QUANTITATIVE FUNDAMENTALS VALUE INVESTING AND SYSTEMATIC FACTOR INSULATION INNOVATIONS

by

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Abstract

Passive indexation through the use of Exchange Traded Funds (ETF) is a highly popular strategy world-wide which helps investment managers diversify their risk profiles and long the market for certain segments of their portfolio while maintaining little tracking error. We want to introduce the advantages of rules based investing which can be implemented and packaged as ETFs and provide managers with returns that are easier to explain, such as indexation, but offer greater return upside and control associated risks. Alternative investment strategies are often overlooked and we will show the advantages of rules based strategies in this paper.

By combining Piotroski's fundamental indicators defining 'Quality' and using screeners/rankers of relative valuation, we intend to define a strategy that provides excess return while maintaining similar risk. In addition, we aim to lower volatility through risk management techniques, which will insulate the strategy from systematic factors by shorting a calculated percentage of the market.

Through this exercise we show the significant advantages to investing in alternative and 'smart beta' strategies compared to indexation in our sample period of 2002 to 2014.

Keywords: Piotroski, Indexation, Qualitative Fundamentals, Trading Strategy, PHE

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Thank you to those who have supported and encouraged you, especially in your intellectual endeavours and this work, in particular. Usually written after one's oral defence. It is important for your future to acknowledge your intellectual debts. This can help maintain your network in your career field.

Personal acknowledgements may be included if desired, including acknowledgement in more detail ("let me count the ways") of the person to whom you [briefly] dedicated the work.

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Glossary

ETF	Exchange Traded Funds
Smart Beta	Alternative investing strategies defined to be a mix of active and passive investing. Usually defined as rules based and non-discretionary.
M2/MRAP	Modigliani and Modigliani: Risk Adjusted Performance
PHE	Purpose Tactical Hedge Equity ETF

1: Introduction

Rob Arnott (2004) argued that market cap weighted indices are not good market proxies, essentially rejecting the Markowitz' mean-variance efficiency theory. He states that market cap weighted indices systemically overweight more expensive stocks and underweight cheaper stocks, and therefore may not truly capture the market portfolio. Rob goes on to propose indices based on fundamentals as a better indicator of market activity, a measure of "Main Street" rather than "Wall Street". This proposition was very intriguing to myself as it meant that there are better ways to track the market portfolio and maintain purchasing power independent of asset inflation and all of this could be implemented rather easily through indexation and electronic non-discretionary trading.

Further research on the topic lead to Purpose Investments, a Toronto-based investment manager that provides ETF based alternative investment strategies. One of their strategies, the Purpose Tactical Hedged Equity Fund (TSX: PHE) implements a strategy based on Rob Arnott's Fundamental Indexation proposition with the addition of risk management innovations. The purpose of this paper is to test the robustness of this strategy and evaluate the effectiveness of the risk management innovations on top. Through this paper, we hope to expose fundamentally available alpha for large investment managers who use cap-weighted indices for passive equity management. As we know, there is a very large portion of the market that does passively invest in indices and although Rob Arnott may claim this to be a better attempt at indexation, we believe this strategy to be an active one and may fall under the modern loose category called Smart Beta.

We aim to prove the effectiveness of this trading strategy, which claims to consistently beat the market while maintaining similar risk attributes as market-cap weighted indices. Our sample test will help us claim superiority of the strategy on a risk-adjusted basis and an opportunity for passive investors to buy 'quality' that's priced 'relatively cheap'. A tilt towards value, we define the strategy as Smart Beta. Rob Arnott's firm Research Affiliates currently recommends a mix of fundamental indexation with low volatility and momentum-based strategies to effectively and efficiently beat the market while maintaining little volatility.

2: Literature Review

2.1 Quality: Value Investing

Piotroski's (2000) work at the University of Chicago's School of Business is the starting basis of literature that will help us with our strategy development. Piotroski analyzed and proved the effectiveness of certain historical financial statement information to identify out performers.

Outperformance of high Book to Market (BM) firms has been proposed by numerous scholars such as Rosenberg, Reid, and Lansterin (1984), Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994). This is the 'Value' investing theory that we have come across so often with the teachings of Ben Graham and Warren Buffet. These firms are warranted to be cheap.

Piotroski argues that the strategy of investing in high BM firms relies on the strong performance of a few firms, while tolerating the poor performance of many deteriorating companies. He builds on this reasoning and shows that on an individual basis buying high BM stocks is not recommended, however a portfolio of high BM stocks can outperform the market for returns.

Piotroski goes on to identify a few historical factors from financial statements that can help screen the selection of winning high BM stocks from losing ones. These factors can be broken down into (1) Profitability, (2) Leverage, liquidity, and source of funds, (3) Operating Efficiency. These factors are further broken down and evaluated in a binary manner and the cumulative score (F_Score) provides an indicator of health quality of the firm. His work identified firms that were in better health in a universe of stocks that is considered to be relatively cheap (high BM).

We will use the F_Score as our initial screener for stock selection to identify companies that have the potential to outperform the market based on historical financial statement information. The calculation of the screener is expanded upon in Section 4.2.

2.2 Relative Value: Fundamental Indexation

The concept of fundamental indexation was first introduced by Arnott (2004), in which he argued that cap-weighted indices are flawed proxies of the market portfolio and rejected the notion that the passive investor cannot capture better than the market portfolio. He went on further to expand that more efficient indices exist, more specifically a 'Fundamental' equity market index that delivers superior mean-variance performance. Proposing the idea of using balance sheet fundamentals to develop an index of stocks, Arnott showed that fundamentals-weighted, non-capitalization based indices consistently provider higher returns and lower risks than the traditional cap-weighted equity market indices while retaining many of the benefits of traditional indexation.

There are definite advantages to cap-weighted indices though. Cap-weighting requires little trading as stocks automatically rebalance as security prices fluctuate. (1) Material readjustment is only required when new companies become large enough to merit inclusion in an index or when others disappear through a merger, failure, or relative changes in capitalization. (2) Market capitalization is highly correlated with trading liquidity, so cap weighting tends to emphasize the more heavily traded stocks thereby reducing portfolio transaction costs. (3) Market cap is highly correlated with investment capacity therefore market cap indices emphasize stocks with greater investment capacities, thus allowing the use of passive indexing on an immense scale by large pension funds and institutions.

To build the fundamentals-weighted index, weighting becomes a function of the ranking of the fundamental of the stock within the investable universe. The following measures of 'fundamentals' are used for this weighting: (1) book value, (2) trailing five year average cash flow, (3) trailing five year average revenue, (4) trailing five year average gross sales, (5) trailing five year average gross dividends, and (6) total employment.

This fundamentals ranking system is the concept we will implement to rank our screened securities to evaluate which the cheapest securities to hold in our portfolio are. We will expand on the fundamentals evaluated by Arnott and use an equal weighted construction process, but we borrow from him the idea of ranking the top stocks based on fundamentals and refer to it as the R_Score.

2.3 Quality & Value Based ETF Investing

Toronto based Purpose Investments has created an ETF by the name of Purpose Tactical Hedge Equity Fund listed on the Toronto Stock Exchange (TSE:PHE). This ETF brings together Piotroski's (2000) Value Investing ideas along with relative valuation to choose from their global stock universe. The ETF takes it one step further by adding risk management solutions on top of this to protect the investor from systematic exposure. This risk management innovation will be a main focus of our exercise to determine if it helps in value protection and also to test if there are better methods and bounds for the implementation, providing better results for the investor.

Risk reduction is conducted via shorting of the SP500 index based on a binary 'momentum' calculation. A mark of 1 or 0 is assigned if the 5-day moving average of the SP500 is greater than the 10-day moving average. Similar marks are provided ten times comparing the 5-day moving average to that of up to 240-days. Every mark out of ten corresponds to a 5% short of the value of the total ETF (from here on this calculation will be referred to as 'momentum') using the SP500 Index (iShares Core S&P 500 ETF). With a minimum short of 15%, the ETF has market exposure of 25% to 75% at any point in time. Shorting of any kind requires a margin and therefore the company rebalances their portfolio monthly to maintain 90% in equities and 10% in cash, which is used for margin. Appendix C shows the construction method of the ETF.

2.4 Risk Adjustment

Another important aspect that we must tackle is adjusting our return for the excess risk that we may take due to the strategy. Since we are making a case for Smart Beta indexation and most such products are marketed towards passive investing arms of large investors, we have to account for the excess risk that occurs due to our strategy. We follow the risk adjusted valuation techniques used by Arugaslan & Samant (2014) for the evaluation of ETFs. They used Sharpe's and Treynor's Ratio in addition to the Modigliani Risk Adjusted Performance measure. Sourd (2007) helps us understand these ratios.

2.4.1 Sharpe's Ratio

Developed by William Sharpe in 1966, this ratio measures the return of the portfolio in excess of the risk free rate compared to the total risk of the portfolio.

$$S_p = \frac{E(R_p) - R_f}{\sigma(R_p)} \tag{2.1}$$

This measure is very simplistic and is used to better distinguish between risk-return characteristics of multiple portfolios.

2.4.2 Treynor Ratio

Developed by Jack Treynor in the early 1960s, they Treynor ratio is much like Sharpe's ratio and measures the relationship between the return on the portfolio, above the risk free rate, and its systematic risk. Unlike Sharpe, this ratio is drawn directly from the CAPM and requires a reference index to be chosen to estimate the beta of the portfolio. The choice of the benchmark can heavily alter the results.

$$T_p = \frac{E(R_p) - R_f}{\beta_p} \tag{2.2}$$

Since it only takes into account systematic risk, the ratio is better for comparing well-diversified portfolios.

2.4.3 Modigliani Risk Adjusted Performance (M2)

Further improvements on these risk adjustment models have been made. Modigliani and Modigliani (1997) showed that a portfolio and its benchmark must have the same risk to be compared in terms of basis points of risk-adjusted performance (Sourd 2007). M2 proposes that the portfolio/strategy be leveraged or deleveraged using the risk free asset.

