Global Horizons

Standard Life Investments

September 2013

Standard Life Investments is one of the world's leading investment companies. Responsible for investing assets on behalf of over five million customers, including the Standard Life Group, we offer global coverage of investment instruments and markets.

We are active fund managers, who place significant emphasis on research and teamwork. After in-depth analysis, our Global Investment Group forms a view of where to allocate assets, based on the prevailing market drivers and on forecasts of future economic indicators. The Global Investment Group is made up of senior investment managers from the Strategy and Asset Class teams and is responsible for providing the overall strategic focus to the investment process.

The House View delivers a consistent macroeconomic framework to our investment decisions. It generates the market and thematic opportunities for us to add value to our customers over the timescales they use to measure our success. It is formulated in such a way as to make timely investment decisions but to also allow all members of the investment teams to influence its conclusions.

Global Outlook, a quarterly summary of the House View, is partnered by **Global Perspectives**, a monthly article on topical issues, **Global Horizons**, an occasional report on thematic and structural trends and **Global Spotlight**, web only articles commenting on current events. The weekly Macro Digest examines the latest statistics from all the major economies. Copies are available on the Market View section of our website www.standardlifeinvestments.com.

Standard Life Investments is a dedicated investment company with global assets under management of approximately £178.8bn (as at 30 June 2013) – this equates to $271.2 billion, C$286.1 billion, A$296.2 billion and €208.7 billion. An exchange rate of £1 : US$1.5167 as at 30 June 2013 has been used.

Frances Hudson
Global Thematic Strategist

Global Horizons comprises part of the Global Series of publications at Standard Life Investments. It allows us to publish some of our more detailed work on topics ranging across asset classes, markets and methodologies.

Behavioural finance provides valuable insights to how the human psyche influences investment outcomes. It has significantly enhanced our understanding of how individual biases combine in various ways either to bolster efficiency or to confound rationality in markets. From this understanding we have developed a suite of behavioural tools and applications, to assist our investment decision process, some of which are described in this report.

Behavioural Finance Applications

Investors can use behavioural finance to improve their understanding of the markets and to enhance decision making. The first part of this publication focuses on some of the insights provided by behavioural finance into collective decisions in the context of financial markets. The second describes how investors interact with machines, using them to improve the quality of trading decisions in applications of artificial intelligence or to speed up the execution of trades in algorithmic trading. The third considers how to promote robust decisions in a committee context, applying some of the lessons from behavioural finance to build a robust scenario process.

The wisdom (or otherwise) of crowds

Markets epitomise crowd decision making. In the best case the aggregation of views in a market results in prices at which transactions occur and individual irrationality and bias are removed, or drowned out by the crowd. For 'efficient markets' aficionados, while individuals may not be privy to all relevant information, aggregate information is disseminated by cascades and feedback loops contributing to an efficient whole where securities trade at fair value. Could one person carry out the function of the market with respect to processing information? Unlikely – even if one were able to consider each new piece of information separately, it may not improve the outcome. To understand why this is the case entails looking at how decisions are made and what influences them.

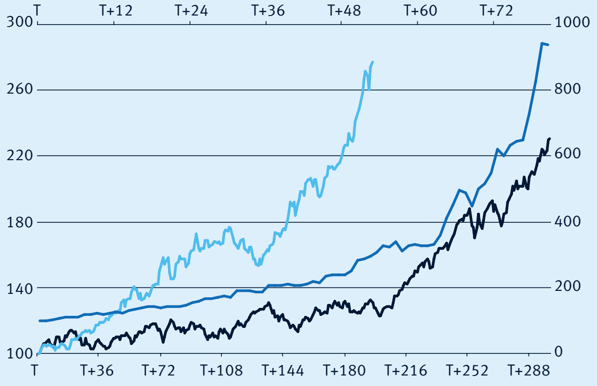
A significant part of behavioural finance is concerned with flaws in decision making. A tendency to ascribe heavier weights to more recent information is one pitfall. We anchor or frame our views using a central belief as a reference point, which may not be the appropriate starting point. Then confirmation bias means that we interpret ambiguous information in a way that favours the views that are already held. The data from markets may be noisy and hard to process. Finally, we may not recognise the relevance of information, treating it as coincidental when it is causal, or vice-versa. Various academics have published research on the challenges of making decisions under uncertainty.

For example, Philip Tetlock of Wharton sets out a three-stage judgement matrix in which decision making can be improved with practice by moving from an instinctive insider view to a more analytical consideration of outside influences and then to balancing the two and reaching a judgement that takes into account both inside and outside aspects.

