



Adaptive Investment Approach

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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-

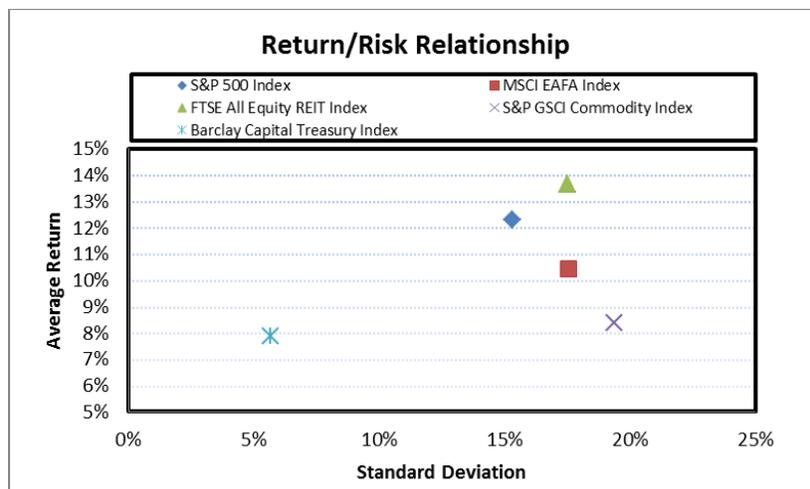


Exhibit 1 The Risk/Return Relationship Across Asset Classes

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

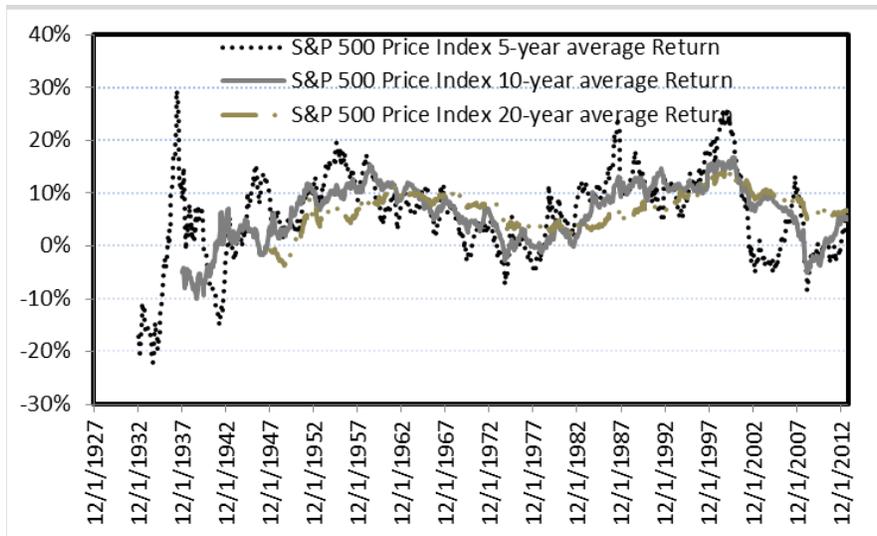


Exhibit 2 Historical Average Returns of the S&P 500 Price Index

Source: Bloomberg

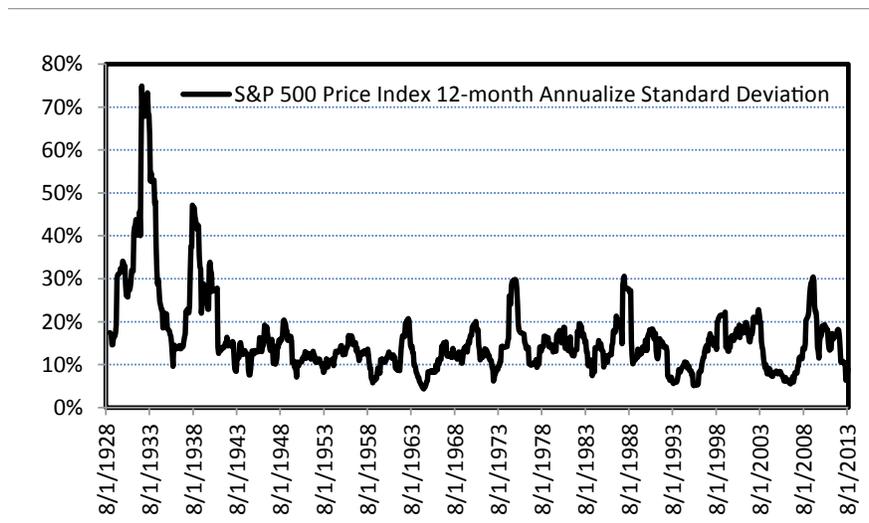


