A Centralised Investment Process: joined up investment thinking

Balancing risks through Strategic Asset Allocation and Populating Portfolios with Winning Funds

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Executive Summary

This paper offers a consistent and rigorous approach to creating appropriate investment portfolios by guiding investors from the financial planning and risk profiling stages, through to the design and implementation of the investing decision itself.

By working with well-established and internationally renowned financial planning and risk tolerance toolkits, we create suitable strategies to meet the required capacity for loss, risk required and risk tolerance of individual investors.

Although we critique the under-researched area of risk profiling in some detail, our main contribution is to construct robust asset allocations in a highly evolving and uncertain world which will have a good chance of meeting client aspirations. The fundamental flaw that pervades much of the existing portfolio optimisation and construction analysis is that the future is forecastable: we totally reject this idea and construct portfolios which do not require forecasts of any variables.

In fact we suggest that even if the portfolio manager/advisor had perfect foresight the chosen portfolios would be inherently unstable and beyond reasonable implementation. Instead we show how our ‘risk balanced’ portfolio approach mimics the ( unknowable) market portfolio over a number of years and its success lies in the exposure of the diversified asset classes to economic sources of risk: basically, at various times the different asset classes will pick up the risk premia from the various macro sources of risk, but in a way in which prediction would not be able to enhance. Attempts to forecast such variables are doomed to failure.

Fortunately, these portfolio allocations evolve fairly slowly over time enabling the advisor to implement any changes in a cost efficient way.

This in itself gives us a number of chosen portfolios designed to meet target maximum loss (drawdowns) and as such can be thought of as a risk balanced multi-asset passive allocation: however we can uplift returns by around 200 bps pa (net) by populating the asset classes with specific active funds chosen by a proven selection process: alternatively the investor and advisor may wish to mix active and passive funds using allocations presented here.
1. Introduction

Identifying a client’s financial requirements, connecting this requirement to their risk tolerance, building an investment portfolio with appropriate proportions in each asset class and then selecting the right funds to populate this portfolio, all in one seamless process, is the holy grail of investment advisory.

In this paper we develop one approach to solving this problem which we believe is both theoretically and empirically robust at every stage, embodying comprehensive financial planning with sophisticated client risk profiling, a sound strategic asset allocation framework, and a fund selection technique for the major UK IMA sectors which has a 15 year proven track record of outperformance of both sector average and investment benchmark performance for many sectors. We believe that such a process will both improve a client’s experience of investment and investment advice immeasurably (which will in turn improve the experience of the adviser too!) while simultaneously addressing the major criticisms offered by the UK regulator of many of the misguided approaches prevalent in the advisory space. In addition, the process that we propose pays particular regard to transactions’ costs, both fiscal and organisational, that an adviser incurs in meeting client needs and which is crucial to the industry-wide acceptability of this or, indeed, any other joined up investment advisory process.

In 2011 the UK financial regulator, the FSA as it then was (now the FCA) published its Finalised Guidance regarding ‘Assessing Suitability’ in the context of the appropriate risk a customer is willing and able to take when making an investment selection. As background, the FSA found that in a recent sample of investment files which had failed their ‘suitability’ test, around half were considered to be unsuitable on the grounds that the investment selection failed to meet the risk that a customer is willing and able to take. It solemnly pronounced:

‘The level of failure in this area is unacceptable’ (FSA, March, 2011, para 1.4, p2).

The FSA study documented common features of processes deemed inadequate in assessing the risk a customer is willing and able to take. In particular, while most advisers did consider a customer’s attitude to risk when assessing suitability, there was a failure in many cases ‘to take appropriate account of their capacity for loss’, (para 1.8, p3), where the latter refers to the ability to absorb falls in the value of their investment. Basically, if any loss of capital would result in a negative impact on the customer’s standard of living, this should be taken into account in assessing the risk that they are able to take. In subsequent sections we draw attention to the way our intellectual framework for thinking about risk was historically subverted from concepts such as ‘maximum loss’ towards measures of volatility such as the standard deviation of investment returns and its close cousin, the Sharpe ratio. This process, begun over 60 years
ago with the advent of Modern Portfolio Theory, has penetrated much standard risk assessment thinking and calibration.

One particular difficulty noted by the FSA involves the need for a robust process in identifying customers that are best suited to holding cash as an investment because they are unwilling or unable to risk the loss of capital. One has to wonder if the absence of cash as an asset class in customer portfolios is related to a lack of incentives in recommending this low risk investment class? Indeed, the foundations of our modern thinking regarding recommended portfolios has its genesis in the above-mentioned Modern Portfolio Theory, a cornerstone of which is that ‘efficient’ portfolios for individuals combine the diversified ‘market’ portfolio’ with the risk-free asset, (so-called Two Fund Separation in the academic literature) with proportions of the two reflecting a client’s risk appetite.

Figure 1 below reflects the familiar textbook approach which still underpins much of the asset allocation recommended portfolio advice in the industry; it is based on combining assets/securities in particular proportions to maximise (expected) portfolio return for a given level of portfolio risk (here, standard deviation of portfolio returns), and requires the adviser or portfolio manager to specify both expected returns and risk for all assets/securities together with the correlations between these returns. Such a process leads to the concave line in Figure 1 which is called the Mean Variance Efficient Frontier (MVEF) – it maps out the highest expected return possible for taking on a given level of risk. In addition, when riskless cash (or T-bills) are added to the range of possibilities then the ‘best’ choice of portfolio for an investor lies on the dotted line which is tangent to the MVEF at the point known as the ‘market portfolio’; in the language of investment performance measurement, it is the Maximum Sharpe ratio portfolio (MSRP), ie, it offers the highest expected excess return (over the risk free rate) relative to its risk, as measured by standard deviation. It is the adviser’s task, following skilful risk assessment, to place the client at the appropriate point on this dotted line, ie, combining cash (a riskless asset) with risky assets. As Figure 1 suggests, the client with a greater appetite for risk will choose portfolios with less cash and more risky assets, ie, further up the dotted line (which is called the Capital Market Line).

There are two very major problems with this analysis:

i) forecasting expected returns, risk and correlations is notoriously difficult, if not impossible; and

ii) measuring risk by standard deviation does not sit easily with investor ideas of what constitutes ‘risk’.
Following the UK’s Retail Distribution Review (RDR) launched early in 2013, the dramatic reforms to the UK annuity market announced in the budget of March, 2014, along with the general demise of defined benefit pensions, the need for skilled financial advisers who can offer rigorous, consistent and intelligent investment solutions to customers has never been greater: there is a clear and present need for ‘joined up’ thinking that straddles the four key elements of any advised solution, that is:

i. financial planning
ii. risk calibration,
iii. portfolio construction, and
iv. fund selection

Each stage in the process should be as scientifically based as possible, drawing upon the most up-to-date industry and academic research available. We hope to show in this paper that such a rigorous and joined up approach is possible. The integrated effort is a blend of art and science\(^1\): investment recommendations will emanate from a combination of scientific tools such as financial planning software or risk tolerance questionnaires, together with an advisor’s ability to use these tools effectively in a rigorous and robust dialogue with the client. This will focus on client needs, mismatches and inconsistencies in their aspirations, and discussing alternative avenues to explore.

Securing an appropriate investment strategy for a given client while taking on board risk in a general sense is called ‘Risk Profiling’, and involves assessing risk required, capacity for loss and risk tolerance, key concepts which we discuss in detail in Section 2. This process will also involve identifying and resolving any mismatches between goals and (expected) investment reality.

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\(^1\) See Risk profiling: Art not science, G. Davey and P. Resnick, Finametrica, June 2012.
We begin with a discussion about financial planning (Section 2) and then move on to risk profiling (Section 3) – two key features in the process. We then consider the portfolio construction process (Section 4) where we draw upon recent academic research results where appropriate. Contrary to much current portfolio construction advice, where opaque algorithms are confusingly presented as tools of scientific progress, and where clients are told ‘*don’t worry about the mathematical details*’, instead we present a straightforward, transparent and intuitively plausible approach to deriving asset allocations for clients. We then discuss one method for choosing funds to populate those portfolios (Section 5), before concluding our report (Section 6).
2. Financial Planning: Separating Risk Tolerance from Capacity for loss

‘Personal financial planning is a process designed to enable consumers to achieve their personal financial goals.’
(ISO Standard 22222-Personal Financial Planning)

In order to help investors visualise their current wealth and show them how their goals and anticipated life events or decisions may financially affect them, advisers use a process called Lifetime Cash Flow Planning. Most people are used to budgeting, whether it be for food shopping, holidays, Christmas etc. Budgeting for life’s events may seem more complex and daunting, but it need not be. With the help from their adviser and utilising either a spreadsheet or specialist financial software, lifetime cash flow planning should be simple. The process can work as follows:

- Initially, advisers ask their clients about their financial goals.
- By agreeing certain assumptions about the future, the process helps to forecast investors’ income, expenditure, assets and liabilities throughout their lifetime.
- Effectively, this process enables advisers to show their clients in a highly visual way the robustness or weakness in their finances.
- This then enables their clients to think about their objectives, what they would like to achieve, and what financial options may be relevant to help mitigate against some or all of the factors detailed above.

