# Outsmarting Smart Beta

## Exploiting Factor Cyclicality

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## Abstract

Smart Beta and factor investing have become very popular and for good reason. Unlike most active management, factors have demonstrated their ability by providing historical returns competitive with and often superior to S&P 500 Index Funds. The Smart Beta phenomenon has inspired a wave of investment products and considerable debate. Topics of debate include: does Smart Beta only apply to re-weighting a market portfolio? How many Smart Beta factors are there? What is the hurdle for accepting a factor strategy as Smart Beta? If value is measured using four different methods, in turn does that make four different factors? Another Smart Beta area of debate that has received much attention is whether it is possible to time Smart Beta factors. Although early research yielded mixed results, recent research has been more positive. This paper summarizes the development of Smart Beta investing and its current popularity then compares it to a 60+ factor method that has been in active use since 1996 by Haugen Equity Signals. Test results are disclosed and then analyzed in the context of investor suitability, return-risk trade-offs, product marketability and implications for investors.

### *Evolution of Smart Beta Investing*

What is Smart Beta? There are a number of definitions but there is a clear industry consensus that it is not a portfolio weighted by market capitalization. This has led some major Smart Beta advocates to refer to market-cap weighted portfolios as "Dumb Beta." Yet, all leading indexes are market-cap weighted, including the S&P 500 Index, the S&P 1500 Index, the FTSE Russell 3000, and MSCI World. Trillions of institutional assets are indexed to these and their component indexes.

Moreover, the data is even more damning for practitioners of active management in the US using the mutual fund wrapper. Analysis of S&P Indices vs. Active Scorecard[1] ending January 31, 2018 shows that 76% of core US equity mutual funds have under-performed the S&P 500 over the 10-year period. Similar results are shown for 5-year and 15-year returns. The data speaks clearly that "Dumb Beta" is an unfairly dismissive categorization.

[1] "S&P Indices Versus Active Indexology®." Indexology. Accessed November 15, 2018. https://us.spindices.com/spiva/#/reports.

Market cap-weighted indexing became the global industry standard for passive investment following the first attempt to apply William Sharpe's Capital Asset Pricing Model[2] to actual asset management[3]. The Samsonite Corporation commissioned Wells Fargo Bank to manage a $6 million dollar pension fund allocation using a market portfolio in keeping with Sharpe's model. The implementation details significantly influenced how index funds would be developed for the next 30 years. Using a strategy based on an equal-weighted index of New York Stock Exchange equities, its execution was described as "a nightmare" with a majority of the profits realized by the portfolio eaten by transaction costs. Today stock transaction and impact costs for most large cap US-equities are trivial. However, this was not the case until more than 20 years later.

The equal-weighting strategy was replaced by a market-weighted strategy using the Standard & Poor's 500 Composite Stock Price Index. The Standard & Poor's 500 Index launched in 1957 drew upon a market-cap-weighted index created by Alfred Cowles to represent and measure consistently the average experience of stock market investors. Although measurement, not ease of portfolio management, was its purpose in design, this little known index at the time was the answer to the prayers of the Wells Fargo team. This evolution debunks the widespread belief that Bill Sharpe's Capital Asset Pricing Model (CAPM) model was based upon a cap-weighted market index. Cap-weighting became standard as a direct result of implementation issues.

### *Challenges to Beta, Market-Cap Weighting and the Search for Anomalies*

Almost as soon as index funds became popular, so did the concept that market-cap weighting was not the most efficient way to derive optimal rates of return. Fischer Black[4], when examining the five-factor Value Line Timeliness Ranking System, was the first efficient market proponent to document empirical results exceeding those prescribed by the Efficient Market Theory. A handful of subsequent academic papers based on empirical studies documented other exceptions, calling them anomalies. One of the most referenced papers was "Risk and the Rate of Return on Financial Assets: Some Old Wine in New Bottles," authored by Robert A. Haugen and James A. Heins[5]. They demonstrated that Beta was a flawed measure of risk as stocks with Betas at higher than 1.00 systematically failed to deliver above-market returns.

About the same time, multifactor equity risk modeling[6] started gaining traction. Stephen Ross theorized with the Arbitrage Pricing Theory[7] that there were systematic sensitivities stocks had

[2] Sharpe, William F. "Capital asset prices: A theory of market equilibrium under conditions of risk." *The Journal of Finance* 19, no. 3 (1964): 425-442.

[3] Bernstein, Peter L. "Capital Ideas." *John Wiley and Sons* (1991): 21 – 38.

[4] Black, Fischer, and Robert S. Kaplan. "Yes, Virginia, there is hope: Tests of the Value Line ranking system." *Financial Analysts Journal* (1973): 10-14.

[5] Haugen, Robert A., and A. James Heins. "Risk and the rate of return on financial assets: Some old wine in new bottles." *Journal of Financial and Quantitative Analysis* 10, no. 5 (1975): 775-784.

[6] Blank, Herbert. "Multifactor Equity Models." *Global Equity Selection Strategies* (1998): 237 – 255.

[7] Ross, S. A. "The arbitrage theory of capital asset pricing, *Journal of Economic Theory* (1976).

to macroeconomic factors not fully explained by Beta.  In the same year[8], the progenitor of what would soon develop into the BARRA US Risk Factor Model was published in the Financial Analyst's Journal.  Although the latter article focused on historical sensitivities to fundamental market factors, both papers reflected the idea that there were systematic market risks not explained by market Beta.  Both papers further posited that historical sensitivities of each stock to each factor could be estimated through time series analysis.  A number of empirical studies[9], including those done by Keith Still[10] along with Smitu P. Kothari and Jay Shanken's [11] validated both sets of assumptions.  Importantly, the models in both papers were positioned as consistent with CAPM but with more granular breakdowns of Beta.

### *Size and Value*

Efficient Market Theory standard-bearers Eugene Fama and Kenneth French went into the asset management business after publishing research that there are certain factors that caused value as measured by the Book/Price ratio and stocks of smaller market capitalization to outperform over time[12].  This led to the logical reasoning that if small cap and value stocks were undervalued, large cap stocks with pronounced growth characteristics must be systematically overvalued.

These are considered seminal findings.  By definition, market-cap weighted indices put increasingly higher weights in stocks as they become higher in relative market cap and relative growth, as defined as the inverse of value, because both increase formulaically with increases in share price.  Therefore, market-cap-weighted indices must contain intrinsic inefficiencies relative to other index weighting schemes.