Before worshiping markets as bastions of good judgement, however, consider that if properly functioning markets are wise, there are just as many examples of dysfunctional, foolish markets. Markets can be subject to the same behavioural foibles as individuals, compounded by herding tendencies where, rather than cancelling each other out, individual biases combine and escalate into extremes or bubbles (see chart 1). Overshooting is a common feature in some markets, suggesting that insider views are prevalent.

The inability of most investors to beat the markets on a consistent basis over a sustained period of time reinforces the notion of the market as a wise crowd. There are of course exceptions to this. Well-known counter examples include legendary value investors such as Ben Graham, John Templeton and Warren Buffet or the endowment model used by some US universities and Soros's Quantum Endowment vehicles, amongst others, in the multi-asset space. It may be argued that what is going on here is that these investors are not facing well-functioning markets but are applying their talents at the places and time frames where the markets are least efficient. Deep value investors are, by definition, fishing for investments amongst the unloved stocks. Interest in stocks that are under-researched or are in inefficient segments of the market is a common trait amongst value investors in both developed and emerging markets, as is the discipline imposed by seeking cost effective execution. The endowment models worked well for a time because they adopted a longer-term approach than most investors, effectively diversified risk and did not incur the costs associated with a need for short-term liquidity. Many also enjoyed significant tax advantages. Time is a key factor. A longer time horizon undoubtedly adds scope for using tools that are suited to these time frames, which includes fundamental analysis and thematic approaches. Artificial intelligence, which is commonly used

Chart 1
Irrational exuberance



Nasdaq Index (Daily price, Rebased = 100 at 31 December 1998, data until 10 March 2000)
Silver (Daily prices, Rebased = 100 at 28 July 2010, data until 28 April 2011)
Bitcoin (Daily prices, rebased = 100 at 14 January 2013, data until 3 April 2013) (Upper Axis and R.H. Scale)
Source: Bloomberg, Bitcoin Charts, Standard Life Investments

Chart 2
Relative strengths and weaknesses

Man	Machine
Innovation	Black Box
Interpretation	
Judgement	
Understanding	
Adaptive	Algorithm

Machine	Man
Agnostic	Fear and Greed
Complexity	Intellect Constraint
Speed	Latency
No Bias	Cognitive Bias
Tireless	Fatigue

Source: Standard Life Investments

in short-term market analysis, may also be applied here. Another attribute shared by these investors is a robust decision-making process and it could be this that has proved more difficult for others to replicate.

It may not matter if markets are foolish - take the position attributed to J M Keynes: ‘Markets can remain irrational longer than you (and I) can remain solvent.’ So, irrespective of whether the market is wise or foolish, betting against it can be costly. History is well-populated with investors who mistakenly thought they could take on the markets and win, either on an individual or corporate basis. Hedge funds and proprietary trading desks have had some spectacular failures and losses, with Long Term Capital Management, Amaranth Advisors, and Tiger Funds among high profile casualties. Barings in the past and Societe Generale, UBS and JP Morgan more recently have also suffered substantial reversals which started with traders misreading the markets and compounding their errors through behavioural biases.

Artificial Intelligence – man versus machine

Investment approaches generally contain both qualitative and quantitative elements. In broad terms human thinking may be better suited to the qualitative side while computers are used to varying extents to add value to quantitative inputs. Chart 2 sets out some of the strengths and weaknesses of the two. With technological advances and increased computational power, machines play a large and increasing role in markets, whether in analysis, trading or risk management.

Some of our most powerful tools for analysing markets make use of artificial intelligence or AI. Observations of behaviour, which can be found in nature and non-human organisms as well as people, are modelled using genetic algorithms (GAs) or artificial neural networks (ANNs). One of the attractions of AI is that even though the underlying data is subject to behavioural biases, AI is capable of filtering the mass of information in such a way that it provides an independent mathematical view. It represents collective intelligence rather than the foolish crowd.

An example from the natural world, observing how ants establish pheromone trails, illustrates two of the overarching concepts in our use of AI; decision making in layers and how networks can improve solutions to optimisation problems. From a simple set of decision making rules, ants are able to select the fastest pathway from their nest to a food source. Initially taking a random route, the ants that find the source, carry food back to the nest leaving a pheromone trail. This trail subsequently attracts fellow ants and, as this reinforcement process continues, the shortest route is pursued as it has the strongest scent.

