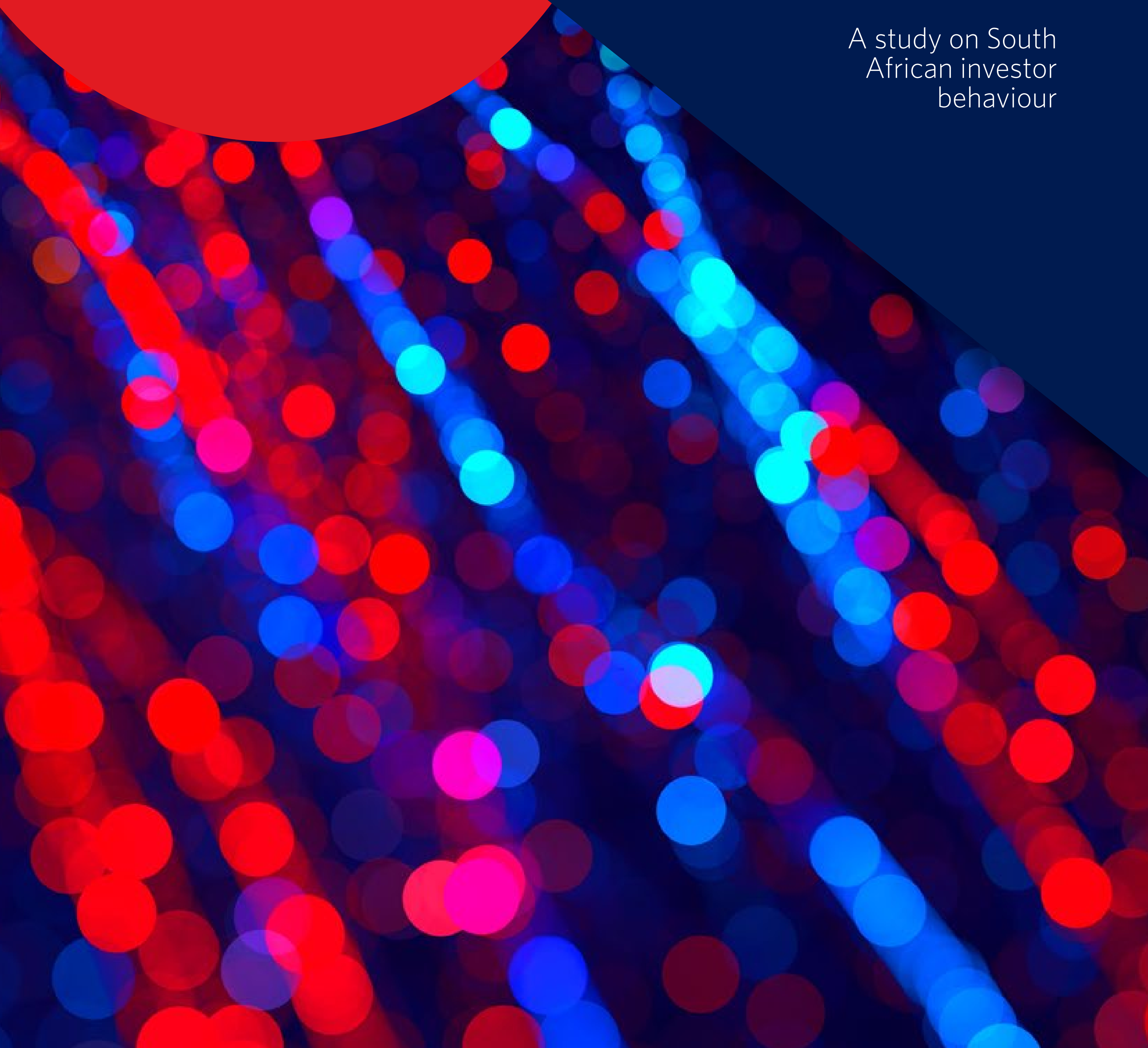
momentum
investments

Understanding the great forces that rule the world

A study on South African investor behaviour



> "Three great forces rule the world: stupidity, fear and greed."
> – **Albert Einstein**

1 Introduction

Robert Thompson, an airline pilot, stopped at a local shop to pick up a few items on the way home. He entered it and promptly turned around and left for no apparent reason (but later reported feeling unsafe). A police officer passed him on the way out and was soon shot and killed as the store (unbeknownst to Thompson) was being robbed at gunpoint at the time. Thompson didn't know why he walked out of the store that day, but he clearly picked up on something (perhaps the anxiety in the store clerks' demeanour) that subconsciously triggered the reaction that may have saved his life (Lo, 2011). Renowned neuroscientist, Joseph Ledoux, used chemical trackers in the 1970s to trace the fear response to the primordial amygdala which became known as the brain's centre for fear and risk.

While this is a great example of how fear circuitry in the brain can be vital to our survival, it can also be counterproductive and even dangerous. This very same instinctual response is trained out of pilots where pulling up on the wheel (pointing the plane towards the sky) is a common natural response to the engine stalling. Similarly, snow skiers are required to lean forward if they want to slow down – a completely counterintuitive response.

