

Applying reference-dependence to understand the association
between economic decision-making and affective states: depressive
symptoms and regret

by

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Statement of originality

I certify that the intellectual content of this thesis is the product of my own work, and that all assistance received in preparing this thesis and all sources have been acknowledged. This thesis has not been submitted for any other degree or purpose.

Artificial intelligence (AI)/generative AI was not used at any stage of writing the text of this thesis. Grammar and spelling were corrected according to automatic feedback from word-processing software (Microsoft Office Word up to v16.106).

Internet searches, including automatic AI responses to these searches, were used to assist with clarifying correct code for statistical analysis conducted in R.

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Only tables and figures in the main text are listed above; supplementary tables and figures are included in appendices.

General introduction

With this thesis, I aim to provide a better understanding of individual economic decision-making during affective states. Specifically, I focus on i) investigating whether reference-dependence can characterise decision-making behaviour as a function of depressive symptoms; ii) clarifying the influence of regret on decision-making, including a comparison of self-report and behavioural measures of regret; and iii) examining how depressive symptoms interact with regret to shape economic decision-making. To achieve my aims, I harness theories and models centred on reference-dependence, a well-established concept within economics. Moreover, regret is of interest in its own right for being a reference-dependent concept with an established role in decision-making.

The motivations for the research contained within this thesis were multiple and overlapping. Understanding behaviour changes owing to depressive symptoms is of necessity given the significant negative impact mood disorders have on human wellbeing. Major depressive disorder (MDD) in particular, represents one of the most severe perturbations of thinking and behaviour. As noted in Chapter 1, MDD and depressive disorders impose vast economic cost on society, while negatively impacting psychosocial functioning across social and occupational domains. A rationale for understanding decision-making during depression is therefore to provide knowledge for policy makers so they can better address this public health challenge. However, affect* also bears on economics in general: it is undoubtably so that moods and emotions influence many of the behaviours economists are interested in. Economics holds great potential for explaining these behaviours by taking into account mood and emotions more explicitly.

The aims and focus of this thesis necessitated an interdisciplinary attitude towards understanding economic decision-making. While grounded in knowledge and models from economics, this thesis was further informed by research from within neuroscience and psychology. This is reflected in the literature reviews preceding each chapter and that

* In this thesis, the word ‘affect’ is used as defined by the American Psychological Association (2018) whereby “both mood and emotion are considered affective states”.

informed the hypotheses and methods employed therein. To help set the stage, more general influences are noted next.

Behavioural economics has furnished theory and models applied within all the empirical studies in this thesis. This area of economics, aimed at describing ‘aberrant’ behaviour, as seen from the perspective of neo-classical economics, has placed emotion in a more central role (Rick & Loewenstein, 2008). Rather than seeing emotions as forces distracting from rational choice, models developed within behavioural economics include affective states as explanatory components for describing preferences and choice. Expanding the purview of economics to include decision-making when affect may be influential can help explain a wider range of important phenomena. In this thesis, affect is given an opportunity to play a more central role than is commonly the case in economic research. To achieve this, reference-dependence is applied and serves as a basis for the models used to investigate the role of affect during decision-making. *Reference-dependence* is a key concept developed within behavioural economics, emphasising that preferences are psychologically dependent on a person’s current *reference point*.

The empirical approach taken within behavioural economics is often experimental. Accordingly, across studies herein, decision-making behaviour is investigated by utilising experimentally controlled reward-contingent environments. These environments were created by applying well-established paradigms from experimental- and behavioural economics. This methodology is also indicated given maladaptive behaviour is a key phenomenon of depression, and the aim of this thesis is to understand how depressive symptoms influence decision-making that is of material significance to people.

Key foundational literature for this thesis also comes from the fields of neuroeconomics and computational psychiatry. Neuroeconomic models of behaviour harness insights from economics (e.g., models of preferences and utility) while incorporating biologically realistic accounts of the brain’s actual information-processing constraints. Chapter 1 employs such a neuroeconomic model of reference-dependence to characterise reward-contingent behaviour across depressive symptomatology. Relatedly, computational psychiatry seeks to describe mechanistic links across explanatory variables (e.g., neurobiology, information-processing, overt behaviour, psychiatric symptoms and environments) with computational techniques and models. Within computational psychiatry, recent decades have seen a boom of interest in

understanding how decision-making is impacted by depressive mood. Particularly reward-processing changes have shown promise for explaining how symptoms such as anhedonia may result in maladaptive behaviour. Nevertheless, our understanding is still nascent. My aim is to contribute knowledge that may help address both the economic and clinical impacts of affective disorders by furthering such research. Specifically, I focus on how depressive states intersect with evaluation and reward-processes via reference-dependence to shape behaviour.

A third, subtler, influence is Heidegger (1962)'s understanding of mood. Heidegger described mood states (e.g., anxiety, depression) as times when we are most aware of our embeddedness in the world: including the things that exist therein, their use to us (i.e., utility), effect on us, and our potential future states - our '*being-in-the-world*' in short. Thus, affective states may be seen as informative when making judgements; that is, depressive symptoms and emotions may be conceptualised as *decisional states*. This perspective is echoed in philosophical accounts of affect that emphasise emotions as reflecting appraisals or evaluative perceptions about one's context.[†] The aims and hypotheses of this thesis are founded on the notion that depressive symptoms and regret play a consequential role in shaping evaluation and in turn economic decision-making.

What is meant by affect? Briefly, affect encompasses emotions and moods (including depressive symptoms such as anhedonia, feeling depressed or anxiousness). In turn, emotions and moods are perhaps best understood by paraphrasing Tappolet (2022)'s philosophical discussion of how moods can be contrasted with emotions: moods appear more diffuse (e.g., last longer) and are usually less intense; moods influence judgement and what we think, but pertain to, or are appraisals of, how things are globally (e.g., most things in your environment). Emotions (e.g., sadness, fear, happiness), on the other hand, appear more immediate or short-lived; are about specific objects, people or events; and motivate specific types of action. Of course, the two may overlap and be related (depressed mood may be reflected in tending to feel sad). Next, the focus of each chapter is reviewed briefly.

In Chapter 1, I investigate whether depressive symptoms and reference points, together, may help explain economic decision-making. As noted, reference-dependence emphasises that

[†] Tappolet (2022) provides a philosophical overview of affective theories that highlight appraisal and perceptual models of affect as fundamental for how emotions and moods are understood.

when evaluations or judgements are formed, these will be influenced by a comparison to a referent value or *reference point* that the decision-maker has in mind, either implicitly or consciously. In this chapter, the moderating influence of depressive symptoms on reference points is tested by applying various methodologies, and across three samples.

Chapters 2 and 3 complement the approach in Chapter 1; here, I explore reference-dependence within the framework of *regret*. Regret has direct links to both decision-making and reference-dependence: regret arises from a comparison between the outcome of a chosen option relative to the outcome of a non-chosen or foregone option. Thus, evaluations (preferences) are influenced by counterfactual outcomes in a reference-dependent manner. Over multiple decades, regret has proven a seminal decisional construct for emphasising the affective component of preference formation. However, the conceptual consistency across different ways of measuring regret (i.e., the convergence across self-report versus behavioural measures) is unclear. In Chapter 2, I explore the convergent validity of regret in the context of economic decision-making.

Building on the methodology developed within Chapter 2, in Chapter 3 I test whether regret-contingent behaviour may vary as a function of depressive symptoms. A significant literature has evidenced links between depression and regret measured via self-report (i.e., one's perceived tendencies or proneness towards regret). However, evidence pertaining to regret measured behaviourally is mixed, necessitating empirical studies that clarify if self-reported regret proneness overlaps with behaviourally exhibited regret during depressive symptoms. This may help determine whether decisional regret is a useful concept for explaining decision-making changes associated with depression.

Across the experimental chapters of this thesis, affect is measured by asking participants to self-report their moods and emotions. Therefore, in the General appendix of this thesis, I discuss the conceptual rationale for operationalising affective states via self-report. This 'optional' chapter complements the empirical focus of this thesis by giving a firmer conceptual footing to the methodology used across studies.

A final practical note: to maintain flow, the chapter-specific appendices are included at the end of each chapter, while the General appendix includes a copy of the key experimental instructions for each chapter/study.

Chapter 1. The links between reference points and depressive symptoms during economic decision-making

Abstract

The effects of depressive symptoms on economic decision-making warrant further attention, particularly given depression is associated with significant societal costs and individual functional impacts. A growing empirical literature emphasises reward processing differences during depression, including reduced reward salience or evaluation of rewards and lower reward expectations. Moreover, recent studies and theoretical proposals have indicated depression may be associated with maladaptive reference points. Reference points play a key role in determining the subjective, or hedonic, aspect of rewarding stimuli. Therefore, individual reference point variation may explain reward-processing impacts due to depressive symptoms, and in turn economic decision-making. To test this, reference points were gauged and related to depressive symptoms across three studies. Two studies recruited large samples ($N = 853$ and $N = 443$) from the general population (Australian and American, US); while a third study followed a clinically depressed cohort ($N = 12$) over two time-points during treatment (4-6 weeks while being treated with ketamine). This was to capture the correspondence between changes in reference points and depressive symptoms. Two standard experimental paradigms were used to measure reference points behaviourally: parametric reference points were estimated by fitting structural models of subjective value to binary choices made during a lottery task; and reward expectations were gauged during a simulated foraging task. In the general population samples, anhedonia was associated with higher parametric reference points and feeling depressed was associated with lower reference points. Additionally, feeling depressed was associated with lower stated long-term income expectations. In the clinical cohort, while total depression severity (across symptoms) was weakly negatively associated with reward expectations; the severity of anhedonia was associated with lower reward expectations and feeling depressed was associated with higher reward expectations. Thus, reference points evidenced different links with depressive symptoms, appearing to diverge across depressive symptoms and across reference point measures. Overall, these findings provide a promising starting point for future research aimed at clarifying how depressive symptoms shape economic decision-making.

Key words: *economic, reference point, decision-making, depression, anhedonia*

1.1 Introduction

In 2020 Major Depressive Disorder (MDD) cost the global community 49.4 million disability-adjusted life-years (Santomauro et al., 2021). Social, occupational or other functional impairments are a key diagnostic criterion; meaning maladaptive behaviour change distinguishes depression from normal moods (American Psychiatric Association, 2022). MDD-related impairments may manifest as relationship ruptures, unemployment (Gutiérrez-Rojas et al., 2020), interpersonal- and occupational challenges (Godard et al., 2012). MDD confers significant costs through absenteeism and presenteeism (reduced productivity), estimated at \$38.4 billion and \$43.3 billion, respectively, in a recent American study (Greenberg et al., 2023). Moreover, these changes effect a significant number of people: approximately 5.7% of the world's adult population (Organization, 2025), while prevalence ranges from 2% (China) to 21% (France) (Gutiérrez-Rojas et al., 2020). The risk of depression recurring is high, even after treatment (Holma et al., 2008), and while depressive symptoms can abate, psychosocial impacts may persist (Godard et al., 2012). This suggests the underlying aetiological (i.e., causing or contributing) mechanisms and their effects on behaviour are less mutable. Taken together, depression imposes significant societal and individual costs.

Other than rare examples (de Quidt & Haushofer, 2016)³, the influence of depression on economic decision-making has received little attention within economics in general. This is surprising: as noted, disorders of mood present a profound societal cost and are therefore a priority for policy makers. Moreover, depression shows a pattern of dysfunction across social and occupational domains, including as seen below, pertaining to reward-contingent decision-making. Within the field of behavioural economics and psychology, a handful of studies have investigated whether greater loss-aversion may be characteristic of depression, yet studies summarised in a recent systematic review (Sediyama et al., 2020) paint a mixed picture. Similarly, within psychology the association between depression and risky decision-making has been investigated; a meta-analysis (Lu et al., 2024) suggest mixed findings. Although these studies are important contributions, it remains unclear through which mechanisms depressive moods may influence economic decision-making. Nevertheless, a *decision-*

³ In this working paper, de Quidt & Haushofer propose to explain depressive symptoms by applying a labour-supply-style model.

theoretic approach holds promise for understanding how potentially normal evaluation may go awry during depression (Huys et al., 2015). In the following sections, it is argued that such a decision-theoretic framework centred on reference-dependence has untapped potential for furthering our understanding of mood-contingent economic decision-making.

1.1.1 Reference-dependent decision-making

Reference-dependence is prominent decision-making framework in economics supported by evidence from neuroscience and psychology, and has recently been put forth as an explanatory framework for elucidating depression-related differences in evaluation (Rigoli et al., 2021; Zavlis et al., 2024). Essentially, reference-dependence emphasises that all potentially rewarding stimuli or outcomes (e.g., money, food, etc.) are valued relative to an internal benchmark, or *reference point*: a stimulus or outcome is subjectively perceived as either better or worse (i.e., positively or negatively reinforcing) depending on whether it represents an increment or decrement relative to the reference point.

Reference-dependence can be illustrated with the following simplified example: imagine you are planning a fishing trip to your usual spot. Before you leave for the trip, your (competitive) sister says she was fishing there the day before and caught 10 fish – this number now becomes your reference point. After a long day of fishing, you have caught 5 fish; according with reference-dependence, your evaluation will be negative for this otherwise objectively rewarding catch. Next, imagine an alternative scenario: before you leave for the trip, your sister says she caught only 2 fish the day before (your reference point). In this case, at the end of the day, your catch of 5 fish will be evaluated positively, despite the number being the same as the preceding scenario. Reference-dependence emphasises that it is not the absolute number of fish you caught that matters for how rewarding the catch is evaluated, as much as the number of fish relative to your reference point, in this case the number of fish your sister (said she) caught.

Broadly defined, reference-dependence has featured in accounts of perception, judgement, preferences, evaluation, and choice across scientific fields, spanning decades (Beebe-Center, 1929; Bell, 1982, 1985; Charnov, 1976; Fechner, 1860/1966; Frederick & Loewenstein, 1999; Glimcher & Tymula, 2023; Helson, 1948; Hollingworth, 1910; Kahneman & Tversky, 1979; Köszegi & Rabin, 2006, 2007, 2009; Loomes & Sugden, 1982, 1986; Markowitz,

1952; Parducci, 1968; Parducci, 1995; Thurstone, 1927). Reference points have been experimentally evidenced as influential on behaviour (Abeler et al., 2011), and found to influence behaviour across diverse real-world contexts: marathon running times (Allen et al., 2017), the labour supply of taxi drivers (Crawford & Meng, 2011) and tax returns patterns (Rees-Jones, 2017) (for a review see O’Donoghue & Sprenger, 2018). Seminally, Kahneman and Tversky’s (1979) Prospect theory prompted economics to recognise the reference point as pivotal in economic decision-making under risk. However, Prospect theory (1979; 1992) left reference points relatively unspecified, describing the reference point as being a person’s status quo, their expectations or their aspirations. Subsequent reference-dependent theories have attempted to define the reference point more clearly; popular theories within behavioural economics have proposed that counterfactual outcomes may act as reference points – these theories have centred either on the emotion of disappointment (Bell, 1985; Loomes & Sugden, 1986) or regret (Bell, 1982; Loomes & Sugden, 1982, 1987) - the latter proving particularly popular (Bleichrodt & Wakker, 2015). Reference points have also been conceptualised as rational expectations within a personal equilibrium model that assumes people are characterised by optimal behaviour in a given environment (Kőszegi & Rabin, 2006, 2007, 2009). This model was later elaborated by Kőszegi (2010) to feature a role for anticipatory emotions (e.g., anxiety), who also discusses how pessimistic expectations may become self-fulfilling via changes in mood and behaviour.⁴ Furthermore, empirical studies have quantified individual variation in reference points with modern statistical methods (Baillon et al., 2020). And people’s reference points have been found to adjust to the history of encountered stimulus values during experiments (Guo & Tymula, 2021; Khaw et al., 2017).

The neurobiological underpinnings of reference-dependent decision-making has received growing attention over the last two decades (Chandrasekhar Pammi et al., 2015; De Martino et al., 2009; Elliott et al., 2008; Louie et al., 2014; Tom et al., 2007). Of note is *Divisive normalisation*, a canonical reference-dependent model of computation arising from decades of research within neuroscience (Carandini & Heeger, 2011). This model emphasises a balance between the accuracy versus the biological cost of stimulus representation by assuming the firing rates of ‘redundant’ neurons are attenuated when adjacent neurons encode the same information. The neuronal encoding of stimuli is thus relative to the stimulus values captured by the pooled activity of related neurons, such that more information is represented

⁴ Although not describing depression specifically.

by fewer action potentials (Carandini & Heeger, 2011; Glimcher, 2022). Theoretically, divisive normalisation allows for efficiently encoding environmental statistics (Bucher & Brandenburger, 2022) and provides testable mappings from neuronal activity to choice behaviour (Steverson et al., 2019). Empirically, divisive normalisation has been evidenced in contextual value-encoding (Louie et al., 2011; Yamada et al., 2018); and in the functioning of sensory systems involving vision (Aqil et al., 2021; Sato et al., 2016; Zoccolan et al., 2005), sound (Schwartz & Simoncelli, 2001) and smell (Olsen et al., 2010); while the model may also help explain attentional processing (Bloem & Ling, 2019; Reynolds & Heeger, 2009). Moreover, divisive normalisation has recently proven capable of explaining a range of evaluation-based and economic behaviours in animals and humans (Guo & Tymula, 2021; Khaw et al., 2017; Louie et al., 2014; Steverson et al., 2019; Webb et al., 2021; Yamada et al., 2018).

Overall, reference-dependence is a well-established concept for understanding economic decision-making. Accordingly, this paper seeks to understand whether economic decision-making differences exhibited by people experiencing depressive symptoms may be understood as a function of reference points. A large number of studies suggest that depression is associated with reward-processing changes, such as reduced reward sensitivity (Huys et al., 2015; Huys et al., 2021). Such studies, reviewed next, provide further clues to how reference points may shape economic decision-making in the context of depression.

1.1.2 Depressive symptoms and reward-processing

A large literature suggests reward-processing dysfunction in depression (Halahakoon et al., 2020). Specifically, MDD may reduce the ability to modulate behaviour in response to rewards (Huys et al., 2008; Vrieze et al., 2013), possibly by attenuating a normal bias people show towards more rewarded stimuli (Pizzagalli et al., 2008). Relatedly, there is evidence of reduced positive affect/arousal in response to rewards (Pizzagalli et al., 2009) and diminished reward sensitivity. This pertains to complex, ‘secondary’, reward stimuli, involving positive visual and emotional stimuli (e.g., movies, conversations), rather than ‘primary’ reward sensitivity (e.g., to sweet solutions) (Huys et al., 2015; Huys et al., 2021). Relatedly, depression has been linked to an underestimation of the history of received reinforcements (Pizzagalli, 2014) and reduced expectations of future rewards (Bishop & Gagne, 2018; Pizzagalli, 2014). Similarly, *anhedonia*, a key symptom of MDD, has been linked to treating

rewards as less rewarding (Huys et al., 2021), a blunted responses to immediate versus delayed rewards (Lempert & Pizzagalli, 2010) and diminished reward learning (Vrieze et al., 2013).

Neurobiological factors likely play a role in reward-processing dysfunction. MDD has been linked to blunted activation of striatal regions, reduced dopamine transmission (Pizzagalli, 2014) and reduced brain activity associated with prediction errors (Gradin et al., 2011).⁵ Reward-processing differences may be predictive of later diagnosis (Vrieze et al., 2013) and can persist after symptom remission (Pechtel et al., 2013). This may explain why recurrence is likely and psychosocial challenges can persist. Moreover, responsiveness to rewards has been found to improve following novel psychological treatments designed to target ‘reward hyposensitivity’ in depression (Craske et al., 2023). The neurobiological substrates for anhedonia have been tricky to establish owing to factors such as sample heterogeneity and anhedonia likely being further subdivisible (Cooper et al., 2018).

From a cognitive information-processing perspective, noted evidence of lower reward expectations may be rooted in the general pessimistic thinking-patterns often seen in depression (Alloy & Ahrens, 1987; MacLeod & Salaminiou, 2001) and which, in turn, may be linked to persistent negative cognitive schemas (Evans et al., 2005; Renner et al., 2012) and information-processing biases (Foland-Ross & Gotlib, 2012; Gotlib & Joormann, 2010).

Overall, there is evidence that depression and anhedonia are associated with changes in reward-contingent behaviour, with increasingly clear neurobiological underpinnings. However, a more nuanced understanding of such differences is needed, such as about symptom-specific effects (Mukherjee et al. (2023)). In this chapter, individual variation in reference points is investigated to help explaining reward-processing differences found during depressive symptoms. The next section describes a particularly promising approach to measuring reference point variation.

⁵ This link has also been challenged (e.g., Rutledge et al., 2017).

1.1.3 Parametric reference points

In seeking to describe economic decision-making, behavioural economists have commonly defined reference points within *structural models* of subjective value. Such models (including those noted in section 1.1.1) explain choice patterns as a function of decisional variables, or parameters, that can be statistically identified from behaviour. Seminally, Prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) emphasised that people's reference points are vital for understanding their preferences and behaviour. However, as noted above and by others (Baillon et al., 2020; Barberis, 2013), the reference point was left relatively unspecified with less guidance given for how to measure it.

A notable attempt at quantifying reference points is described in Baillon et al. (2020): the authors applied a parametric approach, defining a general reference-dependent structural model (encompassing Prospect theory, rational expectations and disappointment-based theories) within a hierarchical Bayesian computational framework. They successfully applied this approach to quantitatively identify the type of reference points their participants most likely applied during decision-making. Results indicated that multiple reference points (of varying magnitudes) shaped preferences and choice.

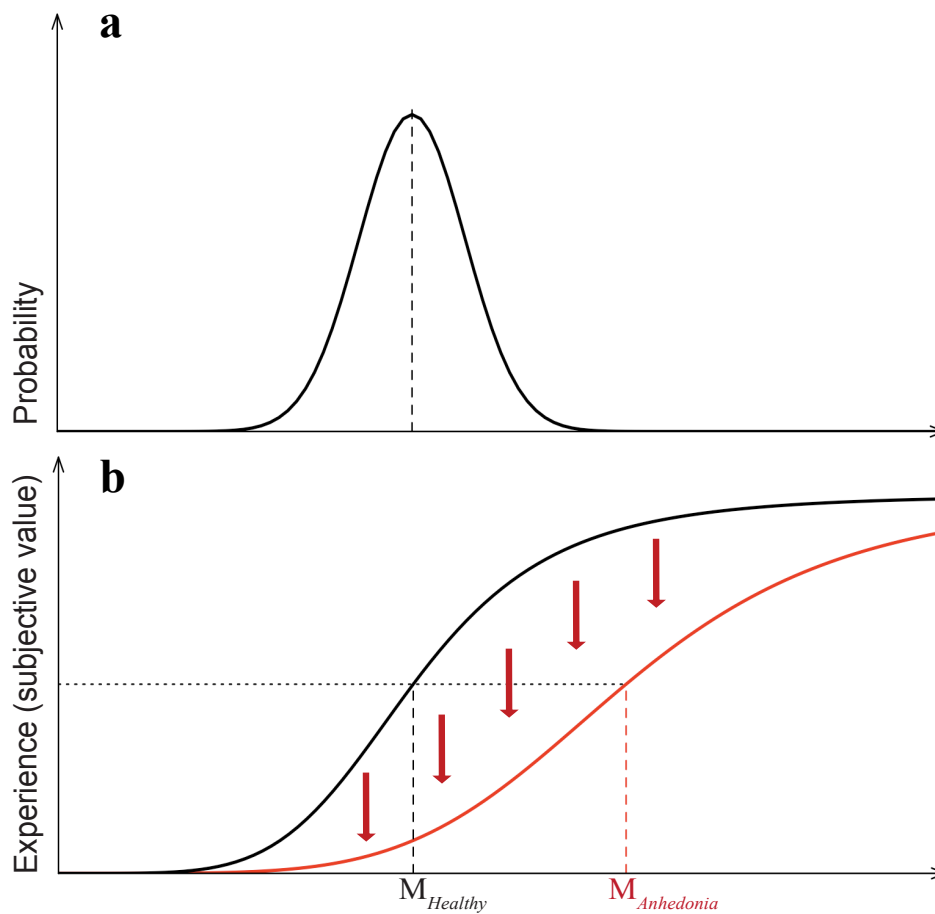
Although promising, for the purpose of the studies here, a general Prospect theory model of reference-dependence may not be preferred. A well-acknowledged feature of Prospect Theory is the multitude of structural variables (parameters) required to characterise preferences (four for the value-function alone, sans probability-weighting). While these features allow Prospect theory to be flexibly applied to explaining behaviour across different contexts, it can be problematic for capturing mood-related variations in reference points per se: both conceptually, given the need to account for multiple structural variables that may also be related to mood; and practically, given the computational challenges involved in statistically estimating a model with up to 5 free parameters (including a noise term).

A favourable alternative model from the field of neuroeconomics is Expected Subjective Value Theory (ESVT) (Glimcher & Tymula, 2023). This model of subjective value is particularly well suited for capturing the reference point. It was developed with the aim of furnishing reference-dependence with insights from neuroscience, emphasising that evaluation must rely on efficient encoding, given the natural constraints of the brain (due to the energy required by neural activity). ESVT incorporates divisive normalization, noted

above, by proposing that subjective values are formed through the normalization of objective reward-stimuli by the decision-makers reference point. This model thus incorporates more naturalistic foundations than traditional reference-dependent models within behavioural economics. Importantly, the reference point is explicitly parameterised from observed choices creating a *parametric reference point*. ESVT therefore lends itself to determining individual variation in reference points from behaviour, which can then be related to depressive symptoms.

A stylised version of the ESVT model is depicted in Figure 1.1. The parametric reference point, M , defines the objective reward that lies at the mid-point of the internal subjective value of all possible rewards. The top panel of Figure 1.1 displays the distribution of rewards in an environment, represented by a black bell-curve. The bottom panel shows the corresponding subjective value function for a ‘healthy’ non-depressed individual (black line). Notice their reference-point is equal to the median of the reward distribution. The level of the reference point is hypothesised to shape the individual’s hedonic experience of reward stimuli in their environment: below this level, objective rewards are perceived as worse, and above this level, perceived as better. ESVT also incorporates alpha (α), a curvature-parameter influencing the overall shape of the subjective value function. Preliminary research has indicated that abnormally elevated reference points may be characteristic of depression (Vittala et al., 2025). This is illustrated with the red line in the bottom panel. Here the reference point is shifted rightward and fixed at this location, reflecting an abnormally high reference point. This is hypothesised to occur during anhedonia, specifically, perturbing the hedonic experience of rewards in any given environment (relative to that of a healthy individual), leaving people generally disinterested. In the example, most of the objective rewards on the x -axis are experienced as subjectively less rewarding (i.e., not interesting enough to pursue). This illustrates how the parametric reference point may help explain symptoms-specific differences in economic decision-making owing to depression.

Figure 1.1 *Subjective value according to reference point variation due to anhedonia*



Note. Panel (a) shows the distribution that reflects the probability of encountering different rewards/outcomes in the actual world. The x -axis represents the objective value of rewards in an environment, while the y -axis reflects the associated probabilities. Panel (b) shows the cumulative distribution function (CDF) that represents the subjective value (or utility) function for a person experiencing anhedonia (red) versus a healthy individual (black). The mid-points (dotted lines) of each are the parametric reference points (M), which is shifted rightward in anhedonia.

1.1.4 Summary and aims

While the costs of depression are well-documented, economic interest and knowledge about the effects of depressive symptoms on economic decision-making is nascent. Evidence has accumulated that depression is associated with reward-processing differences, yet further knowledge is needed to understand the underlying mechanisms behind these. Given the success of reference-dependence for understanding preferences and evaluation in economics, this framework holds explanatory promise. In this paper, reference point variation is tested for its ability to account for economic, reward-contingent, decision-making as a function of

depressive symptoms. Aims include to i) test the association between reference points and depressive symptoms (e.g., anhedonia) within the general population, ii) test whether more pronounced anhedonia is associated with elevated reference points; iii) compare methods for measuring reference points, and iv) extend findings to both non-clinical and clinical samples. Three studies were developed to achieve these aims. An initial study analysed a data set containing a sample of non-clinical participants who were asked to complete a behavioural decision-making task that allowed estimation of parametric reference points. These participants also reported on their levels of anhedonia and whether they experienced negative affect in the form of *feeling depressed*. A second study recruited a sample of American adults (matched to population demographics) who completed a similar behavioural task, mood questionnaires, and provided their stated reference points. These were captured by asking participants about their reward expectations and long-term income expectations. A third and final study involved recruiting a cohort of clinically depressed individuals receiving treatment, and who were followed over two time-points. In this sample, a popular behavioural paradigm for gauging reward expectations behaviourally (the foraging task) was used as an additional measure of reference points. The remaining sections describe each of these studies, after which results from across studies are discussed.

1.2 Study 1: Methods

1.2.1 Participants

Participants were 853 individuals from a sample of the Australian population recruited as part of the Australian Twins Economic Preferences Survey (ATEPS) (Kettlewell & Tymula, 2021). The ATEPS consists of psychological and demographic questionnaires, and incentive-compatible behavioural choice tasks. Participants reported gender as 83% female (17% male) and mean age was 41.71 (SD was 14.22). Further demographics information for the participants included in this study are reported in Appendix 1.A, Table A.1. Responses were collected electronically using Qualtrics⁶ from people who were initially contacted via email, SMS, and phone calls, between September 2020 and March 2021. See Kettlewell and Tymula (2021) for further general details about recruitment, payment and all tasks and questionnaires.

1.2.2 Measurement of depressive symptoms

In ATEPS (Kettlewell & Tymula, 2021) depression symptoms were measured with the two depressive symptom questions of the Patient Health Questionnaire (PHQ-4). The item for *anhedonia* was (PHQ1): “Little interest or pleasure in doing things” and for *feeling depressed* (PHQ2): “Feeling down, depressed or hopeless”. These statements were rated by participants as they applied to them over the preceding 2 weeks on a 4-point Likert scale: “Not at all”, “Several days”, “Over half the days”, and “Nearly every day”. The PHQ-4 is a well-regarded self-report measure of depression and anxiety severity that is commonly used across research. The PHQ-4 is based on the American Psychiatric Association’s (2022) Diagnostic and Statistical Manual 5th edition (DSM-5-TR) criteria for screening MDD, assessing the two core diagnostic symptoms: anhedonia and depressed mood. The questionnaire was developed from previous measures: the PHQ-2 (Kroenke et al., 2003), PHQ-9 (Kroenke et al., 2001), and GAD-2 (Kroenke et al., 2007). The latter assesses generalised anxiety disorder symptoms and was derived from the 7-item General Anxiety Disorder scale (GAD-7) (Spitzer et al., 2006). Both the PHQ-2 and PHQ-4 have good psychometric properties (e.g., sensitivity, specificity, criterion- and construct-validity), as well as correlations in the expected direction with a measure of mental health and social functioning (Kroenke et al., 2003; Kroenke et al., 2009).

⁶ Qualtrics software, Provo, UT, USA. <https://www.qualtrics.com>.

1.2.3 Parametric reference points

To measure parametric reference points, participants completed a lottery task comprised of 46 lottery choices. Participants choose between two lotteries where payoffs (dollar amounts) and their probabilities varied across choices (see Figure 1.2 for an example of all the decision scenarios in the study). The range of payoffs was \$0 to \$43, and the range of probabilities was 0.05 to 0.85 (items are displayed in Appendix 1.B Table B.1). The 46-item lottery task was expected to take approximately 20 min. Detailed written and visual instructions with examples for comprehension were provided to participants before they started the task. This also included information on how the task was incentivised.

Parametric reference points were estimated from the 46 choices by fitting a structural decision-making model statistically via a logistic function that captured the probability of each participant choosing one option over the other. Two complementary statistical methods were used to estimate reference points parametrically i) to estimate a group-level structural model, maximum likelihood (ML) estimation was applied following the approach described in Harrison et al. (2008); ii) the same structural model was also used in a Bayesian Hierarchical Model (BHM) to retrieve posterior distributions of reference points at both the group-level and for each participant individually.

A structural model (Glimcher & Tymula, 2023) based on *divisive normalisation* was applied to account for a participant's aversion to risk by transforming the objective values of each lottery to a subjective value, as is standard practice in economics. In this structural model, the subjective value (SV) of reward x is given by:

$$SV(x) = \frac{x^\alpha}{x^\alpha + M^\alpha}$$

Where $M > 0$ is the reference point parameter and $\alpha > 0$ is a parameter that governs the curvature of the utility function (described as 'predisposition' parameter in Glimcher and Tymula (2023)). The model is useful for explicitly representing the reference point as a free parameter (M) that can be estimated from choice data. Taken together, the value of a whole lottery with three options x_1 , x_2 and x_3 and associated probabilities p_1 , p_2 and p_3 is given by:

$$SV = p_1 \frac{x_1^\alpha}{x_1^\alpha + M^\alpha} + p_{2A} \frac{x_2^\alpha}{x_2^\alpha + M^\alpha} + p_{3A} \frac{x_3^\alpha}{x_3^\alpha + M^\alpha}$$

The same calculation was performed for each of the two lottery options on the lottery task (e.g., A and B). Next a difference-score or index was calculated, $\nabla U = SV(A) - SV(B)$, which was applied in the ML and BHM approaches described next. ML and BHM are complimentary: ML is commonly applied for identifying parameter values across an entire sample, or ‘representative agent’ modelling. Here ML captures the way mood, on average, may be associated with the parametric reference point. However, people may be characterised by relatively unique parameters (e.g., reference points) and representative parameter values may therefore be tricky to converge on. In this case, BHM is an increasingly popular method allowing parameters to be fit both at the group- and individual level.

Figure 1.2 Lottery choice task (study 1)



Note. An example decision scenario in which a participant is choosing between the option on the *left*: \$11 with 10% chance, \$14 with 40% chance and \$26 with 50% chance; or the option on the *right*: \$17 with 40% chance, \$20 with 50% chance and \$29 with 10% chance. The side on which the lottery appeared was randomised across the trials and participants.

1.2.3.1 Maximum likelihood estimation

ML estimation algorithmically chooses the parameter estimate $\hat{\theta}$ (e.g., $\hat{\theta} = \hat{M}$) which maximise the likelihood of observing the actual data. Theoretically, it is obtained from the probability mass function or density $f(\mathbf{y}, \mathbf{X}|\theta)$ - a function of θ given the data (e.g., see Cameron and Trivedi (2005) for a nice explanation). This involves maximising the log-likelihood function, $L_N(\theta|y, X)$, so that the ML estimate conditional on the density of y given x is analytically given by:

$$\frac{1}{N} \frac{\partial \ln L_N(\theta)}{\partial \theta} = \frac{1}{N} \sum_{i=1}^N \frac{\partial \ln f(y_i|x_i, \theta)}{\partial \theta} = 0.$$

The ∇U index described above is linked to observed choices C_i – taking value 1 for choosing option A and 0 for choosing option B - using an inverse of the log odds ratio, transforming any value into a number between 0 and 1:

$$\ln\{\text{logit}^{-1}(C_i|\nabla U, \zeta)\} = \begin{cases} \ln\left\{\frac{\exp(\nabla U \cdot \zeta)}{1 + \exp(\nabla U \cdot \zeta)}\right\}, & \text{if } C_i = 1 \\ \ln\left\{\frac{\exp(-[\nabla U] \cdot \zeta)}{1 + \exp(-[\nabla U] \cdot \zeta)}\right\}, & \text{if } C_i = 0 \end{cases}$$

As in Nilsson et al. (2011) and Baillon et al. (2020), a Fechner sensitivity or noise parameter ζ was included: a larger noise term meant choices were more deterministically based on subjective values, while a smaller noise term meant choices were more random. ML assumes ‘complete pooling’ where a single estimate is produced for each parameter (e.g., the reference point) across the entire sample of participants. This global parametric reference point was modelled as a function of mood and demographic controls, such that for the reference point (M):

$$\begin{aligned} \widehat{M} = & \widehat{M}_0 + \beta_{1/PHQ1}(PHQ1 = 1) + \beta_{2/PHQ1}(PHQ1 = 2) + \beta_{3/PHQ1}(PHQ1 = 3) \\ & + \beta_{1/PHQ2}(PHQ2 = 1) + \beta_{2/PHQ2}(PHQ2 = 2) + \beta_{3/PHQ2}(PHQ2 \\ & = 3) + \text{controls } \boldsymbol{\gamma} + \varepsilon \end{aligned}$$

Where \widehat{M}_0 is the intercept or constant term, β_k are coefficients on dummy variables for anhedonia severity levels (i.e., PHQ1 = 1 through PHQ1 = 3) and feeling depressed (i.e., PHQ2 = 1 through PHQ2 = 3). $\boldsymbol{\gamma}$ is a vector of coefficients on control variables (covariates), and ε is the model error term. Depressive symptoms were dummy coded by severity level to capture potential non-linearities (0 = ‘Not at all’ was used as the baseline comparison category). Control variables were demographic variables likely to be associated with both mood disorder and reference points: gender, age, employment status, education and income. A measure of subjective financial comfort and two items assessing worry and anxiety (from PHQ-4) were also included.

1.2.3.2 Bayesian hierarchical modelling

BHMs are increasingly popular for estimating utility models, such as Prospect theory (Baillon et al., 2020; Murphy & ten Brincke, 2018; Nilsson et al., 2011). As described in Rouder and Lu (2005), BHM allows sampling from the posterior distribution for the parameters of interest $f(\theta|y)$ as a function of priors $f(\theta)$ and the likelihood function $f(y|\theta)$ (based on participant’s choice data, y). That is,

Posterior distribution \propto Likelihood function * Prior distribution.

The hierarchy is owing to the inclusion of group-level priors that are defined stochastically and estimated from the data. This feature allows for information from the overall sample to bear on the estimates of individual-level parameter values, thus improving precision by reducing the influence of outliers/extreme estimates or noise (Murphy & ten Brincke, 2018; Nilsson et al., 2011).

In the BHM, the same ESVT structural model for subjective values was applied as for ML. However, group-level priors were defined: the mean and standard deviation for the distribution of parameter estimates across participants. The individual-level parameters were assumed to come from a lognormal distribution. As in previous work (Baillon et al., 2020; Nilsson et al., 2011), the lognormal was preferred for parameters taking only positive values (a feature of M , α and ζ). The lognormal is also a distribution that describes many physical processes, including anatomical and physiological features of the brain (Buzsáki & Mizuseki, 2014). Summarising, the model was such that for each participant (n):

$$\begin{aligned} M_n &\sim \text{lognormal}(\mu_M, \sigma_M), \\ \alpha_n &\sim \text{lognormal}(\mu_\alpha, \sigma_\alpha), \\ \zeta_n &\sim \text{lognormal}(\mu_\zeta, \sigma_\zeta), \end{aligned}$$

and priors were distributed accordingly:

$$\begin{aligned} \mu_M &\sim U(-2.3, 3.76), \text{ and } \sigma_M \sim U(0, 1.75) \\ \mu_\alpha &\sim U(-2.3, 2.3), \text{ and } \sigma_\alpha \sim U(0, 1.33) \\ \mu_\zeta &\sim \text{norm}(3.05, 2.3), \text{ and } \sigma_\zeta \sim \text{norm}(0.5, 0.5) \end{aligned}$$

Particularly for reference point (M) priors, the uniform distribution was preferred so as not to assume certain reference points were more likely at the population-level. Model-development

culminated in the noise term prior being defined as normally distributed.⁷ For intuition, the priors in logs when converted to non-log values are approximately,

$$\begin{aligned}\mu_M &\sim U(0.1, 43), \text{ and } \sigma_M \sim U(1, 5.75) \\ \mu_\alpha &\sim U(0.1, 10), \text{ and } \sigma_\alpha \sim U(1, 3.78) \\ \mu_\zeta &\sim \text{norm}(21, 10), \text{ and } \sigma_\zeta \sim \text{norm}(1.65, 1.65)\end{aligned}$$

Mean priors for M and α were defined to capture the most plausible range of values: for M the maximum reward possible on the lottery task (\$43). Following Nilsson et al. (2011), the standard deviations σ_M and σ_α were those of the uniform distribution ranges (in log values) for the means (μ_M, μ_α) , calculated as $\approx \sqrt{\frac{(b-a)^2}{12}} \approx (b-a)/\sqrt{12}$. For example, $\sigma_M = 1.75$ because for the mean $\mu_M \sim U(-2.3, 3.76)$, the upper value of the uniform range was given by $\frac{3.76 - (-2.3)}{\sqrt{12}} = 1.75$.

For further intuition, Appendix 1.C Figure 1.C.1 displays different distributions of lognormal functions according to the prior values described above. Lower bounds were imposed on reference point parameters (0.1) and α parameters (0.1) - owing to the requirements of the ESVT structural model. For the noise terms the lower bound was 0.001. Overall, BHM involved sampling the posterior of 2565 parameters: ($n = 853 * 3$ individual level) + (6 priors). The index ∇U was used to predict participants' choices via a Bernoulli probability mass function,

$$\text{Bernoulli}(C_i \mid \text{logit}^{-1}(\nabla U, \zeta)) = \begin{cases} \text{logit}^{-1}(\nabla U \cdot \xi), & \text{if } C_i = 1 = \text{lottery} \\ 1 - \text{logit}^{-1}(\nabla U \cdot \xi), & \text{if } C_i = 0 = \text{sure} \end{cases}$$

After retrieving posterior estimates for the parameters across individuals, these were analysed with OLS regression models.⁸ For individual-level parameter estimates (M , α and ζ) the median of the posterior distribution was used. The median is more robust to outliers than the

⁷ The posterior noise term estimates tended to violate the presumed upper bounds when applying uniform distributions (something that was not the case for M nor α).

⁸ Except for the ML analysis in study 1, all statistical analysis in this paper was conducted in RStudio (PositTeam, 2025). Key packages for deriving regressions estimates were: 'modelsummary', 'stats' (e.g., functions 'glm' for Probit regression and 'lm' for OLS), 'plm' (for panel models); and 'lmtest' and 'sandwich' for robust and cluster-robust estimates (e.g., functions 'vcovCL', 'vcovHC', 'vcovHAC'). Spot-checks comparing a few models estimated in R and Stata indicated standard errors were identical (OLS) or near identical to a high decimal precision (panels).

mean and mode and is preferred for naturally skewed distributions. The BHM was implemented with a MCMC algorithm.⁹ In Appendix 1.D, further information regarding the MCMC sampling strategy and diagnostic tests are provided.

