Research Field: BEHAVIOURAL FINANCE

A SERIES OF EXPERIMENTAL ANALYSES INTO THE DISPOSITION EFFECT AND ITS MANIFESTATIONS AMONG SOUTH AFRICAN INVESTOR TEAMS

by

PHILANI SHANDU

A Doctoral Thesis submitted in fulfilment of the requirements for the degree of DOCTOR OF PHILOSOPHY (Management with specialisation in Finance) in the Wits Business School; Commerce, Law, & Management Faculty of The University of the Witwatersrand, Johannesburg

Supervisor: PROFESSOR IMHOTEP ALAGIDEDE

ABSTRACT

In behavioural finance literature, there is a significant amount of both empirical and experimental evidence to suggest that prior outcomes impact investment decisions through cognitive biases which most (if not all) human investors succumb to. Among the most pervasive of these biases is the disposition effect, which manifests as the tendency of the investor to sell winning stocks too soon and hold on to losing stocks for too long (Shefrin and Statman, 1985). Critically, the disposition effect is understood to lead to suboptimal portfolio returns (i.e., suboptimal levels of investor welfare). While there have been several studies in other emerging markets, studies remain few in Africa and do not address some of the important issues underpinning the intensity and nature of the disposition effect among African investors. This thesis responds to this gap by designing and analysing several field experiments which explore causal relationships between psycho-social, public health-related, and socio-political factors and the emergence, prevalence, and intensity of the disposition effect among South African university student investor teams participating in the 2019, 2020, and 2021 runs of the Johannesburg Stock Exchange (JSE) Investment Challenge. The thesis is organised into three experimental studies, each speaking to specific theme/s that form the research's core objective while employing unique data and sound econometric techniques known to be relevant to experimental analysis in finance studies.

The first study in Chapter 2 of the thesis endeavours to determine (i) whether the disposition effect exists among South African investor teams, (ii) whether it is causally intensified by a set of psycho-social factors, and (iii) whether the disposition effect causally reduces investor welfare. Among the study's main findings are that South African investor teams are susceptible to the disposition effect, and that their susceptibility to the bias causally attenuates their investor welfare. Furthermore, low female representation in an investor team is found to causally intensify the disposition effect, subsequently leading to a decrease in investor welfare. Using

evidence from real-world observation, the study contributes to the literature on team gender diversity and investment decision-making, and – using Hofstede's (2001) cultural dimensions – it offers a comprehensive account for how differences in culture may lead to differences in gender-related disposition effects across different nationalities. The study also introduces to the literature experimental evidence from the field that clearly demonstrates that – among South African investor teams – a causal relationship exists (i) between female representation and the disposition effect, and (ii) between the disposition effect and investor welfare.

The thesis' second study, which is set in the context of the COVID-19 pandemic, finds statistically significant evidence to suggest that (a) quarantining at home in response to high, localised COVID-19 infection rates causally leads to a greater presence of the disposition effect among South African investor teams, and that (b) the presence of the disposition effect among said investor teams causally increases their trading activity. The results of the study are the first to empirically demonstrate how quarantining at home during a public health crisis can causally lead to the emergence of the disposition effect, which subsequently causes an increase in trading volumes. Importantly, the study contributes towards the advancement of the argument that an increase in the salience of stocks' prices in previous trading periods, as investor teams quarantine at home (in response to heightened contagion risk, locally), causally increases the prevalence of the disposition effect among said investor teams. This argument is closely associated with the view that contagion-induced negative mood disorders may have ultimately caused the disposition effect to emerge among the relevant cohort of investor teams in the study's subject pool, by way of mood regulation attempts. Taken together, these two views are the first to offer empirically-sound positions on how a public health crisis can ultimately cause the disposition effect to emerge via both the saliency shock (Fryman and Wang, 2020) and mood regulation (Li *et al.*, 2021) mechanisms.

The final study in Chapter 4 endeavours to assess the relationship between socio-political developments and the disposition effect. In this regard, the study investigates whether mood regulation attempts – in response to negative mood disorders induced by close exposure to incidents of civil unrest – have a causal impact on the disposition effects of South African investor teams, and finds that such mood regulation attempts causally increase said teams' disposition effects by as much as 140 percent. As the first quasi-experimental study on the relationship between socio-political upheaval and the disposition effect, the results of the study extend the literature's understandings regarding the robustness of mood-induced disposition effects beyond their more commonly researched relationship with weather effects.

Keywords: Instrumental Variables (IV) Estimation, Field Experiments, Investment decisions, Portfolio choice, Institutional investors, Behavioral Finance.

JEL Classifications: C26, C93, G11, G23, G40.

PUBLICATIONS AND OUTPUTS

Prior to submission, portions of this thesis have been published in the following peer-reviewed journal, while others are under submission. A previous publication that is closely related to the subject-matter of the current thesis is also noted.

Peer-reviewed Journal Publication

1. Shandu, P. and Alagidede, I.P. (2022), "The disposition effect and its manifestations in South African investor teams", *Review of Behavioral Finance*, ahead-of-print, https://doi.org/10.1108/RBF-01-2022-0027.

Papers under Review

1. Shandu, P. and Alagidede, I.P. (2023), " Quarantining-at-home during the COVID-19 pandemic and the disposition effect", *Financial Analysts Journal*.
2. Shandu, P. and Alagidede, I.P. (2023), " South African civil unrest and the disposition effect: A difference-in-differences analysis", *Journal of Behavioral and Experimental Finance*.

Previous Publication

1. Shandu, P., Boako, G. and Alagidede, P. (2018), "Price leadership in the South African foreign-exchange market: an empirical analysis", *International Journal of Emerging Markets*, Vol. 13 No: 1, pp.87-117. https://doi.org/10.1108/IJoEM-07-2016-0173.

DECLARATION

I, **Philani Shandu**, hereby declare that this thesis is my own work except as indicated in the references and acknowledgements. It is submitted in fulfilment of the requirements for the award of the Doctor of Philosophy degree in the field of Management with specialisation in Finance at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Philani Shandu

Signed at………………Johannesburg, South Africa…………………………….....…………...

On this………………31st ….…………**day of**.....…………July, 2023…...…………………...

DEDICATION

Mthiya! Ndabezitha! Sontshikazi kaMpangazitha! Shandu kaNdaba! I dedicate this thesis to my late Father, S’busiso Shandu – whose passing triggered my embarking on this Ph.D. journey; and my Son, Qhawe Itumeleng Shandu – whose birth motivated me to stay the course.

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LIST OF ABBREVIATIONS

Abbreviation	*Meaning*
2SLS	Two-Stage Least Squares
ALSH	FTSE/JSE All Share Index
AltX	Alternative Exchange Board
AMEX	American Stock Exchange
ATE	Average Treatment Effects
CAGR	Compounded Annual Growth Rate
COVID-19	Coronavirus Disease of 2019
DE	Disposition Effect
DiD	Difference-in-Differences
ETF	Exchange-Traded Funds
ETN	Exchange-Traded Notes
fMRI	Functional Magnetic Resonance Imaging
FTSE	Financial Times Stock Exchange
GDP	Gross Domestic Product
GFI	Global Fear Index
ICASA	Independent Communications Authority of South Africa
IMF	International Monetary Fund
IPO	Initial Public Offering
ISS	Institute of Security Studies
IV	Instrumental Variable
JSE	Johannesburg Stock Exchange
OECD	Organisation for Economic Co-operation and Development
LIML	Limited Information Maximum Likelihood

MSCI	Morgan Stanley Capital International
MTN	Mobile Telecommunications Network
NICD	National Institute of Communicable Diseases
NYSE	New York Stock Exchange
PCR	Polymerase Chain Reaction
PGR	Proportion of Gains Realised
PLR	Proportion of Losers Realised
PSL	Probability of Selling Losers
PSW	Probability of Selling Winners
Q&A	Questions & Answers
S&P 500	Standard and Poor 500 Index
SABC	South African Broadcasting Company
SARB	South African Reserve Bank
SSE	Sustainable Stock Exchanges
SSF	Single Stock Futures
UK	United Kingdom
UNISA	University of South Africa
US	United States
vmPFC	Ventromedial Prefrontal Cortex
vSt	Ventral Striatum
WHO	World Health Organisation
ZAR	South African Rand

CHAPTER ONE

Introduction

1.1. Background to the study

Central to the rationality-based expected utility theory is the idea that investors derive utility from final state wealth, and that they are generally indifferent as to how they might arrive at this terminal state of wealth. An implication of such a theory is that changes in wealth do not factor in determinations of utility, and therefore prior outcomes should not factor in future decisions (Kahneman and Tversky, 1979). On the contrary, there is a significant amount of evidence in the behavioural finance literature to suggest that prior outcomes impact investors' decisions, and ultimately, the performance of their portfolios.

The disposition effect, first discussed in Shefrin and Statman (1985), is a cognitive bias that refers to an investor's tendency to sell winning stocks too soon, and hold on to losers for too long, in a manner consistent with the postulations of prospect theory's S-shaped value function (Kahneman and Tversky, 1979). In support of Shefrin and Statman's (1985) theoretical assertions regarding the disposition effect, Odean (1998) finds empirical evidence that demonstrates that individual investors exhibit a strong tendency to realise winning stock positions rather than losing ones in their portfolios. This disposition effect has been observed in a variety of financial market contexts and across a range of trader types and transactions, including individual day trader transactions (Jordan and Diltz, 2004), professionally-managed trading accounts at a middle-eastern brokerage service provider (Shapira and Venezia, 2001), China-based stock market investors (Feng and Seasholes, 2005; Chen *et al.*, 2007), and experimental markets (Summers and Duxbury, 2012). The existence and prevalence of the disposition effect is not only interesting because it entertains the idea that changes in wealth (rather than final state wealth itself) do indeed affect investment decision-making, but also because it brings to bear the detrimental impact that an investment decision-making error of this kind can pose to portfolio performance. As noted in Roger (2009) and evidenced in Odean (1998) as well as Duxbury *et al.* (2015), the disposition effect results in lower levels of investor welfare, with the extent of such losses in welfare being determined by the intensity of the bias.

From a research design perspective, non-experimental examinations of the impact of prior outcomes on investor decision-making and behaviour – based on actual/real trading data – can prove to be problematic. For instance, under the auspices of rational economic theory, research efforts driven by non-experimental empirical analysis might suggest that observed trading behaviour is largely driven by investors' expectations regarding future asset prices and returns (with such expectations being unobservable and uncontrollable by researchers) instead of the impact of prior outcomes.

The experimental method, on the other hand, enables researchers to not only control or manipulate future expectations, but also allows for isolated measurements of the causal impact of prior outcomes on trading behaviour. In this regard, there is a significant amount of experimental evidence which shows the existence of the disposition effect; with much of it following on Weber and Camerer (1998), who are understood to have conducted the seminal experimental examination of the disposition effect. Be that as it may, experimental studies of the disposition effect are (to the best of our knowledge) non-existent in the African context, with the few non-experimental studies that do exist being methodologically unable to investigate the factors that cause the emergence and prevalence of the disposition effect among African investors, as well as being unable to appropriately interrogate whether a causal relationship exists between the disposition effect and other investor-level variables of interest such as portfolio performance and trading activity.

Understanding the issues above is critical as the disposition effect is known to play an important role in aggregate stock market activity (Kaustia, 2004; Goossens and Knoef, 2020); meaning that market practitioners and regulators who understand the nature and the causes of the disposition effect among African investors might be better equipped to anticipate and respond to the market distortions that may come with the widespread emergence of the bias. Another reason that speaks to the importance of studying the nature and causes of the disposition effect among African investors in particular is the view in the literature that the factors that cause the bias may vary depending on the cultural context of the investors under observation (Rau, 2014). Given the apparent absence of experimental studies of the disposition effect among African investors, it follows that little is understood regarding how nuances between the cultures of African investors and those of investors from other regions of the world inform the nature of the factors that cause the disposition effects of African investors versus those of other investors.

1.2. Objectives of the thesis

To fill the apparent void in the literature of experimental studies that address some of the important issues underpinning the intensity and nature of the disposition effect among African investors, the objective of this thesis is to design and analyse several field experiments which explore causal relationships between psycho-social, public health-related, and socio-political factors and the emergence, prevalence, and intensity of the disposition effect among South African investor teams. Importantly, we expect the thesis' findings regarding the aforementioned relationships to pose notable implications for academic researchers, market regulators, and market practitioners alike.

1.3. Significance of the thesis

The contributions of the thesis' studies to extant literature underscore the significance and justifications for conducting this research. Beginning with the first study, contributions are made to the literature on team gender diversity and investment decision-making, and – using the Hofstede's (2001) cultural dimensions – we offer a comprehensive account of how differences in culture may lead to differences in gender-related disposition effects across different nationalities. The study also introduces to the literature experimental evidence from the field that clearly demonstrates a causal relationship between female representation and the disposition effect, as well as between the disposition effect and investor welfare among South African investor teams.

The second study is the first to introduce to the literature externally valid findings that (1) quarantining at home in response to high, localised COVID-19 infection rates causally leads to a greater presence of the disposition effect, and that (2) the presence of disposition effect causally increases the trading activity of South African investor teams quarantining at home in response to localised COVID-19 waves during the pandemic. Another important contribution of the study is its advancement of the argument that an increase in the *salience* of stocks' prices in previous trading periods, as investor teams quarantine at home (in response to heightened contagion risk, locally), causally increases the prevalence of the disposition effect among said investor teams. This argument is closely associated with the view that contagion-induced negative mood disorders may have ultimately caused the disposition effect to emerge among the relevant cohort of investor teams in the study's subject pool, by way of *mood regulation attempts*. Taken together, these two views are the first to offer empirically-sound positions on how a public health crisis can ultimately cause the disposition effect to emerge via both the saliency shock (Fryman and Wang, 2020) and mood regulation (Li *et al.*, 2021) mechanisms.

As the first quasi-experimental study on the relationship between socio-political upheaval and the disposition effect, the results of the third study extend the literature's understandings regarding the robustness of mood-induced disposition effects beyond their more commonly researched relationship with weather effects. In addition to this, the study introduces to the literature the concept of the *psychological pain of losing*, which refers the burst of disutility experienced by investors as they realise their losing positions and subsequently regulate their risk-taking behaviour. Unlike the realisation effect (Imas, 2016), the pain of paying provides an explanation as to why investors participating in a market with negatively skewed investment opportunities do not 'chase' their unrealised losses (as might be the case in the context of a market with positively skewed investment opportunities (Imas, 2016)). In particular, the concept suggests how the prospect of a large loss (as is the case in a market with negatively skewed investment opportunities) may be perceived in a manner like the prospect of an experience of intense physical pain (Redelmeier *et al.*, 2003), and thus be accordingly avoided. The pain of paying thus consolidates how the realisation effect, realisation utility models, and prospect theory preferences explain the disposition effect.

In sum, the thesis makes important contributions to the behavioural finance literature regarding the causal impact of psycho-social, public health, and socio-political related factors on the emergence and existence of disposition effects among investors. The data employed in the three studies is from the 2019, 2020, and 2021 runs of the JSE Investment Challenge (a real-time JSE market trading simulation), however we suspect that the results of the thesis may very well apply across a broader set of markets. Overall, the results of the thesis are the first to suggest that (i) investor teams composed of more men than women causally demonstrate significantly higher disposition effects; (ii) quarantining at home during a public health crisis causally leads to the emergence of the disposition effect, which subsequently causes an increase in trading volumes; and (iii) close exposure to civil unrest causally increases disposition effects by 140 percent. Collectively, these insights shed new light on the eclectic array of factors that cause the emergence and intensity of the bias, as well as provide support to the commonly made assertion that the disposition effect is among the most pervasive of biases in the behavioural finance literature (Shefrin and Statman, 1985; Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005). More practically, given the disposition effect's important consequence of reducing investor welfare, these insights could be useful in helping asset management firms determine how best to compose investor teams, and could help market practitioners and regulators better anticipate, and respond to the market distortions that may be caused by events (such as a public health crisis or nationwide civil unrest) known to usher in widespread disposition effects.

Another notable novelty of this thesis is exemplified in the methodologies that we employ. Importantly, our employment of different econometric techniques (or what Moffatt (2016) might refer to as "experimetric" techniques) and unique data constitutes a significant advancement in empirical and experimental studies conducted on African investors and within the African market context.

Beyond the experimental inquiries conducted in the current thesis, each research study also contributes several conjectures concerning three behavioural models for the disposition effect. Namely, these are Prospect Theory, the Mean-Reversion Hypothesis, and Realisation Utility.

In brief, the first study conjectures that miscalibrations (i.e., overconfidence) in expectations regarding the future values of losing stocks manifest as the prospect theory preference of risk-seeking-over-losses (Kahneman and Tversky, 1979); a miscalibration that is empirically understood to be more synonymous with men than women (Barber and Odean, 2000; Da Costa *et al.*, 2008).

The second study presents a counter-argument to Weber and Camerer's (1998) view that the mean-reversion does not suffice as an explanation for why the disposition effect occurs. In particular, we argue that a break in a behaviour (e.g., a disruption to the irrational behaviour of holding a losing stock position for too long) due to the introduction of a decision point or partition (e.g., an automatic sell order as in the case of the Weber and Camerer (1998) experiments) mitigates against the intensity of the prevailing bias – (Cheema and Soman, 2008) which in this case is the disposition effect. Therefore, the effect that a given investor's urge to believe in mean-reversion has on their disposition effects holds only on condition that their investment decision-making process is not partitioned.

Regarding realisation utility, as discussed in the paragraph above, the third study introduces to the literature the concept of the psychological pain of losing as means of unifying how realisation utility (Barberis and Xiong, 2012), the realisation effect, and prospect theory explain the emergence and intensity of the disposition effect.

In the main, our analysis of the literature on the sources of the disposition effect shows that prospect theory principles are a ‘common thread’ that weave these models together. For instance, we conjecture that an irrational belief in mean-reversion entrenches the disposition effect largely through risk-seeking in the losses domain and affirm the existing position in the literature that – in the context of realisation utility-informed disposition effects – mood regulation attempts manifest as risk aversion in the gains domain (through, for example, excessive selling of winning stock positions). This common thread, perhaps, can be viewed as yet another rationale for why we go beyond Barberis and Xiong’s (2012) suggestion that only prospect theory preferences and realisation utility models are alternatives to one another, and assert that the mean-reversion hypothesis is also a suitable substitute for either of the former two, particularly under circumstances where an investor’s trading behaviour is not partitioned.

1.4. Structure of the thesis

In all, the contributions of this thesis are organised in three natural-field experimentation research chapters. In the following paragraphs, we summarise the studies in Chapters 2 to 4 by briefly highlighting their respective methodologies, key findings, and contributions to the literature. It is worth bearing in mind that only brief summaries are provided in the paragraphs below, therefore interested readers are encouraged to read in detail the appended research chapters.

Chapter 2: Following a natural-field experimentation design involving a subject pool of human investor teams and robots participating in the 2019 run of the JSE University Investment Challenge, we use regression adjustments, parametric and non-parametric tests, as well as bootstrap tests to investigate the casual implications of a set of psycho-social factors on the intensity of the disposition effect, as well as on the attenuation of market-adjusted *ex post* returns (i.e., investor welfare). In this regard, the study finds (i) that South African investor teams do indeed succumb to the disposition effect, (ii) that investor teams characterised by low levels of female composition show causally more intense disposition effects, and (iii) that factors which intensify investor teams' disposition effects causally decrease their investor welfare. The aforementioned findings (ii) and (iii) are the first of their kind and thus introduce to the literature new perspectives regarding how team gender diversity interacts with the quality of investor groups' decision-making within an African country's cultural context, and how this interaction affects said investor groups' portfolio outcomes.

Chapter 3: We once again follow a natural-field experimentation approach in this essay, however this time a sample of student investor teams participating in the 2020 (i.e., COVID-19 pandemic era) run of the JSE Investment Challenge comprise the study's subject pool. Furthermore, the study tests for average treatment effects (ATEs) by making use of regression adjustments and Wilcoxon tests in order to determine whether quarantining at home in response to high, localised COVID-19 infection rates during the pandemic causally impacts the disposition effects of South African investor teams, and subsequently runs ordinary least squares (OLS), Logit, and Probit regressions as robustness checks on the results of the ATE tests. To establish whether the disposition effects of said investor teams causally increase their trading activity, the study follows the instrumental variable (IV) approach by running two-stage least squares (2SLS) regressions involving order flow volumes as the dependent variable, the presence of the disposition effect as an endogenous regressor, and provinces characterised by high infection rates and low human mobility as an instrumental variable. The results of the study affirm our hypotheses that (a) quarantining at home during a public health crisis causally leads to the emergence of the disposition effect, which (b) subsequently causes an increase in trading volumes. These results are the first in the literature to use experimental means to demonstrate how a public health crisis can ultimately cause the disposition effect to emerge via both the saliency shock and mood regulation mechanisms. Regarding the mood regulation mechanism, researchers and market-practitioners alike might find value in using population mood indicators such as happiness or fear indices to predict market dynamics such as return performance (given the disposition effect's tendency to lead to suboptimal portfolio outcomes) and turnover volumes. In addition, the mood regulation mechanism may pose important implications for employee wellbeing among the staff of investment management firms, as the negative moods of trading desk staff – for example – may hamper portfolio performance through the channel of the disposition effect, if left unchecked.

Chapter 4: In pursuing an investigation into whether mood regulation attempts – in response to negative mood disorders induced by close exposure to incidents of civil unrest – have a causal impact on the disposition effects of South African investor teams, we employ a difference-in-differences (DiD) approach to estimate the impact of a shock that exposes university-level aggregate investor teams to incidents of civil unrest. As a robustness check on the results of the DiD estimations, we conduct Cox proportional hazards estimations at the individual investor team level. In the main, we find that mood regulation attempts among investor teams who are in close proximity to incidents of civil unrest causally increase said investor teams' disposition effects by 140 percent. As the first quasi-experimental study on the relationship between socio-political upheaval and the disposition effect, the results of the study extend the literature's understandings regarding the robustness of mood-induced disposition effects.

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CHAPTER TWO

The psycho-social drivers of the Disposition Effect among South African investor teams

2. Introduction

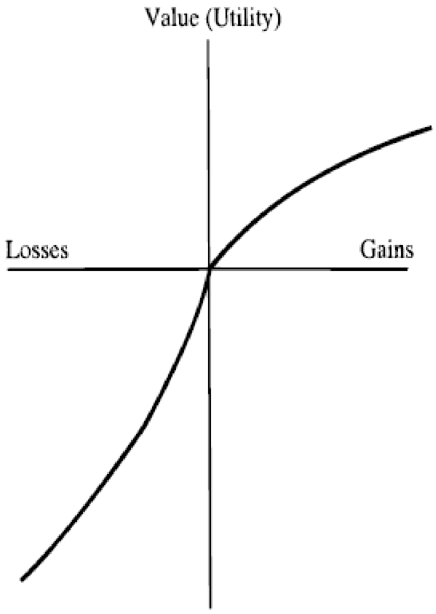
At a theoretical level, a description of the disposition effect begins with first providing a distinction between the neoclassical and behavioural finance approaches towards understanding financial decision-making and asset price formation. What might perhaps be the most critical of these distinctions is the fact that proponents of the neoclassical approach view sentiment as being a minor determinant of market prices and hold the assumptions that the investment decisions of market participants (i.e., investors) are mostly free of biases, and that such investors act in accordance with the rationality-based framework, focusing on the fundamental risks associated with their investment decisions and seeking to maximise the expected utility thereof (Dvorackova *et al.*, 2019). On the other hand, behavioural finance posits that sentiment is in fact a major determinant of market prices and asserts that investors do not always behave in accordance with the rationality-based framework as the quality of their decision-making can be, at times, distorted by several psychological biases.

Prospect theory is understood to be one of the most important theoretical descriptive frameworks describing psychological biases in investment decision-making (i.e., decision-making under the condition of uncertainty) (Kahneman and Tversky, 1979). Simply put, prospect theory describes the manner in which people make choices between probabilistic alternatives that each bear an element of risk, and where the probabilities of outcomes are uncertain (as is the case in the investment decision-making context). The theory asserts that people make decisions based on the potential losses and gains that they face in relation to a specific reference point (e.g., the purchase price of a stock),[1] rather than the final outcome (e.g., final state wealth in the case of expected utility theory). In addition to this, other attributes that distinguish prospect theory from expected utility theory include: (1) the postulation that the manner in which choices are framed (i.e., described) influences the decision-making process, while expected utility theory views people's decision-making processes as being immune to such framing effects; (2) the assumption in prospect theory that – in deciding between alternative options under the condition of uncertainty – people tend to erroneously underweight some probabilities, and overweight others, while expected utility theory assumes that people's perceptions of probabilities are correct; and, (3) the supposition in prospect theory that the tolerance of risk is different when it is concerning gains rather than losses, which stands contrary to expected utility theory's assertion that people's tolerance for risk is uniform (Dvorackova *et al.*, 2019).

The disposition effect, which is perhaps closest to attribute (3) above, is viewed as one implication of extending prospect theory to investment decision-making (Odean, 1998). First discussed in Shefrin and Statman (1985), the disposition effect refers to the tendency of investors to sell winning stocks too soon (risk-aversion-over-gains) and hold losers for too long (risk-seeking-over-losses), in a manner that maximises the S-shaped value function (Figure 2.1 below) proposed in prospect theory (Kahneman and Tversky, 1979).

[1] According to prospect theory, such potential losses and gains are evaluated using cognitive heuristics. Heuristics are also referred to as decision-making 'shortcuts' or 'rules of thumb' (Hutchinson and Gigerenzer, 2005).

Figure 2.1: *Prospect theory value function*



This value function is similar to the standard utility of wealth function with the exception that it is defined in losses and gains rather than in levels of wealth. Another similarity that the S-shaped value function shares with the standard utility function is the former's concavity in the domain of gains, in addition to its convexity in the domain of losses. Furthermore, the S-shaped value function is steeper in the losses domain than it is in the domain of gains, suggesting that people are generally risk-averse. Lastly, and perhaps most critically, a key characteristic of the S-shaped value function is the reference point from which losses and gains are measured; in the investment decision-making context, the role of reference point is typically assumed by the status quo such as the purchase price of a stock, and in other instances, by an expected or aspirational level that differs from the status quo (Odean, 1998).

In both research and the real-world context, the disposition effect is understood to be one the most pervasive biases in all of behavioural finance (Shefrin and Statman, 1985; Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005). Empirically, this assertion finds support in the likes of Brown *et al.* (2006), whose study on the disposition effects of IPO and index investors trading in the Australian Stock Exchange indicates that the disposition effect is pervasive across all observed categories of investors, including both individual and institutional investors (such as government investors and companies), and is observed in all months of the year, save for the last month of the Australian tax year (June) during which a reversal of the disposition effect is observed among non-tax-exempt investors.[2] Critically, the disposition effect is understood to be associated with sub-optimal portfolio returns (i.e., sub-optimal levels of investor welfare).

While there have been several studies in other emerging markets, studies remain few in Africa, and most tellingly, among South African investor teams. The literature is particularly silent on the important issues underpinning the intensity and nature of the disposition effect among African investors, as well as on the causal implications that the bias poses on investor welfare. In response to this apparent void in the literature, the current chapter focuses on using experimental means to determine the intensity, nature and causal implications of the disposition effect among South African university student investor teams participating in the annual JSE University Investment Challenge in 2019.

As a context for studying the disposition effect, the JSE University Investment Challenge is interesting in several ways. Firstly, participants to the game are required to organise themselves in investor teams of two or more individuals, allowing for an investigation, and ultimately a better understanding of the relationship between group dynamics and disposition effects. Secondly, all trades made as part of the game are required to be executed upon on the JSE Investment Challenge trading platform; this effectively renders the Investment Challenge to be a complete market, with all trading data providing full information on the shares traded, share positions held, and portfolios managed by investor teams. Thirdly, investor teams participating

[2] Similar to Odean (1998), Brown *et al.* (2006) understands this disposition effect reversal among tax-incurring investors as being the result of investors selling out of their losing positions in order to reduce their tax burden for the year.

in the game are geographically distributed across the country, as they study in universities located in all nine provinces of South Africa; this allows for an inquiry into how localised factors – such as climate temperatures – may influence the intensity of the disposition effect. Finally, in an effort to understand the impact of the disposition effect on investor welfare, basing our inquiry on the 2019 run of the Challenge allows for enough time to pass, enabling us to look into the *ex post* returns of winning stocks sold and losing stocks held by the study's subjects over an investment horizon of 12 months.

In the remainder of this chapter, Section 2.1 provides a review of the literature on (i) prospect theory as a theoretical descriptive framework which explains the disposition effect, (ii) the disposition effect in empirical and experimental studies, (iii) the relationship between the bias and several psycho-social factors of interest, (iv) the disposition effect and its relationship with investor welfare, and (v) provides the hypotheses of the current study. The methodology and data are discussed in Section 2.2, and the results are covered in Section 2.3. Section 2.4 discusses the implications of the results and concludes the chapter.

2.1. Literature review and hypotheses

2.1.1. Findings from empirical and experimental research on the Disposition Effect

Beginning with Odean (1998) in a study conducted on trades executed by investors participating in the NYSE, AMEX, and Nasdaq stock markets, the literature on behavioural finance has provided ample empirical and experimental evidence that prior outcomes impact investment decision-making.

In his seminal empirical investigation of the disposition effect among the trades of US-based brokerage accounts, Odean (1998) found compelling evidence which showed that individual investors have a strong propensity for realising gains from winning trade positions rather than realising losses in their portfolios. This disposition effect has since been observed by numerous subsequent empirical studies in several other financial market contextual situations and across a range of trader types and transactions, including: (i) individual day trader transactions (Jordan and Diltz, 2004), (ii) professionally-managed trading accounts at a middle-eastern brokerage service provider (Shapira and Venezia, 2001), and (iii) China-based stock market investors (Feng and Seasholes, 2005; Chen *et al.*, 2007).

More recently, in empirical research using individual brokerage account-level by Duxbury *et al.* (2015), it was found that (a) both the disposition effect and the house money effect can coexist contemporaneously in the same stock market,[3] (b) the investment decisions of the majority of individual investors are affected by both of these biases, and (c) the house money effect can act as a 'natural antidote' which moderates – but not completely eliminate – the negative consequences of the disposition effect. Another factor which is known to limit the disposition effect relates to the *locus* of control insofar as investment decision-making is concerned – with the disposition effect not being observed among investors (such as discretionary investors) who experience prior losses and gains but are not responsible for these outcomes (Summers and Duxbury, 2012). In addition to this, Gemayel and Preda (2018) find that the public observation and scrutiny that come with participating in a social trading platform as a trade leader reduces the disposition effect, as holding on to losses for too long may negatively affect said trade leader's reputation.

As compelling as the evidence from non-experimental empirical studies of the disposition effect may be, it is not without its challenges at a research design level. What is perhaps the most significant limitation of such empirical studies is their inability to control, manipulate, and isolate the causal impact of variables that are theoretically expected to affect investment

[3] First mentioned in Thaler and Johnson (1990), the house money effect refers to investors' tendency to exhibit risk-seeking investment decision-making in the presence of prior gains.

decision-making.[4] On the other hand, what Duxbury (2015a) refers to as "the most potent weapon in the hands of the experimenter" is experimental analysis' ability to manipulate the levels of treatment (i.e., intervention) factors, effectively allowing for causal measurements of relationships between variables of theoretical interest and observed investment decision-making. As a result, it is arguable that experimentation is a more rigorous method of scientific inquiry seeing as – unlike the case in non-experimental empirical enquiry – it is not subjected to the limitations of correlational analysis.

In this regard, there is a significant amount of experimental evidence which not only asserts the existence of the disposition effect, but also explains its nature. For instance, in Weber and Camerer's (1998) seminal experimental research on the disposition effect, subjects are tasked with buying and selling risky assets with prices determined by an exogenous, random process running from one period to another – controlling for investor expectations regarding future prices and returns. Varying probabilities of price movements result in assets with positive, neutral, and negative trends. Using experimental means, the study finds evidence of a disposition effect which is analogous to that of the non-experimental, empirical work in Odean (1998), with winning stocks accounting for a relatively larger proportion of sales than losing stocks (60% and 40%, respectively). However, in addition to this, the experimental work in Weber and Camerer (1998) further finds that the intensity of the disposition effect is weakened in a treatment condition where stocks held are automatically sold off at the end of a given period. The theoretical implication of this finding, the authors explain, is such that investors' investment decision-making cannot be driven solely by expectations of future price changes if automatic selling at the end of the period has an impact on the intensity of the disposition effect, particularly since subjects are at liberty to repurchase previously sold stocks at the start of

[4] Indeed, the ability to control, manipulate and isolate variables of interest and their causal impact on observed behaviour is part and parcel of the basic tools of the experimental method (Friedman and Sunder, 1994; Hey, 1991).

subsequent periods. Indeed, it is evident that the prior outcome of realizing a loss or a gain from selling a stock (whether automatically or otherwise) has an impact on subsequent investment decision-making;[5] an insight which could not possibly be surfaced without employing the basic tools of the experimental method.

The experimental design in Weber and Camerer (1998) discussed above has been replicated in numerous subsequent studies, all of which have reported findings supporting the existence, and explaining the nature of the disposition effect. For instance, Da Costa *et al.* (2008) assess the impact of gender differences on the extent to which investors succumb to the disposition effect and find that men exhibit a higher intensity of the disposition effect than women. Specifically, Da Costa *et al.* (2008) find that men's disposition coefficient ($\alpha = 0.351$)[6] is more than three times larger than that of women (which is negative and insignificant at $\alpha = -0.172$), when the previous price of a stock is used as the reference point for a stock sale decision. However, they do not find any significant differences between the disposition effects of men and women when the purchase price of the stock is used as the reference point for a stock sale decision. This distinction in how women's disposition effects compare to those men based on (i) the type of reference point that the investor is exposed to and (ii) its influence on the investor's trading decisions is speculated to be the result of cognitively-based differences in how women and men interpret changing reference points: according to empathising-systemising theory, women's superior visuospatial memory allows them to be highly effective at remembering landmarks, whereas men's 'systemising' minds render them effective at reading maps (Baron-Cohen, 2002).

