
Adaptive Investment Approach

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¹Julex Capital Management, LLC is a multi-asset managed ETF strategy firm offering dynamic investment strategies to deliver consistent returns regardless of market conditions. The views and opinions are those of the author only, and do not necessarily represent those of Julex Capital Management or any of its affiliates and employees. I thank Tony Ash, Jerry Cai, Brian Phelan and Prof. Zhijie Xiao for helpful comments and discussions. Phone: 857-453-6669; email: henry.ma@julexcapital.com; website: www.julexcapital.com

Abstract

During the last decade, we have experienced two deep bear markets as results of internet bubble burst and mortgage crisis. Many investors suffered significant losses and found it hard to achieve their investment goals. The traditional investment theory such as mean-variance portfolio theory and Efficient Market Hypothesis (EMH), and associated practices such as buy-and-hold, or benchmark-centric investments have proved inadequate in helping investors achieve their financial goals. Market participants are now questioning the broad theoretical framework and looking for alternative way to made 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 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, which may serve investors better in the ever-changing financial markets.

In this paper, I will address some of the shortcomings of modern portfolio theory and Efficiency Market Hypothesis as well as 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 risk 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 and environment, this type of strategies aim to deliver consistent returns by adapting a portfolio to constantly changing market conditions.

This approach differs from absolute return strategy in that it generates returns through market betas rather uncorrelated alpha, though 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 has some

flavor of tactical asset allocation (TAA) or global macro. TAA normally under/overweighs certain asset classes relative to its strategic targets. The TAA managers normally make tactical decision mainly based their return forecasts. There is no need to forecast returns with adaptive investment approach. Global macro strategy typically employs shorts and leverage to express the managers' views. The adaptive investment approach is a long-only strategy. In addition, with their rapid development in recent years, ETFs have become the ideal instruments for the implementation of adaptive investment strategies due to their low cost and high liquidity.

The adaptive approach also offers a new way to active investment management. 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 paper, I will show the possibility and potential of improving investment performance with this approach.

I will introduce three different adaptive investment approaches. In the first approach, investors adapt their portfolios to the ongoing economic and business conditions. It has the flavor of a regime-based investment. In the second approach, investors adapt to the recent market performance. Momentum strategies and trend-following strategy 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 also discuss an integrated approach which incorporates all three elements into a robust investment process. In addition, I will show this approach can help enhance returns and diversify risks in the context of asset allocation.

1 Introduction

During the last decade, we have experienced two deep bear markets as results of internet bubble burst and mortgage crisis. Many investors lost significant amount of their wealth, and some of them have to put their retirement plans on hold. The traditional investment theory such as mean-variance portfolio theory and Efficient Market Hypothesis (EMH), and associated practices such as buy-and-hold, or benchmark-centric investments have proved inadequate in helping investors achieve their financial goals. Market participants are now questioning the broad theoretical framework and looking for alternative way to made 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 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 paper, I will address some of the shortcomings of modern portfolio theory and Efficiency 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 risk 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 and environment, this type of strategies aim to deliver consistent returns by adapting a portfolio to constantly changing market conditions. Instead of forecasting future returns under the traditional active investment framework, the adaptive approach focuses more on identifying the market regimes and conditions and adjusting the investment strategies accordingly.

This approach differs from absolute return strategy in that it generates returns

through market betas rather uncorrelated alpha, though 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 has some flavor of tactical asset allocation (TAA) or global macro. TAA normally under/overweighs certain asset classes relative to its strategic targets. The TAA managers normally make tactical decision mainly based their return forecasts. There is no need to forecast returns with adaptive investment approach. Global macro strategy typically employs shorts and leverage to express the managers' views. The adaptive investment approach is a long-only strategy. In addition, with their rapid development in recent years, ETFs have become the ideal instruments for the implementation of adaptive investment strategies due to their low cost and high liquidity.

I will introduce three different adaptive investment approaches. In the first approach, investors adapt their portfolios to the ongoing economic and business conditions. It has the flavor of a regime-based investment. In the second approach, investors adapt to the recent market performance. Momentum strategies and trend-following strategy 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 also discuss an integrated approach which incorporates all three elements into a robust investment process. In addition, I will show this approach can help enhance returns and diversify risks in the context of asset allocation.

2 The Shortcomings of Modern Portfolio Theory and Its Implementation

In the wake of the financial crisis in 2008, modern portfolio theory and 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 approximation of the real world. Those assumptions include:

- There is a linear positive risk/return tradeoff across all financial assets;

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

Although these assumptions may be good approximation for the long run, most of them are hardly the case within reasonable investment horizon of any investors, e.g. 5 - 20 years. In a shorter horizon, all the parameters are highly unstable. Moreover, when modern portfolio theory and efficient market hypothesis were developed between 1950s and 1970s, the majority of empirical research was done on the US equity and bond markets. Nowadays, the asset classes and geographical regions are broadened, which make these assumptions appear more problematic. In this section, I will examine some of shortcomings in the theory and its related practices.

2.1 Risk/return relationship breaks down when including international equities and other asset classes

After Harry Markowitz did his pioneering work on the modern portfolio theory in 1950s, many financial economists and practitioners have tested the theory empirically with data from US equity and bond markets. However, during last few decades, as investors become more sophisticated and economy 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.