Exhibit 3 Historical 12-month Standard Deviation of the S&P 500 Index

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

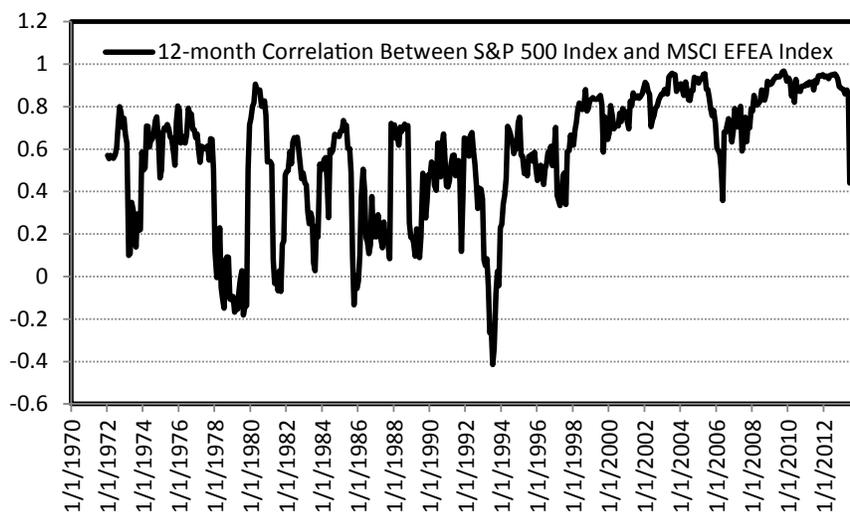


Exhibit 4 Historical 12-month Correlations between the S&P 500 Index and the MSCI EAFE Index

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 than 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-2000	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