[5] Perhaps due to a departure from a previously set reference point (e.g. departure from the purchase price).
[6] Da Costa *et al.* (2008) provide the expression for the disposition coefficient as $\alpha = (S_+ - S\_)/(S_+ + S\_)$, where $S_+(S\_)$ is the number of stock sales following a higher (lower) price at the previous period. The coefficient is +1(-1) if a subject sells on following a gain (loss), in which case there exists a disposition effect (no disposition effect).

Be that as it may, the caveat that Da Costa *et al.* (2008) provide *vis-à-vis* this point is that the matter could be best settled by functional magnetic resonance imaging (fMRI) experiments; in this regard, Brooks *et al.* (2012) conduct an fMRI study to measure the responses of valuation structures of the brain during individuals' decisions to keep or sell assets, and – *inter alia* – ultimately find that the disposition effect is likely driven by an irrational belief in mean reversion. Definitively, an irrational belief in mean reversion is understood to be the instance in which the future expected returns of winning stocks sold are higher than the future expected returns of losers held (Odean, 1998). Such a calibration error could be associated with overconfidence (Duxbury, 2015b), particularly when considering the associations between (a) risk-taking behaviour and overconfidence, as well between (b) risk-taking behaviour and the disposition effect (specifically with respect to the instance in which a disposition effect-impacted investor demonstrates risk-seeking behaviour over losses i.e., holds on to losing positions for too long).

With the linkages between the concepts above in mind, it is plausible that overconfidence (which manifests as a calibration error) may be due to an irrational belief in mean reversion (specifically in relation to losing positions). Given the understanding that men are more prone to overconfidence than women (Barber and Odean, 2000), it is also likely that men are more susceptible to irrational beliefs in mean reversion than women; the latter point then provides an explanation for the finding in Da Costa *et al.* (2008) that men demonstrate more intense disposition effects than women, when looking at the two gender groups in isolation. In the real-world context, however, investors are not always individual men and women. Indeed, in the context of professional investing, the largest (thus, most consequential) portfolios are often managed by investor groups (or, investor teams) compromising both men and women (Preqin, 2019).

Therefore, to understand the impact that a male presence has on investor teams' disposition effects, one might look at both the neuroscience-informed explanation provided by Da Costa *et al.* (2008) as well as other plausible explanations offered by the social psychology literature about group-based investment decision-making, and how it relates to the disposition effect. Further to this, laboratory experiments typically take place in one location (Da Costa *et al.*, 2008; Goulart *et al.* 2013*;* Rau, 2014) effectively disabling an inquiry into the implications of climate temperatures on the intensity of the disposition effect; which is an important and relevant question, considering that the investors participating in the world's 60 stock exchange markets are located across the globe and are thus subjected to different climate conditions and temperatures. For such an inquiry to be conducted, researchers would need – *inter alia* – access to the trading data of a cross-section of investors located in different regions, participating in the same, complete market (i.e., all participants being able to access and trade the same instruments) during the same period. Indeed, as it will be further expanded upon below, the research context of the current chapter allows for such an inquiry (and several others) to be made.

2.1.2. The Disposition Effect and its relationship to three psycho-social factors of interest

The literature on the disposition effect identifies several psycho-social factors that contribute towards this bias's intensity; included among such factors are those relating to a given investor's gender profile (Da Costa *et al.*, 2008; Rau, 2014), the climate temperatures that they are subjected to (Shu *et al.*, 2005; Barber, 2007), and the number of members of a given investor team (Chen, 2013; Rau, 2015).

We begin with the psycho-social factor related to gender diversity and gender representation in the group decision-making context. Researchers have found compelling evidence to suggest that gender matters considerably to the intensity of the disposition effect, however, they tend to reach different conclusions on which gender (between men and women) is most prone to the effect. For instance, Da Costa *et al.* (2008) find that – among Brazilian investors – disposition effects are relatively more intense among men versus women. On the contrary, Rau (2014) finds that German female investors have significantly higher disposition effects than their male counterparts. Rau (2014) concludes that cultural differences in loss aversion between Brazilian and German investors may account for these differences in findings. Given the significance of cultural differences in this regard, it would be interesting – and indeed novel – to determine the group-level gender differences in the disposition effects of South African investor groups. Regarding the impact of team gender diversity in investment decision-making, Bogan *et al.* (2013) interestingly find that that having a male presence in an investment team increases loss aversion, which is understood to be a key driver of the disposition effect (Shefrin and Statman, 1985). Be that as it may, Bogan *et al.* (2013) do not directly investigate the question of whether an investor group's disposition effects loom larger as the male presence increases within said group. Further to this, Bogan *et al.* (2013) conduct their study as a conventional lab experiment, and thus their results suffer from the limitation of low external validity (Harrison and List, 2004). Therefore, as partly a natural-field experimental study into whether gender representation intensifies or dampens the disposition effect, the current chapter contributes to the literature on team gender diversity and investment decision-making with evidence from real-world observation.

Another psycho-social factor that is investigated in the current chapter concerns the locational weather conditions that investor teams are subjected to. In this regard, we ask the question: do differences in the weather temperatures of separate locations have an impact on the intensity of the disposition effect among investor teams?

Indeed, Goulart *et al.* (2013) find strong correlates between body temperature and the intensity of the disposition effect, and Wang (2016) finds compelling empirical evidence to suggest a positive relationship between weather temperatures in London and the intensity of the disposition effects of individual traders in the UK spread-trading market. In the latter study, the theoretical understanding – psychologically – is that weather conditions (and indeed, temperatures) affect mood, and mood changes cause behavioural changes.

In moving away from the finance literature, we find support for this position in Vasko's (2020) contemplative ecological inquiry, where the research posits not only that 'outer weather' (i.e., climate conditions) affects 'inner weather' (i.e., our shifting states of mind and long-term values), but also that inner weather has significant effects on outer weather. In expanding on the idea that outer weather affects inner weather, Vasko (2020) explains that humans have inner weather within them – which is characterised by "shifting and often subtle dynamics in the form of states of mind, emotional inclinations, [and] values." On the other hand, outer weather – which is much more observable and measurable – can affect how people feel on any given day, effectively guiding the very quality of our decision-making and behaviours (Vasko, 2020). Insofar as the impact of human individuals' inner weather on outer weather is concerned, Bai (2012) posits that more and more environmentalism academics and activists are beginning to accept the idea that environmental problems and ecological disorders (although occurring within the environment) are not just problems of the environment, but rather reflect a prior disorder in the thoughts, perceptions, imagination, intellectual priorities, and loyalties of the human psyche. Put concisely then, the ideas advanced by both Vasko (2020) and Bai (2012) collectively suggest that there exists a mutually reinforcing relationship between humanity's prevailing environmental conditions and its psyche.

Returning to the behavioural finance literature, it seems that the directionality from outer to inner weather is perhaps most relevant to our inquiry into the impact of weather temperatures on investors' disposition effects. In this regard, Cao and Wei (2005) posit that lower weather temperatures lead to aggression, and higher temperatures lead to both feelings of aggression and apathy.[7] In turn, aggression is understood to result in more risk-taking behaviour, whereas apathy is said to impede risk-taking. Given the prospect theory-, and thus disposition effect-related understanding that investment decision-makers are risk-seeking-over-losses and risk-averse-over-gains, one might hold the *a priori* expectation that there exists a relationship between (1) being subjected to low temperature weather conditions (thus being prone to risk-taking behaviour) and (2) the intensity of the disposition effect (observably driven by loss aversion). In the context of the current study, evidence to support this theory could be found if investor teams located in South African cities with relatively low weather temperatures are seen to have relatively high disposition effects. Furthermore, and at least within the context of investment decision-making – such a finding would empirically corroborate Vasko's (2020) assertion that outer weather affects inner weather (i.e., investors' psyche), which in turn dictates investor behaviours and actions taken.

Finally, concerning the psycho-social factors relating to the sizes of investor groups, both Cici (2012) and Rau (2015) find that some of the social forces involved in the group investment decision-making context can exacerbate the intensity of the disposition effect. In this regard, their research looks to the two social psychology-based group dynamics of groupthink and group polarisation as means of explaining this phenomenon; both of which are argued to exacerbate investors' proclivity to succumb to the disposition effect within the group-setting. On the contrary, a more recent experimental study by Prates *et al.* (2017) finds that the disposition effect is in fact attenuated in investment decisions made by two-person groups relative to decisions made by individuals; confirming a similar finding in Chui (2004). The explanation given for this finding is that groups make relatively less biased decisions than individuals in competitive situations that involve an opportunity for the best performing

[7] With the feeling of apathy typically dominating that of aggression in such instances.

participants to win a prize (Prates *et al.*, 2017). However, given an inability to statistically confirm the disposition effect for three-person groups, Prates *et al.* (2017) were unable to determine whether the disposition effect is further attenuated (or intensified) across different group-sizes. Since the nature of the relationship between team-size and the disposition effect is still not well understood (particularly in studies using experimental data), and given the relatively greater variation in team-size data that we have available to us in the current study (which includes teams of two, three and four investors), we employ experimental means to answer the following question: does investor team-size have a causal effect on the intensity of the disposition effect?

2.1.3. The Disposition Effect and investor welfare

An important consideration regarding the disposition effect is its impact on investor welfare. Researchers have always understood – to varying levels of extent – that letting go of winning stocks too soon and holding on to losing stocks for too long can be associated with sub-optimal portfolio outcomes. For instance, upon observing investment behaviour which is consistent with the disposition effect among subjects who participated in a series of lab experiments, Weber and Camerer (1998) reflect on how the disposition effect could be potentially harmful given the statistically-sound understanding that falling stock prices typically imply that the stock is on a downward trajectory and therefore should be sold at the soonest in order to minimise portfolio losses.

On the other hand, rising prices suggest that the stock is on an upward trend and therefore should not be sold in order to maximise portfolio gains. However, investors do the opposite of this, potentially leading to sub-optimal portfolio outcomes. Odean (1998) takes this point a step further by calculating the *ex post* returns (in excess of the CRSP value-weighted index) of winning stocks sold and losers held over several investment horizons and finds that, for winning stocks sold, the average *ex post* return over the subsequent 12 month period is 3.4%

higher than it is for losers held. Following an analysis similar to that of Odean (1998), Duxbury *et al.* (2015) also conclude that the disposition effect may be costly to investors, having observed that winning stocks sold by the subjects of their empirical study had, on average, a 3.92% higher return than losers held over the subsequent year.

The research efforts above, and many others (Roger, 2009; Talpsepp, 2010; Shen and Shen, 2022), have contributed a great deal to our understanding of the negative correlation between the disposition effect and investor welfare. However, to the best of our knowledge, a finding that clearly shows the causal effect of the disposition effect on portfolio outcomes has not been provided in the literature. Put differently, it is common cause that the presence of the disposition effect is associated with sub-optimal portfolio outcomes. However, does this mean that the absence of the disposition effect is not associated with sub-optimal portfolio outcomes? This question – to which a scientifically-sound response would contribute towards our understanding of the causal relationship between the disposition effect and investor welfare – requires the involvement of a suitable counterfactual in the inquiry.

2.1.4. The JSE Investment Challenge

The JSE Investment Challenge – an initiative that has been running for nearly 50 years and is driven by the bourse's Marketing and Corporate Affairs division – is a nation-wide online-based trading game which spans over six months each year and involves thousands of university student-, and high school learner-teams comprising tens of thousands of team members (JSE, 2019).[8] As South Africa's largest and longest standing financial literacy initiative, the primary motivation of the Challenge is to introduce young people to the financial markets and encourage their future saving and investment behaviour through risk-free experiential learning. In an effort to democratise the Challenge and bring about the inclusion

[8] For example, in 2019, the entire Challenge involved 6,703 teams of 34,152 South African university students and high school learners from across the country (JSE, 2019).

of non-urban communities in the game, the JSE makes a deliberate effort to promote participation in the Challenge among learners and students living in rural areas and other non-metro areas (SABC News, 2018).

In the university stream of the Challenge, which provides the experimental setting for this thesis, university students from across the country organise themselves into teams (i.e., investor teams) of two to four members and are endowed with a starting portfolio of a lump sum of one million South African Rands (R1 million) in fictious cash. Over the course of the subsequent six months, the investor teams work on growing their portfolios by trading (taking both long and short positions) in actual JSE shares, ETFs, warrants, and single stock futures (SSFs) at their actual face values over the course of the Challenge. In this respect – and several others[9] – the Challenge mirrors the real JSE market-context in every manner save for the simulated nature of the currency used to trade in the aforementioned share instruments. In addition to this, the reality that the Challenge's participants compete on portfolio growth based on their trading decision lends itself well to the requirement in the literature that investors need to feel responsible for their investment decisions and the growth of their portfolios (or wealth, more aptly) in order for the disposition effect to emerge (Lee *et al.*, 2008; Lehenkari, 2011; Dölbrich *et al.*, 2014).

Furthermore, to encourage portfolio diversification, the Challenge requires that no more than 20% of each team's portfolio value is held in any one share or warrant, and no more than 10% of the portfolio value is held in any one SSF (JSE, 2020). Another (less direct, perhaps) effect of the latter requirement could be the stimulation of trading activity, as investor teams recompose their portfolios in response to changes (whether up or down) in the prices of the multiple stocks and derivatives that they hold – insofar as the disposition effect is concerned,

[9] Each trade, for instance, is subject to real-world transactional costs such as brokerage fees, settlement fees, Securities Transfer Tax (SST), and Value-Added Tax (VAT).

a market-environment characterised by strong trading activity is a conducive research context as the accuracy with which the disposition effect is identified and measured relies very much on the order flow volumes of observed subjects (Odean, 1998).

From a competitive perspective, the three investor teams with the highest portfolio growth rates by the end of the six-month period win the Challenge, with prizes for 1st, 2nd, and 3rd place comprising deposits of R25,000.00, R15,000.00, and R10,000.00 (respectively) per investor team into Satrix Investment Plan accounts, as well as an all-expenses-paid trip to an international stock exchange for the team that places 1st (JSE, 2020). In this way, it is plausible to hold that the Challenge's competitive context and prizes at stake incentivise investor teams' engagement with the game.

Figure 2.2 below shows that in the three years leading up to, and including the year 2019, the University Challenge's volume of investor teams increased by 384 – which is equivalent to a compounded annual growth rate (CAGR) of 14.98% – and it's volume of individual participants increased by 741 students (i.e., a CAGR of 11.47%) (JSE, 2019).[10]Indeed, the data support's the JSE's assertion that the Challenge has seen more and more students registering to participate over the years (JSE, 2020). The continued growth in participant volumes that the Challenge has seen over the years, together with the JSE's efforts at including students from both urban and non-urban parts of South Africa in the Challenge, render the Challenge as a research context from which potential research results and findings could be plausibly generalised to real-world investor groups from across the country.

On the other hand, with very little deviation from the three-year mean value of 2.59, Figure 2.3 shows that the Challenge's average investor team sizes haven't varied much between the years 2017, 2018, and 2019. Whereas the proportion of female participants in investor teams has

[10] Between the years 2017 and 2019.

grown steadily across the three-year period at a CAGR of 16.02% (JSE, 2020). Taken together, these insights suggest that the average investor team is evolving over time in a manner that seems to be increasing female team members whilst reducing male team members, resulting in an investor team gender-mix that is becoming more and more representative of the gender-mix of the South African population.

Figure 2.2: *Volumes of investor teams and team-members participating in the JSE University Challenge during the period 2017 to 2019*

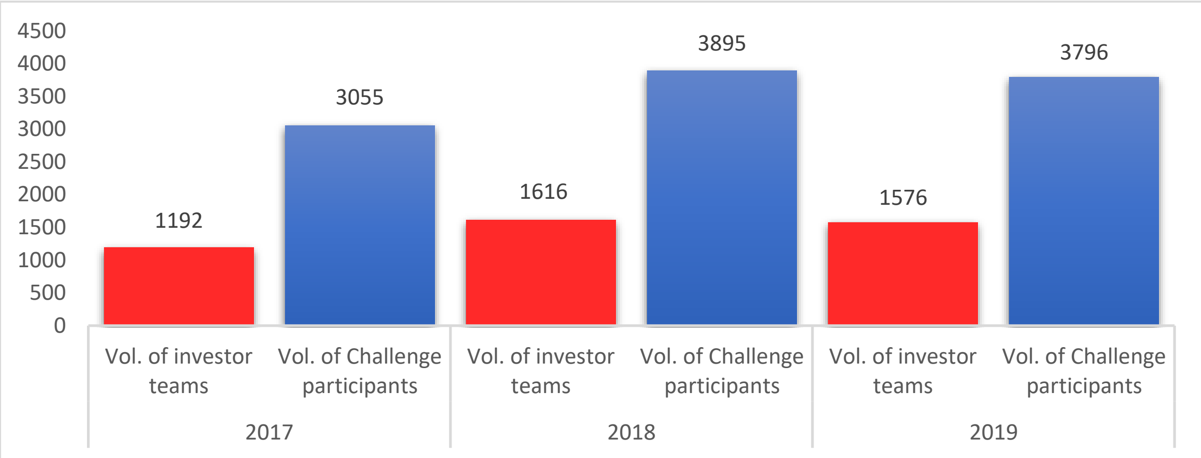
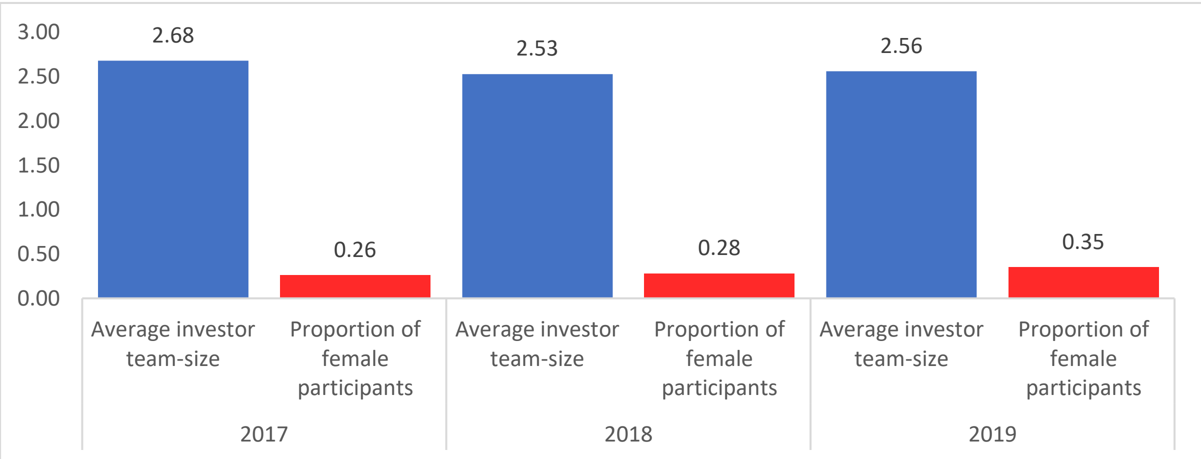


Figure 2.3: *Average investor team-size and proportion of female participants in the JSE University Challenge during the period 2017 to 2019*



2.1.5. Hypotheses

With the literature reviewed above in mind, we formalise our arguments in a series of five hypotheses which we test among South African university students participating in the annual

JSE Investment Challenge. We begin by testing whether South African investor teams are in fact susceptible to the disposition effect (as per H1 below). Testing H1 is important, we believe, not only because studies which use causal inference to establish the disposition effect among African investor teams in general, and South African investor teams in particular, are non-existent – but also because the outcomes of testing H1 are critical to the validity of testing the subsequent hypotheses that follow. In these ways, the outcomes of testing H1 could potentially be both seminal to the literature at large, as well as foundational to the balance of the current study.

H1: South African investor teams are susceptible to the disposition effect.

On the condition that H1 is confirmed, the current study endeavours to test the remaining hypotheses below using experimental means. To test the causal impact of the female composition psycho-social factor on the extent of the disposition effect, we construct hypothesis H2 below. By testing H2, our intention is to – *inter alia* – determine the group-level gender differences in the disposition effects of South African investor teams, within the context of a natural-field experiment. Given the role that cultural dynamics play in the susceptibility of different gender groups to loss aversion (Rau, 2014) – thus the disposition effect – our view is that the outcomes of testing H2 will shed light on how this phenomenon plays out within the South African cultural context.

H2: Ceteris paribus, female composition has a causal effect on the intensity of the disposition effect among South African investor teams.

Our motivation for testing H3 below stems from our understanding that although non-experimental empirical studies which sought to understand the impact of weather effects on stock market behaviour (Cao and Wei, 2005) and the disposition effect (Wang, 2016) exist, experimental research which endeavours to find out whether a causal relationship exists between the weather temperatures that people (and indeed, investor teams) are subjected to and the extent of their disposition effects is limited, if at all existent. Furthermore, we select weather temperature in particular for experimental examination as the outcomes of testing H3 may augment the explanation for the correlates found between low body temperature and the disposition effects of individuals in Goulart *et al.* (2013). H4 further below is constructed to test the causal impact of the investor team-size psycho-social factor on the extent of the disposition effect. By testing H4, our intention is to fill the apparent void in the literature (Chui, 2004; Cici, 2012; Rau, 2015; Prates *et al.*, 2017) regarding whether the disposition effect is progressively intensified or attenuated across different investor group or team sizes. Given the potential presence of the opposing forces of groupthink (Cici, 2012) and group participation in a competitive context (Prates *et al.*, 2017) – which have been found to intensify and attenuate, respectively, the disposition effects of investor teams – in the JSE University Challenge, testing H4 allows for a novel determination of which of these forces have a greater bearing on the disposition effects of investor teams as investor team-sizes are varied.

> *H3: Ceteris paribus, climate temperatures causally intensify the disposition effects of South African investor teams.*

> *H4: Ceteris paribus, investor team-size has a causal effect on the intensity of the disposition effect among South African investor teams.*

Furthermore, the understanding that the disposition effect is associated with sub-optimal investor welfare (i.e., portfolio returns) has been well-established in the literature (Odean, 1998; Roger, 2009; Talpsepp, 2010; Shen and Shen, 2022); however, to the best of our knowledge – the literature is devoid of experimental studies from the field that investigate whether a causal flow exists between the psycho-social factors that characterise an investor team, the intensity of the disposition effects of said team, and their resultant investor welfare. Testing H5 below is thus our attempt at filling this apparent gap.

> *H5: Ceteris paribus, psycho-social factors which intensify the disposition effect causally reduce the investor welfare (i.e., portfolio outcomes) of South African investor teams.*

2.2. <u>Methodology</u>

2.2.1. Experimental design, subject pool and data

Of the 854 investor teams that actively traded (i.e., executed at least one trade) during the 2019 iteration of the JSE Investment University Challenge,[11] we are able to confirm the gender compositions of 52 teams (due to missing data points in the dataset used for the study) who also attend universities domiciled in as wide a distribution of geographical locations across South Africa as possible (JSE, 2019). We therefore select these 52 teams as the subject pool for the current study, as they meet the standard requirement for field studies on the disposition effect (DE) of being active (Odean, 1998; Duxbury *et al.*, 2015; Frydman and Wang, 2020), as well as provide the necessary data to – *inter alia* – investigate the nature of the relationship between gender composition and the DE, as well as between climate temperature and the DE.

With the above as context, the current study – which unfolds as a natural-field experiment – consists of the buy and sell trades of a sample of 52 active investor teams participating in the university stream of the 2019 JSE Investment Challenge, who are collectively characterised by a 4:1 men-to-women participant ratio, attend 21 universities located in 21 different cities or towns distributed across eight of South Africa's nine provinces, and have an average investor team size of two members per team.

[11] Who represent approximately 54% of the 1576 total investor teams who registered for the University Challenge in 2019, as depicted in Figure 2.2 above.

To test whether the intensity of the DE can be explained by the degree of female representation in each investor team, we consider the number of women in each team. To establish whether climate temperatures explain the intensity of the DE among the investor teams, we use the averages of daily maximum and minimum climate temperatures of the cities and towns in which the investor teams' universities are located over the course of the sample period (consistent with the approach in Cao and Wei (2005)) (TuTiempo.net, 2019). Finally, in testing whether investor team-size explains the intensity of the DE, we look at the number of investors in each team. The sample period for this natural-field experiment is the full length of the 2019 run of the Investment Challenge which spanned from 11 March 2019 to 20 September 2019; a period in which the study's investor team subject pool executed a combined total of 5,876 buy and sell trades.

To control the experiment and determine the investor teams' general susceptibility to the DE, we consider the buy and sell trades of 29 robots which each made daily investment decisions on JSE shares, ETFs, single stock futures and warrants following a simple moving average (MA) trading rule. This trading rule, which is employed in Metghlchi *et al.* (2012), asserts that a robot is in the market (buy decision) when MA(5) is greater than MA(20), and out of the market (sell decision) when MA(5) is less than or equal to MA(20). In total, the group of robot traders under observation executed 3,306 buy and sell trades.

Table 2.1 below shows the descriptive statistics of the two types of subjects (investor teams and robots). Among the investor team subjects, the average team consists of four times more men than women. Furthermore, although the investor teams traded a wider variety of individual instruments, the mix of instrument types (i.e., shares, ETFs, SSFs, and warrant) in the portfolios of both investor teams and robots is largely the same. In terms of average number of trades per subject, we find these to also be quite similar across the two types of subjects, at 113 and 114 average trades executed by investor teams and robots, respectively.

Table 2.1: Descriptive statistics of the investor team and robot subjects under study

Subject	Investor teams	Robots	All subjects
No. of subjects	52	29	81
Average team size	2	-	-
Men-to-women ratio	4:1	-	-
No. of shares, ETFs, single stock futures (SSFs), and warrants	433	29	433
Average no. of trades	113	114	113

Table 2.2 below provides a view of the various universities represented in the sample pool of investor teams. In total, the 52 teams attend 21 universities located in 21 different cities or towns, across 8 of the country's 9 provinces. At an average climate temperature of 22°C (TuTiempo.net, 2019) during the sample period, the investor teams attending the University of Zululand (located in Empangeni, Kwa-Zulu Natal) are subjected to the warmest climate temperatures of all others in the subject pool. Further to this, with 13 (or 25%) of investor teams attending the University of Zululand, it is also the university with the highest number of investor teams in the subject pool. In almost complete contrast, investor teams attending universities in Johannesburg are subjected to the coolest climate temperature (15.73°C), with 80% of them falling into the lower bound of the range of number of investor teams per university.

Table 2.2: Characteristics of universities and their respective investor teams in the sample pool

University	City/Town	Average temperature during sample period (°C)	Province	No. of teams from university
University of Zululand	Empangeni	22	Kwa-Zulu Natal	13
University of KwaZulu-Natal	Westville	21.75	Kwa-Zulu Natal	2
Tshwane University of Technology Polokwane	Polokwane	19.71	Limpopo	1
UNISA Pietermaritzburg	Pietermaritzburg	18.7	Kwa-Zulu Natal	1
University of Cape Town	Rondebosch, Cape Town	17.98	Western Cape	5
University of the Witwatersrand	Braamfontein, Johannesburg	15.73	Gauteng	2
UNISA	Muckleneuk, Pretoria	17.89	Gauteng	2
University of Pretoria	Hatfield, Pretoria	17.89	Gauteng	1
University of Fort Hare	Bisho	17.79	Eastern Cape	1
Walter Sisulu University	Umtata Part 1, Mthatha	17.34	Eastern Cape	2
UNISA Mthatha	Umtata Part 1, Mthatha	17.34	Eastern Cape	1
University of the Western Cape	Bellville, Cape Town	16.33	Western Cape	2

University (Cont'd)	City/Town (Cont'd)	Average temperature during sample period (°C) (Cont'd)	Province (Cont'd)	No. of teams from university (Cont'd)
TSIBA Business School	Woodstock, Cape Town	16.33	Western Cape	2
University of Stellenbosch	Stellenbosch Central, Stellenbosch	16.33	Western Cape	5
Rhodes University	Makhanda (Grahamstown)	16.11	Eastern Cape	3
Nelson Mandela University	Glenwood AH, George	16.05	Western Cape	1
University of Johannesburg	Auckland Park, Johannesburg	15.73	Gauteng	4
Milpark Business School	Auckland Park, Johannesburg	15.73	Gauteng	1
UNISA Ekurhuleni	Daveyton, Benoni	15.73	Gauteng	1
Pearson institute of higher education	Midrand, Johannesburg	15.73	Gauteng	1
Boston city campus & business college	Braamfontein, Johannesburg	15.73	Gauteng	1

2.2.2. Measurement techniques

Following a modified version of the methodology in Da Costa *et al.* (2013), the research tests hypotheses H1-4 following a panel data analysis approach. Specifically, we make use of the DE measures provided in Odean (1998), Weber and Camerer (1998), and Dhar and Zhu (2006). An important consideration when measuring the DE is the nature of the reference point used in determining gains and losses. The prevailing understanding is that the DE arises when the purchase price of a stock, or another price of the stock in a previous period is the reference point (Weber and Camerer, 1998; Da Costa *et al.*, 2008; Baucells *et al.,* 2011). The three DE measures named above do not make use of the same type of reference point: Odean (1998) and Dhar and Zhu (2006) use average purchase prices to measure DEs at the group and individual investor levels, respectively, whereas the Weber and Camerer (1998) measure (an equation which defines what they refer to as the 'disposition coefficient') makes use of the previous period's price. In the current study, we thus incorporate average purchase prices and average sale prices as reference points for long and short-sell positions, respectively, in our use of the Odean (1998) and Dhar and Zhu (2006) measures and incorporate previous trading day's prices as reference points for long and short-sell positions when calculating DEs using the Weber and Camerer (1998) measure.

Beyond this, there are several points of distinction between our methodology and that provided in Da Costa *et al.* (2013). Firstly, our experiment is conducted in a live market context involving real-world share instruments instead of artificial ones, and the subjects of our study had no prior knowledge that their trading behaviour would be observed (i.e., natural-field experiment). These first two distinctions are crucial as they not only enhance the external validity of the results obtained in the current study as well as the implications thereof, but they also mitigate against problems common in conventional lab and artefactual experiments such as self-selection bias (which typically results in a given sample of subjects not being representative of the population) and the Hawthorne effect (which describes the phenomenon in which subjects alter their behaviour in response to their awareness that they are being observed, and has the implication of subjects behaving differently to how they would in a real-world setting) (Harrison & List, 2004).

Secondly, instead of using a linear regression model to assess the influence of a given set of variables (such as trading experience the context of Da Costa *et al.* (2013) or psycho-social factors in the current study) we incorporate an augmented version of the approach in Goulart *et al.* (2013) to investigate the several psycho-social factors which may contribute towards the intensity of the DE. Our augmentations of the Goulart *et al.* (2013) approach are as follows: (i) instead of only making use of the Odean (1998) measure (i.e., Equation (2.2)), we also include measures of DE which are not sensitive to portfolio size and trading frequency (i.e., Equations (2.5) and (2.6)) in our analysis), (ii) with respect to Equation (2.2), we not only measure and analyse the DE at an aggregated (i.e., grouped subjects) level, but at a disaggregated (i.e., individualised subjects) level as well, with DE as per Equations (2.5) and (2.6) being measured exclusively at a disaggregated level, and (iii) both parametric and nonparametric tests (instead of only nonparametric tests) are conducted. These augmentations are intended to contribute positively to the robustness of the analyses in Tables 2.7-2.9 further below. Furthermore, our choice to make use of this approach towards determining the influence of certain variables on the intensity of the DE instead of linear regressions as done in Da Costa *et al.* (2013) is based on our view that investing experience (thus, investing skill) makes for a more functional determinant of the intensity of the DE than a psycho-physiological one as in Goulart *et al.* (2013), or indeed a psycho-social one, as in the current study. Therefore, given that the nature of the determinants of the intensity of the DE in the current study are more relatable to those in Goulart *et al.* (2013) than to investing experience in Da Costa *et al.* (2013), our sense is that a more apt and perhaps more appropriate precedent for the current study to somewhat follow (with regards to answering the question of which psycho-social factors drive the intensity of the DE) is that given by Goulart *et al.* (2013).

Thirdly, we add regression adjustment, parametric, non-parametric and bootstrap treatment tests to the methodology as means of investigating whether there is a causal link between different levels of psycho-social factors and the intensity of the DE (Ellingsen & Johannesson, 2004). This is done as a remedy to the problem of the Goulart *et al.* (2013) approach's being limited to only correlational analysis. Fourthly, we observe the share instrument trades of investor teams instead of individual investors as done in Da Costa *et al.* (2013), allowing for our inquiry to focus on how certain variables (psycho-social factors, in this case) influence the intensity of the combined DEs of a team of investors rather than of individual ones. Finally, to test H5, we compute the cumulative market-adjusted *ex post* returns (i.e., *ex post* returns in excess of the FTSE/JSE All Share Index) for the winning stocks sold and losing stocks held (a) until the end of the Challenge on 20/09/2019, and (b) over the next 12 months of trading. The approach is similar to the one employed in Odean (1998). We once again make use of regression adjustments, parametric, non-parametric, and bootstrap treatment tests, however this time to conduct an inquiry into the causal links between the DE and investor welfare.