Figure 1 shows the the return/risk relationship among five asset classes: US Large Cap Equity, International Equity, REITs, Commodity and Treasuries. I used monthly

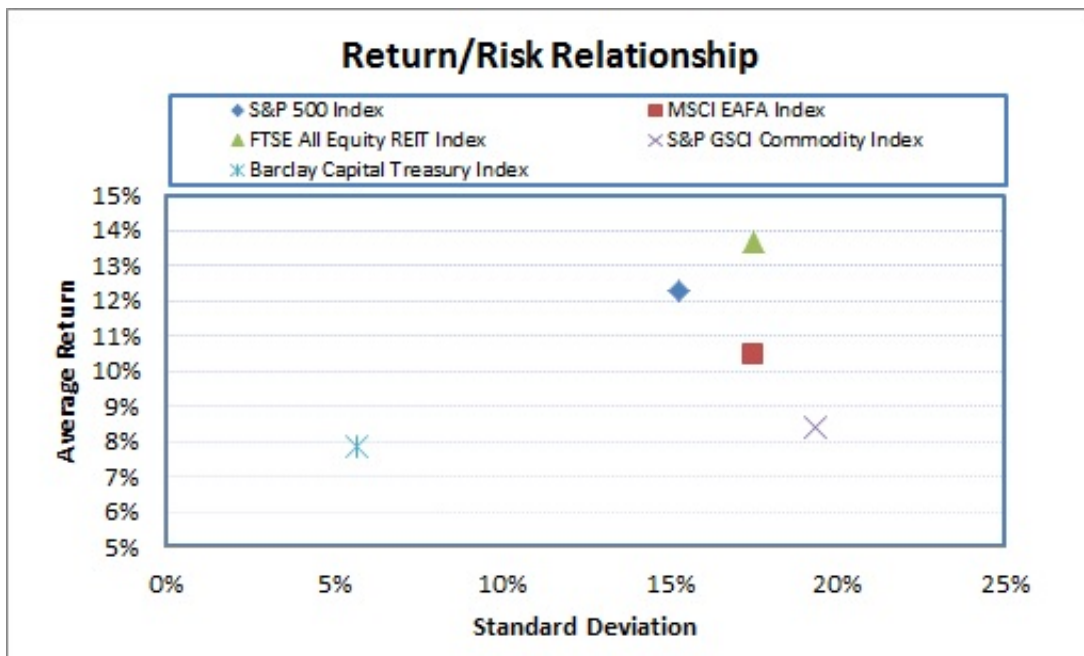


Figure 1: Risk/Return Relationship Across Asset Classes.
Data source: Bloomberg

data including 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 clearly that international equity and commodity are inferior, offering lower returns with higher volatility. This may present a problem for an asset allocator. In a mean-variance efficient frontier, there is little or no room for international equities or commodities.

2.2 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, then 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.

Figure 2 shows the S&P 500 index average annual returns for five-year, ten-year or 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 become more certain, the range of variation is substantial. Whether a person will end up in social welfare or live in a extravagant beach house after he retires will all depend on the timing of his investments.

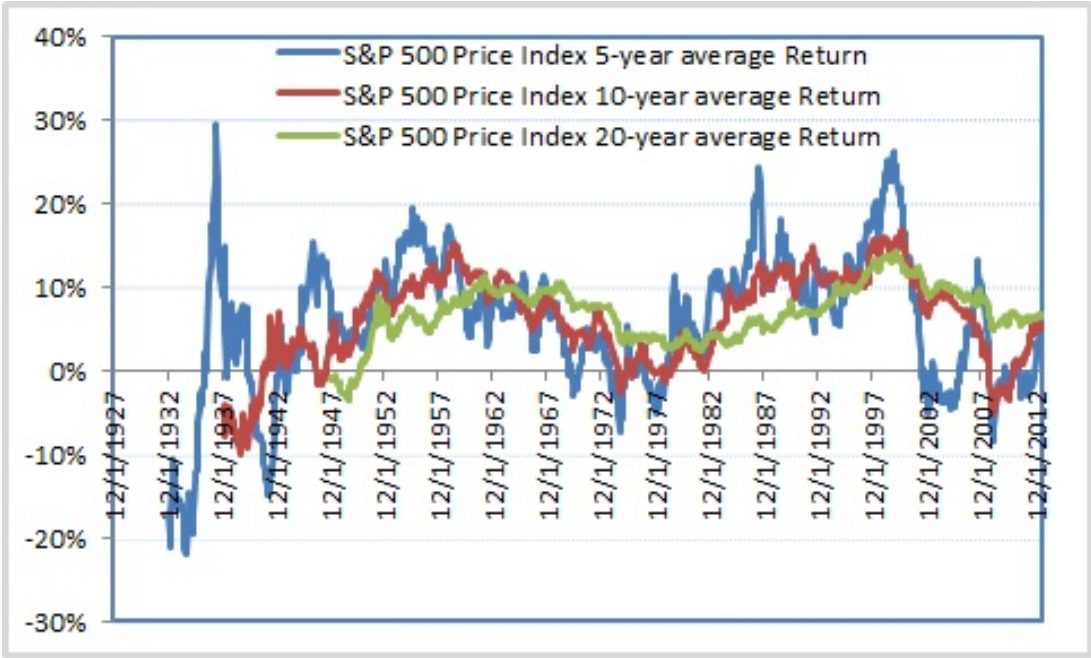


Figure 2: Historical Average Returns of SP 500 Price Index.
Data source: Bloomberg

2.3 Volatility and standard deviation are constantly changing

Another assumption under MPT is the asset return distribution is stationary. In fact, neither the average returns nor the standard deviations, the second moment of a distribution, is stable over time. Figure 3 illustrates the historical 12-month annualized standard deviation of S&P 500 Index between January, 1928 and September, 2013. The volatility level range from the highest of 75% to the lowest of 5%. The wide range of

the standard deviation and volatility makes it hard for any market participant to have confidence on their estimates.