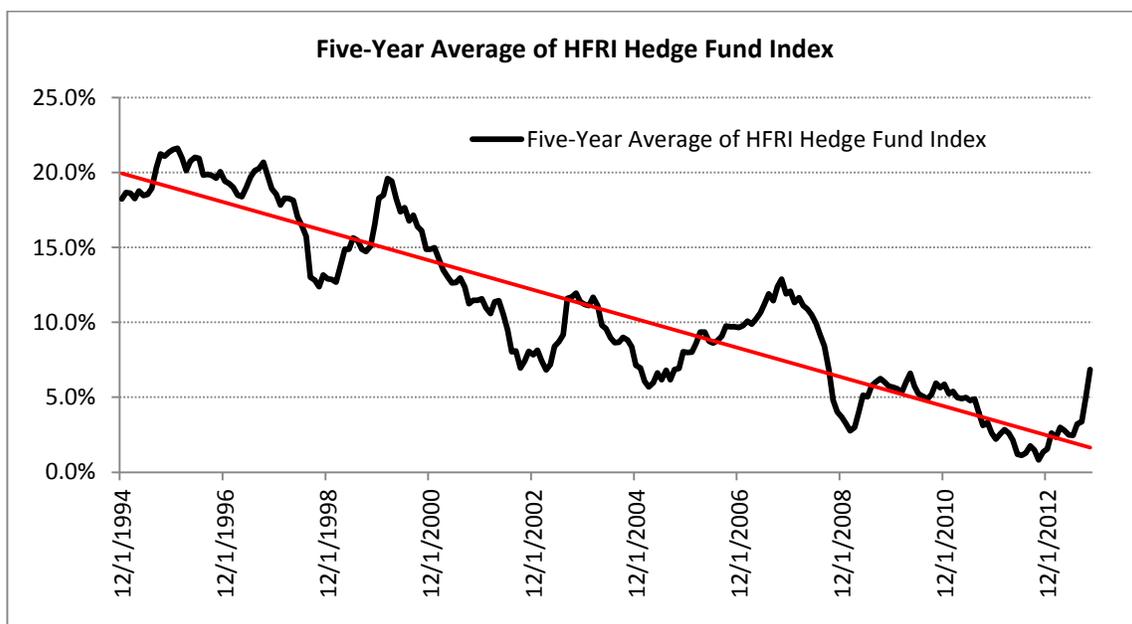


Exhibit 6 Historical 5-Year Average Hedge Fund Performance

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

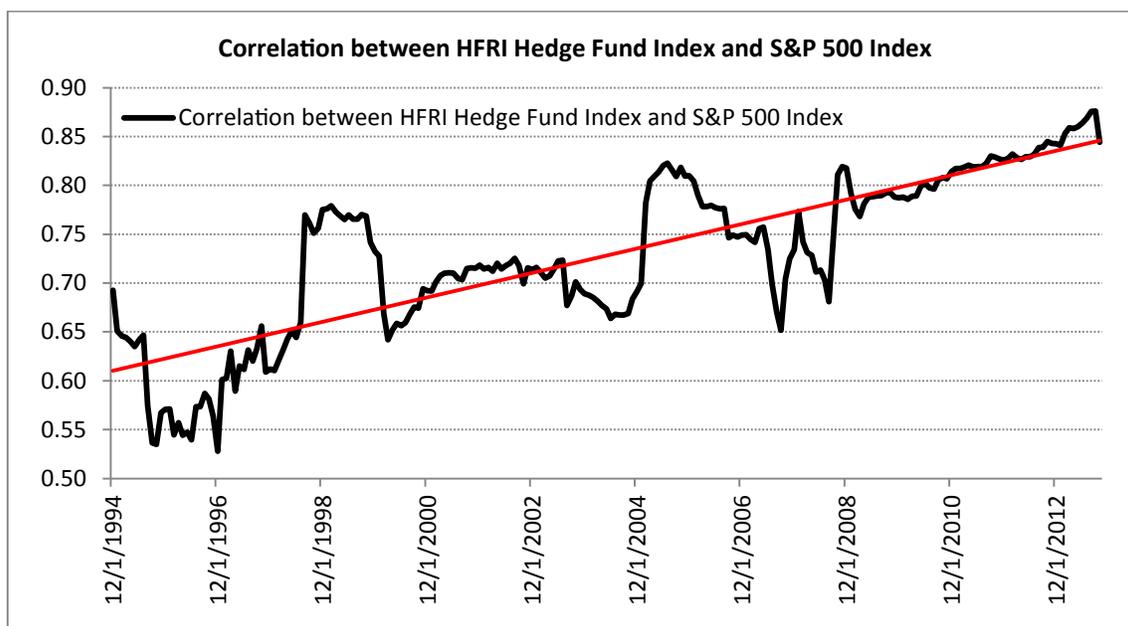


Exhibit 7 Historical Correlations between the Hedge Fund Index and the S&P 500 Index

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 adaptation. 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 contrac-

tion 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.

