Cass Business School
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Smart Beta:
Part 2: What lies beneath?

What is the evidence for smart beta?

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1. Introduction

In the first paper in this series we reviewed the origins of smart beta. These origins can be found in academic research that in some cases stretches back to the 1970s. Often this research set out to test the predictions of the Efficient Market Hypothesis (EMH) and the related Capital Asset Pricing Model (CAPM). However, rather than confirm these predictions they ended up documenting puzzling financial market anomalies. Further research into each 'anomaly' established that they were proxying for, until then, unknown risk factors. It was shown that exposing a portfolio to, for example, the 'size' and 'value' factors would be rewarded with higher risk-adjusted returns than could be earned from exposure to the 'market', that is, exposure to 'beta risk'. These factors were alternative sources of systematic risk, and once these new academic findings came to the attention of the wider investment industry and media they were referred to in more media friendly terms as 'smart betas'.

More generally the term smart beta is now used to describe any, transparent, rules-based investment strategy, the simplest of which can be reproduced as index benchmarks, that is, as 'smart beta' indices that can be compared with the more familiar Market Cap-weighted indices such as the S&P500 Composite or the FTSE-100 indices. In this paper we examine the performance of some relatively well known, commercially available smart beta investment strategies, which investors can index their investment portfolios against, or indeed task their manager to outperform. Having analysed the performance of some of these investment approaches, we then pop the hood and investigate the source(s) of their performance. However, before we report the results of these investigations we couldn't resist the opportunity to present you with the results of Cass's own rules-based, investment strategy – although Cass has no intention of making it commercially available!

2. Cass' new investment methodology

As indicated in the introduction the natural benchmark for 'smart beta' investment strategies is arguably the performance of a Market Capitalisation-weighted index which, as we pointed out in the first paper in this series, can be thought of as a rules-based investment strategy too. In this section of the paper we present our own investment strategy, comparing its performance with that of a Market Capitalization-weighted benchmark. Before we present our results it is also worth remembering the difficulties that active fund managers have in beating such benchmarks on a consistent basis and over the long-term[1].

To test our investment strategy against a Market Cap-weighted benchmark, we put together a comprehensive database. We collected the end month, total returns on all US equities quoted on the NYSE, Amex and NASDAQ stock exchanges spanning the period from January 1964 to December 2014. Using this data we identified the 500 largest stocks by Market Capitalization as at each December in our sample. From this data we constructed a Market Cap-weighted index where we updated the index weights annually. Using the same data we also constructed an index using a different rules-based approach. These rules were in turn based on the popular board game Scrabble™ [2]. Here's how it works.

Every stock in the dataset that we collected has a ticker symbol, that is, a three or four letter code. For example, the ticker for the software group Apple is AAPL and for Exxon Mobil it is XOM. For each company we calculated each company's Scrabble™ score based on the points awarded for each letter in the game:

- A, E, I, O, U, L, N, S, T, R (1 point)
- D, G (2 points)
- B, C, M, P (3 points)
- F, H, V, W, Y (4 points)
- K (5 points)
- J, X (8 points)
- Q, Z (10 points)

We then sum each company's score. For example, AAPL scores six while XOM scores twelve. We then divide each stock's score by the total score of all 500 to give the stock's weight in the index, thus Exxon Mobil will receive twice the weight of Apple. We repeated this process at the end of each year, just as we rebalanced the weights of the Market Cap-weighted index.

