Greed and Investor Behaviour: Evidence from Experimental Studies on the Disposition Effect, Salience, and Framing

Haoyang Yu

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Abstract

This thesis investigates how greed shapes investor behaviour in the realisation of gains and losses and how this relationship changes across different informational contexts. The research focuses on the disposition effect (DE), which refers to investors' tendency to sell winning assets too early while holding losing assets for too long. Although the disposition effect has been widely documented, the underlying motivational and contextual mechanisms that sustain it remain incompletely understood. Drawing on insights from realisation utility and salience theory, this thesis develops an integrated behavioural framework showing how greed interacts with perceptual salience and decision framing to influence biased realisation behaviour.

The analysis is based on a series of three controlled experimental studies involving 244 participants (across the three experiments). All experiments employed computerised stock trading simulation implemented in z-Tree and post-experiment psychological surveys administered through Qualtrics. This consistent design allows a direct comparison of behavioural patterns across treatments while isolating the specific mechanisms under investigation.

Study 1 serves as the baseline analysis and examines the relationship between greed and the disposition effect. Participants traded in a standard environment where prices were displayed in a neutral format and without return displays. The results show, for the first time in the literature, that greed is a strong and statistically significant predictor of the disposition effect. Greedy investors tend to realise gains more frequently and delay selling losses even when controlling for loss aversion, risk preference, and trading experience. These findings confirm that greed is an independent motivational force that drives biased behaviour, and that the desire for immediate reward realisation can systematically distort selling decisions.

Study 2 extends the analysis by introducing visual salience through colour-coded price displays. Participants traded under identical market conditions except that price changes were shown in red (negative changes) or green (positive changes). The results show that colour strongly influences trading behaviour and interacts with greed. Green, signalling gains, heightens the tendency of greedy investors to sell winners. Red, signalling losses, reduces resistance to realising losing positions. The findings suggest that the behavioural expression of greed differs across visual salience conditions, consistent with the view that salient visual signals condition how motivational tendencies are reflected in trading behaviour. This study demonstrates that trading interfaces, which routinely employ colour cues to convey performance, are behaviourally active and can directly shaping investor decisions.

Study 3 examines how numerical framing and price magnitude shape the disposition effect, and how greed moderates these contextual influences. In the low-price regime, asset prices began at $30 with a $600 trading endowment, while in the high-price regime, asset prices began at $300 with a $6,000 endowment. Within each regime, returns were displayed either in dollar or percentage terms. The results show that percentage framing significantly amplifies the disposition effect among greedy investors, especially for low-priced assets, whereas dollar framing in high-price regimes amplifies it. These findings are consistent with the predictions of salience theory by Bordalo et al. (2012) and realisation-utility theory by Barberis and Xiong (2012), confirming that the cognitive salience of numerical information interacts with motivational forces to shape realisation behaviour.

This thesis provides an analysis of how greed and contextual salience jointly shape the disposition effect. It contributes to behavioural finance theory by integrating motivational and cognitive perspectives, showing that investor biases stem from the interaction between internal drives and external representations. Empirically, the study identifies how specific informational and visual cues, such as colour, scale, and framing format, systematically influence realisation behaviour.

The research also has practical implications for investors, trading-platform designers, and regulators. The findings reveal that trading environments are psychologically active components of decision-making. Small variations in how information is presented can meaningfully affect investor attention and behaviour. Platform designers should therefore consider these behavioural effects, regulators should set clearer standards for performance presentation, and investor education could highlight framing and salience effects to help traders manage the influence of greed.

Overall, this thesis advances understanding of how human motivation and information architecture jointly shape trading outcomes and offers guidance for creating more disciplined and welfare-enhancing investment environments. It also offers a foundation for designing trading environments that foster more disciplined and welfare-enhancing investment behaviour.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed:

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1 Introduction

Understanding the psychological forces behind investor behaviour remains a central challenge in behavioural finance. Decades of evidence has documented systematic deviations from rational choice models, referred to as biases, in relation to investor trading decisions. Among these biases, the disposition effect stands out as one of the most pervasive and economically consequential. Defined as the tendency to sell winning investments too quickly while holding onto losing investments too long (Shefrin and Statman, 1985; Odean, 1998), the disposition effect has been linked to diminished portfolio performance, reduced market efficiency, and welfare losses for individual investors (Barberis and Xiong, 2009; Barber and Odean, 2013).

Prior research attributes the disposition bias to cognitive drivers such as reference dependence and loss aversion (Kahneman and Tversky, 1979; Shefrin and Statman, 1985), mental accounting and regret avoidance (Weber and Camerer, 1998), and realisation utility (Barberis and Xiong, 2012). Beyond these cognitive explanations, structural or institutional factors can also influence selling behaviour. For example, tax-motivated trading can influence when investors choose to realise losses (Grinblatt and Keloharju, 2001; Grinblatt et al. 2004). Yet, while these mechanisms are well documented in both field and experimental settings, little is known about stable psychological traits that can underpin the disposition effect. Importantly, none of these cognitive or institutional explanations fully accounts for persistent heterogeneity in the disposition effect across individuals, suggesting that stable psychological traits may play an independent role. This thesis addresses that gap by examining how contextual features of trading environments, such as information salience, colour cues, and return framing shape investors' realisation behaviour and the disposition effect. It further investigates how these contextual influences interact with greed, a stable motivational trait linked to financial decision-making, to provide a deeper understanding of how internal drives and external representations jointly shape investor behaviour.

Greed has long been recognised in cultural and historical accounts as a powerful motivator of economic behaviour (Wang and Murnighan, 2011; Haynes et al., 2015), yet its role in financial decision-making has only recently attracted scholarly attention, where it is conceptualised as a measurable psychological trait with consistent effects on trading behaviour (Seuntjens et al., 2016). Visual salience and information framing are central contextual influences that shape how investors evaluate and realise gains and losses. This thesis investigates how features such as the use of colour when documenting returns and the presentation of returns in percentage versus dollar terms, as well as different price regimes, affect the disposition effect. Greed is incorporated as a boundary condition to assess whether individual motivation amplifies or attenuates these contextual impacts, providing a more comprehensive understanding of how trading environments shape investor behaviour.

The empirical contribution of this thesis is organised around three experimental studies. Study 1 establishes greed as a significant determinant of the disposition effect. Using a controlled trading simulation, I show that greed is strongly associated with the propensity to realise gains prematurely, even after accounting for established predictors such as loss aversion, risk preferences, and trading experience. Regression results indicate that a one-standard-deviation increase in greed raises the proportion of winning stocks that investors sell by around 11-12 percentage points ($p<0.01$), a 25-30% increase relative to the mean. The effect is both statistically robust and economically significant, underscoring the strong influence of greed on investors' tendency to realise gains prematurely.

The effect of greed on the proportion of losses realised (PLR) is small and statistically insignificant, indicating that greed's influence is asymmetric and manifests primarily in the urge to capture gains prematurely rather than in hastening the recognition of losses. Robustness checks confirm this asymmetry. Across multiple alternative measures of the disposition effect, the estimated coefficients on greed range from 0.085 to 0.228 (all significant at conventional levels). These findings position greed as a psychological factor shaping trading biases. It pushes investors to crystallize modest profits rather than allowing them to compound. Study 1 extends the behavioural finance literature by identifying a stable and measurable trait that amplifies the disposition effect beyond the explanatory scope of existing cognitive and preference-based accounts.

Study 2 highlights the powerful role of context and framing in shaping the disposition effect. Trading platforms routinely employ red and green to signal losses and gains, respectively. These cues are intuitive and psychologically powerful. Colour has been shown to trigger affective responses and orient attention (Lichtenfeld et al., 2012; Elliot and Maier, 2014). I test whether these cues amplify or attenuate the behavioural effects of greed.

Colour cues exert strong effects on realisation behaviour within the context of the disposition effect, with green cues exacerbating the bias by increasing gain realisation, while red cues mitigate the bias by encouraging the realisation of losses. Greed moderates these colour-induced effects, amplifying responses to whichever colour cue heightens perceptual salience. When returns are shown in green, greedy investors become much more inclined to sell winning stocks, suggesting that green cues trigger acquisitive impulses and make realised gains feel more rewarding. Conversely, when losses are displayed in red, greedy investors are more likely to close losing positions, indicating that red heightens sensitivity to losses and motivates defensive selling.

Importantly, study 2 finds that colour cues used in trading interfaces significantly shape investor behaviour. Green accentuates premature gain-taking, while red attenuates loss-holding tendencies. This pattern aligns with psychological evidence showing that green evokes approach motivation and reward anticipation, whereas red elicits caution and physiological arousal (Lichtenfeld et al., 2012; Elliot and Maier, 2014). For greedy investors who are already inclined to chase rewards, colour cues serve as situational triggers that exaggerate this behavioural bias. Green cues amplify premature gain-taking, whereas red cues are associated with greater willingness to realise losses and a reduced tendency to hold losing positions. Thus, Study 2 provides novel experimental evidence that greed interacts with contextual design features of the trading environment to shape realisation behaviour.

Study 3 investigates how the framing of returns, either as absolute dollars or percentages, interacts with stock price levels to influence the disposition effect, and how these effects are moderated by greed. The design draws on the law of 100, which posits that percentage changes appear larger and more attention-grabbing when reference values are small, whereas absolute dollar amounts dominate perception when prices are high. I test whether greedy investors respond differently to these frames depending on the underlying stock price regime.

The results show that the impact of framing depends critically on stock price level. For low-priced stocks (around $30), showing returns as percentages makes investors much more likely to sell winning stocks prematurely, increasing the disposition effect by roughly 15–20% compared with dollar framing. For high-priced stocks (around $300), the effect reverses: percentage framing encourages investors to hold winners longer, substantially weakening the bias.

Framing interacts with stock price level to shape selling behaviour. Percentage displays have a stronger effect at low prices, while dollar displays have a stronger effect at high prices. Greed moderates the strength of these framing effects, amplifying the response when the format makes returns more salient. When returns are expressed in percentages, an incremental rise in greed substantially increases the likelihood of premature gain realisation. In contrast, for high-priced stocks, the pattern reverses. Percentage framing tempers rather than intensifies the bias.

Percentage framing magnifies the disposition effect for low-priced stocks. Greed conditions the magnitude of this effect, strengthening it when proportionate gains appear more salient, consistent with salience theories of relative performance evaluation (Bordalo et al., 2012; Barberis, 2018). In the high-price regime, absolute dollar framing exerts a stronger influence. Percentage returns translate large nominal returns into smaller proportional figures, thereby diminishing their salience (Grewal and Marmorstein, 1994). The study further shows the mechanisms of gain versus loss realisation, showing that greed-driven behaviour is contingent not only on investor traits but also on the informational environment in which decisions are made.

These three studies make several novel contributions to behavioural finance. First, they identify greed as a measurable psychological construct that significantly shapes trading behaviour, thereby extending existing explanations of the disposition effect. In doing so, the thesis advances the theoretical foundations of the disposition effect by showing that investor biases arise not only from cognitive limitations or loss aversion but also from underlying motivational forces. Second, it establishes that contextual design features, such as colour salience and return framing, are powerful determinants of the disposition effect, and that greed systematically moderates their influence. This demonstrates that trading biases emerge from the interaction between internal desire and external presentation, providing a dynamic account of how psychological and environmental factors jointly shape financial decisions. Finally, by integrating individual difference measures with experimental manipulations of trading interfaces, the thesis generates novel empirical evidence that bridges motivation, attention, and decision outcomes, thereby extending behavioural finance toward a more comprehensive, context-sensitive framework of investor behaviour.

The findings have direct implications for both theory and practice. For theory, the findings refine behavioural models of investor decision-making by integrating motivational forces into frameworks traditionally centred on cognition and utility. The results extend prospect theory (Kahneman and Tversky, 1979) and Realisation Utility models (Barberis and Xiong, 2009) by demonstrating that greed functions as an independent motivational driver of gain realisation, intensifying investors' tendency to act on favourable outcomes. This advances behavioural finance theory by showing that trading biases stem not only from how investors evaluate outcomes but also from the motivational forces that energise those evaluations.

For practice, the findings suggest several design-relevant implications rather than prescriptive requirements. Trading platforms may wish to consider how visual presentation choices interact with investor biases, particularly among users prone to impulsive trading. While salient green cues can exacerbate premature gain-taking, red cues may help reduce loss-holding by encouraging the realisation of losing positions. Accordingly, interfaces could employ more neutral or muted colour schemes where appropriate or selectively use framing formats (such as dollar-based displays at higher price levels) to reduce excessive gain realisation without discouraging efficient loss realisation.

2 Literature Review

2.1 Disposition Effect

The disposition effect, first defined by Shefrin and Statman (1985), is one of the most extensively studied cognitive biases in behavioural finance. It refers to the tendency of investors to hold losing stocks too long and sell winners too soon. This pattern runs counter to rational asset-pricing and utility-maximisation frameworks and frequently results in suboptimal financial outcomes. Because it is driven primarily by psychological rather than purely rational evaluation, the disposition effect challenges the efficient market hypothesis and carries important implications for market dynamics, investor welfare, and portfolio performance (Shefrin and Statman, 1985; Barberis and Odean, 2013). Researchers have consistently linked the disposition effect to diminished portfolio returns and reduced market efficiency, underlining its economic significance (Odean, 1998; Barberis and Xiong, 2012).

Empirical evidence for the disposition effect is both extensive and robust. The bias has been documented among individual and institutional investors, across developed as well as emerging markets (Odean, 1998; Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006; Feng and Seasholes, 2005; Chen et al., 2007; Frazzini, 2006). In the United States, Odean (1998) is among the first to quantify retail investors' propensity to sell winners more readily than losers, a finding later confirmed by Dhar and Zhu (2006) using brokerage data. Grinblatt and Keloharju (2001) observe similar behaviour among Finnish investors, linking its magnitude to investor characteristics such as gender and cultural background. Evidence from Australia (Brown et al., 2006) and China (Feng and Seasholes, 2005) points to the same pattern. Further studies extend this evidence across asset classes: Locke and Mann (2005) find the disposition effect among professional futures traders, while Genesove and Mayer (2001) demonstrate that even real estate market investors display a comparable reluctance to sell at a loss. Professional status does not eliminate the bias. Lee et al., (2013), for example, show that mutual fund managers in Taiwan also exhibit the disposition effect, indicating that seasoned professionals are not immune. Hartzmark and Solomon (2012) further demonstrate that professional money managers also exhibit realisation-based biases, showing that mutual fund flows respond asymmetrically to realised versus paper gains and losses. These findings confirm that the disposition effect is not a mere curiosity of stock markets but a pervasive feature of human decision-making across a wide variety of financial domains.

Weber and Camerer (1998) replicate the disposition effect in laboratory trading simulations. They demonstrate that even in the absence of taxes, transaction costs, or portfolio rebalancing needs, participants still displayed a reluctance to realise losses. Such findings imply that the disposition effect is rooted in intrinsic psychological processes. More recently, Frydman et al., (2014) employ neuroeconomic methods, including fMRI brain scans, to examine decisions involving gain and loss realisation. They identify distinct brain regions activated when investors chose to sell winners or hold losers, providing physiological evidence consistent with realisation utility theory. However, while these results highlight the internal, neuropsychological roots of the disposition effect, subsequent research shows that social context and situational incentives can also shape its expression. Social and situational factors can also modulate bias. Pelster and Hofmann (2018), for instance, study a social trading platform and show that traders who became "leaders" with followers exhibited a significantly stronger disposition effect than before. Their difference-in-differences analysis suggest that assuming a public advisory role and the reputational consequences attached to it amplified the reluctance to sell at a loss. These findings suggest that although the bias is deeply rooted, its intensity is sensitive to context and incentives.

Despite the consistency of empirical patterns, the underlying causes of the disposition effect remain contested. Several behavioural theories provide complementary explanations. Prospect theory (Kahneman and Tversky, 1979), among the most widely adopted framework for explaining the disposition effect, posits that individuals evaluate outcomes relative to a reference point, often the purchase price, and display loss aversion, meaning losses weigh more heavily than gains. This loss aversion drives investors to realise gains quickly but resist realising losses, thereby prolonging losing positions.

Realisation utility theory offers a related perspective, suggesting that investors derive utility not only from final wealth but also from the act of realising gains or losses (Barberis and Xiong, 2012; Ingersoll and Jin, 2013). Selling a winner generates a positive utility shock, whereas selling a loser produces a negative utility shock, leading investors to avoid the latter.

Chang et al. (2016) advance a cognitive dissonance explanation that realising a loss conflicts with an investor's self-image as a competent decision-maker. To avoid this discomfort, investors rationalise holding losers rather than admitting a mistake. Regret aversion, another common account, suggests that investors delay realising losses because they fear regretting the decision if the stock later rebounds (Shefrin and Statman, 1985). Thaler's (1985) mental accounting framework provides yet another angle, arguing that investors treat each stock as a separate mental account and avoid "closing" an account at a loss.

On the gain side, investors may sell winners too soon because realising a gain affirms their competence and generates positive emotions such as pride or satisfaction. This motivation aligns with realisation utility theory, which suggests that closing a profitable position produces a psychological reward (Barberis and Xiong, 2012; Ingersoll and Jin, 2013). Emotional factors also contribute. While these perspectives collectively explain why investors hold losers too long and sell winners too soon, none fully accounts for the disposition effect on its own. Prospect theory highlights loss aversion as a key driver of reluctance to realise losses (Kahneman and Tversky, 1979; Shefrin and Statman, 1985), while realisation utility emphasises the emotional rewards associated with crystallising gains (Barberis and Xiong, 2012). Related approaches focusing on emotions, self-image, and regret further illuminate important dimensions of selling behaviour (Ingersoll and Jin, 2013; Chang et al., 2016). However, substantial heterogeneity in realisation behaviour remains even after accounting for these factors, suggesting that additional motivational forces contribute to the persistence of the disposition effect.

Recognizing the breadth of this literature, Gutiérrez-Nieto et al. (2023) conduct a bibliometric analysis spanning nearly four decades of research. They identify five thematic clusters: theoretical modelling, empirical testing across markets and investor types, neural and emotional mechanisms, debiasing strategies, and interdisciplinary applications. Their review highlights emerging directions such as the use of machine learning and big data to detect behavioural biases, and the integration of neurofinance insights to capture the interaction of cognition and emotion.

Several studies have also identified individual and market-level factors that moderate the strength of the disposition effect. On the individual side, younger and less sophisticated investors tend to display stronger disposition effect, reflecting the influence of overconfidence and limited experience (Barber and Odean, 2001; Dhar and Zhu, 2006; Talpsepp, 2010). Market conditions also play a role, with rising markets prompting greater gain realisation and downturns reinforcing loss-holding (Kaustia, 2011; Grinblatt and Han, 2005).

On the market and technological side, changes in the investing environment also matter. The rise of online trading and mobile brokerage platforms has increased trading frequency and heightened portfolio visibility. Barber and Odean (2002) show that investors who moved to online trading became substantially more active and overconfident, which amplified trading intensity and reduced performance. This heightened overconfidence is relevant to the disposition effect because overconfident investors are more likely to misjudge their skill, realise gains prematurely, and hold onto losing positions in anticipation of reversal. Consistent with this, Dhar and Zhu (2006) find that retail investors trading through online brokerages exhibited a pronounced disposition effect, realising gains more readily than losses. In some contexts, social cues intensify the effect. On social-trading platforms, seeing peers succeed increases competitive profit-taking and the selling of winners (Pelster and Hofmann, 2018). Conversely, reputational concerns and anticipated embarrassment discourage the realisation of losses (Chang et al., 2016).

By contrast, automated investing services and algorithms seem to reduce the bias. D'Acunto et al. (2021) find that robo-advisors, which manage portfolios without emotional involvement, tended to cut losses and let profits run, effectively circumventing the disposition effect. These findings suggest that technology can either exacerbate or mitigate the bias depending on how it structures investor experience. Brown et al. (2006) observe that institutional and superannuation funds displayed a smaller bias than retail investors, implying that experience and professional discipline attenuate but do not eliminate the effect.

2.2 Greed

2.2.1 The Nature of Greed: Beyond Non-Satiation

In this thesis, greed is conceptualised as a stable psychological characterised by an insatiable desire to acquire more and a persistent dissatisfaction with one's current level of possession, extending beyond standard assumptions of rational preference. Understanding greed in economic behaviour requires distinguishing it from the standard economic concept of non-satiation. Non-satiation is a foundational assumption in microeconomic theory, essentially stating that "more is always better." Individuals are assumed to prefer larger quantities of goods and to derive additional utility from each extra unit consumed (Varian, 1992). This assumption underlies classic consumer choice models and implies an ever-upward-sloping utility function with no point of complete satisfaction. Importantly, non-satiation is value-neutral; it does not assess whether wanting more is good or bad but simply posits a consistent preference for a greater quantity (Pettini and Musikanski, 2023).

Greed, however, extends beyond non-satiation by incorporating motivational intensity and behavioural urgency, rather than merely a stable preference for more. It is typically characterised not only by a desire for more, but also by impatience and a willingness to disregard constraints in the pursuit of additional gains (Seuntjens et al., 2015; Wang and Murnighan, 2011). It often manifests at the expense of other values or of others themselves. Some scholars define greed as an intense, selfish desire for money or material possessions without limit (Bruhn and Lowrey, 2012; Haynes et al., 2015). Others expand the scope to include non-material desires, such as power or status (Levine, 2005; Mussel and Hewig, 2016). Seuntjens et al., (2015) synthesized these perspectives and defined greed as "the dissatisfaction of never having enough and the desire to acquire more." Similarly, Krekels (2015) conceptualised greed as a personality trait marked by an unrelenting urge for acquisition, whether in wealth, possessions, or other goods. Lambie and Haugen (2019) emphasize that greed is often an all-consuming desire, pursued "at all costs."

While most definitions emphasize acquisitiveness, some also acknowledge a retentive dimension: the impulse to hold tightly to what has already been acquired. Wachtel (2003) highlights that greed is not only about accumulation but also about resisting any loss of existing resources. Seuntjens (2016) similarly notes that greedy individuals are motivated both by the desire to maximise gains and by the fear of loss, hating to part with resources as much as they enjoy obtaining them.

Several features distinguish greed from benign non-satiation. First, greed carries an ethical dimension. Historically, it has been portrayed as one of the "deadly sins" and associated with corruption and exploitation. However, recent behavioural literature conceptualises greed as a motivational drive rather than a moral failing. For example, Seuntjens et al. (2019) find that greedier individuals were more willing to lie, cheat, or deceive if they advanced their acquisition goals. Non-satiation by itself would not necessarily push an individual toward dishonesty; greed, with its obsessive quality, might. Second, greed is accompanied by a distinctive emotional tone. Greedy individuals are rarely content, which fosters perpetual dissatisfaction.

Greed also introduces a temporal and dynamic element absent in non-satiation. Greedy individuals often focus on short-term gratification and exhibit impatience, even when it undermines longer-term welfare. Haynes et al. (2017) show that CEO greed was associated with short-term profit chasing and neglect of sustainable growth. Such short-termism can result in underinvestment in long-term projects, corner-cutting, or excessive risk-taking. By contrast, the standard self-interest assumption that underpins non-satiation is fully compatible with rational long-term planning. Intertemporal consumption models assume that agents maximise discounted lifetime utility over streams of current and expected future consumption (Deaton, 1987; Becker and Murphy, 1988). Building on this distinction, Kirchgässner (2014) emphasises that while self-interest is not inherently problematic, greed represents a pathological excess of self-interest that can lead to irrational or self-destructive outcomes, such as taking catastrophic risks in pursuit of ever more wealth.

Recent literature has also challenged the assumption that individuals are never satiated. Baucells and Zhao (2020) develop a dynamic satiation model in which consumption builds up a stock of satiation that temporarily dampens desire, but this stock decays over time so that desire subsequently revives. This cyclical pattern aligns closely with descriptions of greed as a craving that briefly abates after indulgence but soon resurfaces. For example, a greedy investor may feel satisfied after a large gain, only to resume craving the next windfall shortly thereafter.

In summary, greed transcends non-satiation by combining insatiability, moral and emotional dimensions, short-term urgency, and both acquisitive and retentive motives. It is not a simple “more is better” principle but a complex construct with ethical, psychological, and behavioural implications.

2.2.2 Acquisition vs. Retention: A Dual Perspective on Greed

Greed is multidimensional, and one way to conceptualise it is through its dual components: acquisition and retention (Krekels, 2015; Lambie and Stickl Haugen, 2019; Lambie et al., 2022).

Traditionally, academic work has emphasised acquisitive greed, defined as the relentless drive to obtain more resources, wealth, or assets (Seuntjens et al., 2015; Krekels, 2015). This aspect aligns with the stereotypical image of the greedy individual who is never satisfied with what they currently have, always desiring more (Mussel et al., 2015). In financial markets, it manifests as chasing high returns, excessive trading, and speculative risk-taking. Greedy traders may pursue increasingly risky assets, such as derivatives, cryptocurrencies, or highly volatile stocks, and ignore prudent diversification in pursuit of exceptional rewards (Wang and Murnighan, 2011). Empirical work links acquisitive greed to maximization tendencies and impulsivity. Mussel and Hewig (2016) find that individuals high in greed were more likely to engage in risky gambling tasks. On a market-wide scale, acquisitive greed has been implicated in speculative bubbles, where widespread pursuit of rising assets fosters unsustainable booms (Hoyer et al., 2023). Ethical concerns also arise, as acquisitive greed has been shown to predispose actors toward deception (Cohen et al., 2009). Historical accounts of the 2008 global financial crisis frequently cite unchecked greed, manifesting in predatory lending and aggressive pursuit of profits through complex derivatives, as a major contributing factor (Muolo and Padilla, 2010; Mazumder and Ahmad, 2010).

Situational factors can trigger acquisitive greed. Social dilemma experiments demonstrate that when large rewards are salient or anonymity is assured, individuals are more prone to greedy behaviour (Insko et al., 1990; Dawes et al., 1977). In public goods games, participants contribute less and free ride more when potential rewards are made salient or when communication is restricted (Van de Kragt et al., 1983; Poppe and Utens, 1986). Environmental uncertainty, such as fear that resources may become scarce, can activate a “grab it now” mentality (Ludwig et al., 1993). Perceived unfairness can also trigger acquisitive impulses, motivating individuals to catch up with or surpass others (Forsythe et al., 1994). Psychological cues are equally influential. Mortality salience, for example, has been shown to increase materialistic greed, as existential anxiety fosters a stronger desire for wealth and status (Kasser and Sheldon, 2000; Cozzolino et al., 2004). These findings highlight acquisitive greed as a latent tendency that is contextually activated.

Recent research increasingly demonstrates that greed is not solely characterised by acquisitive tendencies but also by a pronounced reluctance to part with existing resources (Lambie and Haugen, 2019; Zeelenberg et al., 2021). Retentive greed, by contrast, is defined by the desire to cling to existing possessions. It is visible in extreme loss aversion, hoarding, and stinginess. In financial decision-making, retentive greed may cause investors to refuse to sell assets at a loss, not because of rational expectations of recovery, but because selling represents the conversion of a paper loss into a realised loss, which greedy investors perceive as surrendering accumulated wealth. The same mechanism can also deter the sale of profitable holdings, since greedy individuals are reluctant to part with resources they already own and may feel attached to an asset that has generated gains or still holds potential for further appreciation. Psychological research shows that individuals high in greed exhibit a strong attachment to possessions, discomfort when giving things up, and a tendency to cling to valuable resources (Seuntjens, 2016; Lambie and Stickl, 2019). Consequently, retentive greed can reinforce both sides of the disposition effect: holding on to losers to avoid surrendering wealth, and holding on to winners because parting with a valuable asset feels aversive.

Haselhuhn and Mellers (2005) argue that fear of losing what one already has can dominate decision-making even more strongly than the lure of new gains. Seuntjens (2016) provides evidence that greed may be more strongly linked to loss aversion than to risk-seeking for gains. They suggest that greedy individuals hate losses disproportionately, and this fear drives extreme protective strategies. In practice, this means greedy actors might take risks when downside exposure appears minimal but otherwise prefer conservative approaches to safeguard existing wealth.

Overall, greed appears to influence selling behaviour through two related but distinct behavioural mechanisms. First, the acquisitive dimension of greed motivates individuals to accumulate wealth rapidly, increasing the salience of realised gains and strengthening preferences for immediate and certain rewards. As a result, greedy investors may be more inclined to realise profitable positions rather than wait for uncertain future appreciation (Seuntjens et al., 2015; Mussel and Hewig, 2016). This mechanism is consistent with theories of reward salience, impatience, and realisation utility. Second, the retentive dimension of greed fosters attachment to existing wealth and reluctance to relinquish possessed resources, increasing resistance to realising losses (Lambie and Stickl, 2019). Consequently, greedy investors may be less willing to sell loss-making positions because doing so converts paper losses into realised losses. The empirical findings of this thesis suggest that the acquisitive mechanism is more important in explaining gain realisation, whereas the retentive mechanism is more closely associated with loss avoidance and reluctance to part with existing wealth.

2.3 Greed and Disposition Effect

Greed has long been invoked in popular discourse as a driver of financial booms and busts. Wall Street lore frequently frames market cycles as oscillating between fear and greed. During bull markets, greed is said to propel investors into bidding up asset prices, while fear dominates during periods of panic. Despite this colloquial wisdom, the academic study of greed's specific impact on investor biases and behaviours remains relatively underdeveloped. Only in recent years have researchers begun to measure greed systematically as an individual trait and examine how it influences financial decision-making. This section explores what is known, and what remains uncertain, about how greed may contribute to the disposition effect, defined as the tendency to sell winners too early and to hold losers too long.

Although prior sections have addressed the disposition effect and the concept of greed separately, their intersection has received limited attention in the literature. Traditional accounts of the disposition effect focus on cognitive biases such as loss aversion or mental accounting, rather than personality traits (Shefrin and Statman, 1985; Odean, 1998; Barberis and Xiong, 2012). Greed introduces an individual-difference perspective, as some investors may be predisposed to the disposition effect due to their greedy nature (Seuntjens et al., 2015; Mussel and Hewig, 2016). It does not assume that all investors share the same level of loss aversion, but rather suggests that motivational tendencies associated with greed may amplify or moderate the behavioural patterns captured by the disposition effect.

There is an intuitive reason to expect such a connection. Greed's retention motive, understood as the desire not to give up what one already has, resembles the reluctance to realise losses that characterises the disposition effect. At the same time, its impact on loss-side behaviour is not unambiguous. A greedy investor who is highly sensitive to any diminution of wealth may decide to sell a losing stock quickly in order to prevent further losses, which is also consistent with a retentive motive focused on preserving overall wealth. A key insight from the disposition effect literature is that paper losses and realised losses do not feel the same. Realisation utility models posit that investors experience a discrete negative utility shock when they crystallise a loss (Barberis and Xiong, 2012; Ingersoll and Jin, 2013), while mental accounting and regret-based accounts argue that closing a position at a loss finalises a painful outcome, triggers regret and admits a mistake, whereas keeping the loss on paper allows investors to postpone this discomfort (Thaler, 1985; Shefrin and Statman, 1985). These mechanisms imply that, even for a greedy investor who dislikes seeing wealth decline, the act of realising a loss can be more aversive than continuing to hold a losing position. In such cases, greed's retention motive may amplify the "hold losers" component of the disposition effect by strengthening the desire to avoid crystallising a loss.

On the gain side, greed's acquisition motive introduces a similar ambiguity. A greedy investor may sell a winning stock quickly in order to lock in the gain, driven by impatience and a preference for immediate, certain rewards, or by a wish to redeploy capital into the next opportunity. Alternatively, the insatiability that defines greed may lead some investors to let winners run longer in the hope of securing an even larger payoff. The net effect of greed on both selling losers and selling winners is therefore theoretically ambiguous and likely depends on how investors trade off preserving wealth against the psychological costs and benefits associated with realising gains and losses.

Research on overearning points in a similar direction: individuals with greedy tendencies sometimes accumulate more money than they can enjoy, driven by the urge to accumulate for its own sake. In a laboratory study of overearning, participants high in greed worked longer and earned more credits than they needed, rather than stopping to enjoy their rewards (Zeelenberg et al., 2020). Transposed to an investment context, this pattern can manifest in more than one way. One possibility is that investors high in greed may continue to hold winning positions in an attempt to extract as much profit as possible or to benefit from further appreciation (Barberis and Xiong, 2012).Another possibility is that greedy investors may instead realise gains quickly so they can release capital and move on to what they see as the next potentially attractive opportunity. consistent with acquisitive motives and reward-seeking behaviour associated with greed (Seuntjens et al., 2015; Krekels and Pandelaere, 2015). For this reason, the implications of overearning-type behaviour for selling winners are ambiguous, since it may encourage holding winners for longer periods or prompt rapid gain realisation and capital rotation depending on whether the investor places greater value on maximising the current payoff or pursuing the next opportunity.

At the intersection of greed and loss aversion, Seuntjens et al. (2015) find that greed is correlated with riskier financial choices and a lower intention to save. Greedy individuals were more likely to borrow and to spend. This finding is consistent with the idea that greedier people may care less about precautionary savings and more about pursuing immediate opportunities for gain. Livingstone and Lunt (1992) earlier observe that attitudes associated with greed, such as materialism and envy, were linked to higher levels of personal debt and lower savings, suggesting a "have it now" mindset. Such a mindset could amplify the "sell winners" side of the disposition effect. A greedy investor who sees a stock rise may rush to sell because the acquisitive motive outweighs the retentive motive. This pattern could increase the frequency of profit-taking trades.

In contrast, greed-driven loss aversion may amplify the "hold losers" side. If a greedy investor cannot bear the thought of losing money on an investment, they may hold onto a losing stock even more stubbornly than the average investor, since selling would make the loss real and reduce their accumulated wealth. Sajko et al. (2021) provide evidence in the corporate context that greedy executives often double down on failing projects, which shows escalation of commitment in the hope of turning them around, rather than accepting losses and moving forward. This executive behaviour parallels the actions of an individual investor clinging to a losing stock, motivated by greed and hubris.

Until recently, there was little direct empirical evidence linking greed to the disposition effect in investor trading. While the disposition effect has been extensively documented, and greed has been studied across various domains, connecting the two required a way to measure individual greed levels and track trading behaviour. The development of scales such as the

Dispositional Greed Scale (DGS) by Seuntjens et al. (2015) made it possible to quantify greed as a personality trait.

2.4 The Role of Salience in Financial Decision Making

Salience refers to the extent to which information stands out from its surroundings and grabs an investor's attention. Because attention is a scarce cognitive resource, salient cues disproportionately influence perception and choice. In financial contexts, salience can arise from vivid visual cues (such as bright colours), extreme numerical values, news headlines, flashing indicators, or the frequency with which information is encountered. Anything that makes certain data more prominent can direct an investor's focus and potentially influence their behaviour. Modern theories in behavioural economics emphasise that people do not weigh all information equally; instead, they overweight the most salient features of a choice or outcome (Bordalo et al., 2012). In other words, investors are prone to concentrate on the loudest or most eye-catching aspects of financial information, sometimes at the expense of a balanced assessment.

Investors may experience the utility impact of gains and losses more vividly when expressed in monetary terms. Frydman and Wang (2020) conduct a randomized field experiment in which the visibility of investors' purchase prices was manipulated to test how visual salience affects trading behaviour. They find that when purchase prices were made more salient on investors' portfolio screens, the tendency to realise gains and hold losses increased substantially, consistent with salience theory.

Colour is only one facet of salience; more broadly, any element that makes information attention-grabbing can shape financial decisions. Because investors have limited cognitive bandwidth, they focus on what stands out, often the most dramatic or novel cues. Barber and Odean (2008) shows that retail investors disproportionately bought attention-grabbing stocks, such as those in the news, exhibiting unusual trading volume, or experiencing extreme one-day moves, rather than scanning the full universe. This behaviour led to suboptimal choices, including the tendency to chase overvalued spikes. Similarly, Da, et al. (2011) use Google search frequency as a proxy for investor attention and find that spikes in searches foreshadowed short-term upward price pressure, often reversing when unsupported by fundamentals, illustrating how attention alone can create ephemeral demand.

Salience also operates through feedback frequency: myopic loss aversion (Benartzi and Thaler, 1995) posits that frequent evaluations amplify loss sensitivity and risk aversion. Gneezy and Potters (1997) confirm this experimentally that participants who received frequent feedback invested less in risky assets, while in practice, investors who check portfolios hourly see constant fluctuations, heightening fear and discouraging bold positions, unlike those who review quarterly and avoid overreacting to noise. Frequent attention also intensifies the disposition effect: seeing gains prompts premature selling, and seeing losses encourages holding, until they become intolerably salient. Dierick et al. (2019) find that investors who logged in frequently were more prone to sell winners and retain losers, as each update spotlighted the biggest gainer or loser, driving action. As Bordalo et al. (2012) argue, outcomes deviating sharply from reference points dominate attention and disproportionately influence choice.

One nearly universal design feature in trading platforms is the use of red and green colour-coding to signal losses or gains. In Western markets, a stock quoted in red means its price is down, whereas green indicates it is up. This intuitive colour scheme conveys “bad vs. good” or “stop vs. go” through deep-seated associations. Red commonly signals danger, caution, or negative outcomes (think of stop signs and warning lights), while green implies safety, permission, or positive outcomes (green light means go). Psychological research shows these colours associations carry emotional weight. Elliot et al. (2007) demonstrate that seeing even a brief flash of red before a test impaired performance, as red triggered avoidance motivation and anxiety in an achievement context. Conversely, green has been linked to more relaxed, approach-oriented states. For example, a study finds that exposing people to green boosted their creative performance on a task (Lichtenfeld et al., 2012). These findings suggest that colour is not a neutral vehicle for information: it can evoke affective responses. An investor staring at red numbers might feel a flash of fear or alarm, whereas green numbers might induce a sense of calm or optimism. Such affective reactions can bias decision-making. For instance, an individual may rush to sell a stock when confronted with a screen full of red, or feel encouraged to hold or even buy more when seeing a portfolio in the green.

These reactions can contribute to phenomena like momentum trading or herding, where investors collectively chase recently rising stocks often coloured green on screens and flee from falling ones (Bazley et al., 2021; Da et al., 2011). Even practitioners have noted this psychological pull. For instance, trading educators at MoneyShow 2019 observed that some traders become excessively negative or panicky merely from visual red cues on charts. A red-filled candlestick or red percentage drop can intimidate them into exiting trades too early or clinging to losing positions in hopes of a reversal.

Notably, not all colours elicit such behavioural responses. Bazley et al., (2021) test other colours like blue and yellow in their experiments and find those did not significantly sway investor decisions. By contrast, red and green appear to possess stronger psychological salience because they are commonly associated with gains, losses, approach motivation, and avoidance motivation in decision-making contexts (Elliot and Maier, 2014; Kawai, 2023). Thus, colour represents a vivid example of salience in finance: it captures attention, conveys meaning, and can subtly influence decision-making processes (Dierick et al., 2019; Bazley et al., 2021). A question that motivates this research is how investor characteristics such as greed interact with these salient environmental cues. Greed may influence what investors attend to and how strongly they react to salient information. A large and highly salient gain may therefore trigger stronger emotional and motivational responses among greedy investors, potentially increasing the tendency toward impulsive gain realisation and reward-seeking behaviour (Seuntjens et al., 2015).

