South African risk behaviour archetypes in the domain of discretionary investments

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Thesis presented in fulfilment of the requirements for the degree of Master of Commerce in the Faculty of Business Management at Stellenbosch University.

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	April 2022

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ABSTRACT

More recent models of decision making under conditions of risk have built on Cumulative Prospect Theory. They propose that, in addition to the framing of choices, individuals' recent experiences of investments can lead to them making investment switching decisions that could potentially harm their chances of reaching their desired investment returns. A dynamic model of risk preferences is key to explaining investor behaviour during evolving market conditions. This study partitions investors into homogenous groups by using the medoids clustering algorithm based on the dimensions highlighted by this body of theory. This provides evidence to support this dynamic perspective on risk-based decision-making behaviour and demonstrates the viability of this method for segmenting investors from an advice, marketing and communications perspective. This should be of value to financial advice and investment management practitioners.

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List of abbreviations

ABIL	African Bank Investment Limited
ALSI	All Share Index
ANOVA	Analysis of Variance
ASISA	Association for Savings and Investments South Africa

CI	Clustering Index
EUT	Expected Utility Theory
FFM	Five Factor Model
HC	Hierarchical Clustering
LISP	Linked Investment Services Provider
MAD	Mean Absolute Deviation
MBTI	Myers Briggs Type Indicator
OBI	Outcome Based Investing
PAM	Partitioning Around Medoids
PCA	Principle Component Analysis
SAVI	South African Volatility Index
SC	Silhouette Coefficient

CHAPTER 1
INTRODUCTION

According to McDowall et al., (2013) in a paper titled "The Folklore of Finance" the authors identify a growing investor distrust and dissatisfaction with the investment management industry. They argue that this may ultimately lead to disintermediation as, while the industry remains profitable, it does not have a very successful record from a client perspective. Success, in this context, should be defined as the extent to which investors are able to reach their investment goals. The authors point out that while 60% of the industry's resources are spent in pursuit of the ever-elusive benchmark outperformance (or "alpha"), only 12% of investors actually reach their desired investment goals. This result, however, is not exclusively the fault of investment management (the supply side). Both the client or investor (demand side) and their adviser (distribution mechanism) play very important roles in determining whether they reach their financial goals or not. Investor switching behaviour can result in lower returns that ultimately place their financial goals in jeopardy. This is commonly referred to as the 'behaviour gap' (Dalbar 2008, Kinnel 2020) or the behaviour tax (Nixon et al., 2019). This behaviour is the focus of this study.

Why don't investors generally reach their goals (assuming that investment managers deliver at least benchmark level performance after fees)? Surely it should be as simple as the adviser aligning an investment solution to an investors' goal and risk preferences? All that remains is for the investor to stay invested as markets and investment managers do their job? It turns out that it is not this simple. Ample evidence exists that self-sabotaging behaviour along the investment journey leads to lower investment returns from risk behaviour along the journey (Dalbar 2008; Nixon et al., 2019; Kinnel 2020). This is reflected by the observed switching behaviour as investors appear to trade off current emotional comfort for future investment returns (Nixon et. al., 2019).

This study examines the current theory of risk-based decision making to identify potential explanatory factors for the investment switches of investors. These factors are then used to structure an empirical analysis of South African investors that aims to identify groups with internally similar patterns of investing behaviour. It is novel in that it uses a large new dataset of observed switching behaviour and an automated categorisation algorithm. It provides evidence for clearly heterogenous groups of investors' switching behaviour. These findings should be of interest to marketers and investment advisors who are interested in understanding their clients better and helping them make more effective investment decisions.

1.1 PROBLEM STATEMENT

Investor switching results in a behaviour gap or behaviour tax on average. This was found in the United States by Dalbar's Quantitative Analysis of Investor Behaviour and Morningstar's annual "Mind the Gap study". The same results appeared in the United Kingdom with the Barclay's white papers in 2013 and 2018 respectively and in South Africa in 2019 with the Momentum Investments study on the "behaviour tax". Do all investors behave in precisely the same manner in destroying this value? Are they heterogonous in their response to market ebbs and flows? This is unlikely. Assuming this is not the case, can they be grouped into similar behaviour patterns that respond in a similar fashion to market stimuli? These critical questions need answers so that financial services providers can start to address the problem of greater investor engagement with their savings that places the achievement of their investment goals in jeopardy.

1.2 BACKGROUND TO THE PROBLEM STATEMENT

While much has been written on the manifestation and indeed symptoms of the problem there exists little on the proposed solution that gives a practical framework for understanding investor decision making under risky conditions that is rooted in economic, finance and psychological (behavioural) theory and tested with extensive transactional data. McDowall et al. (2013) continue in their paper to postulate that investor's not reaching goals will result in "3 D's". These are distrust, dissatisfaction and in the end disintermediation as people explore different channels to consume investment advice. The success of the financial services industry is therefore tightly bound to the extent to which investors are able to reach their financial goals.

The process of investing and staying on the correct course towards a goal involves several critical judgements. According to Hansen (2019) the rules of rationality are complex. The assumption of rationality suggests that people should formulate their beliefs according to the rules of logic and update their beliefs using Bayesian principles (Gilboa and Schmeidler 1993). A descriptive model of human behaviour differs in multiple ways from the various models of epistemic rationality that have been proposed to date (see Von Neumann and Morgenstern (1947), Friedman and Savage (1948), Debreu (1959) and Arrow (1964)). The bounded rationality approach (Simon, 1954) builds on the fact that our limited attention span and information processing capability make accurate belief formation particularly challenging. Humans struggle to correctly assess expected value for example which is a probability weighted average of a mathematical outcome (Li and Chapman 2009).

This study sets the groundwork to assist financial services providers in getting investors to their goals whilst minimising the negative effects of the behaviour tax along the journey. This is achieved by a better understanding of investor risk behaviour based on observed behaviours. Sniehotta et al., (2005) describe the "behaviour-intention" gap as the difference between people's intentions and actions. It is safe to assume that any investor intends to reach their investment goals, but their behaviour reflected in switching activity is often dissonant with this intent. Davies (2021) proposes the concept of "just-in-time" financial education to help investors better understand the potential financial trade-offs they are making. This is a sensible approach in addressing the behaviour-intention gap that will become more achievable as the latent effects of COVID-19 accelerate digital and technology adoption. This view is supported by Mills (2021) who propose that the practice of "nudging" will become more effective as the ability to hyper-personalise messages to the person receiving them in a timely manner improves.

1.3 OBJECTIVES OF THE STUDY

This idea of more targeted nudging sets the scene for the objectives of this research, the primary objective being to better understand South African investors' risk behaviour:

1. Investigate risk behaviour in the context of investment switches that facilitates the design of a framework to classify each investment switch according to set variables.
2. Identify and apply an appropriate research methodology to test for investor behaviour patterns from an extensive dataset.
3. Investigate the statistical significance of clusters provided by unsupervised machine learning to apply a suitable technique.
4. Evaluate the heterogeneity of these different behaviour patterns i.e. how distinctive they are.
5. Design and apply an exploratory methodology that will allow long-term risk preferences to be compared to short term risk perception and resultant risk propensity reflected by switch transactions.

1.4 SIGNIFICANCE OF THE STUDY

A key strength of this study is its access to a novel dataset of nearly 16 full calendar years of investor transactional data (01st January, 2006 until 01st October, 2021) from the Momentum Wealth Linked Investment Services Platform (LISP). This brings credibility and robustness to the findings of the study. As will be explained in more detail in Chapter 3, the investment decision-making behaviour of 35,199 Momentum Wealth investors was examined. A thorough cleaning of the switch behaviour data was performed and nearly 125,000 separate investment switch transactions were identified. Every effort was made to ensure that changing investor preferences reflected by switch behaviour was captured for the correct reasons. Situations where investors are phasing into markets, for example, were excluded from the analysis. This allowed for the entire population of investors that performed switch transactions to be considered over an extended period. This study represents the first of its kind in a South African context that analyses risk behaviour over such an extended period using such an extensive dataset. The nature of the behaviour patterns discovered and indeed the evidence presented of how long-term risk preferences are set aside in the face of market events until reversion to the mean behaviour pattern prevails is a critical step in understanding how to create personalised nudging strategies. This knowledge provides the first step towards engaging with the right investor segment at the right time with the right message. The ultimate goal is to be able to effectively help investors avoid unhelpful actions by keeping them invested. If their investment goals are not changing, then the plan to reaching these goals should not be changing either – but short term events matter to investors and need to be managed to ensure that they reach these investment goals.

1.5 SOUTH AFRICAN INVESTOR RISK BEHAVIOUR

The academic basis for understanding investment decision making is proposed as the study of risk behaviour in the context of retail investors in South Africa over the period January 2006 to October 2021. Chapter 2 presents the comprehensive literature review. A summary of the theoretical framework that was used to approach this thesis is presented in Figure 1.1 and demonstrates that risk behaviour may be decomposed into a long-term and short-term component.

1.5.1 Long-term risk behaviour (Risk Preferences)

Investing is, by its nature, a long-term endeavour. Investment goals should ideally be pinned to our long-term risk preferences that have been identified as character traits of being attracted to or repelled by risk (Weber and Milliman 1997; Douglas and Wildavsky 1982). The widely accepted and applied five factor model (FFM) of personality (Boyle et al., 2008; Costa & McCrae 2011) has been linked on a number of occasions to financial behaviour (Van Raaij 2016; Hansen and Breivik 2001; Lauriola and Levin 2001; Xu et al., 2015). From this perspective, risk preferences, like personality, are viewed as stable and long-term in nature.

1.5.2 Short term risk behaviour (Risk Perceptions and Risk Propensity)

The short term is where decisions are made and where things usually go awry. More sophisticated theoretical models of risk behaviour show that investors often find themselves judging and perceiving risk inherent in a specific (extreme) situation (like when COVID-19 hit markets in March 2020, for example) differently to their normal (i.e. long-term) preference for risk. Sitkin and Pablo (1992) detail a model of risk preferences that identifies potential determinants of (short term) risk perceptions that can vary from long-term risk preferences. This model is built on the problem framing work of Kahneman and Tversky (1979). In their seminal paper Kahneman and Tversky (1979) showed how situational framing as a "loss" elicits risk seeking behaviour contrary to tenets of Expected Utility Theory (EUT). Further compounding this apparent deviation from rationality is work from Sitkin and Weingart (1995) showing how investors' subsequent willingness to take risk (their risk propensity) is also directly affected by their recent outcome experience (in other words whether they're winning or losing). Investors perceive less risk in situations where they are winning and vice versa. Sitkin and Weingart (1995) build on the work of Sitkin and Pablo (1992) where the significant effects in respect of risky behaviour of both problem framing (risk perceptions) and outcome experiences (risk propensity) are identified. Their key finding was that in many cases these two effects are entangled and in fact risk propensity is the key to explaining risky behaviour that appeared to contradict Prospect Theory which only focuses on risk perceptions).

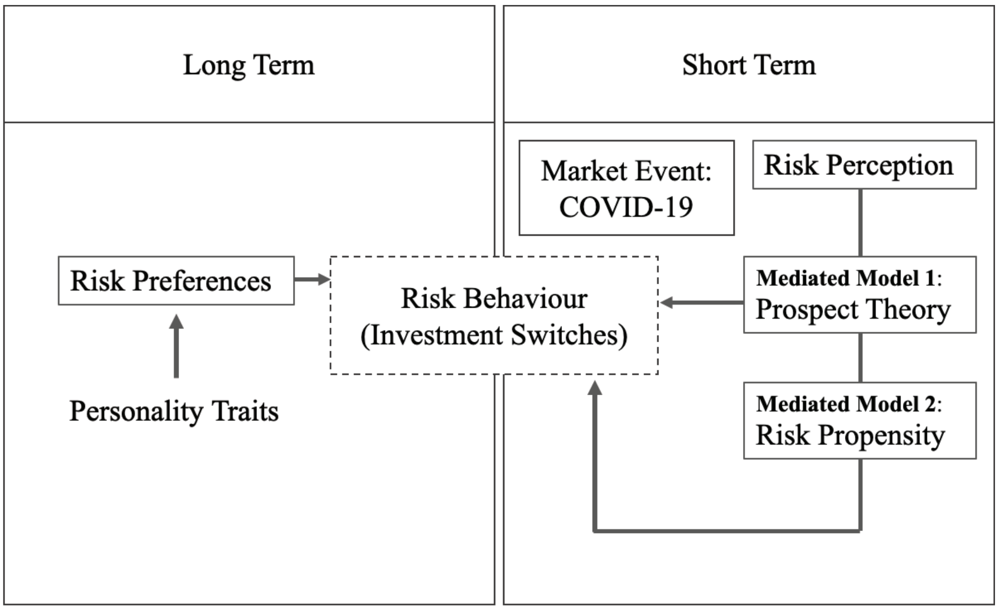

Figure 1.1 Long and short perspectives of risk behaviour

Examining this theoretical framework of risk behaviour with actual investor transactional data is a key feature of this study. It also provides guidance in setting an empirical framework for the different behaviour patterns or investor archetypes that will be empirically estimated in this study.

1.6 LIMITATIONS AND ASSUMPTIONS

This study has three notable limitations:

i. The approach used makes the implicit assumption that, when a switch transaction is executed, there is no change in the investor's current circumstances or investment goals. In reality changes to these dimensions is possible which means that there may be conditioning factors driving the observed behaviour which are not included in the list of potential factors used to categorise the switch. For example, if an investor de-risks their portfolio at the same time as a market crash it may be mistakenly assigned to an "anxious" switch transaction when in fact it is only because the client's circumstances have changed. This study therefore assumes that the investor's goals remain constant over this period. This is not inappropriate in the case of most investors who are using the platform to save for retirement. The volume of switch transactions considered, however, is believed to be sufficient to still gain an accurate view of investor overall behaviour patterns.

ii. Secondly, it is not possible to disentangle the effect of financial advice on the switch transaction as we do not know if the observed switch is the result of an investor's decision making or that of the adviser. In respect of behaviour patterns, it is thus entirely possible that the archetypes identified in this study are a reflection, at least in part, of adviser behaviour rather than client behaviour. It is recommended in future research that a qualitative review of subsets of each cluster are interviewed to interrogate the drivers behind the switch transaction and to identify the effect (positive or negative) of the financial adviser.

iii. Finally, the data extracted pertains specifically to risk behaviour in respect of investment switches performed. Risk behaviour in respect of those investors who do *not* switch is therefore not included in this study. The population of "switchers", however, is substantial and represents approximately 1 in 3 investors on the Momentum Wealth platform according to an internal Momentum investigation.

1.7 RESEARCH QUESTIONS

Given the research objectives the following three key research questions (with sub questions) are what this study will aim to answer:

1. Are there distinct/heterogenous behaviour patterns (or clusters) of investors' switching behaviour?
    a. Are these behaviour patterns statistically significant? Said differently what is the likelihood that these clusters are occurring by chance?

2. Are these behaviour patterns stable over time (at the cluster level)?
    a. Do the cluster proportions change over time?
    b. Do cluster proportions correlate with market return volatility? In other words, do volatile conditions appear to bring short term risk perception sharply into focus for investors?
3. Is cluster membership (at the investor level) relatively stable through time?
    a. Is there a notable difference between average investor behaviour over the entire time period (risk preferences) and risk behaviour during market events from varying risk perceptions.
    b. Is there a notable effect on risk propensity or the subsequent willingness to assume risk?

1.8 STRUCTURE OF THIS STUDY

This study begins with a review of literature in respect of risk behaviour and the relationship between long-term risk preferences and short term risk perceptions and propensities in Chapter 2. Chapter 3 begins by considering and reviewing the clustering variables used, the clustering study and how these relate to the theoretical frameworks discussed in Chapter 2. This is followed by a review of unsupervised machine learning algorithms as well as the significance testing techniques used in the clustering exercise. Chapter 4 delves into the findings of the clustering study and its answers the research questions posed above. Finally, Chapter 5 concludes the study and poses key considerations to financial services providers as well provides some guidance on future research that is needed to further progress this research agenda.

1.9 CONCLUSION

In South Africa and indeed globally, the risk behaviour of investors often erodes value for the investor. This may place their investment goals in jeopardy. Risk behaviour has two constituent parts. The first is rooted in their long-term and stable preferences for assuming risk that are rooted in their personality. The second comes to the fore when markets events (such as COVID-19) in the short-term create the perception of elevated risk levels that result in dissonant risk behaviour or risk behaviour out of sync with long-term risk preferences. In order to address these risk perceptions to improve on investor risk behaviour and ultimately assist in more investors reaching their goals, it is necessary to gain a greater understanding of investor risk behaviour. This will enable more personal nudging strategies delivering the right nudges to the right segment at the right time.

CHAPTER 2
LITERATURE REVIEW

2.1. OVERVIEW

Figure 2.1 guides the discussion and literature review to follow as well as to serve as the focal point of this study of risk behaviour and to provide the links between the various theoretical contributions reviewed in this chapter.

This study examines risk behaviour (represented in the centre of the diagram) in the context of investment switching that is the result of the changing of one or more of its constituents (labelled A to C in Figure 2.1). These components may be separated into one that is long-term in nature and associated with human personality (risk preferences), and two that are determined by external factors that vary in the short term (risk perceptions and risk propensities). Risk preferences (A) are represented on the long-term half of the diagram as they are assumed to be relatively stable in nature due to them being a function of long-term personality traits. It is important to consider these as the baseline for risk behaviour as the empirical work referred to in the short term half of the diagram has shown that investors do not always behave in line with these long-term risk preferences. Much like physical or psychological trauma can cause a shift in our personality so can short term financial trauma alter the behaviour linked with our risk preferences (Tanaka et. al., 2019) but in general risk preferences are relatively constant.

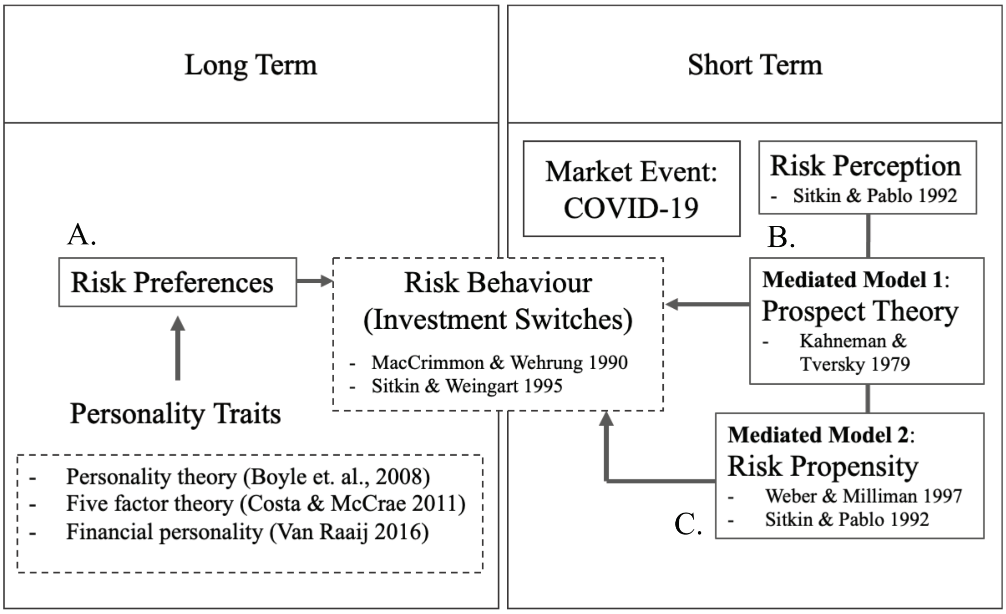

Figure 2.1 Risk behaviour published research summary

The literature review begins with an examination of theories of risk behaviour that explore risk preferences and personality as the stable dimension of risk behaviour. Those who are extroverted for example have been shown to be risk seeking by nature risk (Van Raaij 2016). In addition, links between short term risk behaviour and personality have also been identified risk (Van Raaij 2016). It seems that there are also personality traits[1] that inform the short-term processing of risk information.

This provides a neat segue to the short-term focus as attention shifts across to the right column of the diagram. Kahneman and Tversky's Prospect Theory shows that perceptions of risk are fundamentally different when viewed in the frame of losses vs. gains. It is plausible to propose that an extreme market event like COVID-19 where the market loses 30% of its value in a few days can alter an investor's perception of risk in financial markets (B). In March 2020 investment switching on the Momentum Wealth platform increased to more than 300% of levels seen in January for example.

The literature review will unpack the constituents of risk perception in detail, however, as mentioned, Prospect Theory has served as a widely applied determinant of risk perception in the context of financial behaviour. The prescriptions of Prospect Theory and Expected Utility Theory (EUT) are aligned in the domain of relative gains. The concave nature of the utility function for wealth dictates that the investor receives a greater marginal utility for wealth as wealth increases (initially) and it is this greater utility that results in relative risk aversion. Prospect Theory adds the domain of losses to the Expected Utility Theory to explain the observed contradictory behaviour of decision makers seeking out risk to avoid losses. This highlights that the way people perceive risk may result in behaviours that are rooted in cognitive processing errors (such as problem framing highlighted by Prospect Theory) as well as emotional reactions (such as loss aversion also highlighted by Prospect Theory) to market stimuli. Risk behaviour is more complicated than originally anticipated by EUT. Risk perceptions can result in switch behaviour that is contrary to the long-term risk preferences of the decision makers.

Sitkin and Pablo (1992) build on Prospect Theory by proposing that risk perception alone is insufficient as a descriptive model of risk behaviour because risk seeking behaviour is observed to occur in the relative domain of gains while risk averse behaviour also occurs in the relative domain of losses. These observations are confirmed in the body of literature summarised in Figure 2.6. Sitkin and Pablo's (1992) key assertion is that a mediating model of risk behaviour that accounts for this alternative behaviour is necessary to explain these apparent contradictions of both Expected Utility Theory as well as Prospect

[1] While this is not the focus of this study it sets the scene for future research in tying the behaviour patterns presented by the unsupervised machine learning to personality traits that may assist in predicting risk behaviour with a psychometric assessment.

Theory. They label this mediating variable as risk propensity and propose that risk behaviour is significantly affected by outcome experience – in other words, in an investment context by past investment performance (Weber and Milliman 1997). This is labelled "C" in the Figure 2.1 and is the final component in the model used to deconstruct risk behaviour. This perspective hypotheses that a decision maker's perception of risk is also impacted by recent winning and losing outcomes. Recent winners (or gains) results in them perceiving there to be less risk in the zone of relative gains which results in risk-seeking behaviour. Losing similarly creates the perception of greater risk that results in risk aversion in domain of losses. These predictions represent a significant departure from Prospect Theory and are important in setting the scene for the empirical study of investment switch or risk behaviour.

2.2 THEORIES OF RISK BEHAVIOUR

The academic world has long been interested in the factors that influence an individual's decision-making behaviour in risky contexts (Bernoulli, 1738; Hogarth, 1987; Kahneman and Tversky, 1979). It is well established that risk taking is multidimensional and as such domain specific (Slovic, 1964). Individuals may be willing to take more or less risk in different areas of their lives. MacCrimmon and Wehrung (1986) extended this idea by focussing on taking risk in an economic context. This paper is an investigation of South African investor risk behaviour and its related changes in risk attitudes reflected by switching activity between unit trust funds. Sitkin and Pablo (1992) provides a useful decomposition of "risk" into the following three constituents that may easily be related to risk in the context of investments as the inherent uncertainty regarding potentially disappointing decision outcomes:

2.2.1 *Outcome uncertainty*. In classical decision theory "risk" is regarded as the variation in the distribution of possible outcomes along with their associated probabilities and expected values. As such it is measured by the diminishing marginal utility of money (risk aversion at lower levels of wealth from increased utility) or by excess kurtosis or variance in the distribution of gains and losses (Pratt, 1964; Arrow, 1965). This represents an uncertainty in outcomes as defined by variability that is compounded by a lack of knowledge over the outcome distribution itself (what is possible) and how likely it is that these outcomes will be realised.

2.2.2 *Outcome expectation*. Depending on whether the outcome is expected to be positive or negative fundamentally affects decision framing and subsequent decision-making behaviour. Risk as it applies to financial markets in respect of variance (Markowitz 1952) has been criticised for confounding downside risk with upside opportunity that led to the investigation of semi-variance instead (Fishburn, 1977). The concept of risk as it applies to investor decisions should incorporate the full spectrum of outcomes (both positive and negative) simply because a positive outcome could still be relatively disappointing to the decision maker resulting in subsequent switch behaviour.

2.2.3 *Outcome potential*. Individuals often overweight extreme outcomes (Kahneman and Tversky, 1979) despite their low likelihood. This explains the willingness to purchase lottery tickets where the probability of winning is overinflated by the extreme positive outcome (Allman, 1985). Outcome potential is particularly relevant in the context of investing decisions as investors appear to overestimate market turbulence in relation to their long-term investment goals. This myopia and subsequent loss aversion (Benartzi and Thaler, 1995) creates a desire to act or attend to the imminent threat to wealth that may ultimately result in value destruction by executing a switch to more conservative investment assets.

Ultimately decision risk is the extent to which there is uncertainty about whether a significant or disappointing outcome of a decision will be realised (Sitkin and Weingart, 1995).

Das and Teng (2001) propose that major theories of risk taking can be viewed as two paradigms that often compete. The first is focussed on individual dispositional differences while the second places emphasis on situational factors. In Figure 2.1 this is distinguished by separating long-term risk preferences that are a function of individual differences in personality from short-term situational differences that potentially can cause a deviation therefrom.

According to Bromiley and Curley (1995) the key to understanding risk behaviour is to take an integrative approach that recognises both the individual and situational differences. Sitkin and Pablo (1992) proceed to give three determinants of risk behaviour in respect of individual characteristics as well as problem or situational characteristics aimed at the situation that offer a holistic view on risk behaviour. They are risk preference (focussed on the individuals' attitude towards risk) and risk perception and propensity targeted at the decision makers assessment of risk inherent to a given situation.