On the greed side of the equation a renowned study led by Hans Breiter of the Harvard Medical School that included Nobel Laureate, Daniel Kahneman, determined by using functional magnetic resonance imaging (fMRI) that monetary reward activated the nucleus accumbens, extended amygdala and hypothalamus (Breiter et. al., 2001). The results were all too familiar to Breiter as monetary reward activated the very same regions in the brain as a previous study that he had conducted on cocaine addiction. In both cases dopamine was released into the nucleus accumbens, reinforcing the behaviour. Fear and greed represent strong emotions that we link to perceptions of danger and opportunity for us as decision makers.
Each emotion is backed by the powerful reward and stress chemicals of dopamine and cortisol, the latter increasing our reliance on gut instinct (Margittai et. al. 2016). These emotions are present in all our lives and challenge the normal representation of rationality being the most important factor in terms of explaining our decision making. Kahneman, the joint 2002 Nobel Laureate, wrote his bestseller – Thinking, Fast and Slow – on exactly this issue (Kahneman, 2011).
The investment decisions that people make are most definitely affected by these emotions and their related chemical secretions. The effects of fear and greed on investment decisions and investor portfolio returns are often reflected in the form of a 'behaviour tax'. A behaviour tax is a lower investment return as a result of an investor's behaviour, like switching funds because markets are falling , compared to portfolios which are bought and held (Nixon et al. 2019). Following our instincts for investments often does not serve us well.

This paper contributes to a deeper understanding of South African investor risk behaviour over time through an analysis of the switching decisions of investors on the Momentum Wealth Linked Investor Services Platform (LISP). Relevant academic theory on decision making under risk provides a basis for this empirical work.
We start with Cumulative Prospect Theory (CPT), the theory of decision making under risk that Kahneman developed with Amos Tversky (Kahneman and Tversky, 1979, and Tversky and Kahneman, 1992). CPT highlights the importance of a reference point when making decisions (Kahneman and Tversky, 1979), and decision makers' flawed ability in assessing probabilities correctly (Tversky and Kahneman, 1992). Sitkin and Pablo (1992) extend this work by proposing that while investors each have a 'risk preference' or character trait of being attracted or repelled by risk (Weber and Milliman, 1997), this preference is mediated by our 'risk perceptions' or assessment of risk in any given situation and our 'risk propensity' to take risk, which is a function of recent experience in this space (Sitkin and Pablo, 1992). Humans are particularly poor at assessing risks and can easily be fooled by something as simple as the way a given situation is framed (Kahneman and Tversky, 1979). We underestimate risk when experiencing losses and often look for excess risk at the opportunity of negating such painful losses. Moreover, our propensity to assume risk is significantly affected by prior outcomes (success or failure) (Weber and Milliman, 1997). These effects were clearly demonstrated in the results of the research reported by Nixon et al. (2019). R100 billion of investment flows on the Momentum LISP over a decade (2006 – 2018) were analysed and this clearly showed that twelve-month past investment performance predicted future inflows accurately.

We build on this body of work by developing a South African first: a segmentation of South African investors based on a risk-based analysis of the switching of their holdings in discretionary unit trusts. The approach used allows for a decomposition of the switching decision to capture different elements of investors' risk attitudes and resulting decision making behaviour. Our approach is based on an assessment of both how past investment returns are related with fund switches and how investment performance may be linked to investors deciding to take on a greater or lesser degree of investment risk. We take the level of switches into account as well as the extent to which their decision reflects a desire to chase the past performance of other funds. As shown in Nixon et al. (2019) this can lead to a significant 'behavioural tax' being imposed on their investment returns.

> *Investing is, by its very nature, a long-term endeavour filled with the optimistic belief that a growing enterprise offers.*

Why is this important? Investing is, by its very nature, a long-term endeavour filled with the optimistic belief that a growing enterprise offers. The grouping of investors based on their risk behaviour is useful for several reasons.
Firstly, it allows for the effective linking of their risk preferences or risk tolerance (both stable by nature) securely with their long-term investment goals. Secondly, a better understanding of the compromising nature of myopic risk behaviour (which places too much emphasis on the transient present and its related emotions) is key to understanding client and adviser behaviour, and, more importantly intervening accordingly at the right time to avoid the associated negative implications of these behaviours.
Ultimately, the point is to help investors avoid the harmful outcomes of the third of the great forces that, according to Albert Einstein, rule the world, namely 'stupidity'. These insights are key to achieving this outcome.

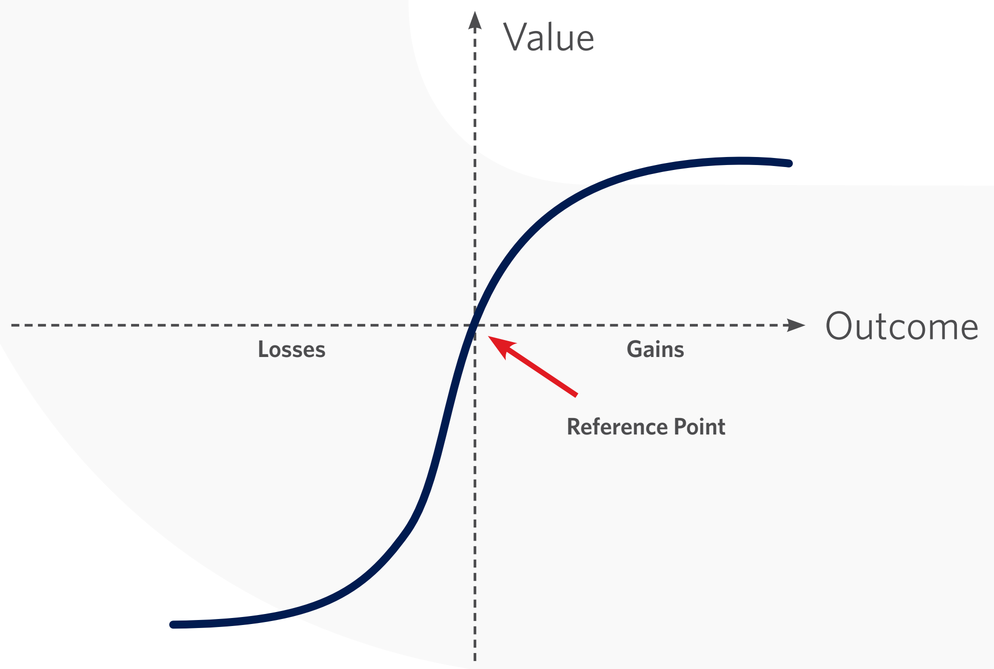
2 A Brief Summary Of The Theory Of Investment Decision Making Under Risk