In a nutshell, lifetime cashflow planning helps advisers to consider financial decisions with their clients and agree a sensible financial strategy for their future. In addition Monte Carlo techniques can help the advisor guide the client to understand that a range of outcomes are possible given the probabilistic nature of investment returns.

In their excellent review paper, Finametrica (2012) suggest that risk profiling should lie at the heart of financial planning. It is the process for determining an appropriate investment strategy with regard to risk, with risk itself having three main aspects:

- **Risk required** – the risk associated with the return that would be required to achieve the client’s goals (a financial characteristic).

- **Capacity for loss** – the extent to which the future can be less favourable than anticipated without derailing the client’s plans (a financial characteristic).
• **Risk tolerance** – the extent to which a consumer is willing to risk experiencing a less favourable financial outcome in the pursuit of a more favourable financial outcome (a psychological characteristic).

Assessing and comparing these three aspects of risk, together with the dialogue which accompanies any mismatches and the resolution of these mismatches, is the process known generically as ‘risk profiling’.

As an example of financial planning it could be that the clients need their investment to grow to a certain amount by a set date in the future. For example, if they wanted a £100,000 investment to grow to £150,000 in 10 years, then their adviser would know that their clients’ portfolio would need to rise by 4.17 percent p.a. in absolute terms, net of all charges. Or alternatively, their objective may be to achieve a return measured as a multiple of cash deposits, e.g., they may want their money to grow at a rate equivalent to 1½ times cash deposits. This would then help inform the adviser how to construct a portfolio designed to achieve this goal.

This part of a financial plan is often described as the ‘risk required’. We find such terminology rather counterintuitive since it is returns which are required, not risk as such (see also comments by Finametrica (2012)). Risk is only ‘required’ to the extent that it is associated with higher expected returns. However, this is a false promise: in fact the opposite outcome has often occurred in financial history (e.g., the recent 30 years of the bond bull market), with lower risk assets producing higher actual returns. A related common error is to refer to ‘growth’ assets and expect them to have higher returns (and risk) than non-growth assets. Indeed a whole area of empirical finance research is currently exploring the relation between low volatility (risk?) assets and higher returns. Perhaps the whole terminology should be surrounded by health warnings?

The term ‘capacity for loss’ or ‘risk capacity’ usually refers to clients’ ability to withstand a fall in their investment, both financially and emotionally, without being driven off course. In many ways, assessing capacity for loss helps to manage clients’ expectations. One of the best ways to measure the amount of loss that clients are able to tolerate is either by way of lifetime cash flow planning or to carry out ‘stress testing’, or, indeed, to combine both. Advisers should realise the need for portfolio recommendations to be tested against a range of possible outcomes to help determine the amount of loss their clients would feel comfortable with. When constructing client portfolios, advisers should also take into account any differences between the portfolio consistent with their cash flow needs, their risk tolerance and their capacity for loss. Financial planning software packages allow a financial plan to be stress-tested so that investors’ risk capacity - their ability to achieve goals in the event of investment underperformance - can be assessed.

While risk tolerance and capacity for loss seem relatively straightforward concepts, there is room for ambiguity regarding the traditional approach to evaluating risk tolerance in that it is a mixture of measuring a client’s attitudes to risk with an assessment of their financial capability to take risk (which will include time horizon, need for income etc). The UK’s FCA (formally, the FSA) made this distinction forcefully in a guidance paper in 2012, while reviewing common industry practices:

*In some instances information such as the customer’s attitude to risk and their capacity for loss is gathered together along with information related to the term of the investment or the age of the customer and conflated into a single output. By bundling information on different*
factors together, the value of each distinct piece of information is potentially lost because arbitrary weightings are applied to different factors, which may negate a preference or need. This can result in output that does not accurately reflect the trade-off decisions that a customer is willing or able to take. Kitces (2014) offers clear examples of the dangerous confusion possible here. Mixing the two concepts in one aggregate composite ‘risk’ score which then is assigned to a portfolio actually confuses a client’s capacity to take risk with their actual need or desire to do so.

As Kitces (2014) puts it very directly:

‘… the optimal portfolio solution is not a combination of risk tolerance and risk capacity: it’s the portfolio that can best achieve the client’s goals, constrained by risk tolerance to ensure that neither the portfolio, nor the goal, exceeds the client’s tolerance in the first place’.

This requires separating the following key concepts which should be properly aligned in the recommended portfolio:

• Does someone need risk?
• Can they afford risk?
• Do they want to take risk?

When assessing risk tolerance, and unlike risk required and risk capacity, which are financial parameters, risk tolerance is very distinctively a psychological parameter. Risk tolerance is how an individual feels about taking risk. Where does the person strike the emotional balance between seeking a favourable outcome versus risking loss?

Questionnaires for risk tolerance often combine attitudes to both the mental and financial ability to manage risk and experience risky events. Financial questions address someone’s risk capacity, ie, will a risky event knock someone off course with regard to their goals. On the other hand, true risk tolerance refers to the client’s attitude to risk, ie, the mental inclination to seek a more favourable outcome at the risk of a less favourable result – this is independent of the ability to afford the risk.

It is clear from this interpretation that risk capacity is a measure of how risky the client’s actual goals are, ie, is there a need for high returns to achieve the goals, or can they be easily achieved with low returns.

On the other hand, risk tolerance is a statement about how much of a risky trade-off a client is willing to undertake: crucially, this may reflect either:

• the investment portfolio which the client chooses; or
• the original goals of the client (or indeed, both).

So neither the portfolio nor the goal should be riskier than the client can actually tolerate: there may well be no portfolio solution consistent with a client’s goals and risk tolerance. Traditional approaches via questionnaires which combine risk tolerance and risk capacity can

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all too often lead to flawed advice: just because a client can afford to take risk (lose money) does not mean that they should be advised to invest in such a way that such a loss is likely. Their risk tolerance may suggest otherwise.

Financial planning is a key ingredient of the advisory process, indeed some would say it is the foundation stone. Kitces (2014) argues forcefully that progress in the advisory process requires the separation of risk tolerance from risk capacity, though this in no way reduces the importance of risk tolerance questionnaires. Lifetime cash flow planning helps advisers to consider financial decisions with their clients and agree a sensible financial strategy for their future: it incorporates an understanding of financial goals, risk capacity and risk tolerance.

We turn now to Risk Profiling, which provides a rigorous methodology to ensure the suitability or otherwise of investment advice.
3. Risk Profiling: Risk capacity v tolerance for risk

Identifying a client’s “risk capacity” is the important second step in the investment process. Where advisers strive to understand a client this is normally achieved via a questionnaire. Such questionnaires can be very sophisticated indeed, often where the questions have been designed with reference to academic research in the area of behavioural finance. At the other end of the scale the identification of client risk capacity can be as superficial as asking a client to specify on a scale of say 1 to 10 how much risk they would be willing to take, with 1 representing none and 10 a great deal of risk.

However, it is not our purpose here to defend any particular method or type of risk profiling tool though we do note that of the 11 tools reviewed by the FSA, 9 had weaknesses which, could, “in certain circumstances, lead to flawed outputs” with a high probability. In particular, the FSA found that when these firms divided the investment-risk range into different categories, the descriptions of these were often too vague and did not effectively explain or differentiate levels of risk. And, indeed, even when the risk profile of the client was correctly assessed, the recommended product or portfolio (and, by implication, the underlying asset allocation), did not always match the profile either because the selected investments were not appropriate for the profile or because a complete view of the client’s financial situation had not been considered.

Firms should have ‘robust procedures, tools and risk category descriptions (where used) to establish and check the level of risk a customer is willing and able to take, as well as assessing the suitability of investment selections’ (FSA, para 1.21, p5). These should include assessing a customer’s capacity for loss and a way of identifying those customers best suited to putting their money in cash deposits. There should always be clarity and transparency regarding the questions and their interpretation. The FSA does not prescribe how firms should assess risk: but it does want firms to ensure they have a ‘clear and robust process that is fit for purpose’, one which will ‘provide structure and promote consistency and so can usefully support the discussion a customer has with their adviser …’ (para 3.9, p10).

Of course, risk profiling as currently practiced has its detractors. For example, Pan and Statman (2012)⁴ list a number of ‘deficiencies’ with risk questionnaires:

(i) If investors consider their portfolios as collections of mental accounts then seeking one global risk tolerance measure misses the reality.
(ii) There is no clear linkage between risk tolerance scores from questionnaires and portfolio asset allocations.

⁴ Pan and Statman (2012), Behavioral Finance, vol 13, no 1, pp54-63)
(iii) Investors’ risk tolerance is not stable: basically, investors are fickle and overly influenced by recent news.

(iv) Risk tolerance assessed in foresight will be different from that assessed in hindsight—regret may be an issue here, and standard questionnaires will not reflect this.

