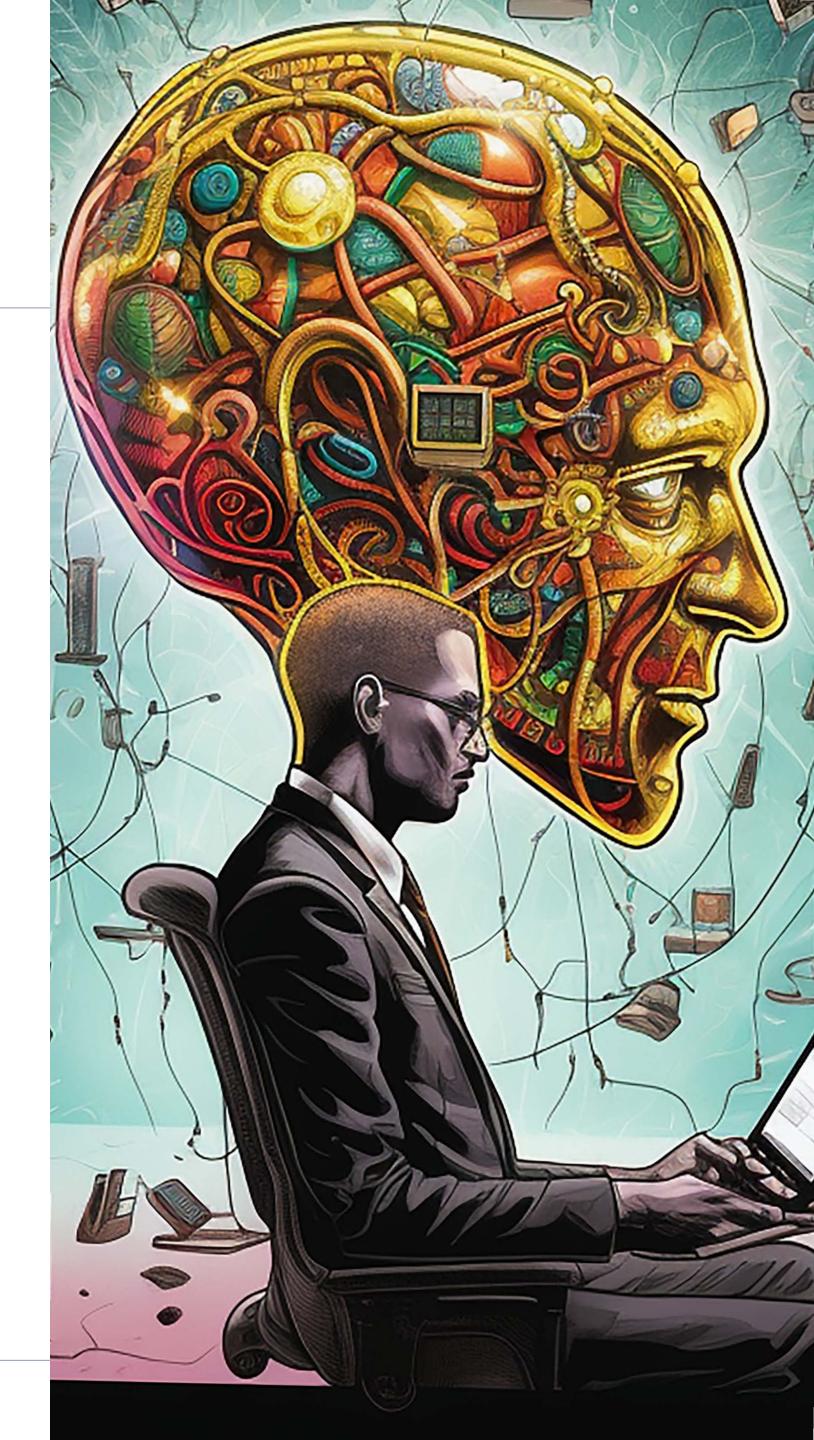




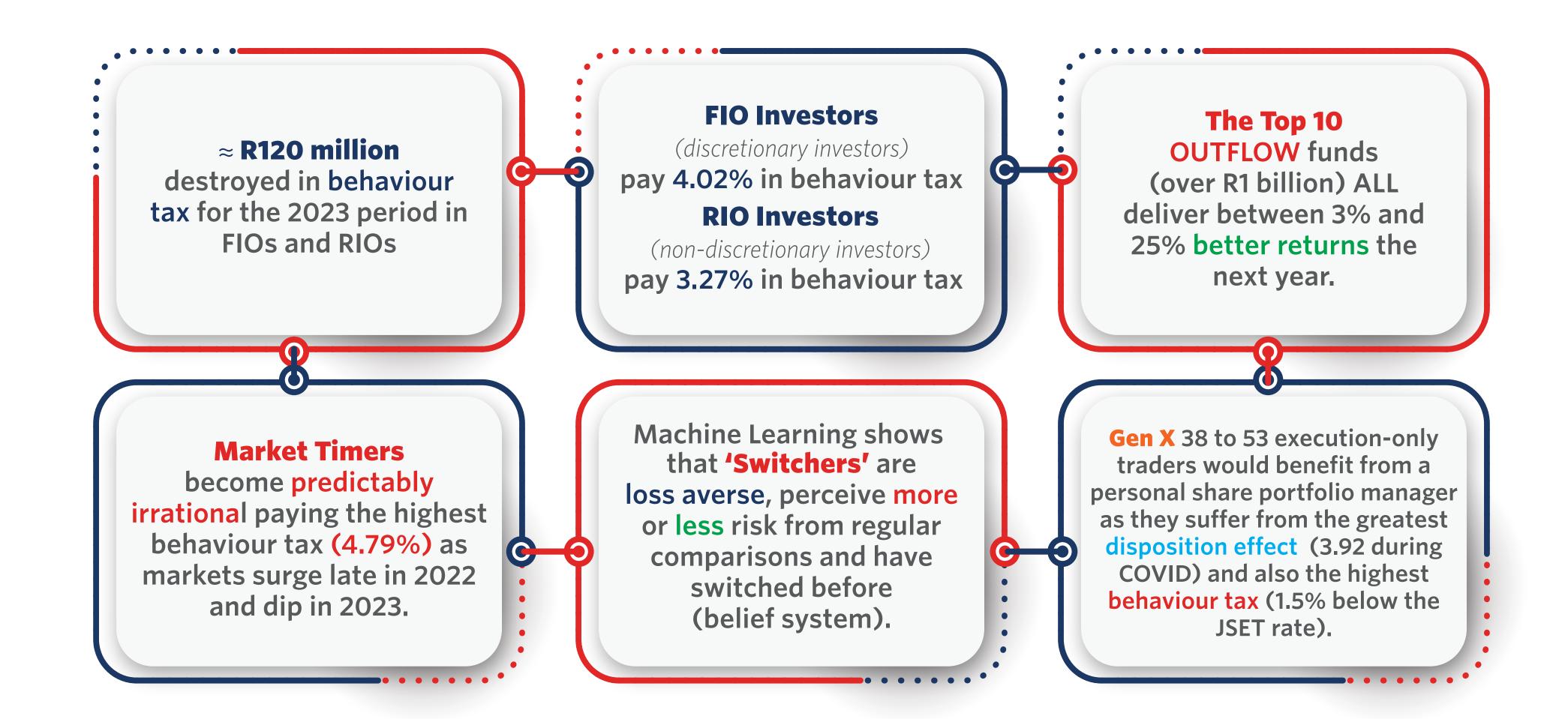
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Sci-Fi Report highlights





Note from the editor

Paul Nixon

Head: Behavioural Finance





Note from the editor

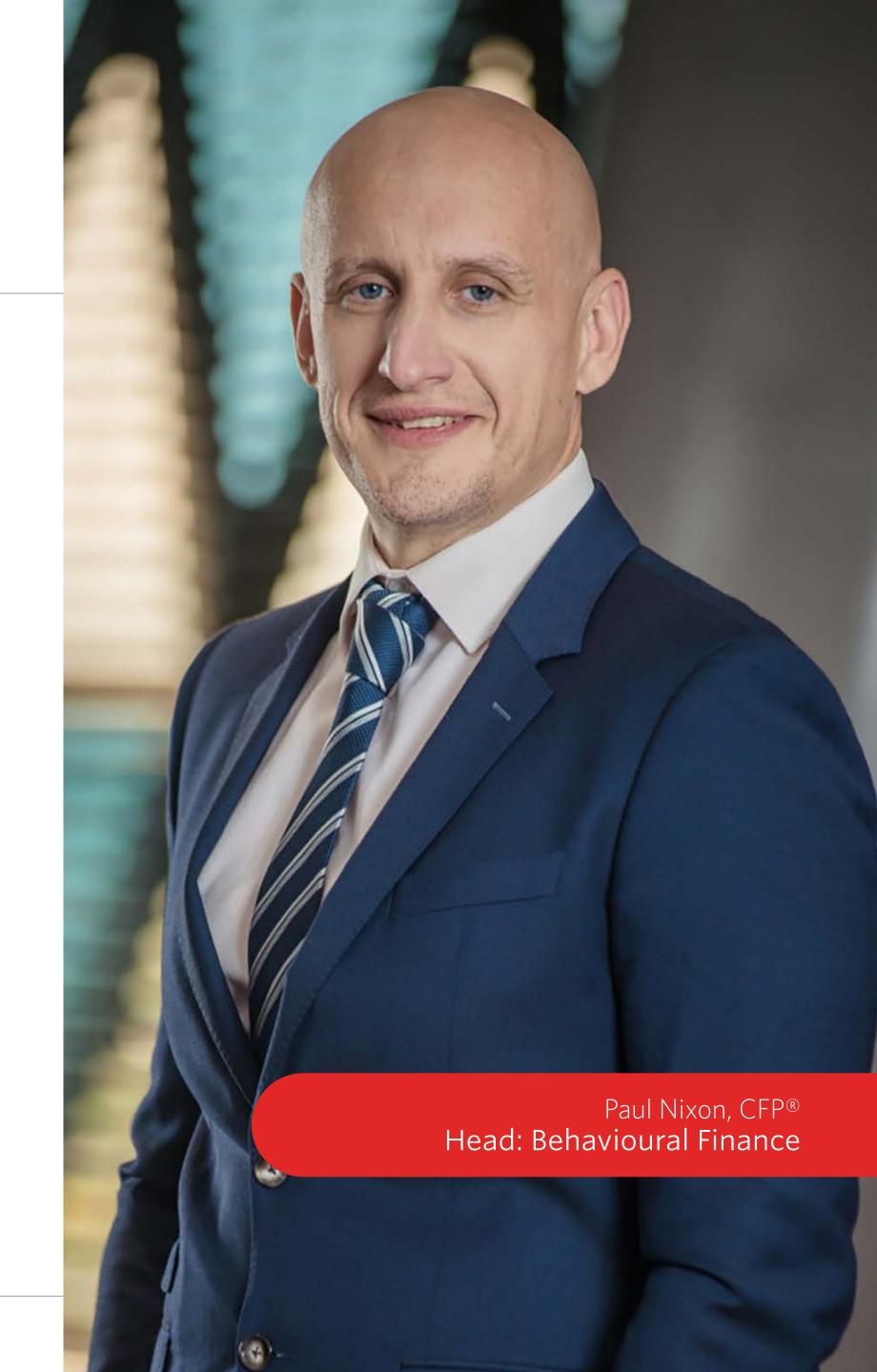
Welcome back to the 2023 edition of the Momentum Investments Sci-Fi report. This year was a bumper year for behavioural finance with many highlights. Undoubtedly, a highlight for us was the partnership with the Global Association of Applied Behavioural Scientists (GAABS) and the CFA Society of South Africa to deliver a ground-breaking behavioural finance webinar on the future of behavioural finance. More than 1 200 attendees and some great media exposure after the event are testament to the growing interest in the intersection of behavioural sciences and technology from various communities. If you missed the webinar, you can watch it here, or check out the articles section where a couple of the presentations have been summarised by an artificial intelligence (AI) tool (Quillbot, to be precise).



In respect of using machine learning (a branch of AI), much progress was also made in coming to a deeper understanding of the investor 'switch itch'.



Using the random forest algorithm (supervised algorithm), the features of investors who switch are revealed in the machine learning section that also unpacks the unsupervised machine learning work (archetype analysis) for the 2023 period (from 30 September 2022 to 1 September 2023). As time passes, we are seeing more consistency in terms of the behavioural patterns that destroy value regularly





Note from the editor

(see section 4). Supervised machine learning now allows us to reliably predict, within acceptable margins, an investor switch to allow advisers to engage proactively.

In tandem with machine learning, however, a branch of psychology (personality theory) also has much to offer in predicting investor behaviour. The Momentum Money Fingerprint that psychometrically measures investor risk tolerance and provides insights into client risk behaviour, money attitudes and personality, has entered the technology proof of concept phase in Momentum Financial Planning and we look forward to launching this in 2024.

Finally, be sure to check out section 5 where we reproduce the paper published in the behavioural economics 'bible' - The BE Guide (2023). Here we show how the disposition effect was amplified during the COVID-19 pandemic. This paper serves as the foundation for releasing an update that also tracks 'behaviour tax' in share trading attributed to the disposition effect. For the first time, a rands and cents value is alluded to for a psychological effect in stock trading.

A bumper year indeed for the evolution of applied behavioural finance and machine learning in the business, as we attempt to help investors and advisers manage a behaviour tax that has accelerated to levels last seen during the COVID-19 pandemic (more than 4% per year).

