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Review article

Unsupervised machine learning to reveal South African risk behaviour archetypes in the domain of discretionary investment decisions

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ABSTRACT

The mediated risk models of decision making under conditions of risk propose that individuals' recent experiences of investments can lead to them making investment switching decisions that would be different to those based on their long term risk preferences. This study used the medoids clustering algorithm applied to a large, novel, dataset to identify four statistically significant patterns of switching behaviour based on the dimensions highlighted by this body of theory. Individual decision makers exhibit three consistent patterns or archetypes of risk-seeking (termed 'assertive'), loss aversion (termed 'anxious') and risk aversion (termed 'avoider') behaviour over most time periods. Each consistent behaviour pattern is, however, susceptible to temporary deviations from 'normal' behaviour. Loss averse investors are on occasion drawn into both risk averse and risk seeking behaviour. Similarly, risk seeking investors are sometimes drawn into both loss averse and risk averse switching behaviour. This provides evidence to support the mediated perspective on risk-based decision-making behaviour and demonstrates the viability of this machine learning-based method for segmenting investors from a financial advice, marketing, and communications perspective.

Contents

1. Introduction

Investors face many difficult challenges on their journey to their desired investment outcome. Staying committed to a course of action that is objectively most likely to give the best chance of achieving a desired investment outcome can be very difficult in a risky context. As pointed by Hansen (2019), the requirements of rationality in this environment are complex and onerous from a computational perspective. The assumption of rationality requires people to formulate their beliefs according to the rules of logic and update them using objective metrics such as Bayes

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Rule as new information arrives (Gilboa and Schmeidler, 1993). Descriptive models of human behaviour differ in multiple ways however from the various models of epistemic rationality that have been proposed to date (see, for example, Von Neumann and Morgenstern (1947)). The bounded rationality approach (Simon, 1955) 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). A review of actual investor behaviour suggests that they are not always very good at making typical investment decisions such as switching between investment funds that are available to them. The term 'the behaviour gap' (Dalbar, 2008; Kinnel, 2020) or 'the behaviour tax' (Nixon et al., 2019) refers to investors' making switches between investment options that often results in lower returns which can negatively affect investors' ability to reach their desired financial goals. A significant body of evidence exists that self-sabotaging behaviour along the investment journey leads to lower investment returns, both globally (Dalbar, 2008; Kinnel, 2020) and in South Africa (Nixon et al., 2019). Volatile investment environments can prompt powerful emotional responses and the observed switches of investors between investment solutions suggests that investors appear to trade off current emotional comfort for future investment returns (Nixon et al., 2019).

The key objective of this research is, therefore, to better understand South African investors' risk behaviour from both a theoretical and empirical context. This is done by firstly identifying the relevant variables that should contextualise investor risk behaviour in both the short and long run. Unsupervised machine learning techniques are then used in the classification of the investment switching behaviour of South African investors that aims to identify groups with internally similar patterns of investing behaviour based on these selected dimensions.

This study is novel firstly, in that it uses a new, large dataset of observed switching behaviour and, secondly, it uses an automated categorisation algorithm to analyse the risk behaviour of these investors. It also provides an indirect test of the predictions of the mediated model of risk decision making.

The study is based on a novel dataset of from the Momentum Wealth Linked Investment Services Platform (LISP). It includes 35,199 investors who made over 130,000 investment switches in a period of nearly 16 years of behaviour (January 2006 to October 2021). A thorough cleaning of the switch behaviour data was performed and nearly 125,000 separate investment switch transactions were identified. 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. This dataset's size brings credibility and robustness to the findings of the study.

The findings of this paper are firstly, different groups of investors exhibit statistically significant heterogeneous patterns of investment switching behaviour. Secondly, short term events do sway them from their usual patterns of behaviour. These short term deviations are also positively correlated with their worst behaviour tax experiences.

The approach adopted in this paper provides a framework for identifying different market segments and can be used as a basis for engaging with these clients to ensure that they have the best chance of reaching their investment goals. The challenge of this latter goal is not explored in this paper.

2. Literature review

The study examines risk behaviour in the context of the investment switching decision. As explained in the next section, investment switching is the decision to switch from one investment fund to another within an individual decision maker's portfolio. This decision is risky in the sense that the future wealth associated with both the current and the new investment fund are not known.

Fig. 1 presents an overview of the relevant body of literature to this study. The focus is the risk behaviour in the context of investment switches (Sitkin and Weingart, 1995).