(v) Finally, investor attributes other than risk tolerance will be present, such as overconfidence, trust, gender, regret, etc.

We believe that while item (ii) is an issue for many risk questionnaires, it certainly does not have to be the case, especially if the risk outcomes can be calibrated directly as quantitative investment experiences, historical or expected (or indeed, as is so often the case, these are one and the same thing). In other words, a desirable feature of an ‘objective’, operational risk profiling mechanism should involve mappings of risk into asset allocation.

We also believe that the other 4 items listed above should be managed in the dialogue between the advisor and the client; points (iii), (iv) and (v) represent exactly what the FSA is concerned about in emphasising the nature, not only of a robust process but also the skills of the advisor. All three issues can be couched in the language of Behavioural Finance and Pan and Statman (2012) examine the relation between their definition of risk tolerance and a variety of such behavioural variables as ‘regret’, ‘overconfidence’ and ‘trust’. To create a precise measurement system incorporating these features may be too challenging to operationalise at present but that is precisely where the role of the sensitive and sophisticated adviser is crucial: to interpret any risk profile results and to ‘know thy client’. As the FSA warned (p8, ‘Finalised Guidance’), regarding ensuring that firms have a robust process, advisers should be …

“… appropriately interpreting customer responses to questions and not attributing inappropriate weights to certain answers”

It is therefore clear that the role of the advisor is crucial but there is still a need for a sophisticated risk profiling tool; the alternative is a misplaced and unnecessary intellectual and scientific vacuum. Similarly with regard to point (i) above, Shefrin and Statman (2000) observe that investors view their portfolios not as a whole, as prescribed by mean-variance portfolio theory, ‘but as distinct layers in a pyramid of assets, where layers are associated with particular goals and where attitudes towards risk vary across layers’ (Pan and Statman (2012, p57)). There are a number of responses to this. First, even though portfolios are described as layered pyramids, consistent with behavioural portfolio theory, investors may well consider them as an integrated whole as consistent with mean-variance portfolio theory: we believe that careful design of risk questionnaires, eg, with reference to mental accounting, is key to avoiding problems here. Second, Das et al (2010) have shown that if each mental account is individually optimised on the mean-variance efficient frontier, then the aggregate portfolio also lies on the mean-variance efficient frontier. This would certainly seem to suggest that it should not be beyond the wit of appropriately designed risk questionnaires in the hands of appropriately skilled advisors to counter the argument that mental accounting thwarts the honest ambitions of risk tolerance calibration.

One very important point that we wish to emphasise regarding risk profiling is the role of ‘capacity for loss’ as a key metric for risk which permeates some of the more serious risk profiling tools. The FSA (p3, para 1.8) is at pains to emphasise the distinction between a client’s

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'attitude to risk' and 'capacity for loss'. Yet Modern (or should it be called ‘Muddled’?) Portfolio Theory (MPT) has focussed on the Standard Deviation of investment returns as a measure of risk, especially since Markowitz’s seminal work in 1952 (eg, see Figure 1); in fact, such a measure was of little or no interest to investment theorists until the delights of statistics and mathematics erupted from Markowitz’s PhD dissertation. Indeed, parallel with Markowitz’s work, Roy (1952) developed an approach to investment decisions that sets a minimum required return for a given level of risk: such a minimum level can be couched in the language of capacity for loss. Roy's safety-first criterion allows portfolios to be compared based on the probability that their returns will fall below this minimum desired threshold. It is calculated by subtracting the minimum desired return from the expected return of the portfolio and dividing the result by the standard deviation of portfolio returns. The optimal portfolio will be the one that minimizes the probability that the portfolio's return will fall below a threshold level. The safety-first ratio (SFR) is calculated as:

\[ SFR = \frac{(\text{Expected return} - \text{Threshold return})}{\text{Standard deviation}} \]

This is also known as the "SF Ratio" and looks very much like the familiar Sharpe ratio. Roy states that an investor will prefer safety of principal first and will set some minimum acceptable return that will conserve the principal. Roy also stated that the investor would prefer the investment with the smallest probability of going below the disaster level or target return. Roy’s concept of an investor preferring safety of principal first when dealing with risk is instrumental in the development of downside risk measures – hence its close relation with ‘capacity of loss’ measures.

Roy is often referred to as the ‘Forgotten Father of Portfolio Theory’ and his ideas were published just a few months after Markowitz’s; indeed the latter is generous in his recognition that MPT may well have turned out very differently if the timings had been reversed: it could have been known as Roy’s Portfolio Theory. Many commentators believe that the ease of calculation has cemented the key role for Standard Deviation as a measure of risk in investment. But is this sensible? With non-normal security return distributions we believe that downside risk measures are more appropriate for investors. Indeed, there is an increasing awareness that maximum drawdown ideas such as ‘tail risk’ should be embedded within our modelling of fund performance. In fact, tail risk has recently been associated with the predictability of stock returns and there is a flourishing research initiative in the area of Maximum Drawdown and Tail Risk.

The importance of ‘capacity for loss’ is now enshrined in forthcoming European legislation. Christoff (2014) outlines the essential features of MiFID 2 (Directive 2014/65/EU) which came into force on 2nd July, 2014, with implementation from 3rd January, 2017. In summary, this legislation moves Europe towards regulating financial advice more comprehensively, bans commissions for independent advice, and contains a more detailed suitability standard emphasising assessments of customers’ risk tolerance and ability to bear investment losses. He quotes Article 25(2), in assessing a client, an investment firm must consider …
“… that person’s financial situation, including his ability to bear losses, and his investment objectives including his risk tolerance so as to enable the investment firm to recommend to the client ... the investment services and financial instruments that are suitable for him and, in particular, are in accordance with his risk tolerance and ability to bear losses.”

This would seem to be a very relevant input into Step 2 of the 6-step standard Financial Planning process, relating to ‘Gathering client data, including goals’.

To conclude our thinking on risk profiling, we very much believe that a key feature of well-designed question processes involves some quantitative output which investors can relate to: and a good example of this is a system that relates risk directly to an easily understandable metric such as maximum loss likely to be experienced over a particular time period. A complete process should then go a step further and propose, based on sound (probably historical) statistical modelling, a portfolio allocation to different assets which is likely to produce the desired outcome.

We turn now to the construction of portfolios and relate risk profiling to the choice of a particular asset allocation.
4. Asset Allocation: how do we decide on an appropriate portfolio construction?

So once an adviser has identified a client’s return requirement with careful financial planning, and their capacity for investment risk with a robust risk profiling questionnaire, how should they allocate the investment portfolio between the range of available asset classes? This is one of the most difficult decisions that any investor has to make. At the same time it is also the most important decision. Research (and common sense) shows that getting asset allocation right is far more important than finding a manager that can outperform their particular market (since managers for a particular asset class will have highly correlated returns in general) – although we show that this is important too.

Many institutional investors, including large insurers and pension funds, make use of sophisticated optimisation software to help them allocate their funds across different asset classes. This technology also extends increasingly to recommending portfolios for retail clients in approaches advocated by some major providers. As we emphasised while discussing Figure 1, the inputs to this software require the user to specify the following:

- Return that they expect on any asset class of interest
- The likely volatility of those returns
- The correlations between the asset class returns.

The technology behind this approach to asset allocation is often used by IFAs too, as they try to identify the ‘optimal’ asset class mix for their clients.

These optimised processes generally give reassuring, scientific-looking charts and statistics. However, in practice they frequently suggest highly concentrated, unrealistic portfolios unless they are heavily constrained by the user, typically going massively ‘overweight’ the asset with the highest (most optimistic?) return, and short selling an appropriate amount of the asset about which one is least optimistic\(^{11}\). Ultimately then, the pseudo-scientific output is only as good as the input. So unless one is very good at forecasting asset class returns, volatilities and correlations into the indefinite future, the results of ALL optimisation processes, however seemingly sophisticated, will be nonsense. Remember the saying: garbage in equal’s garbage out.

Indeed, a growing body of academic research has shown that these apparently sophisticated, optimised approaches to portfolio construction can be outperformed by simple rules that instead seek to benefit from biases in investors’ behaviour. The optimisers fail because at their heart lie the assumptions of an all too fallible human. Unless we have thousands of years of financial data or are very, very sure of the way the world functions, then simple investing rules may well be superior to more complex rules\textsuperscript{12}.

Here we will outline an alternative approach to strategic asset allocation that does not rely for its success on the ability of any user to forecast the future. Indeed, if the recent financial crisis has taught us anything it is that even the world’s most experienced and sophisticated forecasters, including supranational organisations like the OECD and the IMF, central bankers and experienced hedge fund managers, cannot forecast the future.

Instead, as we will explain, our approach is based upon a methodology that has been proven to work by recent, rigorous research, both industry and academic. It employs a disciplined, risk-focussed, rules-based strategic asset allocation solution that benefits from being well diversified across a broad range of IMA sector-compatible asset classes.