### *Style Indices and Cyclicality*

During the 1990's as a direct outgrowth of the Fama-French research, Russell Indexes, now part of FTSE Russell Indices, created the style indices differentiated by size and value.  The Standard & Poor's Indexes soon followed suit although the classification methodologies differed considerably and still do.  Russell Indexes, which grew out of Frank Russell Consulting, started this initiative primarily for benchmarking active managers for their institutional clients so as to provide fair benchmarks for managers that specialized in value vs. growth, or small cap vs. large cap.  The Fama-French research studies provided the rationale for doing so.  Market regime changes favoring value over growth and small cap over large cap would reverse from time to time over cycles of varying duration.  Therefore, it was considered prudent to have at least some

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[8] Rosenberg, Barr, and James Guy. "Prediction of beta from investment fundamentals: part one, prediction criteria." *Financial Analysts Journal* (1976): 60-72.

[9] Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. "Economic forces and the stock market." *Journal of Business* (1986): 383-403.

[10] Sill, Keith. "Macroeconomic risk and the determination of expected returns on stocks." *Managerial Finance* 21, no. 7 (1995): 43-56.

[11] Kothari, Smitu P., and Jay Shanken. "Book-to-market, dividend yield, and expected market returns: A time-series analysis." *Journal of Financial Economics* 44, no. 2 (1997): 169-203.

[12] Fama, Eugene F., and Kenneth R. French. "The cross-section of expected stock returns." *The Journal of Finance* 47, no. 2 (1992): 427-465.

managerial representation in each category so assets could be moved systematically from managers in one category to another in response to these cycle shifts.

The Callan Periodic Table of Investment Returns[13] provides a vivid example of how frequently leadership shifts among nine commonly used institutional asset class benchmarks. Focusing on the two large cap styles, the well documented value anomaly has a very mixed record with plenty of cyclicality during the past 20 years. The S&P 500 Value garnered higher rates of return for 7 straight years from 2000 through 2006 but then posting inferior returns to S&P 500 Growth in 8 of the next 11 years to do no better than an annual split during the 20-year period. The value-growth leadership shifts are not strictly a large cap phenomenon. The small cap Russell 2000 Value and Russell 2000 Growth indexes had precisely the same relative ordering in each of the 20 years. This is ample evidence that each style will outperform in certain market cycles and underperform in others.

Upon reviewing combinations of factors, we observe that four of these indexes focus on the two most popular Smart Beta factors: value and size. They are: S&P 500 (Large Cap) Growth; S&P (Large Cap) Value; Russell 2000 (Small Cap) Growth and Russell 2000 (Small Cap) Value. The preponderance of Smart Beta research supports the contention that Small Cap Value should be the best performer over time. Indeed it was the highest performer of the four indexes over the period at 8.87% , which is 301 basis points better than the 5.86% posted by the S&P 500 on a 20-year annualized basis. Nevertheless, it had the lowest return of the four indexes in 8 of the 20 calendar years, and the most last place finishes of any of the indexes.

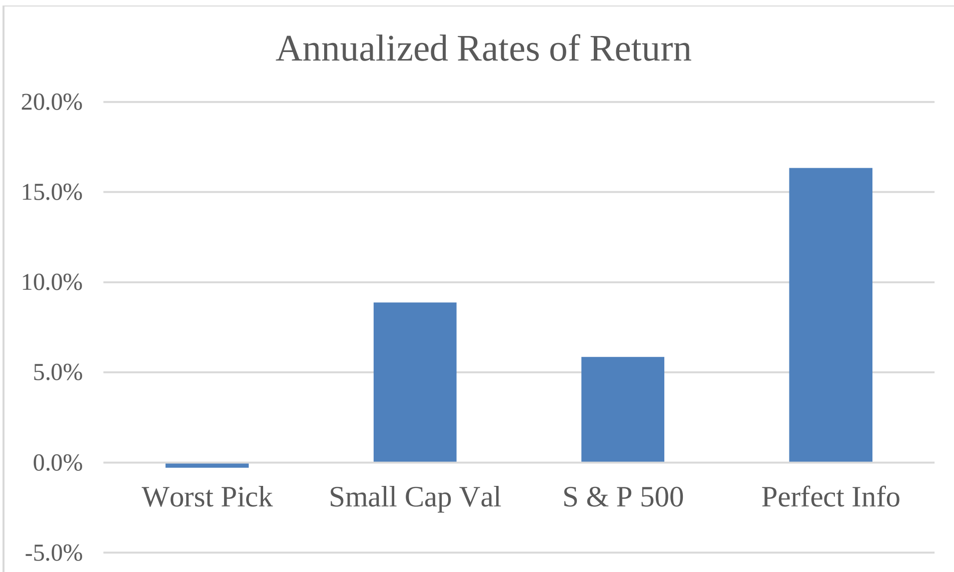
[13] "The Callan Periodic Table of Investment Returns." Callan. 2018. Accessed November 16, 2018. https://www.callan.com/periodic-table/.