In making use of Odean's (1998) measure, which considers the actual and potential[12] share trades of investor team *i* during the sample period, we begin by computing the proportion of gains realised (PGR_i) and proportion of losses realised (PLR_i) as follows:

$$PGR_i = \frac{N_{gr}^i}{N_{gr}^i + N_{gp}^i}, PLR_i = \frac{N_{lr}^i}{N_{lr}^i + N_{lp}^i} \tag{2.1}$$

where N_{gr}^i (N_{lr}^i) represent the number of share trades by investor team i with a realised gain (loss), and N_{gp}^i (N_{lp}^i) represent the number of potential share trades by investor team i with a paper gain (loss). Investor team *i*'s DE (DE_i) is thus:

$$DE_i = PGR_i - PLR_i \tag{2.2}$$

where –1 < DE_i < 1. Equation (2.2) therefore means that a positive value of DE_i is indicative of a smaller proportion of losing shares being sold relative to the proportion of winning shares

12 Potential share trades refer to shares in a portfolio that were not sold but that could have been either winners or losers.

being sold by investor team i, and thus – in such a case – investor team *i* exhibits the DE.[13] The equation is evaluated by the following t-statistic:

$$t = \frac{PGR_i - PLR_i}{SE_i} \tag{2.3}$$

where the standard error SE_i is

$$SE_i = \sqrt{\frac{PGR_i(1-PGR_i)}{N_{gr}^i + N_{gp}^i} + \frac{PLR_i(1-PLR_i)}{N_{lr}^i + N_{lp}^i}} \tag{2.4}$$

Furthermore, the measures provided in Weber and Camerer (1998) and in Dhar and Zhu (2006) are employed. Contrary to that of the measure provided in Odean (1998), the PGR_i and PLR_i of the measures are not sensitive to investor teams' portfolio sizes and trading frequencies, and thus contribute meaningfully to the robustness of the study's analysis. First, using the measure in Weber and Camerer (1998), we consider the difference between the number of share trades with realised gains by investor team *i* and the number of share trades with realised losses relative to the number of all trades, as follows:

$$DE_i = \frac{N_{gr}^i - N_{lr}^i}{N_{gr}^i + N_{lr}^i} \tag{2.5}$$

where –1 < DE_i < 1. Interpretively, the measure suggests that there is no DE if investor team i's number of share trades with realised losses matches their number of share trades with realised gains. Furthermore, we use the measure in Dhar and Zhu (2006), which is provided as follows:

$$DE_i = \frac{N_{gr}^i}{N_{lr}^i} - \frac{N_{gp}^i}{N_{lp}^i} \tag{2.6}$$

13 Intuitively, as the DE asserts that investors behave in a risk-averse manner when faced with gains, and a risk-loving manner when faced with losses (Shefrin and Statman, 1985), Odean's (1998) measure of DE gauges for these tendencies by looking at the frequencies at which decisions to sell-off gaining stocks and hold on to losing ones are made, thus the magnitudes of individual gains or losses are thus uninformative.

As means to determine the significance of the treatment effects, we estimate regression-adjusted average treatment effects (ATEs) and review the p-values of said regression adjustments, as well as those from two-tailed p-values from two sample t-tests, Mann-Whitney tests, and bootstrap tests (with number of bootstrap samples B = 9,999) for differences in mean DEs (Moffatt, 2016). Regression adjustment estimators use contrasts of averages of treatment-specific predicted outcomes to estimate treatment effects, and are know to allow for heterogenous, or multivalued treatments (Chin, 2019; StataCorp, 2023). Given the multivalued nature of the treatment variables under investigation in the current chapter, regression adjustments seem apt to the task at hand. The Mann-Whitney test and bootstrap technique allow us to conduct nonparametric and parametric two-sample z-tests and t-tests, respectively, on our sub-samples of 18 investor teams (thus, 18 observations) per condition without relying on distributional assumptions (e.g. sub-sample sizes of 30 or more observations) regarding the normality of the data used (Efron and Tibshirani, 1993; Ellingsen and Johannesson, 2004; Moffatt, 2016). The Mann-Whitney and bootstrap tests therefore serve as robustness checks on the results of the regression adjustments.

Our first set of treatment effects tests concerning the causal impact of the study's various psycho-social conditions of interest (listed in the first paragraph of Subsection 2.3.3 further below) on the intensity of the DE are estimated using the following equation:

$$\tau_i = DE_{iT} - DE_{iT} = DE_{i1} - DE_{i2} \tag{2.7}$$

Where τ = ATE, DE_{i1} = mean DEs for the condition naturally subjected to treatment T=1, and DE_{i2} = mean DEs for the condition naturally subjected to treatment T=2 (Harrison and List, 2004).[14] Mean DEs are given by Equations (2.2), (2.5) and (2.6).

[14] This is an applied version of the typical ATE equation $\tau = y_{i1} - y_{i0}$, where y_{i1} denotes outcomes with treatment (T=1), and y_{i0} denotes outcomes with no treatment (T=0) i.e., the counterfactual.

In order to understand whether there is a causal flow between the psycho-social conditions that intensify the DE and investor welfare, we once again look to tests of treatment effects, this time following the equation below:

$$\tau_i = DER_{iT} - DER_{iT} = DER_{i1} - DER_{i2} \qquad (2.8)$$

Where τ = ATE, DER_{i1} = mean of differences in cumulative *ex post* returns for the group naturally subjected to treatment T=1, and DER_{i2} = mean of differences in cumulative *ex post* returns for the group naturally subjected to treatment T=2 (Harrison and List, 2004).

2.3. Results and analysis

2.3.1. Disposition effects for grouped and individual subjects

Table 2.3 below provides the various terms involved in a calculation of the DE following Equation (2.2).

Table 2.3: The DE for the groups of subjects participating in the JSE Challenge in 2019 using eq. (2.2)

Subject	Group of investor teams	Group of robots
Ngr	1605	295
Nlr	1352	969
Ngp	291	12
Nlp	477	20
PGR	0.8465	0.9609
PLR	0.7392	0.9798
DE	0.1073	-0.0189
SE	0.0132	0.0119
t-Statistic	8.14***	-1.58

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

At a 1% level of significant, we find that the group of investor teams do indeed succumb to the DE – and on the other hand, we find no evidence of the DE among the study's group of robots. These results thus support the common understanding that cognitive biases feature specifically in the human decision-making process. Interestingly, the study further finds a higher DE value for humans relative to robots despite humans' trading behaviour being characterised by a relatively lower PGR value. Similar studies (Da Costa *et al.*, 2013; Goulart *et al.*, 2013) typically find that the intensity of the DE among subjects with comparatively high DE values is driven by large PGR values. This outcome thus exemplifies the robustness of the idea that the DE is an innately human phenomenon, as it cannot be found among non-human subjects even when the trading behaviour of such subjects is characterised by relatively high values of PGR.

Table 2.4: The DE for individual subjects participating in the JSE Challenge in 2019 using eq. (2.2)

Subject	Individual investor teams	Individual robots
Number of subjects	52	29
Mean	0.1043	-0.0483
Median	0.0616	0.0200
Maximum	0.6553	0.1000
Minimum	-0.6700	-0.4500
Standard deviation	0.2494	0.1230
Jarque-Bera	2.97	19.76***
t-Statistic (mean = 0)	2.99***	-2.11**
Wilcoxon Z-statistic (median = 0)	3.01***	1.28
Subject with DE > 0 (%)	63.5	58.6

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Table 2.5: The DE for individual subjects participating in the JSE Challenge in 2019 using eq. (2.5)

Subject	Individual investor teams	Individual robots
Number of subjects	52	29
Mean	0.0767	-0.5097
Median	0.0601	-0.6596
Maximum	0.9000	0.9286
Minimum	-1.0000	-1.0000
Standard deviation	0.4199	0.4380
Jarque-Bera	0.40	23.47***
t-Statistic (mean = 0)	1.32	-6.27***
Wilcoxon Z-statistic (median = 0)	1.38	3.85***
Subject with DE > 0 (%)	53.8	10.3

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Similar to the approach followed in Da Costa *et al.* (2013), Tables 2.4 and 2.5 provided the descriptive statistics for the DE calculated at an individual subject-level (i.e., calculated per individual subject and individual robot) following Equations (2.2) and (2.5), respectively. Further to this, Tables 2.4 and 2.5 provide two tests – parametric and nonparametric – for the distribution of DE, together with a Jarque-Bera test which establishes the normality of the distribution of DE. In this regard, the effect is normally distributed for investor teams but not for robots, following both Equations (2.2) and (2.5). With respect to Equation (2.2), the same outcomes of the Jarque-Bera test were observed in Da Costa *et al.* (2013).

The parametric t-statistic test seeks to establish whether the hypothesised mean is equal to zero, whereas the nonparametric Wilcoxon z-statistic tests whether the distribution's median is equal to zero. In this instance, the positive values of DE (i.e., the arithmetically calculated identifier of the presence of the DE) of the investor teams are significant at 1% when following Equation (2.2) (Table 2.4), but not when following Equation (2.5) (Table 2.5). However, in turning to Table 2.6 which follows Equation (2.6) – an equation which, like Equation (2.5), is not sensitive to portfolio size and trading frequency – the null is rejected in both parametric and nonparametric tests of the investor teams' DEs at 5% and 1% significance, respectively. On the other hand, given that all values of DE are negative for robots in Tables 2.4-2.6, the conclusion reached is that no evidence of DEs could be found for these subjects.

Table 2.6: The DE for individual subjects participating in the JSE Challenge in 2019 using eq. (2.6)

Subject	Individual investor teams	Individual robots
Number of subjects	52	29
Mean	1.2004	-2.8862
Median	0.3889	-0.0388
Maximum	18.1667	17.0000
Minimum	-2.9130	-9.8958
Standard deviation	3.4211	6.2229
Jarque-Bera	419.72***	5.52*
t-Statistic (mean = 0)	2.53**	-2.50**
Wilcoxon Z-statistic (median = 0)	2.64***	1.12
Subject with DE > 0 (%)	63.5	44.8

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

2.3.2. The impact of climate temperature, female composition, and team-size on investor teams' disposition effects

Following an approach which modifies the methodology used in Goulart *et al.* (2013), the study investigates how female composition, climate temperatures, and investor team-size correlate with the DE. The study's investor team subjects are arranged from highest to lowest values of the aforementioned psycho-social variables, including only the first 18 subjects with the highest values for the variables, and the last 18 subjects with the lowest values. Subjects with mid-values are excluded.[15] Subsequently, their corresponding individual DE values are calculated following Equations (2.2), (2.5) and (2.6). Both parametric and nonparametric tests are then conducted on aggregated and disaggregated values of DE in the subsamples.

[15] As a reference point, the DE values for the full sample of robot subjects are included in the analysis as well.

Table 2.7: Aggregated and disaggregated DEs of subjects participating in the JSE Challenge in 2019 and female composition

Subject	Robots	Investor team sub-sample total	Low female composition	High female composition
Ngr	295	1186	812	374
Nlr	969	961	431	530
Ngp	12	221	110	111
Nlp	20	363	183	180
DE (eq. (2.2)) *Aggregated*	-0.0189 (0.0119)	0.1171 (0.0156)	0.1787 (0.0213)	0.0246 (0.0251)
t-statistic (eq. (2.2)) *Aggregated*	-1.58	7.49***	8.38***	0.98
DE (eq. (2.2)) *Disaggregated*	-0.0483	0.0953	0.1336	0.0570
t-statistic (eq. (2.2)) *Disaggregated*	-2.11**	2.16**	3.19***	0.73
z-statistic (eq. (2.2)) *Disaggregated*	1.28	2.22**	2.89***	0.52
DE (eq. (2.5))	-0.5097	0.0954	0.2788	-0.0881
t-statistic (eq. (2.5))	-6.27***	1.24	3.85***	-0.71
z-statistic (eq. (2.5))	3.85***	1.38	2.79***	0.66
DE (eq. (2.6))	-2.8862	1.1477	1.2422	1.0585
t-statistic (eq. (2.6))	-2.50**	2.39**	3.11***	1.22
z-statistic (eq. (2.6))	1.12	2.28**	2.75***	0.61

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Standard errors in parentheses

Table 2.7 above provides an analysis of the impact of female composition (as proxied by the number of women within an investor team) on the intensity of the DE, following the modified Goulart *et al.* (2013) methodology. Firstly, it is noted that the DE for the full investor team subject subsample (i.e., the combination of both the low female composition and the high female composition groups) is generally higher than that of the full sample of robots. In taking a closer look at the investor team subjects, it is also noted that the low female composition group is characterised by higher values of DE than the high female composition group across all measures, and at both aggregated and disaggregated levels in the case of Equation (2.2).

Furthermore, all DE values for the low female composition group are generally highly significant under both parametric and nonparametric testing.

Table 2.8: Aggregated and disaggregated DEs of subjects participating in the JSE Challenge in 2019 and climate temperatures

Subject	Robots	Investor team sub-sample total	Low climate temperature	High climate temperature
Ngr	295	1070	557	513
Nlr	969	948	377	571
Ngp	12	187	103	84
Nlp	20	324	198	126
DE (eq. (2.2)) *Aggregated*	-0.0189 (0.0119)	0.1059 (0.0158)	0.1882 (0.0243)	0.0401 (0.0204)
t-statistic (eq. (2.2)) *Aggregated*	-1.58	6.70***	7.74***	1.97*
DE (eq. (2.2)) *Disaggregated*	-0.0483	0.1225	0.1630	0.0820
t-statistic (eq. (2.2)) *Disaggregated*	-2.11**	2.86***	3.25***	1.18
z-statistic (eq. (2.2)) *Disaggregated*	1.28	2.88***	2.83***	1.26
DE (eq. (2.5))	-0.5097	0.1146	0.2043	0.0248
t-statistic (eq. (2.5))	-6.27***	1.85*	2.47**	0.2777
z-statistic (eq. (2.5))	3.85***	1.86*	2.16**	0.24
DE (eq. (2.6))	-2.8862	1.4061	1.9225	0.8897
t-statistic (eq. (2.6))	-2.50**	2.17**	1.87*	1.12
z-statistic (eq. (2.6))	1.12	2.33**	2.40**	0.83

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Standard errors in parentheses

Table 2.8 analyses the impact of climate temperatures on the intensity of the DE. Once again, it is noted that the DE for the full investor team subject subsample is generally higher than that of the full sample of robots. In turning the attention to the investor team subjects, it is also noted that the low climate temperature group is characterised by higher values of DE than the high climate temperature group across all measures, and at both aggregated and disaggregated levels in the case of Equation (2.2). Furthermore, all DE values for the low temperature group are generally highly significant under both parametric and nonparametric testing.

Table 2.9: Aggregated and disaggregated DEs of subjects participating in the JSE Challenge in 2019 and investor team-size

Subject	Robots	Investor team sub-sample total	Small investor team-size	Large investor team-size
Ngr	295	1296	669	627
Nlr	969	994	491	503
Ngp	12	211	112	99
Nlp	20	337	170	167
DE (eq. (2.2)) *Aggregated*	-0.0189 (0.0119)	0.1132 (0.0149)	0.1138 (0.0211)	0.1129 (0.0210)
t-statistic (eq. (2.2)) *Aggregated*	-1.58	7.60***	5.39***	5.37***
DE (eq. (2.2)) *Disaggregated*	-0.0483	0.0891	0.0921	0.0861
t-statistic (eq. (2.2)) *Disaggregated*	-2.11**	2.67**	2.27**	1.59
z-statistic (eq. (2.2)) *Disaggregated*	1.28	2.51**	1.96*	1.44
DE (eq. (2.5))	-0.5097	0.1023	0.1419	0.0627
t-statistic (eq. (2.5))	-6.27***	1.54	1.65	0.6092
z-statistic (eq. (2.5))	3.85***	1.64	1.46	0.76
DE (eq. (2.6))	-2.8862	0.9738	0.8930	1.0545
t-statistic (eq. (2.6))	-2.50**	2.25**	2.22**	1.35
z-statistic (eq. (2.6))	1.12	2.36**	2.00**	1.22

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

Standard errors in parentheses

Table 2.9 concludes this part of the study's analysis by pursuing an inquiry into the impact of team-size (i.e., the number of individuals in an investor team) on the intensity of the DE. Similar to the case in Tables 2.7 and 2.8, it is noted that the DE for the full investor team subject subsample in this instance is generally higher than that of the full sample of robots. A comparison between the DE values of the small team-size group and the large team-size group is a lot less conclusive however, as DE for the small team-size group is only marginally higher than that of the large team-size with respect to Equation (2.2) at both the aggregated and disaggregated levels. Further to this, a relatively more peculiar finding is that the statistically insignificant DE value for the large team-size group is higher than that of the statistically significant DE value of the small team-size group following Equation (2.6). In addition, although DE is higher for the small team-size relative to the large team-size following Equation (2.5), the DE values of both groups are insignificant under parametric and nonparametric testing.

All in all, the modified version of Goulart *et al.* (2013) methodology used in this section of the analysis to assess the impact of the three psycho-social factors on the DEs of the investor teams introduces more rigour to the methodology by employing three different measures of DE and conducting both parametric and non-parametric tests on the significance of DE for each sub-sample group. In making use of this methodology, we find – summarily – that investor teams in the low female composition subsample (or, condition) have higher, more significant DEs than the high female composition condition across all measures of DE and statistical tests. The same outcome is seen with respect to the low climate temperature condition, which exhibits higher and more significant DEs than comparison condition characterised by high climate temperature. Thirdly, a clear and consistent outcome between the low team-size and the high team-size conditions cannot be gleaned from this methodology. Although the Goulart *et al.* (2013) approach (particularly in its modified version above) allows for compelling deductions to be drawn from how the various outcomes of the individual sample tests relate to each other, it does not conduct any statistical inquiries into the significance of the differences between the various conditions. The implication here is that there is no scientifically-sound basis upon which to discuss the causal relationship (if any) between the three psycho-social factors under study and the intensity of the DE. For this, we turn to estimates of average treatment effects (ATE) in the next section of the analysis.

2.3.3. Testing for treatment effects

In this section of the analysis, we begin by following a between-subject experimentation approach to estimate the ATEs of the same sub-samples of subjects as in the previous section (following equation (2.7)) who are in the (a) high vs. low climate temperature condition, (b) high vs. low female composition condition, and (c) large vs. small investor team-size condition (Moffatt, 2016). We also estimate ATEs between the full samples of 52 investor teams and 29 robots.

Table 2.10 begins by showing – at the 1% level – the significance of the differences in the DEs of the full samples of investor teams and robot subjects, across all three measures of DE and all four tests. This evidence supports the *a priori* understanding that the DE is a cognitive bias that only humans succumb to.

With respect to female composition, we find that differences between the DEs of the high female composition condition (i.e., investor teams consisting *more* woman members) vs. the low female composition condition (i.e., investor teams consisting *less* woman members) are also significant at the 1% level with respect to the regression adjustment test, and at the 5% level with respect to all of the other three statistical tests, following the Weber and Camerer (1998) measure of DE (i.e., Equation (2.5)). By implication, the evidence suggests that DE intensifies with lesser female composition in investor teams and tapers off with greater female composition.

Finally, with regards to the low climate temperature and high climate temperature sub-samples, as well as the low female composition and high female composition sub-samples, we see that – across all measures of DE – none of the differences are significant.

Table 2.10: Testing for treatment effects: ATE coefficients, regression adjustment p-values, two-tailed p-values from two sample t-tests, Mann-Whitney tests, and bootstrap tests for differences in the mean DEs

Experimental conditions	DE equation	ATE (τ)	Regression Adjustment p-values	Two sample t-test p-values	Mann-Whitney test p-values	Bootstrap test p-values
$\tau = DE_{INVESTOR\ TEAMS} - DE_{ROBOTS}$	Eq. (2.2)	0.1526 (0.0410)	0.000***	0.002***	0.001***	0.001***
	Eq. (2.5)	0.5863 (0.0986)	0.000***	0.000***	0.000***	0.000***
	Eq. (2.6)	4.0866 (1.2288)	0.001***	0.000***	0.001***	0.005***
$\tau = DE_{LOW\ COMP} - DE_{HIGH\ COMP}$	Eq. (2.2)	0.0765 (0.0860)	0.373	0.393	0.217	0.415
	Eq. (2.5)	0.3669 (0.1393)	0.008***	0.015**	0.028**	0.029**
	Eq. (2.6)	0.3060 (0.9256)	0.741	0.750	0.155	0.801
$\tau = DE_{LOW\ TEMP} - DE_{HIGH\ TEMP}$	Eq. (2.2)	0.0810 (0.0833)	0.331	0.352	0.343	0.343
	Eq. (2.5)	0.1795 (0.1184)	0.130	0.150	0.129	0.157
	Eq. (2.6)	1.0328 (1.2657)	0.414	0.433	0.217	0.428
$\tau = DE_{SMALL\ TEAM} - DE_{LARGE\ TEAM}$	Eq. (2.2)	0.0060 (0.0657)	0.928	0.930	0.681	0.932
	Eq. (2.5)	0.0793 (0.1304)	0.543	0.559	0.613	0.563
	Eq. (2.6)	-0.1615 (0.8534)	0.850	0.855	0.558	0.867

(a) $DE_{INVESTOR\ TEAMS} - DE_{ROBOTS}$ = investor teams vs. robots condition, (b) $DE_{LOW\ COMP} - DE_{HIGH\ COMP}$ = low vs. high female composition condition, (c) $DE_{LOW\ TEMP} - DE_{HIGH\ TEMP}$ = low vs. high climate temperature condition, and (d) $DE_{SMALL\ TEAM} - DE_{LARGE\ TEAM}$ = small vs. large investor team-size condition. Standard errors for the regression adjustment tests are provided in parentheses.

*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

In proceeding towards an inquiry into the causal links between the DE and investor welfare, Table 2.11 provides two-tailed p-values of bootstrap tests (B = 9,999) into the significance of differences between the cumulative market-adjusted *ex post* returns (i.e., *ex post* returns in excess of the FTSE/JSE All Share Index) for the winning stocks sold and losing stocks held over two investment horizons, for the two individual experimental conditions (including their associated control conditions) which were identified as having a significant causal impact on the intensification of the DE in Table 2.10 (i.e., the investor team and low female composition conditions).

We do not find any of the individual experimental conditions' differences in *ex post* returns to be significant during the time horizon leading up to the end of the 2019 run of the Challenge. However, we find evidence (at the 1% level) suggesting the significance of the *ex post* return differences over the subsequent 252 trading days (i.e., next 12-month period) for the investor team and low female composition conditions. Interpretively, the positive *ex post* return difference for the investor team condition means that the winning stocks sold by investor teams had a cumulative market-adjusted return of 208 percentage-points higher than that of stocks which incurred a paper loss over the subsequent investment horizon of 252 trading days. For the investor teams under the low female composition condition, their winning stocks sold for a profit have a cumulative market-adjusted return that is 411 percentage-points higher than that of their paper loss stocks.

Summarily then, we find compelling evidence suggesting that the investor team and low female composition conditions – which are understood to be causally-linked to intense levels of the DE – are strongly associated with sub-optimal investor welfare, when looking at the *ex post* cumulative market-adjusted returns of winning stocks sold, and losers held over a subsequent 12-month period. In order to understand whether that the investor team and low female composition conditions have a causal effect on investor welfare, we use equation (2.8) to test for treatment effects.

Table 2.11: Cumulative market-adjusted *ex post* returns for the winning stocks sold and losing stocks held (a) until the end of the Challenge on 20/09/2019, and (b) over the next 12 months of trading

Experimental conditions	Investment horizon	Cumulative *ex post* return on winning stocks	Cumulative *ex post* return on paper losses	Difference in *ex post* returns	Bootstrap test p-values
Investor teams	Until end date of game (20 Sep ’19)	-0.0662	-0.1067	0.041	0.192
	Next 252 trading days	1.9855	-0.0919	2.0774	0.000***
Robots	Until end date of game (20 Sep ’19)	-0.0230	0.0130	-0.0360	0.672
	Next 252 trading days	0.7590	0.3686	0.3905	0.413
Low female composition	Until end date of game (20 Sep ’19)	-0.1169	-0.1781	0.0612	0.167
	Next 252 trading days	3.9741	-0.1381	4.1123	0.001**
High female composition	Until end date of game (20 Sep ’19)	-0.0174	-0.0381	0.0206	0.606
	Next 252 trading days	0.0733	-0.0474	0.1207	0.251

*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

The results provided in Table 2.12 below indicate that the difference in *ex post* returns for the winning stocks sold relative to the losers held over the next 12 months is 169 percentage-points greater for the investor team (i.e., human) condition than it is for the robots, at a 10% level of significance under the two sample t-test and bootstrap test, at a 5% level under the Mann-Whitney test. Furthermore, the results suggest that that the difference in *ex post* returns for the winning stocks sold relative to the losers held over the next 12 months is 399 percentage-points greater for the low female composition condition than it is for the high female composition condition, at a 1% level of significance under the bootstrap test.

Table 2.12: Testing for treatment effects ATE coefficients, regression adjustment p-values, two-tailed p-values from two sample t-tests, Mann-Whitney tests, and bootstrap tests for differences in cumulative market-adjusted *ex post* returns

Experimental conditions	Investment horizon	ATE (τ)	Regression Adjustment p-values	Two sample t-test p-values	Mann-Whitney test p-values	Bootstrap p-values
$\tau = DER_{INVESTOR\ TEAMS} - DER_{ROBOTS}$	Until end date of game (20 Sep '19)	0.0765 (0.0745)	0.304	0.2556	0.1443	0.339
	Next 252 trading days	1.6869 (1.3406)	0.208	0.0821*	0.0492**	0.095*
Experimental conditions (Cont'd)	Investment horizon (Cont'd)	ATE (τ) (Cont'd)	Regression Adjustment p-values (Cont'd)	Two sample t-test p-values (Cont'd)	Mann-Whitney test p-values (Cont'd)	Bootstrap p-values (Cont'd)
$\tau = DER_{LOW\ COMP} - DER_{HIGH\ COMP}$	Until end date of game (20 Sep '19)	0.0406 (0.0559)	0.468	0.4797	0.6309	0.477
	Next 252 trading days	3.9915 (2.6567)	0.133	0.1396	0.8138	0.009***

(a) $DER_{INVESTOR\ TEAMS} - DER_{ROBOTS}$ = investor teams vs. robots condition and (b) $DER_{LOW\ COMP} - DER_{HIGH\ COMP}$ = low vs. high female composition condition. Standard errors for the regression adjustment tests are provided in parentheses.

*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

Finally, as robustness tests on our observed (a) human investor team and (b) low female composition treatment effects of differences in *ex post* returns over the subsequent 12-month trading period (where positive relationships between the independent and dependent variables are interpreted as meaning that a given treatment variable causally reduces portfolio performance), we estimate the regressions to follow using Ordinary Least Squares (OLS), involving robust standard errors.

We begin by confirming the relationship between the low female composition and difference in *ex post* returns variables using the following OLS model:

$$DER_i = \beta_0 + \beta_1 InvestorTeams_i + \mu_i \tag{2.9}$$

Where $InvestorTeams_i$ = a dummy variable that is equal to 1 for investor teams made up of human subjects, and 0 for robot investors.

Table 2.13: OLS regressions on differences in cumulative market-adjusted *ex post* returns over the next 12 months of trading (investor teams vs. robots)

	Coefficient	Standard errors	t-stat.	[95% confidence interval]
Investor Teams	1.6869*	0.964	1.75	-0.2175 – 3.5912
Constant	0.3905	0.553	0.71	-0.7019 – 1.4828
F	3.06*			
n	64			

*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

Table 2.13 above confirms our earlier finding that the difference in *ex post* returns for the winning stocks sold relative to the losers held over the next 12 months is 169 percentage-points greater for the investor team (i.e., human) condition than it is for the robots, at a 10% level of significance.

Furthermore, given the strong positive relationship that is empirically understood to exist between trading frequency and behavioural biases such as the DE (Barber and Odean, 2000; Bootsma and Regaieg, 2018), as well as the causal flow that exists between the DE and portfolio performance as per our findings in the current study, we look into the nature of the relationship between human investor teams with high order flows and the difference in *ex post* returns variable by estimating the following model:

$$DER_i = \beta_0 + \beta_1 HighOrderFlowTeams_i + \beta_2 LowOrderFlowTeams_i + \mu_i \qquad (2.10)$$

Where $HighOrderFlowTeams_i$ = a dummy variable that is equal to 1 for investor teams who execute 90 orders (i.e., the median number of orders executed by all investor teams in the sample) or more over the course of the Challenge, and 0 if otherwise. $LowOrderFlowTeams_i$

= a dummy variable that is equal to 1 for investor teams who execute less than 90 orders (i.e., below the median), and 0 if otherwise.

Table 2.14: OLS regressions on differences in cumulative market-adjusted *ex post* returns over the next 12 months of trading (investor teams with high order flows)

	Coefficient	Standard errors	t-stat.	[95% confidence interval]
Investor Teams (order flows ≥ 90 orders)	3.9343**	1.552	2.53	-2.7575 – 2.1198
Investor Teams (order flows < 90 orders)	-0.3188	1.234	-0.26	0.8676 – 7.0010
Constant	0.3905	0.5434	0.72	-0.6831 – 1.4640
F	4.80***			
n	64			

*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

This time around, we find that human investor teams with high order flows have a markedly higher difference in *ex post* returns, at a 5% level of significance. Secondly, with an F-statistic that is significant at the 1% level (vs. the 10% level), we see in Table 2.14 that Equation (2.10) provides a better fit to the data than Equation (2.9).

Moving along to our inquiry into the relationship between the low female composition treatment effects and portfolio performance, we regress the difference in *ex post* returns variable on the low female composition treatment variable – along with two other control variables related to the psycho-social factors investigated in the current study, as per the following model:

$$DER_i = \beta_0 + \beta_1 LowFemaleComp_i + \beta_2 LowClimateTemp_i + \beta_3 LargeInvestorTeam_i + \mu_i \quad (2.11)$$

Where DER_i = differences in cumulative *ex post* returns for investor team *i*, $LowFemaleComp_i$ = a dummy variable that is equal to 1 if an investor team is characterised by low female composition and 0 if otherwise, $LowClimateTemp_i$ = a dummy variable that is equal to 1 if an investor team is subjected to low climate temperatures and 0 if otherwise, $LargeInvestorTeam_i$ = a dummy variable that is equal to 1 if an investor team is regarded as being of a relatively large size and 0 if otherwise.

Table 2.15: OLS regressions on differences in cumulative market-adjusted *ex post* returns over the next 12 months of trading (psycho-social factors)

	Coefficient	Standard errors	t-stat.	[95% confidence interval]
$LowFemaleComp_i$	7.1910**	2.922	2.46	1.3119 – 13.0701
$LowClimateTemp_i$	2.8704	2.570	1.12	-2.3007 – 8.0415
$LargeInvestorTeam_i$	8.0130***	2.852	2.81	2.2749 – 13.7512
$Constant\ (\beta_0)$	-6.8389**	2.899	-2.36	-12.6715 – -1.0063
F	3.88**			
n	51			

*p-value < 0.1.
**p-value < 0.05.
***p-value < 0.01.

Table 2.15 shows the low female composition treatment variable to be statistically significant at the 5% level. Interestingly, we see a strongly positive relationship (significant at the 1% level) between the large investor team variable and the difference in *ex post* returns variable. Given that we were unable to identify a causal relationship between investor team-size and the DE in Table 2.10 above, we are of the view that the nature of the relationship between the large investor team variable and the dependent variable is more correlational than causal.

2.3.4. Summary of results

Based on the outcomes of the analyses comparing the DEs of investor teams against robots in Tables 2.2 – 2.10, we consistently find significant evidence confirming hypothesis H1 and supporting the *a priori* understanding that the DE is a cognitive bias that only humans are susceptible to.

Furthermore, not only is there a strong negative correlation between female composition and the DE as shown in Table 2.7, but there is also a strong causal relationship between the two variables, following the Weber and Camerer (1998) measure of DE. Specifically, the results in Table 2.10 suggest that the fewer the women in an investor team, the more intense the DEs of the team, and thus confirm hypothesis H2 that female composition explains the intensity of investor teams' DEs.

Regarding the relationship between climate temperatures and the DE, an indication of low climate temperatures being associated with the intensity of the DE is given in Table 2.8, in following our modified Goulart *et al.* (2013) approach. This finding, however, points only to correlation between the two variables rather than to a causal relationship. The outcomes of an inquiry into the latter relationship-type are provided in Table 2.10 and suggest that there are no causal links between climate temperatures and DEs. Considering this, we reject hypothesis H3.

In investigating the link between team-size and DEs, we find that neither the correlation analysis in Table 2.9, nor the tests of causality in Table 2.10 suggest the existence of a relationship between the two variables. This, in turn, leads us to reject hypothesis H4 and conclude that team-size (or, group-size) does not explain the intensity of DEs.

Turning to our inquiry into the relationship between the DE and investor welfare, Table 2.11 shows that DE is associated with sub-optimal investor welfare over a long time-horizon (i.e., over the next 12 months), but not over a relatively shorter time-horizon (i.e., period leading up to the end-date of the Challenge). Furthermore, the conditions understood to be causally linked to more intense levels of the DE (i.e., the investor team and low female composition conditions) are the only ones identified as being strongly associated with sub-optimal investor welfare. In looking into the existence of causal links between the DE and investor welfare, it is worth beginning by reiterating our understanding that investor teams – whom by virtue of being human – are susceptible to the DE. This susceptibility to, or presence of the DE in relation to their investment decision-making causes a reduction in their *ex post* returns of 169 percentage-points relative to the robot (i.e., non-human) condition, as provided in Table 2.12. In relation to the psycho-social factor of female composition, we find that the exclusion of women in investor teams can be highly costly in terms of its impact on portfolio outcomes. In addition, this result suggests that psycho-social factors which are understood to have a causal effect on the intensity of the DE, ultimately lead to sub-optimal investor welfare. These results confirm H5 that the DE causally reduces investor welfare.

The results of the OLS regressions in Tables 2.13 to 2.15 confirm that indeed a strong causal relationship exists between (i) the human investor team treatment and differences in *ex post* returns, as well as between (ii) the low female composition treatment and differences in *ex post* returns of over the subsequent 12-month trading period. In addition to these finding, the results of the OLS regressions show that causal relationship (i) above is especially pronounced when regressing the dependent variable on human investor teams with a relatively high number of orders executed. Furthermore, the results in Table 2.15 – when taken together with those in Table 2.10 – suggest that a strong correlational (and not causal) relationship exists between the dependent variable and large investor teams. This finding is consistent with Goldman and Xhou's (2016) empirical finding that, on average, mutual funds ran by a single fund manager outperform those ran by a team of managers by as much as 1.3% per year. They point to a possible increase in moral hazard risk, due to increased team size as a potential explanation. A further inquiry into this insight would thus be a deviation from our main investigation into the nature and extent of the DE; we therefore conclude – on this point – that the potential causal flow between investor team size and reduced portfolio performance does not involve the DE.