### 4.1 The importance of strategic asset allocation

Strategic asset allocation is arguably \textbf{THE} really big decision that all investors need to get right. It involves making choices between broad asset classes. The importance of the strategic asset allocation decision cannot be overstated. Work on this topic in the 1980s\textsuperscript{13} suggested that a broadly conventional strategic asset allocation that employs conventional active management to manage mainstream asset classes can “explain” over 90 per cent of a portfolio’s performance over time. In addition, a more recent study concluded that around 100 per cent of returns can be attributed to strategic asset allocation\textsuperscript{14}.

Traditionally the process of asset allocation principally involved choosing between equities and bonds. Further allocation decisions were then usually taken within these broad asset classes, for example, within the equity category a choice might be made between domestic versus overseas equities, or within the bond category, between government and corporate bonds. But how hard can it be?

Figure 2 shows the inflation-adjusted, value of £100 invested in three UK asset classes over the last one hundred years or so, where the income from these assets have been reinvested over time.

\textbf{Figure 2: Real, accumulated total returns since 1900}

\begin{footnotesize}
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According to Barclays Capital, £100 invested in the UK equity market at the end of 1899 with the gross dividend income reinvested over time, would have been worth £24,133 in real terms by the end of 2010. Over the same 111-year period an investment in gilts and in cash, with coupons and interest income reinvested, would only have been worth £369 and £286 respectively in real terms15.

On the face of this evidence then, the strategic asset allocation decision appears to be rather straightforward: invest in UK equities and no need to bother with any other asset class. Indeed, during the 1980s and 1990s many UK investors came to the conclusion that UK equities were the most appropriate and most desirable asset class to hold – no need for any others.

However, the collapse of the high tech bubble at the start of this century and then the liquidity/credit crisis that followed the collapse of Lehman Brothers has highlighted the dangers of relying on one asset class. The FTSE-100 ended the Noughties down by 22 per cent. The slightly better news is that when dividends are taken into account, the FTSE 100 produced a positive return of nine per cent over the decade – nearly one per cent a year!

For lesson that many investors took away from the Noughties was that they should not put all their eggs into one asset allocation basket. This is why our approach to strategic asset allocation seeks to diversify risk across a range of asset classes that have a wide range of risk characteristics. This spreading of risk helps to reduce the overall volatility inherent in the investment portfolio.

15 Source: Barclays Capital Equity Gilt Study 2011 p.95.
4.2 Diversification – the only free lunch in finance

In the FSA review of profiling and investing described in section 1 of this paper, they emphasised the importance of diversification to investors. Our approach to strategic asset allocation seeks to benefit from what is commonly referred to as the “only free lunch in finance” – diversification.

The idea of diversification has its roots in the old saying “Don’t put all your eggs in one basket”. The investment equivalent of this, as Harry Markowitz showed in 1952, is “Don’t invest all your wealth in one risky asset or asset class”. Combining assets that are not perfectly correlated, that is, those that do not move closely together over time can reduce the overall risk in a portfolio. By combining assets into portfolios finance researchers have found that investment risk can be reduced significantly.

Figure 3 shows a stylised representation of what happens to the risk of a portfolio as more assets, say equities, are added to it. As the chart indicates, the average risk – or volatility – is highest for a single asset portfolio whereas the risk of portfolios comprising progressively larger numbers of assets falls, quite sharply at first, so that the risk of a ten or fifteen asset portfolio is significantly lower than that of a one asset portfolio.

The sharp decline in portfolio risk comes about from the imperfect correlations among the assets. The risk that can be eliminated by holding a diversifiable portfolio is called, unsurprisingly, “diversifiable risk”, since it can be diversified away.

But Figure 3 also shows that the rate at which portfolio risk declines as more assets are added reaches a kind of floor, such that the inclusion of additional assets cannot further reduce average portfolio risk by any significant amount. The portfolio risk that cannot be diversified away is
known as “undiversifiable risk”, or “market risk”. Indeed, one of the great insights of the early portfolio theorists, like Markowitz, was that we can distinguish between two types of investment risk:

- diversifiable, and
- undiversifiable, or market risk

The former risk can be all but eliminated by holding a diversified portfolio of assets. The same holds true for holding larger and larger numbers of corporate bonds in a bond portfolio, or more and more hedge funds in a fund of hedge funds portfolio, or more and more asset classes in a multi asset class portfolio\(^\text{16}\).

It is important to note, as Figure 3 illustrates, that not all risk can be eliminated through diversification across many risky assets. However, one of the important lessons of modern portfolio theory was that through effective diversification investors can improve the risk-adjusted performance of their portfolios.

Our approach to strategic asset allocation allows investors to dine on this free lunch by providing a set of strategic portfolio recommendations that span a wide range of broad, IMA sector-compatible asset classes.

### 4.3 Demonstrating the risk-balanced approach to asset allocation

In response to the growing dissatisfaction with apparently sophisticated optimisers which simply give us the answer that we have put into them, and which often produce unrealistic portfolios unless heavily constrained by the user, there is now a growing body of academic evidence that shows that alternative and simpler approaches to the same asset allocation problem produce results that are at least as good as those produced by the most ‘sophisticated’ optimisers.

We will outline this process by applying it to the following set of IMA sector-based asset classes:

- Developed economy equities
- Emerging market equities
- Bonds
- Commodities, and
- Commercial property

However, as well as allocating to these five broad asset classes we also allocate to IMA sub-sectors within developed economy equities. These sub-sectors are:

- Asia ex Japan
- Europe ex UK
- Japan

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\(^{16}\) How many alternative asset classes should you have in your investment basket?, A. Clare and N. Motson, CAMR, Cass Business School, London.
In addition, because the IMA “Bond sector” encompasses quite a diverse range of bond asset classes we allocate to two of these bond classes:

- Investment grade
- High yield

Finally, although our process has been developed using UK commercial property REITs within the fund selection process, recommended funds may be UK property market REITs or direct property investment funds.

There are literally an infinite number of ways in which we could allocate capital between this set of asset classes. One such approach, referred to as 1/N investing\(^\text{17}\), advocates allocating equal amounts of capital to each of the asset classes of interest. So, for example, if there are ten (N) asset classes then the approach simply requires that each asset class has a weight 10\% (1/10). Any other type of weighting implies that one knows something about the world. In our view, the events of the last few years have shown us that we know only one thing – and that is that we know very little about the future!

So let us begin by looking at the advantages of simplicity and transparency in constructing portfolios. In an interesting essay Ang (2012)\(^\text{18}\) runs a horse race using real US data between various approaches to asset allocation, ranging from simple rules such as 1/N investing, to a Market Cap approach which simply involves investing in asset classes according to their market capitalisation, to full-blown MVEF optimisation. Table 1 shows the results of this horse race. The MVEF optimised approach is the worst performer by far. The results also demonstrate that increasing complexity is directly related to poorer investment performance, both risk-adjusted and absolute:

<table>
<thead>
<tr>
<th>Portfolio Weighting</th>
<th>Return</th>
<th>Sharpe</th>
<th>Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/N</td>
<td>10.0</td>
<td>0.54</td>
<td>1</td>
</tr>
<tr>
<td>Market Cap</td>
<td>10.25</td>
<td>0.41</td>
<td>2</td>
</tr>
<tr>
<td>MVEF</td>
<td>6.06</td>
<td>0.07</td>
<td>3</td>
</tr>
</tbody>
</table>

There is a further weighting method which we will investigate below called Risk Parity, and it involves weighting asset shares to reflect the ‘riskiness’ or volatility of the asset; in fact the more volatile the asset, the smaller its share will be in the portfolio. We will now move on to describe this process, which we adopt in detail.

The approach that we demonstrate here is similar in spirit to the 1/N approach to asset allocation, but instead seeks to create multi-asset class portfolios where the risks of each asset class are equal, rather than the amounts invested in each asset class. We refer to this as the ‘balanced risk approach’, but it is also referred to as the ‘naive risk parity approach’. The

\(^{17}\) For a reference to this approach see, for example: The Dog and the frisbee, Andrew Haldane, speech at Jackson Hole, 2012, [www.bankofengland.co.uk/publications/Pages/speeches/default.aspx](http://www.bankofengland.co.uk/publications/Pages/speeches/default.aspx). See also: The 1/N investment strategy is optimal under high model ambiguity, G. Pfug, A. Pichtler, and D. Wozaba, (2012), Journal of Banking and Finance, February 2012.

Evidence for the benefits of this approach can be found both in academic research\(^{19}\) and in work by market professionals, e.g. Salient Capital Advisors, who show that such an approach actually delivers portfolios which would have been created using Mean Variance Optimisation with perfect foresight!!!

In other words, when we criticised Mean Variance Optimisation earlier, it was partly based on the difficulty with forecasting the future returns, risk and correlations: the risk parity approach actually produces portfolios which are not that far different from those which we would have created if we had perfect forecasting ability! This is indeed a remarkable result which requires further elaboration.

The ‘balanced risk’ approach is based on the idea that, rather than investing in the asset classes using information from an optimiser, or allocating an equal amount of capital to each one (1/N investing), instead, we should allocate capital in such a way that each asset class adds the same amount of volatility, or risk, to the portfolio over time. So an asset class with low return volatility would need a higher weight than one with high return volatility.