Best **Paul Nixon** P.S. Remember you can download the past versions of the Sci-Fi report here:









Features from our annual behavioural finance conference



Using AI to make better decisions about humans

Applied behavioural science has evolved in the past decade, moving away from focusing on influencing behaviours to understanding behaviours better and making better assumptions about behaviours in decision-making processes. Behavioural scientists typically work in five buckets:

- Defining problems in concrete behaviour terms
- Imagining the world where problems have been solved
- Identifying key behaviours
- Identifying barriers
- Designing solutions based on good understanding of behaviours, and monitoring and evaluating these concretely.

Al can enhance these tasks by providing strong divergent or lateral thinking capabilities. This allows for a more comprehensive understanding of the problem space and considering it from various perspectives. For example, when defining a problem like tax evasion, behavioural scientists can consider the perspectives of sociology, psychology and anthropology. By asking questions about the behaviour, they can better relate to the problem and understand its context. For instance, sociologists examine social norms, psychological factors and societal structures, while anthropologists examine cultural attitudes towards succession and perceived roles of individuals and communities.

Al is particularly useful in opening the problemsolving space and doing some divergent thinking, enhancing existing capabilities in these areas.



Laura is the former head of behavioural science at the UK Cabinet Office (10 Downing Street). She is the founder of Decision Context, specialises in behavioural science advisory services and works with policymakers, communicators and NGOs. Laura is a thought leader in AI and behavioural science.



Using AI to make better decisions about humans

By doing so, AI can help behavioural scientists better understand and design solutions that address the specific needs and challenges of their clients.

So, applied behavioural science offers a valuable tool for behavioural scientists to better understand and design solutions for various problems.



By leveraging AI's divergent thinking capabilities, behavioural scientists can gain a deeper understanding of their subjects and contribute to the field's ongoing progress.



The problem definition process involves identifying relevant audiences and actors associated with a problem, such as the rise in verbal abuse of girls in

school linked to school age boys and misogynistic content creators. AI can list these actors and draw attention to areas that might not have been considered. This enhances divergent thinking and helps in understanding the systemic relationships between actors and their interactions.

Al is particularly helpful for big-picture tasks, where understanding the problem and observing how different actors are related to one another is crucial. For example, using ChatGPT and the 'show me' plugin, an example of online harassment for school-aged girls can be seen.

The next step is to think about alternative behaviours to enable and drive. For example, asking ChatGPT to come up with different target behaviours for various audiences and give a likelihood rating for how able they would be to influence these behaviours through a campaign. This is a black-box approach, but applying

Al at this stage can help narrow down what resources might be available to affect behaviours.

Once a specific behaviour or interactions is decided, it is time to analyse barriers from a behavioural perspective to understand why it doesn't already occur and what actions need to be taken to enable it. There are many different frameworks available to analyse barriers in a systematic scientific way, such as Com-B, which stands for capability, opportunity motivation and behaviour.

The model tells us that for anyone to engage in a behaviour, they need to have the capability to do something, know how to do it, have the physical and mental capacity to engage in the behaviour, have the opportunity to do so and understand the motivation to engage in the behaviour. Incentives around them must also enable them to do it.



Using AI to make better decisions about humans

In summary, problem definition and behavioural science approaches are essential for understanding and addressing large societal problems. By applying AI and analysing barriers from a behavioural perspective, we can develop effective strategies to address the issue at hand.

In the behavioral science process, divergent thinking is essential for understanding potential barriers and identifying potential solutions. Cognitive empathy is a crucial aspect of this process, as it allows us to consider the world from someone else's perspective and the influences that may play a role in that person's life. For example, ChatGPT can conduct a Com-B analysis on a problem like employee turnover, which could involve avoiding the loss of organisational knowledge and high costs associated with recruitment and encouraging employees to stay in their roles for at least two more years.

The results of this analysis can be useful in identifying capability barriers, opportunity barriers and motivational barriers, such as increased turnover in middle management causing instability and loss of confidence in the organisation's future. Al can be used to generate personas of children, which are not necessarily real images but rather synthetic representations. This technology has enhanced our ability to engage in behaviour research and speed up some tasks.

When designing solutions, it is important to simulate what the future should look like and understand how people will react to what we put out. Al is good at giving ideas for what we could do, but it is particularly strong in generating behavioural risks or unintended consequences. For example, AI can generate valuable categories of what could go wrong when a campaign is run to encourage bystanders to intervene when they see someone in distress. By

doing so, AI can help mitigate potential risks through communication materials.

In conclusion, this article provides a background on how AI can be used to think like a behavioural scientist and approach problems in this way. The key question is how to make good decisions about AI and better decisions about humans. It is crucial to consider your own decision-making process, including assumptions about behaviours and the capabilities you use yourself. By enhancing these capabilities with the capabilities AI already has, you can make better decisions about AI and better decisions about humans.



The potential of impact games (gamification) to drive financial understanding

Sea Monster has been developing impact games for the past 12 years, focusing on financial education from kids to adults. We work at senior levels within large organisations worldwide, aiming to nudge behaviour in the real world and the digital world. The purpose of an impact game is to re-present information back to customers in a visual, engaging, bite-size way that gives them agency and feedback about their choices. This facilitates learning.



The preconceived idea of a game is that it is just two teenagers playing Fortnite in their underpants.



However, gaming takes on many different forms across cultures. The Candy Crush generation, who spend more time and money than many other demographics, are some of the heaviest gamers in the world. To make a game successful, it needs a goal, rules, feedback system and voluntary participation. Players must want to play.

Sea Monster has created games for credit committees in big banks across Europe to teach them to consider environmental, social and governance (ESG) scoring as part of their financial scorecard. The key is to get users to want to learn, and they gauge success by measuring how long people play and how many times they return. The company aims to place the user at the centre of the experience, whether it's a marketing or learning experience.



Glenn Gillis is the co-founder and CEO of Sea Monster, and the chairperson of Games for Change Africa. Glenn is an expert on the role that technology plays in storytelling and a thought-leader on how impact games and immersive technologies (artificial reality (AR) and virtual reality (VR)) can be used to drive business goals and social outcomes.



The potential of impact games (gamification) to drive financial understanding

There is also an important difference between extrinsic and intrinsic motivation in reward schemes in businesses (this is where the want comes in). There is a big need for clear instructions and feedback systems to motivate users as discussed earlier. Feedback systems can benefit various aspects of business, such as playful design and gamification and facilitate learning. More than this, they can also influence and enhance the role of social purpose and learning.

Capitec, a data-driven financial institution, approached Sea Monster with the goal of turning its commitment to financial inclusion into a strategic advantage. We developed a game that was designed to focus on users' habits gradually and systematically over time, putting the user

at the centre of the experience. The game loop involves a series of dreams and goals that users want to achieve through avatars. The game's theory of change is that people change their behaviour not because they have more information but because of a psychological tension with the archetype, 'me'. The game aims to help users see themselves in the world around them, make decisions and observe how the avatar behaves.

This is of critical importance. Allowing people to see themselves in the game and make decisions based on their avatars can help businesses build a stronger connection with their customers, learning about their customers while improving their overall performance through feedback.

No discussion on gamification is complete without reference to the metaverse (a persistent virtual world where people can play, shop, connect and experience the world differently) and how it can be used to measure resilience and critical thinking. Here Sea Monster uses existing platform technology in popular games like Roblox and Minecraft to create 'Chow Town' for future Nedbank clients and employees while exploring future value propositions. Chow Town is a 'tycoon game' where the player builds an empire that starts with a restaurant in the metaverse. The game allows players to upgrade their equipment, serve Bunny Chow, Shisanyama, braaivleis or whatever they choose while adding new and interesting items to their menu. It teaches youngsters basic business principles like store and product design and differentiation. You're not the



The potential of impact games (gamification) to drive financial understanding

only store, so how do you make yours different and grow your business? The game also encourages players to watch out for potential staff growth. We believe this game could be a world first, as it could help banks understand their customers' needs and preferences from a young age.

Tycoon games are a popular way for financial institutions to teach kids other practical rules about life, promoting future orientation and delayed gratification (addressing the psychological tension between immediate feedback and delayed gratification in a visual and engaging manner). Nedbank has achieved more than 100 000 visits and an engagement time of 12 minutes per user, compared to traditional marketing channels.

In conclusion, positive design and gamification elements can improve company feedback mechanisms like dashboards, making them more engaging and accessible. The focus is once again on the user, putting them at the centre of the experience, whether they are corporate credit committees or kids. By putting them in the centre, they can realise that through their actions, they can make tomorrow better than today.



How to show clients you're emotionally compatible



Research by our team of behavioural scientists suggests consumers are just as likely to hire a financial adviser for emotional reasons as financial ones.



However, they may not be aware of those emotional reasons or be able or willing to discuss them at the outset of the relationship. While addressing financial needs can be done in a fairly straightforward manner, addressing emotional needs requires a more subtle approach. By taking three simple steps, advisers can build both aspects into their value proposition and prospective client touchpoints, such as websites, brochures, initial meetings and follow-up contact.

Step one

Identify how you address the top three client priorities. The top three categories identified in our research are:

- Discomfort handling behavioural issues: A lack of confidence that they have the skills needed to reach their financial goals, or a lack of knowledge regarding financial issues.
- Behavioural coaching: Help acting in a way that is beneficial to their finances, including explaining the financial plan, motivating the client to stick to the plan and providing guidance on what to do (or not do) in certain financial situations.
- Specific financial needs: Retirement planning, handling life changes or tax management, for example.



Ryan Murphy, PhD, is the global head of behavioural insights for Morningstar and a member of the behavioural insights group. His research is interdisciplinary, bringing together methods from experimental economics, cognitive psychology and mathematical modelling.



How to show clients you're emotionally compatible

Think about everything you do for your existing clients, including the financial and emotional support you provide. Then sort into the three categories. This will give you a sense of how balanced your offering is.

Step two

Work these into your messaging. Review your homepage, client brochure, what you cover in your initial meeting and how you follow up, keeping the following points in mind:

Discomfort handling financial issues: Even though many clients don't feel comfortable dealing with their own finances, highlighting this may not be constructive, as it can reinforce negative feelings. Instead, highlight how your expertise can reduce anxiety, promote peace of mind and help clients reach their goals.

- Behavioural coaching: Our research found people tend not to like hearing they need behavioural coaching, so language matters here. Colloquial language, adding examples and being clear that these are issues we all face, can help engage investors and bring down barriers.
- Specific financial needs: Getting beyond the 'what' of a financial issue to the deeper 'why' that is driving their financial goals can open the door to more meaningful conversations and a plan that is personalised to their true financial objectives.

Step three

Refine and review to make sure your messaging is clear. No doubt you'll find you have a lot of good information to share with clients. But too much information can detract from your key messages.

Choose your key messages and make sure they stand out clearly. Go back over your content and highlight which text relates to the three categories. Then look at what's left from a client's perspective and ask yourself if it's necessary in this context.

It's important for advisers to lead with their ability to provide financial and emotional support when dealing with prospective clients. Our research found clients are more likely to hire an adviser based on emotional rather than financial reasons (60% compared to 40% respectively) but the almost exact reverse was the case for leaving an adviser (42% compared to 58%). The key is in achieving the correct balance and getting communication right with clients from the outset for long-term, mutually rewarding relationships.

Friends: The one about psychology and Al

If you're a Gen-Xer, chances are you watched everyone's favourite Friends deal with relatable trials and tribulations, and mostly from a coffee shop, which is Central Perk in New York City. Each main character had a very strong and unique personality.

Monica was the ultimate planner, seeking to exert control over her environment. These are indicative of higher levels of conscientiousness (being precise and thorough) with neuroticism (anxiety caused from a lack of control). Rachel, on the other hand, was highly spontaneous and social. When she flew to London to tell Ross she loved him when he was about to marry Emily, she wasn't thinking about the consequences of her actions. This means she'd score lower on conscientiousness (doesn't think about the future) and her outgoing nature comes from higher levels of extraversion.

Phoebe was an extremely interesting case and clearly demonstrated how nuanced personality theory is. Phoebe was positive and assertive and also warm (agreeableness), but her broadmindedness (curiosity) manifested in fantasy and feelings, making her a dreamer and a bit 'out there'. Her song 'Smelly Cat' attests to that.

The same trait (broadmindedness) in Chandler with his low score on agreeableness (not too concerned about offending others) provides the perfect cocktail for his defining characteristic being sarcastic and witty.

Unfortunately, we don't have time to discuss Joey and Ross here, but where are we going with this? Behavioural finance is shifting towards a stronger emphasis on psychology – honing in on exactly who the individual is behind the decision being made, instead of the population as a whole. Developing a



Paul is the head of behavioural finance for Momentum Investments and is a PhD candidate at Stellenbosch University. His research focuses on the integration of psychology and artificial intelligence (machine learning) to get better investment outcomes for advisers and clients alike.



Friends: The one about psychology and Al

deep understanding of the individual also enables us to train machines more effectively in human behaviour. This area of behavioural finance is being catapulted forward with techniques like machine learning and AI in the form of natural language processing.



Processing billions of recorded human interactions (like from sitcoms such as Friends) to sharpen these models will soon allow psychological inputs into predictive machine models that can help us overcome our human pitfalls.



This is part of the journey we are on to use technology to understand the person - the financial adviser and client - behind the advice and investment.

We are always looking at innovative ways to enhance the investing experience as well as offer financial advisers and their clients a more personalised one, thereby helping clients to stick to their financial plan and improve their chance of achieving their financial goals.

In 2019, the yearly EmotionX challenge was to develop a predictive model of the emotion (if any) in each line of all the dialogue in the Friends sitcom series. To train the model, initially humans looked at each line of the dialogue and voted on the emotion so as to try and teach the machine model the intended context.

"Okay!", for example, could indicate happiness or anger. The net result of this challenge after the model was trained was an impressive emotional predictor of more than 80%. To further enhance this idea of 'context', the personality of the individual could be a valuable input that will sharpen these models.

So, when Chandler says, "I'm glad we're having a rehearsal dinner. I so rarely get to practice my meals before I eat them," chances are, he's being sarcastic.