Risk Adjusted Performance (M2):

$$M2 = \frac{\sigma_m}{\sigma_i} * \frac{\sum(R_i - R_f)}{n_i} + R_f \tag{2.3}$$

The leverage factor used in this calculation is the standard deviation of the market divided by the standard deviation of the portfolio. Essentially, the return of the portfolio is being scaled for the leverage factor. The M2 is the return the portfolio would have achieved if it had the same riskiness as the benchmark. This model should provide us with a similar risk adjusted return to the CAPM as the Beta is replaced with the leverage factor.

3: Preliminaries

3.1 Data Set

To test this strategy we must define an appropriate data set to use. We start off with the SP500 as the base data set as it represents a diversified account of large-cap securities in the United States and is the most actively held passive investment strategy. Our data set consists of 384 securities that were actively listed on the S&P500 Index through the period starting 2000 until the end of 2013. The remainder of S&P500 securities were not actively listed during the period and there were multiple replacements; to simplify the process we exclude these securities from our universe. We maintain the securities that remained listed, this inherently incorporates biases into our data set. The security list for the data set can be found in Appendix 1. Information was sourced from the Bloomberg Terminal as well as Wharton Research Data Services (WRDS).

3.1.1 Survivorship Bias

Securities that disappeared from the index due to underperformance, delisting, bankruptcy, or mergers are not represented in this sample set.

3.1.2 New Entrant Bias

Securities added to the index after 2000 are not part of the sample set. This includes large internet giants like Google which have changed the dynamics of the market. This sample set is biased away from including large tech companies that have come in to play in the past 14 years.

3.1.3 Bias offset

These two biases should offset each other nicely as a stable group of stocks without extensive decline or increase remain in the index. To make sure we use consistent data, the benchmark thus consists only of the sample set and the historical SP500 returns are not to be used.

3.2 Benchmark

The essence of this exercise is to calculate the excess return gained on market cap weighted benchmark through rules based fundamentals investing so the benchmark has to be relevant. The

benchmark must be built as a market-cap weighted index inclusive of all of our 384 securities. The percentage of the security held in the benchmark will depend on the size of the market cap of the security relative to the capitalization of the security universe (sample data set). As with the rest of the paper, the benchmark is calculated based on information from the first trading day of each month from 2002 to 2013 (184 obs).

It is important to consider the compounding power of reinvesting dividends; Figure 3.1 shows the additional value created because of dividends. Our 'benchmark' will reinvest all dividends received during the period back into the market and not just the security it was received from. From here on all strategies tested will reinvest dividends unless explicitly stated otherwise.

Figure 3.2 shows the effect of our sample set biases mentioned above by illustrating total return against SP500 Total Return index, which reinvests all dividends received in a similar manner to ours. Cherry picking securities from the SP500 betters the performance of the benchmark, and the biases are not completely offset. Therefore, our sample is handicapped versus the actual SP500 index. Within the context though, if our model outperforms, the return only matters on a relative and not absolute level so we may continue forward, acknowledging the bias of the sample set.

Figure 3.1: The steep effect of reinvesting dividends on the benchmark index

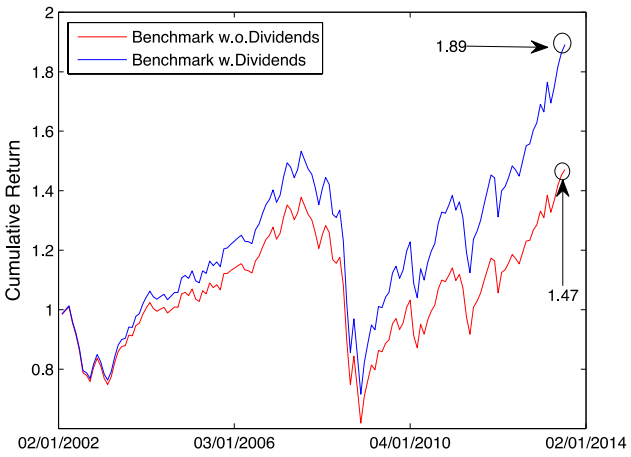
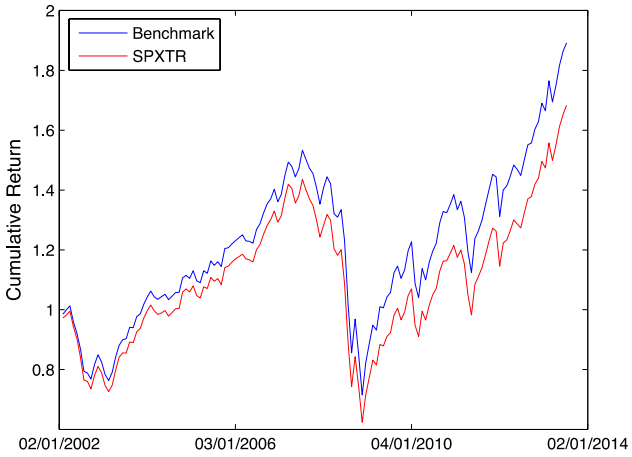


Figure 3.2: SP500 Total Return Index vs our Market-Cap weighted Benchmark of 384 securities



4: Stock Selection and ETF Construction

4.1 Process

Borrowing from the ideas of Arnott (2005), Piotroski (2000), and Purpose Investments, we develop a strategy that has the potential to outperform our benchmark while actively choosing securities from our benchmark on criteria presented by our reviewed scholars. First, we will screen our universe of securities for Piotroski's quality factors much like he did with high BM securities as described in Section 2.2. Once we have identified these securities, we will use Rob Arnott's idea of fundamental indexation and rank our stocks on the basis of their fundamental values, as described in Section 4.3. Further, we will use the risk management techniques to insulate from systematic factor as implemented by Purpose Investments in their PHE ETF.

The portfolio will consist of the top *decile* (10%) of the universe of investable securities and these securities will be *equally* weighted. The portfolio will be rebalanced every *month* and therefore transaction costs may be significant. Kissel (2014) has put together *transaction* costs for trading on the SP500 for January 2014 and we will use his estimate of 25bps as the cost for transaction for every security and future entered in to by the strategy.

Once we have proved that this process will provide us with an automated trading strategy, we will conduct multiple scenario analysis on the risk management innovation to see if we can 'smarten' the hedge in Section 5.

4.2 Piotroski Quality

Our first objective is to screen quality stocks based on fundamental ratios. These ratios from financial statements are backwards looking and identify the state of and trends in the health of the company. In this screening of the sample set, we use Piotroski's F_Score (2000) as the primary analytical tool. Using a binary scoring model we apply scoring across nine metrics, which can be identified under three categories: profitability, financing, and operating efficiency. The historical data used is the information that is available at the time of rebalance. For instance for the rebalance of February for any given year, some firms will only have Q3 data from the previous year made public, while others may have Q4 data public as well. The trading algorithm will take into account the most recently available data and will conduct any trend analysis on a year over year basis.

4.2.1 Profitability

1. Net Income → Give a score of 1 if net income for the trailing 12 months is positive. This identifies the bottom line, the profitability of the firm indicating that positive accounting earnings are actually being bought with selection of such stocks. Not an indicator of future profitability, but a positive sign nonetheless.
2. Cash Flow from Operations (CFO) → give a score of 1 if CFO for the trailing 12 months is positive, zero otherwise. Again, this is an indicator of the cash generated by the firm from operations and considered to be the minimum requirements for a stable investment.
3. ΔReturn on Assets (ΔROA) → give a score of 1 if return on assets for the trailing 12 months is greater than trailing 12 month return on assets a year ago. A measure of return validating if assets are becoming more productive.
4. Quality of Earnings → score 1 if cash flow from operations exceeds net income for trailing 12 months. This considers the relationship between earnings and cashflows. Sloan (1996) shows that earnings driven by accrual adjustments (where net income is greater than CFO), is a bad signal for future profitability and returns. This is known as earnings manipulation and is usually a negative sign.

4.2.2 Financing

5. ΔLeverage → score 1 if the ratio of long-term debt to average total assets decreases over the past 12 month period. Increases in leverage indicate an inability to raise capital internally and is indicative of a cash strapped business, which indicates poor health. If long term debt of the company is zero but the assets are increasing, then score 1 also, as this is a positive sign indicating firm growth.
6. ΔLiquidity → score 1 if the current ratio of the firm increased over trailing 12 months. An increase in working capital is taken as a positive indicator as the ability of the firm to service its debt obligations increases.
7. Dilution → score 1 if the current number of shares outstanding is no greater 12 months ago. Similar to ΔLeverage, dilution indicates a firm's need to raise external capital, which is a sign of poor health.

4.2.3 Operating Efficiency

8. ΔGross Margin → score 1 if the current gross margin is greater than the margin 12 months ago. Improving gross margin signifies a potential improvement in factor costs, a reduction in inventory costs, or a rise in the price of the firm's product. In essence, it hints on the competitive position of the firm.
9. Asset Turnover → score 1 if the percentage change in sales over the trailing 12 month period exceeds the percentage sales in assets in the same period. Greater asset turnover means greater efficiency in the use of assets.

4.2.4 F-Score

The total F_Score is the accumulated value of these nine binary indicators and higher values indicate firms with better health. Figure 4.1 below shows the distribution of this score through the sample set. Based on this data we are confident in screening securities into the portfolio that have an F_Score greater than 6. Figure 4.2 confirms that the number of securities passing the F_Score requirements is greater than or equal to 10% of the portfolio at all times through the sample set and should not cause a selection issue. However in an actual automated trading strategy (ETF) if the number of securities passing the minimum F_Score is less than the requirement of minimum securities held (38) we would implement a loop to identify this issue and lower the F_Score requirement as needed. Figure 4.2 shows that through an economic cycle, approximately 22% of securities have an F-Score of greater than 6 on average, with a minimum of ~10% and a maximum of ~37%.