# The Callan Periodic Table of Investment Returns

## Annual Returns for Key Indices Ranked in Order of Performance (1998–2017)

| 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S&P 500 Growth 42.16% | MSCI Emerging Markets 66.84% | Russell 2000 Value 22.83% | Russell 2000 Value 14.02% | Bloomberg Barclays Agg 10.26% | MSCI Emerging Markets 55.82% | MSCI Emerging Markets 25.55% | MSCI Emerging Markets 34.00% | MSCI Emerging Markets 32.17% | MSCI Emerging Markets 39.38% | Bloomberg Barclays Agg 5.24% | MSCI Emerging Markets 78.51% | Russell 2000 Growth 29.09% | Bloomberg Barclays Agg 7.84% | MSCI Emerging Markets 18.23% | Russell 2000 Growth 43.30% | S&P 500 Growth 14.89% | S&P 500 Growth 5.52% | Russell 2000 Value 31.74% | MSCI Emerging Markets 37.28% |
| S&P 500 28.58% | Russell 2000 Growth 43.09% | Bloomberg Barclays Agg 11.63% | Bloomberg Barclays Agg 8.43% | Bloomberg Barclays High Yield -1.37% | Russell 2000 Growth 48.54% | Russell 2000 Value 22.25% | MSCI World ex USA 14.47% | MSCI World ex USA 25.71% | MSCI World ex USA 12.44% | Bloomberg Barclays High Yield -26.16% | Bloomberg Barclays High Yield 58.21% | Russell 2000 26.85% | Bloomberg Barclays High Yield 4.98% | Russell 2000 Value 18.05% | Russell 2000 38.82% | S&P 500 13.69% | S&P 500 1.38% | Russell 2000 21.31% | S&P 500 Growth 27.44% |
| MSCI World ex USA 18.77% | S&P 500 Growth 28.24% | S&P 500 Value 6.08% | Bloomberg Barclays High Yield 5.28% | MSCI Emerging Markets -6.16% | Russell 2000 47.25% | MSCI World ex USA 20.38% | S&P 500 Value 5.82% | Russell 2000 Value 23.48% | S&P 500 Growth 9.13% | Russell 2000 Value -28.92% | Russell 2000 Growth 34.47% | Russell 2000 Value 24.50% | S&P 500 Growth 4.65% | S&P 500 Value 17.68% | Russell 2000 Value 34.52% | S&P 500 Value 12.36% | Bloomberg Barclays Agg 0.55% | S&P 500 Value 17.40% | MSCI World ex USA 24.21% |
| S&P 500 Value 14.68% | MSCI World ex USA 27.92% | Russell 2000 -3.02% | Russell 2000 2.49% | Russell 2000 Value -11.43% | Russell 2000 Value 46.03% | Russell 2000 18.33% | S&P 500 4.91% | S&P 500 Value 20.81% | Russell 2000 Growth 7.05% | Russell 2000 -33.79% | MSCI World ex USA 33.67% | MSCI Emerging Markets 18.88% | S&P 500 2.11% | MSCI World ex USA 16.41% | S&P 500 Growth 32.75% | Bloomberg Barclays Agg 5.97% | Russell 2000 Growth -1.38% | Bloomberg Barclays High Yield 17.13% | Russell 2000 Growth 22.17% |
| Bloomberg Barclays Agg 8.67% | Russell 2000 21.26% | Bloomberg Barclays High Yield -5.86% | MSCI Emerging Markets -2.61% | MSCI World ex USA -15.80% | MSCI World ex USA 39.42% | S&P 500 Value 15.71% | Russell 2000 Value 4.71% | Russell 2000 18.37% | Bloomberg Barclays Agg 6.97% | S&P 500 Growth -34.92% | S&P 500 Growth 31.57% | Bloomberg Barclays High Yield 15.12% | S&P 500 Value -0.48% | Russell 2000 16.35% | S&P 500 32.39% | Russell 2000 Growth 5.60% | MSCI World ex USA -3.04% | S&P 500 11.96% | S&P 500 21.83% |
| Bloomberg Barclays High Yield 1.87% | S&P 500 21.04% | S&P 500 -9.11% | Russell 2000 Growth -9.23% | Russell 2000 -20.48% | S&P 500 Value 31.79% | Russell 2000 Growth 14.31% | Russell 2000 4.55% | S&P 500 15.79% | S&P 500 5.49% | S&P 500 -37.00% | Russell 2000 27.17% | S&P 500 Value 15.10% | Russell 2000 Growth -2.91% | S&P 500 16.00% | S&P 500 Value 31.99% | Russell 2000 4.89% | S&P 500 Value -3.13% | Russell 2000 Growth 11.32% | S&P 500 Value 15.36% |
| Russell 2000 Growth 1.23% | S&P 500 Value 12.73% | MSCI World ex USA -13.37% | S&P 500 Value -11.71% | S&P 500 Value -20.85% | Bloomberg Barclays High Yield 28.97% | Bloomberg Barclays High Yield 11.13% | Russell 2000 Growth 4.15% | Russell 2000 Growth 13.35% | S&P 500 Value 1.99% | Russell 2000 Growth -38.54% | S&P 500 26.47% | S&P 500 15.06% | Russell 2000 -4.18% | Bloomberg Barclays High Yield 15.81% | MSCI World ex USA 21.02% | Russell 2000 Value 4.22% | Russell 2000 -4.41% | MSCI Emerging Markets 11.19% | Russell 2000 14.65% |
| Russell 2000 -2.55% | Bloomberg Barclays High Yield 2.39% | S&P 500 Growth -22.08% | S&P 500 -11.89% | S&P 500 -22.10% | S&P 500 28.68% | S&P 500 10.88% | S&P 500 Growth 4.00% | Bloomberg Barclays High Yield 11.85% | Bloomberg Barclays High Yield 1.87% | S&P 500 Value -39.22% | S&P 500 Value 21.17% | S&P 500 Growth 15.05% | Russell 2000 Value -5.50% | S&P 500 Growth 14.61% | Bloomberg Barclays High Yield 7.44% | Bloomberg Barclays High Yield 2.45% | Bloomberg Barclays High Yield -4.47% | S&P 500 Growth 6.89% | Russell 2000 Value 7.84% |
| Russell 2000 Value -6.45% | Bloomberg Barclays Agg -0.83% | Russell 2000 Growth -22.43% | S&P 500 Growth -12.73% | S&P 500 Growth -23.59% | S&P 500 Growth 25.66% | S&P 500 Growth 6.13% | Bloomberg Barclays High Yield 2.74% | S&P 500 Growth 11.01% | Russell 2000 -1.57% | MSCI World ex USA -43.56% | Russell 2000 Value 20.58% | MSCI World ex USA 8.95% | MSCI World ex USA -12.21% | Russell 2000 Growth 14.59% | Bloomberg Barclays Agg -2.02% | MSCI Emerging Markets -2.19% | Russell 2000 Value -7.47% | MSCI World ex USA 2.75% | Bloomberg Barclays High Yield 7.50% |
| MSCI Emerging Markets -25.34% | Russell 2000 Value -1.49% | MSCI Emerging Markets -30.71% | MSCI World ex USA -21.40% | Russell 2000 Growth -30.26% | Bloomberg Barclays Agg 4.10% | Bloomberg Barclays Agg 4.34% | Bloomberg Barclays Agg 2.43% | Bloomberg Barclays Agg 4.33% | Russell 2000 Value -9.78% | MSCI Emerging Markets -53.33% | Bloomberg Barclays Agg 5.93% | Bloomberg Barclays Agg 6.54% | MSCI Emerging Markets -18.42% | Bloomberg Barclays Agg 4.21% | MSCI Emerging Markets -2.60% | MSCI World ex USA -4.32% | MSCI Emerging Markets -14.92% | Bloomberg Barclays Agg 2.65% | Bloomberg Barclays Agg 3.54% |

This begs the question of whether those underperforming years could have been avoided. Let's suppose it is known in advance which of the four indexes will be the top performer in any calendar year. The answer is given by the "Perfect Info" bar in the chart below, which uses annual rebalancing to select next year's top performer. You would have achieved an annualized rate of 16.34%, which is close to doubling the annualized return of small cap value. The fact that factor timing can be risky is shown by the Worst Pick bar, which uses annual rebalancing to select next year's worst performer. If somehow one managed to pick the worst performer of the coming year, the result would have been an annualized loss of 0.28% per year.