2.4. Discussion and concluding remarks

2.4.1. Discussion of results

Our findings in relation to H1 are consistent with those in Da Costa *et al.* (2013). However, as points of distinction, our findings in the current chapter relate to a context in which human subjects are proxied by investor teams participating in a live market that is real in every sense, save for in value of currency. In this way, the current chapter introduces to the literature externally valid findings that suggest that investor teams – similar to those one may encounter in asset management firms, investment banks, and hedge funds – are susceptible to the DE.

In confirming hypothesis H2, the implications are as follows: Firstly, we introduce to the literature – for the first time – evidence from a natural-field experiment supporting the understanding that men are more susceptible to the DE than women; an understanding that is indeed robust when one considers not only the internally valid results that support it (such as those in Da Costa *et al.*, 2008), but also – by way of the current study – the externally valid results as well. Both the business science and psychology literature point to women's inclination to take less risks than men (Slovic, 1966; Thomas and Garvin, 1973; Roberts, 1975; Kogan and Dorros, 1978; Karakowsky and Elangovan, 2001) as an explanation for this phenomenon.[16]

On the question of why women might be less inclined to make risky decisions – a question that is seldom (if ever) responded to with experimental evidence – our reading of the literature on the topic (Hsiao and Pi-Chuan, 2006; Da Costa *et al.*, 2008; Brooks *et al.*, 2012; Duxbury *et al.*, 2015) points us to the possibility that men's neurologically-based inclination to believe in mean-reversion can, *ceteris paribus,* lead them to make calibration errors synonymous with the overconfidence bias, ultimately manifesting as a type of risk-taking behaviour (i.e., risk-

[16] More aptly, Dickason and Ferreira (2018) find evidence suggesting South African female investors are less tolerant of risk than South African male investors.

seeking over losing positions) that intensifies the DE. Indeed, we find support for this view in the results of the natural-field experiments of the current study by calculating the PGR and PLR values (as per Equation (2.1)) of the low and high female composition investor teams, using data provided in Table 2.7. With PGR values of 0.8807 and 0.7711, as well as PLR values of 0.7020 and 0.7465 for the low and high female composition groups, respectively; our results mean that the DE identified among low female composition investor teams (i.e., the group of investor teams made up of a relatively higher male composition) is solely driven by said group's disinclination (or more aptly, aversion) to realise their losing stock positions. This analysis, in our view, ultimately fleshes out – both theoretically and methodologically – the finding in Da Costa *et al.* (2008) that men's DEs are driven by an inclination to believe in mean-reversion, however – in contrast to Da Costa *et al.* (2008) – we are of the opinion that the basis of such a belief held by men is fundamentally irrational (given the influence of loss aversion) rather than rational.

Yet another distinguishing feature between Da Costa *et al.* (2008) and the current study is that the former arrives at its conclusions using data on the investment decisions of individuals, whereas the current study bases its inquiry on investor groups. This distinction is noteworthy given the long-standing view in the social psychology literature that individual decision-making is different to group decision-making, particularly when decisions are being made under the condition of uncertainty (i.e., under risk) (Madaras and Bem, 1968). To understand how women behave in the group-based decision-making context, we look to gender role theory (Ridgeway and Smith-Lovin, 1999). As a concept stemming from the sociology literature, gender role theory asserts that women will be more likely to express their views in group-setting where their gender predominates. The theory further posits that men tend to be perceived as being more competent than women in discussions on subjects that are perceived to be masculine (such as future corporate performance and investment decision-making, as found by Gregory *et al.* (2013)). Consequently, the gender role theory leads to the minority status hypothesis, which purports that being a numerical minority in a group-setting – such as an investor team – places women in a lower status relative to men, effectively reducing mentions of their views and beliefs. Relating these concepts back to the results of the current study, a plausible conjecture may be that men's irrational belief in – *inter alia* – mean-reversion resonates and is acted upon in a male-dominated investor team context; however, its resonance tapers off among investor teams in which women are the majority. This conjecture provides a theoretical explanation for why our results show the DE to be more intense among male-dominated investor groups relative to their female-dominated counterparts.

Secondly, if the susceptibility of different genders to the DE is contingent on cultural context as espoused by Rau (2014), then the findings in this chapter introduce to the literature the understanding that – similar to the Brazilian context (Da Costa *et al.*, 2008), and contrary to the German one (Rau, 2014) – South African men, in particular, are more susceptible to the DE than their women counterparts. In taking a closer look at the cultural drivers of DEs in the three geographies, one might look to Hofstede's cultural dimensions, often used to conduct comparative intercultural research on cross-sections of nationalities (Hofstede, 2001). In this regard, the finding in Breitmayer *et al.* (2019) that the cultural dimension of long-term orientation is negatively-correlated with susceptibility to the DE is highly relevant; particularly when considering both the facts that (i) the German population scores more than twice as high as South Africa and Brazil (on average) in the long-term orientation dimension (Hofstede Insights, 2021), and (ii) women have been shown to score higher than men in long-term orientation (AlAnezi and Alansari, 2016).

The logical conclusion that one might then arrive at on this point is that – similar to Brazilian investors – South African investors exist within a cultural context where long-term orientation is valued relatively lowly, which in turn renders South African investors prone to the DE across the gender-divide. Looking more pointedly at gender, our sense is that South African male investors – who are predisposed to being less long-term oriented due to their gender – would resultantly exhibit more intense DEs relative to their female counterparts, even within the context of a nationality that is already generally prone to succumbing to the bias. These deductions offer the most comprehensive explanation for how differences in culture may lead to differences in gender related DEs across different nationalities.

Turning more deliberately to the finding that investor teams composed of fewer women exhibit higher DEs, we find an explanation for this occurrence by conflating the conjectures above relating to the cultural dynamics at play with the literature on the effects of gender composition in collaborative groups. In this regard, Karpowitz *et al.* (2012) find compelling experimental evidence which suggests that in instances where women are assigned to be the numerical minority in deliberating groups (i.e., teams) that are required to make decisions based on majority rule, women are less likely to voice their opinions and be rated by their peers as being more influential than (a) men in their groups, (b) men in the same numerical minority status, and (c) women in other groups. Karpowitz *et al.* (2012) refers to this phenomenon as the 'gender role hypothesis,' and assert that this gender gap in participation and influence in the group decision-making context is especially pronounced when the deliberation's subject-matter is perceived to be of a masculine nature, resulting in men being perceived as being more competent on the topic thus enjoying a higher status in discussions (Karpowitz *et al.*, 2012; Mendelberg *et al.*, 2014). Given the cultural and numerical dominance that men have in the professional investments industry (Riach and Cucher, 2014; Preqin, 2019), it is reasonable to hold that asset allocation may be one such subject that is perceived as being particularly masculine.

With all of the aforementioned in mind, we conjecture that in investor teams characterised by low female composition, men have a greater bearing on the team's investment decision-making by virtue of the gender role hypothesis (Karpowitz *et al.*, 2012); thus, in view of men's relatively low long-term orientation (AlAnezi and Alansari, 2016) as discussed above, it follows that the investment decisions of teams where men are the numerical majority would be highly susceptible to the DE.

Regarding H5, and as discussed at length in the literature review above, the understanding that the DE is associated with sub-optimal investor welfare (i.e., portfolio returns) has been well-established in the literature (Weber and Camerer, 1998; Odean, 1998; Roger, 2009; Talpsepp, 2010; Duxbury *et al.*, 2015; Shen and Shen, 2022). However, to the best of our knowledge – this study is the first to introduce to the literature experimental evidence from the field that clearly demonstrates that a causal relationship exists between the DE and investor welfare, in line with H5. The implications of this finding are extensive and far-reaching. For instance, taken together with the insight from Fischbacher *et al.* (2017) that automatic selling devices (i.e., stop-loss orders which automatically liquidate a stock position when the stock price falls below a pre-set threshold) causally reduce the intensity of the DE by assisting investors to realise their losses, our (relatively newer) finding that the DE causally reduces investor welfare would – through a process of deductive reasoning – lead to the view that stop-loss orders are causally linked to positive portfolio outcomes, by way of their effectiveness in causally reducing the extent of the DE; which would – as evidenced in the current study – causally improve on investor welfare, *ceteris paribus*. Supporting this view's plausibility is (i) Acar and Toffel's (2000) finding that stop-loss strategies outperform buy-and-hold, in instances where market prices trend; (ii) Kaminski and Lo's (2014) conclusion that stop-loss policies can increase expected returns over longer sampling frequencies; and (iii) Talpsepp and Vaarmets (2019) who show that investors with a history of poor academic performance benefit from higher holding period returns when executing stop-loss orders of 5% below the reference price. Our findings in the current study thus augment this perspective in the literature, by conjecturing that it is by way of their moderating impact on the DE that stop-loss orders improve investor welfare. Such a conjecture – in our view – is ripe for future experimental research.

As a slightly more general view, and as evidenced by our findings that robot investors are (a) devoid of DEs, and (b) that their winning stocks sold are not significantly higher than their losers held, we can further deduce from the results of our study that a trading approach that has a reduced reliance on human investors' decision-making faculties (e.g., making use of algorithmic traders or, indeed, automatic selling devices) could causally reduce the intensity of the DE and its negative impact on investor welfare. It is noteworthy, however, to mention that such an approach need not entirely eliminate human involvement in investment decision-making, as human investors have been shown to outperform robot traders during market crashes (Gjerstad, 2007), suggesting that human traders respond and adapt better to instances of extreme market volatility. With this view in mind, it may be wise for market practitioners such as asset managers, investment bankers, and hedge fund managers to pair their investor teams with suitable robot (i.e., algorithmic) traders.

Finally, by finding that low female composition in an investor team causally reduces investor welfare via the DE, our study demonstrates in no uncertain terms how psycho-social factors understood to intensify the DE can negatively impact investor welfare. What of psycho-physiological factors such as those found in Goulart *et al.* (2013)? Can a similar impact on investor welfare be expected? We leave these questions open to be answered by future experimental research; the findings of which would not only contribute new evidence-based views to the literature on the various human nature-related mechanisms through which the DE is intensified (effectively causing an impairment to investor welfare) – but would also guide market practitioners on how to build investor teams in such a way that the altogether costly DE is mitigated against.

2.4.2. Conclusions

In this chapter, we explored the correlational and causal relationship between a set of psycho-social factors and the DE, among a sample of investor teams participating in the 2019 run of the JSE Investment Challenge, as part of a natural-field experiment. In doing so, we found externally valid evidence suggesting that (i) South African investor teams are indeed susceptible to the DE; (ii) an increased male presence (i.e., lower female composition) in an investor team intensifies said team's DEs; and (iii) human factors that intensify the DE also causally impair investor welfare. These outcome's present several implications for researchers and asset managers alike.

In the next chapter, we use data from a sample of investor teams participating in the 2020 run of the JSE Investment Challenge to investigate whether the emergence and intensification of disposition effects could be brought about by a public health crisis such as the COVID-19 pandemic, and whether such disposition effects could subsequently lead to changes in investor teams' trading volumes.

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CHAPTER THREE

Quarantining at home during the COVID-19 pandemic and the disposition effects of South African investor teams

3. Introduction

The COVID-19 pandemic, which is perhaps the most serious international health & safety crisis since World War II – ushering in the most significant constraints to global economic performance since the 2007/2008 financial crisis – has had a notable impact on global stock markets. With this, a curious development that's been observed has been the rise of retail stock traders as market-moving investors whose investment behaviour noticeably supported the liquidity of the US equity market in the months following the COVID-19 stock market crash (Ozik *et al.*, 2021), and caused a modestly valued gaming business' stock price, GameStop, to rally by 1,700 percent in under two months, resulting in several large Wall Street-based hedge funds dumping their short-sell positions on the same stock (Phillips and Taylor, 2021).

With most retail traders executing trades themselves instead of relying on algorithmic traders, it is likely that much of their investment decision-making is distorted by behavioural and cognitive biases such as the disposition effect. In this regard, although several inquiries into the relationship between the COVID-19 pandemic and the disposition effect have been conducted (Goossens and Knoef, 2020; Parveen *et al.*, 2021; Mushir *et al.*, 2021), few – if any at all – have sought to understand the psychological mechanisms and behavioural channels underlying the disposition effects of investors (African investors, especially) within the context of the pandemic, and fewer still have done so using natural-field experimentation means, bringing to question the robustness and external validity of the results of any such existing research efforts. The current chapter responds to this gap in the literature – as well as several other more nuanced gaps discussed in the paragraphs to follow – by using experimental means to (1) understand the nature of the relationship between high, localised COVID-19 infection rates and the disposition effects of South African investor teams, as well as (2) between the disposition effect and trading volumes of South African investor teams. We once again adopt the JSE Investment Challenge as the research context for the current study, however this time with a specific focus on the 2020 run of the Challenge (i.e., during the first year of the pandemic).

In the remainder of this chapter, Section 3.1 provides (i) a review of the literature on the mean-reversion hypothesis as an alternative behavioural model explaining the disposition effect, (ii) an overview of the impact of the COVID-19 pandemic on global financial markets, (iii) a discussion on what the pandemic has meant for the South African equity market, (iv) an account of how aspects of the 'new normal' may possibly entrench the disposition effect, (v) an overview of some of the trends emerging from the JSE Investment Challenge since the onset of the pandemic, and (vi) provides the hypotheses of the current study. The methodology and data are discussed in Section 3.2, and the results are covered in Section 3.3. Section 3.4 discusses the implications of the results and concludes the chapter.

3.1. Literature review and hypotheses

3.1.1. The Disposition Effect and the Mean-Reversion Hypothesis

The intuition behind the mean-reversion hypothesis as a behavioural model for the disposition effect is simple: if an investor holds the belief that winning stocks will soon perform poorly, and losing stocks will soon perform better, their resultant investment decisions would lead to a disposition effect being observed (Frydman *et al.*, 2014). Such beliefs are perhaps irrational for at least two reasons, firstly, they contradict the finding in Odean (1998), in Duxbury *et al.* (2015), and in Chapter 2 of the current thesis that losing stocks held by investors tend to subsequently do poorly, not better; and secondly, investors impacted by the disposition effect are often succumbing to a reluctance to realise losing stock positions (i.e., loss aversion),[17] with their belief in mean reversion perhaps being a *post hoc* rationalisation for their irrational, subconscious bias-driven investment decisions.

Empirically, the findings of numerous studies have supported the mean-reversion hypothesis as an explanation for the disposition effect (Da Costa *et al.*, 2008; Brooks *et al.*, 2012; Jiao, 2017). However, contrary to these studies, an alternative view is suggested by the findings in Weber and Camerer (1998); wherein which one of their stock trading experimental conditions involves the liquidation of subjects' entire portfolio holdings at random times, following which said subjects are asked to reinvest the proceeds of the liquidation however they may see fit. Under experimental testing, the study finds that subjects under this condition – who had been shown to be affected by the disposition effect prior to the liquidation – did not repurchase their losing stocks, effectively weakening the intensity of the subjects' disposition effects (Duxbury, 2015), and contradicting the mean-reversion hypothesis-informed understanding that investors who hold on to losing stocks do so under the expectation that the stock's price trajectory will soon change (Frydman *et al.*, 2014). As compelling as this finding may be, our view is that it does not challenge the mean-reversion hypothesis to an irredeemable extent; particularly when one considers the theory of decision points, as well as the effects of partitions on controlling behaviour.

First introduced in Soman *et al.* (2010), and largely based on the dual system model – which has been discussed at length in the literature on psychoanalytic theory (Freud, 1923), behavioural economics (Tversky and Kahneman, 1974; Thaler and Shefrin, 1981), and even Smithian economics (Smith, 1759 [1981]; Ashraf *et al.*, 2005) – the theory of decision points asserts that individuals who are in the process of consumption start off in a

[17] See Chapter 2, Subsection 2.4 of the current thesis for our analysis supporting this assertion.

deliberative/ego/system 2-driven mode of thinking, where they weigh-up the pros and cons of consumption. However, once they begin consuming, they switch to the automatic/id/system 1-driven mode of thinking where continued consumption is mindless and driven by subconscious forces. Disrupting such mindless consumption with a decision point therefore allows individuals to pause and think (i.e., switch back to the deliberative mode of thinking) about the consumption they are engaging in, effectively mitigating against the scourge of unconscious bias.

Closely linked to the theory of decision points is the partitioning effect; a debiasing strategy which Cheema and Soman (2008) find consistent support for in a series of consumption-oriented experiments. In particular, the results of their experiments demonstrate that partitioning a large quantity of a resource into smaller quantities (e.g., a large box of popcorn partitioned into smaller boxes of popcorn) reduces the rate of the consumption of said resource, as partitions intermittently draw attention to the consumption decision, allowing several opportunities for individuals to employ their deliberative mode of thinking and make prudent consumption decisions. For example, to investigate the effect of partitions on chocolate consumption, one of Cheema and Soman's (2008) experiments involved distributing boxes of chocolates to a group of students across two conditions: those receiving boxes with six unwrapped chocolates (i.e., the aggregate quantity condition) and those receiving boxes of six individually wrapped chocolates (i.e., the partitioned quantity condition). Ultimately, they found that student subjects under the partitioned condition consumed each chocolate at a rate that was almost one-third slower than that of those who were under the aggregate quantity condition; effectively illustrating the attenuating effect of partitions on the intensity of subconscious bias. In a similar vein, our view is that it is plausible that the automatic selling of stocks in the Weber and Camerer (1998) experiment discussed above introduces a partition to the loss aversion-driven urge to hold on to losing stocks, allowing for investors to consciously reflect on their stock holding and subsequently make relatively more rational investment decisions; effectively attenuating the intensity of the disposition effect.

Summarily then, and in building on our view of the mean-reversion hypothesis as it relates to the disposition effect, we conjecture that the irrational belief in mean-reversion, driven by – *inter alia* – loss aversion, is adequate in explaining why the disposition effect occurs. Furthermore, as is the case with other forms of subconsciously processed behaviours, a break in the behaviour (e.g., a disruption to the irrational behaviour of holding on to losing stock positions for too long) due to the introduction of a decision point or partition, mitigates against the intensity of the prevailing bias (e.g., an attenuation of the disposition effect). Therefore, the effect that the urge to believe in mean-reversion has on the disposition effect holds only on condition that the investment decision-making process is not partitioned.

3.1.2. The impact of the COVID-19 pandemic on global financial markets and investor trends

First identified in Wuhan in December 2019, COVID-19 (a coronavirus which leads to respiratory tract infections that range from mild to lethal and is also known as SARS-CoV-2) has since infected people on a global scale over 652 million times and has led to more than 6.6 million human deaths (John Hopkins University & Medicine, 2022). The scale of the spread of the disease led the World Health Organisation (WHO) to declare COVID-19 as a global emergency on the 20th of February, 2020, and later a global pandemic as of the 11th of March, 2020 (Ali *et al.*, 2020). To slow down COVID-19 infection rates and prevent public health systems from being overwhelmed, governments across the world – including the South African government – imposed strong containment measures (i.e., lockdowns) on their societies which included mandatory mask-wearing in public spaces, international and local travel bans, country-wide curfews, school and university closures, and alcohol sale and restaurant dining bans (Tafirenyika, 2021).

Economically, the COVID-19 pandemic has brought about the most serious global crisis since World War II, with virtually all economic sectors affected by a decline in international tourism and business travel, weaker demand for imported goods and services, and extensive disruptions to global supply chains (Allain-Dupré *et al.*, 2020). At its lowest trough during the pandemic, the global GDP growth rate declined by 5.9 percentage-points (or approximately 211 percent) to a rate of -3.1 percent in 2020, from 2.8 percent in 2019 (IMF, 2021). As a result of lower economic output, expectations regarding firms' future cash flows had lowered, consequently leading to notable declines in the fundamental value of company stocks listed in the world's bourses (Mazur *et al.*, 2020).

As an illustration of the pandemic's impact on global financial markets, Ali *et al.* (2020) – in their investigation on the impact of the COVID-19 public health crisis on major stock markets and commodity markets – posit that nearly 30 percent of wealth in the world's bourses was eroded within a period of 100 days. Furthermore, Ali *et al.* (2020) empirically demonstrate how – on average – the volatility of the world's stock markets (as per their use of exponential GARCH models) increased as the COVID-19 scourge advanced from 0.04 percent during the epidemic stage (as of the 20th of February, 2020), to 0.29 percent during the pandemic stage (as of the 11th of March, 2020). On the other hand, Wang and Enilov (2020) – in their study using Granger non-causality tests – found that the number of COVID-19 cases/infections significantly influenced international financial markets' stock returns. More specifically, they find that the number of COVID-19 cases in Canada, France, Germany, Italy, and the US (five of the G7 group of countries) have a significant impact on the returns of said countries' stock market indices. In response to these developments, the central banks of the world adopted both conventional and unconventional expansionary monetary policies, albeit to very limited effect on stock markets, particularly during the earlier days of the pandemic (Wei and Han, 2021).

As an illustration of the pervasiveness of the pandemic's weakening impact on the effectiveness of monetary policy transmission, Wei and Han (2021) find no significant differences in monetary policy effectiveness-weakening across economies with different levels of industrialisation and financial development. By the end of 2020, however, they find that the S&P 500 index had recovered, and the indices of major emerging markets had largely recovered. On reflection, a noteworthy common thread that runs across the emerging literature on the impact of the pandemic on the performance of the world's financial markets is the finding that much, if not all of the observed stock market instability (i.e., market volatility, market decline, and market unresponsiveness to monetary policy changes) occurred in the earlier, short-term period of the pandemic (January to April, 2020). According to Wei and Han (2021), a possible reason for stock markets' unresponsiveness to changes in monetary policy could be market participants' over-reaction to news on the pandemic, as well as other investor behaviours such as herd behaviour. Our view is that these – as well as several other market-distorting behavioural biases and trends seen among investors during the pandemic – could plausibly explain not only stock markets' short-run insensitivities to monetary policy changes, but also the observed volatility and decline in stock market returns around the world as investors 'herd' towards 'safe haven' markets.

Looking more pointedly at changes in the behavioural trends and sentiments of investors as a result of the pandemic, Huber *et al.* (2021) ran a controlled, artefactual experiment (Harrison and List, 2004) that investigated how an extreme event, such the COVID-19 market crash, affects a sample of Europe-based finance professionals' risk-taking behaviour, price expectations, and perceptions regarding the riskiness of an experimental asset. In particular, their experiment looked to determine whether there were any changes in finance professionals' experimental investment decisions and attitudes brought about by the crash, by observing their engagement with the experimental asset in December 2019 (i.e., during the relatively bullish stock market period prior to the onset of the pandemic) and March 2020 (i.e., during the relatively more volatile, bearish stock market period that brought with it the COVID-19 market crash). Conducted online, the experiment involved a subject pool of 202 and 113 Europe-based, finance professionals in the December and March periods, respectively – and was controlled by 282 student subjects in December and 216 students in March; all of whom pursued their studies in economics and business disciplines (Huber *et al.*, 2021).

The results of Huber *et al.'s* (2021) experiment were three-fold, firstly, finance professionals' risk-taking behaviour declined by 9 percentage-points (at the 1% significance level) – from 77 percent to 68 percent of the experimental wealth being invested – between the December 2019 and March 2020 periods, whilst risk-taking behaviour remained unchanged among the control group of students. Secondly, the cohorts of finance professionals' self-reported perceptions about the riskiness of the experimental asset also declined significantly (i.e., by approximately 7.5 percent) between the two periods, with the measure – similar to the previous one – remaining unchanged for the groups of students. And thirdly, price expectations remained unchanged between the two periods for both the finance professionals and student subjects.

The results in Huber *et al.'s* (2021) experiment are instructive in a number of ways. For instance, the change in risk-taking behaviour among finance professionals – in spite of their risk perceptions of the experimental asset declining, and their expectations regarding the future price of said asset remaining the same – suggests that finance professionals' adjustments in their risk preferences, in response to the volatile, bearish market context that prevailed in March 2020, were carried over to how they engaged with the experimental asset with respect to the study. The plausibility of this insight is made more resonant by the finding that student subjects – whom we would expect to be relatively less exposed to the volatility of stock markets in March 2020 than finance professionals (i.e., institutional investors) – did not adjust their risk preferences (as proxied by their unchanged risk-taking behaviour) between the two sample periods.

On the other hand, retail investors have been shown to have markedly increased their participation in the financial markets since the onset of the pandemic, as exemplified by the three-fold increase in retail trading activity between 2019 and 2020, and more than 250,000 new trading accounts opened in March 2020 (more than any prior full-year on record) with US-based retail trading aggregator, Robinhood (Rooney, 2020; Wursthorn *et al.*, 2020). Given the understanding that more than half of Robinhood's customers open their first brokerage account with the retail aggregator, it is conceivable that the majority of the trading accounts opened with Robinhood in 2020 (i.e., following the onset of the pandemic) were opened by people who were novices in financial markets. This wave of new entrants to the financial markets has been made more pronounced by the decision among retail aggregators such as Charles Schwab, TD Amertitrade and E-Trade Financial to do away with commission fees on their trading accounts; a trend ushered in by Robinhood's market disrupting free-trade model, which – through eliminating a significant barrier to entry – has reduced the friction in relation to non-professional investors choosing to participate in the markets (Rooney, 2020).

The impact of this wave of new entrants to stock trading has proven to be market-moving, in some instances. For example, in July of 2020, Citadel Securities – a US-based market-maker who provides liquidity and trade execution to both retail and institutional clients – indicated that retail trading activity accounted for about 20 percent of all US equity market trades during the earlier months of the pandemic (Basak, 2020). Furthermore, in a study seeking to understand the trading behaviour of retail investors and its market implications during the era of the pandemic, Ozik *et al.* (2021) find that although overall liquidity in the US equity market declined between mid-March and mid-May, 2020, the increase in retail trading activity observed during this period improved it, as retail trades narrowed the bid-ask spreads of retail investors' most sought-after stocks by approximately 62 percent (to a spread of 23 basis points for stocks sought by retail investors relative to the average effective spread of 60 basis points).

On reflection of the juxtaposition between professional (i.e., institutional) investors' attenuated appetite to participate in the financial markets *vis-à-vis* the market-moving proliferation of retail trading activity following the COVID-19 pandemic-led crash in the world's financial markets, it is apparent that professional investors have an aversion to risk-taking behaviour that is countercyclical in nature (Huber *et al.*, 2021).[18] Furthermore, it is also apparent that this behavioural bias does not necessarily hold for individuals who have little-to-no previous experience in, or exposure to the financial markets (Cohn *et al.*, 2015; Huber *et al.*, 2021). Which aspects of our human nature may help in explaining this difference in reactions to market boom-bust cycles?

Psychologically, the prevailing understanding is that the emotion of fear causally leads to countercyclical risk aversion being observed among investors (Cohn *et al.*, 2015). Illustrating this understanding's robustness are the findings by Salisu *et al.* (2020) that the global fear index (GFI)[19] is (a) negatively correlated with stock returns in OECD countries,[20] and (b) positively correlated with, as well as strongly predictive of commodity market returns; with the latter finding pointing to institutional investors' well-known proclivity to redirect their portfolios towards commodity markets during times of economic downturn, in pursuit of such markets' safe-haven properties. Interestingly, the findings in both Cohn *et al.* (2015) and Salisu *et al.* (2020) also suggest that for the fear emotion to bring about countercyclical risk aversion, it need not *only* be directly related to worrisome market events such as stock price volatility and

[18] Countercyclical risk aversion suggests that investors are more risk-averse during market bust periods than periods of market booms (Huber *et al.*, 2021).
[19] Constructed by Salisu and Akanni (2020), the global fear index (GFI) captures widespread fear and panic associated with the COVID-19 pandemic across all countries, regions and continents the world over.
[20] With the GFI showing a statistically significant predictability of stock market returns, both during in-sample and out-of-sample forecast horizons (Salisu *et al.*, 2020).

the like; as illustrated – for example – by the observation in Cohn *et al.* (2015) that even exposure to the threat of an aversive electric shock attenuates professional investors' willingness to take risks.

The views above then beg yet another question: if the fear emotion causally leads to countercyclical risk aversion (*ceteris paribus*) among investors, why is it that the consequence of fear (i.e., countercyclical risk aversion) is more consistently observed among professional investors than among novices who make up the bulk of retail brokerages' customer base? Given our discussion above that even exogenously induced fears – such as those related to COVID-19 as a threat to one's physical health (Salisu *et al.*, 2020) – have been shown to dampen investors' appetite for making risky investments, it would be incomplete to conjecture that the difference in reactions to the COVID-19 market crash between professional and retail investors is *only* due to the likelihood that perhaps the superior market analysis expertise held by professional investors allows them to more accurately appraise just how dire the market situation is in such instances, effectively triggering their fear response of refraining from participating in the market.

In our view, particularly within the context of different investor-types' reactions to the COVID-19 market crash, a more comprehensive (thus relatively more plausible) response to the question above can be found in the literature on neurobiology and neuropsychology. In this regard, the functions and development of the prefrontal cortex – the part of the brain located at the front of the frontal lobe (Carlén, 2017) – are most relevant. An essential function of this part of the brain is to "plan and direct motor, cognitive, affective, and social [behaviour] over time" (Kolb *et al.*, 2012); decisions that are driven by four times more excitatory cells than inhibitory ones (Masset, 2016). In young brains, an immature prefrontal cortex means that decision-making is largely governed by excitatory cells while inhibitory cells (conventionally referred to as human-beings' 'inhibitions') lay dormant until early adulthood (well-after the teenage years have gone by) (Arain *et al.*, 2013) – allowing for learning and risk-taking behaviour to take place. Upon full maturation of the prefrontal cortex during adulthood, the brain's inhibitory cells become active, leading to the ability to more effectively filter information and control behaviour (Masset, 2016).

With the above view in mind, we conjecture that it may be that professional investors such as investment bankers and fund managers – whose average age ranges from 43 to 47 years old in the US (Zippia, 2022a; Zippia, 2022b) – are at a stage in their cognitive development where they are, *ceteris paribus*, better able to appreciate their affective (i.e., emotional) state, as well as better control (and in some instances, restrain) their behaviours, including those related to risk-taking (Kolb *et al.*, 2012). On other the hand, the wave of new entrants to the financial markets (i.e., retail traders) seen following the COVID-19 market crash seem to be a comparatively younger cohort of market participants, with ages ranging from 19 to 31 years (Rooney, 2020; Moise and Singh, 2021). Thus, assuming an equal distribution of retail traders across all ages within the range, it is possible that nearly half of all new retail traders are in the sub-25 years adolescent age group: a large sub-segment of retail traders who – neurologically speaking – are characterised by an immature prefrontal cortex and inactive inhibitory transmitters (Kolb *et al.*, 2012). This would effectively increase the likelihood of retail traders more readily partaking in risky behaviours – including making risky investments – that relatively older and more experienced[21] professional investors might shy away from (Arain *et al.*, 2013).

Further exacerbating this wedge in the proclivity to make risky investments *post* the COVID-19 stock market crash between the two investor-types under discussion – at a more practical level – is the general expectation that investment fund managers (especially those managing

[21] Both in the finance industry and in life, more generally.

retirement funds) should exercise a fair amount of caution when investing their clients' funds; a constraint that retail investors who trade their own funds (at least in the legal sense) are not bound by. Secondly, with the growing trend of retail brokers reducing trading account commission fees to zero (Rooney, 2020), together with the US government's periodic rolling out of stimulus checks at values of between $600 and $1,400 each to tens of millions of eligible US citizens and non-citizens (Raymone, 2021),[22] previously existing economic barriers to enter and participate in the financial markets have been significantly reduced (and in some instances, eliminated) for retail traders.

With the above in mind, and in relying on empirical and theoretical insights from a diverse group of disciplines (finance, neurobiology, economics, and psychology), we conclude the current subsection by reaffirming our conjecture that retail traders – whose behaviour in some instances can be deterministic on markets even as large as the US stock market (Basak, 2020) – are more likely to make risky investments following public health crisis-led stock market crashes than professional stock market practitioners. Given our view (discussed at length in Chapter 2 of the current thesis) that investor-types who are understood to have a proclivity for risk-taking behaviour also tend to succumb to the disposition effect (especially in instances when they incur paper losses), it would be plausible to hold the view that retail investors (who are also less experienced in the financial markets) are also more inclined to be affected by the disposition effect than professionals (who are relatively more experienced).[23]

Furthermore, an important set of distinguishing features between these two investor-types are their age ranges, with retail investors' ages (particularly within the context of the era of the pandemic) ranging from 19 to 31 years, and 43 to 47 years in the case of professional investors

[22] Beginning with the stimulus checks extended to eligible US-based recipients by way of the Coronavirus Aid, Relief, and Economic Security (i.e., CARES) Act in April of 2020 (Epperson, 2020).
[23] Supporting this view is the experimental evidence found by Da Costa *et al.* (2013) that experienced investors succumb to the disposition to a significantly lesser extent than inexperienced investors.

(Moise and Singh, 2021; Zippia, 2022a; Zippia, 2022b). Having shown – at a theoretical level – the relationship between age and cognitive development, as well as the implications that this relationship has on the risk appetites of different investor-types in the paragraphs above, we note the relatively young age of the average retail investor renders her or him prone to making risky investments and ultimately succumbing to the disposition effect.

Returning to the context of the current experimental study, the adjacencies between retail investors and student investor teams participating in the university stream of the annual JSE Challenge are at least two-fold: firstly, like retail investors, student investor teams are relatively inexperienced as market practitioners; a trait that has been shown to causally intensify the extent to which investors succumb to the disposition effect (Da Costa *et al.*, 2013). Secondly, similar to retail investors, the individual members of student investor teams (who are of university-attending age) are relatively young, with a large segment of them being in the sub-25 years old age group; a group which we believe is ultimately prone to succumbing to the disposition effect to a greater extent than others, neurologically speaking.