The fundamental thesis behind this study is that observed risk behaviour is the result of the interaction between two related, but conceptually separate, factors. Firstly, decision makers have long term preferences towards risk associated with their personality (their 'risk preferences'). This reflects the contributions of Expected Utility Theory (EUT) in its many forms (starting with Von Neumann and Morgenstern (1947)). Secondly, their perception of risk is determined by external factors that vary in the short term (their 'risk propensity'). This latter factor was proposed by Sitkin and Pablo (1992), building on key contributions by Kahneman and Tversky commonly called Prospect Theory (PT) (see Kahneman and Tversky (1979), Tversky and Kahneman (1992)).

Risk preferences 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 personality traits (Boyle, 2008; Costa and McCrae, 2011; Van Raaij, 2016). It is important to consider these as the baseline for risk behaviour as the empirical contribution referred to in the right half of Fig. 1 has shown that investors can deviate significantly from these long term risk preferences, depending on factors that vary in the short run. Tanaka et al. (2019) point out that, much like physical or psychological trauma can cause a shift in our personality, so can short term financial shocks can alter the behaviour linked with our risk preferences. As risk preferences are relatively constant behaviour will revert to 'normal' as the effects of these shocks fade over time. Those who are extroverted by nature, for example, have been shown to be risk seeking (Van Raaij, 2016).

Shifting attention to the right-hand column of the diagram, there are two key models that have extended the long term preferences approach of EUT to include a role for risk perception. These are called mediated models in this study as they propose the presence of factors in the decision making process that mediate between the long term stable risk preferences and the effects of the volatile short term environment on the perception of risk by decision makers.

Prospect Theory (PT) showed that perceptions of risk are fundamentally different when viewed in the frame of losses vs. gains. The prescriptions of PT and EUT are aligned in the domain of relative gains, but PT adds the domain of losses to explain the observed contradictory behaviour of decision makers seeking out risk to avoid (further) losses. This widely accepted body of work highlights that the way people perceive risk may result in behaviours that are rooted in cognitive processing errors (such as problem framing, highlighted by PT) as well as emotional reactions (such as loss aversion, also highlighted by PT) to market stimuli. It showed that 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) cite empirical work that clearly shows validated contradictions of both EUT as well as PT. They build on PT with the key assertion that a further mediating factor is necessary to better understand risk behaviour. They label their proposed mediating variable 'risk propensity' and propose that

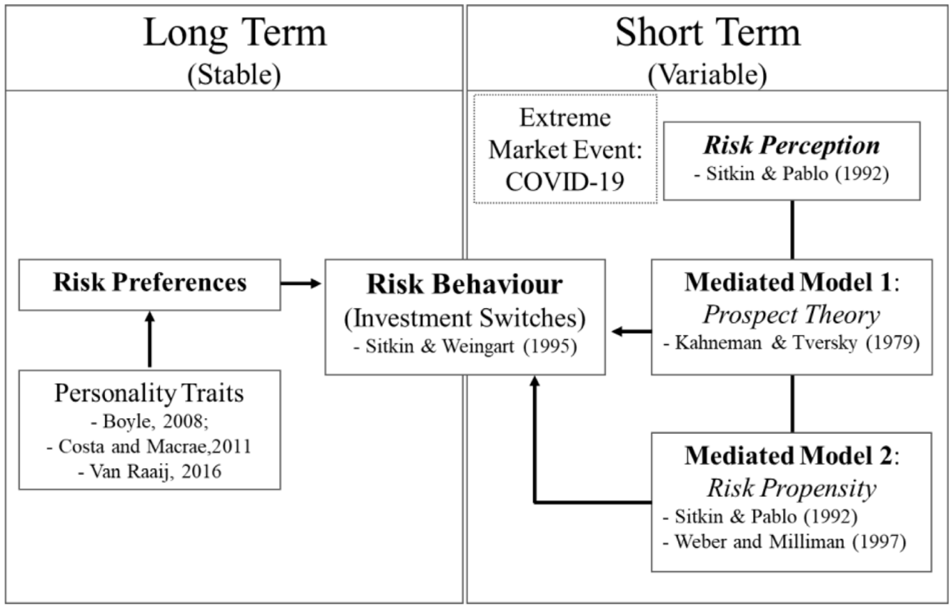

Fig. 1. The theoretical framework for risk behaviour used in this study.