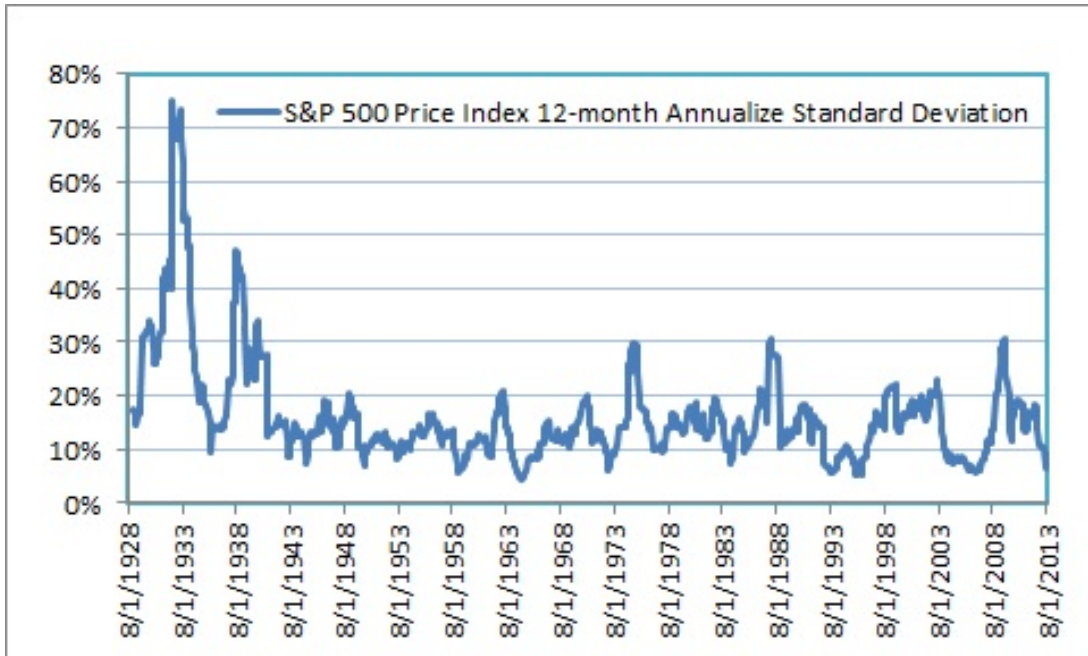


Figure 3: Historical 12-month Standard Deviation of S&P 500 Index
Data source: Bloomberg

2.4 Correlations are unstable and trending higher in the new millennium

One more important input in portfolio construction is correlation, which is assumed to be stationary and stable over time. Figure 4 shows the 12-month correlation between S & P 500 Index and 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 economic integration and globalization.

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

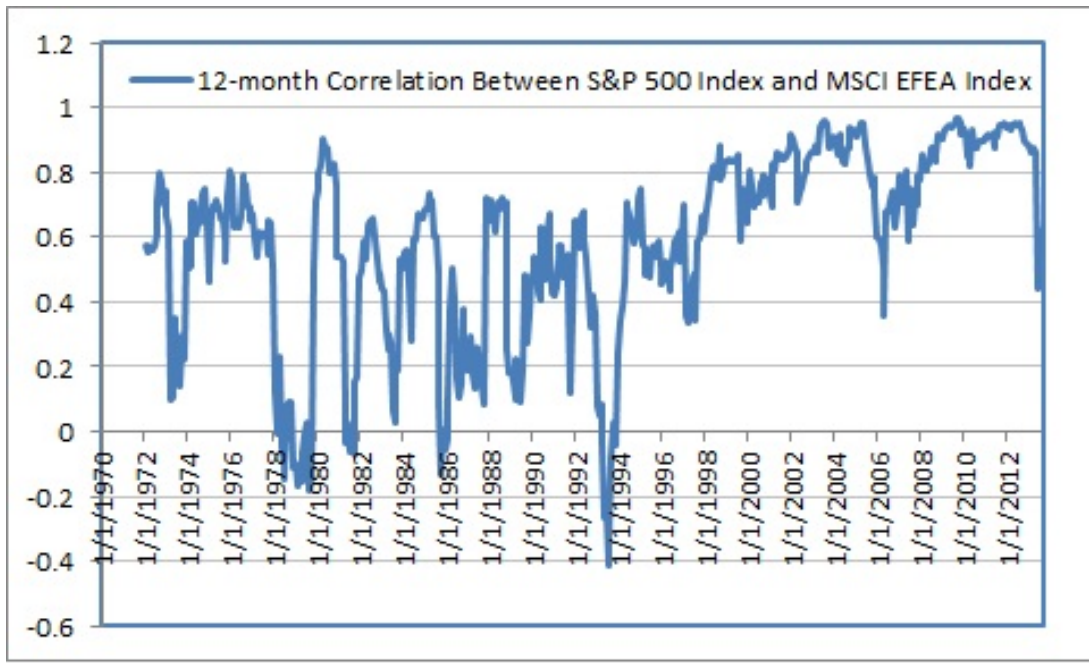


Figure 4: Historical 12-month Correlations between S&P 500 Index and MSCI EAFE Index
 Data source: Bloomberg

allocation.

3 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 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 the security selection than 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 investor without much consideration of the ongoing market conditions. As a consequence, many investors suffered unbearable losses when internet bubble and housing bubble bursted.
- Money managers are obsessed with beating their benchmarks and managing tracking errors. As a result, the industry deliver 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 repackage beta as alpha.

3.1 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 Table 1). In the US, the worst drawdown happened during the Great Depression. The market declined by 86% and recovered after 22 years. The second worst draw down 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 its high reached in 1989 since the Japanese housing bubble bursted.

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

Table 1: Severe Market Downturns

Market Index	Event	Begin	End	Loss	Time to Recover
S&P 500 Index	Great depression	8/1929	6/1932	-86%	22 years
S&P 500 Index	Oil crisis	12/1972	9/1974	-46%	6 years
S&P 500 Index	Internet bubble	3/2000	2/2003	-44%	5 years
S&P 500 Index	Subprime crisis	10/2007	2/2009	-53%	4 years
Nasdaq Index	Internet bubble	3/2000	9/2002	-81%	26% below peak
Nikkei Index	housing bubble	12/1989	4/2003	-78%	62% below peak

markets and were afraid of getting back in when the new bull market began. Buy and hold is a strategy only good for bull markets. It worked very well in the bull markets of 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 recover after losses. However, the time may not on an investor's side, especially for a retiree who lives on his savings and does not have the luxury of waiting for years.

3.2 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 add 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 strategy against certain benchmarks. For example. the managers in the Morningstar Large Cap Blend category normally use S&P 500 Index as a benchmark. Although, this approach serve many purposes such as defining an asset manager's universe and measuring manager's performance, the approach has some significant drawbacks:

- It puts constraints on what managers can do, and limit 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' goal of preserving capital or achieving stable returns. For example, during the financial crisis of 2008, the S&P 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 asset management industry grows and institutional investors become more dominating players in the markets, the opportunities of generating 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 US mutual funds that invest primarily in US equities. It confirms the view that most of the active mutual funds underperformed their benchmarks, especially on an after-fee basis.