To illustrate the issue consider Table 2. This table shows the annualised return and volatility of each of the five broad asset classes listed earlier. The table shows how different the performances of these asset classes were over this period, not just in terms of average return, but also in terms of volatility. An equal allocation to these five asset classes over this period would have meant that each asset class would not have contributed equally to the overall risk in the portfolio. Property, in this case in the form of REITs, and emerging market equities, would have donated a disproportionate amount of risk, while the bond category would have contributed relatively little.

<table>
<thead>
<tr>
<th>Table 2: Asset Class Returns 2003-2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Developed Equity</td>
</tr>
<tr>
<td>------------------</td>
</tr>
<tr>
<td>Annual Return (%)</td>
</tr>
<tr>
<td>Annual Volatility (%)</td>
</tr>
</tbody>
</table>

Our balanced risk approach to strategic asset allocation involves the following steps:

(i) At the end of each month we calculate the volatility of each broad asset class calculated using monthly data over a prior period
(ii) We then calculate the sum of these volatilities
(iii) Next we divide the volatility of each asset class by the volatility sum calculated in (ii)
(iv) We then calculate the inverse of the figures calculated in (iii)
(v) We then sum the inverted figures calculated in (iv)
(vi) Finally, we divide the inverted values calculated in (iv) by the sum of these values calculated in (v). This gives the broad asset class weights.

We have illustrated these steps using the example volatility data shown in Table 3. As can be seen, this process assigns the biggest weight (36%) to Bonds, since its historic volatility (over a 10 year period in this case) is much lower than that of the other asset classes.

Table 3: Calculating broad asset class weights

<table>
<thead>
<tr>
<th></th>
<th>Developed</th>
<th>Emerging</th>
<th>Bonds</th>
<th>Commodities</th>
<th>Property (REITs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i) Volatility (%)</td>
<td>14.1</td>
<td>21.1</td>
<td>7.8</td>
<td>15.5</td>
<td>23.0</td>
</tr>
<tr>
<td>(ii) Sum of volatilities</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>81.54</td>
</tr>
<tr>
<td>(iii) Volatility/Sum of volatilities</td>
<td>17%</td>
<td>26%</td>
<td>10%</td>
<td>19%</td>
<td>28%</td>
</tr>
<tr>
<td>(iv) 1/(Volatility/Sum of volatilities)</td>
<td>5.8</td>
<td>3.9</td>
<td>10.5</td>
<td>5.2</td>
<td>3.5</td>
</tr>
<tr>
<td>(v) Sum of 1/(Volatility/Sum of volatilities)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>28.9</td>
</tr>
<tr>
<td>(vi) Risk-balanced weight (Step 4/Step 5)</td>
<td>20%</td>
<td>13%</td>
<td>36%</td>
<td>18%</td>
<td>12%</td>
</tr>
<tr>
<td>Sum of risk-balanced weights</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

This approach can be applied across broad asset classes, and also within each broad asset class if required. This ensures that the risks are not only balanced across each major asset class, but also within each asset class.

The process ensures that the volatility of the strategic allocation overall comes from a balanced source of risks. It also ensures that exposures to asset classes fall as they become increasingly volatile. This method is advocated in the influential book by Ilmanen (2011)20 and applied within the commodities’ sector by Clare et al (2014)21. Chaves et al (2011)22 conduct a horse race similar to Ang, (2012) between representative risk parity portfolios and other asset allocation strategies, including equal weighting, minimum variance, mean–variance optimization, and the classic 60/40 equity/bond portfolio. While the basic risk parity portfolio does not consistently outperform (in terms of risk-adjusted return) equal weighting, or the 60/40 equity/bond portfolio structure, it does significantly outperform such optimized allocation strategies as minimum variance and mean–variance efficient portfolios. Over the last 30 years, Chaves et al (2011) show that the Sharpe ratios of the risk parity and the equal-weighting portfolios have been much more stable across decade-long sub periods than either the 60/40 portfolio or the optimized portfolios. Although risk parity performs on par with equal weighting, it does provide better diversification in terms of risk allocation; the authors note that actual empirical performance is heavily conditioned by the choice of assets.

What is the justification for using this risk balancing approach? Why should we advocate such a method? Is there evidence or reasoning to support this approach? In a series of recent research papers Salient Capital Advisors LLC23 explore this question beginning with a simple two asset example represented by the S&P500 and the Barclays Aggregate Bond Index from 1978 and 2011. Using this historical data they find that the Maximum Sharpe ratio portfolio (a very desirable portfolio maximising actual excess return relative to risk given the benefit of perfect hindsight) and the balanced risk approach which they refer to as Risk Parity are indeed very similar. They then compare three ex-ante implementable strategies: by ex-ante we mean that we are only using information available in practice at the time, so there is no benefit of knowing the future (known as perfect foresight). The four portfolios are:

- 60/40,
- dynamic risk balanced (using two years of past data to calculate volatilities for risk parity),

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- ex-ante maximum Sharpe (based on the ex-post maximum ratio portfolio using the last 2 years actual data to construct the Mean Variance Efficient Frontier), and
- ex-post maximum Sharpe portfolio (where we have the benefit of knowing the data which actually occurred before it happened, i.e., perfect foresight).

For the period 1989-2011 the following performance statistics for the monthly rolling models were found (see Table 4):

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P500</th>
<th>Barclays Bond</th>
<th>60/40</th>
<th>Dynamic Risk Parity</th>
<th>Dynamic maximum Sharpe</th>
<th>Ex post maximum Sharpe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sharpe</td>
<td>0.34</td>
<td>0.91</td>
<td>0.51</td>
<td>0.96</td>
<td>0.64</td>
<td>0.95</td>
</tr>
<tr>
<td>Excess return</td>
<td>5.1%</td>
<td>3.34%</td>
<td>4.7%</td>
<td>4.1%</td>
<td>3.5%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Volatility</td>
<td>15.1%</td>
<td>3.7%</td>
<td>9.3%</td>
<td>4.3%</td>
<td>5.5%</td>
<td>3.7%</td>
</tr>
</tbody>
</table>

Table 4 suggests that the Dynamic Risk Parity portfolio produces performance at least as good as the (theoretically important but non-implementable) ex-post Maximum Sharpe one, which benefitted from perfect foresight. Measures of skewness and kurtosis which are indicators of risk in the sense of maximum drawdown or loss, are also fairly similar for these strategies, suggesting that:

‘risk parity may serve as an excellent proxy for the theoretical market portfolio as it consistently delivers risk-adjusted returns in the vicinity of the ex-post maximum Sharpe ratio portfolio’.

The above suggests that ex-ante risk parity allocations (which only rely on past data to calculate volatilities) compare favourably with ex-post optimal portfolios (Mean Variance, Maximum Sharpe), which assumes an unrealistic perfect foresight; recall that ex-ante means a portfolio using only information that was available at the time an investment would have been made, and ex-post refers to allocations made with perfect foresight. Hence the alleged superiority of risk parity occurs in a context which requires less information, i.e., is ‘simpler’ in the language of section 4.

Would a risk parity portfolio ever be exactly the same as maximum Sharpe portfolio? The answer is ‘yes’, under certain conditions. Maillard et al (2010) show that the maximum Sharpe ratio portfolio exactly coincides with a risk parity portfolio when all assets have the same Sharpe ratio and the same cross-correlations with each other. This is a potentially powerful result: taking US equities, Treasuries and Commodities from 1958-2011, their Sharpe ratios are 0.28, 0.24, and 0.28 respectively, all very close indeed. The correlations range between -0.11 and 0.16, and hence are quite different, though the overall similarities suggest that the risk-adjusted returns for the 2 portfolios should be fairly similar. In practice, the ex-

ante and easily implementable risk parity portfolio performs very similarly to the maximum Sharpe one: why could this be?

Again staying with the 3 asset example, Salient Capital (2012) try to answer this question using monthly data from 1958 to 2011. Over the whole of that period, and looking backwards, i.e., taking advantage of knowing what actually happened to the asset returns, an optimal (i.e., Maximum Sharpe) portfolio would have been: 16.6% Equity, 35.4% Commodities, and 48% Treasuries, giving 2.85% pa excess return, volatility of 6.65% pa, and hence a Sharpe of 0.43. Yet in practice investors tended to be structurally overweight equities during that period (including the 60/40 portfolio).

In contrast when they look at shorter periods: with perfect foresight using 5 year overlapping periods, the optimal weights for the maximum Sharpe ratio portfolios would have been highly variable from month to month, with different asset classes dominating the optimal portfolio through time. Salient find that equities dominated in short-run optimal portfolios in the late 1960’s, early 1970’s, early/mid 1980’s and the late 1990’s, while Treasuries were more dominant in the late 1950’s, mid-1970’s, and at various periods from the mid-1980’s; while Commodities were important through the 1970’s, early 1980’s and from the early 2000’s. In other words, equities gave higher risk-adjusted returns than other asset classes only over a relatively small fraction of the overall period and hence, unsurprisingly, form only a relatively small part of the optimal portfolio for large parts of that period.