Figure 4.1: Distribution of F-Score with a total of 55,680 observations (384 stocks at 184 intervals)

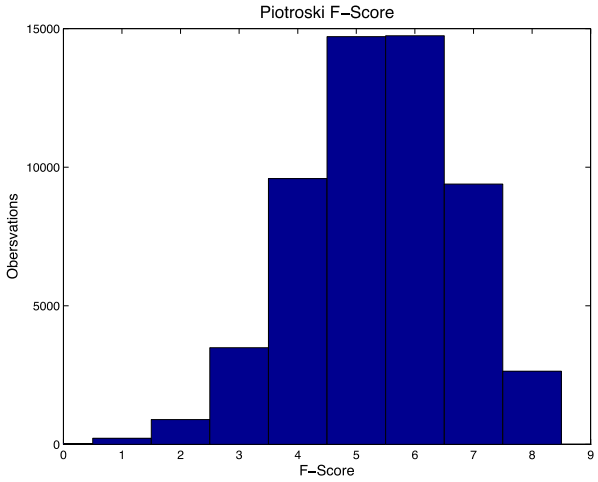
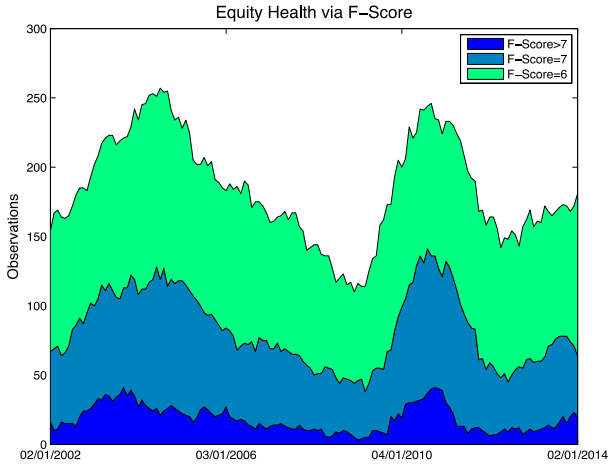


Figure 4.2: Distribution of F-Score cutoff through the sample period



4.3 Relative Valuation

After screening the stocks for Piotroski's factors, we rank these stocks based on relative valuation. This in turn identifies market valuations for quality stocks and capitalizes on stocks that are 'cheap' relative to their respective competitors. Frankel and Lee (1998) used market pricing of fundamentals in addition to growth forecasts by analysts to estimate future stock returns based on current valuations. We use these principles to assert that firms with poor expectations will have higher Book-to-Market (BM) ratios. However, since we will screen these stocks for 'Piotroski's Quality' before determining relative valuation, we can conclude that these stocks are cheaper to purchase but have little risk of financial distress, as most high BM firms do (Fama and French 1992).

An important consideration for relative valuation is to compare valuation of a firm to its peers since risk-return relationships for firms can vastly differ across industry classes. We used Level 2 of Global Industry Classification Standards (GICS) as developed by MSCI and Standard & Poor's, effective from end of Feb 2014 to classify our sample set. Level 1 consists of 10 sectors and is too broad relative to the fundamentals of the business therefore we use Level 2 of GICs, which consists of 24 industry groups.

4.3.1 Factors

The market's valuation of fundamentals can be identified through the book-to-market ratio but we want our ranking of these stocks to be more thorough therefore we add a few more ratios that tell us similar information but reinforce our claims.

1. Earnings yield – Bottom line. How much is the market paying per dollar of earnings for the security.
2. Cash flow yield – Analogous to earnings. How the market prices the cash generating ability of the firm.
3. Dividend yield – For total return. What is the market pricing for firm retention rates? Higher dividend yield means more stable cash flow expectations but smaller earnings growth.
4. Sales yield – Useful for companies with small or negative earnings.
5. Ebitda yield – Useful for firms with high depreciation or leverage.
6. Book yield – Same as used by Fama and French (1992) to identify firms that are trading cheap compared to their book/asset values.
7. EV / sales – Taking net debt into account. Advantages firms with large cash positions, disadvantages high leverage.
8. EV / ebitda – Analogous to EV/sales but gives relevance to real cash flows to firm.

4.3.2 R-Score

For all these indicators, we divide the valuation by the industry (GICS L2) average to quantify the magnitude of valuation difference to competitors in addition to direction. The combined values will give us the R-Score, which will define the ranking of attractiveness of the security. Because this is a magnitude-based calculation, there are many outliers that will skew the number vastly relative to the group mean. The figure 4.3 below shows the effects of these large numbers and therefore we must cap any individual maximum ratio. The figure 4.4 shows how a cap of 3 nicely averages out the outliers.

The adjusted R-Score shows how roughly half of all securities should be undervalued relative to benchmark and half over valued and that is why we see an almost symmetrical distribution around mean 1 (figure 4.4). We want to rank securities in descending order as a higher R-Score means that the security is cheaper than its competitive benchmark (GICS L2).

Figure 4.3: Outliers greatly skew the R-Score

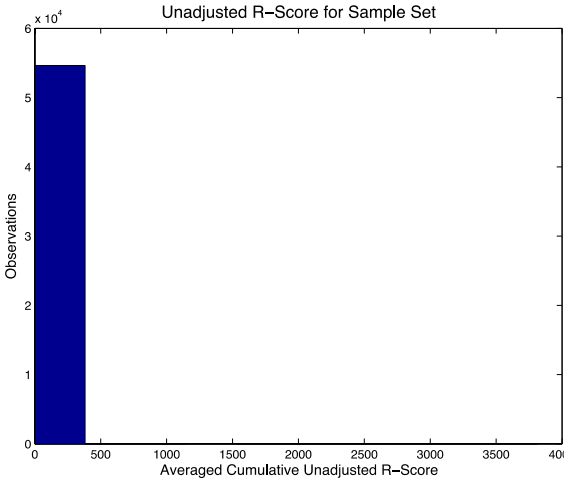
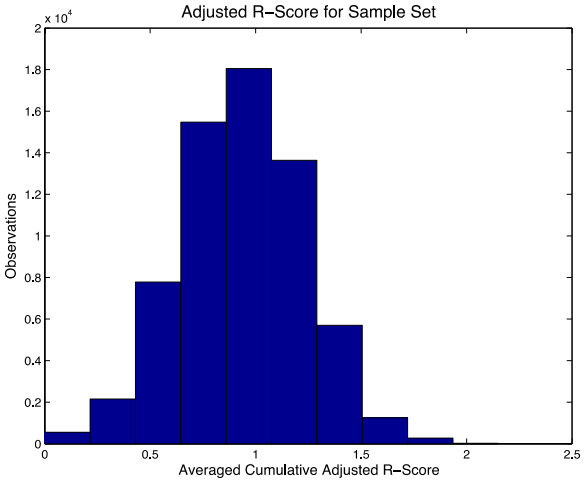


Figure 4.4: Skew in the R-Score can be fixed by capping the maximum score at 3



4.4 Quality & Relative Valuation Combined into an ETF

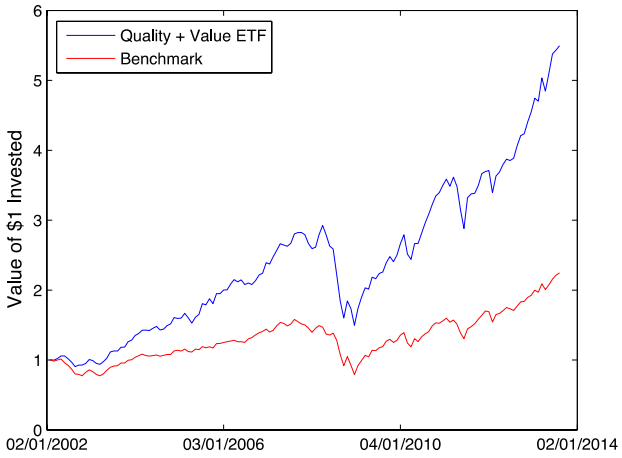
Now we combine our quality and relative valuation attributes and equal weight our investment across 38 securities from our sample set of 384. This will give us our base strategy on top of which we will test systemic factor insulation innovations such as the one applied by Purpose Investments' PHE ETF. Table 4.1 shows that our strategy significantly outperforms in returns while maintaining a similar risk profile, although definitely higher.

Table 4.1: Absolute returns for trading strategies

	Benchmark	Quality + Value
Mean Return (Yearly)	6.75%	14.20%
Standard Deviation (Yearly)	16.69%	17.82%

Figure 4.5 below shows that our strategy of combining Piotroski's quality with relative valuation gives us outperformance in the long term that is not matched by the. Essentially we have identified securities that have good fundamental value based health indicators, and then we have ranked the securities according to their valuations, giving preference to cheaper securities (high BM).

Figure 4.5: The Value of $1 invested in the Quality + Value based ETF against the benchmark.



4.3.2 Risk Adjustment

As mentioned earlier, the point of this exercise is to find a trading strategy that can replace traditional passive market weighted investable indices that are extensively used by market participants. Therefore it is important to adjust our investment strategy for any excess risk that is incurred by the strategy. We use equations from Section 2.4 and 2.5 to determine the risk adjusted returns and follow the precedent of Arugaslan and Samant (2014).

Table 4.2 shows that the strategy of Quality + Value rates better than indexation in all evaluated risk adjustments. Based on standard deviation (Sharpe), the strategy has a significantly more attractive valuation compared to the benchmark. Adjustment based on Beta (Treynor) shows similar higher attractiveness of the strategy. Lastly, scaling of the strategy's returns to match the risk profile of the index shows a very attractive risk adjusted return (MRAP), although it is lower than the original value due to the higher risk of the strategy.

The strategy takes a little more risk than the benchmark but provides more than twice as much return. This proves the effectiveness of investing in rules based strategies. Now if we can lower the risk of the strategy below that of the market, we can provide a product which will consistently beat the market in the long term for returns and maintain a lower risk profile.