3.3 Selling Beta as Alpha

Efficient market hypothesis also takes its toll on hedge funds as the industry grows. Hedge funds, as a 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 2008 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 market inefficiencies disappear quickly. In addition, to manage 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 and run hedge funds. As a result, hedge fund returns have declined steadily over the past two decades. Efficient Market Hypothesis and the law of diminishing returns are taking effect in the hedge fund industry.

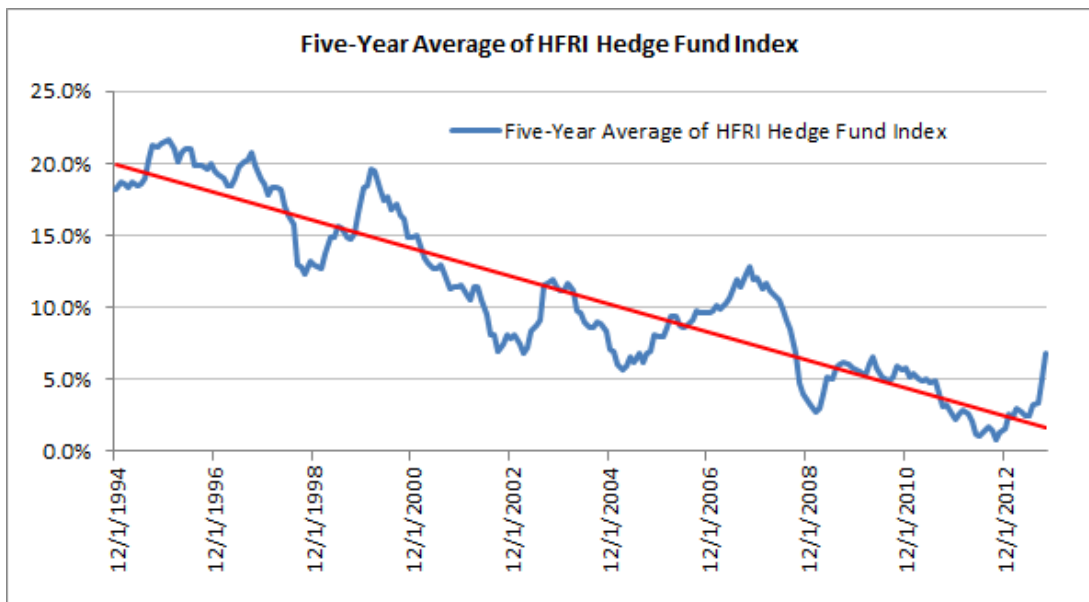


Figure 5: Historical 5-Year Average Hedge Fund Performance.
Data source: Hedge Fund Research

To prove the point, I have calculated annualized five-year rolling returns of Hedge Fund Research Hedge Fund Weighted Index, as shown in Figure 5. There is a very clear downward trend in aggregate hedge fund returns, declining from 20% in 1994 to around 1% in 2012, though rising slightly 2013.

The other undesirable observation is that the correlations between hedge fund per-

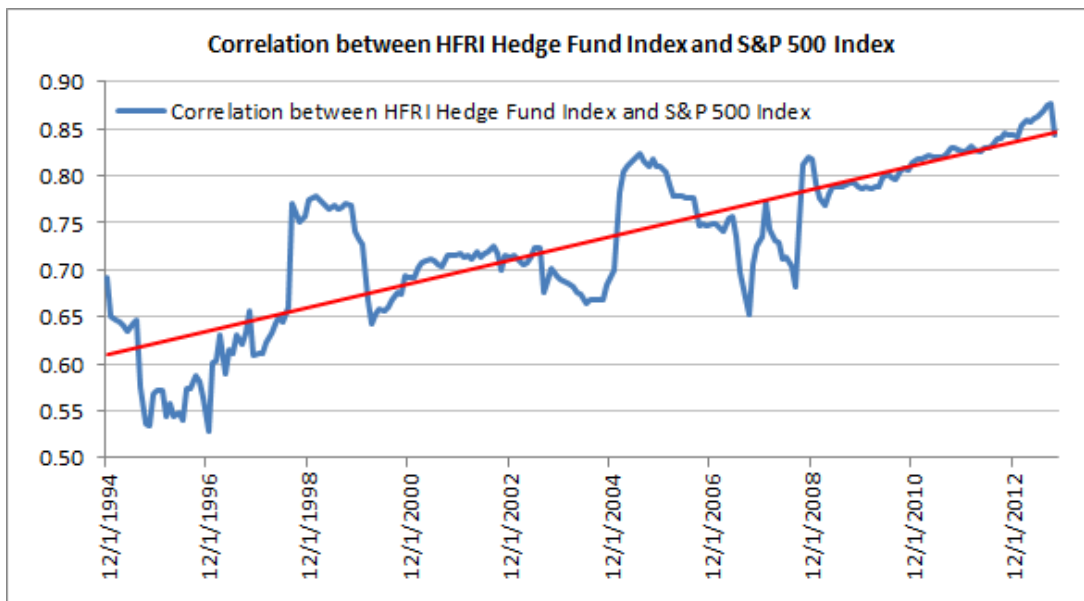


Figure 6: Historical Correlations Between Hedge Fund Index and S&P 500 Index. Data sources: Hedge Fund Research, Bloomberg

formance and equity markets are increasing over the years (see Figure 6 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 - delivery of high uncorrelated returns.

4 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 Efficient Market Hypothesis (EMH) takes effect and markets become more efficient over time. Investors may wonder if there is a better way to 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 Prof. Andrew Lo of MIT 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 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 relation varies, the 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.”

5 Adaptive Investment Approach

The most important implication of 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 incorporate all three elements to deliver more robust results and better risk-adjusted returns.

5.1 Adaptive Regime Approach

There is a well-established relationship between financial market returns and economic and business cycles. Normally, equity markets tend to perform well during economic expansion, and underperform during business contraction. Figure 7 shows the stock

market performance between January, 1957 and October, 2013. During recessions indicated in the shaded areas in the graph, S&P 500 Index were most likely to perform poorly.

