# Abstract Of:

# Equity Sector Rotation via Credit Relative Value

February 28, 2013

Submitted for Review to the

National Association of Active Investment Managers (NAAIM)

Wagner Award 2013

By

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Active investors face a balancing act between achieving superior returns compared to a benchmark while managing multiple types of risk. No matter how well an investment strategy performs over a long time horizon, short-term losses can tarnish the strategy's reputation and reduce investor enthusiasm. The holy grail of investment strategies provides consistent outperformance with lower volatility, lower drawdown risk and positively skewed returns. No approach will deliver all these elements all the time, but developing strategies that are mindful of these factors is a worthy exercise.

This paper outlines a long-only sector rotation strategy using highly liquid ETFs that achieves admirable results in back-test. At its heart, the strategy makes use of relative value across the corporate capital structure to rank sectors and judge when entry and exit are recommended. To implement the investment strategy, we use Standard & Poor's Select Sector SPDR ETFs due to their high liquidity and relatively long history. The nine ETFs can be used, when weighted appropriately, to replicate performance of the S&P 500 index. Our ultimate goal is to choose weights for a portfolio of these ETFs, possibly along with a risk-free asset, to deliver superior returns while mitigating risk.

As a general rule, equity values drop as credit risk rises and vice versa. With good proxies for credit risk, one can use this relationship to judge relative value between the credit and equity markets. The strategy outlined below utilizes this relationship at the index level. The intuition is that if credit risk rises (falls) among a suitably-chosen basket of companies, then equity values will drop (rise) in an equity index.

The core of the relative value model is the relationship between the Bank of America/Merrill Lynch High Yield B (HY/B) credit index and the individual sector ETFs. To judge whether an ETF is expensive or cheap, we use a simple linear model, calibrated via OLS regression, which takes the previous day's HY/B index value as its input. Once fair values are calculated, the sector ETFs are ranked in descending order of percentage disconnect from fair. This ranking forms the basis for a basket selection strategy wherein the top-ranked ETFs are selected, on a weekly basis, for inclusion in a long-only portfolio.

We show that these $Basket_N$ portfolios outperform the SPY ETF and have admirable return characteristics regardless of the number of sector ETFs included in the portfolio. However, many of the risk characteristics of the $Basket_N$

portfolios are not significantly better than a buy-and-hold SPY portfolio, a fact that motivates an enhancement to the strategy.

Additionally, we examine the sensitivity of the strategy to differences in regression timeframes and look at holding periods for each of the nine sector ETFs to ensure we have not inadvertently "data-mined" a portfolio consisting primarily of the top-performing ETFs over the time period analyzed.

We improve the risk characteristics of the strategy and boost portfolio returns by introducing a tactical asset allocation enhancement to the $Basket_N$ approach. We still choose the N top-ranked ETFs for inclusion in our portfolio, but if the fair value model for an individual ETF indicates it is currently expensive, we invest that ETF's share of the portfolio in 3-month Treasuries rather than in the ETF itself. The tactical asset allocation strategy, while simple in concept, has two advantages to the $Basket_N$ strategy outlined above. It raises the expected return of the basket while limiting portfolio drawdown. Thus, we are often partially invested in the stock market while generally also being invested in lower-volatility Treasuries.

In declining markets, the strategy helps limit losses. In ascending markets, the strategy throttles gains. Overall, the tradeoff of lower gains in up markets is

offset by limiting portfolio drawdown. We find that the $TAA_N$ strategies deliver higher returns than the corresponding $Basket_N$ strategies, drawdowns of lower magnitude and lower volatility within the portfolios.

The main challenge to the approach is one of investor mindset. In bull markets, the strategy tends to lag the broader market since it is often partially invested in Treasuries. This underperformance is more than compensated for during periods of down markets as drawdown is limited. However, an investor must be willing to invest in the strategy for a two to three year time period to increase the likelihood of superior results.

After analyzing the $TAA_N$ strategy, we consider a lower-frequency approach to implementation that eliminates weekly rebalancing of the portfolio. We find that this approach experiences only minimal degradation from both risk and return standpoints and that, when transaction costs are considered, might be superior to the weekly rebalance approach.

We believe this type of relative strength investment strategy is worth consideration for investors with multi-year investment horizons. We also note that, given the use of the credit market to judge relative value, this investment strategy is uncorrelated to many popular ranking methodologies and can be used

in conjunction with them as an enhancement to existing strategies. The strategy outlined is certainly not fail-safe, but it does present the investor with a straightforward procedure to adjust the return vs. risk characteristics of an equity portfolio by changing the size of the investment basket. Further, the strategy is designed for long-only investors and can be implemented using highly-liquid index ETFs.

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## 1. Introduction

Active investors face a balancing act between achieving superior returns compared to a benchmark while managing multiple types of risk. No matter how well an investment strategy performs over a long time horizon, short-term losses can tarnish the strategy's reputation and reduce investor enthusiasm. The holy grail of investment strategies provides consistent outperformance with lower volatility, lower drawdown risk and positively skewed returns. No approach will deliver all these elements all the time, but forming strategies that are mindful of these factors is a worthy exercise.

This paper outlines a long-only sector rotation strategy using highly liquid ETFs that achieves admirable results in back-test. At its heart, the strategy makes use of relative value across the corporate capital structure to rank sectors and judge when entry and exit are recommended. To implement the investment strategy, we use Standard & Poor's Select Sector SPDR ETFs due to their high liquidity and relatively long history. The nine ETFs can be used, when weighted appropriately, to replicate performance of the S&P 500 index. Our ultimate goal is to choose weights for a portfolio of these ETFs, possibly along with a risk-free asset, to deliver superior returns while mitigating risk.

Much theoretical work has been published over the past four decades tying the corporate capital structure to market valuations. Merton's structural model[1], which posits that equity can be viewed as a call option on the assets of a firm, inspired many refinements and spawned an entire credit risk advisory industry. While credit and equity analysts focus on different parts of the capital structure, the basic equality of firm assets to firm equity and debt ties their work together. For our analysis, we move away from a structural model and focus on tradable assets across the corporate capital structure; specifically, corporate credit spreads and equity share prices.

As a general rule, equity values drop as credit risk rises and vice versa. With good proxies for credit risk, one can use this relationship to judge relative value between the credit and equity markets. The strategy outlined below utilizes this relationship at the index level. The intuition is that if credit risk rises (falls) among a suitably-chosen basket of companies, then equity values will drop (rise) in an equity index. We do not require a one-to-one match between membership in the credit and equity indices. Indeed, the strategy uses the same credit index to judge the relative value (whether stocks are expensive or cheap) of the collection of sector ETFs.