Why should these 3 assets behave so differently over different historical periods? One explanation would be based on macroeconomic links between the asset returns and economic conditions: in terms of average correlations (see Table 5), equity returns respond positively to economic growth but negatively to inflation; Commodities respond positively to both inflation and economic growth; and Treasuries’ returns respond negatively to both inflation and economic growth. Because each of these economic phenomena are present for large parts of the whole period, then unsurprisingly the ex-post optimal allocation is indeed spread across all 3 assets. They show that the dynamic allocation requires perfect hindsight and hence is not achievable. The highly time-varying optimal allocation would require rather incredible powers of forecasting.

**Table 5: Correlations between asset class returns and Economic Variables: 1958-2011**

<table>
<thead>
<tr>
<th>Economic growth</th>
<th>Inflation</th>
<th>Equity returns</th>
<th>Commodity returns</th>
<th>Treasury returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic growth</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inflation</td>
<td>-0.21</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equity returns</td>
<td>0.34</td>
<td>-0.19</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Commodity returns</td>
<td>0.20</td>
<td>0.23</td>
<td>0.11</td>
<td>1.00</td>
</tr>
<tr>
<td>Treasury returns</td>
<td>-0.31</td>
<td>-0.36</td>
<td>0.01</td>
<td>-0.29</td>
</tr>
</tbody>
</table>

Source: Salient Capital Advisors, LLC, April 2012.

Can ex-ante risk parity offer a similar performance (without the benefit of hindsight)? Salient show that the risk parity weights evolve much more gently than those using Mean-Variance Analysis: this is because asset volatilities and correlations evolve more slowly compared to the short-run optimal portfolios which is largely dependent on which asset class performed best over the previous 5 years. In addition, the risk parity portfolio increased its allocation to Treasuries and commodities at various times ahead of their outperformance; the intuition is
that declining volatility is associated with positive returns. And risk parity produces portfolios weights which slowly move towards those outperforming assets.

In their experiment, Salient’s ex-ante risk parity allocations are on average more similar to the long-run optimal allocation than they are to most of the (highly variable) short-run optimal allocation; the benefits of patient, systematic diversification are available and approximate the optimal static portfolio because risk parity provides equal risk exposure to assets that will perform well in different and unpredictable economic conditions.

There are two important questions which we need to consider with our approach:

4.3.1 What about the ‘risk-balanced’ approach versus full risk-parity?

A very reasonable question to ask is whether our simple weighting of asset shares by inverse asset volatilities with no reference to asset correlations (as in ‘full’ risk parity) is throwing away important information? We answer this in two different ways: firstly we draw on recent published research, and secondly we present a comparative UK exercise using three assets.

The rigorous academic analysis is presented in Chaves et al (2012)26. In this paper they compare the real world performance of multi asset, equity and commodity portfolios formed in 4 ways, all of which eschew the use of expected returns: minimum variance, equal weight, full (optimal) risk parity, and naïve (our risk balanced) risk parity. The remarkable thing is the very similar performance of the latter two methods leading them to assert that ‘we can achieve excellent risk diversification with the naïve Risk Parity method’.

We also created a practical example using four asset classes for the UK investor-using monthly data for UK equities, gilts, commodities and property for the period 1978-2014. We compared equal weights portfolios with naïve and full risk parity portfolios: the results are shown in Table 6.

<table>
<thead>
<tr>
<th></th>
<th>EW</th>
<th>RP(B)</th>
<th>RP(WC)</th>
<th>MV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compound Annual Return (%)</td>
<td>10.41</td>
<td>10.62</td>
<td>10.20</td>
<td>9.84</td>
</tr>
<tr>
<td>Annualized Volatility (%)</td>
<td>10.87</td>
<td>8.31</td>
<td>7.90</td>
<td>6.12</td>
</tr>
<tr>
<td>Sharpe</td>
<td>0.35</td>
<td>0.48</td>
<td>0.46</td>
<td>0.53</td>
</tr>
<tr>
<td>Best Month</td>
<td>10.73</td>
<td>7.82</td>
<td>8.12</td>
<td>6.22</td>
</tr>
<tr>
<td>Worst Month</td>
<td>-14.12</td>
<td>-10.20</td>
<td>-8.49</td>
<td>-5.35</td>
</tr>
<tr>
<td>% Positive Months</td>
<td>64.14</td>
<td>68.74</td>
<td>67.13</td>
<td>68.28</td>
</tr>
<tr>
<td>% Negative Months</td>
<td>35.86</td>
<td>31.26</td>
<td>32.87</td>
<td>31.72</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>36.38</td>
<td>18.58</td>
<td>16.49</td>
<td>10.44</td>
</tr>
</tbody>
</table>

Key: EW=Equal Weight; RP(B)=Risk Parity (Balanced or Naïve); RP(WC)=Risk Parity with correlations.

Clearly the overall performance of both Risk Parity portfolios (RP(B) and RP(WC)) is very similar and both easily outperform the equally-weighted portfolio in risk-adjusted terms. Figures 4 and 5 compare the 4 asset shares over time for the 2 Risk Parity methods:

It is easy to see why the 2 methods produce such similar overall performances: through time the asset allocations are very similar and, most importantly to the advisor, do not suggest dramatic highly frequent changes in portfolio composition. These carry a similar message to the real-world example in Section 5 below.
4.3.2 What if interest rates rise sharply?

Criticism of equal risk contributions (Risk Parity) often centre on what will happen if interest rates rise and portfolios are stranded overweight a falling asset—bonds. This is especially important since the last 30 years has seen a bull market in bonds and the question is often asked in the context of a 60/40 portfolio, which naturally gives bonds huge prominence.

The first and obvious answer to this challenge is that the two-asset examples are extreme in lacking diversification, in direct contrast to the strongest of admonitions of the FSA in its ‘Assessing Suitability’ paper (2011, p23). Second, as a comparator, a practical example will help explain what has happened in probably the most recent sustained and consistent rising in yields: 1971-1982 in the US. In this period the US 10-Year Treasury Bond yielded 6.24% in January 1971 and by September 1981 reached a peak yield (based on month-end values) of 15.32%. Croce et al (2013)\(^{27}\) show empirical evidence using 3 asset classes, Equities, Bonds and Commodities, that critics of Risk Parity potentially understate:

(i) the potentially diversifying influence of Commodities;
(ii) the responsiveness of risk parity strategies to changes in asset volatility; and
(iii) the dynamic incorporation of changing correlations.

In other words, diversification across more asset classes is crucial, together with the realisation that asset allocation will change through time as volatilities change, offsetting the poor performance of the bond component. Of course the 1970s example saw higher coupons and yields generally, and this would also have compensated for falling bond prices.

In conclusion then, we believe that a naïve risk parity approach to portfolio construction has as good a performance as can be expected without the benefit of perfect foresight in predicting asset prices: and even then, risk parity offers much lower transaction costs. Hence we use this method below.


To show how this process can work when used in conjunction with IMA Sectors, we applied the risk parity process to the five broad IMA asset classes, to the five equity sub-asset classes, and to the two bond sub-asset classes. Table 7 shows the performance statistics of the strategy over the ten years from January 2003 to December 2012.

Table 7: The performance of a risk-balanced portfolio

<table>
<thead>
<tr>
<th>Core risk-balanced portfolio</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Compound Annual Return (%)</td>
<td>7.08</td>
</tr>
<tr>
<td>Annualized Volatility (%)</td>
<td>10.97</td>
</tr>
<tr>
<td>Sharpe ratio</td>
<td>0.38</td>
</tr>
<tr>
<td>Best Month (%)</td>
<td>7.56</td>
</tr>
<tr>
<td>Worst Month (%)</td>
<td>-14.09</td>
</tr>
<tr>
<td>% Positive Months (%)</td>
<td>63.57</td>
</tr>
<tr>
<td>% Negative Months (%)</td>
<td>36.43</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>31.45</td>
</tr>
</tbody>
</table>

Table 7 shows that the annualized volatility of the portfolio over this period was just under 11%, which is approximately half the volatility experienced by global equity markets over the same period. The portfolio achieved a Sharpe ratio of 0.38, and experienced a maximum drawdown of 31.45% over the period. Figure 6 shows the asset allocation of the fund over this ten year period that produced this performance.

Figure 6: Asset class weights for the core risk-balanced portfolio

Notice again that the asset class weights shown in Figure 6 evolves over time rather than change rapidly. This means that advisers will not necessarily need to rebalance their clients’ portfolios every month. Thus the process should be quite efficient in terms of transactions costs.

4.5 Creating solutions for the full range of investors

We appreciate that the portfolio created by the above risk-balanced process may not produce the sort of portfolio – in terms of risk – that all investors will be looking for. Some will want
a less risky portfolio, others will be happier with a more risky portfolio. In this section of the paper we demonstrate how the basic process outlined above can be extended to accommodate all investors, from the most risk averse to those that can bear a higher degree of risk.