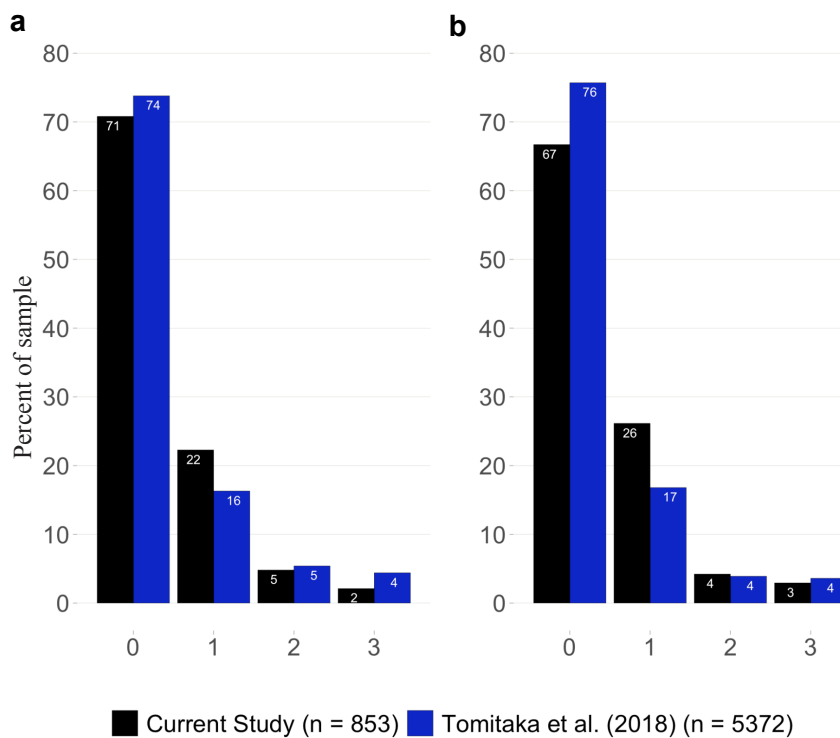
⁹ The MCMC algorithm for deriving posterior distributions applied a Hamiltonian Monte Carlo (HMC), No-U-Turn Sampler (NUTS), and was implemented with RStan software (Stan Development Team, 2025).

1.3 Study 1: Results

1.3.1 The distribution of depressive symptoms and parametric reference points

The rate of depressive symptoms in the current sample overlapped with rates previously identified in a large general population sample. The distributions of anhedonia (PHQ1) and feeling depressed (PHQ2) of study 1 are displayed in Figure 1.3 alongside distributions from a representative survey of 5,372 American adults for comparison (Tomitaka et al., 2018). Overall, distributions were similar across both samples, however, participants in study 1 appeared more likely to report symptoms ‘Several days’ relative to ‘Not at all’. This elevation might have been due to imperfect sampling or due to the different years during which the measurements were conducted (e.g., study 1 sampling occurred during the COVID-19 pandemic).

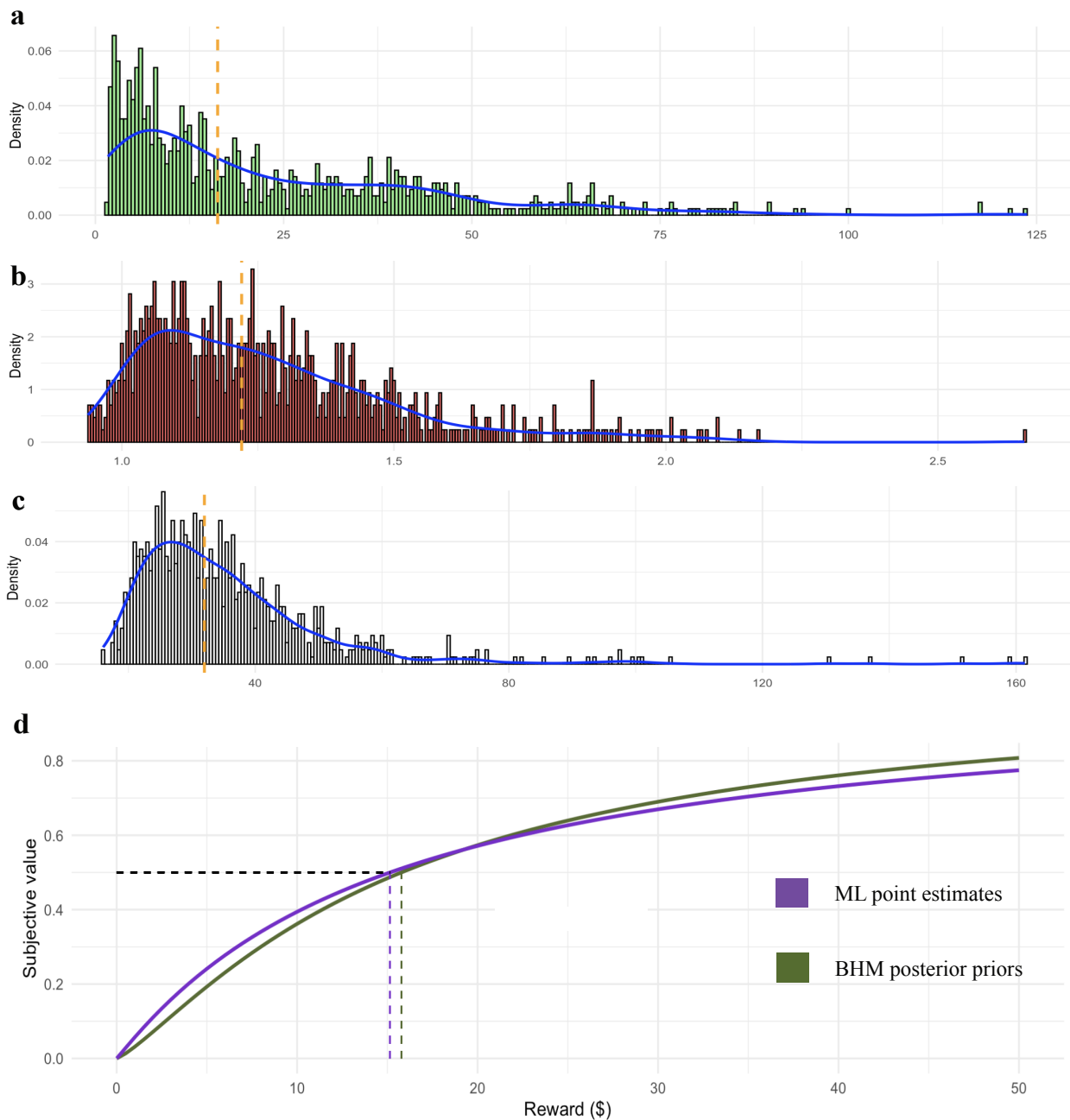
Figure 1.3 Distribution of anhedonia and feeling depressed in study 1 and a comparison sample



Note. Frequencies for study 1 sample ($n = 853$) depicted as black bars; Tomitaka et al.'s (2018) sample is in blue: a nationally representative survey of people in the United States ($n = 5,372$). Scores indicate self-reported frequencies of symptoms: 0 = ‘Not at all’, 1 = ‘Several days’, 2 = ‘More than half the days’, 3 = ‘Nearly every day’. Panel (a) Shows anhedonia (PHQ1). Panel (b) shows feeling depressed (PHQ2).

Most estimated reference points fell within the range of the rewards used in the lottery task. Figure 1.4a displays the distribution of parametric reference points estimated for each participant applying BHM. By design, this distribution was log-normal (i.e., positive skew). Figure 1.4b displays the distribution of the α parameter of the structural model, the distribution fell within the range expected by ESVT. The noise term (ζ) estimates (Figure 1.4c) indicated little randomness, suggesting the model may have characterised behaviour well. Figure 1.4d visualises the group-level parameter estimates for both BHM (mean priors) and ML (point estimates) graphically in the form of two subjective value functions; the close overlap indicates both approaches agree in their characterisation of decision-making behaviour at the group (sample) level.

Figure 1.4. Distribution of individual parameter estimates and group-level estimates (study 1)



Note. Panel (a) shows the distribution of reference points (M). Panel (b) shows the distribution of α . Panel (c) shows the distribution of the noise term (ζ). All parameter estimates are based on the median of posterior distribution. Orange dotted lines locate the median of the estimates across participants (i.e., the median of medians). Medians were for (a) 16.24, (b) 1.22 and (c) 31.99. Minimum values were for (a) 1.68, (b) 0.94 and (c) 16.1. Maximum values were for (a) 123.72, (b) 2.66 and (c) 161.38. Panel (d) depicts the subjective value function calculated from estimates of the reference point (M) and α : the green curve is based on BHM mean prior estimates, $M = 15.77$ and $\alpha = 1.25$; the purple curve is based on the ML point estimates, $M = 15.15$ and $\alpha = 1.03$.

1.3.2 Parametric reference points by mood

Depressive symptoms were associated with reference point variation. Regressions results indicated anhedonia was consistently significantly positively associated with parametric reference points (derived from BHM): for the two highest severity levels of anhedonia, reference points were higher on average than when severity was reported as 0 (i.e., occurring ‘Not at all’). Figure 1.5a shows the coefficients from regressing anhedonia on individual-level reference points reported in Model 6 in Table 1.1; the model also included a full set of control variables. Experiencing anhedonia ‘Nearly every day’ (PHQ1 = 3) relative to ‘Not at all’ (PHQ1 = 0) was on average associated with a reference point that was over 80% higher (coefficient estimate = 12.86) than the population-level mean reference point (prior estimate = 15.77).

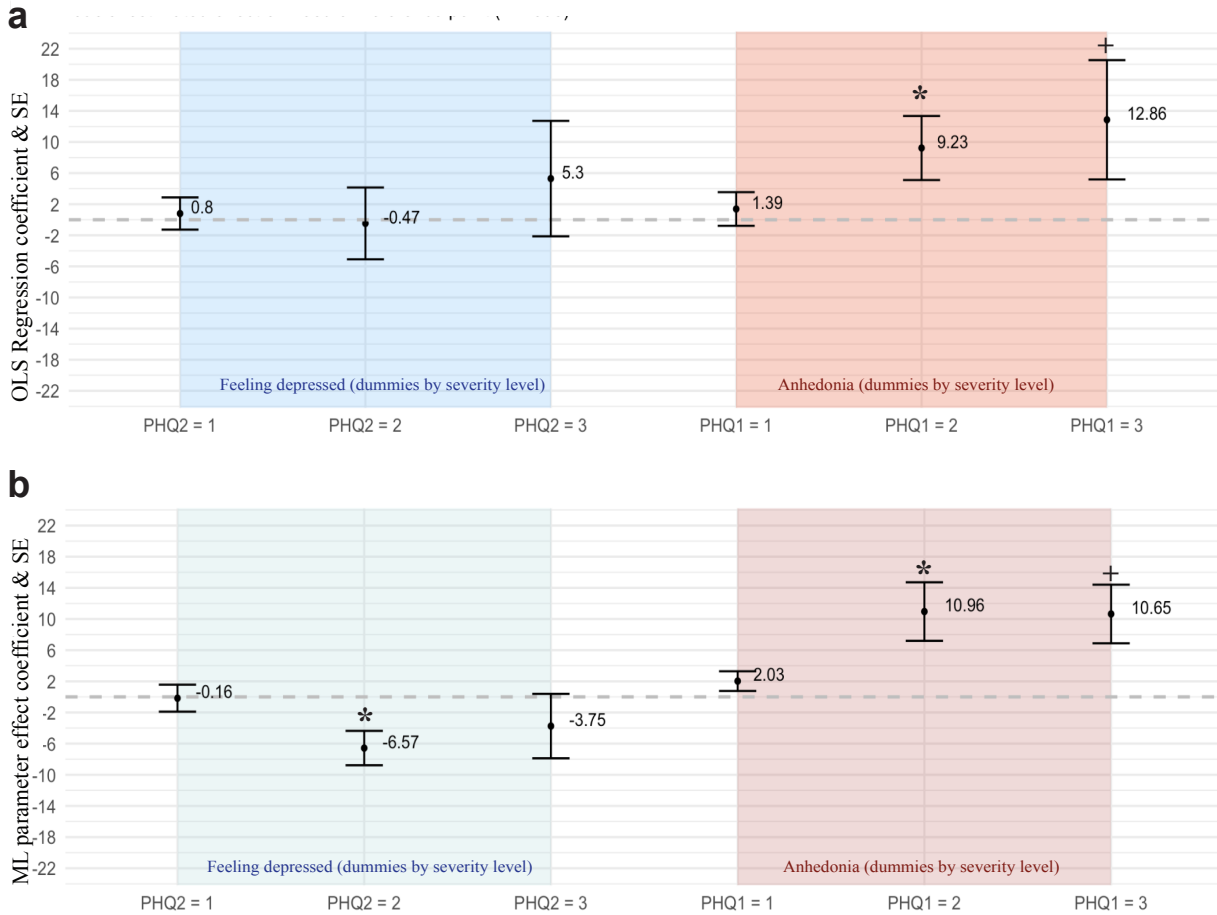
Table 1.1 summarises a series of regressions testing the robustness of this association: anhedonia was a significant predictor, even when not controlling for feeling depressed (Model 1), but including feeling depressed increased the magnitude of anhedonia effects, suggesting omitted variable bias unless both variables were included (model 3).¹⁰ Models 4 – 6 show the effect of anhedonia was robust to including control variables: A) demographics, B) self-reported financial comfort, and C) self-report anxiety and worry. Models 1-6 involved clustering standard errors at the twin-level. Model 7 indicates that not accounting for the possibility that errors are correlated at the twin-level may increase standard errors (risking Type II error), hence Model 6 was preferred. Finally, Model 8 shows that not accounting for the effects of α and noise parameters likely introduced omitted variable bias that attenuates coefficient estimates.

Figure 1.5b shows the effect of anhedonia on reference points applying ML estimation and for a comparable model to Model 6, Model 8 in Table 1.2. The results largely overlapped with individual-level BHM results (Figure 1.5a). However, for the remaining series of ML models reported in Table 1.2, the statistical significance for anhedonia varied more according

¹⁰ Paraphrasing Wooldridge (2013), with some abuse of notation: hypothetically, if the data generation process is reflected in a true model, $y = \beta_0 + \beta_1 x + \beta_2 z + \varepsilon$, but the model is mis-specified as $y = \beta_0 + \beta_1 x + \varepsilon$, and x and z are correlated (captured by the slope of a simple regression δ_1 in $\tilde{z} = \delta_1 x$); then, if the mis-specified model is estimated $\tilde{y} = \tilde{\beta}_0 + \tilde{\beta}_1 x$, the coefficient $\tilde{\beta}_1$ will reflect the true effect of x , $\hat{\beta}_1$, as captured when estimating the true model (inc. the true estimated effect of z , $\hat{\beta}_2$), and the estimated association between the two, $\tilde{\delta}_1$: that is, $\tilde{\beta}_1 = \hat{\beta}_1 + \hat{\beta}_2 \tilde{\delta}_1$. The bias is captured by the magnitude $\hat{\beta}_2 \tilde{\delta}_1$. Bias can be avoided by including a variable belonging to the true model in estimation (i.e., z in this case).

to model specification, while feeling depressed was also found to be significantly negatively associated with parametric reference points.

Figure 1.5 *Parametric reference points according to depressive symptoms severity*



Note. Panel (a) shows the effect of mood on individual-level parametric reference points derived from BHM: coefficient estimates and associated standard errors (cluster-robust) are from OLS regression Model 6 in Table 1.1. Panel (b) shows the effect of mood on reference points based on ML coefficient estimates (inc., heteroskedasticity robust standard error bars) from Model 8 in Table 1.2. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 1.1 Parametric reference points regressed on anhedonia, feeling depressed, α and noise parameters (study 1)

	1	2	3	4	5	6	7	8
Intercept	-8.913** (3.407)	-8.241* (3.399)	-8.854** (3.408)	-4.517 (4.483)	-6.758 (5.836)	-0.510 (6.214)	-0.510 (6.518)	34.758*** (5.907)
Anhedonia (PHQ1) severity 1	0.104 (1.709)		0.949 (2.116)	0.669 (2.167)	0.677 (2.168)	1.387 (2.167)	1.387 (2.121)	0.451 (2.300)
Anhedonia (PHQ1) severity 2	6.406+ (3.536)		8.393* (3.947)	8.151* (4.007)	8.309* (4.008)	9.231* (4.121)	9.231* (4.256)	6.090 (4.350)
Anhedonia (PHQ1) severity 3	11.822+ (6.722)		12.960+ (7.625)	12.808+ (7.627)	13.013+ (7.663)	12.862+ (7.673)	12.862 (8.163)	7.761 (7.758)
Feeling depressed (PHQ2) severity 1		0.137 (1.522)	-0.935 (1.926)	-0.725 (1.950)	-0.620 (1.955)	0.800 (2.072)	0.800 (2.161)	1.671 (2.175)
Feeling depressed (PHQ2) severity 2		0.677 (4.179)	-4.565 (4.271)	-3.804 (4.359)	-3.539 (4.352)	-0.470 (4.621)	-0.470 (4.756)	2.590 (4.604)
Feeling depressed (PHQ2) severity 3		9.615 (6.032)	-0.331 (6.931)	-0.166 (6.997)	0.073 (7.001)	5.296 (7.424)	5.296 (7.341)	9.436 (7.419)
α estimate	33.723*** (3.801)	33.291*** (3.759)	33.864*** (3.780)	34.019*** (3.773)	34.144*** (3.781)	33.873*** (3.760)	33.873*** (3.698)	
noise estimate	-0.304*** (0.081)	-0.301*** (0.080)	-0.307*** (0.081)	-0.313*** (0.081)	-0.314*** (0.081)	-0.309*** (0.082)	-0.309*** (0.079)	
Number obs.	853	853	853	852	852	851	851	851
R^2	0.122	0.118	0.123	0.133	0.134	0.139	0.139	0.025
Adjusted R^2	0.117	0.112	0.115	0.119	0.118	0.121	0.121	0.008
AIC	7527	7532	7532	7525	7527	7518	7518	7619
BIC	7560	7565	7579	7601	7608	7608	7608	7700
Controls	NO	NO	NO	YES: A	YES: B	YES: C	YES: C	YES: C

Note. Controls type A = demographics, B = demographics & financial comfort, C = demographics, financial comfort, anxiety & worry. Demographics are gender ('is male' dummy variable), age, worked in last 7 days (dummy: did vs did not), education (dummies: 'Certificate/Diploma', 'Bachelor or higher' vs baseline 'Year 11 or Year 12'), and income (dummy: is above Australian 2021 median vs not). Heteroskedasticity-robust standard errors with clustering on twin ID presented in parentheses (clustered sandwich estimator used by 'Stata'); except for Model 7 using robust standard errors type 'HC1'. For all regression models except Model 8, F -tests indicated that the overall models were statistically significant ($p < 0.05$). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 1.2 Maximum Likelihood estimates for the effect of anhedonia and feeling depressed on the group-level reference point and α parameters (Study 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reference point (M)								
Anhedonia (PHQ1) severity 1		-1.5670 (1.6147)		-0.3386 (1.6589)	4.7104 (2.9786)	-0.1053 (1.9229)	-0.2077 (1.8914)	2.0252 (1.2658)
Anhedonia (PHQ1) severity 2		3.1031 (3.4901)		9.6492* (4.3667)	29.1310 (32.3115)	9.5914* (4.1814)	8.6658 (6.8462)	10.9573** (3.7590)
Anhedonia (PHQ1) severity 3		0.2109 (3.1460)		6.8786+ (3.9509)	17.0754 (12.2492)	9.8518* (3.9398)	8.7268 (7.8326)	10.6480** (3.7623)
Feeling depressed (PHQ2) severity 1			-0.9637 (1.6086)	-1.1031 (1.7108)	-0.6111 (4.6499)	-0.5221 (1.7554)	-0.5438 (1.7303)	-0.1640 (1.7329)
Feeling depressed (PHQ2) severity 2			-4.3348+ (2.6184)	-9.0270*** (2.3539)	-13.7787*** (2.8410)	-7.9887*** (2.3915)	-7.2951 (5.1621)	-6.5707** (2.2058)
Feeling depressed (PHQ2) severity 3			0.6066 (3.9753)	-5.5576 (4.1485)	-10.7917* (4.3220)	-6.3938+ (3.5528)	-6.0727 (4.8333)	-3.7478 (4.1363)
Constant	15.1486*** (1.7255)	15.3723*** (1.8647)	15.4276*** (1.7787)	15.5257*** (1.8443)	14.5662*** (2.2542)	17.1686*** (3.4332)	17.9591*** (4.9727)	21.4733*** (5.0486)
α								
Anhedonia (PHQ1) severity 1					-0.0563 (0.0857)			
Anhedonia (PHQ1) severity 2					-0.2970* (0.1513)			
Anhedonia (PHQ1) severity 3					-0.2075 (0.3286)			
Feeling depressed (PHQ2) severity 1					-0.0966 (0.1057)			

Feeling depressed (PHQ2) severity 2					0.2761 (0.3045)			
Feeling depressed (PHQ2) severity 3					0.0300 (0.2888)			
Constant	1.0344*** (0.0442)	1.0353*** (0.0444)	1.0409*** (0.0446)	1.0417*** (0.0434)	1.0814*** (0.0699)	1.0694*** (0.0449)	1.0721*** (0.0473)	1.0703*** (0.0447)
Noise (ζ)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Anhedonia (PHQ1) severity 1					7.6306** (2.8407)			
Anhedonia (PHQ1) severity 2					19.4335 (18.0139)			
Anhedonia (PHQ1) severity 3					20.5465 (12.6333)			
Feeling depressed (PHQ2) severity 1					-1.7247 (3.8798)			
Feeling depressed (PHQ2) severity 2					-10.0949** (3.8972)			
Feeling depressed (PHQ2) severity 3					-14.5049** (5.0565)			
Constant	21.4402*** (1.5056)	21.4485*** (1.5032)	21.2852*** (1.4854)	21.4368*** (1.4513)	20.4823*** (2.0575)	20.8048*** (1.3711)	20.7048*** (1.4640)	20.8955*** (1.3768)
Observations	39238	39238	39238	39238	39238	39192	39192	39146
AIC	50992	50992	50991	50975	50960	50889	50892	50818
BIC	51018	51044	51043	51052	51140	51017	51029	50973
Controls	NO	NO	NO	NO	NO	YES: A	YES: B	YES: C

Note. Controls type A = demographics, B = demographics & financial comfort, C = demographics, financial comfort, anxiety & worry. Demographics are gender ('is male' dummy variable), age, worked in last 7 days (dummy: did vs did not), education (dummies: 'Certificate/Diploma', 'Bachelor or higher' vs baseline 'Year 11 or Year 12'), and income (dummy: is above Australian 2021 median vs not). Heteroskedasticity-robust standard errors with clustering on individual ID and twin ID presented in parentheses. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Overall model Wald-tests (chi-squared) indicated models 4, 5, 6, and 8 were statistically significant ($p < 0.01$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.3.3 Sensitivity analysis

Across regression models (Table 1.1), α and noise estimates were controlled for because i) there are natural correlations between parameter estimates applying BHM given these elements will vary together in approximating the structure of a participant's subjective value function; and ii) mood variables were associated with α and noise estimates (Table 1.3), albeit very weakly given the explained variance in noise and α attributed to mood alone was near naught ($adj R^2 = 0.000$ and $adj R^2 = -0.002$). Nevertheless, including α and noise mitigated the chance of omitted variable bias. Table 1.1, model 8 illustrates this bias by omitting α and noise estimates from the equation: in this case, the coefficient on anhedonia was biased downward, as expected given α was positively associated with reference points but significantly and weakly negatively associated with anhedonia. The same rationale holds for noise but the associations are reversed. The results in Table 1.3 suggested that for more severe anhedonia the subjective value function was a little more concave and decision-making less noisy (more deterministic).

As identified during BHM parameter recovery, reference points were likely measured with some error (see Appendix 1.D, Figure 1.D.3c and 1.D.4c). Unsystematic measurement error in the dependent variable tends to inflate standard errors, increasing the chance of Type II error, meaning regression results may have underestimated the significance of the association between depressive symptoms and parametric reference points. For study 1 there did appear to be somewhat greater measurement error for simulated values that were much larger than the max reward of the task (above \$43). Regression models in Table 1.1, models 3 (no controls) and 6 (all controls), were estimated again but excluding individuals with reference point estimates larger than or equal to 43 (removing 144 participants, 17% of total sample). Model statistics for Model 3 were, $F(8,457) = 3.328$, $p < 0.01$, $R^2 < 0.036$; and for Model 6, $F(17,457) = 2.521$, $p < 0.001$, $R^2 < 0.058$. The sign and significance of coefficients on depressive symptoms were similar; although for Model 3, only anhedonia severity level 2 was significant, and the magnitudes were weaker. Importantly, across all regression models in both studies heteroskedasticity robust standard errors were applied. This approach is commonly used to address the risk of non-constant error variance (i.e., heteroskedasticity) that may arise from measurement error.

Table 1.3 Participant α and noise parameter estimates regressed on anhedonia, feeling depressed and reference points estimates (study 1)

	α (1)	α (2)	α (3)	noise (1)	noise (2)	noise (3)
Intercept	1.279*** (0.011)	1.332*** (0.070)	0.984*** (0.070)	35.967*** (0.725)	31.877*** (4.795)	-8.711 (5.943)
Anhedonia (PHQ1) severity 1	-0.019 (0.022)	-0.015 (0.023)	-0.026 (0.021)	2.283 (2.376)	1.430 (2.105)	1.995 (1.955)
Anhedonia (PHQ1) severity 2	-0.070+ (0.037)	-0.079* (0.039)	-0.110*** (0.032)	2.253 (3.178)	1.557 (3.134)	5.133+ (2.647)
Anhedonia (PHQ1) severity 3	-0.126* (0.052)	-0.133* (0.055)	-0.173*** (0.051)	3.254 (3.812)	1.910 (3.638)	7.603* (3.106)
Feeling depressed (PHQ2) severity 1	-0.005 (0.022)	0.008 (0.024)	0.016 (0.022)	-2.195 (2.094)	-1.953 (2.411)	-1.980 (2.214)
Feeling depressed (PHQ2) severity 2	0.030 (0.048)	0.060 (0.054)	0.075 (0.048)	-4.413 (3.052)	-3.333 (3.795)	-5.010 (3.304)
Feeling depressed (PHQ2) severity 3	0.020 (0.051)	0.081 (0.064)	0.082 (0.060)	-6.783+ (3.639)	-4.497 (4.957)	-5.905 (4.467)
Reference point estimate			0.003*** (0.000)			-0.146*** (0.020)
α estimate						34.267*** (2.637)
Noise estimate			0.007*** (0.001)			
Number obs.	853	851	851	853	851	851
R^2	0.007	0.025	0.322	0.005	0.054	0.291
Adjusted R^2	0.000	0.008	0.308	-0.002	0.037	0.277
AIC	-21	-19	-324	7160	7118	6877
BIC	17	62	-234	7198	7199	6967
Controls	NO	YES	YES	NO	YES	YES

Note. Controls are demographics, financial comfort, anxiety & worry. Demographics are gender ('is male' dummy variable), age, worked in last 7 days (dummy: did vs did not), education (dummies: 'Certificate/Diploma', 'Bachelor or higher' vs baseline 'Year 11 or Year 12'), and income (dummy: is above Australian 2021 median vs not). Heteroskedasticity-robust standard errors with clustering on twin ID presented in parentheses (clustered sandwich estimator used by 'Stata'). For all regression models except model denoted 'noise (1)', F -tests indicated that the overall models were statistically significant ($p < 0.05$). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.4 Study 2: Methods

1.4.1 Participants and procedure

A representative sample of the American population (USA) was generated with Prolific online surveys: respondents were divided into three demographics - age, sex and ethnicity - and sample recruitment was proportional from each demographic according to national 2015 US census data. Out of an original sample of 579 individuals who completed the overall study, 443 who completed the lottery choice task in full were selected for analysis. Key characteristics of the sample were gender: 52% female, 47% male, 0.9% non-binary, and 0.5% 'prefer not say'; and age: mean 45.58 (SD 15.76) See Appendix 1.A Table A.1 for further summary statistics.

Detailed written and visual instructions with examples for comprehension were provided to participants for all the reference point elicitation methods (the key instructions pertaining to the tasks used in study 2 can be found in General appendix B). All participants were paid \$8 ('show-up fee') for completing the study. To incentivise performance on the lottery task and stated reference point questions, participants were informed that one-in-ten participants would be randomly selected and paid based on a selected choice from the lottery task and based on an incentivised earnings expectation question. The minimum possible earning (including the show-up fee) was \$8, and the maximum was \$98.^{11 12 13}

1.4.2 Measurement of depressive symptoms

Depressive symptoms were measured with the Patient Health Questionnaire (PHQ-9). The full PHQ-9 is correlated with a person's functional status (Kroenke et al., 2001). As is common in research contexts, the item on suicidal ideation was excluded to create the PHQ-8; the PHQ-8 and PHQ-9 are highly correlated (Kroenke et al., 2009). Anxiety was also

¹¹ Protocols and procedures were approved by the University of Sydney Human Research Ethics Committee (HREC) (application number 2023/503).

¹² Material for this study was a subset of a broader set of decision-making tasks and psychological questionnaires administered to participants as part of a different project.

¹³ The hypothesis that depressive symptoms would be associated with reference point variation was pre-registered with the Open Science Framework (OSF) on the 23rd of October 2023, before commencing the main stage of data collection, and as part of a larger project.

measured as total GAD-7 scores (Spitzer et al., 2006). Cronbach's alpha for the PHQ-8 was 0.92, and for the GAD-7 it was 0.95.

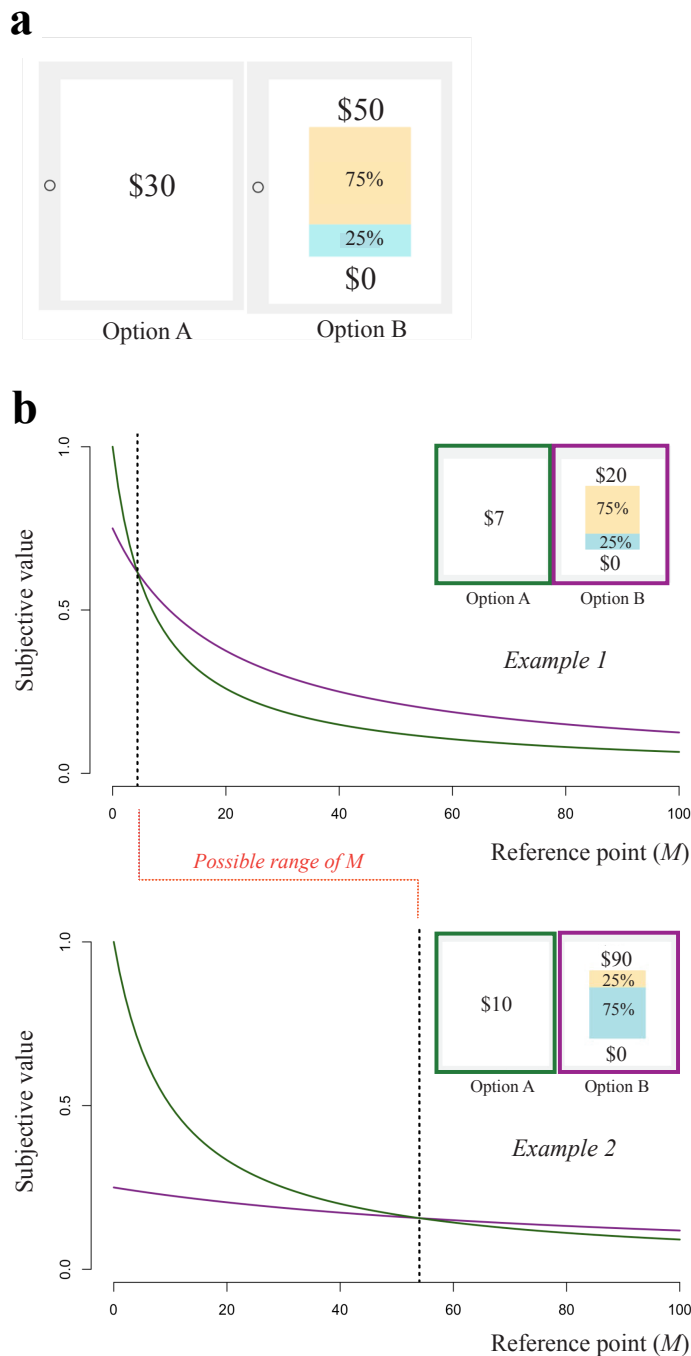
1.4.3 Parametric reference points

As in study 1, parametric reference points were estimated from choices made during a *lottery task*. This lottery task differed from the one used in study 1: it was comprised of 107 choices designed to incorporate stimuli with higher potential rewards (max \$90), to capture a broader range of reference points. The task involved a choice between receiving a certain monetary reward (in US dollars) and a lottery that paid either \$0 or some higher amount according to the stated probability (see Figure 1.6a for an example decision scenario). The sure amounts, lottery payoffs and probabilities in the lottery task varied between trials. Figure 1.6b illustrates the rationale for how the lottery task allows for estimating the reference point, M , using the ESVT structural model. For each choice scenario (as in Figure 1.6a), the subjective value can be plotted for each option as it changes when M increases. The green curve in Figure 1.6b plots how the subjective value of the certain payoff changes as M increases. The purple curve plots how the subjective value of the specific lottery shown in the figure changes as M increases. If a participant prefers the lottery to the certain option, then it must be that M lies to the right of the intersection point of green and purple curves, the locations at which the lottery has a higher subjective value than the safe option. If presented with the choice scenario shown in panel Figure 1.6c, and the participant prefers the safe option, then M must lie below the intersection point on that graph. In this way M can be identified to lie between these two constraints. By employing many such choice scenarios, M can be localised to an arbitrary level of precision.

The range of values used for the sure amounts were: \$2, \$3, \$5, \$7, \$10, \$15, \$20, \$25, \$30, \$40, \$50, \$60 & \$70; the range of values for the high-outcome lottery were: \$5, \$10, \$20, \$50 & \$90; and the probabilities were: 0.10, 0.25, 0.50, 0.75 & 0.90. The amounts, probabilities and their combinations were selected through the following process: first, calculations were made to ensure that, for an initial set of items, each choice item was such that the expected value (EV) and max payoffs of the lottery option were high enough relative to the sure outcome value. However, 5 items when the sure outcome had a higher EV than the lottery (involving 5 USD) were retained to test for "irrational choices" involving first-order stochastic dominance (FOSD) violations. Next, 1000 simulated participants were created, each with a different combination of α and reference points parameters: reference points

ranged from 1 to 100 and α from 1 to 10 for these simulated participants. Various lottery items were trialled where the subjective values and choices of each simulated individual were calculated using the ESVT structural model. Then, a ML estimation taking these simulated choices was used to identify items that were best able to estimate (retrieve) a broad range of reference points. Multiple trials resulted in a final set of 107 lottery task items that are available for inspection in Appendix 1.B, Table B.2.

Figure 1.6 Lottery choice task and behavioural reference point estimation (study 2)



Note. Panel (a) shows an example decision scenario in which a participant is choosing between \$30 for sure or a lottery: paying \$50 with 75% chance and \$0 with 25% chance. The side on which the lottery appeared was randomised across the trials and participants. Panel (b) shows two further examples: insets show the choice problem faced on that trial. Green lines plot the subjective value of the safe option as a function of the reference point (M). Purple lines plot the subjective value of the lottery. For simplicity of presentation α is fixed at 1. Crossing points between the functions (indicate with black dotted line) are the value of the reference point at which a chooser would switch between preferring the safe option and preferring the lottery. The possible range for reference points when a subjected chooses the lottery option for example 1 and sure outcome for example 2 is shown by the orange dotted line.

1.4.3.1 Bayesian hierarchical modelling

The same structural model of subjective value (SV) in study 1 was applied for the lottery and the sure options, given by:

$$SV(\text{lottery}) = p_L \frac{x_L^\alpha}{x_L^\alpha + M^\alpha} + (1 - p_L) \frac{0^\alpha}{0^\alpha + M^\alpha} \quad \text{and} \quad SV(\text{sure}) = \frac{x_S^\alpha}{x_S^\alpha + M^\alpha}$$

The BHM from study 1 was adjusted so the upper bound of the uniform prior on M accommodated the higher maximum reward of the new lottery task (\$90). Despite this, posterior sampling of the prior tended to occur at the upper bound of this range, which can be problematic by biasing estimates, and was likely driven by a subset of participants with very large parameter values. Indeed, subsequent outlier inspection showed a subset had reference points well above the maximum possible reward of the lottery (see distribution in Figure 1.7a below). Therefore, the BHM was re-defined eschewing stochastic priors: rather than including hyper-priors, prior means (μ) and standard deviations (σ) were given pre-specified values. In effect, this meant decoupling participants individual-level parameters (see Appendix 1.D for explanation). The new values for the priors were informed by the mean posterior estimates of priors in study 1. Specifically, the distributions of individual parameters were modelled as:

$$\begin{aligned} M_n &\sim \text{lognormal}(\mu_M = 2.76, \sigma_M = 1.27), \\ \alpha_n &\sim \text{lognormal}(\mu_\alpha = 0.22, \sigma_\alpha = 0.33), \\ \zeta_n &\sim \text{lognormal}(\mu_\zeta = 3.5, \sigma_\zeta = 0.57); \end{aligned}$$

In non-log terms, this meant the mean priors were $\mu_M = 15.8$, $\mu_\alpha = 1.25$, and $\mu_\zeta = 33.12$. Otherwise, only lower bounds were defined for individual parameters estimates, the same as in study 1. For study 2 ML estimation was not applied.

1.4.4 Stated reference points

Stated (consciously accessible and reportable) reference points were measured in five ways. Participants were asked to report the amount of USD that would make them indifferent between engaging or not in a Prolific study of one-hour duration. Their stated amount was taken to be their *reservation wage* or the minimum amount they expected and that was

sufficient to motivate them to complete a study. This was the first stated reference point. Before and after completing the lottery task, participants were incentivised to accurately report their forward- and backward-looking, respectively, *average earning predictions* for the lottery task. These were taken as the second and third stated reference points. Truthful responding was incentivised with a binary scoring procedure that was based on previously used belief-elicitation method (Erkal et al., 2020; Hossain & Okui, 2013). Specifically, participants' chance of receiving a bonus payment of \$1 increased when they were more accurate in their predictions of average earnings relative to their true average earnings (c), using the following formula,

$$\text{Chance of receiving \$1} = \left[1 - \left(\frac{c - \text{prediction}(x)}{100} \right)^2 \right] 100$$

A number between 1 and 100 was randomly generated, and if this number was less than their calculated chance, then the bonus could be paid. All participants were informed of the existence of this scoring rule. Finally, participants were asked simple questions regarding their *income expectations in one year and five years*, which were used as the fourth and fifth stated reference points.

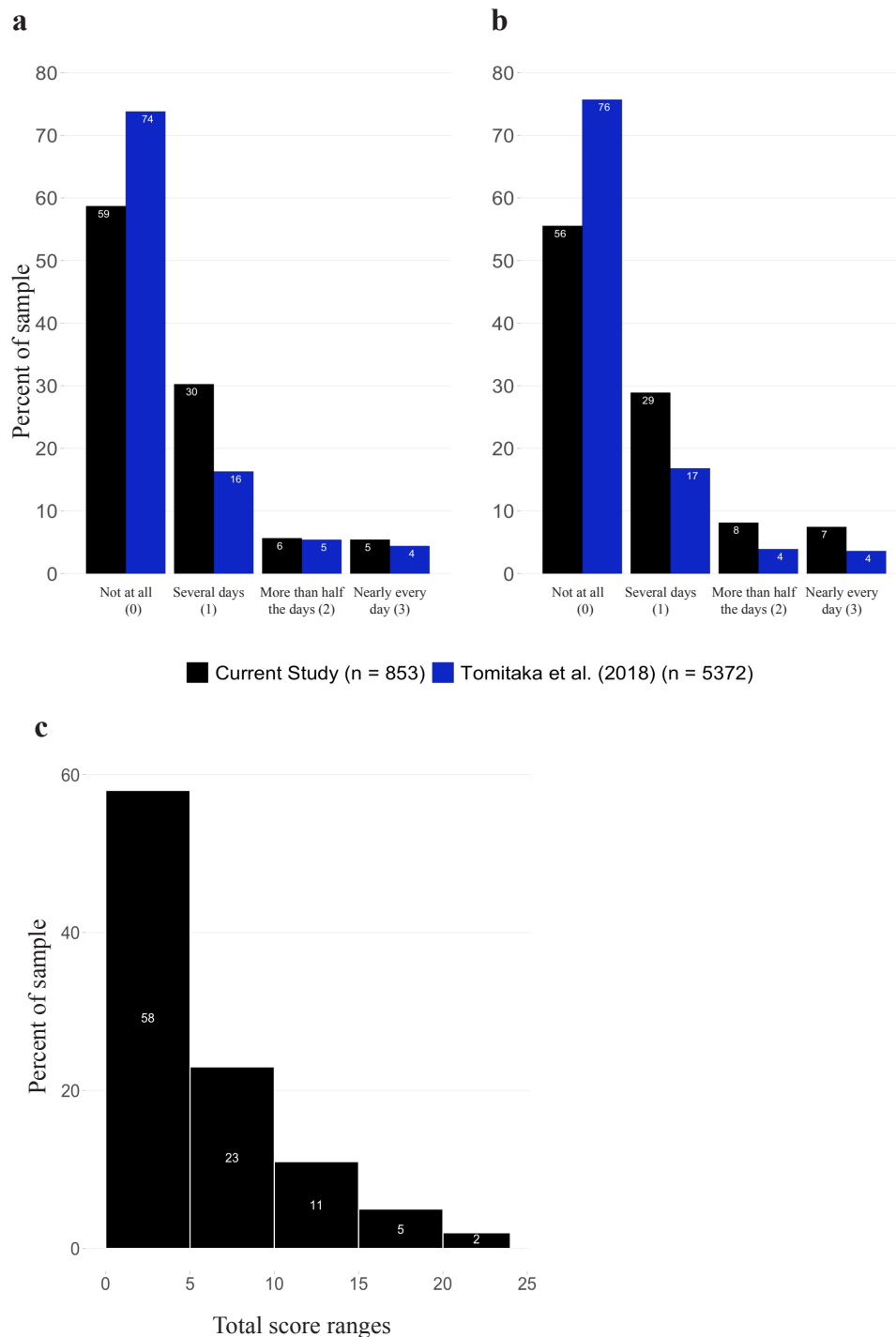
1.5 Study 2: Results

1.5.1 The distribution of depressive symptoms and parametric reference points

Depressive symptom scores were representative of the American population's mood scores: as seen in Figure 1.7a and 1.7b, the distributions were similar to those in (Tomitaka et al., 2018). However, participant reported somewhat elevated severity. Figure 1.7c shows total PHQ-8 scores; about 21% of the sample had scores equal to or higher than 10, a cut-off which has shown adequate sensitivity and specificity in screening for MDD (Kroenke et al., 2001). This is close to the 17.8% incidence of people in the general population who reported they were depressed or were being treated for depression in 2023 (Gallup, 2023).