***Alternative Weighting Schemes***

Every index we've investigated thus far is weighted by market capitalization. Indeed, institutional asset managers used a number of different weighting schemes to enhance index returns in the 1980s and 1990s but it wasn't until this millennium that frictional trading costs and fees became inexpensive enough that potential implementation shortfalls stopped preventing alternative alpha-capture schemes from being implemented on a market-wide scale. The adoption of ETFs into the mainstream also facilitated this trend.

In 2003, an equally weighted version of an S&P 500 index fund (RSP) was launched by Rydex Funds, now part of INVESCO. This set the stage for an apples-to-apples comparison with SPY, the cap-weighted S&P 500 ETF and the flagship of the SPDR fleet. Since its inception in April 2003 through the end of 2017, RSP has delivered a total return 202 basis points per year higher than that of SPY. This demonstrates that by equally weighting S&P 500 constituents, RSP takes advantage of the tendency of market-cap weighting schemes to give disproportionate allocations to overpriced stocks in the majority of periods.

Studying these results led Exponential Shares to create RVRS, the Reverse Market-Cap ETF in 2017. Still using the identical roster of constituents, this innovative weighting scheme is determined by the reciprocals of each constituent's market capitalization. A recent research paper[14] documented a 10 year backtest with more than a 350 basis point per year advantage over SPY and a 170 basis point difference over RSP. This demonstrated that the greater the tilt toward the smaller constituents, the greater the return during the 10-year backtested period. So the size factor is a powerful generator of returns. It is important to note though that RVRS also had a bit more volatility than RSP which in turn had greater volatility than SPY resulting in nearly identical Sharpe ratios for all three.

After RSP, the next major alternative weighting scheme also brought the term Smart Beta to the forefront. A research paper[15] advocating another alternative weighting scheme garnered considerable industry attention. This paper cited earlier research on the inefficiency of capitalization weighted portfolios[16] illustrating that market-cap weighted indexes were doomed by design to systematically underperform. The new paper argued in favor of indexes weighted by companies' fundamentals. This paper gave birth to the RAFI (Research Affiliates Fundamental Indices) family of indexes.

### *Definition of Smart Beta*

This leads us to an affirmative description of Smart Beta. Robert Arnott, who was considered to be the man to popularize the term, says the term originated with consulting firm Towers Watson.[17] In 2013 the firm defined Smart Beta as "Simply about trying to identify good investment ideas that can be structured better. Smart beta strategies should be simple, low cost, transparent and systematic."

### *How Many Smart Beta Factors Are There?*

The extent of Smart Beta Factors that are in existence was best described by Professor John Cochrane from the University of Chicago when he stated at the 2011 Conference the American Financial Association, "We now have a zoo of new factors." Since this statement, the proliferation of factors purporting to deliver excess returns has only accelerated. Between 2010 and 2012, there were 59 new factors discovered. By some counts, there are now over 300 factors in academic and practitioner research. Most investment research and analytics providers narrow

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[14] Blank, Herbert, and Qiao Duan. "The Case for Reverse Market Cap Indexing." *Exponential Shares* (2017).

[15] Arnott, Robert D., Jason Hsu, and Philip Moore. "Fundamental indexation." *Financial Analysts Journal* (2005): 83-99.

[16] Haugen, Robert A., and Nardin L. Baker. "The efficient market inefficiency of capitalization–weighted stock portfolios." *The Journal of Portfolio Management* 17, no. 3 (1991): 35-40.

[17] Arnott, Robert D., Engin Kose. "What Smart Beta Means to Us." Research Affiliates (August 2014): 2.

the number to less than 30. As detailed in an interview with ETF.com[18], Lukas Smart, Portfolio Manager at Dimensional Fund Advisors, one of the pioneering investment managers in the space, insists there are no more than three that have stood up to the test of time. These factors are quality, size and value.

The recently published FTSE Russell article "Taming the Factor Zoo"[19] details the research effort to filter through all the factors found in academic research to identify the most reliable factors that can reasonably be expected to persist. It established three standards for determining the most essential factors: (1) solid academic research confirming its existence and persistence, (2) clear economic rationales, and (3) be determined quantitatively to be robust and unique. At the end of rigorous tests to ensure the standards were met, the FTSE team confirmed the existence of six (6) types of factors:

1. Value;
2. Quality;
3. Size;
4. Dividend;
5. Low Volatility;
6. Momentum.

Since these six are the basis of numerous Smart Beta ETFs (see table below) and are included in the product line of most ETF sponsors, they are used for the core definition of Smart Beta factors.

| XTF List of Smart Beta ETFs | # of ETFs |
|---|---:|
| Dividend/Income | 123 |
| Growth | 46 |
| Multifactor | 164 |
| Quality | 137 |
| Low Volatility | 65 |
| Momentum | 35 |
| Size (Small/Mid/Large Cap) | 144 |
| Value | 111 |
| **Total** | **825** |

[18] Hougan, Matthew. "Why Many Smart Beta Backtests Fail." *ETF* (2017).

[19] Goodwin, Thomas. "Taming the Factor Zoo." *London Stock Exchange Group* (2018).

### *Measuring Smart Beta Factors*

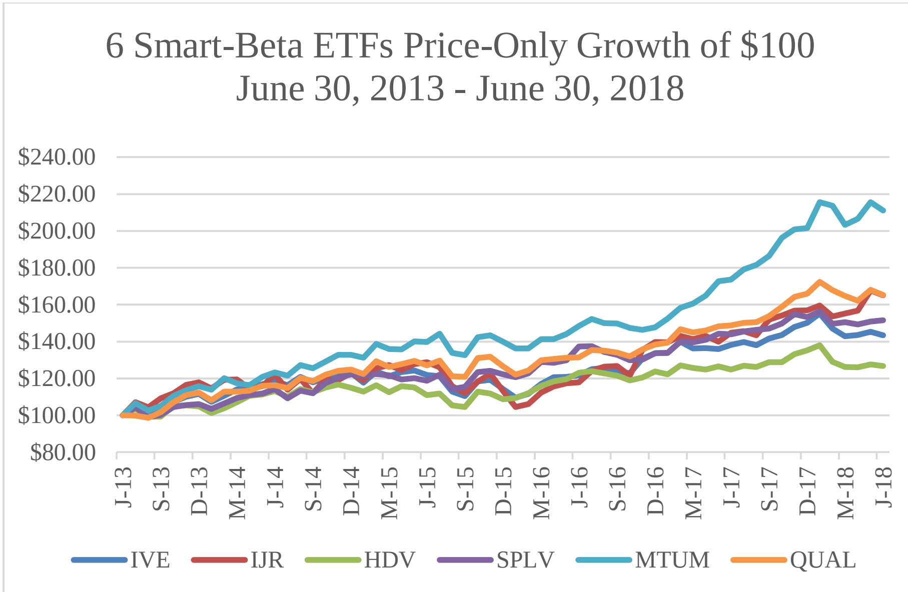
All six types of factors can be measured in many ways, and all of which are frequently used. For instance, value can be measured in a variety of ways such as: book to price; earnings to price; sales-to-price; cash-flow-to-price; dividend-growth-to-price; earnings-growth-to-price; industry-relative price change; etc. Similarly, common quality measures include: return on equity, earnings stability, dividend growth stability, balance sheet strength, and financial leverage among others. Size can be measured by either market cap or revenues and by market cap ranges or self-relative (e.g., deciles). Low Volatility can be measured by the standard deviation of prices with different periodicities or Betas, thus capturing the extent to which prices move with the market. Finally, price momentum, generally measured by various combinations of moving averages, has been one of the most powerful factors for explaining U.S. market prices in recent years.