risk behaviour is significantly affected by an investor's outcome experience. In other words, an individual's risk perception is directly affected by their past investment performance (which varies in the short term). The impact of risk propensity in the investment space was clearly demonstrated by the empirical work of Weber and Milliman (1997). They tested whether a decision maker's perception of risk is impacted by recent winning and losing outcomes. By controlling the recent investment return experience (the proportion of gains or losses) of participants in a stock market investment game they were able to influence the risk perception of the participants. These participants perceived there to be different levels of risk of the (same) game depending on what their experience of wins or losses were. Participants viewed there to be less risk when experiencing investment gains. This led to risk-seeking behaviour (contrary to the tenets of both EUT and PT respectively). Losing created the perception of greater risk that results in risk aversion in the domain of losses (contrary to PT).

In summary, EUT considers people to be generally and consistently risk averse. PT showed that humans are more complex than this and that the context of the risk behaviour is important in understanding their risk behaviour. Risk propensity models (Sitkin and Pablo, 1992) demonstrated that outcome experience can also assist in explaining behaviour contrary to both EUT and PT. According to this approach the perception of risk diminishes in the face of investment gains and intensifies when confronted with successive losses.

The risk mediated approach is important as it informs the design of the clustering framework that needs to capture all possible investment risk behaviour over the timeframe of the study. Investor risk behaviour should clearly show a long term and dominant risk preference that decision makers may deviate from as risk perception changes in the short term according to the mediated models discussed above. Switching their investment to a riskier alternative may be driven by an attempt to eliminate painful investment losses (explained by PT) or decreasing risk perception (explained by the mediated model of risk propensity). These insights were reflected in both the design of the variables used in the clustering study and the results of this study.

3. Data and clustering methodology

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 dataset Nixon et al. (2019) study was extended to include all investor switch transactions from January 2006 until the 1st of October 2021 and included just under 125,000 switch transactions from 35,199 Momentum Wealth LISP clients over this period.

These investors and their investment switches were identified after an extensive and thorough data cleaning exercise. The rule-based system that was applied is as follows:

(1) Criteria for inclusion into the study

   (a) 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.
   (b) An investor needed to make at least one qualifying "behavioural switch" to be included in the study.

(2) Exclusions from the study

   (a) Switch transactions between fund fee classes. 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. Switch from in the fee classes of the same equity fund were excluded from the dataset.
   (b) Transactions deemed to be "phasing in" to the market were 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

Table 1
Data extract used in the cluster analysis.

Investor	(A) Performance chased	(B) Average risk	(C) Risk difference	(D) Chasing past performance > 2%	(E) Neutral (within −2% to +2%)	(F) Worse past performance < −2%
PP021133544	−5.9296%	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

in advance between adviser and client. Similarly switches relating to "phasing out" of the market were excluded.

(c) 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. Return measures

The mediated model of risk preferences discussed in the previous section predicts that past returns of funds and their substitutes will influence investors' switching decisions. To incorporate this into the analysis it is necessary to account for the difference in the levels of past returns between the two funds that were switched — this is called the 'performance chased' variable in this study.

Both the level of (average) performance chased, as well as how many times the investor chased this past performance (or not) is recorded. It was also necessary to record the second as a categorical variable to account for investors who are switching in both directions. This would cause their average performance chased value across all their switches to be lower than it should be.

The following return-related variables were tracked in the study:

(1) Average performance chased: the 12-month past performance of funds switched to minus 12-month past performance of funds switched from.
(2) The percentage of switches chasing *better* levels of relative past performance if average performance chased > +2% p.a.
(3) The percentage of switches to *similar* levels of relative past performance if average performance chased is within −2% p.a. to 2% p.a.
(4) The percentage of switches to *worse* levels of past performance if average performance chased is < −2% p.a.

When combined with the (relative) risk variables (see below) the last three variables listed above provide an opportunity to distinguish those investors seeking to up-risk their portfolios in the face of losses (as predicted by PT) from those investors in search of prospects with better past performance as their perception of risk decreases from positive investment outcomes (as predicted by the risk propensity model). Finally, it is possible that as their perception of risk rises with negative past outcomes, they may seek prospects with worse past relative performance which are usually offered in safer assets. This will be covered by assessing the relative risk of the funds involved in a switch.