Overall behaviour summary

The 2022 Sci-Fi report aptly referred to 'behaviour tax loading...'. Overall, the previous Sci-Fi report was characterised by sharp risk-off behaviour. As markets declined (downward trend evident in the dotted line in figure 1), investors moved quickly to the cash side of the risk spectrum and away from shares. The overall behaviour tax for the 2022 period (01 September 2023) was negative 0.94%, or represented value added from switching. However, it was predicted that this would sharply reverse as markets were expected to recover. And recover they did. The start of the Sci-Fi 2023 report period sees markets surging and breaking records in January 2023. This results in a rapidly accelerating behaviour tax (see Table 2 presented later in this section) and contributes to much of the total value destroyed for the period, which amounted to an alarming 4.02% (the highest levels since the COVID-19 period), or R41 055 859 in rand value.

Figure 1: September 2022 to January 2023 market surge

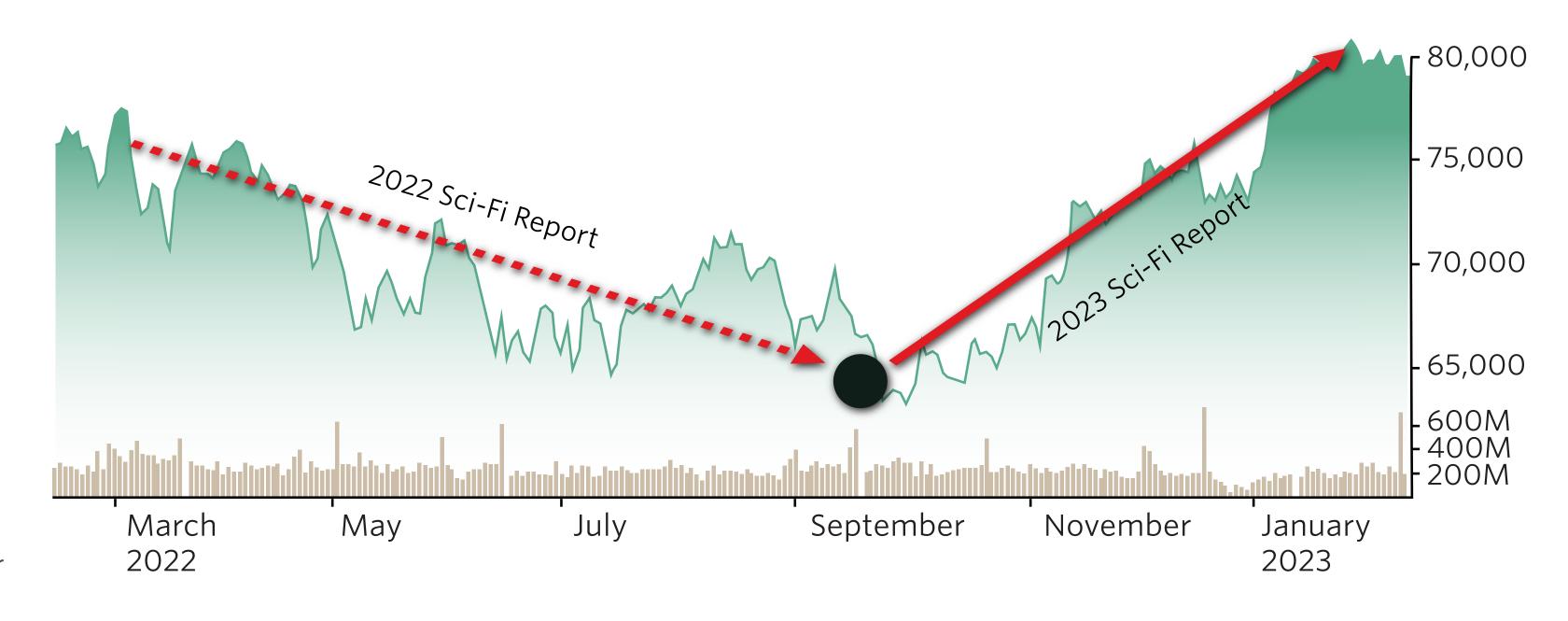
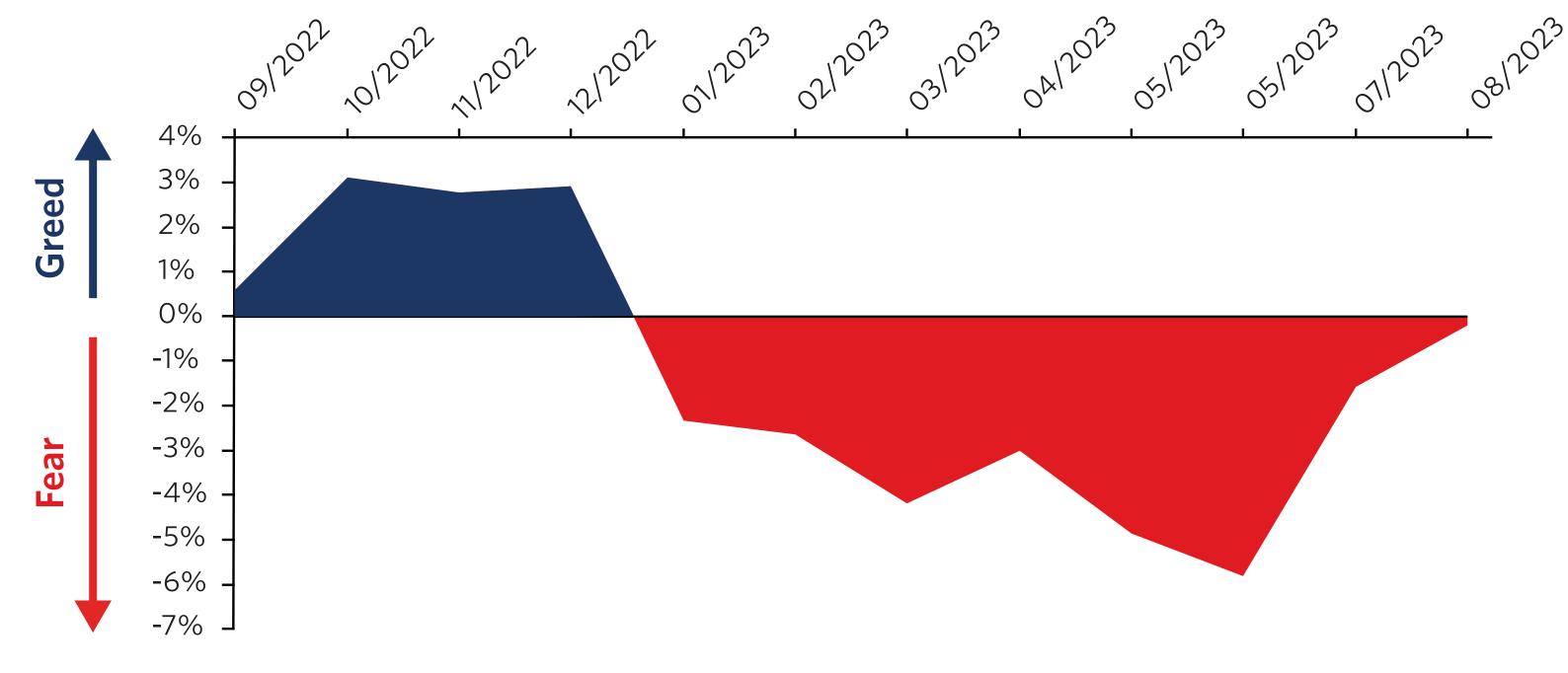




Figure 2 illustrates overall investor behaviour for the period in respect of returns chased. Clearly corresponding to the elevated market returns in the latter part of 2022 is the corresponding investor activity of switching to better-performing funds once more. Coming off the relatively low return base in equities illustrated by the white circle in Figure 1, investors start moving back into equities that historically performed much better (when compared to September 2021). This behaviour is confirmed by the average risk behaviour (based on asset allocation) of investors (de-risking) increasing as markets started declining in 2023. In February and March 2023, there was an overall peak in de-risking from increased volatility and sharp negative market movements.

Figure 2: Corresponding returns chased for market surge and decline





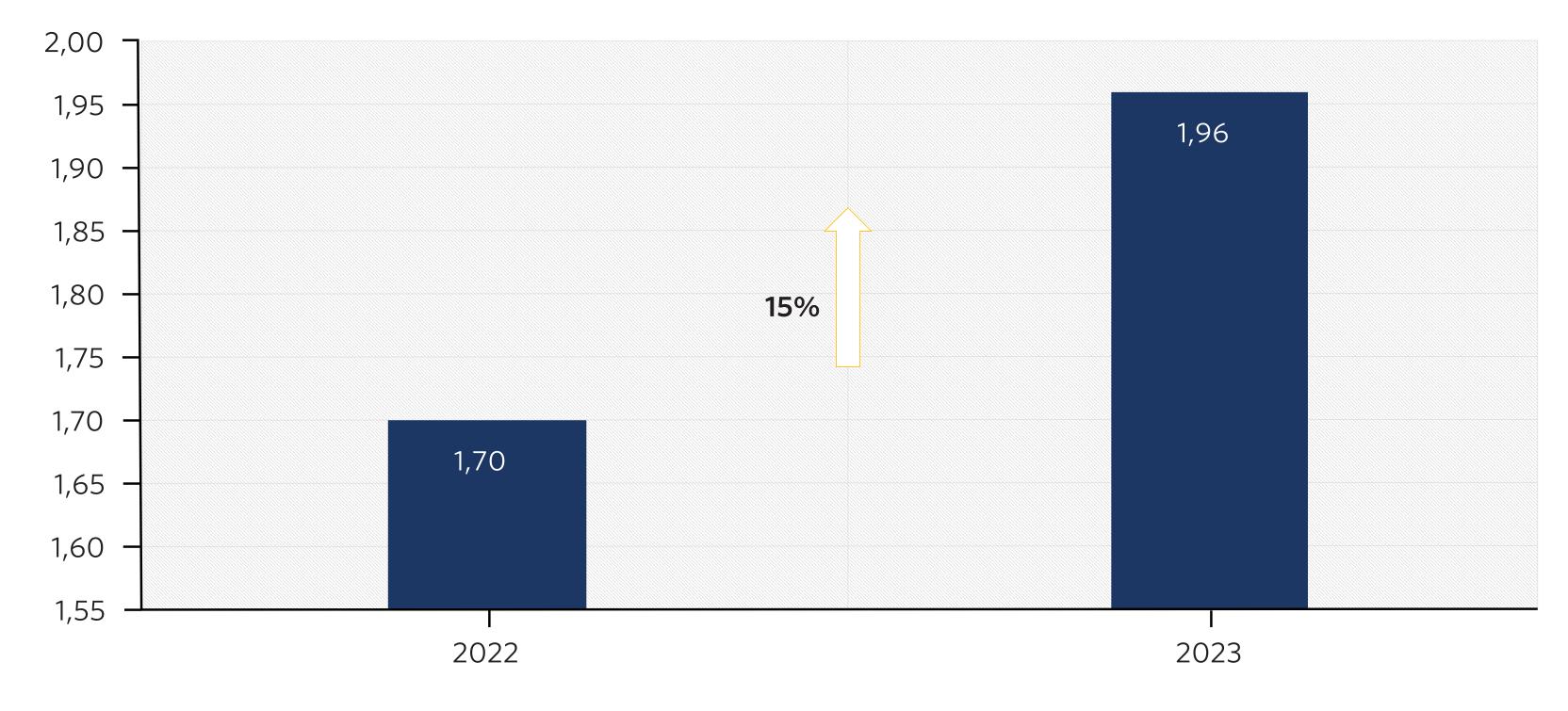


Overall, once again, investors do not manage to add value with their switching behaviour on average. Quite the opposite, in fact, as behaviour tax levels rise to COVID-19 levels once more.

The investor 'switch itch' for 2023

The number of behavioural switches is up slightly from the 2022 period with a 14.81% increase to 27 688 switches. The average number of switches per investor also rose by just more than 15% accordingly from 1.70 to 1.96.

Figure 3: Mean number of switches per investor (FIOs)





A behavioural switch is identified as a change in risk preferences of the investor, and likely due to a change in risk perception. A rule engine is constructed to filter each switch transaction to eliminate regular income withdrawals, switching between fund classes and phasing into or out of markets, for example. It is also important to note that 27 688 switches are well above pre-COVID-19 switching levels (about 35% greater than what was considered normal before the pandemic).

There was also an increase in the number of 'active investors', which are defined as those investors performing at least one behavioural switch. This increased by 6% from 2022 to 14 124 active investors or switchers.

Finally, the average switch amount decreased to just under R150 000 from R179 000 in the 2022 period and peaked at R192 000 in April of 2022.

Following the money 2.3

What was the root cause of the high behaviour tax for discretionary investors? Table 1 to follow clearly shows the top 10 funds (in descending order) with net outflows for the 2023 period. When examining each fund on this list in respect of the one-year rolling preceding returns and post-returns, the latter (2023 returns) is greater than the former (2022 returns) on each occasion. For investors switching exactly one year before the period of this analysis ending (September 2023), there will be one year of forward

returns (2023 returns). As the period rolls forward, there is less and less future return data available and so it is important to note that the right column is not always one-year future returns.

The net result, however, shows clearly how the behaviour tax is formed. Investors left the funds listed (likely because of the preceding one-year returns) and as such missed the higher returns that followed.