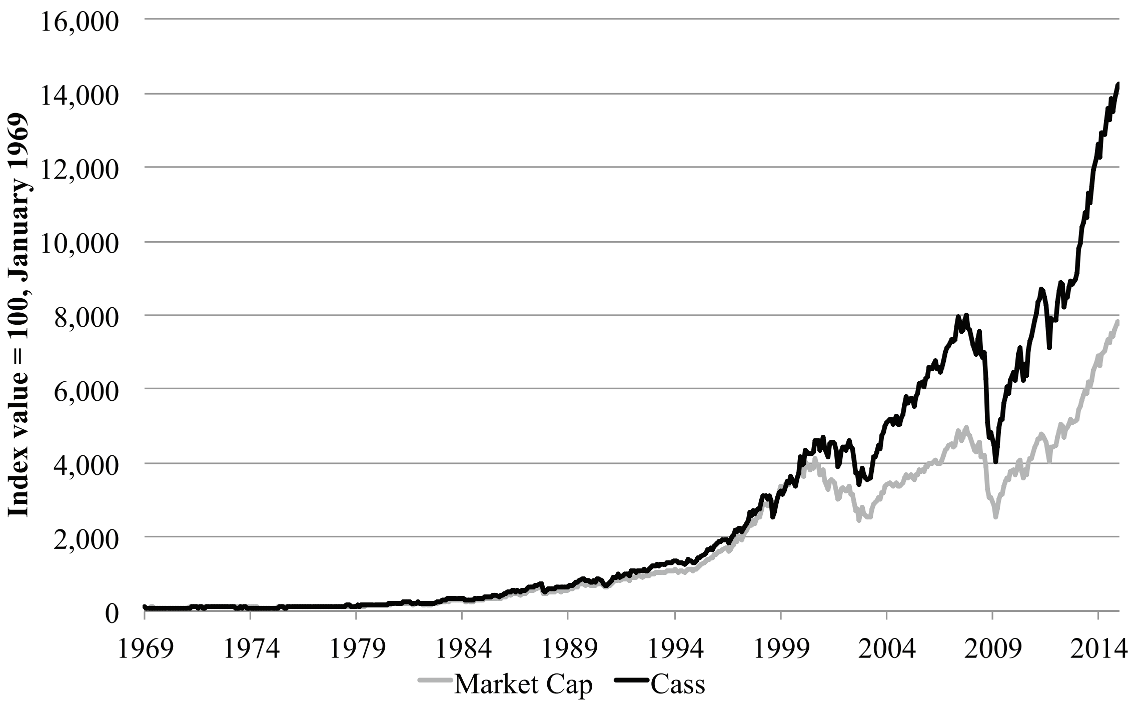
From the same database then we have created two sets of returns, one based on the familiar rules of Market Cap and the other based on the rules of Scrabble™. We were then able to compare the performances of the two approaches

Figure 1 shows the performance of the two strategies. By the end of 2014, $100 invested at the end of December 1968 in the index where weights were determined annually on the basis of Market Cap,

1 For evidence, see The Trustee Guide to Investment, Palgrave, London, pp370-371.
2 This paper is being produced by Cass Business School and Invesco PowerShares. It is not endorsed by any rights holder in respect of the Scrabble game.

would be worth $7,718. Not bad. But the same $100 invested instead at the same time in the index where the weights were determined by each stock's ticker Scrabble™ score, would be worth $14,108, almost double the benchmark. Table 1 presents more detailed analysis of the performance of both strategies. It shows that the Scrabble™ Index outperforms the Market Cap benchmark by 1.53%pa. This outperformance comes with slightly more volatility, 16.32% compared with 15.0%, but that overall the risk-adjusted performance of the Scrabble™ index is better since it achieves a Sharpe ratio of 0.44 compared with 0.38.

Figure 1: Cass' Scrabble™ index versus a Market Cap-weighted index



This figure presents the performance of the market cap weighted and Scrabble™ weighted indices over the sample period of January 1969 to December 2014. Both indices are based upon an annual re-sampling of the 500 largest US stocks from the CRSP database and have an initial value of 100 on 31st December 1968.

Table 1: Cass' Scrabble™ index versus a Market Cap-weighted index

	Terminal Wealth	Mean Return pa	Standard Deviation	Sharpe Ratio
Market Cap-Weighted	$7,718	10.62%	15.00%	0.38
Cass Scrabble™-Weighted	$14,108	12.15%	16.32%	0.44

This table presents performance statistics for each index listed in column 1 over the sample period of January 1969 to December 2014, based upon an annual re-sampling of the 500 largest US stocks from the CRSP database. The terminal wealth value is based on an initial investment of $100 on 31st December 1968. The mean returns and standard deviations are both annualised figures. The Sharpe ratio values are calculated using the appropriate annualised return and volatility values, where the risk free rate was proxied by the monthly return on US T-Bills

Overall then we believe that our investment strategy performed well. Most institutional investors would have been very pleased with outperformance of this kind over this time period from their active fund managers. It is of course very possible that our investment methodology got lucky. But before we deal with the question of luck, in the next section of this paper we present the performance of a selection of smart beta investment strategies that are available commercially in index form so that investors can either track or use them as benchmarks.