[1] Merton, Robert C., "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", Journal of Finance, Vol. 29, No. 2, (May 1974), pp. 449-470

The rest of this paper is divided into six sections. We discuss our data sources. Next, we look at a straightforward linear model to compare the relative value of credit and equity. We then move on to ranking sector ETFs based on the credit-equity relative model and analyze an investment strategy based on the relative strength (ranks) of the sector ETFs. We then refine the strategy with the addition of switching between equity ETFs and Treasuries to boost returns and lower portfolio risk. We examine a realistic implementation of the strategy and finally present conclusions.

## 2. Data Sources

Table 1 lists the nine sector ETFs we use in our analysis. We pull historical prices from Yahoo! Finance (http://finance.yahoo.com). We use the St.Louis Fed's FRED Economic database (http://research.stlouisfed.org/fred2) to pull 3-month Treasury yields as well as option-adjusted spreads for Bank of America/Merrill Lynch's US High Yield B index, henceforth referred to as ***HY/B***. We choose these data sources since the data are freely available to the public. The sector SPDRs were launched in December 1998 and our analysis period spans July 1999 through December 2012, a period of thirteen and a half years. This is a

short period for equity analysis but it includes two major market corrections as well as multiple periods of rising equity prices.

| Ticker | Description |
|---|---|
| XLY | The Consumer Discretionary Select Sector SPDR Fund |
| XLP | The Consumer Staples Select Sector SPDR Fund |
| XLE | The Energy Select Sector SPDR Fund |
| XLF | The Financial Select Sector SPDR Fund |
| XLV | The Health Care Select Sector SPDR Fund |
| XLI | The Industrial Select Sector SPDR Fund |
| XLB | The Materials Select Sector SPDR Fund |
| XLK | The Technology Select Sector SPDR Fund |
| XLU | The Utilities Select Sector SPDR Fund |

**Table 1. Standard & Poor's Select Sector SPDR ETFs.**

## 3. Relative Value Across the Capital Structure

The core of the relative value model is the relationship between the HY/B credit index and the individual sector ETFs. To judge whether an ETF is expensive or cheap, we use a simple linear model:

$$ETF_{Fair}(HYB_{Market}) = A * HYB_{Market} + B$$

We use the HY/B's option-adjusted spread as published in the St. Louis Fed's FRED database. Since credit spreads and equity values move in opposite directions as credit risk changes, we expect the A parameter in the equation to be negative. We calibrate the model via Ordinary Least Squares (OLS) linear regression.

This type of credit-equity relationship is often non-linear when single companies are considered. The intuition is that, for companies with very low credit risk, there is almost no correlation between equity prices and credit spreads. For companies with high credit risk, credit spreads change more rapidly than equity prices because they can theoretically go to infinity. At the index level, it is possible to use a non-linear model but a linear model works well given the credit index chosen.[2] To illustrate the relationship, Exhibit 1 plots the HY/B index against XLF using weekly values from July 2012 through December 2012. Points below the trendline indicate that XLF is cheap compared to HY/B and points above the trendline indicate that XLF is relatively expensive.

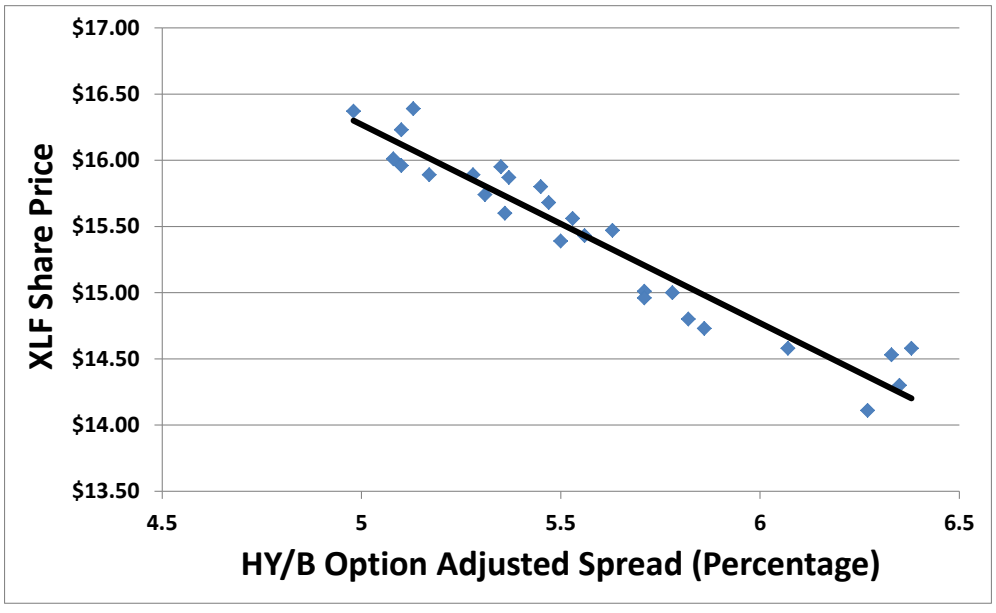


***Exhibit 1: HY/B vs. XLF, weekly values from July 2012 through December 2012***

[2] For an example of using a non-linear model, please see Klein's "Credit-Informed Tactical Asset Allocation, " (June 1,2011) http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1872163

Once the model has been calibrated via linear regression, we can estimate fair value for each sector ETF. More importantly, we can calculate how far, on a percentage basis, each ETF is away from fair value:

$$ETF_{disconnect} = \frac{ETF_{fair} - ETF_{market}}{ETF_{market}}$$

We use the disconnect in two ways. First, we rank the sector ETFs in order to select a basket of ETFs in which to invest. Second, we consider whether the disconnect is positive or negative to determine whether to invest in the ETF or in a risk-free asset. For the purposes of our analysis, we use 3-Month Treasury bills as our risk free security.

We assume the investor invests in a basket of ETFs and rebalances on a weekly basis. We choose a weekly trade frequency since it is not overly onerous for an active investor to adjust a portfolio of up to 9 separate positions at this frequency. Later, once we have developed the full strategy, we implement a more realistic, lower-frequency strategy where only entries and exits are traded and positions in ETFs that remain in the portfolio are not adjusted. We note that it is possible to implement this strategy with a monthly trading frequency although returns are lower.

## 4. Using HY/B to Rank Sector ETFs

As outlined above, once a timeframe and frequency are chosen, it is straightforward to use OLS regression to create a fair value model for each sector ETF using the HY/B index. Once fair values are calculated, the ETFs can be ranked in descending order by fair percentage disconnect. If our model does a good job of ranking, a basket with top-ranked ETFs, those ETFs with the greatest disconnect, should generate higher returns than a basket containing bottom-ranked ETFs.

To begin our analysis, we use a 6-month timeframe and a weekly frequency. Thus, we regress 26 data pairs to generate our model. As a practical matter, we use the previous 26 weeks of data exclusive of the current trading day to build our regression. Further, since the HY/B value is published the following day, we use the previous day's HY/B value to calculate fair value for each ETF.