When trying to understand the decisions of players in a card game it was initially thought that decision makers tried to maximise the expected monetary value of the choices. However, the St Petersburg paradox demonstrated the fallacy of this – it proposed a game with an infinite expected value, yet most people would pay very little for the opportunity to play it. Utility theory was proposed as a counterargument to this notion. According to this theory, decision makers focus on maximising the level of happiness (or utility) associated with the outcomes of their choices (Bernoulli, 1738). The additional, very plausible, assumption of diminishing marginal utility to units of wealth (or consumption) resolves the paradox.

According to Expected Utility Theory (EUT), decision makers use the objective probability of the prospect occurring combined with the utility levels of the expected outcome to identify a weighted average of the utilities to any one course of action. The course of action selected will be the one that maximises this weighted average expected utility level. Von-Neumann and Morgenstern (1944) established four axioms needed for EUT to hold true – in other words, these axioms provide the definition of rationality in this context. In addition to these axioms, the shape of the utility function is vital. This parameter reflects the investor's risk preferences or attitudes – something that the theory assumes is a given – and it is a function of who the person is. In general, risk-averse investors have concave utility functions, risk-seeking possess a convex shaped curve, while risk-neutral investors have a linear utility function of wealth.

This version of EUT came under almost immediate criticism. Allais (1953) highlighted the common ratio and common consequence paradoxes to illustrate how certain of the four axioms are consistently violated in everyday situations. Kahneman and Tversky (1979) extended this criticism conducting a series of experiments where university students and faculty members were given hypothetical choices over two lotteries. They showed that decision makers display the certainty effect – the tendency for decision makers to overweight outcomes seen as certain (or risk-free) relative to those that are probable – thus violating one of the (transitivity) axioms required for EUT. They proposed Prospect Theory (PT) to deal with this. PT is an extension of EUT, with factors such as cognitive biases and heuristics observed in human behaviour included.
PT argues that decision makers assess value as gains and losses relative to a reference point instead of the absolute level of outcomes or wealth values. This reference point can be viewed as the decision maker's current level of wealth, or some benchmark the decision maker is trying to attain. Additionally, Kahneman and Tversky (1979) added that people tend to be risk-averse in gains and are risk-seeking in losses, violating the assumption in EUT that decision makers only have one attitude towards risk. This observation lead to the creation of an S-shaped value function (note how they do not refer to it as a utility function). Lastly, PT posits that the curvature of the value function is steeper in the loss domain than in gains, suggesting a greater sensitivity to losses than to gains of the same magnitude. These mentioned characteristics can be seen by the value function given in figure 1.

Figure 1: Value function proposed by Prospect Theory



Source: Kahneman and Tversky, 1979

Kahneman and Tversky (1992) extended PT into Cumulative Prospect Theory (CPT) to address some issues identified in their earlier work. A key element in this extension is that they recognise that people are unable to evaluate probability from a strictly statistical point of view, but rather a subjective one that violates the traditional laws of probability theory. Instead of using objective probabilities, Kahneman and Tversky (1992) developed a subjective probability weighting function based on the objective probability. They recognise the tendency of decision makers to overweight lower probabilities and underweight higher probabilities.

Sitkin and Pablo (1992) extended this approach by proposing a model of decision making that introduced the concept of risk propensities as a mediating factor between risk preferences and risk perceptions. This explicitly introduces the role history in terms of explaining decisions under conditions of risk (see figure 2).

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Figure 2: Mediated model of the determinants of risky decision-making behaviour

Source: Sitkin and Pablo, 1992

Like CPT, Sitkin and Pablo (1992) see risk preferences (both to gains and losses) as a fixed or stable personality trait – but emphasise that there are other factors that also mediate (or affect) decisions in the short run. Most importantly, they introduce the concept of risk propensity where peoples' prior experiences (success or failure) affect their willingness to risk more or less of their wealth. In other words, their willingness to take on risk (or not) does not only depend on their risk preferences and the framing of the decision (i.e. CPT) but also what happened immediately before they were faced with the risky prospect or choice. Salient factors that are objectively temporary, e.g. recent investment performance or gambling results, directly affect their perceptions of risk.

Weber and Milliman (1997) report the result of a study that involved repeated financial investment decisions. It showed clear evidence that people who were 'winning' from previous stock selections became even more risk seeking and those who were 'losing' based on their previous choices became more risk averse. This work directly supports the risk-propensity mediated model over approaches that rely on (stable) risk-preferences only in this context.

Finally, Frey et al. (2017) reports that, based on psychometric tests, risk preferences have structure similar to measures of general intelligence. As such they tend to be persistent with values that are consistent over time.