Table 1: Top funds ditched and switched for the 2023 period (FIOs)

	Fund	Net outflows	2022 returns	2023 returns¹
10.	Coronation Global Optimum Growth	(R26 371 538.96)	-14.54%	22.21%
9.	Satrix MSCI World Index Fund	(R29 353 060.00)	1.17%	27.05%
8.	PSG Wealth Global Preserver Feeder Fund	(R30 478 494.01)	2.97%	14.15%
7.	Coronation Balanced Defensive Fund	(R33 282 278.40)	2.85%	13.69%
6.	Ninety One Managed Fund	(R34 799 979.04)	1.89%	8.84%
5.	Coronation Balanced Plus Fund	(R35 267 698.02)	2.98%	14.93%
4.	FG SCI Saturn Moderate Fund of Funds	(R53 130 705.00)	5.54%	11.92%
3.	Capita BCI Cautious Fund	(R66 688 112.65)	2.67%	10.12%
2.	Coronation Strategic Income Fund	(R73 530 525.05)	4.52%	9.48%
1.	Momentum Enhanced Yield Fund	(R234 511 116.55)	5.40%	8.36%

Source: Momentum Investments (2023)

¹Note: This return is annualised at the time of writing this report where a full one-year outlook ahead period is not available.



For example, the fund with the biggest net outflows was the Momentum Enhanced Yield Fund, at R234 511 116. This was one of the funds with the biggest inflows during the sharp de-risking of investor portfolios in the 2022 Sci-Fi report. The 2022 return of the fund was 5.40%, but after investors moved their money elsewhere, the fund returned 8.36% and the investors that left (switched out) of the fund missed out on these returns.

If these investors were up-risking their portfolios (moving to the equity side of the risk spectrum), as it appears they were, their 2023 return experience would have likely been lower than this 8.36% from the Momentum Enhanced Yield fund, and this

ultimately results in the behaviour tax that occurs when the fund switched from yields greater returns than the fund switched to. Another good example is the Satrix MSCI World Index fund, that had nearly R30 million in outflows and subsequently delivered returns of just above 27% after investors left the fund, likely due to the low returns delivered in the preceding year.

The behaviour tax 2023 2.4

Behaviour tax is calculated as the difference in future returns between the funds switched from (theoretical buy and hold) and the fund(s) switched to. As such, the 'future return' is annualised to make calculations comparable for switches made where a full one year of future returns are not available.

In the one-year period leading up to 1 September 2023, behavioural switching resulted in a cumulative behaviour tax of R41 055 859. It is important to note that a positive value here is indicative of value lost or destroyed.



Figure 4: Market returns and the behaviour tax (FIOs)

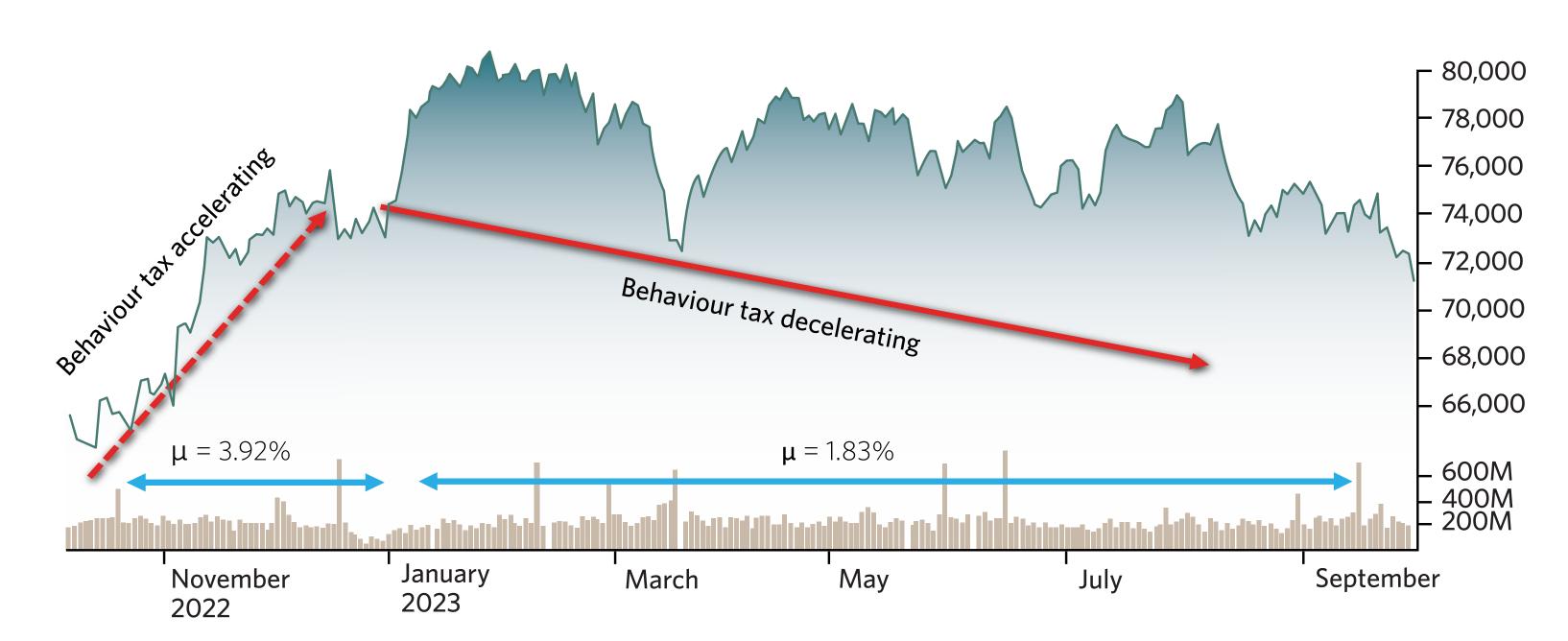


Table 2 to follow shows how the market surge in the latter parts of last year was accompanied by a rapidly accelerating behaviour tax. Investors (particularly the market timers and assertive archetypes) accounted for most of this behaviour tax, but more detail is provided in section 4 of this report. The behaviour tax eases to a large degree, as markets begin to decline and investors revert to the risk-off strategy of the previous period. January and June in 2023 are the only two months where value was added by switching. However, overall for the 2023 period, the behaviour tax reached the levels during the 2021 COVID-19 pandemic of 4.02% (value destroyed).



Table 2: Behaviour tax in the 2023 period (FIOs)

	Returns of fund switched from	Returns of fund switched to	2022 returns	2023 returns
Sep 2022	13.59%	9.71%	3.89%	17.62%
Oct 2022	18.60%	13.27%	5.33%	12.42%
Nov 2022	12.51%	10.75%	1.76%	0.22%
Dec 2022	14.53%	9.81%	4.73%	3.94%
Jan 2023	14.32%	15.08%	-0.76%	-9.56%
Feb 2023	9.00%	6.38%	2.62%	-7.03%
Mar 2023	5.10%	3.91%	1.19%	-3.58%
Apr 2023	16.80%	12.67%	4.12%	-12.01%
May 2023	12.45%	3.96%	8.48%	-0.60%
Jun 2023	9.38%	13.77%	-4.39%	-8.18%
Jul 2023	9.33%	7.78%	1.55%	3.6%
Aug 2023	9.32%	7.77%	1.55%	-4.69%
	Average behaviour tax for the 202	3 period	4.02%	





1. Overall behaviour summary

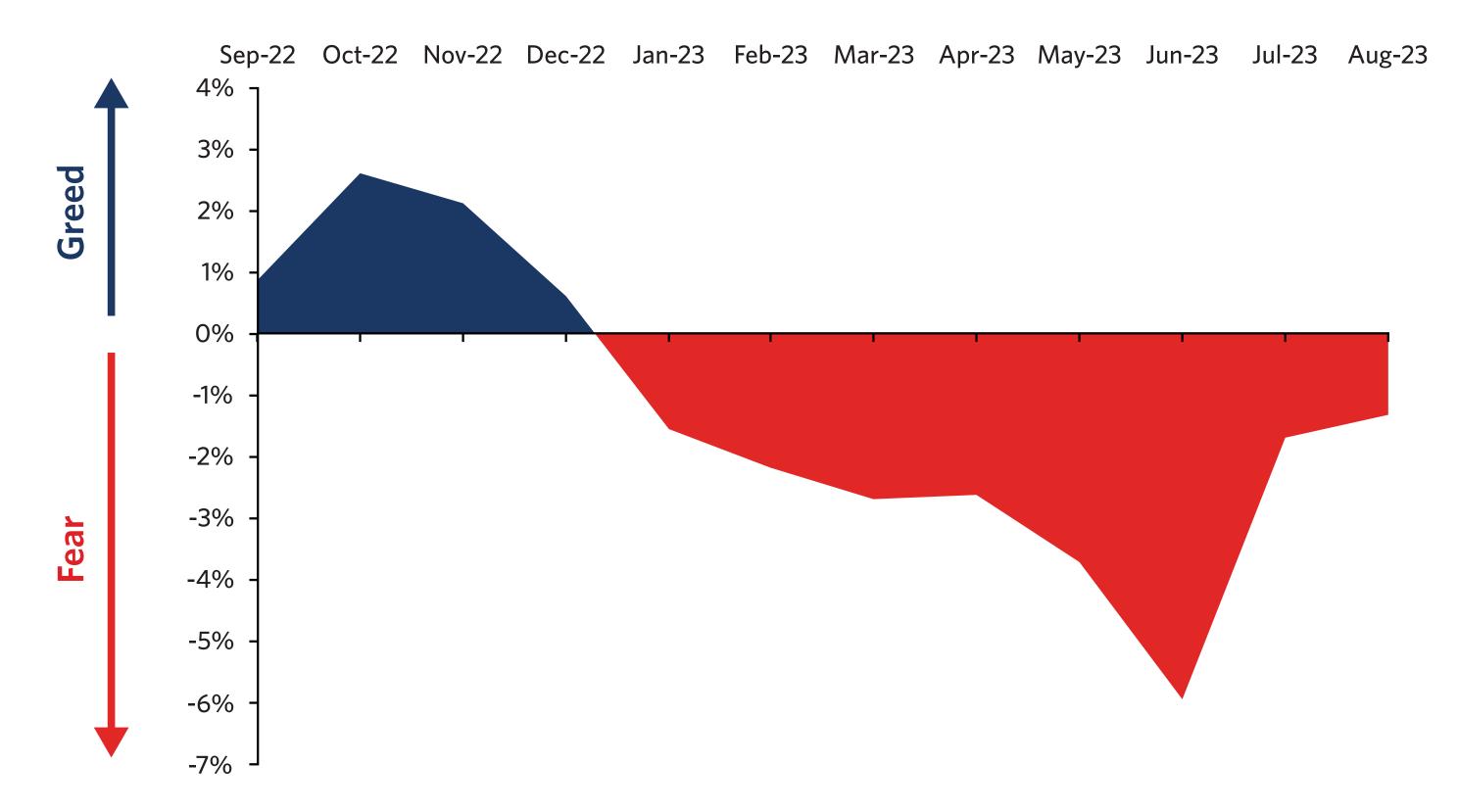
The picture in the Momentum Retirement Income Option (RIO) investment product was very similar. A reminder that a living annuity (RIO) exposes the investor's retirement capital to markets in the hopes of outperforming inflation in the longer term. The behaviour tax is most certainly a threat to these ambitions, however.

RIO investors also chased past investment returns as markets surged in the latter part of 2022 and early in 2023 and then shifted to chasing worse past returns as markets declined. 'Worse' returns often reflect the shift from risky asset classes down the risk spectrum towards cash investments (see Figure 5).

The tale of de-risking in the same period is once again similar to the FIO product, as investors start taking more risk off the table (as markets start their steady decline after breaking records in January). Overall, an annualised behaviour tax for the period of 3.27% was realised, amounting to just under R80 million in value destroyed.



Figure 5: Corresponding returns chased for market surge and decline



Source: Momentum Investments (2022)

2. The investor 'switch itch' for 2023

The number of behavioural switches - 35 468 switches in RIOs - is again substantially higher when compared to the FIO product. When compared against RIO behaviour in the 2022 Sci-Fi report, there is a slight increase of 5.6% in the number of switches for the 2023 period. The average switch amount is also substantially higher in RIOs at R243 369 per switch, which is nearly 70% greater than FIOs, where the average switch value is R143 808. Similarly, the number of switches is about 30% higher than levels experienced before the COVID-19 pandemic.

A behavioural switch is identified as a change in risk preferences of the investor, likely due to a change in risk perception. A rule engine is constructed to filter each switch transaction to eliminate regular income



withdrawals, switching between fund classes and phasing into or out of markets, for example. It is also important to note that 35 468 switches are well above pre-COVID-19 switching levels (about 30% greater than what was considered normal before the pandemic).

The average number of switches per investor is similar to that of FIOs at 1.88 switches. There is also a much higher number of 'active investors' in RIOs compared to FIOs. Active investors are defined as those investors performing at least one behavioural switch. There are 34% more active investors in RIOs when compared to FIOs.

Even though the volatility index (SAVI) decreased steadily, switch activity remained relatively constant throughout the period. December 2022 and January

2023 had lower switch activity that corresponds to the beginning of the SAVI declining and FTSE/JSE All Share Index (ALSI) increasing (briefly), which also aligns with switch activity in FIOs. From January 2023 onward the ALSI maintained a steady downward trajectory corresponding to somewhat higher switching activity.

3. Following the money

Once again, a similar pattern to the FIO is clearly evident. Of the more than R1 billion in net outflows (Table 3 to follow), in all cases the fund switched out of provided a substantially better return in the subsequent year. In fact, returns were between 2.89% (see Momentum Income Plus Fund) and 25.97% (see Ninety One Global Franchise Feeder Fund) better. The net result is that investors who left these funds

missed out on the returns that followed. This is often a source of behaviour tax. This is particularly the case with medium to high local and offshore equity allocations such as the Momentum Focus 6 Fund of Funds, Foord Flexible Fund of Funds, Coronation Balanced Plus Fund, Allan Gray Balanced Fund and the Ninety One Managed Fund. Each of these funds delivered substantially better returns in the following period.