The motivation for the 6-month timeframe is as follows. Six months is long enough to develop a meaningful relationship between the credit index and the ETF but short enough to ignore factors like inflation and dividends. It is also short enough to enable regime changes, like major market disruptions, to pass quickly from influence. Although we use a six month timeframe throughout most of the

analysis that follows, we consider the sensitivity of the model to different timeframes later in the paper.

For purposes of notation, let **$Basket_N$** denote a basket containing the N top-ranked ETFs. In this manner $Basket_1$ contains a single ETF and $Basket_9$ contains all nine ETFs. Our $Basket_N$ trading strategy can be stated by the following rule:

**$Basket_N$ Strategy: each week, invest in an equal-weighted basket of the N top-ranked ETFs**

Baskets are rebalanced on a weekly basis. Notice that the membership of $Basket_9$ will not change since all ETFs are in the basket. We expect the baskets with fewer ETFs to generate greater returns than the baskets with a greater number of ETFs at the expense of higher volatility.

Exhibit 2 shows the equity curves of the basket strategies and the SPY ETF from July 1999 through December 2012 with dividends reinvested. As expected, the $Basket_N$ strategies generate returns over the time period in strictly descending order. Each strategy outperforms SPY quite handily implying that even the simple strategy of holding the sector ETFs in equal weight and rebalancing weekly (*the $Basket_9$ strategy*) is worth consideration assuming transaction costs and tax liabilities can be minimized.

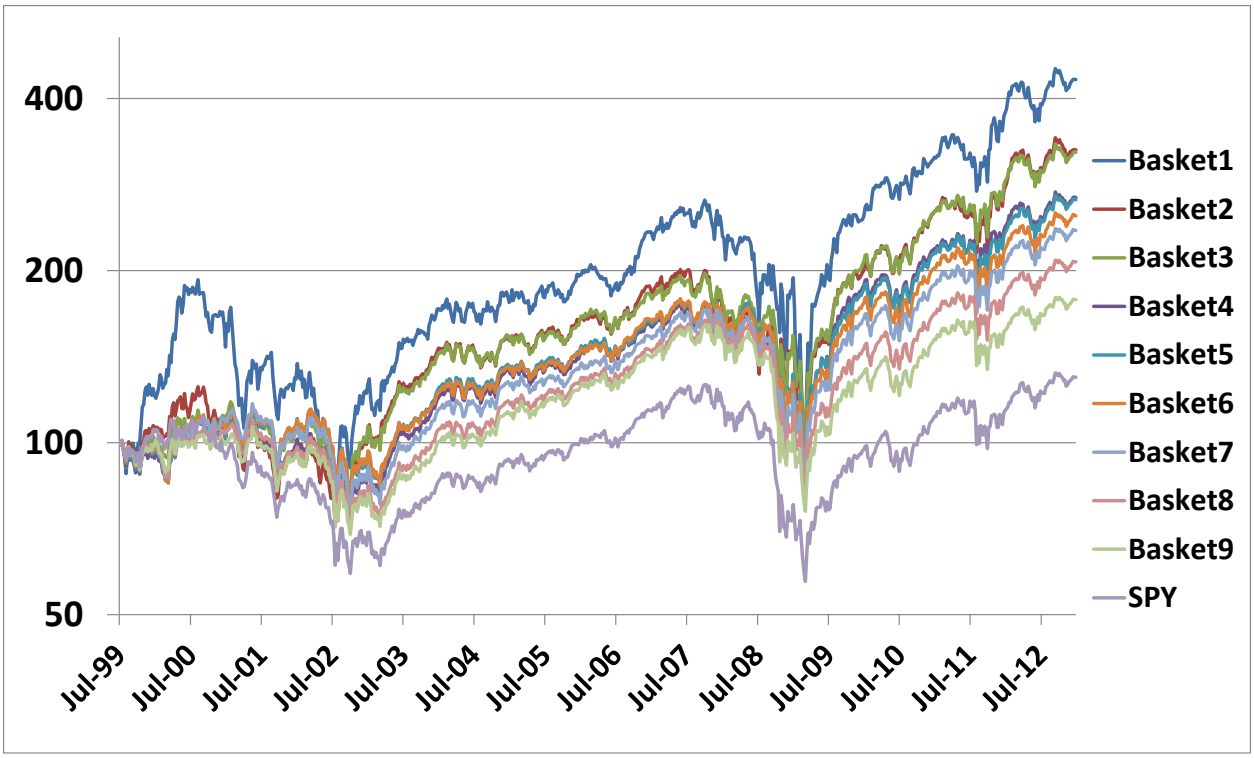


***Exhibit 2: Equity Curves for Basket$_n$ Strategies***

Of course, returns should not be viewed in isolation. Table 2 presents return and risk statistics for each strategy and SPY, including dividends, for the period of July 1999 through December 2012. As expected, volatility decreases as more securities are added to the basket. The Sharpe and Sortino ratios are generally decreasing as well although volatility and drawdown hurt Basket$_1$ and Basket$_2$. Maximum drawdown (MaxDD) is still large in magnitude for all the basket strategies, a fact that motivates a refinement to the basket strategy discussed later in the paper.

| | $Basket_1$ | $Basket_2$ | $Basket_3$ | $Basket_4$ | $Basket_5$ |
|---|---|---|---|---|---|
| **CAGR (13.5 years)** | 12.4% | 9.9% | 9.8% | 8.2% | 8.1% |
| **Volatility** | 31.5% | 25.0% | 22.7% | 21.8% | 21.3% |
| **Sharpe Ratio (2.2%)** | 0.32 | 0.31 | 0.34 | 0.28 | 0.28 |
| **Sortino Ratio** | 0.44 | 0.45 | 0.49 | 0.39 | 0.38 |
| **Skewness** | 0.08 | 0.29 | 0.28 | 0.07 | -0.07 |
| **MaxDD** | -63.2% | -54.0% | -49.7% | -49.2% | -48.2% |
| **Information Ratio** | 0.43 | 0.55 | 0.71 | 0.68 | 0.81 |
| | $Basket_6$ | $Basket_7$ | $Basket_8$ | $Basket_9$ | **SPY** |
| **CAGR (13.5 years)** | 7.6% | 7.1% | 6.0% | 4.7% | 2.1% |
| **Volatility** | 20.8% | 20.4% | 20.1% | 19.9% | 20.3% |
| **Sharpe Ratio** | 0.26 | 0.24 | 0.19 | 0.13 | 0.00 |
| **Sortino Ratio** | 0.35 | 0.32 | 0.25 | 0.16 | -0.01 |
| **Skewness** | -0.07 | -0.14 | -0.20 | -0.35 | -0.37 |
| **MaxDD** | -48.9% | -48.8% | -50.5% | -52.8% | -54.8% |
| **Information Ratio** | 0.80 | 0.82 | 0.76 | 0.56 | |

***Table 2: Return & Risk Statistics for $Basket_N$ Strategies, SPY (Jul 99-Dec 12)***

The information ratio is an interesting statistic to use when balancing risk and return compared to a benchmark. The statistic provides a risk-adjusted measure (the ratio of alpha divided to the standard deviation of alpha) of portfolio outperformance to a benchmark, the S&P 500 in our case. An information ratio above 0.5 places a strategy in the top quartile of active returns.[3] By this measure, $Basket_5$ through $Basket_7$ provide a clear advantage to the other basket strategies and all Baskets except $Basket_1$ have information ratios above 0.5.