In summary, salience is a powerful driver of financial behaviour, steering investor attention and framing decisions in ways that can deviate from pure rationality. Whether through visual cues like colour (red/green) or through the format and frequency of information (percentage changes, daily feedback, news flashes), what stands out most can heavily influence what investors do. By examining greed in high-salience versus low-salience situations, my research aims to clarify how motivational intensity and contextual cues jointly shape investor behaviour. In the chapters that follow, I test whether a greedy investor in a high-salience environment (red or green colour-coded price displays) behaves differently from a greedy investor in a more neutral setting (black price displays). The expectation, grounded in prior evidence, is that greed heightens the motivation to act on favourable outcomes, while salience directs attention toward whichever information is made visually prominent; when these forces coincide, the attention-amplifying effects of salience should magnify the behavioural tendencies associated with greed. Understanding this interplay provides a more comprehensive account of why investors deviate from rational benchmarks. It also highlights how subtle variations in information presentation can mitigate or intensify such biases.

2.5 Numerical Framing: Percentage vs. Absolute Formats

It is a well-established principle in psychology that how information is framed or formatted can substantially alter decision-making (Tversky and Kahneman, 1981). In finance, one key framing issue is whether performance is presented in relative terms (percentages) or absolute terms (dollar amounts). For example, consider an investor holding a stock that rose from \$50 to \$55. This outcome could be described as “a \$5 gain” or as “a 10% gain.” Numerically, they are equivalent, but the salience and psychological impact might differ. A 10%

gain appears substantial in a general sense, whereas $5 might sound small. Conversely, for a very expensive stock, a $5 move could be tiny in percentage terms. In portfolio interfaces, both formats are common and can evoke distinct behavioural responses.

Research in behavioural economics and marketing find that people's perception of numbers can be highly sensitive to framing in relative versus absolute terms (Chen and Rao, 2007; Grewal and Marmorstein, 1994). A classic demonstration asked subjects to consider a calculator priced at $15 in one store and $10 in another across town, compared with a jacket priced at $125 in one store and $120 in another (Tversky and Kahneman, 1981). Many participants were willing to drive 20 minutes to save $5 on the calculator, as $5 is a large share of $15, but most would not do so to save $5 on the $125 jacket, where the discount felt trivial in percentage terms. Objectively $5 is $5, but the relative framing (33% off vs 4% off) made the savings feel different. This suggests that individuals overweight or underweight outcomes depending on how large they appear in percentage terms. Applied to investment returns, this means a given dollar profit can feel more or less significant depending on the stock price and how the return is displayed, especially as percentage framing amplifies the perceived significance of gains in lower-price scenarios.

In investing, this suggests a potential bias. Investors may focus more on percentage returns for cheaper stocks and on absolute returns for more expensive stocks. Prior research shows that framing and salience can influence investor attention and financial decision-making, particularly when information is presented in more vivid or psychologically prominent forms (Kahneman and Tversky, 1979; Bordalo et al., 2012). For example, low-priced and volatile stocks often generate headlines such as "This stock jumped 30% today" which appears dramatic even though the move is only from $3 to $3.9. An investor guided by relative salience might be more inclined to sell after seeing a "+30%" report, believing they have achieved a substantial gain, whereas the description "+$0.9 per share" may appear far less impressive and prompt them to hold the position. In contrast, for a high-priced stock trading at $200, a news report might describe a movement as "up 5%," which seems modest, while the equivalent phrasing "up $10" may feel more concrete. Framing in this way has the potential to shape an investor's willingness to realise gains or losses.

Academic research directly examining percentage versus absolute framing in trading behaviour is relatively limited, but there are useful analogies in finance. For instance, studies on mutual fund fee disclosures have tested whether presenting fees as percentages of assets or as dollar amounts affects investor perception; investors tend to grasp the cost more clearly when it is shown in dollars (Choi et al., 2010).

Applying salience theory (Bordalo et al., 2012) to this context suggests that investors place disproportionate weight on the most salient aspects of outcomes. If a particular framing makes either gains or losses stand out more, those features will disproportionately influence behaviour. For a low-priced stock (e.g., a $30 stock), percentage gains may appear highly salient, prompting investors to overweight their significance and potentially encouraging a quick realisation of profits as the return looks large relative to the initial investment. For a high-priced stock (e.g., a $300 stock), however, the same gain may appear less salient when framed as a small percentage change, reducing the urgency to sell. In contrast, absolute dollar framing can make the pain of a loss feel especially concrete ("I lost $500 on this trade"), whereas percentage framing might soften the perception of the same outcome ("I lost 2%, could be worse"). This dynamic suggests that dollar framing may amplify disposition effect behaviour, as losses become more psychologically aversive, while percentage framing may attenuate it by making the same losses appear more tolerable.

Bringing the framing literature together with the dual-motive view of greed clarifies why greedy investors should react more strongly to percentage-versus-dollar displays. The acquisitive motive (the desire to secure gains quickly) should make greedy investors especially responsive to contexts in which gains appear large and salient. Percentage framing exaggerates the relative size of gains in low-price settings, aligning with acquisitive investors' preference for immediate, certain rewards and increasing their inclination to realise gains rapidly. In contrast, the retentive motive (the urge to avoid surrendering existing resources) heightens sensitivity to cues that make losses feel substantial. Dollar framing renders losses concrete and psychologically painful in high-price settings, which is particularly potent for retentively greedy investors who prioritise wealth preservation. Percentage framing softens this perception, potentially weakening the retentive response. These mechanisms generate clear behavioural predictions: acquisitive greed should strengthen selling of winners under percentage framing, while retentive greed should exacerbate holding of losers under dollar framing.

Overall, the interaction between framing and greed highlights that information format is not merely cosmetic. It shapes which motive becomes dominant in a given context, thereby influencing investors' willingness to realise gains or losses. This perspective provides a theoretically grounded basis for expecting framing effects to differ systematically across individuals with varying levels of greed, while retentive greed should reinforce loss-holding in high-price/dollar contexts.

3 Methodology

3.1 Experimental design

I examine how greed influences the disposition effect using a controlled laboratory experiment that integrates a stock trading simulation with a post-experiment survey[1] measuring personality traits and demographic characteristics.[2]

Following Trejos et al. (2019), I employ a "micro world" experimental approach that represents compromise between experimental control and realism. An experimental approach enables us to conduct research within dynamic, complex decision-making situations while maintaining the experimental control needed to develop generalizable explanations of decision-making processes rather than task-specific descriptions (Funke, 2014). Such experimental settings effectively bridge the gap between laboratory and field research.

The experimental environment was programmed in the Zurich Toolbox for Ready-made Economic Experiments, referred to as z-Tree, (Fischbacher, 2007), which is the most widely used platform for computerized experiments in economics and finance, including studies testing the disposition effect (Rau, 2014; Kirchle et al., 2018; Hermann et al., 2019; Kocher et al., 2019). z-Tree enables real-time, synchronized decision-making and random assignment of treatments. This platform ensured identical interface conditions across participants, allowing precise control over the experimental manipulations of salience and framing.

Participants were recruited from students at Auckland University of Technology, New Zealand. Using university students as a sample in behavioural finance research is a common practice in behavioural finance research. For example, Durand et al., (2013) who investigate investor biases, Rau (2014) and Da Costa et al.,(2013) who examine the disposition effect, and

[1] The screenshots of full questionnaire are provided in the Appendix P.
[2] Our research has received ethical approval from the Auckland University of Technology Ethics Committee under approval number 22/337.

Da Costa et al., (2008) who study gender differences in trading behaviour all employ student samples. To encourage participation, all participants receive a show-up fee of $10 and a chance to win a $300 voucher.

I employ a total sample of 244 participants across the three studies. Study 1 consists of 60 participants and investigates the relationship between greed and the disposition effect under a neutral trading environment. Study 2 consists of 120 participants across three conditions: a control condition using the 60 participants from Study 1, a green-salience condition with 30 participants, and a red-salience condition with 30 participants. Study 3 consists of 124 participants distributed across four experimental conditions: low-price dollar format, low-price percentage format, high-price dollar format, and high-price percentage format, with approximately 31 participants per condition.

My study design is consistent with established experimental research on the disposition effect, which typically employs controlled trading tasks implemented in z-Tree with student samples of modest size. Weber and Camerer (1998), for example, document clear disposition effect patterns in three separate laboratory experiments involving 29, 35, and 39 university students respectively, demonstrating that relatively small experimental samples are sufficient to elicit the bias. Fischbacher et al., (2017) likewise analyse the behaviour of 72 students across three trading sessions, and Rau (2015) conduct a closely related experiment with 84 student participants. These studies illustrate that disposition effect experiments conventionally rely on samples of a few dozen individuals per treatment, with internal validity ensured through standardised instructions, fixed price paths, and controlled information environments.

To assess the adequacy of the sample size, I evaluate statistical power using the effect magnitudes observed in Study 1. In the baseline study, a one-standard-deviation increase in greed is associated with an increase of approximately 0.34 standard deviations in the disposition effect and approximately 0.44 standard deviations in the proportion of gains realised, which corresponds to moderate effect sizes by behavioural-finance standards. Bivariate correlations between greed and key outcome variables range from 0.40 to 0.42, implying that greed explains roughly 16–18% of the variation in realisation behaviour. For effects of this magnitude, standard power calculations indicate that sample sizes on the order of 50–60 participants are sufficient to achieve power close to 0.8 at the 5% significance level. Accordingly, the sample size of 60 participants in Study 1 is adequate for detecting the core behavioural effects of interest, while the larger samples in Studies 2 and 3 provide additional power to study interaction effects and contextual heterogeneity.

Because the disposition effect has been shown to emerge across a broad range of settings, including student experiments (Weber and Camerer, 1998), retail-investor trading records (Odean, 1998), futures-trader transactions (Locke and Mann, 2005), and professional fund-manager decisions (Frazzini, 2006), the use of student participants in a structured trading simulation provides a robust and well-established basis for identifying variation in realisation behaviour across experimental conditions.

Respondents selected a session to attend. The sessions that were randomly assigned to test a particular condition. All sessions followed a standardized protocol. Upon arrival at the laboratory, participants were welcomed by the experimenter, provided with informed consent documents, and given a detailed verbal and on-screen introduction to the trading game.[3] Instructions emphasized that the goal was to maximize wealth.

Participants first completed the trading simulation using the z-Tree interface. The experiment is a replication of Weber and Camerer (1998) setup. Participants in the stock trading simulation were granted $2,000[4] and asked to trade among six different risky assets A, B, C,

[3] The full experimenter script and the informed consent form are provided in the Appendix N and Appendix O.
[4] In Study 3, participants' endowments were scaled to match the price-level manipulation. Specifically, traders in the high-price condition began with $6,000 in experimental currency and traded stocks initially priced at $300, whereas those in the low-price condition began with $600 and traded stocks priced at $30. This adjustment

D, E, and F. The simulation ran over 14 periods, labelled period -3 to 10,[5] where participants observe prices in periods -3 to -1 to give an initial understanding of the stocks' characteristics and then can trade from period 0.[6] Consistent with Weber and Camerer's framework, each stock A–F was assigned a pre-specified probability of price increases[7].The initial price for all six stocks was set to $100 in period -3.[8] Participants then traded the six assets over periods 1 to 10 with the aim of securing the highest portfolio value in period 10.

Following the simulation trading task, participants were directed to an online survey hosted in Qualtrics. They completed a survey which measured participants the greed alongside other variables associated with the disposition effect including loss aversion, risk preference, maximization, trading experience, and demographic factors.[9] Conducting the survey after the trading experiment reduces potential demand effects and common-method variance (Podsakoff et al., 2003; Tourangeau et al., 2000). I also included a directive question ("Please select option 3") to identify inattentive respondents who were excluded from the analysis. Seven participants failed this check and were excluded from the analysis. The use of attention checks has been shown to improve data reliability in online experiments (Meade and Craig, 2012; Chandler and Shapiro, 2016). By combining a z-Tree trading environment for behavioural decisions with a Qualtrics survey for psychometric measurement, the experimental design maximized both behavioural realism and measurement validity, aligning with best practices in experimental and behavioural finance (Hertwig and Ortmann, 2001; Holt and Laury, 2002).

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preserved equal purchasing power and identical relative wealth constraints across conditions, ensuring that behavioural differences could be attributed to price framing rather than budget effects.

[5] Participants start the game with no stocks and throughout the game participants can opt to hold some of the $2,000 as cash.

[6] The 14-period duration provides enough opportunity to observe participants' trading decisions and the impact of psychological biases such as greed. Moreover, the limited scope helps to maintain the focus on specific research questions without introducing excessive complexity.

[7] Two stocks had a 50% probability of increase while increase probabilities of 65%, 55%, 45%, and 35% were assigned to each of the other four stocks, respectively.

[8] In Study 3, two price regimes were introduced to manipulate price level salience: low-priced stocks initially valued at $30 and high-priced stocks initially valued at $300.

[9]Appendix A provides the definitions of all variables used in this study.

Although each study in this thesis addresses a distinct research question, all three build on a common methodological foundation. The core design of z-Tree trading simulations, measurement of the disposition effect via the proportions of gains and losses realised (PGR and PLR), and post-experiment trait assessment administered through Qualtrics remains consistent across Studies 1 to 3. The differences arise from the experimental manipulations layered on top of this foundation. Study 1 establishes the baseline effect of greed on trading outcomes within the standard task. Study 2 extends the design by introducing colour-coded return displays in red or green, allowing us to examine how visual salience cues interact with greed. Study 3 further modifies the environment by framing returns as either absolute dollar values or relative percentages and incorporates two price regimes: low-priced stocks and high-priced stocks. This design allows us to test how price magnitude and framing jointly shape the greed and disposition effect relationship. This consistency in structure ensures comparability across studies while permitting each to isolate specific contextual factors. Detailed descriptions of the procedures, variables, and treatments are provided in the respective methodology sections of each study.

3.2 Disposition Effect Measures

I quantify a participant's disposition effect, using the commonly applied method of Odean (1998), which has become the dominant operationalisation of the disposition effect in both empirical and experimental research (e.g., Frazzini, 2006; Frydman et al., 2014; Pelster and Hofmann, 2018). This PGR–PLR framework is used extensively across studies of retail investors, mutual funds, and laboratory markets, and provides a direct behavioural measure of the extent to which investors are more likely to realise gains than losses.

Although the PGR–PLR method is the standard measure, several alternative approaches to quantifying the disposition effect exist. One class of alternatives varies the reference purchase price used to determine whether a position is in a gain or a loss. Common variants include the average purchase price (AP) across all units held, the value-weighted average purchase price (VWAP), and the last-in-first-out price (LIFO), each of which yields different classifications of gains and losses depending on the assumed liquidation sequence. Another influential alternative is the FHS measure introduced by Fischbacher, Hoffmann, and Schudy (2017), which computes the disposition effect as the difference in the estimated probability of selling a winning asset versus a losing asset, based on a probabilistic choice model rather than realised versus paper outcomes. A further well-established approach is the α-measure of Weber and Camerer (1998), defined as the difference between the probability of selling a winning asset and the probability of selling a losing asset:

$$\alpha = \frac{S_{+} - S_{-}}{S_{+} + S_{-}}$$

where $S+$ ($S-$) is the number of sales of stocks whose prices have gone up (down) in the last period. The disposition coefficient is the difference in sales of winning and losing stocks by one investor, normalized by the sum of sales by this investor. An alpha of 1 (-1) shows that participants only sell stocks after the price goes up (down). This α-measure captures the disposition effect as a behavioural difference in selling propensities rather than as a ratio of realised versus unrealised outcomes.

In addition to these alternative measures, some studies have employed hazard models and reference point dependent approaches to examine the disposition effect dynamically over time. These approaches are particularly useful in settings where investor trading histories and changing reference points can be observed longitudinally. However, the present experimental design captures participants' trading decisions within a controlled simulation and computes disposition effect measures across all transactions simultaneously, rather than tracking evolving reference points over extended time periods. As a result, the structure of the data is more consistent with the conventional PGR–PLR framework than with hazard-based or reference point dependent models, which generally require longer time-series observations and dynamic estimation of investor reference points. Nevertheless, these alternative approaches provide valuable perspectives on investor behaviour and represent useful directions for future research.

A related consideration concerns the estimation of models using PGR and PLR as dependent variables. Because these measures are bounded between zero and one, alternative estimators designed for limited dependent variables, including fractional response models (Papke and Wooldridge, 1996) and Tobit models, may also be considered. Fractional response models are specifically developed for proportional outcomes, whereas Tobit models are primarily designed for censored dependent variables rather than naturally bounded proportions such as PGR and PLR. Nevertheless, OLS remains the standard estimation approach in the disposition effect literature and has been widely employed in studies using PGR–PLR measures. Consistent with prior research, the present study adopts OLS to facilitate comparability of results and straightforward interpretation of interaction effects. Moreover, PGR and PLR in the present sample are not heavily concentrated at their boundary values, thereby reducing concerns regarding boundary-related estimation issues.

Despite the existence of these alternatives, I follow the dominant practice in the literature and compute the disposition effect using the PGR–PLR method. For each participant, I count realised gains, realised losses, paper gains, and paper losses. Paper gains (losses) correspond to the number of profitable (loss-making) assets held in the participant's portfolio at the end of the simulation, while realised gains (losses) are the number of assets sold during the simulation for a gain (loss). I then calculate a participant's disposition effect as the difference between the proportions of gains realised (PGR) and the proportions of losses realised (PLR) as follows:

$$Proportion\ of\ Gains\ Realized\ (PGR) = \frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains}$$

$$Proportion\ of\ Losses\ Realized\ (PLR) = \frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses}$$

$$DE = PGR - PLR$$

When determining whether a position is classified as a gain or a loss, I employ the first-in-first-out (FIFO) convention to identify the reference purchase price. FIFO is the most widely used reference-price rule in the disposition effect literature, and it is employed consistently in prominent field and experimental studies including Weber and Camerer (1998), Odean (1998), Frazzini (2006), Cici (2012), and Rau (2015). Using FIFO ensures comparability with this established body of work and avoids imposing idiosyncratic assumptions about the ordering of trades. In robustness checks, I confirm that the main results remain stable when applying alternative reference-price definitions such as AP, VWAP, LIFO, or the FHS and α measures, indicating that my findings do not depend on the specific implementation of the DE metric.

3.3 Greed Measures

Greed has emerged as an important construct in behavioural economics, psychology, and management research, yet scholars differ in how broadly the concept should be defined. A central issue raised by Lambie and Haugen (2019) concerns whether greed should be understood purely as acquisitiveness, characterised by an insatiable desire for more, or whether it should also encompass retention motives, competitive striving, and even willingness to harm others. These conceptual distinctions have led to several psychometric instruments intended to measure dispositional greed. Although these instruments differ in emphasis, they share substantial overlap and all aim to capture a core motivational tendency reflecting dissatisfaction with what one has and a desire to obtain more.

The most influential and widely used instrument is the seven item Dispositional Greed Scale developed by Seuntjens et al., (2015). This scale defines greed as the desire to acquire more combined with a characteristic sense of never having enough, and it was constructed through extensive prototype analyses across five studies with more than seven thousand respondents. The scale has since become the benchmark measure of greed, largely because it has been repeatedly validated and widely applied across diverse empirical settings. It has been used to study adolescent financial behaviour (Seuntjens et al., 2016), unethical decision making (Seuntjens et al., 2019), labour supply and overearning (Zeelenberg et al., 2020), and individual trading behaviour in experimental asset markets (Hoyer et al., 2021). Furthermore, the scale has been translated and psychometrically validated in Japanese (Masui et al., 2018), Chinese (Liu et al., 2019), and Russian (Shirko and Furmanov, 2020) samples. This extensive empirical use and cross-cultural validation provide strong evidence of the DGS's reliability, generalisability, and standing as the most widely adopted measure of dispositional greed.

Alongside the original DGS, several alternative instruments have been proposed. Krekels and Pandelaere (2015) develop a six item DGS that similarly focuses on acquisitiveness. Mussel et al., (2015) introduce the seven item Greed Trait Measure, which conceptualises greed as the pursuit of more even when such pursuit may come at the expense of others, thereby integrating exploitative tendencies into the construct. Mussel and Hewig (2016) extended this approach in the twelve item GREED scale by adding items related to financial ambition, risk taking, and willingness to benefit at others' expense. Veselka et al., (2014) develop a ten-item greed subscale within the Virtues and Vices Scale grounded in the seven deadly sins tradition. Although this measure theoretically emphasises manipulation and betrayal, many of its items return to acquisitive desire and reluctance to share.

Despite these conceptual differences, recent evidence shows that all major greed scales assess the same underlying construct. In a large-scale psychometric comparison, Zeelenberg et al., (2021) examine thirty items from four scales and thirty-seven items from five scales in two studies with samples of three hundred and one thousand respondents. They find that all greed scales exhibited high internal reliability and very strong correlations with each other.

Exploratory factor analyses consistently revealed a dominant single factor structure, indicating that acquisitive desire is the central component of dispositional greed. Items involving reverse coding and harming others loaded less consistently, suggesting that these elements are peripheral rather than central to the construct. The authors conclude that although scales differ in emphasis, all effectively measure the same underlying greed factor and that scales focused on acquisitiveness capture this factor most cleanly. Given this evidence, I adopt the seven item Dispositional Greed Scale of Seuntjens et al. (2015) as the measure of greed used in this study. The DGS provides a theoretically coherent and empirically validated assessment of the core construct of greed, and it is the measure most widely used in contemporary behavioural research. Participants respond to each item on a five-point Likert scale, and I compute an individual's greed score as the mean of the items.

I use centred greed in all regression analyses. Greed is obtained by subtracting 3 (the midpoint of the 1-5 scale) from each participant's greed score. This transformation recentres the scale so that a value of zero represents the scale midpoint and improves the interpretability of regression coefficients. Centring reduces multicollinearity between the intercept and the predictor and clarifies the interpretation of coefficients without altering substantive relationships among variables (Gelman, 2008). Although Study 1 estimates only main effects, I centre greed to ensure consistent scaling across Studies 1-3 and to facilitate interpretation at a meaningful reference point. For Studies 2 and 3, which introduce moderation terms involving greed (e.g., *Greed* × *Colour* and framing interactions), centring reduces collinearity between main effects and interaction terms and to allow coefficients to be interpreted at the average level of the moderator (Aiken and West, 1991; Cohen et al., 2013). This approach follows established best practice in behavioural, psychological, and econometric research and ensures that the greed variable is treated consistently and rigorously throughout the thesis (Dalal and Zickar, 2012).

3.4 Control Variables

I follow the related literature (Hermann et al., 2019; Rau, 2014) to control for investors' personality and characteristics that may be related to the disposition effect. Specifically, I control for loss aversion which can impede investors from realizing capital losses, thereby strengthening the disposition effect (Barberis and Xiong, 2009), while greedy individuals tend to be more loss averse (Krekels, 2015). Additionally, I control for risk preferences, as prospect theory links asymmetric risk attitudes to the disposition effect. Specifically, investors become risk-averse after gains (sell winners) and risk-seeking after losses (hold onto losers) (Kaustia, 2010). Additionally, I control for trading experience which has been shown to reduce the disposition effect (Da Costa et al, 2013; Feng and Seasholes, 2005; Seru et al, 2010). Research has also shown that the disposition effect varies with gender and age, though findings are mixed (Rau, 2014; Da Costa et al, 2008). Additionally, higher education levels have been associated with a reduction in the disposition effect (Vaarmets et al., 2019). I also consider maximization tendencies, which are conceptually related to greed but reflect the pursuit of the best possible outcome, whereas greed emphasizes the desire to acquire more (Seuntjens, Zeelenberg, Breugelmans, and Van de Ven, 2015).

4 Greed and Realisation Behaviour: Experimental Evidence on the Disposition Effect

4.1 Introduction

Investors consistently exhibit the disposition effect, the tendency to sell winning assets too quickly while holding losing assets for too long (Shefrin and Statman, 1985; Odean, 1998). Traditional explanations for this pervasive bias centre on cognitive factors, such as loss aversion, regret aversion, and realisation utility, which influence how investors respond to gains and losses (Kahneman and Tversky, 1979; Shefrin and Statman, 1985; Barberis and Xiong, 2012). However, less is known about how personality traits influence this behaviour. This chapter introduces greed as a personality trait that may systematically influence the disposition effect.

Greed has long been acknowledged as a powerful motivator in economic behaviour, yet its role in financial decision-making has only recently attracted scholarly attention (Seuntjens et al., 2015; Mussel and Hewig, 2016). By examining greed within the context of one of the most pervasive investor biases, this chapter aims to extend understanding of why some individuals are more prone to suboptimal trading decisions than others.

Greed not only fuels the pursuit of additional gains but also engenders a strong reluctance to part with or lose what one already possesses. This dual perspective provides a useful framework for understanding the disposition effect, because acquisitive motives may encourage rapid gain realisation while retentive motives may reinforce reluctance to realise losses. The acquisition motive might intensify the tendency to sell winners quickly. A greedy investor could be especially inclined to realise gains quickly to secure their gains. At the same time, greed's retention motive could either reinforce the bias on the loss side by making investors unwilling to relinquish losing stocks and accept a loss or mitigate it if the fear of losing overall wealth prompts a faster exit from bad investments. Emerging research suggests that sensitivity to potential losses is one pathway through which greed influences decision making, with evidence that loss aversion can mediate the effect of greed (Li et al., 2019), that greedy individuals show heightened responses to negative outcomes (Mussel and Hewig, 2019; Rodrigues et al., 2023).

The impact of greed must be understood through the distinction between paper and realised losses. Realisation-utility shows that crystallising a loss generates an immediate negative utility shock (Barberis and Xiong, 2012; Ingersoll and Jin, 2013), while mental-accounting and regret theories emphasise that realising a loss finalises a painful outcome and forces an admission of error (Thaler, 1985; Shefrin and Statman, 1985). Keeping a loss unrealised allows investors to postpone this psychological cost. For a greedy investor motivated by retention, the prospect of turning a paper loss into an actual loss is especially aversive, which can strengthen the tendency to hold losing positions. Conversely, for a greedy investor motivated by acquisition, realising a gain converts an uncertain paper gain into a concrete outcome, making early sale of winners psychologically attractive. In this way, greed's retention motive can amplify the "hold losers" side of the disposition effect, even while its acquisitive motive accelerates the sale of winners. These theoretical possibilities underscore the need to disentangle greed's dual effects on selling decisions.

In this chapter, I investigate whether there is a relationship between greed and the disposition effect. In particular, I investigate if greed amplifies the inclination to cash in profitable assets more than its impact on the willingness to cut loss-making positions.

While prior work has established cognitive drivers such as prospect theory and realisation utility, as well as situational influences including salience and information display, explicit examination of stable personality traits remains relatively limited (Barberis and Xiong, 2012; Frydman and Wang, 2020; Da Costa et al., 2023). By focusing on greed, this chapter contributes to the literature by examining whether a personality trait rooted in wealth acquisition motives systematically alters the disposition effect. Importantly, the chapter distinguishes between acquisitive and retentive motives of greed and investigates whether greed affects gain realisation and loss realisation differently. This distinction is important because greed may either amplify harmful trading behaviour by accelerating premature gain realisation or potentially mitigate aspects of the bias if concerns about wealth preservation increase willingness to exit losing positions. By empirically disentangling these competing mechanisms, the chapter provides a more nuanced understanding of how greed shapes investor realisation behaviour.

I find that greed is a significant and economically meaningful predictor of the disposition effect. Across all model specifications, the coefficient on greed is positive and highly significant, indicating that a one-point increase on the greed scale nearly doubles the average disposition effect (mean=0.15). Greedy participants realise winning stocks more frequently while showing limited willingness to sell losers, consistent with acquisitive greed rather than retentive greed. The association remains robust when controlling for risk preference, loss aversion, maximization, and demographic characteristics, and persists across alternative measures of the disposition effect. Economic simulations further illustrate that postponing the sale of winners by just one period would have increased aggregate portfolio returns from 4.62 percent to 5.85 percent. These findings confirm that greed amplifies premature realisation of gains and underpins one of the most pervasive investor biases even under neutral trading conditions.

One possible explanation is that greedy investors derive strong psychological satisfaction from realising gains. Realised gains provide immediate and certain rewards, whereas unrealised gains remain uncertain and subject to future market fluctuations. Consequently, greed may increase the attractiveness of locking in profitable outcomes quickly rather than waiting for potentially larger but uncertain future returns. This interpretation aligns with theories of realisation utility and reward salience, which suggest that investors may experience emotional gratification from converting paper gains into realised gains. Greedy individuals may therefore display a stronger tendency to sell winning assets prematurely in order to secure immediate reward realisation.

4.2 Hypotheses Development

The disposition effect has traditionally been explained through cognitive and emotional mechanisms such as loss aversion (Kahneman and Tversky, 1979), realization utility (Barberis and Xiong, 2012), and cognitive dissonance (Chang et al., 2016). Recent work emphasizes that individual traits can systematically modulate these biases (Cueva et al., 2019; Da Costa et al., 2023). Within this view, greed offers a theoretically coherent trait-level determinant of the disposition effect.

Greed represents a motive that extends beyond the economic assumption of non-satiation. While non-satiation in classical theory simply denotes a preference for “more” (Varian, 1992; Arrow and Debreu, 1954), greed entails an insatiable desire to acquire and retain resources, often accompanied by frustration when one’s holdings fall short of desired levels (Seuntjens et al., 2015; Krekels, 2015). Greed is linked to short-term orientation, heightened sensitivity to gains and losses, and a fear of losing existing wealth (Haynes, Campbell, Hitt, 2017; Mussel and Hewig, 2019). Greed motivates individuals both to acquire more resources and to retain existing resources (Bosse et al., 2010; Mussel and Hewig, 2016; Seuntjens et al., 2016).

Greed therefore expresses itself in behavioural patterns that align closely with the mechanisms underlying the disposition effect. Greedy individuals are strongly motivated to secure gains quickly, derive heightened satisfaction from realised profits, and experience disproportionate frustration when outcomes fall short of their aspirations. These tendencies increase the appeal of crystallising gains while making the acceptance of losses especially hard.

Consequently, the motivational profile associated with greed reinforces the two defining components of the disposition effect: the eagerness to sell winners and the reluctance to sell losers.

Therefore, I propose:

Hypothesis 1: Investors with a higher level of greed will exhibit a stronger disposition effect

Acquisition-oriented greed reflects an insatiable desire to increase one's holdings and to secure accumulated resources. However, unrealised gains remain uncertain because future market fluctuations may erode or eliminate them before they are converted into realised wealth. By contrast, realised gains provide immediate, concrete, and psychologically secure rewards. The realisation utility theory suggests that investors derive emotional gratification from realising gains, while reward salience and short-term orientation increase the attractiveness of immediate and certain outcomes relative to uncertain future appreciation (Barberis and Xiong, 2012; Ingersoll and Jin, 2013; Seuntjens et al., 2015). For greed-prone investors, the psychological satisfaction associated with securing realised gains may therefore become especially salient.

For greedy investors, this distinction is especially important because acquisitive motives intensify the desire to secure gains once they become available. Realising gains therefore becomes a natural behavioural expression of acquisitive greed. By selling winning positions, greedy individuals convert uncertain paper profits into realised wealth, thereby securing control over acquired resources and avoiding the possibility that favourable outcomes disappear before they are captured. In this way, greed may increase the attractiveness of immediate gain realisation even when continued holding could potentially generate larger future returns.

Consequently, investors with higher levels of greed are expected to sell winning stocks more readily and quickly than less greedy investors because the desire to secure and protect realised wealth outweighs the appeal of holding positions for potentially larger but uncertain future gains, thereby reinforcing the gain-realisation component of the disposition effect. Therefore, I propose our 2nd hypothesis as follows:

*Hypoth*esis 2: *Investors with a higher level of greed will sell winning stocks sooner than investors with a lower level of greed.*

Greed's influence on loss holding can be understood through the retention-oriented component of the motive. As Krekels (2015) argues, greed includes a strong desire to maintain control over one's existing resources. This retention motive leads greedy individuals to focus on preserving what they already possess, even when doing so is costly. Supporting this view, Mussel and Hewig (2016) and Seuntjens et al., (2019) show that individuals high in greed exhibit heightened concern about potential reductions in their holdings and a stronger inclination to protect current assets.

From this perspective, selling a losing stock represents an immediate and irreversible contraction of one's asset base. For greedy investors, realising a loss conflicts directly with their motive to retain and safeguard accumulated resources. Holding the position, even when it is objectively unprofitable, allows them to postpone acknowledging this reduction. This behaviour may also partly reflect mechanisms related to loss aversion and anticipated regret, as investors may avoid selling losing stocks in order to delay the psychological discomfort associated with recognising investment losses and potential decision mistakes. However, these mechanisms are conceptually distinct from greed and are not directly examined in the present study. This logic is consistent with evidence from Flepp et al., (2021) and Imas (2016), who find that individuals who are strongly motivated to avoid recognising losses tend to hold losing investments for longer periods. Therefore, I propose our 3rd hypothesis as follows:

Hypothesis 3: Investors with a higher level of greed will hold losing stocks longer than investors with a lower level of greed.

4.3 Method

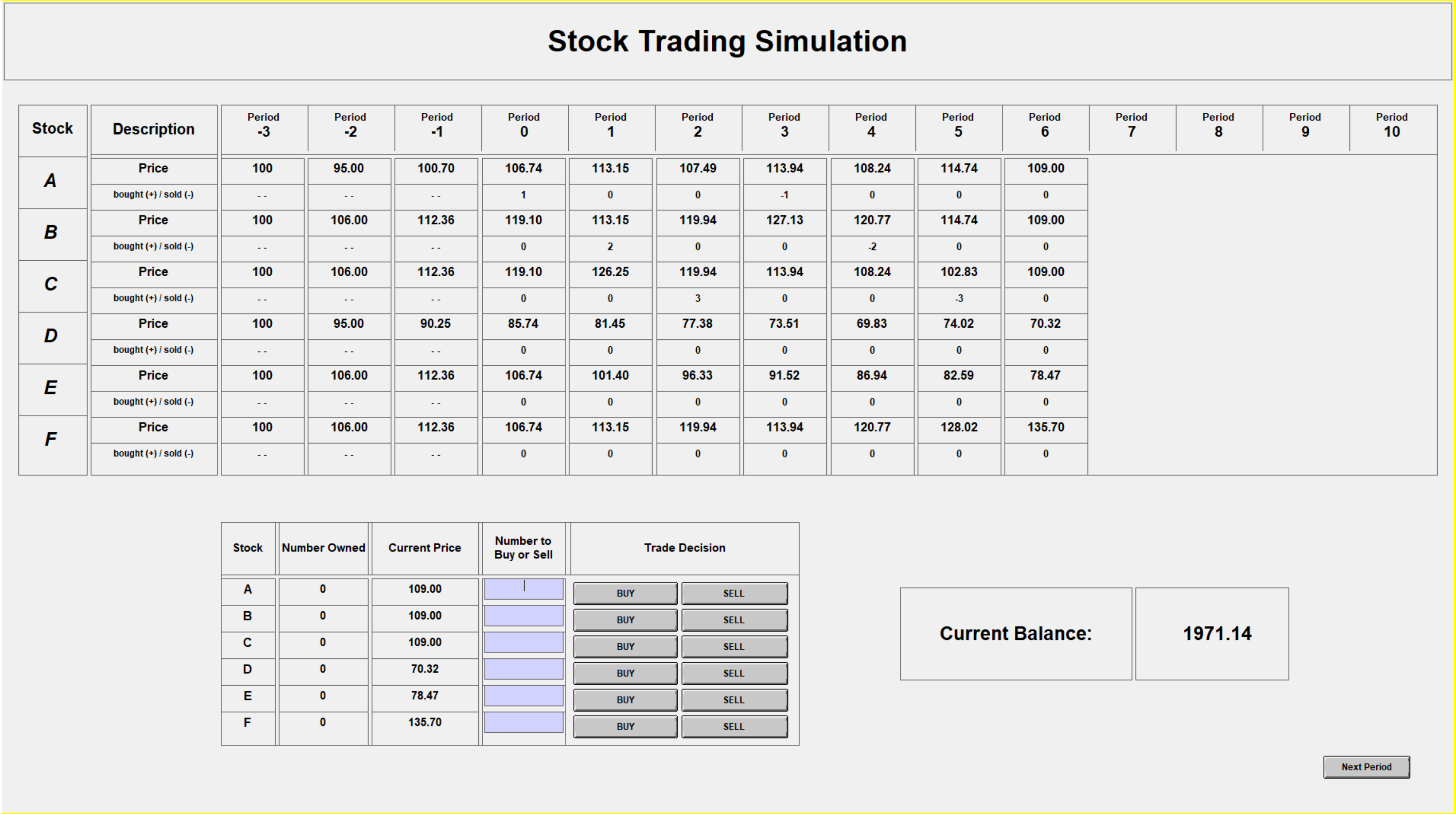
The experiment adopts the baseline design framework described in Chapter 3, which employs a dynamic stock-trading simulation implemented in z-Tree (Fischbacher, 2007). In this base case, no visual or framing manipulations were applied, allowing the analysis to isolate the psychological effect of greed on trading behaviour.

Participants received an initial endowment of $2,000 to trade six risky assets (A–F) over fourteen periods. The first three periods were purely observational, enabling participants to familiarise themselves with price dynamics before active trading began. Each stock followed a pre-defined probability distribution for price changes, ensuring comparability across participants. After completing the trading phase, participants filled out a post-experimental survey measuring greed and other psychological traits, along with demographic information. All participants received a $10 show-up payment and were entered into a $300 voucher draw as an incentive for engagement. Figure 1 displays the trading interface presented to participants in z-Tree. The final sample consisted of 60 university students.

The disposition effect was calculated following the procedure outlined in Chapter 3 (Section 3.2). In brief, it captures the difference between the proportion of gains and losses realised during trading, using the first-in-first-out reference price rule. This measure reflects each participant's tendency to sell winners prematurely and hold onto losers. Greed was assessed using the seven-item Greed Scale developed by Seuntjens et al. (2015). Table 4.1 indicates that the Greed Scale is a valid and reliable measure for use in this study (Cronbach's α=0.79), with an average M=3.11 (SD=0.77).

Figure 1. Study 1 Trading Interface

Figure 1 illustrates the trading simulation interface presented to participants in z-Tree. This corresponds to the baseline study, in which no colour cues or stock returns were displayed.



Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	100	95.00	100.70	106.74	113.15	107.49	113.94	108.24	114.74	109.00				
	bought (+) / sold (-)	- -	- -	- -	1	0	0	-1	0	0	0				
B	Price	100	106.00	112.36	119.10	113.15	119.94	127.13	120.77	114.74	109.00				
	bought (+) / sold (-)	- -	- -	- -	0	2	0	0	-2	0	0				
C	Price	100	106.00	112.36	119.10	126.25	119.94	113.94	108.24	102.83	109.00				
	bought (+) / sold (-)	- -	- -	- -	0	0	3	0	0	-3	0				
D	Price	100	95.00	90.25	85.74	81.45	77.38	73.51	69.83	74.02	70.32				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
E	Price	100	106.00	112.36	106.74	101.40	96.33	91.52	86.94	82.59	78.47				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
F	Price	100	106.00	112.36	106.74	113.15	119.94	113.94	120.77	128.02	135.70				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	109.00		BUY	SELL
B	0	109.00		BUY	SELL
C	0	109.00		BUY	SELL
D	0	70.32		BUY	SELL
E	0	78.47		BUY	SELL
F	0	135.70		BUY	SELL

Current Balance: 1971.14

Next Period

Table 4.1. Properties of the 7-Item Greed Scale

Participants were asked to indicate the extent to which they agreed that these items were descriptive of themselves. Responses were measured on 5-point Likert-scales ranging from 1=strongly disagree to 5=strongly agree.