2.3 RISK PREFERENCE AND PERSONALITY AS RELATIVELY STABLE DIMENSIONS OF RISK BEHAVIOUR

According to Weber and Milliman (1997) risk preference is a character trait of the individual where they are attracted to or repelled by risk. This may also be viewed as an attitude towards risk. Douglas and Wildavsky (1982) refer to a risk attitude as a stable property of an individual that relates to personality development. Another useful description is that risk preference is a tendency to avoid or seek out risk (Van Raaij 2016). These definitions of risk preference provide the steppingstone to our association with personality.

According to Boyle et al., (2008), Gordon Allport is considered a founding father of trait psychology. Allport defines a "trait" as a generalised neuropsychic structure that renders many stimuli as functionally equivalent. Traits therefore generate a consistency in response and as such are stable in nature. Along with Raymond Cattell and Hans Eysenck who are considered co-pioneers with Allport, the study of personality traits has advanced towards what Boyle et al., (2008) refer to as a "normal science". Trait theory has evolved to a point where researchers share a common set of core beliefs supported by empirical evidence. The Five Factor Model (FFM) of Digman (1990) and McCrae & John (1992) remains the most widely accepted theory of personality today despite having attracted healthy debate and critique (Boyle 2008).

McCrae and John (1992) identify two prominent systems for naming the five factors derived from the lexical and questionnaire traditions respectively. Norman's (1963) "adequate taxonomy of personality attributes" was essentially a factor analysis based on Raymond Cattell's natural language (dictionary) trait terms. This is where the FFM began. Three of the five factors that remain today were contributed by Norman being Extraversion (the extent of outgoing and socially confident behaviour); Agreeableness (friendly, cooperative and altruistic nature) and Conscientiousness (awareness of own behaviour and effect on others). The second system originates from the analysis of questionnaires and is the base from which Hans Eysenck added the dimension of Neuroticism (emotional instability, anxiety and negative situational framing). Later Costa and McCrae would add the fifth dimension termed Openness to Experience (willingness to explore with external locus of control). The FFM has since been applied widely and tested accordingly over decades in facets such as job performance (Salgado 2003), and personality disorders (Miller et al., 2005). Furthermore, according to Costa and McCrae (2011) these traits have been found to recur across cultures, are strongly heritable and have indeed been shown to be stable over time. In this construct a trait-anxious person for example therefore consistently interprets and responds to a set of stimuli as threats. Note that the term "trait-anxious" is used here to refer specifically to behaviour related to the personality trait of "anxiety" (a subset of the Neuroticism dimension) and not to anxious behaviour in general that we are all capable of.

Several links have been drawn between the FFM and financial behaviour. According to Lauriola and Levin (2001) trait anxiety provides the most consistent predictions of risk taking. Donnelly and Howell (2012) found that 19.3% of the variance in money management may be accounted for by personality traits. Mayfield et al., (2008) found that anxious investors are less likely to engage in short-term investing while extraverted individuals are significantly more likely to do so. According to Ksendzova et al., (2017), money management is associated positively with conscientiousness and negatively with neuroticism. The strength of personality traits in respect of their financial behaviour predictability is so significant that Xu et al., (2015) refer to the personality traits of conscientiousness and openness as human capital. Those who possess these traits (or low levels of neuroticism and agreeableness) have been shown to earn higher salaries and consequently avoid or suffer less financial distress. Filbeck et al., (2005) established successful links between the Myers-Briggs Type Indicators (MBTI) and personality trait preferences that are also stable by nature. In this case individuals with a preference for "*feeling*" have a lower tolerance for variance (risk aversion) while those that prefer "*thinking*" have a higher tolerance for variance (risk seeking). While investors may have relatively stable risk preferences Sitkin and Pablo's (1992) theory suggests that risk behaviour is determined by the "label" attached to the situation (their risk perception). It is in this manner that often decisions are taken contrary to stable risk preferences.

This review suggests that future research (not forming part of this study) into the stable nature of personality traits and the predictive power thereof from linkages to the FFM would be relevant. These links have already been proposed by Van Raaij (2016) as well as the nature of the relationship (positive or negative). Figure 2.2 to follow demonstrates these relationships. For example, the first personality trait of "extraversion", when positive (i.e. the person has positive levels of extraversion), is associated with greater sensation seeking that ultimately results in risk seeking behaviour. When extraversion is negative, the individual is inclined towards introversion and as a result would exhibit negative risk-seeking or risk averse behaviour. Lower emotional stability leads to greater trait anxiety or anxious behaviour related to the trait of neuroticism that will result in risk averse behaviour (security seeking). Conscientiousness is related to risk behaviour in that lower levels equate to impulsivity associated with risk seeking. Holders (positive levels of conscientiousness) of this trait, however, more easily demonstrate the desired behaviour of delayed gratification important in a financial planning context. Finally, individuals who possess the trait of "openness to experiences" are associated with positive levels of impulsivity that are also associated with risk seeking behaviour.

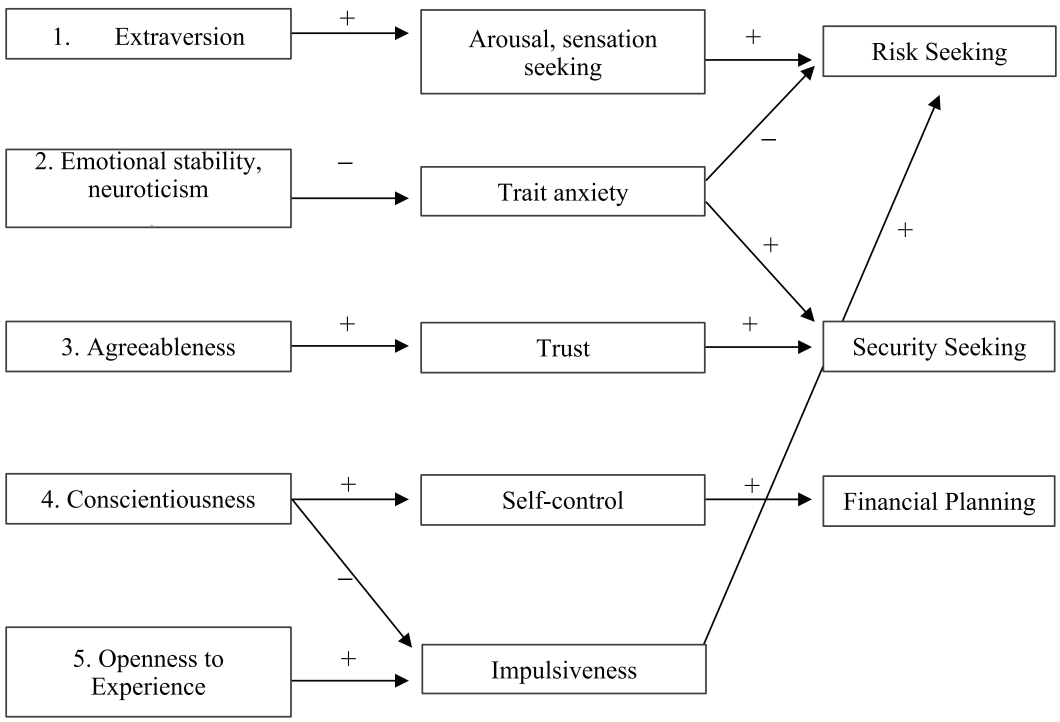

Figure 2.2 Relationship between personality variables (FFM) and financial behaviour

Source*:* Adapted from Van Raaij (2016), p.150.

2.4 MEDIATED MODELS OF RISK BEHAVIOUR

2.4.1 Prospect Theory

Prospect Theory (Kahneman and Tversky 1979; Tversky and Kahneman and Kahneman 1992) was the first and seminal mediated model of risk behaviour. It highlighted the fact that decision making in the domain of losses relative to a reference point was different to the standard Expected Utility Theory (EUT) explanation that classified people as risk averse over both gains and losses. Prospect Theory offered a more descriptive model to EUT where Von Neumann and Morgenstern (1947) proposed a set of axioms that determine decision making of a rational agent. The independence axiom for example stated that the way something is described should not have any effect on the order of preference in prospects – they should be indifferent. Kahneman and Tversky (1981) demonstrate that this invariance is not observed and that preferences depend on the way a prospect is framed or the "framing effect". In their study participants were asked to suppose that the United States is preparing for the outbreak of a rare disease that is expected to kill 600 people. The study divided participants into two groups where the first was asked to choose between a treatment program that would save 200 people and one offering a 1/3rd probability of saving everyone and 2/3rd probability of saving nobody. In this case 72% of participants chose the former option which was risk averse (the group shied away from entertaining the lottery). The second group was offered the choice between a treatment program that would kill 400 people and one where with a 1/3rd probability of saving everybody and 2/3rd probability of saving nobody. In this case 78% of participants chose the latter option which was risk seeking (the group opted in favour of entertaining the lottery). The disease problem thus elegantly demonstrated that changing the frame from lives "saved" to lives "lost" could in fact influence preferences even though both scenarios are in fact identical (saving 200 people is exactly the same as 400 people dying in a group of 600).

Prospect Theory is a descriptive model of decision-making under uncertainty that was proposed to explain deviations of human behaviour from the normative EUT model (Wright et al., 2004). Kahneman and Tversky (1979) provided an alternative to EUT that deviates in four distinct ways:

Table 2.1 Differences between Prospect Theory and Expected Utility Theory

Expected Utility Theory	**Prospect Theory**
Concave utility function (shrinking sensitivity to gains and increasing sensitivity to losses)	S-shaped value function with shrinking sensitivity to both gains and losses
Wealth viewed in absolute terms (more vs. less)	Relative wealth (gains vs. losses)
Always risk averse	Risk-averse (gains) & risk-seeking (losses)
Stated probability	Probability weighting function

Source*:* Wright et al., (2004), p.4/29.

The reason that Prospect Theory is prominent in evaluating investor risk perceptions (shown in Figure 2.1) is that it provides the framework for how risk inherent to a given situation is assessed. From a risk behaviour standpoint it gives weight to the context within which the investment switch is made. The perception of gains and losses depends on a reference point that is not necessarily either static or zero. Purchasing a share for R100 and seeing it grow to R110 one year later may have shifted the reference point of gains so that a decrease of R5 to R105 is perceived as a loss even though wealth in absolute terms has increased. Kahneman and Tversky (1979) present the way we evaluate prospects with a value function. The value function shown in Figure 2.3 presents the different subjective evaluation of gains and losses relative to the threshold point.

Wright et al., (2004) provide three important properties thereof presented in Table 2.1. The first has been discussed already and refers to relative evaluation according to the *reference point*. The second is *shrinking sensitivity*. A share trader for example is much happier about the first R1000 profit than the 10th R1000 profit when referring to the zone of gains. Similarly, this share trader is most annoyed by the first R1000 loss than the 10th R1000 loss. The value function will naturally vary for everyone, however, the convex nature of the function to the left of the reference point (zone of losses) will be steeper in nature as sensitivity to losses increases sharply initially and then increases at a decreasing rate. This implies the third property, namely *loss aversion*. Losses loom larger than gains and Tversky and Kahneman (1991) estimate that most of us would feel a loss 2 to 2.5 times more intensely than the equivalent gain. This effect is clearly demonstrated in Figure 2.3 as 100 units of utility or value are associated with a R20 gain (for example) while the same loss of R20 gives 150 negative units of utility. Naturally in respect of investing this would also depend on the amount of money at stake and the proportion of total wealth invested.

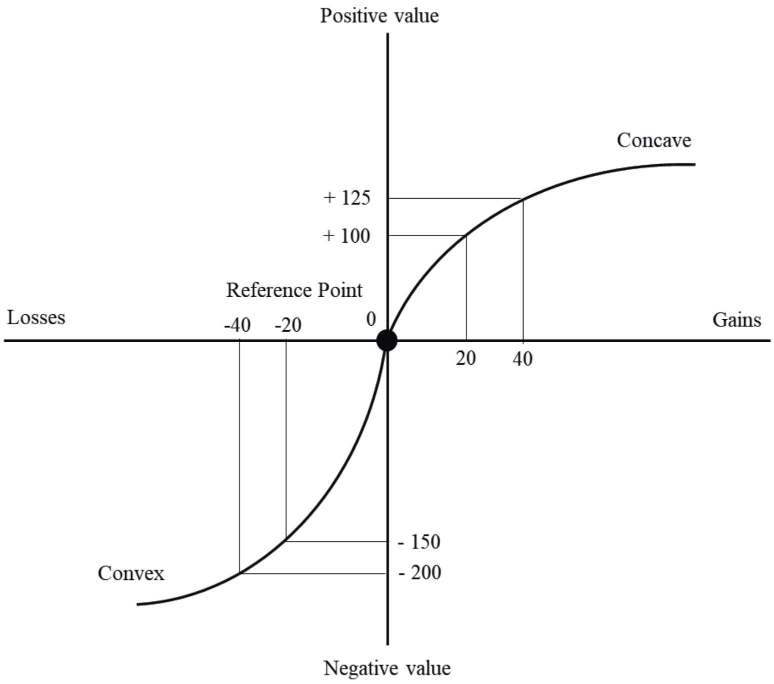

Figure 2.3 Prospect Theory value curve

Source*:* Adapted from Van Raaij (2016), p.175.

Wright et al., (2004) also provide a reminder that the effects of shrinking sensitivity for gains and losses and the impact of framing endure in many contexts in everyday life. This is particularly true for financial markets where investors choose to constantly evaluate their investment portfolios en route to their investment destination as markets ebb and flow. The Prospect Theory model of risk perception *should* show that investors choose safer alternatives in the domain of gains and more risky ones in the domain of losses.

Prospect Theory was expanded in 1992 and termed “Cumulative Prospect Theory” by demonstrating varying risk behaviour according to the decision-maker’s assessment of a prospect’s probability. In this case risk aversion for gains and risk seeking for losses of high probability prospects was evident and risk seeking for gains and risk aversion for losses of low probability prospects was recorded (Tversky and Kahneman 1992). While this enhanced the original model further there remained scope for even more descriptive approaches to risk behaviour that would expand on the construct of risk perception and later introduce another mediated model of risk behaviour that would include the new dimension of risk propensity.

2.4.2 Expanded models of risk behaviour

2.4.2.1 Expanding the determinants of risk perception

Sitkin and Weingart (1995) define risk perception as the individuals' assessment of inherent risk in each situational problem. Individual interpretation of course opens the distinct possibility of misinterpretation. The inherent judgement places individuals at risk of over or underestimation of risk depending on the situation at hand. In financial markets, according to Hoffman et al. (2015) investor risk perceptions contribute significantly to understanding observed trading and risk-taking decisions. A risk assessment can be difficult to perform accurately, and this is particularly relevant in the context of making an investment decision. There exists outcome uncertainty associated with a lack of knowledge of possible outcomes and the likelihood of achieving these. The plethora of investment options available to South Africans who are looking for a discretionary investment is testament to this. Compounding this are outcome expectations where, depending on whether these are positive or negative, the expected utility from an investment decision can be distorted and thus alter investor risk behaviour. Furthermore, investors under and overestimate the outcome potential of extreme events – something that can often drive them to act in ways counter to their long-term risk preferences.

Three determinants of risk perception linked to cognitive biases in assessing the inherent risk of a situation are proposed by Van Raaij in Figure 2.4. This expands on the mediated model put forward by Prospect Theory that focussed more on the problem framing dimension and associated loss aversion. In this case regret avoidance plays a similar role as loss aversion as people fear making the incorrect choice and want to avoid this. The dimensions associated with Prospect Theory are highlighted in grey.

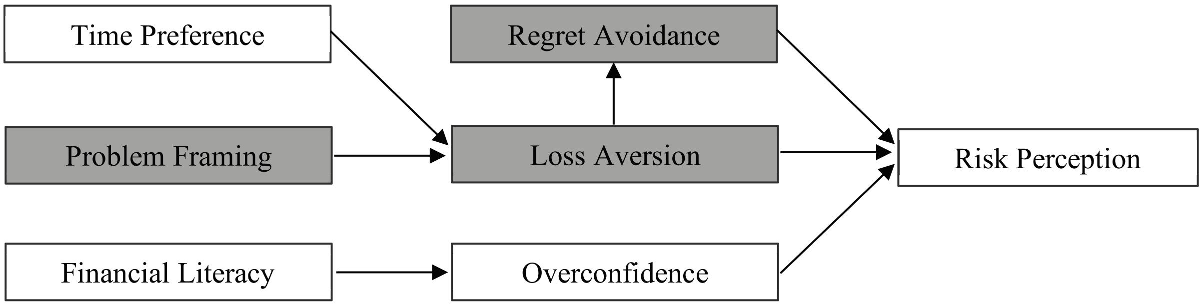

Figure 2.4 Determinants of Risk Perception

Source*:* Adapted from Van Raaij (2016), p.187.

Van Raaij, however, also posits the likely impact of two other determinants (time preference and financial literacy) in Figure 2.4. Before exploring these it is important to note another possible omission to the model that is conspicuous by its absence. Sitkin and Pablo (1992) examine risk preferences in an organisational context but they also identify the importance of social influences on risk perception. The UNICEF behavioural drivers model as well as Stangor and Sechrist (2001) refer to the marked impact on belief formation of one's social and peer group. These are not dealt with in the Van Raaij model. According to Wang and Siegrist (2011) risk and uncertainty are not only mathematical and statistical concepts but psychological constructs too. While certain of such constructs (such as loss aversion) are dealt with here, the impact of the individual's environment and social influence are not. Furthermore Gilad and Kliger (2008) also show that nonconscious priming effects can have a marked impact on investor risk perception. A priming investment success story caused professional investors to have a riskier attitude.

Returning to the Van Raaij model in Figure 2.4, levels of financial literacy have been shown to influence the assessment of risk inherent to a situation. This was demonstrated by Broihanne et al., (2014). Financial professionals are predisposed to overconfidence from lower risk perceptions linked to their higher levels of financial literacy. Furthermore with investments, lower risk is also perceived in familiar assets (Coval and Moskowitz 1999).

The role of time in preferences emerged when Samuelson (1937) proposed the discounted utility model. Theoretically the compensation a person accepts for delaying consumption should be the same as the cost to speed this up over the same period. However, it was found that people value money they will receive in future considerably less than money received now. The discount function appeared to resemble a hyperbola and so was referred to as "hyperbolic" showing that time distorts preferences (Rubenstein 2003). Leland and Schneider (2017) propose a unifying approach in framing risk together with intertemporal choice, however, that is beyond the scope of this paper.

2.4.2.2 A new mediating variable – risk propensity

Sitkin and Weingart's (1995) key finding was that in many cases risk perception is in fact entangled with another variable which they called risk propensity. They conclude that the inclusion of risk propensity is the key to explaining risky behaviour that appeared to contradict Prospect Theory (lowering risk when experiencing a relative loss and increasing risk when experiencing a relative gain). Their mediated model of the determinants of risky decision-making behaviour are reproduced in Figure 2.5 below where antecedent characteristics affecting risky decision making are illustrated. Initially the dotted line connecting risk propensity and risky decision-making was proposed as statistically significant, but this was not found to be the case in their study. The remaining solid lines all represent relationships with empirical confirmation. Their study thus suggests that problem framing may either have a direct bearing on risk behaviour or may impact the assessment of risk that is mediated by previous outcomes (risk propensity) that may drive alternative risk behaviour. Risk propensity plays this mediating role on risk perception. The possible effects of previous experience (outcome history) as well as the context of gains and losses to the switch decision both require attention when explaining risk behaviour. These relationships will become clearer in the next section where risk propensity is discussed in more detail.

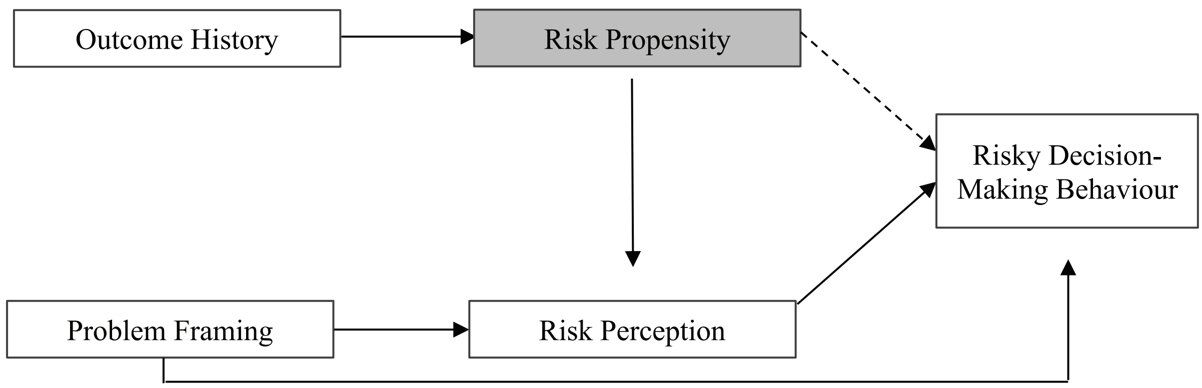

Figure 2.5 Mediated Model of the Determinants of Risk Decision-Making Behaviour

Source*:* Adapted from Sitkin, and Weingart (1995), p.1586.

2.4.3 Risk propensity

Risk propensity was initially argued as being a trait that is stable in nature (Rowe 1977; Fischhoff et al., 1978; MacCrimmon and Wehrung 1990; Gerrans et al., 2012). Specifically, MacCrimmon and Wehrung (1990) define "risk propensity" as a willingness to take risks and therefore should reveal a consistent pattern of risk taking or aversion that impacts on how risks are evaluated. Said differently, risk propensity was initially thought to be constant in nature and attributed to one's inherent personality traits such as the level of "sensation seeking" or "locus of control" (Hansen and Breivik 2001). These are personality traits that allude to the stable and long-term risk preferences discussed earlier.

Contradictory evidence was simultaneously emergent that seemed to favour a more situational approach (Das and Teng 2001). Schoemaker (1990) discovered a low correlation of risk propensity across decision domains alluding to inconsistent risk behaviour in different contexts. Similarly, March and Shapira (1987) found when interviewing managers in an organisational context that there were distinct differences in reported risk behaviour that may be attributed to contextual factors. A notable example was that managers demonstrated greater propensity towards risk taking when questions were framed as business decisions than when they were framed as personal decisions. This may also be related to a belief system that risk is inherent and even necessary in business.

A more useful descriptor of risk propensity is provided by Sitkin and Pablo (1992) and Sitkin and Weingart (1995) as the individual's *current* tendency to take or avoid risks. In the context of this study this represents the current tendency to perform an investment switch (risk behaviour). Both papers acknowledge that stable risk preferences are part of risk propensity but take it further by saying that this is not where the relationship ends. This was reinforced shortly after by Weber and Milliman (1997) who showed that situational variables (winning or losing in a simulated stock market program) affect risk perception rather than inherent risk preferences. This finding is particularly relevant from an investment context as individuals with similar investment risk preferences show changing risk perceptions based on the success or failure of their investment choices.

In Weber and Milliman's (1997) study the stability of risk preference was clear in that the overall exposure of the participants to risky assets remained relatively constant in both experiment groups (those experiencing both positive and negative outcomes). What is important is that the individual stocks chosen in respect of riskiness (defined by their beta values) varied markedly as a result of their outcome experience (success or failure). Participants also reported more or less perceived risk depending on whether they were winning or losing in the simulation. This is in line with observed investor behaviour in South African financial markets where relative investment performance in discretionary unit trusts appears to be a good predictor of investment decisions in the short run. Poor investment performance elevates investor risk perception that is usually followed by a switch decision into another investment that is performing better.

This reinforces risk propensity or the tendency to take investment risk as the mediating variable between that predicted by Prospect Theory or Expected Utility Theory and actual risk behaviour. Returning to Sitkin and Pablo (1992), they provide a useful summary of the interaction between risk propensity levels and situational characteristics (positive or negative outcomes) that may predict risk behaviour together with supporting research. As mentioned earlier EUT predicts risk averse behaviour in general while Prospect Theory predicts risk seeking behaviour when experiencing relative losses. Reality however, (supported by Sitkin and Pablo's research) provides many examples of contrary behaviour (risk seeking behaviour when experiencing gains and risk averse behaviour when experiencing losses).

Figure 2.6 shows quadrant 1 and 4 as consonant behaviour with Prospect Theory and quadrants 2 and 3 as dissonant behaviour as well as research explaining the likely reasons therefore. These research findings did not consider risk propensity explicitly as a mediating variable but demonstrate clearly the behaviour that is contrary to that predicted by Prospect Theory. Literature that found low risk behaviour (see quadrant 2 in Figure 2.6) tended to examine more bureaucratic risk-averse contexts. For example, Janis and Mann (1977) focussed on decision makers in government while Straw et al., (1981) included universities and large public firms. The likelihood here is that large structures are risk averse by nature and have many past failures (extensive negative outcome history).

This is a stark contrast with quadrant 4 (in Figure 2.6) predicting high risk behaviour where March and Shapira (1987) report on manager views of risk as "part of business" clearly in a more entrepreneurial setting (are more risk seeking to begin with). Quadrants 1 and 4 in Figure 2.6 represent the well documented risk aversion and risk seeking behaviour when faced with gains and losses. Recall that these are associated with the assessment of the situation or risk perception in the situational context of whether the prospect is framed as a gain or loss. It is likely here that risk propensity in these quadrants (1 and 4) is reinforcing the situational characteristics while overwhelming risk behaviour in quadrants 2 and 3 (the result of the opposing risk behaviour). Said differently the variable of "risk propensity" was always there but was reinforcing previous mediated models of risk behaviour such as Prospect Theory where it remained hidden for this reason.