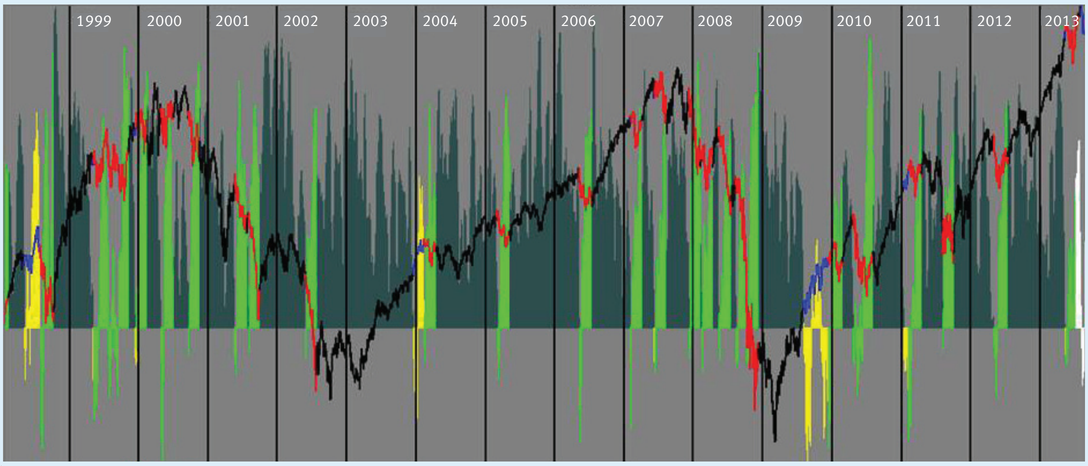
AI can incorporate fundamental and technical indicators as well as price. It is consistent compared with human analysis and lends itself to building decisions in layers in a way that resembles 3D printing. By using multiple AI systems, we are able to develop numerous forward-looking interpretations of market outcomes. For example, Standard Life Investments uses a combination of AI measures from fundamentals, flows and behaviour to establish what sort of market environment or regime is extant and then AI based on clustering or proximity measures to identify appropriate investments for that regime.

Of course, behavioural bias can still creep in when it comes to assessing the output of AI. In the case where humans have the final word, at the very least, if the AI suggests a positive interpretation when our view is negative or vice versa we should question our judgement. In fact, confirmation bias makes it more likely that the AI conclusions will be accepted when they support the view held, leading to overconfidence, and questioned or discarded when they conflict, ostensibly to avoid ‘cognitive dissonance’. In this way bias may be exacerbated in a less than robust system. In a situation where the final outcome devolved to the AI, it disregards the human conclusion, whether positive or negative. In this way AI can never be party to ‘groupthink’.

Evolving outcomes

A Darwinian approach allows us to apply the principles of natural selection to modelling investor behaviour via a genetic algorithm. Just as ant behaviour displays collective

Chart 3
Evaluating the GA reference pattern



Source: Standard Life Investments (as of 27 August 2013) problem solving to establish the best route to food, GAs can solve the optimisation problem of identifying a pattern of indicators that emerges prior to a market fall. Importantly, even if investor or ant behaviour differs on an individual level, we assume that behavioural patterns on an aggregate level are predictable.

Inserting a pool of eight indicators, the GA creates a set of reference patterns which improve through iteration via selection, mutation and crossover. This basic set of biological mechanics underlines the gradual process of genetic evolution.

The fitness of each particular solution can simply be evaluated according to whether the market rose or fell as the indicator reference pattern emerged. Chart 3 depicts one of the GA's solutions. A green spike occurs where the reference pattern emerges and the market falls within 40 days while the yellow spike displays the error outcome, whereby the reference pattern emerged but the market failed to fall within the 40 days. Although the GA is neither perfect nor infallible it does display a valid interpretation of the market. As such, it can be utilised as a useful forward-looking indicator.

Importantly, while solutions are generated using a computer based algorithm, the criteria for fitness evaluation, mutation rates, crossover rates and termination are determined by the human user. Therefore, the final solution is influenced by both man and machine. The use of machines does not necessarily negate the role of human judgement in understanding the market but can enrich analysis beyond the capabilities of human intellect

Neural cartography; mapping investor behaviour

Measuring the correlation of investor behaviour to market swings involves processing a huge quantity of data. On this scale, the human brain is not best equipped to deal with the complexity of data or to derive recognisable patterns. Here, artificial neural networks, for example in the form of Kohonen self-organising maps (SOM), can be used to create a two dimensional representation of the data. The SOM independently learns to classify data in the map. The location of that data expresses a particular correlation that the SOM has learned. In contrast to GAs, the Kohonen map does not require an output objective to work towards. Therefore, the potential for human bias distorting the results to fit a preconceived idea is arguably smaller.