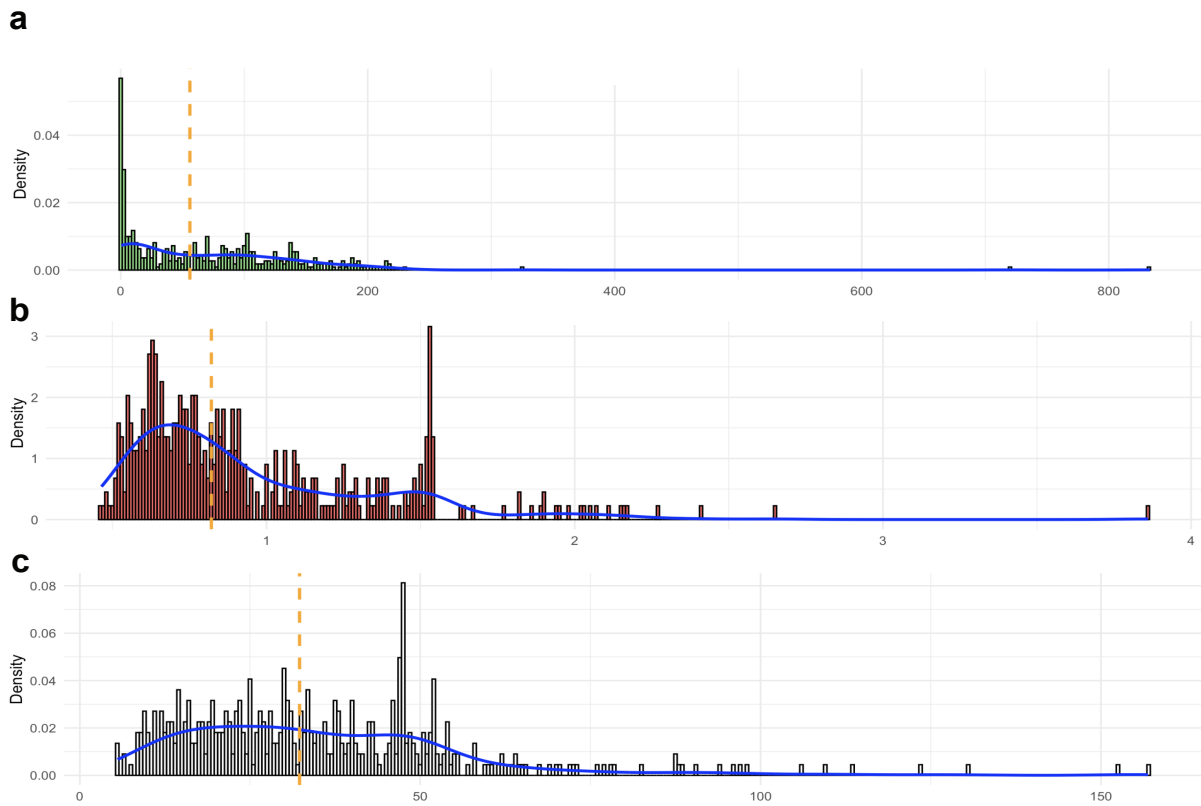
Figure 1.8 displays the distribution of reference points, α and the noise term for participants in study 2 – these are the median of the posterior estimate for each participant across the three parameters. Most parametric reference points spanned the range of reward values used in the lottery task. However, there were some participants with high (outlier) values. Estimates of α and noise were within the expected ranges and similar to values in study 1.

Figure 1.7 Distributions of anhedonia, feeling depressed and total PHQ-8 scores in study 2 and a comparison sample



Note. Frequencies for study 2 sample ($n = 443$) depicted as black bars; Tomitaka et al.'s (2018) sample in blue: a nationally representative survey of people in the United States ($n = 5,372$). Scores indicate self-reported frequency of symptoms: 0 = 'Not at all', 1 = 'Several days', 2 = 'More than half the days', 3 = 'Nearly every day'. Panel (a) shows anhedonia (PHQ1), panel (b) shows depressed mood (PHQ2) and panel (c) shows Total PHQ-8 scores by PHQ-9 severity categories: 0 - 4 = *None*, 5 - 10 = *Mild*, 10 - 15 = *Moderately*, and 15 - 20 = *Moderately Severe*, 20 - 27 = *Severe*.

Figure 1.8 Distribution of individual participant parameter estimates from Bayesian Hierarchical model (study 2)



Note. Panel (a) shows the distribution of reference points (M). Panel (b) shows the distribution of α . Panel (c) shows the distribution of the noise term (ζ). All parameter estimates are based on the median of posterior distribution. Orange dotted lines locate the median of the estimates across participants (i.e., the median of medians). Medians were for a) 55.98, b) 0.82, (c) 32.28. Minimum values were for (a) 0.46, (b) 0.46, (c) 5.55. Maximum values were for (a) 833.41, (b) 3.86, (c) 156.9.

1.5.2 Parametric reference points by depressive symptoms

The associations between depressive symptoms and parametric reference points were tested by estimating a series of regression models, these are displayed in Table 1.4. Total depression scores, based on the full set of symptoms measured with PHQ-8, were weakly but not significantly associated with reference points (see Model 1 and Model 2 including controls). However, a non-parametric correlation was weakly positive, $r_s = 0.11$, $p < 0.05$. As in study 1, anhedonia was positively associated with reference points. However, in study 2 the effect was non-significant (Model 3) before feeling depressed was also controlled for (Model 5).

Similarly, feeling depressed in a regression without other variables was non-significant (Model 4). However, when anhedonia was controlled for (Model 5), feeling depressed was strongly negatively associated with reference points. These results across models 3, 4 and 5 indicate that omitting either mood variable likely biased the estimate for the other variable. Models 6 and 7 show findings persisted after inclusion of multiple covariates: demographic variables, self-reported financial comfort, anxiety (Model 6), and the remaining depressive symptoms captured by the PHQ-8 (Model 7). Although multicollinearity diagnostics did not indicate reason for concern; Model 7 comes with a higher risk of multicollinearity, leaving Model 6 preferred. As in study 1, there was likely bias apparent when omitting α and noise, albeit not as pronounced (compare models 6 to 8). The sizes of the coefficients on moods were notably larger in study 2 than study 1. This was likely owing to the lottery tasks differing in that the rewards used in study 2 were larger (e.g., max lottery reward was \$90 in study 2 relative to \$43 in study 1). Accordingly, Figure 1.8a shows the range of estimated reference points was wider for study 2.

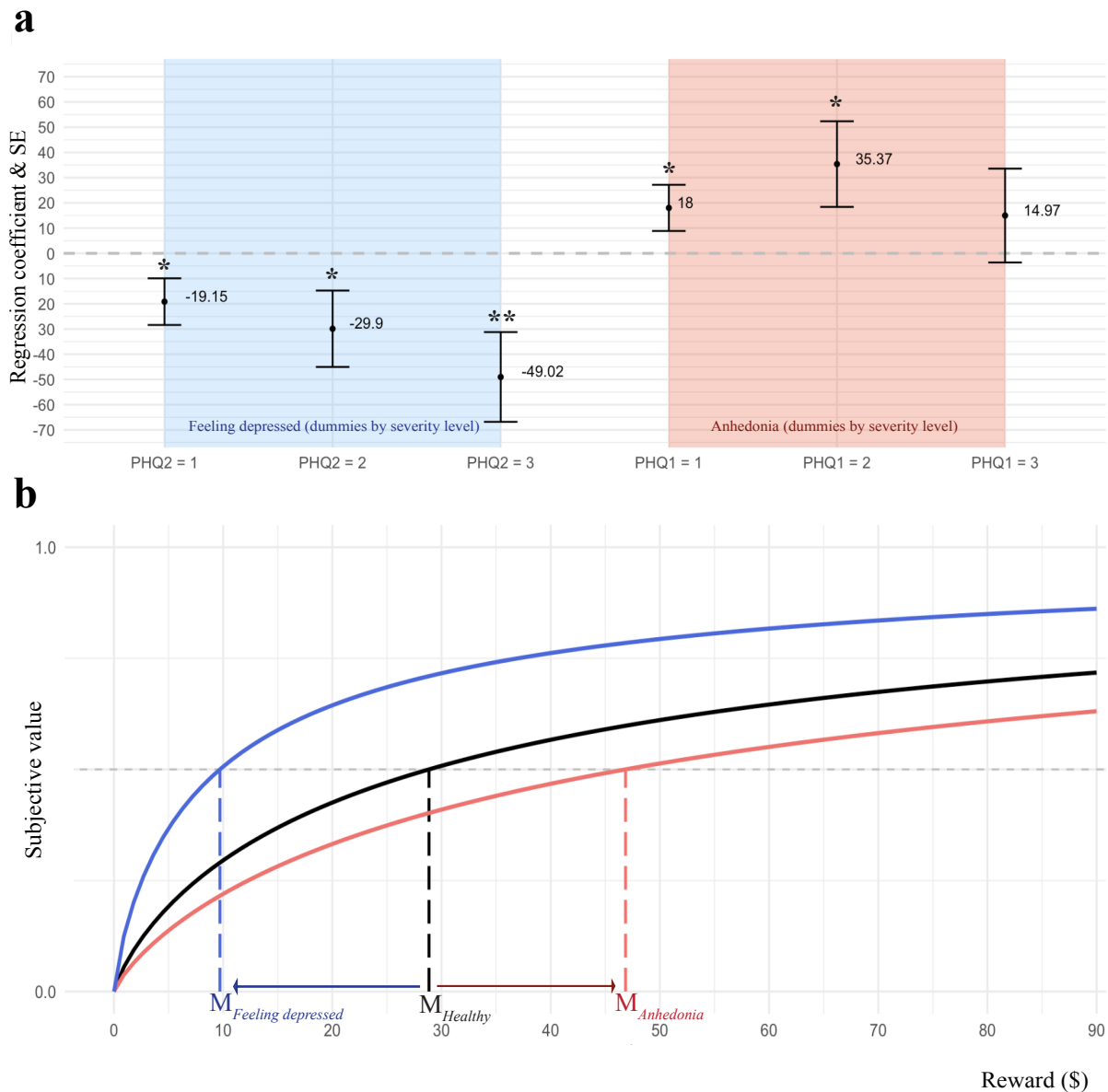
Figure 1.9a displays the coefficient estimates from Model 6 in Table 1.4. Figure 1.9b illustrates the effect on the subjective value function of moving from reporting no depressive symptoms (severity = 0: 'Not at all') to reporting some depressive symptoms (severity = 1: 'Several days') as a function of the coefficient estimates in Model 6. In the figure, the y -axis represents the subjective value of the objective monetary rewards (captured by the x -axis). The black line is the estimated subjective value for a chooser who reports no anhedonia nor feeling depressed. The figure shows how anhedonia moves the parametric reference point higher (red line), meaning the subjective values are generally lower across rewards. Feeling depressed moves the parametric reference point lower (blue line), meaning subjective rewards are higher when encountered.

Table 1.4 Parametric reference point regressed on total PHQ-8 scores, anhedonia, feeling depressed, α and noise parameters estimates (study 2)

	1	2	3	4	5	6	7	8
Intercept	13.546 (10.616)	28.160 (23.305)	10.978 (10.086)	14.565 (9.999)	13.664 (9.881)	28.850 (22.807)	22.687 (23.328)	84.373*** (19.615)
Total PHQ8	0.157 (0.580)	0.114 (0.861)						
Anhedonia (PHQ1) severity 1			8.527 (7.020)		22.781* (8.946)	18.003* (9.158)	13.270 (9.523)	19.164+ (9.979)
Anhedonia (PHQ1) severity 2			19.936 (13.580)		40.976* (16.582)	35.367* (16.978)	32.314* (15.464)	42.473* (17.003)
Anhedonia (PHQ1) severity 3			-12.761 (12.612)		19.692 (18.259)	14.965 (18.608)	6.026 (20.178)	22.686 (18.296)
Feeling depressed (PHQ2) severity 1				2.153 (7.409)	-15.862+ (8.958)	-19.148* (9.253)	-25.177* (10.364)	-15.935 (10.180)
Feeling depressed (PHQ2) severity 2				-1.299 (9.937)	-25.348+ (13.484)	-29.899* (15.138)	-50.311** (16.840)	-28.798+ (16.814)
Feeling depressed (PHQ2) severity 3				-15.573 (10.982)	-36.265* (15.616)	-49.019** (17.792)	-76.820*** (22.243)	-45.650* (18.208)
α estimate	13.833 (15.661)	14.697 (15.449)	14.620 (15.592)	14.322 (15.487)	14.086 (15.537)	14.716 (15.414)	16.334 (16.266)	
noise estimate	1.193*** (0.161)	1.150*** (0.162)	1.182*** (0.163)	1.192*** (0.161)	1.180*** (0.163)	1.155*** (0.164)	1.151*** (0.164)	
Number obs.	443	443	443	443	443	443	443	443
R^2	0.116	0.134	0.123	0.119	0.130	0.149	0.167	0.045
Adjusted R^2	0.110	0.110	0.113	0.109	0.114	0.115	0.122	0.011
AIC	50756	5085	5076	5079	5079	5087	5089	5134
BIC	5096	5142	5105	5107	5120	5165	5192	5203
Controls	NO	YES: A	NO	NO	NO	YES: A	YES: B	YES: A

Note. Controls type A: demographics, anxiety (Total GAD7) and financial comfort; B: variables in A and additional PHQ8 symptoms (6 items). Demographics were age, gender ('is female' dummy), weekly income, university education (dummy: baseline is less-than university education); employment (dummies: 'unemployed', 'retired', and 'student' vs baseline 'employed'). Additional PHQ-8 symptoms were sleep disturbance, feeling tired/low energy, appetite disturbance, feeling bad about oneself, concentration difficulty, and psychomotor changes. Heteroskedasticity-robust (type HC1/'Stata') standard errors in parentheses. All tests of overall model significance (F -tests) were statistically significant ($p < 0.05$). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 1.9 Parametric reference points according to mood disorder severity and subjective value functions calculated from these estimates (study 2)



Note. Panel (a) shows the BHM coefficient estimates and associated standard errors (robust) for Model 6. Panel (b) depicts how reward valuation is predicted to change due to depressive symptoms based on estimates: the ESVT subjective value function is shown for reference points calculated based on Model 6 coefficients. The blue line depicts the predicted value of reference points when feeling depressed severity = 1 ('Several days') and the red line depicts the predicted value of reference points when anhedonia severity = 1, the black line depicts the reference point when both anhedonia and feeling depressed severity = 0 ('Not at all'). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.5.3 Stated reference points by depressive symptoms

Complementing the analysis of parametric reference points estimated from behaviour, stated reference points were examined for their associations with depressive symptoms. As seen in Table 1.5, the predictions participants made about rewards they would receive from the lottery task, elicited before and after they completed the task, were largely not associated with symptom scores. An exception was that post-task reward predictions were robustly lower for feeling depressed with moderate severity. Participants also reported their reservation wage; this stated reference point was generally not associated with depression scores. An exception was a non-robust higher reservation wage for moderate severity anhedonia. Results suggest consciously reported predictions about immediate rewards were at best weakly linked to depressive symptoms. There were no significant associations found for total PHQ-8 scores.

Long-term expectations were negatively and robustly associated with depressive symptoms: expected income in 1-year was lower for those reporting feeling depressed, predicted to be ca. \$20,000 lower for the most severely afflicted participants (see model 3). It is worth nothing that including controls accounted for a large degree of this association – there is a large jump in adjusted R^2 from 7.3% to 51% - suggesting these stated reference points are to a greater extent influenced by individual characteristics other than mood. There was also a negative effect on 5-year income expectations, but this was not robust to including other depressive symptoms and controls. Finally, there was a negative association between anhedonia and 5-year income expectations, but that was not robust to including the full set of controls.

Table 1.5 Stated reference points regressed on anhedonia and feeling depressed

	Pre-task pred. (1)	Pre-task pred. (2)	Pre-task pred. (3)	Post-task pred. (1)	Post-task pred. (2)	Post-task pred. (3)	Reservati on wage (1)	Reservati on wage (2)	Reservati on wage (3)	1-year income exp. (1)	1-year income exp. (2)	1-year income exp. (3)	5-years income exp. (1)	5-years income exp. (2)	5-years income exp. (3)
Intercept	9*** (2)	11 (8)	12 (9)	28*** (6)	113** (40)	133** (50)	9*** (0)	6*** (2)	7*** (2)	56233*** (3113)	5004 (7764)	1866 (7974)	120244*** (10843)	30217 (30034)	40341 (31694)
Anhedonia (PHQ1) severity 1	-1 (2)	-4 (4)	-2 (2)	6 (8)	-10 (12)	-5 (13)	1 (1)	1 (1)	1 (1)	2246 (5896)	2391 (3290)	2248 (3574)	-5523 (14300)	-9475 (12010)	-6150 (12974)
Anhedonia (PHQ1) severity 2	4 (4)	1 (6)	4 (5)	116 (93)	94 (89)	99 (87)	4 (3)	4 (3)	4 (3)	-8760 (7005)	-1144 (5231)	-2006 (5823)	-41672* (16224)	-30353* (14070)	-24860 (15739)
Anhedonia (PHQ1) severity 3	1 (4)	-5 (7)	-0 (6)	135 (92)	98 (84)	92 (86)	2 (2)	2 (2)	2 (2)	9516 (9739)	7834 (6354)	10260 (7337)	31075 (41925)	21305 (38819)	25207 (37968)
Feeling depressed (PHQ2) severity 1	-1 (2)	-5 (6)	-5 (6)	7 (12)	-16 (19)	-7 (23)	-1 (1)	-0 (1)	-1 (1)	-14445* (5844)	-5174 (3466)	-7856* (3934)	-27543+ (15449)	-10356 (13296)	-3631 (14185)
Feeling depressed (PHQ2) severity 2	-1 (3)	-9 (10)	-9 (11)	-59+ (32)	-98+ (51)	-97* (49)	-3+ (2)	-2 (2)	-3 (2)	-25090*** (6943)	-5582 (5231)	-8544 (6406)	-30957 (19690)	11517 (16865)	23065 (20814)
Feeling depressed (PHQ2) severity 3	-3 (3)	-13 (14)	-12 (14)	-23 (44)	-78 (56)	-69 (48)	-2 (2)	-0 (3)	-2 (3)	-39105*** (8993)	-15165* (7606)	-20660* (9233)	-70171* (33055)	-19179 (34310)	-7931 (33558)
Number obs.	443	443	443	443	443	443	443	443	443	443	443	443	443	443	443
R ²	0.003	0.048	0.060	0.040	0.074	0.090	0.025	0.084	0.101	0.073	0.507	0.515	0.029	0.173	0.179
Adjusted R ²	-0.011	0.015	0.013	0.026	0.042	0.045	0.012	0.051	0.056	0.060	0.489	0.491	0.015	0.144	0.138
AIC	4195	4192	4198	5824	5825	5830	2719	2709	2713	10673	10412	10416	11743	11689	11698
BIC	4228	4262	4293	5856	5895	5924	2751	2779	2807	10706	10481	10511	11776	11759	11792
Controls	NO	YES: A	YES: B	NO	YES: A	YES: B	NO	YES: A	YES: B	NO	YES: A	YES: B	NO	YES: A	YES: B

Note. Displays OLS regressions models for the five stated (self-reported) reference point measures i) pre-lottery task reward predictions ('Pre-task pred.'), ii) post-lottery task reward predictions ('Post-task pred.'), iii) reservation wage, for 1-hour of Prolific research participation, iv) income expectations in 1-year ('1-year income exp.') and v) income expectations in 5-years ('5-years income exp.'). Controls type A = demographics, anxiety (Total GAD7) & financial comfort, B = variables in A & additional PHQ8 symptoms (6 items).

Demographics are age, gender (dummy 'is female'), weekly income, university education (dummy: baseline is less-than university education); employment (dummies: 'unemployed', 'retired', and 'student' vs baseline 'employed'). Additional PHQ8 symptoms: PHQ3 = sleep disturbance, PHQ4 = feeling tired/low energy, PHQ5 = appetite disturbance, PHQ6 = feeling bad about oneself, PHQ7 = concentration difficulty, PHQ8 = psychomotor changes. Values rounded to zero decimal points. Heteroskedasticity-robust (type HC1/Stata) standard errors in parentheses. Only models where the regressand was '1-year income exp.', '5-year income exp.' and 'Reservation wage' (models 2 and 3) were significance overall based on *F*-tests ($p < 0.05$). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.5.4 Sensitivity analysis

Inspecting parametric reference point distributions (Figure 1.8) revealed a small number of individuals with large estimates. As a sensitivity test, regression models in Table 1.4 were re-estimated excluding 5 individuals who had relatively high reference points (> 99th percentile); the results are reported in Table 1.6. This significantly improved the variance in reference points that the models accounted for - approximately doubling R^2 and *adj* R^2 estimates – and the main results regarding anhedonia and feeling depressed were not notably different.

Models were also estimated excluding participants violating FOSD: choosing the lottery options despite the sure options paying the same as high amount of the lotteries, on any 1 to 5 items included to test for FOSD. As seen in Table 1.6, there was a similar and significant but attenuated pattern of results observed for anhedonia and feeling depressed relative to the main results (Table 1.4).

While all the covariates included as controls were conceptually distinct (demographics, anxiety, worry, PHQ-8 symptoms and MCMC parameters), multicollinearity was still investigated due to correlations between these variables (e.g., the correlation between anhedonia and feeling depressed was $r_s = 0.81$, $p < 0.001$). However, variance inflation factors were not of concern (max was 5.33 for PHQ2, and 3.52 for PHQ1) and the $R^2 = 0.72$ from regressing anhedonia on the remaining PHQ-8 symptoms, demographic variables and parameter estimates. This indicated multicollinearity was not of notable concern for regression models overall.

As seen in Table 1.7, there was no pattern of relationships between symptoms and neither α nor noise parameters; the exception was that feeling depressed (severity = 3) was positively associated with noise. There was also an association between parametric reference points and noise (positive) but not between reference points and α .

Appendix 1.E presents additional analysis pertaining to parametric reference points when symptoms of anhedonia and feeling depressed were co-elevated. Finally, there were positive correlations between the two modalities measuring reference points (parametric versus stated), which are discussed in Appendix 1.E.

Table 1.6 Parametric reference point regressions excluding outliers and FOSD violators

	M-Excl. outliers (1)	M-Excl. outliers (2)	M-Excl. outliers (3)	M-FOSD (1)	M-FOSD (2)	M-FOSD (3)
Intercept	45.085** (15.884)	43.493** (15.651)	41.893** (16.168)	47.753** (17.330)	48.159** (16.966)	44.005** (16.852)
Total PHQ8	0.386 (0.812)			0.735 (0.811)		
Anhedonia (PHQ1) severity 1		16.965* (8.132)	14.687+ (8.329)		19.739* (7.962)	16.094+ (9.018)
Anhedonia (PHQ1) severity 2		27.075+ (15.661)	26.310+ (14.971)		23.797 (17.069)	23.302 (17.073)
Anhedonia (PHQ1) severity 3		17.477 (16.513)	10.263 (17.808)		19.792 (17.581)	11.248 (20.277)
Feeling depressed (PHQ2) severity 1		-10.970 (7.857)	-12.903 (8.251)		-14.360+ (8.211)	-18.153+ (10.007)
Feeling depressed (PHQ2) severity 2		-19.096 (13.165)	-29.358* (13.508)		-18.487 (13.813)	-32.918+ (16.789)
Feeling depressed (PHQ2) severity 3		-40.336** (15.413)	-52.432** (17.905)		-33.919* (16.374)	-54.918* (23.635)
α estimate noise estimate	-9.747 (6.330) 1.306*** (0.125)	-9.426 (6.116) 1.309*** (0.126)	-9.768 (6.437) 1.321*** (0.123)	-6.666 (12.914) 1.303*** (0.158)	-6.403 (13.194) 1.299*** (0.157)	-4.665 (14.463) 1.308*** (0.159)
Number obs.	438	438	438	397	397	397
R^2	0.278	0.295	0.305	0.240	0.249	0.263
Adjusted R^2	0.257	0.266	0.266	0.216	0.215	0.218
AIC	4718	4718	4723	4395	4401	4405
BIC	4775	4795	4825	4451	4476	4505
Controls	YES: A	YES: A	YES: B	YES: A	YES: A	YES: B

Note. 'M-Excl. outliers' refers to models excluding 5 participants with outlier values (above 99th percentile) for parametric reference point estimates (M): 218.850, 230.904, 325.240, 720.937 and 833.409. 'M-FOSD' refers to excluding individual who violated FOSD on either 1, 2, 3, 4 or 5 (max) choice items designed to test for this. Controls type A = demographics, anxiety (Total GAD7) & financial comfort, B = variables in A & additional PHQ8 symptoms (6 items). Demographics are age, gender (dummy: 'is female'), weekly income, university education (dummy: baseline is less-than university education); employment (dummies: 'unemployed', 'retired', and 'student' vs baseline 'employed'). PHQ8 symptoms: PHQ3 = sleep disturbance, PHQ4 = feeling tired/low energy, PHQ5 = appetite disturbance, PHQ6 = feeling bad about oneself, PHQ7 = concentration difficulty, PHQ8 = psychomotor changes. Heteroskedasticity-robust (type HC1/'Stata') standard errors in parentheses. All models were statistically significant overall based on F -tests ($p < 0.001$). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 1.7 Individual α and noise parameter estimates regressed on anhedonia, feeling depressed and parametric reference points (study 2)

	α (1)	α (2)	α (3)	noise (1)	noise (2)	noise (3)
Intercept	0.939*** (0.024)	0.972*** (0.121)	0.896*** (0.109)	34.847*** (1.456)	35.687*** (5.938)	26.141*** (6.798)
Anhedonia (PHQ1) severity 1	0.010 (0.069)	0.016 (0.070)	0.006 (0.071)	0.081 (2.790)	0.807 (2.772)	-0.871 (2.573)
Anhedonia (PHQ1) severity 2	0.078 (0.132)	0.079 (0.134)	0.053 (0.132)	5.912 (6.802)	5.152 (6.724)	1.325 (6.829)
Anhedonia (PHQ1) severity 3	0.285 (0.194)	0.296 (0.191)	0.282 (0.190)	3.884 (6.149)	2.913 (6.150)	0.264 (5.489)
Feeling depressed (PHQ2) severity 1	0.012 (0.066)	0.005 (0.072)	0.009 (0.074)	2.324 (2.901)	2.724 (3.009)	4.078 (2.767)
Feeling depressed (PHQ2) severity 2	-0.052 (0.121)	-0.077 (0.146)	-0.065 (0.149)	-3.060 (4.260)	1.929 (5.022)	4.579 (4.650)
Feeling depressed (PHQ2) severity 3	-0.109 (0.144)	-0.144 (0.162)	-0.127 (0.164)	-1.754 (4.828)	4.746 (5.511)	8.999+ (5.414)
Reference point estimate			0.000 (0.000)			0.086** (0.032)
α estimate						2.386 (3.542)
Noise estimate			0.001 (0.002)			
Number obs.	443	443	443	443	443	443
R^2	0.013	0.022	0.035	0.007	0.059	0.158
Adjusted R^2	-0.000	-0.013	-0.004	-0.006	0.026	0.124
AIC	486	450	498	3986	3980	3935
BIC	518	569	576	4018	4049	4012
Controls	NO	YES	YES	NO	YES	YES

Note. Controls include demographics, financial comfort, and anxiety (Total GAD7). Demographics are age, gender (dummy: 'is female'), weekly income, university education (dummy: baseline is less-than university education); employment (dummies: 'unemployed', 'retired', and 'student' vs baseline 'employed').

Heteroskedasticity-robust (type HC1/'Stata') standard errors in parentheses. Only models noise (2) and noise (3) were statistically significant overall based on F -tests ($p < 0.05$). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.6 Study 3: Methods

1.6.1 Reference points as reward expectations: background

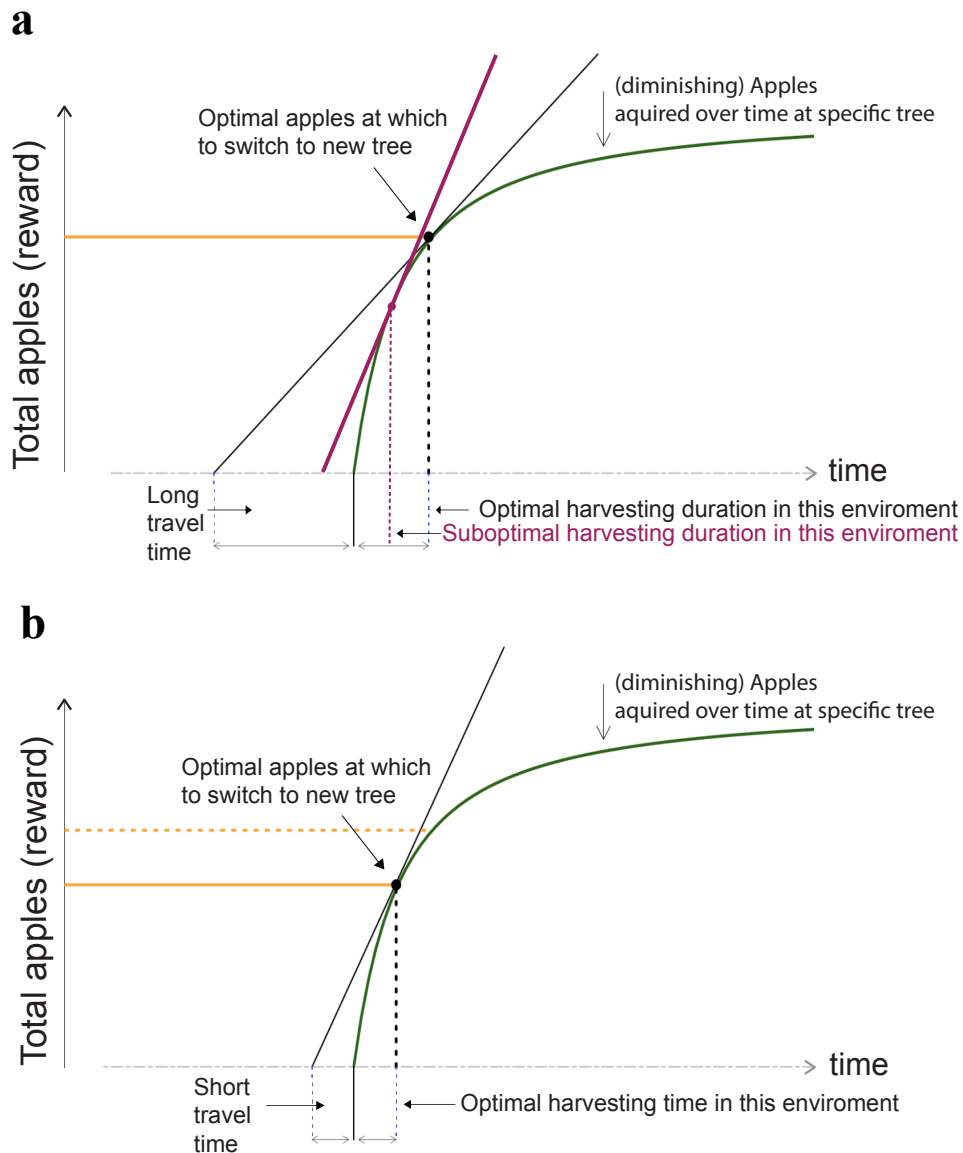
A complementary measure of the reference point is a person's *reward expectation*. The *Foraging task* paradigm provides a straightforward behavioural measure of reward expectations; while also providing an experimentally controllable, more naturalistic environment.¹⁴ This task builds on Optimal Foraging Theory, developed within population biology and anthropology, and allows for applying Charnov's (1976) Marginal Value Theorem to determining reward expectations. The theorem proposes that an animal's decision of whether to continue exploiting their current area, or 'patch', for resources or to explore a new patch, will depend on reward optimisation. At the optimum, "The predator should leave the patch it is presently in when the marginal capture rate in the patch...drops to the average capture rate for the habitat" (p. 132). The *capture rate* here refers to food intake or intake of some other reward. As described in Constantino and Daw (2015), this involves comparing the current patch's immediate reward (marginal return) to the opportunity cost of exploiting rather than exploring. This opportunity cost is the long-run reward per time-step, or reward expectation, reflecting the overall richness of the environment. In turn, this long-run reward expectation can be learned over time from trial and error, yielding a time-weighted average, or aspiration-level, against which harvests are compared. Thus, reward expectations constitute a reference-dependent decisional variable that dictates whether one continues harvesting or switches to a new patch.

A version of the foraging task involving simulated apple-tree picking has been used in several past studies (Bustamante et al., 2024; Bustamante et al., 2023; Constantino et al., 2017; Constantino & Daw, 2015; Vittala et al., 2025). During this task, participants make decisions about whether to harvest apples at their current tree (patch) or to switch to a new tree (new patch) in an apple-tree orchard (the environment). Every time the participant chooses to harvest apples from their current tree (i.e., to 'exploits') the tree is depleted of apples, yielding less apples upon subsequent harvests. If the person instead switches to a new tree ('explores'), this comes with the cost of travelling between trees. Importantly, whether a participant chooses to harvest again at the same tree or switch to a new tree indicates their

¹⁴ As reward expectations measured with the Foraging task were used in study 3 only, the conceptual and empirical background is first reviewed here for better flow.

reward expectation for the overall orchard environment: switching implies an expectation that the environment on average can yield a higher reward than the current tree. Thus, *reward expectations are operationalised as the number of apples at which the participants decide to switch to a new tree*. Figure 1.10, adapted from Bettinger (1991), shows the dynamics of this task and the theorem: the total accumulated (objective) rewards at a specific tree (y -axis) is displayed as a function of time (x -axis). When the travel time to reach a tree is longer, one's reward expectation should be lower due to the extra cost of travel meaning the environment is less rich (in apples) on average. This is modelled as a flatter slope reflecting reward expectations. If behaviour is optimal, a lower reward expectation should prompt a longer harvesting times (i.e., later patch-switch), because at optimum the tangent-point of the (flatter) reward expectation slope occurs at lower marginal rate of return. Conversely, in richer environments, such as with shorter travel (costs) between trees, the reward expectation will be higher, modelled with a steeper slope and a shorter harvesting time per tree.

Figure 1.10 *Theoretical optimal foraging dynamics in a hypothetical apple orchard*



Note. Panels (a) and (b) show that the decision to stop harvesting at a current apple tree and switch to a new tree is a function of i) the apples received at the current tree (the y -axis); ii) the travel time associated with a tree switch (x -axis); iii) the long-run reward expectation of the individual (the linear slope); and iv) the depletion-rate, which creates a diminishing return to harvests: the green curve represents the total apples (rewards) accrued over successive harvests at a tree, which is concave due to the diminishing apples per harvest. Importantly, the tangent slope on this curve, or the *marginal reward*, will decrease with successive harvests. When behaviour is optimal, exit to a new tree occurs when this slope overlaps with the slope capturing the individual's *long-run reward expectation*. The orange line indicates the total apples harvested at a tree after which a tree-switch is optimal. During optimal behaviour, environments with longer travel time (greater costs to travel) imply a tree-switch later during harvesting. Panel (A) also shows a suboptimal reward expectation slope (red) and the associated (shorter) time spent harvesting (i.e., sooner tree-switch).

The Foraging task has previously been applied to understand whether reward-contingent behaviour in depression is a function of reference-dependence. Vittala et al. (2025) found that 50 clinically depressed individuals had elevated reward expectations on average relative to 70 healthy controls. This result held in both rich (short travel) and poor (long-travel) environments. Additionally, reward expectations were positively correlated with depression severity (measured with a structured interview). Elevated reward expectations, above that implied by optimal behaviour, means depressed individuals systematically accumulate less rewards overall than is possible from their environment. This is illustrated in the top panel of Figure 1.10 as the red slope (tangent line). The steeper slope (higher reward expectation) means patches are exited prematurely, leading to under-exploitation. However, Bustamante et al. (2024) describe contrasting findings: no diagnostic group (non-MDD vs MDD) differences were observed for reward expectations, and reward expectations were negatively correlated with depression severity. These differences may be owing to variation in task-design between studies: while both applied simulated tree-harvesting tasks, Vittala et al. (2025) varied environmental cost with longer or shorter travel-time between trees. By contrast, Bustamante et al. (2024) introduced costs as cognitive or physical effort tasks. Additionally, in a non-clinical study of healthy adults, van Dooren et al. (2021) explored whether affect moderated foraging behaviour. Mood-induction was applied to manipulate affect, and a foraging task was used that differed from Vittala et al. (2025) and Bustamante et al. (2024) in allowing greater exploration of hidden rewards. Results showed that feeling more unpleasant relative to pleasant affect (rated on a Likert scale) was associated with more exploration than exploitation. The authors reported that over-exploration (vs under-exploration) may be due to an over-estimation of average rewards; their results therefore align somewhat with Vittala et al. (2025) finding of higher reward expectations in individuals with MDD (which can include unpleasant affect). For the purposes of the current study, reward expectations serve as a complimentary gauge of reference-dependence to parametric reference points. This allows for a robust test of whether depressive symptoms correlate with reference points during economic decision-making.

1.6.2 Participants and procedure

Participants in study 3 were 12 people diagnosed with MDD, receiving outpatient treatment at the Ketamine Treatment Clinic. The clinic was part of the Sydney Local Health District

(SLHD), located on the grounds of a large metropolitan hospital in Sydney. Participation was voluntary, independent of treatment within the clinic, and experiments were conducted by researchers not involved in care provision. Recruitment was carried out over 24 months from October 2023 to November 2025, given the difficulty of recruiting from this population. Inclusion and exclusion criteria were assessed as part of clinical care and were in summary: *Inclusion* i) a diagnosis of MDD according to DSM-5-TR criteria, with current symptoms; ii) ages 18 to 65; iii) fluency in English. *Exclusion* i) high suicide risk; ii) primary bipolar-, psychotic- or anxiety disorder; iii) current substance use or history of gambling disorder; iv) significant opiate use; v) cognitive impairment or a history of neurological disorders; vi) unstable medical disorders; or vii) pregnancy/breastfeeding. The age of participants ranged between 23 and 64, mean was 44.36 and SD was 13.82. Self-reported gender was 9 females and 3 males.

The aim was to recruit a cohort of participants who may experience a change in their mood symptoms over a relatively brief period following ketamine treatment. Each participant completed two experimental sessions, approximately 4-6 weeks apart in time: the first experimental session occurred immediately prior to their first treatment session, while the second experimental session occurred 4-6 weeks into their treatment (varying to accommodate the participant's schedule). Treatment involved intranasal ketamine spray or racemic ketamine.

Each experimental session was comprised of the same psychological questionnaires and tasks, administered on laptop computers, and involving a one-on-one session with the researcher (key instructions are displayed in General appendix C). 15 participants originally agreed to commence the study, but three could not complete either one or both sessions. Each experimental session was expected to last approximately 90 minutes. The sequence of stimuli was identical for every participant: 1) information sheets and consent form, 2) psychological questionnaires, 3) the lottery task and 4) Foraging task. Detailed instructions were provided before each segment, including physical examples: for the lottery task, 5 bags were created containing proportions of coloured chips (coins) that mirrored the lottery options of the task, and which the participants could inspect to understand the way the lottery task outcomes were decided.¹⁵

¹⁵ Additional questionnaires and a fluid reasoning task were completed which were not the focus of this chapter.

Depressive symptoms were assessed with the PHQ-9 (Kroenke et al., 2001). Cronbach's alpha for the PHQ-9 was 0.69 at time 1 and 0.88 at time 2. Anxiety was measured with the GAD-7 (Spitzer et al., 2006) and Cronbach's alphas for the GAD-7 was 0.82 for time 1 and 0.79 for time 2.

Participants were incentivised to make decisions according to their true preferences by being paid a \$AUD amount for one of their choices on one of the two decision-making tasks (foraging or lottery task), selected at random by a coin-flip at the end of the experiment. For the lottery task, a bag was created with numbered chips (1 to 107) from which the participants could draw to indicate the item selected for payment. The range of possible rewards was \$0 to \$105. Additionally, participants received a \$15 AUD 'show-up' fee for each session. Payments were provided at the end of each session in cash.^{16 17 18}

1.6.2.1 Power analysis

Power analysis was conducted to clarify the minimum detectable effect size for simple mean-difference tests (e.g., comparing reference points across dummies indicating whether participants experienced improvement in depression scores over time). Assuming $\alpha = 0.05$, power = 0.8 and between-subjects (within-subjects) two-tailed t-test, the required effect size (d) was very large: 1.20 (0.9).¹⁹ Moreover, the sample size was likely underpowered for reliable inferences applying the same methods with parametric reference points as study 1 and study 2. Specifically, power analysis indicated that our sample size of $n = 443$ in study 2 was well above the $n = 116$ indicated for estimating an ordinary least squares (OLS) regression model with overall effect size roughly that of our regression models from study 1 including anhedonia, feeling depressed (dummies), alpha and noise terms: Cohen's $f^2 = R^2 / (1 - R^2) = 0.123 / (1 - 0.123) \approx 0.140$, assuming $\alpha = 0.05$, power = 0.8, and 8 variables in the model. The sample size of study 3 fell notably short of this required sample size, and short of

¹⁶ The study was approved by the Sydney Local Health District Human Research Ethics Committee (RPAH Zone), the Royal Prince Alfred Hospital Research Governance Officer and the University of Sydney Human Research Ethics Committee.

¹⁷ Recruitment via physical poster advertisement was also approved for three local psychology clinics in Sydney; but there was no response to this recruitment approach and is therefore not described here.

¹⁸ The hypothesis that depressive symptoms would be associated with foraging behaviour was pre-registered with the OSF on the 12th of October 2023.

¹⁹ G*Power (version 3.1) software was used for power analysis.

the equivalent calculation for the effect size of study 2 for the same 8 variable model ($f^2=0.15$, which indicated a required sample size of 109).

1.6.3 Parametric reference points

Parametric reference points were estimated based on participant's choices on the same lottery task as that used in study 2, and the same structural BHM approach was applied. MCMC estimation mirrored that of study 2, and the same preliminary MCMC diagnostics (reported in Appendix 1.D for study 2) indicated no concern with estimation based on neither time 1 nor time 2 data.