Table 3: Top funds ditched and switched for the 2023 period (RIOs)

	Fund	Net outflows	2022 returns	2023 returns³
10.	Momentum Focus 6 Fund of Funds	(65 082 117.39)	3.94%	10.71%
9.	Foord Flexible Fund of Funds	(75 757 241.58)	0.11%	13.22%
8.	Momentum Bond Fund	(82 614 620.09)	3.12%	6.55%
7.	Coronation Balanced Plus Fund	(100 380 062.55)	2.98%	14.93%
6.	Ninety One Global Franchise Feeder Fund	(101 644 353.31)	-0.81%	25.16%
5.	Coronation Balanced Defensive Fund	(104 019 030.93)	2.89%	13.73%
4.	Ninety One Managed Fund	(105 826 057.80)	1.74%	8.66%
3.	Momentum Enhanced Yield Fund	(117 662 362.88)	5.38%	8.34%
2.	Allan Gray Balanced Fund	(144 608 751.79)	9.24%	16.39%
1.	Momentum Income Plus Fund	(157 559 062.83)	6.06%	8.95%

Source: Momentum Investments (2023)

³Note: This return is annualised at the time of writing this report where a full one-year outlook ahead period is not available.

4. The behaviour tax for 2023

Behaviour tax is calculated as the difference in future returns between the funds switched from (theoretical buy-and-hold portfolio) and the fund(s) switch to. It is important to note that 'future returns' is calculated from the end of the month a switch was made up to the end of August 2023. The future return is annualised to make calculations comparable for switches made in different months. In the one-year period leading up to August 2023, behavioural switching resulted in a cumulative behaviour tax of R79 234 052 (value eroded).

Figure 6: Market returns and the behaviour tax (RIOs)

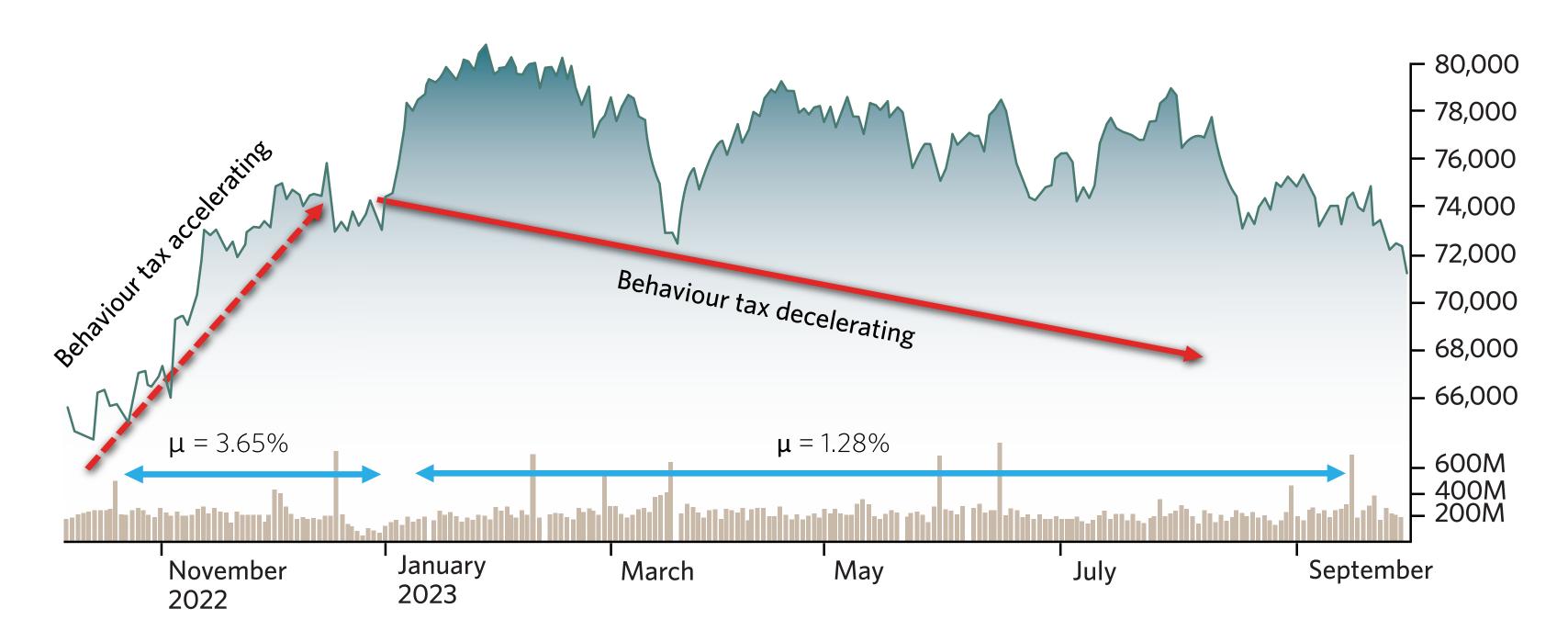




Table 4 to follow shows how, similarly to the FIO analysis, the market surge in the latter parts of last year was accompanied by a rapidly accelerating behaviour tax. Investors (particularly the market timers and assertive archetypes) accounted for most of this behaviour tax, but more detail is provided in section 4 of this report. The behaviour tax eases to a large degree, as markets begin to decline and investors revert to the risk-off strategy of the previous period. January and June 2023 are again the only two months where value is added by switching. However, for the 2023 period overall, the behaviour tax reaches 3.27% - levels seen during 2021 COVID-19 levels.

Table 4: Behaviour tax in the 2023 period (RIOs)

	Returns of fund switched from	Returns of fund switched to	Difference (behaviour tax)	Market return
Sep 2022	13.69%	9.42%	4.27%	17.62%
Oct 2022	18.02%	11.69%	6.33%	12.42%
Nov 2022	12.51%	10.50%	2.00%	0.22%
Dec 2022	12.33%	10.35%	1.98%	3.94%
Jan 2023	12.57%	12.66%	-0.09%	-9.56%
Feb 2023	8.93%	6.35%	2.58%	-7.03%
Mar 2023	6.43%	5.90%	0.54%	-3.58%
Apr 2023	15.36%	11.99%	3.37%	-12.01%
May 2023	10.81%	5.57%	5.24%	-0.60%
Jun 2023	9.25%	13.05%	-3.81%	-8.18%
Jul 2023	9.07%	7.97%	1.10%	3.6%
Aug 2023	9.09%	7.98%	1.11%	-4.69%
Average	behaviour tax for the	2023 period	3.27%	



Insights from unsupervised as well as supervised machine learning algorithms



Archetype analysis

4.1 Archetype analysis for 2023 using unsupervised machine learning

Figure 7 provides the summary of how the archetypes fared when using the k-means clustering algorithm on 16 years of switching behaviour on the Momentum Wealth platform.

As expected, 'Market Timers' were the most active archetype in 2023 as markets surged and then began a steady decline. 'Market Timers' also predictably made the most number of switch transactions (2.68 switches each on average). This usually results in a lower average amount switched when compared to the other archetypes (in line with the 2022 Sci-Fi report). 'Market Timers' had the highest annualised behaviour tax at 4.79%.

'Assertive' investors realised the second-largest annualised behaviour tax at 4.53% of the switched amount lost on average. Given that 'Assertive' investors on average switch larger amounts, this archetype also had the highest average rand value lost per investor. 'Assertive' investors are the return chasers and are testament to the adage that past returns often don't relate to future returns.

Figure 7: Behaviour tax ranking and summary since COVID-19 (2020)

Population proportion	Archetype	Average switch frequency	Annualised Behaviour Tax
34%	Market Timer	2.68	4.79%
22%	Assertive	1.29	4.53%
28%	Anxious	1.69	3.73%
16%	Avoider	1.58	2.23%



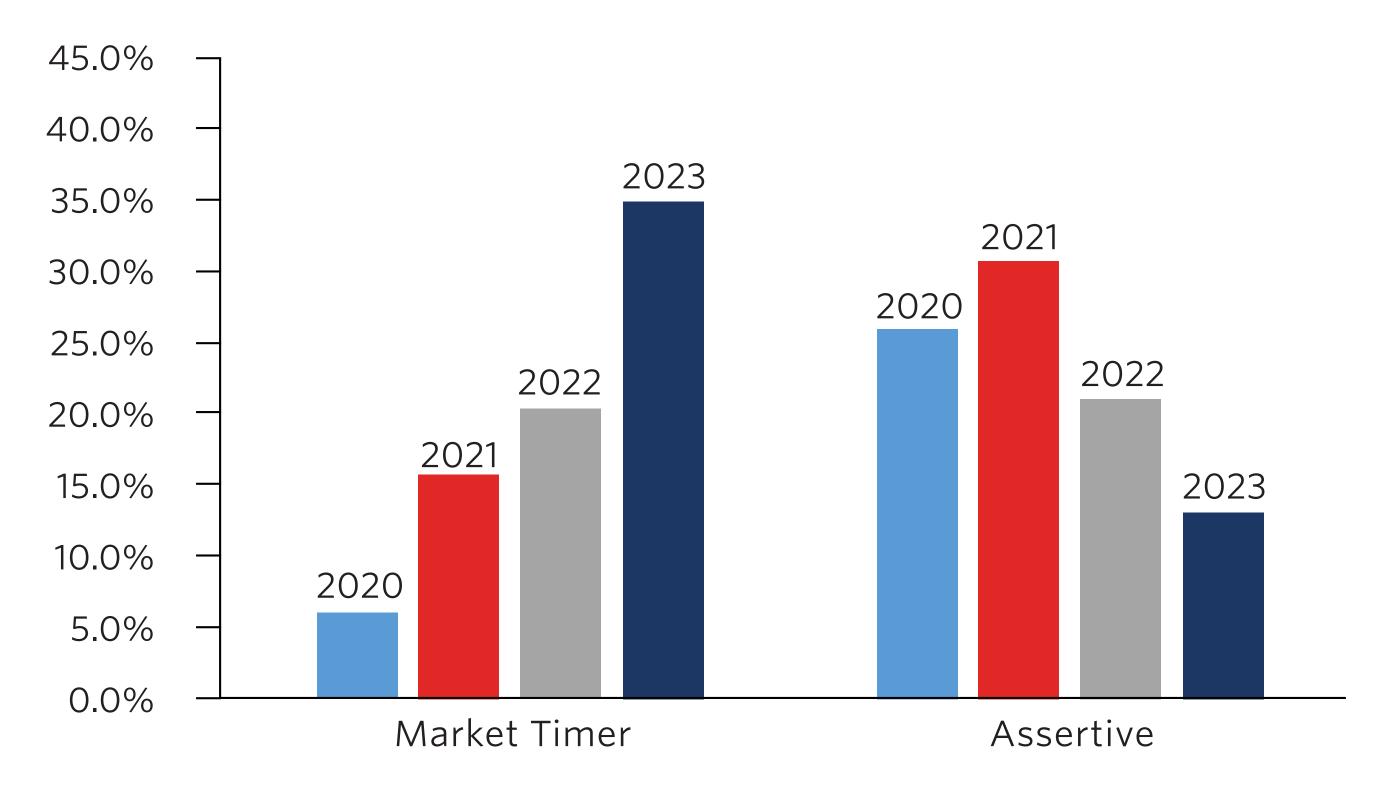
Archetype analysis

For 'Anxious' investors the fear factor results in an annualised behaviour tax of 3.73%. The fund outflows also correspond with this as investors leaving lowerperforming funds often miss the subsequent returns. The fear of lower investment returns in the short term often results in elevated behaviour tax levels.

Lastly the 'Avoiders' also (as usual) incur lower behaviour tax than the other archetypes by avoiding the market more (taking lower risk and switching in a neutral return band). This behaviour still led to slightly higher than normal behaviour tax at 2.23%.

When considering the recent trend in archetype proportions, it becomes clear that the 'Market Timers' are increasing in proportion (see Figure 8), largely at the expense of the 'Assertive' archetype. As markets (particularly since COVID-19) entered fairly choppy territory, it appears investors are being tempted into managing this volatility with increased switching on upturns as well as downturns.