Table 4.2: Absolute and risk adjusted returns for trading strategies

	Benchmark	Quality + Value
Mean Return (Yearly)	6.75%	14.20%
Standard Deviation (Yearly)	16.69%	17.82%
Sharpe Ratio	0.1913	**0.5976**
Treynor Ratio	0.0319	**0.1084**
RaR – M2	6.75%	**13.53%**

4.5 Systemic Factor Insulations

4.4.1 PHE Hedge

To reduce the risk of our rules-based strategy to be below the standard deviation of the market-cap based benchmark we explore techniques of reducing systematic risk. An intuitive way to do this will be to short the systematic momentum in the market; this will lead us to higher idiosyncratic risks but lower portfolio risk. This will also cause loss of upside offered by our rules –based strategy but in a smaller proportion.

Our starting point to explore this risk minimization is to implement the risk control strategy of PHE ETF strategy developed by Purpose Investments. As described in section 2.2, this hedge is based on a binary momentum strategy. There is a fixed part to the hedge as the minimum percentage of exposure hedged at all times is equal to 15%, therefore giving maximum market exposure of 75% (15% hedge + 10% cash margin). The maximum hedge at the point of least upward market momentum is 65%, which means that there is total market exposure of 35%.

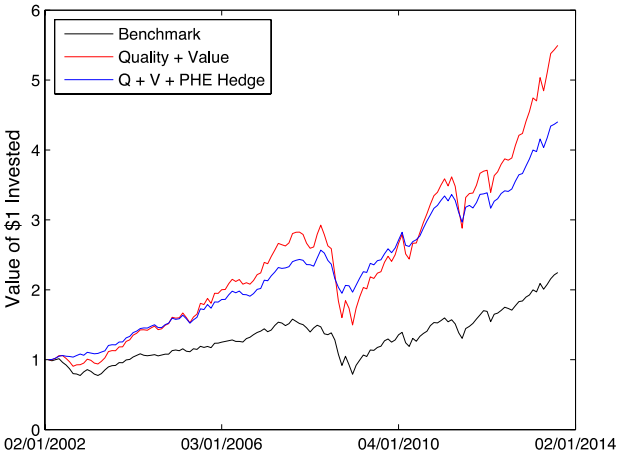
We implement this strategy by shorting SP500 futures, which we use as a proxy for the benchmark portfolio. This is done primarily because the benchmark is calculated only monthly and our momentum is calculated on daily values. Figure 3.2 shows the narrow difference between the returns of these two indices and helps justify the use of proxy.

The combination of Table 4.3 and Figure 4.6 shows the reduction in returns over our rules based strategy but also develops a picture of the lower volatility, which is the direct result of the systematic hedge. Our risk adjustment ratios show that the hedge provides us with the most attractive strategy on a risk to reward basis.

Table 4.3: Basic descriptive statistics of trading strategies

	Benchmark	Quality + Value	Q+V + PHE
Mean Return (Yearly)	6.75%	14.20%	12.35%
Standard Deviation (Yearly)	16.69%	17.82%	9.92%
Sharpe Ratio	0.1913	0.5976	**0.8872**
Treynor Ratio	0.0319	0.1084	**0.1971**
RaR – M2	6.75%	13.53%	**18.37%**

Figure 4.6: Base-case hedged ETF based on binary momentum strategy



5: Smartening the Hedge

Now that we have constructed our ETF, which we will refer to as base case, we can start testing the construction of this strategy and develop a sensitivity analysis. The point of the exercise here is to come up with the best strategy for reducing risk while maintaining return. We can measure the effectiveness of these hedges through risk-reward ratios.

5.1 Hedge Percentage Calculation

The current strategy implements a binary momentum indicator based strategy as described in 4.4.1. We want to test whether this binary method is ideal or if we can improve upon this method. The two ideas we will test out in this capacity will focus on taking into account the magnitude and the timing of the momentum.

5.1.1 Strength – Magnitude of Momentum

The binary hedge takes into account momentum based on the number of moving averages above or below the 5-day moving average, it does not account for the strength of this momentum. In other words, the 'binary' momentum strategy measures the direction of the momentum but not the magnitude of the direction. To implement this strategy we will divide the 5-day moving average by the ten other moving averages (Appendix C) and then take the average of these ten numbers to define the hedge percentage. Because this 'strength' number will not have any limits on magnitude, we must define the maximum and minimum so that we may effectively define the hedge.

Figure 5.1 shows the adjustment of the 'strength' indicator and plots the values beside the values of the binary indicator. The bottom two graphs in the figure show the similarities between the two momentum indicators. With this adjustment, we build an ETF based on the 'strength' strategy. Figure 5.2 and Table 5.1 show the differences in value and risk adjusted returns of the two strategies.

Figure 5.1: Adjustment of 'Strength' momentum indicator

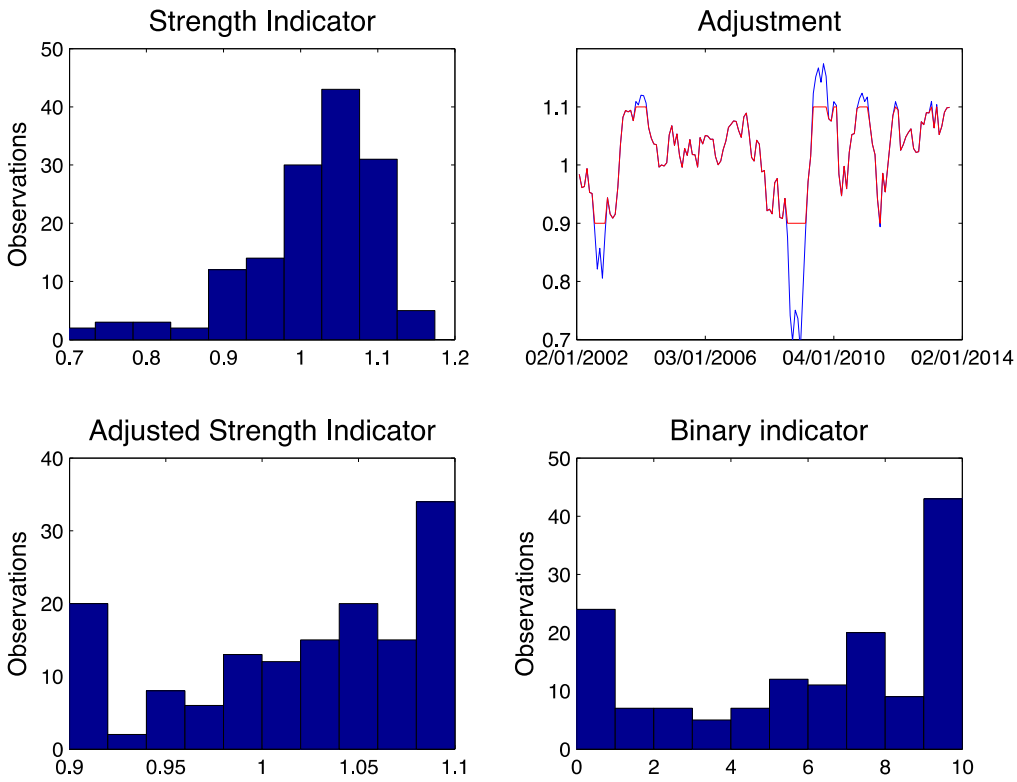


Figure 5.2: Quality + Value + Hedge strategy testing Binary vs Strength based hedge

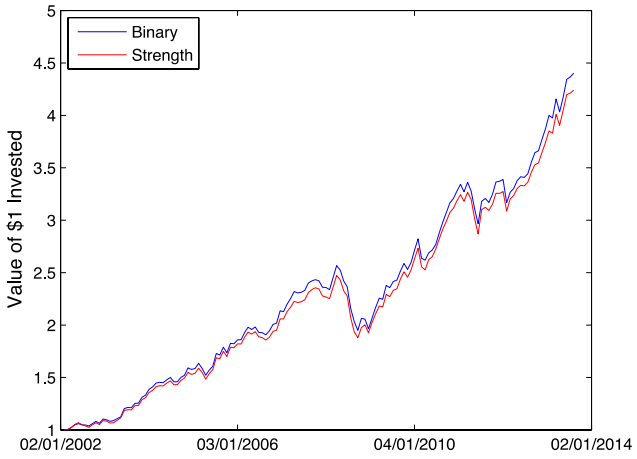
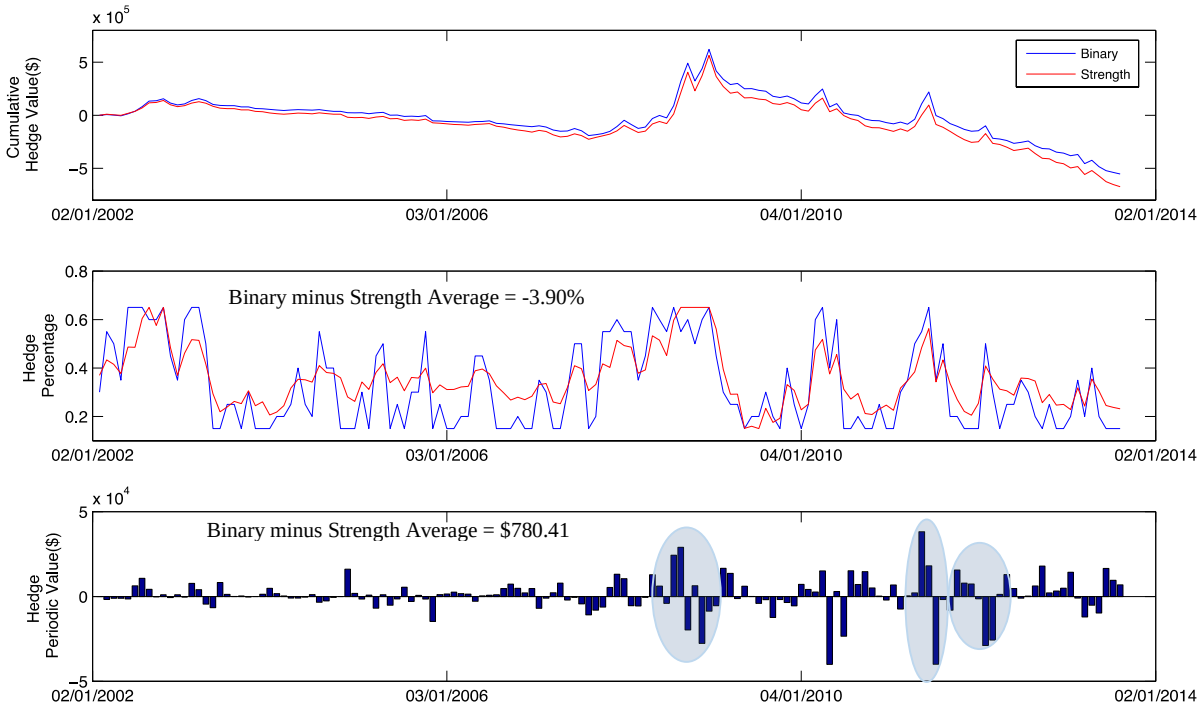