1.6.4 Reward expectations

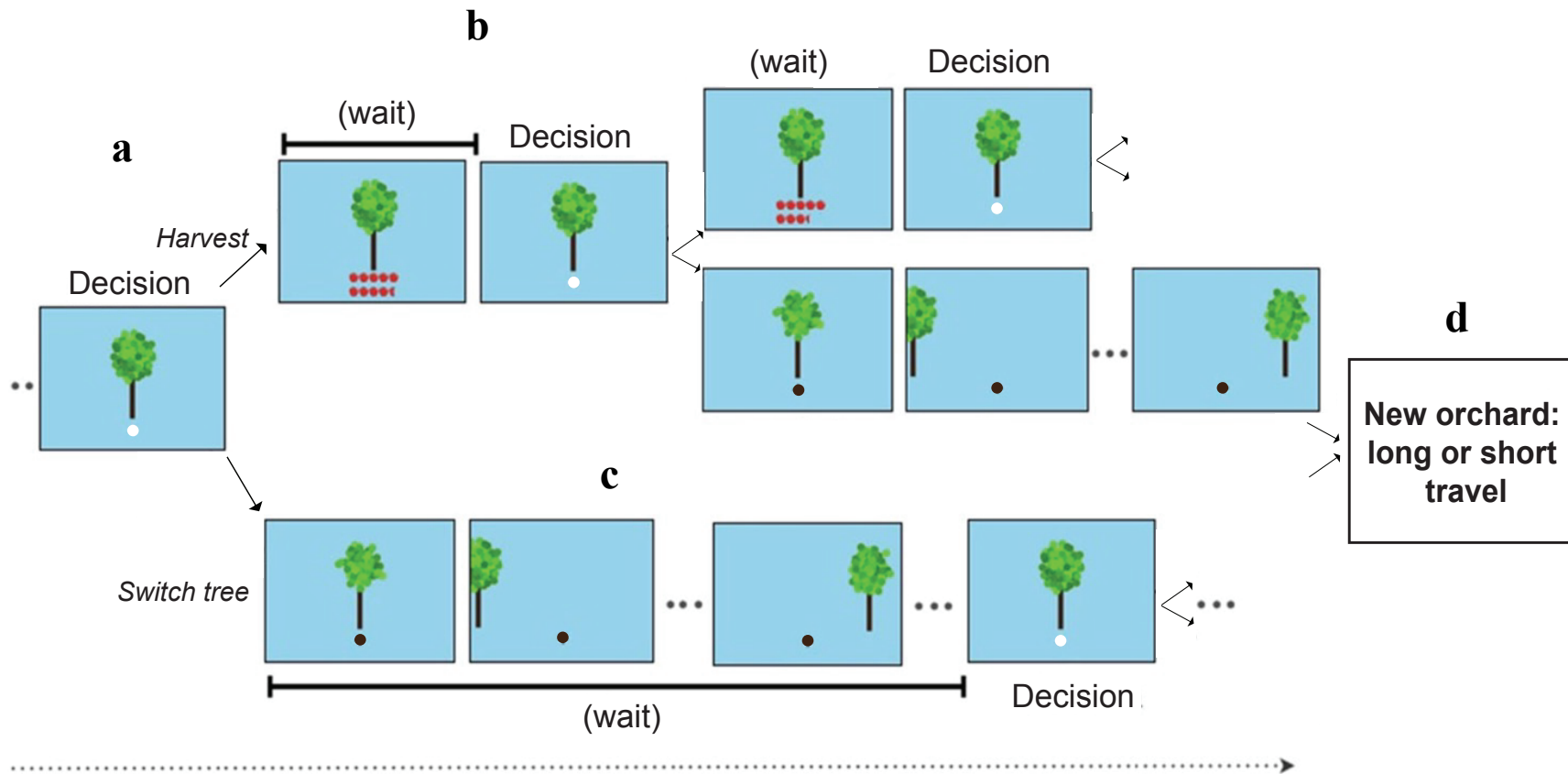
1.6.4.1 Foraging task

The Foraging task²⁰ was presented during the experiment in a similar manner to that in previous studies (Constantino & Daw, 2015; Vittala et al., 2025). As can be seen in Figure 1.11, an image of an apple tree was displayed on a computer screen, and participants could choose to either harvest apples from this tree or switch to a new tree with key presses (down arrow or right-side arrow, respectively). If harvest was the chosen action, the tree shook and the number of apples the tree yielded was displayed. The tree was then automatically depleted by a multiplicative factor.²¹ Apples could be displayed as fractions of apples (i.e., not just whole apples). When switching to a new tree, the initial number of apples followed a normal distribution with a mean of 10 and a standard deviation of 1. Before commencing the task, participants completed a short training version of the task, involving a sequence of detailed instructions with examples on the mechanics of the task. At the end of the actual task, which took 24 minutes to complete in full (barring breaks), participants were shown the total rewards they had accrued across all orchards as a dollar amount (AUD). Earnings ranged between \$20.36 to \$29.95, with mean of \$27.07 and SD of \$2.42.

²⁰ Thanks go to Glimcher Lab, New York University, for sharing the software for this task.

²¹ The average depletion rate was based on a beta-distribution (beta = 2.033008, alpha = 14.90873). The equivalent normal distribution has a mean = 0.88 and a SD = 0.077. Average initialisation rate was 10, with SD = 1. The time taken to receive apples after a harvest was 1 seconds.

Figure 1.11 Simulated foraging task



Note. The sequence of the computerised simulated foraging task: (a) the participant was asked to choose between harvesting apples at the current tree or switch to a new tree. (b) Harvesting involved a short (1 second) wait, before the resulting harvest of apples was displayed below the tree. Afterwards, the participant was again asked to decide. The white dot indicated a choice was to be made, while a brown dot indicated a decision could not be made at that time. (c) If the decision was to switch trees, the participant was shown a tree moving gradually from right to left indicating travel. There were two types of travel duration, reflecting two different orchards: a 10 second delay for the long-travel orchards and a 3 second delay for the short-travel orchards. Harvesting in each of the long and short orchards lasted 7 minutes regardless of the participant's choices, after which the participant was informed in writing and with a change in background colour that they had entered a new orchard (d). Each orchard was encountered twice so that the total duration of the task was 24 minutes. After two blocks, the participant could take an optional short break before proceeding. The order of orchards was random for each participant (either *long-short-long-short* or *short-long-short-long*). The participant had brief time to click to make their decision, and if they did not do so in time, a written prompt was provided on the screen, followed by another opportunity to make their decision. Figure 1.11 was modified from "Fig.1" in Constantio & Daw (2015).

1.6.4.2 Econometric approach

Reward expectations were defined as the ‘number of apples received by a participant prior to a choice to switch to a new apple tree’. This operationalisation has been applied in prior simulated foraging studies. For a subset of the analysis, mean reward expectations across orchards were calculated and related to depression scores. Moreover, the *time-series* of reward expectations per choice (trial) over time was used when estimating pooled ordinary least squares (OLS), fixed- and random-effects models. The higher number of observations reflected in this time-series meant analysis pertaining to reward expectations were less encumbered by the statistical power challenges noted above.

For time-series data, pooled (between) estimators treat the data as cross-sectional, in-effect collapsing the time-series of reward-expectations across time. When relating reward expectations to depressive symptoms, the pooled estimates indicate the effect, on average, on reward expectations from changing the severity *level* of depression across participants. The fixed effects (within) estimator captures the effect of *change* in a participant’s depression scores (from time 1 to time 2) on reward expectations. This estimator is vital if one suspects unobserved effects linked to reward expectations are also correlated with depression scores: the fixed effects within-transformation removes these effects via demeaning of the data across time (i.e., choice/trials). Finally, random effects apply a quasi-demeaning to the data that accounts for serial correlation of errors (which leaves pooled OLS standard errors incorrect unless these are corrected) but allows for time-constant explanatory variables. However, random effects assume that unobserved effects are uncorrelated with the explanatory variables, and its statistical properties are less known with small n and large t (characterising the current data set). As recommended in Wooldridge (2013), the three estimators were presented together and compared. For pooled OLS, the model was,

$$Reward_i = \beta_0 + \beta_1 TravelTime_i + \beta_2 Depression_i + \beta_3 T + \epsilon_i$$

Where for individual i , the dependent variable (left side of equation) $Reward_i$ is reward expectations. $TravelTime_i$ is a dummy variable capturing whether the foraging orchard involved a short (taking value 1) or a long travel time (taking value 0) between trees, with associated coefficient β_1 . $Depression_i$ refers to the depression scale: either total PHQ-9 scores, anhedonia (PHQ1) and/or feeling depressed (PHQ2) scores. β_2 is the effect of

depression score on reward expectations. T is a dummy-variable that takes the value 0 for time 1, and 1 for time 2 (with associated coefficient β_3). β_0 is the intercept term.

The fixed effect model was given by,

$$Reward_{it} = \beta_1 TravelTime_{it} + \beta_2 Depression_{it} + \beta_3 T + \alpha_i + \delta_t + \epsilon_{it}$$

This model includes a time (choice/trial) index t . α_i is a time-invariant individual fixed effect. δ_t is an individual-invariant time fixed effect. The model implies removing time-invariant unobserved individual effects and individual-invariant time-order effects. This leaves the remaining unexplained variance in reward expectations to be associated with depression scores. Including T captures any effects of whether the foraging task was completed at time 1 or time 2 that is invariant across participants and trials. Although $Depression_{it}$ takes on two different values from time 1 to time 2, unlike T , depression also varies within time-points across participant, meaning it is not entirely cancelled out by including fixed effects and the time-point dummy variable. The random effects models are similar to fixed effects but include an intercept term, β_0 .

Note that the models were estimated by combining the two data series of rewards expectations for each participant at time 1 and time 2, creating a continuous series of reward expectations across both time-points. Some models included an additional interaction-term $\beta_4(TravelTime_{it} * Depression_{it})$ to capture potential depression-related insensitivity to the travel-time across orchards.

Preliminary diagnostic tests for the presence of unobserved individual- or time- fixed effects (Wooldridge's, pF, Breusch-Pagan, GHM and Honda tests, at alpha level 0.05) provided mostly evidence for both, but results were mixed: while Wooldridge's tests for unobserved time effects were significant, for fixed effects this was the case only at alpha level 0.1. The decision was to proceed with both individual and time effects. A Hausman Test indicated that a random effects model was supported. All models were estimated with robust standard errors cluster at the individual level to account for correlations within a participant's responses; this helped address the unbalanced nature of panels (varying number of observations across participants). Although clustering can account for serial correlation in errors, for pooled

models, standard errors specifically accounting for serial correlations were also inspected: this did not change inference.

1.7 Study 3: Results

1.7.1 Change in depression, parametric reference points and reward expectations

Participants experienced improvement in depressive symptoms over time: this was supported by a paired t-test, indicating a mean-change of -7.9 in total PHQ-9 scores that was statistically significant, $t(11) = 3.51, p < 0.005$. Significant improvement was also evident for anhedonia (at $p < 0.05$) and feeling depressed (at $p < 0.01$). Figure 1.12 displays depression and decision-making variables across participants and time-points (black-filled bars indicate time 1, white-filled bars time 2). As indicated by the shading of the panels, half of participants experienced a clinically significant improvement in total depression scores (50% reduction in total PHQ-9 relative to baseline). Four more experienced some improvement, while two experienced an increase in scores. The aim of capturing a clinically depressed cohort experiencing relatively rapid change in their depressive symptoms appeared achieved.²²

While sections 1.7.2 and 1.7.3 (below) report further inferential statistics (including econometric time-series analysis), mean reward expectations and parametric reference points for each participant were visually inspected to identify any descriptive patterns overall vis-à-vis depressive symptoms over time.

Figure 1.12 displays mean reward expectations and the parametric reference points for each participant, over time. There were no obvious visual patterns of change in the two reference point measures, nor were differences statistically significant.

Participants evidenced optimal behaviour: visually comparing Figures 1.13 a to c (time 1) and comparing Figure 1.13 b to d (time 2) suggested that the majority of participants displayed lower average reward expectations in poorer environments involving longer travel time – as is predicted by the Marginal Value Theorem.²³ Comparing across time-points (Figure 1.13 a to b and 13 c to d) - and by implication mood scores (relative to the median) given these significantly changed from time 1 to time 2 – did not suggest clear evidence that mean reward

²² There was no statistically significant association between depression scores and earnings on the task, nor significant difference in earnings from time 1 to time 2 (paired t-test).

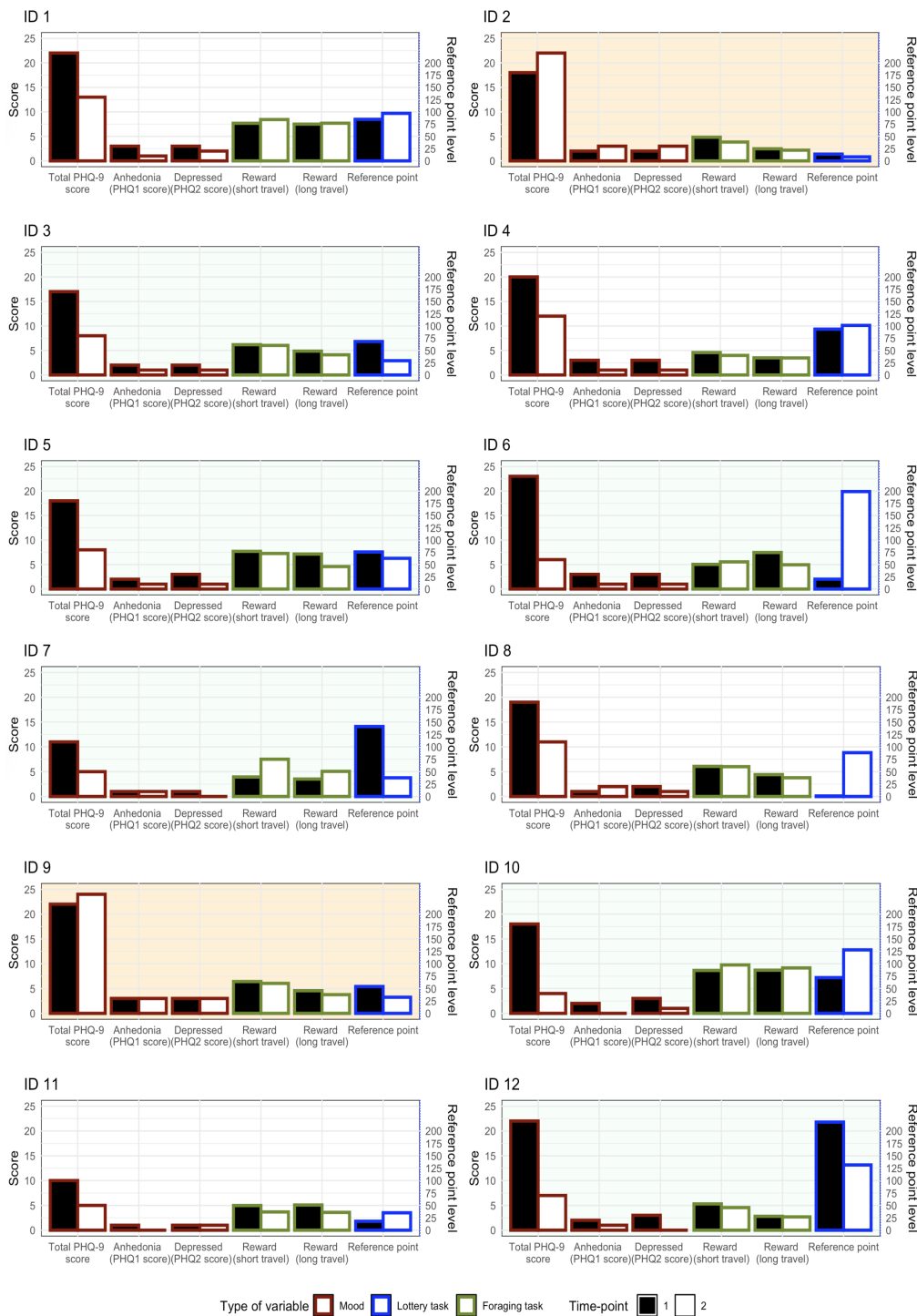
²³ At time 1, IDs showing visual adjustment according to environment were: 2, 3, 4, 5, 6, 7, 8, 9, 12; and at time 2, these were IDs: 1, 2, 3, 5, 6, 7, 8, 9, 10, 12.

expectations clustered more nor less around the optimal values as a function of time (symptoms). The only exception is perhaps for long travel, time 2 (compare Figure 1.13 c to d).²⁴

There was no visual link between depressive symptom change and reference point change. Figure 1.14 displays the change (time 2 values minus time 1 values) in reward expectations and parametric reference points (y -axis) by depressive symptom change (x -axis): total PHQ-9 (Figures 14 a, b, c), anhedonia (d, e, f) and feeling depressed (g, h, i). A positive association (slope) would suggest that an increase in depression scores was associated with an increase in reference points. Overall, there was no notable visual relationships nor consistent patterns between change in reference points and change in depression symptoms.

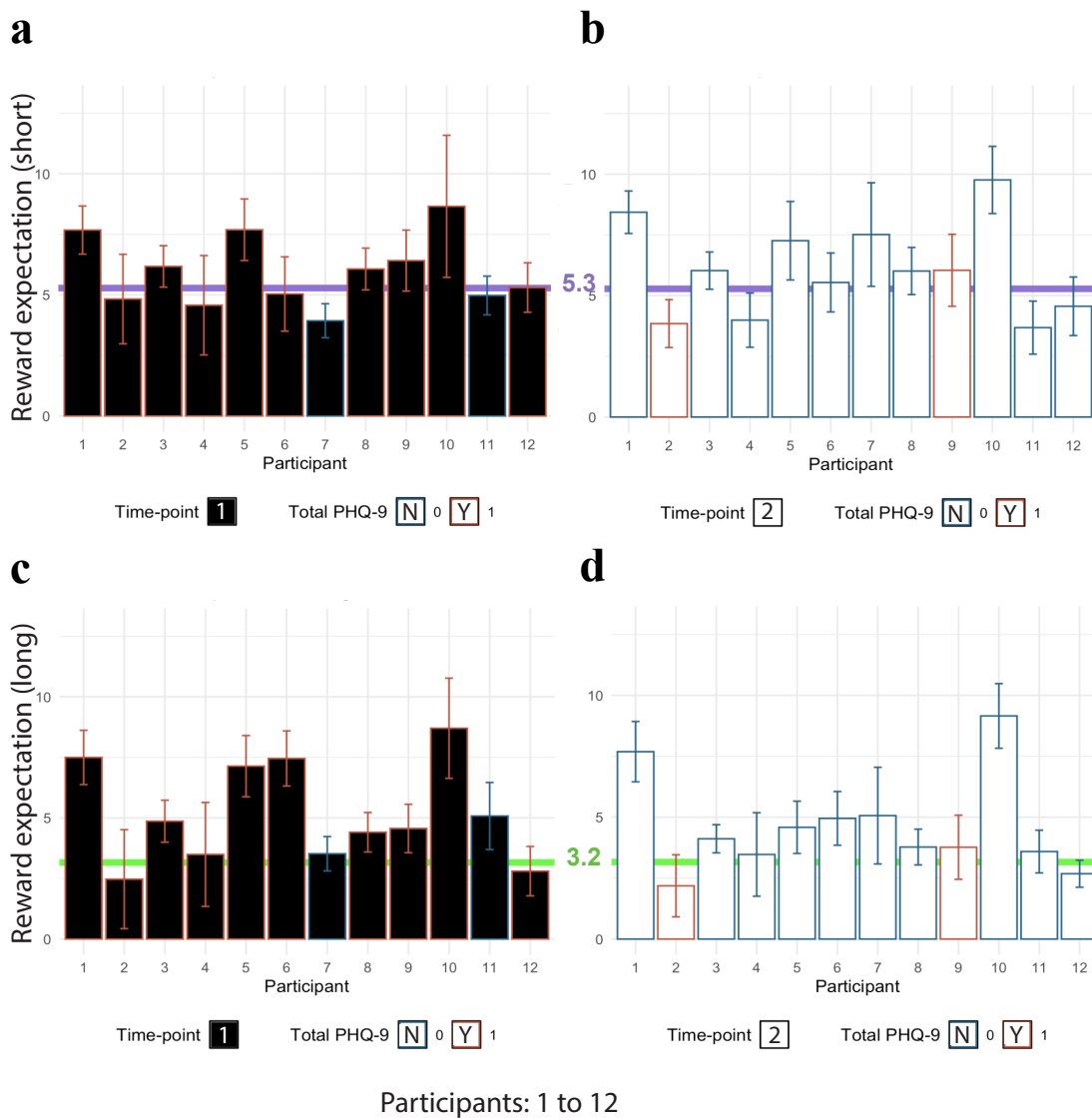
²⁴ Thanks are due to Dr Nanyin Yang for providing the Python code used to calculate the two optimal values in the two environments (5.3 and 3.2), shown in Figure 1.13.

Figure 1.12 Individual depression scores and reference points across time-points



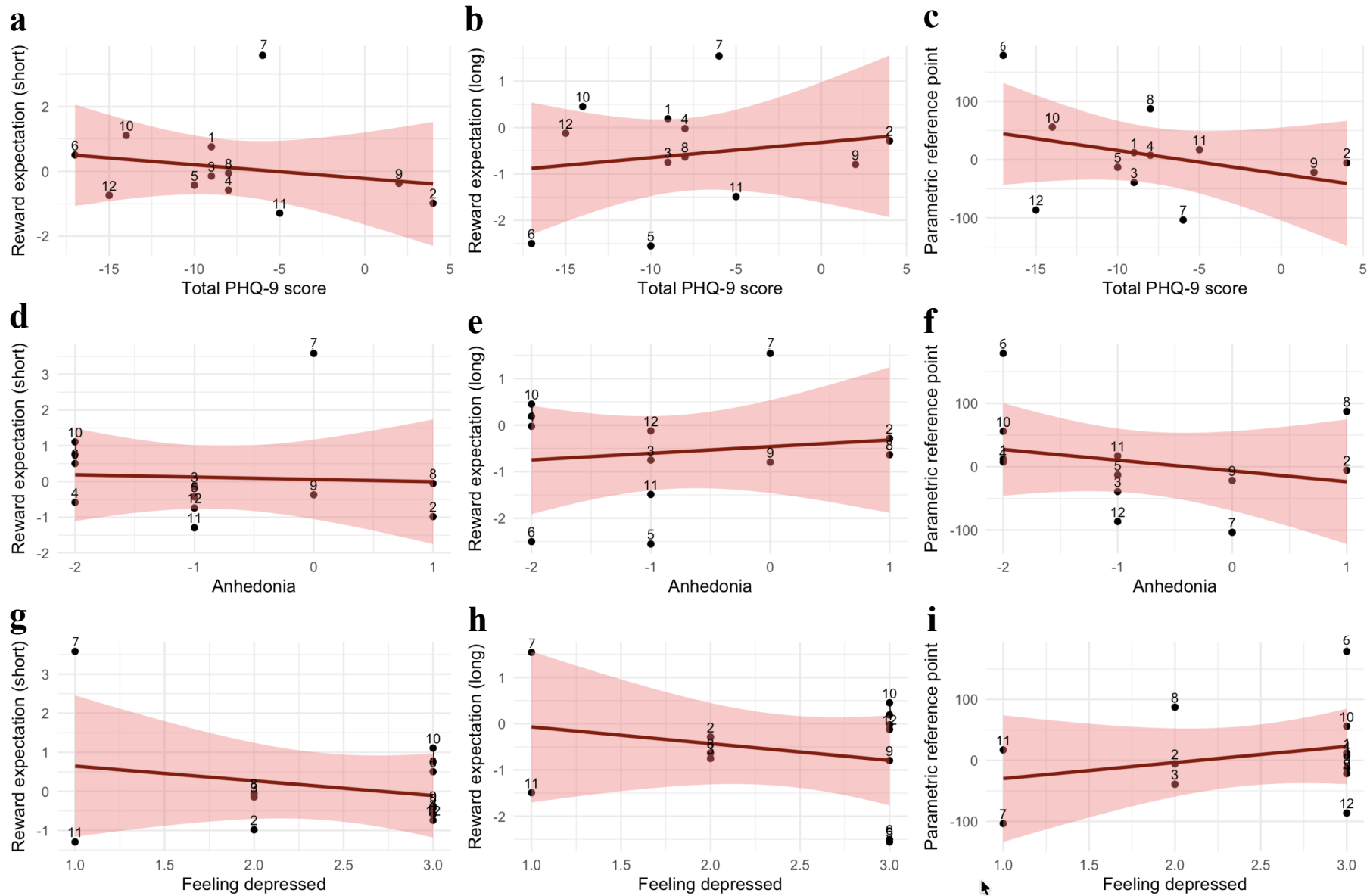
Note. Displays for each participant ('ID') the total PHQ-9 scores, anhedonia scores, feeling depressed scores, mean reward expectations (short and long travel time orchards) and parametric reference points (median of posterior estimates). The depression scores and reward expectations are measured on the primary y-axis (left side); while parametric reference points are measured on the secondary y-axis (right-side). All variables are displayed for time 1 and time 2. Panels with slight green tint indicate the participant experienced a clinically significant change in depression scores: at-least a 50% reduction in total PHQ-9 scores. Yellow tinted panels indicate the participant experienced an increase in depression scores.

Figure 1.13 Average reward expectation prior to tree-switch across travel time and time-points



Note. Panels (a) and (b) show reward expectations for short travel environments, for time 1 (a) and for time 2 (b) – optimal point (number of apples) of tree-switch depicted as purple line (apple rewards = 5.3). Panels (c) and (d) show reward expectations for long travel environments for time 1 (c) and for time 2 (d) – optimal point of tree-switch depicted as green line (apples rewards = 3.2). The colour of bars indicate whether the participant’s score at the time was above-or-equal-to (red) or below (blue) the median PHQ-9 score of 15. Error bars are standard deviations.

Figure 1.14 Scatter plots showing change in reference points by change in depressive symptoms



Note. Panels (a), (b), and (c) show the change in reference points by change in total depression score (PHQ-9); panels (d), (e) and (f) show the change in reference points by change in anhedonia scores (PHQ1); and panels (h), (i) and (j) show the change in reference points by change in feeling depressed (PHQ2). Red slopes are a linear models fitted to the variables and shaded areas reflect standard errors. Black dots are labelled according to the individual (participants 1 through 12). Reward expectations pertaining to long-travel environments are labelled ‘(long)’ and short travel time are labelled ‘(short)’.

1.7.2 Parametric reference points by depression symptoms

A link between parametric reference points and depressive symptoms could not be inferred. The association between parametric reference points and depression scores was investigated with OLS regressions. Data was pooled across participants and both time-points, and standard errors were clustered at the level of the participant. A simple regression of reference points on total PHQ-9 scores yielded a non-significant association: $b = -1.8$, $SE = 2.1$, $t(11) = -0.9$, $p = 0.4$. There was no significant association between parametric reference points and anhedonia: $b = -15.1$, $SE = 19.6$, $t(11) = -0.78$, $p = 0.5$ nor feeling depressed: $b = 4.0$, $SE = 14.6$, $t(11) = 0.3$, $p = 0.8$. Total PHQ-9 scores were recoded into a categorical (or ‘dummy’) variable capturing whether a participant’s score fell above or below the median PHQ-9 total score. Regression results did not indicate an association with reference points for this variable: $b = -27.23$, $SE = 24.26$, $t(11) = -1.18$, $p = 0.3$. However, a caveat to these results is the low degrees of freedom involved ($df = 11$ for clustered standard errors, $df = 21$ without clustering) meaning only potentially quite large effect-sizes were detectable.

Finally, no significant correlations were found between parametric reference points and mean reward expectations in short, $r_p = 0.06$, $p = 0.7$, nor long travel orchards, $r_p = 0.03$, $p = 0.9$.

1.7.3 Reward expectations by depression symptoms

Further visual inspection of the data pertaining to reward expectations indicated some divergence across depressive symptoms but no strong link total depression scores:

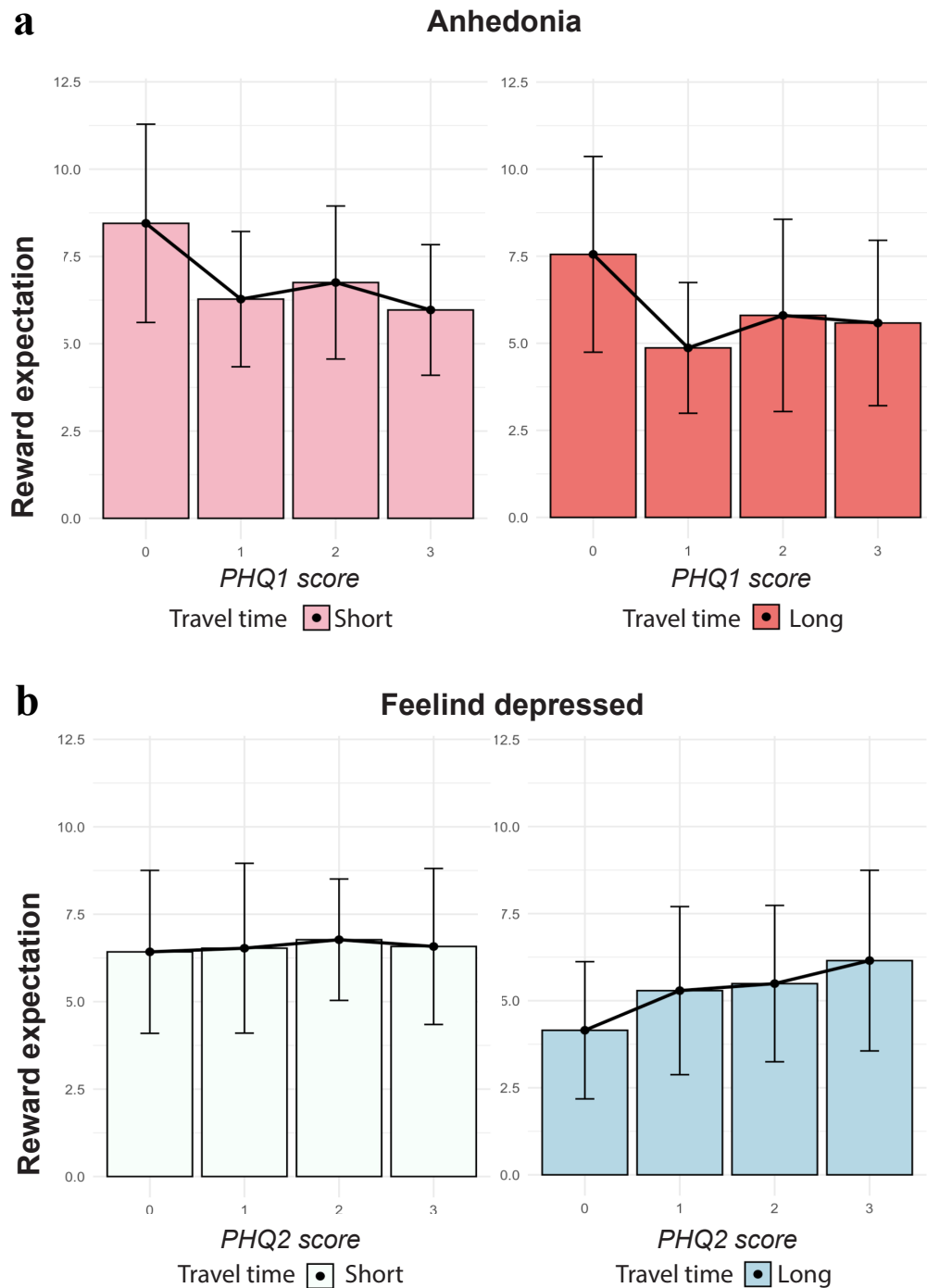
Figure 1.15 displays mean reward expectations across severity of anhedonia and feeling depressed. The two symptoms appeared to have a divergent association with reward expectations: greater severity of anhedonia appeared associated with lower mean reward expectations across orchards, while feeling depressed appeared associated with higher mean reward expectations for long-travel time orchards.

Figure 1.16 a and b show the distribution of reward expectations for all participants across time-points and delineated by whether their total PHQ-9 scores fell above (purple bars) or below (green bars) the median at the time of measurement. The median was 15, incidentally also the recommended screening cut-off for identifying *minimal* to *moderate* versus *moderately severe* to *severe* depression. For long-travel orchards, there appeared to be a weak

pattern of higher reward expectations when depression scores were above the median. However, reward expectations regressed (cluster-robust regressions) on a dummy-variable indicating whether PHQ-9 scores fell above or below the median were non-significant for long-travel orchards: $b = 0.29$, $SE = 0.62$, $t(11) = 0.47$, $p = 0.65$; and non-significant for short-travel orchards: $b = -0.37$, $SE = 0.48$, $t(11) = -0.77$, $p = 0.47$.

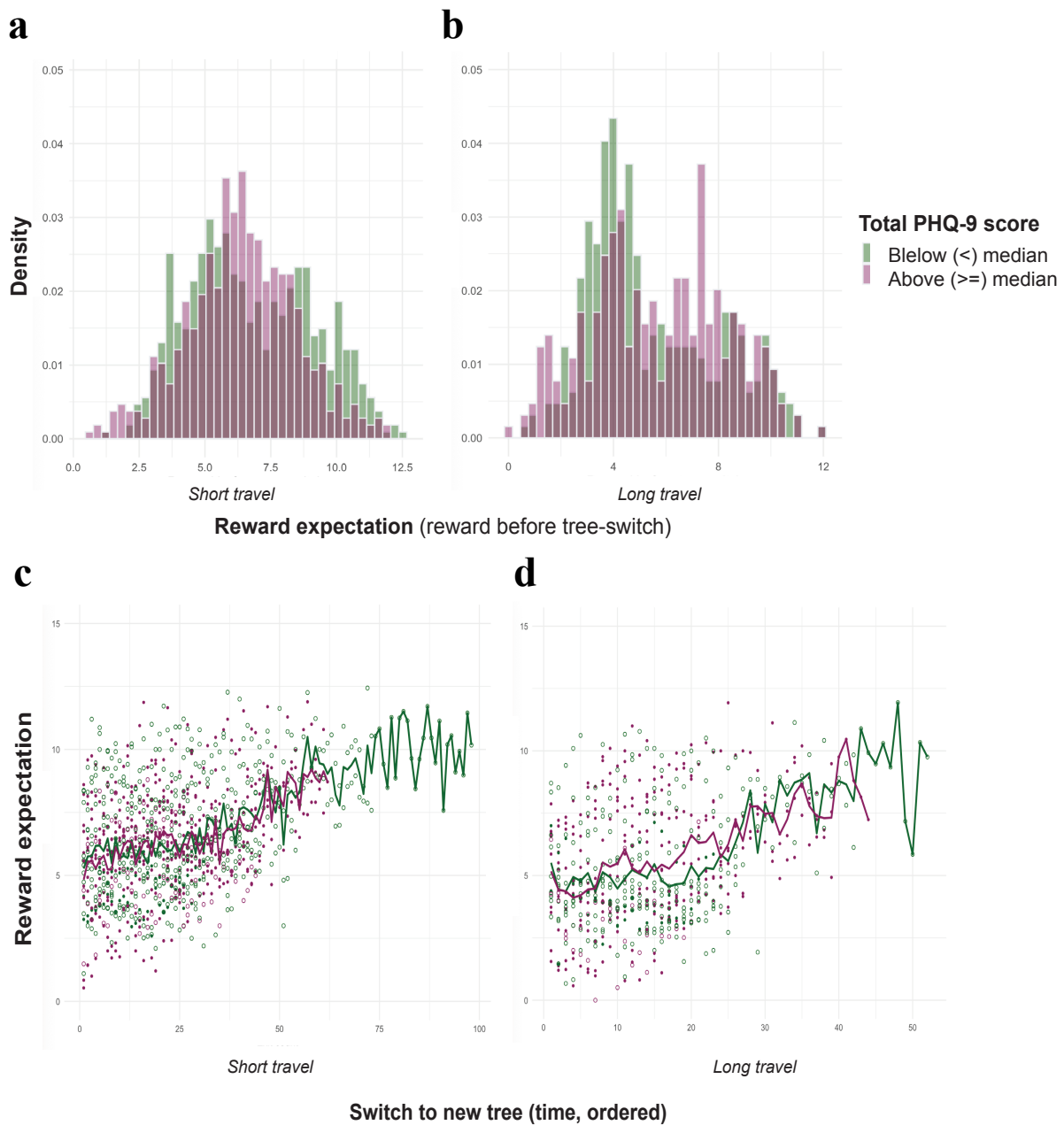
Figure 1.16 panels c and d show the time series of reward expectation (apples preceding a tree-switch) across both time-points and delineated by whether a participant's depression score fell above (purple line) or below (green line) the median. In neither orchards with short- nor long-travel times was there visual evidence that reward expectations were contingent on depression severity. However, panel regressions were applied to statistically test these associations and are reported next.

Figure 1.15 *Reward expectations by anhedonia and feeling depressed across travel time*



Note. Panel (a) shows the mean reward expectation (apple rewards prior to tree-switch) across orchards involving short- and long travel time depending on severity of anhedonia (PHQ1 score). Panel (b) shows the mean reward expectation across orchards involving short- and long travel time depending on severity of feeling depressed (PHQ2 score). Scores were: 0 = 'Not at all', 1 = 'Several days', 2 = 'More than half the days', 3 = 'Nearly every day'. Means are displayed for both time-points combined. Error bars are standard deviations.

Figure 1.16 Time-series of reward expectations by PHQ-9 score (above/below median)



Note. Panels (a) and (b) show densities for pooled reward expectations. Reward expectations are for all participants across both times completing the task, delineated by whether the participant was in a short (a) or long (b) travel orchard. The frequency of reward expectations is shown by whether the participant's total PHQ-9 depression scores were above-or-equal (purple shade) or below (green shade) the median score (15) at the time of decision-making. Above the median indicated the participant was experiencing moderately severe to severe depressive symptoms at the time. Panels (c) and (d) show time-series of reward expectations, delineated by total PHQ-9 depression scores across both time 1 (solid dots) and time 2 (empty dots), across orchards with short travel time (c) and long travel time (d).

Econometric models provided some evidence of a connection between the time-series of reward expectations and depressive mood: both total scores and individual symptoms. Table 1.8 reports models testing the effect of total PHQ-9 scores on reward expectations while accounting for the orchard travel time (slow versus long) and the experimental time-point (time 1 vs time 2). Pooled estimates are displayed for models with and without controls included. These controls were: age, gender, self-reported financial comfort and anxiety. The remaining PHQ-9 symptoms are not included in these models given the low sample size and higher risk of multicollinearity. One participant had a missing value for age.

Pooled Model 4 (inc. controls) yielded evidence that the level of total depression scores (PHQ-9) was negatively associated with reward expectations on average. This was only the case when including controls variables (as seen across models 2 and 3). However, for fixed- and random- effects models, which capture the association between changes in depression scores and reward expectations, there were no significant effects (applying only individual and both individual and time effects). This non-significance may be due to the demeaning (quasi-demeaning) involved in fixed (random)-effects models, leaving less information available (i.e., less variation in depression scores) for coefficient estimation. Alternatively, the result may indicate temporal changes in depression are not associated with reward expectations. Otherwise, there was no evidence of depression severity moderating the effect of travel-time (i.e., neither evidence of rigidity nor flexibility in reward expectations).

All models (1 – 4) show that being in an orchard involving short (vs long) travel time was associated with a higher reward prior to switching to a new tree. This agrees with the dynamics of the marginal value theory, and indicated participants on average adjusted their behaviour to the richness of the environment.

Table 1.9 reports the results of regression models delineating the effects of anhedonia and feeling depressed. Pooled models 2 to 4 indicated a consistent negative effect from anhedonia and positive effect from feeling depressed on reward expectations. There was also evidence that feeling depressed left participants on less likely to increase reward expectations in orchards with shorter travel time. Estimators accounting for serial correlation did not evidence notable differences other than the interaction term now being significant only at $p < 0.1$ ($p = 0.055$). Finally, as before, there were no significant effects for fixed- nor random-effects models. Accounting for anhedonia and feeling depressed yielded superior model fit to

using total PHQ-9 scores (compare the adjusted R^2). Including anhedonia and feeling depressed also notably improved the model relative to when only travel-time was included: for Model 4, 18.3% of the variance in reward expectations was accounted for, relative to only 4.2% for Model 1.

By design panels were unbalanced; Appendix 1.F presents further analysis pertaining to the effect of panel length, tests for multicollinearity, and evidence regarding non-linear effects from depressive symptoms.

Table 1.8 Reward expectations (apples before tree-switch) regressed on travel-time, total PHQ-9 score and time-point

	Pooled (1)	Pooled (2)	Pooled (3)	Pooled (4)	Pooled (4) controls	FE (4)	RE (4)
Intercept	5.581*** (0.686)	6.122*** (1.267)	5.654*** (1.366)	6.195** (2.102)	12.476*** (3.748)		4.944* (2.189)
Short travel	1.002*** (0.267)	0.993*** (0.277)	1.737*** (0.466)	1.738*** (0.469)	1.863** (0.567)	1.572** (0.509)	1.480** (0.452)
Total PHQ-9		-0.038 (0.058)	-0.005 (0.070)	-0.028 (0.102)	-0.226* (0.097)	0.019 (0.062)	0.013 (0.105)
Short travel by Total PHQ-9			-0.053 (0.039)	-0.052 (0.039)	-0.055 (0.045)	-0.040 (0.041)	-0.033 (0.039)
Time is 2				-0.443 (0.807)	-1.116 (0.738)	-0.116 (0.661)	-0.152 (0.795)
Number Obs.	1720	1720	1720	1720	1618	1720	1720
Participants (N)	12	12	12	12	11	12	12
DF	11	11	11	11	10	4,1450	4
R ²	0.042	0.053	0.058	0.063	0.357	0.096	0.049
Adjusted R ²	0.041	0.052	0.057	0.061	0.354	-0.072	0.047
AIC	7798	7779	7772	7765	6713	9114	11294
BIC	7815	7801	7799	7798	6767	17017	20641

Note. Individual- & time-fixed effects ('FE'), random effects ('RE'), and pooled ('Pooled') OLS models, where rewards expectations (apples received immediately prior to switching to a new tree) were regressed on the following variables i) 'Short travel', a dummy reflecting the travel time of the block (baseline comparison is long travel time); ii) 'Time is 2' is a dummy variable capturing if the results are for the time 2 measurement (baseline is time 1); iii) 'Total PHQ-9' is the summed total score on the Patient Health Questionnaire (9-items) rated on a 4-point Likert scale (0 = 'Never', 1 = 'Sometimes', 2 = 'Often' and 3 = 'Always'). For panel models, time series ranged from 90-255. For pooled models, controls ('controls') were i) 'Financial comfort', reflecting self-reported financial comfort given current needs and financial responsibilities, rated on a 7-point Likert scale from 'very poor' to 'prosperous'; ii) 'Is female' a dummy that took value 1 when participants reported their gender as 'female' (baseline comparison was 'male'). 'Age' in years calculated by subtracting participants' birth year from the year of completing the study. Anxiety was measured with the Generalised Anxiety Disorder 7-item scale (GAD-7) using total scores. Standard errors in parentheses: all models applied cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Degrees of freedom (DF). For FE and RE, R² applies to non-robust estimates. All models passed F-tests (or χ^2 -test for RE) of overall model significance ($p < 0.05$), not applied to robust models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 1.9 Reward expectations (apples before tree-switch) regressed on orchard travel-time, anhedonia, feeling depressed and time-point

	Pooled (1)	Pooled (2)	Pooled (3)	Pooled (4)	Pooled (5)	Pooled (6)	Pooled (6) controls	FE (6)	RE (6)
Intercept	5.581*** (0.686)	6.180*** (1.199)	5.162*** (0.829)	5.467*** (0.753)	4.917*** (0.741)	4.373*** (0.866)	7.925** (2.677)		4.819*** (1.011)
Short travel	1.002*** (0.267)	0.992*** (0.283)	1.011*** (0.260)	1.017*** (0.282)	1.890*** (0.316)	1.885*** (0.317)	2.003*** (0.346)	1.657*** (0.389)	1.625*** (0.328)
Anhedonia (PHQ1)		-0.370 (0.443)		-1.455+ (0.804)	-1.655+ (0.917)	-1.623+ (0.923)	-1.833* (0.758)	-0.097 (0.416)	-0.297 (1.236)
Short travel by anhedonia (PHQ1)					0.309 (0.361)	0.297 (0.364)	0.298 (0.427)	0.192 (0.345)	0.382 (0.336)
Feeling depressed (PHQ2)			0.222 (0.226)	1.312* (0.595)	1.776** (0.667)	1.909** (0.644)	1.021* (0.454)	0.255 (0.273)	0.421 (1.002)
Short travel by feeling depressed (PHQ2)					-0.733*** (0.217)	-0.727*** (0.219)	-0.753** (0.232)	-0.512** (0.186)	-0.657** (0.216)
Time is 2						0.493 (0.540)	0.046 (0.720)	-0.089 (0.610)	-0.132 (0.620)
Number Obs.	1720	1720	1720	1720	1720	1720	1618	1720	1720
Partici. (N)	12	12	12	12	12	12	11	12	12
DF	11	11	11	11	11	11	10	11	11
R ²	0.042	0.064	0.050	0.183	0.195	0.201	0.370	0.104	0.058
Adjusted R ²	0.041	0.063	0.049	0.182	0.193	0.199	0.367	-0.064	0.055
AIC	7798	7759	7784	7527	7506	7494	6684	9096	11271
BIC	7815	7781	7806	7554	7544	7538	6748	16987	20607

Note. Individual- & time-fixed effects ('FE'), random effects ('RE'), and pooled ('Pooled') OLS models, where rewards expectations (apples received immediately prior to switching to a new tree) were regressed on the following variables i) 'Short travel', a dummy reflecting the travel time of the block (baseline comparison is long travel time); ii) 'Time is 2' is a dummy variable capturing if the results are for the time 2 measurement (baseline is time 1); iii) anhedonia (PHQ1 item) and feeling depressed (PHQ2 item) from the PHQ-9 scale, rated on a 4-point Likert scale (0 = 'Never', 1 = 'Sometimes', 2 = 'Often' and 3 = 'Always'). For panel models, time series ranged from 90-255. For pooled models, controls ('controls') were i) 'Financial comfort', reflecting self-reported financial comfort given current needs and financial responsibilities, rated on a 7-point Likert scale from 'very poor' to 'prosperous'; ii) 'Is female' a dummy that took value 1 when participants reported their gender as 'female' (baseline comparison was 'male'). 'Age' in years calculated by subtracting participants' birth year from the year of completing the study. Anxiety was measured with the Generalised Anxiety Disorder 7-item scale (GAD-7) using total scores. Standard errors in parentheses; all models applied cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion and DF = Degrees of freedom. For FE and RE, R² applies to non-robust estimates. All models passed F-tests (or χ^2 -test for RE) of overall model statistical significance ($p < 0.05$); not applied to robust models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

1.8 Discussion

Across three studies, reference-dependence was successfully applied to characterise the association between depressive symptoms and economic decision-making. Specifically, there was consistent evidence across the two larger non-clinical samples that anhedonia was associated with elevated parametric reference points; this was based on choices made during an economics lottery task. Moreover, parametric reference points had divergent associations with anhedonia and feeling depressed, the latter being associated with lower parametric reference points in study 2 (and less consistently study 1). In study 2, feeling more depressed was also robustly negatively associated with a measure of long-term income expectations. Finally, in the clinical sample, anhedonia was associated with lower behaviourally gauged (e.g., implicit) reward expectations, while feeling depressed was linked to higher reward expectations. This divergence contrasted with findings for parametric reference points. Next, findings are discussed relative to past research and concerning their economic and clinical implications.