3. The performance of some smart beta methodologies

The first column of Table 2 presents the investment methodologies that we evaluate. The performance of each one is derived from the same, underlying dataset described above. In each case we use the appropriate set of rules to fix the weights of the 500 stocks annually. The rules for some are fairly straightforward, while others are much more complex. For the Equally-weighted strategy, each of the 500 stocks has an equal weight (0.2%). The Diversity-weighted index can be thought of as a cross between the Market Cap-weighted approach and an equally-weighted approach. The Inverse Volatility-weighted strategy involves assigning the biggest weight to the stock with the lowest volatility and the lowest weight to the stock with the highest volatility. The Equal Risk Contribution strategy is similar to the Inverse Volatility approach, with the subtle difference that the weight of each stock is calculated so that the contribution of every stock to the volatility of the portfolio overall is the same. The Minimum Variance Portfolio approach assigns weights such that the weighted combination of stocks produces the lowest portfolio volatility of any combination of stocks. The Maximum Diversification approach to investment chooses stock weights so that the combination maximises the diversification of the stocks within the portfolio. The Risk Efficient approach attempts to maximize the Sharpe ratio where the expected return of each stock is assumed to be proportional to its' historical downside deviation. Finally, the Fundamentally-weighted approach assigns weights according to a company's book value, sales, dividends and cash flow.[3]

We applied each of these rules-based portfolio construction processes to the data described earlier to produce a continuous, monthly set of returns from January 1969 to December 2014 for each one. The results are presented in Table 2. Every one of the investment approaches produced a higher level of terminal wealth than the Market Cap-weighted approach, and in some cases, almost twice as much; five of the strategies produced a lower level of volatility (standard deviation); and every one produced higher risk-adjusted return, as represented by the Sharpe ratio.

Table 2: Smart beta performance

	Terminal Wealth	Mean Return pa	Standard Deviation	Sharpe Ratio
Market Cap-Weighted	$7,718	10.6%	15.00%	0.38
Equally-Weighted	$12,957	11.9%	16.15%	0.43
Diversity-Weighted	$8,938	11.0%	15.27%	0.39
Inverse Volatility-Weighted	$13,993	11.8%	14.13%	0.48
Equal Risk Contribution	$13,803	11.9%	14.93%	0.46
Minimum Variance Portfolio	$10,247	10.8%	12.04%	0.49
Maximum Diversification	$12,872	11.6%	14.16%	0.47
Risk Efficient	$14,119	12.0%	15.62%	0.45
Fundamentally-Weighted	$13,981	11.9%	14.81%	0.47

This table presents performance statistics for each index listed in column 1 over the sample period of January 1969 to December 2014, based upon an annual re-sampling of the 500 largest US stocks from the CRSP database. The terminal wealth value is based on an initial investment of $100 on 31st December 1968. The mean returns and standard deviations are both annualised figures. The Sharpe ratio values are calculated using the appropriate annualised return and volatility values, where the risk free rate was proxied by the monthly return on US T-Bills

[3] For a more detailed description of all these approaches we refer interested readers to the following two links and the references therein: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2242028 and http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2242034

These results seem to put the Scrabble™-related investment methodology in a less flattering context, although it performed well, the results show that the Market Cap-weighted investment strategy was outperformed by all the other strategies.

The results presented in Table 2 do not reveal much about the make-up of each strategy, or take into account such real world issues as turnover and transactions costs. Table 3 presents more information about the smart beta investment strategies and our own Scrabble™ methodology. Column 2 of table 3 presents the average size of each index's constituents as a proportion of the average size of the constituent's in the index generated by the Market Cap strategy. The results in this column show, for example, that the average size of the stocks in the Equally-Weighted strategy are 24% of the average size of the Market Cap-weighted strategy. Indeed all of the strategies invest in stocks that are, on average, smaller than those in the familiar benchmark. The alternative strategy that involves investment in the largest stocks on average is the Fundamentally-weighted approach, where we observe that on average the stocks in this portfolio are 87% of the size of the Market Cap-weighted strategy. Overall though, it would be fair to say that these smart beta approaches tend to have a bias towards smaller stocks.