[3] Grinold, Richard C. and Ronald N. Kahn, 2000. *Active Portfolio Management: A Quantitative Approach for Providing Superior Returns and Controlling Risk.* New York: McGraw-Hill.

Given its relatively high CAGR and high information ratio, we use the $Basket_6$ strategy to further analyze strategy performance. The reason for choosing $Basket_6$ rather than, say $Basket_5$ or $Basket_7$, is to maintain consistency as we refine the strategy below. We also note that, different investors may prefer different basket sizes given the variety of return and risk statistics.

Next, we consider the sensitivity of the ranking strategy to the regression timeframe employed. The analysis above used a six-month timeframe. Table 3 compares performance of the $Basket_6$ strategy for the 3, 4, 5, 6, 7, 8 and 9 month timeframes from October 1999 through December 2012. Note that the beginning of our time period is later than the prior analysis to accommodate the 7, 8 and 9 month timeframes. Most statistics are similar although the 7 month and 8 month timeframes provide superior information ratios and CAGR. Our use of a six month timeframe throughout this paper is admittedly arbitrary. It stems from past work in single-name credit-equity models and the credit-implied tactical asset allocation model mentioned previously. There is nothing "magic" about the six-month timeframe and investors would do well to consider a 7-8 month period as well.

| | 3 Months | 4 Months | 5 Months | 6 Months | 7 Months | 8 Months | 9 Months |
|---|---|---|---|---|---|---|---|
| **CAGR (13.5 years)** | 8.0% | 8.2% | 8.2% | 8.3% | 9.0% | 8.9% | 7.6% |
| **Volatility** | 21.0% | 21.1% | 21.0% | 20.9% | 21.0% | 20.9% | 20.9% |
| **Sharpe Ratio** | 0.28 | 0.28 | 0.28 | 0.29 | 0.32 | 0.32 | 0.26 |
| **Sortino Ratio** | 0.37 | 0.39 | 0.38 | 0.38 | 0.44 | 0.43 | 0.35 |
| **Skewness** | -0.06 | -0.11 | -0.14 | -0.08 | -0.12 | -0.17 | -0.22 |
| **MaxDD** | -48.1% | -47.5% | -48.3% | -48.9% | -47.3% | -49.1% | -52.4% |
| **Inf. Ratio** | 0.87 | 0.86 | 0.84 | 0.84 | 0.93 | 0.92 | 0.75 |

***Table 3: Performance and Risk Statistics for Basket$_6$ Strategy by varying Model Regression Timeframe (Oct 99 – Dec 12)***

When back-testing a rotation strategy, it is informative to consider how often each candidate security is held within the portfolio. Superior returns can be "data-mined" by simply picking the securities with the greatest return and holding them over the back-test period. Table 4 displays the percentage of time each sector ETF is held in the Basket$_6$ portfolio and also the CAGR of the ETF over the entire analysis period, July 1999 through December 2012. If the ETF selections were distributed evenly, we would expect each to be included 6/9 (66.7%) of the time. The Basket$_6$ strategy holds XLF and XLK the most, the two sector ETFs with the worst dividend-adjusted performance over the period. It holds XLE the least amount of time and this ETF had the best performance over the time period.

| | CAGR (July 99-Dec 12) | Percentage of Weeks in Portfolio |
|---|---|---|
| **XLY** | 4.8% | 66.8% |
| **XLP** | 4.6% | 68.6% |
| **XLE** | 9.1% | 55.3% |
| **XLF** | -1.8% | 72.9% |
| **XLV** | 3.9% | 64.8% |
| **XLI** | 3.6% | 74.0% |
| **XLB** | 5.0% | 64.1% |
| **XLK** | -1.9% | 71.7% |
| **XLU** | 4.8% | 61.9% |

***Table 4. CAGR and %Time ETF is included in the Basket$_6$ portfolio (Jul99-Dec12)***

Of course, it is important to look at performance when the ETF is held to get a sense for how well the strategy does at ranking sectors. To accomplish this, we consider how each sector ETF performs when included in the portfolio compared to the average return of the 3 ETFs not held each week in the Basket$_6$ portfolio. The motivation is to compare the returns missed by the portfolio by including one of the ETFs at the expense of the excluded ETFs.

For example, assume for one week that XLY is included in the portfolio and XLP, XLE and XLF are excluded. We record XLY's 1-week log return and the average of XLP, XLE and XLF's log returns. We do this for each week in the time period and each ETF held that week.

Table 5 displays the annualized return for each sector ETF when included in the portfolio, the annualized return of the 3 ETFs excluded and the difference

(outperformance) between the returns. All sector ETFs show positive outperformance compared to the excluded ETFs which implies that the strategy does a reasonable job of picking 6 ETFs each week. Outperformance is not uniform across sectors and two ETFs (XLP and XLK) have negative performance when held in the portfolio. While this type of outperformance is gratifying, more can be done to improve performance and mitigate risks. In the next section, we consider an enhancement to the strategy that helps limit portfolio losses.

| | ETF Annualized Return | Annualized Return of 'Excluded' ETFs | Strategy Outperformance |
|---|---|---|---|
| **XLY** | 2.0% | -4.2% | 6.3% |
| **XLP** | -2.0% | -11.3% | 9.3% |
| **XLE** | 33.6% | 12.3% | 21.3% |
| **XLF** | 11.3% | 7.3% | 4.0% |
| **XLV** | 5.0% | -3.2% | 8.2% |
| **XLI** | 7.0% | -3.0% | 10.0% |
| **XLB** | 6.0% | -1.7% | 7.6% |
| **XLK** | -4.5% | -6.1% | 1.5% |
| **XLU** | 4.3% | -4.6% | 8.9% |

***Table 5. Annualized Return and Percentage Time each ETF is held in the $Basket_6$ portfolio.***

## 5. Beyond Ranks – Tactical Asset Allocation

The $Basket_N$ strategy analyzed above produces superior results to a buy-and-hold SPY investment policy. Further, the strategy increases returns as N decreases and risk can be balanced with return by varying the number of ETFs

held in the basket. Still, the drawdown of each basket is comparable to the buy-and-hold SPY investment and sometimes worse. Additionally, volatility is higher for most baskets compared to SPY.