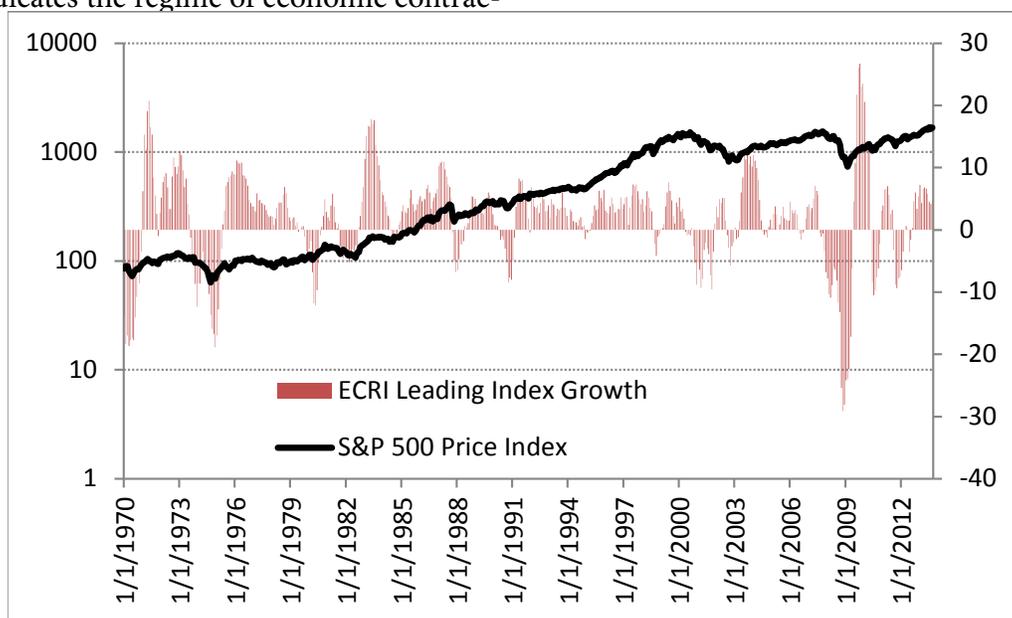


Exhibit 9 Stock Market Performance and WLI Growth

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.

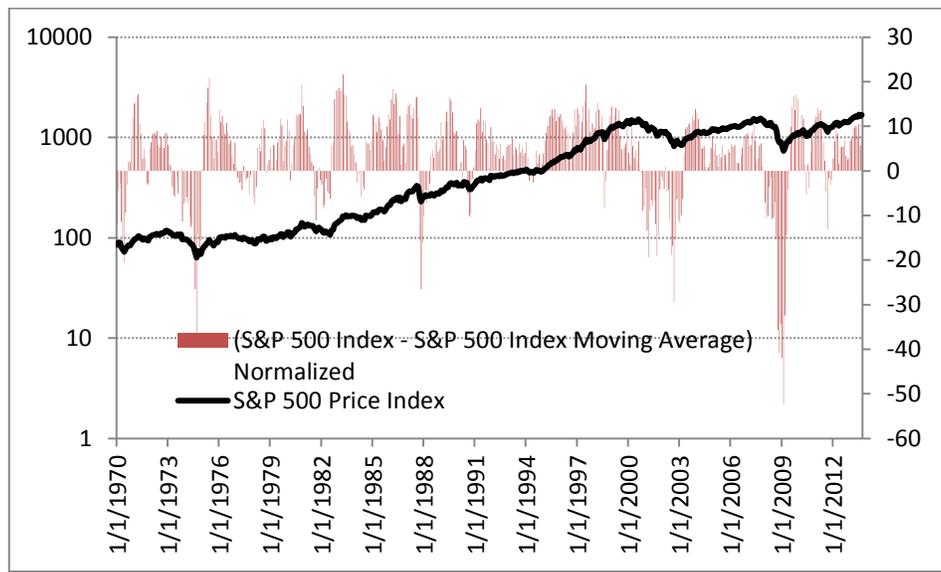


Exhibit 11 Stock Market Performance and Market Moving Average

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 $W = \{w_1, w_2, \dots, w_p, \dots, w_N\}$ 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:

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

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

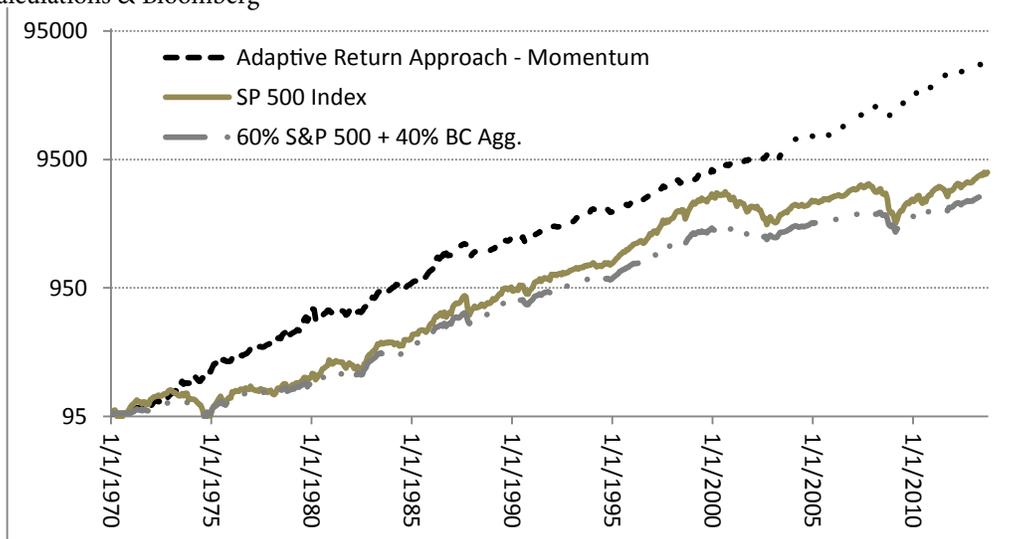


Exhibit 15 Cumulative Value of Initial Investment of \$100

Source: Bloomberg

the assets. $(\Sigma W)_i$ is the i th row of the $N \times I$ 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 $W = \{w_1, w_2, \dots, w_p, \dots, w_N\}$ in a portfolio, the weight of i th 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 i th 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 over-

all 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 draw-downs 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 hold-

ings, 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

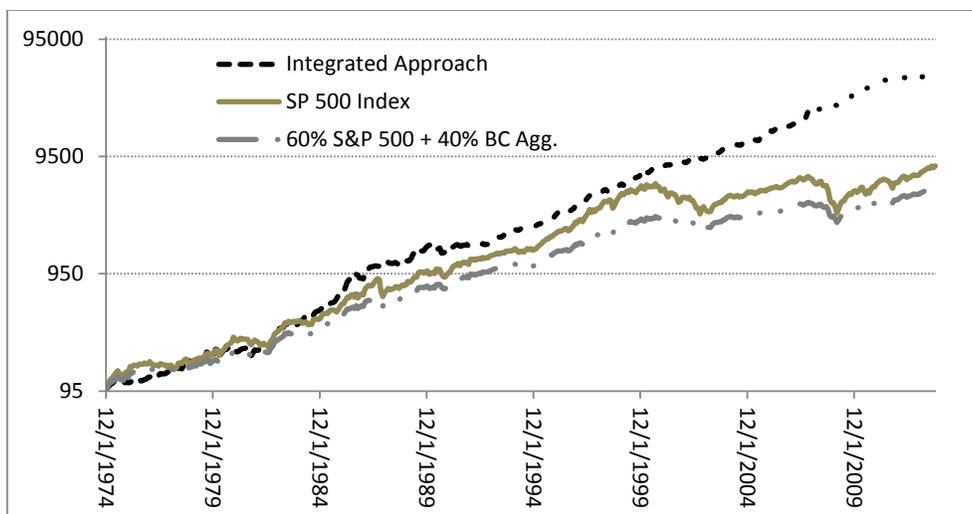


Exhibit 18 Cumulative Value of Initial Investment of \$100 - Integrated Approach

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.

fyng 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.