Elsewhere, Kohonen maps are widely used for electronic speech recognition in mobile devices. In an investment context, that facility for pattern recognition enables their deployment for predicting future market direction from a set of indicators. In our example, the Kohonen grid is sensitised to input vectors which define money flow and stock price data of each individual stock from a selection of indices. The two variables are used to characterise investor behaviour.

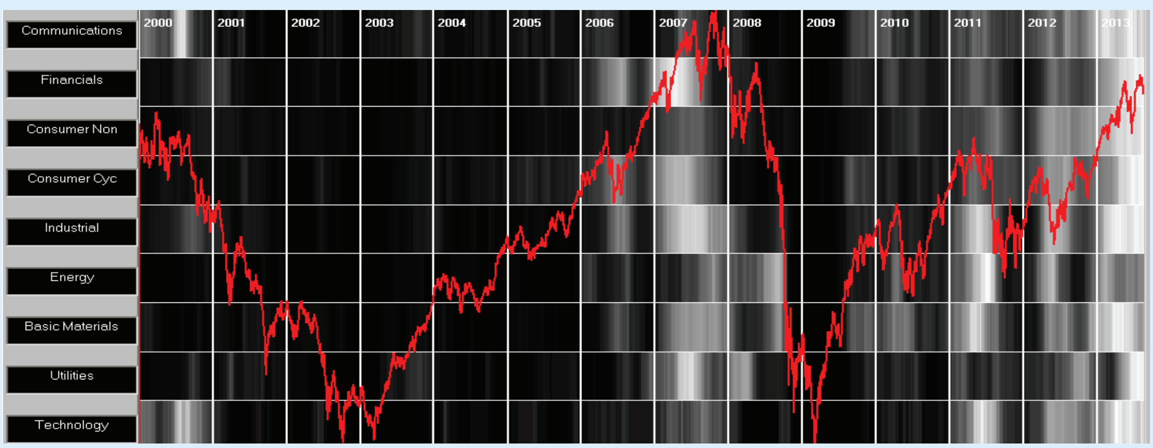
Given the SOM's unsupervised ability to learn data correlations which are expressed according to locality on the map, the human user can identify a long and short area. For instance, when multiple input correlations are similar to the pattern in the short area, the Kohonen method indicates that the market may fall. This is because investors are displaying similar behaviour, even if potentially irrational, to that which appeared in a previous market fall.

Chart 4 is a graphical representation of the Kohonen results where equities are split into sectors and the red line traces the performance of the S&P500 index over the period. White areas occur where there is a potential for shorting behaviour. Thus, the Kohonen indicator is identifying downside risk and predicting possible sector or market falls. Essentially, emergent global stock market behaviour is captured by the Kohonen map. In this case, the machine is able to develop a better grasp of investor behaviour than investors themselves.

Black box

While the previous examples illustrated the utility of AI in consistently analysing large datasets and complex relationships and incorporating different types of indicator

Chart 4
Kohonen network application



Source: Standard Life Investments (as of 27 August 2013) without introducing bias, there is another group who mix markets with machines. Rather than providing a layer or layers in decision making, in the realm of the algorithmic trader the algorithm determines and executes the trade. This type of trading, where humans have been more or less relegated to spectators, is not new. Markowitz was involved in the design of algorithms in the 1950s and 60s that were loaded onto an IBM computer and used to analyse market data and subsequently to 'guide' trades. Today, a subset of systemic or algorithmic traders, High Frequency Traders (HFTs), dominates the landscape. HFTs reportedly account for up to 70% of trading volumes in the US. Their systems are designed to execute trades based on algorithms with speed of execution as the differentiating factor. Latency is measured in microseconds on the trading side or milliseconds when it comes to data releases.

HFTs predominantly operate using two trading strategies, market making and market latency arbitrage. The former consists of posting orders to capture spreads and receive per share liquidity rebates from exchanges. The latter describes actively trading temporary price differentials between securities and markets. Essentially, HFTs assume that markets will eventually move to their fair price and they trade on that movement. Therefore, their rationale for trading is underpinned by the Efficient Market Hypothesis (EMH) whereby markets are rational and prices contain all available information, an interesting counter to the common belief that the financial crisis has undermined the EMH.