Table 5.1: Basic descriptive statistics: Quality + Value + Hedge strategy testing Binary vs Strength based hedge

Quality+Value+Hedge	Binary	Strength
Mean Return (Yearly)	12.35%	12.04%
Standard Deviation (Yearly)	9.92%	9.77%
Sharpe Ratio	**0.8872**	0.8686
Treynor Ratio	**0.1971**	0.1962
RaR – M2	**18.37%**	18.06%

Figure 5.3: Hedge effectiveness on ETF starting value of $1M



With a higher risk-reward ratios and M2, we find that the 'binary' strategy performs marginally better than the 'strength' based strategy we devised. Figure 5.3 breaks down where most of the difference in value comes from. As the graphs show, there is no significant divergence in the value of the two strategies until the financial crisis of 2008. A quick rebound (highlighted) after the initial decline in 2008 was over-hedged by the 'strength' based strategy since it still accounted for very strong negative momentum that was part of the decline. The 'binary' strategy was able to readjust quicker in this time period and therefore provided excess protection by lowering the hedge. Part three of Figure 5.3 shows that most of the time the differences in hedge values for 'binary' and 'strength' are offset by the timing. However the mean of the value gained via the binary hedge strategy is about 7.8bps above the mean value gained via the strength hedge strategy. We can conclude that including magnitude in our calculation does not significantly better or worsen the results on a risk-adjusted basis.

5.1.2 Weighted – Timing of Momentum

Now that we have established that binary is the better and easier (calculation wise) strategy to implement, maybe we can find ways to improve this strategy based on the timing of the momentum. We suggest the use of a non-equal weighted binary strategy that tests the switch in emphasis between short and long term. Table 5.2 highlights the difference in the weighting.

Table 5.2: Modification to 'binary' strategy by changing momentum emphasis

Moving averages considered for momentum based hedge calculation	Binary Emphasis	Short Term Emphasis	Long Term Emphasis
5-day			
Vs			
10 day MA	10%	18%	6%
20 day MA	10%	16%	6%
40 day MA	10%	14%	6%
60 day MA	10%	12%	6%
90 day MA	10%	10%	6%
120 day MA	10%	6%	10%
150 day MA	10%	6%	12%
180 day MA	10%	6%	14%
210 day MA	10%	6%	16%
240 day MA	10%	6%	18%

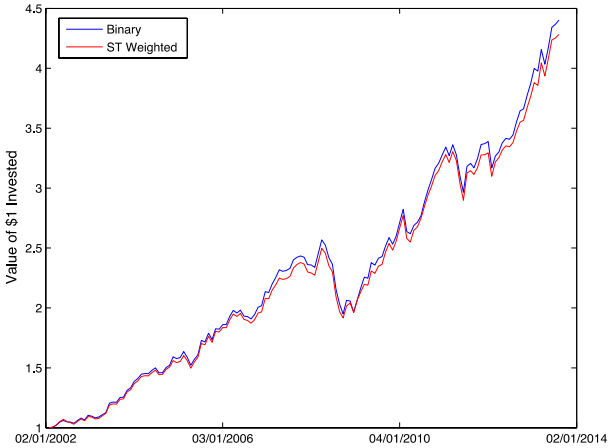
Evaluating the effect of placing emphasis on more recent or shorter-term momentum, Figure 5.5 shows that there is little difference between the hedged percentage of the market between the binary and the short-term weighted strategy. In general, the binary strategy hedges less than a weighted strategy while providing average excess return of 6 bps every month. From this we can extrapolate that heavier reaction to changes in short term momentum does not significantly improve or worsen the results.

Figure 5.4: Quality + Value + Hedge strategy testing Binary vs Long Term Weighted hedge

Table 5.3: Basic descriptive statistics: Quality + Value + Hedge strategy testing Binary vs ST Weighted hedge

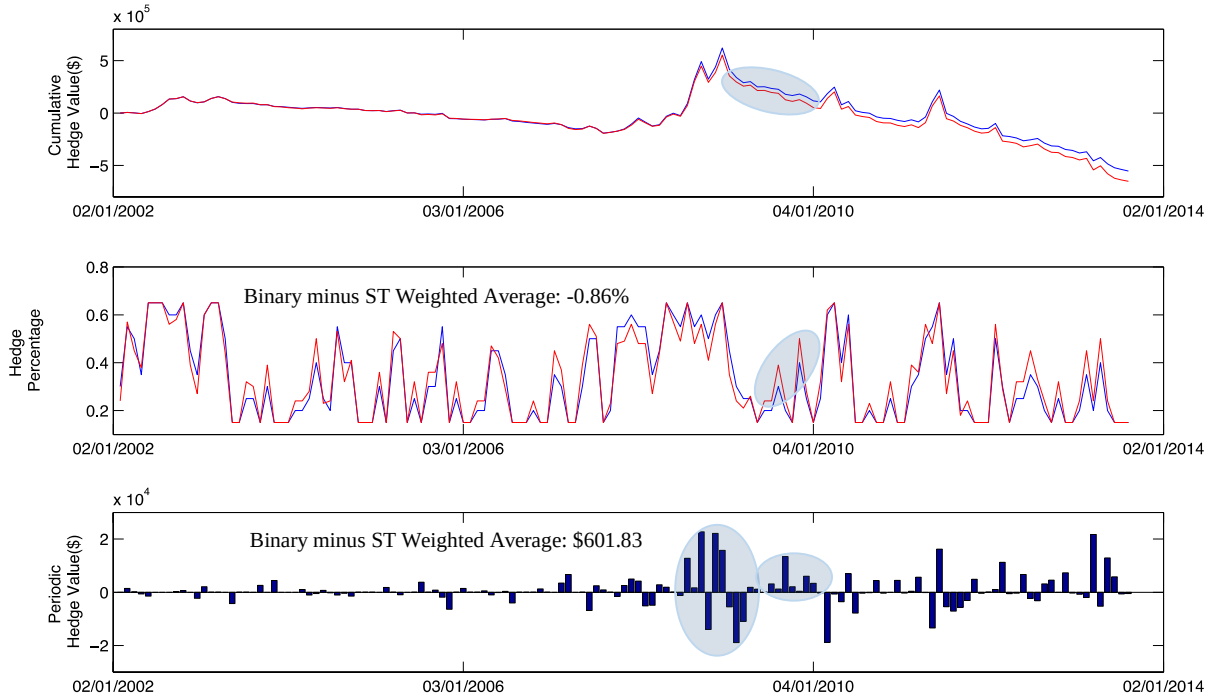
Quality+Value+Hedge	Binary	ST Weighted
Mean Return (Yearly)	12.35%	11.95%
Standard Deviation (Yearly)	9.92%	9.98%
Sharpe Ratio	**0.8872**	0.8415
Treynor Ratio	**0.1971**	0.1840

RaR – M2	**18.37%**	17.61%



Quality+Value+Hedge	Binary	LT Weighted
Mean Return (Yearly)	12.35%	12.69%
Standard Deviation (Yearly)	9.92%	9.93%
Sharpe Ratio	0.8872	**0.9197**
Treynor Ratio	0.1971	**0.2073**

Figure 5.5: Short Term (ST) weighted: Hedge effectiveness on ETF starting value of $1M



To identify a relationship that may exist between better hedging and an emphasis towards longer-term trends in the market, we flip the weighting relationship presented above. Table 5.4 below shows outperformance relative to the binary strategy of a hedging strategy with longer-term emphasis. Figure 5.7 shows that the longer-term weighted strategy hedges less than the binary strategy as it does not react to shorter-term changes in momentum as quickly and presents roughly 5bps of extra return every month.