Situational Characteristics
(Objective or Perceived)

Risk Propensity	**Positive Situation**	**Negative Situation**
Risk Averse	1. Prospect Theory – Conservation of Prior Gains (Kahneman and Tversky 1979) Loss Prevention Bias (Jackson & Dutton 1988) **Prediction**: Low Risk Behaviour	2. Threat Rigidity (Straw, Sandelands & Dutton 1981) Hypervigilance (Janis and Mann 1977) **Prediction**: Low Risk Behaviour
Risk Seeking	3. Attention to Opportunities (March and Shapira 1987) **Prediction**: High Risk Behaviour	4. Prospect Theory – Going for Broke (Kahneman and Tversky 1979) **Prediction**: High Risk Behaviour

Figure 2.6 Extant Theoretical Models and Predictions of Risk Behaviour

Source: Adapted from Sitkin and Pablo (1992), p. 27.

For risk-averse individuals, the exacerbating influence of negative situational characteristics will always result in choices consistent with risk aversion (no matter how severe). For risk-seeking individuals however, the reinforcement disappears on surpassing a threshold level. This is proposed to be the individuals inherent character trait of being attracted to or repelled by risk which closes the loop neatly on the interlink to personality theory detailed earlier. Van Raaij (2016) argues that the concept of risk propensity may also be viewed as a mediating variable between personal characteristics and risky financial behaviour and used to explain risk behaviour dissonant with that predicted by inherent personality traits. This definition reinforces that risk propensity is a willingness to undertake risk for a certain payoff that may also explain a deviation from inherent risk preferences (those connected to one's personality).

A key assertion of Sitkin and Weingart (1995) deserves brief attention before concluding this section. Their paper also acknowledges the importance of a decision maker's cumulative experience. The assertion that risk propensity becomes more stable as the decision maker develops an "outcome history" makes much sense. Early on in an investors' journey they will be the most vulnerable to changing risk propensity with relatively fewer outcomes in their "domain career". As time passes risk propensity becomes more difficult to influence. With respect to altering investor decision making behaviour in the

South African context this is crucial. Straw et al., (1981) proposed that under threatening situations individuals tend to rely heavily on experience and elicit well-learned responses. This was reinforced by the Wharton Business School (Nave, 2020) study which demonstrated that increased cortisol during the stress response predisposes individuals to using their gut instinct. Weber and Milliman (1997) propose that distinguishing between changes in risk preference and risk perception is key to understanding the underlying processes that may drive suboptimal choice behaviour and the resulting remedies. Should changes in risk perception be the driving force of the undesired behaviour remediation should target cognitive processes (target formation of more realistic risk perception). It is therefore key to set these more realistic risk perceptions as early on in the investment journey as possible, so investor's build an outcome history of time in the market linked to perceived investment success.

In conclusion, the theoretical framework proposed by Sitkin and Pablo (1992) that describes the drivers of risk behaviour is particularly relevant in financial services in a way that is superior to the relatively simplistic approach of Prospect Theory. It seems plausible that investors begin with high levels of outcome uncertainty with bounded rationality playing its part in the ability (or lack thereof) to assess all possible outcomes with their associated probability distributions. An easy way of minimising this uncertainty is to seek information on the immediate past performance of a prospect. This sets an outcome expectation that the prior success of the prospect will continue. This ultimately sets the investor up for disappointment when often this success is not repeated. Worse still, however, when the investor is faced with market turbulence the outcome potential is misjudged and ultimately the investor looks for another prospect.

2.5 CONCLUSION

The theoretical framework provided by this risk behaviour literature review provides critical guidance to this study. Firstly, if risk preferences are indeed stable and long-term in nature the results of this study should reveal this in the average behaviour of the segments over time. This should almost be viewed as the investor's "factory setting". In the short term, however, market turbulence and opportunity risk perceptions may indeed shift investors away from their long-term preferences through the mediating factors of risk perception and risk propensity. In this regard the context of the investment switch should be important – firstly, whether it is executed in the relative frame of gains or losses and secondly, by the investment returns preceding the switch decision. Risk aversion in the relative zone of gains is expected or risk seeking behaviour in the zone of relative losses. This may not be the full picture and as such the ultimate tendency of the investor to perform a switch (risk propensity) may in fact be dominated by their outcome experience. It is therefore important as well to consider the past investment performance or experience of the investor that may ultimately be driving the risk behaviour.

The research design section sets out the proposed investigation into the quantifiable and demonstrable elements of investment risk behaviour as proposed by Sitkin and Weingart (1995). This exploration takes place in the context of discretionary investments in South African unit trusts with relatively lower friction costs in executing such risk behaviour (switching is easier and in many cases is facilitated by the adviser). This arena is also one with shorter time preferences. Discretionary investors are saving for many shorter term goals other than for retirement for example. The anticipated more regular engagement provides a better indication of risk behaviour and the effects of changing risk perception. The gradually increasing switching behaviour to almost 9% of total active contracts (nearly 1 in 10 investors are switching at least once per year) confirmed by an internal Momentum Investments analysis justifies the focus on discretionary investments.

The assertion of Sitkin and Pablo (1992) that risk propensity is based on outcome experience deserves exploration in this context. Is increasing investor sensitivity to lower returns followed by the search for greater investment returns predicted by Prospect Theory? Or do investors search for more safety (decreasing risk levels) where recent poor investment experience overrides problem framing? These risk behaviour patterns are captured in the quadrants provided in Figure 2.6. A cluster analysis will identify groupings of these risk behavioural patterns.

The proposed use of a clustering algorithm to identify systematic differences between groups of investors serves to highlight differences in this risk behaviour and identify clear behaviour patterns to structure deliberate interventions to alter this risk behaviour for better investment outcomes. This is built on the premise of engaging with different segments at different times as required to ultimately provide better investment outcomes.

CHAPTER 3
RESEARCH METHODOLOGY

The review of relevant literature has highlighted the interplay between long-term relatively stable risk preferences and the short term processing of risk that is often out of sync with these long-term risk preferences. Prospect Theory, as the first mediated model of risk behaviour, assists us in understanding differences in risk behaviour depending on whether investors are in the zone / context of gains or losses. This suggests that investors often exhibit risk seeking behaviour in the domain of losses (contrary to Expected Utility Theory) to eliminate the associated pain of such losses, but the subsequent mediated model of risk behaviour (Sitkin and Weingart, 1995) shows that the perception of risk is also altered depending on their (recent) investment outcome experience. The concept of risk propensity was introduced to explain behaviour dissonant with the Prospect Theory model. In this approach lower risk levels are perceived as further gains are recorded and vice versa and this affects people's risk propensity or subsequent willingness to assume risk. The aim of this paper is to answer the following three research questions relating to this risk behaviour:

1. Are there distinct/heterogenous behaviour patterns (or clusters) of investors' switching behaviour?
    a. Are these behaviour patterns statistically significant? Said differently what is the likelihood that these clusters are occurring by chance?
2. Are these behaviour patterns stable over time (at the cluster level)?
    a. Do the cluster proportions change over time?
    b. Do cluster proportions correlate with market return volatility? In other words, do volatile conditions appear to bring short term risk perception sharply into focus for investors?
3. Is cluster membership (at the investor level) relatively stable through time?
    a. Is there a notable difference between average investor behaviour over the entire time period (risk preferences) and risk behaviour during market events (risk perception).
    b. Is there a notable effect on risk propensity or the subsequent willingness to assume risk?

In answering these questions this paper aims to lay the groundwork for understanding risk behaviour so that the investment advisers and financial services providers have the framework to implement behaviour change through custom engagement of each of these investor "archetypes" or behaviour patterns. It uses an unsupervised clustering algorithm to identify the groups of similar switching behaviour and then tests for the statistical significance of these groups against the backdrop of the second mediated model of risk behaviour being risk propensity.

3.1 BACKGROUND AND DATA PREPARATION FOR STUDY

This paper builds on work that was published in the Momentum Investments White Paper (Nixon et al., 2019) that investigated value eroded by 17,994 South African investors in discretionary unit trusts over a decade (2008 – 2018) on the Momentum Wealth linked investment service platform (LISP) from investment switching decisions. The value eroded was measured as a "behaviour tax" by comparing the portfolio of investments switched *to* against the portfolio switched *from* over time. In other words, subtracting the investors actual investment return from the theoretical buy-and-hold portfolio. For example, assume a client switches R10,000 from Fund A into Fund B. Over the next 12 months Fund A realises a return of 10% p.a. whereas Fund B earns an 8% p.a. return. The client in this case has R10,800 in his or her account at the end of the period. The theoretical "buy-and-hold" scenario, however, *would* have resulted in R11,000 in the client's account. A behaviour tax of R200, or 2% of the R10,000 switched is therefore recorded.

The dataset was extended for this study specifically and this extensive dataset will be discussed shortly.

In this study, the behaviour tax was measured by comparing the following two variables for each switch included in this study:

> **Returns of funds switched from**: 12-month future performance of buy-and-hold scenario (weighted performance based on amounts switched from each fund in the given month).
> **Returns of funds switched to**: 12-month future performance of actual scenario (weighted performance based on amounts switched into each fund in the same month).

The results clearly show the extent of the switching behaviour problem in South Africa in Figure 3.1 to follow. Positive values (above zero) indicate value lost by investors (fund returns switched from > fund returns switched to). The asymmetric nature of the overall behaviour tax is clear. Rarely is more than 2% gained from switching but the behaviour tax breaches the 2% in value lost on multiple occasions. The extremes are also evident as a spike in behaviour tax was recorded during the COVID-19 market crash largely as markets recovered very quickly leaving investors selling low and scrambling to buy back into markets after the recovery.

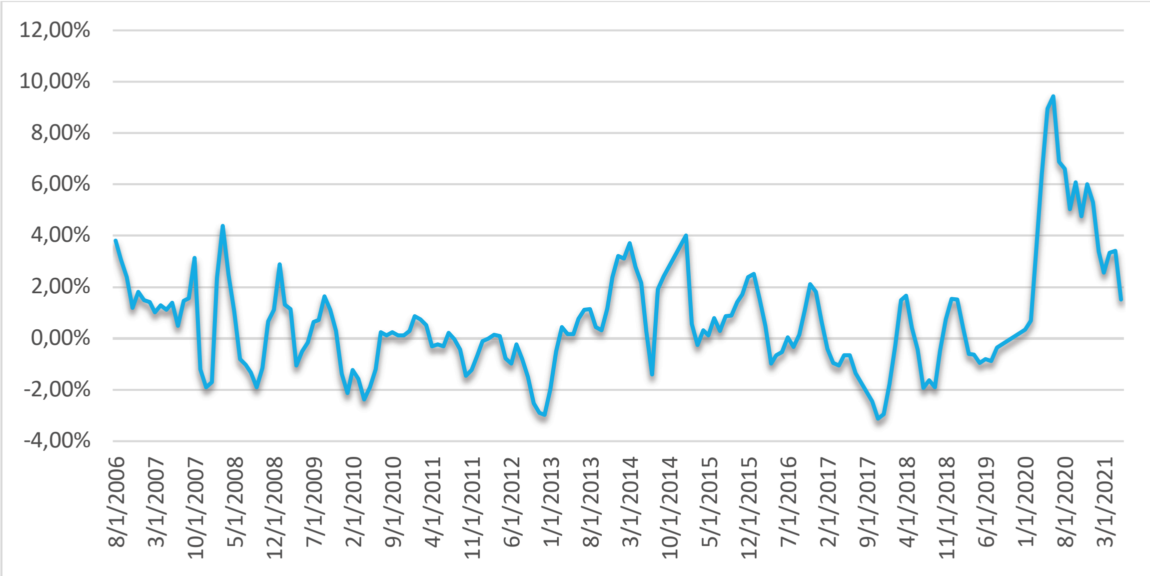

Figure 3.1 3-month moving average South African behaviour tax (01/01/2006 – 01/10/2021)

3.1.1 Behavioural engine construction

In the original Nixon et al. (2019) study, these 17,994 investors were identified after an extensive and thorough data cleaning exercise in building a "behavioural data engine". Some transactions recorded as a 'switch' on the system are not behavioural in nature. For example, those where an investor moves between investment classes to take advantage of preferential pricing (switching to a lower fee class). The same engine was maintained into this study and as such it is important to detail exactly how this was constituted.

The list to follow presents a summary of the rule-based system that is applied whenever data from the Momentum Wealth LISP is imported for behavioural analysis:

3.1.1.1 Criteria for inclusion into the study

i. Only investors in discretionary unit trusts were considered (Momentum Flexible Investment Option). The reason was that discretionary unit trusts likely present an investment product where values are checked more frequently and so would capture risk perception better than a retirement product for example.
ii. An investor needed to make at least one qualifying "behavioural switch" to be included in the study.

3.1.1.2 General data cleaning

i. Transactional switch data from the LISP was usually labelled as "switch unit". However, in some cases an investor would "sell" from one unit trust fund and "buy" the same amount (or a near similar amount with the difference being accounted for in fees) of units in another fund in the same month. Such a transaction combination would also be considered as a switch. Another case would be where a sale of units occurs in one month and a value-matching purchase of units in the following month was traced.

ii. All further buy/sell transactions were tracked and matched. The above list is extended to match units sold across multiple funds, and a single fund bought, or vice versa. Alternatively, where units are sold from multiple funds and units in multiple new funds are bought but in different percentages.

iii. Unit trust funds that changed fund codes were traced and matched with new fund codes. The new fund codes were then applied retrospectively to ensure a single fund code reference.

3.1.1.3 Exclusions from the study

i. Switch transactions between fund fee classes. For example, a switch from the Allan Gray equity fund class A to class C. Unit trust funds have different classes that reflect different pricing structures such as an institutional class versus retail class for example where the former receives preferential pricing to account for the sheer scale of assets.

ii. Switch transactions related to the African Bank (ABIL) liquidation. Asset managers were changing exposure to ABIL shares and creating “side pockets” to return some funds to investors. As such any related switch transactions were excluded from the list.

iii. Phasing into the market switching is ignored. For example, where a money market account is bought initially and gradually liquidated over three months to buy higher risk funds. This was deemed a deliberate strategy agreed to in advance between adviser and client.

iv. Similarly switches relating to phasing out of the market are excluded.

v. Investors with clear data errors were excluded. This was extremely infrequent (≈ 0.1%) and included anomalies where initial investor values were negative for example.

3.1.3 Dataset for this study

The aforementioned dataset (discussed in 3.1) was expanded on to encompass all investor switch transactions from January 2006 until the 01st of October, 2021 and included just under 125,000 switch transactions from 35,199 Momentum Wealth LISP clients over this time period. This dataset formed the basis for plotting Figure 3.1.

3.1.4 Framework through which to view investor behaviour

Before presenting the unsupervised machine learning algorithm with this extensive dataset it was necessary to provide the appropriate variables from which to identify patterns of behaviour. Initially the context of the investment decision (i.e. whether the investor was in the frame of gains or losses) was proposed as a clustering variable based on Prospect Theory. On the initial presentation and examination of the results this did little to explain differences in behaviour or indeed even confirm that investors were generally risk seeking in the domain of losses. This suggested that the second mediated model of risk propensity would provide a better basis to identify significantly different behavioural patterns. As is demonstrated in Figure 2.6 both risk seeking and risk averse behaviour in both the domains of gains as well as losses should be used to clustering the observed switching behaviour.

3.1.4.1 Return variables considered

1. **Average performance chased**
   a. calculated as the 12-month past performance of funds switched to *less* 12-month past performance of funds switched from.
2. The percentage of switches **chasing past performance**
   a. Average performance chased > +2% p.a.
3. The percentage of switches to **similar past performance**
   a. Average performance chased is within -2% p.a. to 2% p.a.
4. The percentage of switches to **worse past performance**
   a. Average performance chased is < -2% p.a.

The rationale for including these return variables was to account for both average performance chased (variable 1) as well as how many times the investor chased this past performance (or not) represented in variables 2 - 4. It was necessary to add the categorical variables to account for investors whose average performance chased value across all their switches was being averaged out by switching in both directions. In respect of the quantum of performance chased (variables 2 – 4) they also account for investors seeking to up-risk their portfolios in the face of losses (according to the first mediated model of risk behaviour being Prospect Theory) as well as investors in search of prospects with better past performance as their perception of risk decreases from positive investment outcomes (according to the second mediated model of risk behaviour being risk propensity). Alternatively, as their perception of risk rises with negative outcomes, they may seek prospects with worse past relative performance usually offered in safer assets. Finally, investors may also be in search of prospects within the same relative past performance range that may be attributed to a change in brand preference (for example) that was not explicitly considered here.

3.1.4.2 Risk variables considered

It is necessary to spend some time on how to define "risk" in this context. To assess whether investors are increasing or decreasing overall risk levels of their portfolios 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 (according to the minimum disclosure document), 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 can more closely match equity-like volatility, rather than cash-type returns. The Momentum Investments Outcome-Based Investing (OBI) funds have real return targets of CPI + 2% through to CPI + 6%. Mapping all funds on the platform to the nearest asset allocation of the OBI funds therefore provides the necessary scale to assess whether the investor is selecting more or less risk. 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 (an investment risk rating of 7). Pure equity, property funds and all offshore funds are classified as the highest risk category (an investment risk rating of 8). As mentioned, the currency volatility alone in the offshore category was deemed sufficient to place these funds in category 8.

The risk side of the equation was therefore accounted for by considering the following two variables:

1. The **average risk rating of the investor's portfolio**
   a. To provide an indication of the investor's risk preference.
2. The **average change in this risk rating** for each investment switch
   a. Calculated as the risk rating of the portfolio switched from *less* the risk rating of the portfolio switched to.

The rationale for including the risk variables is precisely the same as the return variables. The mediated model of risk propensity accounts for decreasing risk perception as positive outcomes accrue and vice versa. Investors in this case may up-risk or de-risk their portfolios accordingly. However, investors framing recent outcomes as a loss relative to their previous year's returns as the reference point may indeed behave consonantly with Prospect Theory (up-risking portfolios to account for these painful losses).

The completed framework including the 6 variables is now presented in Table 3.1 to follow. The data is prepared by listing all qualifying investors with at least one behavioural switch. Columns A, D, E and F correspond with the first four variables discussed (relating to investment returns) while columns B and C relate to the final two variables detailed (relating to investment risk changes) Note that in columns D, E and F the cell is marked with a “1” and the remaining two cells marked with a “0” in the case of all 10 of these samples. These are clear examples where the investor has either performed 1 switch or all of their switches fell into this category. Where they did not an average was calculated. The sum across columns D, E and F will therefore always equal 1 or 100%.

Table 3.1 Data extract used in the cluster analysis

	(A)	(B)	(C)	(D)	(E)	(F)
Investor	Performance chased	Average risk	Risk Difference	Chasing past performance > 2%	Neutral (within -2% to +2%)	Worse past performance < -2%
PP021133544	-5,8296%	6,3333	(5,00)	0	0	1
PP021058363	2,7094%	4,7500	3,50	1	0	0
PP020484974	0,5034%	6,2222	0,17	0	1	0
PP021345795	-1,7978%	6,6667	(2,50)	0	1	0
PP022148281	2,2656%	7,8333	(1,00)	1	0	0
PP021974611	6,2433%	6,0000	3,67	1	0	0
PP022048303	-6,9552%	5,8333	(4,25)	0	0	1
PP021878505	2,5858%	4,1000	1,00	1	0	0
PP020203886	1,4511%	5,3750	0,17	0	1	0
PP021926575	1,4511%	5,3750	0,17	0	1	0

3.2 DATA ANALYSIS

In this section the approach to analysing the three research questions is detailed. Before proceeding, however, it is important to examine the types of data used in this study. The variables relating to columns A to C in Table 3.1 are numerical and continuous in nature. Columns D to F, however, represents categorical data that is nominal by nature. Nominal values represent discrete units and are used to label variables that have no quantitative value (Donges, 2018). Data is therefore both numerical and categorical in nature which is significant in respect of the algorithm considered. Data analysis techniques for each of the research questions are now considered.

3.2.1 Selection of clustering algorithm and measure of distance

The first research question relates to the identification of statistically significant behaviour patterns. To accomplish this the data is prepared by placing each investor with their associated switch transactions according to the variables identified in tabular format. The next consideration was that of an appropriate clustering technique to reveal groups of similar risk behaviour. According to Kaushik (2020) although over 100 clustering algorithms exist, conceptually there are four types:

i. *Connectivity models*: The central premise is that data points closer in data space are more similar than those lying further away. Prominent here is the hierarchical clustering (HC) algorithm where the data are not grouped into clusters or classes in a single step (Everitt et al., 2011). One of two approaches may be used, fusing smaller groups into a single large group (agglomerative) or vice versa where large groups are continually separated into smaller ones (divisive).
ii. *Centroid models*: These are iterative algorithms that define similarity by the distance of data in relation to the centroid (middle) of the cluster. The most popular form in this category is known as the K-means algorithm where prior knowledge of the data is required (number of desired clusters is known from the outset). Another popular method here is the K-medoids or partition around medoids (PAM) clustering algorithm which is distinct from the K-means approach in that it uses an actual observation as the centroid and not an average which makes the K-means approach very sensitive to outliers.
iii. *Distribution models*: As the name implies, the data points using these methods are assessed in terms of the probability of being in a cluster belonging to the same distribution (for example a normal distribution). A popular example of these models is the Expectation-Maximization or EM algorithm which uses multivariate normal distributions.
iv. *Density models*: These models search data space for varied density levels of data points while isolating these regions and assigning membership to the same cluster in respect of this density. Popular techniques here included DBSCAN and OPTICS.

The discussion begins with excluding clustering algorithms that are less appropriate. Kaushik (2014) explains that the HC algorithm is limited when it comes to large datasets. The size of the dataset used for this paper is too cumbersome and would hinder adequate visual representation of the resultant clusters. The HC algorithm was therefore not considered further. Next distribution-based algorithms were also discarded on the basis that they are designed to fit the data on the probability of observations forming part of a normal or Gaussian distribution. These algorithms are complex and more applicable for synthetic data (not obtained by direct measurement) where the cluster sizes may vary greatly (Priy 2021). Given the relatively limited universe for investment preferences (risk seeking versus risk averse) and that investor personality types essentially boil down to risk seeking or risk averse behaviour (Van Raaij 2016) it is not expected that the size and cluster membership will vary greatly. Finally, density-based algorithms were reviewed. According to Verma and Chen (2012) and Kassambara (2017) density based algorithms such as DBSCAN are especially useful when considering data that is very noisy, with a high degree of outliers and also where data may take a specific "shape". Centroid approaches by nature are very efficient at detecting circular and convex shapes of data clustered around a central point for example (Berba 2021). Furthermore according to Cai et al., (2016) density-based clustering does not suit a financial dataset. They recommend that

centroid-based clustering techniques where the ideal number of clusters is well explored will be the best approach for analysing data in a financial context.
There is sufficient literature to show that financial personality types and associated behaviour may be associated with the five personality traits proposed by the FFM of personality (Mayfield et al., 2008). Associated personality archetypes whether associating links to the FFM or not generally fluctuate between 4 and 8 (Goldberg and Lewis 1978; Yamauchi and Templar 1982; Forman 1987; Tang 1992; Ridgeway et al., 2008; Nemeth et al., 2016). The likely number of clusters is therefore known.
This further refined the search for an appropriate technique to centroid-based methods in which each cluster is represented by a central vector, and the objects are assigned to the clusters based on proximity. The immediate appeal was to consider the K-means algorithm that represents one of the most popular and simplest clustering algorithms (Kassambara 2017). Unfortunately, in that simplicity resides a few important limitations: firstly, having to specify the number of clusters in advance and secondly, selecting initial centroids randomly can make the reproducibility of the study a challenge. These challenges are not insurmountable, but that aside, the primary challenge is that the K-means approach should not be employed where different types of data are used for example the numerical as well as categorical data present in this study (Shendre 2021). The reason is simply that finding a mathematical mean or average is not possible between a numerical value of "1" for example and the categorical variable of say "yellow". The discovery process was therefore further steered to the most common k-medoids clustering method being the partitioning around medoids or PAM algorithm (Kaufman & Rousseeuw 2009). These "medoids" provide an estimate of the central position of each potential cluster that is based on an actual observation as opposed to the average (used in the K-means algorithm). Clusters are formed in this case that would be based on the distance between observations (investor switches) and these medoids (data central points), and between the medoids themselves.

In respect of measuring these distances there are several distance measures available such as the Euclidean distance (Kassambara 2017) when using PAM (or indeed any clustering algorithm). The Euclidian distance is popular in the K-means approach and is calculated by determining the shortest possible route (straight line) between two points. Once again this remains a challenge when considering mixed data types. Fortunately, the Gower distance measure solves this issue and is recommended specifically when dealing with such mixed data (Shendre 2021). The Gower distance measure solves this by considering dissimilarities of data based on both numerical as well as qualitative features where partial dissimilarity is allowed for by assigning a value of "1" where observations have a different value and "0" where these values are identified as the same (Filaire 2018). An example of this is found later in this paper.

3.2.1.1 Number of representative clusters

The final consideration involved the selection of the number of clusters or proposed behaviour patterns to apply the clustering algorithm to. In this regard the silhouette method via the silhouette coefficient (SC) is used to find the optimal number of clusters as well as for the interpretation and validation of consistency within clusters of data. The silhouette method computes silhouette coefficients of each point that measure how much a point is similar to its own cluster compared to other clusters (Kumar 2020).

In respect of the silhouette coefficient the range of outcomes are as follows:

i. A silhouette coefficient of "+1" indicates that the sample is far away from the neighbouring clusters or that is an excellent representation.
ii. A Silhouette coefficient of "0" indicates that the sample is on or very close to the decision boundary between two neighbouring clusters. Clusters are thus not well defined, and observations are represented by potentially more than one cluster.
iii. Silhouette coefficient <0 indicates that those samples might have been assigned to the wrong cluster or are outliers.

By plotting the respective silhouette coefficients in relation to the number of clusters it will be possible to ascertain the number of clusters that will give the greatest silhouette "width" or the number of clusters that will yield the greatest differentiation in behaviour patterns.

3.2.2 Significance testing of clustering

Testing the statistical significance of clusters is an evolving arena that has presented many challenges to practitioners and academics alike. Clustering algorithms are designed to draw out as much difference as possible from a set of data and so traditional difference in means tests such as ANOVA (both one and two way) will not necessarily reveal anything that is not already known – that the means are different. As noted in Liu et al., (2008) a difference between subgroups in terms of means is not advisable because clustering methods will split even a truly Gaussian population (mean based) into statistically significant subgroups.