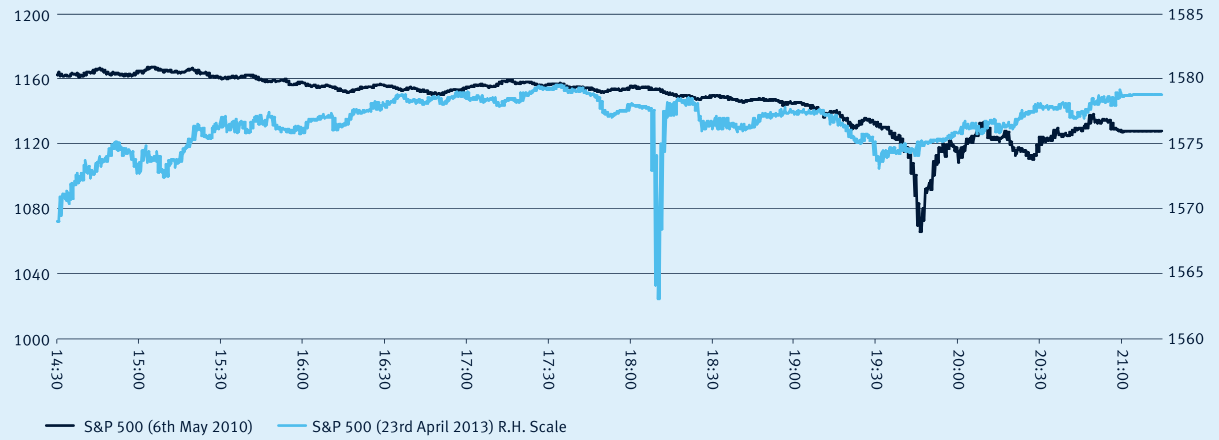
Adherents argue that this exercise provides an important service to the financial industry. Acting as market makers providing faster quotes, HFTs could increase market liquidity. Furthermore, by creating more competition in the market place, the presence of HFTS could narrow bid/offer spreads and consequently reduce transaction costs. Arguably, actively pursuing arbitrage strategies allows faster fair price discovery which could be considered indicative of a more efficient market.

More critically, in their pursuit of arbitrage opportunities in the context of low latency, HFTs rely on simple algorithms predicated on price alone. Ignoring the long-term relationship between asset prices and fundamental value means that, as HFTs gain market share, the dislocation between price and fundamentals could become more pronounced at a market level. Replacing some human bias with speed in this case does not reduce systemic risk. Another behavioural trait, herding, can traverse to machines. Where positive feedback occurs, multiple algorithms will simultaneously trade a stock in the same direction, culminating in rapid larger movements and thus increasing market volatility. Thirdly, these algorithms rely on a quantitative interpretation of market conditions within a defined set of parameters. If those parameters are breached, HFTs could immediately cease trading causing a rapid reduction in liquidity. In contrast, Human investors are able to form a qualitative judgment when faced with uncertainty.

These weaknesses could be an explanatory factor in the 'flash crash' of May 2010 or the hoax AP Twitter flash crash of April 2013 (Chart 5). In fact, some industry experts argue that mini flash crashes have become a common occurrence in the market. Far from increasing liquidity and reducing volatility in the market through more efficient fair price value realisation, HFTs can instantaneously shut the liquidity tap and create more volatile market conditions. In August 2012 a trading error blamed on 'technology breakdown' at HFT Knight Capital caused major disruption on the New York Stock Exchange and the near failure and subsequent sale of the firm.

Their rapid growth is a concern for regulators, as is the concentration of ownership. Given that this is relatively unknown territory, there is perceived systemic risk in allowing an agnostic black box to act as a dominant market maker. With 70% of trading volumes in the US controlled by 2% of trading firms, and a more modest 27% of London volumes, there have been initiatives aimed at slowing the markets down by batching trades as well as more direct regulatory salvos, such as the EU's proposed Financial Transactions Tax. The cost of progress in this case may be too high for comfort.