### *Efficacy and Cyclicality*

Although all the above factors have been substantiated in research and by major index providers to provide a source of excess risk-adjusted returns in lengthy time periods, none of them provides such returns every quarter, every year, or in every two – five year period during the past 40 years.

When moving over to the ETF world to chart the behaviors of the six most popular single-factor models, we selected the largest in each category, according to ETF.com, by assets under management. The ETFs are detailed below along with their performance comparisons in the following graph:

Value – IVE
Small Cap – IJR
Dividend Yield – HDV
Low Volatility – SPLV
Momentum – MTUM
Quality - QUAL




The graph above shows that MTUM, the price-momentum ETF, took the leadership from Small Cap in January 2014. The ebbs and flows of cyclicality among the other five are also clearly demonstrated. IJR, the S&P 600 Small Cap ETF led in the last 6 months of 2013, dropped to dead last in January 2016, then rallied to tie for second in the last two months of the period. IVE, the S&P 500 Value ETF, ranked as high as second during the period but eventually fell to fourth. After assuming the leadership in June 2014, the strategy that really ran away from the pack was price momentum as represented by MTUM. Therefore, many asset managers and ETF providers combine three or more of these factors in their portfolios in attempts to mitigate the effects of cyclicality.

The correlation matrix[20] below shows how these factors have moved with respect to each other from 1991 – 2017, a period characterized by market stress in 1994, from 2000 – 2002 and especially in 2008 – 2009. Momentum has provided the most diversification to other Smart Beta factors with negative or near-zero correlations to each. Low volatility provided good diversification for all the factors except for Quality and Dividend Yield.

[20] Stoneberg CFA, Matthew and Smith, Bradley, INVESCO White Paper 2017 "Getting Smart about Beta: Examining Smart Beta Strategies and Their Impacts over Several Market Cycles": 9.

| Factor | Quality | Value | Small Cap | Momentum | Low Vol | Div Yield |
|---|---|---|---|---|---|---|
| **Quality** | 1.00 | | | | | |
| **Value** | 0.52 | 1.00 | | | | |
| **Small Cap** | 0.36 | 0.84 | 1.00 | | | |
| **Momentum** | -0.09 | -0.28 | -0.21 | 1.00 | | |
| **Low Vol** | 0.77 | 0.23 | 0.09 | 0.05 | 1.00 | |
| **Div Yield** | 0.71 | 0.77 | 0.63 | -0.22 | 0.62 | 1.00 |

There are myriad ways to use and combine Smart Beta factors in portfolio management. While many multi-factor Smart Beta ETFs use modified market cap weighting, others use equal weighting, and fundamental weighting schemes. All three of these weighting schemes are indifferent to the cyclical nature of factor regimes.

Dynamic weighting is an alternative scheme that attempts to time factors. Such schemes have been the subject of sometimes heated industry debate in recent years. The issue is whether it is possible to time factors consistently over the long run. Conventional wisdom holds that market timing risks tend to outweigh the potential rewards and that the same must be true of factor timing. Nevertheless, this entire paper has documented how market theory once held sacrosanct has evolved over the years in the face of empirical evidence with solid research underpinnings. Some papers are attempting to make the same case for factor timing.

One intriguing paper[21] demonstrates that it can be achieved but cautions that it is difficult and lacks the evidence thus far to be conclusive over long periods. Another[22] used a macroeconomic regime-timing scheme to arrive at similar conclusions. More optimistically, Ric Thomas and Rob Shapiro[23] demonstrated that excess returns can be achieved over a 10-year period by timing the use of three distinct single-factor Smart Beta portfolios, allocating 100% to one and 0% to the other two according to overall market valuations along the three dimensions using methodologies in keeping with Campbell and Shiller. The issue is far from decided. An article published by Research Affiliates[24] demonstrating factor cyclicality could be exploited by a simple buy low/sell high strategy was challenged publicly for alleged methodology flaws in an article published in AQR Insights/Perspectives[25]. PIMCO believed in the Research Affiliates

[21] Bender, Jennifer, Xiaole Sun, Ric Thomas and Volodymyr Zdorovtsov, "The Promises and Pitfalls of Factor Timing", *The Journal of Portfolio Management Quantitative Special Issue 2018* 44 (4): 79-92.

[22] Hodges, Philip, Ked Hogan, Justin R. Peterson, and Andrew Ang. "Factor timing with cross-sectional and time-series predictors." *The Journal of Portfolio Management* 44, no. 1 (2017): 30-43.

[23] Thomas CFA, Ric and Rob Shapiro CFA, "IQ Insights: Dynamic Timing of Smart Beta Strategies: Is It Possible?" Publication, State Street Global Advisors 2015

[24] Arnott, Robert D., Noah Beck, and Vitali Kalesnik. "Timing 'Smart Beta' Strategies? Of Course! Buy Low, Sell High!." (2016).

[25] Asness, Cliff, "Factor Timing is Hard." *AQR Insights/Perspectives* (2017).

findings enough to launch three dynamically weighted ETFs using methodologies inspired by the paper.

### *Smart Beta Factor Decomposition: 6 Factor Types, 60 Factors*

We examined the timing of factor components by evaluating the Haugen Model, which is an investment methodology that has been employed since 1996, long before the Smart Beta terminology became popular. This methodology requires rigor and sophistication that is aided by its machine learning processes. It is closer in construct to the multifactor equity risk models of Ross or Rosenberg than it is to the Smart Beta rotation techniques described by Thomas and Shapiro or Arnott's valuation timing model. It uses fundamental, market and macro-economic factors in order to explain and recalibrate the risk sensitivities of each stock.