1.8.1 Parametric reference points

Reference-dependence has shown great promise for understanding economic choice. In this paper, a neuroscientifically-informed model of reference-dependence (ESVT; Glimcher & Tymula, 2023) was applied to characterise economic decision-making as a function of depressive symptoms. Theoretically, elevated reference points reduce the hedonic aspects of reward stimuli, suggesting a mechanism for explaining past findings: depression, and anhedonia in particular, has been linked to reduced reward sensitivity or salience (Halahakoon et al., 2020; Huys et al., 2015; Huys et al., 2021; Mukherjee et al., 2023). Results herein suggest that for anhedonia, such findings could be attributable to elevated parametric (implicit) reference points. This finding also complements recent theoretical models in which maladaptive evaluation in depression has been proposed to be a function of reference-dependence, and aberrant reference points specifically (Rigoli et al., 2021; Zavlis et al., 2024).

Importantly, this study suggests that psycho-social impacts and societal costs owing to anhedonia - the depressive symptom associated with persistent disinterest in environmental reinforcers - may be mechanistically linked to elevated reference points. Elevated reference

points were found for people with sub-clinical symptoms (general-population samples). Thus, reference-dependent reward processing changes may help explain maladaptive behaviour across the severity and developmental course of depressive disorders, extending beyond the clinical realm.

Contrasting with anhedonia, reporting feeling depressed (i.e., negative affect) was associated with lower parametric reference points. Lower reference points may reflect the cognitive-affective nature of *feeling* depressed: including the pessimism that commonly characterises depression (Alloy & Ahrens, 1987; MacLeod & Salaminiou, 2001) or persistent negative cognitive schemas (Evans et al., 2005; Renner et al., 2012). Relatedly, depression has been linked to cognitive-affective information-processing biases (e.g., difficulty disengaging from negative stimuli and preferential recall of negative information), which may play a role in the onset, maintenance, and recurrence of depressive episodes (Foland-Ross & Gotlib, 2012; Gotlib & Joormann, 2010). Lower parametric reference points while feeling depressed may reflect such information-processing biases.

Taken together, parametric reference points may capture different underlying mechanisms shaping behaviour due to anhedonia versus feeling depressed. Each of these may represent maladaptive evaluation, in turn, influencing decision-making in different ways. During anhedonia, reference-dependent blunting may lead to disinterest in one's environment, with interpersonal and occupational consequences. Feeling depressed may involve pessimistically low reference points that, while leading to higher evaluations upon encountering rewards, may nevertheless represent a maladaptive mismatch with the status (i.e., statistics) of a person's environment.

1.8.2 Stated reference points

In study 2, conscious reference points were also gauged by asking participants to report on their reward predictions and longer-term income expectations. These stated reference points were less reliably associated with depressive symptoms. The methodological implication is that mood effects may not manifest as readily, or at least not as immediately, in measures of reference points reliant on conscious awareness thereof. However, a clear exception was long-term income expectations, which were robustly associated with feeling depressed. In a review of neuroscience findings, Bishop and Gagne (2018) note that there is evidence of reduced

expectations for future rewards in depression. Such expectations are likely linked to the negative information biases noted above. However, the present study has helped identify these as symptoms-specific to feeling depressed. For the economist, these results suggest long-term, consciously held, income expectations are a second avenue through which depression may exert an influence on economic decision-making.

1.8.3 Reward expectations

In study 3, a depressed cohort completed the foraging task at two time-points. Their foraging task behaviour allowed for gauging reference-dependent decision-making in the form of implicit reward expectations pertaining to their (simulated) environment. While there was evidence of lower reward expectations for higher aggregated levels of symptoms (PHQ-9 total scores); divergent associations were found at the symptom level too: lower (higher) reward expectations for anhedonia (feeling depressed).

While interpretation is tentative given the low samples size meant the study was underpowered, the results in study 3 help reconcile mixed results across Vittala et al. (2025), van Dooren et al. (2021) and Bustamante et al. (2024). The current study did not evidence a strong positive association between total depression scores and reward expectations as in Vittala et al. (2025). Instead, there was evidence of a weak negative association between total PHQ-9 scores and reward expectations, as in Bustamante et al. (2024). As noted above, differences between Vittala et al. (2025) and Bustamante et al. (2024) may be due to how environmental costs were operationalisation. However, an alternative explanation is that feeling depressed may have been more pronounced in the MDD group tested in Vittala et al. (2025), and anhedonia more pronounced in the MDD group in Bustamante et al. (2024). Although neither of the two studies primarily aimed to delineate depressive symptoms, Bustamante et al. (2024) reported on the association between reward expectations and anhedonia specifically, finding a negative association – as in the current study - although the association fell short of significance in Bustamante et al.. Theoretically, a reduced tendency to explore one's environment owing to lower reward expectations aligns with the nature of anhedonia: a reduced or lacking interest in one's environment. Conversely, the finding that feeling depressed was associated with higher reward expectations, implying a drive to exploration, agrees with van Dooren et al. (2021)'s finding that over-exploration was

associated experiencing unpleasant affect. Overall, findings point to depressive symptoms shaping the implicit reward expectations a person forms over time within an environment. However, a caveat to making strong inferences here is the low sample size of study 3 (noted further under limitations).

1.8.4 Accounting for reference point divergences

The findings summarised above suggest depressive symptoms differ in their influence on economic decision-making, as reflected in reference points. The divergent effects by specific symptoms found across the 3 studies may explain mixed findings in prior literature. For example, inspecting the results of a recent systematic meta-analysis examining various risk-elicitation methodologies by Lu et al. (2024), it appears that out of the 73 effect sizes presented, 44 indicated a preference for risk seeking and 27 indicated a preference for risk aversion in depression (Figure 1.2, p. 6). Similarly, Mukherjee et al. (2023) highlight mixed findings in reinforcement learning studies, concluding “more evidence is needed in order to parse the separate contributions of prediction-error updating and reward sensitivity to learning, as well as how they may be differentially affected by depression” (p. 5). Moreover, inspecting the results reported across studies in a meta-analysis on loss aversion by Sediya et al. (2020) indicated depression was positively associated with greater loss aversion in some studies (Baek et al., 2017; Chandrasekhar Pammi et al., 2015; Huh et al., 2016; Trimmer et al., 2015); but not other studies (Charpentier et al., 2017; Engelmann et al., 2017; Hadlaczky et al., 2018). Finally, as noted above there have been conflicting findings for reward expectations during foraging (Bustamante et al., 2024; Vittala et al., 2025). In this paper, the recruitment of two large samples allowed testing whether depression as a construct evidence uniformity, by examining distinct symptoms while holding fixed the effect of other depressive symptoms and various controls. Indeed, in addition to divergent effects for anhedonia and depressed mood, total depression scores (combining symptoms) were a poor predictor of parametric reference points, and a weak predictor of reward expectations. Had analysis been limited to total scores, the conclusion may have been that depressive symptoms had no or little influence. A similar scenario is illustrated in Bustamante et al. (2024): depression severity was unexpectedly associated with a decreased subjective cost of physical effort, but the authors uncovered a symptom-specific association of anhedonia with effort costs. The importance of a sufficient sample size is underscored in another depression study by Rutledge et al. (2017): significant effects for anhedonia versus other MDD symptoms were found on emotional impacts due to reward prediction errors. But

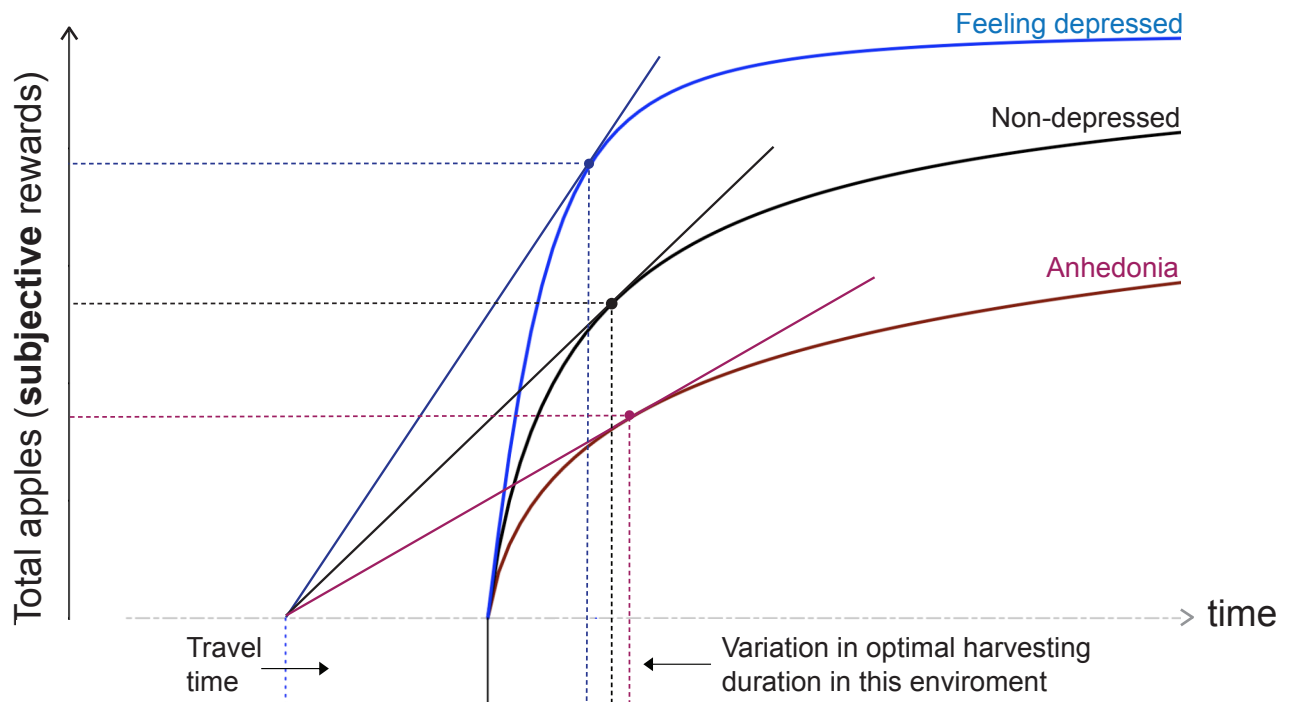
this was only the case in their larger non-clinical sample ($N = 1833$), not their sample of MDD vs control groups ($N = 74$). The divergent associations observed for anhedonia and feeling depressed also underscore how these symptoms and their effects on behaviour may involve distinct aetiological mechanisms. A distinction between the two is also recognised clinically: MDD can be diagnosed despite the absence of one of these symptoms; while anhedonia per se is also recognised as a symptom of other mental disorders (e.g., Schizophrenia).

Conceptualising parametric reference points as distinct from reward expectations may explain their contrasting and bi-directional association with depressive symptoms. Both reward expectations and parametric reference points likely shape the evaluation of reinforcers. However, parametric reference points, defined here as shaping the subjective value of rewards, may reflect a computational variable that determines reward salience and evaluation more immediately or directly. Concurrently, reward expectations may develop gradually over time within an environment, and as a function of perturbed reward evaluations due to parametric reference points. Specifically, it is proposed that reward expectations are based on the average accumulated *subjective* rewards owing to parametric reference points. In turn, reward expectations exert their own reference-dependent effects on behaviour by determining exploration-vs-exploitation within a given environment. While parametric reference points shape an earlier and more immediate stage of reward computation, reward expectations are the consequence thereof as the person adapts to this evaluation-tendency and the environment. This proposal is illustrated in Figure 1.17, which displays the dynamics of optimal foraging (similar to Figure 1.10) while accounting for the proposed effects of anhedonia and feeling depressed on parametric reference points (similar to figures 1.1 and 1.9b) *and* reward expectations. The optimal foraging dynamics now accommodate reward salience due to parametric reference points: reward curves reflect the total *subjective rewards* (y -axis) accumulated during an apple harvest at a specific tree. The figure shows three curves: a flatter red curve for anhedonia, given higher parametric reference points are associated with lower subjective rewards; and a steeper blue curve for feeling depressed, given lower reference points are associated with higher subjective rewards (in the moment). The black curve reflects the case of no depression symptoms. A flatter curve for anhedonia implies a lower reward expectation (flatter tangent-slope) and therefore longer exploitation times (i.e., fewer apples when deciding to tree-switch). The converse holds for feeling depressed, implying more exploration. Importantly, the model can explain findings across the three studies. Notice that while the symptom-specific associations for reward expectations could

also be modelled as depression prompting suboptimal behaviour (i.e., non-tangential slopes), this is not necessary for explaining behaviour. Instead, optimality is maintained based on the subjective value of the individual, even though behaviour may be sub-optimal compared to that of a person whose subjective value is not impacted by depressive symptoms. In other words, for a depressed person their behaviour may be ‘optimal to them’ while not being optimal from an objective perspective. Furthermore, the econometric results of study 3 indicated only some evidence of attenuated adjustment to environmental richness (travel time): only for participants feeling depressed per se. In general, the clinical cohort appeared to adjust reward expectations to environmental richness, as predicted by theory. Overall, the model suggests depression changes the hedonic strength of rewards – under-valued in anhedonia and overvalued when feeling depressed – which, in-turn, manifests as changes to foraging behaviour via long-run reward expectations. A challenge to the model is the finding that stated long-term income expectations were lower when feeling depressed was more frequent. While the model can account for the role of implicit, behaviourally-inferred, reference points, it may not extend to consciously held reference points. Stated reference points may be owing to different information-processing mechanisms. Moreover, in study 3 there was no association between parametric reference points and reward expectation expected from the model. However, this lack of correlation may very likely be due to the study being underpowered.

The mechanisms that change the proposed up-stream reward computation (e.g., evidence in parametric reference points) may link to hedonic blunting of secondary reward stimuli evidence in past literature. Changes in reward expectations may link to down-stream differences in learning from history of rewards and expectation formation documented in depression. Importantly, paradigms investigating hedonic experience (including neurobiological measures) are best combined with behavioural and self-report gauges of learning and expectations (capturing reward expectations forming dynamically over time); and investigated in both general and clinical populations. This can help clarify if reward-processing delineates across symptoms in a dynamic manner, involving bidirectional feedback with affective states.

Figure 1.17 Reward evaluation and optimal foraging according to symptom-specific reference points



Note. A model of how depressive symptoms influence reward salience via parametric reference points, and consequently, apple-tree foraging behaviour via reward expectations. Anhedonia and feeling depressed are associated with divergent parametric reference points that result in distinct subjective values for objective rewards. Therefore, the curve capturing accumulated rewards may best be re-conceptualised as reflecting the accumulated subjective rewards. Accordingly, these curves can be delineated by depressive symptoms: feeling depressed linked to higher subjective values (blue curve); ii) anhedonia linked to lower subjective values (red curve); or iii) no depressive symptoms (black curve). Given a fixed travel time, each mood state and associated subjective reward curve will, when behaviour is optimal, have different tangent-slopes indicating long-run reward expectations. Specifically, anhedonia will be associated with lower reward expectations and therefore a reduced tendency towards exploration (longer harvesting time / lower apples before a tree-switch); and while feeling depressed a higher reward expectation and tendency towards greater exploration (shortest harvest time / higher apples preceding a tree-switch).

1.8.5 Contributions to economics, clinical implications, limitations and future directions

In this paper, a neuroeconomic model was applied to model and quantify the impacts of depressive symptoms on economic decision-making. As highlighted in the introduction, despite the high disorder prevalence and vast societal costs, our economic understanding of how depressive moods effect behaviour is relatively nascent. To the authors knowledge, this is the first investigation into depression quantifying reference-dependence parametrically to understand reward-contingent behaviour. It is also the first study to differentiate the effect of different symptoms by utilising reference points as a computational marker. For the economist and policy maker, findings suggest that the mood of person in the general population bears on their economic decision-making and warrants understanding. Measuring whether anhedonia or feeling depressed characterises certain groups of interest may help steer policy. Methods currently used to gauge market and consumer sentiments could be adapted for these purposes. Furthermore, policy tools may be developed to attenuate or compensate for symptom-specific effects on economic decision-making and other behavioural impacts of mood. For example, addressing disengagement (e.g., absenteeism, presenteeism) in anhedonia, or pessimistic long-run income expectations that may shape inter-temporal choice while feeling depressed.

The present paper also contributes conceptual and methodological innovations to the field of behavioural economics. The neuroeconomic model developed for parametrically identifying reference points highlights the potential of modern computational methods for quantifying reference-dependence during choice. As shown here in the context of mental health, such parametric reference points can be applied to understanding individual and group differences in economic decision-making.

Depressive moods appear to be decisional states involving reward-processing changes that shape evaluation and decision-making. Such a conceptualisation of depression confers useful treatment implications: clinicians may supplement standard interviews and psychometric procedures with methods that assess a person's reward-contingent behaviour and questions eliciting expectations. For example, this could help identify behavioural reward-processing changes specific to anhedonia, including their occurrence in other psychiatric disorders featuring anhedonia (Guineau et al., 2023; Horan et al., 2006). Enhanced assessments would allow for better treatment tailoring; indeed, a decision-theoretic elaboration of cognitive

behaviour therapy, Positive Affect Treatment (Craske et al., 2023), has shown promise. For the policy maker, findings point to the importance of designing tailored systems of psychiatric care.

A major limitation of the third study was a small sample size narrowing the effect size detectable for any association between depressive symptoms and reference points. As a partial remedy, the time-series nature of reward expectations allowed for more reliable statistical inference. However, while pooled models may have been less impacted, fixed effects models were likely underpowered. For fixed effects models, despite the large number of time-points, the smaller sample meant that a substantial variation in depressive symptoms was likely eliminated. This meant associations could only be inferred between reward expectations and the level of depressive symptoms a person was experiencing at the time. A stronger link, between changes in reward expectations and changes in depressive symptoms across time-points, could not be detected. To help address these issues, the design of study 3 should be replicated in a larger sample from the general population. This would allow more sophisticated modelling that incorporates further variables of interest (e.g., psycho-social functioning).

Conceptual and statistical care must be shown when investigating correlated symptoms, as multicollinearity is a valid concern. Multicollinearity can negatively impact the reliability of coefficient estimates and reduces the chance of detecting true associations. However, choosing to omit correlated variables with links to the variable of interest (i.e., depression symptoms with reference points), risks model misspecification and omitted variable bias. This is particularly true in depression, where the symptoms comprising the diagnostic classification are necessarily co-occurrent, yet are phenomenologically and conceptually distinct and should not be conflated (e.g., experiencing negative affect, such as feeling depressed, is a distinct phenomenon to anhedonia and a general lack of interest). A good intermediate approach pursued in this paper is to estimate and inspect models hierarchically, as is common in psychology and applied microeconomics.

Of note is the finding that parametric reference points may reflect a fundamental mechanism that explains perturbed reward evaluation in anhedonia. Future research may apply experimental methodology to further delineate the hedonic (or 'liking'), motivational and learning components of reward-processing in anhedonia. Particularly given evidence of common and dissociable neurobiological underpinnings for these components (Borsini et al.,

2020; Cooper et al., 2018). Reference-dependence can provide a decision-theoretic framework for such research. Moreover, different reference-dependent models may also hold promise: Prospect theory (Kahneman & Tversky, 1979), models based on rational expectations (Kőszegi, 2010; Kőszegi & Rabin, 2006), models emphasising anticipatory regret (Bell, 1982; Loomes & Sugden, 1982), or more recent models (Rigoli et al., 2021; Zavlis et al., 2024). Overlap and differences from applying such models can help ‘triangulate’ information to converge on the mechanisms that shape decision-making during depression. Economists may also seek to extend the methodology of the three studies by adapting larger-scale representative panels to identify the associations between depressive symptoms and economic choice.

1.8.6 Conclusion

Reference-dependence is a framework that can characterise economic decision-making during depressive symptoms. Applying an interdisciplinary approach - featuring a novel neuroeconomic model, economic methodology and harnessing modern computational statistics - parametric reference point variation was shown to quantify and distinguish the effect of anhedonia and feeling depressed on economic choice. Depressive symptoms were also linked to reference points as stated long-run income expectations, and reward expectations inferred from reward-contingent behaviour in a simulated naturalistic environment. To the economist, these findings present a starting point for future research that may inform policy designed to address the significant societal costs of depression.

Appendix 1.A

Table A.1. Demographic information for study 1 ($n = 853$) and study 2 ($n = 443$)

Study 1		Study 2	
Variable	Statistics	Variable	Statistics
Gender	Percent	Gender	Percent
Female	83	Male	47
Male	17	Female	51.7
Worked in last 7 days	Percent	Non-binary	0.9
Yes	80.7	Prefer not to say	0.5
No	19.3	Employment status	Percent
Education	Percent	Full time	43.1
Year 11 or below	5.9	Part-time	12.4
Year 12 or equivalent	9.8	Self-Employed	14.2
Certificate III or IV	12.5	Unemployed and looking for work	10.6
Diploma/Advanced diploma	12.9	Unemployed and not looking for work	6.1
Bachelor or honours	34	Retired	10.4
Graduate diploma/graduate certificate	10.1	Student	3.2
Post-graduate masters or doctorate	14.8	Education	Percent
Income	Percent	None	0.5
\$3,000 or more	8.2	High school Diploma	31.2
\$2,000-\$2,999	7.5	Associates/ Junior College (AA)	14.9
\$1,750-\$1,999	4.2	Bachelor's Degree (BA, BS)	34.5
\$1,500-\$1,749	11.1	Masters degree (MA, MS, MBA)	13.5
\$1,250-\$1,499 (Australian median in 2021)	13.4	Professional degree (DDS, JD, MD)	2.5
\$1,000-\$1,249	12.4	GED	1.8
\$800-\$999	8.5	PhD	1.1
\$650-\$799 (ca. median of sample)	6.9	Income	Distribution
\$500-\$649	6.2	Mean	1105.14
\$400-\$499	4.6	SD	1295.01
\$300-\$399	4.2	Median	700
\$150-\$299	3.3	Min	0
\$1-\$149	2.9	Max	10000
Nil income	4.2	Age	Distribution
Unsure	2.3	Mean	45.58
Age	Distribution	SD	15.76
Mean	41.71	Median	46
SD	14.22	Min	19
Median	41	Max	77
Min	18		
Max	67		

Appendix 1.B

Table B.1 *Lottery-task stimuli used in study 1*

Choice items	x1a	x2a	x3a	x4a	p1a	p2a	p3a	p4a	x1b	x2b	x3b	x4b	p1b	p2b	p3b	p4b
1	17	20	29	0	0.4	0.5	0.1	0	11	14	26	0	0.1	0.4	0.5	0
2	7	16	29	0	0.6	0.15	0.25	0	3	12	20	24	0.3	0.1	0.05	0.55
3	7	18	0	0	0.85	0.15	0	0	1	10	15	0	0.1	0.7	0.2	0
4	16	23	35	0	0.35	0.55	0.1	0	12	19	27	31	0.05	0.55	0.1	0.3
5	17	38	0	0	0.85	0.15	0	0	6	22	33	0	0.05	0.7	0.25	0
6	9	20	32	0	0.15	0.8	0.05	0	3	15	26	37	0.1	0.35	0.45	0.1
7	17	32	0	0	0.55	0.45	0	0	7	27	36	0	0.25	0.7	0.05	0
8	7	16	0	0	0.2	0.8	0	0	4	10	21	0	0.2	0.5	0.3	0
9	19	32	0	0	0.8	0.2	0	0	11	28	37	0	0.35	0.45	0.2	0
10	17	32	0	0	0.45	0.55	0	0	12	22	41	0	0.05	0.7	0.25	0
11	7	17	0	0	0.8	0.2	0	0	1	10	14	20	0.1	0.4	0.45	0.05
12	7	14	0	0	0.3	0.7	0	0	4	9	12	19	0.25	0.3	0.05	0.4
13	15	24	0	0	0.75	0.25	0	0	9	18	21	27	0.35	0.05	0.45	0.15
14	10	18	0	0	0.55	0.45	0	0	2	6	14	27	0.05	0.05	0.85	0.05
15	9	15	0	0	0.8	0.2	0	0	4	7	13	17	0.2	0.1	0.6	0.1
16	17	28	0	0	0.4	0.6	0	0	7	12	23	39	0.05	0.1	0.6	0.25
17	17	26	0	0	0.7	0.3	0	0	12	15	23	29	0.3	0.2	0.1	0.4
18	19	27	0	0	0.7	0.3	0	0	11	23	31	35	0.05	0.85	0.05	0.05
19	14	23	0	0	0.6	0.4	0	0	4	18	27	32	0.15	0.7	0.1	0.05
20	4	13	0	0	0.45	0.55	0	0	1	7	16	19	0.4	0.05	0.5	0.05
21	11	28	0	0	0.6	0.4	0	0	0	5	28	0	0.25	0.05	0.7	0
22	19	42	0	0	0.75	0.25	0	0	12	27	42	0	0.15	0.7	0.15	0
23	9	18	0	0	0.75	0.25	0	0	6	12	18	0	0.15	0.7	0.15	0
24	10	16	21	0	0.7	0.05	0.25	0	5	8	21	0	0.4	0.1	0.5	0

25	7	34	0	0	0.3	0.7	0	0	7	25	43	0	0.1	0.8	0.1	0
26	9	21	0	0	0.2	0.8	0	0	9	25	0	0	0.45	0.55	0	0
27	4	19	0	0	0.3	0.7	0	0	4	14	25	0	0.05	0.85	0.1	0
28	8	14	21	0	0.1	0.05	0.85	0	8	24	27	0	0.5	0.3	0.2	0
29	7	0	0	0	1	0	0	0	1	14	0	0	0.45	0.55	0	0
30	17	0	0	0	1	0	0	0	0	22	0	0	0.25	0.75	0	0
31	21	0	0	0	1	0	0	0	6	28	36	0	0.35	0.45	0.2	0
32	15	0	0	0	1	0	0	0	8	11	23	0	0.45	0.05	0.5	0
33	15	0	0	0	1	0	0	0	7	11	18	22	0.3	0.05	0.5	0.15
34	29	0	0	0	1	0	0	0	13	34	0	0	0.25	0.75	0	0
35	22	31	0	0	0.55	0.45	0	0	14	18	26	39	0.05	0.05	0.85	0.05
36	16	26	0	0	0.45	0.55	0	0	13	20	29	32	0.4	0.05	0.5	0.05
37	19	0	0	0	1	0	0	0	13	26	0	0	0.45	0.55	0	0
38	27	0	0	0	1	0	0	0	20	24	35	0	0.45	0.05	0.5	0
39	16	32	0	0	0.3	0.7	0	0	16	26	37	0	0.05	0.85	0.1	0
40	23	40	0	0	0.6	0.4	0	0	12	17	40	0	0.25	0.05	0.7	0
41	19	27	0	0	0.7	0.3	0	0	11	23	31	35	0.05	0.85	0.05	0.05
42	7	34	0	0	0.3	0.7	0	0	7	25	43	0	0.1	0.8	0.1	0
43	17	32	0	0	0.45	0.55	0	0	12	22	41	0	0.05	0.7	0.25	0
44	10	18	0	0	0.55	0.45	0	0	2	6	14	27	0.05	0.05	0.85	0.05
45	8	15	17	0	0.5	0.4	0.1	0	6	7	15	0	0.1	0.4	0.5	0
46	8	13	15	0	0.1	0.4	0.5	0	6	12	14	0	0.25	0.25	0.5	0

Table B.2 *Lottery-task stimuli used in study 2*

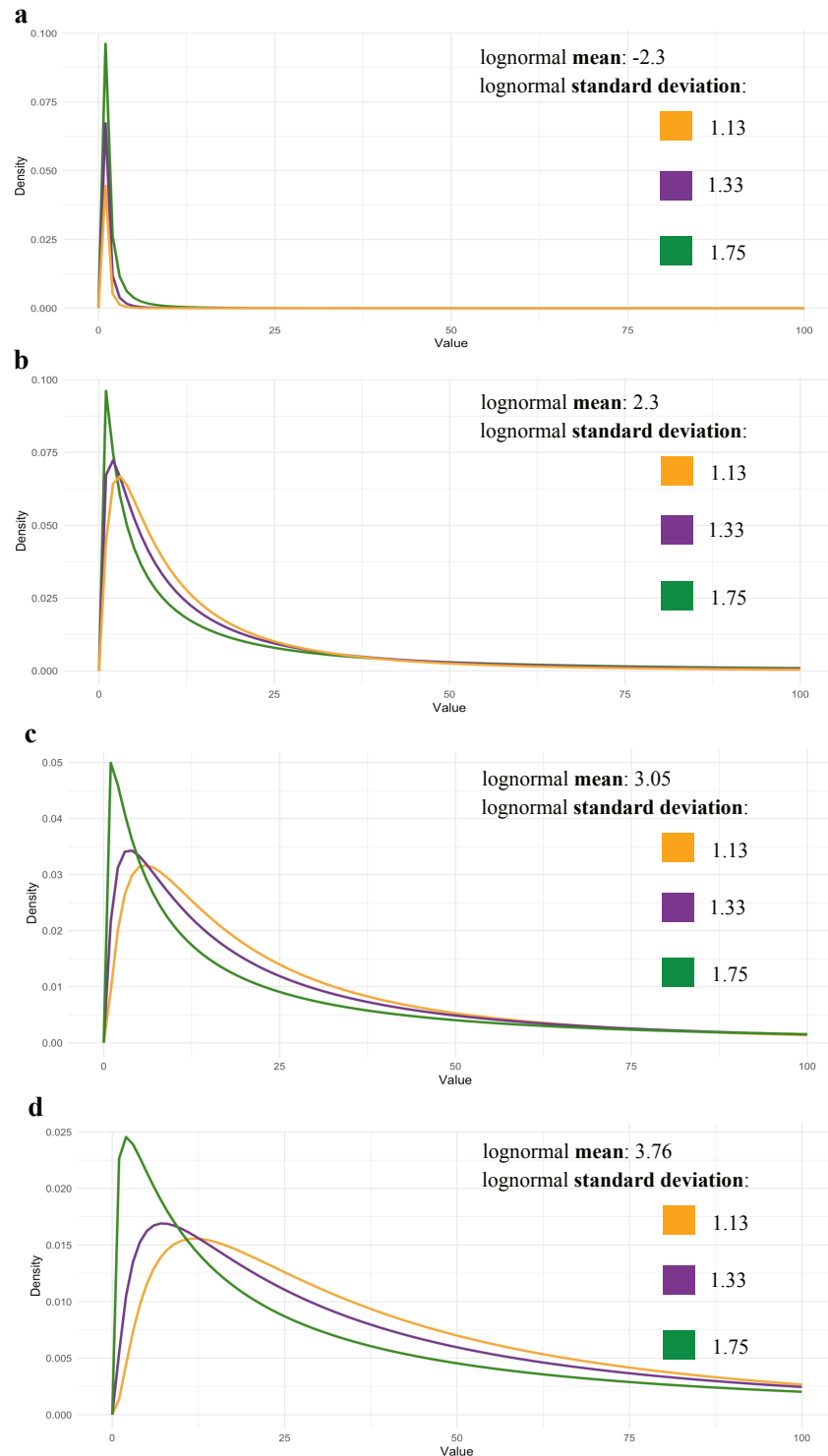
Choice items	p1a	p2a	x1a	x2a	p1b	p2b	x1b	x2b
1	0.9	0.1	0	5	1	0	5	0
2	0.75	0.25	0	5	1	0	5	0
3	0.5	0.5	0	5	1	0	5	0
4	0.25	0.75	0	5	1	0	5	0
5	0.1	0.9	0	5	1	0	5	0
6	0.1	0.9	0	10	1	0	5	0
7	0.25	0.75	0	10	1	0	5	0
8	0.5	0.5	0	10	1	0	5	0
9	0.75	0.25	0	10	1	0	5	0
10	0.9	0.1	0	20	1	0	5	0
11	0.75	0.25	0	20	1	0	5	0
12	0.5	0.5	0	20	1	0	5	0
13	0.9	0.1	0	50	1	0	5	0
14	0.75	0.25	0	50	1	0	5	0
15	0.75	0.25	0	5	1	0	2	0
16	0.5	0.5	0	5	1	0	2	0
17	0.25	0.75	0	5	1	0	2	0
18	0.1	0.9	0	5	1	0	2	0
19	0.9	0.1	0	10	1	0	2	0
20	0.75	0.25	0	10	1	0	2	0
21	0.5	0.5	0	10	1	0	2	0
22	0.9	0.1	0	20	1	0	2	0
23	0.75	0.25	0	20	1	0	2	0
24	0.9	0.1	0	50	1	0	2	0
25	0.75	0.25	0	5	1	0	3	0
26	0.5	0.5	0	5	1	0	3	0
27	0.25	0.75	0	5	1	0	3	0
28	0.1	0.9	0	5	1	0	3	0
29	0.9	0.1	0	10	1	0	3	0
30	0.75	0.25	0	10	1	0	3	0
31	0.5	0.5	0	10	1	0	3	0
32	0.25	0.75	0	10	1	0	3	0
33	0.9	0.1	0	20	1	0	3	0
34	0.75	0.25	0	20	1	0	3	0
35	0.9	0.1	0	50	1	0	3	0
36	0.75	0.25	0	10	1	0	7	0
37	0.5	0.5	0	10	1	0	7	0
38	0.25	0.75	0	10	1	0	7	0
39	0.1	0.9	0	10	1	0	7	0
40	0.75	0.25	0	20	1	0	7	0
41	0.5	0.5	0	20	1	0	7	0
42	0.25	0.75	0	20	1	0	7	0

43	0.1	0.9	0	20	1	0	7	0
44	0.9	0.1	0	50	1	0	7	0
45	0.75	0.25	0	50	1	0	7	0
46	0.9	0.1	0	90	1	0	7	0
47	0.75	0.25	0	20	1	0	10	0
48	0.5	0.5	0	20	1	0	10	0
49	0.25	0.75	0	20	1	0	10	0
50	0.1	0.9	0	20	1	0	10	0
51	0.9	0.1	0	50	1	0	10	0
52	0.75	0.25	0	50	1	0	10	0
53	0.5	0.5	0	50	1	0	10	0
54	0.9	0.1	0	90	1	0	10	0
55	0.75	0.25	0	90	1	0	10	0
56	0.75	0.25	0	20	1	0	15	0
57	0.5	0.5	0	20	1	0	15	0
58	0.25	0.75	0	20	1	0	15	0
59	0.1	0.9	0	20	1	0	15	0
60	0.9	0.1	0	50	1	0	15	0
61	0.75	0.25	0	50	1	0	15	0
62	0.5	0.5	0	50	1	0	15	0
63	0.25	0.75	0	50	1	0	15	0
64	0.9	0.1	0	90	1	0	15	0
65	0.75	0.25	0	90	1	0	15	0
66	0.75	0.25	0	50	1	0	20	0
67	0.5	0.5	0	50	1	0	20	0
68	0.25	0.75	0	50	1	0	20	0
69	0.1	0.9	0	50	1	0	20	0
70	0.9	0.1	0	90	1	0	20	0
71	0.75	0.25	0	90	1	0	20	0
72	0.5	0.5	0	90	1	0	20	0
73	0.75	0.25	0	50	1	0	25	0
74	0.5	0.5	0	50	1	0	25	0
75	0.25	0.75	0	50	1	0	25	0
76	0.1	0.9	0	50	1	0	25	0
77	0.9	0.1	0	90	1	0	25	0
78	0.75	0.25	0	90	1	0	25	0
79	0.5	0.5	0	90	1	0	25	0
80	0.25	0.75	0	90	1	0	25	0
81	0.75	0.25	0	50	1	0	30	0
82	0.5	0.5	0	50	1	0	30	0
83	0.25	0.75	0	50	1	0	30	0
84	0.1	0.9	0	50	1	0	30	0
85	0.75	0.25	0	90	1	0	30	0
86	0.5	0.5	0	90	1	0	30	0
87	0.25	0.75	0	90	1	0	30	0
88	0.1	0.9	0	90	1	0	30	0
89	0.5	0.5	0	50	1	0	40	0

90	0.25	0.75	0	50	1	0	40	0
91	0.1	0.9	0	50	1	0	40	0
92	0.75	0.25	0	90	1	0	40	0
93	0.5	0.5	0	90	1	0	40	0
94	0.25	0.75	0	90	1	0	40	0
95	0.1	0.9	0	90	1	0	40	0
96	0.75	0.25	0	90	1	0	50	0
97	0.5	0.5	0	90	1	0	50	0
98	0.25	0.75	0	90	1	0	50	0
99	0.1	0.9	0	90	1	0	50	0
100	0.75	0.25	0	90	1	0	60	0
101	0.5	0.5	0	90	1	0	60	0
102	0.25	0.75	0	90	1	0	60	0
103	0.1	0.9	0	90	1	0	60	0
104	0.25	0.75	0	90	1	0	70	0
105	0.5	0.5	0	90	1	0	70	0
106	0.1	0.9	0	90	1	0	70	0
107	0.9	0.1	0	90	1	0	5	0

Appendix 1.C

Figure 1.C.3 *Illustrative examples of lognormal priors used in Bayesian Hierarchical model*



Note. Panels show four different log-mean and three log-standard deviation (SD) examples. Panel (a) shows the probability density function for log-mean = -2.3 (ca. $\ln 0.1$) and log-SD = 0.5, 1, & 1.75. Panel (b) shows distributions for log-mean = 2.3 (ca. $\ln 10$). Panel (c) Shows log-mean = 3.05 (ca. $\ln 21$). Panel (d) shows log-mean = 3.76 (ca. $\ln 43$).

Appendix 1.D

MCMC sampling diagnostics, parameter recovery and sensitivity tests - study 1

Sampling diagnostics

As is customary when applying Markov Chain Monte Carlo (MCMC) sampling, 4 chains were run simultaneously, each chain was composed of 5000 draws (iterations), of which 1000 initial *warm-up* draws were discarded, leaving a total of 16000 draws per chain. To facilitate exploration of difficult posterior parameter spaces with smaller algorithm step-size, the target average proposal acceptance probability was increased from the default of 0.95 to 0.99. Random initial values were specified to the range [-1,1].

Computational checks are an important feature of the MCMC modelling workflow (Baribault & Collins, 2023). Sampling passed diagnostic checks²⁵, and sampling statistics are reported in Table D.1. Note the standard errors (SE) of posterior estimates were quite low, except for a subset of participant's reference point (M) estimates; however, the median SE for M was 0.32 and the 3rd Quartile was 0.66, meaning most individuals had small SEs.