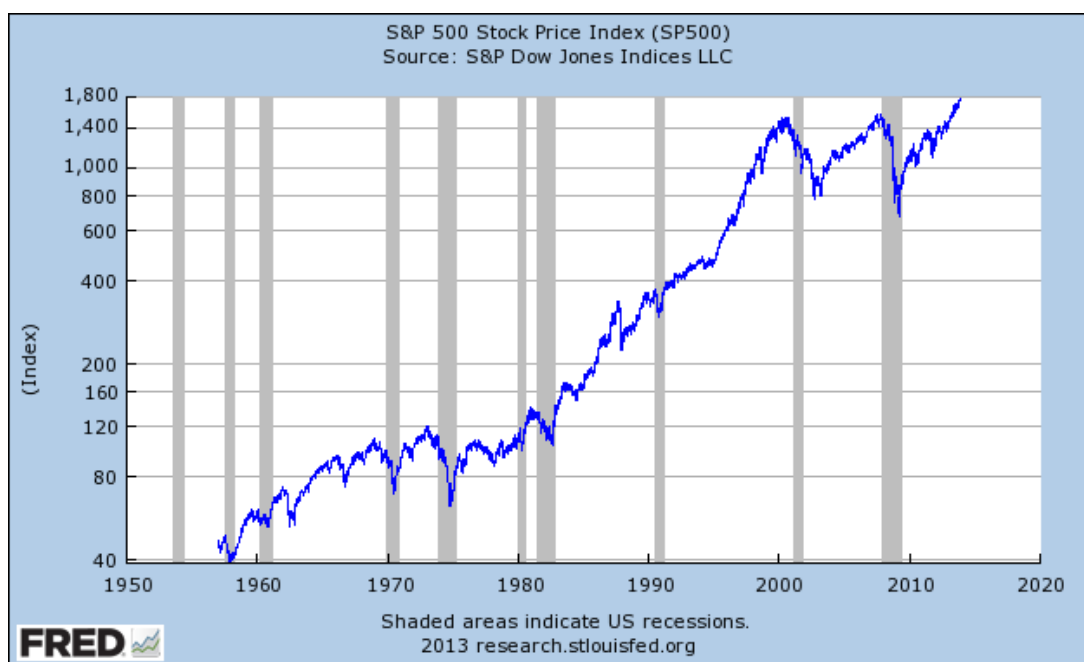


Figure 7: Stock Market Performance and Business Cycle.
Data Source: Federal Reserve Bank of St. Louis

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 forecast macroeconomic variables. Hamilton (2005) summarized how regime-switching model can be used to forecasting business cycles. Here I will use a simple and popular indicator- Weekly Leading Index (WLI) published by Economic Cycle Research Institute (ECRI), to identify economic regimes and show an adaptive regime approach can help improve risk-adjusted returns. How to best forecast or identify the economic regimes is out of the scope of this paper.

ECRI published WLI and WLI Growth weekly. The components of the index are considered proprietary. ECRI said it used some proprietary components in addition to the ten components the Conference Board uses. Those ten components include: average weekly hours, manufacturing; average weekly initial claims for unemployment insurance; manufacturers' new orders of consumer goods and materials; ISM Index of

$\left\{ \begin{array}{ll} \text{Invest in S\&P 500 Index,} & \text{if WLI growth} > 0 \\ \text{Invest in Barclay Capital US Aggregate Bond Index,} & \text{otherwise.} \end{array} \right.$

New Orders; Manufacturers' new orders of non-defense capital goods excluding aircraft orders; building permits, new private housing units; stock prices of 500 common stocks; Leading Credit IndexTM; interest rate spread of 10-year Treasury bonds less federal funds;

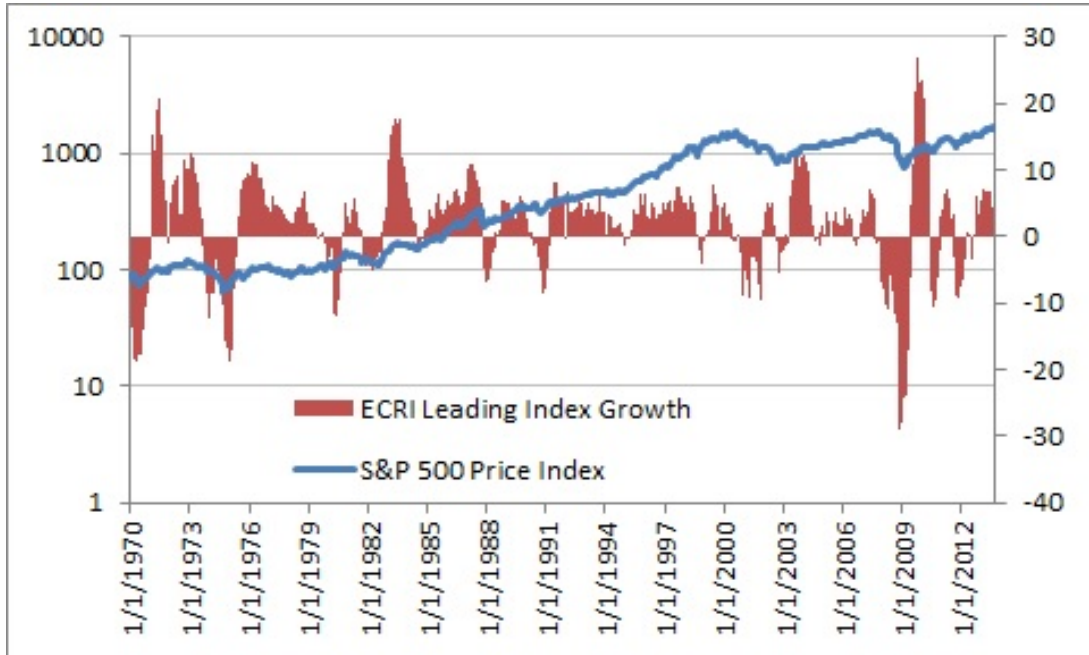


Figure 8: Stock Market Performance and WLI Growth
 Data Source: ECRI, Bloomberg

Figure 8 shows the relationship between WLI growth and 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. Therefore, the adaptive regime approach here follows a simple rule:

Table 2 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. Without sacrificing returns, the simple adaptive regime approach dramatically reduces the draw-down risk from 51% to 23%, when compared to a buy-and-hold strategy of S&P 500n

Table 2: Performance Statistics of Adaptive Regime Approach

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%
Years to Recover	2.1	4.6

Index. In addition, the risk-adjusted return, measured by Sharpe Ratio, also improves from 0.38 to 0.51. Of course, we can always find more sophisticated rule to get better performance results, but the objective of this paper is only to show how the adaptive investment rule works rather than propose optimal trading rules.