In short, while investors may have stable risk preferences, ultimately decision-making behaviour in risky conditions is also affected by the 'label' attached to the situation by the decision makers (their risk perception) and their past experience of similar decisions as being profitable or otherwise (their risk propensity). The combination of these factors can trigger emotions which can lead to decisions being taken that appear contrary to their stable risk preferences. This emotion-mediated theoretical framework informed the empirical analysis of investor switching behaviour reported below.

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3 Empirical Analysis of Investor Switching Behaviour

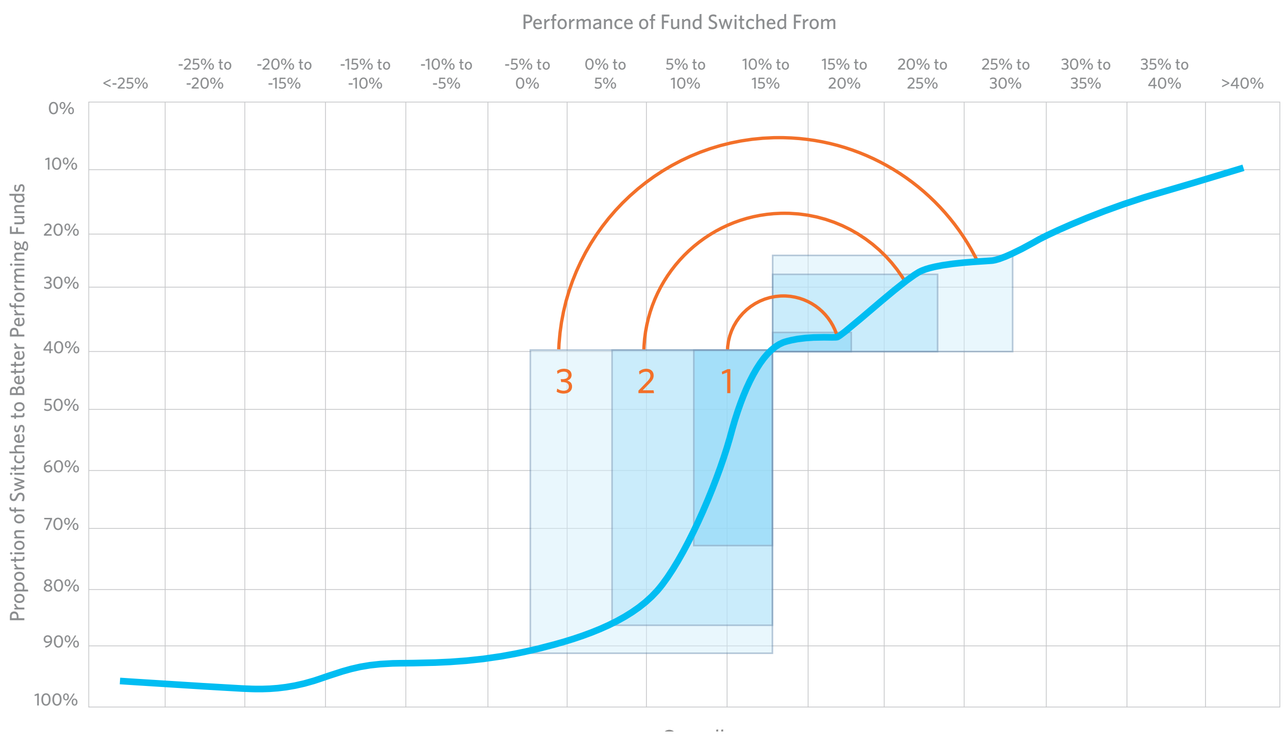
To understand more about investors' decision-making behaviour, we looked at the decisions by clients of the Momentum Wealth LISP to switch their holdings in investment funds. We looked at 44 815 switches by 23 390 clients holding funds on the platform for the period January 2006 to December 2017.

We identified the following elements of their switching behaviour:
- What is the average level of switches through time by individual clients?
- What is the correlation of relative performance over the 12 months preceding a switch with the choice of fund switched to?
- Does the switch reflect a change in the level of investment risk of the client?

The second element addresses the impact of context (past relative performance) on the switching decision as highlighted by Sitkin and Pablo (1992) while the last one looks at the intention to change the level of risk of their fund via the switching decision. To do this, both the levels of the (absolute) performance of the fund held over the 12 months before the switch and the relative levels of investment risk of the fund being switched into (i.e. a more aggressive/defensive/similar fund) were tracked for each investor.

Switches, historical absolute performance, and the inflection point

Figure 3: Cumulative switches and the inflection point



Source: Momentum Investments, 2020

Empirical Analysis of Investor Switching Behaviour

All switches in the period under review were ranked by their returns over the previous 12 months. The proportion of switches made into funds with a better return over the same period is plotted in figure 3. The solid line represents the proportion of switches made into better performing funds, ranked by the historical performance of their funds over the previous 12 months.

The data suggests that there is a clear inflection point within a range of historical investment returns around 12.5%. The inflection point reflects the level at which there is a sea-change in investor behaviour. Below this point, the investor is significantly more likely to switch funds into a better performing fund. Above it, switches still happen, but the rate of change of the proportion of switches into better performing funds slows significantly.