According to Hennig et al., (2015) the "SigClust" method effectively addresses the problem of assessing statistical significance of clustering as a testing procedure. The null hypothesis is that the data are from a single Gaussian distribution. The significance of a given clustering is judged by calculating an appropriate p-value. The Sigclust method uses a test statistic called the cluster index (CI) which is defined to be the sum of within-class sums of squares about the mean divided by the total sum of squares about the overall mean. The null distribution of the CI can be approximated by simulating from a single Gaussian distribution and the fit to the data. This choice of null hypothesis is more sensible than say a difference between subgroups in terms of means. The Sigclust method was used to test for significance of the clusters in this study.

3.2.3 Behaviour patterns over time as markets ebb and flow

The second and third research questions explore the important question of how these behaviour patterns are changing over time. The literature reviewed has explained how people can have long-term and relatively stable risk preferences which are often overridden as risk is perceived differently and often incorrectly in the short term, usually paired with market events. This affects our subsequent willingness to assume risk (risk propensity) that can be to the detriment of long-term investment goals. Applying the PAM clustering algorithm will give each investor membership to a cluster based on observations in relation to a unique medoid. Recall that a medoid is the data point for which the sum of dissimilarities (Gower distance) to all other data points in the respective cluster is minimal. This membership represents an average of behaviour over time and is not time specific.

To examine behaviour as markets fluctuate two lenses through which to view risk behaviour may be used. The first lens shifts the analysis to switch-level data (switches with an associated time stamp). A monthly timeline is created for each archetype and all the switches made in this timeframe are divided into each of the four archetypes to assess their proportionate change over time. This will also capture how risk behaviour is changing over time as the types of switches performed changes (or doesn’t change). The switch-level approach yields interesting insights about behaviour patterns as it unpacks average behaviour over time into time-specific behaviour. This is not sufficient, however, as it does not provide an indication of cluster membership over time. The switch-level approach shows the behaviour patterns relating to the types of switches performed but the underlying investors may still be shifting between archetypes and if this activity is not predictable it would not be possible to develop a nudging strategy for each archetype. The final section below deals with cluster membership stability (the second lens).

3.2.3.1 Stability of cluster membership

The third and final research question to be answered from this study is regarding the stability of cluster membership. It is possible to gain insights into long-term risk preferences by examining the results of the PAM algorithm that reveals an average of risk behaviour over time. Likewise, the average behaviour pattern in respect of the switching matrix (discussed later in Table 4.2) may be compared to investor’s short term risk behaviour stemming from risk perception. To ascertain whether cluster membership is changing it would be necessary to use the methodology of assigning a cluster to each investment switch based on the Gower distance to check which cluster each *investor's* switch actually belonged to over time. This is distinct from the switch-level exercise. In the former case monthly switches are allocated to a cluster based on the results of the PAM algorithm that yielded average behaviour. This would deconstruct this average behaviour to monthly behaviour that may yield more detailed insights (proportionate change of archetype switches over time). In the latter case each switch transaction is assigned a Gower distance to check which medoid it is actually closer to. It would then be possible to say for example that the investor was a member of cluster "X" on average and furthermore what percentage of their individual switches through time belonged to cluster "X". This will provide insights into risk behaviour in respect of the long-term versus short-term risk behaviour at the investor level.

An example of calculating the Gower distance per switch and associated medoid assignment is given below. To reiterate, this is done by calculating the observed Gower distance (dissimilarity) between that observation (switch transaction) and each of the cluster medoids. The observation is then assigned to the cluster whose medoid is the closest (most similar) to the observation.

Table 3.2 Extract to demonstrate Gower distance per investment switch

	(A)	(B)	(C)	(D)	(E)	(F)	Gower Distance between this data and Cluster medoid				
Investor	Performance chased	Average risk	Risk Difference	Chasing past performance > 2%	Neutral (within -2% to +2%)	Worse past performance < -2%	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster Chosen (closest)
PP021133544	-5,8296%	6,3333	(5,00)	0	0	1	4,94	3,63	2,79	4,76	3
PP021058363	2,7094%	4,7500	3,50	1	0	0	4,44	3,13	2,29	4,26	3
PP020484974	0,5034%	6,2222	0,17	0	1	0	2,68	3,35	0,82	2,86	3
PP021345795	-1,7978%	6,6667	(2,50)	0	1	0	2,31	2,98	2,45	0,49	4
PP022148281	2,2656%	7,8333	(1,00)	1	0	0	4,78	3,65	4,62	2,66	4
PP021974611	6,2433%	6,0000	3,67	1	0	0	4,15	3,89	4,30	2,34	4
PP022048303	-6,9552%	5,8333	(4,25)	0	0	1	2,51	2,70	4,36	4,33	1
PP021878505	2,5858%	4,1000	1,00	1	0	0	0,08	2,34	2,22	2,27	1
PP020203886	1,4511%	5,3750	0,17	0	1	0	2,36	3,10	4,21	4,18	1
PP021926575	1,4511%	5,3750	0,17	0	1	0	2,11	3,67	4,99	3,99	1

3.2.5 Conclusion

This chapter has presented the transactional investor data which has been cleaned to identify relevant behavioural transactions. The framework was then presented with which to classify investor transactions that will be used as the basis for the clustering analysis. The mixture of numerical data as well as categorical data resulted in the PAM clustering algorithm being selected paired with the Gower distance metric to work with such mixed data. The movement from average investor behaviour to behaviour over time has also been detailed together with the associated methodology of classifying each switch transaction to a cluster or medoid based on an individual switch "distance" from the nearest medoid to ascertain the stability of cluster membership. The next chapter presents the results and findings of the analysis that will clearly demonstrate four distinct investor behaviour patterns.

CHAPTER 4
RESEARCH FINDINGS

This chapter will unpack the research findings according to the three research questions presented in this paper.

4.1 SOUTH AFRICAN RISK BEHAVIOUR ARCHETYPES

The first research question was addressed by applying the unsupervised machine learning algorithm known as partitioning around medoids (PAM) detailed in Chapter 3. The first consideration in applying this methodology was to get a sense of how many clusters of behaviour would be optimal. As discussed in Chapter 3, financial behaviour archetypes reviewed in literature generally tally between 4 and 8.

To assist with this exercise the silhouette coefficient (SC) was calculated for a range that included this number of potential clusters. The SC is calculated below (Bhardwaj 2021) using the mean intra-cluster distance (a) and the mean nearest-cluster distance (b) for each observation (i). The coefficient is therefore expressed as:

$$s(i) = \frac{b(i) - a(i)}{\max\,(a(i)\,;\; b(i))}$$

To clarify, b is the distance between an observation and the nearest cluster that this observation is *not* a part of. The results are shown below in Figure 4.1 and demonstrates that between 3 and 5 clusters are optimal in respect of bringing out the biggest differences in the behaviour patterns.

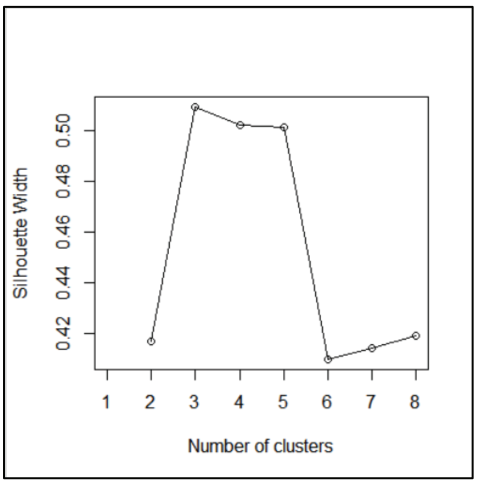

Figure 4.1 Silhouette coefficient results

The results prompt two important questions. The first is whether the SC was high enough to proceed with the study? If this is deemed to be the case, the second question would be how many clusters should be used when applying the algorithm to the extensive dataset?

The results of the SC calculation can vary between the values of -1 to 1. The clustering results are said to be meaningful if the SC value is positive. This occurs when (a (i) < b (i)) and a (i) is close to 0 so that the maximum SC of 1 will be generated when (i) = 0. A result of 1 therefore indicates that the observation (i) is in the correct cluster. Conversely if s(i) is 0 the observation lies in-between two clusters and therefore may easily be assigned to either cluster A or B for example. Negative values therefore provide an indication that observations have been assigned to the incorrect cluster. Mulyawan et al., (2019) suggests the following general interpretation may be used for guidance when assessing the SC:

Table 4.1 Silhouette coefficient analysis

Silhouette coefficient (SC)	**Indicative structure**	**Comment**
$0.70 < SC \leq 1.00$	Strong structure	Proceed
$0.50 < SC \leq 0.70$	**Medium structure**	
$0.25 < SC \leq 0.50$	Weak Structure	Proceed with caution
$SC \leq 0.25$	No structure	Redefine data analysis

Source*:* Adapted from Mulyawan et al., (2019), p.3.

The silhouette score for the switch data provided at 4 clusters is greater than 0.50 and so falls into the second category above – in other words, showing a medium structure to the clustering. This is an indication that observations in some cases fall in between clusters and so the danger of misallocation is greater, but overall, there is a reasonable structure and integrity to the clusters. Literature does not provide much further guidance in respect of a set cut-off point save for results *below* the 0.25 mark that indicates no observable structure to the data. Ideally a SC in excess of 0.5 is preferable which is the case in this study. Furthermore, given the fairly limited research conducted into the practicalities of risk behaviour particularly in the financial services sector it was deemed that this research would be very valuable in setting the platform for future studies that may improve the insights generated.

The second consideration relates to the choice of the number of clusters. Figure 4.1 shows that using 3 clusters provides a SC of just below 0.51 while using 4 clusters provides a SC just above 0.50. When examining the preliminary results of using 3 clusters, however, it appeared that market timer behaviour was being lost in the analysis perhaps because market timers appear skittish in times of volatility and overconfident in times of rising markets. Given the minute difference in SC it was therefore decided to use 4 clusters.

4.1.1 Cluster results

Table 4.2 presents the result of applying the PAM clustering algorithm to the dataset. The clusters are labelled and membership to each respective cluster is shown in respect of the population proportion of behaviour according to the 6 variables. Recall that two clustering variables were used to capture changes in investment risk being the average risk over time and changes in the risk profile or risk level of the investor's portfolio. Four variables relate to investment returns being the average past investment performance chased as well as three variables relating to the quantum of this movement to better, neutral or worse performing prospects. More than a 2% better or worse past investment performance is required to trigger this category of switch while remaining neutral accounts for between a 2% increase or decrease in the current portfolio's performance. While the average number of switches was not included specifically as a clustering variable when they were investigated post the allocation to a cluster they also bring out some notable differences that are discussed here.

Table 4.2 Switch matrix cluster results

Population Total		**35199**			
Population Proportion (investor level)		**27%**	**34%**	**17%**	**22%**
Cluster		**1**	**2**	**3**	**4**
Average Investment Risk →		**5.37**	**5.44**	**5.46**	**4.63**
Average switches per year →		**0.52**	**1.26**	**0.67**	**0.48**
Risk Profile Change (Average over switches)	Risk reduction	26%	17%	36%	13%
	No risk change	42%	67%	44%	75%
	Risk Increase	33%	15%	19%	13%
Past Performance difference (Average over switches)	Better relative Past performance	98%	46%	4%	3%
	Neutral	1%	25%	5%	92%
	Worse relative past performance	1%	29%	91%	5%
Archetype		**ASSERTIVE**	**MARKET TIMER**	**ANXIOUS**	**AVOIDER**

The respectable SC is now apparent when reviewing the results of the clusters in Table 4.2. The grey highlighted cells each show an area where that cluster has the highest or lowest value or where there is a notable explanation or behaviour pattern. Said differently, the presence and quantum of differences in the grey highlighted cells is a positive attribute indicative of a higher SC that showcases different behavioural patterns in the data. Each cluster is now discussed in more detail.

4.1.1.1 South African investor behavioural archetypes

The following four behavioural archetypes emerge when applying the PAM clustering algorithm. These are labelled and discussed below.

(a) *Cluster 1*: the "**assertive**" investor as the label implies is more comfortable with investment risk. In respect of risk profile, this cluster increases risk as would be expected (from the given cluster name) on 33% of occasions when performing an investment switch. This is 73% greater than the next highest figure of 19% in cluster 3. Similarly, when reviewing the returns side of clustering variables, the assertive investor is switching to prospects that have better past performance on 98% of occasions. This is 113% greater than the second highest figure in cluster 2. One may have expected an "assertive" investor to also maintain the most aggressive portfolio in the grouping, however there are not major differences attributed here across the clusters. Cluster 1, 2 and 3 are all assuming average investment risk of between 5.37 and 5.46. Recall that this refers to the asset allocation similar to the CPI + 4% OBI solution. This is perhaps more of a problem in using averages that tend in many cases to mute differences.

(b) *Cluster 2*: the "**market timer**" is characterised by the greatest number of switch transactions at 1.26 transactions per annum. This is 88% greater than the next most active archetype in cluster 3. The market timer is perhaps influenced by others? When examining the return variables the market timers are the only archetype that are active in switching to both investment prosects that perform better as well as those that perform worse indicating that they are active in both market downturns as well as upturns. There is not much notable difference in the risk profile changes on average, however, as it appears the primary driver here is the past performance of prospect and not the risk level of the prospect. This is confirmed by the market timer remaining in a risk neutral band on 67% of occasions. Finally, they are also the largest cluster at just over a third of the total population.

(c) *Cluster 3*: the "**anxious**" investor is characterised primarily by their risk aversive behaviour once invested. This is clear in both the investment risk variables and return-related variables. In the former instance the anxious group are reducing risk in their portfolios on 36% of occasions which is 38% more than the nearest figure in cluster 1. In the case of the latter return-related variables the anxious investor is switching to prospects with worse past investment performance on 91% of occasions. An anxious investor holding a multi-asset portfolio for example in a market crash and switching to cash would usually appear to be switching to a prospect with worst past investment performance when considering the 12-month relative performance of both prospects. The anxious investor cluster is the smallest at 17% of the total population.

(d) *Cluster 4*: the "**avoider**" is characterised by the lowest value in respect of switch frequency at 0.48 switches per annum. Furthermore, on average, these investors have the lowest average exposure to risk at a score of 4.63 (towards the conservative end of the asset allocation spectrum relating to the CPI + 3% target return) indicating that they are the most risk averse group. The label of "avoider" is applied due to the level of risk aversion and, also, the associated level of inactivity in engagement once invested. This is also clear in both the investment risk variables and return-related variables. In the former instance the avoider group are remaining risk-neutral on 75% of occasions (12% greater than the next highest figure in cluster 2). In the case of the latter return-related variables the avoider is switching to return-neutral prospects on 92% of occasions. As mentioned previously the utility here could be associated in shifting to prospects that are trusted more or with stronger associated brand equity. It is highly possible that due to the "neutral" label being defined as shifting within the -2% to + 2% investment performance range that these investors prefer shifting to prospects that are relatively similar in return profile. In other words shifting between cash and cash-plus type prospects.

4.2 STATISTICAL SIGNIFICANCE OF CLUSTERS

As discussed in Chapter 3, applying a clustering algorithm to a dataset by its very nature will split the data into what are likely to be statistically different subgroups. As a result, the traditional p-value and resultant t-tests will usually yield each cluster as statistically different from one another. This problem is addressed using the "Sigclust" package that tests for statistical significance by presenting the null hypothesis that the comparative data of two respective clusters are from a single Gaussian distribution. For example:

H_0 : Data are from a single Gaussian distribution

H_1 : Data are from a mixture of at least two Gaussian Distributions

The significance of a given cluster is judged by calculating a test statistic that is conceptually similar to a traditional significance test using p-values. The SigClust method uses the two-mean cluster index (CI) which is defined to be the sum of within-class sum of squares about the mean divided by the total sum of squares about the overall mean. Conceptually this represents the ratio of within-cluster variation to the total variation. A lower CI is therefore indicative of larger differences in variation between the cluster and total variation that indicates statistical significance. The null distribution of the CI is approximated by Monte Carlo simulations from a single Gaussian distribution that is fitted to the data. In essence the underlying eigenvalues (ascertaining variance in data in a particular direction) of the covariance matrix are found.

Table 4.3 presents the results of the running the Sigclust package on each possible pair of clusters as well as the respective CI values. Overall, each cluster pairing was found to be significant. Note the p-values of exactly "0" returned by the Sigclust package are likely due to the number of zeros before any positive value. For purposes of explanation the comparison of cluster 1 to 2 is discussed in more detail. The CI value when comparing cluster 1 and 2 is greater than all the other cluster comparisons at 0.5775, however, this comparison along with all the others shows statistical significance.

Table 4.3 Significance test results of clusters using package "Sigclust"

<table>
<tr><td></td><td colspan="2">Cluster 1
Avoider</td><td colspan="2">Cluster 2
Market Timer</td><td colspan="2">Cluster 3
Anxious</td><td>Cluster 4
Assertive</td></tr>
<tr><td>Cluster 1
Avoider</td><td colspan="2"></td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td rowspan="3">Cluster 2
Market Timer</td><td>p-value</td><td>0</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td>CI</td><td>0.5775</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td colspan="2">*Significant*</td><td colspan="2"></td><td colspan="2"></td><td></td></tr>
<tr><td rowspan="3">Cluster 3
Anxious</td><td>p-value</td><td>0</td><td>p-value</td><td>0</td><td colspan="2"></td><td></td></tr>
<tr><td>CI</td><td>0.3070</td><td>CI</td><td>0.2699</td><td colspan="2"></td><td></td></tr>
<tr><td colspan="2">*Significant*</td><td colspan="2">*Significant*</td><td colspan="2"></td><td></td></tr>
<tr><td rowspan="3">Cluster 4
Assertive</td><td>p-value</td><td>0</td><td>p-value</td><td>0</td><td>p-value</td><td>0</td><td></td></tr>
<tr><td>CI</td><td>0.3459</td><td>CI</td><td>0.3817</td><td>CI</td><td>0.00</td><td></td></tr>
<tr><td colspan="2">*Significant*</td><td colspan="2">*Significant*</td><td colspan="2">*Significant*</td><td></td></tr>
</table>

Figure 4.2 to follow shows a summary plot of the Sigclust results. The blue dots represent data entries selected from the sample (n = 5000). The vertical "density" label is important only in terms of representation or visualisation (plotted with random "jitter" to add random noise that highlights greater differences in observations). Two observations with exactly the same characteristics would be shown as one point but creating "jitter" adds noise that visually would show these as two distinct observations (slightly apart). In essence this also gives the plot greater height. The dashed curve is the Gaussian fit based on the estimated background noise while the solid curve is a kernel density estimate of this distribution.

Figure 4.2 shows 1000 blue dots representing samples from the null distribution and calculates the CI for each randomly generated simulation. The empirical distribution is obtained from these simulated CIs. A p-value is then calculated for this distribution and whether the CI is different from the CI of the original dataset is examined. Although the CI in this instance is higher than the other comparisons there is an apparent difference in the distributions hence the p-value of zero indicating statistical significance. Note the green dotted line in Figure 10 represents the CI value (in this comparison being 0.5775).

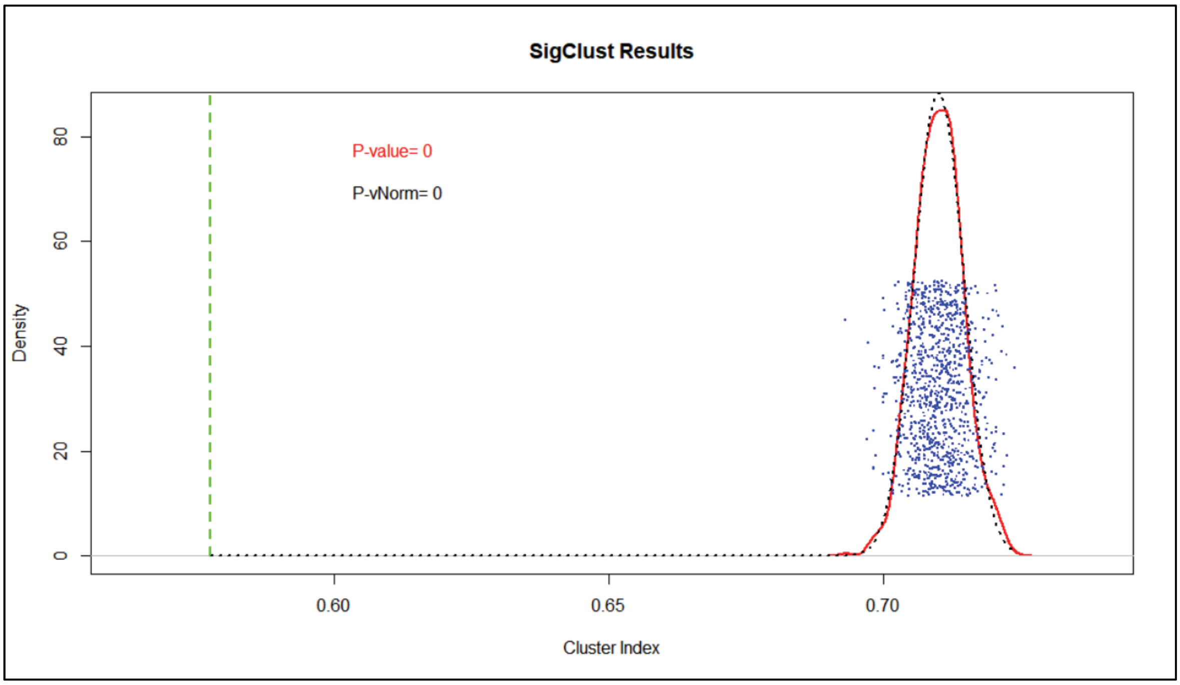

Figure 4.2 Sample data plot and Gaussian fit between cluster 1 and 2

The conclusion in this case is that the differences in the clusters are indeed as a result of something other than chance alone. The complete set of results of the Sigclust package for this cluster comparison have been included in this section. The complete set of results between all clusters are included in Appendix 2, as well as the relevant Q-Q plots.

Figure 4.3 shows the randomly sampled data points (in green) of n = 5000 from the relevant cluster datasets across all variables and shows the distribution thereof. Additionally, the procedure fits a Gaussian distribution and gives a “hard to interpret” flag whenever mean absolute deviation (MAD) is greater than the standard deviation. No such flag was triggered in this case.

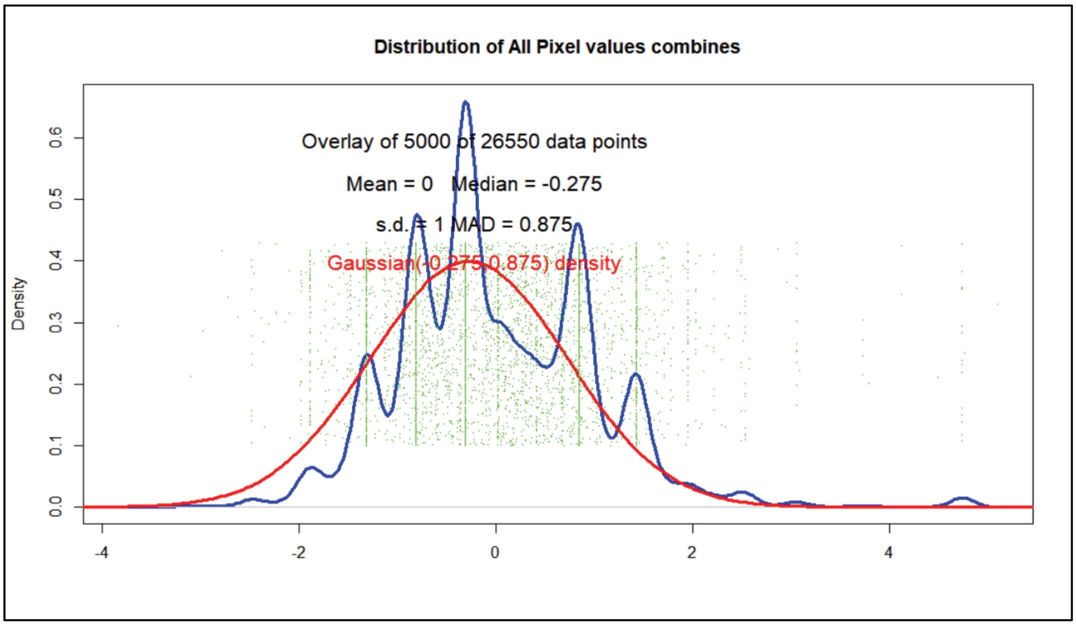

Figure 4.3 Sample data plot and Gaussian fit between cluster 1 and 2

Figure 4.4 shows the Q-Q plot of empirical data (entire cluster dataset) against the fitted Gaussian distribution. If the empirical data points trend away from the diagonal (Gaussian distribution) line between quantiles 0.25 and 0.75 then the estimate of standard deviation may be unreliable and so also the Sigclust inference. In this case the fit between these plots is deemed sufficient.