Figure 8: Behaviour tax ranking and summary since COVID-19 (2020)

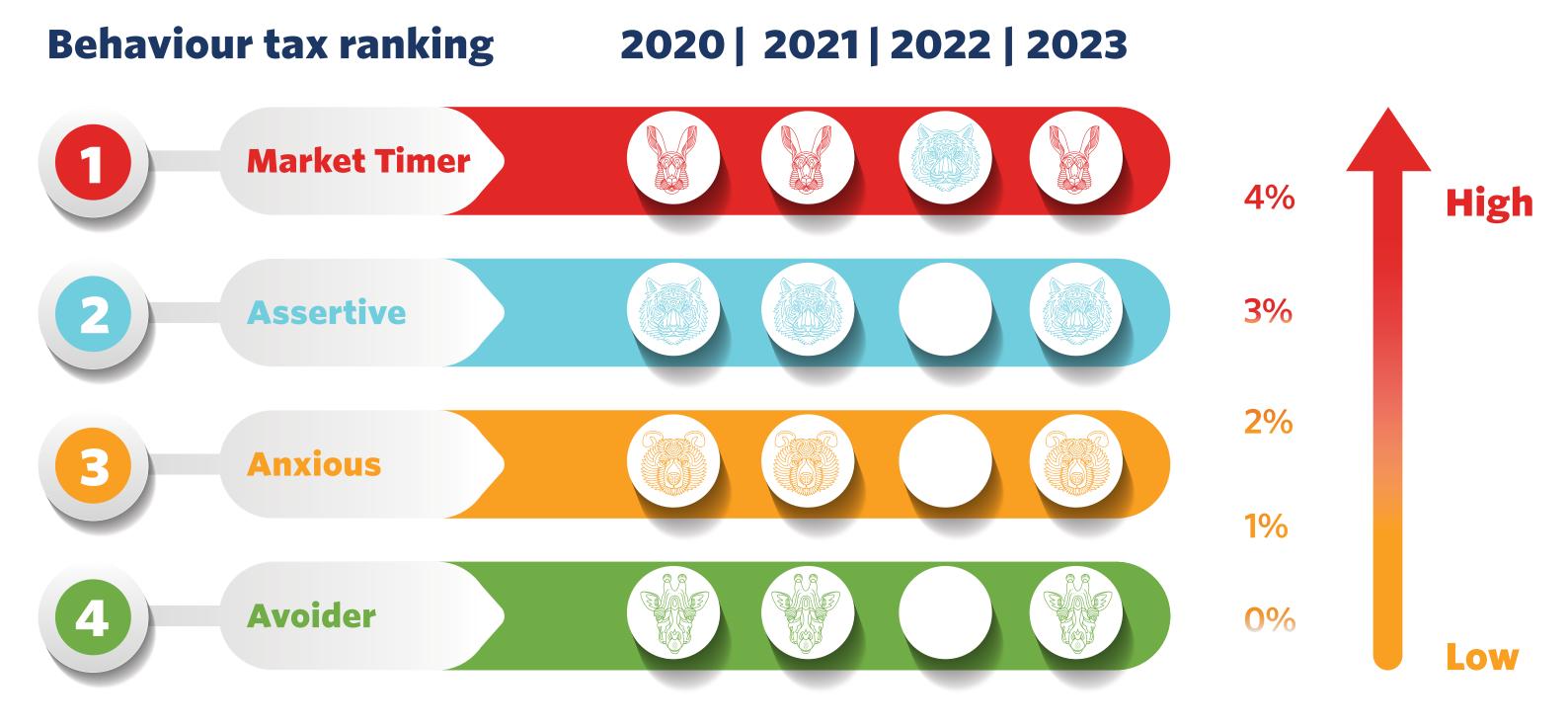


Source: Momentum Investments



Figure 9 shows the behaviour tax ranking since the COVID-19 period began in 2020. Two important insights are revealed here. Firstly, there is consistency. In three of the four analysis periods (75%) and in all periods where an overall behaviour tax was paid (by all archetypes) in 2020, 2021 and 2023, 'Market Timers' pay the worst behaviour tax and 'Avoiders' pay the least behaviour tax. Secondly, just because the overall behaviour tax is negative (as was the case in 2022), does not mean that all behaviour patterns escape the behaviour tax. In 2022, FIOs incurred a negative behaviour tax of 0.94% (value added from switching). Every archetype managed to escape the behaviour tax in 2022, except the 'Assertive' investor, who still incurs a substantial loss of 4.5%.

Figure 9: Behaviour tax ranking and summary since COVID (2020)



Source: Momentum Investments



Insights about the features of investors who switch

Supervised machine learning is a foundational approach within the field of artificial intelligence that involves training algorithms to learn patterns and make predictions based on labelled datasets. A suitable model is provided with input data and corresponding desired output labels (such as 'switch' or 'don't switch') enables the algorithm to learn the underlying relationships between the inputs (such as outcomes or past returns) and outputs (switches). This is useful behavioural analysis as the algorithm can reveal what the important factors are to investors when switching (detailed in Figure 10) and predict the behaviour.

Figure 10 shows that three important factors are driving the inclination of investors to perform switches:

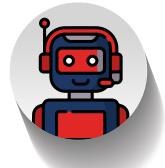
- **Loss aversion:** Those investors with more to lose (older with higher portfolio values) and also more funds (a greater number of funds is usually found with investors that have higher account balances indicative of the behavioral science principle of operational transparency⁴). We should expect those with more to lose and shorter period available to recover losses to be loss averse and more likely to switch in the perceived loss situation.
- **Belief system:** Those investors who make larger switches (in line with the first point), have performed at least one switch and have switched in the past year are more likely to continue this behaviour. This alludes to their belief system (win-stay; lose-move).

Risk perception: Finally, peer fund and market comparisons change the investor's perception of risk (how I am performing relative to others and to the market?). Sixmonth and one-year returns of the fund invested in as well as compared to overall market returns are good predictors of the investor continuing the behaviour of regular switching.

⁴Operational transparency refers to the tendency to pick a greater number of funds for investors with higher account balances to demonstrate more work (analysis) for the higher rand value of fees paid.

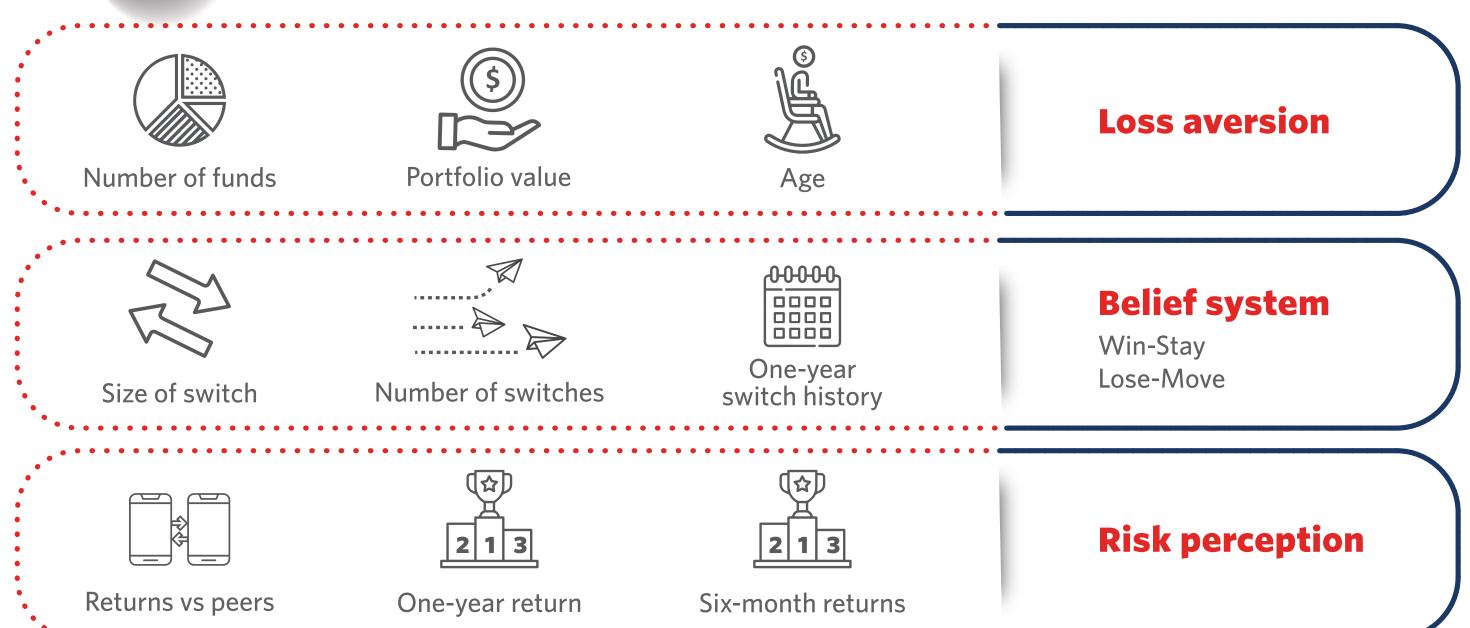


Figure 10: Random forest algorithm showing the features of investors that switch



Why do investors switch?

Machine learning using more than 12 million observations tells us



Source: Momentum Investments (2023)

Moving towards predictive models of investor switching

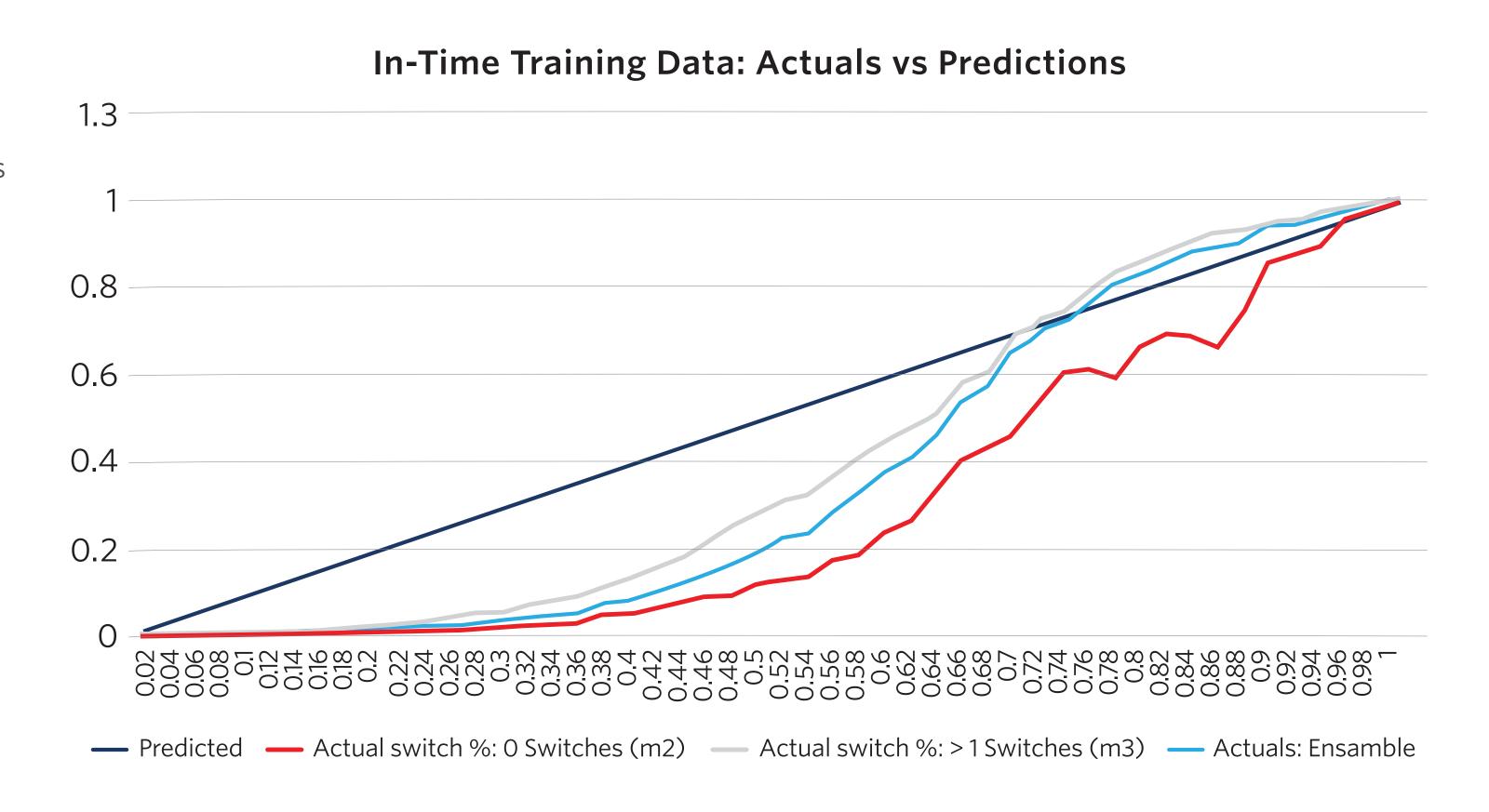
Using the random forest technique, we have produced a robust model of predictive investor switches based on the data features presented in the previous section. The diagonal blue line in figure 11 predicts investor switching (based on the feature discussed) and the light blue line (labelled 'ensemble') shows the returns of two models combined: One where investors have never switched before and one where investors have performed at least one prior switch.

The results are robust and surpass all commercial standards when using predictive machine learning models. While at low probabilities (< 70%), the model predicts more switches than the actual switch rate, this is not a problem as at low predicted switch rates a client or adviser would not be notified in any event.



Importantly, at higher probabilities (> 70%) the ensemble line tracks very well with the prediction (actuals switching matches predicted switching well). It should be noted that Figure 11 shows results using what is termed 'in-time' training data for the model. The model was trained on four years of data using over 12 million observations (switches and non-switches). The results of the 'out-of-time' model returns will be released soon.

Figure 11: Predicted compared to actual switching using random forest technique



Source: Momentum Investments (2023)



Ultimately, we are in an excellent position now to attempt to reduce the behaviour tax. We have excellent insights into the behaviour patterns over time as well as a good understanding of what 'inthe-moment' factors are important to investors when considering an investment switch that translates into an actual 'probability marker' for each investor on the platform that gives advisers the insights and time to intervene. In addition to this, the Momentum Money Fingerprint provides important psychological (personality) variables that will ultimately enhance these models even further.