3.2. Risk variables

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 listed on the Momentum Wealth platform. 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 provided a scale to assess whether the investor is selecting a different level of risk in their switch. An investment risk rating from a scale of 3–8 was applied to all funds that were included in the switching analysis as follows:

- CPI + 2% = low risk — Investment Risk rating of 3
- CPI + 4% = medium risk — Investment Risk rating of 5
- CPI + 6% = high risk — Investment Risk rating of 7
- Pure equity, property funds and all offshore funds are classified as the highest risk category — Investment Risk rating of 8

The risk side of the switching decision was accounted for by considering:

(1) The average risk rating level of the investor's current portfolio at the time of the switch — this will provide an indication of the investor's current risk preference.
(2) The average change in this risk rating for each investment switch — this is calculated as the risk rating of the portfolio switched from *less* the risk rating of the portfolio switched to.

An example of the dataset used in the clustering analysis is presented in Table 1.

3.3. Range of data types used in the clustering analysis

It is important to recognise that a range of types of data were used in the clustering analysis. The variables relating to columns A to C in Table 1 are numerical and continuous in nature. Columns D to F however represents categorical data that is nominal by nature. Data is therefore a combination of both numerical and categorical data types.

3.4. Selection of clustering algorithm

Kaushik (2020) points out that there are four types of distance definition and clustering algorithms based on them. The two most common models are discussed below:

- 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).

- 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. 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.

Kaushik and Mathur (2014) explains that the HC algorithm is limited when it comes to large datasets — which is the case here.

In centroid-based methods each cluster is represented by a central vector, and the objects are assigned to the clusters based on their proximity to the nearest cluster centre. There are several centroid-based methods. 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. Ignoring this, the primary challenge for the use of the K-means approach is that it 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 alternative k-medoids clustering method was used instead. This method partitions around "medoids" (Kaufman and Rousseeuw, 2009). These medoids provide an estimate of the central position of each potential cluster (which is based on an actual observation as opposed to the average used in the K-means algorithm). Clusters are formed based on minimising the distance between observations (investor switches) and these medoids (data central points), as well as maximising the distance between the medoids themselves.

Centroid approaches by nature are very efficient at detecting circular and convex shapes of data clustered around a central point for example (Berba, 2021). Cai et al. (2016) 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.

3.5. Choice of distance measure

When implementing any clustering algorithm there are several distance measures available for use such as the Euclidean and Gower measures (Kassambara, 2017). 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 however 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).

3.6. Selecting the optimal number of representative clusters

The final consideration involved the selection of the number of clusters or proposed behaviour patterns identified by the clustering algorithm. The silhouette method (via the silhouette coefficient, or 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 the SC for each point in the cluster. It measures how similar a point is to its own cluster when compared to the nearest neighbourhood cluster (Kumar 2020). The equation for the calculation of the SC is given below (Bhardwaj 2021). It uses the mean intra-cluster distance ($a(i)$) and the mean nearest-cluster distance ($b(i)$) for each observation (i). The coefficient is therefore expressed as:

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

These coefficients can take a value from -1 to 1 and should be interpreted as follows:

- A silhouette coefficient of greater than 0 and $<=1$ indicates that the sample is different to the neighbouring clusters. The closer it is to 1, the more distinct the clusters are.
- 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.
- A silhouette coefficient < 0 indicates that those samples might have been assigned to the wrong cluster or are outliers.

By plotting the respective average silhouette coefficients for all the points in the cluster it is 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.

3.7. Significance testing of clustering

Testing the statistical significance of clusters is an area 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 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.

3.8. Identifying changes in behaviour patterns over time

The mediated decision making models showed how people can have long term and relatively stable risk preferences which can be overridden as risk is perceived differently and often incorrectly in the short term, usually paired with extreme market events. This affects our subsequent willingness to assume risk (their risk propensity) that can be to the detriment of long term investment goals. It is thus important to understand how stable the observed behaviour patterns are over time by the individual.

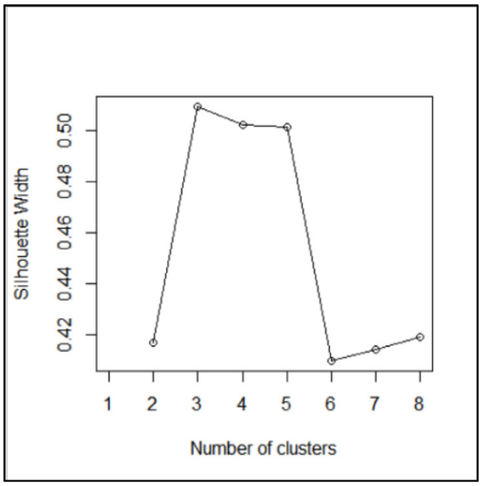

Fig. 2. Silhouette Coefficient results — Pooled data.