Table 3: Looking under the Smart Beta hood

	Average Market Cap as % of Market Cap	Active Share	Turnover	Transaction costs to equalise Sharpe ratio
Market Cap-Weighted	100%	0.00%	5.44%	-
Equally-Weighted	24%	44.23%	17.89%	3.8%
Diversity-Weighted	73%	12.91%	7.24%	7.9%
Inverse Volatility-Weighted	29%	44.43%	16.54%	6.7%
Equal Risk Contribution	26%	43.29%	16.90%	5.8%
Minimum Variance Portfolio	41%	88.42%	37.31%	2.1%
Maximum Diversification	21%	78.89%	47.93%	1.6%
Risk Efficient	23%	50.64%	29.59%	2.6%
Fundamentally-Weighted	87%	28.16%	11.75%	10.7%
Cass Scrabble™-Weighted	24%	46.90%	18.31%	4.3%

This table presents descriptive statistics for each index listed in column 1 over the sample period of January 1969 to December 2014, based upon an annual re-sampling of the 500 largest US stocks from the CRSP database. The Average Market Cap is calculated as the sum of the product of the index weight and market cap for each stock. Active Share is calculated using the market cap index as the benchmark. Turnover is the mean annual one-way turnover. The transaction costs to equalise Sharpe ratio is solved iteratively to identify the level of transaction costs when applied to the turnover of both the market cap and alternative indices that would result in an identical Sharpe ratio.

Column 3 in Table 3 presents the average Active Share of each index, relative to the Market Cap index. This statistic is becoming a popular way of ascertaining how active one's active fund manager is; the higher the number the more active the manager. In this case we have calculated the degree of "activeness" relative to the Market Cap-weighted strategy (which is the typical approach), which explains why the 'active' element of this portfolio is 0.0%. Most have a relatively high active share, but the active share of the Minimum Variance (88.4%) and Maximum Diversification (78.9%) strategies are particularly high. If these statistics were produced by an active fund manager, in the absence of other information, we would be justified in concluding that these were 'benchmark unconstrained' managers, that is, managers that constructed portfolios with little or no reference to their benchmark.

The fourth column in Table 4 presents the turnover statistics for each methodology. This turnover activity is generated by the annual rebalancing of the indices. The methodology with the lowest turnover – by far – is the Market Cap-weighted strategy where, on average we were required to sell 5.44% of the portfolio at the end of each year. The three strategies with the highest average, annual turnover are the Minimum Variance (37.3%), Maximum Diversification (47.9%) and Risk Efficient (29.6%) strategies. High levels of turnover of course imply high levels of transactions costs. To see whether the higher turnover of the smart beta approaches would in practice reduce the attractiveness of these relative to the Market Cap benchmark, we calculated a break-even level of transactions costs. That is, using the turnover statistics we calculated the level of transactions costs that would cause the Sharpe ratios of the alternative strategies to be equal to performance of the Market Cap-weighted strategy. These estimates are presented in the last column of Table 3. So, for example, we estimate that if the bid-ask spread on US stocks averaged 3.8% then the Equally-Weighted strategy would have produced the same Sharpe ratio as the Market Cap-weighted strategy. In all cases the transactions costs would have had to have been implausibly high to wipe out the performance advantage of the smart beta approaches. In the case of the Fundamentally-weighted strategy, bid-ask spreads would have had to average 10.7%.

Our conclusion is that although the alternative strategies may involve higher portfolio turnover this is not sufficient to explain the performance differences. Furthermore, in practice the smart beta indices upon which these strategies are based often introduce rules to reduce turnover.

4. Bad luck or bad design?

So if turnover and transactions costs cannot account for the superior performance of the smart beta strategies, perhaps luck can? In any 'horse race' between any ten investment strategies it should not be surprising that one will win and one will lose, perhaps then the Market Cap approach was just unlucky?

The infinite monkey theorem states that a monkey hitting keys at random on a typewriter keyboard for an infinite amount of time will eventually type a given text, such as the complete works of Shakespeare. There are clearly an infinite number of possible combinations of portfolio weights for 500 stocks that would sum to 100%, some of these will outperform the Market Cap approach while others will underperform; thus far however we have only considered ten of the possible weighting schemes.