	M	SD
1. I always want more	3.81	0.92
2. Actually, I'm kind of greedy.	2.98	1.11
3. One can never have too much money.	3.30	1.33
4. As soon as I have acquired something. I start to think about the next thing I want.	3.43	1.14
5. It doesn't matter how much I have. I'm never completely satisfied.	2.75	1.35
6. My life motto is "more is better."	2.47	1.26
7. I can't imagine having too many things.	2.63	1.21
Cronbach's α=0.79		
Total	3.11	1.17

To ensure that greed's influence was not confounded by other behavioural traits, the analysis controlled for individual differences in loss aversion, risk preference, and maximization tendencies, as well as demographic variables including age, gender, education, income, and self-reported trading experience. These controls variables were operationalised following established practice in experimental and behavioural finance literature (Rau, 2014; Hermann et al., 2019). Loss aversion was elicited using the incentivised multiple price list developed by Gächter et al. (2022), producing an index where higher scores indicate stronger aversion to losses. Risk preference was measured with the multiple-choice item from Guiso et al. (2018), which categorises respondents along a 1–4 scale of increasing risk tolerance. Maximization tendencies were assessed using the seven-item Maximization Scale (Diab et al., 2008), scored from 1 ("strongly disagree") to 5 ("strongly agree"), with higher values indicating a stronger preference for exhaustive comparison of alternatives. Trading experience was self-reported on a 1–10 scale (Dhar and Zhu, 2006), where 1 denotes no prior trading experience and 10 indicates extensive experience. Demographic controls were coded as follows: gender equals 1 for male and 0 for female; age is measured in years; income is reported in ordered NZD brackets from 0 to “more than $200,000”; and education reflects the highest qualification attained on a 0–4 ordinal scale. These operational definitions correspond to Appendix A.

Overall, Study 1 provides a baseline test of the relationship between greed and trading behaviour under standard trading conditions. The design establishes the benchmark against which later chapters introducing colour cues (Study 2) and framing manipulations (Study 3) can be compared.

4.4 Results

4.4.1 Descriptive Statistics

I begin by examining the components of the disposition effect. Participants realise 37% of gains (PGR) and 22% of losses (PLR). While realising roughly one-third of gains is not unusual in experimental trading settings, the key behavioural signal is the sizeable 15-percentage-point gap between PGR and PLR. This asymmetry shows that participants are substantially more willing to sell winners than losers.

Using these components, the average disposition effect (DE) computed under FIFO is 0.15. For comparison, Rau (2014) reports a DE of 0.29 for a German student sample, while Cecchini, Bajo, Russo, and Sobrero (2019) document a much smaller DE of 0.02 for Italian and Chinese investors.

For remaining variables, greed averages 3.11 (SD=0.75), indicating moderate levels of dispositional greed typical of student cohorts. Loss aversion is relatively high (mean=4.75, SD=1.10), and participants are generally risk-averse, with an average risk-preference score of 2.28 (SD=1.00). Maximization tendencies are moderately high (mean=4.72, SD=0.99), reflecting a preference for thorough evaluation of alternatives. As expected for a university cohort, trading experience is limited (mean=1.98), and the average age is 25 years (SD=6.99). The sample consists of 60 participants, of whom 28 are male and 32 are female (46% male). For comparison, Rau's sample includes 55 subjects, 28 of whom are female, while Da Costa et al. (2008) study 96 subjects, including 52 females. Mean income in my study is 2.45 on the 1–6 scale, and mean education is 1.73 on the 0–4 scale.

Table 4.2. Descriptive Statistics

This table reports the summary statistics for all the variables, disposition effect (FIFO), proportion of gains realised (PGR), proportion of losses realised (PLR), greed, loss aversion, risk preference, maximization, trading experience, age, gender, income and education.

Variable	Obs	Mean	Median	Stdev	Min	Max
PGR	60	0.37	0.38	0.21	0.00	0.85
PLR	60	0.22	0.20	0.20	0.00	0.90
Disposition Effect	60	0.15	0.15	0.31	-0.90	0.85
Greed	60	3.11	3.14	0.75	1.43	5.00
Loss Aversion	60	4.75	5.00	1.10	2.00	7.00
Risk Preference	60	2.28	2.00	1.00	1.00	4.00
Maximization	60	4.72	4.72	0.99	2.66	6.77
Trading Experience	60	1.98	2.00	1.15	1.00	4.00
Age	60	25.01	21.00	6.99	18.00	52.00
Gender	60	0.46	0.00	0.50	0.00	1.00
Income	60	2.45	2.00	1.08	1.00	6.00
Education	60	1.73	2.00	1.11	0.00	4.00

Table 4.3 presents the pairwise correlation coefficients among the variables used in Study 1. Consistent with Hypothesis 1, DE correlates positively with greed (p<0.01), indicating that greedier individuals suffer from a stronger disposition effect. The correlations also show a stronger correlation with PGR (0.40) than PGL (0.24). DE correlates positively with loss aversion and negatively with risk preference. This pattern aligns with prospect theory interpretations (Shefrin and Statman, 1985; Weber and Camerer, 1998), which predict that individuals who are more averse to losses or more cautious in their risk attitudes are less willing to realise losses. It is also consistent with models such as Barberis and Xiong (2009), who show

that stronger aversion to losses amplifies the disposition effect. Empirical evidence from Dhar and Zhu (2006) indicates that financially sophisticated investors, who tend to be less risk averse exhibit a weaker disposition effect.

Among demographics, age shows a modest positive relation with DE ($p<0.05$), while gender is not significant. DE is negatively associated with income ($p<0.10$) and education ($p<0.10$), indicating that individuals with higher socioeconomic standing exhibit weaker biases. This is consistent with Dhar and Zhu (2006), who show that higher-income investors exhibit a significantly smaller disposition effect. Education displays a similar pattern. Goo et al. (2010) find that investors with higher degrees experience a lower disposition effect. Vaarmets et al. (2019) demonstrate that both educational attainment and stronger learning ability substantially mitigate the tendency to realise gains and hold losses. Correlations among psychological traits are theoretically coherent. Greed is strongly correlated with maximization ($p<0.01$), moderately negatively with risk preference ($p<0.05$), and positively with age ($p<0.05$). Trading experience is negatively associated with DE ($p<0.01$) and positively with risk preference ($p<0.05$), in line with evidence that investor sophistication and learning-by-doing attenuate the disposition effect (Feng and Seasholes, 2005; Seru et al., 2010; Da Costa et al., 2013). Overall, correlations are moderate, indicating no multicollinearity and supporting the validity of the constructs for subsequent regression analysis.

Table 4.3. Correlations Coefficients

This table shows the correlations coefficients between these variables. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect											
2.PGR	0.77***										
3.PLR	-0.73***	-0.13									
4. Greed	0.42***	0.40***	-0.24*								
5. Loss Aversion	0.44***	0.30	-0.36***	0.15							
6. Risk Preference	-0.58***	-0.43***	0.44***	-0.28**	-0.38**						
7. Maximization	-0.05	-0.11	-0.02	0.45***	-0.19	0.02					
8. Trading Experience	-0.38***	-0.25*	0.34***	-0.09	-0.04	0.27**	-0.01				
9. Age	0.29**	0.19	-0.25**	0.31**	-0.16	-0.27*	0.18	0.03			
10. Gender	-0.09	-0.07	0.07	0.13	0.04	-0.12	-0.03	-0.10	-0.16		
11. Income	-0.35*	-0.43***	0.08	0.03	-0.08	-0.15	0.28**	0.33***	0.05	-0.09	
12. Education	-0.42*	-0.45	0.18	0.01	-0.19	0.37***	0.14	0.12	0.06**	0.04	0.25*

4.4.2 Regression Analysis

To test whether investors' strategy to realise gains and losses was affected by greed level, I ran the following OLS regression model:

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_k X_{k,i} + \varepsilon \quad (1)$$

where X_k denotes a vector of participants' characteristics and demographics as control variables.[10] Regression results in Table 4.4 provide strong evidence for a positive relationship between centred greed[11] and the disposition effect (DE). Across all six models, the coefficient for greed remains positive and highly significant ($p<0.01$), ranging from 0.112 to 0.192.[12] This consistent finding suggests that individuals with higher levels of greed are more likely to exhibit a stronger disposition effect.[13] Focusing on the most comprehensive model (Column (6)), I observe that a one-point increase on the greed scale corresponds to a 0.14 increase in the disposition effect, with this coefficient being highly significant ($p<0.01$). Considering that the mean disposition effect in the sample is 0.15, a single point increase in greed nearly doubles the disposition effect.

The relationship persists even when controlling for various factors such as loss aversion, risk preference, maximization tendency, trading experience, and demographic variables. Notably, the inclusion of these control variables improves the model's explanatory power, as evidenced by the increase in adjusted R^2 from 0.168 in the simplest model to 0.622 in the most comprehensive model in Column (6). Results for control variables are generally consistent with previous literature. The disposition effect is higher for investors who are more risk averse

[10] In assessing the possibility of multicollinearity in our regression models, I compute the variance inflation factors (VIFs) for the explanatory variables. As the VIFs remain well below 10, I conclude that multicollinearity is not likely to significantly impact our results.
[11] I re-estimated all models using the standardised greed variable reported in Appendix E, and the results are robust to those presented in Table 4.4.
[12] I adjust standard errors for heteroscedasticity using White (1980) and clustering by experimental session.
[13] The results are also robust to using a binary variable of greed (see Appendix C).

(Shefrin and Statman, 1985), score higher in loss aversion (Barberis and Xiong, 2009), and have less trading experience (Seru et al., 2010). Moreover, I find that female investors, and investors with lower level of education tend to exhibit a higher degree of disposition effect, consistent with Breitmayer et al., (2019). While our results also show a significantly negative association between maximization and DE, they indicate an insignificant effect of income on DE.[14] Finally, adjusted R^2s in Table 4.4 are stronger than those in other studies; for example, Rau (2015) reports an R^2 of just 9.7%.[15] [16]

[14] For robustness, I also capture participants' regret aversion, overconfidence, locus of control, financial literacy and financial capability, and Big 5 personality traits. The inclusion of these variables does not alter our findings. These results are available upon request.

[15] The regression with only control variables yields an adjusted R^2 of 55.2%, while adding greed increases the adjusted R^2 to 0.622. This 7% boost highlights greed's significant role in explaining the disposition effect beyond the control variables alone.

[16] To isolate greed's unique contribution and address multicollinearity, I conducted an orthogonalization process. In the first stage, I regress greed on the control variables to obtain the residuals of greed. These greed residuals (*Greed_Residual*) capture the variation in greed that is orthogonal to participants' characteristics. In the second stage, I re-estimate Eq. (1) by replacing *Greed* with *Greed_Residual* and find its coefficient continues to be positive and statistically significant. The results are shown in Appendix D.

Table 4.4. Greed and Disposition Effect

This table presents regression results examining the relationship between centred greed and the disposition effect (DE), along with other control variables. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. Greed and control variables are defined as in Appendix A. Columns (7) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.134***	0.195	-0.364*	0.518***	0.558***	0.296	0.296
	(0.037)	(0.148)	(0.193)	(0.162)	(0.191)	(0.274)	(0.269)
Greed	0.172***	0.140***	0.112***	0.116***	0.192***	0.140***	0.142***
	(0.048)	(0.041)	(0.037)	(0.039)	(0.044)	(0.042)	(0.042)
Loss Aversion			0.098***			0.071***	0.065***
			(0.024)			(0.026)	(0.021)
Risk Preference				-0.095***		-0.061**	-0.072**
				(0.032)		(0.032)	(0.028)
Maximization					-0.089**	-0.056**	-0.067***
					(0.035)	(0.030)	(0.022)
Trading Experience		-0.065**	-0.070***	-0.048**	-0.068***	-0.067***	-0.066***
		(0.028)	(0.024)	(0.026)	(0.027)	(0.023)	(0.019)
Age		0.084**	0.111***	0.005	0.101***	0.127**	0.013***
		(0.004)	(0.003)	(0.004)	(0.004)	(0.046)	(0.004)
Gender		-0.080*	-0.926*	-0.099*	-0.107*	-0.109**	-0.122*
		(0.060)	(0.052)	(0.056)	(0.058)	(0.050)	(0.063)
Income		-0.034	-0.023	-0.036	-0.007	-0.026	-0.018
		(0.030)	(0.027)	(0.028)	(0.031)	(0.027)	(0.019)
Education		-0.095***	-0.075***	-0.065**	-0.088***	-0.057**	-0.044
		(0.027)	(0.024)	(0.027)	(0.026)	(0.024)	(0.033)
Observations	60	60	60	60	60	60	60
Adj. R^2	0.168	0.462	0.586	0.534	0.512	0.622	0.661
Standard errors adjusted for clustering	No	No	No	No	No	No	session

Individual investors tend to respond differently to gains and losses (Meyer and Pagel, 2022)**.** To investigate this in our sample, I assess greed's impact on the proportions of realised gains (PGR) and losses (PLR) separately in Table 4.5. In particular, I run the following regression:

$$PGR_i = \beta_0 + \beta_1 Greed_i + \beta_k X_{k,i} + \varepsilon \tag{2}$$

$$PLR_i = \beta_0 + \beta_1 Greed_i + \beta_k X_{k,i} + \varepsilon \tag{3}$$

The findings in Table 4.5 reveal a consistent and significant positive association between greed and PGR across Columns (1), (2) and (3) with coefficients ranging from 0.109 to 0.124 (p<0.01). This suggests that greedier investors are more likely to realise gains, with a one-unit increase in greed corresponding to a 0.124 increase in the proportion of gains realised in the most comprehensive model. Conversely, the relationship between greed and PLR is less consistent, ranging from negative and marginally significant (-0.063, p<0.1) in model (5) to insignificant when any controls are added. These results imply that greed amplifies the disposition effect primarily by increasing willingness to sell winning stocks, while its effect on selling losing stocks is weak at best. Columns (4) and (8) replicate the comprehensive models in Columns (3) and (7) with standard errors clustered at the session level. The results remain robust.[17] Greed remains strongly positive and significant for PGR, and insignificant for PLR. This confirms that the main findings are not driven by within-session correlation in trading behaviour.

The control variables in the model provides additional insights. Loss aversion shows a significant negative relationship with PLR (-0.056, p<0.01), indicating that more loss-averse investors are less likely to realise losses.[18] Trading experience is positively associated with

[17] I re-estimated Columns (1) - (3) and (5) - (7) using the standardised greed variable reported in binary, and the results are robust to those presented in Table 4.5.

[18] I examine how loss aversion interacts with greed to influence investor behaviour by running a regression on their interaction. The results show that the interaction term has a positive and significant effect on the proportion

PLR (0.060, $p<0.01$), suggesting that more experienced traders are more willing to cut their losses. Age shows a significantly positive relationship with PLR in the comprehensive models. Education is negatively associated with PGR (-0.055, $p<0.01$), implying that more educated investors are less prone to realizing gains prematurely. Income shows a negative and statistically significant relationship with PGR in Columns (2) to (4), suggesting that higher-income participants are initially less likely to realise gains. For PLR, income is generally insignificant across the specifications, with only a marginal negative effect appearing in Column (8). The models explain a substantial portion of the variance in PGR (adjusted R^2 up to 0.457) and, to a lesser extent, PLR (adjusted R^2 up to 0.312). In addition, the results for PGR and PLR imply that (i) the motive to quickly secure gains prevail over the desire to wait for potentially larger gains when investments increase in value, and (ii) this retention motive does not seem to affect the selling behaviour of investors when stock prices decrease.

of losses realized (PLR) ($\beta=0.068$, $p<0.01$). When loss aversion is low, greedier investors tend to hold onto losing stocks longer. However, as loss aversion increases, their willingness to realize losses also increases. Results available upon request.

Table 4.5. The Impacts of Greed Components on the PGR and PLR

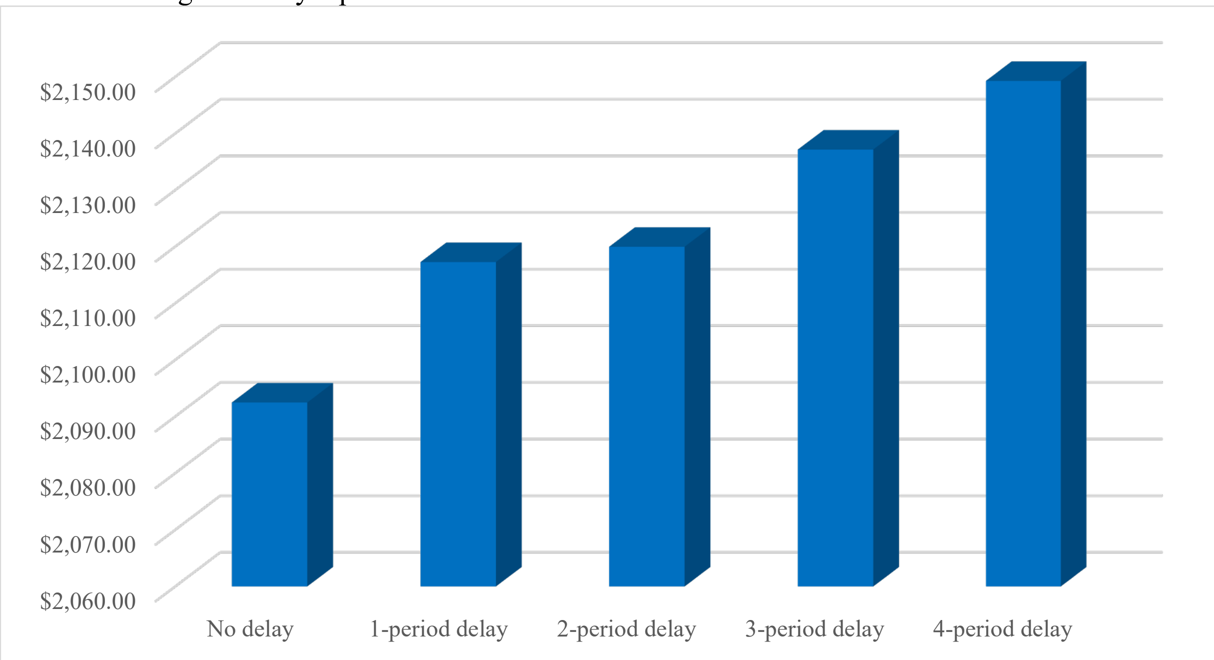
The table reports OLS estimates of the proportion of gains realised (PGR) and the proportion of losses realised (PLR) as measured by Odean (1998), Proportion of gains realised (PGR)=Realised Gains/ (Realized Gains + Paper Gains) and proportion of losses realized=Realised Losses/ (Realised Losses + Paper Losses). *Greed* and control variables are defined as in Appendix A. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. Columns (4) and (8) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PGR	PGR	PGR	PGR	PLR	PLR	PLR	PLR
Intercept	0.375***	0.556***	0.799***	0.785***	0.221***	0.343***	0.486**	0.489**
	(0.025)	(0.112)	(0.236)	(0.219)	(0.025)	(0.109)	(0.229)	(0.206)
Greed	0.109***	0.110***	0.124***	0.121***	-0.063*	-0.03	-0.016	-0.020
	(0.034)	(0.029)	(0.033)	(0.035)	(0.033)	(0.032)	(0.035)	(0.038)
Loss Aversion			0.014	0.013			-0.056***	-0.051***
			(0.021)	(0.019)			(0.022)	(0.017)
Risk Preference			-0.028	-0.048			0.028	0.025
			(0.025)	(0.037)			(0.027)	(0.026)
Maximization			0.044*	-0.049*			0.016	0.018
			(0.026)	(0.026)			(0.027)	(0.021)
Trading Experience		-0.004	-0.002	-0.003		0.061***	0.060***	0.063***
		(0.020)	(0.020)	(0.017)		(0.022)	(0.021)	(0.017)
Age		0.001	0.001***	0.002		-0.008**	-0.009***	-0.011***
		(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)
Gender		-0.028	-0.049	-0.055		0.052	0.07	0.067*
		(0.043)	(0.042)	(0.041)		(0.047)	(0.044)	(0.038)
Income		-0.062**	-0.048**	-0.058**		-0.028	-0.038	-0.039*
		(0.022)	(0.023)	(0.023)		(0.024)	(0.024)	(0.022)
Education		-0.070***	-0.055***	-0.017		0.025	0.004	0.027
		(0.019)	(0.020)	(0.025)		(0.021)	(0.021)	(0.025)
Observations	60	60	60	60	60	60	60	60
Adj. R^2	0.141	0.418	0.457	0.478	0.042	0.182	0.312	0.432
Standard errors adjusted for clustering	No	No	No	session	No	No	No	session

Given the above impact of greed on PGR, I next examine the potential benefits if participants had delayed selling their winning stocks by one or more periods. The actual average final portfolio value per participant was $2,092, which represents a 4.62% increase relative to the initial $2,000 endowment. As shown in Figure 2, if participants had postponed their winner sales by one period, the average portfolio value would have increased to $2,117, an improvement of 1.24 percentage points relative to the actual outcome. Extending the delay to four periods yields an average hypothetical portfolio value of $2,149, corresponding to a 7.46% return, which is economically large in the context of a ten-period trading simulation.

Figure 2. Average Portfolio Value (Per Participant)

This figure shows the average final portfolio value per participant across the 60 student traders. The 'No delay' bar indicates the actual average portfolio value based on participants' realised trades. The x-period delay bars show the hypothetical average portfolio value if participants had postponed their sales of winning stocks by x periods.



4.4.3 Robustness Checks

In this section, I provide robustness checks for our main results on the effect of the greed on the disposition effect.

In Tables 4.4 and 4.5, I measured the disposition effect (DE) using the first-in-first-out (FIFO) rule to classify realised sales as gains or losses. Since gain or loss classification can depend on the reference purchase price, I conduct robustness checks using alternative benchmarks. I re-estimate equation (1) using these five approaches. Table 4.6 reports the results across these five alternative measures. In all specifications, the coefficient on greed remains positive and statistically significant, with effect sizes ranging from 0.085 (AP) to 0.228 (Alpha). These findings confirm that greed robustly predicts the disposition effect irrespective of how gains and losses are defined. In other words, the link between greed and DE is not an artefact of the measurement approach but reflects a consistent behavioural pattern across methodologies.

Table 4.6. The Impacts of Greed on Alternative Measures of the Disposition Effect

The table provides estimation results from an OLS regression that investigates the impact of greed on the disposition effect (DE), along with other control variables. I use five different approaches to define reference purchase prices gain/loss calculations. AP denotes the average purchase price; VWAP denotes is the value-weighted average purchase price; LIFO is based on the last-in-first-out approach, FHS is the possibilities-based approach proposed by Fischbacher, Hoffmann, and Schudy (2017); and Alpha is the approach proposed by Weber and Camerer (1998). Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1) AP	(2) VWAP	(3) LIFO	(4) FHS	(5) Alpha
Intercept	0.424*	0.495*	0.217	0.553**	1.176
	(0.219)	(0.249)	(0.266)	(0.245)	(0.742)
Greed	0.085**	0.089**	0.112***	0.089**	0.228**
	(0.030)	(0.039)	(0.042)	(0.036)	(0.108)
Loss Aversion	0.045*	0.045*	0.069**	0.032	0.044
	(0.024)	(0.025)	(0.026)	(0.023)	(0.068)
Risk Preference	-0.095***	-0.101***	-0.071**	-0.102***	-0.076
	(0.027)	(0.029)	(0.032)	(0.026)	(0.078)
Maximization	-0.058**	-0.069**	-0.052*	-0.071**	-0.136*
	(0.029)	(0.031)	(0.032)	(0.028)	(0.083)
Trading Experience	-0.54**	-0.060**	-0.066**	-0.051**	-0.161**
	(0.022)	(0.024)	(0.025)	(0.022)	(0.064)
Age	0.01**	0.009**	0.011**	0.007*	0.02*
	(0.010)	(0.005)	(0.004)	(0.004)	(0.012)
Gender	-0.071*	-0.076*	-0.078*	-0.056*	-0.408**
	(0.047)	(0.050)	(0.052)	(0.046)	(0.135)
Income	-0.028	-0.022	-0.016	-0.02	-0.054
	(0.025)	(0.026)	(0.028)	(0.024)	(0.072)
Education	-0.03	-0.008	-0.033	-0.005	-0.112
	(0.030)	(0.026)	(0.027)	(0.023)	(0.071)
Observations	60	60	60	60	60
Adj. R^2	0.585	0.59	0.556	0.584	0.356

Table 4.7 presents robustness tests assessing whether the relationship between greed and trading behaviour is sensitive to alternative definitions of the disposition effect (DE). Panel A reports regressions using the proportion of gains realised (PGR) as the dependent variable, while Panel B reports regressions for the proportion of losses realised (PLR). Four alternative

computation methods are employed: the average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), and the Fischbacher, Hoffmann, and Schudy (2017) approach (FHS). All models include centred greed and a full set of control variables, with robust standard errors. By construction, the α-measure of the disposition effect cannot be decomposed into separate PGR and PLR components, and is therefore not included in these panel-specific regressions.

Panel A shows that greed is positive and highly significant in every specification. The estimated coefficients range from 0.081 to 0.102 ($p<0.01$), confirming that higher greed reliably predicts a greater tendency to realise profitable positions. The adjusted R^2 values (0.416 to 0.504) demonstrate substantial explanatory power. The consistency of magnitude and significance across all four DE measures affirms that the positive link between greed and gain realisation is not an artefact of any specific method. This robustness provides strong evidence that greed systematically enhances investors' propensity to realise positive outcomes, in line with realisation-utility theory (Barberis and Xiong, 2009) and the notion that greedy individuals display heightened sensitivity to immediate reward (Seuntjens et al., 2016). By contrast, Panel B shows that greed exhibits a negative but statistically insignificant association with PLR across all four specifications. This suggests that while greed strongly amplifies investors' tendency to lock in gains, it exerts little or no influence on their willingness to realise losses.

Table 4.7. Regression of PGR and PLR for Alternative DE Calculations

Panel A provides OLS regression results in which the dependent variable is proportion of realised gains (PGR), measured as PGR=RG/ (RG+PG) where RG being the realised gains and PG being the paper gains. Panel B provides OLS regression results in which the dependent variable is proportion of realised gains (PLR), measured as PLR=RL/ (RL+PL) where RL being the realised losses and PL being the paper losses. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. I use four different approaches to define reference purchase prices gain calculations. AP denotes the average purchase price; VWAP denotes is the value-weighted average purchase price; LIFO is based on the last-in-first-out approach, FHS is the possibilities-based approach proposed by Fischbacher et al. (2017). The alpha measure does not account for realised or paper gains/losses. Greed and control variables are defined as in Appendix A. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. PGR for Alternative DE Calculations

	(1) AP	(2) VWAP	(3) LIFO	(4) FHS
Intercept	0.682***	0.714***	0.741***	0.683***
	(0.036)	(0.217)	(0.234)	(0.225)
Greed	0.081***	0.090***	0.102***	0.085**
	(0.076)	(0.032)	(0.035)	(0.032)
Controls	yes	yes	yes	yes
Observations	60	60	60	60
Adj R^2	0.484	0.504	0.416	0.502

Panel B. PLR for Alternative DE Calculations

	(1) AP	(2) VWAP	(3) LIFO	(4) FHS
Intercept	0.258	0.219	0.523***	0.131
	(0.162)	(0.164)	(0.191)	(0.141)
Greed	-0.008	-0.016	-0.009	-0.009
	(0.030)	(0.032)	(0.035)	(0.027)
Controls	yes	yes	yes	yes
Observations	60	60	60	60
Adj R^2	0.383	0.403	0.411	0.351

4.5 Conclusion

This study makes several empirical contributions to the literature on behavioural finance and investment decision-making. I document a new factor, greed, that can influence individuals' stock trading behaviour, particularly by amplifying investors' propensity to realise gains prematurely, thereby intensifying the disposition effect. By establishing greed as a measurable and significant factor in investment decision-making, this study extends prospect theory's framework (Kahneman and Tversky, 1979) and refine disposition effect theory through the incorporation of this crucial emotional element.

This study makes several primary contributions. First, I enhance the theoretical understanding of behavioural biases by demonstrating how greed interacts with cognitive biases in financial decision-making, building upon the foundational work of Shefrin and Statman (1985). Notably, the findings reveal a nuanced relationship between greed and trading behaviour in which greed intensifies the premature realization of gains. This suggests that greed heightens the urgency to realise gains, whereas its influence on loss realisation is weak. These differential effects of greed on gain and loss realization provide novel insights into the psychological mechanisms driving the disposition effect, supporting earlier research suggesting that greed has complex effects on individual financial well-being (Seuntjens et al., 2016).

Despite these findings, several limitations should be acknowledged when interpreting the results. One limitation of the study is that the sample consists primarily of relatively young participants, with an average age of approximately 25 years. Younger participants may differ from older investors in financial experience, trading behaviour, and risk perception, which may affect the external validity of the findings. However, the relevance of the sample should be considered not only in terms of age but also in relation to investor experience. Prior literature documents the disposition effect across a wide range of investor groups, including retail investors, professional investors, and futures traders, suggesting that the bias itself is not confined to a particular age cohort or investor category (Locke and Mann, 2005; Dhar and Zhu, 2006; Vaarmets et al., 2019). Many retail investors, particularly in New Zealand, are relatively inexperienced participants in equity markets, especially following the substantial increase in retail investing activity after COVID-19. The rapid growth of retail investment platforms has introduced large numbers of novice investors into the market, many of whom may exhibit behavioural characteristics similar to those observed among younger and less experienced participants. Consequently, the experimental setting may still capture behavioural tendencies relevant to a substantial segment of contemporary retail investors. Nevertheless, caution should be exercised when generalising the findings to highly experienced institutional or professional investors. Future research could examine whether the relationship between greed and the disposition effect differs across investors with varying levels of trading experience and market sophistication.

These findings suggest that greed influences selling behaviour primarily through acquisitive mechanisms linked to reward salience, realisation utility, and preference for immediate gain realisation. Greedy investors appear to derive stronger psychological satisfaction from securing realised gains, which increases the tendency to sell winning positions prematurely. By contrast, the weaker effect on loss realisation suggests that retentive motives associated with attachment to existing wealth may operate differently from acquisitive motives linked to reward seeking.

In addition, the findings offer practical insights for investors, advisors, and educators, while recognising the limits of what can be inferred for trading-platform design. For individual investors and financial advisors, the results show that greed is a reliable psychological marker for identifying those who are especially prone to the premature realisation of gains. Understanding a client’s acquisitive tendencies can therefore help advisors anticipate situations in which investors are most vulnerable to the disposition effect and provide more tailored guidance. These insights reinforce the value of incorporating psychological assessments into advisory relationships, not to label clients as "greedy," but to better understand the motivational forces shaping their trading behaviour.

For market designers and institutions, the findings must be considered alongside existing business models. Trading platforms generate revenue from trading activity, making it commercially unlikely that they would introduce features aimed at discouraging trades influenced by greed. A more realistic implication of the evidence is that some investors, particularly those with strong acquisitive motives, may struggle to manage their own trading biases effectively. For such individuals, relying on external structure or professional management may offer a practical way to mitigate the behavioural tendencies associated with greed.

Finally, the results contribute to financial education efforts by demonstrating that modest adjustments to selling behaviour can meaningfully improve investment outcomes. Educators and policymakers can incorporate these insights into programmes aimed at helping investors recognise and manage the disposition effect, particularly when acquisitive motives intensify the urge to secure gains too quickly. By clarifying how greed interacts with realisation behaviour, this study enhances the behavioural finance literature and provides a foundation for developing more targeted educational and advisory interventions that support more deliberate and informed financial decision-making.

5 Red Greed, Green Greed: How Colour Amplifies Greed in the Disposition Effect

5.1 Introduction

Salience refers to the phenomenon whereby attention is disproportionately drawn to certain features of the environment (Taylor and Thompson, 1982). According to salience theory (Bordalo et al., 2012), individuals overweight salient attributes when making decisions, becoming risk-seeking when upside potential is highlighted and risk-averse when downside risk is emphasised. In modern financial markets, where trading increasingly takes place through digital interfaces, visual elements such as colour affect the salience of information and have become central to how investors process information and make decisions (Hirshleifer and Teoh, 2003; Barber and Odean, 2008). A growing body of research supports the view that salience shapes investor behaviour. For example, altering the visual prominence of purchase price information has been shown to reduce the disposition effect by up to 25% (Frydman and Rangel, 2014).

Among the various forms of salience, colour has proven to be particularly influential (Elliot, Fairchild, and Franklin, 2015; Mehta and Zhu, 2009). Red is typically associated with caution, avoidance, and heightened sensitivity to negative outcomes (Elliot et al., 2007), while green is linked to approach motivation and positive affect (Lichtenfeld et al., 2012; Elliot and Maier, 2014). In financial settings, presenting losses in red has been found to reduce risk-taking (Bazley et al., 2021). As a cognitive bias that potentially reduces the wealth of investors, finding ways, such as changing the salience of key information, to mitigate or attenuate the disposition effect offers the possibility of benefiting investors.

This chapter extends the analysis by examining how colour-induced salience interacts with individual greed. Greed strengthens the motivational pull toward cues that signal gains or losses, while salience determines which cues are most prominent. When motivation and attention align, the effect of each is magnified. Therefore, red and green price displays should have stronger behavioural consequences among greedier investors. Green cues intensify acquisitive motives in the domain of gains, while red cues intensify retentive motives in the domain of losses. I investigate whether red and green price displays amplify or attenuate the impact of greed on trading behaviour. By combining trait-level variation in greed with situational variation in visual cues, the study provides a more nuanced understanding of how psychological and contextual factors jointly shape the disposition effect.

This study makes several important contributions to the literature on behavioural finance and decision-making. First, it highlights that greed is a psychological driver of biased trading behaviour, yet it has received relatively limited empirical attention in finance. By establishing greed as a systematic determinant of the disposition effect, the study broadens the range of psychological traits considered in models of investor behaviour. Second, I confirm salience theory by demonstrating how visual cues, specifically colour, can systematically alter financial decision-making through attention allocation mechanisms. Third, the study provides a novel contribution by showing that internal motives such as greed and external visual cues such as colour do not operate in isolation but instead work together to shape investment behaviour. By measuring individual differences in greed and examining their moderating effects on colour-induced trading biases, I show that psychological traits can significantly amplify or attenuate the impact of visual salience.

5.2 Hypotheses Development

Salience theory provides a comprehensive foundation for understanding how visual presentation formats systematically influence investor decision-making by guiding selective attention and triggering automatic emotional responses. Perceptually prominent features, such as vivid colours or unusually positioned elements, “pop out” of a visual field and disproportionately influence subsequent judgments (Theeuwes, 1994). In economic choice contexts, this means that attributes made salient through visual or contextual cues receive excessive weight relative to equally relevant but less salient information (Bordalo et al., 2013, 2020). Evidence from consumer choice, probability weighting, financial media, and retirement defaults demonstrates that individuals reliably overweight salient information even when fully aware that such cues should not alter optimal decisions (Huber et al., 1982; Tversky and Simonson, 1993; Prelec, 1998; Tetlock, 2007; Da, Engelberg, and Gao, 2011; Engelberg and Parsons, 2011; Solomon et al., 2014; Benartzi and Thaler, 1995; Carroll et al., 2009; Chetty et al., 2014).

Salience affects behaviour along two pathways. First, salient information becomes more cognitively accessible and dominates working memory, leading individuals to overweight this information in decisions (Tversky and Kahneman, 1973; Higgins, 1996). Second, salient cues trigger stronger emotional responses that can bypass deliberative reasoning (Loewenstein et al., 2001; Slovic et al., 2007). These processes make salience-induced distortions highly persistent, even when individuals consciously recognise that presentation format is normatively irrelevant (Strack and Deutsch, 2004).

In financial settings, colour-coded price displays represent a particularly powerful form of visual salience. Red has been shown to increase avoidance motivation, heighten perceived risk, and evoke negative affect (Elliot, Fairchild, and Franklin, 2015; Bazley et al., 2021). Exposure to red cues reduces risk-taking and induces more pessimistic expectations (Elliot et al., 2007). In contrast, green activates approach motivation, positive evaluations, and reward-seeking tendencies (Elliot and Maier, 2012; Lichtenfeld et al., 2012, 2019). Studies in environmental and cognitive psychology show that green stimuli promote exploration, increase perceived opportunities, and strengthen goal pursuit (Akers et al., 2012; Briki and Majed, 2019; Bouhassoun et al., 2023; Kawai, 2023). In the trading context, salient colour cues can therefore direct investor attention to gains or losses and shape subsequent realisation behaviour (Dierick et al., 2019; Frydman and Wang, 2020).

Greed interacts with these attention and emotion mechanisms in systematically meaningful ways. Greed is characterised by an insatiable desire for more, heightened sensitivity to fluctuations in wealth, and a strong motivation to retain accumulated resources (Seuntjens et al., 2015, 2019). Greedy individuals engage in intensified monitoring of their financial positions, making them more responsive to vivid cues that highlight changes in value. When losses are displayed in red, the perceptual vividness of value depletion may activate a protective wealth-preservation motive. Under this mechanism, greedy investors may realise losses more quickly to prevent further erosion of their holdings, leading to a reduction in the disposition effect (H1a).

However, greed's retention motive can also amplify loss persistence. Greedy individuals often derive utility from maintaining possession and may experience heightened emotional attachment to losing positions (Seuntjens et al., 2019). When losses are made salient in red, this emotional activation may intensify loss-recovery motives, encouraging investors to hold their losing assets in hopes of recouping value. This mechanism strengthens the disposition effect by promoting resistance to loss realisation (Shefrin and Statman, 1985; Sleesman et al., 2018).

Therefore, I propose a competing hypothesis:

H1a: Investors exhibiting higher levels of greed will sell losing stocks faster when losing assets are made more salient (i.e., in colour red), leading to a smaller disposition effect.

H1b: Investors exhibiting higher levels of greed will sell losing stocks more slowly when losing assets are made more salient (i.e., in colour red), leading to a larger disposition effect.

Our second hypothesis focuses on the interaction between greed and gain salience. Green displays have been shown to activate approach-oriented tendencies and heighten reward sensitivity (Elliot and Maier, 2014). Brief exposure to green enhances creative performance in tasks that require exploration, which is interpreted as arising from associations between green and growth-oriented goals (Lichtenfeld et al., 2012; Lichtenfeld et al., 2019). Exposure to green environments or green visual stimuli also improves mood and reduces perceived effort during physical activity, further supporting the link between green and approach motivation (Akers et al., 2012; Briki and Majed, 2019). Recent evidence shows that green is consistently associated with opportunity, positive valence and good decisions, in contrast with red which is more closely tied to avoidance and negative evaluation (Bouhassoun et al., 2023; Kawai, 2023).

For greedy investors, whose utility functions are particularly sensitive to monetary rewards, the visual prominence of green-coloured gains should accelerate this realization process. This effect aligns with findings from Dierick et al. (2019), who show that increased attention to winning stocks amplifies the disposition effect. While gain salience may prompt immediate realisation through heightened reward sensitivity (H2a), greed's acquisition motive may also reinforce confidence in profitable positions, encouraging continued holding for greater accumulation (H2b).