To address the drawdown issue as well as boost portfolio return and lower portfolio volatility, we return to our fair value regression model. Previously, we paid no attention to the sign of the percentage difference from fair. Now, we enhance our $Basket_N$ strategy by switching between the sector ETFs and three-month Treasury bills depending on whether the sign of the difference is positive (that is, the ETF is *inexpensive*) or negative (the ETF is *expensive*). Our new ***tactical asset allocation ($TAA_N$)*** strategy is as follows:

**$TAA_N$ Strategy:**

1) **Each week, choose the N top-ranked ETFs & divide assets into N equal shares.**
2) **For each of the chosen ETFs:**
    a. **If the fair value is greater than market value, invest the asset share in the ETF.**
    b. **If not, invest the asset share in 3-month Treasuries instead.**

In this manner, we still choose the top-N ETFs as in the $Basket_N$ strategy. However, we only invest in those ETFs for which our fair value model has a

*positive* expected return. The tactical asset allocation strategy, while simple in concept, has two advantages to the $Basket_N$ strategy outlined above. It raises the expected return of the basket while limiting portfolio drawdown. The mechanics and motivation for this type of tactical asset allocation strategy were discussed in Klein's "Credit-Implied Tactical Asset Allocation."[4] A key difference between that strategy and this one is that we are investing in multiple ETFs, some of which may be inexpensive and others of which may be expensive. Thus, we are often partially invested in the stock market while generally also being invested in lower-volatility Treasuries.

In declining markets, the strategy helps limit losses. In ascending markets, the strategy throttles gains. Overall, the tradeoff of lower gains in up markets is offset by limiting portfolio drawdown. Exhibit 3 displays the equity curves of the 9 $TAA_N$ strategies from July 1999 through December 2012 as well as SPY's equity curve. Periods where the strategy is heavily invested in Treasuries, such as 2003, are much less volatile than SPY.

[4] Klein, David, Credit-Informed Tactical Asset Allocation (June 1, 2011). http://ssrn.com/abstract=1872163

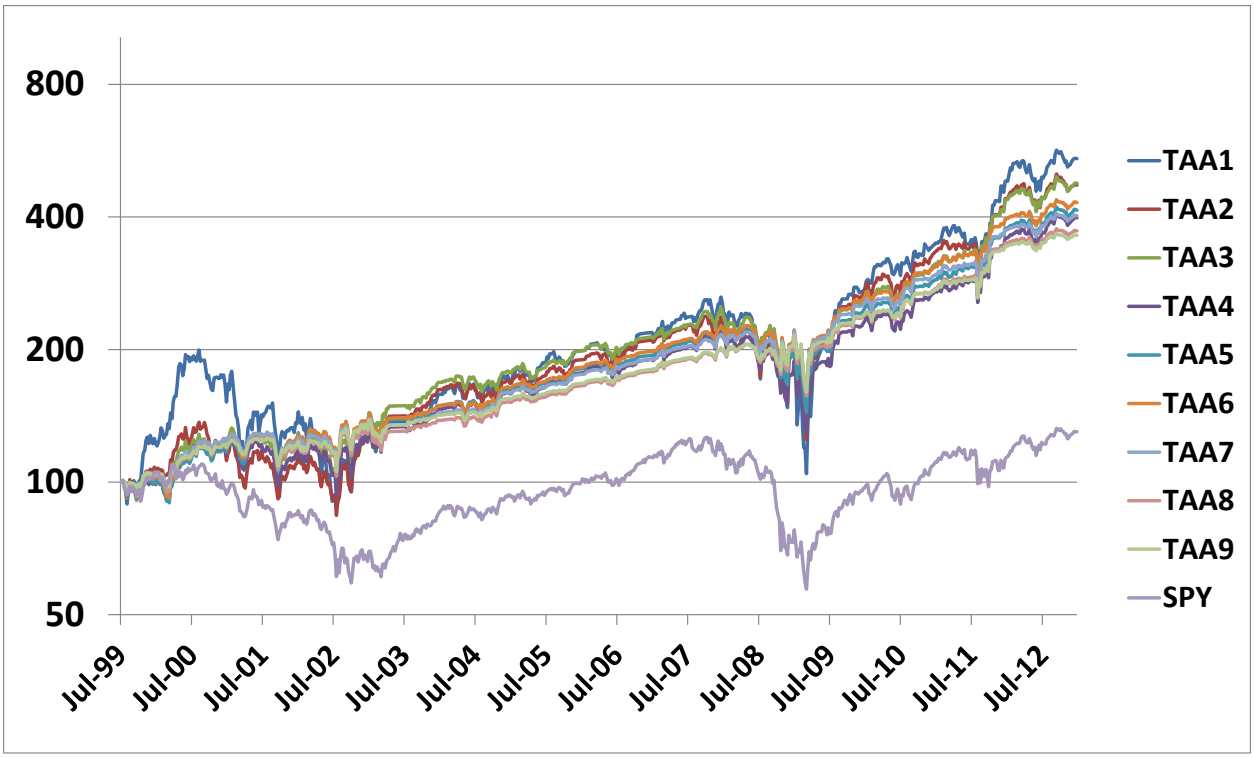


***Exhibit 3: Equity Curves of $TAA_N$ Strategies (Jul99-Dec12).***

To get a better sense of how a $TAA_N$ strategy compares to the comparable $Basket_N$ strategy, Exhibit 4 displays the $TAA_6$, $Basket_6$ and SPY equity curves. The superior returns and diminished drawdown of the $TAA_6$ strategy are readily apparent. However, since the strategy is generally invested at least partially in Treasuries, it lags the $Basket_N$ strategy during bull markets.

For example, for the period stretching from October 7, 2002 through April 23, 2007, the $Basket_N$ strategy returned 117% compared to the $TAA_N$ strategy's 77% and SPY's 103%. This is a challenge faced by strategies that seek to limit drawdown. Many investors will not care that the TAA strategy produced its 77%

return with far less volatility. In hindsight, they might only regret that they missed out on a 117% gain. Still, an investor who takes the long view will recognize that a lower volatility strategy that limits drawdown can be far more desirable than a buy-and-hold strategy or one that exposes a portfolio to sharp market corrections.