Note: The full Behavioural Economics Guide (2023) is available <u>here</u>:





THE BEHAVIORAL ECONOMICS GUIDE

2023

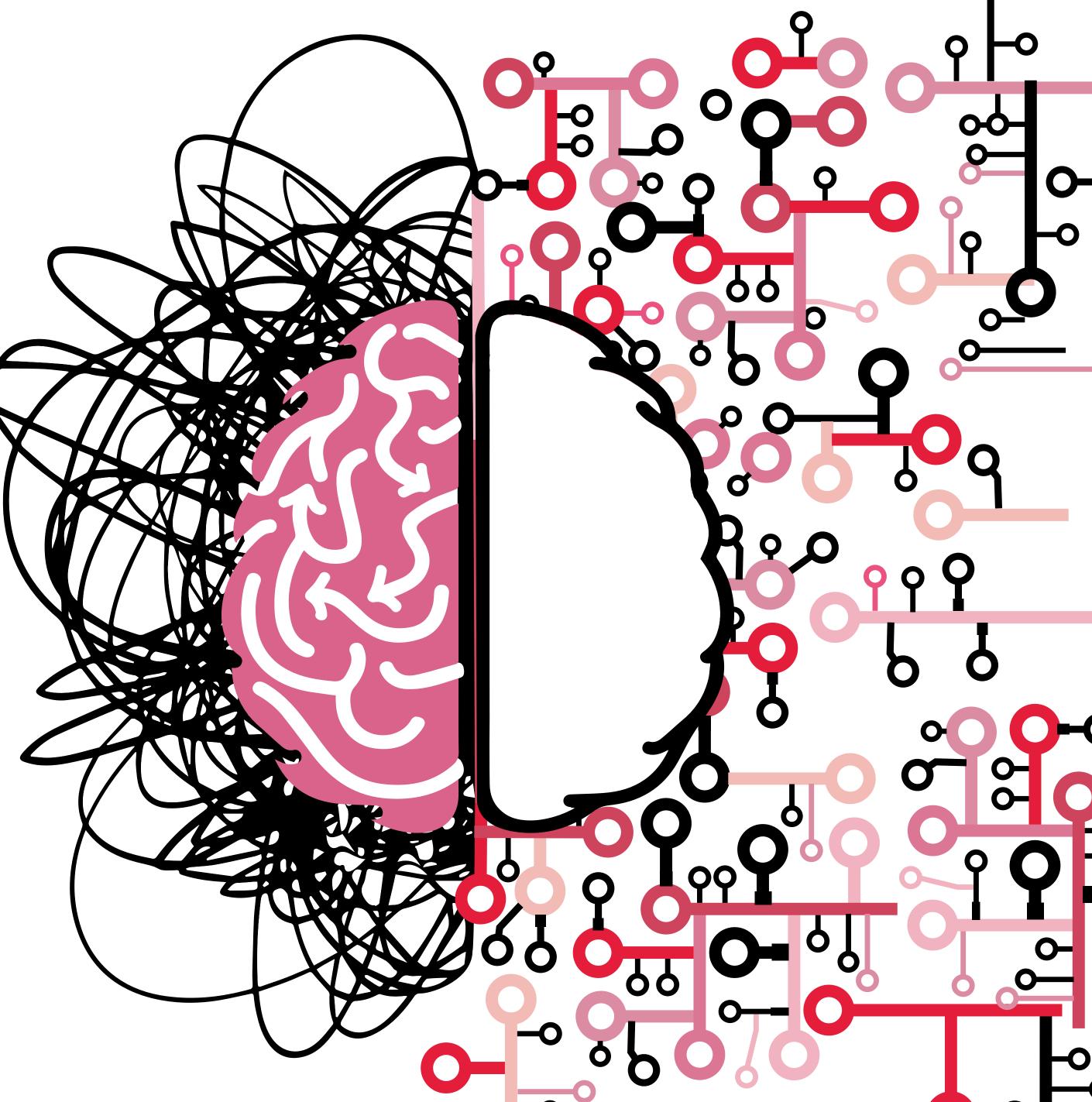
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South African Traders Show a Sunny COVID-19 Disposition (Effect)

PAUL NIXON¹ AND EVAN GILBERT

Momentum Investments

The decision to sell a stock can be influenced by whether that decision is framed as either a gain or a loss. This can influence investor trading behaviour in two ways: first, investors may hang on to losing positions for too long (loss aversion), and second, they may trade winning positions too frequently (regret aversion). Together, these two behaviours form one of the most widely studied biases in investment behaviour, namely, the disposition effect (DE). This paper examines the presence and size of the DE for a large group of South African traders on the Momentum Securities trading platform, before and during the COVID pandemic, which provides a natural experiment to examine differences

in trading behaviour driven by crisis events. The segmentation approach adopted in this paper (age and gender) offers novel insights that will allow stock brokerages to nudge the most severely affected clients to secure better investment outcomes.

Introduction

It was Benjamin Franklin who suggested that one's happiness depends more on their inward disposition of mind than on outward circumstances. The term "disposition" itself can be used to describe someone's inherent qualities of mind (a tendency to have a pleasant or "sunny" outlook) as well as the way something is arranged in relation to other things (relative to a point of reference), which creates perspective. An architectural plan shows the disposition of rooms, for example, from a particular perspective. Both descriptions help us understand one of the most widely documented behavioural biases, the disposition effect (DE), which refers to the general

inclination of investors to sell off winning assets too hastily and hold on to losing ones for too long. First demonstrated for investors by Odean (1998), the DE has been shown to hold for households, businesses (financial and otherwise), government, and even not-for-profit investors (Grinblatt & Keloharju, 2001). From a behavioural finance perspective, in 1985, economist Hersh Shefrin and behavioural economist Meir Statman would identify a similar change in preferences, depending on the investor's perspective. The change in perspective in this case depends on the reference point—a term credited by Daniel Kahneman to fellow psychologist Harry Helson in his 1964 paper on adaptation-level theory.

As shown in Figure 1, we tend to experience an unequal amount of dissatisfaction when wealth decreases by, say, \$50 when compared to the same satisfaction when our wealth increases by

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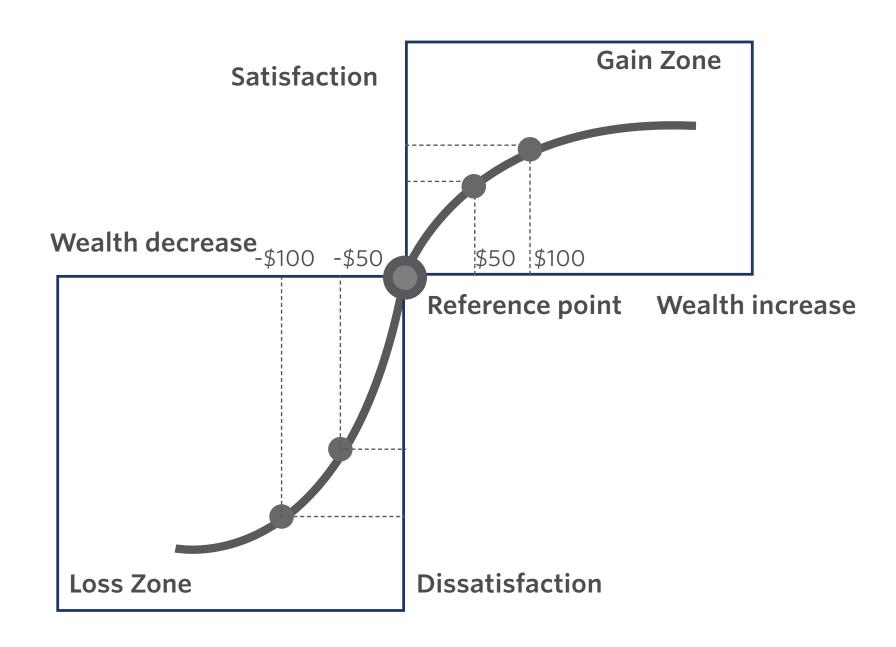




the same amount (\$50). Said differently, finding two \$50 notes on the street and losing one on the way home is not the same feeling as finding one \$50 note on the street. Our net change in wealth is the same (+\$50), but we don't feel the same after these two experiences because losses hurt more than the happiness created by the gain. Tversky and Kahneman (1979) termed this effect "Prospect Theory" (PT) and demonstrated it by offering participants choices or prospects that were framed as gains or losses, observing their change in preferences accordingly. Participants would generally accept a greater degree of risk to avoid painful prospective losses but were comfortable to avoid risk and accept a certain smaller gain.

For the purposes of this paper, it is not necessary to venture into a specification of the asymmetric value function in Figure 1, since the DE simplifies this to an extent by referring only to differences in behaviours on either side of the reference point. As we shall explain, it assumes that each frame (the relative gain or loss) subjects the investor to a separate al bias that leads to different types of behaviours in each zone or area. The DE thus makes a simple causal claim: there will be differences in behaviour around the reference point, and these will lead to non-rational behaviour in the wealth-maximising sense. It is also likely that this will be affected by external conditions.

Figure 1: Change in perceived value in investment gains versus losses. Source: Adapted from Van Raaij (2016).



From a psychological stress point of view, recent times have pushed people—and indeed investors to their limits. Tei and Fujino (2022) propose that the same social ties that have served the survival and continued thriving of our species caused significant psychological distress during the COVID-19 pandemic. Fears of being rejected (excluded from unvaccinated groups), infecting others (and indeed loved ones), and the breaking of social ties from forced lockdowns are just a few examples of how anxiety was amplified. From an investment perspective, we would expect the same anxiety in a financial context (Qin et. al., 2019)2 to amplify biases such as the DE.

This paper empirically examines the changes in behaviour of execution-only traders3, before and during the COVID-19 pandemic, on the Momentum Securities platform in South Africa. It reveals novel, statistically significant differences in the DE by

age group as well as by gender in the pre- and post-COVID periods. These findings strongly support the link between anxiety and the DE, which has implications for financial advice and other forms of engagement

with clients in an effort to help them from shooting themselves in the foot—financially at least—as they try to make themselves feel less anxious.

Possible Causes of the Disposition Effect (DE)

Measuring the DE is conditional on the specification of the reference point. As this is a subjective phenomenon, any measurement thereof is open to criticism, but from an investment perspective the initial purchase price is an obvious starting point, as it provides an objective basis against which to assess gains/losses and could credibly reflect the core reasons for the investor's emotions around their decision to buy at that price. Building on this base,

we can see that as the market price fluctuates, the investor will drift between so-called "paper losses" (current market price < purchase price) and "paper gains" (current market price > purchase price). Relevant biases that may affect the decision to realise these (sell the stock) at any specific point in time include the following.

The aversion to losses: Selling a losing share will turn a paper loss into a real one. If traders are loss-averse, then they are unlikely to realise this loss—there is always the temptation to wait a bit longer in the hope they turn into winners (Shah & Malik, 2021). The expectation is that they will hold on to "losers" for longer than they should.

The aversion to regrets: Selling out of a profitable position turns a paper gain into a real one and makes the trader feel good. Waiting for a larger profit can mean that a (currently) winning position could turn into a losing one (Shah and Malik, 2021). This

tendency encourages the selling of winners too quickly, as the trader fears the regret of the winning position reversing into a (painful) loss.

Baker and Nofsinger (2002) highlight two additional supporting concepts.

Mental accounting: Thaler (1985) introduces the concept of mental accounting whereby individuals have separate psychological accounts for investments in different contexts, such as retirement versus cash windfalls. Shefrin and Statman (1985) propose that when buying a stock, the trader opens a new mental account and considers value in relation to the purchase price or reference point.

Cognitive dissonance: It is also necessary to consider that factors other than simply realisation utility4 may be at play. It is plausible that we don't want to

sell a stock because doing so means admitting we were wrong, and this may be at odds with our selfimage (the savvy trader). The value of avoiding this psychological cost may be meaningful, even if the financial costs are clear.

DE of Execution-Only Traders on the Momentum Securities Platform

To examine the potential DE of South African execution-only traders, transactional data was obtained for a pre-COVID (1st January 2016 - 31st December 2019) period and COVID-period (January 1st 2020 to October 1st 2021) respectively. Execution-only traders are individuals trading via their own account (i.e., their accounts are not managed in any way).

The trader's DE is calculated in the same way as the seminal paper by Odean (1998), who predicted that investors would realise more gains, relative to the

number of gains that were available at the time, and fewer losses, realised relative to the number of losses available, again at that point in time. Following his methodology, a timeline of trading activity was then established for each trader. Each time a trade was executed (realised), the trader's portfolio was placed under the microscope to ascertain:

- The number of stock positions sold for a gain (1)
- The number of positions sold for a loss (2)
- The number of open positions (i.e., not sold) showing a gain [a paper gain] (3)
- The number of open positions (i.e., not sold) showing a loss [a paper loss] (4)

The benefit from selling assets and realizing a gain.

There were no explicit hypotheses on the differences between age and gender groupings at the onset. These variables were exploratory.



These gains and losses were all judged against the original purchase prices, using the closing prices on the day.

Tallying the realised gains (1) plus the paper gains

- (3) presents the total count of gains available for realisation at that point in time. Similarly, summing
- (2) and (4) gives the total count of losses available for realisation. These may be expressed as ratios:

Proportion of gains=
$$(Realised gains)$$
realised (PGR) $(Realised gains+Paper gains)$ Proportion of losses= $(Realised losses)$ realised (PLR) $(Realised losses+Paper losses)$ Disposition Ratio = PGR
PLR

A Disposition Ratio of >1 would indicate the proclivity of investors to realise more gains than losses, hence the existence of the DE. Note that for brevity the average of the ratio for the two periods is reported. Monthly results are also available.

Data and Preliminary Results

It was decided to segment the population according to age and gender, as these demographic variables were readily available in the dataset5. Table 1 not only shows each population group and the average Disposition Ratio (DR) over the time period, but it also separates the pre-COVID and COVID periods with a vertical line. The investor count (n), assets held on the trading platform by this group, and the average DE for the group are shown in the final column. Table 2 shows the difference in the DE from the pre-COVID to the COVID period, respectively.

Statistical Significance Testing Methodology

The following groups were compared with each other to ascertain any statistically significant effects of the COVID-19 pandemic in the DR, using the methodology summarised in Figure 2.

The Student's t-test was employed to test whether there was a difference in the means of the two particular groups (between the pre-COVID and COVID periods in this case). An important assumption for the Student's t-test, however, is that the variances of the two groups should be equal, so in order to ascertain this point, a Levene's Test was conducted. A Welch's two-sample t-test was used where differences in variances were found.