In creating this range of strategic asset allocation solutions we have paid close attention to Finametrica’s risk profiling process. We offer seven portfolio strategies that broadly align with Finametrica’s seven risk groups. We have also aligned the portfolio solutions so that they map in to the European Commission’s UCITS IV Directive relating to the “Key Investor Information Document” (KIID)\(^\text{28}\). This mapping demonstrates how stages 1 and 2 of the investment process can be joined up with stage 3.

First, for investors that wish to invest in a portfolio with lower risk than that represented by the core risk-balanced portfolio we created five alternative portfolios. Each one combines a cash holding with the core risk-balanced portfolio, from 90% of the total holding down to 10%. We refer to these as portfolio strategies 1, 2, 3, 4, and 5. We can think of these portfolios as representing combinations of the risk-free asset (cash) and the ‘market’ portfolio (here the ‘core’, risk balanced portfolio), exactly as advocated by Modern/Muddled Portfolio Theory-with the added bonus that such portfolios tend to behave over long periods of time as Maximum Sharpe portfolios (with perfect foresight).

Next, for investors with a greater tolerance for risk than represented by the core risk-balanced portfolio we created two further strategies. Each strategy was created by imposing a constraint on the process designed to create the core risk-balanced portfolio. To create portfolio strategy 6 we imposed a constraint that meant that the minimum investment at any point in time in the combination of developed and emerging economy equities was 50% of the total portfolio. Within the developed economy equity broad asset class component the process described above was still applied to find the weights of the individual equity markets.

We then constructed a second portfolio, portfolio 7, with the constraint that the minimum investment at any point in time in the combination of developed and emerging economy equities was 100% of the total portfolio. Of course this means that this portfolio comprised no bonds, commercial property or commodities. However, once again, within the developed economy equity broad asset class component the process described above was still applied to find the weights of the individual equity markets.

The historic performance of the seven portfolio strategies are shown in Table 8. The table also shows two important metrics relating to Finametrica’s risk groups. The first shows the asset allocation of the risk group across high, medium and low risk asset classes. So, for example, Finametrica’s recommended asset allocation for risk group 1 is 0% in high risk, 15% in medium risk and 85% in low risk asset classes (0-15-85)\(^\text{29}\). The second statistic relates to the maximum loss that would make people in this group “uncomfortable”. This can be thought of as being the maximum drawdown that an investor might be willing to tolerate. Indeed these Finametrica maximum loss values for each risk group, broadly align with the maximum drawdown statistics for each of the seven portfolio strategies. They are not meant to match up perfectly, mainly because risk profiling is a very inexact science. Finally, the table provides an indicative EC KIID risk rating.

---


\(^{29}\) In fact, Finametrica suggest an asset allocation of 0/0/100 or 0/30/70 for this risk group, the average of which is 0/15/85.
Table 8: Performance statistics on the range of portfolios

<table>
<thead>
<tr>
<th>Portfolio strategy</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finametrica (asset alloc)</td>
<td>0-15</td>
<td>0-30</td>
<td>10-40</td>
<td>30-40</td>
<td>50-40</td>
<td>70-30</td>
<td>100-0</td>
</tr>
<tr>
<td>Finametrica (max loss)</td>
<td>0%</td>
<td>0%</td>
<td>10%</td>
<td>20%</td>
<td>20%</td>
<td>33%</td>
<td>50%</td>
</tr>
<tr>
<td>EC KIID risk rating</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>% in cash</td>
<td>90</td>
<td>70</td>
<td>50</td>
<td>30</td>
<td>10</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>Min in equities</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compound Annual Return (%)</td>
<td>3.40</td>
<td>4.29</td>
<td>5.15</td>
<td>5.96</td>
<td>6.72</td>
<td>7.56</td>
<td>8.57</td>
</tr>
<tr>
<td>Annualized Volatility (%)</td>
<td>1.17</td>
<td>3.28</td>
<td>5.47</td>
<td>7.66</td>
<td>9.87</td>
<td>12.52</td>
<td>17.31</td>
</tr>
<tr>
<td>Sharpe</td>
<td>0.39</td>
<td>0.41</td>
<td>0.40</td>
<td>0.39</td>
<td>0.38</td>
<td>0.37</td>
<td>0.33</td>
</tr>
<tr>
<td>Best Month (%)</td>
<td>0.83</td>
<td>2.31</td>
<td>3.81</td>
<td>5.31</td>
<td>6.81</td>
<td>8.49</td>
<td>13.04</td>
</tr>
<tr>
<td>Worst Month (%)</td>
<td>-1.14</td>
<td>-4.02</td>
<td>-6.90</td>
<td>-9.78</td>
<td>-12.65</td>
<td>-14.23</td>
<td>-14.59</td>
</tr>
<tr>
<td>% Positive Months (%)</td>
<td>81.40</td>
<td>72.87</td>
<td>66.67</td>
<td>64.34</td>
<td>63.57</td>
<td>64.34</td>
<td>60.47</td>
</tr>
<tr>
<td>% Negative Months (%)</td>
<td>18.60</td>
<td>27.13</td>
<td>33.33</td>
<td>35.66</td>
<td>36.43</td>
<td>35.66</td>
<td>39.53</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>2.23</td>
<td>8.68</td>
<td>15.51</td>
<td>22.16</td>
<td>28.44</td>
<td>33.25</td>
<td>43.30</td>
</tr>
</tbody>
</table>

The performance statistics in Table 8 show how the returns rise as we move progressively from portfolio strategy one to portfolio strategy seven. It also shows how volatility and the maximum drawdown statistics rise, and how the ‘worst month’ gets progressively worse. Figure 7 show this progression graphically for some of these performance statistics.

Figure 7: The performance of the 7 risk-balanced strategies
We believe that this approach can offer ‘something for everyone’, from highly risk averse investors to those more tolerant of higher risk. The quantitative link between the Finametrica scores, historic (and hence ‘expected’) drawdown and asset allocation is transparent and direct and rebuts some of the criticisms of risk profiling in Section 3.
5 Populating the portfolios with winning funds: Proof that it is possible

We could of course populate the sectors of the core risk-balanced portfolio with representative ETFs or tracker funds mimicking the sector returns. But is it possible to find a better solution by choosing ‘winning’ mutual funds? The predictability and persistence of selecting winning mutual funds is a topic which has been exhaustively researched by the academic and practitioner community, particularly in the language of ‘luck versus skill’ in the choice of portfolio managers. And this research is heavily overweight the equity sector and US data. Yet the impact of the investment adviser’s choice of individual fund can have a substantial influence on both a customer’s wealth and emotional investing experience. The results presented in the previous section were produced using the returns from representative financial market indices to represent a particular investing class. But what if one could offer a substantial uplift to these numbers by choosing ‘above average’ funds?

There is such a technology which offers such an uplift for the UK IMA sectors with an approximately 15 year track record, and it is our purpose here to introduce its methodology and performance. This is the system created by Clever Adviser Technology Ltd (hereafter ‘Clever’).

Given the preponderance of UK advisory investing in the IMA sectors the system seeks to choose the best outperforming funds for each sector on a monthly basis, but with an acute practical overlay which constrains rapid churn of the recommendations which would overburden an adviser with administrative overload and be completely impractical, and indeed probably also disturbing for clients – the optimum balance is sought to implement the ‘right’ amount of changes in recommendations.

The Clever method involves a scoring system which is created by assessing each fund, in each sector against a list of recognisable criteria:

- The Sharpe ratio
- Alpha
- Average 6 months’ performance
- Average 36 months’ relative performance
- Relative volatility
- Research rating
- Micropal star rating

30 For more information go to: http://Cleveradviser.com/
• Relative maximum loss
• Beta

Many of these criteria will be familiar to finance academics and practitioners alike with their focus on momentum/persistence of performance as one of the most extensively researched (and indeed successful) ideas in empirical finance and investment modelling\textsuperscript{31}. For each of the above criteria the fund data is normalised with the best funds achieving a score of 10, and the worst a score of 0. The 9 scores are aggregated each month to give a total score and this is compared to a Threshold Score for each sector: a fund score below the Threshold leads to a sell recommendation, while a value above the number leads to that fund remaining in the portfolio. The Threshold score for each sector is reassessed every 6 months. Similarly, to emerge as the preferred fund in a sector it will be the one with the highest aggregate score.