5.2 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 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 over-react 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 the price trend last for a while. They try and take

advantage of these trends by observing the current direction and using this 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 this strategy 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.

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 case we have discussed in the previous section. In the second example, I will apply a momentum strategy to a multi asset setting.

5.2.1 Example One: Trend Following Strategy

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

$$\left\{ \begin{array}{ll} \text{Invest in S\&P 500 Index,} & \text{if S\&P 500 Index is above} \\ & \text{its 9-month moving average} \\ \text{Invest in Barclay Capital US Aggregate Bond Index,} & \text{otherwise.} \end{array} \right.$$

Table 3 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

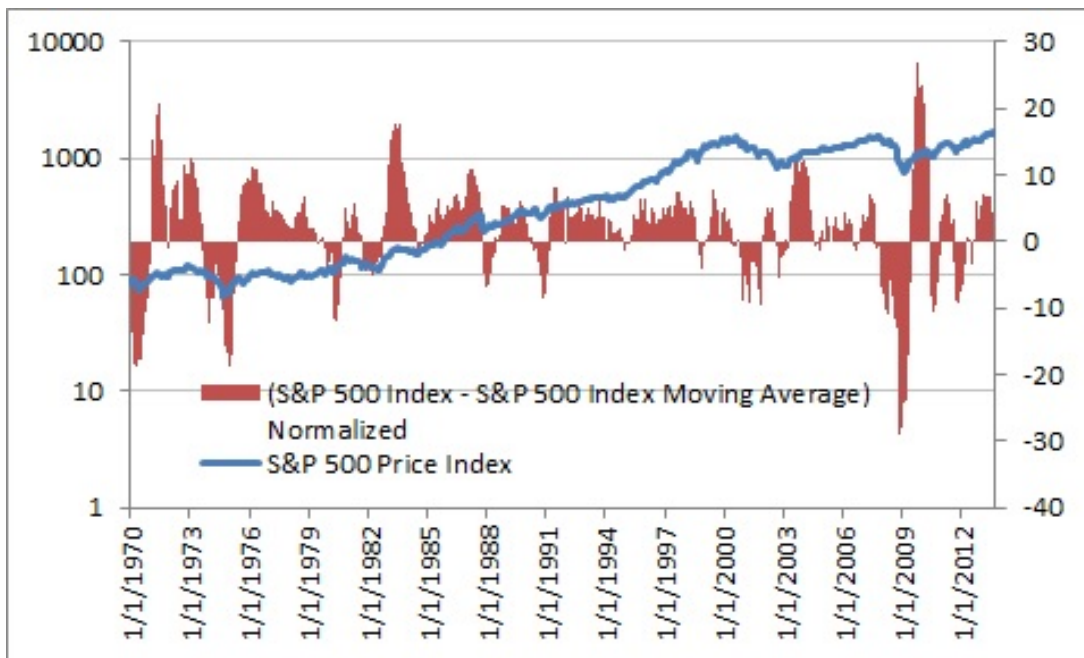


Figure 9: Stock Market Performance and Market Moving Average
Data Source: Bloomberg

Table 3: Performance Statistics of Adaptive Return Approach - Trend Following

Performance Metrics	Trend Following	S&P 500 Index
Average Monthly Return	1.1%	0.9%
Monthly Standard Deviation	3.5%	4.5%
Annualized 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%
Years to Recover	1.8	4.6

average 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 S&P 500 Index.

5.2.2 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

Table 4: Asset Classes

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	Gold	GLD
8	Commodity	SPGC Commodity Index	GSG
9	High Yield	Barclays Capital High Yield Index	JNK
10	US Bond	Barclays Capital US Aggregate Bond	AGG
11	Inflation	Barclays Capital TIPS Index	TIP
12	Medium Term Treasuries	Barclays Capital Treasury	IEF
13	Long Term Treasuries	Barclays Capital Long Term Treasury	TLT
14	T-bill		

Table 5: Performance Statistics of Adaptive Return Approach

Performance Metrics	Momentum	S&P 500 Index
Average Monthly Return	1.3%	0.9%
Monthly Standard Deviation	3.3%	4.5%
Annualized Return	15.4%	11.0%
Annualized Standard Deviation	11.4%	15.5%
Sharpe Ratio (risk-free rate = 5%)	0.91	0.38
Maximum Drawdown	-21.1%	-50.9%
Years to Recover	1.4	4.6

includes four of the 14 asset classes listed in Table 4. For all 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.

Table 4 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 10 shows the cumulative value of an initial investment of \$100 in 1970. It is clear that the momentum strategy has outperformed both S&P 500 Index and a balanced portfolio of 60% S&P 500 and 40% Barclays Aggregate with lower volatility and drawdown.