Figure 5.6: Quality + Value + Hedge strategy testing Binary vs Long Term Weighted hedge

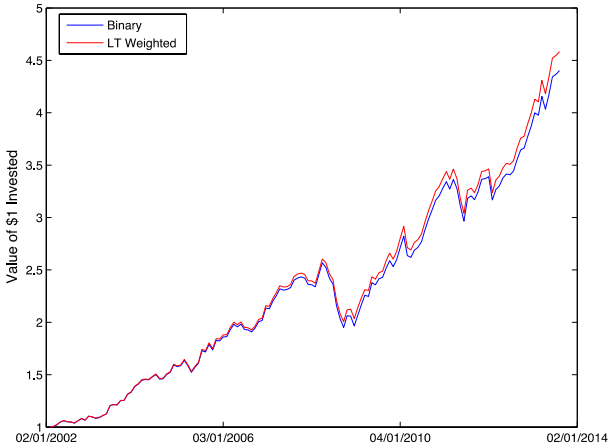
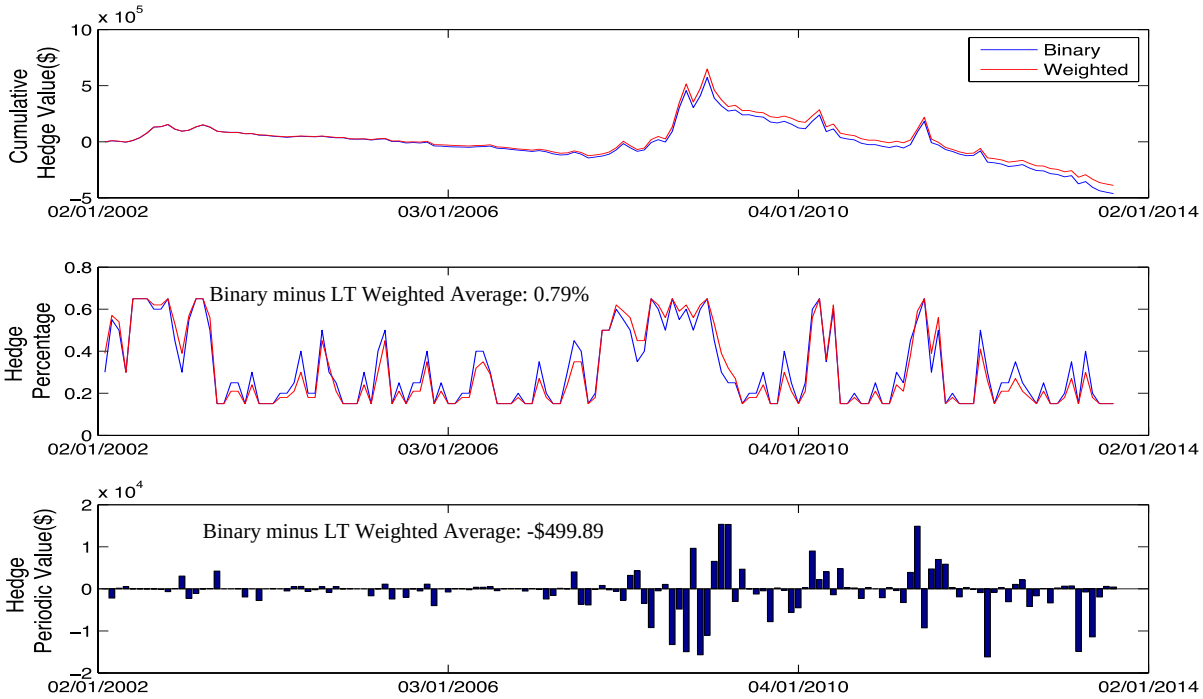


Table 5.4: Basic descriptive statistics: Quality + Value + Hedge strategy testing Binary vs LT Weighted hedge

Figure 5.7: Long Term (LT) weighted: Hedge effectiveness on ETF starting value of $1M



We can establish that the longer term weighted strategy does perform better than the binary weighted strategy although not significantly over single periods. The compounding power of an average of 5 bps every period however leads to an annualized 34bps of better performance over the sample period, which is roughly 4% of the total return. It is also important to recognize that due to the nature of the momentum strategy, which has more short-term indicators than long term as shown in Table 5.2, there is an innate emphasis introduced and we have just offset that emphasis by strategically weighing these indicators. On the whole, if the indicators are properly balanced through time (even intervals), then we should see the binary momentum hedge strategy work just fine. On the whole the weighting does not significantly better or worsen our results.

Through these two exercises (5.1.1 & 5.1.2) we can conclude that implementing momentum ('strength') and timing ('weighted') into the hedge strategy does not improve our results in a significant enough manner to change the original momentum calculation implemented by Purpose Investments. In addition, the combination of strength and weighted strategy does not provide a significant improvement either.

5.2 Scope of Hedge

The next step to finding the perfect hedging strategy that we want to test is the total exposure of the hedge. PHE uses the variable hedge to always hedge a minimum of 15% of the market exposure, combined with the 10% cash the strategy is to always hold, the maximum market exposure for the strategy is 75%. On the flip side, the strategy hedges a maximum of 65% of the market exposure, and again combined with the 10% cash requirement, the strategy has a minimum market exposure of 25% at any point in time. Essentially this aspect of the strategy is to minimize variance in return because of systematic factors and focus on the choice of quality + value factors to maximize alpha. We will now test the upper and lower bounds of the strategy on a risk-adjusted basis to find the best balance. The cost of the hedge will be the margin requirements. We will assume that our base case (PHE) represents the requirements; 65% ETF value hedge requires 10% ETF value cash (10/65 ~ 15%).

5.2.1 Upper Limit

First we will test the maximum hedge limit to find the sensitivities of the risk-adjusted returns. As mentioned above a 10% move in the upper limit will require approximately 1.5% more cash to be held in the ETF to comply with margin requirements (i.e the trade-off). We completed the calculations for the upper limit range of 25% to 155% and the complete results can be viewed in Appendix D.

Table 5.5: Selected descriptive statistics for hedge upper bound sensitivity

Upper Limit	BASE	25%	65%	105%	155%
Cash Held	10%	3.75%	9.75%	15.75%	23.25%
Mean Return (Yearly)	12.35%	13.09%	12.38%	11.43%	10.03%
Standard Deviation (Yearly)	9.92%	13.89%	9.94%	7.80%	8.09%
Sharpe Ratio	0.8872	0.6868	0.8881	**1.0109**	0.8008
Treynor Ratio	0.1971	0.1303	0.1973	**0.3991**	n/a
RaR – M2	18.37%	15.02%	18.38%	**20.44%**	16.93%

Results of this exercise, summarized in Table 5.5, indicate that as we increase the upper limit of the hedge the volatility of the strategy decreases, as do returns, mostly due to a larger cash position. The relationship of returns to standard deviation stays marginally positive until we reach 105% hedge level, where it turns negative. This is the optimum hedge level for the strategy as it has the best risk adjusted returns according to Sharpe, Treynor, and M2. From this we extrapolate that the best level of systematic risk insulation is to hedge the market risk in an amount proportional

to the total exposure of the strategy. This is not the best solution to obtain the highest nominal returns, but to obtain the highest risk adjusted returns.

5.2.2 Lower Limit

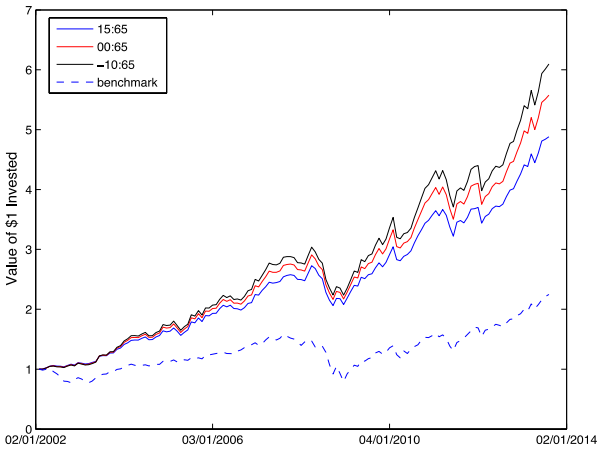
The lower limit of this strategy is a bit more interesting to test compared to the upper limit. Currently fixed at 15%, we can test two additional cases, one that defines the lower limit as 0%, calculating our maximum market exposure as 90% (minus 10% cash as held through strategy), and the other case can be defined as using the 10% cash during extreme positive momentum into the strategy, giving a maximum total market exposure of 100%. This dynamic cash holding strategy will increase our transaction costs but should provide better returns.

Table 5.6: Selected descriptive statistics for hedge lower bound sensitivity

Lower Limit	BASE	35%	25%	15%	00%	-10%
Mean Return (Yearly)	12.35%	11.75%	12.48%	13.21%	14.32%	15.06%
Standard Deviation (Yearly)	9.92%	9.16%	9.76%	10.43%	11.51%	12.29%
Sharpe Ratio	0.8872	0.8959	0.9143	0.9265	0.9355	**0.9369**
Treynor Ratio	0.1971	**0.2091**	0.2084	0.2075	0.2060	0.2049
RaR – M2	18.37%	18.52%	18.82%	19.02%	19.17%	**19.19%**

The results shown in Table 5.6 indicate that there is definite nominal advantage to reinvesting excess cash into the strategy but this increases the volatility of the strategy significantly. The risk-adjusted returns however do indicate that the marginal relationship of risk to return is still positive as we reinvest excess cash. Figure 5.8 shows how reinvesting all cash can result in superior returns and compounding power over time as well.

Figure 5.8: Performance of ETF w.r.t hedge lower bound



From this analysis we can conclude that an upper limit of 105% and a dynamic lower limit that reinvests all excess cash in positive momentum is the best amount of systematic risk to insulate for in context of the investment strategy.

6: Conclusion

The goal of this exercise was to prove the viability of an automated rules based trading strategy that was built on quantitative fundamentals from financial statement and incorporated aspects of relative valuation and risk management. This strategy would be compared against indexation (passive investing), which is a large part of the global portfolio. Indexation has historically been market-cap weighted and provides investment managers with very little to zero tracking error.

Figure 6.1: Quality + Value: Hedge momentum with emphasis towards long term, hedge maximum of 105% and hedge minimum of 0%, reinvesting excess cash

	Benchmark	Base	Optimum
Mean Return (Yearly)	6.75%	12.35%	14.78%
Standard Deviation (Yearly)	16.69%	9.92%	10.52%
Sharpe Ratio	0.1913	0.8872	**1.0676**
Treynor Ratio	0.0319	0.1971	**0.3548**
RaR – M2	6.75%	18.37%	**21.38%**

By applying the quality and value based screeners and rankers to pick our equity securities we were able to significantly outperform the benchmark in the sample period with the sample securities. Significantly higher risk adjusted returns for the 'quality+value' strategy were very attractive but the volatility of the portfolio was in excess of the benchmark. Therefore the concept of risk management is introduced to see if we can lower the volatility of the returns while maintaining the strategy's alpha.