To deal with time-varying behaviour as markets fluctuate, two lenses were applied to identify individual risk behaviour over time. The first lens shifts the focus of the clustering analysis to individual switches with an associated time stamp. By using their cluster membership identified from the pooled analysis, and aggregating these through time, a picture can be drawn as to the relative importance of each of the behavioural clusters in aggregate over time. The second lens looks at the switches by individual decision makers. It looks at their distance from the average cluster definitions over the entire period. The first lens indicates how often each cluster-type of switch happens over time while the second lens identifies the stability of cluster membership by individual decision makers over time. This provides insights into long term risk preferences as well as an investor's short term risk behaviour stemming from (changing) risk perception.

Applying the first lens (establishing the aggregate distribution of the incidence of switch clusters over time) a monthly timeline of all switches was created, and all the switches made in this timeframe are allocated to each of the four archetypes based on their membership of each of these archetypes identified using the pooled dataset. This unpacks the aggregate behaviour over time into time-varying behaviour but does not provide an indication of cluster membership by individual decision makers over time. It thus does not control for the possibility that underlying investors may be shifting between switching archetypes over time.

Applying the second lens (ascertaining whether individual's switches reflect different cluster behaviour or membership over time) each individual decision maker's investment switches were assigned to the clusters identified from the pooled data. This is done based on identifying each switch's Gower distance from the average clusters' medoids. This allowed for the identification of the individual's membership of each aggregate cluster over time.

4. Results

4.1. Aggregate clusters — Pooled dataset

As explained in the previous section the choice of the number of clusters is driven by the silhouette coefficient (SC) for each number of clusters. The results for the SC pooled dataset are shown in Fig. 2 and indicate that the maximum difference in clusters of behaviour patterns lies between 3 and 5 clusters.

This result prompt two questions — are these SC results good enough to justify the use of the possible clusters? If so, how many clusters should be used? Mulyawan et al. (2019) suggests that the following general interpretation may be used for guidance when assessing the SC (see Table 2). The results of the SC analysis for clusters 3–5 meet the recommended minimum level.

Table 2
Silhouette coefficient — recommendations for use.
Source: Adapted from Mulyawan et al. (2019), p. 3.

SC value	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

In terms of the optimal number of clusters, the relatively small differences in the SC values for 3–5 clusters suggest that this is not a very good basis for making this decision. A comparison of the results of both three and four clusters showed that the use of an additional cluster helps significantly from an interpretive perspective. What is called the 'Market Timer' cluster disappeared if 3 clusters were used — but having four allowed for a significantly different and insightful (from a risk behaviour perspective) pattern to be included in the analysis. On this basis four clusters were chosen.

The results of the four clusters based on the pooled dataset are presented in Table 3. The shaded cells in the table reflect the highest values for the specific variable across the archetypes.

The four behavioural archetypes based on this cluster-specific behaviour are discussed below.

(1) The "Assertive" investor, as the label implies, is more comfortable with investment risk. In respect of risk profile, this cluster increases risk on 33% of occasions when performing an investment switch. This is 73% greater than the next highest figure of 19% in the Anxious cluster. 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 the Market Timer cluster. 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. Recall that this refers to the asset allocation most similar to the Momentum CPI + 4% OBI solution. This may reflect that using averages tend in many cases to mute within cluster differences.
(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 (the Anxious cluster). The Market Timer is influenced by the behaviour others. When examining the return variables, the Market Timers are the only archetype that are active in switching to both investment prospects that perform better as well as those that perform worse. 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 the 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 of switches.
(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

Table 3
Cluster results — pooled dataset.

Population Total		35 199			
Population Proportion (investor level)		27%	34%	17%	22%
Cluster Archetype Name		Assertive	Market Timer	Anxious	Avoider
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 change	42%	67%	44%	75%
	Risk increase	33%	15%	19%	13%
Past Performance difference (Average over switches)	Better	98%	46%	4%	3%
	Neutral	1%	25%	5%	92%
	Worse	1%	29%	91%	5%

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.

(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 — the Market Timers). In the case of the return-related variables the Avoider is switching to return-neutral prospects on 92% of occasions. It is 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, they are shifting between cash and cash-plus type prospects.