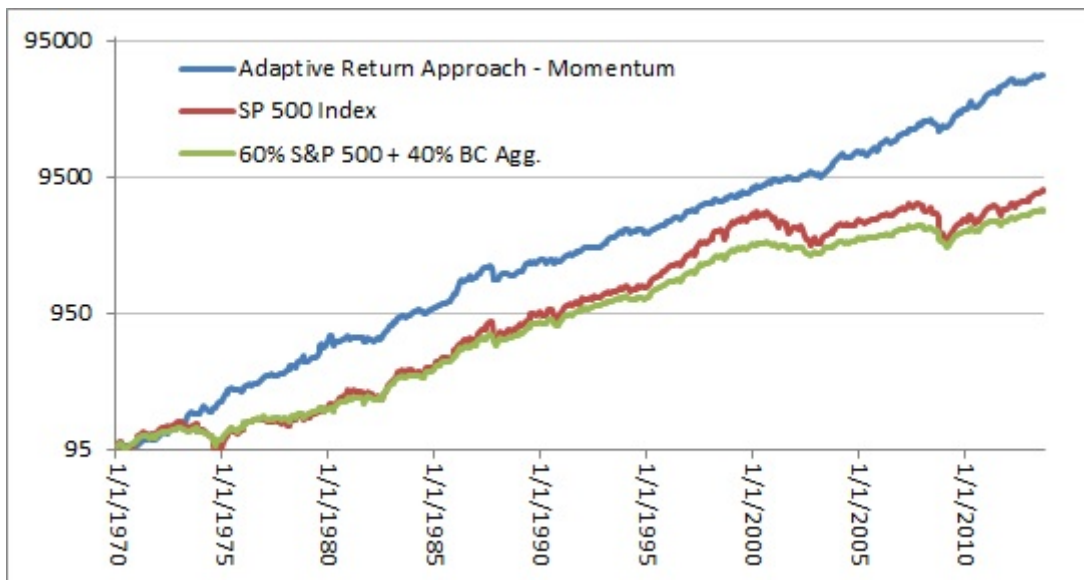


Figure 10: Cumulative Value of Initial Investment of \$100

5.3 Adaptive Risk Approach

In addition to adapting to economic regime or market return, investment strategies can be adapted to changing 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 have the ability to reduce exposures, and automatically lower risks and limit drawdown.

5.3.1 Example One: Risk-Parity Portfolio

Risk parity is portfolio management approach which focuses on allocation of risk, usually defined as volatility, rather than 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 a higher Sharpe ratio and can be more resistant to market downturns than the traditional portfolio. Interest in the risk parity approach has increased since the 2007-2009 financial crisis as the risk parity approach fared better than traditionally constructed portfolios, as well as many hedge funds.

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

$$\sigma_p = \sqrt{W^T \Sigma W}, \quad (1)$$

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:

$$w_1 \times \frac{(\Sigma W)_1}{\sigma_p} = w_2 \times \frac{(\Sigma W)_2}{\sigma_p} = \dots = w_i \times \frac{(\Sigma W)_i}{\sigma_p} = \dots = w_N \times \frac{(\Sigma W)_N}{\sigma_p} = \frac{\sigma_p}{N}, \quad (2)$$

under which the risk contributions are equal across all the assets. $(\Sigma W)_i$ is the i th row of the $N \times 1$ matrix ΣW .

5.3.2 Example Two: Volatility-Weighted Portfolio

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 risk parity approach, which intends to create a more diversified and balanced portfolio. 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 $W = \{w_1, w_2, \dots, w_i, \dots, w_N\}$ in a portfolio, the weight of i th asset can be expressed as

Table 6: Performance Statistics of Adaptive Risk Approach

Performance Metrics	Vol-Weighted	Risk Parity	Equal Weight
Average Monthly Return	0.8%	0.8%	0.9%
Monthly Standard Deviation	1.8%	1.8%	2.4%
Annualized 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%
Years to Recover	1.6	1.5	2.9

$$w_i = \frac{1/\sigma_i}{\sum_1^N 1/\sigma_i}, \quad (3)$$

where σ_i is the standard deviation of *ith* asset.

Table 6 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 used are shown in Table 4 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 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 returns of volatility-weighted portfolios is better than those 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.

Table 7: Performance Statistics of Integrated Approach

Performance Metrics	Integrated Approach	S&P 500 Index
Average Monthly Return	1.4%	1.0%
Monthly Standard Deviation	3.3%	4.4%
Annualized Return	16.7%	12.5%
Annualized Standard Deviation	11.3%	15.3%
Sharpe Ratio (risk-free rate = 5%)	1.04	0.49
Maximum Drawdown	-18.2%	-50.9%
Years to Recover	1.1	4.1

5.4 Integrated Approach

So far, I have discussed three possible approaches to create dynamic and adaptive investment strategies. All 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 *Adaptive Regime Approach*;
2. Select the best assets in the economic regime identify in step (1) with *Adaptive Return Approach* such as momentum;
3. Construct portfolios with the assets selected in step (2) with *Adaptive Risk Approach* such as risk parity.

Table 7 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 both momentum strategy or regime-based strategy alone. Figure 11 illustrates the cumulative return over time. The integrated approach generates higher returns with less volatility and drawdown than S&P 500 Index.

5.5 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

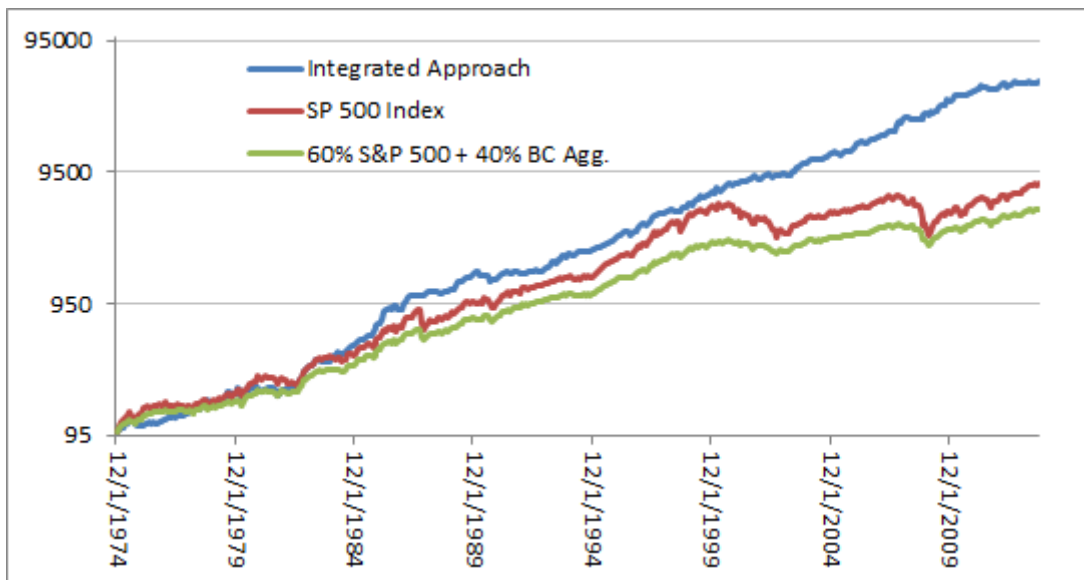


Figure 11: Cumulative Value of Initial Investment of \$100 - Integrated Approach

profile in the context of asset allocation. Figure 12 shows the 12-month correlation between adaptive return and 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 Figure 13, by adding adaptive return to the traditional asset mix of stocks and bonds (represented by S&P 500 Index and Barclays Capital 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.