Following PHE's strategy for risk management, we found our portfolio (ETF) to have significantly lower volatility compared to the benchmark while maintaining excess returns. This meant that hedging out market beta from the portfolio would expose us to more alpha from stock selection and therefore our risk adjusted returns are much higher than the benchmark or the 'quality+value' strategy.

Understanding the specifics of the hedge are important as well, therefore we tested the calculation technique of the hedge for magnitude and timing and we also tested the scope to the hedge with respect to the upper and lower bounds. Through this testing we found that magnitude does not have much significance in creating a better risk-adjusted return strategy but long-term momentum is important and should be better represented in the weighting scheme. Also, increasing the maximum hedge to match full market exposure at around 100% in times of duress and reinvesting any excess cash in times of affluence can have positive impacts on the strategy. Figure 6.1 summarizes the improvement over the market-cap based benchmark that can be implemented by the Quality + Value strategy with the PHE hedge technique (Base). It also shows how small

changes in hedge calculation as mentioned above can significantly improve the risk-adjusted performance of our overall trading strategy.

A structured, rules-based approach to investing, which emphasizes financial fundamentals instead of market pricing (capitalization) as indicators of market performance is a better approach to passive investment. There is an identifiable gap between fundamentals and pricing that is rooted in behavioural finance and this bias can be offset by rules based investing. We recommend investment managers to minimize free-riding by investing in market-cap based indices and look towards alternative ways of better understanding and capturing the quality widely available in the securities market to balance their portfolios.

Appendices

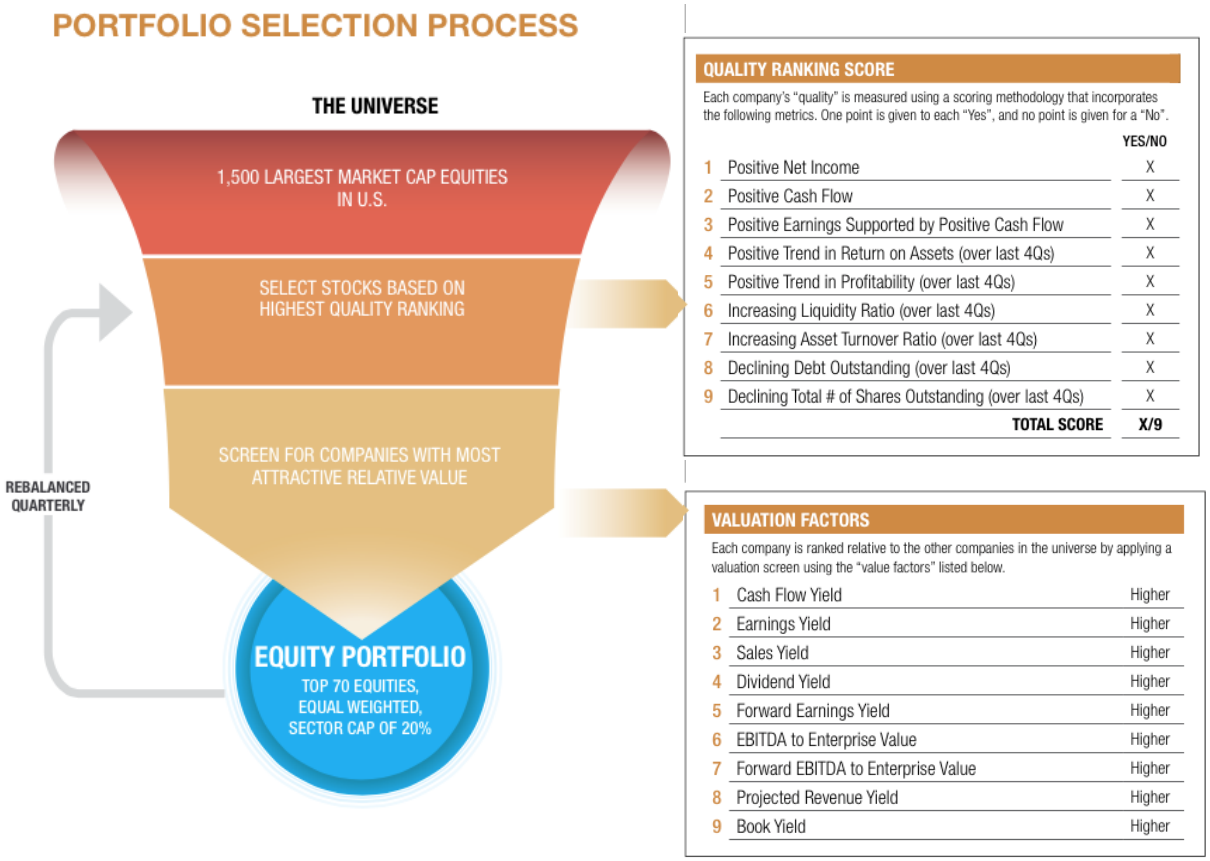
Appendix A: List of Stocks in sample set