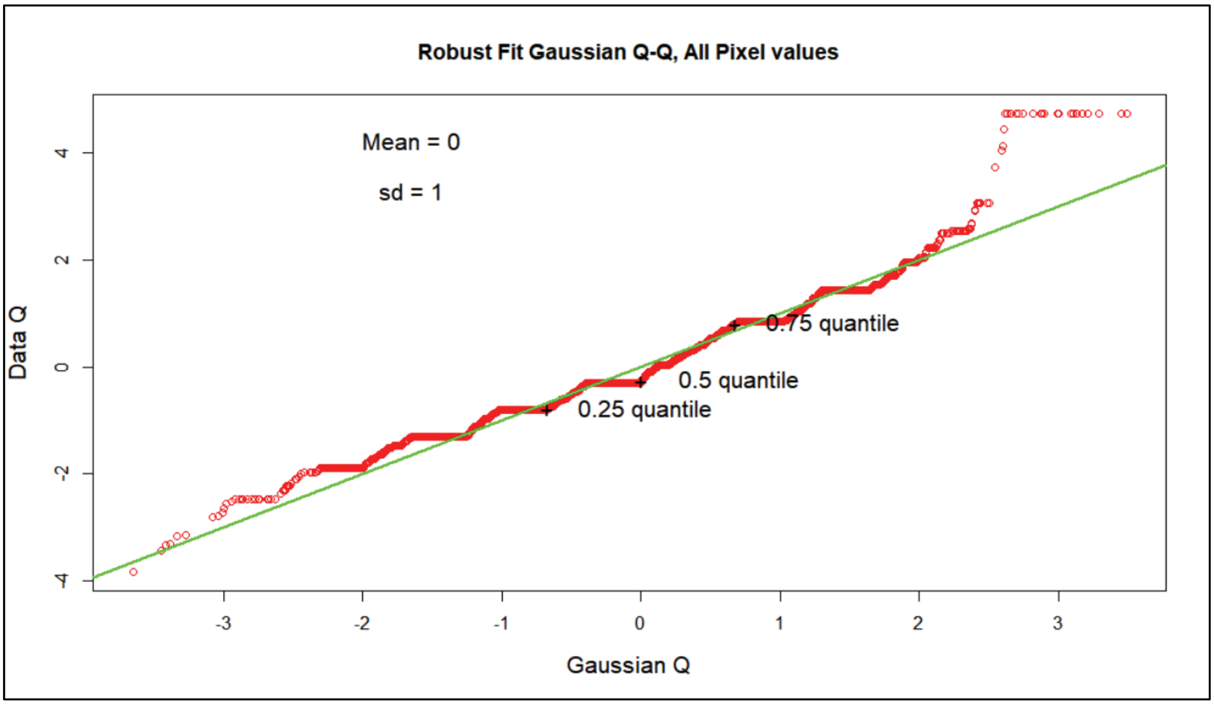

Figure 4.4 Q-Q plot results comparing cluster 1 and 2

4.3 ARCHETYPE BEHAVIOUR OVER TIME

The second and third research questions concern archetype behaviour over time. It is worth reiterating that the results of applying the PAM clustering algorithm to the investment switching transactions from the 01st of January 2006 to the 01st October 2021 show average behaviour over this period. In this sense there is no time stamp or indication of a particular investor or group of investor cluster membership through time nor cluster behaviour over time. It is important to add this dimension to the analysis to observe the behaviour in the context of prevailing market conditions that may be associated with greed and fear respectively.

To approach this, it was necessary to get a view of monthly switch transactions that would assist in deconstructing average behaviour into monthly behaviour. An extract of 10 switch transactions is provided in Table 4.4 for the month of June 2008. The table format and labelling has been altered slightly for simplification purposes, however, it represents the same clustering variables detailed earlier. The investor number is also provided and then referenced to the results of the PAM algorithm in section 4.1. In essence this classifies each switch transaction as belonging to one of the four archetypes identified. Note that this is labelled "long-term" as each resultant switch is matched to the average cluster membership indicative of the investor long-term risk behaviour.

Table 4.4 Switch data and comparison of long-term versus short-term behaviour

Clustering Variable→	Average Risk	Average Performance Chased	Risk Difference	Past Performance chased			**LT**
				↑	→	↓	Average Cluster*
PP022067565	4,25	0,3455%	3,50	0	0	0	1
PP022093143	4,56	-5,8296%	(3,00)	0	0	0	4
PP022282453	3,33	2,7094%	1,33	0	0	0	1
PP022165670	6,60	0,5034%	3,50	0	0	0	1
PP022100819	5,25	-1,7978%	3,50	0	0	0	1
PP022439430	5,67	2,2656%	3,50	0	0	0	1
PP021948499	4,14	6,2433%	0,67	0	0	0	2
PP022269091	3,57	-6,9552%	0,67	0	1	0	2
PP021935829	4,67	2,5858%	0,67	0	0	0	2
PP022097840	5,83	1,4511%	(2,25)	0	1	0	2

* Result of applying PAM clustering algorithm to data (01/01/2006 – 01/10/2021)

The result of this classification will provide the proportion of switches from the different archetypes over time and is illustrated in the following section. It is important to note that this methodology will provide a heavier weighting to the archetype that switches the most. Taking an extreme example, consider an investor that makes 100 switches that is classified as a market timer by the PAM algorithm in the original analysis. This would be partially based on their switch frequency. This is also a defining factor of the market timer archetype. Representation of this investor in the original analysis is limited to one "entry" because the methodology seeks to classify behaviour at an investor level (each investor is represented once). Moving to a switch level, however, places a higher weight on the number of switches because this same investor now has 100 "entries" as each switch they make is assigned the "market timer" tag when viewed at a switch level. The effect of this will become clear in the next section where it is evident that market timer switches dominate the proportion of switches over time. The exercise remains useful to examine at a high level behaviour patterns over time.

To gain insights into cluster membership through time (the third research question) to examine the relationship between long-term preferences (average behaviour) and the effect of short-term perception of risk (gains and losses from market movements) on resultant risk propensity it is necessary to ascertain the characteristics of each switch transaction and to determine whether each transaction is consonant with long-term risk preferences. Once again, these long-term preferences were revealed by the investor-level archetype allocation using the PAM clustering algorithm (the first research question).

To approach this, the medoids (statistical estimates of the cluster centres) were taken from the average behaviour and then compared to the individual Gower distances of monthly switch transactions over time. In essence each switch is characterised manually in respect of its distance to the nearest cluster and assigned accordingly. The medoid is the data point for which the sum of dissimilarities (Gower distances) to all other data points in the respective cluster is minimized. The switch transactions were then assigned to the nearest medoid to ascertain if cluster membership changed over time. This will be dealt with in section 4.4. A simplified example is provided below to demonstrate this process showing the Gower distance calculation for two numerical and two categorical variables respectively.

Table 4.5 Individual Gower distance calculation at each switch interval

Variable →	Risk Difference	Average investment risk	Chasing past performance > 2%	Chasing past performance < 2%	Gower distance	Assigned Cluster **Closest**
Switch 1 [1]	0.42	4.25	1	0	0.3260	[1] 0.3260
Medoid 1 [2]	0.48	5.00	1	1		
Switch 1 [1]	0.42	4.25	1	0	0.6025	
Medoid 2 [3]	0.32	5.17	1	0		
***Range**	**0.81**	**3.21**	N/A	N/A		

* range over entire dataset

distance ([1], [2]) = (0.074 + 0.23 + 1 + 0 / 4) = 0.326

Switches per month:	absolute difference ((0.42 – 0.48) / 0.81)	= 0.074
Average investment risk:	absolute difference ((4.25 – 5.00) / 3.21)	= 0.23
Risk reduction:	(same)	= 1
Risk increase:	(different)	= 0

distance ([1], [3]) = (0.12 + 0.29 + 1 + 1 / 4) = 0.6025

Switches per month:	absolute difference ((0.42 – 0.32) / 0.81)	= 0.12
Average investment risk:	absolute difference ((4.25 – 5.17) / 3.21)	= 0.29
Risk reduction:	(same)	= 1
Risk increase:	(same)	= 1

This example demonstrates the assignment to a cluster through time of each switch transaction in the dataset. Each investor in the dataset is assigned to one of the four clusters based on the Gower distance metric as calculated above. In each case the cluster is assigned based on minimising the distance to each of the medoids calculated when analysing aggregate investor behaviour. This example also demonstrates how the combination of numerical and categorical data is handled in the exercise.

4.3.1 Proportion of archetype switches over time

This section examines the proportion of archetype switches through time that addresses the second research question relating to cluster proportionate change. This provides a switch-level view of the archetypes. There is no link to specific investors at this point. Said differently this analysis shows how the proportion of anxious-type switches (for example) is changing as markets change. “Stability” in this case refers to the proportion of switches belonging to each archetype classification and not the proportion of investors belonging to each archetype. For example, the proportion of anxious-type switches for a given period may appear relatively stable but cluster membership at the investor level may not be stable (investor "X" may not regularly form part of the "anxious" cohort). The investor-level stability relates to the third research question and is discussed shortly. It is worth reiterating that the switch-level methodology does place a heavier weight by the *number* of switches conducted. Figure 4.5 clearly shows this as the dominant proportion of switches through time appears to be the market timer even though on average they represent 34% of the population (see Table 4.2). The sum of the four lines at each datapoint will equal 1 or 100%. The 3-month moving average is plotted in Figure 4.5 and shows that while some short periods correlate with relative switch-level stability, overall the picture is rather noisy. A key assertion put forward in the literature review, however, was that long-term risk preferences should be stable but may be derailed by short term risk perception. There does appear to be slightly higher levels of noise in archetype switches leading up to and during the Global Financial Crisis (beginning of the timeline) as well as towards the end of the timeline that includes market volatility experienced amidst the COVID-19 global pandemic. These are labelled as period's "A" and "C" respectively. There appears to be switch-level instability evident in period's A and C and this coincides with higher levels of market volatility as measured by the standard deviation of monthly returns (JTSE / JSE All Share Index). Period A has a 65% higher standard deviation of monthly returns when compared to period B and period C has a 43% greater standard deviation of monthly returns when compared to period B.

When considering the switch-type volatility (measured by the standard deviation of the change in archetype switches) over these same periods a similar relationship is found.

Table 4.6 Switches by archetypes changing in more volatile markets

Archetype	**Period A** *σ % change*	**Period B** *σ % change*	**Period C** *σ % change*
Anxious	19% **greater**	3,01%	2,05% **greater**
Assertive	32,59% **greater**	4,04%	3,02% **greater**
Avoider	132,42% **greater**	1,82%	145,05% **greater**
Market Timer	8,66% **greater**	5,80%	15,86% **greater**

The column highlighted in grey represents the standard deviation of the change in archetype switches from 2010 - 2020. The two adjacent columns correspond with period A (2006 – 2010) and C (2020 – October 2021) where additional market return volatility was shown to occur. It is clear from the table that archetype switches are more unstable during these periods of market volatility.

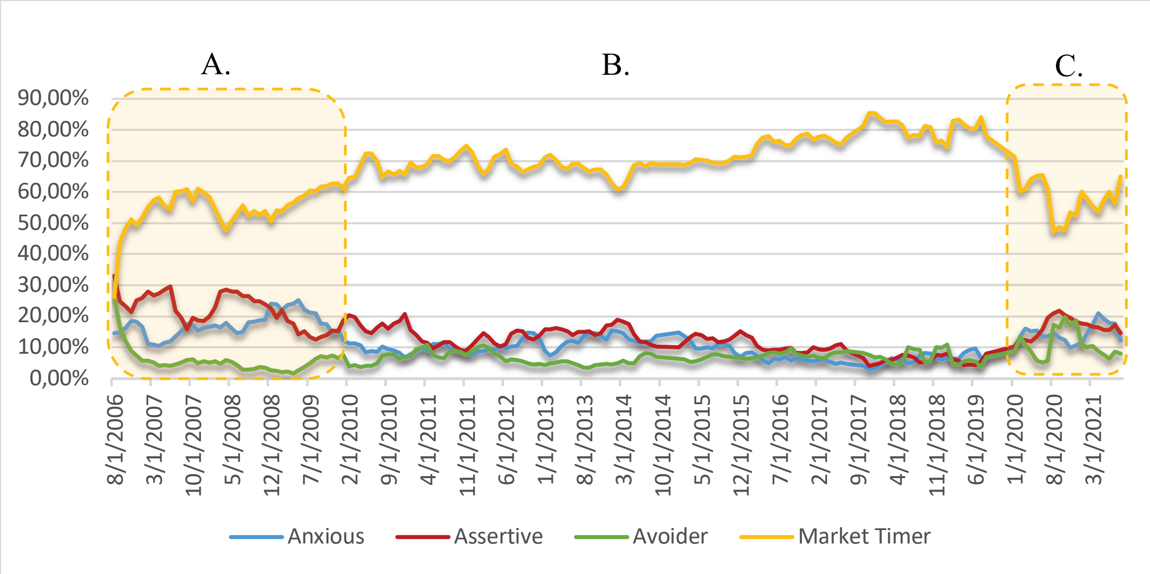

Figure 4.5 Overall change in proportion of switches (3-month moving average)

At this point it is also useful to re-introduce the behaviour tax work but broken down in respect of the four archetypes. This is presented in Table 4.7 to follow. When corresponding period A and C with the behaviour tax per archetype it is also clear that these two periods have higher levels of behaviour tax (particularly 2006 / 2007 and 2020 / 2021). It appears on face value that in periods of elevated market volatility there is more proportionate change in archetype switches and also elevated levels of behaviour tax. It is also worthwhile noting that this pattern does surface briefly as the bull market subsequent to the Global Financial Crisis ends mid-2014 and market volatility in the remainder of 2014 and 2015 increases. This is matched by two periods of relatively higher behaviour tax entries confirmed by Table 4.7 in 2014 and 2015. There is no clear change in archetype proportions in Figure 4.5 for this period. Also of particular interest although not specifically relevant to this section is that the anxious investor archetype defined primarily by risk reduction and moving to prospects with worse past investment performance incurs the most consistent behaviour tax (numbers highlighted in red) and in fact only escapes the behaviour tax in 4 of the ≈16 years of analysis. The quantum of the behaviour tax is also significantly higher.

Table 4.7 Behaviour tax per archetype over time

Archetype	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Anxious	6.6%	-1.1%	4.3%	-1.3%	2.5%	1.6%	3.6%	2.6%	1.8%	2.1%	-0.2%	0.2%	-0.7%	0.7%	1.2%	5.4%
Assertive	-3.9%	4.8%	-3.1%	3.5%	-2.7%	-1.7%	-4.8%	-2.2%	2.5%	1.0%	3.6%	-1.6%	-1.0%	-1.2%	7.5%	0.6%
Avoider	4.3%	1.2%	-3.3%	0.3%	0.3%	0.5%	1.1%	0.4%	1.4%	1.4%	0.4%	-0.6%	-0.8%	-0.6%	1.9%	1.0%
Market Timer	4.0%	1.4%	-0.6%	1.2%	-1.3%	-0.4%	-1.1%	0.2%	1.2%	1.3%	0.4%	-0.9%	-0.4%	0.2%	5.0%	4.2%
12-month Behaviour Tax	**2.7%**	**1.8%**	**-0.5%**	**1.0%**	**-1.1%**	**-0.3%**	**-0.9%**	**0.1%**	**1.5%**	**1.4%**	**0.7%**	**-0.9%**	**-0.5%**	**0.1%**	**6.5%**	**3.5%**

In conclusion it does appear that elevated levels of market volatility result in switch-level archetype instability. This was evident in the pre-crash and 2008 Global Financial Crisis periods as well as the market volatility surrounding the COVID-19 pandemic in 2020 and 2021. It does appear that the volatility in archetype switches gives way to a state of higher stability as market volatility subsides and this will become clearer when addressing the third research question next that deals with investor-level archetype membership over time.

4.4 STABILITY OF BEHAVIOURAL ARCHETYPES

The third research question relates to an important proposition identified in the literature review, namely that risk preferences are relatively stable over time but risk perception (because of cognitive and emotional processing errors as well as outcome experience) may result in varying behaviour in the short term. To investigate this, it was necessary to allocate each investment switch to a cluster through time to ascertain the extent of differences between long-term preferences and short-term behaviour. This deals specifically with archetype membership stability. If investor “X” is labelled as an “anxious” investor, by applying the clustering algorithm, this reveals their average behaviour. If this behaviour, however, is not consistent it is also not predictable, which would be required in respect of proactive engagement or nudging strategies.

Recall that when applying the PAM algorithm to investors’ switch transaction history four clusters were revealed. These results are time independent and as such only reveal average behaviour over this time-period. When adding a temporal dimension and more importantly cluster membership of each switch transaction over time it is necessary to examine the Gower distance of each switch and subsequently assign this to an investment cluster based on the lowest Gower distance (closest medoid).

Combining these two methodologies provides a view of the interplay between long-term preferences (average behaviour over ≈16 years) and the proportion of subsequent switch transactions that fitted into this “preferred” behaviour. Table 4.8 to follow, provides an extract of 10 investment switch transactions that took place between the 01st of June 2008 and the 01st of July 2008. The investor who executed the transaction is listed on the left followed by the 6 clustering variables (columns 3 – 8). To recap briefly the first investor on the list (PP022067565) on average had a portfolio risk of 4.25. In other words, this investor was on average exposed to assets over the term of their investment on the Momentum Wealth platform that resembled the asset allocation of the Momentum Investments CPI + 3% outcome-based solution. This investor on average performed 0.11 switches per month or 1.32 switches per year (this was not an explicit clustering variable). The switch transaction increased the level of their portfolio risk by 1,2870 “points” according to the risk rating mechanism described earlier and on average this investor moved to prospects that performed just over 17% better on a 12-month relative basis. Lastly all of this investor’s switches were chasing better past investment performance (at least 2% better than the current portfolio).

Investor PP022067565 is then traced to their average behaviour archetype prepared using the PAM algorithm that was detailed in Section 4.1. This represents long-term risk preferences. The methodology explained in Section 4.3 is then used to classify the switch in question using the Gower distance. The result represents risk perception and subsequent propensity to take risk in the short term.

Table 4.8 Switch data and comparison of long-term versus short-term behaviour

Clustering variable	Monthly Switches	Average Δ risk	Average Risk Rating	Average Performance Chased	Average Performance Chased			Long Term	Short Term
					↑	→	↓	Average cluster	Switch cluster
PP022067565	0,11	1,2870	4,25	0,1702	1	0	0	1	1
PP022093143	0,12	0,1167	4,56	-0,0533	0	0	1	4	4
PP022282453	0,30	0,5417	3,33	0,0110	0	1	0	1	1
PP022165670	0,30	-0,2500	6,60	-0,0265	0	0,5	0,5	1	1
PP022100819	0,08	0,1296	5,25	0,0048	0	1	0	1	1
PP022439430	0,29	1,3333	5,67	0,0360	0,5	0	0,5	1	1
PP021948499	0,19	0,3917	4,14	0,0177	1	0	0	2	3
PP022269091	0,25	-1,5000	3,57	0,1348	0,8	0	0,2	2	4
PP021935829	0,29	-0,9292	4,67	0,1349	1	0	0	2	4
PP022097840	0,04	0,1296	5,83	0,1806	0,8571	0	0,1428	2	1

* Result of applying PAM clustering algorithm to data (01/01/2006 – 01/10/2021)

The overall results of this exercise are presented in Table 4.9 to follow and demonstrate overall that investor long-term risk preferences are indeed fairly constant as defined by the clustering algorithm. This is encouraging as it suggests that the statistically significant behavioural patterns are likely to be linked to individual behaviour and not just aggregate behaviour. It would be entirely possible to have one without the other. In other words, for there to be many “anxious” investors in market turmoil would be expected but that investor “X” is consistently part of the anxious investor cohort provides the human risk preference connection. This preference appears to be present more often than not when analysing most of the 4 archetypes. The short-term variation in the behavioural archetype may be explained by the link to risk perceptions and outcome experience proposed by the first and second mediated models of risk behaviour presented in the literature review.

Table 4.9 Risk Preference versus Risk Propensity (archetype stability)

Average Investor Cluster	Switch Cluster	Proportion
Avoider	**Avoider**	**74,66%**
	Anxious	12,83%
	Assertive	12,51%
Market Timer	Avoider	32,20%
	Anxious	44,53%
	Assertive	23,28%
Anxious	Avoider	11,55%
	Anxious	**77,75%**
	Assertive	10,69%
Assertive	Avoider	4,95%
	Anxious	3,29%
	Assertive	**91,75%**

4.4.1 Stability of the avoiders

On average ≈75% of the switch transactions performed by the avoider cluster were consistent with their long-term preferences or were "avoider-type" switches. Both Table 4.9 and Figure 4.6 to follow show the other types of switches that the avoider performed. On 12,83% of occasions avoiders behaved like the anxious investor and on 12,51% like the assertive investor respectively. Risk propensity in the short term results in avoiders up-risking (assertive) or de-risking (anxious) their portfolios. Figure 4.6 shows a relatively stable pattern of behaviour or risk preference from the avoider archetype. At each point the sum of the three lines will be equal to 1 or 100%. It is interesting to note that the avoiders appear to perform more avoider-type switches in the greater market volatility early on in the timeline, at the mid-point when the bull market ends in mid-2014 and near the end of the timeline during the COVID-19 pandemic.

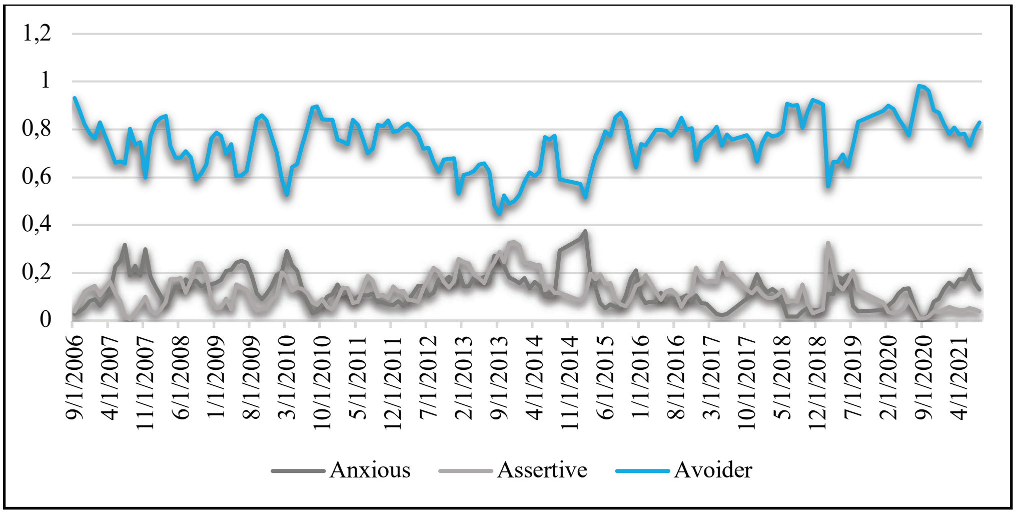

Figure 4.6 Avoider archetype stability

4.4.2 Stability of the anxious archetype

On average ≈78% of the switch transactions performed by the anxious cluster were consistent with their long-term preferences or were "anxious-type" switches. When the anxious investor makes a different type of switch it is related to the avoider archetype on 11,55% of occasions or the assertive archetype on 10,69% of occasions. Once again, the highest levels of anxious-type switches appear near the beginning and end of the timeline. Leading up and to and including the Global Financial Crisis between 80% and 95% of anxious investor switches are near to the anxious cluster medoid or mid-point. During the market recovery and subsequent bull market anxious investors start behaving more like avoiders and assertive-type investors.

In the former case, this may be from a loss of confidence in financial markets and in the latter case from the fear of missing out on the market recovery. Recall from the archetype characteristic that anxious investors appear comfortable in taking market risk (in fact they invested the most aggressively on average), however, they don't appear to have much resilience in the face of market volatility de-risking their portfolios and switching to prospects with worse past investment performance. Figure 4.7 does show a more defined "W" shape in the behaviour that coincides with elevated market volatility. This would be expected from the anxious investor archetype.

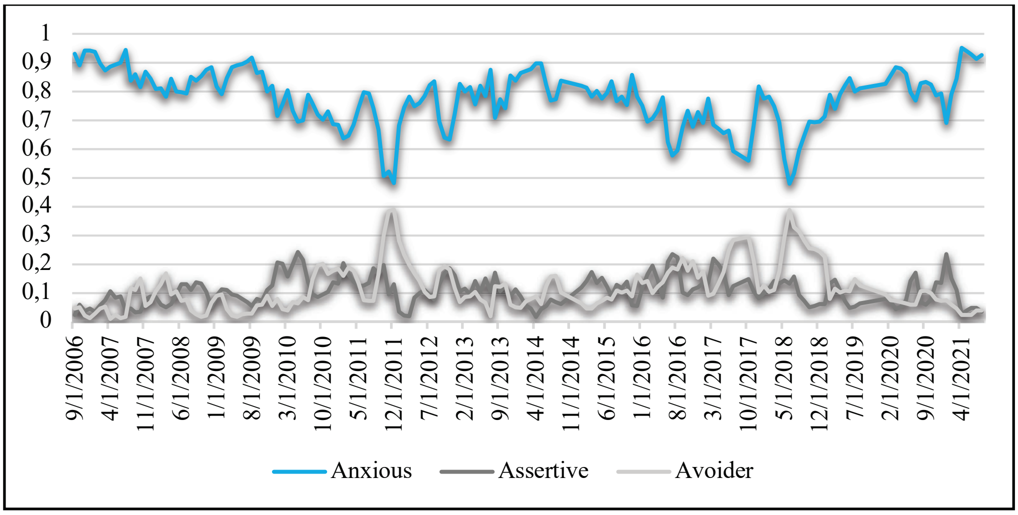

Figure 4.7 Anxious archetype stability

4.4.3 Stability of the assertive investor

The assertive investor is the most stable of the archetypes with ≈92% of switches matching their long-term or average archetype assignment. 4,95% and 3,29% of other switch transactions resemble the avoider archetype and anxious archetype respectively. Once again it is clear that the market volatility of the financial crisis in 2008 resulted in a high amount of switch transactions that resemble the anxious archetype. There does appear to be a relatively consistent level of assertive-type behaviour throughout the time period with between 80% and 100% of switches matching their archetype assignment until 2017 where there appears to be a sharp drop-off that is correlated with an equal increase in avoider-type behaviour. This may also be a trend of up-risking but remaining relatively risk-neutral thereafter that may resemble the avoider archetype. Soon thereafter, however, behaviour reverts to the mean “channel” of 80% to 100%.