The boxes plotted around the inflection point provide a visual representation of the relative proportion of switches to better performing funds below and above the inflection point based on 5% increments in terms of the funds' returns over the past 12 months. The area of the rectangles to the left of the inflection point are, on average, nine times as large as the ones to the right.
These findings are robust according to the time-period and the risk level of the fund. The same analysis was conducted for the following periods: 'Pre-crisis' (2006 – 2007), 'Post-crisis' (2008 – 2009), 'Bull-trend' (2010 – 2013) and 'Fluctuating market' (2014 – 2017) – all with similar very similar results. All switches were awarded a score for being above, or below, the inflection point.

Based on their switching behaviour, each investor would get a score based on how many switches fell either above or below the inflection point. We have used the term 'Greed' to describe investors making switches to better performing funds above the inflection point; and 'Fear' to those switches made below the inflection point.

Categorising switches based on the level of past relative performance

The data presented in figure 3 relates to switches into better performing funds. The other choices available to the investor were to switch into funds that performed similarly, or worse, than the current fund. This behaviour was tracked for all switches both above, and below, the inflection point.

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Changes in the risk profile of the switched funds

Looking at how investors change the risk profile of their investments (i.e. how they switch into funds with relatively higher or lower levels of investment risk[1]) gives insights regarding their emotional reaction to expected future events. Investors' switches were then tracked to observe how many times they switched to funds with different investment risk ratings and in what direction that relative movement was. An investor's switches were then allocated to one of the following changes in investment risk categories based on the extent of the differences between the investment risk rating of the current fund and that of the fund being switched into:

- Down: Switch to fund with an investment risk rating that is lower by at least two units on the investment risk rating scale;
- Neutral: Switch to fund within a band of +/-one investment risk rating unit; and
- Up: Switch to fund with a greater investment risk rating of two or more units.

The goal was to identify groups of investors with similar types of switching behaviour on these dimensions.

[1] To assess whether investors were increasing or decreasing overall risk levels of their investments it was necessary to create a scale to evaluate the existing risk level of every unit trust on the Momentum Wealth platform. Initially it was thought to use the risk profile classification of the fund, however, these classifications may be misleading, for example a dollar-denominated income fund is classified as low risk but for the South African investor the currency exposure alone mimics equity-like volatility. It was therefore decided to align the risk profile of each fund with the asset allocation of the closest matching Momentum Investments outcome-based investment (OBI) fund. The Momentum Investments OBI funds have real return targets of CPI + 2% through to CPI + 6%. An investment risk rating from a scale of 3 - 8 was applied to all funds that were included in the switching analysis. The CPI + 2% to 6% fund range provides a continuum of risk for evaluation. CPI + 2% = low risk (investment risk rating of 3); CPI + 4% = medium risk (investment risk rating of 5); CPI + 6% = high risk (investment risk rating of 7). Pure equity and property funds were classified as the highest risk category (investment risk rating of 8).

The Switching Matrix

To get a view of the all the factors linked to switching behaviour, we combine the inflection point, past performance and risk profile change elements into the matrix reported in table 1.

Table 1: Switching Matrix

		Below the inflection point (Fear)			Above the inflection point (Greed)		
Past performance		Higher	Neutral	Lower	Lower	Neutral	Higher
Change in Investment Risk	Up	●	●	●	●	●	●
	Neutral	●	●	●	●	●	●
	Down	●	●	●	●	●	●

All switches per individual were captured using the matrix and the results in each cell for an investor were reported as a percentage of the total number of switches of that investor.

Switching frequency and average asset allocation

In addition to the data captured in the Switching matrix (table 1), we calculated the switch frequency and average investment risk rating value for each investor. Looking at how frequently investors move money between funds can give an indication of difference in behaviour. An investor attempting to time the market, for example, will switch more frequently than an investor that is prone to exhibit a kind of 'status-quo bias'. The variable used is the number of switches per month. This ranges from 0 up to 1, where 1 would mean that the investor switches between funds every month.

Identifying investor archetypes

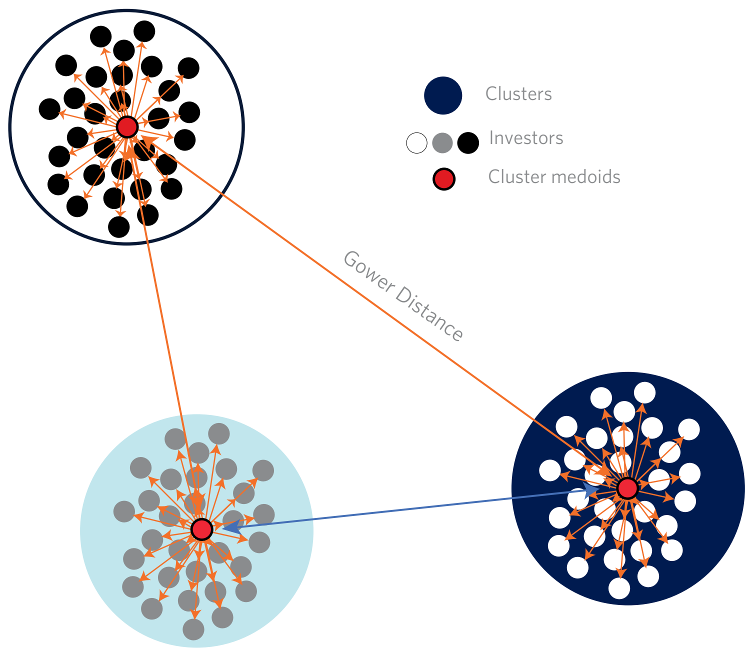
Hierarchical Clustering (HC) methods were used to cluster the observed switching behaviour as recorded in the matrix for clients who switched funds on the Momentum Wealth LISP. The goal was to identify groups of investors with similar types of switching behaviour on these dimensions. With further investigation into the general behaviour exhibited by each of these clusters, it was possible to identify potential investor archetypes[2].

