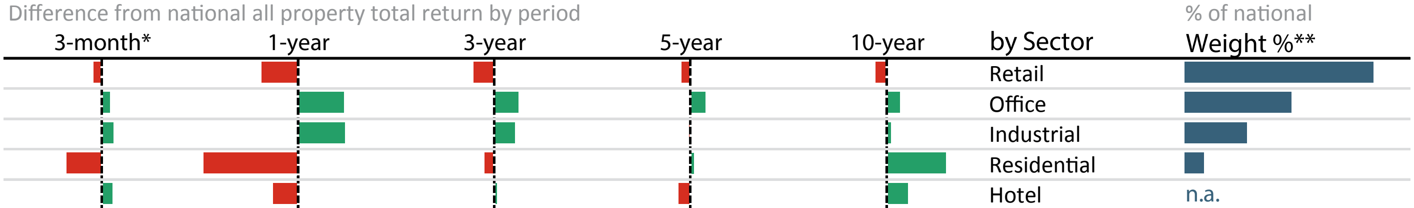
RELATIVE PERFORMANCE CONTRIBUTION

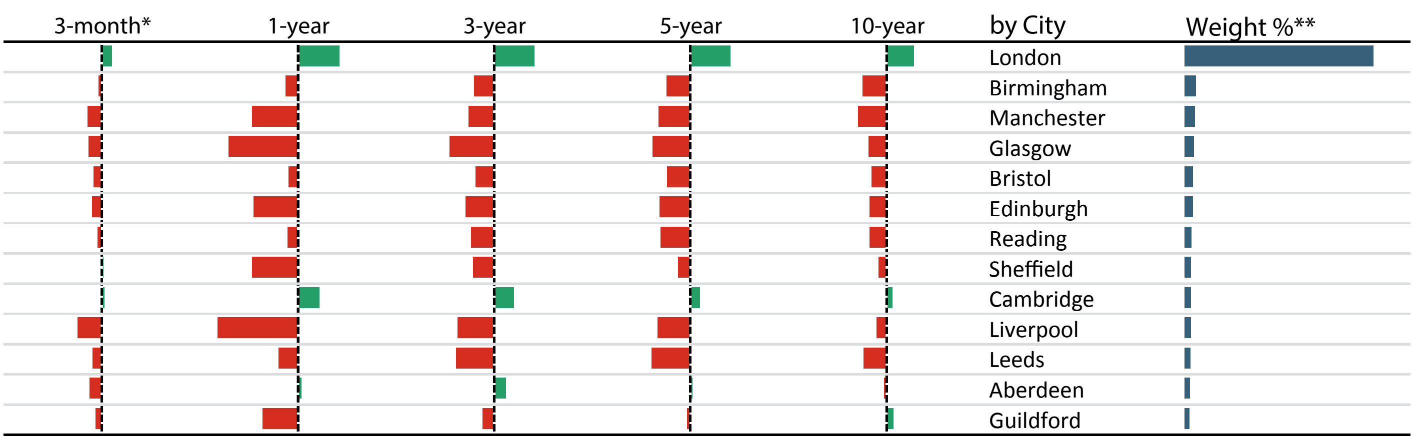
Relative annualized all property total return by sector and geography