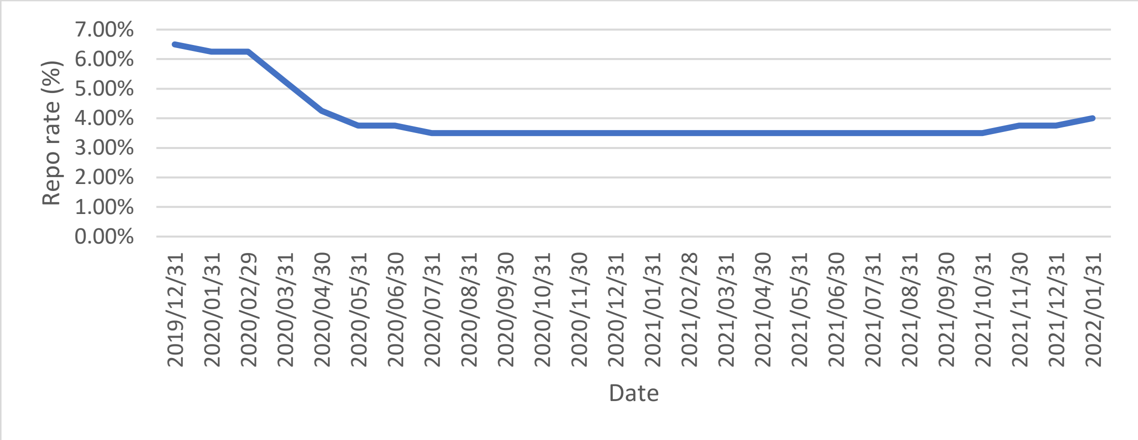
3.1.3. COVID-19 and the South African equity market

On the 5th of March, 2020 – only six days before the WHO declared the COVID-19 outbreak a global pandemic – the first COVID-19 case was detected in South Africa (Giandhari *et al.*, 2021). Two days afterwards, South African President Cyril Ramaphosa made a public statement confirming the detection of yet another COVID-19 case and announcing a requirement for all international travellers to be screened for COVID-19 symptoms at several ports of entry, as an initial policy response. With the first case of local transmission confirmed a couple of days earlier, President Ramaphosa addressed the nation once again on the 15th of March; this time declaring the COVID-19 outbreak in South Africa as a national state of disaster. Accompanying this declaration were several restrictive regulations, including a prohibition against the gathering of more than 100 people at a time, a ban on all travel into

South Africa by foreign nationals, the cancellation of all visitor visas, and a requirement for all foreign nationals who had recently entered the country to report for PCR testing (Giandhari *et al.*, 2021). By the 18th of March, several points of entry into the country had been closed, along with all local schools and universities. On the following week, the President announced that the government would be imposing further restrictions on human movement by enforcing a lockdown regulation from the 27th of March, which would – *inter alia* – effectively restrict the South African populace to their homes, with the exception of only leaving home to buy groceries, attend to medical matters, or attend to banking affairs. Furthermore, the sale of alcohol and tobacco products was prohibited. The government's expressed intention behind these restrictions – as extensive as they may have been – was to limit the contagion, as well as protect the public health system from being overwhelmed (South African Government, 2022).

Meanwhile, anticipating the economic fallout to be ushered in by the COVID-19 outbreak and the accompanying restrictive policy responses by the government, the South African Reserve Bank (SARB) – the country's central bank – reduced the repo rate by 100 basis points to 5.75 percent on the 21st of March, 2020 (Giandhari *et al.*, 2021; SARB, 2022). Figure 3.1 below shows that the SARB continued to reduce the repo rate by an average monthly rate of nearly 50 basis points, until reaching a period low of 3.5 percent in July of the same year – a rate that was maintained until October of the following year (SARB, 2022). Furthermore, given the widespread sell-off of securities that prevailed over the South African markets during Q1 2020 – *inter alia* – the SARB increased the size and duration of its repo facilities as well as its purchasing of government bonds, effectively injecting some much-needed liquidity into the country's financial markets (SARB, 2020) – the sum total of which are owned and controlled by the Johannesburg Stock Exchange.

Figure 3.1: *Monthly South African repo rates during the period 1 January 2020 to 31 January 2022*

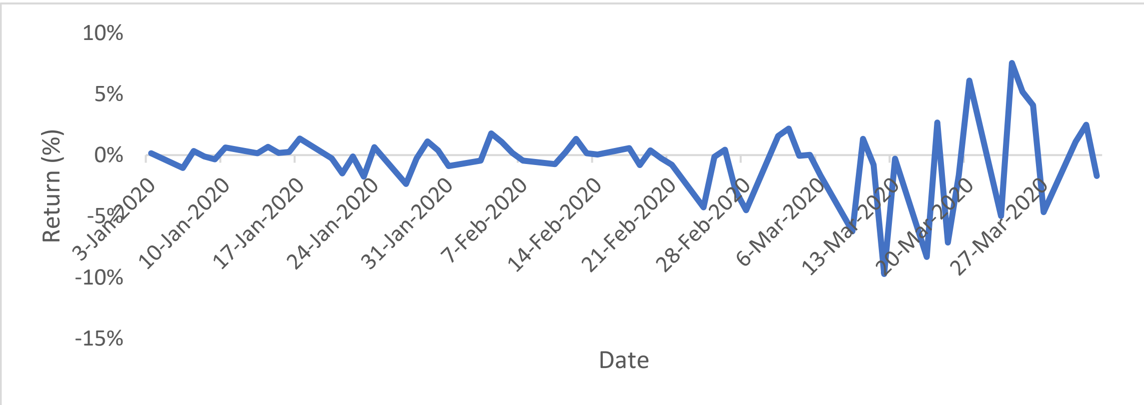


Formed in 1887 during the South African gold rush and characterised by a market capitalisation value of R21.427 trillion as of the 18th of March, 2022, the Johannesburg Stock Exchange (JSE) is the oldest and largest stock exchange in Africa, and the 17th largest stock exchange in the world (JSE, 2022a; JSE, 2022b; SSE Initiative, 2022). Since the early 2000s, the JSE has expanded and diversified its securities offerings to broadly include financial markets in equities and bonds, as well as commodity, financial and interest rate derivatives. The JSE's (i.e., South African) equity market, the bourse's oldest financial market with over 120 years in operation, consists of the Main Board – where the JSE's Top 40 stocks, and financial instruments such as exchange-traded funds (ETFs), exchange-traded notes (ETNs), and warrants are listed – as well as the Alternative Exchange Board (AltX) – which lists companies with small-to-mid-size levels of capitalisation. At present, more than 800 securities are available to be traded on the JSE's equity market, and approximately 400 companies are listed across both its Main Board and the AltX Board (JSE, 2022a).

The JSE equity market is also considered to be highly liquid, with its level of capitalisation and volatility changing constantly as new information on relevant variables – such as interest rates, exchange rates, the price of gold, the performance of international equity markets (Samouilhan, 2006), and (as of late) public health – is priced in.

Market panic regarding the COVID-19 outbreak first hit the JSE around the 17th of February, 2020. By the 16th of March (around a month afterwards), The FTSE/JSE All Share Index (ALSH) – which tracks the performance of 99 percent of equities list on the JSE – had fallen by 32.6 percent, year-to-date (Claasen, 2020). Illustrating these developments is Figure 3.2, which shows a relatively smooth trend of ALSH daily returns between early-January 2020 and the 16th of February of the same year (with a standard deviation of 0.01), followed by a notably volatile returns trend between the 17th of February and the 31st of March (at a four-fold larger standard deviation of 0.04). Figure 3.3 shows that by the 19th of March, the value of the ALSH had declined by 34.3 percent from R578.10 on the first trading day of 2020 to a period low of R379.63; a price fall that was accompanied by a R49bn drop in the ALSH's market capitalisation (and a R4.48 trillion decline in the market capitalisation of the JSE in its entirety[24] (JSE, 2022b)), as per Figure 3.4 (EquityRT, 2022).

Figure 3.2: *Daily FTSE/JSE ALSH index daily returns during the period 3 January 2020 to 1 April 2020*



[24] As gleaned from the *JSE Markets' Weekly Statistics 20200103* and *20200320*.

Figure 3.3: *Daily FTSE/JSE ALSH index daily prices during the period 3 January 2020 to 1 April 2020*

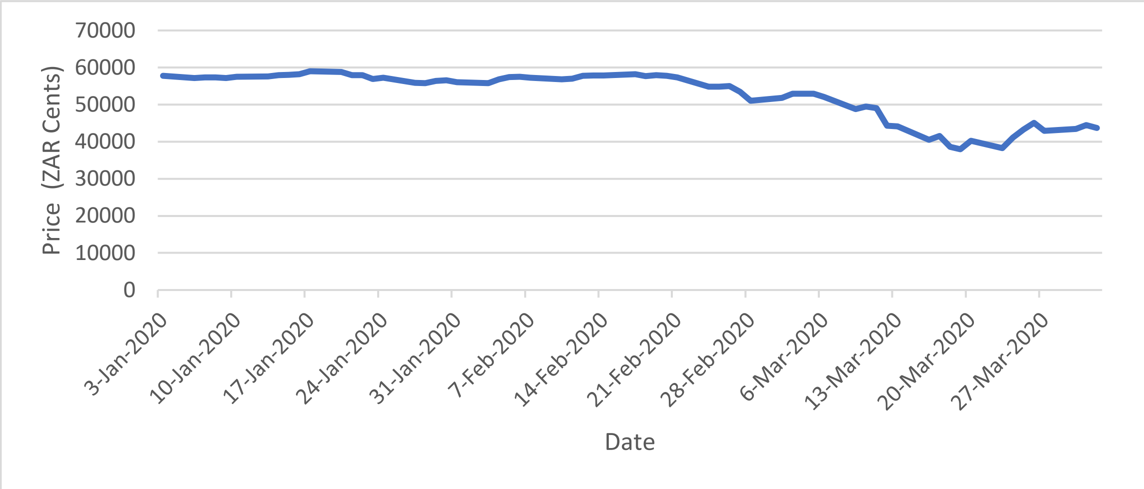
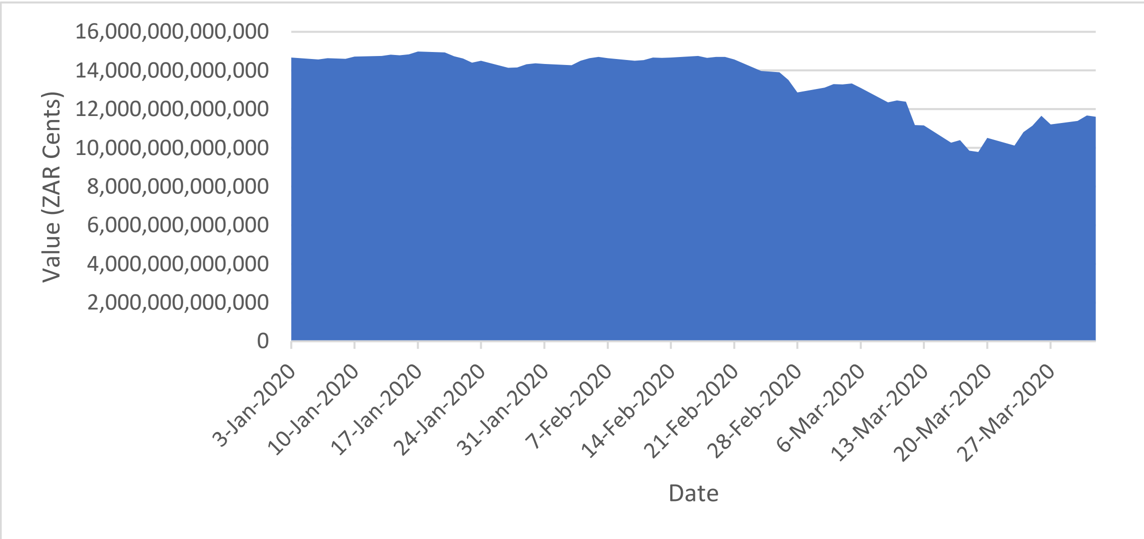
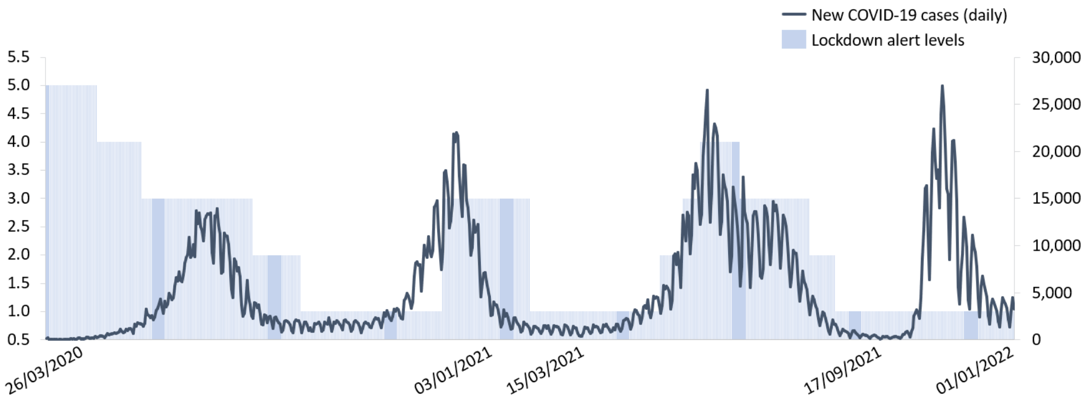


Figure 3.4: *Daily FTSE/JSE ALSH index market capitalisation values during the period 3 January 2020 to 1 April 2020*



By early-April of 2020, the government of South Africa had informed the South African populace of the five-level COVID-19 alert system for managing the easing and intensification of the lockdown. This "risk-adjusted approach is guided by several criteria, including the level of infections and rate of transmission, the capacity of health facilities, the extent of the implementation of public health interventions and the economic and social impact of continued restrictions" (South African Government, 2022). Practically speaking, the extent of social and economic restriction is progressively intensified with each lockdown alert level, as a policy response to higher levels of COVID-19 spread coupled with lower levels of health system readiness. Figure 3.5 below shows how the South African Government (2022) maintained lockdown alert levels of three or above during the first three COVID-19 waves (i.e., periods of increased COVID-19 transmission) which occurred sporadically between the period June 2020 and mid-September 2021 (Media Hack Collective, 2022). In general, Figure 3.5 shows that the South African Government's lockdown alert level policy tracked infection case volumes – particularly during the first three new infection waves – [25] reasonably well; with each rise in new infections attracting higher, more restrictive alert levels and declines in infections attracting lower, less restrictive alert levels.

Figure 3.5: *National new COVID-19 infection cases (daily) and lockdown alert levels - 2020 to 2022*



Given the restrictions on numerous economic activities that intensify with each progressive lockdown alert level, it would seem sensible to expect a negative relationship between lockdown alert levels and the performance of the stock market. This notion is made more palpable by the general understanding that – as the so-called 'barometer' of a national economy – the stock market is typically the first to react to news on government policies that affect economic activity ahead of the real economy (Wei and Han, 2021).

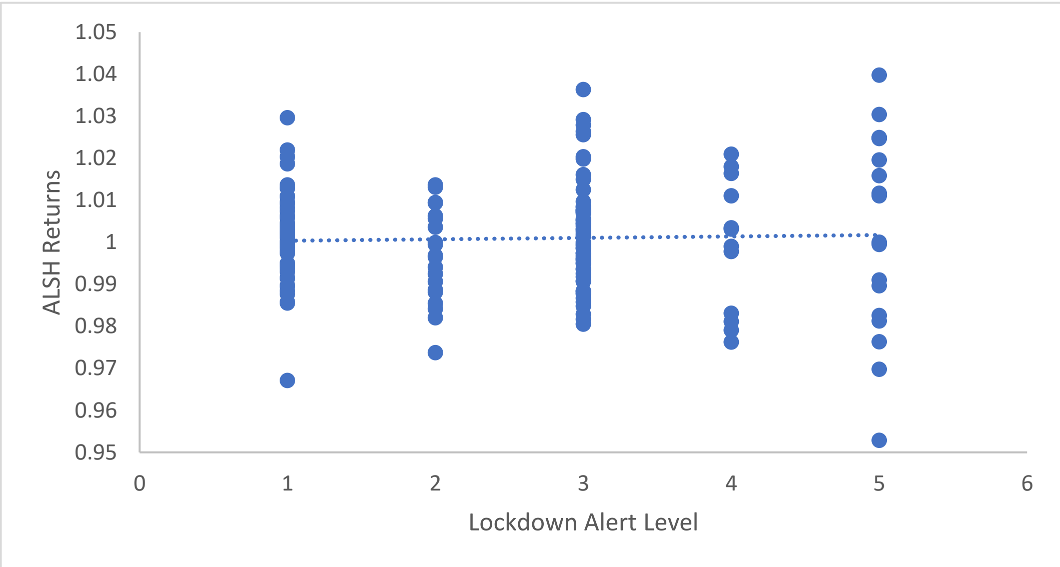
[25] The fourth wave of new infections – which was driven by the so-called Omicron COVID-19 variant and lasted between late-November 2021 and late-January 2022 – did not attract a higher lockdown alert level as hospitalisation and mortality rates during the period were low enough to not pose a threat to the public health system (South African Government, 2022).

Referring to the literature, an empirical study on the effect of a wave of new COVID-19 infections on South African stock market performance by Akinola *et al.* (2021) uses a fixed-effects model to regress a set of 20 JSE listed stocks' returns on daily COVID-19 infection rates, as well as dividend-adjusted share prices and dollar-rand exchange rates as control variables, during a 90-day sample period that spans between November 2020 and January 2021. Interestingly, they find a slow but significantly positive relationship between the returns of their study's selected 20 stocks and infection rates and suggest that this positive relationship may be as a result of the "sales of stock at the stock market during the new wave of COVID-19 [which occurred during their study's sample period] were not put-on hold in South Africa" (Akinola *et al.*, 2021).

With lockdown alert levels tracking infection rates as well as they do (making them an appropriate proxy for the level of infection in the country), it would seem that the main finding in Akinola *et al.* (2021) is in direct contrast to our *a priori* expectation above that JSE stock returns and infection rates are negatively correlated. However, in looking more critically at the methodology followed in Akinola *et al.* (2021), our view is that their results may be biased seeing as (a) their selected sample of 20 stocks are not market drivers in JSE and therefore cannot fully account for the performance of the entire bourse, and (b) their analysis is conducted on only one of the four new infection waves seen to-date in South Africa. Figure 3.6 below shows the relationship between the daily returns of the FTSE/JSE Top40 index (which tracks the JSE's 40 largest stocks, representing over 80 percent of the total market capitalisation of all JSE listed companies (SA Shares, 2022)) and lockdown alert level restrictions imposed during the 13-month period between 1 January 2020 and 31 January 2021 – effectively capturing three of the four new infection waves that South Africa has been subject to to-date.

The notably flat fitted line in the diagram given by Figure 3.6 suggests that neither a positive nor negative relationship exists between the variables; a phenomenon which seems misaligned with the *a priori* expectation that the stock market would react negatively to government-imposed economic restrictions which progressively become more stringent with each lockdown alert level. A possible explanation for the market's apparent unresponsiveness to lockdown levels (hence, restricted economic conditions) is that – subsequent to the March 2020 crash – investors may have expected, *ceteris paribus*, the reserve bank's expansionary monetary policy (illustrated in Figure 3.1) to ultimately redress much of the harm to the real economy brought about by restrictive economic policies. This view seems to be corroborated by market-practitioners (Siziba, 2021).

Figure 3.6: *Relationship between daily FTSE/JSE Top40 index returns and SA lockdown alert levels during the period 1 January 2020 to 31 January 2021*



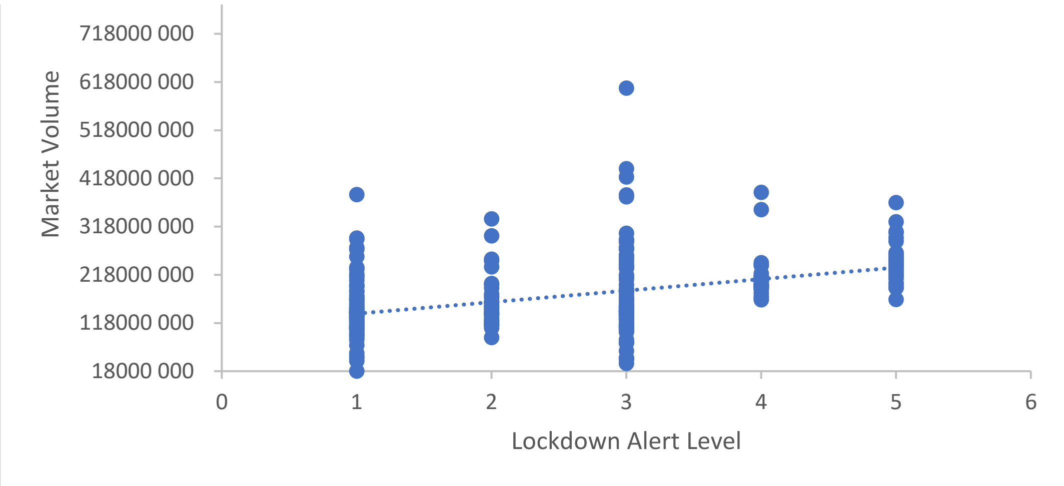
Interestingly, a more plausible stock market-related correlate of the lockdown alert levels seems to be trading volume. In this regard, Figure 3.7 below shows that during the period between 1 January 2020 and 31 January 2021, the volume of trading on the FTSE/JSE Top40 index was positively-related to the South African COVID-19 lockdown alert level. Corrobrating this view regarding increased trading in South Africa during the era of the pandemic are the findings in Chiah and Zhong (2020), who show that daily share turnover – i.e., the proportion of shares traded daily over the total number of shares available in the market

– in the South African equity market increased by approximately 0.121 percentage-points (or, 49.3 percent) from 0.245 percent prior to the onset of the pandemic to 0.366 percent in the pandemic era. In a similar vein, Nixon *et al.* (2021) – who are investments professionals from South African asset manager Momentum Investments – note that investment switching[26] on their Momentum Wealth platform increased by nearly 300 percent in March 2020 (pandemic era) relative to January 2020 (pre-pandemic era).

On reflection, though partly explained by the world-wide stock market sell-off in March 2020 (a period which coincided with the South African Government's first and only alert level 5 imposition of its lockdown restrctions), the generally positive relationship between all five of the lockdown alert levels and Top40 index trading volumes speaks to another, perhaps exogenous, variable that may be driving the trend; a supposition which is made more resonant when considering the unresponsiveness of Top40 index returns to lockdown restrictions as discussed above. Taken together then, Figures 3.6 and 3.7 suggest that – with market sentiment (as proxied by the Top40 index's daily returns) clearly being independent of lockdown restrictions on human movement and economic activity – the increasing trend of trading volumes as lockdown restrictions are made more stringent is a function of variables other than market fundamentals and sentiment; variables which more than likely are the consequences of the lockdown restrictions.

[26] "An investment switch represents a change in strategy – moving from the current portfolio of investments to another that often represents a trade-off of future investment returns for current emotional comfort. The flight to safety." Nixon *et al.* (2021).

Figure 3.7: *Relationship between daily FTSE/JSE Top40 index volumes and SA lockdown alert levels during the period 1 January 2020 to 31 January 2021*



3.1.4. Aspects of 'the new normal' which potentially entrench the Disposition Effect

In their examination of the impact of COVID-19 on stock markets' trading volumes, Chiah and Zhong (2020) find compelling empirical evidence to suggest that increases in trading volumes seen around the world as countries impose lockdown controls in efforts to curb the scourge of wide-spread disease are – *ceteris paribus* – driven by (1) new entrants to stock markets using share trading as a substitute for gambling, and (2) a large number of the working population working from home (especially young people) thus having savings from reduced commuting costs and ample time to participate in stock markets.

Chiah and Zhong's (2020) substitute for gambling proposition is borne of the temporary shutting of casinos and other avenues for gambling as part of countries' lockdown restrictions on human movement and public gatherings, together with the postulation by Gao and Lin (2015) and Kumar (2009) that individual investors make use of stock markets for gambling purposes. As empirical support for this proposition, Chiah and Zhong (2020) observe pronounced increases in trading volumes during the pandemic era in markets with greater gambling opportunities. Further support for this proposition can be found in the psychiatric literature where Hakansson *et al.* (2021) note that stock trading is increasingly being viewed as a worrying gambling type occurring among a subset of treatment-seeking gambling disorder patients. In illustrating the pervasiveness of this problem, they indicate that previous research has found that the trading behaviour of approximately 8 percent of investors in financial markets has fulfilled the criteria for problematic gambling, with as much as half of those investors meeting the criteria for gambling disorder (an established addictive disorder). Hakansson *et al.* (2021) proceed to note that "during the COVID-19 pandemic, rapid, online investment services have been increasingly discussed in the context of addictive gambling;" a point corroborated by media report suggestions that individuals with intense gambling problems may have turned to stock trading as a substitute for gambling behaviour, given that professional sports have been put on hold and casinos have been temporarily shut (Rooney, 2020). With the aforementioned in mind, the channel through which the substitute for gambling proposition explains the observed increase in stock market trading volume is thus clear. However, how might the proposition relate to the disposition effect?

To answer the question above, one could begin by considering a hypothetical scenario discussed in Tversky and Kahneman (1981), which involves a gambler who has lost $140 during an afternoon at a racetrack and is considering a $10 bet on a 15:1 long shot on the last horserace of the day. From a prospect theory perspective, we might expect the gambler to view his present state as a loss of $140 for the betting day, and thus frame the prospective $10 bet as a chance to return to the reference point of zero gains and losses (the equivalent of a stock's purchase price in the context of the disposition effect), or to increase their loss to $150 for the day. Thus, by way of the sunk-cost effect – the tendency for one to follow through on an endeavour if they have already invested resources into it in spite of whether the current costs outweigh the benefits – the gambler in the scenario views the all-together likely prospect of losing an additional $10 on a long shot bet as being negligible relative to the larger $140 loss that they have already incurred while also being attracted to the bet by the highly unlikely prospect of returning to the reference point. This inclination – we conjecture – is similar to the inclination of the investor who holds on to a losing trading position for too long in the hopes that their fortunes may at some point turn and the stock price will return to the reference point (i.e., risk-seeking-over-losses), consequently intensifying their disposition effects as further losses are incurred (Shefrin and Statman, 1985). We therefore augment the substitute for gambling proposition in Chiah and Zhong (2020) to suggest that the gambler who substitutes into stock trading during the pandemic era not only contributes towards the aggregate increase in market trading volumes by virtue of their participation in the market, but is also susceptible to succumbing to the disposition effect given their prospect theory-based proclivity to behave in a risk-seeking fashion (e.g., take long shot bets) after having sustained losses to their wealth.

Along with the substitute for gambling proposition, Chiah and Zhong (2020) advance the argument that investors' motivators for increasing stock market trading activity (resultantly increasing aggregate trading volumes in the markets) during the pandemic era include but are not limited to the fear-of-missing out, get-rich-quick schemes, and bargain hunting. On the other hand, a notable enabler facilitating the increase in trading behaviour seen during the pandemic – they find – is an abundance of time available to investors as lockdown controls restrict people to their homes. In the interest of brevity, we refer to this phenomenon as the time at home proposition. Unlike the substitute for gambling proposition which Chiah and Zhong (2020) find empirical support for by observing pronounced increases in trading volumes during the pandemic era in markets with greater gambling opportunities, the time at home proposition is supported by what is (at best) circumstantial evidence linking the imposition of lockdown controls to increased trading volumes without directly observing an increase in time spent at home by investors and its relationship with trading activity.

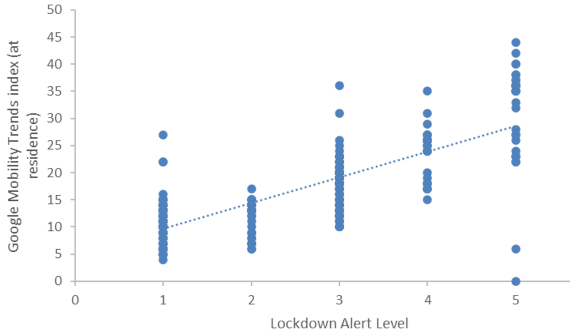
To establish the nature of the relationship discussed above, within the context of the South African equity market, one might begin by selecting a variable that appropriately represents human movement in public environments. For this, we look to Google's Community Mobility and Apple's Mobility Trends index datasets, which track daily changes in human movement relative to pre-pandemic baselines, and are based on Google Maps and Apple Maps usage (web-based mapping applications commonly accessed using smartphone devices) (Google, 2022; Apple, 2022).[27] Figures 3.8 (a) and (b) below show the relationships between two categories of Google and Apple mobility index data in relation to South Africa, and South African lockdown alert levels. More specifically, the relationship depicted in Figure 3.8 (a) involves the "residential" category of Google's mobility data on the y-axis – which tracks changes in Google Maps users' smartphones reporting that they are at their place of residence (as per their residential address details captured on the application) – and the relationship illustrated in Figure 3.8 (b) incorporates the "driving" category of Apple's mobility data on the y-axis – which tracks changes in Apple Maps users' smartphones reporting that they are driving on public roads.

The relationships illustrated in Figures 3.8 (a) and (b) very clearly show that (a) the volume of people staying at home increases markedly as lockdown levels increase and restrictions on human movement (*inter alia*) intensify, and (b) the volume of people driving on public roads sharply declines with increases in lockdown levels and accompanying controls – with both relationships ultimately showing the responsiveness of human movement to lockdown requirements as the national COVID-19 infection rate rises and falls.

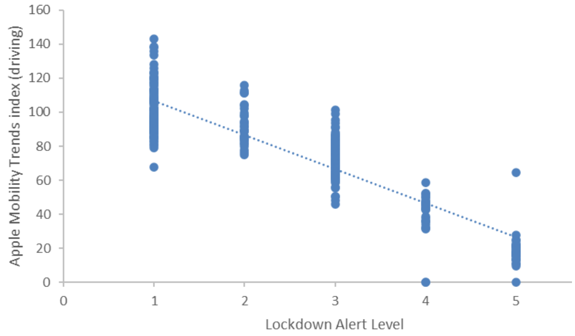
[27] With around 53.4 million smartphone subscriptions in South Africa as at 30 September 2019, smartphone penetration among the South African population stands at more the 90 percent (ICASA, 2020); mobility data from two of the most used mapping applications can thus be reasonably expected to robustly represent human movement in public environments across the country.

Figure 3.8: *Relationships between daily SA Google/Apple mobility trends, SA lockdown alert levels, and FTSE/JSE Top40 index volumes and during the period 1 January 2020 to 31 January 2021*

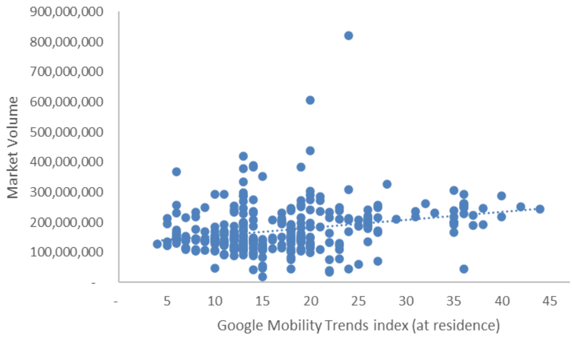
(a) Google mobility (at residence) and lockdown levels



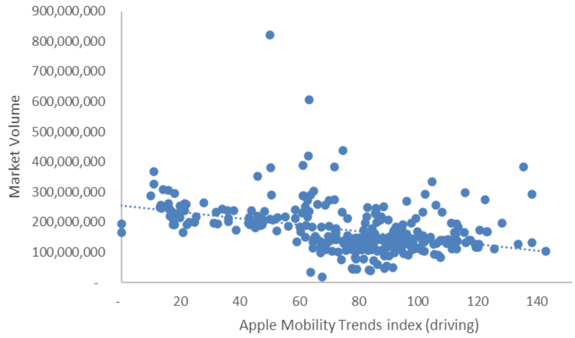
(b) Apple mobility (driving) and lockdown levels



(c) Top40 index trading volumes and Google mobility (at residence)



(d) Top40 index trading volumes and Apple mobility (driving)



Figures 3.8 (c) and (d) illustrate the relationships between the Top40 index trading volumes and residential category Google mobility data, as well as between the Top40 index trading volumes and driving category Apple mobility data. Interestingly, they show (relatively flatter) relationship trends that are directionally similar to those in Figures 3.8 (a) and (b), respectively; with trading volumes increasing as investors heed calls to stay at home during periods of rising infection rates, and trading volumes decreasing as human movement in public spaces becomes more prevalent during times of declining infections. Taken together, the relationships depicted in Figure 3.8 provide compelling support for Chiah and Zhong's (2020) time at home proposition (discussed further above) in the context of the South African equity market. With the relationship between human mobility and stock market trading volumes during the era of the pandemic being well-understood at this stage, how might an increase (decrease) in trading

volumes, as fostered by a decrease (increase) in human mobility, relate to the emergence (or even the intensification) of disposition effects among investors? Much of the available literature on this question confirms the existence of a causal relationship between trading volume and the disposition effect. Specifically, the prevailing view is that the disposition effect causes the turnover of a stock to rise as the stock's price trends upwards and as investors sell the stock in order to realise capital gains (Grinblatt and Keloharju, 2001; Kaustia, 2004; Huddart *et al.*, 2009).