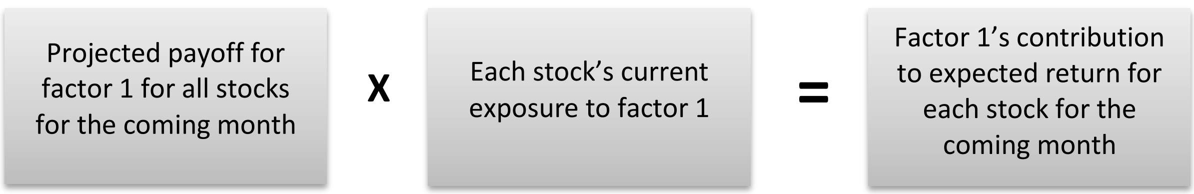
Another layer of rigor is derived from the fact that there are many different formulae for measuring value, price momentum, quality, etc. The six types of Smart Beta factors incorporated into the Haugen Model are calculated using on average 10 different measures for each of the factor types. Instead of six or fewer market ratios determining allocations to six or fewer types of Smart Beta ETFs, the Haugen Model considers the historic sensitivities of 4,000+ stocks to 60 factor measures along with the relative timeliness and importance of those factors. The vast majority of these 60 ratio-determined measurements considered by the model can be mapped to one of the six types of Smart Beta factors defined throughout this paper. Each different method of measuring a factor is considered by the Haugen Model as its own factor and at the most granular level. Research of the historical time series of different measurements in the same factor type (e.g., Earnings/Price, Book/Price) show significantly different cyclical behaviors in amplitude and duration even though they are generally highly correlated. Another level of complexity is that the Haugen Model also uses historical stock sensitivities to a few significant macroeconomic factors, such as business cycle, inflation, and others.

### *Dynamic Weighting Using a "Microscope": A Machine Learning Approach*

The Haugen Model dynamically weighted its factors from its start in 1996. Over time the process has evolved in both rigor and complexity. Rather than rotating among three or more factor portfolios with between 50 and 500 stocks, this process continually re-evaluates the attractiveness of more than 4,000 U.S. stocks in the selection universe on an expected-return basis. The stocks are then grouped according to market capitalization and liquidity.

The Haugen Model achieves this by utilizing iterative machine learning processes. On a monthly basis, the over 4,000 stocks are put through advanced statistical modeling algorithms, to produce a projected "payoff" or "score" for over each of the 60 factors applied to every stock. For example, if in a given month the payoff for the book-to-price factor is negative, this means in that month the model is favoring companies with low book-to-price values over stocks with high book-to-price values. Payoffs for all factors are estimated using machine learning across a database of historic sensitivities in a seriatim process for each of the 4,000+ stocks.

This creates a huge matrix that is then used to calculate expected returns for all stocks in the vast universe. On a monthly basis, the latest market aggregate and individual stock data are retrieved and input into the Haugen Model. The projected monthly payoff for exposure to each of the 60 factors is then calculated. Simultaneously, each stock's current exposure level to each factor is recalculated. The expected return for each stock is then the multiplicative sum of each stock's exposure to each projected payoff. The following diagram illustrates the process for one such factor.




Each stock is ranked by its expected return in the coming month in order to calculate deciles differentiating the most attractive from the least attractive stocks. Admittedly, the level of complexity involved in creating monthly matrices with more than 240,000 elements in order to create buy/sell signals and long/short portfolios rejects conventional practice regarding Smart Beta strategies. Most webinars, seminar panels, and papers reinforce the belief that only the simplest, most basic, and most time-tested strategies are best.

The complexity involved in creating the signals derived from the Haugen Model can be fully justified if excess returns are consistently and significantly higher than simple implementations such as the one outlined by Thomas and Shapiro. A closer inspection is needed to explain how and why the achievement of such returns is plausible. Unlike models with fixed, "all weather" rules for picking stocks, the vast array of factors empowers the Haugen Model to be responsive to market regime changes, similarly to what active management attempts to demonstrate. Only through the consumption and analysis of so much data is it conceivable that a customized financial system could accurately forecast future performance in a complex environment with constantly changing conditions.

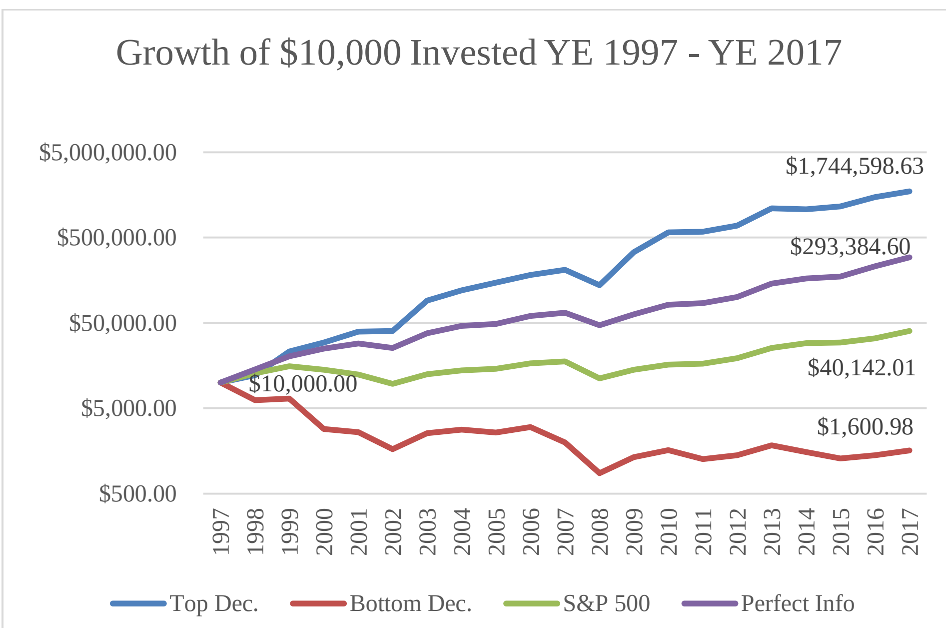
Beyond the abstract, specific examples help explain the usefulness of the methodology. Machine learning allows the Haugen Model to accurately project both size and sign changes in the payoff of a given factor. For example, payoffs of stocks paying relatively high dividends might be positive one month, but negative the next. The result is superior timing of portfolio adjustments through the anticipation of market cycle shifts.

***Long-Short Applications – Testing Methodology***

The first test we conducted involved the construction of many 50-stock portfolios in the following manner. The universe is populated by more than 4,000 U.S. stocks by market cap. After calculating expected returns on these, the stocks are ranked from lowest to highest expected return in order to form more than 800 of the 50-stock portfolios in order to create 10 deciles.  No additional constraints were imposed.  At the end of the month we rebalanced each portfolio. All backtests use date-stamped data to eliminate the possibility of look-ahead bias.