Chart 5
Algorithms can crash



Source: Bloomberg (as of 23 August 2013)

The constitution of committees

Committees and the quality of the decisions made by them are not universally admired: a camel is a horse designed by a committee (Financial Times); a committee is a group of men who individually can do nothing but as a group decide that nothing can be done (Fred A Allen); a committee is a cul-de-sac down which ideas are lured and then quietly strangled (Barnett Cock); we always carry out by committee anything in which any one of us alone would be too reasonable to persist (Frank Moore Colby). The more serious points being made are concerned with compromise leading to sub-optimal outcomes, an inability to agree on anything beyond the lowest common denominator – how often do notes of committee proceedings prompt criticisms of time wasted with minimal results? Participants feel their best ideas are stifled by vested interests and entrenched positions. Conversely, because they allow the abdication of responsibility at an individual level, committees can lead to more extreme collective outcomes as the members egg each other on. This is evident in politics and regulation as well as psychology test results.

Despite the potential flaws, committee decisions determine or influence most aspects of our lives. One of their challenges is to take limited amounts of information and extrapolate in order to form policy for an uncertain future. Leaving aside the potential for errors in the information that is being considered, are there ways in which the committee function can be improved? Agreeing terms of reference and establishing a common language are a useful first step in establishing a framework under which information or evidence can be assessed. Committees also should aspire to some mechanistic traits, such as consistency and taking into account failure as well as success – adopting an agnostic approach. Committees as well as individuals can benefit from being aware of and seeking to avoid cognitive bias. Rather than predicating the future on single analogies or past correlations, in which circumstance and context can have played a large part, a range of outcomes can be considered using, say, conditional probabilities. 'What if' is a powerful construct and introducing flexibility, so that decisions can be reversed if required, is a useful form of risk management, described by Peter Bernstein. He also favours situations where a degree of control can be exercised.

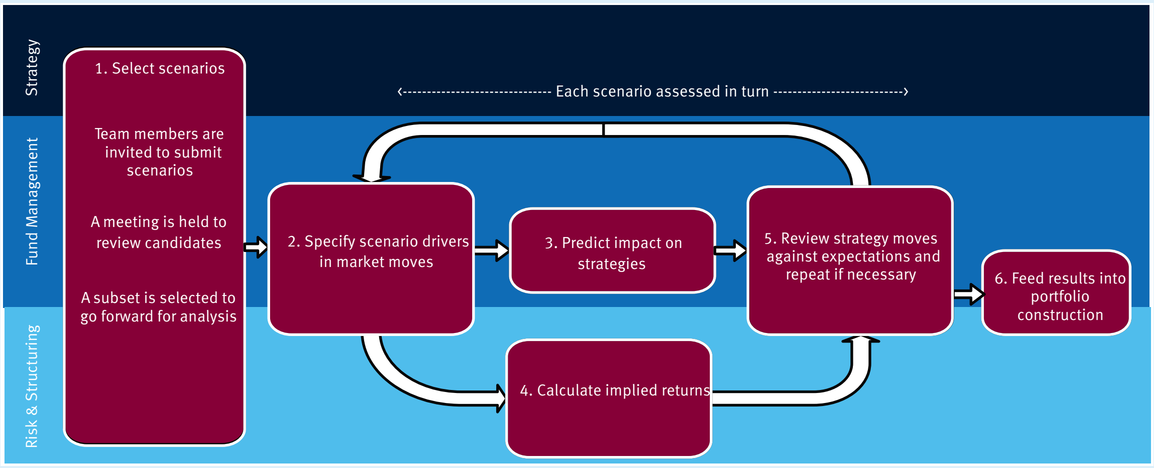
In a sense a committee is a special case of a crowd and many of James Surowiecki's conclusions regarding the conditions for 'wise' crowds can also be applied to committees. The successful ones will include a variety of opinions that have been arrived at independently; members will meet to share their specialised knowledge and there will be an effective aggregation process that turns individual judgements into collective decisions.

Scenarios – man and machine

Setting up a workable scenario process entails circumnavigating the pitfalls of committees and progressing towards better collective decisions. The rationale for discussing what could go wrong is not an exercise in appeasing the pessimists. Two major benefits lie in increased tolerance for occasions when events, inevitably, deviate from expected outcomes and, secondly, the discussion can provide an opportunity and prompt to take pre-emptive action if required. This promotes a more robust approach. Chart 6 sets out a six stage method for identifying and using scenarios in a multi-asset context.