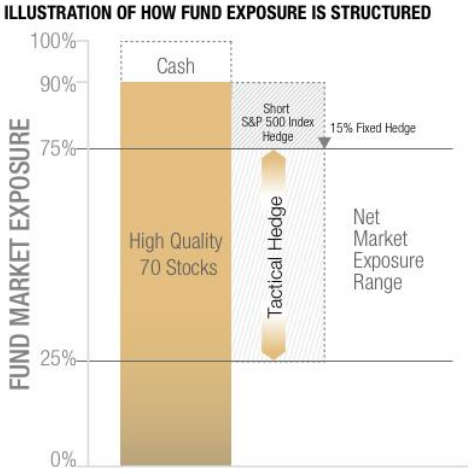
ALCOA INC
APPLE INC
AMERISOURCEBERGE
ABBOTT LABS
ADOBE SYS INC
ANALOG DEVICES
AUTOMATIC DATA
AUTODESK INC
AMEREN CORP
AMERICAN ELECTRI
AES CORP
AFLAC INC
ALLERGAN INC
AMERICAN INTERNA
AK STEEL HLDG
ALLSTATE CORP
ALTERA CORP
ALEXION PHARM
APPLIED MATERIAL
ADV MICRO DEVICE
AMGEN INC
AMAZON.COM INC
AUTONATION INC
APACHE CORP
ANADARKO PETROLE
AIR PRODS & CHEM
AMPHENOL CORP-A
APOLLO EDUCATION
AIRGAS INC
ALLEGHENY TECH
AVALONBAY COMMUN
AVON PRODUCTS
AVERY DENNISON
AMERICAN EXPRESS
AUTOZONE INC
BOEING CO/THE
BANK OF AMERICA
BAXTER INTL INC
BED BATH &BEYOND
BB&T CORP
BEST BUY CO INC
CR BARD INC
BECTON DICKINSON
FRANKLIN RES INC
BROWN-FORMAN -B
BAKER HUGHES INC
BIG LOTS INC
BIOGEN IDEC INC
BANK NY MELLON
BALL CORP
BEMIS CO
BRISTOL-MYER SQB
BOSTON SCIENTIFC
BOSTON PROPERTIE
CITIGROUP INC
CA INC
CONAGRA FOODS
CARDINAL HEALTH
CAMERON INTERNAT
CATERPILLAR INC
CHUBB CORP
COCA-COLA ENTER
CARNIVAL CORP
CELGENE CORP
CERNER CORP
CHESAPEAKE ENERG
CH ROBINSON
CIGNA CORP
CINCINNATI FIN
COLGATE-PALMOLIV
CLIFFS NATURAL R
CLOROX CO
COMERICA INC
COMCAST CORP-A
CUMMINS INC
CMS ENERGY CORP
CENTERPOINT ENER
CONSOL ENERGY
CAPITAL ONE FINA
CABOT OIL & GAS
CONOCOPHILLIPS
COSTCO WHOLESALE
CAMPBELL SOUP CO
COMPUWARE CORP
COMPUTER SCIENCE
CISCO SYSTEMS
CSX CORP
CINTAS CORP
CENTURYLINK INC
COGNIZANT TECH-A
CITRIX SYSTEMS
CVS HEALTH CORP
CHEVRON CORP
DOMINION RES/VA
DU PONT (EI)
DEERE & CO
DEAN FOODS CO
QUEST DIAGNOSTIC
DR HORTON INC
DANAHER CORP
WALT DISNEY CO
DISH NETWORK-A
DOLLAR TREE INC
DENBURY RESOURCE
DIAMOND OFFSHORE
DOVER CORP
DOW CHEMICAL CO
DARDEN RESTAURAN
DTE ENERGY CO
DIRECTV
DEVRY EDUCATION
DAVITA HEALTHCAR
DEVON ENERGY CO
ELECTRONIC ARTS
EBAY INC
ECOLAB INC
CONS EDISON INC
EQUIFAX INC
EDISON INTL
ESTEE LAUDER
EMC CORP/MA
EASTMAN CHEMICAL
EMERSON ELEC CO
EOG RESOURCES
EQUITY RESIDENTI
EQT CORP
EXPRESS SCRIPTS
E*TRADE FINANCIA
ENTERGY CORP
EXPEDITORS INTL
FORD MOTOR CO
FASTENAL CO
FAMILY DOLLAR ST
FEDEX CORP
FIRSTENERGY CORP
F5 NETWORKS
FIRST HORIZON NA
FISERV INC
FIFTH THIRD BANC
FLIR SYSTEMS
FLOWSERVE CORP
FMC CORP
GANNETT CO
GENERAL DYNAMICS
GENERAL ELECTRIC
GRAHAM HOLDING-B
GILEAD SCIENCES
GENERAL MILLS IN
CORNING INC
KEURIG GREEN MOU
GENUINE PARTS CO
GAP INC/THE
GOLDMAN SACHS GP
GOODYEAR TIRE
WW GRAINGER INC
HALLIBURTON CO
HARMAN INTL
HASBRO INC
HUNTINGTON BANC
HUDSON CITY BNCP
HEALTH CARE REIT
HCP INC
HOME DEPOT INC
HESS CORP
HARTFORD FINL SV
HARLEY-DAVIDSON
HONEYWELL INTL
STARWOOD HOTELS
HEWLETT-PACKARD
H&R BLOCK INC
HORMEL FOODS CRP
HARRIS CORP
HENRY SCHEIN INC
HOST HOTELS & RE
HERSHEY CO/THE
HUMANA INC
IBM
INTL FLVR & FRAG
INTL GAME TECH
INTEL CORP
INTUIT INC
INTL PAPER CO
INTERPUBLIC GRP
ITT CORP
ILLINOIS TOOL WO
JABIL CIRCUIT
JOHNSON CONTROLS
J.C. PENNEY CO
JDS UNIPHASE
JACOBS ENGIN GRP
JOHNSON&JOHNSON
JUNIPER NETWORKS
JPMORGAN CHASE
NORDSTROM INC
KELLOGG CO
KEYCORP
KIMCO REALTY
KLA-TENCOR CORP
KIMBERLY-CLARK
COCA-COLA CO/THE
KROGER CO
KOHLS CORP
LOEWS CORP
L BRANDS INC
LEGGETT & PLATT
LENNAR CORP-A
LABORATORY CP
L-3 COMM HLDGS
LINEAR TECH CORP
ELI LILLY & CO
LEGG MASON INC
LOCKHEED MARTIN
LINCOLN NATL CRP
LOWE'S COS INC
SOUTHWEST AIR
MACY'S INC
MARRIOTT INTL-A
MASCO CORP
MATTEL INC
MCDONALDS CORP
MICROCHIP TECH
MCKESSON CORP
MOODY'S CORP
MEREDITH CORP
MEDTRONIC INC
MCGRAW HILL FINA
MCCORMICK-N/V
MARSH & MCLENNAN
3M CO
MONSTER BEVERAGE
ALTRIA GROUP INC
MERCK & CO
MARATHON OIL
MORGAN STANLEY
MICROSOFT CORP
MOTOROLA SOLUTIO
M&T BANK CORP
MURPHY OIL CORP
MAXIM INTEGRATED
MYLAN INC
NOBLE ENERGY INC
NEXTERA ENERGY
NEWMONT MINING
NISOURCE INC
NIKE INC -CL B
NORTHROP GRUMMAN
NATL OILWELL VAR
NORFOLK SOUTHERN
NETAPP INC
NORTHERN TRUST
NORTHEAST UTILS
NUCOR CORP
NVIDIA CORP
NEWELL RUBBERMAI
NEW YORK TIMES-A
OFFICE DEPOT INC
OGE ENERGY CORP
OWENS-ILLINOIS
OMNICOM GROUP
ORACLE CORP
O'REILLY AUTOMOT
OCCIDENTAL PETE
PAYCHEX INC
PEOPLE'S UNITED
PITNEY BOWES INC
PACCAR INC
PG&E CORP
PRICELINE GROUP
PRECISION CASTPT
PATTERSON COS
PUB SERV ENTERP
PEPSICO INC
PFIZER INC
PROCTER & GAMBLE
PROGRESSIVE CORP
PARKER HANNIFIN
PULTEGROUP INC
PERKINELMER INC
PALL CORP
PNC FINANCIAL SE
PINNACLE WEST
PPG INDS INC
PPL CORP
PUBLIC STORAGE
PRAXAIR INC
PIONEER NATURAL
QUALCOMM INC
QLOGIC CORP
RYDER SYSTEM INC
REYNOLDS AMERICA
REGENERON PHARM
REGIONS FINANCIA
ROBERT HALF INTL
RED HAT INC
RALPH LAUREN COR
ROCKWELL AUTOMAT
ROPER INDS
ROSS STORES INC
RANGE RESOURCES
RR DONNELLEY & S
RAYTHEON CO
SBA COMM CORP-A
STARBUCKS CORP
SCANA CORP
SCHWAB (CHARLES)
SEALED AIR CORP
SHERWIN-WILLIAMS
SIGMA-ALDRICH
JM SMUCKER CO
SCHLUMBERGER LTD
SNAP-ON INC
SANDISK CORP
SOUTHERN CO
SIMON PROPERTY
STAPLES INC
STERICYCLE INC
SEMPRA ENERGY
SUNTRUST BANKS
ST JUDE MEDICAL
QUESTAR CORP
STATE ST CORP
CONSTELLATION-A
SUNEDISON INC
SUPERVALU INC
STANLEY BLACK &
SOUTHWESTRN ENGY
SAFEWAY INC
STRYKER CORP
SYMANTEC CORP
SYSCO CORP
AT&T INC
MOLSON COORS-B
TECO ENERGY INC
INTEGRYS ENERGY
TERADYNE INC
TARGET CORP
TIFFANY & CO
TJX COS INC
TORCHMARK CORP
THERMO FISHER
T ROWE PRICE GRP
TRAVELERS COS IN
TRACTOR SUPPLY
TYSON FOODS-A
TESORO CORP
TOTAL SYS SERVS
TEXAS INSTRUMENT
TEXTRON INC
UNITEDHEALTH GRP
UNUM GROUP
UNION PAC CORP
UNITED PARCEL-B
US BANCORP
UNITED TECH CORP
VARIAN MEDICAL S
VF CORP
VALERO ENERGY
VULCAN MATERIALS
VORNADO RLTY TST
VERISIGN INC
VERTEX PHARM
VENTAS INC
VERIZON COMMUNIC
WABTEC CORP
WALGREEN CO
WATERS CORP
WESTERN DIGITAL
WISCONSIN ENERGY
WELLS FARGO & CO
WHOLE FOODS MKT
WHIRLPOOL CORP
WASTE MANAGEMENT
WILLIAMS COS INC
WAL-MART STORES
WEYERHAEUSER CO
US STEEL CORP
XCEL ENERGY INC
XILINX INC
EXXON MOBIL CORP
DENTSPLY INTL
XEROX CORP
YAHOO! INC
YUM! BRANDS INC
ZIONS BANCORP

Appendix B: Global Industry Classification Standards (February 2014)

Sector		Index	Industry Group		Index (USED)	Sample Set Count
10	Energy	S5ENRSX Index	1010	Energy	S5ENRSX Index	29
15	Materials	S5MATR Index	1510	Materials	S5MATR Index	26
20	Industrials	S5INDU Index	2010	Capital Goods	S5CPGS Index	33
		S5INDU Index	2020	Commercial & Professional Services	S5COMS Index	7
		S5INDU Index	2030	Transportation	S5TRAN Index	9
25	Consumer Discretionary	S5COND Index	2510	Automobiles & Components	S5AUCO Index	4
		S5COND Index	2520	Consumer Durables & Apparel	S5CODU Index	12
		S5COND Index	2530	Consumer Services	S5HOTR Index	12
		S5COND Index	2540	Media	S5MEDA Index	9
		S5COND Index	2550	Retailing	S5RETL Index	26
30	Consumer Staples	S5CONS Index	3010	Food & Staples Retailing	S5FDSR Index	9
		S5CONS Index	3020	Food, Beverage & Tobacco	S5FDBT Index	20
		S5CONS Index	3030	Household & Personal Products	S5HOUS Index	6
35	Health Care	S5HLTH Index	3510	Health Care Equipment & Services	S5HCES Index	23
		S5HLTH Index	3520	Pharmaceuticals, Biotechnology & Life Sciences	S5PHRM Index	17
40	Financials	S5FINL Index	4010	Banks	S5BANKX Index	18
		S5FINL Index	4020	Diversified Financials	S5DIVF Index	14
		S5FINL Index	4030	Insurance	S5INSU Index	13
		S5FINL Index	4040	Real Estate	S5REAL Index	12
45	Information Technology	S5INFT Index	4510	Software & Services	S5SFTW Index	22
		S5INFT Index	4520	Technology Hardware & Equipment	S5TECH Index	18
		S5INFT Index	4530	Semiconductors & Semiconductor Equipment	S5SSEQX Index	14
50	Telecommunication Services	S5TELSX Index	5010	Telecommunication Services	S5TELSX Index	4
55	Utilities	S5UTILX Index	5510	Utilities	S5UTILX Index	27
						384

Appendix C: PHE





Moving averages considered for momentum based hedge calculation
5-day
Vs
10 day MA
20 day MA
40 day MA
60 day MA
90 day MA
120 day MA
150 day MA
180 day MA
210 day MA
240 day MA

Appendix D: Scope: Upper Limit Results

	1525	**1535**	**1545**	**1555**	**1565**	**1575**	**1585**
Cash Held	0.0375	0.0525	0.0675	0.0825	0.0975	0.1125	0.1275
Mean	0.1309	0.1294	0.1277	0.1259	0.1238	0.1217	0.1193
Std Dev	0.1389	0.1277	0.1173	0.1079	0.0994	0.0921	0.086
Sharpe	0.6868	0.7354	0.7860	0.8375	0.8881	0.9349	0.9741
Treynor	0.1303	0.1428	0.1575	0.1753	0.1973	0.2255	0.2632
MRAP	0.1502	0.1583	0.1668	0.1754	0.1838	0.1917	0.1982
	1595	**15105**	**15115**	**15125**	**15135**	**15145**	**15155**
Cash held	0.1425	0.1575	0.1725	0.1875	0.2025	0.2175	0.2325
Mean	0.1169	0.1143	0.1117	0.1089	0.1061	0.1032	0.1003
Std Dev	0.0813	0.0780	0.0761	0.0756	0.0763	0.0782	0.0809
Sharpe	1.0009	1.0109	1.0011	0.9715	0.9250	0.8663	0.8008
Treynor	0.3167	0.3991	0.5438	0.8673			
M2	0.2027	0.2044	0.2028	0.1978	0.1900	0.1802	0.1693

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