***Long-Short Applications – Performance Comparisons***

The returns generated from the power of the unconstrained Haugen Model were immediately evident.  For the 20 year period ending December 31, 2017, the top-decile portfolio returned $1.7 million from a $10,000 investment, an annualized return of 28.2%.  This can be compared with $40,142 for the S&P 500 based investment with an annualized return of only 5.9%.  The Haugen Model's bottom decile was the worst performer of the 10 Haugen decile portfolios.  The initial $10,000 shrank to $1,601 during the test period for an annualized return of -6.57%.  Referencing back to the Callan "Periodic Table", even the index we created showing the power of perfect annual foresight of which institutional size and style index were going to have the best return for that calendar year, does not do nearly as well as the Haugen Model's unconstrained top decile portfolio, returning a still very impressive 16.3% annualized and amassing nearly $300,000 in aggregate wealth. Since the Haugen Model's top decile outperforms even perfect foresight in selecting the right size/style index ahead of time, its more granular factor loadings down to the individual factor component expected return level must have more information related to the next month's returns than is possible even using the best combination of the oldest recognized Smart Beta factors.  It is quite plausible to expect that monthly rebalancing is giving the Haugen Model more actionable information than the annual constraint used for the perfect-foresight index.




Many may ask what might be the perceived negatives for traditional institutions that may consider investing in unconstrained top decile portfolios?  The portfolio returns are highly volatile with an annualized standard deviation during the period of more than 44%.  Institutions uncomfortable with large tracking errors to institutional equity portfolios might find these numbers especially challenging to explain to an advisory board. The Sharpe ratio for the period for the unconstrained top decile of 0.63 is only slightly more impressive than Russell 2000 Small Cap Value Sharpe ratio of 0.49. The fabricated best of the four size/value indexes portfolio would have the best Sharpe ratio of 0.87, but it requires perfect foresight.

***Low Volatility Smart Beta Strategy: Testing Methodology***

Haugen Equity Signals also provides an index tethered to the institutional constraints by directly incorporating low volatility as a constraint in the stock selection process. It is called the Low Volatility Smart Beta Strategy. The construction methodology reflects this additional constraint in the following manner:

<u>Empirical Testing – Creating an index to test against the FTSE Russell 3000 Index.</u>

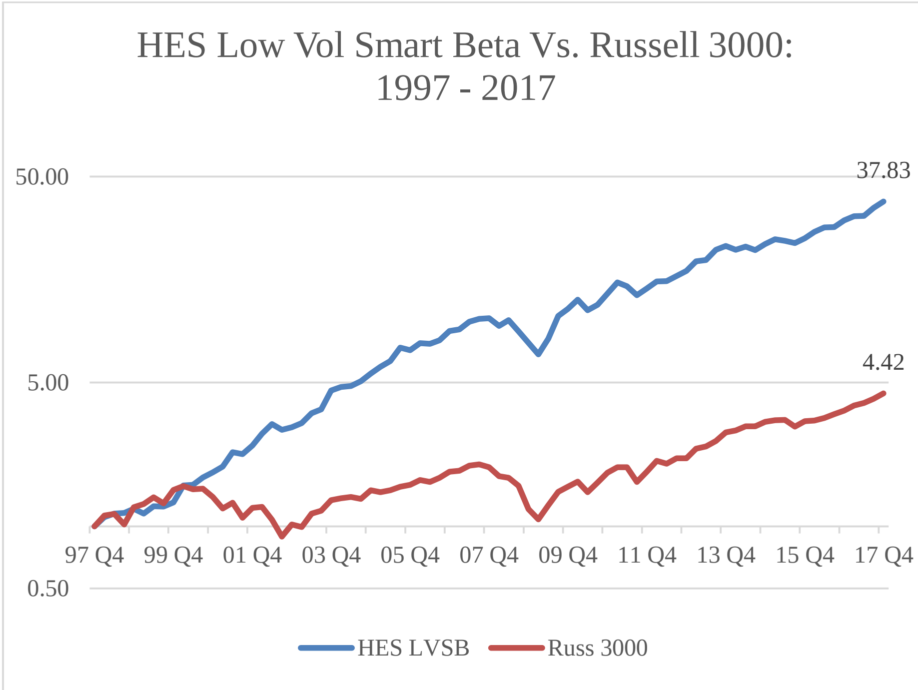
1. Start with the top 2,000 stocks by market cap
2. Filter out stocks with a market capitalization of under $300M
3. Filter out stocks with a closing price of under $5
4. Assign a Smart Beta / low vol rank as follows
    a) Sort the expected returns in descending order and assign a rank
    b) Sort the volatility numbers in ascending order and assign a rank
    c) Calculate the total rank:

    SmartBetaLowVolRank = (ERRank * ERWeight) + (LowVolRank * LowVolWeight)
    with ERWeight = 100% and LowVolRank = 25%
5. Take the top 50 (i.e. lowest ranked) SmartBetaLowVolRanks to hold, equally weighted, in the portfolio.

The statistics in the following table show the effectiveness of applying these constraints. Using the same time frame, the standard deviation was decreased by nearly two-thirds (2/3) from 44.2% to 15.4%. Even with an annualized return that is more than 900 basis points lower than the unconstrained Haugen Model, the Low Vol Smart Beta Model provides a much better Sharpe ratio of 1.29 as compared with 0.63.

| | **Low Vol Smart Beta Model** | **Russell 2000 Value** | **Russell 3000 Value** |
|---|---|---|---|
| **Annualized Total Return** | 19.92% | 8.87% | 7.72% |
| **Standard Deviation** | 15.42% | 18.20% | 17.12% |
| **Sharpe Ratio** | 1.29 | 0.49 | 0.45 |

The growth of a dollar line graph comparison below also demonstrates better traditional institutional suitability for the Low Vol Smart Beta model.




***Implications for Potential Haugen Model ETFs***

Since the early portion of this paper focused on the Smart Beta revolution and its acceleration by the availability of Smart Beta products in ETF wrappers, it would be remiss not to discuss the potential for ETFs to exploit factor cyclicality with a high degree of granularity. The success of single factor and multi-factor ETFs would predict that the space is worth exploring. This is true but there are further considerations that would need to be identified and analyzed for the feasibility of adapting the Haugen Model to this area.

Given the huge return swings and other uncomfortable aspects of the unconstrained Haugen Model's top decile, the equity signals from that model would first appear to be more suitable for hedge funds or similarly sophisticated institutions in combining them with other strategies rather than for the general risk profile of institutional and other ETF investors. However, the constraints and stability of the Low Vol Smart Beta model provide a much more conventional and appealing profile. The possible concerns of monthly rebalancing rather than the more common Smart Beta ETF practice of quarterly rebalancing can likely be surmounted.