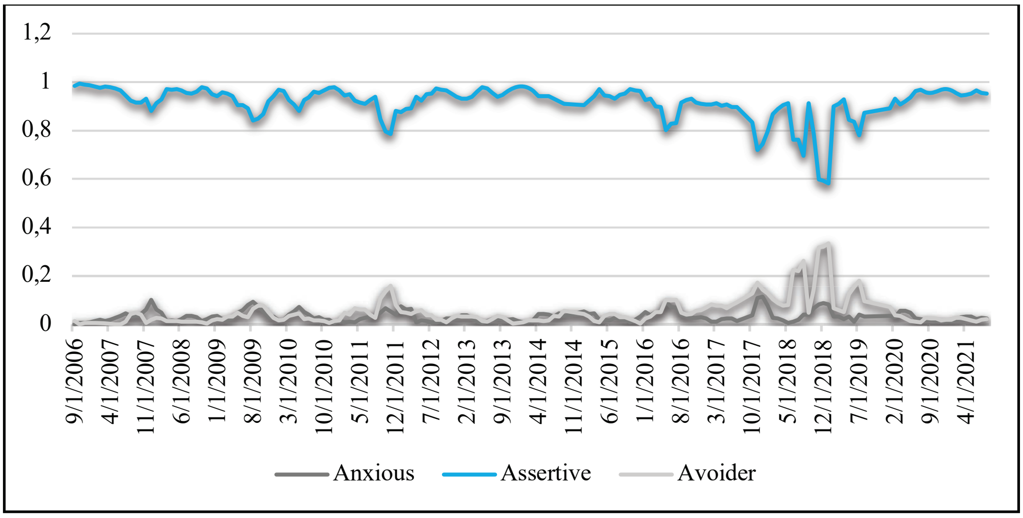

Figure 4.8 Assertive archetype stability

4.4.4 Stability of the market timer

The market timer has been left to last for discussion. There are some interesting phenomena at play here. Table 4.9 clearly shows that when viewing market timers (defined by their switch frequency in general and propensity to do what others are doing) through the lens of individual switches there are zero “market timer” switch transactions. Each switch transaction when viewed in respect of its individual Gower distance is classified according to one of the other three archetypes (switches are closer to the 3 remaining archetypes). This shows high levels of instability in cluster membership, however, this is intuitive in the sense that a marker timer by nature likely gains additional comfort from doing what others are doing (may be defined by the other cluster characteristics). From a mathematical standpoint it shows that the risk and return variables that will bring out most of the cluster differences are doing just that (showing each observation as closer to one of the remaining medoids) . Table 4.9 shows that market timer switches when viewed at the switch level are allocated to the three remaining archetypes. 32,20% to the avoider, 44,53% to the anxious investor and 23,28% to the assertive investor.

4.5 CONCLUSION

Chapter 4 has provided insights into the three central research questions of this paper. Four statistically significant behavioural archetypes were identified across the time period that described average investor behaviour. When investigating the switch-level stability of the archetypes through time by clustering at monthly intervals based on the investor’s most recent switch transactions and examining the standard deviation of these proportionate changes there were interesting correlates with market volatility. All archetypes displayed much more variation or proportionate change when compared to the elevated market volatility particularly related to the Global Financial Crisis and COVID-19 pandemic. Furthermore, when considering the stability of cluster membership through time there was a clear indication that long-term risk preferences are generally prevalent in the avoider, assertive and anxious investor archetypes with more than ¾ of all switch transactions relating to their average archetype or risk preference. The assertive investor showed even greater levels of consistent behaviour. There is evidence that risk propensity in the short term, however, is de-railing investors from their long-term risk preferences. Unfortunately, there is not always a firm indication as to exactly what this reason is. Further research is likely warranted in respect of other variables that may be related to the behaviour.

CHAPTER 5
CONCLUSION, DISCUSSION AND RECOMMENDATIONS

Chapter 5 provides conclusions based on the research presented so far, as well a discussion of the results and recommendations for future research.

This study revealed four statistically significant investor behaviour patterns or clusters of behaviour over this time period that are labelled “avoider”, “market timer”, “anxious” and “assertive” behaviour respectively. Furthermore, there does appear to be relative stability over time in three of these behaviour patterns (all except the market timer) where market events do result in divergent temporary behaviour that appears to revert to long-term risk preferences over time.

This chapter begins with a brief summary as a reminder of this study’s main purpose and the research questions answered in the context of the risk behaviour framework provided by the literature review. The results of a follow-up study on investor behaviour during the COVID-19 pandemic using the behavioural archetypes from this paper is discussed briefly to reinforce the value of these results. The primary findings of this study are then presented and discussed briefly with the main conclusions, and recommendations for practice and for further research.

5.1 SUMMARY

An investment “switch” represents a change of portfolio holdings which can be used to infer investor preferences. Switches represent selling out of all or part of the current fund or basket of funds and changing to another fund or set of funds that are seemingly more consonant with the investor’s preferences. This is termed “risk behaviour” as the actions are in response to risk (perceived or otherwise) and likewise opportunity (perceived or otherwise) in the hope of better investment outcomes.

Although often this leads to a so-called “behaviour tax” for investors (see Table 4.7) it is important to remember that not all investment switches are necessarily poor decisions. A change in investment goals and circumstances may well necessitate a change in investment strategy and as discussed in the study limitations (Chapter 1) the fact that it was not possible to examine this context (changing goals or circumstances) would create some noise in evaluating risk behaviour. Changing investment goals during market volatility for example may be mistakenly attributed to greater perceived risk in markets. Similarly, it is not possible to disentangle the effect of financial adviser influence on these investment switches without a qualitative survey interrogating a sample of investment switches post the behaviour. These are two of the key limitations of this study that will be addressed in future research.

A risk behaviour framework was proposed in the literature review that reveals the critical interplay between the long-term and the short term. Psychometric traits that form the foundation of investor personality are similarly the roots of stable risk preferences over time. Extensive literature has linked financial behaviour to the so-called "Big Five" traits in personality theory. It is also well established that while personality drives behaviour the situation at hand may strongly affect choices. This is no different in respect of risk behaviour where a market event like COVID-19 in March 2020 resulted in the perception of high risk. In such circumstances Prospect Theory presents a highly descriptive value function that assists in explaining behaviour rooted in loss aversion that often sees investors seeking out risk in the domain of losses to avoid such painful losses. This is not the complete picture, however, and subsequent research has clearly demonstrated that the investor's propensity to assume risk is also influenced by their outcome experience. Said differently people perceive less risk when they are winning and more when they are losing. Literature presented Prospect Theory and risk propensity as the first and second mediated models of risk behaviour.

Both considerations were central to constructing the lens through which to examine investor risk behaviour reflected by switching activity. Long-term risk preferences were captured by considering the average level of risk the investor was exposed to over time. The effect of market conditions and the resulting effect on risk perception was accounted for by examining whether the investor was up-risking or de-risking the portfolio in relation to their long-term established risk preferences. On the return side of the equation an important dimension was whether the investor was seeking better or worse relative past performance (funds with relative worse past performance often reflect safety).

To assist in processing the large dataset it was necessary to turn to unsupervised machine learning algorithms to seek out notable patterns. The PAM clustering algorithm was utilised to process the combination of categorical and numerical data and the result of the exercise produced four statistically significant patterns of investor behaviour. It is worthwhile to note that the silhouette width of the clusters as defined in the research methodology chapter revealed a respectable SC indicating a reasonable integrity to the clusters. Future research may refine the associated variables in an attempt to hurdle the 0.70 level of SC indicating even stronger and clearer groupings. Encouraging, however, were the very clear differences that can be attributed to long-term risk preferences, switching frequency and short-term risk behaviour reflected by up-risking, de-risking or indeed neutral risk neutral behaviour as well as the extent to which past investment performance was deemed desirable in switching prospects.

The results of the clustering algorithm revealed four clusters or patterns of behaviour on average (2006 - 2020). These were used to compared risk behaviour against in the short-term by adding a temporal dimension to the analysis. This was done by calculating a Gower distance for each switch transaction to compare with the average medoid. The results here largely were consonant with the literature review. Market events appear to derail investor long-term risk preferences, however, as time passes the investor tends to revert to their average behavioural preferences. There does remain additional hidden complexity here however and future research may be needed to broaden market variables from volatility alone to include currency movements and investor preferences for offshore prospects for example.

5.2 DISCUSSION

This study has investigated the risk behaviour from just under 125,000 switch transactions performed by 35,199 investors using the PAM unsupervised machine learning algorithm across:

i. The 2006 – 2010 global financial crisis and market recovery;
ii. The 2010 – mid-2014 bull market;
iii. The flat and fluctuating market from mid-2014 onwards ending in December 2020; and
iv. The 2020 COVID-19 crash and 2021 market recovery.

The key findings that addressed the three main research questions were as follows:

1. There are four statistically significant clusters or behaviour patterns. Clear differences exist between these clusters in respect of risk behaviour and were attributed to six clustering variables representing risk and return over time. These differences may be labelled descriptively as:

    a. *The avoider*: This archetype invests the most conservatively (resembling a CPI + 3% asset allocation) and remains risk neutral after investing (92% of the time). They appear the least sensitive to market volatility.
    b. *The market timer*: The market timer is characterised by their switching frequency (88% more switches than the next highest). It is also clear that market timers are the most active in switching to prospects with both better and worse past investment performance. This alludes to herd behaviour or being more comfortable in doing what others are doing.
    c. *The anxious investor*: The anxious investor is characterised primarily by de-risking investment portfolios and switching to prospects with worse relative past performance. These investors are not averse to taking risk but tend to react the most to market volatility.

d. *The assertive investor*: The final archetype is characterised primarily by up-risking their investment portfolios (91% of the time). They are also very active with chasing past investment performance.

The framework established in the literature review proposed differences between long-term preferences and short term risk propensity. In order to empirically test this it was necessary to gauge if switch behaviour was changing over time. By clustering and matching monthly investment switches performed with the archetype assigned to that switch it was possible to gauge the proportion of monthly switches attributable to each archetype. A notable finding here was that this methodology predictably presented the market timer (defined by the volume of switches) as the dominant proportion of switches. While there was noise when viewing the archetype switch-level proportions at each point in the data series it was clear that the mean change in archetype proportions as well as the standard deviation of this change was much greater during periods of market volatility.

The key findings of this exercise were as follows:

i. Increased archetype activity (switches) coincides with higher levels of market volatility as measured by the standard deviation of monthly returns (JTSE / JSE All Share Index). Period A (2006 – 2010) had a 65% higher standard deviation of monthly returns when compared to period B (2010 – 2020) and period C (2020 – October 2021) had a 43% greater standard deviation of monthly returns when compared to period B.
ii. The mean proportionate change in anxious switches is 19% greater in period A than period B and 2,05% greater in period C than period B.
iii. The mean proportionate change in assertive switches is 32,59% greater in period A than period B and 3,02% greater in period C than period B.
iv. The mean proportionate change in avoider switches is 132,42% greater in period A than period B and 145,05% greater in period C than period B.
v. The mean proportionate change in market timer switches is 8,66% greater in period A than period B and 15,86% greater in period C than period B.

2. The final research question related to the consistency or stability of these archetypes over time at the investor level. In essence this relates to cluster membership and will answer the question of how short term market movements potentially changed cluster membership. This was important in respect of the literature review to ascertain if market movements were getting investors to behave in a manner that was not consonant with their long-term risk preferences or if these risk preferences were indeed stable over time. This was achieved by calculating a Gower distance for

each investment switch and checking how many "assertive" switches were being performed by assertive investors (for example). The findings for this research question were as follows:

i. The avoider archetype is relatively stable at 74.66%. Said differently, avoiders make avoider-type switches 74.66% of the time.
ii. The anxious archetype is also relatively stable at 77,75%. Said differently, anxious investors make anxious-type switches 77,75% of the time.
iii. The assertive investors is the most stable investor archetype at 91,75%.
iv. Market timers never make purely market timer-like switches. When calculating the individual Gower distances of switches these are always closer to one of the other three archetypes. This is intuitive given the stronger effects relating to the risk and return clustering variables. The market-timer is therefore the least stable archetype.
v. The effects of long-term risk preferences revealed by the average behaviour or initial archetypes when set against the short term risk perception revealed by the archetype stability clearly show how market events derail long-term risk preferences but only temporarily. The avoider, anxious and assertive patterns appear mean reverting over time.

The overall conclusion for this study supports the framework set forth by the literature review. Investors appear to possess long-term risk preferences as revealed by applying the PAM algorithm to behaviour over nearly 16 years (2006 to 2021) that shift when market events occur as these same investors have differing risk perception in the short term (executing a switch) that affects their risk propensity or willingness to assume investment risk (funds switched *to*).

This knowledge lays the foundation for the development of a predictive model of investor behaviour. Making personal nudges that address and manage specific behaviour as well as building portfolios for investors that prefer certain characteristic present valuable insights for investment advice, financial services providers and indeed investment management firms. This study poses important considerations for such entities:

i. How do we manage engagement with anxious investors during market turbulence?
ii. How do we report to anxious investors on their investment performance that doesn't highlight market volatility (show 10-year volatility aligned with a 10-year investment goal versus 3-month volatility that is irrelevant in isolation).
iii. How do we manage risk perceptions during market events specifically?
iv. What client engagement systems and triggers can we use to identify changing risk perceptions:

a. Proactively such as:
   i. Checking portfolio values;
   ii. Downloading minimum disclosure documents;
   iii. Downloading switch forms;
   iv. Increase in adviser engagement with client information;
b. Reactively such as:
   i. A threshold market movement (markets down or up by 20% triggers engagement);
   ii. Tracking stale conservative investment strategies in relation to inflation;
   iii. Cash deployment nudges;

v. How do we get avoiders more engaged in markets?
vi. Can we match investment products to archetypes? For example are structured products a mechanism to give avoiders capital protection while giving them market-linked upside?
vii. How do we get inflation-risk across to the avoider archetype or segment?
viii. Do anxious investors need more protection in their investment portfolios?
ix. Should we be suggesting exposure to things like cryptocurrency for assertive investors who clearly value the spikes in returns while being resilient to the volatility?
x. How do we create information cascades that lure the market timer away from the herd?
xi. Can we create more certainty or security for market timers and anxious investors?
xii. What other metrics can we create that place more emphasis on the investment destination as opposed to the journey?
xiii. What do "behaviourally efficient" portfolios look like for these archetypes? Is it necessary to limit the investment opportunity set to design portfolios that these archetypes are more likely to stick with over the investment journey?
xiv. What platforms do we have that can facilitate just-in-time financial education.

At the very least this paper has provided sound evidence that different groups of investors are destroying investment value at different times and that engagement strategies should be employed to decrease investor engagement with their portfolios unless their investment goals have changed.

5.3 FURTHER RESEARCH

While there are substantive findings to this study it is recognised that the strength of these relationships are far from conclusive. While it was initially hoped for example that a clear group of investors would emerge that up-risks their portfolios in the face of market volatility that would be consonant with the first mediated model of risk behaviour (Prospect Theory), this was not revealed (at least not on aggregate). The results of this study would appear to support the second mediated model of risk behaviour (risk propensity) in that investors are in search of winners and ditch losers quite quickly and frequently and that some investors are more sensitive to the investment journey than others.

Further research is needed into switching threshold levels for example. In order to fuel the nudging strategy more research is needed into the archetypes and their triggers in respect of switching behaviour. There is sufficient evidence to show distinct preferences but exactly where the roots of these preferences lie is less certain.

The issue of assessing the impact of adviser behaviour will be discussed shortly as this presents a rich and relatively unexplored area for investigation. In respect of addressing the other limitation that does not account for the change in investor circumstances or goal related to a switch transaction, this can only be accounted for if this data is collected at a platform level. In other words, on the relevant documentation specifically requesting information that pertains to the investor's goals and whether they have changed. This is currently an internal Momentum Investments project. Alternatively, this data may be gathered qualitatively via a post-switch survey.

The above discussion refers to specific improvements to this study. There also exists an opportunity to expand the scope of the risk behaviour research in three key areas:

i. *Investor and adviser risk preferences*: A mechanism to diagnose new-to-platform investors is also required where no behaviour track record exists. This mechanism should be predictive in nature and so should be able to diagnose the investor long-term and stable risk preferences as well as the associated cognitive and emotional processing errors that may derail these preferences in the short term specifically during extreme conditions (market crashes, bull and bear markets). A rich base of literature exists to develop a South African financial personality assessment founded on psychometric principles. This would reveal long-term risk preferences that in essence reveal an investor's long-term willingness to trade off risk and return – their risk tolerance. The subsequent testing of short-term market movements and outcome experience on the client's risk propensity or how much risk they decide to take in various market conditions may then be explored and documented. This should also be applied to advisers to begin disentangling the effect of financial advice on risk behaviour.

ii. *Adviser versus investor risk propensity*: On understanding South African investor and adviser risk behaviour the possibilities exist to examine the "leaking" of adviser personality onto clients as well as the influence levels of different adviser archetypes on their clientele. Further investigation into adviser and client pairing or matching is also possible. Could anxious clients for example benefit from being paired with assertive advisers?

iii. *Linking psychometric traits with behavioural archetypes*: Finally, the question begs as to whether it is possible to link the four behavioural archetypes with these psychometric traits or risk preferences. Do anxious investors for example exhibit psychological traits of neuroticism? What about assertive investors and the psychological trait of extroversion? Likewise, market timers and impulsivity rooted in the trait known as openness to experience.

There is little doubt that there exists a plethora of further research opportunities within the framework set down in respect of South African investor risk behaviour. Additional data sources exist and should also be explored in respect of different investment product offerings such as stockbroking or even retirement products for example.

5.4 CONCLUSION

Statman, (2019) alluded to a global survey that revealed what investors *want* from their portfolios. Number one on the list was “financial security”. This has two dimensions, one related closely to risk and the other related to returns. Investors want to avoid financial ruin but also to take advantage of opportunities and these lay at the centre of switch behaviour. Unfortunately, in forming belief systems human beings substitute easy questions for difficult ones (Kahneman et al., 2021). It is far easier to answer the question, “how has this investment performed?”, then the consideration involved in answering the question, “is this a good investment?”. Investors need help in setting and sticking to their investment goals.

Investor switching behaviour during COVID-19 effectively and clearly demonstrated that investors remain significantly engaged with their discretionary investments – but in a self-harming way on average. This study is the first step in a larger research project, the goal of which is ultimately to enable the development of a predictive model of risk behaviour. This will be used to mediate investors’ switching choices and minimise the behaviour tax.

The practice of “nudging” is centred on engagement and this research has posed several critical questions relating to the investment advice and investment management industry. Are we as an industry placing enough weight on what people want from their investments? What about the expressive benefits of investing? Do people want to say something about themselves with their investments implying that picking winners is an opportunity to identify oneself as a winner perhaps? These questions are compounded when we consider the influence of financial advisers many of whom openly admit to picking funds as part of their value proposition.

This research has set the scene for embedding a behavioural finance proposition in an investment advice or management firm in South Africa. Engaging with the right people (archetypes) at the right times with the right message will be a key dimension in managing the investor behaviour tax.

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APPENDICES

APPENDIX 1: Clustering algorithm source code: partitioning around medoids (PAM)

The appendix to follow presents the source code used in applying the PAM clustering algorithm as well as the process to arrive at the cluster outputs. Firstly the packages listed are loaded in the RStudio statistical analysis package. The code to follow then draws on these additional packages to perform the requisite functions. For example the "cluster" package will give access to the algorithms mentioned in the research methodology section such as the k-means, hierarchical clustering and partitioning around medoids (PAM) algorithms. The "dplyr" package allows the setting up and manipulating of data in tabular formats. The "ggplot" package is used to access visualisation techniques that may assist in the analysis. The "readr" package is a recent addition that assists in reading very large datasets and the "rtsne" package is utilised in data normalisation. The next step (step 2) is to import the dataset. Step 3 then follows by computing the Gower distance as explained in the research methodology section which is displayed in tabular format in a dissimilarity matrix (how dissimilar each observation is from the rest). Step 4 involves computing the silhouette coefficient before forcing the number of clusters in this step into step 5 which applies the PAM clustering algorithm (for 4 clusters in this case). The remaining steps deal with assigning the related cluster to the original dataset and exporting back to Excel to conduct further analysis presented in the body of this document.

Source of code structuring: https://towardsdatascience.com/clustering-on-mixed-type-data-8bbd0a2569c3

1. Load packages

```
library(cluster)
library(dplyr)
library(ggplot2)
library(readr)
library(Rtsne)
```

2. Load data

```
setwd("C:/Users/Paul Nixon/Desktop/MastersThesis")    #(Set path to where the data is stored)

dataset1 = read.csv('Clusterdata_OldandNew.csv')      #(read data (from csv format)))
dataset2 = dataset1[,c(10,23,25,33:41)]               #(select columns with variables incl PP number)

df <- dataset2[,2:12]                                 #(drop PP number, retain clustering variables)
```

3. Compute Gower distance (Dissimilarity matrix)

```
gower_dist1 <- daisy(df, metric = "gower")
gower_mat1 <- as.matrix(gower_dist1)
```

4. Silhouette width plot to identify number of clusters to use

```
sil_width <- c(NA)                              #(create blank variable)
for(i in 2:10){                                 #(loop for different number of clusters)
  pam_fit <- pam(gower_dist1, diss = TRUE, k = i)
  sil_width[i] <- pam_fit$silinfo$avg.width
}
plot(1:10, sil_width,                           #(Plot resulting silhouette width)
     xlab = "Number of clusters",
     ylab = "Silhouette Width")
lines(1:10, sil_width)
```

5. Select number of clusters (k) and apply PAM clustering

```
k <- 4
pam_fit <- pam(gower_dist1, diss = TRUE, k)
```

6. Summarise clusters per variable

```
pam_results <- df %>%
  mutate(cluster = pam_fit$clustering) %>%
  group_by(cluster) %>%
  do(the_summary = summary(.))
pam_results$the_summary
```

7. Visualisation

```
tsne_object <- Rtsne(gower_df, is_distance = TRUE)
tsne_df <- tsne_object$Y %>%
  data.frame() %>%
  setNames(c("X", "Y")) %>%
  mutate(cluster = factor(pam_data$clustering))
ggplot(aes(x = X, y = Y), data = tsne_df) +
  geom_point(aes(color = cluster))
```

8. Output Clustering results

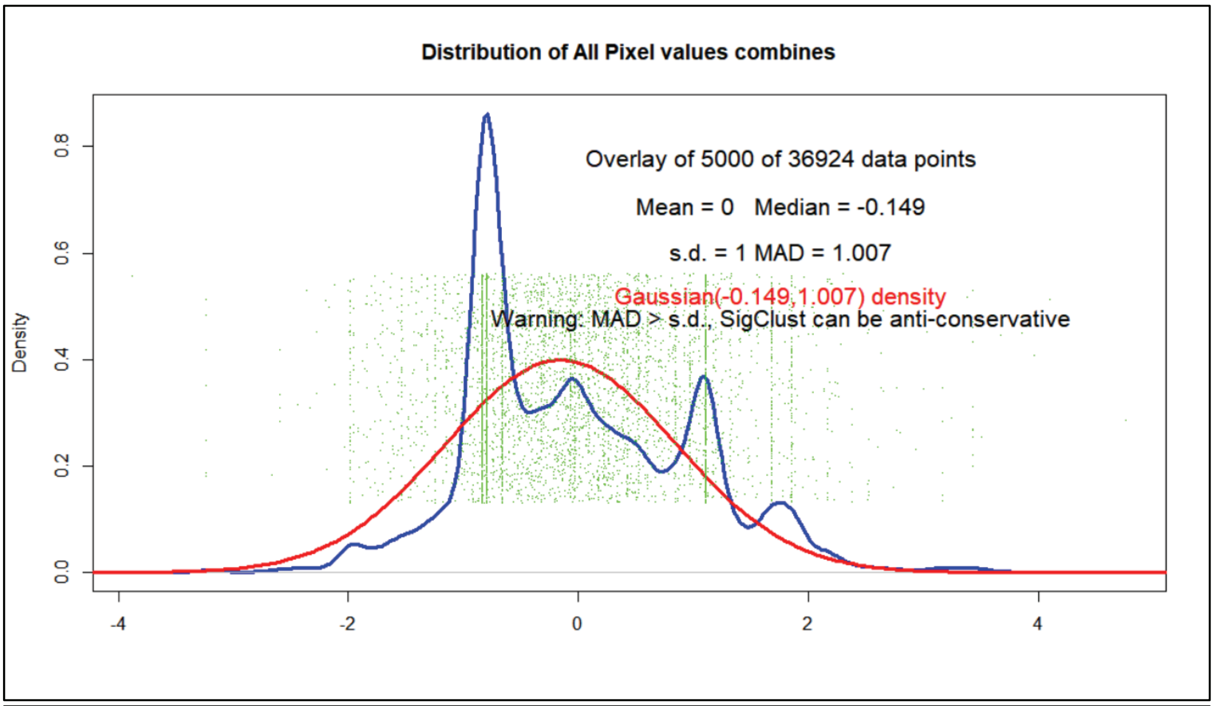
```
dataset_F <- dataset1 %>%
        mutate(cluster = pam_fit$clustering)    #(add clusters to initial data)

write.csv(dataset_F,"C:/Path/PAM_SCORED.csv")  #(write results to desired path)
```