6 Concluding Remarks

This paper 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

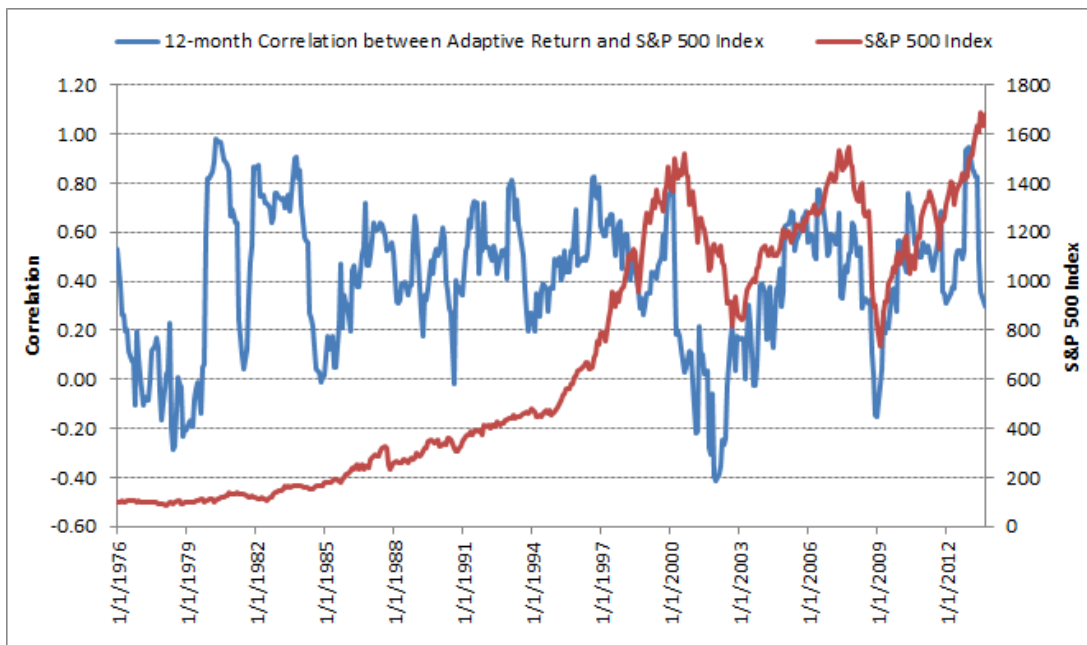


Figure 12: Correlation between Adaptive Return and S&P 500 Index

to investment industry. Some common practices such as buy and hold, tracing benchmarks and packaging beta to alpha, result in sub-optimal outcomes from investors' standpoint. As an alternative, Adaptive Market Hypothesis (AMH) allows for evolution towards market efficiency and a dynamic and adaptive approach to investing. This paper introduced an adaptive investment framework, under which investors can adapt their investment strategies to economic 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 paper, I have shown the possibility and potential of improving investment performance with this approach.

In the paper, I have used some simple examples to show how adaptive investment strategies can be built and how investment performance can be improved with this

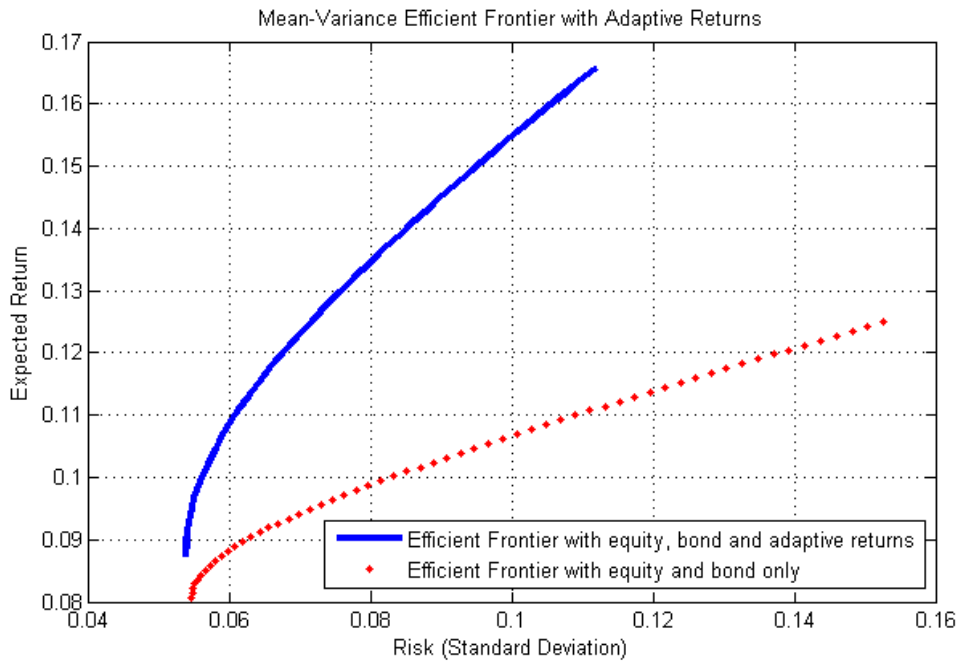


Figure 13: Efficient Frontier with Adaptive Return

type of strategy. However, the examples should only serve as starting points for further research and may not be considered 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 the 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.

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