In the absence of an infinite number of real monkeys in order to determine the degree of luck involved in the performance of all of the investment strategies we designed a simple, though computationally strenuous experiment. At the beginning of each year in our sample we 'asked' the computer to assign weights to the 500 stocks by:

i. Asking the computer to chose at random one of the 500 stocks
ii. This stock was assigned an index weight of 0.2%,
iii. We then repeated this process 500 times. If a stock was chosen once it would therefore be assigned a weight of 0.2%, if it was never picked it would be given a weight of 0.0%, if it was picked at random 500 times in a row, then it would be assigned an index weight of 100%.
iv. We then repeated this process for every year in our sample, which ultimately produced the returns on an index that may just as well have been chosen by a monkey.
v. We then repeated steps (i) and (iv) 10,000,000 times producing 10,000,000 indices where the weights had been chosen every year at random.
vi. Finally, we then analysed the performance of all ten million formulations of this random index construction technique, and compared their performance with the performance of the smart beta strategies.

Table 4 contains a summary of the results of this experiment. We compared many aspects of the performance of the monkey-constructed indices with those constructed using the smart beta methodologies, but in Table 4 we focus on the Sharpe ratio produced by each. The first row in the column shows that 9,988,179 randomly constructed indices beat the Market Cap-weighted approach; the former 'won' on only 0.12% of occasions. This is a remarkable result, and one which is highly statistically significant. It suggests that we can be almost 99.9% sure that the relatively poor risk-adjusted performance of the Market Cap strategy was due to bad design rather than to bad luck.

Table 4: Luck or skill – Monkeys versus smart beta Sharpe ratios

	Sharpe Ratio	Monkeys winning	Monkeys losing	% of monkeys losing
Market Cap-Weighted	0.38	9,988,179	11,821	0.12%
Equal-Weighted	0.43	4,369,089	5,630,911	56.3%
Diversity-Weighted	0.39	9,783,093	216,907	2.2%
Inverse Volatility-Weighted	0.48	19,540	9,980,460	99.8%
Equal Risk-Contribution	0.46	307,272	9,692,728	96.9%
Minimum Variance Portfolio	0.49	10,335	9,989,665	99.9%
Maximum Diversification	0.47	134,851	9,865,149	98.7%
Risk Efficient	0.45	949,554	9,050,446	90.5%
Fundamentally-Weighted	0.47	177,443	9,822,557	98.2%
Cass Scrabble™-Weighted	0.44	2,615,774	7,384,226	73.8%

This table compares the performance of each index listed in column 1 over the sample period of January 1969 to December 2014 to the performance of 10 million randomly created indices, based upon an annual re-sampling of the 500 largest US stocks from the CRSP database. The Sharpe ratio values are calculated using the appropriate annualised return and volatility values, where the risk free rate was proxied by the monthly return on US T-Bills

Now consider the results for the smart beta strategies. With the exception of the Equally-Weighted (56.2%) and Diversity-Weighted (2.2%) strategies, the other commercially available smart beta approaches beat at least 90% of the monkeys, with the Minimum Variance Portfolio beating 99.9% of the monkeys, meaning that we can be sure 99.9% sure that the risk-adjusted performance of this approach was due to good design rather than to good luck. Even our own Scrabble™ strategy beats 73.8% of the monkeys.

5. Where does the smart beta performance come from?

Sections 3 and 4 of this paper suggest that the performance of the smart beta investments strategies that we examined cannot be explained by turnover and transactions costs, and that it cannot be put down to luck either. This begs the following question: where does smart beta performance come from?

To answer this question we used the Fama-French three factor model, enhanced with an additional factor, momentum. As we explained in the first paper in this series, this model decomposes the returns on any investment portfolio into return that comes from exposure to the following risk factors: the Market; Size; Value; and Momentum. What remains is either due to manager skill, or to either good or bad luck. Using this model we attributed the excess smart beta strategy performance to these four factors. A summary of these results are shown in Table 5.

Table 5: Excess Performance Attribution (pa)

	Total	Market	Size	Value	Momentum	Residual
Equally-Weighted	**1.32%**	0.24%	0.35%	0.60%	-0.26%	0.38%
Diversity-Weighted	**0.36%**	0.09%	0.09%	0.18%	-0.06%	0.06%
Inverse Volatility-Weighted	**1.17%**	-0.39%	0.16%	1.16%	-0.09%	0.33%
Equal Risk Contribution	**1.26%**	-0.11%	0.24%	0.90%	-0.17%	0.40%
Minimum Variance Portfolio	**0.21%**	-1.94%	-0.01%	1.62%	0.15%	0.40%
Maximum Diversification	**1.00%**	-0.65%	0.28%	0.61%	0.19%	0.58%
Risk Efficient	**1.42%**	0.04%	0.34%	0.99%	-0.50%	0.54%
Fundamentally-Weighted	**1.27%**	-0.01%	0.04%	1.25%	-0.48%	0.48%
Cass Scrabble™-Weighted	**1.53%**	0.25%	0.37%	0.42%	-0.25%	0.75%

This table presents performance attribution for each index listed in column 1 over the sample period of January 1969 to December 2014 calculated using OLS regression estimates where the excess return on each index listed in column 1 is the dependent variable and the four independent variables are the risk factors obtained from Kenneth French's data library.