Table 1: Disposition Ratio Across All Groups

	2016	2017	2018	2019	2020	2021	n	Assets %	Average
All Traders	1.14	1.10	1.15	1.28	2.68	1.78	7474	100%	1.47
Males	1.21	1.10	1.18	1.28	3.14	1.93	2765	63%	1.64
Females	0.99	1.08	1.12	1.37	1.96	1.37	4709	37%	1.32
Gen Z (0 - 21)	2.14	1.39	1.20	1.22	1.73	2.41	450	2.18%	1.53
Millennials (22 – 37)	1.14	0.99	0.93	1.54	1.83	1.77	1292	7.03%	1.28
Gen X (38 - 53)	1.17	1.32	1.41	1.44	3.92	2.36	2344	27.35%	1.92
Boomers I (54 – 63)*	1.46	1.20	1.26	1.31	1.67	1.32	1918	33.16%	1.37
Boomers II (64 – 72)**	1.05	0.82	0.89	1.04	1.57	1.38	1470	30.29%	1.04

^{*} It was decided to split the overall Boomers group into two subgroups with clear behavioral differences.

** Clients over the age of 72 were not included in this analysis, as their trade frequency is very low.



Table 2: Average Distribution Ratios for the Pre-COVID and COVID Periods

	Pre-COVID DR	COVID DR	% Increase
All traders	1.17	2.23	91%
Males	1.19	2.54	113%
Females	1.14	1.67	46%
Gen Z	1.49	2.07	39%
Millennials	1.15	1.80	57%
Gen X	1.33	3.14	136%
Boomers I	1.31	1.50	15%
Boomers II	0.95	1.48	56%



The tables and figures that follow set out the results of the various statistical significance tests. A specific example of the entire population is first given in detail to illustrate the testing process followed herein. A box and whisker plot of the DR results for the two periods is illustrated in Figure 3, which clearly highlights the differences in the behaviour at an aggregate level for these two periods. The results for the other groups are reported in Table 4.

Discussion and Key Findings

The key findings from the sections 5 and 6 of this paper are as follows:

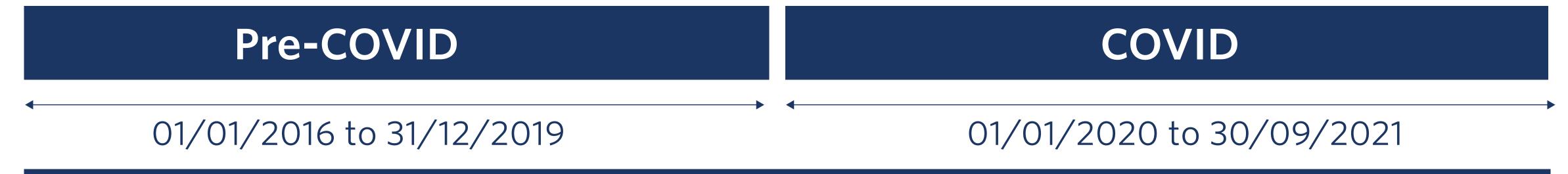
- From 2018 to 2021, there existed a statistically significant DE (a DR of > 1) across all traders at a 95% confidence interval in each year 6.
- There is a 95% certainty the DR is significantly
- greater during COVID for the entire sample.
- Both males and females show a statistically
- significantly greater DR during COVID.

These tests are not shown here but are available from the corresponding author on request.



Figure 2: Statistical significance and testing process.

Disposition Effect



Group 1: All Traders (n=7474)

Group 2: Males (n=4633) Females (n=2841)

Group 3: Age Group: Gen Z; Millennials; Gen X; Boomer I; Boomer II

Behavioral Economics Guide 2023 🚊



Figure 2: Statistical significance and testing process.

Levene Test to establish differences in variance between pre-COVID and COVID groups

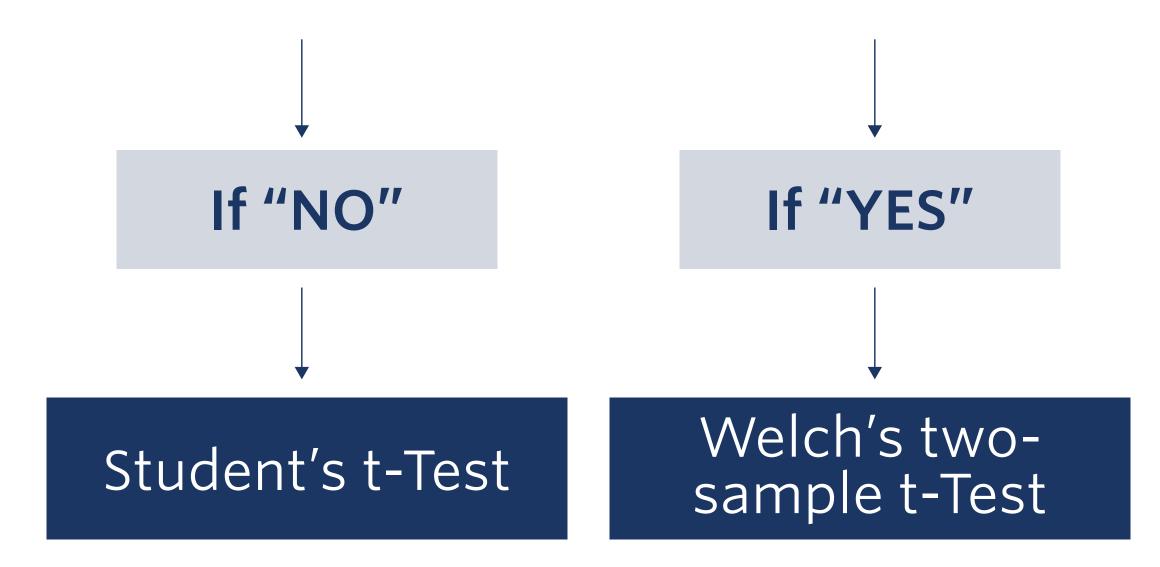




Table 3: Testing for the Effect of COVID on the DRs for All Traders

Statistical Test	Hypotheses	Test Results	Outcome
Levene's test	H0: Groups have equal variances. H1: Groups have different variances.	p=.000	Reject H0 and use Welch's t-test
Welch's t-test	HO: There is no difference in means. H1: The difference in means is greater than 0.	p=.000 $t(20.425) = 5.473$ Lower bound (one-tailed test) = 0.789 $Sample estimate$ $(COVID) = 1.167$	Accept H1: Overall traders DRs were higher during the COVID-19 period. There is a 95% chance that the DE was greater during COVID.



Figure 3: Box and whiskers plot of overall traders' DRs pre-COVID vs COVID.

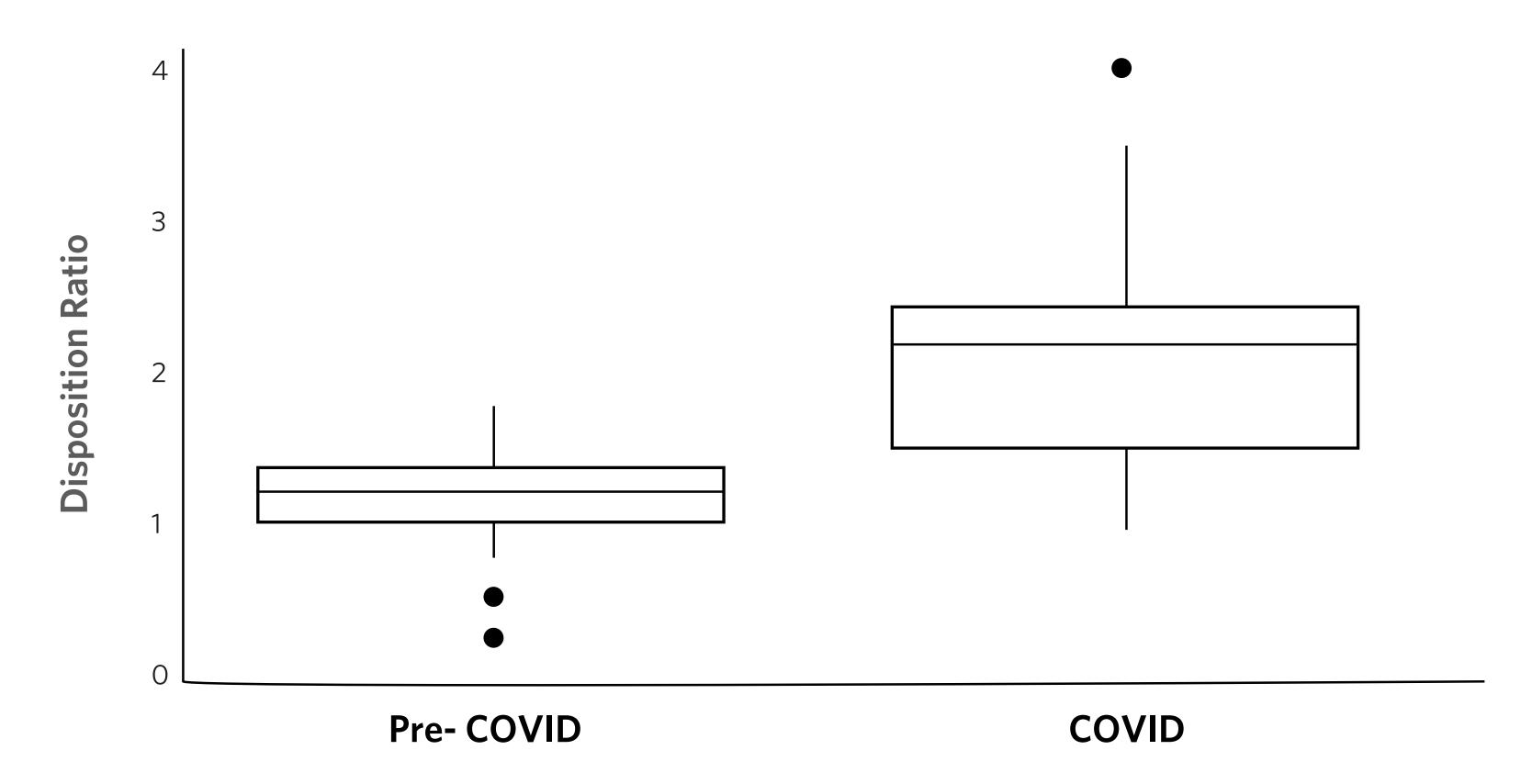




Table 4: Testing for Differences in DR Pre-COVID vs COVID—Remaining Groups

Statistical Test	Hypotheses	Test Results	Outcome
Males	0.000	0.000	DR was higher during COVID
Females	0.007	0.000	DR was higher during COVID
Gen Z	0.370	0.098	No differences in DR during COVID
Millennials	0.818	0.000	DR was higher during COVID
Gen X	0.004	0.000	DR was higher during COVID
Boomers I	0.212	0.034	No differences in DR during COVID
Boomers II	0.000	0.000	DR was higher during COVID



- Although this is not reported above, females have a lower variance in DR as well as a lower DR on average.
- The Gen Z group (0 21) are the smallest pro- portion of the population but have the highest DE prior to the pandemic (in normal market conditions). This is consistent with Steves (2022), who cites Gen Z as the most risk-averse generation.
- Gen Xers have an extremely high DE during COVID of 3.92, indicating that ≈ 80% of trades take place in the gain zone or ≈ 20% in the loss zone.
- Gen Xerscomprise 31% of the studiedpopulation and 27% of the invested assets studied. They are therefore the obvious target for the intervention studies discussed in the conclusion.

The Millennial, Gen X, and Boomer II groups all show statistically significant increases in DE during COVID and therefore are more prone to elevated loss and regret aversion.

The evidence suggests that emotions and anxiety are related to the size of the overall DE (in both males and females) and in the Millennial, Gen Xer, and Boomer II groups7. This diversity in age group behaviour suggests that there may be specific age-related conditional factors that affect this behaviour.

Conclusion and Recommendations

This study confirms the existence of the DE for this population of investors over the period studied and indicates that the size of the effect was significantly positively affected by the COVID environment. Furthermore, it provides insights into the segmentation of the trader population, clearly revealing preferences that are statistically significant in respect of gender differences and (some) age groupings, both before8 and during the COVID period9. The presence of age-related differences in the specific responses suggests that there are additional potential factors at play, which should be explored further.

These insights will allow trading securities platforms to begin focusing their nudging strategies on segments where they are most needed. This paper determines how Gen Xers—and particularly male Gen Xers—need the most help in trying to minimise their DE10. Trading and securities platforms can nudge this cohort to use advanced trading strategies such as stop-losses to create a predefined floor on investment losses, thereby forcing the trader to execute a trade and not allowing losses to run. Richards et. al. (2017) show that this strategy is effective in minimising the DE in the zone of losses as well as gains.

Having the psychological assurance that losses are somewhat limited appears to give traders the confidence to hold on to their winners for longer (trade less). More innovative social trading strategies are emerging as well, as demonstrated by Jin and Zhu (2021), who posited that having trades open to public view appears to curb the DE. Moreover, many stockbroking offerings in South Africa offer the services of a professional portfolio manager to buy and sell stocks on behalf of the investor, and in this regard Shapira and Venezia (2001) show that employing such services also reduces the DE.

These are many possibilities to explore in rela-

tion to helping (South African) investors to better outcomes and the important role that stockbroking firms could play in achieving this by understanding their customers' disposition effect. Further research

is also underway in understanding the probability distributions of investor trading behaviour around the reference point, as well as different calculations of this reference point, to understand better any causal relationships. Age-related differences also suggest the presence of other important explanatory factors.

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⁷ While anxiety is not specifically studied as a variable published research suggests that market turbulence is linked to anxiety (Qin, 2019).

⁸ These tests are available from the corresponding author.

⁹ Further research is also recommended in respect of comparing the period of market turbulence that COVID presented with the 2008 Global Financial Crisis for example where the turbulence was longer to examine the effects on the DE (if any). 10 Further research is needed in respect of age and gender differences as well psychological differences such as personality traits that may contribute to a better understanding of differences in the samples.



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