Difference from national all property total return by period

Sector/city weights

% of national

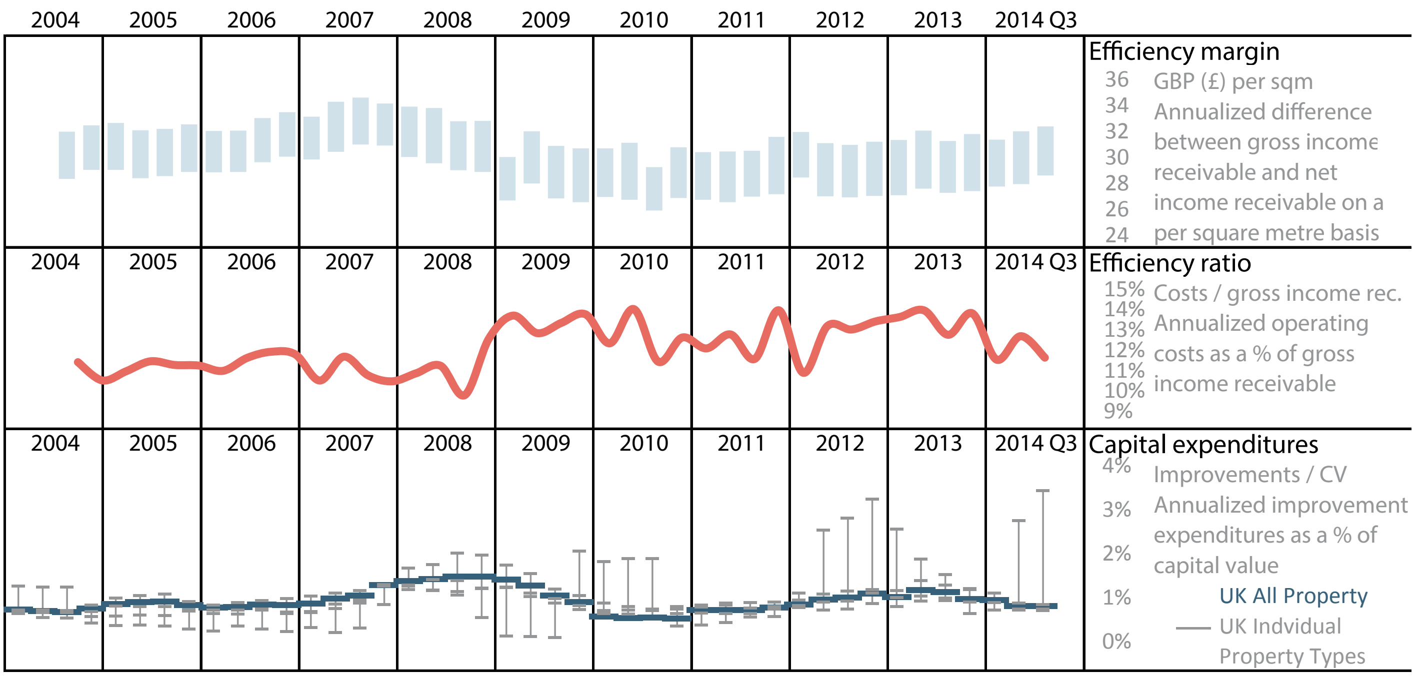




*3-month return is quarter-over-quarter. All others are annualized

**sector weights based on 2013 market size estimates in USD; cities weighted separately on IPD Databank capital values at 2014 Q3 in GBP

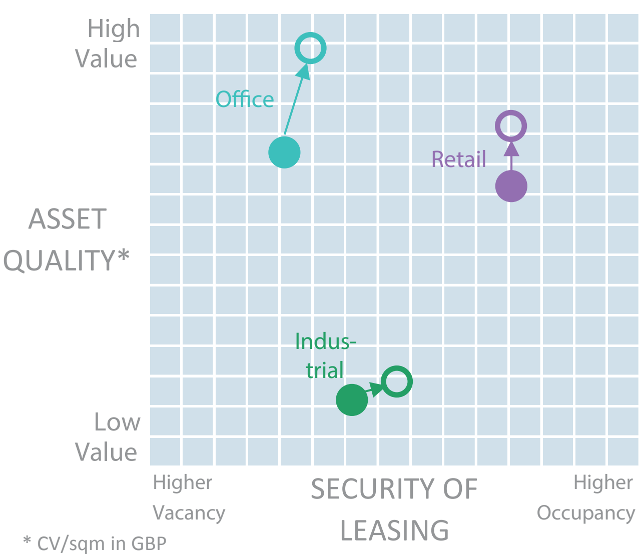
OPERATIONS & INVESTMENT



ASSET MGMT. STRATEGY

UK property types

Historical avg.
2014 Q3



* CV/sqm in GBP

FUND RECONCILIATION

as of 2014 Q3 (UK)

Total Return (%)	3-month Q / Q	1-year Y / Y	5-year Annualized
NET FUND	3.81	15.90	9.72
+/- IMPACT OF: leverage, cash, fund costs, mgmt. fees, etc.	-0.90	-1.42	-0.86
DIRECT REAL ESTATE	4.71	17.32	10.57

Note: The UK sample size used for fund reconciliation differs from the broader UK sample, thus the direct real estate return shown here differs slightly from the remainder of the Global Intel dataset.

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