The second column in Table 5 presents the annualised excess performance of each strategy, for example, the Equally-Weighted strategy outperforms the Market Cap-Weighted strategy by 1.32%pa. The next five columns decompose this excess performance into its component parts and together sum to the total. The third column shows the additional performance that is derived from exposure to the broad market. Perhaps surprisingly, for five of the strategies, the Market exposure actually detracts from the excess performance. To be clear this does not mean that these strategies have a negative exposure to the broader market; instead it means that it is, on average, less exposed to this risk factor. In a similar vein, the fourth column in the table indicates that exposure to the Size risk factor generally contributes positively to excess performance. The very small negative value of -0.01% for the Minimum Variance approach, indicates that this strategy derives virtually no additional performance from this risk factor. The results in Table 5 indicate clearly that most of the additional performance for most of the strategies comes from a positive exposure to the Value factor. For example, the Fundamentally-Weighted approach derives additional performance of 1.25%pa from exposure to this factor, while the Minimum Variance approach derives additional performance of 1.62%pa. The penultimate column in Table 5 shows that only the Minimum Variance and Maximum Diversification approaches derives additional performance from exposure to the Momentum risk factor; for the rest of the investment strategies a lower exposure to this risk factor detracts from excess performance. Finally, the last column in Table 5 presents the amount of additional performance that cannot be attributed to the four risk factors. In some cases this value is quite high, for example, in the case of the Maximum Diversification strategy it is 0.58%pa.

The results in Table 5 demonstrate that at least some portion of these smart beta investment strategies can be attributed to some of the risk factors described in paper one in this series. However, it seems that they are not garnering the full benefit of each risk factor. For example, we calculated that the performance advantage of the 20% of stocks with the highest price momentum over the 20% of stocks with the lowest price momentum was 2.61%. So although the smart beta strategies were adding value through exposure to the Value factor, their often negative exposure to the Momentum factor meant that they are possibly missing out on the additional performance that exposure to this factor offers. This begs the question then as to whether it is possible to combine exposure to risk factors in a way that can help investors add value from exposure to all of these factors?

6. Conclusions

In this paper we have explored the evidence for smart beta investing. We have seen how easy it has been to construct an index, based on simple, transparent rules that can outperform an index constructed according to Market Cap weights. Even an index constructed with the help of the rules of Scrabble™ can do it! We explored generic versions of a few of the commercially available smart beta approaches to investment, all of which also outperformed a Market Cap-weighted approach over the period from 1969 to 2014. Of course, past performance is no guarantee to future performance, but the "monkey-based" experiments indicate that the outperformance appears to be driven by the bad design of the Market Cap-weighted process and/or the superior design of the smart beta approaches, rather than by luck. We also dug into the DNA of these smart beta investment processes and showed that a significant component of the smart beta outperformance over the Market Cap-weighted benchmark could be decomposed into different combinations of the very same factors that had been identified in the academic literature as constituting the 'origins of smart beta'.

The results presented in this paper may lead some investors to consider one of the smart beta approaches examined here, or possibly other similar commercially available investment vehicles. However, the evidence that a significant part of smart beta performance can be broken down into component parts leads to an interesting question: is it possible to produce portfolios with attractive risk and return characteristics by combining these component parts? And, if it is possible, how should these components be combined? The next paper in this series will explore both of these questions, combining smart beta building blocks using both static and dynamic, transparent approaches.