[2] Note that as the clustering reported on here is based purely on correlated behaviour, the interpretation of the observed clusters is based on business knowledge and intuition.

Clustering method

To cluster investors by their switching behaviour, the PAM (Partition Around Medoids) clustering algorithm was used. The main idea behind clustering is to find groups of investors with similar switching behaviour. This is done through the creation of statistical objects called medoids that provide an estimate of the central position of each potential cluster. To measure the distance between individual investors and these medoids, and the medoids themselves, the Gower distance measure[3] was used. The clusters are chosen to both minimise the distance from the investors in each cluster and its medoid as well as maximising the distance between the medoids of each cluster.

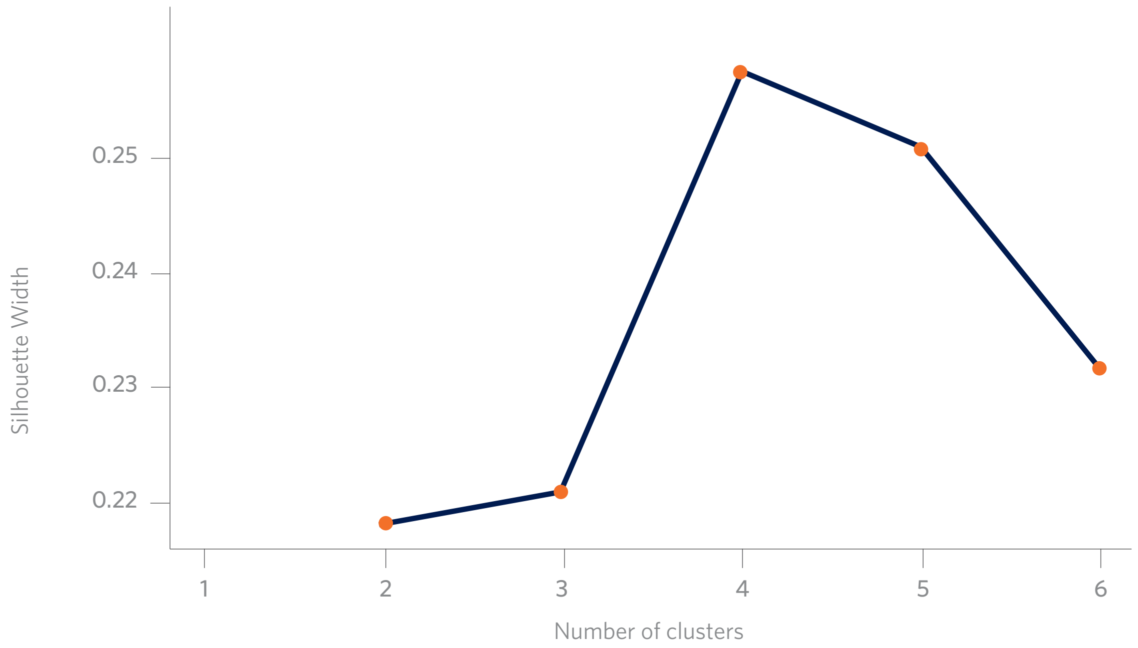
Figure 4: Illustration of the intuition behind the PAM clustering approach



A key problem with this clustering approach is that it does not tell you what the optimal number of clusters is. One of the ways to resolve this is to plot the average distances between clusters and see how this varies with the number of clusters. This gives rise to the Silhouette Plot (figure 5.) Based on the maximum average silhouette score or 'distance between clusters'[4], the optimal number of clusters to use would be four.

[3]The Gower distance measures the dissimilarity of two items based on mixed numeric and non-numeric data (categorical in this case).
[4]The silhouette score is a measure of the average similarity of the objects within a cluster and their distance to the other objects in the other clusters. This can be calculated for each group of clusters and the global silhouette score is the average of these scores – this is what is reported in figure 5.

Figure 5: Silhouette width plot



Source: Momentum Investments, 2020

Five clusters were used for the following reasons: firstly, the Five Factor Model (FFM) of Digman (1990) and MCrae & John (1992) remains the most widely accepted theory of personality today. According to this approach the five main traits that guide individuals' behaviour are: Extraversion (the extent of outgoing and socially confident behaviour); Agreeableness (friendly, cooperative and altruistic nature); Conscientiousness (awareness of own behaviour and effect on others); Neuroticism (emotional instability, anxiety and negative situational framing); and Openness to experience (willingness to explore with external locus of control). These have all been connected to financial decision making by previous studies (Van Raaij, 2016). This suggested that it would appropriate to see if these five behavioural patterns emerged from the data. Secondly, the use of five clusters instead of four allowed for the identification of a separate group of investors (the Contrarians) that had a significantly different pattern of behaviour on the dimension of chasing past performance. Unlike all the other groups, these investors consistently chose to switch to relatively underperforming funds. This was sufficiently important from a behavioural perspective to justify overriding the relatively naïve findings of the silhouette analysis. Finally, using five clusters does not cause much deterioration in the global silhouette width. Consequently, we divided the data into five clusters and tested the significance of the identified clusters on this basis.