Bearing the above view in mind, we return to the question at hand and conjecture the following: investors who quarantine at home may very well be more aware of the continuous changes that their wealth undergoes as they more regularly observe the prices of the stocks that they hold rise and fall throughout the trading day. This heightened salience of, or attentiveness to the moment-by-moment dynamics of the value of one's own portfolio leads to an increase in the frequency with which they realise gains from winning stocks as soon as said stocks begin 'winning' i.e., begin exceeding their reference points (which may be their purchase prices or prices in a previous periods). The resultant increase in the investor's trading activity ultimately contributes towards increased aggregate trading volumes seen across the market. This position is made more plausible by Frydman and Wang's (2020) recent finding that an increase in the perceptual salience[28] of a stock's purchase price causally increases the disposition effect by 17 percent, and Barber *et al's* (2022) findings that attention-induced traders trade more frequently and are more susceptible to succumbing to behavioural biases which lead to negative returns. In a similar vein, we conjecture that investors who spend more time at home during the pandemic era are likely to be more attentive to their trading accounts than what might be the case under normal circumstances. This increases the number of opportunities for home-based

[28] First discussed by Taylor and Fiske (1975), perceptual salience – or the salience bias – is the predisposition that people have to focus less on items that are unremarkable and more on those that are prominent and emotionally striking, regardless of the relevance of this difference by objective standards.

investors to succumb to the disposition effect and thus trade more frequently as they more regularly sell their winning stocks in order to realise gains (i.e., risk-aversion-over-gains).

In summary, our reading of the existing literature on the disposition effect, market trading volume dynamics and the emerging investor behaviour trends seen since the onset of the COVID-19 pandemic points to the importance of Chiah and Zhong's (2020) (1) substitute for gambling, and (2) time at home propositions in explaining, *ceteris paribus,* not only the observed rise in market participation, but also the channels through which the resultant increase in trading volume causes, and is caused by the disposition effect. Returning to the ultimate source of these phenomena and channels, it would seem that COVID-19 infection rates (which inform lockdown controls and social distancing mandates) are ultimately deterministic on the disposition effects of investors during the pandemic era. Should this conjecture indeed hold in practice, one might expect differences in the rate of infection across different regions to track differences in the trading activity and disposition effects of investors located in those regions. Indeed, an experimental probe into this conjecture could possibly provide new evidence on the impact that public health crises could have on the disposition effects of market participants; a behavioural bias which not only attenuates investor welfare (as demonstrated in Chapter 2) but has important implications for aggregate market dynamics as well (Goossens and Knoef, 2020).

3.1.5. Emerging trends in the JSE University Challenge in the era of the COVID-19 pandemic

In the era of the pandemic, much of how the JSE University Challenge is conducted didn't change given that registration for, and participation in the Challenge are both traditionally conducted on web-based platforms (JSE, 2020).[29] However, given restrictions on public gatherings and movement controls imposed on South African university campuses, investor

[29] See Subsection 2.1.4 of Chapter 2 of the current thesis for a comprehensive overview of the JSE Investment Challenge.

teams (who may have otherwise met in-person) were encouraged to meet virtually to deliberate on matters concerning their investment decisions, the performance of their portfolios, etc. In addition to this, the annual JSE Challenge award ceremony – during which the Challenge's winners are announced – took place exclusively via live YouTube stream in 2020 and was partly in-person and partly virtual in 2021 when government controls on public gathering were slightly relaxed (JSE, 2021a). Furthermore, in an effort to facilitate nation-wide knowledge sharing deliberations, the JSE introduced regular online Q&A sessions which involved expert lectures by thought leaders in the investments and securities industry and discussions between participants and the Challenge's managerial team (JSE, 2021b).

Table 3.1: Demographic and trading behaviour trends concerning investor teams participating in the JSE University Challenge during the period 2018 to 2021

	Pre-COVID era		*COVID era*	
Subject	2018	2019	2020	2021
Total number of universities participating the Challenge	70	90	42	33
Total number of investor teams participating the Challenge	1,616	1,576	208	316
Female-to-male ratio of Challenge participants	0.28	0.35	0.34	0.66
Average volume of trade orders submitted per investor team	11.45	11.82	25.73	15.22

From a more quantitative perspective, Table 3.1 above shows that the number of universities with students participating in the JSE University Challenge declined by approximately 53.12 percent from an average of 80 universities in the two years preceding the pandemic, to an average of 37.5 universities during the period 2020 to 2021 (i.e., the COVID pandemic era) (JSE, 2022c). An even more pronounced decline is seen in the volume of investor teams participating in the Challenge, with investor team volumes decreasing by approximately 83.58 percent, from a two-year average of 1596 in the pre-COVID era to an average of 262 during the COVID era. From the perspective of the female-to-male ratio of Challenge participants – a variable shown to explain the intensity of investor teams' disposition effects in Chapter 2 of the current thesis – we see a notable improvement in the ratio over the course of the four-year period between the pre-COVID and COVID era, with the ratio almost doubling between the period 2020 to 2021. Interestingly, the average volume of trade orders submitted per investors team peaked at 25.73 trades in 2020 – the year of the onset of the pandemic – which was more than twice as many trades per team in 2019. Furthermore, over the course of the four-year period, average trade order volumes grew from 11.45 to 15.22 per team, representing a compounded annual growth rate (CGAR) of 7.37 percent between the pre-COVID and COVID era.

On reflection, the trends in Table 3.1 show that although fewer universities and investor teams participated in the Challenge following the onset of the pandemic (perhaps due to movement controls and restrictions on public gatherings), trade volumes per investor team have increased significantly. This phenomenon is consistent with the time at home proposition as discussed at length further above. Increases in the female-to-male ratio among the Challenge's participants are consistent with the JSE's agenda to deliberately increase female representation within the annual competition (SABC News, 2018), and – taken together with the finding in Chapter 2 of the current thesis that increases in the female composition of investor teams attenuates their disposition effects – we would expect the disposition effects of the Challenge's participating investor teams to be at their lowest level of intensity in 2021, when the female-to-male ratio peaks at 0.66.

3.1.6. Hypotheses

Bearing in mind the literature reviewed above, we formalise our main arguments regarding the COVID-19 pandemic and its relationship with South African investor teams' (1) disposition effects and (2) trading activity in a set of two hypotheses which we test among South African university students participating in the annual JSE Investment Challenge during the pandemic era.

We begin by testing H1, which – as a hypothesis – has the effect of suggesting the existence of a causal flow between localised COVID-19 infection rates, quarantining at home (i.e., human immobility), and investor teams' disposition effects. Our view is that outcomes from testing H1 would provide important evidence in relation to our conjecture (proposed in the literature review above) that investors (or, investor teams in this instance) who spend more time at home during the pandemic era are likely to be more attentive to their trading accounts and thus to observe continuous changes to their wealth in relation to relevant reference points such as previous prices (Weber and Camerer, 1998), effectively increasing the number of opportunities for them to succumb to the disposition effect.

H1: Quarantining at home in response to high, localised COVID-19 infection rates during the pandemic has a causal impact on the disposition effects of South African investor teams.

H2, which proposes the existence of a causal relationship between the disposition effects of investors quarantining at home and their levels of trading activity, is consistent with our augmented Chiah and Zhong (2020) time at home proposition for explaining observed increases in trading activity during the pandemic, as discussed in the literature above. Specifically, our augmented view is that home-based investors, who are confronted by increased opportunities to succumb to the disposition effect (as per H1) trade more frequently as they more regularly sell their winning stocks in order to realise gains (i.e., risk-aversion-over-gains). Given the novelty of this view, our endeavour to test H2 is therefore an effort at determining whether this postulation can be supported by concrete, externally valid evidence.

H2: The disposition effect causally increases the trading activity of South African investor teams quarantining at home in response to localised COVID-19 waves during the pandemic.

3.2. Methodology

3.2.1. Experimental design, subject pool and data

In order to test our hypotheses above, we begin by selecting South African provinces that are comparable to each other in terms of population size and volume of student investor teams participating in the Challenge. Given the South African convention of reporting on COVID-19 infection rates provincially as the lowest level at which national infection rates are disaggregated (Media Hack Collective, 2022), we test H1 and H2 by comparing between the infection rates, mobility, disposition effects (i.e., DEs), and trading volumes of JSE Investment Challenge-participating student investor teams located in different provinces across South Africa during the 2020 run of the Challenge. With COVID-19 being understood to be a highly communicable disease, provincial population size is adopted as a selection criterion given our expectation that a positive relationship exists between infection rates and population size, as – for example – largely populated provinces are expected to be characterised by greater contagion risk. The volume of investor teams participating in the Challenge in each province is used as an additional selection criterion to promote comparability between the cross-section of selected provinces. In this regard, Table 3.2 below shows that Gauteng (GP) is highly comparable to KwaZulu-Natal (KZN) in terms of investor team volume, with the two provinces being most comparable to each other in terms of population size. Table 3.2 also shows that Western Cape (WC) and Eastern Cape (EC) are highly comparable to each other in terms of investor population size and are most comparable with each other in terms of investor team volume.

The study thus unfolds as a set of two between-subject, natural-field experiments involving investor teams located in the provinces of GP and KZN, as well as those located in WC and EC, with their locations being given by the locations of their universities. The sample period for this natural-field experiment is the full length of the 2020 run of the Investment Challenge which spanned from 9 March 2020 to 18 September 2020; a period in which the study's subject pool executed a combined total of 4,810 buy and sell trades. To test whether a causal flow indeed exists between infection rates, quarantining at home, and DE, we consider (a) the daily rate of new COVID-19 infections[30] in each of the provinces under study (Media Hack Collective, 2022), (b) the daily changes in human movement relative to pre-pandemic baselines based on Google Maps[31] and Apple Maps[32] usage (Google, 2022; Apple, 2022), and (c) the buy, sell and hold decisions of the total sample of 143 investor teams across the four provinces who meet the standard requirement for field studies on the DE of being active (Odean, 1998; Duxbury *et al.*, 2015; Frydman and Wang, 2020; JSE, 2022c). To establish whether DE has a causal impact on trading volumes, we use the average volume of trades executed per team in the sample.

Table 3.2: Provincial populations and investor team volumes during the 2020 run of the JSE Investment Challenge

Subject	GP	KZN	WC	EC	LP	MP	NW	FS	NC
Population size[a]	15.2m	11.3m	6.8m	6.7m	6m	4.6m	4m	2.9m	1.3m
Volume of active investor teams participating in Challenge[b]	49	47	27	20	2	1	1	7	3

GP = Gauteng; KZN = KwaZulu-Natal; WC = Western Cape; EC = Eastern Cape; LP = Limpopo; MP = Mpumalanga; NW = North West; FS = Free State; NC = Northern Cape

[a]Stats SA (2020)
[b]JSE (2022c)

[30] Which is based on the daily number of new infections data collected and combined by Media Hack Collective (2022) from the National Institute of Communicable Diseases (NICD), news media reports, social media, as well as other sources.

[31] Based on Google Maps data, Google's Community Mobility Reports provide human movement trends by region (e.g., province), across different categories of places (e.g., 'at residence' or 'at workplace'). For each category in a region, the reports provide the daily headline number – used in the current research – which compares human mobility between the report date and the pre-pandemic, baseline date. This daily headline number is made available for each report date as a negative or positive percentage (Google, 2022).

[32] Apple's Mobility Trends tool uses data "generated by counting the number of requests made to Apple Maps for directions. The data sets are then compared to reflect a change in volume of people driving, walking or taking public transit around the world" (Apple, 2022).

3.2.2. Measurement techniques

Similar to the methodology in Chapter 2 of the current thesis, we test hypotheses H1 and H2 following a panel data approach. For the sake of brevity, we adopt only the Weber and Camerer (1998) measure of the DE (Equation (2.5) in the previous chapter), and refrain from also making use of the Odean (1998) and the Dhar and Zhu (2006) measures (as had been done in the previous chapter). The current study therefore assumes that the DEs of investor teams participating the JSE Investment Challenge are informed by stocks' previous trading day prices as reference points for buy, sell, or hold decisions.

We begin our inquiry by first understanding the inherent differences in COVID-19 infection rates, human mobility, and order volumes between the two province pairs of interest (i.e., GP and KZN, as well as WC and EC).

We then proceed to test for average treatment effects (ATEs) by conducting regression adjustments and Wilcoxon tests on the DEs of the investor teams located in the provinces under study, as means of establishing whether the DE is indeed more pronounced among investor teams located in provinces characterised by high COVID-19 infection rates and low human mobility (in line with H1). In this regard, individual team-level mean DEs are calculated using Weber and Camerer's (1998) disposition coefficient (i.e., Equation (2.5)). Across the two sets of experiments, ATE's are estimated using the following equation:

$$\tau_i = DE_{iP} - DE_{iP} = DE_{i1} - DE_{i2} \qquad (3.1)$$

where τ = ATE, DE_{i1} = mean DEs of investor teams located in province P = 1, and DE_{i2} = mean DEs of investor teams located in province P = 2 (Harrison and List, 2004). To determine the treatment effects' significance, we estimate regression-adjusted ATEs, and review the *p*-values of said regression adjustments as well as those of Wilcoxon tests (as a robustness check) for differences in mean DEs between the province pairs.

Based on the results of the ATE tests, we subsequently run ordinary least squares (OLS), Logit and Probit regressions on the presence of the DE within an investor team's investment decisions (as the dependent variable), provincial location, and a vector of control variables, as per the following equation:

$$DEdummy_i = \beta_0 + \beta_1 \cdot GPBased_i + \beta_2 \cdot X'_i + \varepsilon_i \qquad (3.2)$$

where $DEdummy_i =$ a dummy variable that is equal to 1 if investor team *i* shows presence of the DE – based on the understanding that investor teams with positively-signed DE values exhibit the DE (Da Costa *et al.*, 2013) – and 0 if otherwise; $GPBased_i$ = a dummy variable that is equal to 1 if investor team *i* is located in GP, and 0 if otherwise; with β_2 (our coefficient of interest) representing the increased likelihood of the investor team exhibiting DE if located in GP; X'_i = a vector of covariates understood to causally intensify the DE, including $TeamSize_i$ = number of people in investor team *i* – which is based on the understand that some of the social forces involved in the group investment decision-making context – such as groupthink – can exacerbate the intensity of the DE (Cici, 2012; Rau, 2015); $NumberofMales_i$ = number of males in investor team *i* – which relates to the understanding that men are more susceptible to the DE than women based on the differences in their respect gender dynamics discussed at length in Chapter 2 above (Da Costa *et al.*, 2008; Shandu and Alagidede, 2022); and $Numberof1stYears =$ number of first-year undergraduate students in investor team *i*, as a proxy for the average level of education within the team, with lower levels of education being understood to exacerbate the DE through the mechanism of learning ability (Goo *et al.*, 2010; Vaarmets *et al.*, 2019). ε_i represents a random error term capturing all omitted factors.

Finally, to determine whether a causal flow exists between high COVID-19 infection rates, human immobility, DE, and transaction order volumes (i.e., to test H2) we follow the

Instrumental Variable (IV) approach by running two-stage least squares (2SLS) regressions involving order flow volumes as the dependent variable, the presence of the DE as an endogenous regressor, and provinces characterised by high infection rates and low human mobility as an instrumental variable. With the first-stage regressions being conducted in accordance with Equation (3.2) above, the estimation for the second-stage is given as follows:

$$OrderFlow_i = \pi_0 + \pi_1 \cdot \widehat{DEdummy}_i + \pi_2 \cdot X'_i + \mu_i \tag{3.3}$$

where $OrderFlow_i$ = the volume of orders executed by investor team *i*; $\widehat{DEdummy}$ = a dummy variable – based on the first stage regression – representing the effect of the presence of DE on the volume of orders executed by investor team *i*, with π_1 as the coefficient of interest; and other specifications being the same as those in Equation (3.2).

3.3. Results and analysis

3.3.1. Provincial COVID-19 infection rates, human mobility and investor team order flows

Tables 3.3 and 3.4 below provide comparisons on daily COVID-19 infection rates, Google mobility (at residence) and Apple mobility (driving) trends, average volume of orders per investor team located between Gauteng and KwaZulu-Natal (GP and KZN), as well as between Western Cape and Eastern Cape (WC and EC), respectively. Table 3.3 shows that – during the 2020 run of the Challenge – GP's daily rate of new COVID-19 cases was 547 daily cases, or 84 percent higher than that of KZN. Furthermore, the table shows that people in GP stayed at home more and drove their vehicles less than those in KZN, as gleaned from the Google and Apple mobility trends data. The table finally shows that investor teams in GP executed significantly more trading orders (17, or 77 percent more orders) than those executed in KZN. In this regard, the provincial comparisons provided in Table 3.3 offer some initial support for the view that locations which are heavily impacted by the contagion are characterised by greater levels of people quarantining at home, and – ultimately – high trading activity.

On the other hand, although Table 3.4 shows that the province with a significantly higher rate of infection (i.e., WC) – at approximately 116, or 24 percent more daily infections – is also characterised by more people quarantining at home, and less people driving their vehicles, there is no statistically meaningful difference between the order volumes of investor teams located in WC and EC. This perhaps may be due to the relatively smaller difference in daily infections in WC and EC (with WC's infections being 24 percent above those in EC) than the difference in daily infections between GP and KZN (at 84 percent more infections in GP relative to KZN).

Table 3.3: Total new daily provincial COVID-19 infection cases, average daily provincial mobility, and average orders per team during the 2020 run of the JSE Investment Challenge – Gauteng versus KwaZulu-Natal

	GP			*KZN*			*Differences*		
Variables	μ	η	σ	μ	η	σ	μ	*t*-stat	Wilcoxon *p*-value
New COVID-19 cases	1198	378	1613	650	188	935	547	3.97	<0.01
Google mobility (at residence)	22	22	9	17	15	7.5	4.9	5.65	<0.0001
Apple mobility (driving)	64	69	26.5	77	82	32.2	-13	-4.05	<0.0001
Average volume of orders per team	39	15	62.7	22	10	31.3	17	1.70[a]	<0.05[a]

GP = Gauteng; *KZN* = KwaZulu-Natal.

μ = Mean; η = Median; σ = Standard Deviation.

$n_{Gauteng} = 183$; $n_{KwaZulu\text{-}Natal} = 183$.

[a]Bootstrap tests (with number of bootstrap samples *B* = 9,999).

Table 3.4: Total new daily provincial COVID-19 infection cases, average daily provincial mobility, and average orders per team during the 2020 run of the JSE Investment Challenge – Western Cape versus Eastern Cape

	WC			*EC*			*Differences*		
Variables	μ	η	σ	μ	η	σ	μ	*t*-stat	Wilcoxon *p*-value
New COVID-19 cases	603	410	542	487	149	637	116	1.88	<0.0005
Google mobility (at residence)	20	19	8.4	16	15	7.9	4.6	5.43	<0.0001
Apple mobility (driving)	50	52	22.1	70	71	30.5	-19	-6.87	<0.0001
Average volume of orders per team	33	15	42.1	49	22	63.7	-16	-0.99[a]	0.330[a]

WC = Western Cape; *EC* = Eastern Cape.

μ = Mean; η = Median; σ = Standard Deviation.

$n_{Gauteng} = 183$; $n_{KwaZulu\text{-}Natal} = 183$

[a]Bootstrap tests (with number of bootstrap samples *B* = 9,999)

We postulate the relatively muted difference in new infections between WC and EC has the knock-on effect of attenuating the difference in the rate of people quarantining at home (from 4.9 points between GP and KZN to 4.6 points between WC and EC), ultimately weakening the hypothesised causal flow between human immobility, DE, and order flows. We thus expect differences in the DEs of investor teams between the WC and EC provinces to also be attenuated relative to those between GP and KZN.

3.3.2. Testing for treatment effects

Based on Equation (3.1), Table 3.5 below shows that the DEs of investor teams based in Gauteng (GP) are significantly higher than those of teams based in KwaZulu-Natal (KZN) – an outcome which is consistent with our expectation that investor teams located in provinces experiencing sufficiently high levels of contagion and lower levels of human mobility would also be characterised by more intense DEs. Furthermore, through a process of deductive reasoning, this outcome, taken together with the outcome in Table 3.3 that GP teams' order flows are significantly higher than those of teams in KZN, supports the view that investor teams with high DEs tend to demonstrate high trading activity as well.

Table 3.5: Testing for treatment effects | ATE values, regression adjustment p-values and p-values from Wilcoxon rank sum tests for differences in mean DEs between provinces

Provincial conditions	**DE equation**	**ATE (τ)**	**Regression Adjustment *p*-values**	**Wilcoxon test *p*-values**
$\tau = DE_{GAUTENG} - DE_{KWAZULU-NATAL}$	Eq. (2.5)	0. 2546 (0. 1107)	<0.05	<0.05
$\tau = DE_{WESTERN\ CAPE} - DE_{EASTERN\ CAPE}$	Eq. (2.5)	0. 1532 (0. 1484)	0.302	0.151

$n_1 = 96$.
$n_2 = 47$.

Robust standard errors for the regression adjustment tests are provided in parentheses.

Table 3.6: OLS, Logit and Probit regressions on the presence of DE using the Weber and Camerer (1998) measure (Equation (2.5))

$DEdummy$	(1) **OLS**	(2) **Logit**	(3) **Probit**
$GPBased$	0 .4318*** (0.1009)	1.8562**** (0.4903)	1.1507**** (0.2967)
$TeamSize$	0. 0167 (0.1174)	0 .0868 (0.5444)	0.0570 (0.3419)
$NumberofMales$	0. 0374 (0.0944)	0 .1796 (0.4478)	0.1116 (0.2734)
$Numberof1stYears$	-0 .0461 (0.0811)	-0.2212 (0.3859)	-0.1438 (0.2445)
$Constant$	0 .2388 (0.1447)	-1 .1535* (0.6915)	-0 .7154* (0.4331)
F (4, 91)	5.15***		
Log pseudo-likelihood		-57.72	-57.71
Wald χ^2		16.08***	16.99***
R^2	0.18		
Pseudo R^2		0.13	0.13

n = 96
**p*-value < 0.1; ***p*-value < 0.05; ****p*-value < 0.01; ****p-value < 0.001.
Robust standard errors for all regressions are provided in parentheses.

Table 3.5 continues to show that – although positively signed – the difference in mean DEs between WC- and EC-located investor teams is not statistically significant; effectively confirming our expectation that the difference in DEs between the two provinces would be subdued based on the results of Table 3.4 above.

To verify our observation that investor teams located in GP are more likely to be impacted by the DE, we regress the presence of the DE within the investment decisions of an investor team *i* on whether said investor team is located in GP – along with several other control variables which are understood to be related to the DE (as discussed at length in Subsection 3.2.2 above) – using OLS, Probit, and Logit regression techniques, with robust standard errors.

In this regard, the results of Table 3.6 above – which follow Equation (3.2) – show that being located in GP is positively associated with the presence of the DE, with the significance of the relationship between the two variables spanning from the 1% level in the case of the OLS regression, to the 0.1% level in the Logit and Probit regressions. These outcomes thus verify our earlier results suggesting the existence of a causal link between localised COVID-19 infection rates, people quarantining at home, and the presence of DE among affected investor teams.

3.3.3. Testing for causal flow between provincial COVID-19 infections, DE, and order flows

Having completed our inquiry into the validity of H1 in the preceding subsections, we sought to verify earlier indications in the results above that a causal flow may exist between quarantining at home, the DE, and order volumes (in line with H2). To do this, we run a 2SLS regression where the presence of the DE is regressed on whether a given investor team is located in GP (as a proxy for being subjected to high, localised infection rates and quarantining at home) in the first-stage (following Equation (3.2)). Additionally, order volumes are regressed on the presence of the DE as an endogenous regressor, with the dummy variable indicating whether an investor team is located in GP serving as an instrumental variable (IV) in the second-stage. The estimation for the second-stage is given by Equation (3.3).

Table 3.7: 2SLS and LIML regressions on order flow volumes

Variables	(1) **First-Stage** $DEdummy$	(2) **Second-Stage** $OrderFlow$	(3) **LIML** $OrderFlow$	(4) **First-Stage** $DEdummy$	(5) **Second-Stage** $OrderFlow$	(6) **LIML** $OrderFlow$
$\beta_1 \cdot GPBased$	0.4173**** (0 .0937)			0 .4318**** (0.1009)		
$\pi_1 \cdot \widehat{DEdummy}$		50.9623* (29.7537)	75.9401 (46.6367)		72.3700** (36.1662)	73.8264** (36.9728)
$DEdummy$						
$TeamSize$				0 .1667 (0.1174)	32.3019** (24.5618)	32.4445 (24.6217)
$NumberofMales$				0 .0374 (0.0944)	-1.1651 (10.8330)	-1.2866 (10.9362)
$Numberof1stYears$				-0 .0461 (0.0811)	-24.6034** (15.0358)	-24.7551 (15.1087)
$Constant$	0.2766*** (0.0659)	5.6747 (12.6127)	-6.5540 (21.0670)	0 .2388 (0.1447)	-31.5743 (33.5166)	-32.2959 (33.8274)
2SLS and LIML diagnostics tests						
Endogeneity tests						
Woolridge's score χ^2 test Stat.		$\chi^2(1) = 4.01$**			$\chi^2(1) = 4.91$**	
Regression-based *F* test Stat.		$F(1,93) = 4.14$**			$F(1,90) = 4.84$**	
Over identification tests						
Woolridge's score χ^2 test Stat.		$\chi^2(4) = 2.47$			$\chi^2(1) = 0.40$	
p-value		0.6493			0.5252	
Anderson-Rubin χ^2 test Stat.			$\chi^2(4) = 6.88$			$\chi^2(1) = 0.35$
p-value			0.1423			0.5519
Basmann *F* test Stat.			$F(4,90) = 1.61$			$F(1,90) = 0.33$
p-value			0.1779			0.5661
First-Stage *F*-Statistic	4.59****		4.59**** (First-Stage)	10.24****		10.24**** (First-Stage)

n = 96
**p*-value < 0.1; ***p*-value < 0.05; ****p*-value < 0.01; ****p-value < 0.001.
Robust standard errors for all regressions are provided in parentheses.

Accordingly, in Table 3.7 above, models (1) and (4) report the results of the first stage regressions, and models (2) and (5) tabulate those of the second stage analysis. The results of the first stage regressions are consistent with those of the preceding ATE, Logit and Probit tests,[33] in that being located in GP (a province characterised by a high COVID-19 infection rate and increased levels of people quarantining at home during the sample period) leads to a greater presence and intensity of the DE. This outcome can be interpreted to mean that quarantining at home (as a large contingent of GP-based investor teams did) suffices as a reasonable instrument to introduce exogenous shocks into said investor team's investment decision-making, leading to trading behaviours that are synonymous with the DE as a first order effect, *ceteris paribus*.

Continuing with Table 3.7 above, the results of the second stage regressions show that instrumented $DEdummy$ (denoted as $DE\widehat{dummy}$) significantly increases the volume of trading orders executed by investor team i, *ceteris paribus*, at the 10% level under model (2) and 5% level under model (5). These results – especially in the case of model (5) – can be taken to be in support of hypothesis H2 that the presence of the DE among investor teams quarantining at home causally increases their order flows. As a robustness check on our second-stage regression outcomes, the columns for models (3) and (6) report the results of estimating limited information maximum likelihood (LIML) regressions, with model (6) confirming the significance, size, and positive-signage of the $DE\widehat{dummy}$ variable's coefficient (π_1) seen under model (5), as it relates to order flow. Furthermore, at 10.24, the F-Statistic for first-stage model (4) is large enough for the second-stage instrumented estimator in model (5) to be reliable, as the model contains only one endogenous regressor (Stock *et al.*, 2002).

[33] With the results of model (4) being completely identical to those of the OLS model in Table 3.6.

3.4. Discussion and concluding remarks

3.4.1. Discussion of results

Like the case of the study in Chapter 2 of the current thesis, we once again find evidence of the presence of the DE among university student investor teams participating in the JSE Investment Challenge. This time around, we find evidence of the bias within the context of the era of the COVID-19 pandemic, its accompanying market crash, and the list of unfavourable market conditions that the crash ushered in (including widespread stock market volatility and illiquidity). However, at a mean value of 0.05 for the full sample of individual investor teams across all four provinces under study,[34] the DEs of teams participating in the Challenge in the pandemic era (during the year 2020) are relatively smaller than those of teams who participated during the pre-pandemic era (in 2019), who had a mean DE value of 0.08 as reported in the previous chapter. This apparent improvement in the rationality of investment decision-making between the two eras is perhaps driven by an attenuated proclivity to make risky decisions – such as, for example, the proclivity to hold on to losing positions for too long – given the perilous market conditions that prevail over 2020, which the current study's sample of investor teams are exposed to. Such a change in risk-taking behaviour among student subjects seems to contradict Huber *et al.'s* (2021) finding (discussed at length in Subsection 3.1.2. above) that student investors do not adjust the riskiness of their investment decisions between the pre-pandemic and pandemic eras.

The conflict above, however, is resolved interpretively; as Huber *et al.* (2021) take their finding to mean that the student cohorts that participate in their study's experimental markets do not adjust their risk-taking behaviour between the two eras, as they are not exposed to the turbulent climate of the real-world stock market in early-2020. We therefore take this to mean that the

[34] Following Equation (2.5).

riskiness of investment decision-making, thus DE, of student investor teams participating in the Challenge is regulated by their exposure to real-world market developments – which is yet another feature of our field research context that speaks to the external validity of our findings. A feature which experimental, or synthetic markets are devoid of.

Turning to our listed hypotheses, we conclude that the results analysed above confirm hypothesis H1 that quarantining at home in response to high, localised COVID-19 infection rates causally leads to a greater presence and intensity of the DE. The mechanism underlying this causal relationship – we propose – is investor teams' heightened salience of, or attentiveness to moment-by-moment changes in their wealth while quarantining at home. This leads to an increase in the frequency with which they realise gains from winning stocks as soon as said stocks begin 'winning' i.e., begin exceeding their reference points. Support for this salience bias's (Taylor and Fiske, 1975) role in invoking the DE can be found in Frydman and Wang's (2020) conclusion that changes to a web-based trading platform which increased the salience of stocks' purchase prices causally increase the extent to which Chinese investors succumb to the DE. In a similar vein, the results of the current study advance the argument that an increase in the salience of stocks' prices in previous trading periods among investor teams quarantining at home in response to heightened contagion risk (locally) causally increases the extent and prevalence of the DE among said investor teams.

Interestingly, Li *et al.* (2021) – who find that air pollution causally increases DEs among Chinese mutual fund investment account-holders – propose that the mechanism underlying the causal relationship observed in their study may be mood self-regulation. The view here is that investors burdened by air pollution-induced mood disorders may sought to regulate their moods by increasing their realisation of winning positions as an action understood to yield positive bursts of utility in line with the assertions of realisation utility models (which we discuss in greater detail in the research chapter to follow). In turn, such an action towards mood regulation would plausibly lead to the establishment and deepening of the DE in the gains domain. It would be reasonable, in our view, to argue that this mechanism (i.e., mood regulation) may also be relevant to the findings of the current study, as perceptions regarding the COVID-19 contagion's prevalence (which induce quarantining behaviour) are understood to be strongly associated with symptoms of depression and mental strain (Bendau *et al.*, 2021). It is thus plausible that GP-based investor teams in the current study (who are located in a province experiencing the highest COVID-19 infection rate in the sample) may sought to regulate their depressed moods by realising more winners, thus invoking the DE. With the DE increasing through investors selling winning stocks via both Li *et al.'s* (2021) mood regulation mechanism and the current study's saliency shock mechanism, we ultimately resolve that both mechanisms are plausible in explaining the identified causal relationship between quarantining at home and the DE. We leave the task of measuring the extents to which these two mechanisms contribute to the intensity of DE to future studies.

Notably, with the WHO indicating in September of 2022 that the pandemic is close to ending (Mishra, 2022), quarantining at home in response to spikes in the rate of contagion is steadily becoming a thing of the past. With this, we believe, would come a reduction of the effect of the saliency mechanism on the DE, *ceteris paribus*. A potentially more persistent mechanism, however, may very well be that of mood regulation, as investors will continue to experience life under different environmental, social, and personal mood-altering circumstances long after the pandemic has ended. Given the DE's investor welfare-attenuating effect, researchers and market-practitioners alike might find value in using population mood indicators such as happiness or fear indices to predict market dynamics such as changes to return performance and turnover volumes, as a result of the DE. In addition, the mood regulation mechanism may pose important implications for employee wellbeing among the staff of investment management firms, as the negative moods of trading desk staff – for example – may hamper portfolio performance through the channel of the DE, if left unchecked.

Furthermore, we conclude that the results above confirm hypothesis H2 that the DE causally increases the trading activity of South African investor teams quarantining at home in response to localised COVID-19 waves during the pandemic. Taken together with H1 above, the current study introduces to the literature the following comprehensive causal flow: investors who are subjected to high COVID-19 infection rates subsequently quarantine at home. By way of the current study's augmented time at home proposition (which we discuss and motivate for in Section 3.2 above), these home-based investors are confronted by a higher likelihood of succumbing to the DE as information regarding frequent changes to their wealth relative to previous prices of stocks held in their portfolios is made more salient by their increased amount of time spent on trading platforms. With a secondary source of their DEs being the actions that they take to regulate their negative moods which are the result of the morbid context of disease prevalence that they are subjected to. The combination of the two mechanisms thus leads investors towards realising more gains than losses, which effectively establishes and deepens the intensity of their DEs. Finally, this increased propensity to sell winning stocks ultimately results in increases in trading activity observed through a rise in observed trading volumes both at the micro (i.e., individual) level, and the macro (i.e., market-wide level). Indeed, the depicted relationship between South Africans quarantining at home and Top 40 index trading volumes in panel (c) of Figure 3.8 above is indicative of the market-level reach of the causal flow, *ceteris paribus*. This renders the causal flow as being important to not only researchers and market practitioners, but market regulators as well.

3.4.2. Conclusions

In this chapter, we used a natural-field experimentation approach to investigate the nature of the relationship between (1) high, localised COVID-19 infection rates and the DE, as well as (2) between the disposition effect and trading volumes, among a sample of investor teams participating in the 2020 run of the JSE investment Challenge (i.e., during the era of the COVID-19 pandemic). In turn, the chapter introduces to the literature externally valid findings that (1) quarantining at home in response to high, localised COVID-19 infection rates causally leads to a greater presence of the DE, and that (2) the presence of the DE causally increases the trading activity of South African investor teams quarantining at home in response to localised COVID-19 waves during the pandemic. We present several implications which may be relevant to researchers, market regulators, and market practitioners alike.

In the upcoming fourth and final chapter of this thesis, we use data from a sample of investor teams participating in the 2021 run of the JSE Investment Challenge to mainly establish whether a causal relationship exists between incidents of socio-political unrest and the disposition effect.