H2a: Investors exhibiting higher levels of greed will sell winning stocks faster when winning assets are made more salient (i.e., in colour green), leading to a higher disposition effect.

H2b: Investors exhibiting higher levels of greed will sell winning stocks more slowly when winning assets are made more salient (i.e., in colour green), leading to a smaller disposition effect.

5.3 Method

5.3.1 Experimental Design

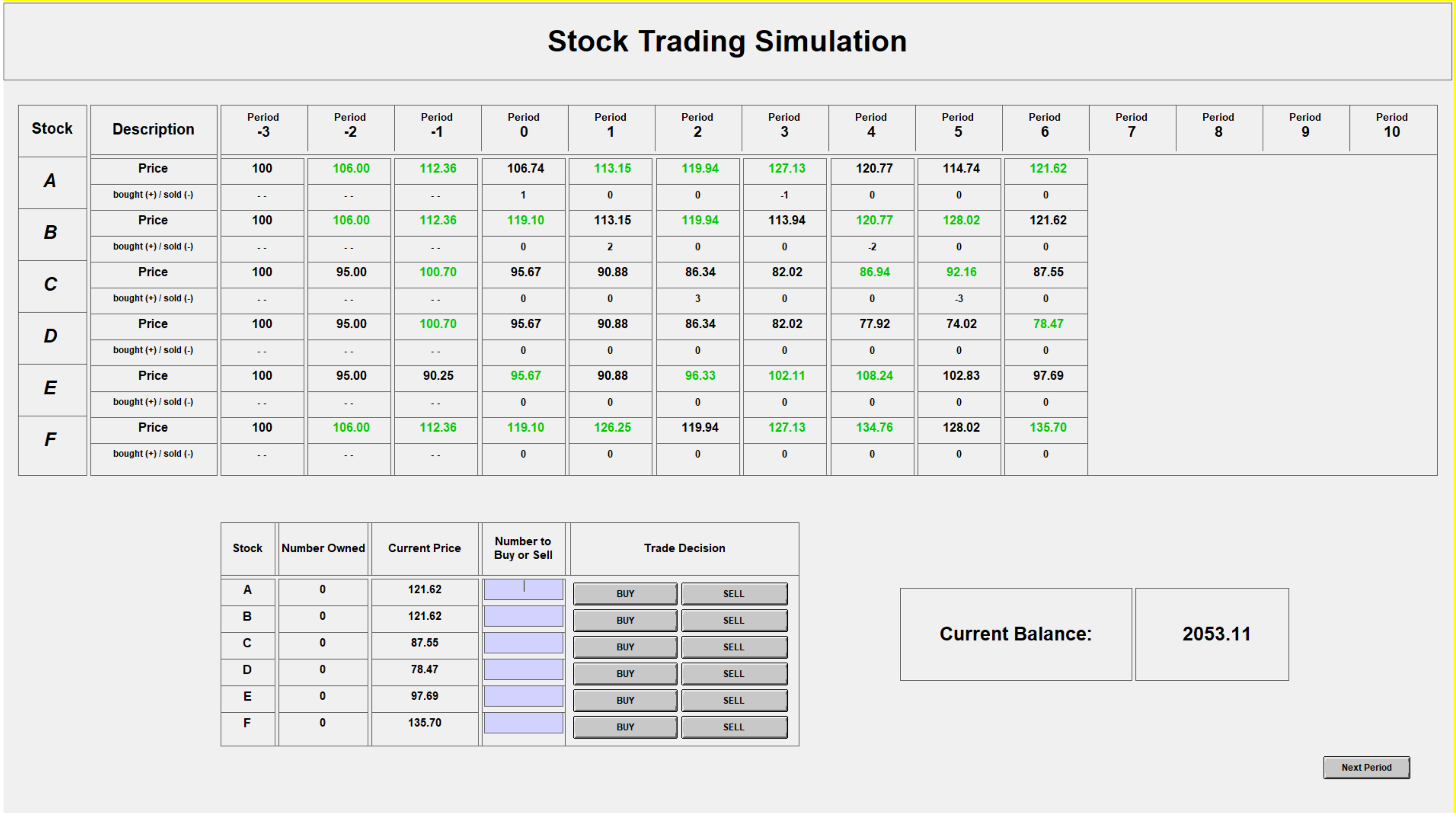
This study investigates how visual price indicators influence the relationship between greed and disposition effect in a simulated trading environment. The experimental procedures and measurement framework are consistent with those described in Chapter 3. Figure 3 shows the trading interface used in the z-Tree experiment.

To conduct this experiment I utilise three conditions, no colour induced salience, green salience, and red salience. I utilise the data of the study 1's participants for whom all information was displayed in black to act as the no colour induced salience control sample. In addition, 60 additional participants were recruited with 30 randomly assigned to get gains shown in green, with the other 30 participants getting losses displayed in red. This design allows for a direct comparison between the original baseline and the colour salience treatment.

Study 2 followed the same trading task structure described in Study 1, including the 14-period price sequence and $2,000 endowment. What distinguishes this study is the introduction of a colour-salience manipulation. Participants were allocated to two visual display conditions. In the green-signal condition (n = 30), prices changed from black to green when a stock increased. In the red-signal condition (n = 30), prices changed from black to red when a stock decreased. The control condition consists of the 60 participants from Study 1, where stock prices remained black regardless of price movement. Apart from the colour manipulation, all other features of the task were identical across conditions, ensuring that performance differences can be attributed to visual salience.

Figure 3. Study 2 Trading Interface

Panel A shows an example of the trading platform screen when the stock price increases and is displayed in green. Panel B shows an example of the trading platform screen when the stock price decreases and is displayed in red.



Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	100	106.00	112.36	106.74	113.15	119.94	127.13	120.77	114.74	121.62				
	bought (+) / sold (-)	--	--	--	1	0	0	-1	0	0	0				
B	Price	100	106.00	112.36	119.10	113.15	119.94	113.94	120.77	128.02	121.62				
	bought (+) / sold (-)	--	--	--	0	2	0	0	-2	0	0				
C	Price	100	95.00	100.70	95.67	90.88	86.34	82.02	86.94	92.16	87.55				
	bought (+) / sold (-)	--	--	--	0	0	3	0	0	-3	0				
D	Price	100	95.00	100.70	95.67	90.88	86.34	82.02	77.92	74.02	78.47				
	bought (+) / sold (-)	--	--	--	0	0	0	0	0	0	0				
E	Price	100	95.00	90.25	95.67	90.88	96.33	102.11	108.24	102.83	97.69				
	bought (+) / sold (-)	--	--	--	0	0	0	0	0	0	0				
F	Price	100	106.00	112.36	119.10	126.25	119.94	127.13	134.76	128.02	135.70				
	bought (+) / sold (-)	--	--	--	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	121.62		BUY	SELL
B	0	121.62		BUY	SELL
C	0	87.55		BUY	SELL
D	0	78.47		BUY	SELL
E	0	97.69		BUY	SELL
F	0	135.70		BUY	SELL

Current Balance: 2053.11

Next Period

Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	100	106.00	100.70	95.67	90.88	86.34	91.52	97.01	92.16	97.69				
	bought (+) / sold (-)	- -	- -	- -	1	0	0	-1	0	0	0				
B	Price	100	95.00	100.70	95.67	101.40	107.49	102.11	97.01	92.16	87.55				
	bought (+) / sold (-)	- -	- -	- -	0	2	0	0	-2	0	0				
C	Price	100	106.00	112.36	119.10	126.25	119.94	113.94	108.24	102.83	109.00				
	bought (+) / sold (-)	- -	- -	- -	0	0	3	0	0	-3	0				
D	Price	100	95.00	90.25	85.74	90.88	86.34	82.02	77.92	74.02	70.32				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
E	Price	100	106.00	100.70	106.74	101.40	96.33	102.11	108.24	114.74	121.62				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
F	Price	100	106.00	100.70	106.74	113.15	107.49	113.94	120.77	128.02	121.62				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	97.69		BUY	SELL
B	0	87.55		BUY	SELL
C	0	109.00		BUY	SELL
D	0	70.32		BUY	SELL
E	0	121.62		BUY	SELL
F	0	121.62		BUY	SELL

Current Balance:	1935.74

Next Period

5.4 Results

5.4.1 Descriptive Statistics

Table 5.1 presents descriptive statistics for the full sample of 120 participants, categorized into three subsamples shown in Panels A, B and C, which are, *Black* (control, *N*=60), *Red* (*N*=30), and *Green* (*N*=30). The mean disposition effect (DE) varies markedly across groups. Participants in the *Green* condition display the strongest bias, with an average DE of 0.34, indicating that they realised gains 34 percentage points more often than losses. In contrast, participants in the *Red* condition exhibit a negative mean DE of -0.07, implying that, they realised losses more frequently than gains. The control group falls in between, with a mean DE of 0.15. These patterns suggest that colour cues exert a directional influence on trading behaviour, amplifying or dampening the disposition effect.

The *Green* condition also shows the highest mean proportion of gains realised (PGR=0.56), reinforcing the view that green cues heighten attention to gains and accelerate profit-taking. Conversely, the *Red* condition exhibits the highest PLR (0.44), consistent with greater willingness to realise losses when they are visually highlighted in red. However, PGL for the *Green* condition, and the PGR for the *Red* condition are roughly the same as the control group. This suggests that the effect on DE is driven by trading consistent with the information that is being made more salient.

Table 5.1. Descriptive Statistics

Panel A presents the summary statistics for the control group where all price information appeared in black text regardless of movement direction. Panel B presents the summary statistics for *Red* condition where price decreases were displayed in red text while prices remained black when increasing. Panel C presents the summary statistics for *Green* condition where price increases were displayed in green text while prices remained black when decreasing. Variables included *Disposition Effect* (FIFO), proportion of gains realised (*PGR*), proportion of losses realised (*PLR*), *Greed, Loss Aversion, Risk Preference, Maximization, Trading Experience, Age, Gender, Income and Education*.

Panel A. Descriptive Statistics for *Black* (N=60)

Variable	Obs	Mean	Median	Stdev	Min	Max
Disposition Effect	60	0.15	0.15	0.31	-0.90	0.85
PGR	60	0.37	0.38	0.21	0.00	0.85
PLR	60	0.22	0.	0.20	0.00	0.90
Greed	60	3.11	3.14	0.75	1.43	5.00
Loss Aversion	60	4.75	5.00	1.10	2.00	7.00
Risk Preference	60	2.28	2.00	1.00	1.00	4.00
Maximization	60	4.72	4.72	0.99	2.66	6.77
Trading Experience	60	1.98	2.00	1.15	1.00	4.00
Age	60	25.01	21.00	6.99	18.00	52.00
Gender	60	0.46	0.00	0.50	0.00	1.00
Income	60	2.45	2.00	1.08	1.00	6.00
Education	60	1.73	2.00	1.11	0.00	4.00

Panel B. Descriptive Statistics for *Red* (N=30)

Variable	Obs	Mean	Median	Stdev	Min	Max
Disposition Effect	30	-0.07	-0.07	0.48	-0.75	0.89
PGR	30	0.38	0.35	0.27	0.00	1.00
PLR	30	0.44	0.28	0.39	0.00	1.00
Greed	30	3.39	3.14	0.92	2.00	5.00
Loss Aversion	30	4.43	5.00	1.41	1.00	7.00
Risk Preference	30	2.17	2.00	0.83	1.00	4.00
Maximization	30	4.64	4.88	1.01	2.44	6.78
Trading Experience	30	2.93	2.00	1.20	1.00	4.00
Age	30	25.36	22.5	6.86	18.00	45.00
Gender	30	0.60	1.00	0.56	0.00	1.00
Income	30	2.60	2.00	1.13	1.00	5.00
Education	30	1.53	1.00	1.11	0.00	4.00

Table 5.1 — *Continued*

Panel C. Descriptive Statistics for *Green* (N=30)						
Variable	Obs	Mean	Median	Stdev	Min	Max
Disposition Effect	30	0.34	0.52	0.48	-0.52	0.96
PGR	30	0.56	0.58	0.31	0.07	1.00
PLR	30	0.21	0.11	0.25	0.00	0.75
Greed	30	3.32	3.14	0.91	1.29	4.71
Loss Aversion	30	4.20	4.00	1.80	1.00	7.00
Risk Preference	30	2.30	2.00	0.87	1.00	4.00
Maximization	30	5.02	5.05	0.88	3.20	6.40
Trading Experience	30	2.26	1.50	1.41	1.00	4.00
Age	30	25.1	22.00	6.88	19.00	42.00
Gender	30	0.53	1.00	0.43	0.00	1.00
Income	30	2.53	2.00	1.11	1.00	5.00
Education	30	1.86	2.00	1.11	0.00	4.00

Table 5.2 reports univariate comparisons across experimental conditions using both t-tests and Wilcoxon rank-sum tests. Panel A focuses on the *Black* versus *Red* comparison. Here, DE is significantly lower in the *Red* group (-0.07 vs. 0.15; $p<0.05$). This difference is driven by the higher PLR in *Red* (0.44 vs. 0.22; $p<0.01$). These results suggest that red salience attenuates investors' reluctance to sell at a loss, effectively reversing the usual disposition effect. Panel B compares *Black* and Green conditions. DE is significantly higher in the *Green* group (0.34 vs. 0.15; $p<0.10$), accompanied by a substantially higher proportion of gains realised (0.56 vs. 0.37; $p<0.05$). This pattern is consistent with green cues intensify attention to gains, strengthening premature gain realisation. Trading experience also differs significantly between the *Black* and *Red* groups (1.98 vs. 2.93; $p<0.001$). Although this difference does not undermine the colour effects observed in Panel A, it indicates that the *Red* group is more experienced on average. In Panel B, however, trading experience does not differ significantly between the *Black* and *Green* groups, reducing concerns about experience-based confounds in the *Green* comparison.

Panel C reports direct comparisons between the *Red* and *Gree*n treatment conditions. Relative to the *Green* condition, the *Red* condition is associated with a significantly lower disposition effect and proportion of gains realised, alongside a significantly higher proportion of losses realised. The mean disposition effect decreases from 0.34 under *Green* framing to -0.08 under *Red* framing, with the difference statistically significant under both parametric and non-parametric tests. Similarly, PGR is significantly lower and PLR significantly higher under *Red* framing relative to *Green* framing. These results indicate that positive and negative colour cues generate economically and statistically distinct trading responses, consistent with colour-based salience affecting investors' gain-realisation behaviour.

Table 5.2. Univariate Analysis

Panel A compares the *Black* and *Red* conditions, Panel B compares the *Black* and *Green* conditions, and Panel C compares the *Red* and *Green* conditions. In the control group, all price information appeared in black text irrespective of price movement. In the *Red* condition, price decreases were displayed in red while increases remained black, whereas in the *Green* condition, price increases were displayed in green while decreases remained black. Variables included *Disposition Effect* (FIFO), proportion of gains realised (*PGR*), proportion of losses realised (*PLR*), *Greed, Loss Aversion, Risk Preference, Maximization, Trading Experience, Age, Gender, Income and Education*. Reported statistics show mean, median, mean differences, t-tests, and Wilcoxon rank-sum *p*-values.

Panel A: *Black* vs *Red*							
	Black		*Red*		Difference		
Variable	Mean	Median	Mean	Median	Mean	*t*-test *p*-value	Wilcoxon *p*-Value
Disposition Effect	0.15	0.15	-0.07	-0.07	0.22	0.02**	0.021**
PGR	0.37	0.38	0.38	0.35	-0.01	0.84	0.902
PLR	0.22	0.20	0.44	0.28	-0.22	0.01***	0.011**
Greed	3.11	3.14	3.39	3.14	-0.28	0.14	0.272
Loss Aversion	4.75	5.00	4.43	5.00	0.32	0.21	0.408
Risk Preference	2.28	2.00	2.17	2.00	0.11	0.60	0.618
Maximization	4.72	4.72	4.64	4.88	0.08	0.75	0.716
Trading Experience	1.98	2.00	2.93	2.00	-0.95	0.00**	0.000**
Age	25.01	21.00	25.36	22.5	-0.35	0.83	0.808
% Male	0.46	0.00	0.60	1.00	-0.14	0.21	0.214
Income	2.45	2.00	2.60	2.00	-0.15	0.55	0.526
Education	1.73	2.00	1.53	1.00	0.20	0.44	0.546

Table 5.2 — *Continued*

Panel B: *Black* vs *Green*							
	Black		*Green*		Difference		
Variable	Mean	Median	Mean	Median	Mean	*t*-test *p*-value	Wilcoxon *p*-Value
Disposition Effect	0.15	0.15	0.34	0.52	-0.19	0.07*	0.082*
PGR	0.37	0.38	0.56	0.58	-0.19	0.02**	0.019**
PLR	0.22	0.20	0.21	0.095	0.01	0.89	0.851
Greed	3.11	3.14	3.32	3.14	-0.21	0.30	0.320
Loss Aversion	4.75	5.00	4.20	4.00	0.55	0.19	0.201
Risk Preference	2.28	2.00	2.30	2.00	-0.02	0.90	0.912
Maximization	4.72	4.72	5.02	5.06	-0.30	0.11	0.101
Trading Experience	1.98	2.00	2.26	1.75	-0.28	0.24	0.255
Age	25.01	21.00	25.10	22.25	-0.09	0.94	0.949
% Male	0.46	0.00	0.53	1.00	-0.07	0.46	0.456
Income	2.45	2.00	2.53	2.00	-0.08	0.74	0.731
Education	1.73	2.00	1.86	1.50	-0.13	0.60	0.598

Table 5.2 — *Continued*

Panel C: *Red* vs *Green*							
	Red		Green		Difference		
Variable	Mean	Median	Mean	Median	Mean	*t*-test *p*-value	Wilcoxon *p*-Value
Disposition Effect	-0.08	-0.07	0.34	0.52	-0.42	0.002***	0.002***
PGR	0.38	0.35	0.56	0.59	-0.17	0.02**	0.03**
PLR	0.44	0.27	0.22	0.11	0.22	0.01**	0.02**
Greed	3.40	3.14	3.27	3.14	0.13	0.59	0.67
Loss Aversion	4.43	5.00	4.20	4.00	0.23	0.58	0.37
Risk Preference	2.17	2.00	2.30	2.00	-0.13	0.55	0.50
Maximization	4.64	4.89	5.03	5.06	-0.39	0.12	0.15
Trading Experience	3.80	3.50	3.37	3.00	0.43	0.47	0.54
Age	25.37	22.50	25.10	22.00	0.27	0.88	0.65
% Male	0.60	1.00	0.63	1.00	-0.03	0.81	0.79
Income	2.60	2.00	2.53	2.00	0.07	0.82	0.88
Education	1.53	1.00	1.87	2.00	-0.33	0.25	0.13

Table 5.3 reports the correlations coefficients among key variables.[19] The disposition effect (DE) is strongly and positively correlated with the PGR (0.76, p<0.01) and strongly and negatively correlated with the PLR (-0.78, p<0.01). Greed is significantly and positively associated with both DE (0.35, p<0.01) and PGR (0.45, p<0.01), but shows no significant relationship with PLR (0.07, p>0.10). This indicates that greed primarily operates through accelerating gain realization rather than influencing loss realization.

Loss aversion is modestly but significantly correlated with DE (0.22, p<0.05) and PGR (0.18, p<0.05), while being negatively related to PLR (-0.14, p<0.05). This pattern is consistent with prospect theory (Kahneman and Tversky, 1979), whereby loss-averse investors are reluctant to realise losses but more likely to lock in gains. Risk preference displays strong negative correlations with DE (-0.38, p<0.01) and PGR (-0.35, p<0.01), and a positive correlation with PLR (0.23, p<0.01). This suggests that more risk-tolerant individuals are inclined to maintain losing positions and less likely to realise gains prematurely, thereby dampening the disposition effect.

[19] Correlation coefficients for all subsamples are reported in Appendix F.

Table 5.3. Correlations Coefficients (N=120)

This table shows the correlations coefficients between these variables. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect											
2.PGR	0.76***										
3.PLR	-0.78***	-0.19**									
4. Greed	0.35***	0.45***	0.07								
5. Loss Aversion	0.22**	0.18**	-0.14**	0.04							
6. Risk Preference	-0.38***	-0.35***	0.23***	-0.25**	-0.19**						
7. Maximization	0.17	0.04*	0.05	0.43***	-0.13	0.02					
8. Trading Experience	-0.15*	-0.08*	0.18**	-0.09	-0.17	0.19**	-0.03				
9. Age	0.10**	0.02	-0.05	0.16**	0.08	-0.12	0.16*	0.05			
10. Gender	-0.24***	-0.18**	0.15	-0.06	-0.06	-0.04	-0.06	0.08	-0.11		
11. Income	-0.14	-0.12*	0.15	0.11	-0.1	0.11	0.12**	0.26**	0.15	0.11	
12. Education	0.02	0.02	-0.01	0.17*	-0.12	0.10**	0.08	0.1	0.60***	-0.16	0.25*

5.4.2 Regression Analysis

To investigate the impact of investors' greed levels on the disposition effect based on different colour coding for stock price presentation, I conducted the following OLS regression models:

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Colour_i + \beta_k X_{k,i} + \varepsilon \qquad (1)$$

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Colour_i + \beta_3 Colour_i \; x \; Greed_i + \beta_k X_{k,i} + \varepsilon \qquad (2)$$

where X_k denotes a vector of participants' characteristics and demographics as control variables. Following Study, I use centred greed in all regressions. Table 5.4 presents our baseline regression analysis examining the general impact of colour on the disposition effect.[20] Column (1) establishes that greed has a positive and significant association with the disposition effect (0.166, p<0.01), controlling for individual characteristics. This finding is consistent with Study 1 and confirms that individuals with higher greed levels tend to exhibit stronger disposition effects.

Column (3) extends our analysis by examining the interaction between greed and colour. The coefficient for greed remains significant but decreases slightly (0.140, p<0.05), though its magnitude decreases slightly relative to Columns (1)-(2) suggesting that introducing colour information modestly attenuates the direct influence of greed on the disposition effect. The interaction term (*Greed* × *Colour*) shows a positive but statistically insignificant coefficient.

Among control variables, loss aversion shows a consistent positive association with the disposition effect across all models (0.042, p<0.10), consistent with the notion that more loss-averse investors are reluctant to realise losses (Barberis and Xiong, 2009; Frydman and Rangel, 2023). This pattern mirrors the results observed in Study 1 (Chapter 4), reinforcing that loss aversion systematically predicts stronger realisation asymmetry across experimental contexts.

[20] I re-estimated Columns (1) - (3) using the standardised greed variable reported in Appendix G, and the results are robust to those presented in Table 5.4.

Risk preference continues to demonstrate a robust negative relationship (-0.116, $p<0.01$), in line with prior studies demonstrating that more risk-tolerant individuals are less prone to selling winners prematurely and thus exhibit weaker disposition biases (Odean, 1998; Dhar and Zhu, 2006). The gender effect is notably strong, with female participants exhibiting significantly lower disposition effects (-0.21, $p<0.01$) across all columns. This finding is not only consistent with Study 1 but also accords with extensive evidence that female investors tend to exhibit greater risk aversion and more disciplined trading behaviour (Barber and Odean, 2001; Charness and Gneezy, 2012).

Columns (4) to (6) repeat the analysis with standard errors clustered at the session level to account for potential within-session correlations. The key findings remain unchanged: greed continues to load positively and significantly, while the general colour variable remains insignificant. The persistence of results under clustered standard errors strengthens the robustness of our conclusions, indicating that they are not driven by session-specific effects.

Table 5.4. Overall Colour Influence on Disposition Effect

The table provides estimation results from an OLS regression that investigates whether colour situationally intensifies the impact of greed on the disposition effect (DE), along with other control variables. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. Colour is a dummy variable that takes a value of 1 if the stock price changes to red or green, and 0 if it remains constant at black. *Greed* and control variables are defined as in Appendix A. Columns (4) to (6) report estimates with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.516**	0.515**	0.494*	0.516**	0.516**	0.494*
	(0.268)	(0.272)	(0.278)	(0.238)	(0.250)	(0.261)
Greed	0.166***	0.166***	0.140**	0.166***	0.166***	0.140***
	(0.044)	(0.045)	(0.072)	(0.055)	(0.054)	(0.051)
Colour		0.001	0.002		0.001	0.002
		(0.980)	(0.071)		(0.780)	(0.074)
Greed x *Colour*			0.041			0.041
			(0.088)			(0.096)
Loss Aversion	0.042*	0.042*	0.043*	0.041	0.041	0.042
	(0.025)	(0.025)	(0.025)	(0.034)	(0.035)	(0.035)
Risk Preference	-0.116***	-0.116**	-0.116***	-0.116***	-0.116***	-0.116***
	(0.040)	(0.039)	(0.039)	(0.035)	(0.036)	(0.035)
Maximization	-0.028	-0.029	-0.024	-0.027	-0.027	-0.023
	(0.037)	(0.038)	(0.039)	(0.033)	(0.033)	(0.033)
Trading Experience	-0.021	-0.02	-0.022	-0.02	-0.02	-0.022
	(0.028)	(0.029)	(0.029)	(0.033)	(0.035)	(0.035)
Age	0.003	0.003	0.003	0.002	0.002	0.003
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Gender	-0.213***	-0.212***	-0.207***	-0.213***	-0.213***	-0.207***
	(0.068)	(0.067)	(0.069)	(0.056)	(0.056)	(0.057)
Income	-0.023	-0.025	-0.027	-0.024	-0.024	-0.026
	(0.034)	(0.033)	(0.034)	(0.027)	(0.028)	(0.027)
Education	-0.03	-0.03	-0.03	-0.029	-0.029	-0.029
	(0.039)	(0.039)	(0.018)	(0.037)	(0.037)	(0.036)
Observations	120	120	120	120	120	120
Adj. R^2	0.27	0.263	0.258	0.324	0.325	0.327
Standard errors adjusted for clustering	No	No	No	session	session	session

To further examine the influence of individual colours (red or green) on the disposition effect, I conducted the following OLS regression models:

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_k X_{k,i} + \varepsilon \quad (3)$$

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Green_i + \beta_k X_{k,i} + \varepsilon \quad (4)$$

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_3 Green_i + \beta_k X_{k,i} + \varepsilon \quad (5)$$

Table 5.5 provides a more nuanced analysis by disaggregating the colour variable into red and green conditions. The results suggest that specific colour stimuli significantly influence investors' trading behaviour. In Column (1), the coefficient on *Red* is -0.201 ($p<0.01$), and in Column (3) it strengthens to -0.232 ($p<0.01$). When *Red* is reintroduced in Column (5), the effect is again strongly negative (-0.283, $p<0.01$). These estimates suggest that when price decreases are highlighted in red, the DE falls by roughly 0.20-0.28 percentage points. This finding aligns with Bazley et al., (2021), who document that red displays in trading platforms reduce investors' risk-taking.

Conversely, the *Green* variable shows the opposite pattern. In Column (2), the coefficient is 0.248 ($p<0.01$), in Column (4) it remains positive at 0.231 ($p<0.01$), and in Column (5) it is 0.246 ($p<0.01$). The results indicate that when price increases are highlighted in green, the DE rises by about 0.23-0.25 units. Thus, green salience intensifies investors' attention to gains, heightening the psychological appeal of securing profits. This is consistent with the theoretical framework proposed by Frydman and Wang (2020) on the role of attention in trading behaviour. The opposing signs but comparable magnitudes of the red and green coefficients explain why the combined colour variable in Table 5.4 yielded no significant effect. These findings provide strong evidence that colour coding acts as a powerful visual cue that influences investor behaviour, with the specific colour carrying psychological significance that affects decision-making differently.[21]

[21] I re-estimated all models using the standardised greed variable reported in Appendix H, and the results are robust to those presented in Table 5.5.

Table 5.5. Individual Colour Influence on Disposition Effect

The table provides estimation results from an OLS regression that investigates whether red or green influences the disposition effect (DE), along with other control variables. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while green is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.641**	0.141	0.743**	0.541**	0.623***
	(0.301)	(0.273)	(0.298)	(0.213)	(0.237)
Greed			0.097**	0.298***	0.193***
			(0.044)	(0.038)	(0.039)
Red	-0.201***		-0.232***		-0.283 ***
	(0.075)		(0.074)		(0.077)
Green		0.248***		0.231***	0.246***
		(0.078)		(0.059)	(0.074)
Loss Aversion	0.048*	0.050*	0.050*	0.038*	0.046**
	(0.028)	(0.028)	(0.026)	(0.021)	(0.022)
Risk Preference	-0.163***	-0.138***	-0.146***	-0.070**	-0.121***
	(0.036)	(0.040)	(0.036)	(0.032)	(0.034)
Maximization	-0.039	0.012	-0.059*	-0.102***	-0.060**
	(0.035)	(0.040)	(0.035)	(0.034)	(0.033)
Trading Experience	-0.023	-0.011	-0.018	-0.033	0.01
	(0.029)	(0.032)	(0.029)	(0.024)	(0.025)
Age	0.007	0.007	0.007	0.013**	0.006
	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)
Gender	-0.184***	-0.188***	-0.203***	-0.210***	-0.235***
	(0.065)	(0.072)	(0.064)	(0.055)	(0.058)
Income	-0.033	-0.013	-0.042	0.006	-0.024
	(0.031)	(0.037)	(0.031)	(0.028)	(0.029)
Education	-0.065**	-0.067**	-0.07**	-0.044	-0.067**
	(0.038)	(0.037)	(0.038)	(0.029)	(0.034)
Observations	90	90	90	90	120
Adj. R^2	0.387	0.272	0.416	0.581	0.447

Table 5.6 presents important findings regarding the interaction effects between colour coding and greed on disposition effect. I estimate the interaction effect of colour in a regression framework using the following models:

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_3 Red_i \ x \ Greed_i + \beta_k X_{k,i} + \varepsilon \quad (6)$$

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Green_i + \beta_3 Green_i \ x \ Greed_i + \beta_k X_{k,i} + \varepsilon \quad (7)$$

$$DE_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_3 Green_i + \beta_4 Red_i \ x \ Greed_i + \beta_5 Green_i \ x \ Greed_i + \beta_k X_{k,i} + \varepsilon \quad (8)$$

It is important to distinguish between the direct colour effects and the interaction effects reported in Table 5.6. The direct colour coefficients (*Red* and *Green*) capture the average impact of colour cues on the disposition effect when greed is held constant at its centred value. In contrast, the interaction terms (*Red* × *Greed* and *Green* × *Greed*) capture whether colour changes the strength of the relationship between greed and the disposition effect. Therefore, the interaction coefficients should not be interpreted as standalone colour effects, but rather as moderating effects showing how colour alters the behavioural influence of greed on trading decisions.

The baseline effect of greed remains consistently positive and significant across all columns (0.171-0.182, $p<0.01$)[22]. Column (1) focuses on the interaction between red colour (price decreases), and greed (*Red* × *Greed*). The coefficient of greed in Column (1) is 0.177, indicating that when *Red*=0 greed increases DE by 17.7%. The *Red* × *Greed* coefficient is -0.174 ($p<0.05$), indicating that when losses are highlighted in red the effect of greed is nearly completely mitigated (0.177-0.174=0.003). This suggests that the use of red for losses draws attention to losses and counteracts the reluctance of greedy investors to realise these losses. This is consistent with H1a.

[22] I re-estimated all models using the standardised greed variable reported in Appendix I, and the results are robust to those presented in Table 5.6.

Column (2) examines the interaction between green colour and greed (*Green* × *Greed*), showing a significant positive interaction effect (β=0.268, p<0.01). This result supports H2a. The strong positive coefficient suggests that green colour enhances the relationship between greed and the disposition effect, potentially by amplifying the tendency of greedy investors to prematurely sell winning stocks. This model demonstrates remarkably strong explanatory power (Adjusted R^2=0.654), indicating that the interplay between green colour and greed captures a substantial portion of the variation in the disposition effect. The direct effect of green colour remains significantly positive (0.223, p<0.01), indicating that green cues increase the disposition effect even when greed is held at its centred level.Column (3) incorporates both colour interactions simultaneously, confirming that the opposing interaction effects remain robust in a comprehensive model. The interaction between *Greed* and *Red* remains negative (-0.195, p<0.05), while the interaction between *Greed* and *Green* remains positive (0.241, p<0.01). The direct effects of red (-0.251, p<0.01) and green (0.224, p<0.01) are both significant, indicating that red reduces and green amplifies the disposition effect, even after accounting for interactions with greed. These findings indicate that colours exert both direct effects on the disposition effect and moderating effects on the relationship between greed and trading behaviour. The explanatory power of this comprehensive model (Adjusted R^2=0.547) is substantially higher than our baseline models, reinforcing the importance of considering both psychological traits and contextual factors in understanding investment biases.

Risk preference shows a significant negative relationship with the disposition effect, suggesting that risk-tolerant investors are less prone to this bias. Gender effects remain significant, with female investors exhibiting a lower disposition effect, contributing to the literature on gender differences in investment behaviour (Barber and Odean, 2001). Education level consistently shows a negative association with the disposition effect, supporting previous findings about the role of financial literacy in mitigating behavioural biases (Feng and Seasholes, 2005; Chang et al., 2016).

Table 5.6. Individual Colour Interaction Influence on Disposition Effect

The table provides estimation results from an OLS regression that investigates whether colour situationally intensifies the impact of greed on the disposition effect (DE), along with other control variables. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while *Green* is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	DE	DE	DE
Intercept	0.796***	0.545**	0.656***
	(0.221)	(0.217)	(0.213)
Greed	0.177***	0.171***	0.182***
	(0.059)	(0.046)	(0.043)
Red	0.234***		-0.251***
	(0.073)		(0.071)
Red x *Greed*	-0.174**		-0.195**
	(0.087)		(0.082)
Green		0.223***	0.224***
		(0.054)	(0.068)
Green x *Greed*		0.268***	0.241***
		(0.064)	(0.080)
Loss Aversion	0.032	0.036*	0.027
	(0.029)	(0.018)	(0.020)
Risk Preference	-0.147***	-0.069**	-0.119***
	(0.035)	(0.029)	(0.031)
Maximization	-0.083**	-0.078**	-0.076**
	(0.037)	(0.031)	(0.031)
Trading Experience	-0.017	-0.024	0.002
	(0.028)	(0.022)	(0.023)
Age	0.006	0.013***	0.008*
	(0.005)	(0.004)	(0.005)
Gender	-0.219***	-0.155***	-0.208***
	(0.063)	(0.052)	(0.054)
Income	-0.026	0.002	-0.002
	(0.013)	(0.025)	(0.026)
Education	-0.078**	-0.043*	-0.069**
	(0.037)	(0.026)	(0.031)
Observations	90	90	120
Adj. R^2	0.437	0.654	0.547

Individual investors often react differently to gains and losses (Meyer and Pagel, 2022). In our analysis, I examine the specific impact of colour on the specific components of the disposition effect: proportions of gains realised (PGR) and losses realised (PLR) separately. In particular, I run the following regressions:

$$PGR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_k X_{k,i} + \varepsilon \quad (9)$$

$$PGR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Green_i + \beta_k X_{k,i} + \varepsilon \quad (10)$$

$$PLR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_k X_{k,i} + \varepsilon \quad (11)$$

$$PLR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Green_i + \beta_k X_{k,i} + \varepsilon \quad (12)$$

Table 5.7 decomposes the disposition effect into its components: the Proportion of Gains Realised (PGR) and the Proportion of Losses Realised (PLR), allowing us to understand the specific decision mechanisms driving our earlier findings.[23] Columns (1) and (2) reveal that greed has a significant positive relationship with PGR (0.093, $p<0.01$; 0.192, $p<0.01$, respectively), confirming that greedy investors are more likely to realise gains prematurely. This finding aligns with the notion that greed drives individuals to secure immediate profits rather than allowing investments to reach their full potential.

The colour effects are asymmetric across PGR and PLR. For PGR, green significantly increases the proportion of gains realised (0.195, $p<0.01$), while red shows no significant effect. The asymmetric effects across PGR and PLR suggest that colour salience operates in a domain-specific rather than generalised manner. Green cues selectively intensify attention toward gains and therefore increase gain realisation without materially affecting loss realisation. Conversely, red cues primarily influence the loss domain by increasing the propensity to realise losses, while exerting no significant effect on gain realisation. The absence of statistically significant cross-domain effects indicates that colour cues do not broadly alter trading behaviour across

[23] I re-estimated all models using the standardised greed variable reported in Appendix J, and the results are robust to those presented in Table 5.7.

all decision dimensions, but instead amplify attention toward the specific outcome domain made visually salient. This interpretation is consistent with salience-based theories of decision-making, whereby attention is disproportionately allocated to visually emphasised outcomes. The findings support H2a but not H2b, indicating that green framing strengthens gain realisation behaviour among greedy investors rather than encouraging the retention of winning positions.

For PLR, I observe the opposite pattern. *Red* significantly increases the proportion of losses realised (0.221, $p<0.01$), while green shows no significant effect. This indicates that red colour, signalling losses, makes these losses more psychologically available and potentially reduces the pain of realizing them, thus countering loss aversion. This finding supports H1a and rejects H1b, as greedy investors are shown to sell losers more quickly rather than delaying loss realisation when losses are made salient in red. This aligns with the findings of Dierick, Heyman, Inghelbrecht, and Stieperaere (2019), who discover that heightened attention is linked to a greater tendency to sell losses. These contrasting effects explain the opposing impacts of red and green on the overall disposition effect reported in Table 5.5.

Control variables reveal additional patterns across PGR and PLR. Risk preference consistently shows a negative relationship with PGR (-0.068, $p<0.01$), suggesting that risk-tolerant individuals are less likely to realise gains prematurely. Gender differences are pronounced, with females showing lower PGR (-0.136, $p<0.01$) but higher PLR in the green condition (0.120, $p<0.01$), indicating gender-specific responses to both investment outcomes and colour cues. The model fit statistics (Adjusted R^2 ranging from 0.260 to 0.494) suggest that our variables explain a substantial portion of variation in both PGR and PLR, with models for PGR generally showing higher explanatory power compared to PLR models.