Contributors

Prof. Andrew Clare

Andrew Clare is the Professor of Asset Management at Cass Business School and the Associate Dean responsible for Cass's MSc programme, which is the largest in Europe. He was a Senior Research Manager in the Monetary Analysis wing of the Bank of England which supported the work of the Monetary Policy Committee. While at the Bank Andrew was responsible for equity market and derivatives research. Andrew also spent three years working as the Financial Economist for Legal and General Investment Management (LGIM), where he was responsible for the group's investment process and where he began the development of LGIM's initial Liability Driven Investment offering. He is the co-author of "The Trustee Guide to Investment". He has also published extensively in both academic and practitioner journals on a wide range of economic and financial market issues. In a survey published in 2007, Andrew was ranked as the world's ninth most prolific finance author of the past fifty years. Andrew serves on the investment committee of the GEC Marconi pension plan, which oversees the investments and investment strategy of this £4.0bn scheme, and is a trustee and Chairman of the Investment Committee of the £2.5bn Magnox Electric Group Pension scheme.

Prof. Stephen Thomas

Steve Thomas is Professor of Finance and Course Director for the Executive MBA at Cass Business School, London. Prior to this he has been a Professor of Finance at the University of Wales, Swansea, and at Southampton University, and a Visiting Professor at the ICMA Centre,University of Reading,and Queen's University, Canada. He has been a Houblon-Norman Fellow at the Bank of England (1990).

Steve has published widely in the areas of market microstructure, economics, and investment strategy and in 2005 was ranked 11th in Europe for published finance research over the previous decade. His research has won a number of awards including prizes, for the Best Paper, Global Finance Conference, Dublin, 2005 and the Best Market MicroStructure Paper, Mid-West Finance Meetings, Chicago,2006. He has also co-authored the 13 editions of the Official Training Manual for the Investment Management Certificate for CFA UK.

Steve has been involved in private client investment strategy for Firecrest Hambro, and fund strategy with Hasley Investment Management and WM Capital; he was a director of Bear Stearns Global Alpha Macro Hedge strategy London, 2005-7. In 2011 he helped create Solent Systematic Investment Strategies which creates and advises on quantitative investment strategies. He was a member of the SME Business Finance Review Advisory Board for the Welsh Assembly Government(2013).

Dr. Nick Motson

Dr Nick Motson holds a BSc from City University Business School, an MSc from London Business School and a PhD from Cass Business School. Following a 13 year career as a proprietary trader of interest rate derivatives in the City of London for various banks including First National Bank of Chicago, Industrial Bank of Japan and Wachovia Bank, Nick returned to Cass in 2005 to pursue his doctoral studies. Upon completion of his PhD he joined the faculty of finance full-time in 2008.

Nick's research interests include asset management, portfolio construction, hedge funds, alternative assets and structured products. In 2009 he was awarded the Sciens Capital Award for Best Academic Article, in The Journal of Alternative Investments for his paper Locking in the Profits or Putting It All on Black? An Empirical Investigation into the Risk-Taking Behaviour of Hedge Fund Managers.

Nick teaches extensively at masters level on alternative investments, derivatives and structured products and in recognition of the quality of his teaching he was nominated for the Economist Intelligence Unit Business Professor of the Year Award in 2012.

As well as teaching and researching at Cass, Nick actively consults for numerous banks and hedge funds and has provided research or training clients including ABN Amro, Aon Hewitt, Barclays Wealth, BNP Paribas, Financial Express, FM Capital Partners, Invesco Perpetual, NewEdge, Old Mutual and Société Générale.

Source: Cass Business School, as at end of October 2015.

About Invesco PowerShares

PowerShares was founded in the US in 2003 on a vision of delivering investment performance through the benefit-rich Exchange Traded Fund (ETF) structure. In January 2006, PowerShares expanded its vision by becoming part of Invesco Ltd, whose global presence took the Invesco PowerShares story beyond the US.

When the first ever ETF was launched in 1993, its purpose was simple — to track the S&P 500 Index while trading on a major exchange. Since then, many traditional ETFs have been designed to mirror a number of different benchmark indices. Not all ETFs, however, seek to simply track a measure of a market.

Invesco PowerShares offers a selection of ETFs that track "next generation" indices: indices that go beyond merely tracking a particular market. These indices seek to outperform the performance of a particular market through intelligent security selection and weighting.

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About Cass Business School

In 2002, City University's Business School was renamed Sir John Cass Business School following a generous donation towards the development of its new building in Bunhill Row. The School's name is usually abbreviated to Cass Business School.

Sir John Cass's Foundation

Sir John Cass's Foundation has supported education in London since the 18th century and takes its name from its founder, Sir John Cass, who established a school in Aldgate in 1710. Born in the City of London in 1661, Sir John served as an MP for the City and was knighted in 1713.

Important information

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