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CHAPTER FOUR

South African civil unrest and the Disposition Effect: A difference-in-differences analysis

4. Introduction

Protest action and civil unrest have a long history in the South African body politic. From anti-colonial and anti-apartheid demonstrations prior to the commencement of the constitutional dispensation in 1994, to mostly service delivery protests emanating from communities' dissatisfaction with municipal service delivery in the post-apartheid era (Nleya *et al.*, 2011). The so-called 'Free Zuma' civil unrest – which occurred mainly in the South African provinces of KwaZulu-Natal and Gauteng, and spanned between the 7th and the 19th of July 2021 – is considered to be the country's worst occurrence of socio-political protest action since Apartheid (Vhumbunu, 2021; Elumalai *et al.*, 2022).

Given the understanding in the psychology and epidemiology literature that proximity or close exposure to social upheaval can have a negative effect on people's mental health, and more specifically their moods (O'Reilly and Stevenson, 2003; Kelleher, 2003; Satcher *et al.*, 2007; Tremblay *et al.*, 2009) – and the view in the behavioural finance literature that the disposition effect is caused by investors' attempts at regulating their negative moods, *ceteris paribus* (Henriksson, 2020; Li *et al.*, 2021) – the current study unfolds as a quasi-experimental investigation into whether investors' close exposure to incidents of civil unrest can causally result in the emergence and intensification of the disposition effect. This, it seems, is a question that no other study in the behavioural finance field has interrogated, rendering the answer to the question as not only novel to the literature, but also important for understanding the psychological mechanisms underlying investors' behavioural responses to incidents of protest action. We once again make use of the JSE Investment Challenge as the research context for the current study; this time, however, with a specific focus on the period 9 June to 8 August 2021 – a period of time during which the Free Zuma protests are recorded as having occurred.

In the remainder of this chapter, Section 4.1 provides a review of the literature on (i) the realisation utility theory as an alternative behavioural model explaining the disposition effect, (ii) mood regulation and its relationship with the disposition effect, (iii) the July 2021 civil unrest in South Africa and its impact on the South African equity market, and (iv) provides the hypothesis of the current study. The methodology and data are discussed in Section 4.2, and the results are covered in Section 4.3. Section 4.4 discusses the implications of the results and concludes the chapter.

4.1. <u>Literature review and hypothesis</u>

4.1.1. The Disposition Effect and Realisation Utility

The most recent of models seeking to explain the behavioural sources of the disposition effect is the class of realisation utility models. First analysed for its implications for trading behaviour and asset price formation by Barberis and Xiong (2012), realisation utility asserts that investors succumb to the disposition effect because they receive bursts of positive utility whenever they sell risky assets trading at a gain, and bursts of negative utility (or, disutility) when they sell risky assets trading at a loss. In these models, realisation utility is viewed as a consequence of two underpinning cognitive processes. First, instead of solely considering the return earned on their portfolios when reviewing their investing history, investors are more inclined to rather consider their investing history as a series of episodes, with each episode being defined by the name of the asset invested in, and the asset's purchase and sale prices. Buying MTN shares at 100 South African Rands (R) and selling them at R120 is one such example of an episode. The second cognitive process refers to how investors go about evaluating each investing episode; in this regard, selling an asset at a gain relative to the purchase price is viewed as a good investing episode which investors receive bursts of positive utility from. On the contrary, selling at a loss is a bad episode from which negative bursts of utility are derived.

Similar to the prospect theory framework discussed earlier in Chapter 2 of the current thesis, realisation utility models are an acute departure from expected utility theory as they postulate that the bursts of utility (be they positive or negative) experienced by investors from selling risky assets are independent of considerations of what these trading decisions mean for final state wealth, and are instead more reliant on risky assets' purchase price-related information at moments of sale (Kahneman and Tversky, 1979; Barberis and Xiong, 2012; Ingersoll and Jin, 2013).

On the other hand, what appears to be a salient break from behavioural finance researchers' previous applications of prospect theory on the disposition effect is realisation utility theory's general view that investors who succumb to the disposition effect derive utility from realised gains and losses (Shefrin and Statman, 1985; Barberis and Xiong, 2009; Barberis and Xiong, 2012). This perspective perhaps plays down the more conventional approach of considering both realised and paper-based gains and losses in a manner consistent with the disposition effect measure (Equation (2.2) of Chapter 2 of the current thesis) first introduced by Odean (1998). Barberis and Xiong's (2012) motivation for breaking from this convention stems from the realisation utility-oriented argument in Shefrin and Statman (1985) which references the concept of mental accounting – a term used to explain how economic agents tend to consider, organise and evaluate their financial transactions. In particular, Barberis and Xiong (2012) postulate the following: in instances when an investor sells a risky asset, the investor is effectively closing a mental account that was opened when they first bought the stock; moments of sale thus become natural points in time for investors to evaluate the transaction, at which points realised gains are appraised as good outcomes carrying positive utility and *vice versa* in relation to realised losses.

Another (perhaps, more nuanced) distinction between prospect theory-informed models of the disposition effect and realisation utility is the latter's adoption of a linear functional form[35] for utility (which demonstrates how the amount of utility received by an investor is linearly associated with the difference between the sale and purchase prices of a stock that they sell) instead of a functional form for utility that is concave in the gains domain and convex over losses (as is the case in relation to prospect theory's S-shaped value function curve (Kahneman and Tversky, 1979; Shefrin and Statman, 1985)), together with a sufficiently positive time discount rate (which, for example, explains an investor's inclination to realise a gain today, rather than to hold out for a larger gain at a later date); a consideration which prospect theory-informed models are devoid of. Be that as it may, the S-shaped value function curve of prospect theory and the positive time discount rate of realisation utility as distinct features of two behavioural models explain the same observable behaviour of investors selling risky assets *too soon* when in the *concave,* gains domain, and holding on to risky assets for *too long* when in the *convex*, losses domain (Frydman *et al.*, 2014). Viewing the disposition effect from this perspective perhaps gives clarity as to why Barberis and Xiong (2012) do not regard models of the disposition effect that are based on prospect theory preferences as being invalidated by the realisation utility model that they derive, but rather view the two approaches as alternatives to one another that both do well in explaining why investors may expedite the realisation of gains and postpone the realisation of losses.

Regarding their comparison of the mean-reversion hypothesis and realisation utility, however, Barberis and Xiong (2012) reach a relatively less harmonious conclusion. Specifically, they draw their views in this regard based on findings in Weber and Camerer (1998) (discussed in greater detail in earlier chapters of the current thesis); wherein which one of the stock trading

[35] As per the version of the model derived by Barberis and Xiong (2012).

experimental conditions observed involves the involuntary liquidation of subjects' entire portfolio holdings at random times, a treatment which seemingly attenuates subjects' disposition effects relative to those of subjects who did not receive the automatic liquidation treatment, and – according to Barberis and Xiong (2012) – has the empirical impact of supporting the realisation utility view over the mean-reversion hypothesis as a behavioural source of the disposition effect.

In response to the position above, we reaffirm our conjecture made earlier in Chapter 3 that an investor under Weber and Camerer's (1998) involuntary liquidation condition may plausibly succumb to the disposition effect – as per the irrational belief in mean-reversion model – until the point where said investor's behaviour is debiased by a partition (Cheema and Soman, 2008) in the form of the automatic liquidation of their portfolio. Rather than invalidating it entirely, this view qualifies the mean-reversion hypothesis by postulating that it holds as a source of the disposition effect on condition that trading behaviour is not partitioned. All-in-all, we agree with Barberis and Xiong (2012) that models based on prospect theory preferences and realisation utility act as alternatives to one another, however we go further to suggest that the irrational belief in mean-reversion model is also a suitable substitute for either of the former two, particularly under circumstances where an investor's trading behaviour is not partitioned.

Another point of reflection for us on the realisation utility model derived by Barberis and Xiong (2012) relates to their expectation that realisation utility (and its impact on the disposition effect as well as other patterns of investor behaviour) is not necessarily important for all investor types. In elaborating, they posit that well-trained, professional investors – unlike novice individual investors who trade on the platforms of retail aggregators – are more likely to consider their investing history in terms of portfolio returns rather than investing episodes that occur with each stock sale. Indeed, the notion that professional investors succumb to the disposition effect to a lesser extent than non-professional investors is not new to the literature

(Garvey and Murphy, 2004; Lee *et al.*, 2008). What may however be peculiar in this instance is the almost exclusive attribution of a disposition effect-invoking mechanism to a specific type of investor.

Given that professional investors have also been shown to succumb to the disposition effect to some extent (Shapira and Venezia, 2001; Dhar and Zhu, 2006; Da Costa *et al.*, 2013), a potential criticism of realisation utility thus relates to its inability to robustly explain disposition effects among the different types of investors with whom they have been observed. In relation to the research context of the current thesis, we observe the investment behaviour of student investor teams participating in the annual JSE Investment Challenge, where investor teams are acutely aware of their objective to build portfolios which deliver superior returns over a seven-month period at a time. This context thus begs the question: are realisation utility model assertions applicable in circumstances involving groups of relatively novice investors participating in a short-term simulation of the typical institutional investor's experience and objectives?

We might expect an affirmative response to the question above given the parallels between the relatively novice nature of the students who make up the investor teams participating in the Challenge and the theoretical prediction that realisation utility-informed disposition effects are more relevant in the case of novice investors and less relevant in the case of "trained professionals" (Barberis and Xiong, 2012). On the other hand, one might consider the parallels between the short-term, portfolio return-oriented objectives of the Challenge's investor teams and realisation utility's prediction that investors who are inclined to appraise their investing history based on portfolio returns are less likely to succumb to realisation utility-informed disposition effects. With this consideration in mind, an affirmative response to the question above may potentially expand on realisation utility's *a priori* views on the type of investors that are impacted by it. The motivation for providing an evidence-based response to such a question is made that much more compelling when considering that – to the best of our knowledge – the literature is devoid of any empirical studies which directly interrogate whether professional investors succumb to realisation utility-informed disposition effects (but see Schmidt (2019)).

Apart from research efforts such as Weber and Camerer (1998) who develop and experiment using a measure of the disposition effect that is exclusively a function of realised gains and realised losses (i.e., the so-called 'disposition coefficient'), and Frydman and Wang (2020) who make use of a difference-in-differences regression model based on – *inter alia* – realised gains, realised losses, and the propensity to sell risky assets in their investigation of whether the inclusion of purchase price information on the front-end of a trading platform invokes the disposition effect (by way of the salience bias), studies which empirically affirm realisation utility as a behavioural model for the disposition effect and empirically distinguish it from other behavioural models are few and far in between (if at all existent beyond the aforementioned two).

As Frydman *et al.* (2014) point out, this apparent void in the literature is perhaps due to the difficulties of observing underlying cognitive processes when relying on behavioural data only, particularly in instances when observable behavioural phenomena such as letting go of winning stocks too soon and holding on to losers for too long could plausibly be informed by either the psychological mechanisms of prospect theory preferences or present bias (as per realisation utility) which are generally difficult to observe in the absence of neurological data. This, perhaps, is the rationale for a contingent of the emerging empirical realisation utility literature's reliance on combining neural measurement with experimental analysis as means of evaluating the neural and behavioural patterns of subjects engaged in investment decision-making against the predictions of the realisation utility-cum-disposition effect hypothesis. In this regard, Frydman *et al.* (2014) – in what may likely be the first neurofinance study of realisation utility

– make use of fMRI analysis to test the predictions of realisation utility (as they relate to the disposition effect) on a pool of subjects trading in an experimental stock market designed in line with the approach in Weber and Camerer (1998). The study's fMRI measurements, Frydman *et al.* (2014) argue, reveal neural activity patterns which are – to a great extent – consistent with the neurological predictions of realisation utility.

In particular, Frydman *et al.*'s (2014) study first confirms that – at the time of making a decision to sell a risky asset – the capital gain or loss of selling the asset positively correlates with activity in the ventromedial prefrontal cortex (vmPFC); a part of the brain which has been proven to be involved in value computations with regards to available options. Second, they find relatively stronger disposition effects among subjects whose capital gains and losses correlate with their vmPFC activity at the time of sale (i.e., subjects shown to succumb to the disposition effects driven by realisation utility as a mechanism). And third, they find that parts of the ventral striatum (vSt) – the regions of the brain which encode positive (negative) prediction errors – are stimulated (depressed) at moments in time when investors realise capital gains (losses). This, it seems, is because of the role played by prediction errors – i.e., miscalibrations which are characterised by differences between rewards received and rewards predicted – in economic decision mechanisms (Schultz, 2016). This is because economic agents such as investors impacted by realisation utility receive bursts of utility synonymous with positive prediction errors (which neurologically manifest as the observable excitation of dopamine neurons in parts of the brain's vSt region) when they realise capital gains and receive bursts of disutility synonymous with negative prediction errors (manifesting as the observable depression of activity in the vSt) when losses are incurred and realised. These bursts of utility are thus said to generate changes in the expected net present value of utility, which "should be reflected at the moment of sale in the prediction error computed by the vSt" (Frydman, *et al.*, 2014).

More recently, Imas (2016) uses experimental means to find support for a theoretical concept which complements much of what has been discussed above regarding realisation utility – namely, the realisation effect. In the main, the realisation effect posits that investors avoid risk following realised losses, and take on greater risk following unrealised paper losses. In this regard, Imas' (2016) research efforts relating to the realisation effect are said to build on the literature distinguishing between realised and unrealised investment outcomes and provides a view into how an investor switches their risk preferences depending on the type of investment outcome that they face, *ceteris paribus*.

Imas (2016) finds support for the realisation effect from the results of three experiments. The first experiment – which intends to identify differences between the effects of realised and unrealised (i.e., paper) losses on risk-taking by observing the behaviour of a subject pool of undergraduate students (n = 128) participating in four rounds of an experimental lottery – randomly assigns its subjects into realised and paper treatment cohorts, with those who incurred losses under the realised condition having to pay the experimenter (from an experimental endowed account) the amount of money lost during the penultimate round of the lottery before placing final bets in the fourth round, and those who incurred losses under the paper condition proceeding to place their final bets in the fourth round without having to realise their losses during the penultimate round. In a pair of outcomes that are consistent with the predictions of the realisation effect, the results of the experiment showed that subjects who lost under the realised condition, on average, decreased the size of their bets in the fourth round by $0.15 (a decrease in the average size of the bets which is equivalent to 1.88 percent of the $8 amount endowed to each subject at the beginning of the experiment), and also showed that subjects who lost under the paper condition (i.e., those who did not realised their losses in the penultimate round of the lottery) increased their bets in the fourth round by $0.25, on average (which is equivalent to an increase in bets of 3.13 percent of the initial $8 endowment).

The second experiment endeavours to test the robustness of the results of the first experiment by (a) determining whether the decline in risk-taking among subjects who had incurred losses under the realised condition was due to the transfer of funds out of their own accounts (as predicted by the realisation effect) or whether it was due to their being separated from physical cash; and (b) conducting two iterations of the experiment on an additional two subject pools: *n* = 246 members of the general public with an average age of 26.9 years and average income of $18,000 per annum, and *n* = 151 individuals recruited from the Amazon Mechanical Turk crowdsourcing marketplace. In both iterations of the experiment, subjects who incurred losses under the paper condition once again increased their risk-taking in the fourth round of the lottery, with those who lost under the transfer condition (where losses were realised and paid for by means of a cashless account transfer mechanism) exhibiting a proclivity to decrease risk-taking in the fourth round. Interestingly, in the iteration of the experiment involving members of the general public, Imas (2016) observes subjects under – *inter alia* – both the transfer condition and the realised (i.e., physical cash separation) condition and finds that those who lost under the realised condition decreased the size of their bets in the fourth round twice as much as those under the transfer condition. However, an explanation for this phenomenon is not provided.

To fill this gap, we conjecture that perhaps those subjected to the realised treatment are relatively more reluctant to take on further risk following loss realisation due to the physical cash payment inducing the pain of paying. First introduced by Zellermayer (1996), the psychological pain of paying refers to the negative emotions that people experience when making a purchase. This occurs as a result of humans' inherent aversion to losses (or, loss aversion) – an undesirable feeling which is made more salient when paying with physical cash than alternative cashless mechanisms. The use of physical cash as a payment mechanism is thus understood to be a notable regulator of spend behaviour (Soman, 2003). Relating the pain of paying to the context of risky decision-making (such as the case of Imas' (2016) second experiment), it is plausible that investors (gamblers) who participate in financial markets (lotteries) using physical cash to transact are more likely to regulate their risk-taking behaviour (especially following the realisation of losses) than those who transact using cashless mechanisms.

The third experiment in Imas (2016) investigates the impact of flexibility, regarding when positions can be realised, on risk-taking behaviour. Operationally, this is done by introducing a flexibility condition to the experiment, which is observed alongside the realised and paper conditions of the first experiment, and grants subjects the choice to realise their positions either during the penultimate or fourth round of the lottery. The design of this condition thus mimics the real-world context in asset markets – or even in casinos – where people typically have the agency to endogenously realise their positions by, for example, executing sell-orders on long positions or folding in a game of poker. Subsequent to conducting the experiment on a subject pool of undergraduate students (n = 120), the experiment's results showed that those who incurred losses under the flexibility condition (a) exercised their option to realise their positions during the penultimate round only 13 percent of the time, and (b) during the fourth round, they made the largest increase to their bets of all three cohorts under observation with an increase that's 13.79 percent higher than that of those subjects who were under the paper condition. Interestingly, the experiment also found that subjects who earn gains under the flexibility condition exercise their option to realise their gains 44 percent of the time (approximately 31 percentage-points or 238 percent above those who incurred losses), a phenomenon which comprehensively exemplifies the disposition effect (Shefrin and Statman, 1985; Odean, 1998).[36]

[36] If we apply Odean's (1998) measure, for instance, we see that the aggregate proportions of gains and losses realised (PGR and PLR) by the experiment's subjects are 0.44 and 0.13 respectively, implying a DE value of 0.31.

In reconciling the evidence on the realisation effect with the postulations of realisation utility discussed further above, one might begin with the view that the realisation of a loss from, for example, selling an asset for a lower price than it was purchased is a phenomenon that characterises what realisation utility refers to as a bad investing episode (Barberis and Xiong, 2012), and which yields a burst of disutility, or what otherwise might be referred to as the *psychological pain of losing*: a concept which we believe does better in describing the phenomenon under discussion than the pain of paying (Zellermayer, 1996), and refers directly to the mechanism (i.e., loss aversion) underlying the disutility generated by both the experiences of losing money directly in its form as a medium of exchange (e.g., paying for goods, services, etc.) and losing money indirectly in its form as a unit of account (e.g., selling a financial asset at a price that is lower than its purchase price).

Neurologically, this burst of disutility, or pain of losing, is synonymous with the brain's encoding of a negative predictive error, effectively depressing activity in parts of the brain's vSt region at the moment of realising a capital loss (Frydman *et al.*, 2014; Schultz, 2016). Similar to how the pain of paying is an effective regulator of spending behaviour by consumers (Zellermayer, 1996; Soman, 2003), the second experiment in Imas (2016) shows how the pain of losing can mitigate against further risk-seeking behaviour under circumstances where losses are realised (i.e., the realisation effect). This realisation effect becomes more pronounced as the loss is made more salient in instances where its realisation involves a separation from physical cash.

Furthermore, in an attempt to avoid the pain of losing, investors holding on to unrealised losses – just like the subjects under the paper condition or 87 percent of those under the flexibility condition in Imas' (2016) third experiment – are likely to increase their risk-taking behaviour. Thus, similar to the prospect theory-illustrating scenario of the race track gambler (discussed in Tversky and Kahneman (1981) and in Chapter 3 of the current thesis) who bets $10 on a long-shot in the last race of the day after having lost a cumulative total $140 for the day, the investor or gambler who seeks more risk following a loss (especially an unrealised one) does so in the hope of at least returning to the reference point of zero losses and zero gains; effectively intensifying their disposition effects. The concept of the pain of losing is therefore, in our view, effective in consolidating how realisation utility models, the realisation effect, and prospect theory preferences explain the disposition effect.

As comprehensively as Imas' (2016) paper explains the realisation effect in relation to losses, the article is almost completely silent on how the effect might relate to gains. Furthermore, the experimental lotteries in Imas (2016) are exclusively conducted under positively skewed conditions, meaning that – with each gamble – subjects face a high probability of incurring modest losses and an existent, but relatively low probability of earning large gains (Gibson *et al*, 2019). Ignoring the other possible skewness conditions for gambles (balanced skewness and negative skewness) brings into question the external validity of Imas' (2016) results. In response to these issues, Merkle *et al.* (2021) examine (i) whether the realisation effect exists for gains, and (ii) whether the realisation effect depends on the skewness of the underlying risk-taking opportunity (such as a gamble or investment). In doing so, they replicate the result in Imas (2016) insofar as paper losses are concerned and proceed further to evidence that the realisation effect also exists for paper gains, and that the effect only holds under the condition of a positively skewed distribution of outcomes.

On the face of it, Merkle *et al's* (2021) finding that people can have a proclivity to increase their risk-taking following both unrealised losses and gains may come across as being contradictory to the disposition effect's assertion that people are risk averse in the gains domain. A perhaps more apt bias for explaining the phenomenon of people seeking more risk following gains is the house money effect (Thaler and Johnson, 1990) – the idea that people use proceeds from prior gains to place bets in subsequent gambles. However, as Duxbury *et al.*

(2015) empirically demonstrate using real-world trading data, the disposition effect and the house money effect can contemporaneously coexist in the same stock market with the majority of the investors that their study observes (53.5%) succumbing to both biases simultaneously. Merkle *et al's* (2021) extension of the realisation effect to both losses and gains is thus consistent with the understanding that the disposition effect and house money effect can contemporaneously coexist.

With regards to the finding that the realisation effect exists only within the bounds of positively skewed lotteries (where the probability of incurring modest losses is high and the probability of earning large gains is existent, but relatively low) and not for balanced lotteries (where the probabilities of gains and losses are equal) nor negatively skewed lotteries (where the probability of earning modest gains is high and the probability of incurring a large loss is existent, but relatively low), we may perhaps find an explanation for this in the psychological research on how physical pain is perceived by humans. In a study of outpatients undergoing colonoscopy procedures, Redelmeier *et al.* (2003) found that patients whose colonoscopies end soon after the moment of the most intensive part of the procedure reported to have felt more pain than those who underwent the same procedure for a slightly longer duration of time with the procedure ending at the moment of relatively less intensive pain, in spite of the latter cohort objectively experiencing more pain than the former given the extension of the duration of the procedure.

Thus, the principle that flows from Redelmeier *et al.*'s (2003) finding above is that people reflect on painful experiences based on – *inter alia* – the intensity of pain during the worst part of the experience. Furthermore, patients who reported to have felt more pain were less likely to return for a follow-up colonoscopy more than five years after the initial procedure; suggesting the persistence of people's memories of experiences that they perceive to be intensely painful. How might these insights on how people reflect on pain relate to how people adjust their risk-taking behaviour based on the skewness of the distribution of the outcomes of a given risk-taking opportunity?

Our view is that people's inclinations to be risk-loving in situations where they face the prospect of incurring modest losses and risk-averse when confronted by the prospect of a large loss are tendencies that are plausibly governed by what we refer to (further above) as the pain of losing: an acutely unpleasant feeling which is more psychological than physiological in nature, with the unpleasantness of the feeling being correlated with the intensity, or size of the loss. Therefore, in the context of the investor who incurred a large, unrealised loss in an asset market where investment opportunities are negatively skewed, for example, the prospect of subsequently incurring yet another sizeable and painful loss renders further risk-taking undesirable (much like the colonoscopy patients in Redelmeier *et al*'s (2003) study who did not return for their follow-up procedures), regardless of how relatively low the likelihood of such a loss might be. Through this conjecture, the pain of losing thus provides a possible explanation for why the realisation effect does not exist under the conditions of non-positively skewed distributions of outcomes.

Realisation utility theory and the realisation effect thus do well as behavioural models for the disposition effect, considering the literature reviewed and the conjectures made above. Next, we discuss a psychological mechanism underlying investment decision-making which some have argued has the effect of exacerbating investors' proclivity to sell winning stocks sooner rather than later, in pursuit of positive bursts of utility. Namely, mood regulation.

4.1.2. The disposition effect and mood regulation

Much has been discussed in the literature regarding mood as a mechanism through which weather variables affect investment decision-making, and ultimately impact stock market performance (Saunders, 1993; Cao and Wei, 2005; Muhlack *et al.*, 2022). In relation to the disposition effect, Wang (2016) finds a correlation between weather temperatures – *inter alia* – and the disposition effects of investors participating in the UK spread-trading market (a relationship which we were unable to find a causal link for under experimental analysis among our sample of investor teams in Chapter 2 of the current thesis). Henriksson (2020) also finds that a relationship exists between the disposition effect and natural disasters (such as floods, hurricanes, droughts, etc.), and suggests that investors who are subjected to negative environmental utility shocks are more likely to attempt to offset such disutility with bursts of positive utility received from realising winning stock positions.

Further to the above, Henriksson (2020) shows that the intensity of the disposition effects of natural disaster-affected investors increases based on the severity of the natural disaster (i.e., disaster-affected investors sell more winning stocks the more sever the disaster is, *ceteris paribus*); a phenomenon which conflates the linearity of utility under the realisation utility theory with the idea that investors regulate their externally induced negative moods by selling their winning stocks. With regards to the latter part of this conflation, we first mention Li *et al.*'s (2021) postulation that the mechanism underlying the causal link that their study identifies between air pollution and the disposition effect is mood regulation in Chapter 3 of the current thesis and suggest the plausibility of this mechanism as an explanation for our finding that high, localised COVID-19 infection rates causally result in the presence of the disposition effect. The rationale for mood regulation as a mechanism underlying the relationship between environmental conditions and disposition effects begins with the acknowledgement that psychology research has long noted people's tendency to take actions to maintain positive moods and eliminate negative ones.[37] Given realisation utility's assertion that people receive positive (negative) bursts of utility when realising gains (losses), the realisation of a winning

[37] See Li *et al.* (2021) for references from the psychology literature.

stock position might plausibly be seen as an attempt at doing away with a negative mood, while holding on to a losing position could be the result of the investor's reluctance to exacerbate their negative mood.

Furthermore, Bruyneel *et al.* (2009) find empirical support for the view that risky decision-making is as a consequence of the depletion of the investor's abilities to maintain self-control and resist tempting behaviours (i.e., the depletion of the investor's ability to inhibit tempting behaviours), and active mood regulation is understood to rely on the same limited cognitive resources that inhibition relies on (Muraven and Baumeister, 2000). Since investors holding on to losing positions are understood to be demonstrating risk-seeking behaviour, we conjecture that this may be as a result of Bruyneel *et al.*'s (2009) depletion hypothesis, *ceteris paribus,* on the condition that the investor is suffering from a negative mood disorder. We thus have a complete set of theoretical explanations for how mood regulation entrenches the disposition effect via both the gains and losses domains.

On reflection, we've seen how mood regulation-cum-disposition effects can be induced by exogenous factors such as unfavourable weather conditions, natural disasters, and public health crises. But what of widespread rioting and destructive protest action? How might exposure to socio-political upheaval of this sort affect investors' moods as well as their efforts at regulating their moods? Offering relevant context for answering these questions are the 'Free Zuma' civil unrest incidents which occurred in South Africa during the month of July 2021.

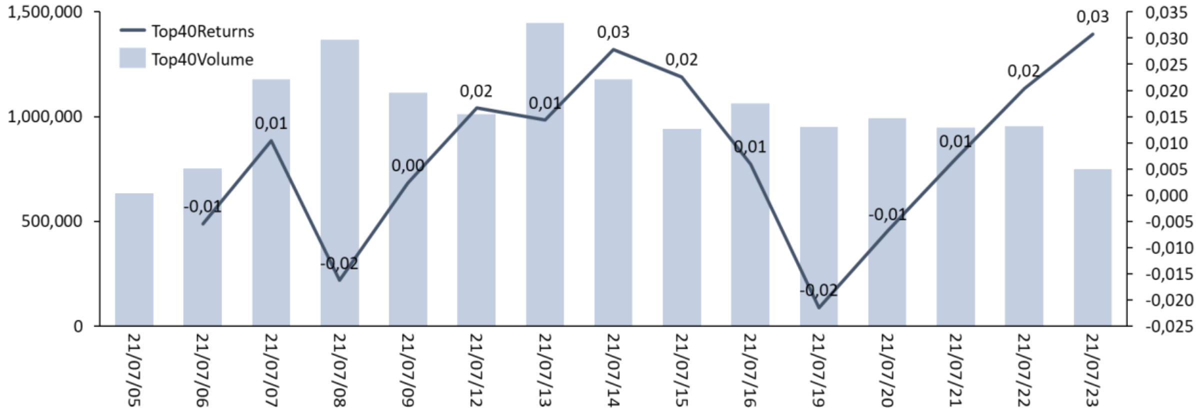
4.1.3. The July 2021 civil unrest in South Africa and stock market returns

Ushered in by the incarceration of former South African President Jacob Zuma on the 7th of July, 2021 after having been found guilty of a contempt of court charge by the Constitutional Court, the so-call 'Free Zuma' protest action is considered to be the country's worst unrest since Apartheid (Vhumbunu, 2021; Elumalai *et al.*, 2022). Over and above the jailing of the former president, the widespread rioting was said to be borne out of many South Africans' frustrations over COVID-19 lockdown restrictions, and intensified by the country's weakened security systems, its high unemployment rate, as well as its economic instability. Characterising the unrest which spanned between 7 and 19 July, 2021 was the widespread looting of businesses and shops, the vandalisation of private property and public amenities, and the burning of buildings, trucks and warehouses in the KwaZulu-Natal and Gauteng provinces. Numerically, 4199 stores, 161 malls, 11 warehouses, and 8 factories were among those that were looted and extensively damaged by protestors. More concerning consequences of the unrest were the killing of over 300 people (Elumalai *et al.*, 2022), and disruptions to the nation's COVID-19 vaccination drive during the country's prolonged third wave of rising COVID-19 infection rates (Vhumbunu, 2021; Jassat *et al.*, 2022). The economic fallout from the unrest was approximated to stand at R50 billion (or just under 1 percent of South Africa's GDP during 2021) in the value of property lost or damaged over the nine-day protest period, and 150,000 jobs being at risk due to temporary and permanent business closures (in a country with an unemployment rate of 33.56 percent).

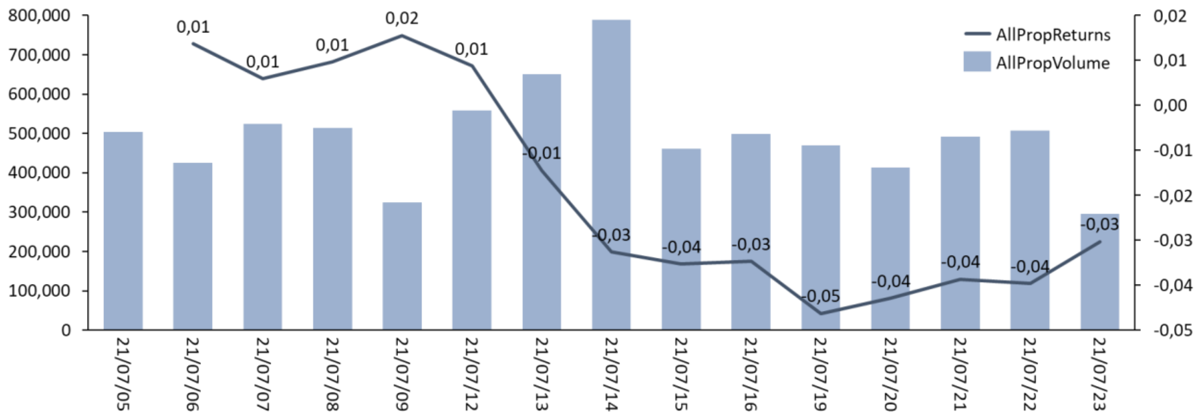
How might such a bout of extensive rioting and socio-political upheaval impact financial markets? In response to a similar question, Barrett *et al.* (2021) uses an event-study approach to quantify the impact of social unrest on the returns of stock indices from 72 countries, and find that the average social unrest episode in a typical country results in a 1.4 percentage-point decline in excess returns (i.e., returns in excess of the returns of the MSCI All Country World Index) over a two-week event window, *ceteris paribus.* With reference to how South African financial markets were affected by the July 2021 protest action, Figure 4.1 below depicts the daily returns and trading volumes of indices and shares of interest spanning between the first trading day of the week during which the civil unrest began (05/07/2021) and the last trading day of the week in which it ended (23/07/2021).