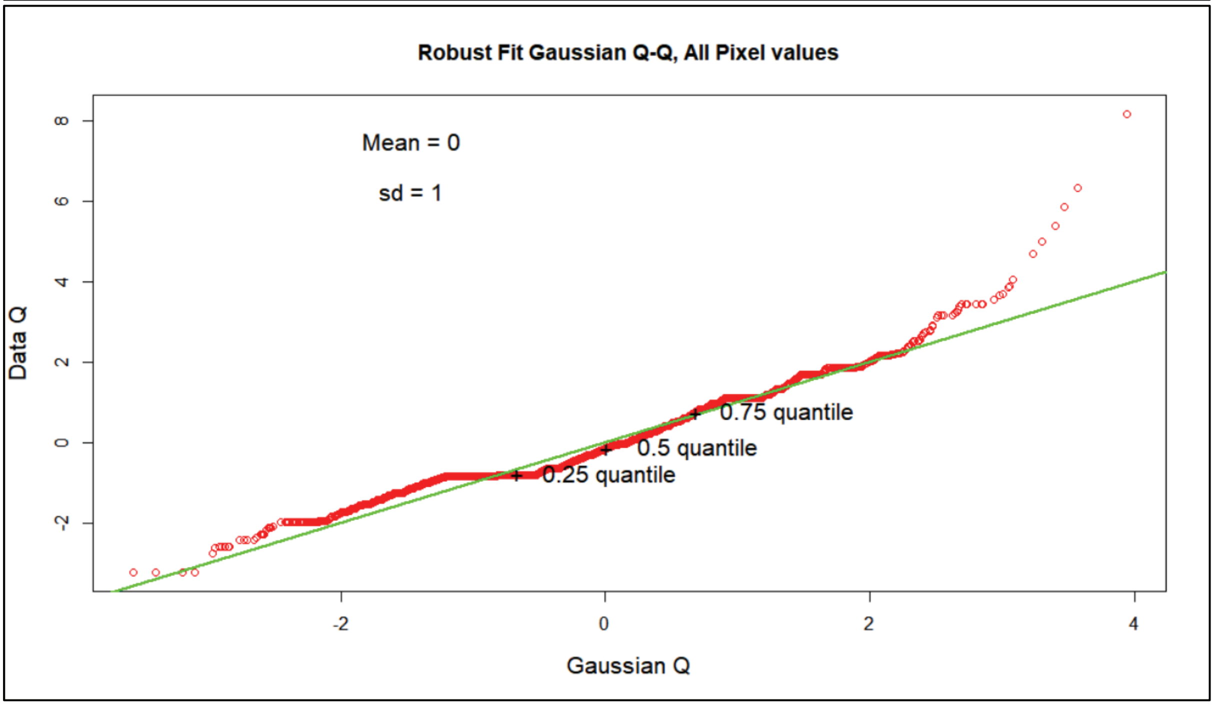
APPENDIX 2: Cluster significance code and detailed results

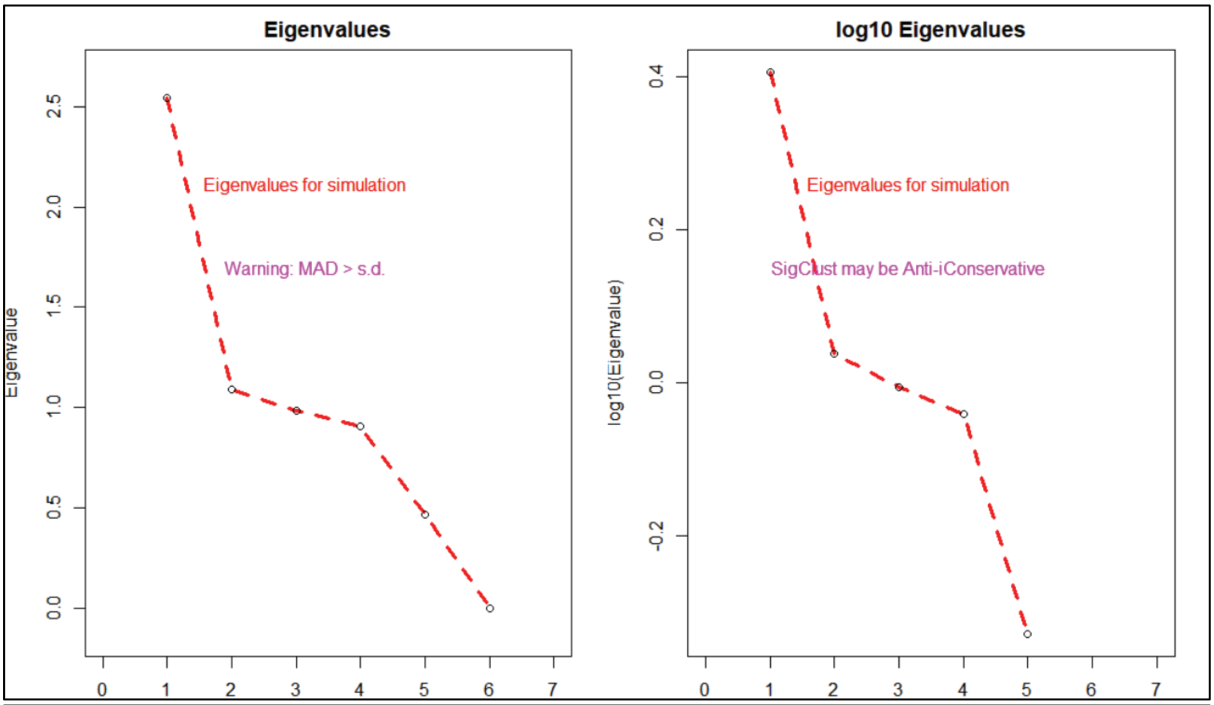
```
#install.packages("sigclust")
library("sigclust")

# Select only clusters 1 and 2 from the data and keep in Matrix format

test_1_2<-as.matrix(dataset_F[c(dataset_F$cluster==1|dataset_F$cluster==2),2:12]) #(Select only clusters 1 and 2 from the data and keep in Matrix format)

# Standardise matrix data

test_1_2<- scale(test_1_2)
test_1_2_cl<-c(dataset_F$cluster[c(dataset_F$cluster==1|dataset_F$cluster==2)])   #(assign clusters to vector)

# assign clusters to vector

test_1_3<-as.matrix(dataset_F[c(dataset_F$cluster==1|dataset_F$cluster==3),2:12])
test_1_3<- scale(test_1_3)
test_1_3_cl<-c(dataset_F$cluster[c(dataset_F$cluster==1|dataset_F$cluster==3)])

# Repeat for remainder of clusters

test_1_4<-as.matrix(dataset_F[c(dataset_F$cluster==1|dataset_F$cluster==4),2:12])
test_1_4<- scale(test_1_4)
test_1_4_cl<-c(dataset_F$cluster[c(dataset_F$cluster==1|dataset_F$cluster==4)])

test_2_3<-as.matrix(dataset_F[c(dataset_F$cluster==2|dataset_F$cluster==3),2:12])
test_2_3<- scale(test_2_3)
test_2_3_cl<-c(dataset_F$cluster[c(dataset_F$cluster==2|dataset_F$cluster==3)])

test_2_4<-as.matrix(dataset_F[c(dataset_F$cluster==2|dataset_F$cluster==4),2:12])
test_2_4<- scale(test_2_4)
test_2_4_cl<-c(dataset_F$cluster[c(dataset_F$cluster==2|dataset_F$cluster==4)])

test_3_4<-as.matrix(dataset_F[c(dataset_F$cluster==3|dataset_F$cluster==4),2:12])
test_3_4<- scale(test_3_4)
test_3_4_cl<-c(dataset_F$cluster[c(dataset_F$cluster==3|dataset_F$cluster==4)])

Sigtest_1_2 <- sigclust(test_1_2,nsim = 1000,labflag = 1,label = test_1_2_cl,nrep = 5,icovest = 2)
Sigtest_1_3 <- sigclust(test_1_3,nsim = 1000,labflag = 1,label = test_1_3_cl,nrep = 5,icovest = 2)
Sigtest_1_4 <- sigclust(test_1_4,nsim = 1000,labflag = 1,label = test_1_4_cl,nrep = 5,icovest = 2)
Sigtest_2_3 <- sigclust(test_2_3,nsim = 1000,labflag = 1,label = test_2_3_cl,nrep = 5,icovest = 2)
Sigtest_2_4 <- sigclust(test_2_4,nsim = 1000,labflag = 1,label = test_2_4_cl,nrep = 5,icovest = 2)
Sigtest_3_4 <- sigclust(test_3_4,nsim = 1000,labflag = 1,label = test_3_4_cl,nrep = 5,icovest = 2)

plot(Sigtest_1_2)
plot(Sigtest_1_3)
plot(Sigtest_1_4)
plot(Sigtest_2_3)
plot(Sigtest_2_4)
plot(Sigtest_3_4)
plot(Sigtest)
```

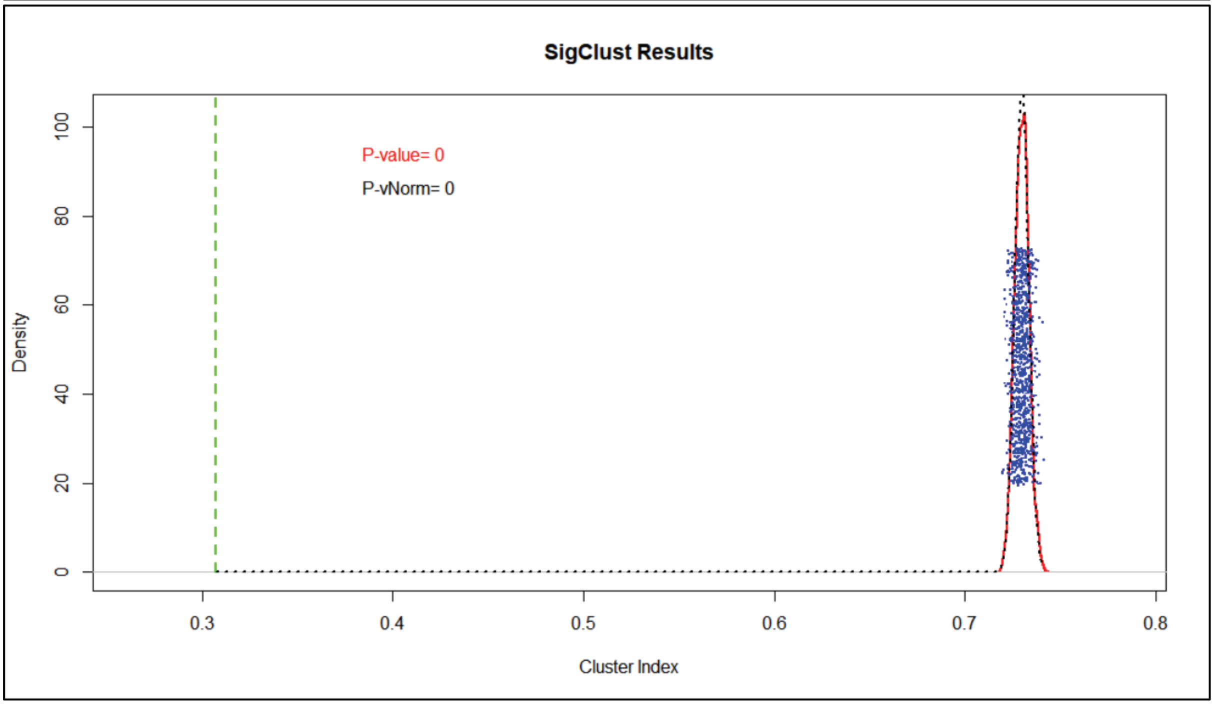
CLUSTER 1 to CLUSTER3

CI = 0.3070

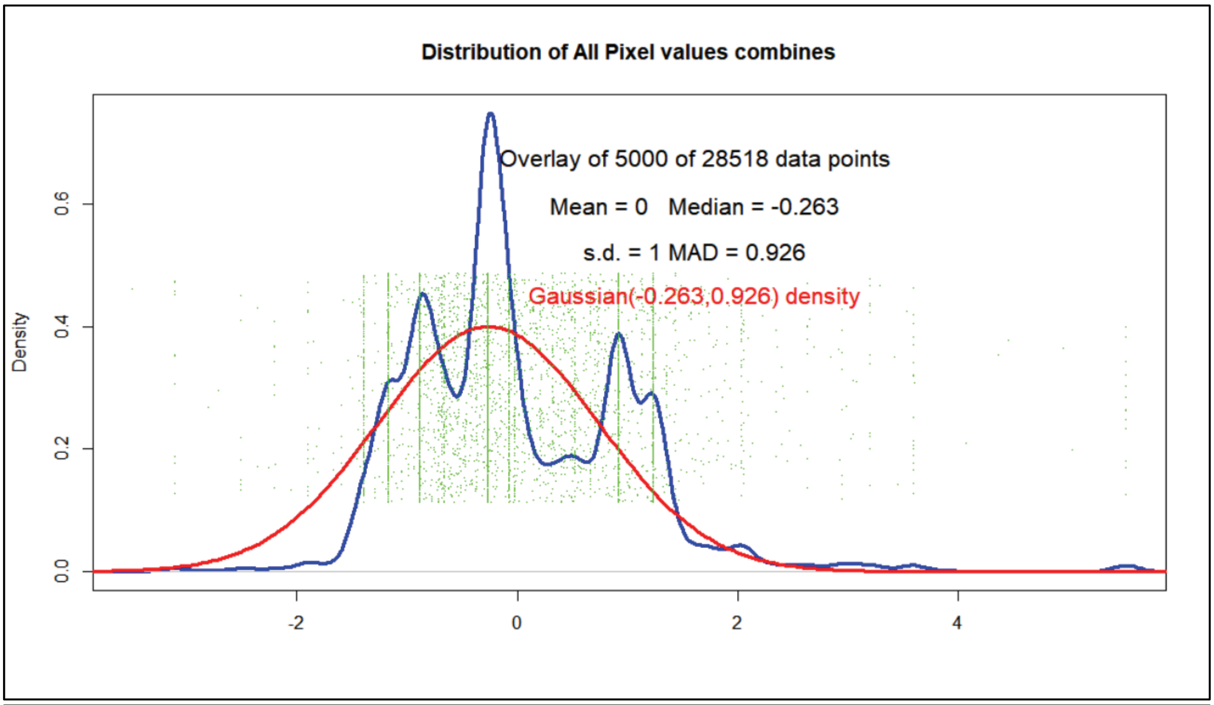


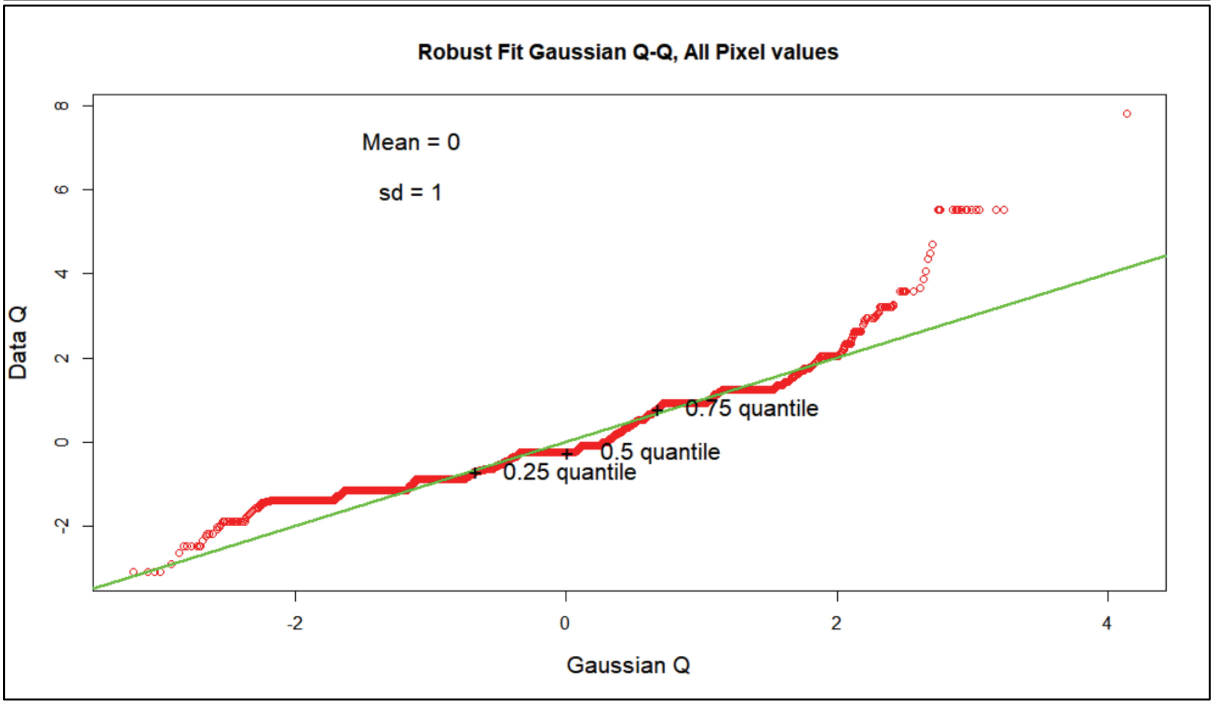


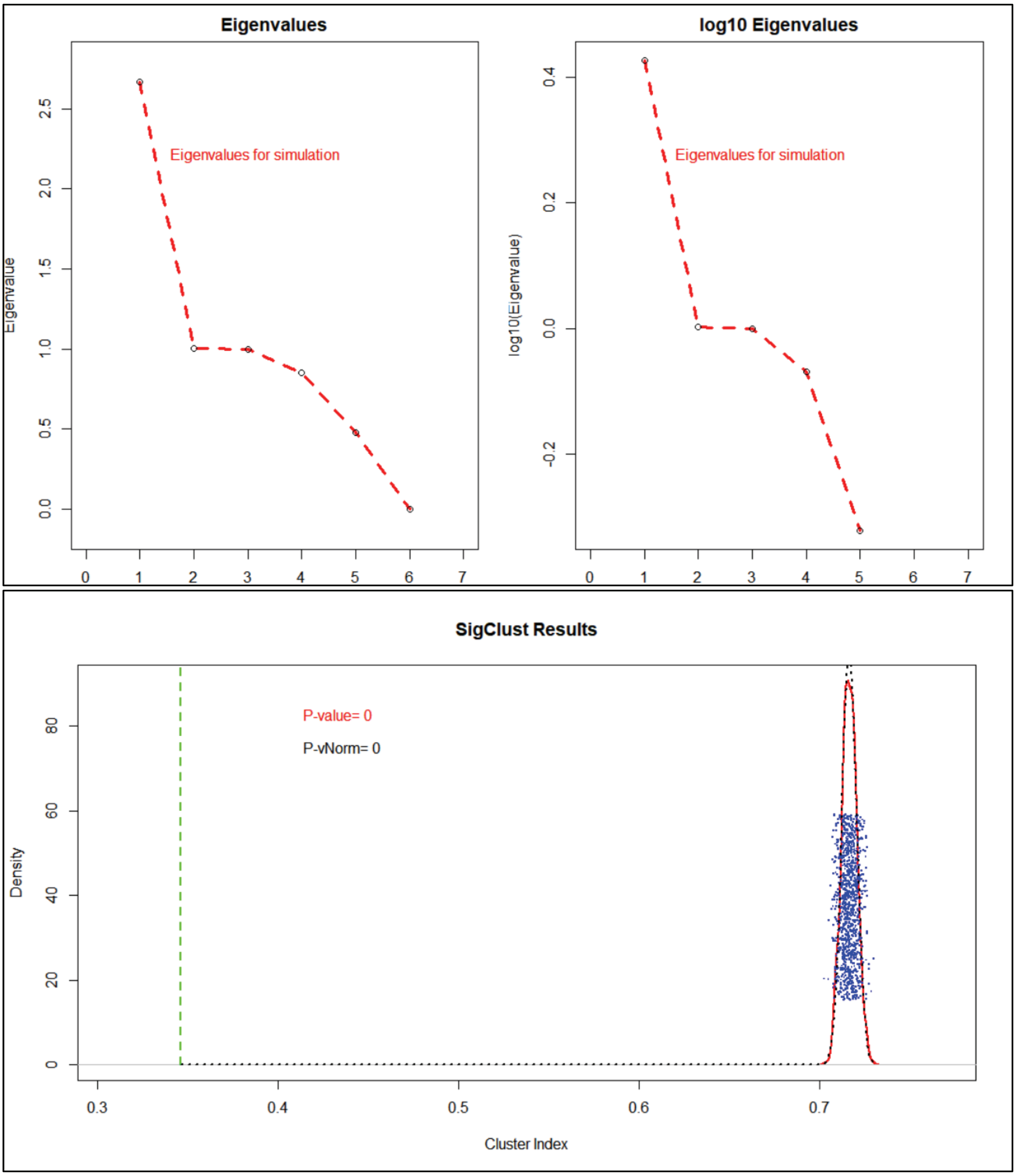




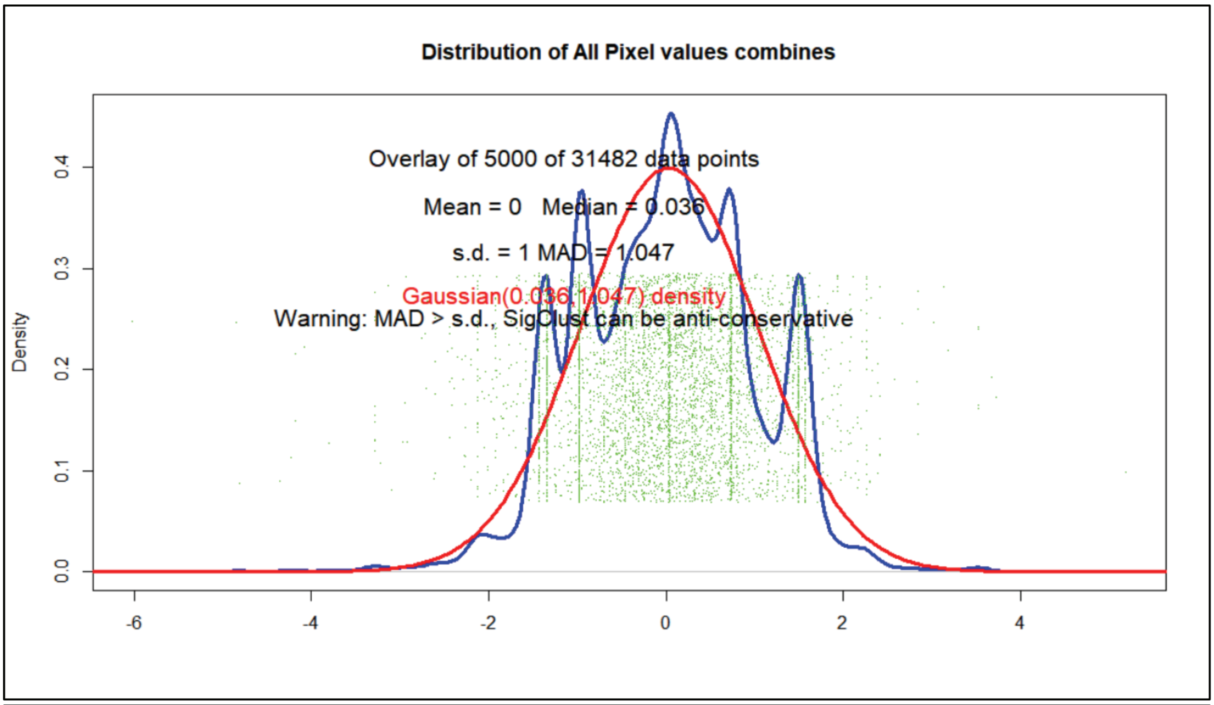
CLUSTER 1 to CLUSTER4
CI = 0.3459

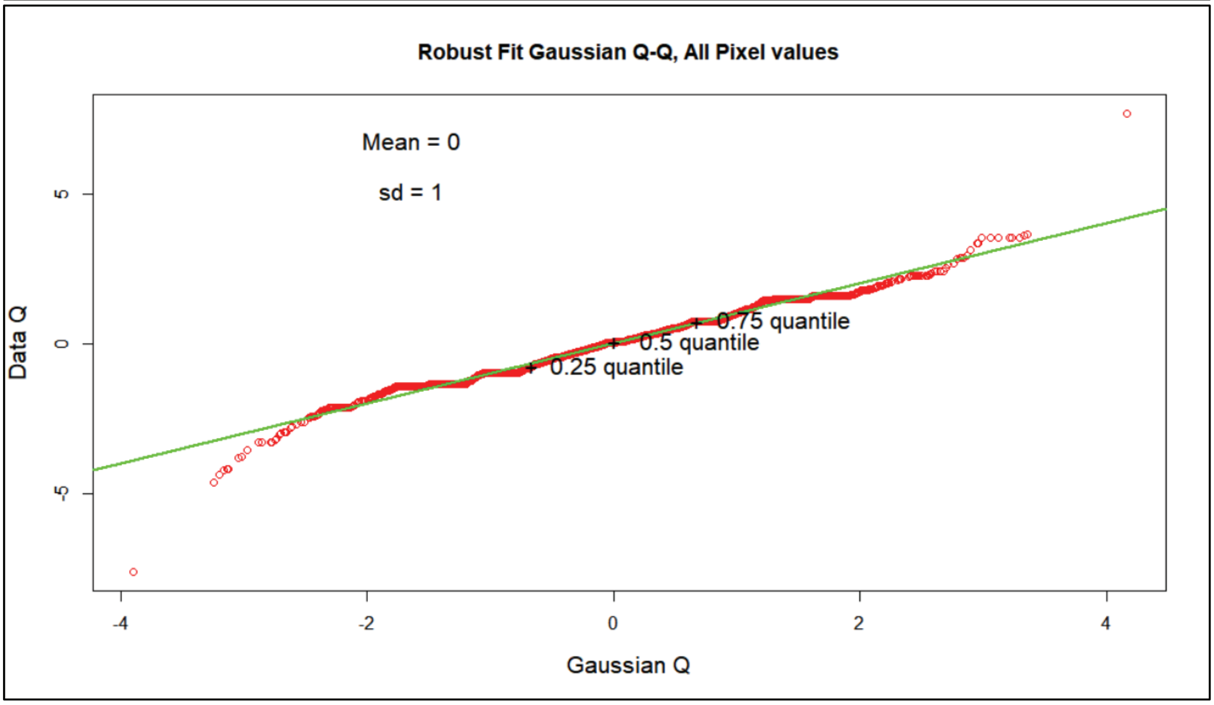

Distribution of All Pixel values combines
Overlay of 5000 of 28518 data points
Mean = 0   Median = -0.263
s.d. = 1 MAD = 0.926
Gaussian(-0.263,0.926) density
Density
0.0
0.2
0.4
0.6
-2
0
2
4