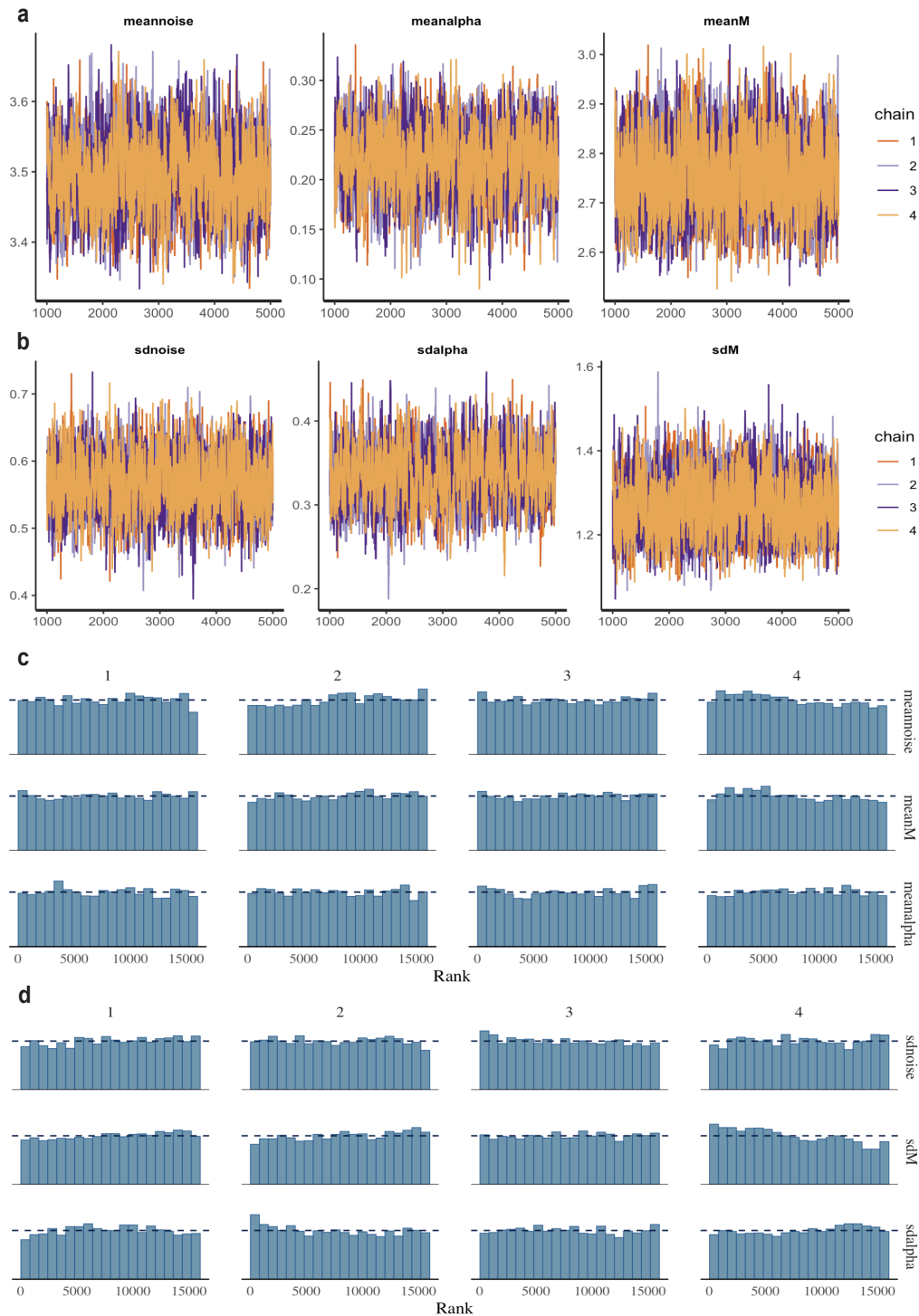
Table D.1 *Sampling specifications and diagnostic for study 1*

Sampling specifications		Sampler Diagnostics <i>(across 4 chains)</i>	
Chains	4	Divergent transitions	0, 0, 0, 0
Iterations per chain	5000	\hat{R}	0.99 to 1.01
Warm-up	1000	ratio of effective to actual sample size (min & max)	0.05 1.59
Total Samples (across 4 chains)	16000	E-BFMI	0.31, 0.27, 0.29, 0.27
adapt_delta	0.99	maximum tree depth	7, 7, 7, 8
init_r	[-1,1]		
ESS Summary stats.	Median	Min	Max
	14413.0	797.9	25516.7
SE range: priors	SE range: α	SE range: M	SE range: noise
0.001 to 0.002	0.001 to 0.01	0.01 to 5.58	0.06 to 0.98

²⁵ RStan also performs a subset of these diagnostic checks automatically and provides warnings with the MCMC sampling results if the algorithm fails to pass these tests.

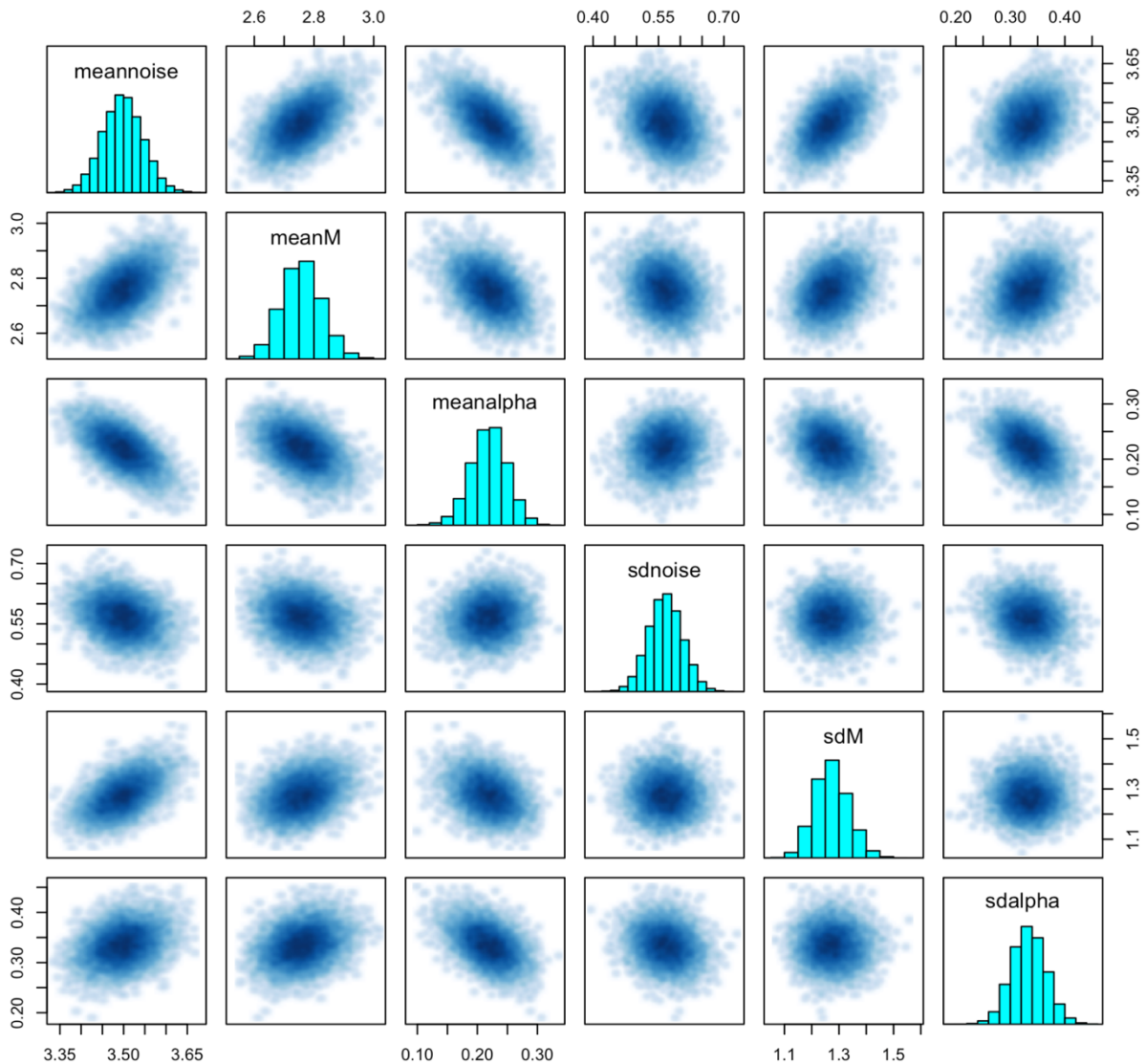
Figures 1.D.1a and D.1b show plots of iterations across chains (trace plots) for prior variables (mean and SDs); there appeared to be agreement across chains. All priors appeared to be centred within the expected range of values, which is also visible in Figure 1.D.2 presenting pairs plots for priors. It was not feasible to present plots for all participant's individual parameters (of which there are $3 \times 853 = 2559$). Rank plots across chains for the prior parameters appeared uniformly distributed (Figure 1.D.1c and D.1d), further suggesting convergence across chains.

Figure 1.D.1 Trace and rank plots characterising iterations across MCMC sampling of prior parameter posteriors



Note. Group-level prior estimates: panel (a) shows trace plots for mean noise (ζ), mean alpha (α) and mean reference points (M). Panel (b) shows trace plots for standard deviations (sd) of noise (ζ), alpha (α) and reference points (M). Panel (c) shows rank plots for mean noise (ζ), mean reference points (M) and mean alpha (α). Panel (d) shows rank plots for standard deviations (sd) of noise (ζ), reference points (M) and alpha (α).

Figure 1.D.2 Pairs plots for prior parameters: distributions of posterior sampling and their relationships



Note. Plots show mean of noise (ζ), alpha (α) and reference points (M); and standard deviation (sd) of noise (ζ), alpha (α) and reference points (M).

Parameter recovery & sensitivity tests

Two parameter recovery checks were performed for the model:

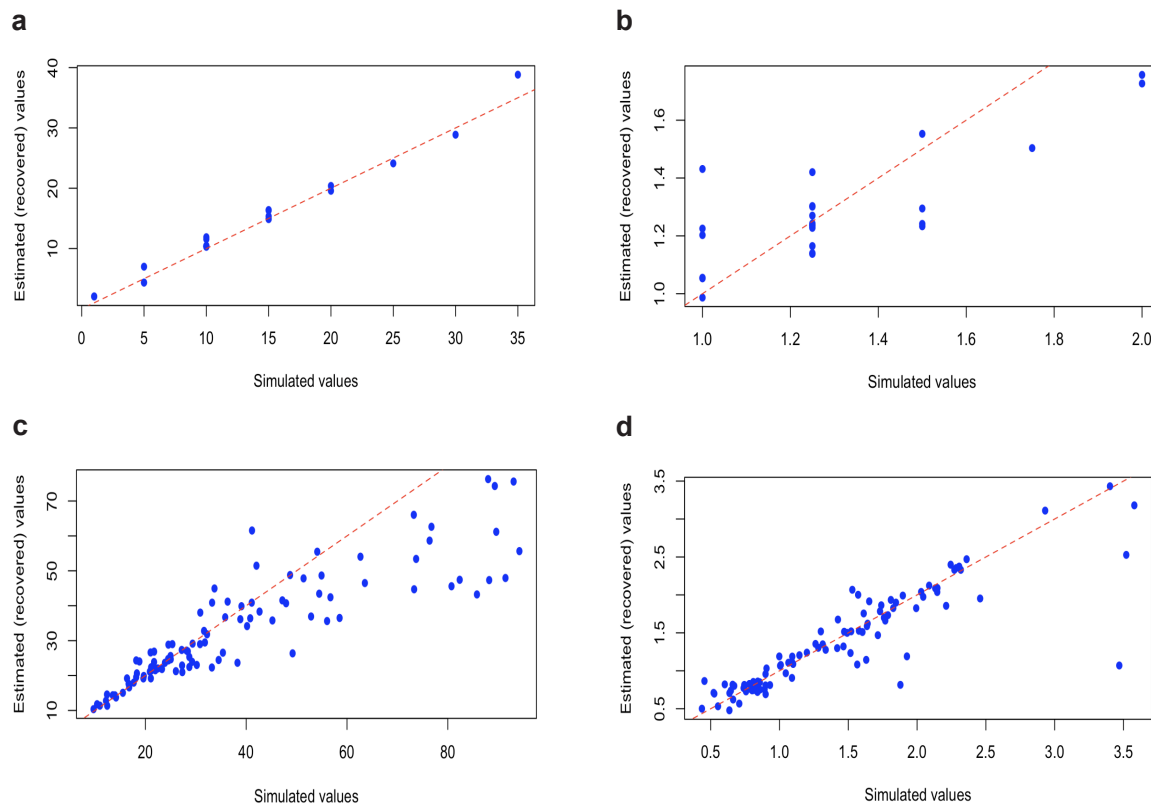
1. A dataset of 25 individuals was simulated where reference points (M) and α were handpicked so that M s were: 1, 5, 10 [mode], 15, 20, 25, 30 and 35; and α were: 1, 1.25 [mode], 1.5, 1.75 and 2. The noise term (ζ) was generated by random draws so that it was lognormally distributed (mean-log 2, SD-log 0.5).
2. A data set of 100 individuals was simulated so that all three parameters were randomly drawn and lognormally distributed. For reference point (M): mean-log =

3.5, SD-log = 0.5. For α : mean-log = 0.22, SD-log = 0.5. For noise (ζ): mean-log = 3.5, SD-log = 0.5.

For both simulation 1 and 2 there were computational warnings indicating divergent transitions, tree-depth being exceeded, ESS being low, and chains not mixing. The computational diagnostics were likely due to the noise term being extremely large across individuals and at the group level. Moreover, the estimated noise terms were not correlated with the simulated estimates. This was likely the result of the sampling algorithm attempting to account for the high degree of determinism of the simulated choices (given these were defined strictly according to the subjective value [ESVT] model). In effect, the noise term was estimated to imply a near step-function characterising the probability of choosing one option over the other according to relative lottery evaluations.

For simulation 1 and 2, parameter recovery was very accurate and indicated the BHM was able to capture a variety of true underlying parameter values. For α , the correlations between the true simulated values and the median of the posterior (recovered values) were $r_p(23) = 0.80$, $p < 0.001$ and $r_p(98) = 0.88$, $p < 0.001$. For reference points, the correlations were $r_p(23) = 0.99$, $p < 0.001$ and $r_p(98) = 0.89$, $p < 0.001$. Figure 1.D.3 illustrates these associations as scatterplots for true and sampled α and reference point values (M). There did appear to be some measurement error for reference points that appeared weekly associated with the magnitude of the reference point: roughly, values larger than the max reward of the lottery task (\$43).

Figure 1.D.3 Scatterplots showing association between simulated parameters and their MCMC estimated (recovered) values, applying the BHM utilised in study 1



Note. Panel (a) shows scatterplot for reference points (M) from simulation 1 ($n = 25$). Panel (b) shows scatterplot for α from simulation 1 ($n = 25$). Panel (c) shows scatterplot for reference points (M) from simulation 2 ($n = 100$). Panel (d) shows scatterplot for α from simulation 2 ($n = 100$).

Alternative noise term

The prior noise term parameter was chosen based on the ML estimated noise term to have a normal distribution with mean 21, and standard deviation 10. Despite being relatively diffuse, this represents a weakly informative prior. To further check the sensitivity of the BHM results to informative priors, the noise term was re-defined to have a mean of 5 and standard deviation of 2.5. This value was informed by Nilsson et al. (2011), who used a range of 0.1 to 5 for their noise prior. As with the first model, this model passed simulation diagnostics and visual inspection of trace, rank and pairs plots; indicating chains had converged and the algorithm had explored the posterior distribution well. Correlations were calculated between participant-level estimates of α , reference points (M) and noise terms across the two BHMs: applying normal noise centred on 21 (the main model) versus normal noise centred on 5.

Correlations were for α : $r_p(851) = 0.9996$, for reference points: $r_p(851) = 0.9999$, and for noise term: $r_p(851) = 0.9998$; all $p < 0.001$. These high correlations indicate the BHM was robust to variations in (weakly) informative noise priors.

MCMC sampling diagnostics, parameter recovery and sensitivity tests - study 2

Sampling diagnostics

Sampling specifications and diagnostics for study 2 are reported in Table D.2. Sampling passed automatic diagnostics and performed well across all measures of convergence and simulation sample size. As the diagnostics for the BHM were good applying a lower number of iterations than in Study 1, this was preferred for ease of replication. The SEs of the posterior estimates were quite low, except for a subset of participant's reference point (M) estimates; however, the median SE for M was 0.64 and the 3rd Quartile was 1.27, meaning most individuals had smaller SEs.

Table D.2 *Sampling specifications and diagnostic for study 2*

Sampling specifications		Sampler Diagnostics <i>(across 4 chains)</i>	
Chains	4	Divergent transitions	0, 0, 0, 0
Iterations per chain	2500	\hat{R}	0.999 to 1.003
Warm-up	500	ratio of effective to actual sample size (min & max)	0.10 1.97
Total Samples (across 4 chains)	8000	E-BFMI	0.99, 0.93, 0.96, 0.99
adapt_delta	0.99	maximum tree depth	7, 7, 7, 8
init_r	[-1,1]		
ESS Summary stats.	Median	Min	Max
	14413.0	797.9	25516.7
SE range: α	SE range: M	SE range: noise	
0.001 to 0.012	0.02 to 11.40	0.01 to 0.82	

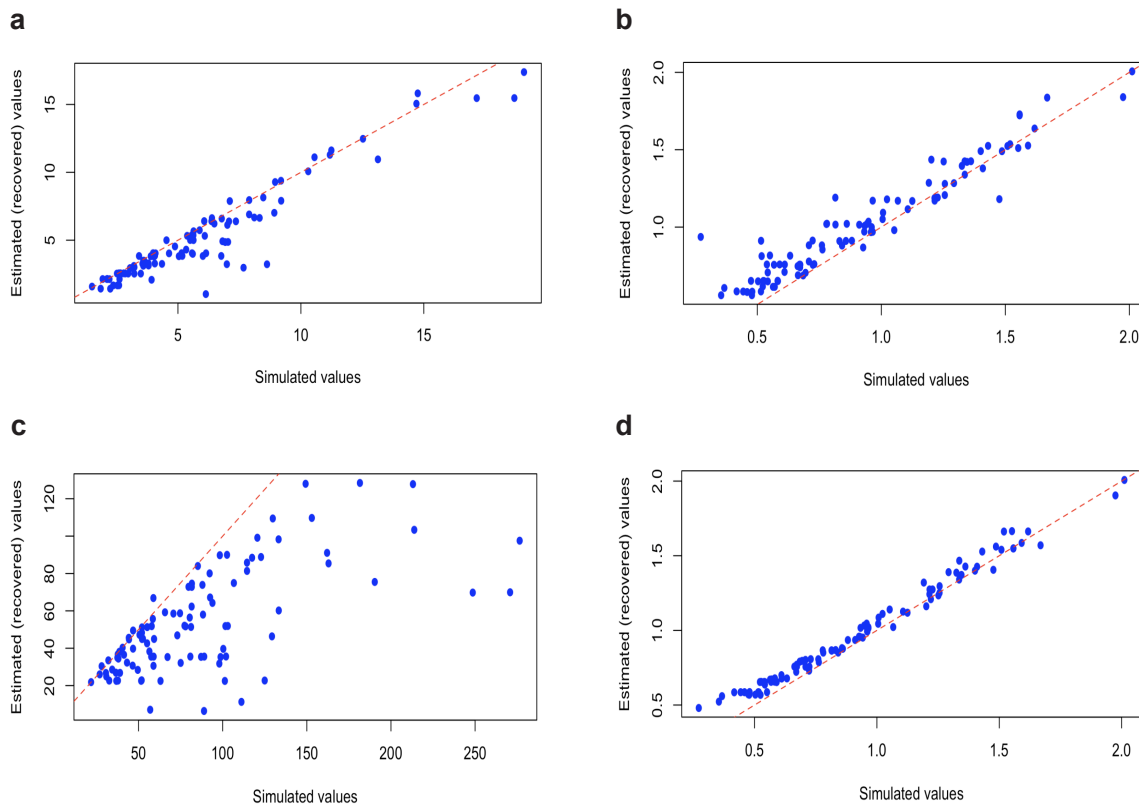
Parameter recovery tests

Two parameter recovery checks were performed for the BHM:

1. A dataset of 100 individuals was simulated where reference points (M) and α were randomly generated so that the mean-log reference points were lower than the median of all the participants' actual estimated reference points (72.52 or in log form 4.28). Specifically, for reference point (M): mean-log = 1.51, SD-log = 0.5. For α : mean-log = 0.84, SD-log = 0.5). And for noise: mean-log = 3.5, SD-log = 0.5.
2. 100 individuals were simulated where the distribution of reference points was randomly generated so the mean-log reference points equalled the median of the actual participants' estimated reference points (72.52 or in log form 4.28). α and noise were the same as in simulation 1. This specification allowed for some individuals to be simulated as having relatively large reference points, clarifying how the model handled these individuals with reference points high above the max reward of the lottery task (\$90).

Both simulation 1 and 2 passed all automatic diagnostic tests. As in the simulation tests for study 1, noise terms were larger than simulated and uncorrelated with the simulated noise terms. For α , the correlations between true (simulated) values and the median of the posteriors were $r_p(98) = 0.96, p < 0.001$ and $r_p(98) = 0.99, p < 0.001$, for simulation 1 and 2 respectively. For reference points, the correlations were $r_p(98) = 0.95, p < 0.001$ and $r_p(98) = 0.68, p < 0.001$, for simulation 1 and 2 respectively. Supplementary Figure 1.D.4 illustrates these associations as scatterplots for true and sampled (recovered) α and reference point values. For simulation 2, there did appear to be some unsystematic measurement error for reference points (as indicated by the lower correlation).

Figure 1.D.4 Scatterplots showing association between simulated parameters and their MCMC estimated (recovered) values, applying the BHM utilised in study 2



Note. Group-level prior estimates: Panel (a) shows scatterplot for reference points (M) from simulation 1 ($n = 100$). Panel (b) shows scatterplot for α from simulation 1 ($n = 100$). Panel (c) shows scatterplot for reference points (M) from simulation 2 ($n = 100$). Panel (d) shows scatterplot for α from simulation 2 ($n = 100$).

Appendix 1.E

Co-elevated anhedonia and feeling depressed

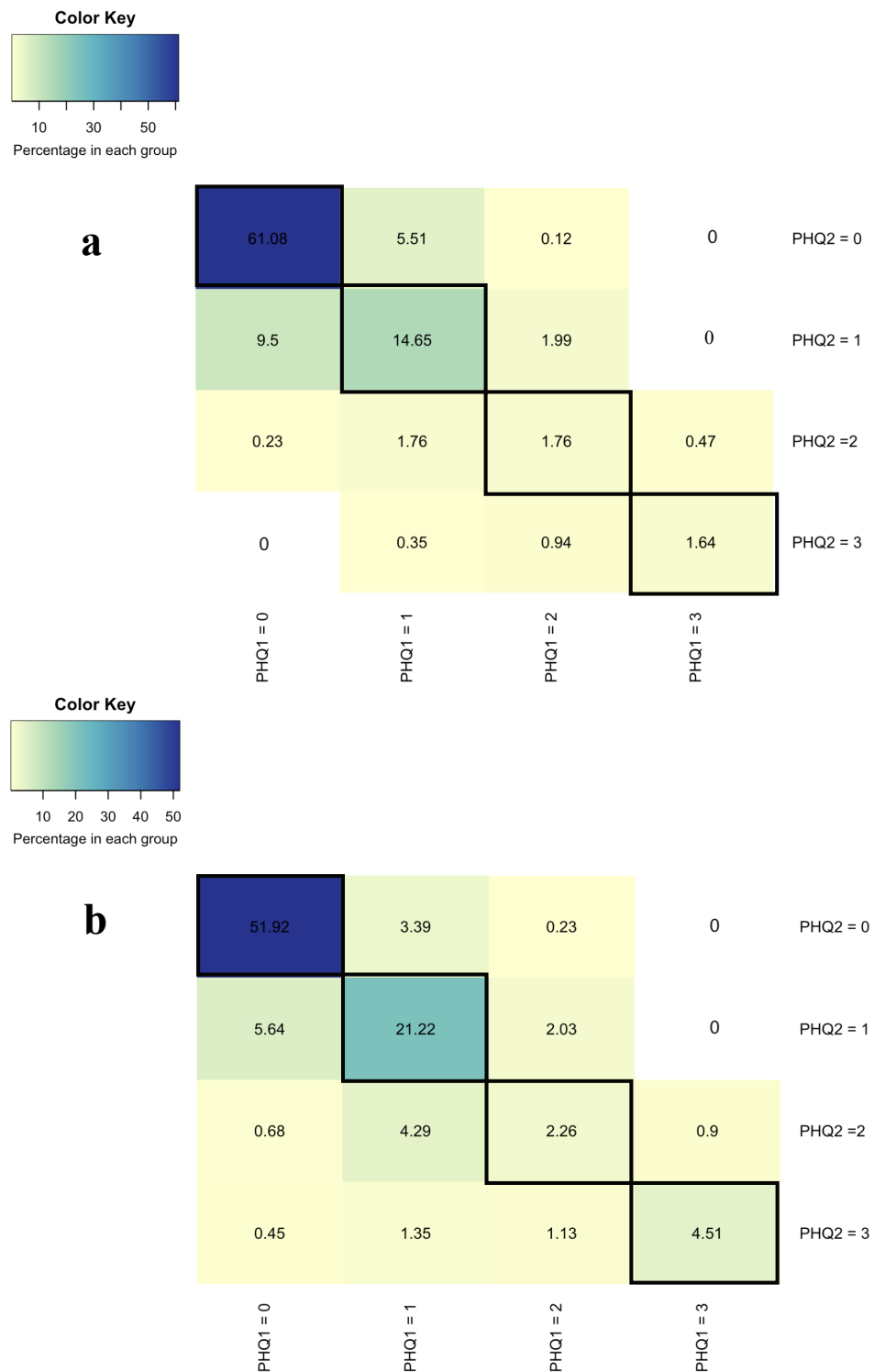
To test the predictions of regression models that elevated anhedonia and depressed mood scores may cancel one another out at the level of the parametric reference point, participants with co-elevated (equal severity) anhedonia and feeling depressed scores were inspected. Table E.1 reports the mean and standard deviations of parametric reference point statistics for participants in study 1 and 2 characterized by co-elevated (equal) severity levels. Overall, there was no strong evidence apparent of an increase nor decrease in the mean reference point by severity groupings. An exception was that for study 1, where the means did appear higher when severity was 2 or 3 (symptoms occurring ‘More than half...’ to ‘Nearly every day’).

It is important to note that anhedonia and feeling depressed are not perfectly colinear. When considering only participants reporting at least some symptoms of either anhedonia and/or feeling depressed, ca. 54% and 42% did not report equally elevated symptoms in study 1 and study 2, respectively. This is illustrated in Figure 1.E.1a and 1.E.1b. In these participants with greater severity of one symptom, divergent associations between mood and reference points may be more salient.

Table E.1 *Individual reference point estimates for participants with equally severe anhedonia and feeling depressed scores (study 1 and 2)*

Reference points	Anhedonia = 0 & Feeling depressed = 0	Anhedonia = 1 & Feeling depressed = 1	Anhedonia = 2 & Feeling depressed = 2	Anhedonia = 3 & Feeling depressed = 3
Study 1				
Mean	22.99	22.00	36.38	35.11
St. dev.	20.42	20.89	30.15	34.12
N	521	125	15	14
Study 2				
Mean	67.38	77.31	62.02	60.31
St. dev.	92.01	62.08	66.94	54.22
N	230	94	10	20

Figure 1.E.1 Percentage of sample by severity grouping (study 1 and study 2)



Note. The sample percentages for each grouping of anhedonia (PHQ1) and feeling depressed (PHQ2) scores are reported inside colour-coded heatmaps. Black frames contain percentages for participants with equal severity of anhedonia and despair. Panel (a) shows percentages for the sample in study 1 ($n = 853$) and panel (b) shows for the sample in study 2 ($n = 443$).

Association between parametric- and stated- reference points

For study 2, the association between parametric reference points and stated reference points were examined. Table 1.9 shows parametric reference points were significantly positively correlated with both pre- and post-task reward predictions, but not with reservations wage nor income expectations. This suggests there was consistency overall between self-reported (conscious) and parametric (implicit, behavioural) reference points for the lottery task. Further, long-term expectations were consistent: the correlations between income expectations in 1-year and 5-years was positive, $r_p = 0.71$, $p < 0.001$.

Table E.2 *Correlations between parametric and stated reference points (study 2)*

	Parametric reference point (M)	Reservation wage	Pre-task reward prediction	Post-task reward prediction	Income expectation (1 year)
Reservation wage	0.0631				
Pre-task reward prediction	0.0934*	0.0624			
Post-task reward prediction	0.1606***	0.0806+	0.3731****		
Income expect. (1 year)	0.0414	0.1427**	-0.0271	0.0562	
Income expect. (5 year)	0.0603	0.0642	0.1227**	0.1230**	0.7152****

Note. Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.001$

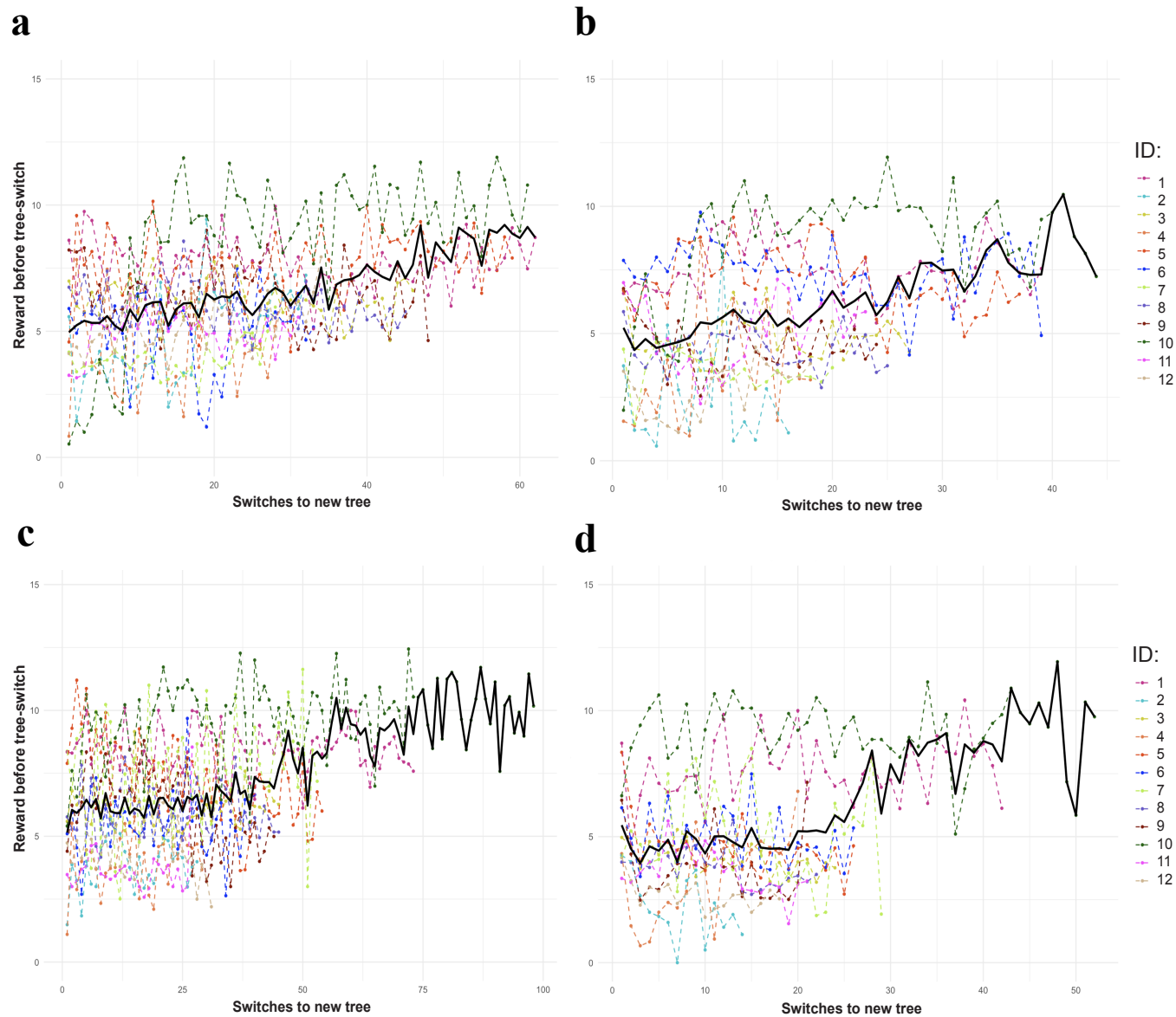
Appendix 1.F

Figure 1.F.1 displays the time-series of reward expectations for each participant separately. Comparing across orchards with short and long travel (A to B and C to D) indicated that reward expectations were higher for short orchards. Moreover, there were more data points for short travel by design due to the higher number of trees encountered. Two participants (IDs 1 and 10) had a longer reward process (due to sooner tree-switches).

As noted above, there were two individuals with a longer reward process that risked having an outsize effect on estimates. Tables F.1 and F.2 show that limiting the length of the reward process for each participant at each time point to a maximum of 35 for short and long travel orchards separately, yielded comparable results to those reported in Table 1.8 and Table 1.9. The main difference was that the main effect of anhedonia in the model sans controls was non-significant, ‘Pooled (4)’. Moreover, the coefficient on the travel time dummy was less frequently significant (which was expected given less comparisons were possible between short and long orchards).

Multicollinearity was investigated given high correlations between anhedonia and feeling depressed: $r_s = 0.82$, $p < 0.001$. A non-concerning variance inflation factor (VIF) was observed when including only anhedonia, feeling depressed, time-point- and travel-time-dummies in a pooled OLS without interaction terms (max was 3.17 for feeling depressed). Similarly, the R-square of 0.62 from regressing anhedonia on the remaining variables in this list was not of concern. When all control variables were included, the VIF for feeling depressed notably rose to 7.04; still below the rule of thumb value 10 taken to indicate problematic multicollinearity. Including controls only raised the R-square for the regression predicting anhedonia a little, to 0.70.

Figure 1.F.1 *Time-series of reward expectations for each participant*



Note. Panels show the individual time-series of rewards prior to switching apple trees for participants separately. Panel (a) shows rewards for orchards with short travel time in time 1 (first time completing the task). Panel (b) shows rewards for orchards with long travel time in time 1. Panel (c) Shows rewards for orchards with short travel time in time 2 (second time completing task). Panel (d) shows rewards for orchards with long travel time in time 2.

Table F.1 Reward expectations (reward before tree-switch) regressed on orchard travel-time, total PHQ-9 score and time-point - only the first 35 tree-switches

	Pooled (1)	Pooled (2)	Pooled (3)	Pooled (4)	Pooled (4) controls	FE (4)	RE (4)
Intercept	5.380*** (0.618)	5.503*** (1.030)	5.241*** (1.151)	5.644*** (1.696)	11.214** (3.655)		5.042** (1.635)
Short travel	0.690+ (0.363)	0.691+ (0.363)	1.156 (0.716)	1.144 (0.723)	1.438* (0.717)	1.196* (0.525)	1.271+ (0.698)
Total PHQ-9		-0.009 (0.047)	0.010 (0.063)	-0.007 (0.087)	-0.193* (0.088)	0.008 (0.062)	0.006 (0.083)
Short travel by Total PHQ-9			-0.032 (0.050)	-0.031 (0.051)	-0.035 (0.051)	-0.022 (0.045)	-0.023 (0.048)
Time is 2				-0.332 (0.656)	-0.769 (0.662)	0.193 (0.804)	-0.177 (0.620)
Number Obs.	1394	1394	1394	1394	1292	1394	1394
Participants (<i>N</i>)	12	12	12	12	11	12	12
DF	11	11	11	11	10	11	11
R^2	0.023	0.023	0.026	0.029	0.284	0.074	0.026
Adjusted R^2	0.022	0.022	0.023	0.026	0.280	-0.092	0.024
AIC	6208	6209	6208	6205	5395	7443	8989
BIC	6223	6230	6234	6236	5446	13631	16267

Note. Individual- & time-fixed effects ('FE'), random effects ('RE'), and pooled ('Pooled') OLS models, regressing rewards expectations (apples received immediately prior to switching to a new tree) on i) 'Short travel' a dummy reflecting the travel time of the block (baseline comparison is long travel time); ii) 'Time is 2', a dummy variable capturing if the results are for the time 2 measurement (baseline is time 1); iii) 'Total PHQ-9' is the summed total score on the Patient Health Questionnaire (9-items) rated on a 4-point Likert scale (0 = 'Never', 1 = 'Sometimes', 2 = 'Often' and 3 = 'Always'). For panel models, time series ranged from 90-140. Across participants, for each environment (short- and long-travel), only the first 35 time-series was used for each time point. For pooled models, controls ('controls') were i) 'Financial comfort', reflecting self-reported financial comfort given current needs and financial responsibilities, rated on a 7-point Likert scale from 'very poor' to 'prosperous'; ii) 'Is female' a dummy that took the value 1 when a participant reported their gender as 'female' (baseline comparison was 'male'). 'Age' in years calculated by subtracting participants' birth year from the year of completing the study. Anxiety was measured with the Generalised Anxiety Disorder 7-item scale (GAD-7) using total scores. Standard errors in parentheses; all models applied cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Degrees of freedom (DF). For FE and RE, R^2 applies to non-robust estimates. Only models denoted Pooled (4) controls, FE (4) and RE (4) passed F -tests (or χ^2 -test for RE) of overall model significance ($p < 0.05$); not applied to robust models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table F.2 *Reward expectations (reward before tree-switch) regressed on orchard travel-time, anhedonia, feeling depressed and time-point – only the first 35 tree-switches*

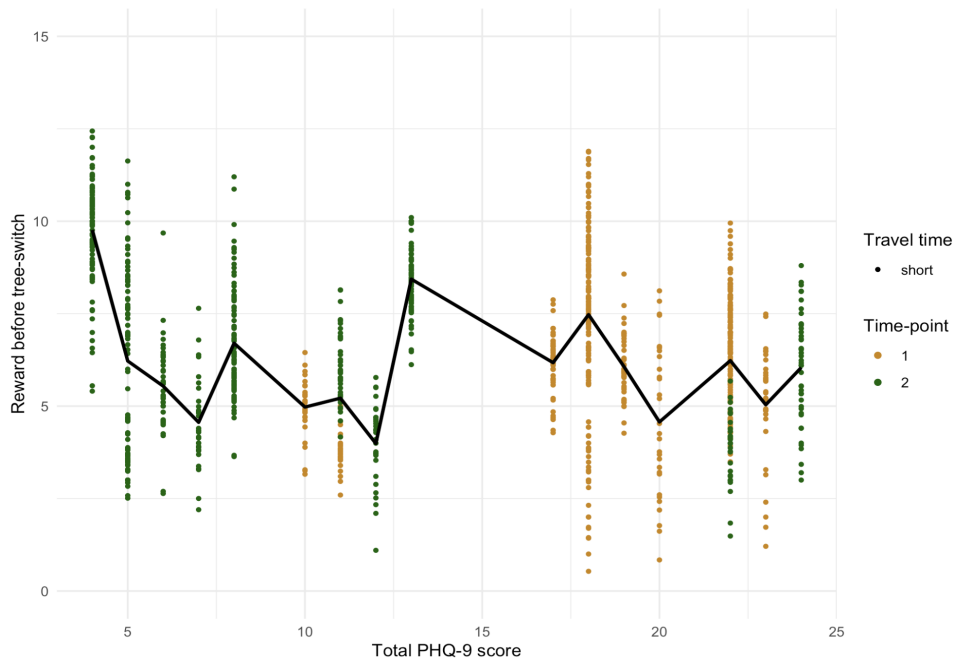
	Pooled (1)	Pooled (2)	Pooled (3)	Pooled (4)	Pooled (4) controls	FE (4)	RE (4)
Intercept	5.380*** (0.618)	5.113*** (0.714)	4.726*** (0.706)	4.313*** (0.776)	7.325** (2.754)		4.867*** (0.847)
Short travel	0.690+ (0.363)	0.747* (0.341)	1.401** (0.500)	1.423** (0.506)	1.622** (0.538)	1.310** (0.414)	1.415** (0.488)
Anhedonia (PHQ1)		-1.061 (0.762)	-1.428 (0.904)	-1.412 (0.904)	-1.700* (0.779)	-0.039 (0.400)	-0.358 (1.055)
Short travel by anhedonia (PHQ1)			0.650 (0.460)	0.626 (0.470)	0.473 (0.533)	0.327 (0.417)	0.556 (0.498)
Feeling depressed (PHQ2)		1.077+ (0.550)	1.607* (0.673)	1.714* (0.676)	0.993* (0.481)	0.102 (0.233)	0.450 (0.880)
Short travel by feeling depressed (PHQ2)			-0.931** (0.294)	-0.923** (0.300)	-0.802* (0.338)	-0.529* (0.262)	-0.745* (0.373)
Time is 2				0.383 (0.522)	0.256 (0.667)	0.179 (0.680)	-0.149 (0.544)
Number Obs.	1394	1394	1394	1394	1292	1394	1394
Participants (N)	12	12	12	12	11	12	12
DF	11	11	11	11	10	11	11
R ²	0.023	0.112	0.129	0.134	0.299	0.086	0.043
Adjusted R ²	0.022	0.110	0.126	0.130	0.294	-0.079	0.038
AIC	6208	6077	6054	6049	5371	7420	8958
BIC	6223	6104	6091	6091	5433	13598	16226

Note. Individual- & time-fixed effects ('FE'), random effects ('RE'), and pooled ('Pooled') OLS models, regressing rewards (immediately prior to switching to new tree) on i) 'Short travel' a dummy reflecting the travel time of the block (baseline comparison is long travel time); ii) 'Time is 2', a dummy variable capturing if the results are for the time 2 measurement (baseline is time 1); iii) anhedonia (PHQ1 item) and feeling depressed (PHQ2 item) from the PHQ-9 scale, rated on a 4-point Likert scale (0 = 'Never', 1 = 'Sometimes', 2 = 'Often' and 3 = 'Always'). For panel models, time series ranged from 90-140. Across participants, for each environment (short- and long-travel), only the first 35 time-series was used for each time point. For pooled models, controls ('controls') were i) 'Financial comfort', reflecting self-reported financial comfort given current needs and financial responsibilities, rated on a 7-point Likert scale from 'very poor' to 'prosperous'; ii) 'Is female', a dummy that took value 1 when a participant reported their gender as 'female' (baseline comparison was 'male'). 'Age' in years calculated by subtracting participants' birth year from the year of completing the study. Anxiety was measured with the Generalised Anxiety Disorder 7-item scale (GAD-7) using total scores. Standard errors in parentheses; all models applied cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Degrees of freedom (DF). For FE and RE, R² applies to non-robust estimates. All models except models denoted 'Pooled (1)' passed F-tests (or χ^2 -test for RE) of overall model significance ($p < 0.05$); not applied to robust models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

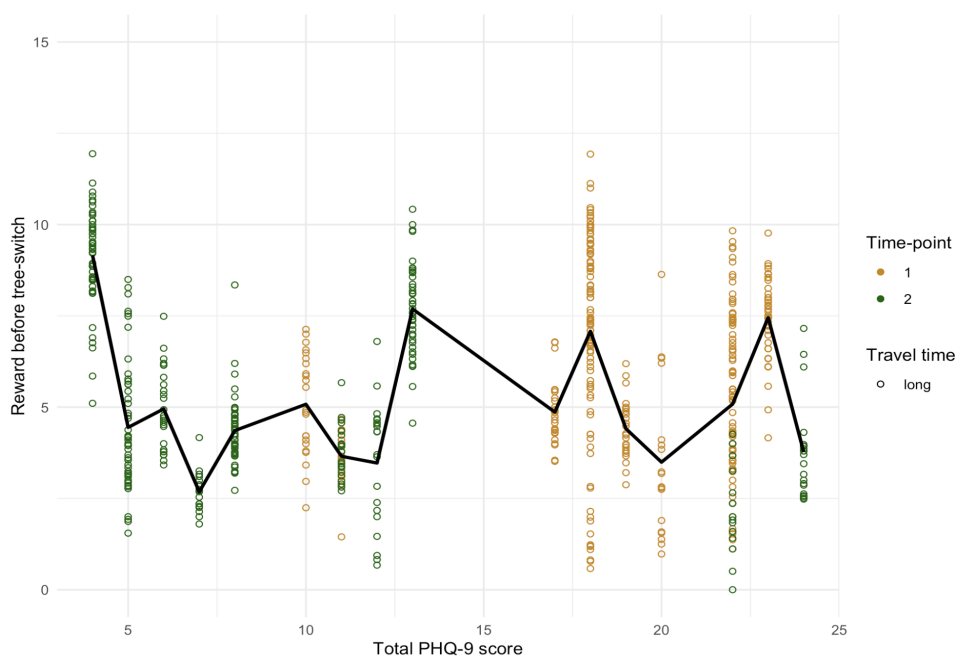
To identify potential non-linearities, scatterplots were inspected between reward expectations and depressive symptoms capturing their cross-sectional relationships – these are displayed in Figure 1.F.2. Clear non-linearities were not apparent for total PHQ-9 scores; nor was this indicated for anhedonia nor feeling depressed (see Figure 1.15 in main text). However, for comprehensiveness, and to identify non-linearity in the time-series estimates, models were estimated with anhedonia and feeling depressed as dummy variables according to severity (baseline being no symptoms reported). These models are reported in Table F.3. The magnitude of the significant coefficients increased according to severity for anhedonia. Conversely, it appeared that dummy-coding left feeling depressed a less reliable predictor of reward expectations across models. For fixed effects, a change in feeling depressed was associated with a lower reward expectation. This difference may be due to interaction effects being excluded given the high number of terms that would have been required when using dummy-coding. Given similarity of results, and to keep the model simple while including interaction terms, the non-dummy models were preferred (i.e., Table 1.9).