The first requirement is to move beyond the inside view. Generally, when discussing scenarios the starting point is the status quo, so the current assessment of the situation is given higher probability, because that is where conviction is highest. It also may be overlaid with an optimistic tilt; human nature leads us to flatter our own judgements. The value of an approach that does not start with a central scenario is that it avoids anchoring, i.e. the tendency to weight the results of the other scenarios towards the 'house' view. Utilising our *Focus on Change* philosophy, the starting point for a plausible scenario need not be related to financial markets. While the macro economy and economic policy are rich sources, geopolitics feeds into event risks; technological change, resource shocks and even the environment may underpin market developments. Other considerations are behavioural – are the markets priced for perfection in relation to a particular outcome? The contrarian thought process required in coming up with plausible rather than probable extreme scenarios that could upset the existing portfolio is designed to move beyond the 'insider' view at the outset. Another option is to include

Chart 6
Generating scenarios



Source: Standard Life Investments

opinionated outsiders when asking for scenario suggestions, for instance asset class experts from other teams. Stipulating that the submission of ideas is without prior discussion or consultation serves to avoid bias caused by 'groupthink'.

An inside perspective encourages the highlighting of differences, treating the current situation as novel, i.e. lacking in precedent - which avoids having to learn from past experience and raises the perceived value of the human component. It is important that each of the proposed scenarios have a reasoned path or set of events that could lead to the suggested outcome. Experts can then predict the impact of the drivers of each scenario on their asset class (Chart 7). Quantitative (machine-based) techniques add uncertainty to point forecasts and identify vulnerabilities in the portfolio. The assessment stages of our process draws on past periods which have similar characteristics, albeit using them for information rather than as quantitative templates. Rather than solely relying on historic correlations, Monte Carlo simulations employ computational algorithms to model possible outcomes. Determining the transmission channels and relationships between risk factors under conditions of stress is enhanced by the use of entropy pooling. Coping with future uncertainties is best served by an iterative process as information feeds back and scenarios are fine-tuned.

Conclusion

Crowds in the form of markets have the potential to be either wise or foolish. Wise crowds and efficient financial markets can add value beyond the sum of their individual constituents, leading to accurate price discovery. Whereas foolish ones exacerbate inefficiencies; behavioural failings result in increased volatility, bubble formation and occasional crashes. The collective wisdom displayed by markets is no more infallible than any consensus view but markets have the firepower to outgun investors who may think they know better. Investors often do not realise how unpredictable a complex world can be, one where exogenous shocks can knock a finely crafted forecast off track. In addition, it is human nature not to think about extreme events, or realise that their probability can be relatively high, as any statistical analysis of fat tail events can show.

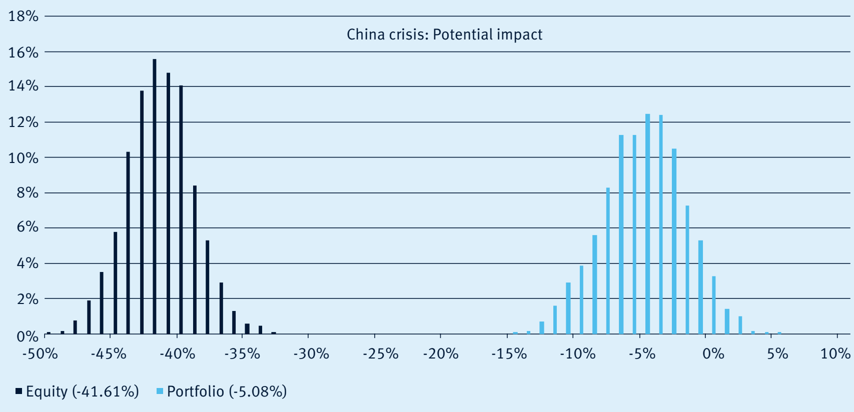
Where smaller groups are concerned, it is less likely that behavioural biases will be cancelled out. In that case, the discipline imposed by longer time horizons and contrarian thinking may offset some of the effects of momentum and short-term noise. Attention is given to the structure of committees and the types of input required for a robust decision-making process. Rather than consensus thinking, independent and outside views are valuable in promoting understanding of and circumventing possible adverse outcomes.

Humans and machines bring different strengths to the table. Humans score more highly on innovation, interpretation, adaptation and judgement while machines are consistent, quick, tireless, agnostic and able to cope with complexity. Taking a multi-layered approach to investment decisions allows us to develop an enriched understanding of the instincts that govern investor behaviour and incorporate different factors into decision making. For instance, Standard Life Investments has sought to combine human expertise and judgement with advanced computer applications in areas such as risk management and scenarios, in turn helping to understand and predict the likelihood and impact of extreme events. Artificial intelligence applications have enhanced our understanding and analysis of financial market behaviour, adding to the range of predictive tools.