4.2. Statistical significance of the clusters

The SigClust method uses a two-mean cluster index (CI) measure 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. The results for the differences between the four clusters identified here are reported in Table 4.

Table 4
Cluster results significance test results using the SigClust method.

	Avoider		Market Timer		Anxious	
Market Timer	*p*-value CI *Significant*	0 0.5775				
Anxious	*p*-value CI *Significant*	0 0.3070	*p*-value CI *Significant*	0 0.2699		
Assertive	*p*-value CI *Significant*	0 0.3459	*p*-value CI *Significant*	0 0.3817	*p*-value CI *Significant*	0 0.00

Note that there are additional tests which the SigClust method reports. In the interest of minimising length, these are not reported here. The results are all supportive of the above conclusion and are available from the corresponding author on request.

4.3. Archetype behaviour over time

This section examines the proportion of switches per archetype through time. It based on a switch-level view of the archetypes over the period under review. Initially, there is no link to specific investors, but this is then introduced. It is worth reiterating that the switch-level methodology does place a heavier weight by the number of switches conducted. Fig. 3 clearly shows this as the dominant proportion of switches through time appears to be the Market Timers even though, on average, they represent 34% of the population of investors. The 3-month moving average is plotted in Fig. 3 and shows that while there are some short periods with relative switch-level stability, overall, the picture is rather variable. This is consistent with a key assertion put forward by the mediated risk models that long term risk preferences should be stable but will be affected by changes in short term risk perception.

On casual inspection there does appear to be different (higher) levels of non-market timing archetype switches leading up to and during the Global Financial Crisis (from the beginning of the timeline up until the end of 2009) as well as the period that includes the market volatility experienced amidst the COVID-19 global pandemic (end of the timeline). These periods are correlated with higher levels of behavioural tax as calculated by Nixon et al. (2021) and applied to these archetypes. The average levels of behavioural tax by switch archetype by calendar year are presented in Table 5. The shaded cells refer to the two periods under discussion.

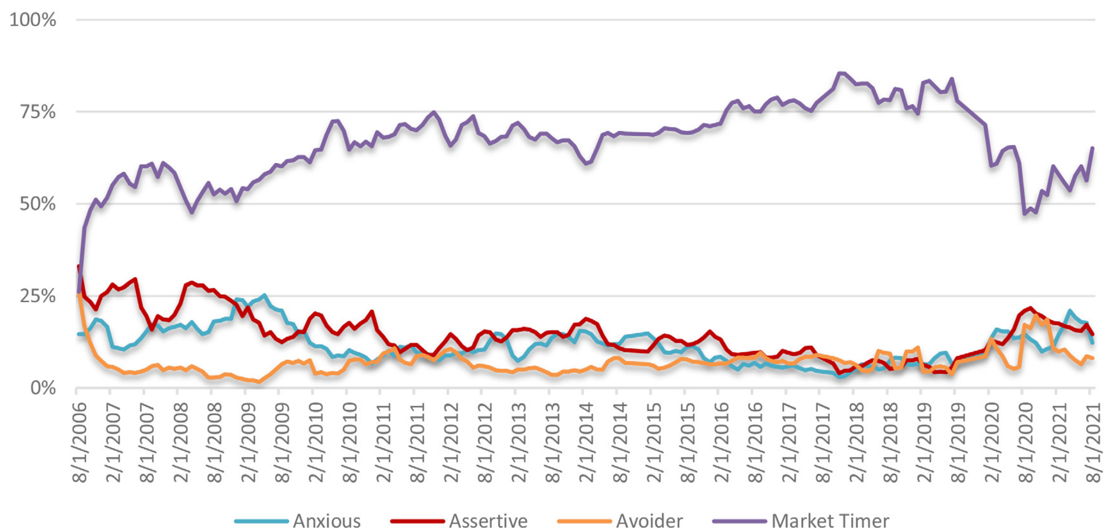

Fig. 3. Overall change in proportion of switches (3-month moving average).

Table 5
Behaviour tax per archetype by calendar year.