Figure 1.F.2 Pooled reward expectations by total PHQ-9 scores

a



b



Note. Panels show reward expectations (apples before tree-switch) cross-sectionally by total PHQ-9 scores and by whether the orchard involved a short travel time (a) or a long travel time b).

Table F.3 Reward expectations (reward before tree-switch) regressed on orchard travel-time, anhedonia, feeling depressed and time-point – dummy-variable approach

	Pooled (1)	Pooled (2)	Pooled (3)	Pooled (4)	Pooled (5)	FE (5)	RE (5)
Intercept	5.581*** (0.686)	7.492*** (1.634)	4.961*** (0.969)	7.763*** (1.969)	7.227*** (1.976)		7.348* (3.145)
Short travel	1.002*** (0.267)	0.994*** (0.284)	1.010*** (0.261)	1.018*** (0.283)	1.005*** (0.282)	0.996*** (0.271)	1.018*** (0.283)
Anhedonia (PHQ1) severity 1		-2.362 (1.615)		-2.808+ (1.600)	-2.717+ (1.627)	-0.757 (0.874)	-0.874 (2.758)
Anhedonia (PHQ1) severity 2		-1.716 (1.337)		-3.948* (1.861)	-3.752* (1.863)	-0.686 (0.879)	-0.795 (2.830)
Anhedonia (PHQ1) severity 3		-2.281 (1.696)		-5.481* (2.389)	-5.408* (2.392)	-1.259 (1.147)	-1.290 (3.945)
Feeling depressed (PHQ2) severity 1			0.473 (1.436)	-0.287 (1.142)	-0.197 (1.082)	-2.023* (0.932)	-1.766 (1.202)
Feeling depressed (PHQ2) severity 2			0.704 (1.286)	1.154 (1.390)	1.397 (1.227)	-1.660 (1.047)	-1.301 (1.969)
Feeling depressed (PHQ2) severity 3			0.835 (1.019)	2.913* (1.398)	3.263** (1.096)	-1.341 (1.049)	-1.190 (2.058)
Time is 2					0.454 (0.552)	-0.360 (0.624)	-0.217 (0.578)
Num. Obs.	1720	1720	1720	1720	1720	1720	1720
Partici. (N)	12	12	12	12	12	12	12
DF	11	11	11	11	11	11	11
R^2	0.042	0.137	0.051	0.230	0.235	0.137	0.073
Adj. R^2	0.041	0.135	0.049	0.227	0.231	-0.026	0.069
AIC	7798	7623	7786	7433	7425	9027	11242
BIC	7815	7656	7819	7482	7479	16908	20567

Note. Individual- & time-fixed effects ('FE'), random effects ('RE'), and pooled ('Pooled') OLS models, regressing rewards on i) 'Short travel' a dummy reflecting the travel time of the block (baseline comparison is long travel time); ii) 'Time is 2', a dummy variable capturing if the results are for the time 2 measurement (baseline is time 1); iii) anhedonia (PHQ1 item) and feeling depressed (PHQ2 item) from the PHQ-9 scale dummy-coded by severity (baseline is severity = 0: 'Not at all'), rated on a 4-point Likert scale (0 = 'Never', 1 = 'Sometimes', 2 = 'Often' and 3 = 'Always'). For panel models, time series ranged from 90-255. For pooled models, a model with controls was not estimated due to the number of regressors exceeding or near exceeding the number of clusters. Standard errors in parentheses; all models applied cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). For FE and RE, R^2 applies to non-robust estimates. All models passed F -tests (or χ^2 -test for RE) of overall model statistical significance ($p < 0.05$); not applied to robust models. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chapter 2. Regret and decision-making: links between self-report and behavioural measures of regret

Abstract

Regret is an important emotion for understanding economic decision-making. A broad literature has developed eliciting regret with various methodologies, however, the correlation across methods is less clear. This paper examines the consistency of regret as a phenomenon: regret was elicited in three different ways across different stages of decision-making i) as self-reported (perceived) regret proneness before decision-making, ii) behavioural regret aversion during decision-making, iii) and post-decisional affect ratings following feedback on choices. Participants generally exhibited behavioural regret aversion, although there was individual variation in whether behaviour agreed with Regret theory. Importantly, the link between self-reported regret and behavioural regret aversion was weak and task dependent. Otherwise, post-decisional affect ratings were negative following feedback designed to elicit regret, and this pattern was stronger for those who self-reported a greater tendency towards regret. There was also mixed evidence for a temporal link between exposure to regret and subsequent regret averse behaviour. Overall, findings suggest regret may not be a unidimensional construct. Self-reported regret proneness and associated affective experiences may be separate phenomena from regret aversion measured behaviourally. This has implications for how methodologies are applied and interpreted in future research.

Key words: *economic, regret, behaviour, self-reports, decision-making*

2.1 Introduction

“If only I had chosen otherwise” exemplifies the regret that can follow one’s decision. Even the anticipation of regret can influence one’s appraisal of options and ultimately choice. Accordingly, regret has garnered a significant literature in the context of decision-making. This literature spans economics (Baillon et al., 2014; Bell, 1982; Birnbaum & Diecidue, 2015; Bleichrodt et al., 2010; Loomes & Sugden, 1982, 1987), finance (Fioretti et al., 2022; Lin et al., 2006), insurance (Braun & Muermann, 2004), consumer choice (Tsiros, 1998; Tsiros & Mittal, 2000), neuroeconomics (Camille et al., 2004; Camille et al., 2010; Coricelli et al., 2005; Giorgetta et al., 2013), psychology (Birnbaum & Diecidue, 2015; Broomhall et al., 2017; Roese, 1997; Zeelenberg et al., 1996) and psychiatric pathology (Chase et al., 2010; Eryilmaz et al., 2014; Gillan et al., 2014; Markman & Miller, 2006; Roese et al., 2009; Zheng et al., 2021).

A broad range of measures and experimental methodologies have been applied to understanding the influence of regret. These have centred on collecting self-reports about people’s perceived tendency to experience regret or on measuring regret behaviourally as decision-making patterns. Self-report methods can vary in either pertaining to i) decision-making/choice situations (e.g., “Whenever I make a choice, I try to get information about how the other alternatives turned out.”, in Schwartz et al., 2002); ii) more general thinking-styles or attitudes (Roese et al., 2009); or iii) specific types of counterfactual cognitions, regarding oneself or others (Rye et al., 2008). These measure regret as a trait-like propensity or tendency. In turn, one might expect that such perceived tendencies would be associated with both actually experiencing more regret affectively (when the situation dictates) and with behaviour indicating a greater awareness or sensitivity to potential regret.²⁶ The latter is often measured using choices between options designed to vary in potential regret. This allows for testing whether regret shapes preferences and choice, including whether potential regret is avoided: *regret aversion*. Overlap across self-report and behavioural measures would suggest convergent validity for regret as a concept. However, conflating self-report and behavioural measures has been criticised on account of low correlations between these for certain constructs (Dang et al., 2020). For example, self-report and behavioural measures may not measure the same underlying phenomenon of self-control (Allom et al., 2016; Duckworth &

²⁶ *Affective forecasting* is a related but different topic to the focus here.

Kern, 2011; Wennerhold & Friese, 2020) nor risk-preferences (Bagaiini et al., 2025). Whether this applies to regret warrants further understanding. As emphasised by Bagaiini et al. (2025), obstructing clarity regarding the overlap or convergence across measurement is a piecemeal approach of adopting only one measure in research. This paper empirically explores the association between three types of regret i) regret measured via self-reports before decision-making, ii) regret aversion (i.e., sensitivity) measured behaviourally from decision-making patterns, and iii) post-decisional affective experiences after receiving feedback designed to elicit regret. The methodology used to elicit regret behaviourally adapted approaches used within economics, neuroeconomics and psychology. Individual overlap across different regret measures can be taken as support that these are measuring a unitary concept or construct, while an absence of overlap would challenge such an inference regarding regret. For economists, particularly behavioural and experimental economists, clarifying the convergent validity of regret can help clarify what inferences are warranted by each method. This may provide better guidance for elucidating the role of regret in economic decision-making.

2.1.1 Regret as a decisional emotion

“Regret is the emotion that we experience when realizing or imagining that our current situation would have been better, if only we had decided differently.” (Zeelenberg & Pieters, 2007, p. 1). Regret therefore involves a comparison of what occurred to what could have hypothetically occurred, if one had taken a *different course of action*; this alternative outcome acts as a reference point against which the received outcome is compared. The focus on the counterfactual choice or action in this definition distinguishes regret from *disappointment*, which involves a simple comparison between the obtained versus hypothetical or expected outcome of the chosen option (Zeelenberg et al., 1998) (e.g., “I’m disappointed that my flight was cancelled”). Moreover, regret is the opposite of *relief*²⁷, which involves a comparison where the current situation or outcome is better than that of the hypothetical alternative choice.

Regret is an example of *upward counterfactual thought* (e.g., ‘if I’d studied more, I could have done *better*’), and often involves an undoing of past events that has been conceptualised as a type of natural human tendency (e.g., *simulation heuristic*, Kahneman and Tversky

²⁷ Some models use the word ‘rejoice’ instead of ‘relief’.

(1982)). Such a tendency may aid in decision-making (Byrne, 2016); specifically, the negative affect associated with regret may act as a biological learning signal to spur an organism towards corrective action (Roese, 1997), particularly in situations when one's environment does not correspond with one's current hedonic adaptation level (Kahneman & Tversky, 1982). Moreover, counterfactual thought appears to become automatically activated during negative affect, and will tend to revolve around negative, usually extreme, outcomes of a situation (Roese, 1997). However, counterfactual thought may also produce further negative affect. Therefore, to avoid negative affect, people may imagine a lower counterfactual outcome (i.e. *downward counterfactual thought*) in order to maintain positive affect or repair negative affective states (Johnson et al., 2012; Parikh et al., 2021). Accordingly, economists have highlighted that the potential for experiencing regret may enter one's utility function and shape both preferences and choice (Bell, 1982; Loomes & Sugden, 1982). Accordingly, experimentally-induced regret has been found to predict choice behaviour (e.g., Coricelli et al. (2005)). Overall, "...counterfactual thinking may be seen primarily as a useful, beneficial, and utterly necessary component of behaviour regulation." (Epstude & Roese, 2008, p. 3).

As noted, methodologically, one's perceived tendency to experience regret can be directly assessed with targeted self-report questions pertaining to decision-making; Schwartz et al. (2002) provide such a scale. However, for behavioural methods, a broad number of models and methods have been developed, warranting a further summary. The next section therefore summarises past models and methods, providing further context for the methodology used here. This summary highlights the variety of ways that regret-effects have been conceptualised. To stay within scope, this is necessarily a selective not exhaustive summary.

2.1.2 Models, theories and methods for eliciting regret behaviourally

Regret has tended to be operationalised behaviourally as involving a comparison of (usually two) options, where the outcomes one may receive are compared to the outcomes one may forego. Regret is then identified behaviourally via choice patterns modelled as a function of the relatively regret of one option over the other. Furthermore, economists have tended to focus on behavioural tasks that allow testing various utility- or value- functions proposed to capture the influence of regret. Both these approaches are reviewed.

To aid in describing these approaches, assume a simple choice context consisting of two prospects, ‘1’ and ‘2’, referred to as *lotteries*; each having two possible outcomes, x or y ; where $x > y$, and their respective probabilities are p and $(1 - p)$, where $0 < p < 1$. These two lotteries can thus be described as $(x_1, p_1; y_1, [1 - p_1])$ and $(x_2, p_2; y_2, [1 - p_2])$, the subscript referring to lotteries 1 and 2.

Savage (1951)’s *minmax principle* – where the decision-maker is modelled as aiming to minimize the maximum loss – is an early model that conceptually overlaps with regret. Another example is Lee (1971a, 1971b)’s models, where the preference for a lottery 1 over an alternative lottery 2 is determined by the *Expected Regret Ratio*. The interesting element is that the numerator of this ratio for lottery 1 is a probability-weighted difference score, $p(x_1 - x_2)$. Note in Lee’s model the two lotteries are *correlated*. Correlated prospects share the same probabilities or *states of the world* ($p_1 = p_2 = p$): in state p the outcome received is x_1 if one chose lottery 1, and x_2 if one chose lottery 2, and accordingly y_1 or y_2 if the state is $(1 - p)$.

Subsequent literature within psychology and neuroeconomics (Camille et al., 2004; Coricelli et al., 2005; Gillan et al., 2014) has defined regret sans outcome-probabilities. As an example, a person’s probability of choosing lottery 1 over 2 can be modelled as a function of *anticipated regret* (r),

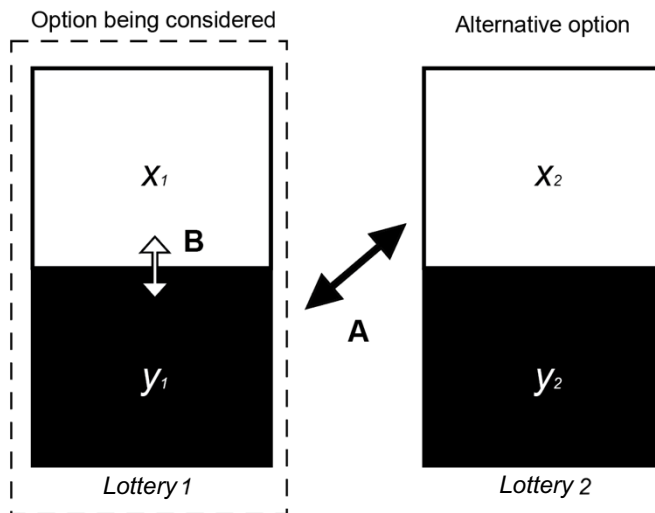
$$r = |(y_2 - x_1)| - |(y_1 - x_2)|,$$

where r captures whether the relief-difference, $|(y_2 - x_1)|$, associated with option 1 (because $x > y \rightarrow x_2 > y_1$ and $x_1 > y_2$) is large enough to overcome the regret-difference, $|(y_1 - x_2)|$.²⁸ The lotteries are usually left uncorrelated in these experiments (i.e., can have $p_1 \neq p_2$). For intuition, Figure 2.1 illustrates the method of comparison with an abstract example of a choice context involving two uncorrelated binary lottery options. The figure highlights the potential maximum regret (A) and disappointment (B) the decision-maker may experience (anticipate) when considering choosing lottery 1 over lottery 2. Presumably, a

²⁸ Gillan et al. (2014) use a version without taking absolute values, and where the location of the two differences is reversed. Another variation is in Chase et al. (2010), who also calculate a regret score as the difference between the foregone outcome and the expected value of the chosen lottery.

regret averse decision-maker would choose lottery 1 only if they anticipated that this would lead to less maximum regret than choosing lottery 2.

Figure 2.1 *Hypothetical effect of regret during choices between lotteries*



A) is potential regret for lottery 1

B) is potential disappointment for lottery 1

Note. General example of a choice context where one lottery is being considered (1) over another (2). A) Potential regret a decision-maker will anticipate where they compare the high outcome of the lottery that they are considering forgoing (lottery 2) with the low outcome of the lottery they are considering choosing (lottery 1). B) the potential disappointment a person may anticipate when considering lottery 1 (high outcome vs low outcome of same lottery).

Complementing the focus on anticipatory regret, post-decisional (affective) regret ratings have also commonly featured in decision-making studies. These ratings have been elicited after a participant has made their choice, upon seeing the outcome of the option they choose (received) and the option that they did not choose (forgone). Ratings are usually made by participants on numeric scales and anchored with word-labels (the specific display and word-labels have varied across studies) (Camille et al., 2004; Camille et al., 2010; Chase et al., 2010; Coricelli et al., 2005; Gillan et al., 2014; Zheng et al., 2021). Affect ratings can be considered another self-report measure but which are assumed to capture regret experienced immediately post choice (compared to perceptions about one's more general tendencies, captured with questionnaires). Indeed, ratings can be modelled as a function of feedback magnitudes (received vs forgone values) to identify individual variation in affective regret.

For example, in a study of financial decision-making, Lin et al. (2006) applied ordinary least squares (OLS) where subjective regret ratings were regressed on received outcomes and foregone outcomes. The coefficient estimates reflected regret effects according to outcome type: as expected, when investment outcomes were lower than the best counterfactual outcome (i.e., upward counterfactual comparison), this prompted significantly higher regret ratings.

Economists have developed mathematically explicit theories and models of anticipatory regret. These aim to capture a decision-maker's subjective experience of the difference between the potentially received versus foregone outcomes. Two theories (models) developed by Bell (1982) and Loomes and Sugden (1982, 1987) have arguably been seminal. These theories are reference-dependent in highlighting that counterfactual referent outcomes feature as comparison values, shaping one's preferences. Such models align with several other reference-dependent theories of individual preferences that highlight the role of other anticipatory emotions (e.g., Prospect Theory by Kahneman and Tversky (1979), and more recently Köszegi (2010)).

Bell (1982) defined decisional regret as captured by the function $f(\cdot)$, so that $f(x - y)$ captured the regret felt when x is the outcome of the option being considered, whereas y is the outcome of the potentially foregone option.²⁹ Loomes and Sugden (1982) similarly modify the utility function to include a *regret-rejoice function* $R(\cdot)$. Their original explication initially assumed that actions and consequent outcomes were *state-dependent* or correlated. To capture state-dependence better, and to align with these theories, the notation will be switched to that displayed in Table 2.1 involving actions (but these can equivalently be thought of as lottery choices).

²⁹ Bell (1982) contrasted decisional regret with “psychological regret” and made the point that people's decision-regret may also be shaped by how their choices will be seen by others (one's boss for example). In this definition a simplification is applied, also found in Bell (1982), that the value functioning $v(x)$ on x , capturing satisfaction with final asset position, is linear (i.e., $v(x) = x$). In Bell (1982) $f(\cdot)$ is a monotonically increasing and decreasingly concave function.

Table 2.1 Choice context involving two actions between lotteries/prospects that have correlated, state-dependent, outcomes

	State $j = 1$	State $j = 2$	State $j = 3$
Action 1	x_{11}	x_{12}	x_{13}
Action 2	x_{21}	x_{22}	x_{23}

The value of potentially choosing Action 1 (x_{1j}) over Action 2 (x_{2j}) is given by,

$$m(x_{1j}, x_{2j}) = u(x_{1j}) + R(u(x_{1j}) - u(x_{2j})),$$

Where j is determined by nature and $R(u(x_{1j}) - u(x_{2j}))$ reflects the regret-rejoice comparison felt by the decision-maker. Note that $u(\cdot)$ is the ‘choiceless utility’, the utility derived from the objective outcome independent of one’s actions and alternatives. Loomes & Sugden (1982) further define a Q -function that captures the *curvature of regret*, or strength of regret-relief effects. Specifically, if z is taken to capture the difference in utility between the (potentially) received and forgone outcomes, then,

$$Q(z) = z + R(z) - R(-z)$$

The link to $R(\cdot)$ can be seen by considering a situation where a person is indifferent between Action 1 and Action 2,

$$m(x_{1j}, x_{2j}) = m(x_{2j}, x_{1j})$$

Which is equivalent to,

$$u(x_{1j}) + R(u(x_{1j}) - u(x_{2j})) = u(x_{2j}) + R(u(x_{2j}) - u(x_{1j}))$$

Or re-ordering terms,

$$u(x_{1j}) - u(x_{2j}) + R(u(x_{1j}) - u(x_{2j})) - R(u(x_{2j}) - u(x_{1j})) = 0$$

Which, when applying the Q -function and $z = u(x_{1j}) - u(x_{2j})$, becomes,

$$Q(u(x_{1j}) - u(x_{2j})) = 0$$

Finally, including the probabilities associated with each state j , indifference over the two Actions (1 and 2) can be characterised by,

$$\sum_{j=1}^n p_j Q(u(x_{1j}) - u(x_{2j})) = 0$$

When $\sum_{j=1}^n p_j Q(u(x_{1j}) - u(x_{2j})) > 0$, Action 1 is preferred, and when $\sum_{j=1}^n p_j Q(u(x_{1j}) - u(x_{2j})) < 0$, Action 2 is preferred, or,

$$A_1 > A_2 \leftrightarrow \sum_{j=1}^n p_j Q(u(x_{1j}) - u(x_{2j})) > 0$$

A key proposition by Loomes and Sugden (1986) is that $Q(z)$ is convex for all positive values of z . People with preference described by a convex Q -function would be expected to display behaviour indicating sensitivity to the potential regret and relief of a choice-context, including regret aversion. Convexity of $Q(z)$ implies that larger regret and relief differences are felt non-proportional, as opposed to the case of a linear $Q(z)$.³⁰

Regret theory has seen further elaboration beyond the scope of this chapter (Loomes & Sugden, 1982, 1987; Sugden, 1993); see review by Bleichrodt and Wakker (2015). However, few attempts have been made at quantitatively measuring the convexity of the regret function, that is, the strength of regret effects empirically (Andersson et al., 2023). An early example is di Cagno and Hey (1988), who used a two-stage procedure for estimating the choice-less utility and then the regret curvature, based on asking participants to report indifference-values to lotteries. Their results were not strongly supportive of the basic version of Regret theory, described above. Later, based on criticism that earlier methodology confounded regret with

³⁰ The Q -function also has the following properties: $Q(z) = -Q(-z)$, and $Q(0) = 0$.

*event-splitting*³¹, Bleichrodt et al. (2010) used a multi-stage binary choice procedure. This “trade-off method”, first estimates the choice-less utility $u(\cdot)$ and then the regret function curvature $Q(\cdot)$. The authors applied additional methods, including parametrically measuring utility and regret curvature as power functions.³² Bleichrodt et al. found their 55 participants were disproportionately averse to larger regrets (implying convexity), although there was individual variation: about 10% to 1/3 of subjects evidenced concavity instead depending on the test. In a working paper Andersson et al. (2023) closely adopted the methods in Bleichrodt et al. (2010) in their online study of 455 participants.³³ Results were more equivocal, suggesting individual variation and violations of Regret theory. Another approach involves the identification of transitivity violations (intransitivity) predicted by Regret theory (Baillon et al., 2014; Birnbaum & Diecidue, 2015; Birnbaum & Schmidt, 2008). However, at least the cited studies found little evidence thereof.

Methods have been developed to experimentally separate regret aversion from other features of the choice context. In three experiments, Zeelenberg et al. (1996) presented participants with risky or safe lotteries, that also involved potential regret, to disentangle which aspect influenced behaviour. The experiments applied different types of feedback conditions: *partial*, information on only one outcome (chosen) or *full*, information on both the chosen and forgone outcomes. Results pointed towards regret rather than risk driving behaviour because participants became either risk seeking or risk averse as a function of what type of feedback condition they were in (i.e., what type of counterfactual outcome they may be exposed to). That is, participants may have been “...protecting themselves from threatening feedback on the foregone option.” (Zeelenberg et al., 1996, p. 156). Regret effects were found using both mixed lotteries (gain and loss outcomes) and gain-only lotteries³⁴. The authors also observed high-variance lotteries were associated with stronger regret effects. Finally, a small number of participants appeared more motivated to experiencing rejoicing rather than avoid regret, although the latter weighed heavier overall. Somasundaram and Diecidue (2017)

³¹ “According to event splitting, an event with a given probability is weighted more heavily if it is considered as two subevents than if it is considered as a single event” (Bleichrodt et al., 2010), p 162). Baillon et al. (2014) citing Humphrey (2001), recommend that choices/acts have the same number of states, and that zero is avoided as it may drive event-splitting effects.

³² Andersson et al. (2023) noted they attempted but abandoned applying nonlinear least squares to estimate the regret curvature function parametrically due to non-convergence.

³³ Over 50% of the original sample was removed due to various reasons (e.g., incorrect responses to comprehension questions, etc.).

³⁴ Zeelenberg et al. (1996) note that previous research indicates a stronger regret-effect tends to occur for gain-only lotteries.

also attempted to separate out the effect of regret. They used choices between two three-outcome lotteries, designed so that one lottery was preferable to the regret-averse or regret-seeking individual, while holding EV the same between the two choices. Lotteries were presented as matrices similar to Table 2.2 below.³⁵ They assumed linear utility for money (i.e., choice-less utility), arguing past research had born this out for moderate amounts.³⁶ The majority of their participants appeared to be regret averse, and their Q -function curvature parameters indicated convexity.

Three-outcome lotteries, as applied in past studies (Birnbaum & Diecidue, 2015; Somasundaram & Diecidue, 2017), can be adapted to measure regret as violations of the *Equivalence axiom*: “...courses of action associated with identical probability distributions of consequences are equivalent to one another.” (Loomes & Sugden, 1982, p. 818). As explained in Bleichrodt and Wakker (2015), outcomes matched in a particular way leaves two options non-equivalent according to Regret theory yet equivalent according to expected utility theory (EU), expected value (EV) and disappointment-effects.³⁷ Thus, the presence of regret effects, specifically convexity of the Q -function, can be identified. An example of such a context is provided in Table 2.2, involving two three-outcome lotteries: action 1 (x_{11}, x_{12}, x_{13}) and 2 (x_{21}, x_{22}, x_{23}). The probability of each state ($j = 1,2,3$) is identical (say an urn containing 99 balls: 33 coloured red, 33 blue and 33 green).

Table 2.2 *Three-outcome prospects identifying regret aversion (holding EU, EV and disappointment constant)*

	State $j = 1$	State $j = 2$	State $j = 3$
Action 1	450	850	50
Action 2	50	450	850

Regret aversion would predict a preference for 2 over 1 because the difference between the outcomes in each state will not be perceived linearly for a person with a convex Q -function: regretting a larger difference is more painful than the sum of two small differences (see Appendix 2.A for calculation) - Action 1 \prec Action 2 because,

³⁵ The numeric values used for their lotteries (see Somasundaram & Diecidue (2017) Table 16 Appendix B) could be a bit hard for participants to compare, especially those with less developed numeracy.

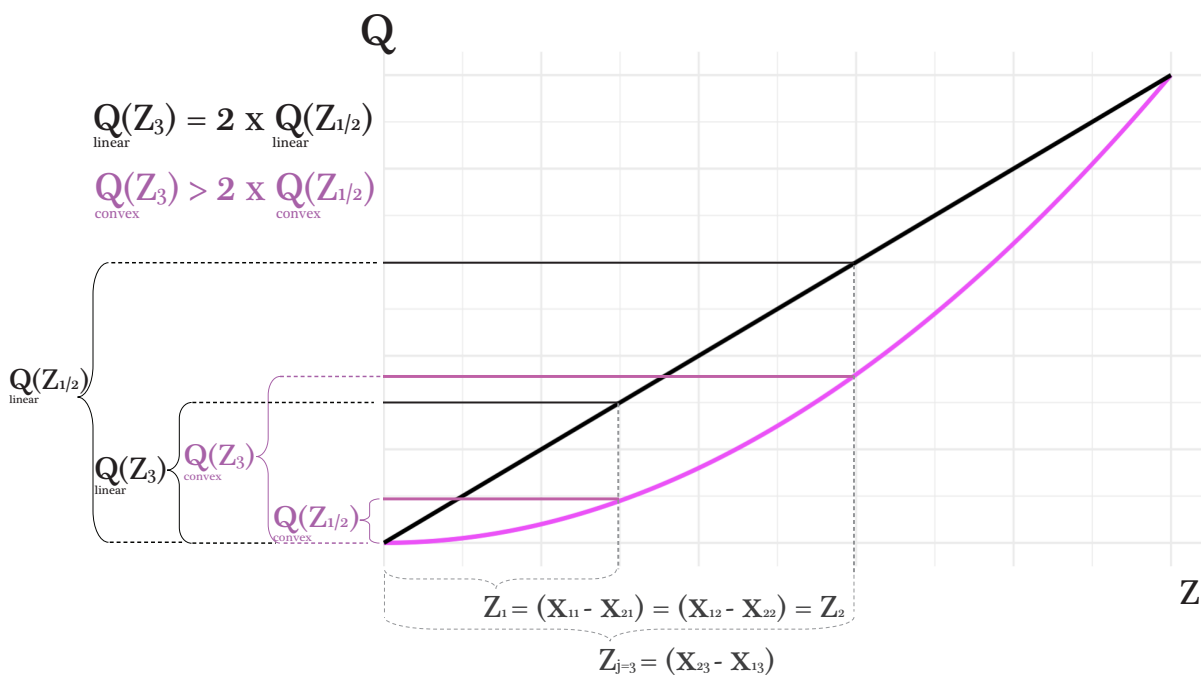
³⁶ Also supported by the estimations presented in Bleichrodt et al. (2010).

³⁷ For examples, Bleichrodt and Wakker (2015, Table 4, p. 498), Zeelenberg et al. (1996, Table 1 p. 149) and Loomes and Sugden (1982, Table 6, p. 822).

$$Q(50 - 850) < Q(50 - 450) + Q(450 - 850)$$

Figure 2.2 illustrates this more generally, here a convex Q -function is contrasted with a linear Q -function: the latter implies regret-relief effects on preferences are absent. Regret theory emphasises that choice patterns exhibiting an avoidance of larger regret differences may be taken as evidence of convex regret preferences (i.e., a regret averse chooser). The decision-maker with a convex regret function will always avoid (seek) an option with a larger potential subjective regret (relief), $Q(z_3)$, even if the alternative leads to two smaller outcomes that are of equal objective value, $Q(z_{1/2})$ (i.e., where $z_1 + z_2 = z_3$).

Figure 2.2 Convex preferences over regret-relief differences



Note. Visual illustration showing convexity of Q -function proposed by Regret theory (Loomes & Sugden, 1982). Here, linear ‘choice-less’ utility is assumed for simplicity (i.e., for objective values, x). When considering choosing Action 1, z_1 reflects the difference between potentially receiving x_{11} and forgoing x_{21} in state $j = 1$, and z_2 reflects the difference between potentially receiving x_{12} and forgoing x_{22} in state $j = 2$. When considering choosing Action 2, z_3 reflects the difference between potentially receiving x_{23} and forgoing x_{13} in state $j = 3$. Note that $z_1 = z_2$ and $z_3 = 2 * z_{1/2}$. A convex Q -function implies $Q(z_3) > 2 * Q(z_{1/2})$, compared to a linear Q -function that implies $Q(z_3) = 2 * Q(z_{1/2})$.

This rationale also extends to lotteries with more outcomes (e.g., four, as described in Loomes and Sugden (1982)). This is a nod back to early minmax conceptions of regret noted at the start of this section: "... that one computes the maximum of possible regret for each option and then chooses the option where this maximum regret is smallest." (Zeelenberg, 1999, p. 94). A benefit of this approach is that there is no difference in terms of event-splitting across prospects, a key concern raised regarding early regret experiments. As for *framing effects* - that matrix displays may be more likely to prompt *up-and-down* comparison required for regret theories than say strip-displays (Humphrey, 2001) - this is less a concern if one is interested in inducing and measuring regret sensitivity and comparing to other methods (as is the aim here). Finally, another elicitation method is *matching* tasks: eliciting indifference-values from participants by asking for a value to fill an outcome left blank (e.g., di Cagno and Hey (1988)). However, Attema and Brouwer (2013) discuss evidence that the latter approach is potentially more vulnerable to inconsistent choices and sensitive to strategic responding, necessitating careful incentivisation for truthful preferences.

2.1.3 Summary and aims

The preceding review highlights the popularity of regret for understanding economic decision-making, while also summarising the variety of approaches used to measure regret effects. This paper seeks to clarify the nature of regret by examining the convergent validity of regret, specifically the degree of overlap between self-reported and behavioural elicitation of regret. For the latter, an attempt was made to remain broad in the methods applied, allowing for various behavioural approaches to be examined and compared with self-reported regret. Overall, the aim was to see if people who perceive themselves as prone to experiencing regret by their own account, also display regret averse behaviour (sensitivity to potential regret) and stronger affect upon receiving feedback designed to elicit regret.

2.2 Study 1: Methods

2.2.1 Participants

194 university psychology students were recruited via a university-administered online recruitment website. Age ranged from 18 to 64; mean age 21.7 (median 19) and SD 7. Reported gender was: 155 (80%) female, 35 (18%) male, 2 (1%) non-binary and 2 (1%) ‘preferred not to say’. About half (53.6 %) of participants reported being full-time, part-time or self-employed (in addition to being students). The median reported weekly income of the sample was \$300-500 (categorical variable). 79% were born in Australia.

2.2.2 Procedure

All study material was presented online using Qualtrics, and it was a requirement for the students to complete the task on a laptop or stationary computer for proper stimulus display.³⁸ After signing up for the study, students could complete the Qualtrics experiment at the time of their choosing. The experiment was advertised and active between the period of February and May 2025. Participants were first provided brief information summarising the focus of the study; there was no deception involved with any part of this research. Then participants completed a consent form, followed by the questionnaires and then experimental tasks.³⁹ Prior to each experimental task, participants read a detailed instructions and completed comprehension questions (see Appendix 2.B for summary of comprehension task responses). The key instructions can be inspected in General appendix D. The full experimental survey was expected to take ca. 45-60 min to complete. For ethical reasons, participants were not forced to respond to questionnaires, however, most participants who signed up to the study completed all questionnaires.⁴⁰

³⁸ Specific browsers were required: *Chrome* or *Firefox*

³⁹ Participants also completed questionnaires and one experimental task related to different projects.

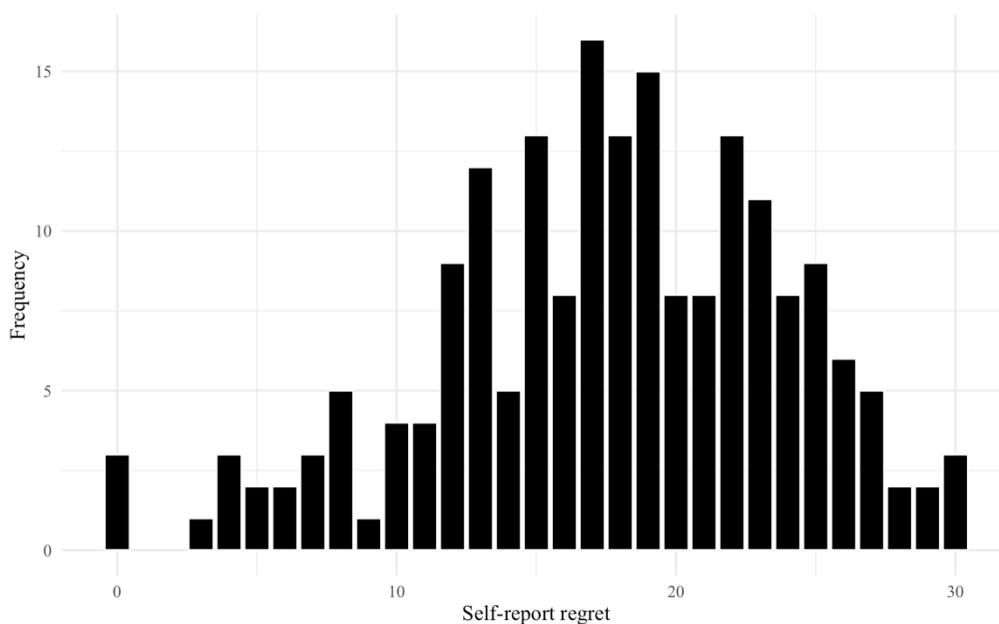
⁴⁰ The hypothesis that self-reported regret would be associated with decisional-regret (regret aversion), was registered under the OSF on 10/31/2023 (accessible via this link <https://osf.io/7xwd2/overview>). However, the methodologies described in the registration were updated and differ somewhat from the original registration. The registration was part of a broader project registration in the context of the author’s Doctor of Philosophy.

2.2.3 Materials

2.2.3.1 Self-report regret

The 5-item self-report *regret Scale* (Schwartz et al. 2002) was designed to measure a person's self-perceived tendency or proneness to experience regret in the context of decision-making. Example questions were: 'Whenever I make a choice, I'm curious about what would have happened if I had chosen differently' and 'If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better.' The questions were rated on a scale from 1 = *completely disagree* to 0 = *completely agree* (one question is reverse scored).⁴¹ Schwartz et al. reported a low but acceptable Cronbach's alpha of 0.67; while in the present study it was good at 0.78. Figure 2.3 shows that the distribution of responses was roughly bell-shaped and indicated individual variability in Self-report regret tendencies.

Figure 2.3 Distribution of total scores on Self-report regret in study 1



The tasks designed to measure the influence of potential regret on behaviour and post-decisional regret on affect ratings are described next.

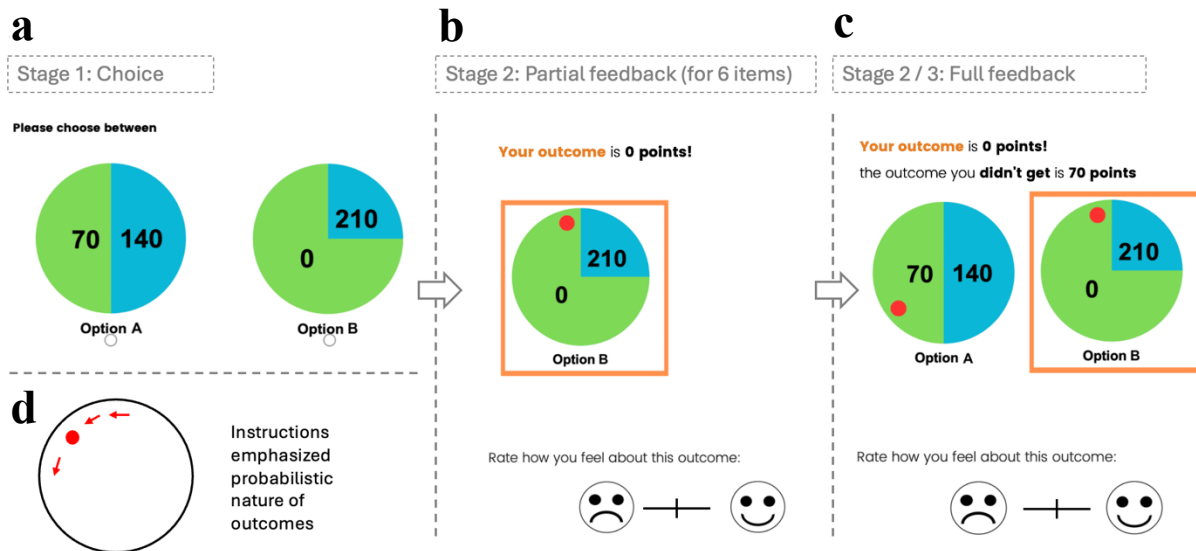
⁴¹ During analysis, the range was re-scaled to be 0 to 6 for appropriate interaction estimates.

2.2.3.2 *Wheel of Fortune task*

The Wheel of Fortune (WOF) task was based on methodology used across a series of previous neuroeconomics studies and studies investigating depression and regret. An example is given in Figure 2.4. Participants made 16 choices between two prospects (options A and B), that each had two possible outcomes. Participants were instructed to choose their preferred option and told there were no correct or incorrect answers. Outcomes were in the form of experimental currency units ('points'). Gain-only lotteries were used with values: 0, 70, 140 and 210 points, and were chosen for compatibility with past studies. The probabilities associated with each outcome was indicated by the size of shaded area. Participants were asked to imagine that, after their choice, a red ball was spun around the circular area of each prospect (A and B), and the computer would determine where the red ball landed and hence their outcome and the alternative (foregone) outcome. The outcomes were uncorrelated (e.g., blue area could be selected for option A even if green area was selected for option B, and vice versa). Moreover, outcomes were truly probabilistic and selected by the computer according to the displayed probabilities. For ease of comprehension and compatibility with previous studies, probabilities were kept to 0.25/0.75 and 0.5/0.5. The chosen option was highlighted by framing it with an orange square. Post-decisional feedback displayed the options with a red ball inside to indicate which outcomes the computer had selected. The values of the received and forgone options were also stated in writing. After outcomes were presented, participants were asked to rate how they felt about the outcome on a visual analogue scale (slider-scale) anchored by a sad face or a smiley face. The scale ranged from 0 to 100, but scale-numbers were not displayed to participants. The slider starting point was always presented in the mid-point initially.

Of the 16 choices, 3 occurred twice. Whether option A or B had a higher variance (difference between high and low outcomes), a higher EV or greater potential regret could be the same or differ between options. For one item, one option was first-order-stochastically-dominated (FOSD) by the other to test for rationality of behaviour (option A: 140,0.75; 210, 0.25 dominated option B: 140,0.75; 70, 0.25) (see Appendix 2.B for details). For the first 6 items partial feedback (outcome of chosen option only) was provided first to highlight to participants the difference between the chosen outcome versus the foregone outcome. The order of items was identical across participants.