The opportunity offered by increases in computational power has been exploited in different ways by diverse market participants. High frequency traders focus on speed of execution, sometimes sacrificing complexity in their algorithms in order to reduce latency. A note of caution is sounded where computers become the major drivers of markets, resulting in increased systemic risk. At the other end of the spectrum, long-term investors can benefit from computers' consistent application of collective intelligence to financial markets. Sound analysis of the complex relationships that characterise markets can complement traditional methods and judgement in stock selection, asset allocation and risk management.

Chart 7
Extreme outcomes

Thematic scenarios
QE bubble
Abrupt end to QE
EU disintegration
Commodity shock
Trade war
China crisis



These are examples of thematic scenarios analysed in SLI's Multi Asset Investing team and the potential impact of one of them.
Source: Standard Life Investments

Appendix: More on methodologies

Scenario analysis

The selected scenarios from the discussion phase are modelled using Monte Carlo simulation techniques and entropy pooling.

The Monte Carlo method is a computerised, sampling technique which creates a set of possible outcomes for each uncertain factor.

Entropy measures the randomness in a system. Entropy pooling involves re-weighting possible outcomes so that they agree with pre-specified views.

Firstly, Monte Carlo simulations are produced. This involves iterating through time and producing (n) Monte Carlo simulations for each time step (t). Strategy returns are then calculated for each simulation.

Secondly, entropy pooling optimisation is used. From this, a mean underlying vector is produced and pre-specified values are substituted into this vector to compute strategy returns and the fund return distribution.

Thirdly, knowing the outcomes for each factor, fund returns are computed using a full re-evaluation of all option positions.

Output:

1. Conditional mean vector of all underlying conditions.

2. Implied strategy vector.

3. Implied fund return.

4. Distribution over fund returns from the second Monte Carlo simulation.

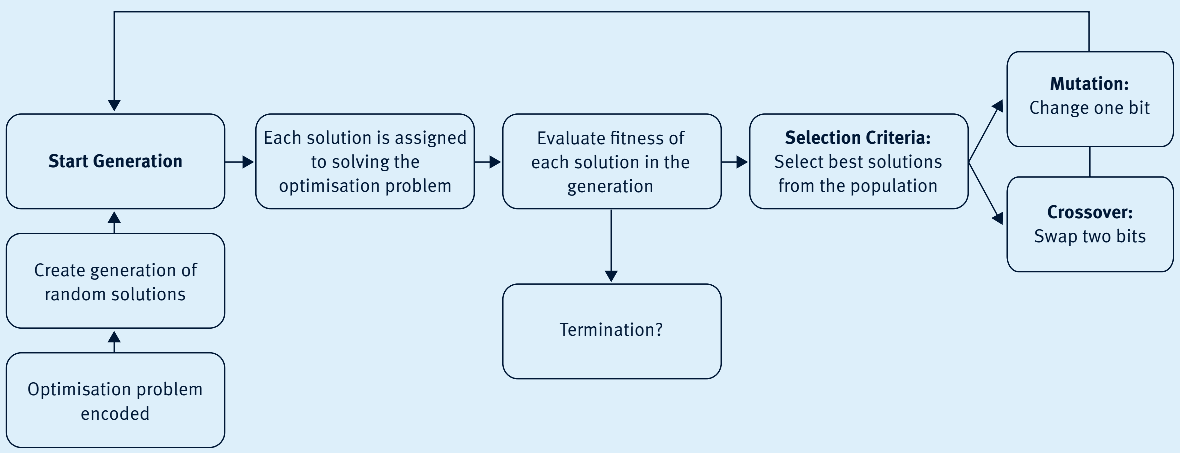
Genetic Algorithm

GAs generate a set of solutions to an optimisation problem where the method is derived from the process of natural evolution.

Organisms grow according to a set of rules encoded within its genes which are connected together by chromosomes. When two organisms reproduce, the resultant offspring has an equal combination of its parents' genes. Occasionally, a gene may mutate to contain a new rule set. Via the process of natural selection, beneficial genetic mutations emerge in subsequent generations. As a result of combination and mutation, generations evolve to possess better traits.

Via iteration, the GA is able to produce a set of improving solutions to the optimisation problem. When the termination criteria are met, iteration stops and solutions fit for the function are taken. See chart 8 for a further description.

Chart 8
GA methodology



Source: Standard Life Investments

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