Archetype	Anxious	Assertive	Avoider	Market Timer	All investors
2006	**6.60%**	**−3.90%**	**4.30%**	**4.00%**	**2.70%**
2007	**−1.10%**	**4.80%**	**1.20%**	**1.40%**	**1.80%**
2008	**4.30%**	**−3.10%**	**−3.30%**	**−0.60%**	**−0.50%**
2009	**−1.30%**	**3.50%**	**0.30%**	**1.20%**	**1.00%**
2010	**2.50%**	**−2.70%**	**0.30%**	**−1.30%**	**−1.10%**
2011	1.60%	−1.70%	0.50%	−0.40%	−0.30%
2012	3.60%	−4.80%	1.10%	−1.10%	−0.90%
2013	2.60%	−2.20%	0.40%	0.20%	0.10%
2014	1.80%	2.50%	1.40%	1.20%	1.50%
2015	2.10%	1.00%	1.40%	1.30%	1.40%
2016	−0.20%	3.60%	0.40%	0.40%	0.70%
2017	0.20%	−1.60%	−0.60%	−0.90%	−0.90%
2018	−0.70%	−1.00%	−0.80%	−0.40%	−0.50%
2019	0.70%	−1.20%	−0.60%	0.20%	0.10%
2020	**1.20%**	**7.50%**	**1.90%**	**5.00%**	**6.50%**
2021	**5.40%**	**0.60%**	**1.00%**	**4.20%**	**3.50%**

Table 6
Relative stability of switches in more volatile markets.

Archetype	2006–2010 *Relative Std Dev*	2011–2019 Std Dev	2020–2021 *Relative Std Dev*
Anxious	19% greater	3.0%	2.1% greater
Assertive	32.6% greater	4.0%	3.0% greater
Avoider	132.6% greater	1.8%	145.0% greater
Market Timer	8.7% greater	5.8%	15.7% greater

When considering the standard deviation of the change in archetype switches over these same periods a similar positive relationship is found as reported in Table 6.

This suggests that all archetype switches are more prevalent during these periods of market volatility (especially for non-market timer archetypes), and this leads to higher levels of negative outcomes as measured in terms of each switch's behavioural tax.

4.4. Stability of individual membership of the behavioural archetypes

The mediated theory of risk decision making suggests that an individual's risk behaviour is a function of a combination of their long term risk preferences and short term factors which determine their risk propensity. If correct, we should see a consistent long term pattern of switch archetype membership for individuals combined with short term variations in their behaviour as captured by their membership of other clusters. A summary of the percentage of the total time that the switch decision of each individual member of a cluster (on average) fall into their 'home' cluster as well as the other clusters is presented Table 7. The shaded cells in this table reflect the proportion of the time the switches are consistent with their average (pooled) categorisation. Note the lack of a highlighted value for the market timer cluster.

All three of the Avoider, Anxious and Assertive clusters present the expected pattern of behaviour. Most of their switches are consistent with their classification, but not all. The Market Timing cluster is the apparent anomaly. It seems that the nature of the behaviour this type of individual exhibits can be best characterised as continually changing between other patterns of behaviour.

5. Conclusion

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 - while there are periods of divergent behaviour, these appear to be temporary, and they revert to that which is consistent with their long term risk preferences.

This is an important finding in several key areas. 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. Greg B. Davies of Oxford Risk proposes the concept of "just-in-time" financial education (Davies 2021) to help investors better understand the potential financial tradeoffs 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.

The differences in, and time-varying nature of, the behaviour patterns discovered is a critical step in understanding how to create personalised strategies that can 'nudge' investors away

Table 7
Individual membership of archetype over the period 2006–2021.

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%

from what may be emotionally soothing decisions in the short run with negative outcomes in hindsight. The insights provided by this study are the first step towards engaging with the right investor segment at the right time with the right message to help them avoid making avoidable mistakes.

The presence of four clusters, with three of them demonstrating consistent cluster membership in the main, combined with time-period specific deviations into other patterns of behaviour indicates that a predictive model of switching behaviour based on this approach is possible. The presence of the anomalous market-timer cluster suggests that this confidence must be tempered by a recognition that this approach is based on a cluster methodology that is sensitive to the choices of underlying variables used to cluster the observed behaviours. The paper does, however, clearly demonstrate the potential for the use of these tools in this context and does suggest that the mediated model of risk decision making has empirical support.

This study has three notable limitations that must be recognised:

(1) The approach used makes the implicit assumption that, when a switch transaction is executed, there is no related change in either the investor's current circumstances or their investment goals. Changes to these dimensions are 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. The volume of switch transactions considered however is believed to be sufficient to gain an accurate view of investor overall behaviour patterns.
(2) 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.
(3) Finally, as the study only focuses on switching decisions, it does not explicitly include the investor risk behaviour associated with doing nothing during turbulent times.

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