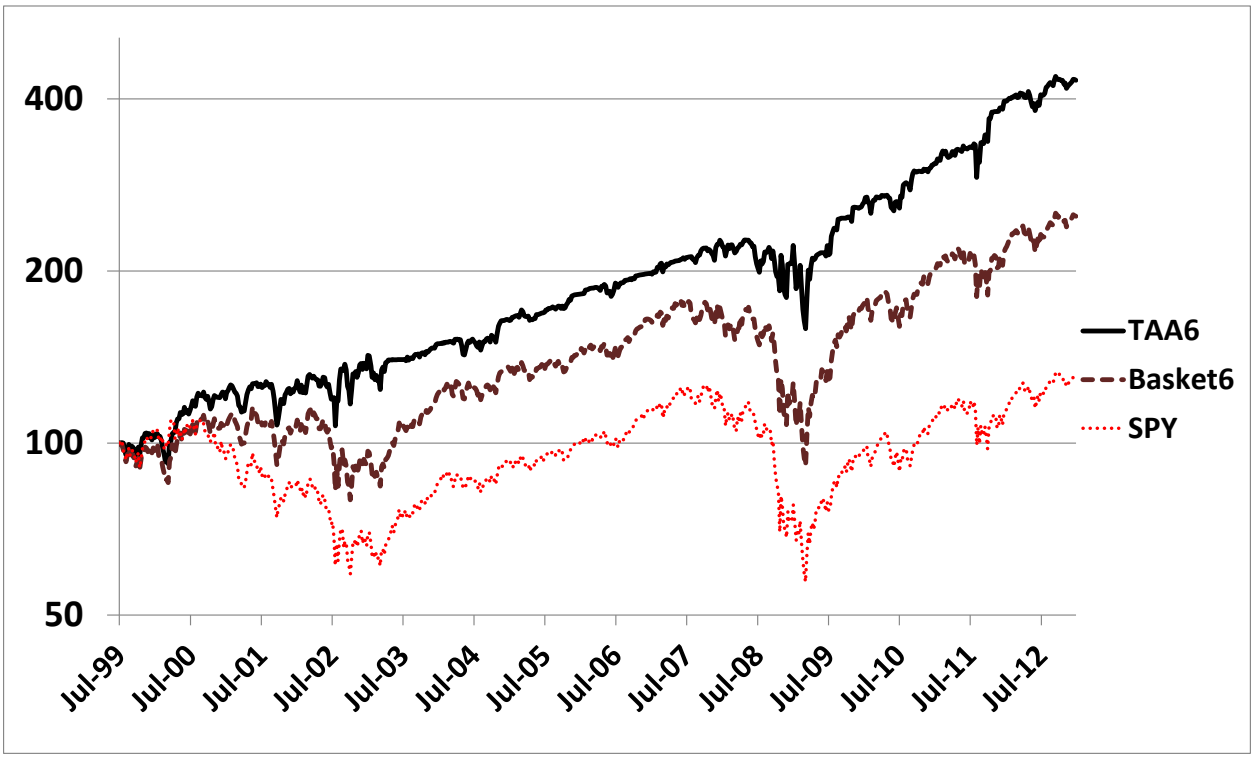


***Exhibit 4: Equity Curves of $TAA_6$ Strategy, $Basket_6$ Strategy and SPY Strategies(Jul99-Dec12).***

To illustrate this point, we note that the $TAA_6$ portfolio peaked on April 28, 2008 and recovered to that level on July 13, 2009; a period of just over one year. A weekly buy-and-hold SPY portfolio (with dividends) peaked much earlier, on October 8, 2007 and did not recover until March 12, 2012; a period of almost four

and a half years. Not only was the drawdown much less severe for the $TAA_6$ portfolio, the period between high water marks was far shorter as well.

| | $TAA_1$ | $TAA_2$ | $TAA_3$ | $TAA_4$ | $TAA_5$ |
|---|---|---|---|---|---|
| **CAGR (13.5 years)** | 14.5% | 13.2% | 13.3% | 11.7% | 12.0% |
| **Volatility** | 31.0% | 23.9% | 21.1% | 19.5% | 18.3% |
| **Sharpe Ratio (2.2%)** | 0.40 | 0.46 | 0.53 | 0.48 | 0.54 |
| **Sortino Ratio** | 0.50 | 0.62 | 0.70 | 0.62 | 0.68 |
| **Skewness** | 0.08 | 0.33 | 0.41 | 0.28 | 0.28 |
| **MaxDD** | -60.3% | -47.6% | -44.7% | -41.3% | -36.3% |
| **Information Ratio** | 0.50 | 0.72 | 0.86 | 0.79 | 0.82 |
| | $TAA_6$ | $TAA_7$ | $TAA_8$ | $TAA_9$ | **SPY** |
| **CAGR (13.5 years)** | 12.4% | 11.8% | 11.1% | 10.9% | 2.1% |
| **Volatility** | 17.2% | 16.2% | 15.0% | 13.9% | 20.3% |
| **Sharpe Ratio** | 0.59 | 0.59 | 0.59 | 0.62 | 0.00 |
| **Sortino Ratio** | 0.75 | 0.73 | 0.73 | 0.79 | -0.01 |
| **Skewness** | 0.42 | 0.40 | 0.60 | 0.85 | -0.37 |
| **MaxDD** | -30.1% | -27.5% | -26.6% | -25.8% | -54.8% |
| **Information Ratio** | 0.83 | 0.76 | 0.69 | 0.65 | |

***Table 6: Return & Risk Statistics for $TAA_N$ Strategies, SPY (Jul 99-Dec 12)***

We again consider how the strategy performs for different choices of basket size. Table 6 shows return and risk statistics for the TAA portfolios. The returns are greater for each TAA strategy compared to its associated Basket strategy and volatility is strictly decreasing as basket size increases. Volatility is lower than the comparable Basket's vol as well. However, CAGR is not strictly decreasing with increasing basket size. For example, there is a benefit to holding more ETFs in the $TAA_6$ portfolio, say, compared to the $TAA_4$ portfolio. The introduction of switching to Treasuries for expensive ETFs helps mitigate the

losses when stocks are overvalued and provides an investment synergy over the time period considered.

The choice of basket size gives an investor the opportunity to tailor a portfolio based on expected return, expected drawdown and expected risk-adjusted outperformance. An investor who favors low drawdown and low volatility over higher returns might choose the $TAA_9$ portfolio over $TAA_6$ because of its risk characteristics. An investor who favors high returns above all else might choose $TAA_1$ because of its dominant expected return. For the remainder of this discussion, we focus on the $TAA_6$ strategy since it offers a mix of high information ratio and enviable risk characteristics.

In the appendix, Table 8 breaks out $TAA_6$ return by year and month with red cells indicating losses and green cells indicating gains. One immediate takeaway is the fact that the strategy made gains in every year of the analysis period. Granted, a 0.5% gain in 2008 could just as easily have been a loss based on what day of the week the portfolio was rebalanced. However, we believe a long-only investor would happily break even with $TAA_6$ rather than endure the loss made by SPY in 2008. Gains are by no means uniform throughout the period. As the equity curves show, the strategy often does best in down stock markets due to its

combination of switching to Treasuries from overvalued ETFs and staying long undervalued ETFs.