4 Results

1. Results summary

Table 2 below summarises the characteristics of each cluster by looking at the average value of each behavioural variable in the Switching Matrix for each of the five clusters[5]. The colour coding of the values in each cell reflects its relative value when compared across all the clusters (i.e. across the rows). Green is usually the cluster with the highest relative value on any specific dimension while red is usually the lowest.

Table 2: Summary of results by Cluster

Cluster		Avoiders	Contrarians	Market timers	Anxious Investors	Assertive Investors
Average OBI (investment risk) score		4.45	5.41	5.14	5.01	5.19
Switch Activity (Average number of switches per year)		1.01	1.62	1.60	1.10	1.15
Risk Profile Change (Average for all switches)	Risk reduction	2%	46%	26%	90%	6%
	Risk increase	3%	11%	30%	5%	86%
	No risk change	91%	38%	43%	4%	6%
Switch below inflection point (Fear)	Better relative past performance	65%	25%	63%	69%	78%
	Neutral	15%	27%	10%	12%	8%
	Worse relative past performance	20%	48%	27%	19%	15%
Switch above inflection point (Greed)	Better relative past performance	52%	14%	31%	47%	64%
	Neutral	18%	4%	5%	6%	5%
	Worse relative past performance	30%	82%	64%	47%	31%

[5] Most of these dimensions were found to be statistically significant. Details of these test and their results can be obtained from the authors.

2. Identifying investor archetypes based on their observed switching behaviour

Based on these results we can make some preliminary conclusions regarding the investor archetype associated with each cluster.
We have identified names for each cluster which, we believe, reflect their fundamental investment risk characteristics:

1. Cluster 1: "The Avoiders"
These investors tend to have low risk appetite and rather avoid risk altogether. They therefore stick to a more conservative asset allocation and do not switch often. However, when they do switch, the decision to do so is likely a result of fear rather than greed. Keeping with avoiding risk and avoiding change, they are likely to remain in funds with similar (low) risk. They are relatively likely to chase past performance when current performance is below inflection. This behaviour seems to be more common in older investors and slightly more common with females compared to other archetypes.

2. Cluster 2: "The Contrarians"
As the name suggests, these investors are seemingly showing the opposite behaviour than that of the other archetypes. They have a seemingly high risk preference and a high tolerance of downside risk. Whether performance is high or low, these investors rarely chase past performance, in fact they are more likely to switch to funds with worse past performance. Keeping with the title of this archetype, this was the only cluster which realised a positive behaviour tax.

3. Cluster 3: "The Market Timers"
The main driver here is switch frequency, since we expect that market timers will constantly move between funds in an attempt to beat the market and maximise returns. These investors show a mix between fear and greed driving switches. We see that such behaviour leads to high behaviour tax during periods of crisis and periods of fluctuating markets.

4. Cluster 4: "The Anxious Investors"
Investors in this group seem to have a low risk appetite, however, they do not avoid risk altogether. These investors are very sensitive to down-side risk and are likely to act out of fear when underperformance looms. Anxious investors are very likely to down-risk and chase past performance when current funds are performing below inflection. Such behaviour led to high behaviour tax, especially during periods of growth where they would be 'missing out' on performance.

5. Cluster 5: The "Assertive Investors"
These investors are more risk tolerant and clearly set on chasing past performance, hence high greed being associated with switches. When chasing past performance, it is mostly between funds with similar risk profiles. We expect these investors to be overconfident and to follow their own ways and not be influenced as much by advisers.