Figure 4.1: *Daily returns and trading volumes on JSE-listed instruments during the period 5 to 23 July 2021*

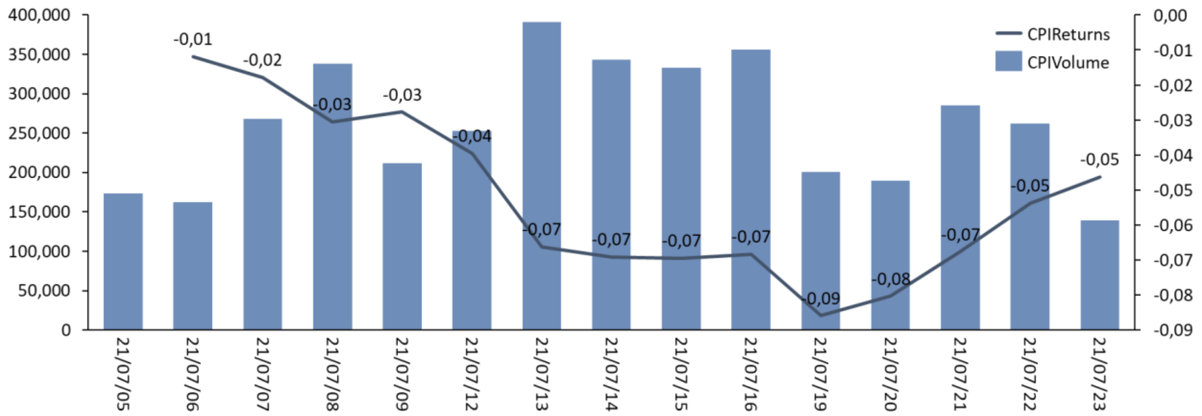
Panel A: Daily FTSE/JSE Top40 index returns and trading volumes



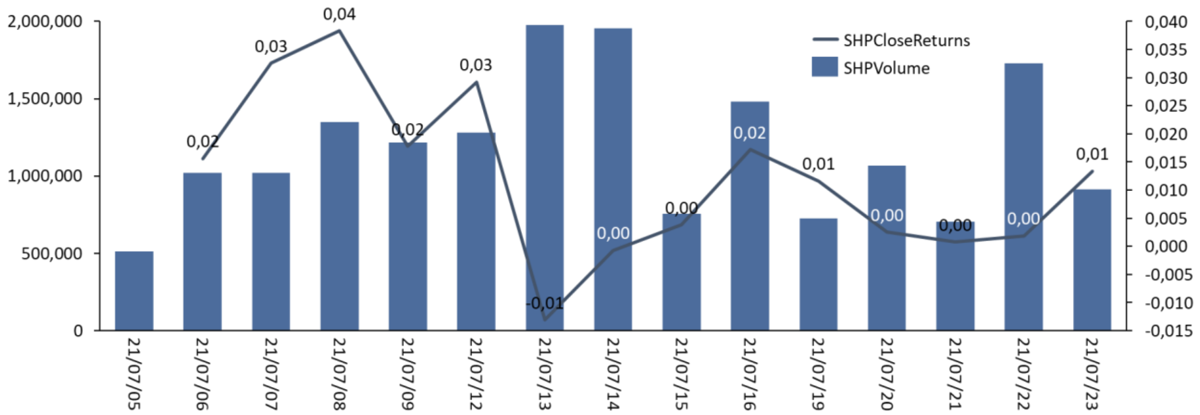
Panel B: Daily FTSE/JSE All Property index returns and trading volumes



Panel C: Capitec Bank Holdings Ltd. share returns and trading volumes



Panel D: Shoprite Holdings Ltd. share returns and trading volumes



Note: All daily returns based on instruments' close prices on 05/07/2021.

Panel A above shows slight variations in trading volumes along with a fairly volatile daily returns trend concerning the FTSE/JSE Top40 index, with the negative consequences of the civil unrest only being priced in by the market on the day after the first day (08/07/2021) of the unrest period and on the last day (19/07/2021) of recorded protest action as the index's daily return rate declines by 3 percentage-points to -2% (or, -0.02) in both instances. On the other hand, the All Property index market's response to the unrest was less immediate but was sustained over a relatively longer period of time, as seen by the downtrend of the index's returns depicted in panel B, and spanning between 09/07/2021 and the last day of the unrest; a period during which the index's returns declined six-fold to a period low of -5%. The magnitude of the All Property index's response to the unrest can be said to be a function of the extensive damage to stores, malls, and other immovable property that the unrest brought with it, which was estimated to amount to R50 billion as discussed further above (Vhumbunu, 2021). Banking and retail sector heavyweights Capitec and Shoprite – who closed over 300 branches and ATMs (Mchunu, 2021) and suffered looting in over 200 stores (Naidoo, 2021) during the unrest period, respectively – also saw significant declines in the value of their shares, with Capitec share returns notably declining by approximately 7 percentage-points to -9% by the last day of the unrest. All-in-all, this brief analysis thus provides some rudimentary support for the assertion in Barrett *et al.* (2021) that episodes of civil unrest are detrimental to stock market returns.

With the effect of the 2021 ‘Free Zuma’ civil unrest on stock market returns having been reviewed above, as well as with realisation utility and mood regulation as a mechanism for the disposition effect having been discussed further above, we move on to the next subsection where we build a hypothesis on how the relationship between the July 2021 civil unrest and stock market performance may plausibly have been intermediated by mood regulation and the disposition effect, *ceteris paribus*.

4.1.4. Hypothesis

Our investigation into the existence of a causal flow between civil unrest, mood regulation, and the disposition effect is rendered plausible by the long-standing view in the psychology and epidemiology literature that proximity or close exposure to social upheaval has a negative effect on people’s mental health (O’Reilly and Stevenson, 2003; Kelleher, 2003; Satcher *et al.*, 2007; Tremblay *et al.*, 2009). We also note the novelty of the current inquiry’s adoption of exposure to socio-political, rather than environmental upheaval (as is the case in all of the weather effect-related studies discussed above) as a trigger for the aforementioned causal flow. We thus view the results of such an inquiry as being contributory to general understandings regarding the robustness of mood-induced disposition effects, and accordingly test H1 below.

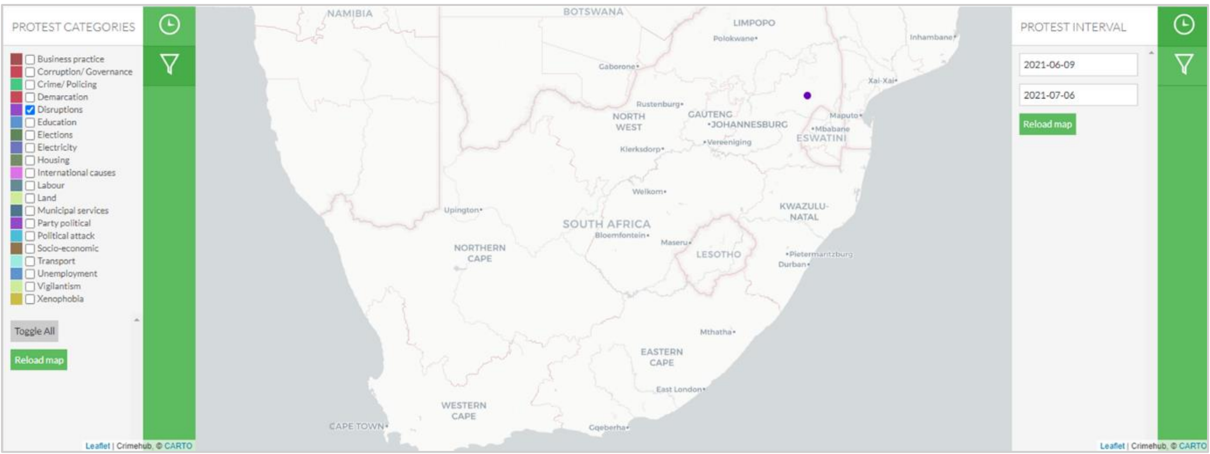
H1: Mood regulation attempts, in response to negative mood disorders induced by proximity to civil unrest hot-spots, have a causal impact on the disposition effects of South African investor teams, ceteris paribus.

4.2. <u>Methodology</u>

4.2.1. Experimental design, subject pool and data

To test our hypothesis, we begin by locating the concentration of reported disruptions during the July 2021 civil unrests. To do this, we make use of the ISS's (2022) public protest and violence map which locates and tracks incidents of unrest across South Africa. Figures 4.2 and 4.3 below confirm that the overwhelming majority of reported incidents of unrest occurred in the KwaZulu-Natal (KZN) and Gauteng (GP) provinces during the four-week period following the onset of the civil unrest (on 07/07/2021), relative to four weeks prior. It is thus plausible to assume that student investor teams who participate in the 2021 run of the JSE Investment Challenge and attend universities located in KZN and GP would be in close proximity to the recorded unrest hot-spots.[38]

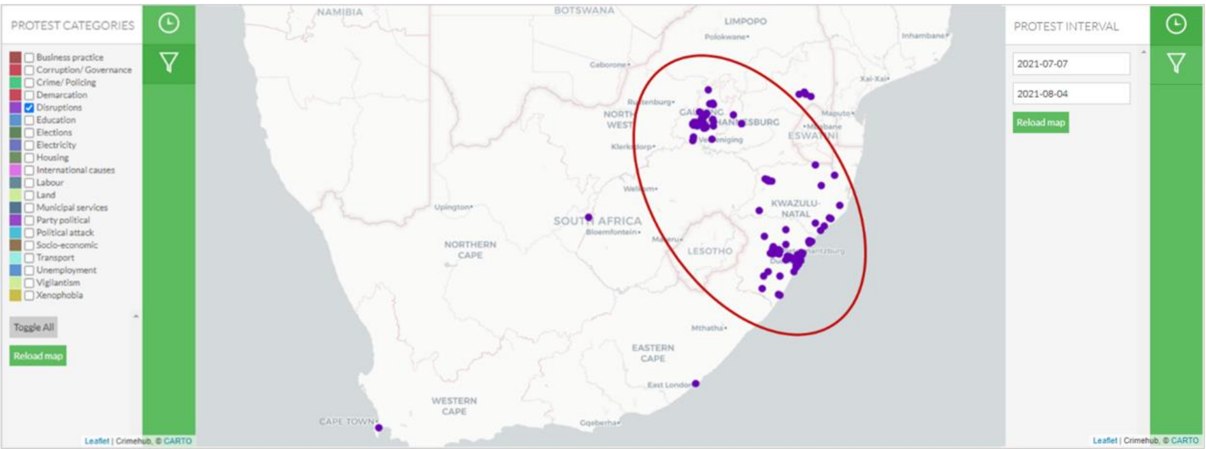
Figure 4.2: *Map showing prevalence and locations of reported protest action during the pre-unrest period*



Source: Lancaster (2018), ISS (2022)

[38] For instance, the much discussed and televised looting of a blood bank in Queensmead Mall in KZN (Mabuza, 2021) during the July 2021 unrest is a mere 2.9km's walk from the University of KwaZulu-Natal's Howard Campus (Google Maps, 2022).

Figure 4.3: *Map showing prevalence and locations of reported protest action during the unrest period*



Source: Lancaster (2018), ISS (2022)

For the study's subject pool, we thus select investor teams from seven of KZN and GP's largest universities participating in the 2021 run of the JSE Investment Challenge as the current study's high-proximity-to-unrest group (or, treatment group), and select investor teams from a similar set of seven universities located outside of the provinces of KZN and GP as the study's low-proximity-to-unrest-group (or, control group). Table 4.1 below provides a descriptive view of the universities and provincial locations of the study's cohorts of investor teams, as well as views of the average volumes of males and first-year students per investor team per university (as variables that have been understood to be associated with the disposition effect). Table 4.2 further below shows how the investor teams in the treatment group were in close proximity (i.e., exposed) to approximately 98 percent of all recorded protest incidents following the onset of the civil unrest (ISS, 2022). Furthermore, Table 4.2 shows that investor teams from both the high- and low-proximity-to-unrest groups are highly comparable to each other in terms of average volume of trading orders executed and investor team-size. Thus, following the approach in Li *et al.* (2021), we link investor behaviour to proximity to civil unrest hot-spots by aggregating investor teams' trading activities at the university campus level. We refer to these investor teams as university-level aggregate teams, or university teams.

The observational effect of this approach is that each university team describes the trading activities of a representative student investor team who buys and sells JSE-listed shares during their time as participants to the JSE Investment Challenge. As a difference-in-differences quasi-experiment, the study unfolds during the 2021 run of the JSE Investment Challenge, with the full length of the specific sample period spanning over the eight weeks between 9 June, 2021 and 4 August, 2021. The four weeks between 9 June and 6 July represent the quasi-experiment's pre-treatment (or, pre-unrest) period, and the four weeks between 7 July and 4 August represent the post treatment (or, unrest) period. The transactional data used for the experiment represents the buy, sell and hold decisions of the total sample of 280 investor teams who meet the standard requirement for field studies on the disposition effect (DE) of being active (Odean, 1998; Duxbury *et al.*, 2015; Frydman and Wang, 2020). These 280 investor teams are located in 14 universities across six South African provinces, and executed a combined total of 626 share trades across both the pre- and post treatment periods. Similar to the approach in Frydman and Wang (2020), we limit our analysis to trading decisions made only on ordinary shares, and there is no short-selling of ordinary shares in our data.

Table 4.1: Total number no. of investor teams, average no. of males per team, average no. of first-year students per team during the 2021 run of the JSE Investment Challenge between investor teams exposed to unrest vs. not exposed to unrest

	High proximity to unrest							*Low proximity to unrest*						
	KZN			GP				EC			WC		NW	FS
	UKZN	MUT	UZ	WITS	UP	UJ1	UJ3	RU	NMMU	WSU	UCT	SU	NWU	UFS
No. of investor teams	41	1	31	10	71	87	11	1	3	3	14	3	3	1
Average no. of males per team	0.63	1	0.61	1	0.66	0.71	0.64	2	1	1.33	0.93	0.67	0.33	1
Average no. of first-year students per team	0.15	1	0.1	0.1	0.03	1.22	1	0	0.67	0.67	0.14	0	0	1

*Provinces: KZN = KwaZulu-Natal; GP = Gauteng; EC = Eastern Cape; WC = Western Cape; NW = North West; FS = Free State
**Universities: UKZN = University of KwaZulu-Natal, Howard Campus; MUT = Mangosuthu University of Technology; UZ = University of Zululand; WITS = University of the Witwatersrand; UP = University of Pretoria; UJ1 = University of Johannesburg, Auckland Park Campus; UJ3 = University of Johannesburg, Bunting Campus; RU = Rhodes University; NMMU = Nelson Mandela Metropolitan University; WSU = Walter Sisulu University; UCT = University of Cape Town; SU = Stellenbosch University; NWU = North West University; UFS = University of the Free State.

Table 4.2: Proportion of July unrest incidents, average volume of orders per team, and average team-size during the 2021 run of the JSE Investment Challenge between investor teams in the high proximity to unrest vs. low proximity to unrest group

	High proximity to unrest		*Low proximity to unrest*		*Differences*		
Variables	Mean	Median	Mean	Median	Mean	*t*-stat	Wilcoxon *p*-Value
Proportion of unrest incidents (%)	98.01	1	1.99	1	96.02	478.94	<0.0001
Average volume of orders per team	16.09	9	16.25	3.5	-0.16	-0.03	<0.05
Average Team-Size	1.23	1	1.18	1	0.05	0.49	>0.10

$n_{Unrest} = 251$; $n_{NoUnrest} = 29$

4.2.2. Measurement techniques

In the spirit of Li *et al.* (2021), we compute DE following the methodology in Ben-David and Hirshleifer (2012) which views DE as being the difference between the probability of selling winners (PSW) and the probability of selling losers (PSL). With reference to the current study, we compute PSW (PSL) as a ratio of a given university team's realised gains (losses) from selling some of their shares to their unrealised capital gains (losses) from their share trading activities. This difference thus provides the university-level DE as per the equation below:

$$DE_{j,s,t} = PSW_{j,s,t} - PSL_{j,s,t} \tag{4.1}$$

where $DE_{j,f,t}$ = the DE for the aggregate investor team of university *j*, as it relates to their trading of share *s*, during period *t*. We also include a set of control variables known to be related to the DE.[39]

To test hypothesis H1 above more pointedly, we follow a cross-sectional data approach – which mainly investigates potential changes in the DEs of the treatment group attributable to being in

[39] See Subsection 3.3.2 of Chapter 3 of the current thesis for detailed definitions of these variables.

close proximity (thus, exposed) to waves of civil unrest[40] – in using the following difference-in-differences (DiD) specification with time- and city-fixed effects:

$$DE_{j,t} = \rho_0 + \rho_1 \cdot Treated_{j,t} + \rho_2 \cdot Post_{j,t} + \rho_3 \cdot Treated_{j,t} \cdot Post_{j,t} + \rho_4 \cdot X'_{j,t} + \varepsilon_i \qquad (4.2)$$

where $Treated_{j,t}$ = a dummy variable that takes a value of 1 if university *j* on day *t* is in the treatment group, and 0 if in the control group; and $Post_{j,t}$ = a dummy variable that takes a value of 1 if day *t* is in the post treatment period, and 0 if in the pre-treatment period. The vector $X'_{j,t}$ consists of control variable understood to causally intensify the DE.[41] The coefficient of interest is ρ_3 (before the interaction term $Treated_{j,t} \cdot Post_{j,t}$), and it captures the difference in the DE between the treatment and control groups induced by being exposed to waves of civil unrest.

More generally, the logic of the DiD method is best explained by considering an example involving two groups and two periods. In period 1, none of the groups are exposed to the causing variable (i.e., treatment). In period 2, only one of the groups is exposed to the causing variable, and not the other. The nature and size of the treatment effect on outcomes of interest is subsequently captured following a two-stage process: in the first stage, the difference in the mean of the outcome variable between periods 2 and 1 is taken for both groups; and in the second stage, the difference between the differences calculated for the two groups in the first stage is taken. "This second difference [thus] measures how the change in outcome differs between the two groups, which is interpreted as the causal effect of the causing variable" (Schwerdt and Woessmann, 2020). The method is well-regarded for its transparency, and

[40] With the counterfactual case being provided by the control group who are not in close proximity to waves of unrest.
[41] See Equation (3.2) in Chapter 3 above for a detailed explanation of these variables.

suitability in estimating the effect of acute changes in an economic environment (Angrist and Krueger, 1999).

Examples of the DiD method's use in research can be traced back to as early as the mid-19th century (Angrist and Pischke, 2009). Since then, there have been hundreds of studies in economics that have made use of the method to answer a wide array of causal questions, including whether immigration has a causal effect on the employment rates of natives (Card, 1990), and whether private school vouchers (which subsidise the costs of private school education for pupils from public schools) have a causal impact on pupils' maths scores (Rouse, 1998). In the finance literature, studies using the DiD method have found that a salience shock which renders stock purchase price information more readily available to online retail traders causally increases the DE by 17 percent (Frydman and Wang, 2020), with Li *et al.* (2021) – who make use of the DiD method in a manner that the current chapter largely follows – finding that high levels of air pollution (i.e., poor air quality) causally increase the DE in both statistically and economically meaningful ways, through the mechanism of mood regulation. It is this very literature that serves as precedent for the appropriateness of the current study's adoption of the DiD method.

4.3. Results and analysis

4.3.1. Testing for treatment effects using the difference-in-differences measurement approach

The main results of the current study are reported in Table 4.3 below. Models (1) and (2) provide the multivariate results of DiD regressions of the DE following the Ben-David and Hirshleifer (2012) sampling approach expressed in Equation (4.1) above without and with the control variables captured in vector $X'_{j,t}$, respectively. Across both models, close exposure to the July 2021 unrest incidents significantly increases the DE of the treatment group, as the interaction term $Treated_{j,t} \cdot Post_{j,t}$ is significantly positive. Furthermore, this increase in the DE of the treatment group is economically large. Following the intuition in Frydman and Wang (2020) that the economic magnitude of the treatment's effect on the DE is given by the ratio of the DiD estimate (i.e., ρ_3) to the baseline DE of the treatment group in the pre-treatment period, as well as the understanding in Angrist and Pischke (2009) that the aforementioned baseline DE can be given by the sum of the coefficients ρ_0 and ρ_1, we find that close exposure to civil unrest causally increases the DE by 140 percent $\left(\frac{0.3037}{0.2164}\right)$ using model (1) estimates, *ceteris paribus*.

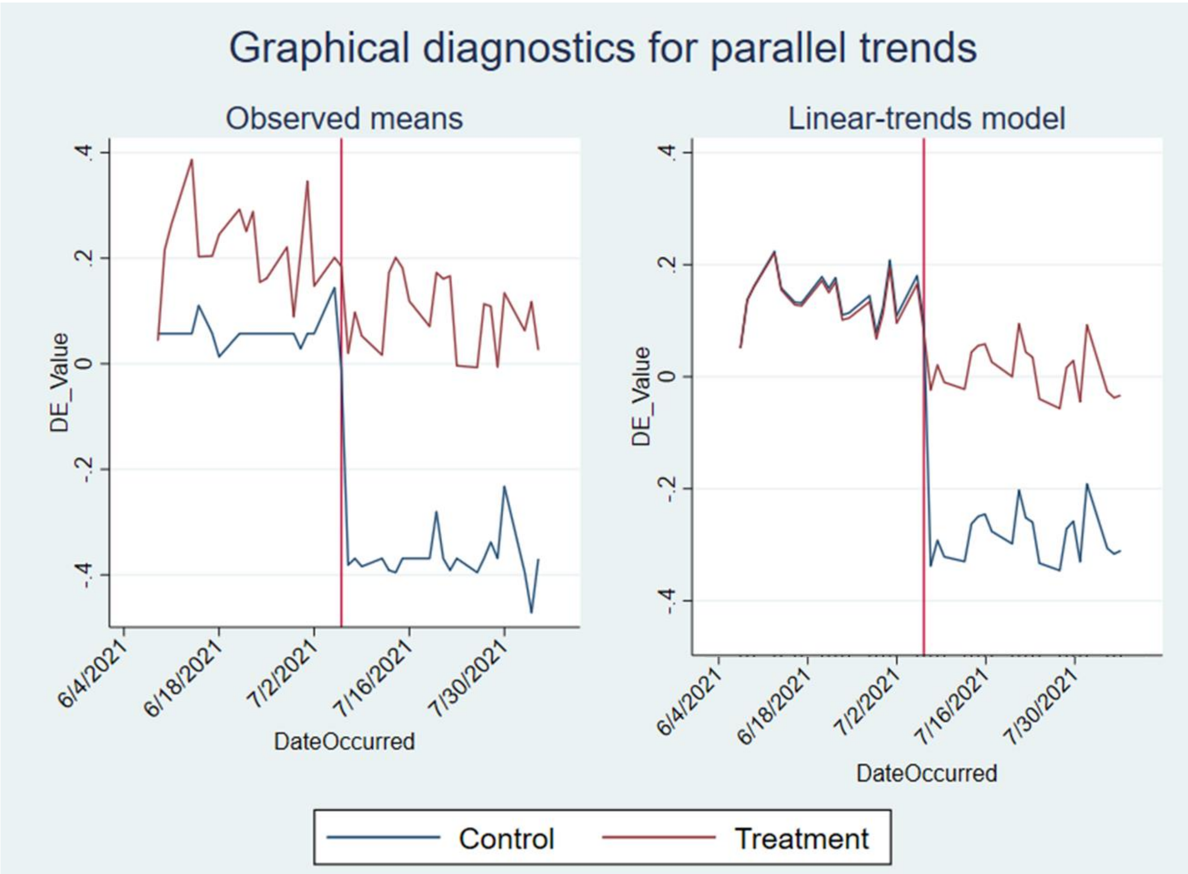
Table 4.3: Difference-in-differences regressions of the DE using high proximity to unrest as the treatment effect

Variables	(1)	(2)	(3)	(4)
	Using Ben-David and Hirshleifer (2012) sampling criterion		Using Odean (1998) sampling criterion	
$Treated \cdot Post$	0.3037**** (0.0336)	0.3037**** (0.0337)	0.2713**** (0.0344)	0.2713**** (0.0345)
$Treated$	0.1593**** (0.0307)	0.1594**** (0.0308)	0.2060**** (0.0276)	0.2085**** (0. 0273)
$Post$	-0.4260**** (0.0071)	-0.4260**** (0.0072)	-0.3929**** (0.0101)	-0.3929**** (0.0101)
$TeamSize$		0.0587 (0.0600)		0.0682 (0.0500)
$NumberofMales$		-0.0380 (0. 0466)		-0.0348 (0.0375)
$Numberof1stYears$		0.0068 (0.0088)		0.0046 (0.0811)
$Constant$	0.0571**** (0.0063)	0.0215 (0.0324)	-0.0172*** (0.0045)	-0.0675** (0.0302)
Time and university FE	Yes	Yes	Yes	Yes
n	560	560	560	560
R-squared	0.626	0.626	0.653	0.654

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01; ****p-value < 0.001.
Robust standard errors for all regressions are provided in parentheses.

As robustness checks, models (3) and (4) in Table 4.3. above report the results of re-estimations of Equation (4.2) based on the Odean (1998) sampling approach expressed in Equation (2.2) (in Chapter 2 of the current thesis). We find that our results remain robust to this alternative method of sampling. Furthermore, Figure 4.4 below shows that the Ben-David and Hirshleifer (2012) DE trends of the treatment and the control groups are parallel to each other during the pre-treatment period, based on the linear-trends model. Interpretatively, this means that close exposure to civil unrest is correctly identified as having a causal effect on the DE.

Figure 4.4: *Graphs showing parallel trends of treatment and control groups' daily DE values between the study's pre-unrest and unrest periods*



Parallel-trends test (pre-treatment time period)

H_0: Linear trends are parallel

F(1, 13) = 0.02

p-value = 0.9023

4.3.2. Investor team-level robustness check

Our main results above focus on university-level aggregate investor teams. However, is the identified causal relationship between exposure to civil unrest and the DE robust against disaggregation to the individual investor team level? This question is important as we run the risk of introducing systemic distortions to the relationship between unrest and the DE by aggregating data on investor team behaviour to the university level (Li *et al.*, 2021). We therefore estimate the following Cox proportional hazards model at the individual investor team level:

$$h_i(t) = \gamma(t) \cdot exp\{\beta_1 \cdot Gain_{i,t-1} + \beta_2 \cdot Gain_{i,t-1} \cdot Unrest_t + \beta_3 \cdot Unrest_t + \beta_4 \cdot X'_{i,t}\} \quad (4.3)$$

where $h_i(t)$ = the hazard function describing the selling decision of an investor team since the purchase of a given stock/share; $\gamma(t)$ = the baseline hazard; and $Gain_{i,t-1}$ = a dummy variable that takes on the value of 1 if the underlying stock of investor team *i* infers capital gains on date *t*, and 0 if it indicates capital losses. Since the term $Gain_{i,t-1}$ represents an investor team's propensity to sell a winning (rather than losing) stock (i.e., the DE), we expect the influence of civil unrest on the DE to be captured by the coefficient β_2. Put differently, if civil unrest causally increases the DE – as we have seen from our main results above – the coefficient β_2 should be positive. Similar to Li *et al.* (2021), we follow Ivković *et al.* (2005) and Ivković and Weisbenner (2009) to exclude sales in our subsample that are preceded by multiple purchases and include only the first sale if a single purchase is followed by multiple sales. Table 4.4 below shows that exposure to unrest significantly enhances the DEs of investor teams across both models (1) and (2). These results thus confirm the causal relationship between unrest and DE at the investor team level. Interestingly, the coefficient β_1 is negligibly small and insignificant, suggesting that the average investor team in the subsample does not exhibit the DE. With this in mind, β_2 can be interpreted to mean that the exposure to unrest treatment not only enhances the DE among individual investor teams but establishes it to begin with.

Table 4.4: Investor team level robustness check: The effect of proximity to unrest in Cox proportional hazards models (investor team level analysis on selling decisions)

Variables	(1)	(2)
$Gain$	2.43E+17 (0.000)	5.19E+17 (0.000)
$Gain \cdot Unrest$	2.7753*** (0.9967)	2.7341*** (1.004)
$Unrest$	0.7156 (0.2090)	0.5396* (0.1748)
$TeamSize$		0.2637* (0.2096)
$NumberofMales$		0.8194 (0.6563)
$Numberof1stYears$		3.8122 (3.1903)
LR $\chi^2(2)$	122.81****	127.28****
n	152	152

*p-value < 0.1; **p-value < 0.05; ***p-value < 0.01; ****p-value < 0.001.
Standard errors for all regressions are provided in parentheses.

4.4. Discussion and concluding remarks

4.4.1. Discussion of results

Based on the results above, we confirm hypothesis H1 that mood regulation attempts – in response to negative mood disorders induced by proximity to civil unrest hot-spots – have a causal impact on the disposition effects of South African investor teams, *ceteris paribus*. More comprehensively, the causal flow alluded to by H1 begins with the acknowledgment that exposure to incidents of civil unrest negatively impacts the general mood of a given investor team's members, *ceteris paribus* (O'Reilly and Stevenson, 2003; Kelleher, 2003; Satcher *et al.*, 2007; Tremblay *et al.*, 2009). This mood disorder triggers mood regulation attempts by said investors (Li *et al.*, 2021). These mood regulation attempts manifest as the pursuit of positive bursts of utility (or so-called 'dopamine rushes') by selling shares trading at a gain as means of regulating the mood, as well as the avoidance of bursts of disutility (which may exacerbate their already depressed mood) by holding onto shares in the portfolio that are trading at a loss; with the risk-seeking nature of this loss avoidance behaviour being consistent with Bruyneel *et al's* (2009) depletion hypothesis discussed further above. These mood-regulating dynamics of investor team behaviour are thus synonymous with what one might observe as being the DE. As the first quasi-experimental study on the relationship between socio-political upheaval and the DE, the results of the current study contribute to the literature's understandings regarding the robustness of mood-induced DEs, which – as this study shows – extend beyond the weather effects and environmental conditions which inform the DE-related results in Wang (2016), Henriksson (2020), and Li *et al.* (2021) to name a few.

Furthermore, although not directly observed in an fMRI scan, the evidence provided by the study supports the plausibility of the suggestion that the DEs of the high-proximity-to-unrest group of investor teams are informed by the realisation utility theory. Given the observed investor type's (i.e., participants to the JSE Investment Challenge) inclination to consider their investing history in terms of overall portfolio returns (by virtue of their participation in a competition that incentivises them to pursue optimal portfolio outcomes) instead of investing episodes, as well as our finding that investor teams exposed to incidents of unrest succumb to the DE, our more general finding that participants to the JSE Investment Challenge succumb to the DE can be taken to mean that these sorts of investors violate the realisation utility-oriented *a priori* expectation in Barberis and Xiong (2012) that investors who are cued on portfolio returns are less likely to be affected by the DE. Deductively, this violation can be taken to suggest that professional investors – who are understood to also be cued on portfolio returns rather than investing episodes – may plausibly succumb to the DE in instances where they are exposed to waves of civil unrest, *ceteris paribus*. This view thus expands on the set of investor-types who succumb to the DE – according to realisation utility theory – to include professionally-trained investors as well.

More practically, it is common cause that the decline in the values of the shares and indices depicted in Figure 4.1 above is largely attributable to the highly publicised incidents of looting and destruction to property in two of South Africa's major provinces. However, it is also plausible to conjecture that socio-political unrest (particularly in instances where it might be distributed more broadly across the country) may bring about the emergence of realisation utility-informed DEs among a wide set of investor-types, leading to a general decline in market performance given investors' increased propensity to sell off winning stocks. Indeed, the DE has been found to play a role in aggregate stock market activity (Kaustia, 2004; Goossens and Knoef, 2020). This perspective thus introduces to the literature the notion that market-moving investor sentiments can be driven by investors' increased inclination to succumb to realisation utility-informed DEs, through the mechanism of mood regulation, during widespread bouts of civil unrest.

Finally, at a more conceptual level, this chapter introduces to the DE literature the idea of the *psychological pain of losing*; a notion which we propose explains DE-impacted investors' reluctance to continue behaving in a risk-seeking manner following the realisation of a losing position. Similar to how Zellermayer's (1996) psychological pain of paying regulates spending behaviour among consumers, we assert that the finding in Imas (2016) and in Merkle *et al.* (2021) that loss realisation leads to risk aversion, *ceteris paribus*, is an example of how the pain of losing regulates risk-taking behaviour among investors. Yet another parallel between these two concepts relates to whether a transaction involves the transfer of physical cash. More specifically, whereas Soman (2003) finds that the use of physical cash as a payment mechanism exacerbates the pain of paying – thus exacerbating the regulation of spending behaviour, we argue that the realisation of a losing trading position through separation from physical cash exacerbates the pain of losing – thus, the extent to which investors regulate their risk-taking behaviour.

Indeed, support for the argument above can be found in Imas' (2016) observation that experimental subjects who are required to realise their losing positions by way of separation from physical cash reduce their subsequent risk-taking behaviour by twice as much as those who realise their losses through cashless transfers of money. Furthermore, in reviewing the psychology literature into how people perceive physical pain (Redelmeier *et al.*, 2003) for possible explanations into why the realisation effect is not robust against negatively skewed lotteries (Merkle *et al.*, 2021), we arrive at the view that the pain of losing is an acutely unpleasant feeling which is more psychological than physiological in nature, with the unpleasantness of the feeling being correlated with the intensity, or size of the realised loss. This view effectively brings the concept in alignment with realisation utility's assertion regarding the linearity of the relationship between the scale of a realised loss and the disutility that comes from it (e.g., the greater the realised loss incurred, the more psychologically painful the experience) (Barberis and Xiong, 2012). The notion of the pain of losing thus does well to not only explain previously unexplained investor behaviours seen in realisation effect research (such as, for example, an investor's avoidance of risky investments following their realisation of a loss involving their separation from physical cash (Imas, 2016)), but also in consolidating how the realisation effect, realisation utility models, and prospect theory preferences explain the disposition effect.

Be that as it may, the pain of losing is still a largely untested theoretical concept, with the evidence supporting its existence and relevance being, at best, circumstantial. Thus, for future research, we recommend the pursuit of experimental inquiries more pointedly into the concept itself. In this regard, research efforts might seek to understand whether, for example, gamblers who realise a losing bet by way of being separated from their physical cash moderates their risk-taking behaviour in subsequent bets by – for instance – risking relatively smaller amounts of money. Methodologically, a natural-field experimental investigation into this question might involve a comparison of the relative sizes and frequencies of bets of gamblers who incur preceding losses at both cash and cashless bet-taking bookmakers, who would essentially act as the experiment's treatment and control conditions, respectively. Following an approach such as this, we hope, might provide useful, empirically-sound and externally valid views into the existence of the pain of losing as well as shed light on the concept's causal dynamics.

4.4.2. Conclusions

In this chapter, we've made use of a difference-in-differences approach to determine the nature of the relationship between civil unrest and the DE and have found sufficient evidence to suggest that mood regulation attempts – in response to negative mood disorders induced by proximity to civil unrest hot-spots – causally increase the disposition effects of South African investor teams participating in the 2021 run of the JSE Investment Challenge by as much as 140 percent. As the first quasi-experimental study on the relationship between socio-political upheaval and the DE, the results of the study in the current chapter contribute to the literature's understandings regarding the robustness of mood induced DEs.

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