Also in the appendix, Table 9 breaks out $TAA_6$ relative outperformance compared to SPY over the same period. We define *outperformance* as strategy performance minus SPY performance. Red cells indicate when SPY outperforms the strategy and green cells indicate when the strategy outperforms SPY. The strategy outperforms SPY in 86 of the 162 months in the time period, 53% of the time. However, average monthly outperformance was 2.9% and average monthly underperformance was -1.6% further skewing the strategy towards outperformance.

The best year for outperformance was 2008 followed by 2002, both down years for the market. The worst year for outperformance was 2003, a year when the market made strong gains and equities were consistently deemed expensive by the ETF relative value models.

2003 and late 2010 through mid-2011 bring one of the challenges of the strategy into sharp focus. Through an entire cycle, the strategy performs admirably, but investors often do not focus on full cycles. An investor at the end of 2003 might ignore the spectacular outperformance the strategy provided

through 2002 and instead focus on the relatively paltry gains of 4.8% the strategy produced in 2003. Often, missing out on losses is not felt as keenly as missing out on gains. Still, periods of strategy underperformance do not tend to last long and an investor with a two or three year time-horizon would have been amply rewarded for sticking with the strategy throughout the time period analyzed.

## 6. Real-World Implementation – Reducing Portfolio Transactions

The ETF ranking strategy combined with tactical asset allocation produces a portfolio with superior returns and benign risk characteristics. Until now, we ignored transaction costs. We continue to ignore tax consequences because a this type of strategy is not designed to minimize tax liabilities. Switching between ETFs will produce short-term capital gains and this strategy will add to the tax liability of a non-exempt investor compared to a buy and hold investment strategy.

When digging into the $TAA_6$ strategy from July 1999 through December 2012, we find that a sector ETF is included in the portfolio for an average of 7.7 weeks before exiting. Exhibit 5 charts the count of ETFs by the consecutive weeks held. Note that by 'held' we mean the ETF is one of the top 6 ranked ETFs regardless of whether it is deemed expensive or inexpensive relative to the HY/B

index. The longest an ETF was held is 68 weeks and 1 week is the holding period for more than a quarter of the positions.

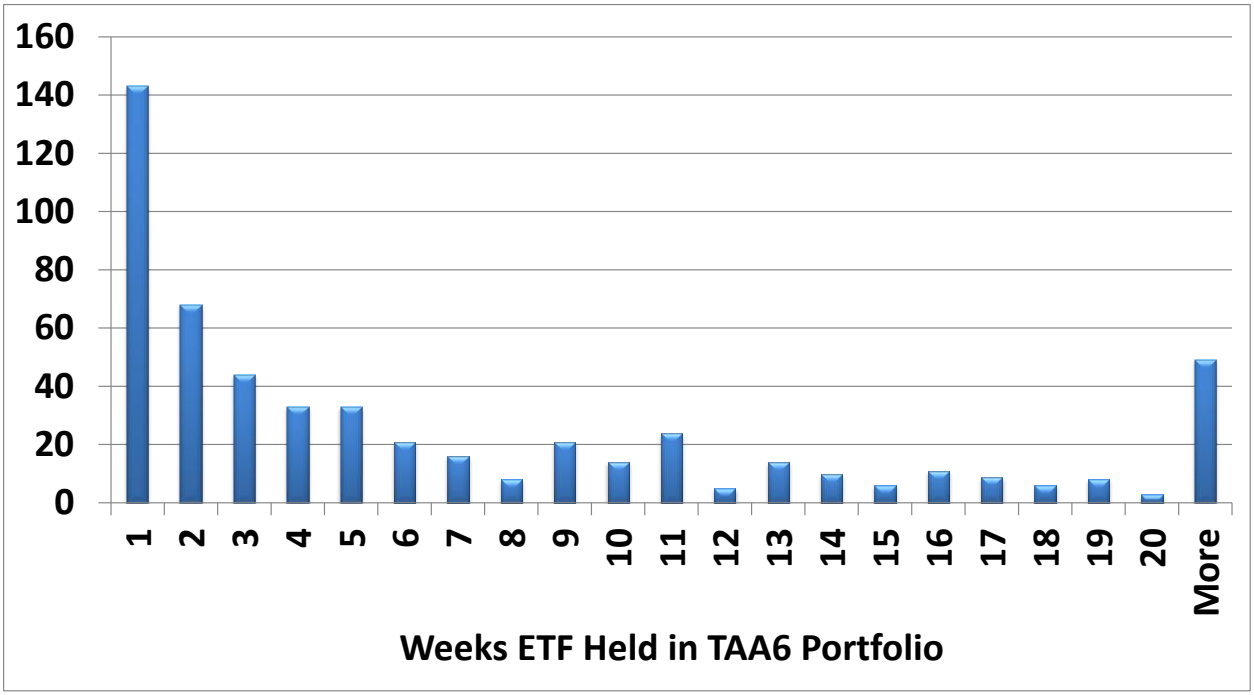


***Exhibit 5: Count of ETF Positions by Weeks Held in $TAA_6$ Portfolio (Jul 99-Dec 12)***

Since almost three quarters of positions are held more than one week, we examine the effect refraining from rebalancing the portfolio has on return and risk. 'Refraining from rebalancing' means a position is not altered until the underlying ETF either drops out of the portfolio or moves from expensive to cheap or cheap to expensive. This drops the number of transactions to 1,717 (2.4 per week) from 4,764 (6.8 per week) over the time period of July 1999 through December 2012. Theoretically, that would drop the transaction costs by approximately 64% and make the strategy easier to execute. Table 7 compares

the return and risk statistics for the $TAA_6$ portfolio and the 'lower-frequency' execution of the $TAA_6$ strategy ignoring transaction costs.

| | $TAA_6$ Weekly Rebalance | $TAA_6$ Lower Frequency |
|---|---|---|
| **CAGR (13.5 years)** | 12.4% | 12.2% |
| **Volatility** | 17.2% | 17.0% |
| **Sharpe Ratio (2.2%)** | 0.59 | 0.59 |
| **Sortino Ratio** | 0.75 | 0.73 |
| **Skewness** | 0.42 | 0.38 |
| **MaxDD** | -30.1% | -30.6% |
| **Information Ratio** | 0.83 | 0.81 |

***Table 7: Return & Risk Statistics for $TAA_6$ and $TAA_6$ Lower-Frequency Strategies***

Given how similar the statistics are, we would not be surprised to see the "lower frequency" implementation beat the weekly-rebalanced implementation once realistic transaction costs are considered. Regardless, the two implementations present almost identical return and risk characteristics, making the lower-frequency implementation preferable simply due to its lower number of transactions.

## 7. Conclusions

This paper extends the fundamental relationship of asset prices across the corporate capital structure to the index level. We construct linear relative value models using the HY/B credit index and S&P sector ETFs and then rank the ETFs

based on their distance from fair value. This ranking underlies a straightforward relative strength investment strategy that produces superior absolute and risk-adjusted returns when compared to the S&P 500. Further, we extend the strategy to only invest in ETFs that are viewed as inexpensive and to take a position in Treasuries for those that are viewed as expensive; an enhancement that boosts returns, lowers volatility, limits portfolio drawdown and results in faster recovery to previous high water marks.