The marketing may be a trickier challenge. The major ETF providers have generally attempted to provide Smart Beta products that can be used by Registered Investment Advisors (RIAs) as well as institutional investors as stand-alone core portfolio holdings and as part of an advisor's tactical framework. In the majority of cases, they have been successful in doing these by erring on the side of being simple and easily understandable rather than seeking the most optimal incremental returns. Therefore, successful ETF providers might be uncomfortable knowing that (1) the model is complex; and (2) the methodology is not fully disclosed for competitive reasons. For ETF providers, perhaps the most useful take-away is that this study documents the fact that superior incremental returns on a risk-adjusted basis are achievable through more granular factor rotation. This evidence is both proof of concept for what already is available and reason to continue to develop potentially superior portfolio products.

***Summary***

The increased popularity of Smart Beta portfolios and ETFs into mainstream investing is marked by the billions of dollars in global inflows into such products throughout the past decade. Data on single factor ETFs showed that most could be classified into one of six factor types. Indexes that have been weighted based on these factors have demonstrated performance histories marked by cyclicality. Dynamic weighting schemes attempt to exploit this cyclicality. Recent research explored different methods that trigger rotation among Smart Beta factors. Some results are promising but require long-term validation. The simplicity of some proposed factor rotation models have also been vigorously challenged.

In contrast, the Haugen Model is not simple but rather sophisticated and uses machine learning processes. It is based upon an extremely granular breakdown of factor types into 60 factors each with their own sensitivities to market movements which are translated into portfolio weightings. Using as many as 12 different measures as separate factors for a single factor type will be dismissed by many investment professionals as being too complex. Yet, the consistency and magnitude of the superior rates of return over 20 years of top decile portfolios produced by the Haugen Model should demand further attention and scrutiny. The returns of the low-volatility Smart Beta portfolios are not quite as high in magnitude but are just as consistent. The portfolios demonstrate significantly higher incremental returns on an absolute and a risk adjusted basis. These are actual returns – not backtested returns. The factors and the returns created by each of the deciles portfolios have been produced in real time since 1996. This series of returns would be nearly impossible to achieve with the timing methods used in the research with only six Smart Beta factors in the set. The additional information from decomposing these factor types into 60 factors has made the Haugen Model smart enough to outsmart Smart Beta.

*Disclosure: Global Finesse LLC was engaged to devise and perform independent analyses and prepare a research paper for Haugen Equity Signals LLC. The client provided these data and gave us full access to its history and derivations as covered under a confidentiality agreement. Thus, while the authors believe these data and the analyses contained within to be accurate and consistent, we disclose that we did not ourselves derive or validate the co-efficient weights utilized in the calculation of security or portfolio returns. Global Finesse LLC is a consulting firm that does not sponsor, manage or directly sell any investment vehicles.*

**REFERENCES**


Arnott, Robert D., Noah Beck, and Vitali Kalesnik. "Timing 'Smart Beta' Strategies? Of Course! Buy Low, Sell High!." (2016).

Arnott, Robert D., Jason Hsu, and Philip Moore. "Fundamental indexation." *Financial Analysts Journal* (2005): 83-99.

Arnott, Robert D., Engin Kose. "What Smart Beta Means to Us." *Research Affiliates* (August 2014): 2.

Asness, Cliff, "Factor Timing is Hard." *AQR Insights/Perspectives* (2017).

Bender, Jennifer, Xiaole Sun, Ric Thomas and Volodymyr Zdorovtsov, "The Promises and Pitfalls of Factor Timing", *The Journal of Portfolio Management Quantitative Special Issue 2018,* 44 (4): 79-92.

Bernstein, Peter L. "Capital Ideas." *John Wiley and Sons* (1991): 21 – 38.

Black, Fischer, and Robert S. Kaplan. "Yes, Virginia, there is hope: Tests of the Value Line ranking system." *Financial Analysts Journal* (1973): 10-14.

Blank, Herbert. "Multifactor Equity Models." *Global Equity Selection Strategies* (1998): 237 – 255.

Blank, Herbert, and Qiao Duan. "The Case for Reverse Market Cap Indexing." *Exponential Shares* (2017).

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. "Economic forces and the stock market." *Journal of Business* (1986): 383-403.

Fama, Eugene F., and Kenneth R. French. "The cross-section of expected stock returns." *The Journal of Finance* 47, no. 2 (1992): 427-465.

Goodwin, Thomas. "Taming the Factor Zoo." *London Stock Exchange Group* (2018).

Haugen, Robert A., and A. James Heins. "Risk and the rate of return on financial assets: Some old wine in new bottles." *Journal of Financial and Quantitative Analysis* 10, no. 5 (1975): 775-784.

Haugen, Robert A., and Nardin L. Baker. "The efficient market inefficiency of capitalization–weighted stock portfolios." *The Journal of Portfolio Management* 17, no. 3 (1991): 35-40.

Hodges, Philip, Ked Hogan, Justin R. Peterson, and Andrew Ang. "Factor timing with cross-sectional and time-series predictors." *The Journal of Portfolio Management* 44, no. 1 (2017): 30-43.

Hougan, Matthew. "Why Many Smart Beta Backtests Fail." *ETF* (2017).

Kothari, Smitu P., and Jay Shanken. "Book-to-market, dividend yield, and expected market returns: A time-series analysis." *Journal of Financial Economics* 44, no. 2 (1997): 169-203.

Rosenberg, Barr, and James Guy. "Prediction of beta from investment fundamentals: part one, prediction criteria." *Financial Analysts Journal* (1976): 60-72.

Ross, S. A. "The arbitrage theory of capital asset pricing", *Journal of Economic Theor*y (1976).

Sharpe, William F. "Capital asset prices: A theory of market equilibrium under conditions of risk." *The Journal of Finance* 19, no. 3 (1964): 425-442.

Sill, Keith. "Macroeconomic risk and the determination of expected returns on stocks." *Managerial Finance* 21, no. 7 (1995): 43-56.

"S&P Indices Versus Active Indexology®." Indexology. Accessed November 15, 2018. https://us.spindices.com/spiva/#/reports.

Stoneberg CFA, Matthew and Smith, Bradley, INVESCO White Paper 2017 "Getting Smart about Beta: Examining Smart Beta Strategies and Their Impacts over Several Market Cycles".

"The Callan Periodic Table of Investment Returns." Callan. 2018. Accessed November 16, 2018. https://www.callan.com/periodic-table/.

Thomas CFA, Ric and Rob Shapiro CFA, "IQ Insights: Dynamic Timing of Smart Beta Strategies: Is It Possible?" Publication, State Street Global Advisors 2015: 9.