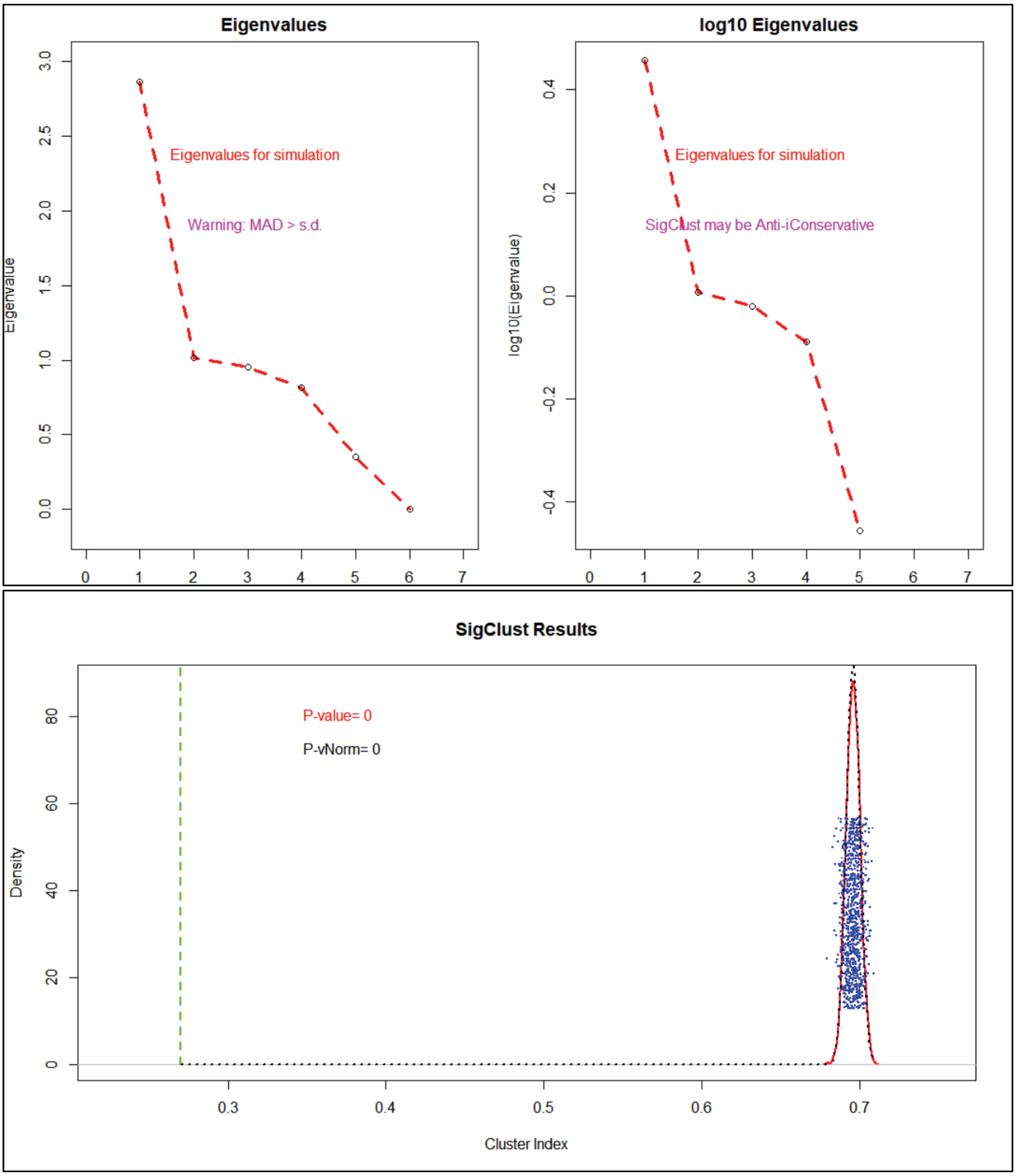

Robust Fit Gaussian Q-Q, All Pixel values
Mean = 0
sd = 1
0.75 quantile
0.5 quantile
0.25 quantile
Data Q
Gaussian Q
-2
0
2
4
6
8



CLUSTER 2 to CLUSTER3
CI = 0.2699

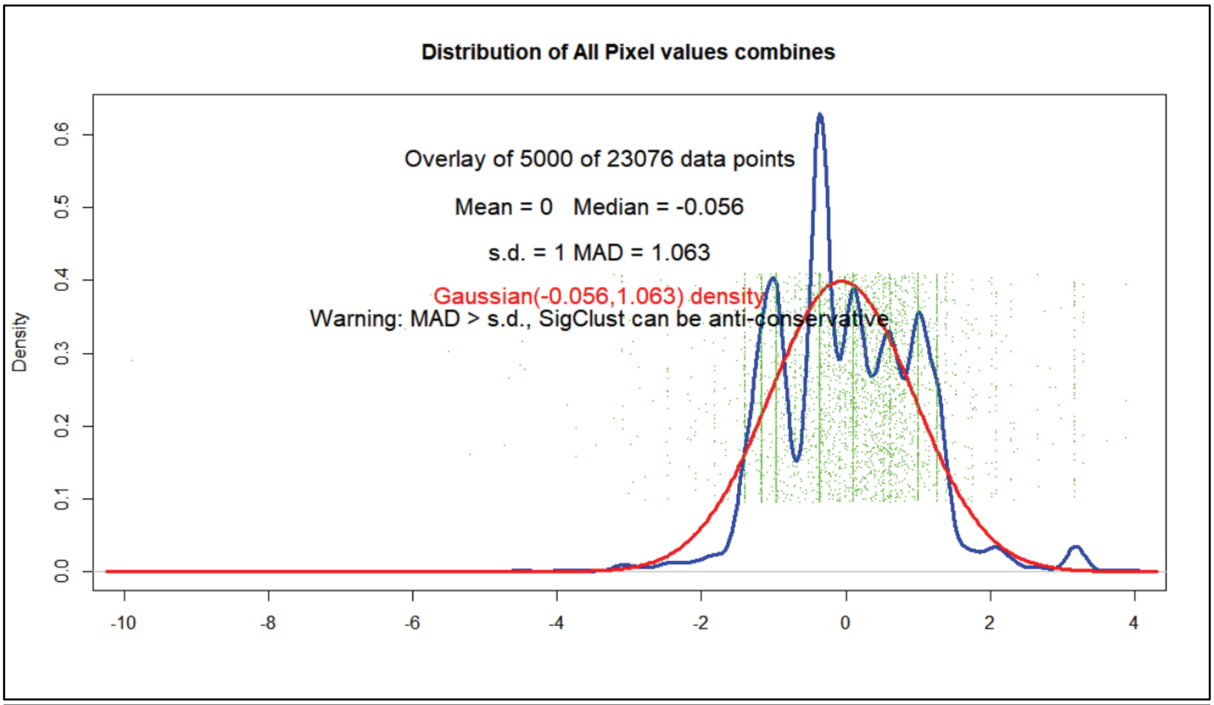

Distribution of All Pixel values combines
Overlay of 5000 of 31482 data points
Mean = 0 Median = 0.036
s.d. = 1 MAD = 1.047
Gaussian(0.036,1.047) density
Warning: MAD > s.d., SigClust can be anti-conservative
Density
0.0
0.1
0.2
0.3
0.4
-6
-4
-2
0
2
4


Robust Fit Gaussian Q-Q, All Pixel values
Mean = 0
sd = 1
0.75 quantile
0.5 quantile
0.25 quantile
Data Q
-5
0
5
-4
-2
0
2
4
Gaussian Q

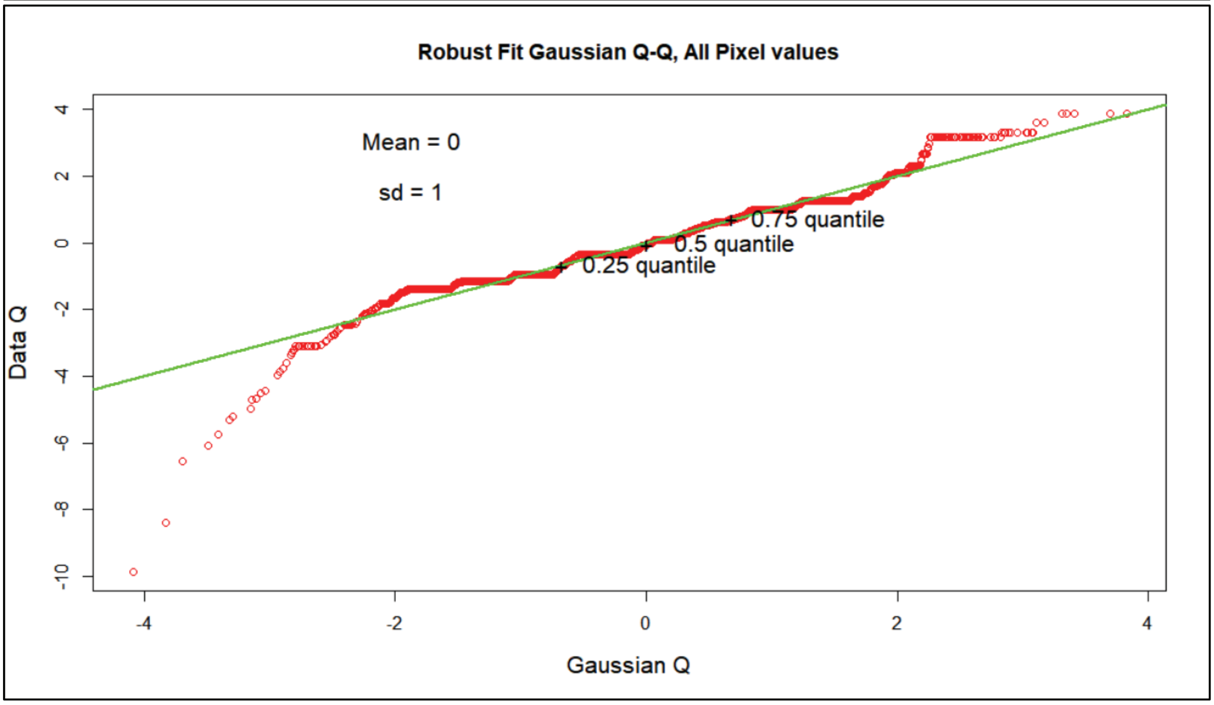


CLUSTER 2 to CLUSTER 4

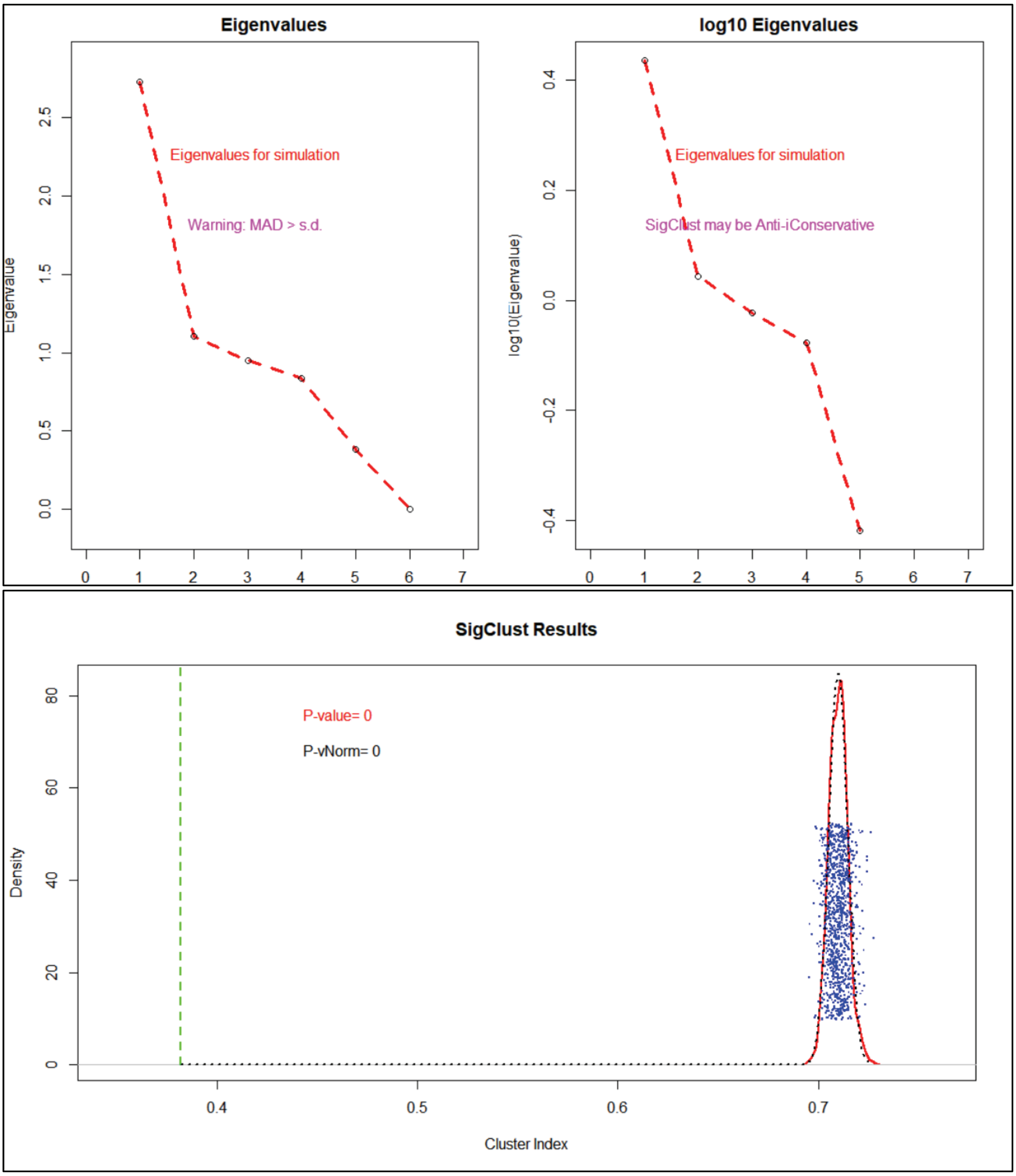
CI = 0.3817



Distribution of All Pixel values combines
Overlay of 5000 of 23076 data points
Mean = 0 Median = -0.056
s.d. = 1 MAD = 1.063
Gaussian(-0.056,1.063) density
Warning: MAD > s.d., SigClust can be anti-conservative
Density

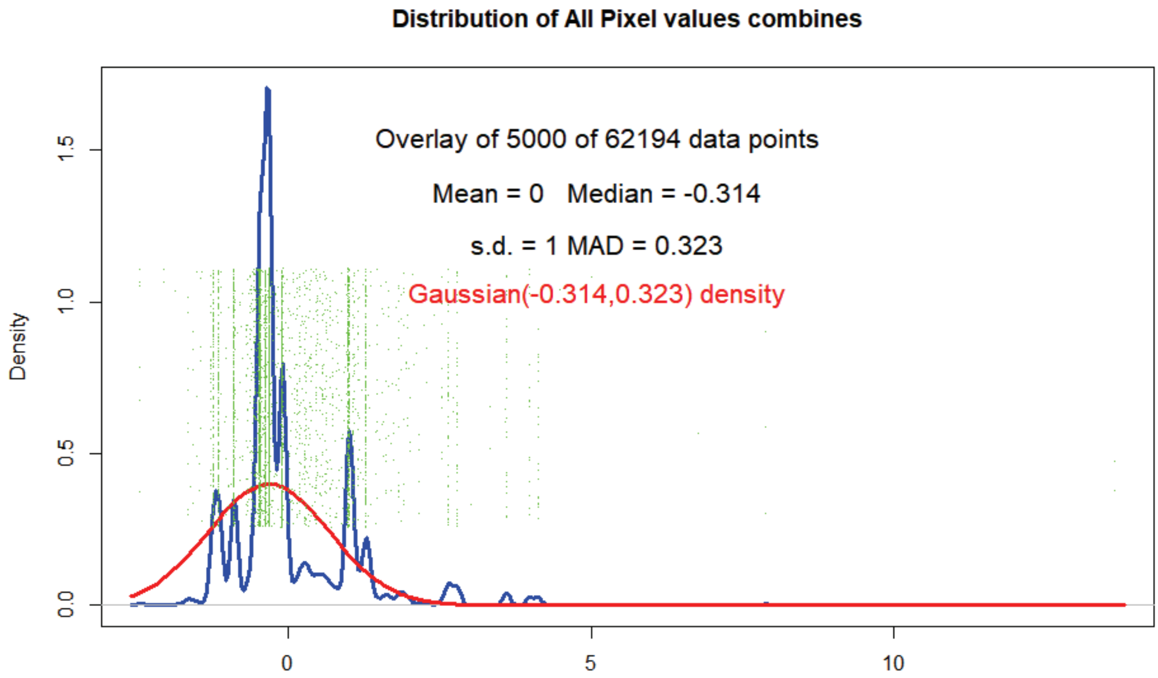


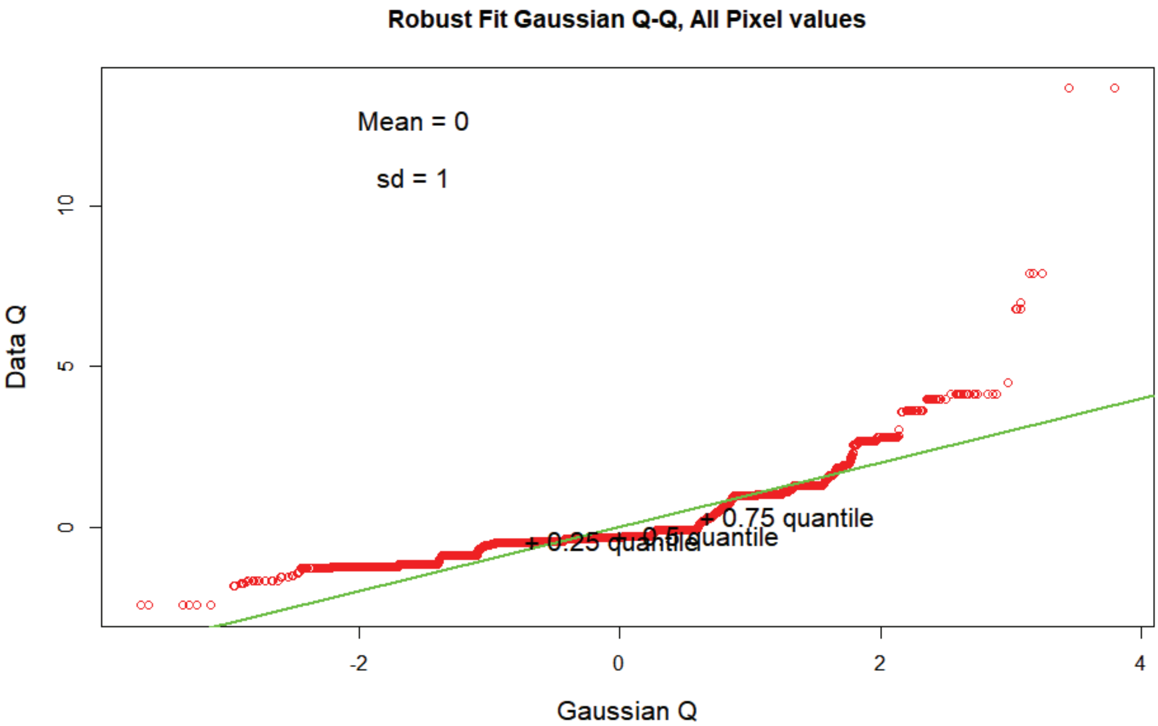
Robust Fit Gaussian Q-Q, All Pixel values
Mean = 0
sd = 1
0.75 quantile
0.5 quantile
0.25 quantile
Data Q
Gaussian Q

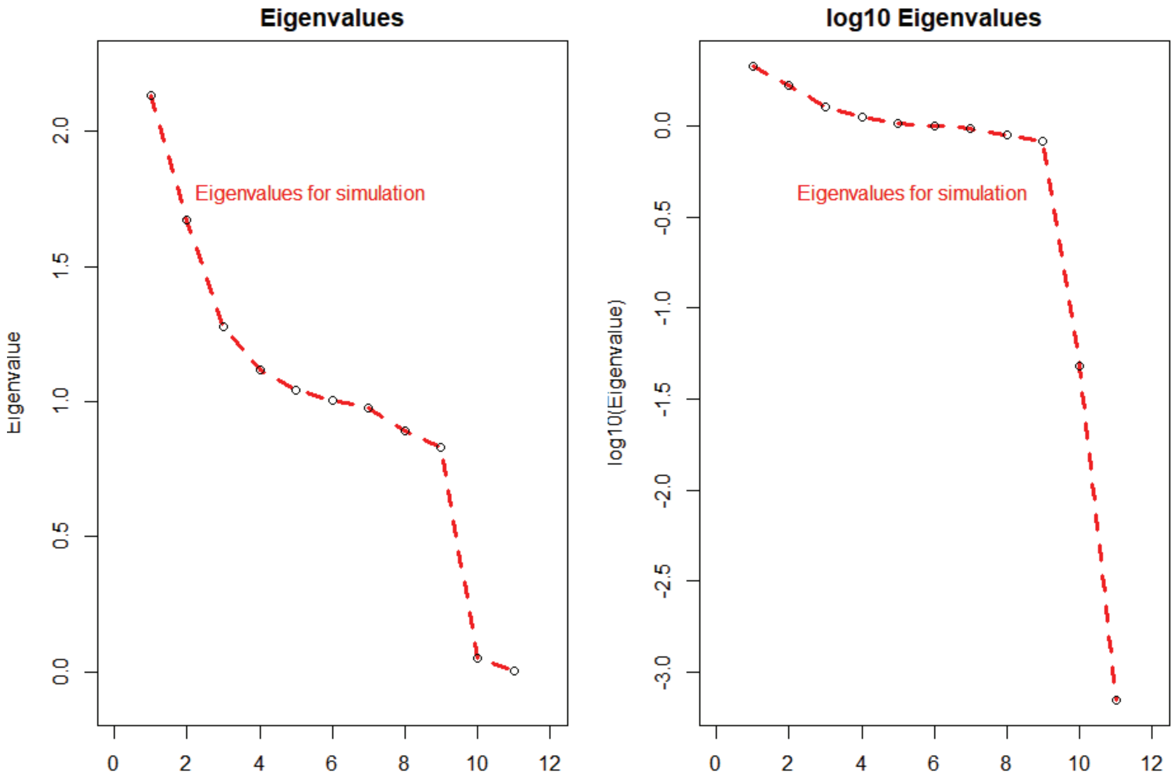


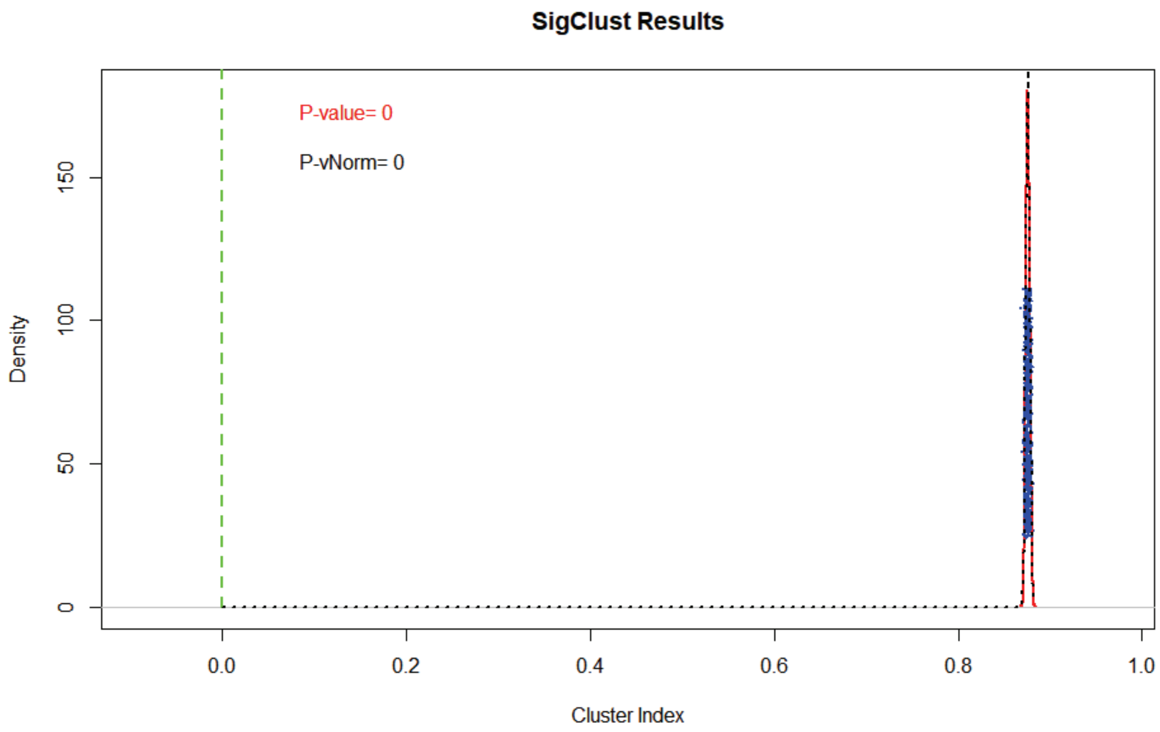
CLUSTER 3 to CLUSTER 4

CI = 0.00


Distribution of All Pixel values combines
Overlay of 5000 of 62194 data points
Mean = 0 Median = -0.314
s.d. = 1 MAD = 0.323
Gaussian(-0.314,0.323) density
Density
0.0
0.5
1.0
1.5
0
5
10


Robust Fit Gaussian Q-Q, All Pixel values
Mean = 0
sd = 1
+ 0.25 quantile
+ 0.5 quantile
+ 0.75 quantile
Data Q
Gaussian Q
0
5
10
-2
0
2
4


Eigenvalues
Eigenvalues for simulation
Eigenvalue
log10 Eigenvalues
Eigenvalues for simulation
log10(Eigenvalue)


SigClust Results
P-value= 0
P-vNorm= 0
Density
Cluster Index