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 identi-

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-

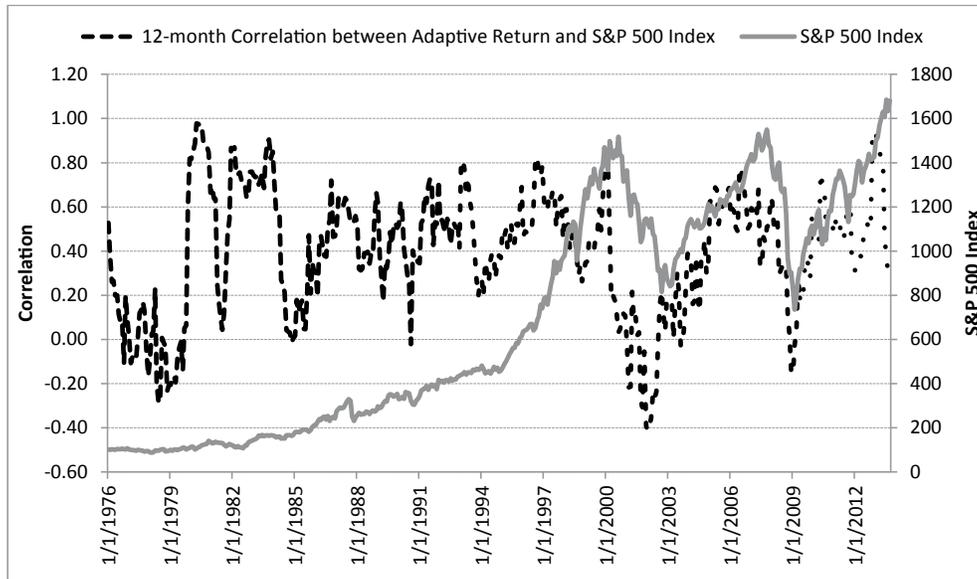


Exhibit 19 Correlation between Adaptive Return and the S&P 500 Index

Source: ECRI, Bloomberg

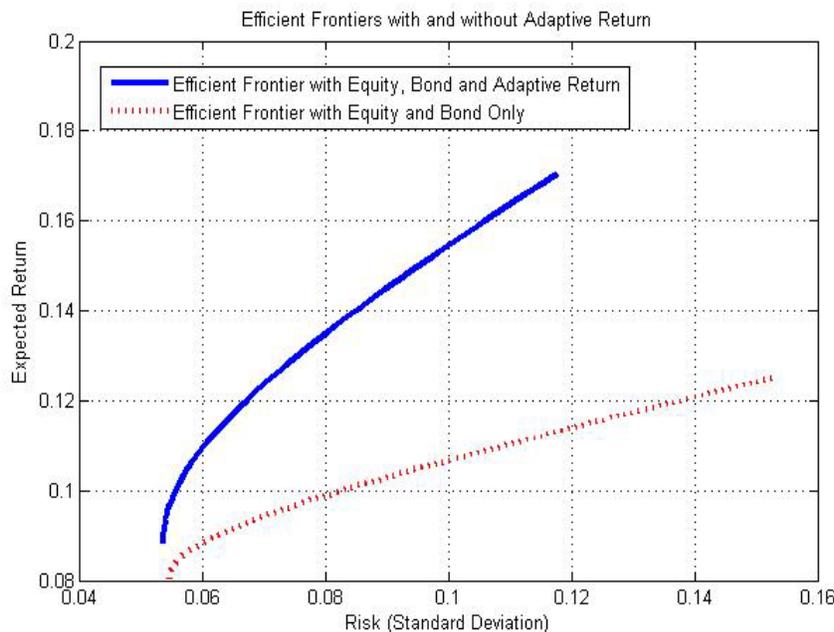


Exhibit 20 Efficient Frontier with Adaptive Return

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

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