Table 5.7. Individual Colour Influence on Proportion of Gains Realised (PGR) and Proportion of Losses Realized (PLR)

The table provides estimation results from an OLS regression that investigates whether red or green influences the Proportion of Gains Realised (PGR) and Proportion of Losses Realised (PLR), along with other control variables. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while *Green* is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	PGR	PGR	PLR	PLR
Intercept	0.706***	0.696***	0.047	0.143
	(0.191)	(0.174)	(0.284)	(0.153)
Greed	0.093***	0.192***	-0.004	-0.106***
	(0.029)	(0.028)	(0.039)	(0.028)
Red	0.005		0.221***	
	(0.048)		(0.068)	
Green		0.195***		-0.037
		(0.044)		(0.043)
Loss Aversion	0.026	0.021	-0.023	-0.017
	(0.018)	(0.015)	(0.025)	(0.015)
Risk Preference	-0.068***	-0.036	-0.073**	0.034
	(0.023)	(0.024)	(0.072)	(0.023)
Maximization	-0.029	-0.057	0.035	0.045*
	(0.023)	(0.025)	(0.032)	(0.025)
Trading Experience	-0.016	0.014	0.002	0.027
	(0.019)	(0.018)	(0.026)	(0.018)
Age	0.003	0.004	-0.004	0.008*
	(0.004)	(0.003)	(0.005)	(0.003)
Gender	-0.136***	-0.091**	0.058	0.120***
	(0.041)	(0.041)	(0.057)	(0.040)
Income	-0.029	-0.022	0.016	-0.029
	(0.020)	(0.021)	(0.028)	(0.020)
Education	-0.039	-0.048**	0.04	0.014
	(0.020)	(0.021)	(0.034)	(0.021)
Observations	90	90	90	90
Adj. R^2	0.308	0.494	0.26	0.365

Table 5.8 further decomposed these effects by examining how colour-greed interactions influence the specific components of the disposition effect: the Proportion of Gains Realised (PGR) and the Proportion of Losses Realised (PLR).[24] Specifically, I estimate the following models:

$$PGR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_3 Red_i \, x \, Greed_i + \beta_k X_{k,i} + \varepsilon \quad (13)$$

$$PGR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Green_i + \beta_3 Green_i \, x \, Greed_i + \beta_k X_{k,i} + \varepsilon \quad (14)$$

$$PLR_i = \beta_0 + \beta_1 Greed_i + \beta_2 Red_i + \beta_3 Red_i \, x \, Greed_i + \beta_k X_{k,i} + \varepsilon \quad (15)$$

$$PLR = \beta_0 + \beta_1 Greed_i + \beta_2 Green_i + \beta_3 Green_i \, x \, Greed_i + \beta_k X_{k,i} + \varepsilon \quad (16)$$

For PGR, Column (1) shows that the interaction between red and greed is negative but not statistically significant (*Red* × *Greed*: -0.026, p>0.10), suggesting that red cues do not significantly moderate how greed influences gain realisation. However, Column (2) reveals a strong positive interaction between green and greed on PGR (*Green* × *Greed*: 0.162, p<0.01), indicating that green framing amplifies the tendency of greedy investors to realise gains prematurely. This finding provides a component-level explanation for the positive interaction between green and greed on the overall disposition effect observed in Table 5.6.

It is important to distinguish between the direct colour effects reported in Table 5.7 and the interaction effects reported in Table 5.8. The direct colour coefficients in Table 5.7 capture the average effect of colour cues when greed is held at its centred value. By contrast, the interaction terms in Table 5.8 examine whether colour modifies the relationship between greed and trading behaviour. Accordingly, a statistically insignificant direct effect of *Green* on PLR does not preclude a significant *Green* × *Greed* interaction effect. The insignificant direct coefficient indicates that green cues do not materially influence loss realisation for the average investor, whereas the negative interaction term indicates that green framing weakens the

[24] I re-estimated all models using the standardised greed variable reported in Appendix K, and the results are robust to those presented in Table 5.8.

tendency of highly greedy investors to realise losses. The interaction effects therefore capture heterogeneity in behavioural responses across different greed levels rather than average treatment effects.

For PLR, the interaction patterns are similarly pronounced. Column (3) shows a significant positive interaction between red and greed (*Red* × *Greed*: 0.158, $p<0.05$), suggesting that red cues increase the willingness of greedy investors to realise losses. Conversely, Column (4) shows a significant negative interaction between green and greed on PLR (*Green* × *Greed*: -0.106, $p<0.05$), indicating that green framing reduces the likelihood that greedy investors will realise losses. These interaction effects on PLR help explain the negative interaction between red and greed on the overall disposition effect. Specifically, red moderates greed by increasing the propensity to sell losing positions, thereby attenuating the overall disposition effect.

The contrasting interaction effects across PGR and PLR demonstrate that colours influence the relationship between greed and investment behaviour through distinct psychological mechanisms. Green colour seems to primarily operate by amplifying the eagerness of greedy investors to secure gains (increasing PGR), while red colour works by reducing their resistance to realizing losses (increasing PLR). These component-level analyses provide a more complete understanding of how visual cues interact with psychological traits to shape financial decision-making. The model fit statistics for PGR models (Adjusted R^2=0.302 and 0.550) are generally higher than for PLR models (Adjusted R^2=0.196 and 0.315), suggesting that our variables better explain gain realization decisions compared to loss realization decisions.

Table 5.8. Individual Colour Interaction Influence on Proportion of Gains Realised (PGR) and Proportion of Losses Realised (PLR)

The table provides estimation results from an OLS regression that investigates whether colour situationally intensifies the impact of greed on the Proportion of Gains Realised (PGR) and Proportion of Losses Realised (PLR), along with other control variables. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while *Green* is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% level.

	(1) PGR	(2) PGR	(3) PLR	(4) PLR
Intercept	0.731***	0.562***	-0.201	0.201
	(0.203)	(0.151)	(0.276)	(0.153)
Greed	0.105***	0.115***	-0.078	-0.056
	(0.039)	(0.039)	(0.054)	(0.034)
Red	0.011		0.188***	
	(0.051)		(0.068)	
Red x *Greed*	-0.026		0.158**	
	(0.058)		(0.079)	
Green		0.115***		-0.011
		(0.036)		(0.044)
Green x *Greed*		0.162***		-0.106**
		(0.050)		(0.051)
Loss Aversion	0.023	0.019	-0.006	-0.016
	(0.019)	(0.015)	(0.026)	(0.015)
Risk Preference	-0.069***	-0.036	0.074**	0.034
	(0.023)	(0.022)	(0.032)	(0.023)
Maximization	-0.032	-0.042*	0.057*	0.036
	(0.024)	(0.024)	(0.033)	(0.025)
Trading Experience	-0.015	0.008	0.002	0.032*
	(0.019)	(0.017)	(0.025)	(0.017)
Age	0.002	0.005	-0.004	-0.008**
	(0.004)	(0.003)	(0.005)	(0.003)
Gender	-0.138***	-0.058	0.073	0.097**
	(0.024)	(0.042)	(0.057)	(0.041)
Income	-0.027	-0.025	0.002	-0.027
	(0.021)	(0.020)	(0.028)	(0.020)
Education	-0.039	-0.029	0.041	0.014
	(0.025)	(0.021)	(0.034)	(0.020)
Observations	90	90	90	90
Adj. R^2	0.302	0.55	0.196	0.315

5.4.3 Robustness Checks

To further assess the robustness of our findings, I replicated the analyses from Table 5.6 using alternative methods for measuring the disposition effect, as reported in Table 5.9. While Table 5.6 relied on the first-in-first-out (FIFO) approach, Table 5.9 presents results using five additional benchmarks: average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), and the method proposed by Fischbacher, Hoffmann, and Schudy (2017) (FHS). I also include the alpha coefficient method proposed by Weber and Camerer (1998), which measures the relative tendency to sell winners versus losers independently of gain magnitude.

Across all five methods, I observe a consistently positive and statistically significant main effect of greed on the disposition effect (coefficients ranging from 0.140 to 0.286), reinforcing our core finding that greed exacerbates this behavioural bias. More importantly, the interaction terms between colour and greed remain significant and in the expected directions. Specifically, the interaction between *Red* × *Greed* is negative and significant under all methods (e.g., -0.166 under AP, -0.285 under Alpha), while *Green* × *Greed* consistently shows a positive and significant effect, confirming that red reduces and green amplifies the impact of greed on disposition-prone behaviour.

Control variables show stable patterns: risk preference and maximization are negatively associated with the disposition effect across all columns, while gender remains a significant predictor, with males exhibiting lower disposition effect scores. Other variables such as age, education, and trading experience demonstrate modest and mixed effects.

Table 5.9. The Impacts of Colour and Greed on Alternative Measures of the Disposition Effect

The table provides estimation results from an OLS regression that investigates whether colour situationally intensifies the impact of greed on the disposition effect (DE), along with other control variables. DE=PGR – PLR where PGR being the proportion of realised gains (PGR) and PLR being the proportion of realised losses (PLR). I use five different approaches to define reference purchase prices gain/loss calculations. AP denotes the average purchase price; VWAP denotes is the value-weighted average purchase price; LIFO is based on the last-in-first-out approach, FHS is the possibilities-based approach proposed by Fischbacher, Hoffmann, and Schudy (2017); and Alpha is the approach proposed by Weber and Camerer (1998). *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while *Green* is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1) AP	(2) VWAP	(3) LIFO	(4) FHS	(5) Alpha
Intercept	0.771***	0.802***	0.657***	0.847***	1.577***
	(0.209)	(0.211)	(0.208)	(0.202)	(0.436)
Greed	0.144***	0.160***	0.170***	0.140***	0.286**
	(0.053)	(0.054)	(0.053)	(0.052)	(0.111)
Red	-0.262***	-0.267***	-0.286***	-0.283***	-0.355**
	(0.067)	(0.067)	(0.066)	(0.064)	(0.138)
Red x *Greed*	-0.166**	-0.184**	-0.169**	-0.135*	-0.285*
	(0.078)	(0.079)	(0.078)	(0.076)	(0.163)
Green	0.191***	0.192***	0.206**	0.229***	0.216
	(0.064)	(0.064)	(0.064)	(0.061)	(0.132)
Green x *Greed*	0.264***	0.242***	0.253***	0.199***	0.270*
	(0.076)	(0.076)	(0.076)	(0.073)	(0.158)
Loss Aversion	0.013	0.016	0.021	0.008	0.016
	(0.019)	(0.019)	(0.019)	(0.018)	(0.040)
Risk Preference	-0.122***	-0.128***	-0.105***	-0.122***	-0.106*
	(0.029)	(0.029)	(0.029)	(0.028)	(0.061)
Maximization	-0.084***	-0.089***	-0.078***	-0.083**	-0.167***
	(0.029)	(0.030)	(0.029)	(0.028)	(0.061)
Trading Experience	0.011	0.002	0.001	0.009	0.019
	(0.021)	(0.022)	(0.022)	(0.021)	(0.045)
Age	0.008*	0.008*	0.009*	0.006	0.008
	(0.005)	(0.005)	(0.005)	(0.004)	(0.009)
Gender	-0.181***	-0.188***	-0.159***	-0.156***	-0.475***
	(0.051)	(0.051)	(0.051)	(0.050)	(0.106)
Income	0.002	0.001	0.003	-0.016	-0.061
	(0.025)	(0.025)	(0.025)	(0.024)	(0.052)
Education	-0.062**	-0.063**	-0.072**	-0.064**	-0.073
	(0.030)	(0.029)	(0.030)	(0.028)	(0.062)
Observations	120	120	120	120	120
Adj. R^2	0.543	0.551	0.552	0.533	0.373

Recall that our main results in Table 5.8 use the FIFO method to measure the disposition effect and to examine how individual colour cues interact with greed in shaping the proportion of gains realised (PGR) and the proportion of losses realised (PLR). I now test the robustness of these findings using alternative measurement of the disposition effect. Table 5.10 reports the results based on four alternative rules: Average Price (AP), Volume-Weighted Average Price (VWAP), Last-In-First-Out (LIFO), and Fischbacher (FHS). Across all specifications, the core interaction patterns remain consistent with the baseline.

In Panel A, the coefficient on *Green* × *Greed* is positive and highly significant across all measures, indicating that green displays amplify the tendency of greedy investors to realise winning positions. Similarly, the *Red* × *Greed* term remains negative across specifications, reaffirming that red cues mitigate the resistance to realise losses among the highly greedy investors. However, some individual coefficients lose statistical significance under certain alternative measurement approaches. For example, the direct effect of *Red* in Panel A, Column (1) based on the *AP* specification is not statistically significant, although the coefficient remains negative and directionally consistent with the main findings. Likewise, in Panel B, the coefficient on *Green* × *Greed* in Column (4) under the *FHS* specification remains negative but is no longer statistically significant. These results suggest that while the overall behavioural patterns remain broadly robust across alternative measures of the disposition effect, the strength of some individual coefficients varies depending on the measurement approach employed. These effects persist after controlling for loss aversion, risk preference, maximization tendency, trading experience, and demographics, with adjusted R^2 values ranging from 0.45 to 0.55. Panel B shows that the colour–greed interactions on PLR are likewise stable. *Red* continues to increase the likelihood of realising losses, while *Green* × *Greed* retains its significantly negative sign. Overall, the evidence suggests that the main findings are not driven by any single DE measurement approach, although the statistical significance of some individual coefficients varies across alternative specifications. The colour and greed interplay are robust across all realisation’s methods, underscoring the behavioural salience of visual cues in modulating trading bias.

Table 5.10. The Impacts of Colour and Greed on Alternative Measures of the PGR and PLR

Panel A provides OLS regression results in which the dependent variable is proportion of realised gains (PGR), measured as PGR=RG/ (RG+PG) where RG being the realised gains and PG being the paper gains. Panel B provides OLS regression results in which the dependent variable is proportion of realised gains (PLR), measured as PLR=RL/ (RL+PL) where RL being the realised losses and PL being the paper losses. Greed is calculated by subtracting 3 from each participant's greed score, which shifts the distribution. I use four different approaches to define reference purchase prices gain calculations. AP denotes the average purchase price; VWAP denotes is the value-weighted average purchase price; LIFO is based on the last-in-first-out approach, FHS is the possibilities-based approach proposed by Fischbacher et al. (2017). The alpha measure does not account for realised or paper gains/losses. *Greed* and control variables are defined as in Appendix A. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: PGR	(1)	(2)	(3)	(4)
	AP	VWAP	LIFO	FHS
Intercept	0.761***	0.827***	0.826***	0.857***
	(0.120)	(0.149)	(0.134)	(0.167)
Greed	0.109***	0.124***	0.125***	0.130***
	(0.032)	(0.039)	(0.037)	(0.042)
Red	-0.009	0.216***	0.146**	0.347***
	(0.058)	(0.075)	(0.070)	(0.072)
Red x *Greed*	-0.151**	-0.192**	-0.203***	-0.187**
	(0.066)	(0.078)	(0.069)	(0.085)
Green	0.198***	0.197***	0.170***	0.213***
	(0.025)	(0.027)	(0.029)	(0.034)
Green x *Greed*	0.171***	0.149***	0.161***	0.141***
	(0.036)	(0.041)	(0.041)	(0.050)
Loss Aversion	0.004	0.007	0.009	0.001
	(0.010)	(0.014)	(0.015)	(0.012)
Risk Preference	-0.054**	-0.070**	-0.055*	-0.075***
	(0.022)	(0.027)	(0.029)	(0.026)
Maximization	-0.062***	-0.071**	-0.057**	-0.072***
	(0.020)	(0.027)	(0.025)	(0.026)
Trading Experience	0.006	0.025	0.026	0.017
	(0.015)	(0.019)	(0.019)	(0.019)
Age	0.004**	0.004	0.002	0.005
	(0.002)	(0.003)	(0.002)	(0.003)
Gender	-0.050*	-0.071**	-0.055	-0.072**
	(0.026)	(0.033)	(0.033)	(0.035)
Income	-0.022	-0.023	-0.031	-0.030
	(0.017)	(0.019)	(0.022)	(0.020)
Education	-0.038**	-0.044**	-0.050***	-0.053***
	(0.014)	(0.018)	(0.019)	(0.019)
Observations	120	120	120	120
Adj. R^2	0.529	0.488	0.453	0.552

Table 5.10 – *Continued*

Panel B: PLR	(1) AP	(2) VWAP	(3) LIFO	(4) FHS
Intercept	0.144	0.128	0.257	0.058
	(0.145)	(0.143)	(0.154)	(0.125)
Greed	-0.029	-0.039	-0.043	-0.021
	(0.039)	(0.043)	(0.048)	(0.034)
Red	0.181***	0.179***	0.137**	0.176***
	(0.044)	(0.046)	(0.051)	(0.035)
Red x *Greed*	0.080	0.090	0.094	0.093
	(0.061)	(0.063)	(0.059)	(0.055)
Green	0.049	0.045	0.001	0.008
	(0.038)	(0.040)	(0.046)	(0.031)
Green x *Greed*	-0.146**	-0.132**	-0.122*	-0.085
	(0.060)	(0.062)	(0.067)	(0.055)
Loss Aversion	0.013	0.011	0.003	0.010
	(0.013)	(0.014)	(0.016)	(0.012)
Risk Preference	0.006	0.009	0.011	0.005
	(0.022)	(0.021)	(0.020)	(0.020)
Maximization	0.019	0.021	0.008	0.029
	(0.020)	(0.020)	(0.021)	(0.018)
Trading Experience	0.009	0.011	0.007	0.005
	(0.018)	(0.018)	(0.017)	(0.014)
Age	-0.008***	-0.008***	-0.008**	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Gender	-0.037	-0.030	-0.022	-0.018
	(0.044)	(0.046)	(0.043)	(0.039)
Income	0.015	0.011	0.010	0.006
	(0.017)	(0.017)	(0.018)	(0.015)
Education	0.019	0.019	0.020	0.015
	(0.023)	(0.025)	(0.029)	(0.021)
Observations	120	120	120	120
Adj. R^2	0.314	0.304	0.268	0.305

5.5 Conclusion

In this chapter, I provide insights into the intersection of behavioural finance, greed, and visual salience, demonstrating that the colour-coding of financial information significantly influences investor decision-making. Our results provide evidence consistent with Frydman and Wang (2020), suggesting that the display of information influences investor behaviour. Our results confirm that greed amplifies the disposition effect, but its impact varies based on the presentation of financial data. When stock price decreases are displayed in red, investors exhibited a 22.1 percentage points higher proportion of realised losses, indicating that red can accelerate loss-cutting behaviour. Conversely, when stock price increases are highlighted in green, investors showed a 19.5 percentage points higher proportion of realised gains, reinforcing their tendency to sell winning stocks too soon. The interaction effects further revealed that highly greedy investors became significantly more prone to realizing gains when prices were displayed in green but were also more likely to hold onto losing stocks when price drops were shown in red.

Our results are applicable because there has been a significant shift toward making investment decisions on digital platforms (Benartzi, 2017). Our findings have direct implications for financial platform design, investment advisory services, and policy interventions aimed at reducing biased trading behaviours. Digital trading platforms should be aware of how visual cues influence investor psychology, and regulators may consider guidelines to ensure that interface designs do not inadvertently exacerbate cognitive biases. Future research could further explore how additional visual and contextual factors - such as animation, framing effects, and personalized investor interfaces - interact with psychological traits to shape financial behaviours. By deepening our understanding of how cognitive biases can be either reinforced or mitigated through environmental cues, this study contributes to the broader discourse on improving financial decision-making in digital investment environments.

It is important to note that our colour manipulation using red for losses and green for gains may combine two distinct psychological mechanisms, the intrinsic attention-capturing effect of colour and the enhanced visual salience it provides relative to black text. As demonstrated by Frydman and Wang (2020), even colours without strong emotional associations, such as blue, can influence behaviour, likely by drawing greater attention. Ideally, to remove these effects, an additional condition in which losses are shown in green and gains in red would help determine whether the observed behavioural changes are driven by the meaning assigned to specific colours or simply by the use of colour to enhance salience. As our design does not include such a condition, the current results should be interpreted as reflecting a combined influence of colour-specific interpretation and general salience, and I encourage future studies to explore this distinction more systematically.

6 Percentage vs. Dollar: The Role of Greed in Amplifying Framing Effects on the Disposition Effect

6.1 Introduction

Investors' decisions are influenced by how information is framed (Tversky and Kahneman, 1981; Levin et al., 1998; Barberis, 2018). The same investment outcome presented as a percentage return or as an absolute dollar change can alter the decision-making process. This chapter examines the research problem of how such framing affects investor behaviour, particularly in the context of the disposition effect.

Previous research in psychology, behavioural economics, and neurofinance demonstrates that individuals do not respond to "objective" outcomes alone, but to their subjective interpretations shaped by reference points, emotions, and contextual framing (Loewenstein et al., 2001; Frydman and Camerer, 2016; Frydman and Wang, 2020; Kőszegi and Rabin, 2006; De Martino et al., 2006; Chapman et al., 2023). For instance, a gain framed as "25%" may carry a different psychological impact than a gain of "$250", even though both convey the same increase in value. In investment settings, such differences in informational framing can meaningfully alter investors' perceptions and evaluations of outcomes. For example, expressing returns in percentage terms tends to highlight proportional gains or losses, which can appear large for low-priced stocks (especially where even small dollar moves translate into big percentages). Conversely, absolute dollar frames might appear larger in the case of high-priced stocks. Framing effects thus serve as a cognitive lens that can magnify or downplay aspects of gains and losses, influencing how investors evaluate their positions.

While framing effects on investor decisions are well documented, less is known about how personality traits like greed interact with these effects. This chapter posits that greed serves as a moderator of framing influences on the disposition effect. Greed, as characterized earlier, entails an intense focus on accumulating wealth and a sensitivity to opportunities for gain. Prior research provides evidence that greedy individuals exhibit enhanced reactivity to reward cues and reduced restraint in the face of temptation (Seuntjens et al., 2015; Seuntjens et al., 2016; Mussel and Hewig, 2016; Liu et al., 2021). Greedy investors also tend to closely monitor financial information for chances to maximize returns. Because of this heightened vigilance and enhanced response to rewards investors who have stronger greed tendencies are especially susceptible to whichever framing format inflates the perceived significance of an outcome (i.e. percentage for low valued stocks and dollar value for high value stocks). In other words, a greedy individual's bias could be amplified by the format that makes gains most enticing (or losses most pressing).

If a percentage display causes a profit to appear large, a greedy trader may feel a stronger urge to realise that gain immediately. Likewise, when a particular framing makes a loss especially salient, a greedy investor may either hasten to cut the loss to protect overall wealth or, conversely, double down to avoid giving up what they already possess. The behavioural direction depends on which aspect of greed, acquisitive or retentive is activated. In this chapter, I explore how these trait-driven tendencies play out when cognitive framing is manipulated.

I position this study at the intersection of two streams of behavioural finance research. One on how situational factors like information presentation affects decision-making, and another on how personality-based factors lead to differences in investor behaviour. Cognitive biases such as framing do not operate in isolation, their impact depends on the characteristics of the investor. This exploration enriches behavioural finance theory by integrating cognitive and personality perspectives, showing that an investor's greed level can significantly alter the effect of information framing on their trading choices. The central question is whether greedy investors respond differently to percentage vs. dollar frames, and if so, in what direction. By shedding light on this interaction, the chapter offers a more detailed understanding of investor behaviour. Such insights also have practical resonance. Overall, this chapter's focus on percentage vs. dollar framing under varying levels of greed reveals an important facet of the disposition effect. It is jointly driven by how outcomes feel due to framing, and by how greedy the investor is. This dual emphasis moves us closer to a comprehensive understanding of why investors sometimes deviate from rational strategies, and how subtle changes in presentation and individual disposition can together shape financial decision-making outcomes.

I find that numerical framing interacts powerfully with greed to shape investors' realisation behaviour. When returns are displayed in percentage terms, the disposition effect is substantially stronger (mean DE=0.28) than when returns are shown in dollar amounts (mean DE=0.09), with the difference being most pronounced for low-priced stocks where percentage changes appear larger relative to their base value. Regression analyses reveal a positive and highly significant interaction between greed and percentage framing, showing that greedy investors are especially responsive to relative performance cues. The effect is most pronounced for low-priced stocks, where percentage changes appear visually larger and thus more salient, prompting premature profit taking (PGR increases by roughly 0.17). In contrast, dollar framing anchors investors to absolute monetary outcomes and weakens the greed–disposition relationship. The full model, which includes framing format, price level, and greed interactions, explains about 57 percent of the variance in selling behaviour. These results demonstrate that cognitive framing and personality traits jointly determine the magnitude of the disposition effect.

This study makes two principal contributions to the behavioural finance literature. First, it extends research on framing and investor decision-making by providing evidence that the numerical format used to present returns (percentages versus dollar amounts) alters the magnitude of the disposition effect. While prior work has examined framing in consumer choice, risk assessment, and belief updating (Tversky and Kahneman, 1981; Levin et al., 1998;

De Martino et al., 2006), evidence linking numerical return frames to realisation behaviour has been limited. This chapter shows that percentage framing substantially strengthens the disposition effect for low-priced stocks where proportional changes appear visually larger and more salient.

Second, the study advances the integration of personality traits into contextual models of investor behaviour. By demonstrating that greed moderates the influence of numerical frames, the chapter reveals that framing effects are not homogeneous but depend on investors' underlying motivational tendencies. This framing and greed interaction identifies a new boundary condition for realisation-utility, salience, and attention-based theories, helping explain why some investors are disproportionately sensitive to specific information formats. Overall, these contributions deepen our understanding of how cognitive presentation and individual disposition jointly shape trading behaviour.

6.2 Hypotheses Development

6.2.1 Primary Salience Effect: Explicit Return Display versus No Display

Study 3 investigates how the presentation of returns in percentage versus dollar format influences the disposition effect across different price regimes, and how these framing effects interact with investor greed. In contrast to Studies 1 and 2, this study examines numerical return framing as a subtler but theoretically powerful source of salience variation. The prediction is that the perceived magnitude of gains and losses depends not only on the objective economic value but also on how that value is presented.

When return information is absent, investors must mentally compute performance, generating a low-salience decision environment where emotional responses to gains and losses are relatively weak. Previous research shows that when information is not visually or verbally highlighted, decision-makers underweight it due to the cognitive effort required to retrieve and process it (Tversky and Kahneman, 1973; Higgins, 1996).

Introducing explicit return information transforms the decision environment by making performance immediately visible. Displaying returns whether as "+10%" or "+$6" removes the cognitive burden of computation, increases attentional capture and makes the outcome more emotionally vivid. In behavioural finance, explicit feedback is known to heighten sensitivity to both positive and negative outcomes, thereby amplifying outcome-driven behaviour such as gain realisation and loss aversion (Loewenstein et al., 2001; Barberis and Xiong, 2012; Frydman and Camerer, 2016). Explicit return presentation should therefore strengthen the disposition effect by making realised and unrealised outcomes more salient.

H1: *The disposition effect will be smaller in the low-saliency (no return information is provided) than in the high-saliency condition (in either percentage or dollar format).*

6.2.2 Salience Mechanisms in Financial Return Presentation

The central theoretical mechanism in Study 3 relates to how percentage and dollar formats differentially influence the salience of returns depending on the stock's price level. The "Rule of 100" (Thomas and Morwitz, 2010; Berger, 2013) proposes that percentage frames are more psychologically impactful for base values below $100, while absolute dollar amounts become more influential when the underlying value exceeds $100. This principle has been widely demonstrated in consumer psychology, marketing, and economic choice settings.

This reasoning extends naturally to investment contexts. Investors evaluating returns engage in magnitude comparison processes that depend partly on the reference scale activated by the frame (Dehaene, 2003). Percentage frames evoke proportional thinking, causing individuals to assess the return relative to the price level, magnifying the perceived importance of small absolute changes. Dollar frames evoke concrete magnitude representation. Absolute dollar figures carry more psychological weight when they are large enough to feel financially meaningful.

In low-price contexts, percentage framing inflates the perceived magnitude of gains and losses by activating proportional reasoning. For example, a \$3 gain on a \$30 stock appears more impactful when framed as "10%," even though the economic outcome is identical. Because salience intensifies emotional responses to outcomes, percentage framing in low-price regimes should strengthen both components of the disposition effect.

H2a: *For stocks priced below \$100, the disposition effect will be significantly stronger under percentage presentation than under dollar presentation.*

In high-price regimes (stocks trading above \$100), the salience advantage should reverse in favour of dollar presentations. When absolute dollar amounts are large, they convey concrete, tangible value that feels more meaningful than abstract percentage figures. For example, a \$30 gain on a \$300 stock appears more impactful when presented as "\$30" rather than "10%" because the dollar amount emphasizes the concrete monetary value while the percentage seems relatively small and abstract.

This reversal in salience should produce a corresponding reversal in disposition effect behaviours. Under dollar presentation, the enhanced salience of absolute monetary gains should create stronger positive emotions and increase profit-taking behaviour, while the enhanced salience of absolute monetary losses should intensify loss aversion and reduce loss realization. Under percentage presentation, the reduced salience should attenuate these emotional responses and produce weaker disposition effect behaviours.

H2b: *For stocks priced above \$100, the disposition effect will be significantly stronger under dollar presentation than under percentage presentation.*

6.2.3 Individual Differences: Greed as a Moderator of Salience Effects

Despite a robust literature on framing effects in marketing and decision theory (Bordalo et al., 2012; De Martino et al., 2006; Levin et al., 1998; Tversky and Kahneman, 1981), the specific mechanisms by which framing shapes trading behaviour, and how these mechanisms interact with individual traits such as greed, remain underexplored. Frydman and Rangel (2014) manipulate the salience of the purchase price anchor in a laboratory trading experiment and show that downplaying this absolute dollar cue reduces the disposition effect by about 25%, consistent with lower decision weight on capital gains and losses when the anchor is less salient. Related work on number format and scale effects indicates that percentage framing can heighten both gain and loss salience, particularly for low base prices: eliciting returns rather than prices shifts expectations (Glaser et al., 2007), and base value neglect leads people to overweight percentage changes relative to their monetary base (Chen et al., 2012). In our setting, these scale effects motivate the prediction that percentage displays make both gains and losses more attention grabbing for greedier investors, strengthening tendencies to realise winners and to act on losses.

Neuroscientific evidence provides mechanistic support for greed-salience interactions across both gain and loss domains of the disposition effect. The brain's reward and valuation systems demonstrate asymmetric processing of gains versus losses, with distinct neural pathways governing approach and avoidance behaviours that directly influence trading decisions (Kuhnen and Knutson, 2005; Tom et al., 2007). Greed should magnify the impact of framing salience on trading behaviour by heightening sensitivity to whichever outcomes the presentation format makes most attention-grabbing, because greedy individuals exhibit elevated reward-circuit reactivity and diminished top-down control (Mussel et al., 2015; Kumar, 2009). On the gain side, activity in the ventral striatum increases monotonically with anticipated reward magnitude (Knutson et al., 2001; Knutso et al., 2005), and value signals in vmPFC scale with subjective value across rewards (Bartra et al., 2013; Levy and Glimcher, 2012). Thus, frames that make a gain look larger (e.g., “+10%” vs. “+$6” on small bases) should, by implication, amplify these valuation signals and strengthen sell-gain impulses (Frydman, Barberis, Camerer, Bossaerts, and Rangel, 2014).

On the loss side, neural loss aversion reflects asymmetric processing in threat-detection and avoidance circuits: prospective losses evoke stronger deactivations in the striatum and heightened amygdala–ACC activation, encoding negative value and triggering avoidance responses (Bush et al., 2000; Tom et al., 2007; Sokol-Hessner et al., 2013). This intensified anticipatory "pain" signal makes loss cutting more difficult and prolongs holding onto losers. Because greedy individuals also exhibit diminished top-down control and an overriding drive for reward, they are especially vulnerable to these amplified loss cues, which further delaying loss realizations under high-salience framing (Mussel et al., 2015; Kumar, 2009).

Sokol-Hessner, Camerer, and Phelps (2013) demonstrate that amygdala activity during loss anticipation directly predicts individual differences in loss aversion behaviour, with heightened amygdala responses correlating with stronger tendencies to avoid realizing losses. The anterior cingulate cortex (ACC) plays a key role in conflict monitoring, becoming active when individuals juggle competing motivations, such as the rational urge to cut losses versus the emotional aversion to admitting defeat (Bush et al., 2000). Enhanced ACC activation during loss scenarios reflects the cognitive effort required to override natural loss-avoidance tendencies, explaining why investors often delay loss realization despite rational economic incentives to sell.

Greater loss aversion is associated with stronger amygdala responses to prospective losses and with structural links spanning amygdala, thalamus, and striatum; ventral striatal responses show bidirectional coding that scales with individual loss aversion (Canessa Crespi et al., 2013). Under emotional cues, increases in loss aversion can coincide with stronger striatal amygdala coupling (Charpentier et al., 2016). This enhanced connectivity suggests that emotional salience amplifies loss aversion through direct modulation of valuation circuits, creating a neurobiological mechanism by which framing effects can systematically bias loss-related decisions.

In the low-price regime, percentage framing transforms modest absolute gains into psychologically larger proportional increases, activating reward circuits more strongly than equivalent dollar presentations. For instance, where stocks trade below $100, when a $6 gain on a $60 stock is framed as a "10%" increase, it activates neural reward circuits as strongly as larger absolute gains, thereby amplifying the subjective value signal. Greedy investors, with their heightened reward system sensitivity, show exaggerated responses to this neural amplification, driving stronger disposition effects under percentage framing. Conversely, under dollar framing in the same low-price context, the $6 change appears less dramatic, providing a weaker stimulus for greedy traders to initiate trades while eliciting minimal variation among more deliberative, non-greedy investors (Peters et al., 2006).

In high-price regimes (stocks above $100), the pattern reverses: percentage labels abstract a $30 gain on a $300 stock into a "10%" figure that downplays its concrete value (Grewal and Marmorstein, 1994), thereby attenuating the emotional gratification that drives the disposition effect (Weber and Camerer, 1998; Barberis and Xiong, 2009). Greedy investors—despite their elevated reward sensitivity - will feel a diminished urge to realise gains under percentage framing in high-price contexts, leading to a weaker disposition effect. By contrast, absolute dollar framing restores and magnifies salience: a "$30" gain on a high-priced stock delivers a clear, tangible reward than 10% that greedy traders find difficult to resist, intensifying profit-taking impulses far beyond those of less greedy counterparts.

H3a: *In the low-price regime, investors exhibiting higher greed will exhibit a greater disposition effect under percentage framing than under absolute framing.*

H3b: *In the high-price regime, investors exhibiting higher greed will exhibit a greater disposition effect under absolute dollar framing than under percentage framing.*

6.3 Method

The experimental framework, procedures, and measurement definitions follow the baseline methodology outlined in Chapter 3. Participants engaged in a computerised stock-trading simulation implemented in z-Tree (Fischbacher, 2007) followed by a post-experiment survey administered through Qualtrics, allowing trading behavioural data to be captured independently from psychological self-reports. Figure 3 presents the trading interface used in the z-Tree experiment. Study 3 extends this framework by jointly manipulating the stock price regime and the numerical format in which returns are displayed, thereby examining how framing interacts with price magnitude to shape the greed and disposition effect relationship.

Participants were randomly assigned to one of four experimental conditions representing all combinations of price level and display format: low priced with dollar returns (N=31), low priced with percentage returns (N=31), high priced with dollar returns (N=32), and high priced with percentage returns (N=30). This yielded a total of 124 participants in the four treatment conditions. In addition, the 60 participants from the baseline study (Study 1) served as the control group. Combining the 124 treatment participants with the 60 baseline participants resulted in a final sample of 184 individuals.

The four conditions therefore consisted of: (1) low-priced stocks with dollar return displays, (2) low-priced stocks with percentage return displays, (3) high-priced stocks with dollar return displays, and (4) high-priced stocks with percentage return displays. This design allows the study to isolate how numerical framing interacts with stock price level to influence the salience of investment outcomes.

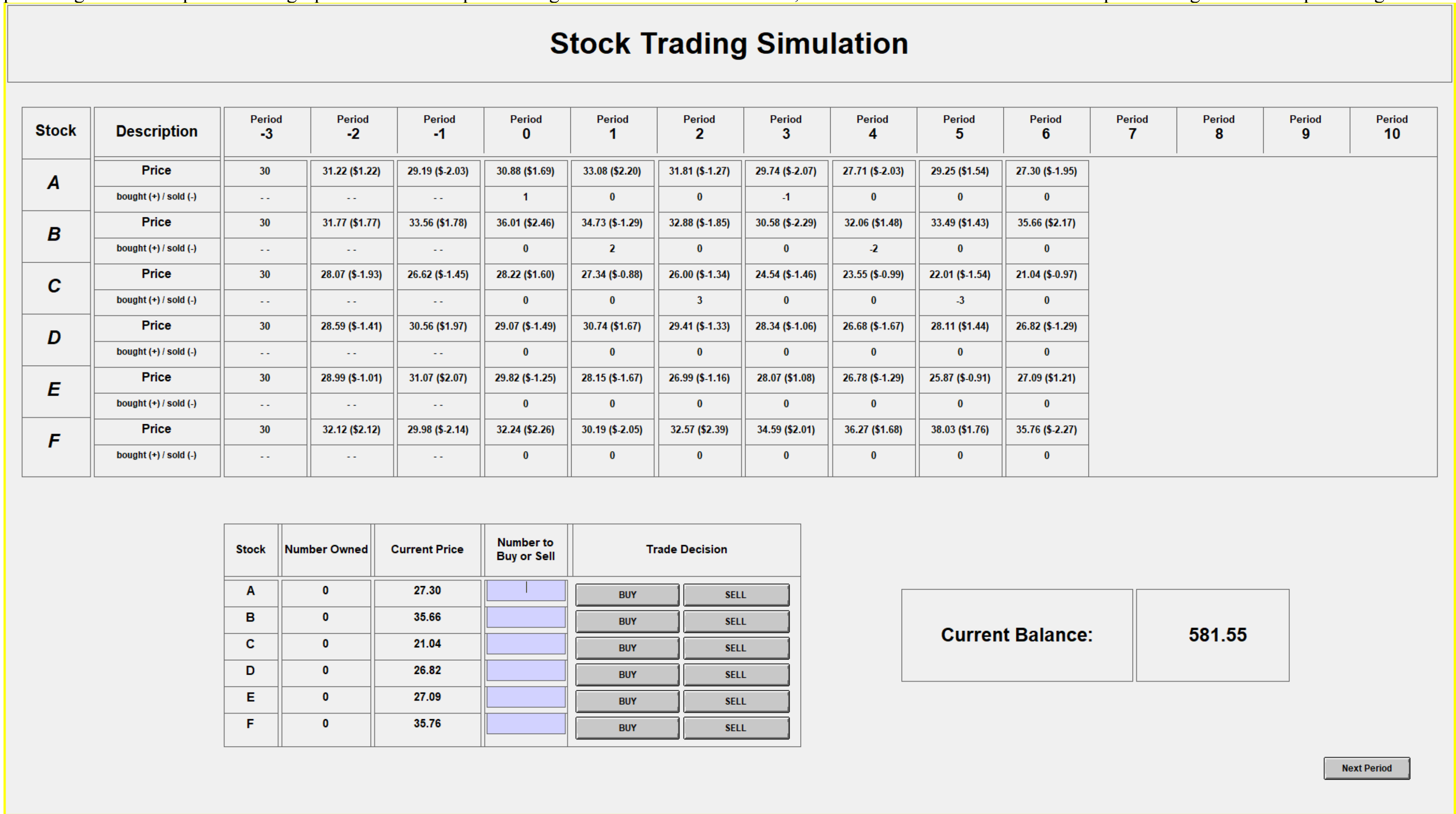
In the low-price regime, each of the six traded assets (A-F) are initially priced at $30, and participants receive an initial endowment of $600 in trading tokens. In the high-price regime, asset prices started at $300 with an endowment of $6,000. Apart from these scale adjustments, all trading parameters, and probability structures were identical to those in

Chapter 3, ensuring that any behavioural differences arise purely from the framing and price-level manipulations.

During trading, price changes were displayed either in absolute dollar terms (e.g., “+$6”) or in relative percentage terms (e.g., “+10%”), replicating the informational formats commonly used in retail trading platforms (Chen and Rao, 2007; Glaser et al., 2007). In sum, Study 3 builds on the baseline trading paradigm by introducing variations in price magnitude and numerical framing, enabling a clean test of how information scale and presentation format jointly shape the behavioural manifestation of greed in the disposition effect.

Figure 4. Study 3 Trading Interface

Panel A displays the trading interface for a low-priced stock with price changes shown in absolute dollars; Panel B shows the same stock with price changes shown in percentages. Panel C presents a high-priced stock with price changes shown in absolute dollars; Panel D shows the same stock with price changes shown in percentages.



Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	30	31.22 ($1.22)	29.19 ($-2.03)	30.88 ($1.69)	33.08 ($2.20)	31.81 ($-1.27)	29.74 ($-2.07)	27.71 ($-2.03)	29.25 ($1.54)	27.30 ($-1.95)				
	bought (+) / sold (-)	- -	- -	- -	1	0	0	-1	0	0	0				
B	Price	30	31.77 ($1.77)	33.56 ($1.78)	36.01 ($2.46)	34.73 ($-1.29)	32.88 ($-1.85)	30.58 ($-2.29)	32.06 ($1.48)	33.49 ($1.43)	35.66 ($2.17)				
	bought (+) / sold (-)	- -	- -	- -	0	2	0	0	-2	0	0				
C	Price	30	28.07 ($-1.93)	26.62 ($-1.45)	28.22 ($1.60)	27.34 ($-0.88)	26.00 ($-1.34)	24.54 ($-1.46)	23.55 ($-0.99)	22.01 ($-1.54)	21.04 ($-0.97)				
	bought (+) / sold (-)	- -	- -	- -	0	0	3	0	0	-3	0				
D	Price	30	28.59 ($-1.41)	30.56 ($1.97)	29.07 ($-1.49)	30.74 ($1.67)	29.41 ($-1.33)	28.34 ($-1.06)	26.68 ($-1.67)	28.11 ($1.44)	26.82 ($-1.29)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
E	Price	30	28.99 ($-1.01)	31.07 ($2.07)	29.82 ($-1.25)	28.15 ($-1.67)	26.99 ($-1.16)	28.07 ($1.08)	26.78 ($-1.29)	25.87 ($-0.91)	27.09 ($1.21)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
F	Price	30	32.12 ($2.12)	29.98 ($-2.14)	32.24 ($2.26)	30.19 ($-2.05)	32.57 ($2.39)	34.59 ($2.01)	36.27 ($1.68)	38.03 ($1.76)	35.76 ($-2.27)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	27.30		BUY	SELL
B	0	35.66		BUY	SELL
C	0	21.04		BUY	SELL
D	0	26.82		BUY	SELL
E	0	27.09		BUY	SELL
F	0	35.76		BUY	SELL

Current Balance: 581.55

Next Period

Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	30	32.17 (7.2%)	34.70 (7.9%)	32.38 (-6.7%)	34.78 (7.4%)	36.55 (5.1%)	34.92 (-4.5%)	32.66 (-6.5%)	30.91 (-5.4%)	29.67 (-4.0%)				
	bought (+) / sold (-)	- -	- -	- -	1	0	0	-1	0	0	0				
B	Price	30	28.88 (-3.7%)	27.24 (-5.7%)	28.83 (5.8%)	30.58 (6.1%)	32.92 (7.7%)	31.33 (-4.8%)	32.72 (4.4%)	30.52 (-6.7%)	29.11 (-4.6%)				
	bought (+) / sold (-)	- -	- -	- -	2	0	0	0	-1	0	0				
C	Price	30	31.89 (6.3%)	30.03 (-5.8%)	28.47 (-5.2%)	29.93 (5.1%)	31.29 (4.6%)	32.72 (4.6%)	31.06 (-5.1%)	32.61 (5.0%)	30.94 (-5.1%)				
	bought (+) / sold (-)	- -	- -	- -	3	-2	0	0	0	-1	0				
D	Price	30	29.02 (-3.3%)	31.17 (7.4%)	30.15 (-3.3%)	31.94 (5.9%)	34.19 (7.1%)	36.24 (6.0%)	35.03 (-3.3%)	33.89 (-3.2%)	32.26 (-4.8%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
E	Price	30	27.96 (-6.8%)	29.13 (4.2%)	27.65 (-5.1%)	25.99 (-6.0%)	24.80 (-4.6%)	23.80 (-4.1%)	25.31 (6.3%)	23.70 (-6.3%)	22.68 (-4.3%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
F	Price	30	28.32 (-5.6%)	30.01 (5.9%)	28.80 (-4.0%)	29.96 (4.0%)	28.27 (-5.6%)	29.64 (4.8%)	31.28 (5.5%)	33.05 (5.6%)	31.36 (-5.1%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	29.67		BUY	SELL
B	1	29.11		BUY	SELL
C	0	30.94		BUY	SELL
D	0	32.26		BUY	SELL
E	0	22.68		BUY	SELL
F	0	31.36		BUY	SELL

Current Balance:	584.67

Next Period

Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	300	281.61 ($-18.39)	298.07 ($16.46)	319.32 ($21.26)	335.34 ($16.01)	351.30 ($15.96)	328.07 ($-23.23)	308.57 ($-19.49)	326.81 ($18.24)	308.88 ($-17.93)				
	bought (+) / sold (-)	- -	- -	- -	1	0	0	-1	0	0	0				
B	Price	300	313.03 ($13.03)	295.83 ($-17.21)	280.93 ($-14.90)	298.78 ($17.85)	311.16 ($12.38)	327.42 ($16.26)	315.36 ($-12.06)	304.10 ($-11.27)	286.67 ($-17.43)				
	bought (+) / sold (-)	- -	- -	- -	0	2	0	0	-2	0	0				
C	Price	300	314.74 ($14.74)	329.88 ($15.14)	348.65 ($18.77)	335.66 ($-12.98)	351.75 ($16.09)	366.63 ($14.88)	388.94 ($22.31)	363.55 ($-25.39)	391.72 ($28.17)				
	bought (+) / sold (-)	- -	- -	- -	0	0	3	0	0	-3	0				
D	Price	300	312.36 ($12.36)	337.20 ($24.84)	317.54 ($-19.66)	302.27 ($-15.26)	326.09 ($23.82)	339.18 ($13.09)	321.85 ($-17.33)	344.63 ($22.78)	325.38 ($-19.24)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
E	Price	300	284.47 ($-15.53)	269.97 ($-14.50)	281.59 ($11.62)	297.65 ($16.06)	313.75 ($16.09)	298.80 ($-14.94)	318.43 ($19.63)	306.71 ($-11.73)	321.43 ($14.72)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
F	Price	300	318.33 ($18.33)	300.54 ($-17.79)	290.28 ($-10.26)	272.80 ($-17.48)	262.02 ($-10.77)	280.16 ($18.14)	292.92 ($12.76)	274.47 ($-18.45)	287.62 ($13.15)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	308.88		BUY	SELL
B	0	286.67		BUY	SELL
C	0	391.72		BUY	SELL
D	0	325.38		BUY	SELL
E	0	321.43		BUY	SELL
F	0	287.62		BUY	SELL

Current Balance:	6077.31

Next Period

Stock Trading Simulation

Stock	Description	Period -3	Period -2	Period -1	Period 0	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	Period 9	Period 10
A	Price	300	286.28 (-4.6%)	301.87 (5.4%)	281.08 (-6.9%)	294.19 (4.7%)	282.61 (-3.9%)	296.39 (4.9%)	308.62 (4.1%)	296.82 (-3.8%)	311.92 (5.1%)				
	bought (+) / sold (-)	- -	- -	- -	1	0	0	-1	0	0	0				
B	Price	300	282.98 (-5.7%)	301.69 (6.6%)	318.90 (5.7%)	341.46 (7.1%)	321.09 (-6.0%)	303.12 (-5.6%)	315.51 (4.1%)	336.02 (6.5%)	349.92 (4.1%)				
	bought (+) / sold (-)	- -	- -	- -	0	2	0	0	-2	0	0				
C	Price	300	279.56 (-6.8%)	298.81 (6.9%)	315.11 (5.5%)	298.97 (-5.1%)	289.52 (-3.2%)	308.42 (6.5%)	297.29 (-3.6%)	309.35 (4.1%)	289.91 (-6.3%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	3	0	0	-3	0				
D	Price	300	287.96 (-4.0%)	269.29 (-6.5%)	260.35 (-3.3%)	249.85 (-4.0%)	264.46 (5.9%)	256.40 (-3.1%)	242.51 (-5.4%)	231.17 (-4.7%)	218.24 (-5.6%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
E	Price	300	321.32 (7.1%)	307.76 (-4.2%)	323.69 (5.2%)	347.44 (7.3%)	325.73 (-6.2%)	310.86 (-4.6%)	335.57 (7.9%)	319.12 (-4.9%)	339.21 (6.3%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				
F	Price	300	319.95 (6.6%)	335.54 (4.9%)	324.11 (-3.4%)	344.25 (6.2%)	324.62 (-5.7%)	341.04 (5.1%)	365.07 (7.0%)	390.27 (6.9%)	363.62 (-6.8%)				
	bought (+) / sold (-)	- -	- -	- -	0	0	0	0	0	0	0				

Stock	Number Owned	Current Price	Number to Buy or Sell	Trade Decision	
A	0	311.92		BUY	SELL
B	0	349.92		BUY	SELL
C	0	289.91		BUY	SELL
D	0	218.24		BUY	SELL
E	0	339.21		BUY	SELL
F	0	363.62		BUY	SELL

Current Balance: 6022.88

Next Period

6.4 Results

In this section, I begin by presenting descriptive statistics and correlation patterns for the control group and the framing treatments to show how the disposition effect and its components vary across display formats and price regimes. I then examine the main effects of percentage versus dollar framing and low- versus high-price regimes on the disposition effect, followed by tests of whether individual greed moderates these framing patterns. Next, I decompose the disposition effect into gain- and loss-realisation components to assess whether the underlying mechanisms differ by condition. Finally, I evaluate the robustness of all findings using alternative measures of the disposition effect. This progression links directly to the hypotheses in Section 6.3.

6.4.1 Descriptive Statistics

Panel A of Table 6.1 reports descriptive statistics for the base sample (N=60) and the salience sample (N=124). The key dependent variable is the disposition effect (DE), along with its two components: the proportion of gains realised (PGR) and the proportion of losses realised (PLR). The table also includes the primary explanatory variable, greed, and the control variables.

In the Return Salience Sample (N=124), the mean disposition effect (DE=0.19) which is insignificantly higher than the base sample's 0.15, but the difference is not statistically significant. The PGR rises to 0.43 while the PLR falls slightly to 0.23, widening the gap relative to the base sample and producing the larger disposition effect. Mean greed in the Return Salience Sample is 3.12, similar to the base sample, implying that the observed DE difference is not simply due to a change in the greed distribution. Loss aversion averages 4.75 in the base sample and 3.55 in the salience treatment. Risk preference averages 2.49, slightly higher than the base sample's 2.28, and maximization tendency is similar at 4.62. Demographics are broadly comparable, with mean age at 25.23 years, a slightly higher proportion of male participants (58% vs. 46%), and similar income and education levels. These variables do not differ significantly between samples.

Table 6.1 Descriptive Statistics

This table reports the summary statistics for the Base Sample (Study 1) and the Return Salience Sample (Study 3). Variables included *Disposition Effect* (FIFO), proportion of gains realised (*PGR*), proportion of losses realised (*PLR*), *Greed, Loss Aversion, Risk Preference, Maximization, Trading Experience, Age, Gender, Income and Education*.

	Base Sample (N=60)					Return Salience Sample (N=124)				
Variable	Mean	Median	Stdev	Min	Max	Mean	Median	Stdev	Min	Max
Disposition Effect	0.15	0.15	0.31	-0.9	0.85	0.19	0.22	0.34	-0.71	1
PGR	0.37	0.38	0.21	0	0.85	0.43	0.42	0.26	0	1
PLR	0.22	0.2	0.2	0	0.9	0.23	0.19	0.23	0	1
Greed	3.11	3.14	0.75	1.43	5	3.12	3.13	0.91	1.29	5
Loss Aversion	4.75	5	1.1	2	7	3.5	3	1.58	1	7
Risk Preference	2.28	2	1	1	4	2.49	3	0.81	1	4
Maximization	4.72	4.72	0.99	2.66	6.77	4.62	4.66	1.01	1.88	6.56
Trading Experience	1.98	2	1.15	1	4	2.01	2.01	1.18	1	4
Age	25.01	21	6.99	18	52	25.23	22	7.54	18	50
Gender	0.46	0	0.5	0	1	0.58	1	0.49	0	1
Income	2.45	2	1.08	1	6	2.48	2	1.08	1	7
Education	1.73	2	1.11	0	4	1.5	2	1.05	0	4

Table 6.2 reports univariate comparisons of investor characteristics and trading behaviour across the baseline, salience, and framing conditions. Panel A contrasts the baseline sample with the return salience condition. The average disposition effect is 0.19 in the salience sample compared with 0.15 in the base sample. However, the difference is not statistically significant. As shown later in Table 6.4, once such heterogeneity is controlled for, salience does exert a statistically significant positive effect on the disposition effect. Loss aversion scores are significantly lower in the salience group (mean=3.5 vs. 4.75, t=–2.25, *p*=0.012). Because loss aversion is a dispositional trait rather than something affected by situational manipulations, this difference likely reflects sample composition rather than an effect of salience.

Panels B and C compare absolute versus percentage change framing for low and high-priced stocks, respectively. In Panel B, the results show that the disposition effect is significantly stronger under percentage change framing (mean=0.32 vs. 0.08, *t*=2.60, Wilcoxon *p*=0.030). This pattern suggests that showing return in percentage changes amplify behavioural biases when the stock price is low. Percentage returns on low-priced stocks can appear disproportionately large relative to their economic value, prompting investors to overweight these signals and realise gains more readily. This pattern is consistent with salience-based theories of decision-making (Bordalo et al., 2012), which predict that disproportionately salient percentage outcomes attract excessive attention and distort trading behaviour. The stronger disposition effect under percentage framing is primarily explained by higher gain realization. Specifically, PGR increases from 0.36 under absolute framing to 0.50 under percentage framing (mean difference=-0.14, *t*-test *p*=0.090, Wilcoxon *p*=0.480). By contrast, PLR declines but the differences are not statistically significant (mean difference=0.10, *t*-test *p*=0.360, Wilcoxon *p*=0.510). Thus, the stronger disposition effect under percentage returns for low-priced stocks is attributable to more aggressive gain realization, consistent with the idea that salient percentage gains induce disproportionate attention and realization pressure.

Panel C shows that the disposition effect is significantly stronger under absolute framing for high-priced stocks, increasing from 0.08 under percentage framing to 0.30 under absolute framing (t=2.60, Wilcoxon p=0.020). PLR declines under absolute framing relative to percentage framing. This difference is marginally significant in mean comparisons but not supported by median-based tests. Overall, the stronger disposition effect is driven mainly by higher PGR, with some weaker evidence that reduced PLR also contributes.

Table 6.2. Univariate Comparisons

This table reports univariate comparisons of investor characteristics and trading behaviour across experimental conditions. Panel A contrasts the baseline sample with the return salience condition, Panels B and C compare absolute versus percentage change framing for low and high-priced stocks, respectively. Variables included *Disposition Effect* (FIFO), proportion of gains realised (*PGR*), proportion of losses realised (*PLR*), *Greed, Loss Aversion, Risk Preference, Maximization, Trading Experience, Age, Gender, Income and Education*. Reported statistics are means and medians for each condition, with differences shown alongside t-tests for equality of means and Wilcoxon rank-sum tests for equality of distributions. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Base vs Return Salience

	Base		Return Salience		Difference		
Variable	Mean	Median	Mean	Median	Mean	*t*-test *p*-value	Wilcoxon *p*-Value
Disposition Effect	0.15	0.15	0.19	0.22	-0.04	0.710	0.330
PGR	0.37	0.38	0.43	0.42	-0.06	0.160	0.260
PLR	0.22	0.20	0.23	0.19	-0.01	0.710	0.980
Greed	3.11	3.14	3.12	3.13	-0.01	0.670	0.680
Loss Aversion	4.75	5.00	3.50	3.00	1.25	0.012**	0.012**
Risk Preference	2.28	2.00	2.49	3.00	-0.21	0.540	0.960
Maximization	4.72	4.72	4.62	4.66	0.10	0.540	0.780
Trading Experience	1.98	2.00	2.01	2.01	-0.03	0.860	0.690
Age	25.01	21.00	25.23	22.00	-0.22	0.880	0.920
% Male	0.46	0.00	0.58	1.00	-0.12	1.53	1.53
Income	2.45	2.00	2.48	2.00	-0.03	0.880	0.720
Education	1.73	2.00	1.50	2.00	-0.32	0.170	0.026**

Table 6.2 — *Continued*

Panel B: Low-Priced Stocks with Absolute Change vs Percentage Change							
	Absolute Change		Percentage Change		Difference		
Variable	Mean	Median	Mean	Median	Mean	*t*-test *p*-value	Wilcoxon *p*-Value
Disposition Effect	0.08	0.16	0.32	0.31	-0.24	0.010**	0.030**
PGR	0.36	0.30	0.5	0.46	-0.14	0.090*	0.480
PLR	0.28	0.19	0.18	0.17	0.10	0.360	0.510
Greed	3.17	3.14	3.14	3.14	0.03	0.450	0.510
Loss Aversion	3.30	3.00	3.600	3.00	-0.30	0.630	0.660
Risk Preference	2.38	3.00	2.48	3.00	-0.10	0.600	0.560
Maximization	4.70	4.66	4.49	4.66	0.21	0.450	0.540
Trading Experience	2.09	2.00	2.13	2.00	-0.04	0.600	0.450
Age	26.90	22.00	27.16	22.00	-0.26	0.610	0.660
% Male	0.55	1.00	0.48	0.00	0.07	0.551	0.551
Income	2.33	2.00	2.65	2.00	-0.32	0.660	0.660
Education	1.81	2.00	1.62	2.00	0.19	0.460	0.640

Table 6.2 — *Continued*

Panel C: High-Priced Stocks with Absolute Change vs Percentage Change							
	Absolute Change		Percentage Change		Difference		
Variable	Mean	Median	Mean	Median	Mean	*t*-test *p*-value	Wilcoxon *p*-Value
Disposition Effect	0.30	0.29	0.08	0.17	0.22	0.010**	0.020**
PGR	0.47	0.43	0.38	0.50	0.09	0.010**	0.010**
PLR	0.17	0.20	0.30	0.28	-0.13	0.090*	0.480
Greed	3.02	2.96	3.06	2.71	-0.04	0.450	0.520
Loss Aversion	3.65	3.00	3.50	3.00	0.15	0.510	0.810
Risk Preference	2.53	2.50	2.36	2.50	0.17	0.680	0.660
Maximization	4.56	4.56	4.75	4.94	-0.19	0.450	0.530
Trading Experience	2.12	2.00	1.83	1.55	0.29	0.580	0.450
Age	22.81	21.00	24.00	22.00	-1.19	0.620	0.610
% Male	0.62	1.00	0.66	1.00	-0.04	0.332	0.332
Income	2.22	2.00	2.53	2.00	-0.31	0.530	0.660
Education	0.94	1.00	1.68	2.00	-0.74	0.460	0.410

Table 6.3 presents correlations for the salience condition.[25] The relationships between the disposition effect, PGR, and PLR remain strong. The disposition effect is positively correlated with PGR (0.76, $p<0.01$) and negatively correlated with PLR (−0.66, $p<0.01$), confirming that biased realisation behaviour in the salience condition continues to be driven primarily by differential responses to gains and losses.

In contrast, correlations between the disposition effect and psychological traits are generally weaker under salience. The association with loss aversion is positive but modest (0.16, $p<0.10$), while the correlation with greed is small and statistically insignificant. This attenuation suggests that when return information is made salient, stable individual traits play a reduced role in explaining realisation behaviour. Instead, decision weights appear to shift toward salient payoff information, consistent with salience theory (Bordalo et al., 2012), which predicts disproportionate attention to prominent outcomes.

Among demographic characteristics, education remains negatively correlated with the disposition effect (−0.23, $p<0.01$), indicating that greater sophistication continues to mitigate biased selling behaviour, in line with prior evidence (Calvet et al., 2009).

[25] Correlation coefficients for all subsamples are reported in Appendix L.

Table 6.3. Correlations Coefficients

This table reports the correlations for the Return Salience Sample (Study 3). The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Salience Sample (N=124)										
	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect	-										
2. PGR	0.76***										
3. PLR	-0.66***	-0.02									
4. Greed	0.03	0.1	0.07								
5. Loss Aversion	0.16*	0.11	-0.13	-0.08							
6. Risk Preference	0.02	-0.02	-0.07	-0.11	-0.03						
7. Maximization	-0.13	-0.11	0.08	0.26***	-0.02	-0.05					
8. Trading Experience	-0.09	-0.04	0.08	-0.17*	-0.13	0.12	-0.03				
9. Age	0.21**	0.15*	-0.15*	-0.08	0.07	-0.11	-0.02	0.08			
10. Gender	-0.11	0.01	0.16*	0.25***	-0.04	0.03	0.18**	-0.15	-0.12		
11. Income	-0.11	-0.18**	-0.05	0.11	-0.06	0.01	0.11	-0.06	0.21**	-0.02	
12. Education	-0.23***	-0.15	0.19**	0.09	-0.17*	-0.13	0.03**	-0.02	0.24***	0.05	0.31***

6.4.2 Regression Analysis

I begin with the following OLS framework to test H1 (salience vs. no-salience):

$$DE_i = \beta_0 + \beta_1 High\_Salience_i + X_{k,i} + \varepsilon \quad (1)$$

$$DE_i = \beta_0 + \beta_1 Percentage\_Change_i + \beta_2 High\_Initial\_Price_i + \beta_3 (Percentage\_Change_i \; X \; High\_Initial\_Price_i) + \beta_k X_{k,i} + \varepsilon \quad (2)$$

All regressions are estimated by OLS and the standard errors are heteroskedasticity-robust (White, 1980). Following Study, I use centred greed in all regressions. Panel A of Table 6.4 uses the full sample of 184 participants and presents baseline models with and without psychological and demographic controls. Column (1) compares investors who do not view any return-based cues (non-salience condition) with those who see either a percentage or dollar label (salience condition). The coefficient is positive (β=0.044) but statistically insignificant, mirroring the non-significant mean difference in DE between the base and salience samples reported in Table 6.1. This initial result suggests that the framing manipulation does not uniformly influence investor behaviour when different return formats and price regimes are pooled together. As later results show, the behavioural effects depend importantly on how returns are framed and on the underlying stock price level. Aggregating across heterogeneous framing conditions may therefore obscure behavioural patterns that become more apparent once these contextual differences are modelled explicitly.

When control variables are added in Column (2), the salience coefficient becomes both economically and statistically significant (β=0.115, $p<0.05$). This estimate implies that salience return displays increase DE by 11.5 percentage points, equivalent to approximately 77% of the base-sample mean DE. Among the controls, Loss aversion is positively associated with DE (β=0.038, $p<0.05$), consistent with reluctance to realise losses under prospect theory (Kahneman and Tversky, 1979), while risk preference is negatively related (β=-0.038, $p<0.10$), aligning with Barberis and Xiong's (2009) prediction that risk-tolerant investors are less inclined to lock in gains.

Panel B uses the salience subsample of 124 participants and incorporates framing and price-regime variables to assess whether the salience effect depends on how returns are displayed and stock price level. Importantly, salience is not directly measured in the empirical models. Instead, the experimental design manipulates framing conditions through return presentation format and stock price level, which are theorised to influence the relative salience of percentage versus dollar outcomes. Column (1) shows that including display format and price regime variables substantially improves explanatory power (Adj. R^2=0.112) and yields strong evidence that the effect of return format depends critically on the stock's price level. The implied disposition effect levels for each condition are positive across all four combinations of framing and price regime.[26] The result for *Percentage_Change* in Column (1) indicates that for the low-priced stocks, displaying returns in percentage increases DE by 24.8 percentage points (p<0.01) relative to presenting returns in absolute dollars while the result for *High_Initial_Price* indicates that showing returns in absolute dollars increases DE by approximately 21.5 percentage points (p<0.01) for high-priced stocks relative to low-priced stocks. The interaction term between *High_Initial_Price* and *Percentage_Change* is large and negative (β=-0.461, p<0.01), indicating that the positive effect of percentage framing observed for low-priced stocks not only diminishes but fully reverses for high-priced stocks. In the high-price regime, dollar framing produces a higher DE than percentage framing, exactly as predicted by H2a and H2b. The findings align with Weber and Camerer's (1998) insights into

[26] The linear combination tests show that the disposition effect is statistically significant under two of the four conditions: low-priced percentage framing ($\beta_0 + \beta_1$, $p < 0.01$) and high-priced dollar framing ($\beta_0 + \beta_2$, $p < 0.05$). In contrast, the estimates for low-priced dollar framing (β_0) and high-priced percentage framing ($\beta_0 + \beta_1 + \beta_2 + \beta_3$) are not statistically different from zero.

outcome framing, namely, that how gains and losses are presented fundamentally alters their psychological impact and, by extension, investors' trading decisions.

After adding controls in Column (2), the coefficients on *Percentage_Change* (β=0.210, $p<0.01$), *High_Initial_Price* (β=0.235, $p<0.01$), and their interaction (β=-0.434, $p<0.01$) remain virtually unchanged, indicating that the price-dependent framing effect is robust to controlling for investor traits. Finally, Column (3) clusters standard errors at the session level to account for within-condition dependence. The salience coefficient remains significant (β=0.210, $p<0.01$), and the framing and price interactions remain large and highly significant.

Table 6.4. Salience Impact on the Disposition Effect

Panel A reports OLS regression estimates examining the overall effect of return salience on the disposition effect (DE). *Salience* is a dummy variable equal to 1 when returns are displayed either in percentage or absolute (dollar) terms and 0 when no return information is shown. Panel B presents results that further investigate how different display formats and price levels jointly influence the DE. *Percentage_Change* equals 1 when returns are displayed in percentage terms, and *High_Initial_Price* equals 1 for stocks start with $300. The interaction term (*High_Initial_Price* × *Percentage_Change*) captures whether the impact of percentage framing varies with initial price level. Columns (3) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A	(1)	(2)	(3)
Intercept	0.081***	0.196	0.196
	(0.039)	(0.187)	(0.150)
Salience	0.044	0.115**	0.115**
	(0.050)	(0.056)	(0.057)
Loss Aversion		0.038**	0.038**
		(0.019)	(0.021)
Risk Preference		-0.038*	-0.038*
		(0.029)	(0.052)
Maximization		-0.022	-0.022
		(0.025)	(0.029)
Trading Experience		-0.02	-0.02
		(0.019)	(0.024)
Age		0.013***	0.013***
		(0.003)	(0.005)
Gender		-0.058	-0.058
		(0.045)	(0.066)
Income		-0.046***	-0.046***
		(0.018)	(0.018)
Education		-0.062	-0.062
		(0.034)	(0.039)
Observations	184	184	184
Adj. R^2	0.004	0.205	0.205
Standard errors adjusted for clustering	No	No	session

Table 6.4 — *Continued*

Panel B	(1)	(2)	(3)
Intercept	0.079	0.071	0.071
	(0.080)	(0.244)	(0.241)
Percentage_Change	0.248***	0.210***	0.210***
	(0.089)	(0.076)	(0.025)
High_Initial_Price	0.215***	0.235***	0.235***
	(0.094)	(0.086)	(0.048)
High_Initial_Price x Percentage_Change	-0.461***	-0.434***	-0.434***
	(0.120)	(0.116)	(0.061)
Loss Aversion		0.021	0.021
		(0.020)	(0.011)
Risk Preference		0.021	0.021
		(0.040)	(0.054)
Maximization		-0.021	-0.021
		(0.039)	(0.044)
Trading Experience		-0.018	-0.018
		(0.023)	(0.023)
Age		0.012***	0.012***
		(0.005)	(0.009)
Gender		-0.034	-0.034
		(0.056)	(0.084)
Income		-0.026	-0.026
		(0.024)	(0.016)
Education		-0.060**	-0.060**
		(0.026)	(0.037)
Observations	124	124	124
Adj. R^2	0.112	0.239	0.239
Standard errors adjusted for clustering	No	No	session

Table 6.5 reports OLS regression estimates examining how salience interacts with individual greed to influence disposition effect (DE).[27] Across all model specifications, greed emerges as a strong and consistent predictor of DE. However, the magnitude is smaller than in the baseline sample (Study 1), where the greed coefficient and model fit (R^2 = 16.8%) were both notably larger. The coefficient on greed ranges from β=0.084 (p<0.05) in the baseline model (Column (1)) to β=0.168 (p<0.01) when salience, interaction terms, and controls are included (Column 4)). This magnitude implies that a one-unit increase in greed raises the proportion of gains realised relative to losses by roughly 8 to 17 percentage points, which is economically meaningful given a mean DE of 0.15. This translates to an increase of about 50 to 110 per cent relative to the sample mean.

Salience also exerts a positive and significant effect on DE. When return information is visually highlighted (Column (2)), the coefficient on Salience is β=0.037 (p<0.05), indicating that visible feedback increases investors' tendency to realise gains. When the *Salience* × *Greed* interaction is introduced (Column (4)), the unconditional salience coefficient rises to β=0.078 (p<0.05), suggesting that part of the salience effect depends on individual greed levels. The full model in Column (4), which controls for psychological factors (loss aversion, risk preference, maximisation tendency) and demographics, yields a negative and statistically significant interaction term (β=-0.112, p<0.05). This negative interaction indicates that the marginal effect of salience on DE weakens among greedier participants.

[27] I re-estimated all models using the standardised greed variable reported in Appendix M, and the results are robust to those presented in Table 6.5.

Table 6.5. The Impacts of Salience and Greed on the Disposition Effect

The table reports OLS regression estimates examining the effects of return salience and greed on the disposition effect (DE). *Salience* is a dummy variable equal to 1 when returns are displayed either in percentage or absolute (dollar) terms and 0 when no return information is shown. *Greed* represents each participant's greed score mean-centred by subtracting 3 from the original scale. Columns (5) and (6) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.176***	0.138***	0.344**	0.284	0.355*	0.284
	-0.024	-0.038	-0.173	-0.181	(0.204)	(0.207)
Greed	0.084**	0.160***	0.122***	0.168***	0.079	0.168***
	(0.034)	(0.058)	(0.032)	(0.051)	(0.046)	(0.026)
Salience		0.037**		0.078**		0.094*
		(0.048)		(0.048)		(0.057)
Salience x Greed		-0.150**		-0.112**		-0.112**
		(0.074)		(0.064)		(0.119)
Loss Aversion			0.024	0.037**	0.024	0.037**
			(0.015)	(0.018)	(0.015)	(0.015)
Risk Preference			-0.025	-0.024	-0.025	-0.024
			(0.029)	(0.028)	(0.047)	(0.048)
Maximization			0.048**	-0.048**	0.048**	-0.048**
			(0.032)	(0.025)	(0.021)	(0.024)
Trading Experience			-0.035**	-0.015	-0.014**	-0.015
			(0.017)	(0.019)	(0.017)	(0.013)
Age			0.014***	0.014***	0.014**	0.014***
			(0.003)	(0.003)	(0.006)	(0.005)
Gender			-0.083**	-0.082**	-0.083**	-0.082**
			(0.042)	(0.044)	(0.038)	(0.042)
Income			-0.044**	-0.045***	-0.044**	-0.045***
			(0.017)	(0.018)	(0.017)	(0.016)
Education			-0.074***	-0.068***	-0.074**	-0.068***
			(0.023)	(0.022)	(0.021)	(0.023)
Observations	184	184	184	184	184	184
Adj. R^2	0.028	0.045	0.249	0.254	0.249	0.276
Standard errors adjusted for clustering	No	No	No	No	session	session

Table 6.6 extends the analysis by examining how individual greed levels interact with display format conditions and price regimes to influence the disposition effect. The negative coefficient on *Greed* in the baseline specification should be interpreted relative to the omitted reference condition, namely low-priced stocks displayed in dollar terms. Accordingly, this coefficient does not represent the unconditional effect of greed on the disposition effect. Rather, it reflects the marginal effect of greed within the omitted reference category, namely low-priced stocks displayed in dollar terms. This differs from Chapter 4, where the positive greed coefficient reflects the average effect of greed in a neutral trading environment without framing or price-regime interactions. The interaction terms in Table 6.6 therefore indicate that the effect of greed is context-dependent and becomes substantially stronger under alternative framing and price conditions, particularly when returns are presented in more psychologically prominent formats. .

In Column (1) the *Percentage_Change* × *Greed* coefficient is positive and statistically significant (0.399, p<0.01), implying that greedier investors exhibit a substantially higher DE in this condition than under the dollar-framing baseline. More specifically, a one-point increase in greed corresponds to a 39.9 percentage-point higher DE in the low-price percentage-framing condition, relative to the low-price dollar-framing. This finding directly supports H3a. When stock prices are low, percentage changes translate small nominal moves into large relative gains, heightening perceived performance. For high-greed investors, who are predisposed to seize gains, this inflated salience strengthens realization utility (Barberis and Xiong, 2012) and accelerates gain-taking behaviour. The mechanism is consistent with Seuntjens et al. (2016), who document that greed is associated with stronger acquisitive motives and heightened responsiveness to opportunities for gain.

In Column (2), the interaction of *High_Initial_Price* × *Greed* is positive and highly significant (β=0.608, p<0.01), suggesting that in the dollar-framing condition, each one-point increase in greed is associated with a 60.8 percentage-point larger DE for high-price stocks relative to low-priced stocks. This supports H3b, which predicts that dollar framing strengthens the DE among greedy investors when stock prices are high. The *High_Initial_Price* × *Percentage_Change* term is strongly negative (β=-0.343, p<0.01), consistent with the results in Panel B of Table 6.4 that the percentage-framing premium observed for low-priced stocks reverses when prices are high.

Most importantly, the three-way interaction term (*High_Initial_Price* × *Percentage_Change* × *Greed*) is negative and statistically significant, indicating that the positive association between greed and the disposition effect is weaker when high-priced stocks are presented in percentage terms rather than dollar terms. In economic terms, greed increases the disposition effect under high-price dollar framing, whereas percentage framing attenuates this relationship. This finding suggests that percentage displays reduce the incremental tendency of greed-prone investors to realise gains in high-price conditions. Columns (3) and (4) re-estimate Columns (1) and (2) using session-clustered standard errors. The coefficient estimates and statistical significance remain largely unchanged. The two-way interaction terms (*Percentage_Change* × *Greed, High_Initial_Price* × *Greed, and High_Initial_Price* × *Percentage_Change*) remain economically and statistically significant, while the three-way interaction remains negative and statistically significant, confirming the robustness of the main findings.

Table 6.6. The Impacts of Greed, Price Regime, and Price Change Format on the Disposition Effect

The table reports OLS regression estimates examining how greed interacts with price-regime (*High_Initial_Price*) and return-format (*Percentage_Change*) framing to influence the disposition effect (DE). *Percentage_Change* equals 1 when returns are displayed in percentage terms and 0 when displayed in absolute (dollar) terms. *High_Initial_Price* equals 1 for stocks with higher initial prices. *Greed* represents participants' greed scores mean-centred by subtracting 3 from the original scale. Interaction terms capture the joint moderating effects of greed, price level, and framing format. Columns (3) and (4) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.136***	0.198	0.092*	0.198
	(0.048)	(0.203)	(0.051)	(0.204)
Greed	-0.331***	-0.308***	-0.331***	-0.308***
	(0.044)	(0.048)	(0.047)	(0.066)
Percentage_Change	0.167**	0.156**	0.221***	0.156***
	(0.068)	(0.066)	(0.066)	(0.051)
High_Initial_Price	0.147***	0.139***	0.231***	0.221***
	(0.054)	(0.048)	(0.053)	(0.034)
Percentage_Change x Greed	0.399***	0.377***	0.399***	0.377***
	(0.071)	(0.078)	(0.071)	(0.087)
High_Initial_Price x Greed	0.620***	0.608***	0.620***	0.608***
	(0.054)	(0.065)	(0.055)	(0.071)
High_Initial_Price x Percentage_Change	-0.451***	-0.343***	-0.451***	-0.343***
	(0.095)	(0.091)	(0.075)	(0.071)
High_Initial_Price x Percentage_Change x Greed	-0.541***	-0.513***	-0.541***	-0.513***
	(0.113)	(0.123)	(0.123)	(0.147)
Loss Aversion		0.014		0.014
		(0.014)		(0.004)
Risk Preference		-0.036		-0.036
		(0.035)		(0.033)

Table 6.6 — Continued

	(1)	(2)	(3)	(4)
Maximization		-0.008		-0.008
		(0.024)		(0.010)
Trading Experience		-0.011		-0.011
		(0.016)		(0.019)
Age		-0.004		-0.004
		(0.004)		(0.005)
Gender		-0.078*		-0.078
		(0.047)		(0.073)
Income		0.021		0.021
		(0.021)		(0.017)
Education		-0.042**		-0.042**
		(0.021)		(0.032)
Observations	124	124	124	124
Adj. R^2	0.519	0.569	0.205	0.569
Standard errors adjusted for clustering	No	No	session	session

Table 6.7 examines how greed, together with price regime and return framing, influences the proportion of gains realised (PGR, Panel A) and the proportion of losses realised (PLR, Panel B).[28] In Column (1) of Panel A, the main effect of *Greed* (β = –0.144, p<0.01) applies only to the low-priced stocks displayed in dollar terms. This indicates that among low-priced stocks shown in dollar format, greedier investors are less likely to realise gains. The interaction between *Percentage_Change* and *Greed* is positive and significant, showing that when returns are framed in percentage terms under low-price conditions, greedy investors become more prone to realise gains. The interaction between *High_Initial_Price* × *Greed* is strongly positive (β=0.379, p<0.01), suggesting that while higher prices generally increase gain realization if returns are expressed as dollar gains, this tendency is mitigated when investors exhibit stronger greed. Most importantly, the negative and significant coefficient on *High_Initial_Price* × *Percentage_Change* × *Greed* (β=–0.219, p<0.05) shows that the gain realization observed in high-priced stocks with dollar-framing returns is attenuated for greedier investors. These patterns remain robust once demographic and psychological controls are added in Column (2).

Panel B reports the results for loss realisation (PLR). In Column (1), the main effect of *Greed* is positive and highly significant (β=0.188, p<0.01), applying only to the reference category of low-priced stocks displayed in dollar terms. This indicates that among low-price, dollar-framed stocks, greedier investors are more willing to realise losses. The interaction *Percentage_Change* × *Greed* is strongly negative (β=–0.282, p<0.01), showing that greed substantially reduces loss realisation when returns are framed in percentage terms at low prices. Similarly, *High_Initial_Price* × *Greed* is negative and significant (β=–0.239, p<0.01), indicating that greed lowers loss realisation for high-priced stocks shown in dollars. The

[28] I re-estimated all models using the standardised greed variable reported in Appendix M, and the results are robust to those presented in Table 6.7.

interaction *High_Initial_Price* × *Percentage_Change* is positive and significant (β=0.148, p<0.05), meaning that percentage framing increases loss realisation more for high-priced stocks than for low-priced ones. The three-way interaction *High_Initial_Price* × *Percentage_Change* × *Greed* is positive and highly significant (β=0.289, p<0.01), indicating that the negative moderating effects of greed are partially offset when percentage framing is applied to high-priced stocks. The dampening effect of greed on loss realisation is weaker in this condition. These results remain stable once demographic and psychological controls are added in Column (2), and when session-clustered standard errors are applied in Columns (3) and (4), confirming that the moderating role of greed is robust across specifications.