We believe this type of relative strength investment strategy is worth consideration for investors with multi-year investment horizons. We also note that, given the use of the credit market to judge relative value, this investment strategy is uncorrelated to many popular ranking methodologies and can be used in conjunction with them as an enhancement to existing strategies. The strategy outlined is certainly not fail-safe, but it does present the investor with a straightforward procedure to adjust the return vs. risk characteristics of an equity portfolio by changing the size of the investment basket. Further, the strategy is designed for long-only investors and can be implemented using highly-liquid index ETFs.

## Appendix. $TAA_6$ Strategy Performance and Outperformance by Month

| | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1999 | | | | | | | -2.0% | 0.8% | -2.0% | 5.6% | 1.7% | -1.6% | 2.2% |
| 2000 | -1.3% | -7.6% | 11.3% | 6.2% | 4.8% | -1.2% | 5.5% | 0.5% | -0.2% | 0.3% | -0.9% | -0.4% | 16.9% |
| 2001 | 5.3% | -4.0% | -5.9% | 10.3% | 1.3% | -0.2% | 0.2% | -2.9% | -10.5% | 10.0% | 0.5% | 5.4% | 7.6% |
| 2002 | -4.7% | 6.9% | 0.0% | -4.0% | 0.7% | -5.7% | -0.7% | 13.0% | -12.6% | 14.0% | 3.3% | 3.3% | 10.7% |
| 2003 | -6.8% | -2.8% | 7.2% | 1.2% | 0.1% | 0.1% | -0.3% | 1.9% | 0.8% | 0.8% | 1.4% | 1.8% | 4.8% |
| 2004 | 0.2% | 0.7% | 0.9% | -2.6% | 1.0% | 0.7% | -0.2% | 1.2% | 1.5% | 0.7% | 5.5% | 0.0% | 9.7% |
| 2005 | 2.0% | 2.3% | -2.6% | -1.3% | 2.3% | 0.8% | 1.5% | 0.5% | 0.4% | 2.7% | 1.9% | 0.3% | 11.3% |
| 2006 | 1.7% | 0.6% | 0.2% | 0.6% | -1.9% | 3.3% | 0.1% | 1.2% | 0.7% | 1.3% | 0.4% | 0.4% | 8.8% |
| 2007 | 2.4% | -1.9% | 2.8% | 1.5% | 0.7% | 0.8% | -0.7% | 1.6% | 2.9% | -1.1% | 1.4% | 0.4% | 11.3% |
| 2008 | 0.6% | -1.4% | 1.8% | 1.7% | -1.2% | -9.7% | 2.8% | 5.8% | -9.3% | 6.9% | -15.7% | 23.4% | 0.5% |
| 2009 | -13.9% | -14.4% | 24.8% | 4.3% | 1.1% | -0.9% | 11.3% | 4.1% | 0.0% | -1.3% | 5.4% | 2.5% | 18.9% |
| 2010 | -0.7% | 1.6% | 1.9% | 0.1% | -5.5% | 0.4% | 10.4% | 1.8% | 2.8% | 0.2% | 1.2% | 2.2% | 17.0% |
| 2011 | 3.8% | -0.7% | 1.7% | 0.9% | 0.4% | 0.6% | 0.7% | 1.0% | 0.4% | 12.8% | 1.5% | 2.8% | 28.5% |
| 2012 | 1.6% | -0.2% | 1.5% | -0.6% | -5.9% | 6.5% | 3.5% | 0.2% | 2.4% | -1.3% | -0.2% | 1.3% | 8.8% |

*Table 8: $TAA_6$ Strategy Performance by Month*

| | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1999 | | | | | | | 2.6% | -1.0% | 1.3% | 1.8% | -3.4% | -3.6% | -2.5% |
| 2000 | 0.9% | -5.9% | 2.6% | 9.2% | 4.7% | -1.6% | 4.9% | -1.6% | 4.7% | 0.4% | 6.8% | 2.8% | 30.7% |
| 2001 | -0.1% | 4.5% | 2.6% | -0.2% | 0.4% | 2.1% | 3.4% | 3.0% | -3.0% | 3.6% | -1.9% | 2.0% | 17.2% |
| 2002 | 1.3% | 1.5% | 0.7% | 4.3% | 1.7% | 1.1% | 15.0% | 7.2% | -2.9% | -1.0% | 0.0% | 4.1% | 36.9% |
| 2003 | 0.4% | -0.3% | 2.0% | -4.3% | -4.4% | -3.6% | 1.9% | -2.4% | -0.6% | -1.2% | -0.1% | -3.0% | -14.7% |
| 2004 | -1.2% | -1.2% | 1.3% | 0.1% | 0.5% | 1.0% | 0.6% | -0.5% | 0.3% | 1.0% | 0.1% | -1.4% | 0.6% |
| 2005 | 2.2% | 0.1% | 1.3% | -0.3% | -0.8% | 0.1% | -1.1% | 0.4% | 0.9% | 3.0% | -1.6% | -0.3% | 3.8% |
| 2006 | 1.8% | -0.6% | -1.4% | 0.0% | 0.6% | 2.3% | 0.0% | -1.7% | -0.8% | -2.4% | -1.9% | -0.2% | -4.3% |
| 2007 | 0.0% | 3.5% | -1.0% | -4.4% | -1.4% | 1.9% | 3.1% | -0.3% | -1.0% | 1.7% | 3.0% | 4.4% | 9.4% |
| 2008 | 3.1% | 1.7% | -1.2% | -1.1% | 0.1% | -0.1% | 2.8% | 3.3% | 10.2% | 15.2% | -0.3% | 8.3% | 49.2% |
| 2009 | -3.2% | 0.1% | 4.6% | -4.0% | -3.0% | 4.0% | -0.5% | 1.6% | -1.5% | -1.6% | -0.8% | -0.3% | -4.8% |
| 2010 | 3.2% | -1.0% | -4.4% | -1.2% | 5.8% | 4.5% | 0.7% | 4.7% | -1.4% | -3.8% | -2.3% | -1.8% | 2.4% |
| 2011 | 0.0% | -0.3% | -0.1% | -1.3% | 6.0% | -3.5% | 4.7% | 11.2% | 6.3% | -1.8% | 1.5% | 1.1% | 25.4% |
| 2012 | -3.7% | -1.9% | -2.6% | 2.8% | 0.7% | -0.5% | 1.2% | -0.8% | -0.5% | 0.4% | 0.1% | -0.1% | -4.7% |

*Table 9: $TAA_6$ Strategy Outperformance relative to SPY.*