\textbf{Table 9: \textit{Clever Performance (1999-2013)}}
Cumulative excess performance of Clever fund choices in excess of IMA sector average and financial index. The t-values in the table indicate significance of performance difference.

\begin{tabular}{lcc}
\hline
 & Difference v IMA Sector & Difference v financial index \\
\hline
\textbf{Equities} & & \\
UK all companies & 7.9 & 8.1 \\
& t-value 4.3 & 4.1 \\
North America & 3.8 & 2.8 \\
& t-value 1.4 & 0.9 \\
Europe ex UK & 6.9 & 7.2 \\
& t-value 3.7 & 3.5 \\
Japan & 8.8 & 11.0 \\
& t-value 1.5 & 1.2 \\
Asia Pac ex Japan & 5.5 & 5.4 \\
& t-value 3.0 & 2.2 \\
Emer. Markets & 3.4 & 2.5 \\
& t-value 2.1 & 1.4 \\
\hline
\textbf{Fixed Income} & & \\
Money market & 0.5 & -0.8 \\
& t-value 2.6 & -2.5 \\
£ Corp bond & 2.0 & 0.3 \\
& t-value 2.2 & 0.3 \\
£ High Yield & -0.7 & -3.1 \\
& t-value -1.2 & -1.2 \\
\hline
Property & 3.0 & 1.0 \\
& t-value 1.1 & 0.4 \\
\hline
Commodities & 7.2 & 18.8 \\
& t-value 2.1 & 2.5 \\
\hline
Source: \textit{Clever}
\end{tabular}

Table 9 compares the chosen funds with the IMA sector median ranked fund (both net of charges) and the chosen fund’s net return with a relevant benchmark’s gross return, all for the asset classes contained in the core portfolio in section 4. The Clever choices give a total return net around 8% pa for All UK Companies, 5.5% pa for Asian equities ex-Japan, about 7% pa for European equities ex-UK, nearly 9% pa for Japanese equities, and between 2.6% and 3.4% pa for Emerging Market equities. All possess t-values that suggest at least marginal statistical significance. Only North American Equities show a notably weaker statistical performance, though we note that the chosen funds do generate between 2.8% and 3.8% pa additional return.

The Commodity funds also outperform the sector median (by 7.2% pa) and the benchmark (by over 18% pa), though with marginal statistical significance. The results for Money Market funds, Property, £ High Yield bonds and £ Investment Grade bonds’ categories offer less support for the Clever chosen funds, though with no noticeable loss of returns versus the peer groups. Figure 8 presents the cumulated performance of the fund selections shown in Table 9.

As regards volatility and maximum loss, (not shown here but available on request), the Clever choices generally show lower ‘risk’ or similar to the sector averages, with only a relatively small number having clearly lower volatility and maximum loss than the Clever choices.

A possibly important question from an adviser’s point of view is how frequently (i.e. what proportion of the time) does the Clever choice outperform the sector average. Is there frequent Clever outperformance or is it the occasional massive excess return followed by regular underperformance? We take one of the more important sectors for a more detailed examination of this phenomena.

For the UK All Companies sector, the Clever process outperforms the sector median fund 62% of the time (months), and the appropriate benchmark (without costs deducted from the
benchmark) 59% of the time. This accumulates to threefold outperformance (see also Figures 8 and 9) by the *Clever* chosen fund relative to both the sector median and the benchmark. The chosen fund outperforms the sector median by 1.6% pa when *Clever* is correct and underperforms it by 1.2% when it is wrong; similar relative numbers apply versus the benchmark\(^\text{32}\).

The frequency with which the recommended fund changes is a very important issue for any adviser that has to implement the sell and buy for each client as well as justify the decision to change funds. The average number of fund changes per sector per year was well under 1 (at around 0.6); out of 120 months in an earlier data set, only Property-Full IMA sector (with 14 changes) and Japan (at 13), had over 12 fund changes, while Asia Pacific ex Japan, Asia Pacific incl. Japan and Europe incl. UK each had 12 changes. Some sectors had hardly any changes: Global and £ High Yield, had only 2 changes in recommendation in 10 years; UK All Companies, Global Emerging Markets, and UK Smaller Companies each had 3 changes; UK Gilts had 4 changes over that period.

Overall it would seem that inserting the specific funds recommended using the *Clever* choices would have led to an improvement in the performance of our ‘core’ portfolio of possibly 200 bps p.a. with little or no increase in volatility or, crucially, maximum loss. The *Clever* results suggest strongly that it is possible to select winning funds to populate the sort of well-designed asset allocation described in Section 4.

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\(^{32}\) A full set of similar data for each asset class/sector is contained in the Appendix.
6 Summary

We took as our starting point the FSA’s review of the advisory process and the shortcomings therein: we believe that in a world which is fundamentally unpredictable it is important to give customers the best which the science of investing can provide, and hence to offer them a good chance of avoiding the regret which poor long-term savings’ choices will impose.

Breaking the process down into its component parts and offering transparent and rigorous solutions at each stage would seem the very least a customer is entitled to: from financial planning (required return), risk profiling (capacity for loss and risk tolerance), through to portfolio construction/asset allocation, to choice of assets/funds – joined up investment thinking.

We have focussed in particular in this paper on simple, rule-driven portfolio construction principles which minimise our need for heroic (and usually ‘wrong’) forecasting assumptions and opaque complexity; we believe, other things being equal, in simple, intuitive and easily understandable models. In particular, we emphasise:

- the benefits of diversification
- having a risk-balanced approach to asset allocation; and
- understanding investors’ tolerance for risk and their capacity for loss, versus their required return.

As a result, this should help to empower the financial planner and enhance their confidence in the investment planning part of the advice process. The benefits of our approach are that:

- outcomes should be more consistent with ex ante aims where they seek to minimise maximum losses (maximum drawdown, or “tail risk”);
- the financial planner should find the process accessible, which in turn will help them make clearer decisions because they will be better informed;
- the different stages should be as frictionless as possible;
- any commercial application of this ‘joined up investment thinking’ should ultimately provide an Investment Policy Statement supported by rigorous, academic, cutting edge research.

We noted in our introduction that the FSA was particularly concerned about the lack of rigour in allocating wealth to cash for those (many) customers who cannot afford any losses: we believe our transparent allocation to well-designed risk strategies makes such a process very clear indeed for use by a responsible adviser.

And last but not least, we believe that academic finance teaching has not served advisers well in developing robust real world measures of risk to help clients make important decisions: the FSA is correct to criticise ‘volatility’ as a measure and the increasing focus on ‘capacity for loss’/maximum loss in our process we believe is both intuitively and academically persuasive. If Roy (1952) had published his study a few months earlier, ahead of Markowitz, then we might have not spent 50 years giving undue importance to a flaky risk metric and recommending unsuitable portfolios based on inappropriate investment strategies.
Appendix

This appendix presents the results of the *Clever* selected fund performance versus the IMA sector median and a relevant financial market benchmark, using monthly data from 1998 to 2013 (Source: *Clever* Adviser Technology Ltd).

i. UK All Companies

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>67.37%</td>
<td>59.28%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>1.62%</td>
<td>1.94%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-1.18%</td>
<td>-1.50%</td>
</tr>
</tbody>
</table>

ii. N. American equities

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>53.09%</td>
<td>48.45%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>1.93%</td>
<td>2.59%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-1.60%</td>
<td>-2.10%</td>
</tr>
</tbody>
</table>

iii. European equities excluding the UK

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>61.86%</td>
<td>58.76%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>1.34%</td>
<td>1.81%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-0.99%</td>
<td>-1.54%</td>
</tr>
</tbody>
</table>

iv. Japanese equities

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>50.52%</td>
<td>45.88%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>3.16%</td>
<td>4.07%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-2.26%</td>
<td>-2.52%</td>
</tr>
</tbody>
</table>

v. Asia Pacific Equities excluding Japan

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>60.82%</td>
<td>55.15%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>1.51%</td>
<td>2.13%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-1.31%</td>
<td>-1.81%</td>
</tr>
</tbody>
</table>

vi. Emerging Market equities

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>55.15%</td>
<td>53.61%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>1.31%</td>
<td>1.64%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-1.05%</td>
<td>-1.54%</td>
</tr>
</tbody>
</table>
vii. Money Market

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>70.10%</td>
<td>18.04%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>0.12%</td>
<td>0.13%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-0.15%</td>
<td>-0.11%</td>
</tr>
</tbody>
</table>

viii. £ Investment Grade Corporate Bonds

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>58.76%</td>
<td>44.33%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>0.47%</td>
<td>0.71%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-0.27%</td>
<td>-0.52%</td>
</tr>
</tbody>
</table>

ix. £ High Yield bonds

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>50.00%</td>
<td>45.36%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>0.57%</td>
<td>2.45%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-0.69%</td>
<td>-2.39%</td>
</tr>
</tbody>
</table>

x. Commodities

<table>
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<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>57.22%</td>
<td>58.76%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>2.75%</td>
<td>5.24%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-2.87%</td>
<td>-4.51%</td>
</tr>
</tbody>
</table>

xi. Property

<table>
<thead>
<tr>
<th></th>
<th>Sector</th>
<th>Benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Months that <em>Clever</em> outperforms</td>
<td>52.26%</td>
<td>47.10%</td>
</tr>
<tr>
<td>Outperformance when <em>Clever</em> is correct</td>
<td>1.57%</td>
<td>2.26%</td>
</tr>
<tr>
<td>Underperformance when <em>Clever</em> is incorrect</td>
<td>-1.32%</td>
<td>-1.90%</td>
</tr>
</tbody>
</table>