Table 6.7. The Impacts of Greed Components, Price Regime, and Price Change Format on the PGR and PLR

The table reports OLS regression estimates examining how greed interacts with price-regime (*High_Initial_Price*) and return-format (*Percentage_Change*) framing to influence the disposition effect (DE), using alternative measures: the proportion of gains realised (*PGR*) in Panel A and the proportion of losses realised (*PLR*) in Panel B. *Greed* represents participants' greed scores mean-centred by subtracting 3 from the original scale. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Panel A: PGR	(1)	(2)	(3)	(4)
Intercept	0.381***	0.431***	0.381***	0.431***
	(0.036)	(0.156)	(0.016)	(0.183)
Greed	-0.144***	-0.117***	-0.144***	-0.117***
	(0.034)	(0.038)	(0.015)	(0.028)
Percentage_Change	0.131***	0.133***	0.146***	0.143***
	(0.050)	(0.059)	(0.041)	(0.044)
High_Initial_Price	0.082*	0.128**	0.133***	0.128***
	(0.051)	(0.049)	(0.035)	(0.041)
Percentage_Change x Greed	0.118*	0.07	0.118*	0.07
	(0.064)	(0.068)	(0.057)	(0.066)
High_Initial_Price x Greed	0.379***	0.349***	0.379***	0.349***
	(0.053)	(0.060)	(0.045)	(0.057)
High_Initial_Price x Percentage_Change	-0.254***	-0.226***	-0.254***	-0.231***
	(0.083)	(0.084)	(0.066)	(0.068)
High_Initial_Price x Percentage_Change x Greed	-0.219**	-0.185*	-0.251**	-0.185
	(0.087)	(0.107)	(0.100)	(0.116)
Loss Aversion		0.012		0.012
		(0.015)		(0.015)
Risk Preference		-0.035		-0.035
		(0.022)		(0.023)
Maximization		-0.007		-0.007
		(0.023)		(0.025)
Trading Experience		0.002		0.002
		(0.018)		(0.011)
Age		0.004		0.004
		(0.003)		(0.004)
Gender		0		0
		(0.045)		(0.049)
Income		-0.024		-0.024
		(0.019)		(0.016)
Education		-0.014		-0.014
		(0.022)		(0.017)
Observations	124	124	124	124
Adj. R^2	0.313	0.354	0.313	0.354

Panel B: PLR	(1)	(2)	(3)	(4)
Intercept	0.245***	0.248*	0.245***	0.248*
	(0.038)	(0.151)	(0.035)	(0.138)
Greed	0.188***	0.192***	0.188***	0.192***
	(0.039)	(0.044)	(0.040)	(0.051)
Percentage_Change	-0.037	-0.065	-0.075*	-0.065**
	(0.047)	(0.048)	(0.040)	(0.029)
High_Initial_Price	-0.055	-0.081	-0.087	-0.081*
	(0.046)	(0.050)	(0.052)	(0.046)
Percentage_Change x Greed	-0.282***	-0.308***	-0.282***	-0.308***
	(0.050)	(0.056)	(0.044)	(0.049)
High_Initial_Price x Greed	-0.239***	-0.255***	-0.239***	-0.255***
	(0.049)	(0.058)	(0.043)	(0.054)
High_Initial_Price x Percentage_Change	0.148**	0.169**	0.187**	0.169**
	(0.072)	(0.073)	(0.069)	(0.064)
High_Initial_Price x Percentage_Change x Greed	0.289***	0.324***	0.289***	0.324***
	(0.080)	(0.088)	(0.067)	(0.081)
Loss Aversion		-0.003		-0.003
		(0.012)		(0.014)
Risk Preference		0.001		0.001
		(0.024)		(0.016)
Maximization		0.003		0.003
		(0.018)		(0.018)
Trading Experience		0.01		0.01
		(0.016)		(0.017)
Age		0.001		0.001
		(0.003)		(0.002)
Gender		0.068*		0.068
		(0.037)		(0.046)
Income		-0.049***		-0.049***
		(0.015)		(0.013)
Education		0.033*		0.033**
		(0.018)		(0.013)
Observations	124	124	124	124
Adj. R^2	0.284	0.366	0.284	0.366
Standard errors adjusted for clustering	No	No	session	session

6.4.3 Robustness Checks

In this section, I present robustness checks for our main findings on how return salience and greed interact to shape the disposition effect.

Recall that the results in Table 6.5 employ the first-in-first-out (FIFO) to measure the disposition effect. In Table 6.8, I re-estimate those results using five alternative measurements. Specifically, the average purchase price (AP), the volume-weighted average purchase price (VWAP), the last-in-first-out (LIFO) rule (Rau, 2015), Fischbacher et al., (2017) method (denoted as FHS), and Alpha coefficient (Odean, 1998). Across all measures, the results remain virtually unchanged. Greed continues to load positively and significantly, salience maintains a positive association, and the *Salience* × *Greed* interaction stays negative and significant. The explanatory power of the models is stable across Columns. These findings demonstrate that our main conclusions are robust to alternative approaches for measuring the disposition effect.

Table 6.8. Robustness Checks on Salience and Greed using Alternative Measures of the Disposition Effect

The table reports OLS regression estimates testing the robustness of the effects of return salience and greed on the disposition effect (DE) using alternative measurement approaches. The DE is calculated using five methods: average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), FHS method, and the Alpha measure. *Greed* represents participants' mean-centred greed scores, and the interaction term (*Salience* × *Greed* captures whether the influence of salience differs by greed level. *Salience* is a dummy variable equal to 1 when returns are displayed either in percentage or absolute (dollar) terms and 0 when no return information is shown. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	AP	VWAP	LIFO	FHS	Alpha
Intercept	0.334*	0.352*	0.309	0.375**	1.077***
	(0.180)	(0.187)	(0.193)	(0.176)	(0.383)
Greed	0.117***	0.133***	0.147***	0.111***	0.228**
	(0.044)	(0.047)	(0.047)	(0.039)	(0.097)
Salience	0.043	0.046	0.065	0.034	0.126
	(0.046)	(0.048)	0.05	(0.042)	0.093
Salience x Greed	-0.076	-0.087	-0.114*	-0.044	-0.186
	(0.057)	(0.060)	(0.060)	(0.052)	(0.114)
Loss Aversion	0.021	0.023	0.028	0.025	-0.003
	(0.017)	0.018	(0.019)	(0.016)	(0.032)
Risk Preference	-0.035	-0.034	-0.026	-0.052**	-0.089
	(0.027)	0.028	(0.028)	(0.026)	(0.055)
Maximization	-0.048**	-0.049**	-0.047*	-0.055**	-0.117**
	(0.024)	0.024	(0.026)	(0.023)	(0.045)
Trading Experience	-0.038**	-0.043***	-0.032*	-0.037**	-0.049
	(0.016)	0.016	(0.017)	(0.015)	(0.035)
Age	0.014***	0.014***	0.013***	0.013***	0.022***
	(0.003)	0.003	(0.003)	(0.003)	(0.006)

Table 6.8 — *Continued*

	AP	VWAP	LIFO	FHS	Alpha
Gender	-0.072*	-0.076*	-0.061	-0.076**	-0.317***
	(0.038)	0.04	(0.043)	(0.038)	(0.084)
Income	-0.037**	-0.037**	-0.046***	-0.022	-0.047
	(0.015)	0.015	(0.017)	(0.015)	(0.040)
Education	-0.066***	-0.065***	-0.063***	-0.073***	-0.122***
	(0.022)	0.023	(0.023)	(0.021)	(0.043)
Observations	184	184	184	184	184
Adj. R^2	0.279	0.265	0.245	0.289	0.239
Standard errors adjusted for clustering	No	No	No	No	No

Next, to assess the robustness of our baseline findings in Table 6.6, I re-estimate the disposition effect regressions using alternative measurement approaches. The results in Table 6.9 remain closely aligned with the baseline models. Across these alternative constructions, the coefficients of interest remain virtually unchanged. Greed remains a positive and significant determinant of the disposition effect, while salience also exerts a positive influence. The interaction between salience and greed is consistently negative and statistically significant. The explanatory fit remains stable across the columns. Overall, the robustness checks confirm that the main results are not driven by the choice of disposition effect measure.

Table 6.9. The Impacts of Alternative Greed, Price Regime, and Price Change Format on the Disposition Effect

The table reports OLS regression estimates examining the robustness of the interactive effects between greed, price regime (*High_Initial_Price*), and return-format framing (*Percentage_Change*) on the disposition effect (DE) using alternative DE measures. The DE is computed using five approaches: average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), FHS method, and the Alpha measure. Columns (6) to (10) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. *Percentage_Change* equals 1 when returns are displayed in percentage terms and 0 when displayed in absolute (dollar) terms. *High_Initial_Price* equals 1 for stocks start with $300. Interaction terms capture the joint moderating effects of greed, price level, and framing format. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	AP	VWAP	LIFO	FHS	Alpha	AP	VWAP	LIFO	FHS	Alpha
Intercept	0.127	0.125	0.177	0.154	0.703*	0.127	0.125	0.177	0.154	0.703
	(-0.190)	(-0.200)	(-0.206)	(-0.183)	(-0.413)	(-0.192)	(-0.205)	(-0.202)	(-0.215)	(-0.416)
Greed	-0.302***	-0.299***	-0.333***	-0.233***	-0.453***	-0.302***	-0.299***	-0.333***	-0.233***	-0.453***
	(-0.047)	(-0.048)	(-0.050)	(-0.041)	(-0.094)	(-0.076)	(-0.074)	(-0.072)	(-0.054)	(-0.089)
Percentage_Change	0.160***	0.155***	0.220***	0.095	0.378***	0.160***	0.155***	0.220***	0.095**	0.378***
	(-0.052)	(-0.054)	(-0.061)	(-0.059)	(-0.127)	(-0.049)	(-0.050)	(-0.044)	(-0.043)	(-0.106)
High_Initial_Price	0.231***	0.233***	0.199***	0.231***	0.303**	0.231***	0.233***	0.199***	0.231***	0.303**
	(-0.049)	(-0.051)	(-0.053)	(-0.052)	(-0.127)	(-0.042)	(-0.044)	(-0.037)	(-0.049)	(-0.111)
Percentage_Change x Greed	0.386***	0.388***	0.388***	0.363***	0.635***	0.386***	0.388***	0.388***	0.363***	0.635***
	(-0.062)	(-0.064)	(-0.075)	(-0.064)	(-0.146)	(-0.086)	(-0.088)	(-0.091)	(-0.075)	(-0.179)
High_Initial_Price x Greed	0.605***	0.600***	0.601***	0.554***	0.826***	0.605***	0.600***	0.601***	0.554***	0.826***
	(-0.066)	(-0.067)	(-0.068)	(-0.059)	(-0.152)	(-0.081)	(-0.079)	(-0.079)	(-0.063)	(-0.120)
High_Initial_Price x Percentage_Change	-0.395***	-0.381***	-0.387***	-0.316***	-0.736***	-0.395***	-0.381***	-0.387***	-0.316***	-0.736***
	(-0.085)	(-0.090)	(-0.093)	(-0.092)	(-0.199)	(-0.071)	(-0.077)	(-0.069)	(-0.072)	(-0.203)

Table 6.9 - *Continued*

	(1) AP	(2) VWAP	(3) LIFO	(4) FHS	(5) Alpha	(6) AP	(7) VWAP	(8) LIFO	(9) FHS	(10) Alpha
High_Initial_Price x Percentage_Change x Greed	-0.566***	-0.548***	-0.493***	-0.562***	-0.977***	-0.566***	-0.548***	-0.493***	-0.562***	-0.977***
	(-0.114)	(-0.119)	(-0.122)	(-0.116)	(-0.250)	(-0.149)	(-0.154)	(-0.152)	(-0.141)	(-0.226)
Loss Aversion	0.006	0.007	0.011	0.014	-0.026	0.006	0.007	0.011	0.014	-0.026
	(-0.014)	(-0.015)	(-0.016)	(-0.015)	(-0.031)	(-0.011)	(-0.011)	(-0.012)	(-0.015)	(-0.031)
Risk Preference	-0.046	-0.039	-0.041	-0.065*	-0.136*	-0.046	-0.039	-0.041	-0.065**	-0.136**
	(-0.035)	(-0.036)	(-0.037)	(-0.035)	(-0.071)	(-0.029)	(-0.031)	(-0.031)	(-0.029)	(-0.066)
Maximization	-0.002	-0.001	-0.009	-0.012	-0.047	-0.002	-0.001	-0.009	-0.012	-0.047
	(-0.022)	(-0.023)	(-0.026)	(-0.024)	(-0.049)	(-0.023)	(-0.023)	(-0.024)	(-0.030)	(-0.043)
Trading Experience	-0.011	-0.016	-0.005	-0.009	0.016	-0.011	-0.016	-0.005	-0.009	0.016
	(-0.016)	(-0.016)	(-0.017)	(-0.017)	(-0.043)	(-0.013)	(-0.014)	(-0.013)	(-0.012)	(-0.042)
Age	0.005	0.005	0.003	0.006*	0.008	0.005	0.005	0.003	0.006	0.008
	(-0.003)	(-0.004)	(-0.004)	(-0.003)	(-0.008)	(-0.004)	(-0.005)	(-0.005)	(-0.004)	(-0.008)
Gender	-0.092**	-0.099**	-0.058	-0.111**	-0.256**	-0.092**	-0.099**	-0.058	-0.111**	-0.256**
	(-0.044)	(-0.046)	(-0.048)	(-0.046)	(-0.111)	(-0.042)	(-0.043)	(-0.050)	(-0.040)	(-0.115)
Income	0.024	0.022	0.005	0.037*	0.067	0.024	0.022	0.005	0.037	0.067*
	(-0.020)	(-0.020)	(-0.021)	(-0.021)	(-0.048)	(-0.022)	(-0.023)	(-0.023)	(-0.024)	(-0.039)
Education	-0.033	-0.031	-0.026	-0.039*	-0.051	-0.033*	-0.031*	-0.026	-0.039*	-0.051
	(-0.021)	(-0.021)	(-0.021)	(-0.023)	(-0.052)	(-0.017)	(-0.017)	(-0.021)	(-0.021)	(-0.048)
Observations	124	124	124	124	124	124	124	124	124	124
Adj. R^2	0.566	0.546	0.547	0.505	0.399	0.566	0.546	0.547	0.505	0.399
Standard errors adjusted for clustering	No	No	No	No	No	session	session	session	session	session

Recall that our main results in Panel A of Table 6.7 use the FIFO-based proportion of gains realised to examine how greed interacts with price regime and return format. I now assess whether these findings are robust to alternative measures of the proportion of gains realised (PGR). Table 6.10 presents the results using four additional PGR proxies: average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), and Fischbacher, Hoffmann, and Schudy's (2017) FHS method. Across all specifications, the coefficient on the key triple interaction term (*High_Initial_Price* × *Percentage_Change* × *Greed*) remains negative and statistically significant at conventional levels, indicating that the attenuating effect of high-priced levels on the salience–greed relationship is not driven by the choice of DE measurement. The signs and magnitudes of the main effects also closely mirror those reported in Table 6.7. Overall, these robustness checks confirm that the interaction between greed, price regime, and return format systematically influences investors' tendency to realise gains, independent of the specific computational approach used to measure the disposition effect.

Table 6.10. The Impacts of Alternative Greed, Price Regime, and Price Change Format on PGR

The table reports estimation results from OLS regressions examining how greed, price regime, and return-format framing influence the proportion of gains realised (PGR). The dependent variable, *PGR*, measures the proportion of realised gains relative to total potential gains. *Percentage_Change* is a dummy variable equal to one when returns are displayed in percentage terms and zero when displayed in absolute (dollar) terms. *High_Initial_Price* equals one for stocks start with $300. Interaction terms (*Percentage_Change* × *Greed*, *High_Initial_Price* × *Greed*, *High_Initial_Price* × *Percentage_Change*, and *High_Initial_Price* × *Percentage_Change* × *Greed*) capture the combined moderating effects of greed, price level, and return-format framing. The DE is computed using four alternative approaches: average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), and Fischbacher, Hoffmann, and Schudy's (2017) realised-gain method (FHS). Variables included *Disposition Effect* (FIFO), proportion of gains realised (*PGR*), proportion of losses realised (*PLR*), *Greed, Loss Aversion, Risk Preference, Maximization, Trading Experience, Age, Gender, Income and Education*. Columns (5) to (8) reports estimate with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AP	VWAP	LIFO	FHS	AP	VWAP	LIFO	FHS
Intercept	0.400***	0.391**	0.490***	0.24	0.400**	0.391**	0.490***	0.24
	(0.143)	(0.150)	(0.160)	(0.150)	(0.145)	(0.153)	(0.166)	(0.172)
Greed	-0.114***	-0.114***	-0.115***	-0.063	-0.114***	-0.114***	-0.115***	-0.063***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.020)	(0.021)	(0.023)	(0.021)
Percentage_Change	0.098**	0.093*	0.145***	0.102*	0.098**	0.093**	0.145***	0.102*
	(0.047)	(0.048)	(0.054)	(0.056)	(0.042)	(0.042)	(0.045)	(0.051)
High_Initial_Price	0.131***	0.129***	0.113**	0.161***	0.131***	0.129***	0.113**	0.161***
	(0.049)	(0.049)	(0.051)	(0.053)	(0.039)	(0.040)	(0.041)	(0.048)
Percentage_Change x Greed	0.07	0.073	0.05	0.06	0.07	0.073	0.05	0.06
	(0.056)	(0.056)	(0.065)	(0.064)	(0.046)	(0.049)	(0.061)	(0.059)
High_Initial_Price x Greed	0.362***	0.358***	0.303***	0.333***	0.362***	0.358***	0.303***	0.333***
	(0.061)	(0.062)	(0.065)	(0.061)	(0.053)	(0.055)	(0.059)	(0.053)
High_Initial_Price x Percentage_Change	-0.176**	-0.165**	-0.169**	-0.214**	-0.176**	-0.165**	-0.169**	-0.214***
	(0.080)	(0.081)	(0.084)	(0.085)	(0.070)	(0.069)	(0.068)	(0.076)
High_Initial_Price x Percentage_Change x Greed	-0.267**	-0.264**	-0.17	-0.263**	-0.267**	-0.264**	-0.17	-0.263**
	(0.105)	(0.106)	(0.109)	(0.106)	(0.105)	(0.108)	(0.117)	(0.121)

Table 6.10 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AP	VWAP	LIFO	FHS	AP	VWAP	LIFO	FHS
Loss Aversion	0.013	0.013	0.016	0.024	0.013	0.013	0.016	0.024
	(0.015)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)	(0.018)
Risk Preference	-0.048**	-0.046**	-0.041*	-0.032	-0.048*	-0.046*	-0.041	-0.032
	(0.022)	(0.022)	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)	(0.022)
Maximization	-0.009	-0.004	-0.02	-0.002	-0.009	-0.004	-0.02	-0.002
	(0.021)	(0.022)	(0.025)	(0.023)	(0.020)	(0.021)	(0.024)	(0.027)
Trading Experience	-0.003	-0.006	-0.004	-0.017	-0.003	-0.006	-0.004	-0.017
	(0.017)	(0.017)	(0.017)	(0.017)	(0.013)	(0.014)	(0.012)	(0.014)
Age	0.005	0.005	0.004	0.006*	0.005	0.005	0.004	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Gender	-0.002	-0.007	0.012	-0.033	-0.002	-0.007	0.012	-0.033
	(0.042)	(0.044)	(0.047)	(0.045)	(0.047)	(0.048)	(0.049)	(0.045)
Income	-0.021	-0.024	-0.037*	-0.012	-0.021	-0.024	-0.037*	-0.012
	(0.017)	(0.017)	(0.020)	(0.019)	(0.015)	(0.015)	(0.019)	(0.017)
Education	-0.012	-0.01	-0.01	-0.015	-0.012	-0.01	-0.01	-0.015
	(0.021)	(0.021)	(0.022)	(0.022)	(0.011)	(0.012)	(0.016)	(0.011)
Observations	124	124	124	124	124	124	124	124
Adj. R^2	0.357	0.341	0.321	0.363	0.357	0.341	0.321	0.363
Standard errors adjusted for clustering	No	No	No	No	session	session	session	session

Finally, I examine whether our main result in Panel B of Table 6.7 remain robust to different measurements to compute the proportion of losses realised (PLR). Table 6.11 presents the results based on four alternative PLR specifications. Across all models, the key triple interaction term (*High_Initial_Price* × *Percentage_Change* × *Greed*) remains positive and statistically significant. The direction and magnitude of the coefficients closely mirror those in Panel B of Table 6.7, confirming that the relationship between greed, price framing, and salience is stable across both gain- and loss-side measures of the disposition effect. Overall, these results reinforce the robustness of our findings.

Table 6.11. The Impacts of Alternative Greed, Price Regime, and Price Change Format on PLR

The table reports estimation results from OLS regressions examining how greed, price regime, and return-format framing influence the *proportion of losses realised (PLR)*. The dependent variable, *PLR*, measures the proportion of realised losses relative to total potential losses. *Percentage_Change* is a dummy variable equal to one when returns are displayed in percentage terms and zero when displayed in absolute (dollar) terms. *High_Initial_Price* equals one for stocks starting with a price of $300. Interaction terms (*Percentage_Change* × *Greed*, *High_Initial_Price* × *Greed*, *High_Initial_Price* × *Percentage_Change*, and *High_Initial_Price* × *Percentage_Change* × *Greed*) capture the combined moderating effects of greed, price level, and return-format framing. The DE is computed using four alternative approaches: average purchase price (AP), volume-weighted average purchase price (VWAP), last-in-first-out (LIFO), and Fischbacher, Hoffmann, and Schudy's (2017) realised-gain method (FHS). Variables included *Disposition Effect* (FIFO), proportion of gains realised (*PGR*), proportion of losses realised (*PLR*), *Greed, Loss Aversion, Risk Preference, Maximization, Trading Experience, Age, Gender, Income and Education*. Columns (5) to (8) report estimates with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AP	VWAP	LIFO	FHS	AP	VWAP	LIFO	FHS
Intercept	0.198	0.186	0.245	0.013	0.198	0.186	0.245*	0.013
	(0.139)	(0.141)	(0.151)	(0.114)	(0.133)	(0.134)	(0.136)	(0.134)
Greed	0.176***	0.173***	0.207***	0.159***	0.176***	0.173***	0.207***	0.159***
	(0.043)	(0.042)	(0.042)	(0.034)	(0.062)	(0.060)	(0.055)	(0.048)
Percentage_Change	-0.057	-0.056	-0.071	0.012	-0.057*	-0.056*	-0.071**	0.012
	(0.045)	(0.045)	(0.047)	(0.045)	(0.030)	(0.031)	(0.029)	(0.048)
High_Initial_Price	-0.091*	-0.095**	-0.077	-0.061	-0.091**	-0.095**	-0.077*	-0.061*
	(0.047)	(0.046)	(0.049)	(0.040)	(0.036)	(0.035)	(0.039)	(0.033)
Percentage_Change x Greed	-0.301***	-0.299***	-0.323***	-0.290***	-0.301***	-0.299***	-0.323***	-0.290***
	(0.057)	(0.057)	(0.056)	(0.049)	(0.068)	(0.065)	(0.059)	(0.057)
High_Initial_Price x Greed	-0.223***	-0.220***	-0.277***	-0.201***	-0.223***	-0.220***	-0.277***	-0.201***
	(0.055)	(0.053)	(0.056)	(0.048)	(0.067)	(0.063)	(0.058)	(0.053)
High_Initial_Price x Percentage_Change	0.175**	0.169**	0.177**	0.06	0.175***	0.169***	0.177***	0.06
	(0.068)	(0.069)	(0.072)	(0.065)	(0.053)	(0.053)	(0.056)	(0.070)

Table 6.11 – *Continued*

	(1) AP	(2) VWAP	(3) LIFO	(4) FHS	(5) AP	(6) VWAP	(7) LIFO	(8) FHS
High_Initial_Price x Percentage_Change x Greed	0.321***	0.309***	0.344***	0.322***	0.321***	0.309***	0.344***	0.322***
	(0.089)	(0.087)	(0.088)	(0.073)	(0.094)	(0.093)	(0.085)	(0.072)
Loss Aversion	0.001	0.001	-0.001	0.005	0.001	0.001	-0.001	0.005
	(0.012)	(0.012)	(0.013)	(0.010)	(0.013)	(0.013)	(0.013)	(0.010)
Risk Preference	0.002	-0.002	0.004	0.038	0.002	-0.002	0.004	0.038*
	(0.023)	(0.023)	(0.025)	(0.025)	(0.015)	(0.014)	(0.019)	(0.019)
Maximization	0.011	0.015	0.006	0.026	0.011	0.015	0.006	0.026
	(0.019)	(0.019)	(0.019)	(0.017)	(0.020)	(0.019)	(0.020)	(0.019)
Trading Experience	0.012	0.014	0.004	-0.005	0.012	0.014	0.004	-0.005
	(0.016)	(0.016)	(0.017)	(0.012)	(0.017)	(0.017)	(0.017)	(0.013)
Age	-0.001	-0.001	0.001	0.001	-0.001	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Gender	0.080**	0.081**	0.056	0.068**	0.080*	0.081**	0.056	0.068**
	(0.034)	(0.034)	(0.036)	(0.030)	(0.039)	(0.038)	(0.046)	(0.029)
Income	-0.041***	-0.041***	-0.038***	-0.045***	-0.041***	-0.041***	-0.038***	-0.045**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.012)	(0.016)
Education	0.025	0.024	0.019	0.027*	0.025*	0.024*	0.019	0.027
	(0.018)	(0.018)	(0.019)	(0.016)	(0.013)	(0.013)	(0.013)	(0.017)
Observations	124	124	124	124	124	124	124	124
Adj. R^2	0.365	0.367	0.366	0.355	0.365	0.367	0.366	0.355
Standard errors adjusted for clustering	No	No	No	No	session	session	session	session

6.5 Conclusion

In this study, I extend the analysis of greed and the disposition effect by examining how numerical framing interacts with price magnitude to shape investor behaviour. Using a controlled experimental design that varied price regime and return-display format, I demonstrate that framing outcomes in percentage versus dollar terms exerts a powerful and systematic influence on realisation behaviour. In low-price contexts, percentage framing magnifies perceived performance and strengthens the tendency to realise gains prematurely, whereas in high-price contexts, dollar framing makes monetary amounts more salient and reinforces the reluctance to realise losses. Framing and price-regime manipulations exert strong influences on realisation behaviour. Greed serves as a boundary condition, intensifying or weakening these contextual effects depending on which presentation format makes returns more salient.

These findings align with salience theory (Bordalo et al., 2012) and realisation-utility models (Barberis and Xiong, 2012), indicating that cognitive focus on numerically salient outcomes interacts with dispositional motives to produce predictable biases in trading behaviour. By showing that the behavioural expression of greed depends critically on how information is framed, this study advances behavioural finance beyond trait-only or context-only explanations and demonstrates that investor biases arise from their joint manifestation.

The findings further suggest that acquisitive and retentive motives of greed may be activated differently across framing conditions. In low-price environments, percentage framing magnifies proportional gains and may strengthen acquisitive motives by making potential profits appear larger and more attention-grabbing. In contrast, dollar framing in high-price environments may activate retentive motives because large absolute monetary amounts become more psychologically concrete, increasing investors' sensitivity to preserving accumulated wealth.

The findings also have practical relevance. In trading and reporting environments, the choice of return format can systematically steer investor attention and thereby influence realisation decisions. Platform designers and policy makers should recognise that informational architecture is not behaviourally neutral, as subtle formatting choices can shape risk-taking, feedback sensitivity, and portfolio turnover. Overall, this study contributes to a more integrated understanding of how motivational and cognitive mechanisms jointly drive the disposition effect and offers concrete insights for designing trading environments that promote more disciplined decision-making.

7 Concluding Remarks

This thesis investigates how investors' realisation behaviour is shaped by the interaction between greed and the informational context in which trading decisions occur. Across three controlled experimental studies, the evidence shows that contextual features of the trading environment, such as colour cues, return format, and price magnitude, systematically influence the disposition effect, the tendency to sell winners too early and hold losers too long. In informationally neutral settings, the disposition effect emerges in its conventional form. Greed then acts as a boundary condition, amplifying or dampening the behavioural response elicited by these contextual features. Rather than operating as a standalone driver, greed strengthens or weakens the impact of specific presentations of information depending on which cues heighten the salience of gains or losses. This integrated perspective demonstrates that both the structure of the environment and individual motivational differences jointly shape trading behaviour.

Study 1 established greed as a robust dispositional determinant of the disposition effect, providing the first experimental evidence that this trait systematically predicts investors' realisation behaviour. Participants scoring higher on greed were significantly more inclined to realise gains prematurely, even after controlling for loss aversion, risk tolerance, and trading experience, yet they showed little change in their propensity to realise losses. This asymmetry indicates that greed operates primarily through an acquisitive impulse to capture rewards rather than through differential sensitivity to losses.

Study 2 demonstrated that perceptual salience operationalised through colour cues modulates this motivational effect. When positive returns were displayed in green, greedy investors exhibited a heightened urge to realise gains. When negative returns were displayed in red, their reluctance to realise losses diminished. These findings reveal that interface-level perceptual design can act as a behavioural catalyst, amplifying or attenuating underlying dispositional tendencies.

Study 3 extended the salience framework by examining how numerical framing interacts with price magnitude. Percentage versus dollar displays systematically guided greedy investors' attention and realisation decisions, showing that contextual representations of value influence not only perception but also the motivational weight assigned to outcomes. Greedy investors responded most strongly to whichever format magnified the apparent size of returns, underscoring that their bias is driven by attention to salience rather than by absolute valuation.

The three studies provide convergent evidence that investor biases emerge not from isolated traits or external features alone but from their dynamic interaction. Greed functions as a psychological amplifier of salience, magnifying the behavioural impact of whichever informational cue renders outcomes most vivid, emotionally charged, or cognitively accessible. This integrated perspective advances behavioural finance by linking dispositional motives with the perceptual architecture of choice, offering a unified account of how motivation and information jointly distort financial decision-making.

The findings contribute to behavioural finance by integrating motivational psychology with salience-based models of choice. They show that investor behaviour is jointly determined by what people want and how information is presented. This synthesis extends prospect theory and realisation-utility models by introducing greed as a dynamic moderator that links attention, emotion, and decision framing. It also bridges personality-based and cognitive-based explanations of bias, demonstrating that even stable traits manifest differently across informational contexts. In doing so, the thesis advances a more comprehensive understanding of bounded rationality, embedding individual motivation within the perceptual structure of financial environments.

Methodologically, the thesis provides a unified experimental framework for studying dispositional and contextual determinants of trading bias. All three studies employ consistent behavioural metrics within controlled trading simulations implemented in z-Tree. This design allows direct comparison across manipulations of greed, colour salience, and numerical framing, thereby isolating causal mechanisms. Empirically, the findings contribute experimental evidence that greed interacts systematically with interface design variables to shape investment behaviour. This integration of psychology and financial decision-making complements existing field evidence and opens a pathway for more nuanced models of investor heterogeneity.

The results underscore that financial interfaces and communications are not behaviourally neutral. Even seemingly minor design choices, such as red or green colour schemes, percentage versus dollar reporting can bias decision-making in predictable ways. For practitioners and platform designers, awareness of these effects can inform interface standards that reduce cognitive distortion. For regulators and educators, the findings highlight the value of interventions that promote reflective decision-making and transparency in performance presentation. Recognising that greed interacts with informational salience also helps identify investors most vulnerable to impulsive or welfare-reducing behaviour.

7.1 Implications

The findings carry several theoretical, practical, and regulatory implications. Theoretically, the thesis demonstrates that investor biases are jointly shaped by motivation and informational salience, rather than by either factor in isolation. By identifying greed as a moderator of contextual framing effects, the research extends behavioural finance models that traditionally focus either on cognitive heuristics or stable personality traits independently. The results therefore contribute to a more integrated account of financial decision-making in which motivation, perception, and presentation interact dynamically.

Practically, the findings suggest that financial interfaces and trading environments are not behaviourally neutral. Seemingly minor presentation features, including colour schemes and return-display formats, systematically influence investors' realisation decisions. Platform designers, brokers, and fintech providers should therefore recognise that interface architecture can amplify behavioural biases, particularly among greed-prone investors. More behaviourally informed interface standards may help reduce impulsive gain realisation and improve trading discipline.

The findings also have regulatory and educational implications. Regulators may wish to consider whether certain presentation formats unintentionally encourage biased trading behaviour, particularly in increasingly gamified retail trading environments. Investor education initiatives could similarly benefit from emphasising how perceptual framing and emotional salience influence trading decisions beyond traditional concepts such as risk and return.

7.2 Future Research

Several avenues for future research emerge from this thesis. First, future studies could examine whether the behavioural effects identified here generalise beyond experimental trading environments to real-world trading data. Linking greed-related traits and interface design features to field trading behaviour would strengthen external validity and provide further insight into how salience operates in naturally occurring financial settings.

Second, future research could investigate additional forms of informational salience beyond colour and numerical framing, including animation, alerts, social trading signals, or interface gamification. As retail trading platforms become increasingly interactive, understanding how different interface features influence investor behaviour represents an important direction for behavioural finance research.

Third, future work could explore cultural and individual heterogeneity in colour and framing effects. The present thesis discusses evidence suggesting that colour associations may depend partly on learned cultural meanings and personal conditioning. Future studies could therefore examine whether the behavioural impact of red and green cues varies across cultural backgrounds, trading experience, or personality profiles.

Finally, future research could investigate whether interventions designed to reduce salience-driven trading behaviour improve long-term investment outcomes. Experimental testing of debiasing mechanisms, alternative interface designs, or reflective decision prompts may help identify practical methods for mitigating the disposition effect and related behavioural biases.

By uniting dispositional and situational explanations, this thesis advances a richer behavioural model of the disposition effect. Greed emerges as a fundamental motivational force that shapes attention and interpretation of financial outcomes, while the informational environment determines how that motive is expressed. Human desire and informational design co-produce trading behaviour. Understanding this interplay provides theoretical clarity and practical direction, as mitigating biases requires addressing not only investors' internal dispositions but also the architectures through which they encounter information. The research therefore contributes to a deeper, more integrated account of how cognition, motivation, and context jointly determine financial decision-making.

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Appendices

Appendix A. Definition of Variables

This appendix provides definitions and measurement descriptions for all variables used in the thesis.