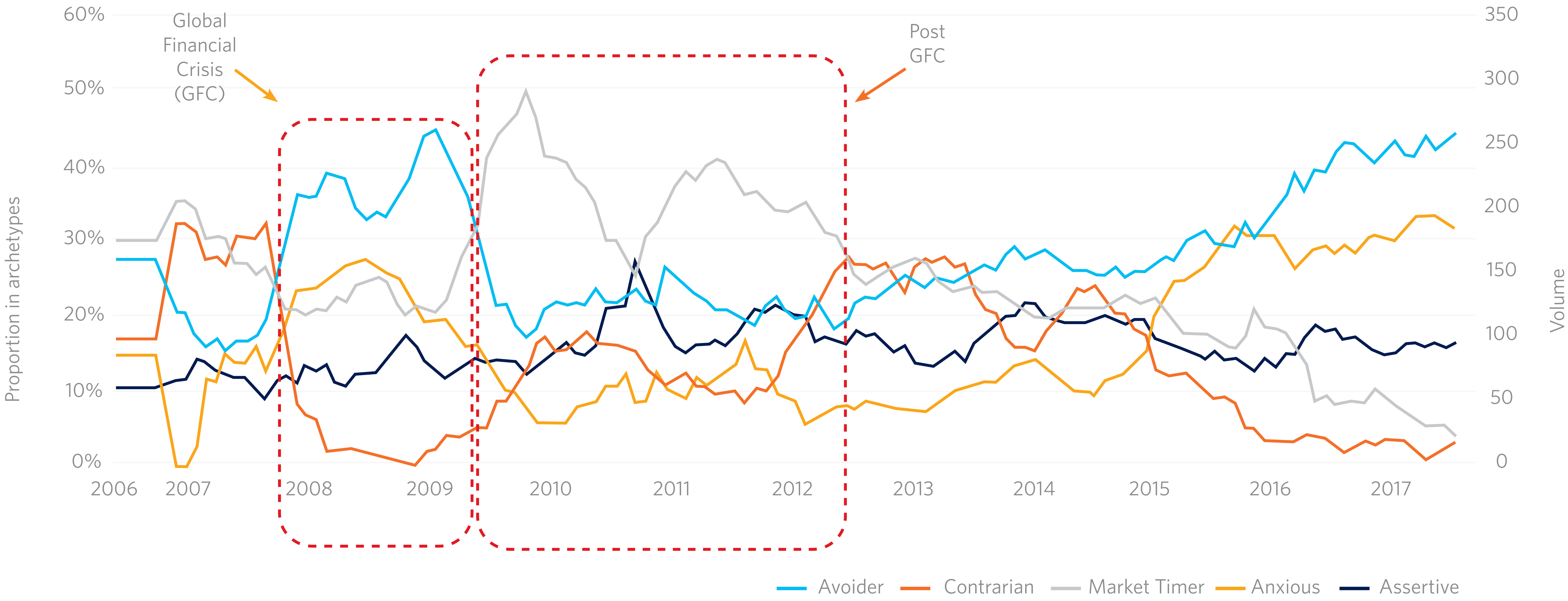
Results

3. Change in the switching behaviour by clusters over time

Figure 6 represents the proportion of switches by each of the clusters on a rolling 6-month average basis. The lines represent the proportion of each archetype that is switching at each point in time while the data in the bar chart reflects the total number of switches included in the analysis. This gives us a view of the varying distribution of the switching activities of the archetypes during different economic events.

Context matters – a clear example of how context can drive different behaviour from the different investor clusters can be seen during and after the 2008 Global Financial Crisis (GFC). During the GFC, switching behaviour was mostly linked to the Avoiders and Anxious investor clusters. Very few Contrarian type investors were active in this crisis period. During market recovery post GFC there seemed to be a lot of market timers active, and during bullish market periods we see an increase in Contrarian type investors. As markets start to fluctuate during and after 2014, we again see an increase in Avoiders and Anxious investors. The Assertive type of investors seemed to remain relatively constant during all economic cycles reflecting their likely predisposition to overconfidence.

Figure 6: Distribution of switches by Cluster



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5 Conclusion

Conclusion

The point of better understanding South African investors' switching behaviour from a risk behaviour perspective is simple. Investors are prone to making short-term investment decisions that are not aligned with their long-term investment goals. The aim is to reduce the possibility of these decisions leading to a behaviour tax on the investor's portfolio that contributes to disappointing investment outcomes.

There are three key hurdles to overcome. Firstly, a sound and objective basis for the accurate assessment of investor risk preferences or risk tolerance is needed. Theory suggests that these are both stable and long term in nature but measuring them accurately is something the industry has been battling with for some time and is of concern to regulators. Earlier in 2020, a determination by the Ombud for financial services providers (Du Preez versus Ernest Venter, with findings against the investment adviser) mentions 'risk' 18 times. More specifically in the judgement, reference was made to the clear lack of a 'risk assessment', 'risk analysis' and failure to adequately assess the client's 'risk tolerance' by the adviser. These are constructs that, while defined, have significant variation in their interpretation. The review of the academic literature in this paper suggests that the biggest challenge is that advisers use many instruments that by design capture the wrong things. They attempt to measure the client's assessment of, or propensity to take risk by using arbitrary 'win-loss' scenarios or even their 'sensation-seeking' preferences in an attempt to gauge risk preferences. The problem, as pointed out in the decision-making theory reviewed in this paper, is that these are variable over time and sensitive to recent events. Conducting these kinds of assessments a day or month apart may yield vastly different results. When we link the choice of an investment strategy to such a measurement it is likely to be doomed from the outset as these are not stable foundations for long-term planning. Trait psychology and psychometric testing has been proven to provide a stable read on risk preferences over time (Frey et al. 2017). This is an important area for future research to provide a more stable basis for investment planning.

The second hurdle is that each investment fund's history experienced places the investor at risk of making decisions being driven by their (changing) risk propensity. Simply put, their current tendency to take risk may have shifted out of sync with their long-term preferences due to recent experiences. Propensity to take risk is an emotional decision link to recent, salient events and if used as the basis for choices can lead to inconsistent investment outcomes. Either investors switch into safe assets in a market crisis which can result in poor returns when the portfolio is not timeously reinvested, or they may be tempted to take on more risk when markets are yielding more than their previous expectations – again leading to poor outcomes when these investment bubbles 'pop'. Cognitive biases are also commonplace here where decisions are framed in a positive or negative light.

The final hurdle to overcome is a difficult one – the effects of time. Evidence reviewed in this study suggests that belief formation is a significant predictor of future behaviour and while an investor's risk propensity is variable, it becomes increasingly difficult to influence over time as investment outcome experience builds. If we as an industry are not successful at intervening from the early onset of investment outcomes, the challenge in getting investors to stick to long-term investment goals becomes increasingly challenging.

This paper has provided a novel and thorough understanding of risk behaviour based on a significant sample size and found five distinct patterns of risk behaviour through different market cycles. This study has gone a long way to overcoming this hurdle in an area which was previously not thoroughly understood. This opens the opportunity to provide segmented and tailored marketing and communication campaigns to investors with predictable behaviour patterns at different times in the market cycle.

Investors are prone to making short-term investment decisions that are not aligned with their long-term investment goals.

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If we as an industry are not successful at intervening from the early onset of investment outcomes, the challenge in getting investors to stick to long-term investment goals becomes increasingly challenging.

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