Variable	Definition
DE	Disposition Effect. Defined as the differences between proportion of gains realized and proportion of losses realized (Odean, 1998).
Greed	A desire to acquire more than one has or retain what one already has (Lambie & Haugen, 2019; Seuntjens et al., 2015).
Portfolio Value	Total value of the portfolio at the end of the experiment.
PGR	Proportion of gains realized.
PLR	Proportion of losses realized.
Loss Aversion	Measured using the incentivized multiple price list introduced by Gachter et al. (2022).
Risk Preference	Multiple choice question to assess risk preference follow Guiso et al. (2018).
Maximization	7 items using a scale from 1 to 5 where 1 means “strongly disagree” and 5 means “strongly agree” (Diab et al., 2008).
Trading Experience	Stock trading experience measured by a 1- 10 scale (1=very low; 10=very high) (Dhar and Zhu, 2006).
Age	Age in years given by participants.
Gender	1 if the participant is male, 0 otherwise.
Income	Annual income (NZD) in this order.
	$0
	$1 - 25,000
	$25,001 - 50,000
	$50,001 - 70,000
	$70,001 - 100,000
	$100,001 - 150,000
	$150,001 - 200,000
	More than $200,000
Education	Highest level of education participants has attained in this order.
	0. Refuse to say
	1. Graduate Diploma
	2. Bachelor's Degree
	3. Postgraduate's degree
	4. Doctoral’ s Degree

Appendix B. Study 1: Standardised Greed and Disposition Effect

This table presents regression results examining the relationship between greed and the disposition effect (DE), along with other control variables. *Greed* is the standardized greed score, calculated as x(i) - mean of all x(i)) / stdev. of x(i). *Greed* and control variables are defined as in Appendix A. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.154***	0.212	-0.351***	0.531***	0.581***	0.313
	(0.036)	(0.149)	(0.194)	(0.162)	(0.193)	(0.276)
Greed (Standardised)	0.131***	0.106***	0.083***	0.086***	0.150***	0.107***
	(0.036)	(0.033)	(0.030)	(0.030)	(0.035)	(0.032)
Loss Aversion			0.102***			0.065***
			(0.026)			(0.027)
Risk Preference				-0.110***		-0.072***
				(0.031)		(0.030)
Maximization					-0.100***	-0.067***
					(0.036)	(0.033)
Trading Experience		-0.077***	-0.079***	-0.055***	-0.082***	-0.066***
		(0.029)	(0.026)	(0.027)	(0.028)	(0.025)
Age		0.015***	0.015***	0.009***	0.017***	0.013***
		(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Gender		-0.076	-0.091	-0.100***	-0.107***	-0.122***
		(0.063)	(0.056)	(0.057)	(0.060)	(0.053)
Income		-0.050	-0.037	-0.047	-0.018	-0.018
		(0.032)	(0.028)	(0.029)	(0.032)	(0.028)
Education		-0.080***	-0.049***	-0.054***	-0.080***	-0.044
		(0.032)	(0.029)	(0.030)	(0.030)	(0.028)
Observations	60	60	60	60	60	60
Adj. R^2	0.166	0.408	0.536	0.515	0.475	0.601

Appendix C. Greed Dummy and Disposition Effect

This table presents regression results examining the relationship between a greed dummy and the disposition effect (DE), along with other control variables. The greed dummy equals 1 for participants with a greed score of 3 or higher and 0 otherwise. Greed and control variables are defined as in Appendix A. Column (7) reports estimates with standard errors clustered at the session level, where a "session" refers to the actual experimental trading session. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.025	0.105	-0.503**	0.465***	0.314*	0.022	0.022
	(0.060)	(0.136)	(0.193)	(0.170)	(0.157)	(0.242)	(0.246)
Greed (dummy)	0.234***	0.178***	0.170***	0.148***	0.217***	0.179***	0.179***
	(0.075)	(0.058)	(0.053)	(0.054)	(0.058)	(0.051)	(0.060)
Loss Aversion			0.114***			0.084***	0.084***
			(0.025)			(0.026)	(0.024)
Risk Preference				-0.117***		-0.073**	-0.073**
				(0.033)		(0.032)	(0.033)
Maximization					-0.064*	-0.042	-0.042
					(0.036)	(0.030)	(0.031)
Trading Experience		-0.073*	-0.071**	-0.049*	-0.076*	-0.059**	-0.059**
		(0.038)	(0.027)	(0.029)	(0.039)	(0.026)	(0.022)
Age		0.015***	0.015***	0.009**	0.017***	0.012***	0.012***
		(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Gender		-0.053	-0.075	-0.083	-0.067	-0.097*	-0.097
		(0.065)	(0.055)	(0.061)	(0.064)	(0.053)	(0.061)
Income		-0.060*	-0.047*	-0.056*	-0.042	-0.036	-0.036
		(0.030)	(0.025)	(0.031)	(0.031)	(0.024)	(0.022)
Education		-0.070*	(0.037)	(0.045)	(0.068)	(0.028)	(0.028)
		(0.042)	(0.033)	(0.036)	(0.043)	(0.032)	(0.031)
Observations	60	60	60	60	60	60	60
Adj. R^2	0.146	0.435	0.596	0.555	0.468	0.649	0.649
Standard errors adjusted for clustering	No	No	No	No	No	No	session

Appendix D. Study 1: Orthogonalization Procedure and Robustness

Note: This appendix table reports the orthogonalization procedure used to isolate the unique effect of greed on the disposition effect (DE). Panel A presents the first-stage regressions in which Greed is regressed on participant characteristics. The residuals from these models (Greed_residual) represent the variation in greed that is orthogonal to all observed controls. Panel B reports the second-stage regressions, where Greed_residual replaces Greed in Equation (1). Column (1) uses the baseline set of control variables, and Column (2) adds additional psychological characteristics described in footnote 12. Standard errors are clustered at the session level, where a "session" refers to an experimental trading session. Values in parentheses are standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	(1)	(2)
Intercept	0.688	1.423
	(0.839)	(1.621)
Loss Aversion	0.146	0.243*
	(0.084)	(0.090)
Risk Preference	-0.087	-0.114
	(0.107)	(0.121)
Maximization	0.384***	0.454**
	(0.088)	(0.138)
Trading Experience	-0.066	-0.081
	(0.083)	(0.086)
Age	0.006	0.004
	(0.019)	(0.018)
Gender	0.18	0.23
	(0.169)	(0.192)
Income	-0.047	-0.076
	(0.072)	(0.085)
Education	(0.082)	(0.099)
	(0.078)	(0.091)
Regret Aversion		-0.013
		(0.045)
Overconfidence		0.196
		(0.200)
Locus of Control		-0.015
		(0.098)
Financial Literacy		-0.064
		(0.079)
Financial Capability		0.06
		(0.067)
Extraversion		0.073
		(0.132)
Agreeableness		-0.215
		(0.135)

Appendix D – *Continued*

Panel A	(1)	(2)
Conscientiousness		-0.069
		(0.162)
Emotion		0.11
		(0.123)
Openness		-0.252
		(0.211)
Observations	60	60
Adj. R^2	0.376	0.515

Appendix D – *Continued*

Panel B	(1)	(2)
Intercept	0.218	0.436
	(0.249)	(0.325)
Greed_Residual	0.140***	0.178***
	(0.045)	(0.045)
Loss Aversion	0.065**	0.044
	(0.023)	(0.027)
Risk Preference	-0.072*	-0.105***
	(0.031)	(0.029)
Maximization	-0.067*	-0.090**
	(0.026)	(0.029)
Trading Experience	-0.086**	-0.071*
	(0.025)	(0.034)
Age	0.016***	0.016**
	(0.004)	(0.005)
Gender	-0.101	-0.097
	(0.052)	(0.053)
Income	-0.007	-0.005
	(0.022)	(0.030)
Education	(0.042)	(0.043)
	(0.029)	(0.036)
Regret Aversion		-0.02
		(0.013)
Overconfidence		-0.029
		(0.055)
Locus of Control		0.011
		(0.030)
Financial Literacy		0.019
		(0.018)
Financial Capability		-0.048
		(0.017)
Extraversion		0.043
		(0.031)
Agreeableness		0.024
		(0.045)
Conscientiousness		0.042
		(0.036)
Emotion		-0.019
		(0.036)
Openness		-0.008
		(0.056)
Observations	60	60
Adj. R^2	0.662	0.747

Appendix E. Study 1: The Impacts of Greed Components on the PGR and PLR

The table reports OLS estimates of the proportion of gains realised (PGR) and the proportion of losses realised (PLR) as measured by Odean (1998), Proportion of gains realized (PGR)=Realized Gains/ (Realized Gains + Paper Gains) and proportion of losses realized=Realized Losses/ (Realized Losses + Paper Losses). *Greed* is the standardized greed score, calculated as x(i) - mean of all x(i)) / stdev. of x(i). The dummy gender takes value of 0 if female, 1 if male. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) PGR	(2) PGR	(3) PGR	(4) PLR	(5) PLR	(6) PLR
Intercept	0.375***	0.555***	0.799***	0.220***	0.343***	0.486***
	(0.025)	(0.112)	(0.236)	(0.025)	(0.109)	(0.229)
Greed (Standardized)	0.083***	0.082***	0.092***	-0.048***	-0.024	-0.016
	(0.026)	(0.025)	(0.027)	(0.025)	(0.024)	(0.027)
Loss Aversion			0.013			-0.051***
			(0.023)			(0.022)
Risk Preference			-0.048***			0.025
			(0.026)			(0.025)
Maximization			-0.049***			0.018
			(0.028)			(0.027)
Trading Experience		-0.011	-0.003		0.067***	0.063***
		(0.022)	(0.021)		(0.022)	(0.021)
Age		0.004	0.002		-0.012***	-0.011***
		(0.004)	(0.004)		(0.004)	(0.004)
Gender		-0.027	-0.055		0.049	0.067
		(0.047)	(0.045)		(0.046)	(0.044)
Income		-0.076***	-0.058***		-0.026	-0.039***
		(0.024)	(0.024)		(0.023)	(0.023)
Education		-0.032	-0.017		0.048***	0.027
		(0.024)	(0.024)		(0.024)	(0.023)
Observations	60	60	60	60	60	60
Adj. R^2	0.140	0.300	0.384	0.042	0.222	0.330

Appendix F. Study 2: Correlations Coefficients for Subsamples

This table reports the correlation coefficients among the key variables used in the analysis. Panels A, B, and C present results for the Red, Green, and combined *Red* + *Green* conditions, respectively. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A:Red (N=30)	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect											
2.PGR	0.604***										
3.PLR	-0.78***	-0.009									
4. Greed	-0.053	0.173	0.199								
5. Loss Aversion	0.164	0.17	-0.071	-0.32*							
6. Risk Preference	-0.443**	-0.426**	0.204	-0.174	0.142						
7. Maximization	-0.264	-0.033	0.337	0.091	-0.369**	-0.121					
8. Trading Experience	-0.001	-0.178	-0.126	0.065	-0.268	0.046*	-0.064				
9. Age	-0.228	-0.128**	0.216	0.098	0.197	0.224	-0.102	-0.009			
10. Gender	-0.402	-0.501	0.113	0.034	-0.252	0.22	0.173	0.112	-0.246		
11. Income	-0.034	0.175	0.187	0.433**	0.026	-0.11	0.009	0.03	0.348*	0.065	
12. Education	-0.267	-0.074	0.302	0.15	0.201	0.199	-0.05	0.054	0.923***	-0.255	0.314*

Appendix F – *Continued*

Panel B:Green (N=30)	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect											
2.PGR	0.897***										
3.PLR	-0.84***	-0.515***									
4. Greed	0.878***	0.861***	-0.649***								
5. Loss Aversion	0.154	0.237	-0.009	0.18							
6. Risk Preference	-0.261	-0.26	0.187	-0.293	-0.191						
7. Maximization	0.252	0.249	-0.184	0.272	0.217	0.26					
8. Trading Experience	0.153	0.187	-0.068	0.072	0.248	0.239	0.012				
9. Age	0.103	-0.01	-0.212	0.011	0.278	0.086	0.399**	0.235			
10. Gender	-0.381	-0.228	0.459**	-0.285	0.086	-0.056	-0.354*	0.246	-0.142		
11. Income	0.059	0.098	0.006	-0.026	-0.159	0.22	0.199	0.347*	0.351*	0.119	
12. Education	0.149	0.125	-0.136	0.167	0.307*	0.043	0.106	0.2	0.641***	0.161	0.258

Appendix F – *Continued*

Panel C:Red + Green	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect											
2.PGR	0.782***										
3.PLR	-0.809***	-0.286**									
4. Greed	0.35***	0.491***	-0.097								
5. Loss Aversion	0.115	0.178	-0.014	-0.035							
6. Risk Preference	-0.288**	-0.297**	0.155	-0.239*	-0.055						
7. Maximization	0.062	0.159	0.073	0.156	-0.072	0.076					
8. Trading Experience	-0.027	-0.045	-0.007	0.084	0.06	0.128	-0.076				
9. Age	-0.065	-0.068	0.052	0.056	0.242	0.151	0.124	0.123			
10. Gender	-0.345**	-0.337**	0.21	-0.116	-0.075	0.09	-0.047	0.164	-0.198		
11. Income	-0.001	0.119	0.119	0.208	-0.074	0.055	0.088	0.2	0.35**	0.088	
12. Education	0.008	0.074	0.071	0.146	0.244*	0.129	0.053	0.089	0.769**	-0.055	0.278

Appendix G. Study 2: Overall Colour Influence on Disposition Effect

The table provides estimation results from an OLS regression that investigates whether colour situationally intensifies the impact of greed on the disposition effect (DE), along with other control variables. *Greed* is the standardized greed score, calculated as x(i) - mean of all x(i)) / stdev. of x(i). Colour is a dummy variable that takes a value of 1 if the stock price changes to red or green, and 0 if it remains constant at black. *Greed* and control variables are defined as in Appendix A. Values in parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
Intercept	0.552**	0.552**	0.524*
	(0.270)	(0.274)	(0.281)
Greed (Standardized)	0.140***	0.140***	0.118*
	(0.037)	(0.038)	(0.060)
Colour		0.001	0.002
		(0.980)	(0.072)
Greed (Standardized) x *Colour*			0.041
			(0.088)
Loss Aversion	0.042*	0.042*	0.043*
	(0.025)	(0.025)	(0.025)
Risk Preference	-0.116***	-0.116**	-0.116***
	(0.040)	(0.039)	(0.039)
Maximization	-0.028	-0.029	-0.024
	(0.037)	(0.038)	(0.039)
Trading Experience	-0.021	-0.02	-0.022
	(0.028)	(0.029)	(0.029)
Age	0.003	0.003	0.003
	(0.006)	(0.006)	(0.006)
Gender	-0.213***	-0.212***	-0.207***
	(0.068)	(0.067)	(0.069)
Income	-0.023	-0.025	-0.027
	(0.034)	(0.033)	(0.034)
Education	-0.03	-0.03	-0.03
	(0.039)	(0.039)	(0.018)
Observations	120	120	120
Adj. R^2	0.27	0.263	0.258

Appendix H. Study 2: Individual Colour Influence on Disposition Effect

The table provides estimation results from an OLS regression that investigates whether red or green influences the disposition effect (DE), along with other control variables. *Greed* is the standardized greed score, calculated as x(i) - mean of all x(i)) / stdev. of x(i). *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while green is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.641**	0.141	0.743**	0.541**	0.623**
	(0.301)	(0.273)	(0.298)	(0.213)	(0.237)
Greed (Standardized)			0.081**	0.251***	0.162***
			(0.037)	(0.032)	(0.033)
Red	-0.201***		-0.232***		-0.283 ***
	(0.075)		(0.074)		(0.077)
Green		0.248***		0.231***	0.246***
		(0.078)		(0.059)	(0.074)
Loss Aversion	0.048*	0.050*	0.050*	0.038*	0.046**
	(0.028)	(0.028)	(0.026)	(0.021)	(0.022)
Risk Preference	-0.163***	-0.138***	-0.146***	-0.070**	-0.121***
	(0.036)	(0.040)	(0.036)	(0.032)	(0.034)
Maximization	-0.039	0.012	-0.059*	-0.102***	-0.060**
	(0.035)	(0.040)	(0.035)	(0.034)	(0.033)
Trading Experience	-0.023	-0.011	-0.018	-0.033	0.01
	(0.029)	(0.032)	(0.029)	(0.024)	(0.025)
Age	0.007	0.007	0.007	0.013**	0.006
	(0.006)	(0.006)	(0.006)	(0.004)	(0.005)
Gender	-0.184***	-0.188***	-0.203***	-0.210***	-0.235***
	(0.065)	(0.072)	(0.064)	(0.055)	(0.058)
Income	-0.033	-0.013	-0.042	0.006	-0.024
	(0.031)	(0.037)	(0.031)	(0.028)	(0.029)
Education	-0.065**	-0.067**	-0.07**	-0.044	-0.067**
	(0.038)	(0.037)	(0.038)	(0.029)	(0.034)
Observations	90	90	90	90	120
Adj. R^2	0.387	0.272	0.416	0.581	0.447

Appendix I. Study 2: Individual Colour Interaction Influence on Disposition Effect

The table provides estimation results from an OLS regression that investigates whether colour situationally intensifies the impact of greed on the disposition effect (DE), along with other control variables. *Greed* is the standardized greed score, calculated as x(i) - mean of all x(i)) / stdev. of x(i). *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while *Green* is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Intercep*t*	0.934***	0.399**	0.116
	(0.308)	(0.197)	(0.226)
Greed (Standardized)	0.149***	0.144***	0.153***
	(0.049)	(0.039)	(0.047)
Red	-0.234***		-0.252***
	(0.073)		(0.071)
Red x *Greed (Standardized)*	-0.146**		-0.164**
	(0.072)		(0.069)
Green		0.224***	0.224***
		(0.054)	(0.067)
Green x *Greed (Standardized)*		0.225***	0.202***
		(0.054)	(0.067)
Loss Aversion	0.032	0.036*	0.027
	(0.029)	(0.018)	(0.020)
Risk Preference	-0.147***	-0.069**	-0.119***
	(0.035)	(0.029)	(0.031)
Maximization	-0.083**	-0.078**	-0.076**
	(0.037)	(0.031)	(0.031)
Trading Experience	-0.017	-0.024	0.002
	(0.028)	(0.022)	(0.023)
Age	0.006	0.013***	0.008*
	(0.005)	(0.004)	(0.005)
Gender	-0.219***	-0.155***	-0.208***
	(0.063)	(0.052)	(0.054)
Income	-0.026	0.002	-0.002
	(0.013)	(0.025)	(0.026)
Education	-0.078**	-0.043*	-0.069**
	(0.037)	(0.026)	(0.031)
Observations	90	90	120
Adj. R^2	0.437	0.654	0.547

Appendix J. Study 2: Individual Colour Influence on Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR)

The table provides estimation results from an OLS regression that investigates whether red or green influences the Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR), along with other control variables. *Greed* refers to the standardized greed measure. *Red* is a dummy variable that takes a value of 1 if the stock price decreases, while *Green* is a dummy variable that takes a value of 1 if the stock price increases. Definitions for greed and the control variables can be found in Appendix A. Standard errors are shown in parentheses. Statistical significance is indicated by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	PGR	PGR	PLR	PLR
Intercept	0.724***	0.673***	-0.044	0.132
	(0.194)	(0.159)	(0.271)	(0.156)
Greed (Standardized)	0.078***	0.161***	-0.003	-0.089***
	(0.024)	(0.024)	(0.033)	(0.024)
Red	0.005		0.221***	
	(0.048)		(0.068)	
Green		0.195***		-0.037
		(0.044)		(0.043)
Loss Aversion	0.026	0.021	-0.023	-0.017
	(0.018)	(0.015)	(0.025)	(0.015)
Risk Preference	-0.068***	-0.036	-0.073**	0.034
	(0.023)	(0.024)	(0.072)	(0.023)
Maximization	-0.029	-0.057	0.035	0.045*
	(0.023)	(0.025)	(0.032)	(0.025)
Trading Experience	-0.016	0.014	0.002	0.027
	(0.019)	(0.018)	(0.026)	(0.018)
Age	0.003	0.004	-0.004	0.008*
	(0.004)	(0.003)	(0.005)	(0.003)
Gender	-0.136***	-0.091**	0.058	0.120***
	(0.041)	(0.041)	(0.057)	(0.040)
Income	-0.029	-0.022	0.016	-0.029
	(0.020)	(0.021)	(0.028)	(0.020)
Education	-0.039	-0.048**	0.04	0.014
	(0.020)	(0.021)	(0.034)	(0.021)
Observations	90	90	90	90
Adj. R^2	0.308	0.494	0.26	0.365

Appendix K. Study 2: Individual Colour Interaction Influence on Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR)

This table reports the results of OLS regressions examining how red and green interact with greed to influence the proportion of gains realised (PGR) and the proportion of losses realised (PLR). *Greed* denotes the standardized greed measure. *Red* is a dummy variable equal to one when the stock price decreases, and *Green* equals one when the stock price increases. Control variables include loss aversion, risk preference, maximization, trading experience, age, gender, and income. Variable definitions are provided in Appendix A. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) PGR	(2) PGR	(3) PLR	(4) PLR
Intercept	0.753***	0.587***	-0.218	0.188
	(0.205)	(0.152)	(0.281)	(0.155)
Greed (Standardized)	0.088***	0.097***	-0.065	-0.046
	(0.033)	(0.031)	(0.045)	(0.031)
Red	0.005		0.223***	
	(0.049)		(0.066)	
Red x *Greed (Standardized)*	-0.022		0.13**	
	(0.048)		(0.067)	
Green		0.191***		0.034
		(0.042)		(0.042)
Green x *Greed (Standardized)*		0.136***		-0.089**
		(0.042)		(0.042)
Loss Aversion	0.023	0.019	-0.006	-0.016
	(0.019)	(0.015)	(0.026)	(0.015)
Risk Preference	-0.069***	-0.036	0.074**	0.034
	(0.023)	(0.022)	(0.032)	(0.023)
Maximization	-0.032	-0.042*	0.057*	0.036
	(0.024)	(0.024)	(0.033)	(0.025)
Trading Experience	-0.015	0.008	0.002	0.032*
	(0.019)	(0.017)	(0.025)	(0.017)
Age	0.002	0.005	-0.004	-0.008**
	(0.004)	(0.003)	(0.005)	(0.003)
Gender	-0.138***	-0.058	0.073	0.097**
	(0.024)	(0.042)	(0.057)	(0.041)
Income	-0.027	-0.025	0.002	-0.027
	(0.021)	(0.020)	(0.028)	(0.020)
Education	-0.039	-0.029	0.041	0.014
	(0.025)	(0.021)	(0.034)	(0.020)
Observations	90	90	90	90
Adj. R^2	0.302	0.55	0.196	0.315

Appendix L. Study 3: Correlation for Subsamples

This table reports the correlation coefficients among key variables for each subsample. Panel A presents correlations for low-priced stocks with absolute change, Panel B for low-priced stocks with percentage change, Panel C for high-priced stocks with absolute change, and Panel D for high-priced stocks with percentage change. The disposition effect is measured as the difference between the proportion of gains realised (PGR) and the proportion of losses realised (PLR). Control variables include loss aversion, risk preference, maximization, trading experience, age, gender, income, and education. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A	Low-Priced Stocks with Absolute Change (N=31)										
	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect	-										
2. PGR	0.77***										
3. PLR	-0.86***	-0.36									
4. Greed	-0.78***	-0.63***	0.66***								
5. Loss Aversion	0.29	0.21	-0.26*	-0.33							
6. Risk Preference	-0.58***	-0.43***	0.44***	-0.28**	-0.02						
7. Maximization	-0.37**	-0.24	0.36**	0.37**	-0.22	-0.26					
8. Trading Experience	0.15	0.01	-0.21	-0.09	-0.07	0.19	-0.22				
9. Age	0.58***	0.63***	-0.36**	-0.41**	-0.01	-0.17	-0.04	0.11			
10. Gender	-0.55***	-0.44**	0.47***	0.26	-0.05	-0.28	0.35	-0.14	-0.36		
11. Income	-0.16	-0.28	0.02	0.36**	-0.16	-0.09	0.25	-0.17	-0.19	-0.09	
12. Education	-0.41**	-0.28	0.38**	0.25	-0.23	-0.28	0.29	0.01	-0.06	0.51	0.26*

Appendix L – *Continued*

Panel B	Low-Priced Stocks with Percentage Change (N=31)										
	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect	-										
2. PGR	0.75***										
3. PLR	-0.43**	-0.27									
4. Greed	0.25	-0.11	-0.51***								
5. Loss Aversion	0.29	0.24	-0.11	0.22							
6. Risk Preference	-0.14	0.02	0.22	-0.26	-0.23						
7. Maximization	0.14	-0.07	-0.31*	0.35*	0.12	-0.11					
8. Trading Experience	0.04	0.11	0.09	-0.33*	0.01	0.27	-0.18				
9. Age	-0.17	-0.26	-0.11	0.07	0.29	-0.08	0.02	-0.04			
10. Gender	0.24	-0.03	-0.39**	0.38**	0.11	0.05	0.13	-0.22	-0.06		
11. Income	-0.18	-0.26	-0.11	-0.18	0.03	0.02	0.01	-0.15	0.41**	-0.21	
12. Education	-0.34*	-0.31*	0.08	-0.02	-0.22	-0.04	-0.13	-0.21	0.38**	-0.22	0.22

Appendix L – *Continued*

Panel C	High-Priced Stocks with Absolute Change (N=32)										
	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect	-										
2. PGR	0.86***										
3. PLR	-0.28	0.21									
4. Greed	0.87***	0.73***	-0.28								
5. Loss Aversion	0.12	0.11	-0.03	0.11							
6. Risk Preference	0.12	-0.02	0.29	0.18	0.02						
7. Maximization	-0.29	-0.32	-0.04	-0.24	0.31	0.12					
8. Trading Experience	-0.37**	-0.13	0.37**	-0.29	-0.11	-0.01	0.18				
9. Age	-0.04	0.04	0.11	-0.05	-0.01	-0.11	-0.08	-0.13			
10. Gender	0.31*	0.15	-0.39**	0.44**	-0.08	0.43**	0.17	-0.17	-0.05		
11. Income	-0.23	-0.24	-0.11	-0.23	-0.18	-0.16	-0.11	0.04	0.43**	0.06	
12. Education	-0.24	-0.27	0.03	-0.27	-0.28	0.01	-0.07	0.03	0.08	-0.33	0.26

Appendix L – *Continued*

Panel D	High-Priced Stocks with Percentage Change (N=30)										
	1	2	3	4	5	6	7	8	9	10	11
1. Disposition Effect	-										
2. PGR	0.69***										
3. PLR	-0.53***	0.23									
4. Greed	0.41**	0.32**	-0.17								
5. Loss Aversion	-0.01	-0.08	-0.09	-0.24							
6. Risk Preference	-0.27	-0.24	0.09	-0.06	0.14						
7. Maximization	0.19	0.18	-0.03	0.44**	-0.21	0.14					
8. Trading Experience	-0.33	-0.12	0.29	-0.11	-0.38**	0.07	0.18				
9. Age	0.29**	0.19	-0.25**	0.31**	-0.16	-0.27*	0.18	0.26			
10. Gender	-0.06	0.33	0.47**	0.05	0.17	-0.03	0.07	0.08	0.25		
11. Income	0.19	0.06	-0.18	0.17	0.18	0.04	0.07	-0.01	0.47***	0.15	
12. Education	0.25	0.31	0.02	0.26	0.06	-0.15	-0.06	-0.02	0.47**	0.26	0.42**

Appendix M. Study 3: The Impacts of Salience and Greed on the Disposition Effect

This table presents OLS regression results examining the effects of salience and greed on the disposition effect. The dependent variable is the disposition effect (DE), defined as the difference between the proportion of gains realised (PGR) and the proportion of losses realised (PLR). *Greed* is the standardized greed score, calculated as x(i) - mean of all x(i)) / stdev. of x(i). Salience is a dummy variable equal to 1 when returns are displayed either in percentage or absolute (dollar) terms and 0 when no return information is shown. *Salience* × *Greed* captures the interaction between salience and greed. Control variables include loss aversion, risk preference, maximization, trading experience, age, gender, income, and education. Standard errors are shown in parentheses and are adjusted for clustering at the session level where indicated. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.183	-0.342**	0.355**	-0.209	0.355**	-0.209
	(0.025)	(0.189)	(0.171)	(0.212)	(0.204)	(0.201)
Greed (Standardized)	0.041*	0.138***	0.068***	0.165***	0.068**	0.168***
	(0.034)	(0.049)	(0.028)	(0.049)	(0.041)	(0.026)
Salience		0.037		0.094**		0.444**
		(0.048)		(0.049)		(0.361)
Salience x Greed (Standardized)		-0.129**		-0.112**		-0.112**
		(0.063)		(0.063)		(0.119)
Loss Aversion			0.024	0.037**	0.024	0.037**
			(0.015)	(0.018)	(0.015)	(0.015)
Risk Preference			-0.025	-0.024	-0.025	-0.024
			(0.029)	(0.028)	(0.047)	(0.048)
Maximization			0.048**	-0.048**	0.048**	-0.048**
			(0.032)	(0.025)	(0.021)	(0.024)
Trading Experience			-0.035**	-0.015	-0.014**	-0.015
			(0.017)	(0.019)	(0.017)	(0.013)
Age			0.014***	0.014***	0.014**	0.014***
			(0.003)	(0.003)	(0.006)	(0.005)

Appendix M – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Gender			-0.083**	-0.082**	-0.083**	-0.082**
			(0.042)	(0.044)	(0.038)	(0.042)
Income			-0.044**	-0.045***	-0.044**	-0.045***
			(0.017)	(0.018)	(0.017)	(0.016)
Education			-0.074***	-0.068***	-0.074**	-0.068***
			(0.023)	(0.022)	(0.021)	(0.023)
Observations	184	184	184	184	184	184
Adj. R^2	0.028	0.045	0.249	0.276	0.249	0.276
Standard errors adjusted for clustering	No	No	No	No	session	session

Appendix N. Study Protocol

During each session of data collection, participants will enter the financial trading lab and be greeted by the proctor, Damon Yu. Each participant will find a copy of the consent form and a pen on their desk. At the start time, the data collection begins. The procedure is as follows:

1. Introduction

Verbal script:

Thank you all for coming and participating in my research. My name is Damon Yu, and I am a PhD candidate in the Finance Department at AUT. This research is being undertaken as a requirement of my PhD. In this research, I aim to understand the role individual characteristics play in financial decisions.

You will see on the desk in front of you a copy of a consent form. Please take a moment now to read through. [give participants a couple of minutes] Does anyone have any questions I can answer? If no questions and you are happy to begin, please sign the consent form using the pen provided.

When you are ready, raise your hand and I will collect your signed consent form. This information is stored separately from your responses to the study today.

2. Instruction[29]

Verbal script:

There will be two parts in today's research project. The first part is a stock trading simulation game. The second part is a survey I will ask you to fill in on the computer.

Please look at the big screen for a preview of the game (see Figure 1 below). You can trade $2000 game currency in six different risky assets A, B, C, D, E, and F over 14 periods labelled period -3 to 10. The first three periods are trial periods, and you will be able to see how prices are changing but won't be able to buy or sell stocks. You can start trading at period 0. When you want to buy (sell) a stock, place the number of units in the coloured box in the lower left table and click on the buy (sell) button. The 'Number Owned' column in that table shows the total number of stock units that you have in your portfolio. The 'Stock Price' shows stock prices in the current period. When you have finished making your purchases and sales, you can move on to the next period by clicking on the "next period" button in the bottom right corner of the screen. Please click on the "finish" button in the bottom right corner after the final period, period 10. The purpose of this game is to make the most money by trading these stocks. Your total portfolio will be the money left in your current balance; plus, the current market value of any stocks you still own at period 10 (after you have made your trading decisions for that period). After you have completed the trading game, please raise your hand and I will lead you to the online survey page. If you have any questions while you are completing the survey, please also raise your hand.

[29] The procedures for Study 2 and Study 3 followed the same overall structure (consent, instructions, trading task, survey), but the trading task and on-screen information differed. Study 2 introduced colour-based salience manipulations (red/green displays), while Study 3 introduced percentage-versus-dollar framing and low- versus high-price regimes.

In exchange for your time, you will get a $10 gift card and a chance to win a $300 gift card (1 to be won). Please leave your contact details at the end of the survey if you are willing to enter the draw. It is separate from the original survey. All information provided will be kept confidential. Any questions? Now you may start the trading game (Damon to launch z-tree).
3.After participants finish the stock trading game and raise their hands, open up the online survey for them to complete.

4. Hand out the $10 gift cards to all participants.

Appendix O. Consent Form

Project title: ***Personality Trait and Financial Decision-making***
Project Supervisor: ***Prof. Nhut (Nick) H. Nguyen***
Prof. Aaron Gilbert
Assoc. Prof. Sommer Kapitan
Researcher: ***Damon Yu***

○ I have read and understood the information provided about this research project in the Information Sheet dated 07/08/2023.

○ I have had an opportunity to ask questions and to have them answered.

○ I understand that taking part in this study is voluntary (my choice) and that I may withdraw from the study at any time without being disadvantaged in any way.

○ I agree to take part in this research.

○ I wish to receive a summary of the research findings (please tick one): Yes○ No○

Participant's signature:
....

Participant's name:
....

Participant's contact details (if appropriate):
....

Date:

Approved by the Auckland University of Technology Ethics Committee on 22 March 2023 AUTEC Reference number 22/337

Note: The Participant should retain a copy of this

Appendix P. Questionnaire Screenshots

AUT

Participant Information Sheet

Date Information Sheet Produced:

29/11/2022

Project Title

Personality Traits and Financial Decision-making.

An Invitation

My name is Damo Yu and I am a PhD candidate in Finance Department. I am writing to request your participation in a stock trading game and a survey about individual characteristics. The information of this survey will be used in my research which will contribute to my PhD thesis. The survey is completely anonymous, and you will be into win a $300 voucher.

What is the purpose of this research?

In this research I aim to contribute to the understanding of the role psychological factors play in financial decisions. More specifically, I focus on the psychology of greed and explore if differences in greed between individuals can influence their financial decision making.
This research is being undertaken as a requirement of my PhD. The findings of this research may be used for academic publications and presentations.

How was I identified and why am I being invited to participate in this research?

The potential participants of this online survey are all current AUT students, AUT faculty staff and general society. You are being invited because you are one of the AUT students/staff or from general society.

How do I agree to participate in this research?

You agree to participate in the research by completing the Consent Form, which can be obtained from the link provided on the advisement posters.

Your participation in this research is voluntary (it is your choice) and whether or not you choose to participate will neither advantage nor disadvantage you. You are able to withdraw from the study at any time. If you choose to withdraw from the study, then you will be offered the choice between having any data that is identifiable as belonging to you removed or allowing it to continue to be used. However, once the findings have been produced, removal of your data may not be possible.

What will happen in this research?

The project includes a stock trading game and a survey. It will take place on WF211, AUT Trading Lab. Participants will need to play a laboratory trading simulation game. After the game, participants will be asked to complete a questionnaire collecting sociodemographic variables and greed scales.

What are the discomforts and risks?

The stock trading game and the survey contains no discomfort questions and there will be no risks.

What are the benefits?

This research will assist me in obtaining my qualification- Doctor of Philosophy. The research will also contribute to finance literature by providing new evidence of relationship between personality traits and financial decision making.

How will my privacy be protected?

Your privacy will be protected with highest level of confidentiality. The data will be collected by the researcher with password known by the researcher only. The process of the data will be de-identified and fully anonymous.

What are the costs of participating in this research?

The stock trading game and the survey may take potential participants 30-40 minutes to complete.

What opportunity do I have to consider this invitation?

Potential participants are given two weeks to consider participating in this research.

Will I receive feedback on the results of this research?

Yes, all participants will receive a summary of the findings for this research. URL: https://autuni-my.sharepoint.com/:f:/g/personal/hxd2527_autuni_ac_nz/EvgzjwSclNJOgZawymwlNokBeqgqyL5T3i9dD7N7ylVmkQ?e=K8TFWS

What do I do if I have concerns about this research?

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor,
Primary Supervisor: Professor Nhut (Nick) Hoang Nguyen
Nhut.Nguyen@aut.ac.nz 09-921-9999 Ext.7151
Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, *ethics@aut.ac.nz* , (+649) 921 9999 ext 6038.

Whom do I contact for further information about this research?

Please keep this Information Sheet and a copy of the Consent Form for your future reference. You are also able to contact the research team as follows:

Researcher Contact Details:

Primary Researcher: Damon Yu. Haoyang.yu@autuni.ac.nz

Project Supervisor Contact Details:

Primary Supervisor: Professor Nhut (Nick) Hoang Nguyen Nhut.Nguyen@aut.ac.nz +64 9 921 9999 Ext.7151

I agree to participate in the study.

- ○ Agree
- ○ Disagree

→

Personality Traits and Financial Decision-making

We appreciate you taking some time to answer this survey.

All the responses will be held in strictest confidence.

You will be in to win a $300 Voucher !

By clicking next page ("the right arrow") provides an evidence of consent that you agree to participant in this research study.

→

When you sell a stock, what is your reference point (the stock price you compare with)?

- ○ the first purchase price
- ○ first in, first out
- ○ the last purchase price
- ○ last in, first out
- ○ the highest purchase price
- ○ the lowest purchase price
- ○ weighted average purchase price
- ○ weighted average purchase price minus average profit/loss for the portion of shares sold in the interim time
- ○ none of the above (please describe in detail the method of calculation)

How much regret do you feel when you <u>own shares</u> that <u>decrease in value</u> compared to the previous period?

No regret 1	2	3	4	5	6	7	8	9	Strong regret 10
○	○	○	○	○	○	○	○	○	○

How much regret do you feel when you <u>sold shares</u> that <u>increase in value</u> compared to the previous period?

No regret 1	2	3	4	5	6	7	8	9	Strong regret 10
○	○	○	○	○	○	○	○	○	○

→

What percentage of participants in this session have better investing skills than you?

0 10 20 30 40 50 60 70 80 90 100

What percentage of participants in this session will end up making more money than you?

0 10 20 30 40 50 60 70 80 90 100

Which of the following statements comes closest to the amount of financial risk that you are willing to take when you make your financial investment:

- a very high return, with a very high risk of losing money
- high return and high risk
- moderate return and moderate risk
- low return and no risk.

→

In this choice task, you decide for each of six lotteries whether you want to accept (that is, play it) or reject it (and receive nothing). In each lottery the winning price is fixed at 6 and only the losing price is varied (between 2 and 7).

	Click to write Column 1	
	Accept	Reject
If the coin turns up heads, then you lose \$2; if the coin turns up tails, you win \$6.	○	○
If the coin turns up heads, then you lose \$3; if the coin turns up tails, you win \$6.	○	○
If the coin turns up heads, then you lose \$4; if the coin turns up tails, you win \$6.	○	○
If the coin turns up heads, then you lose \$5; if the coin turns up tails, you win \$6.	○	○
If the coin turns up heads, then you lose \$6; if the coin turns up tails, you win \$6.	○	○
If the coin turns up heads, then you lose \$7; if the coin turns up tails, you win \$6.	○	○

Please select the best response that represents you.

	Strongly disagree 1	2	3	4	5	6	Strongly agree 7
I feel that I have control over the things that happen to me.	○	○	○	○	○	○	○
Today I was able to deal with my problems.	○	○	○	○	○	○	○
Today I was able to manage my health well.	○	○	○	○	○	○	○

→

How many years have you been investing?

- ○ 0 year
- ○ less than 2 years
- ○ 2 to 5 years
- ○ More than 5 years

How high do you estimate your experience in the private trading of stocks? Please answer on a scale 1–10 (1=very low; 10 = very high).

Very low 1	2	3	4	5	6	7	8	9	Very high 10
○	○	○	○	○	○	○	○	○	○

→

Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

- More than $102
- Exactly $102
- Less than $102
- Don't know
- Prefer not to say

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today
- Don't know
- Prefer not to say

If interest rates rise, what will typically happen to bond prices?

- They will rise
- They will fall
- They will stay the same
- There is no relationship between bond prices and the interest rate
- Don't know
- Prefer not to say

A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.

- True
- False
- Don't know
- Prefer not to say

Buying a single company's stock usually provides a safer return than a stock mutual fund.

- True
- False
- Don't know
- Prefer not to say

→

I am good at dealing with day-to-day financial matters, such as checking accounts, credit and debit cards, and tracking expenses

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
○	○	○	○	○	○	○

How would you assess your overall financial knowledge?

Very low 1	2	3	4	5	6	Very high 7
○	○	○	○	○	○	○

→

For the following items, please select the best response that represents you.

I am someone who:

	Strongly Disagree 1	2	3	4	Strongly Agree 5
Tends to be quiet	○	○	○	○	○
Is dominant, acts as a leader	○	○	○	○	○
Is full of energy	○	○	○	○	○
Is compassionate, has a soft heart	○	○	○	○	○
Is sometimes rude to others	○	○	○	○	○
Assumes the best about people	○	○	○	○	○
Tends to be disorganized	○	○	○	○	○
Has difficulty getting started on tasks	○	○	○	○	○
Is reliable, can always be counted on	○	○	○	○	○
Worries a lot	○	○	○	○	○
Tends to feel depressed, blue	○	○	○	○	○
Is emotionally stable, not easily upset	○	○	○	○	○
Has little interest in abstract ideas	○	○	○	○	○
Is fascinated by art, music, or literature	○	○	○	○	○

Please select the best response that represents you.

	Strongly Disagree 1	2	3	4	Strongly Agree 5
I always want more.	○	○	○	○	○
Actually, I'm kind of greedy.	○	○	○	○	○
One can never have too much money.	○	○	○	○	○
As soon as I have acquired something, I start to think about the next thing I want.	○	○	○	○	○
It doesn't matter how much I have. I'm never completely satisfied.	○	○	○	○	○
My life motto is "more is better."	○	○	○	○	○
I can't imagine having too many things.	○	○	○	○	○

→

Please select the best response that represents you.

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
I admire people who own expensive homes, cars, and clothes.	○	○	○	○	○	○	○
Some of the most important achievements in life include acquiring material possessions.	○	○	○	○	○	○	○
The things I own say a lot about how well I'm doing in life.	○	○	○	○	○	○	○
I like to own things that impress people.	○	○	○	○	○	○	○
I'd be happier if I could afford to buy more things.	○	○	○	○	○	○	○
It sometimes bothers me quite a bit that I can't afford to buy all the things I'd like.	○	○	○	○	○	○	○
No matter what it takes, I always try to choose the best thing.	○	○	○	○	○	○	○
I don't like having to settle for "good enough".	○	○	○	○	○	○	○
I am a maximizer.	○	○	○	○	○	○	○
No matter what I do, I have the highest standards for myself.	○	○	○	○	○	○	○
I will wait for the best option, no matter how long it takes.	○	○	○	○	○	○	○

Please select 3 as an attention check.	O	O	O	O	O	O	O
I never settle for second best.	O	O	O	O	O	O	O
I am uncomfortable making decisions before I know all of my options.	O	O	O	O	O	O	O
Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment.	O	O	O	O	O	O	O
I never settle.	O	O	O	O	O	O	O

→

What is your age?

- 18 – 24
- 25 – 34
- 35 – 44
- 45 – 54
- 55 – 64
- 65+

What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is the highest level of education you have attained?

- Doctoral Degree
- Master's Degree
- Postgraduate Diploma
- Bachelor's Degree with Honours
- Bachelor's Degree
- Graduate Diploma
- Refuse to Answer

What is your ethnic background?

- ☐ New Zealand European
- ☐ Māori
- ☐ Pacific Peoples
- ☐ Other European
- ☐ Chinese
- ☐ Indian
- ☐ Other Asian
- ☐ Middle Eastern / Latin American / African
- ☐ Other Ethnicity

What is your annual income in NZD?

- ○ $0
- ○ $1 – 25,000
- ○ $25,001– 50,000
- ○ $50,001 – 70,000
- ○ $70,001 – 100,000
- ○ $100,001 – 150,000
- ○ $150,001 – 200,000
- ○ More than $200,000

→

Would you like to enter a raffle for the chance to win a $300 Voucher?

- ○ Yes
- ○ No

→

Please fill out the information below to join the draw to WIN a $300 Voucher!

Name	
Email	
Preferred Phone	

→