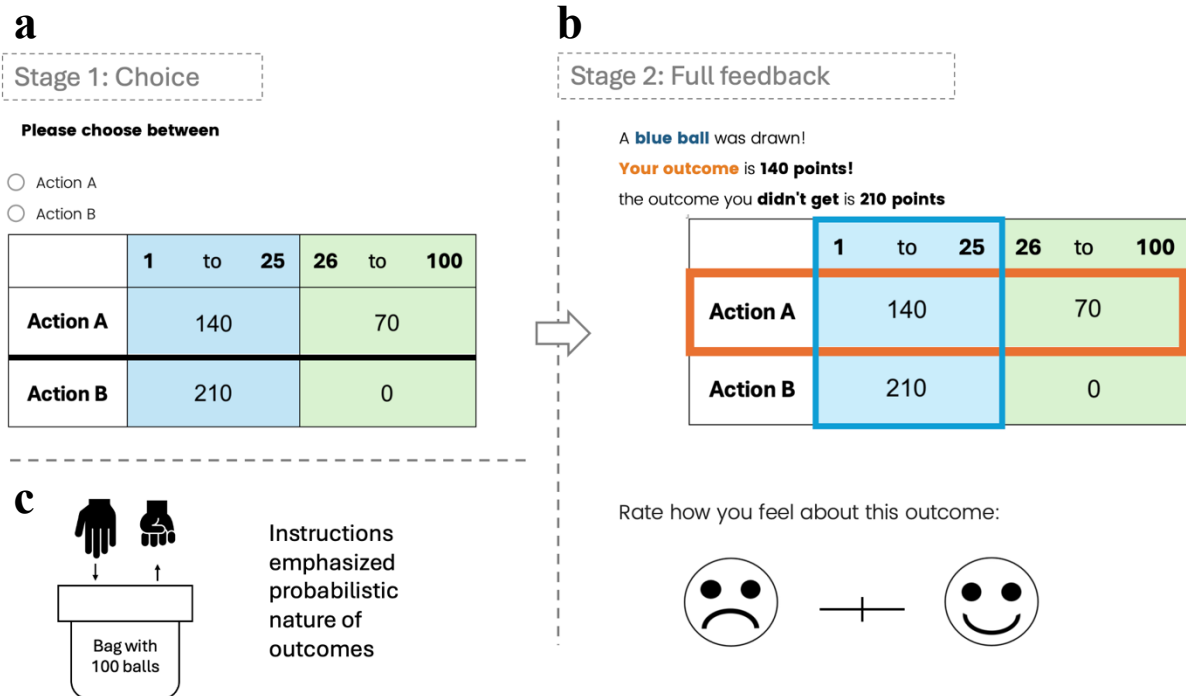
Figure 2.4 The Wheel of fortune task sequence: Panel (a) displays choice stage, (b) displays partial feedback and (c) full feedback; including visual instruction regarding probabilities (d)



2.2.3.3 2x2 Matrices task

The *2x2 Matrices* task asked participants to choose between two options A and B, across 7 items, but outcomes were presented in the format of matrices (Figure 2.5). The task was designed to involve the same outcomes and probabilities as the WOF but with correlated prospects. To emphasise this, outcomes were described as the result of actions and states of the world: participants were told to imagine a bag of 100 balls coloured either blue or green, and the computer drawing a ball to determine the state of the world and their outcomes. This presentation format is often used to motivate Regret theory in economics and argued to induce the type of comparison required for the formation of regret-effects. Given the correlated nature of the prospects, a smaller number of items could be created from this set of outcomes and probabilities. One FOSD item was included (see Appendix 2.B). No items were repeated. The difference in outcome spread, expected utility and maximum regret was both varied and kept the same across items. The chosen option was highlighted with an orange square, while an additional frame indicated the state of the world selected by the computer. Finally, after receiving feedback on the received and forgone outcomes, participants were asked to rate how they felt on a VAS.

Figure 2.5 The 2x2 Matrices task sequence: Panel (a) displays choice stage and (b) displays full feedback, including visual instruction regarding probabilities (c)

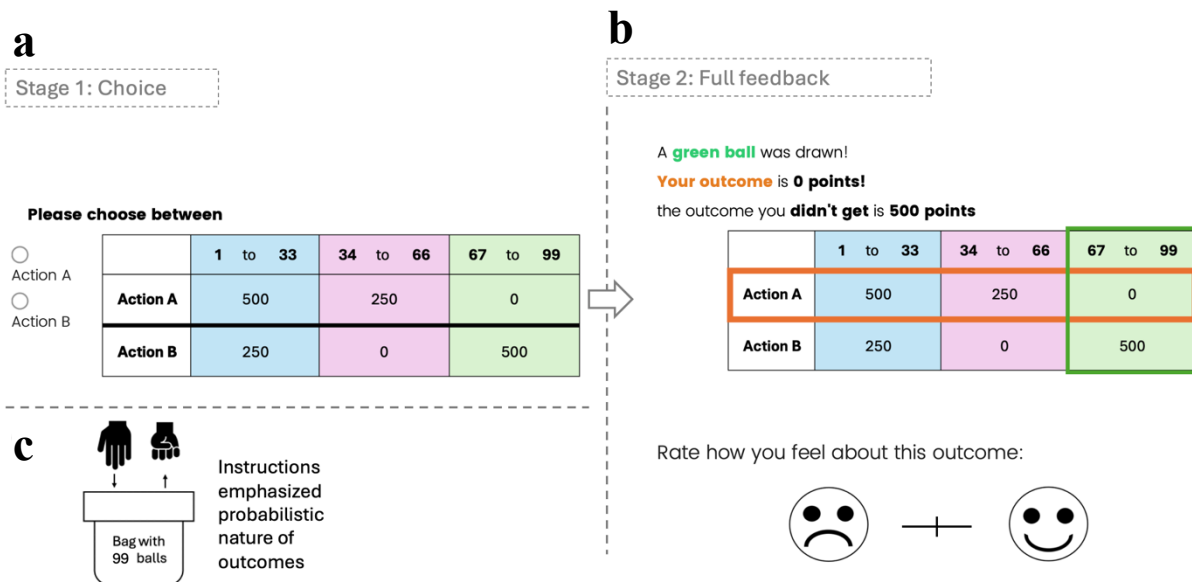


2.2.3.4 2x3 Matrices task

The 10-item 2x3 Matrices task identified regret aversion and whether participants systematically behaved in accordance with convexity in choosing between A or B. As seen in Figure 2.6, one option had chance of a larger regret difference: in this example choosing option A means higher regret (lower relief) and would be avoided when a person was regret averse (Q -function curvature is convex). Each item also isolated regret effects by ensuring expected value, potential disappointment and expected utility (risk-preferences) were the same across options. The probability of each outcome was always 1/3: participants were asked to imagine a bag of balls, this time numbering 99, of three different colours. The task display was otherwise like that of the 2x2 Matrices task. The outcomes used in the task were: 0, 100, 250, 300, 400, 450, 500, 550, 700 and 900 points. These allowed for items with a range of max differences from 300 points to 1000 points (e.g., Figure 2.6 illustrates an example where the max difference is 500 points). Whether option A or B was the choice that

minimised the maximum difference was varied across items. Again, outcomes were probabilistic as selected by the computer.

Figure 2.6 *The 2x3 Matrices task Sequence: Panel (a) displays choice stage and (b) displays full feedback, including visual instruction regarding probabilities (c)*



2.2.4 Incentivisation

Participants received course credit for participating in the study. Quite a variety of incentivisation approaches appear in the literature, including no payment, fixed payment and random selection of a choice (also varying in whether experimental currency was used). Here, to ensure that all choices were incentivised (consequential), participants were told that the 5 participants with the highest total points would receive a gift card worth 50 AUD when the study finished. Entering into this draw was voluntary due to ethics requirements: 107 (55%) of the participants chose to provide their email at the end of the survey.⁴² Rewarding participants based on total points is a procedure used in some previous regret experiments. To

⁴² RedCap was also used to collect contact email for those participants volunteering for the points-based incentive scheme.

avoid “wealth effects” (temporal changes to the utility function as a function of points accrued) total points were not displayed during the experiment.⁴³

2.2.5 Models

2.2.5.1 Variable creation

To determine regret aversion behaviourally, the following *potential-regret* variables were constructed from the task outcomes and probabilities. These variables were then incorporated in models predicting choices statistically. In general, the following variables assume binary choices involving: option A, with high outcome x_A and low outcome y_A (associated probabilities p_{x_A} and p_{y_A}), and option B: with high outcome x_B and low outcome y_B (associated probabilities p_{x_B} and p_{y_B}).

For the WOF task, a regret-difference variable was created to align with past literature applying this task. For each item, the difference in maximum potential regret for option A over B was defined as,

$$\begin{aligned} \text{Regret Diff} &= \text{Max Regret (A)} - \text{Max Regret (B)}, \\ \text{Max Regret (A)} &= (x_B - y_A), \\ \text{Max Regret (B)} &= (x_A - y_B) \end{aligned}$$

Max Regret reflects the highest value of the alternative option minus the smaller value of the chosen option; a higher *Max Regret* would be expected to negatively predict choosing option A, if a person is averse to regret.

To account for potential disappointment the following variable was also created,

$$\begin{aligned} \text{Dissapointment Diff} &= \text{Max Dissapointment (A)} - \text{Max Dissapointment (B)}, \\ \text{Max Dissapointment (A)} &= (|y_A - x_A|)p_{y_A}, \\ \text{Max Dissapointment (B)} &= (|y_B - x_B|)p_{y_B} \end{aligned}$$

⁴³ This incentive scheme could encourage participants to choose options with higher possible points to accrue more points relative to others (increasing risk-seeking), therefore deviating from their true preferences. As discussed in Appendix E, there was no obvious evidence of this comparing study 1 with study 2 that used a different incentive scheme.

Finally, an *EVDiff* variable was constructed capturing the EV difference between option A and option B,

$$EVDiff = EV(A) - EV(B) = (x_A * p_{x_A} + y_A * p_{y_A}) - (x_B * p_{x_B} + y_B * p_{y_B})$$

For the 2x2 Matrices task, given the correlated nature of prospects, a variable was designed to capture the behavioural effect of both relief and regret associated with each option while incorporating the associated probabilities,

$$RegretReliefDiff = RegretRelief(A) - RegretRelief(B),$$

$$RegretRelief(A) = [(x_A - x_B)p_{x_A} + (y_A - y_B)p_{y_A}]$$

$$RegretRelief(B) = [(x_B - x_A)p_{x_B} + (y_B - y_A)p_{y_B}]$$

Due to the correlated nature of the task, $p_{x_A} = p_{x_B}$ and $p_{y_A} = p_{y_B}$. This calculation was based on mathematical regret-models found in economics (e.g., Bell, 1982; Loomes and Sugden 1982) but omits the consumption utility to focus purely on the probability-weighted regret/relief difference. A higher *RegretReliefDiff* meant option A should be chosen over B in order to minimise regret (maximise relief).

For the 2x3 Matrices task, a *Regret Diff* variable was created that reflected the difference between the max possible regret associated with option A over that of option B. Using Figure 2.6 as an example, $Regret Diff = MaxRegret(A) - MaxRegret(B) = 500 - 250$. While the term *Regret Diff* was chosen for ease of understanding, the option with less maximum regret difference also meant choosing the option with maximum relief (again as seen in Figure 2.6), as both are predicted by a convex regret *Q*-function.⁴⁴

Post-decisional affect was measured as the VAS ratings participants gave post-feedback (full only). These ratings ranged from [-48,52], values below 2 indicating regret (ratings toward frowny face) and above 2 relief (towards smiley face). Note there were 2 more points above the mid-point due to a small design error whereby the bar used for rating appeared slightly towards the frowny face by 2 out of 100 rating-points at the start. However, this was not perceptible to participants as participants were not shown the numeric values.

⁴⁴ Using the label 'regret' rather than 'relief' aligns with the focus on regret over relief in Regret theory.

2.2.5.2 Choice model

The association between a self-reported, perceived, regret tendency and behavioural regret aversion was tested with a model predicting choices from the potential regret of the two options, interacted with self-reports. This interaction term captured the degree to which self-reports magnified or minimised regret aversion. For the WOF task, the probability of choosing option A over B was modelled as,

$$P(\text{Chose A over B}|X) = \Phi(X\beta),$$

$$X\beta = \beta_0 + \beta_1 \text{EVDiff} + \beta_2 \text{Dissapointment Diff} + \beta_3 \text{RegretScale} + \beta_4 \text{Regret Diff} \\ + \beta_5 (\text{Regret Diff} * \text{RegretScale})$$

Regret Diff is the regret difference variable capturing the potential regret of option A minus that of option B (for WOF and 2x3 Matrices tasks), and *RegretScale* is participant's Self-report regret measured as total scores on the psychological regret scale (Schwartz et al. 2002). The coefficient β_5 is the coefficient of interest: a negative interaction effect means that higher Self-report regret magnifies the negative effect of potential regret (assuming regret aversion is present). Specifically, using this model, the partial effect of regret difference is given by,

$$\frac{\Delta \text{choice}}{\Delta \text{Regret Diff}} = \beta_4 + \beta_5 \text{RegretScale}$$

For 2x2 Matrices, *Regret Diff* is replaced with *RegretReliefDiff* to yield the following partial effect,

$$\frac{\Delta \text{choice}}{\Delta \text{RegretReliefDiff}} = \beta_4 + \beta_5 \text{RegretScale}$$

Here, β_4 would be expected to be positive, while β_5 would be expected to be positive in that Self-report regret magnifies the effect of regret/relief on a participant's choices.

A probit link function was used across models, where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.⁴⁵ Similar to previous studies applying the WOF (Camille et al., 2004; Coricelli et al., 2005), the models also accounted for *EVDiff* and *Dissapointment Diff*. In models with 2x2 Matrices neither *EVDiff* nor *Dissapointment Diff* were included to avoid multicollinearity. For the 2x3-Matrices task EV and disappointment are identical across the two options.

All models were estimated with robust standard errors cluster at the individual level to account for correlations within individual's responses. Models were estimated with and without fixed effects to account for unobserved individual-specific effects on choice.

2.2.5.3 Econometric approach: affect ratings

Participants provided affect ratings after receiving feedback on their choices. The affect ratings were modelled as a function of choice-context and Self-report regret. Specifically, affective ratings were modelled applying panel OLS to estimate,

$$\begin{aligned} \text{Affect ratings}_{it} = & \alpha_i + \lambda_t + \beta_1 \text{received}_{it} + \beta_2 \text{forgone}_{it} + \beta_3 \text{Feedback}_{it} + \\ & \beta_4 (\text{Feedback}_{it} * \text{RegretScale}_i) + \\ & X'_{it} \delta + \epsilon_{it} \end{aligned}$$

In the model above, α_i is a participant-fixed effect, λ_t is a time/choice-item-fixed effect, *received_{it}* is the received outcome (points), *forgone_{it}* is the foregone outcome, and *Feedback_{it}* is the feedback scenario: *regret* vs *relief* (vs neutral only on WOF). Feedback scenario coefficients β_3 capture the effect of the relative difference between outcomes per se, while the preceding covariates imply holding the magnitude of the outcomes fixed. The interaction term coefficient β_4 on *Feedback_{it}* * *RegretScale_i* captures the moderating effect of Self-report regret on the response to feedback.

⁴⁵ The probit estimator coefficient indicates the change in the z-score of the underlying latent variable modelled as determining the binary dependent variable's value. A positive value indicates a positive shift in z-score and therefore a higher probability of observing the dependent variable (but not the actual probability change itself).

Diagnostic tests for unobserved time- and participant- effects were significant, while fixed effects were supported over random effects model.⁴⁶ However, results for random effects models and pooled OLS are reported in Appendix 2.D, Table D.1 for comprehensiveness. Appendix 2.C, Figure 2.C.1 and Figure 2.C.2 shows there was evidence of heteroskedasticity, which was also confirmed by Breusch-Pagan and White's tests. Final models were therefore estimated with robust standard errors clustered at the participant level. Appendix 2.C Figure 2.C.2 shows residuals appeared normally distributed (allowing more confident inference). There was evidence of mild serial correlation from visual inspection of autocorrelation plots, and there was evidence of higher order serial correlation⁴⁷, which was likely due to similarity between items. Finally, unit-root tests indicated a stationary stochastic process, as required for OLS.

2.3 Study 1: Results

2.3.1 Behavioural regret aversion and self-report regret

There was relatively consistent support for regret aversion. However, there was little evidence for being associated with Self-report regret.

Table 2.3 reports the results of models predicting choices from the potential regret or regret/relief that could be anticipated. For the WOF task, when the potential regret of an option was higher than that of the alternative, there was a lower chance that option was chosen. This held while controlling for EV and potential disappointment. However, there was no evidence of a significant interaction effect between potential regret and Self-report regret. A similar pattern was found for the 2x2 Matrices task: the option with more relief relative to regret was preferred on average, but there was no significant interaction with Self-report regret.

For 2x3 Matrices an unexpected effect was observed whereby the option with the higher maximum regret tended to be chosen. This pattern conflicts with the predictions of Regret theory: a convex preference over regret differences should predict the opposite pattern, suggesting instead regret curvature was on-average concave. In other words, participants may

⁴⁶ Wooldridge's, pF, Breusch-Pagan, GHM and Honda tests for unobserved time and participant effects ($p < 0.001$). Hausman Test indicated support for a fixed effects over a random effects model ($p < 0.01$).

⁴⁷ No significant first-order serial correlations (BFN-Durbin-Watson test) but significant higher order serial correlations (e.g., Breusch-Godfrey test).

have avoided (preferred) two small outcomes involving regret (relief). Nevertheless, the significant, albeit small, interaction term with Self-report regret indicated that perceiving oneself as more prone to regret reduced the unexpected effect, bringing behaviour back in line with Regret theory and convexity. For example, applying model ‘2x3 (2) FE’ (Table 2.3) for a hypothetical participant scoring maximally on the Regret scale (value = 31), the effect of *Regret Diff* is negative as predicated by Regret theory:

$$\begin{aligned} & [(\beta_5 * RegretScale) + \beta_4] * Regret Diff \\ \rightarrow & [(-0.006 * 31) + 0.145] * RegretDiff \\ \rightarrow & -0.041 * RegretDiff . \end{aligned}$$

For intuition, Figure 2.7 displays the average marginal effects (AME) for the Probit models but without the interaction terms.⁴⁸ Instead of the interaction terms, the average marginals are displayed for individuals scoring below the 25th Quantile and above the 75th Quantile on the self-report Regret scale. This helps reveal the degree of regret aversion in participants with low and high perceived regret proneness. For the WOF task, a 100-point higher potential regret of an option over the alternative predicted on average a 0.2 lower chance of that option being chosen. For the 2x2 Matrices, a 100-point higher regret/relief for one option over the alternative, increased the probability on average that that option would be chosen by about 0.1. The results were not notably different for participants with high vs low Self-report regret. For 2x3 Matrices, and in line with regression results (Table 2.3), options with higher maximum regret were more likely to be chosen, but for the participants with higher Self-report regret, this effect was non-significant.

Overall, there was clear evidence of regret aversion on both WOF and 2x2 Matrices. However, regret preferences appeared to be heterogenous across individuals as measured with the 2x3 Matrices. Other than for 2x3 Matrices, there was little support for an association between Self-report regret and behavioural regret aversion.

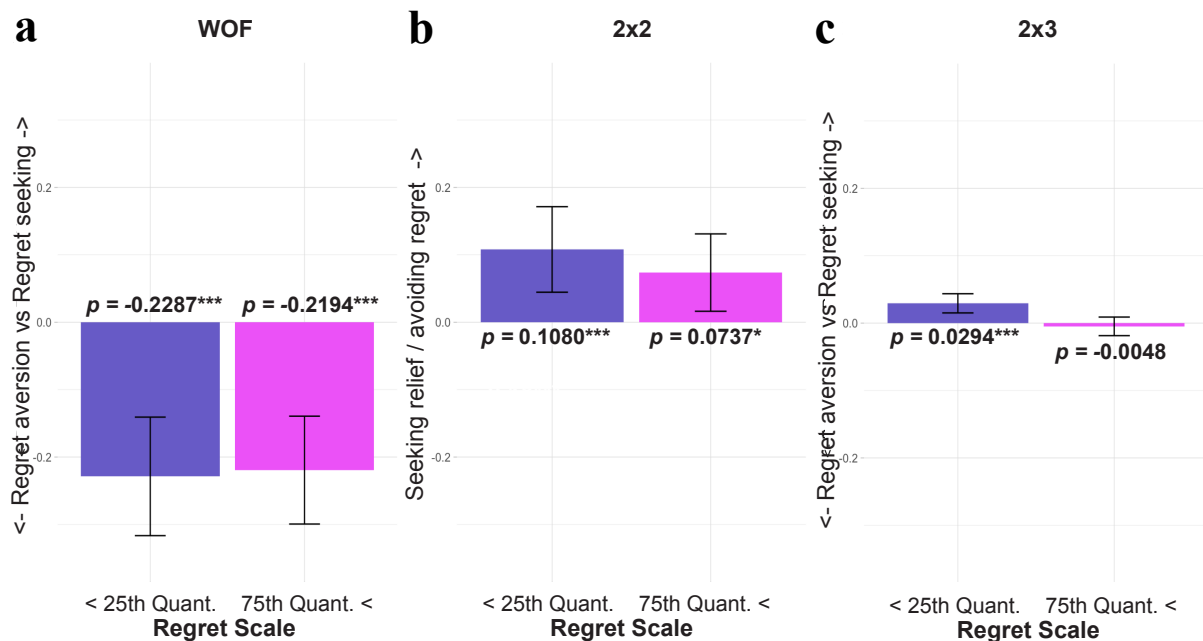
⁴⁸ While the interaction term estimates in Table 2.3 capture the relationship between behavioural and Self-reported regret, the estimates do not reflect the actual change in predicted probability, rather the estimates reflect the change in the z-score of the probability. Average marginal effects, on the other hand, reflect the average expected change in probability for a one-unit increase in the predictor. However, these marginals are complicated to calculate and interpret for interaction effects. Hence, marginals were displayed by Regret scale severity group (< 25th Quantile vs 75th Quantile <).

Table 2.3 Choices regressed on constructed potential regret variables and Self-report regret

	WOF (1)	WOF (2)	WOF (3)	WOF (3) FE	2x2 (1)	2x2 (2)	2x2 (2) FE	2x3 (1)	2x3 (2)	2x3 (2) FE
Intercept	0.015 (0.026)	-0.075** (0.025)	-0.107 (0.075)	-1.196*** (0.043)	0.203*** (0.038)	0.139 (0.111)	-1.544*** (0.065)	0.066+ (0.034)	0.059 (0.108)	-1.871*** (0.025)
EV difference	1.356*** (0.097)	0.655*** (0.126)	0.654*** (0.126)	0.703*** (0.134)						
Disappointment difference		-0.681*** (0.087)	-0.681*** (0.087)	-0.722*** (0.094)						
Regret diff (A-B)	-0.182*** (0.043)	-0.606*** (0.071)	-0.600*** (0.147)	-0.641*** (0.155)						
Regret diff (A-B) by Self-report regret			-0.000 (0.007)	-0.000 (0.008)						
Regret/relief diff (A-B)					0.292*** (0.042)	0.331** (0.128)	0.397** (0.150)			
Regret/relief diff (A-B) by Self-report regret						-0.002 (0.007)	-0.003 (0.008)			
Regret diff (A-B)								0.036*** (0.010)	0.123*** (0.027)	0.145*** (0.031)
Regret diff (A-B) by Self-report regret									-0.005** (0.002)	-0.006*** (0.002)
Self-report regret			0.002 (0.004)	0.045*** (0.002)		0.004 (0.006)	0.088*** (0.003)		0.000 (0.006)	0.073*** (0.001)
Number Obs.	3104	3104	3104	3104	1358	1358	1358	1940	1940	1940
Participants (<i>N</i>)	194	194	194	194	194	194	194	194	194	194
Choices items	16	16	16	16	7	7	7	10	10	10
Log-likelihood	-1994	-1916	-1916	-1805	-867	-867	-759	-1331	-1325	-1160
AIC	3995	3840	3844	4005	1737	1741	1909	2667	2658	2711
BIC	4013	3864	3880	5201	1748	1762	2931	2678	2680	3803

Note. Probit 'link' function used to model choices (chose option A over B) as a function of regret variables constructed from task stimuli and 'Self-report regret' (Schwartz et al., 2002 self-report questionnaire). 'WOF' refers to choices on Wheel of Fortune task, '2x2' for 2x2 Matrices task and '2x3' for 2x3 Matrices task. For WOF and 2x3 Matrices, 'Regret diff (A-B)' is the max potential regret of option A minus option B; for 2x2 Matrices 'Regret/relief diff (A-B)' is the relief and regret for option A minus option B (a higher value indicated more relief over regret). Coefficients reflect change in 100s of points of regret variable (i.e., scaled variables). Models denoted as 'FE' include participant (dummy) fixed effects. For models involving interaction terms, the fixed effect (factor level) for one of the participants (ID = 194) caused a singularity and was automatically excluded when estimating the final models. All models use clustered heteroskedasticity-robust errors (Stata method). Model fit summaries - Log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) - are from models that do not apply a robust covariance matrix. For non-FE models, Wald-tests were calculated: all of these models were statistically significant ($p < 0.001$). Standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2.7 Marginal effect capturing the effect of potential regret on behaviour (study 1)



Note. Panels refer to (a) WOF task, (b) 2x2 Matrices and (c) 2x3 Matrices. Panels show Average Marginal Effects (AME) from Probit models predicting choices (choosing option A over B) from the relative potential regret (*RegretDiff* for WOF and 2x3 Matrices tasks) or potential regret relative to relief of options (*RegretRelief* for 2x2 Matrices task). Results displayed separately by Self-report regret scores (questionnaire from Schwartz et al., 2002) according to quantiles: participants falling below the 25th Quantile compared with participants falling above the 75th Quantile. Estimates indicated the change in probability of choosing option A over B for a 100-point change in the *RegretDiff* or *ReliefRegretDiff* variables. Cluster-robust standard errors (non-marginal effects) were applied for *p-values*; however, error bars represent 95% confidence intervals based on AME estimates. Fixed effects not applied. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.3.2 Post-decisional affect ratings and self-report regret

The link between Self-report regret and post-decisional affect ratings was tested next. A higher Self-report regret would be expected to be associated with more negative affect ratings when regret is elicited (i.e., feedback such that received outcome < foregone outcome).

A hierarchical series of panel models are reported for the aggregated data across WOF, 2x2 Matrices and 2x3 Matrices in Table 2.4. As expected, the higher the outcome participants

received the higher were affect ratings on average (ratings towards smiley face), while a higher forgone outcome was associated with lower ratings (ratings towards frowny face) – see Model 1. Participants appeared to experience regret: ratings were more negative after feedback designed to elicit regret (see dummy variable coefficient in Model 2). Participants also evidenced relief in the relief feedback scenario. Notice also that the associations for received and forgone outcomes per se became weaker and/or non-significant in Model 2: this suggests ratings were more directly linked to feedback scenario. Importantly, models 2 and 2-robust show that there was a statistically significant interaction: Self-report regret was associated with feeling more negative after a regret scenario. This suggests a congruence across self-reports and post-decisional affect associated with regret. A caveat however is that the final Model 3, including all variable and robust standard errors, had non-significant interaction terms. However, it may also be that including the interaction term twice by this stage reduced the chance of the coefficient being significant.⁴⁹ Interestingly, Self-report regret also was associated with a magnification of relief, but this effect was less strong. Notice also that the regret effect on its own was nearly twice that of the relief effect on affective ratings, suggesting regret weighed heavier emotionally than relief.

Post-decisional affect ratings may be contingent on the task used (the way regret was induced). To investigate, models were also estimated separately for each task. As seen in Table 2.5, the statistical strength of effects varied across tasks, stronger for 2x3 Matrices and weaker for WOF. However, the main effect for Regret feedback was consistently statistically significant. Moreover, the interaction term with Self-report regret was significant and magnified the effect of Regret scenario, most notable for 2x2- and 2x3- Matrices.

⁴⁹ Model 2 and Model 3 were both estimated because WOF involved feedback that was neutral (received = forgone outcome) but 2x2 and 2x3 Matrices did not. Thus, Model 2 compared regret scenario to neutral *and* relief for WOF; whereas for 2x2- and 2x3- Matrices both models 2 and 3 compared regret scenario to relief scenario.

Table 2.4 Ratings regressed on task stimuli, feedback scenario and Self-report regret

	(1)	(2)	(2-robust)	(3)	(3-robust)
Received outcome	8.340*** (0.223)	3.903*** (0.219)	3.903*** (0.262)	3.459*** (0.218)	3.459*** (0.258)
Alternative outcome	-5.120*** (0.220)	0.266 (0.227)	0.266 (0.231)	1.052*** (0.230)	1.052*** (0.239)
Regret Scenario dummy		-26.083*** (1.863)	-26.083*** (5.394)	-19.210*** (2.945)	-19.210*** (5.582)
Regret Scenario dummy by Self-report regret		-0.746*** (0.093)	-0.746** (0.286)	-0.458** (0.153)	-0.458 (0.294)
Relief Scenario dummy				10.470*** (2.875)	10.470** (3.752)
Relief Scenario dummy by Self-report regret				0.352* (0.150)	0.352+ (0.194)
Number Observations	6402	6402	6402	6402	6402
Participants (<i>N</i>)	194	194	194	194	194
Choices items	33	33	33	33	33
R ²	0.348	0.506	0.506	0.522	0.522
Adjusted R ²	0.324	0.488	0.488	0.505	0.505
AIC	59517	57735	70069	57529	69855
BIC	59537	57769	111819	57576	111591

Note. Individual- & time-fixed effects models regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario and total Self-report regret (Schwartz et al., 2002 questionnaire). Results aggregated across Wheel of Fortune, 2x2 Matrices task and 2x3 Matrices task. For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2 and 2x3 matrices, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario (i.e., there was no neutral condition). All panels were balanced. Standard errors in parentheses; all models denoted 'robust' apply cluster-robust standard errors of type HC1. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R^2 applies to non-robust estimates. Only F -test of overall fit for models '1', '2' and '3' were statistically significant ($p < 0.0001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.5 Ratings regressed on task stimuli, feedback scenario and Self-report regret – WOF, 2x2- and 2x3- Matrices tasks separately

	(WOF)	(WOF-robust)	(2x2)	(2x2-robust)	(2x3)	(2x3-robust)
Received outcome	12.942*** (1.052)	12.942*** (1.049)	12.928*** (1.120)	12.928*** (1.171)	2.948*** (0.286)	2.948*** (0.302)
Alternative outcome	-1.506 (1.133)	-1.506 (1.093)	-1.753 (1.330)	-1.753 (1.345)	-0.468+ (0.284)	-0.468+ (0.240)
Regret Scenario dummy	-10.971** (3.517)	-10.971+ (5.614)	-14.212** (4.404)	-14.212* (6.728)	-21.489*** (3.381)	-21.489** (6.749)
Regret Scenario dummy by Self-report regret	-0.594*** (0.176)	-0.594* (0.298)	-0.818*** (0.194)	-0.818* (0.346)	-0.827*** (0.150)	-0.827* (0.336)
Relief Scenario dummy	8.495* (3.416)	8.495* (4.163)				
Relief Scenario dummy by Self-report regret	0.260 (0.170)	0.260 (0.207)				
Number Observations	3104	3104	1358	1358	1940	1940
Participants (<i>N</i>)	194	194	194	194	194	194
Choices items	16	16	7	7	10	10
R ²	0.500	0.500	0.549	0.549	0.634	0.634
Adjusted R ²	0.463	0.463	0.469	0.469	0.591	0.591
AIC	27790	33554	11799	14097	16860	20316
BIC	27833	51005	11825	20114	16888	29970

Note. Individual- & time-fixed effects models regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario and total Self-report regret (Schwartz et al., 2002 questionnaire). Results dis-aggregated across Wheel of Fortune ('WOF') task, 2x2 Matrices task ('2x2') and 2x3 Matrices task ('2x3'). For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2 and 2x3 matrices, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario. All panels were balanced. Standard errors in parentheses; all models denoted 'robust' apply cluster-robust standard errors of type HC1. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). *R*² applies to non-robust estimates. Only *F*-test of overall fit for models 'WOF', '2x2' and '2x3' were statistically significant ($p < 0.0001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.3.3 Post-decisional affect ratings and behavioural regret aversion

Do negative affect ratings, outcomes or feedback scenarios influence subsequent regret aversion? To answer this, choices were regressed on i) the affective ratings participants provided during the preceding feedback scenario, ii) the outcomes of the preceding choice item, and iii) whether the preceding feedback scenario was regret, relief or neutral. A new choice variable was defined taking the value '1' when an option with lower potential regret was chosen subsequently (i.e., exhibiting regret aversion) and '0' otherwise. This was analysis restricted to the WOF and 2x3 Matrices tasks, and for the WOF, task only items where one options had a higher potential regret than the other.

There was no evidence from the WOF task (Table 2.6) that the preceding affect ratings influenced subsequent regret aversion. Being exposed to a higher forgone outcome during feedback did appear to predict regret aversion subsequently, while a higher received outcome was associated with the reverse pattern (i.e., being more rewarded associated with becoming less regret averse). However, the pattern for feedback scenario was unexpected: being exposed to a regret scenario predicted less regret aversion subsequently, and vice versa for relief scenario. However, comparing models 3 FE and 4 FE showed that accounting for Self-report regret left feedback scenario non-significant, suggesting the effect may be less reliable.

The results for the 2x3 Matrices task (Table 2.7) showed affect ratings and feedback influenced subsequent choices: in Model 1, a negative rating as a sole predictor increased the likelihood of regret aversion. However, the effect was reversed in models accounting for feedback scenario (3) – suggesting ratings may be directly linked with feedback scenario. Regret feedback also predicted subsequent regret aversion. There was also evidence that a higher Self-report regret magnified this association (Model 4 FE). Finally, a higher received outcome predicted regret aversion, while a higher forgone outcome predicted choosing the option with higher regret (less relief).

Overall, while on the WOF task regret aversion appeared associated with the magnitude of the forgone outcome, during 2x3 Matrices regret aversion was linked to the feedback scenario (received outcome < forgone outcome). Lower affect ratings were only associated with subsequent regret averse behaviour on the 2x3 matrices task, and only when feedback scenario was unaccounted for.

Table 2.6 *Dependent variable: chose option with less potential regret, regressed on preceding period's affect ratings, outcomes, feedback scenario or Self-report regret interactions (WOF task)*

	(1)	(2)	(3)	(3) FE	(4)	(4) FE
Intercept	-0.123** (0.039)	-0.170* (0.068)	-0.212* (0.097)	0.139 (0.087)	-0.055 (0.238)	1.562*** (0.211)
Ratings (previous period)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.002 (0.002)	0.000 (0.001)	-0.002 (0.002)
Received outcome (previous period)		-0.011 (0.052)	-0.270** (0.089)	-0.195+ (0.105)	-0.271** (0.089)	-0.193+ (0.106)
Foregone outcome (previous period)		0.053 (0.043)	0.338*** (0.086)	0.306** (0.101)	0.338*** (0.086)	0.306** (0.101)
Regret Scenario (previous period)			-0.346** (0.131)	-0.375* (0.156)	-0.522+ (0.288)	-0.410 (0.327)
Relief Scenario (previous period)			0.395** (0.130)	0.477** (0.154)	0.078 (0.288)	0.181 (0.338)
Regret Scenario (previous period) by Self-report regret					0.010 (0.015)	0.002 (0.017)
Relief Scenario (previous period) by Self-report regret					0.018 (0.014)	0.017 (0.016)
Number Obs.	1552	1552	1552	1552	1552	1552
Participants (N)	194	194	194	194	194	194
Choices items	8	8	8	8	8	8
Log-likelihood	-1069	-1068	-1063	-938	-1062	-936
AIC	2142	2145	2137	2273	2141	2276
BIC	2153	2166	2169	3338	2189	3350

Note. Probit 'link' function used to model choices (chose option A over B) on Wheel of Fortune task, as a function of the previous choice's outcome ('previous period') variables. The are affect ratings (VAS) given post-feedback ('Ratings'), received outcome, forgone outcome, feedback scenario ('Regret Scenario' or 'Relief Scenario'); and total Self-report regret (Schwartz et al., 2002 questionnaire) interaction effects. Models named 'FE' include participant fixed effects. Coefficients on received and forgone outcome reflect change in 100s of points (i.e., scaled variables). All models use clustered heteroskedasticity-robust errors (Stata method). In Model 4 (FE) for one of the participants (ID = 194) the fixed effect could not be estimated. Model fit summaries - Log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) - are from models that do not apply robust covariance matrix. For non-FE models, Wald-tests were calculated: only models '3' and '4' were statistically significant ($p < 0.05$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.7 *Dependent variable: chose option with less potential regret, regressed on preceding period's affect ratings, outcomes, feedback scenario or Self-report regret interactions (2x3 Matrices task)*

	(1)	(2)	(3)	(3) FE	(4)	(4) FE
Intercept	-0.071*	-0.098	-4.134***	-3.739***	-4.124***	2.087***
	(0.035)	(0.069)	(0.180)	(0.202)	(0.224)	(0.242)
Ratings (previous period)	-0.006***	-0.011***	0.007***	0.008**	0.007***	0.009**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Received outcome (previous period)		0.055***	0.776***	0.914***	0.774***	0.917***
		(0.014)	(0.026)	(0.043)	(0.026)	(0.043)
Foregone outcome (previous period)		-0.037**	-0.792***	-0.931***	-0.792***	-0.938***
		(0.013)	(0.026)	(0.043)	(0.026)	(0.044)
Regret Scenario (previous period)			8.096***	9.578***	7.839***	8.997***
			(0.264)	(0.460)	(0.303)	(0.483)
Regret Scenario (previous period) by Self- report regret					0.015	0.040*
					(0.011)	(0.017)
Number Obs.	1940	1940	1940	1940	1940	1940
Participants (N)	194	194	194	194	194	194
Choices items	10	10	10	10	10	10
Log-likelihood	-1305	-1291	-606	-492	-605	-489
AIC	2613	2589	1223	1381	1225	1377
BIC	2624	2611	1251	2484	1264	2485

Note. Probit 'link' function used to model choices (chose option A over B) on 2x3 Matrices task, as a function of previous choice's outcome ('previous period') variables. These are affect ratings (VAS) given post-feedback ('Ratings'), received outcome, forgone outcome, feedback scenario ('Regret Scenario' or 'Relief Scenario'); and total Self-report regret (Schwartz et al., 2002 questionnaire) interaction effects. Models named 'FE' include participant fixed effects. Coefficients on received and forgone outcome reflect change in 100s of points (i.e., scaled variables). All models use clustered heteroskedasticity-robust errors (Stata method). For models 3 FE and 4, estimation returned the warning that fitted probabilities were numerically 0 or 1 for some observations. This may be due to overfitting or the presence of outliers, but does not invalidate results, although coefficients may be less reliable. Model fit summaries - Log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) - are from models that do not apply robust covariance matrix. For non-FE models, Wald-tests were calculated: all models were statistically significant ($p < 0.0001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.4 Study 2: Methods

2.4.1 Participants

124 university psychology students were recruited via a university-administered online recruitment website. Age ranged from 18 to 62, mean age 24.9 (median 19) and SD 10.51. 92 (74 %) were female, 31 (25 %) male, and 1 (0.8%) reported gender as non-binary. 78 (63%) of participants reported being full-time, part-time or self-employed (in addition to being students). The median reported weekly income of the sample was \$ \$500 - \$750 (categorical variable). 91 (73%) were born in Australia.

2.4.2 Procedure

The procedure for experiment 2 was very similar to that of experiment 1. All study material was presented online using Qualtrics and the experiment was advertised and active between the period of September and December 2025.⁵⁰

2.4.3 Materials

Study 2 extended on analysis in study 1 by including additional economic decision-making tasks aimed at measuring regret behaviourally. The key instructions for these additional tasks can be inspected in General appendix E. Additionally, the possibility of social desirability influencing affect ratings was captured by including a measure of social desirability.⁵¹

2.4.3.1 Self-report regret

Self-report regret was measured with the 5 items/questions from Schwartz et al. (2002) used in study 1 to gauge perceived tendency or proneness to experience regret in the context of decision-making. The Cronbach's alpha was 0.82.

⁵⁰ A second pre-registration was submitted on 08/30/2025 to OSF, after preliminary analysis of study 1 and before data collection for study 2. The registration updated methodological details and hypothesis (pertaining to self-reported, behavioural and post-decisional regret). The second registration is accessible via the following link <https://osf.io/c4wap/overview>.

⁵¹ Participants also completed additional questionnaires related to different projects.

2.4.3.2 Social Desirability Scale

One item from the *Social Desirability Scale-17 (SDS-17)* (Stober, 2001) was included in analysis: ‘I always accept others’ opinions, even when they don’t agree with my own’ (True/False answer).

2.4.3.3 Wheel of Fortune task

6 items with loss-or-zero only outcomes (see example Figure 2.8a) were added to the original set of items used in study 1. These had equivalent magnitudes to gain-only items. To prevent participants finishing the experiment with negative points, participants were endowed with 250 points. Participants were told this would be added to their extra payment if they were one of the 5 randomly selected participants to receive an additional reward (see incentive scheme below). The negative items were presented after all the other tasks to avoid interference from the 250-points endowment. Additionally, for the positive items only, the 6 occasions of partial feedback (always preceding full feedback) were interspersed rather than occurring at the start of the task (as in study 1). This was to encourage continual distinction of regret versus disappointment. Otherwise, the task was as described under study 1.

2.4.3.4 2x2 Matrices task

A set of 7 items with loss-or-zero only outcomes (example in Figure 2.8b) were added near the end of the experimental survey. Values were equivalent in magnitude to the values of the gain-only items in study 1

2.4.3.5 2x3 Matrices task

This task was unchanged relative to study 1.

2.4.3.6 2x4 Matrices task

A 10-item⁵² version of the original 2x3 Matrices was designed that instead of three had four options (see example in Figure 2.8c). The 2x4 Matrices task allowed for a comparison with the 2x3 Matrices and constituted a more sensitive test of regret curvature: convexity versus concavity. Specifically, if the value function (Q) has the property $Q''(z) > 0$ or $Q''(z) < 0$

⁵² A design error with one of the items meant that from an original 10 items, 9 items were left for some of the analysis.

over the domain of differences z (between received and forgone options), a task that involves a maximal regret (relief) difference that is three times the size of the minimum regret (relief) difference (i.e., as on 2x4 Matrices) would be more likely to manifest in different choice patterns.

2.4.3.7 2x3 Matching task

A version of the 2x3 Matrices task that involved *matching* was developed. As seen in Figure 2.8 d, the 2x3 Matching task involved the same presentation as in the 2x3 Matrices task, except that the highest outcome for one of the options was left blank.⁵³ Participants were incentivised to indicate what value for the blank option that would make them indifference between options A and B. Using the example in Figure 2.8d, providing a value for the blank space in B that was smaller than the maximum value of A (800) would indicate that the person had a convex function over differences between outcomes, convex enough to accept receiving option B with an expected value that was lower in order to make A and B equivalent preference-wise (either owing to A's chance of a high regret difference or B's chance of higher relief difference). The magnitude of the difference between the indifference value elicited and the value for the blank space that make the options equivalent in EV, indicates the degree of Q-function curvature according to Regret theory.

To prompt truthful responses for the indifference value, a relatively standard BDM mechanism was used. Participants were told that a number would be randomly drawn from a certain range by the computer. If i) their stated indifference value was higher than the computer's value for the blank space (e.g., in B, Figure 2.8d), then they would be provided with the other lottery without the blank space (e.g., A in Figure 2.8d), because their stated indifference implied this lottery was preferred using the computer's value for the blank-space lottery. Conversely, if ii) their stated value was below the computer's value, then they would be provided the lottery with the blank space, because this lottery was more valued with the computer's value for the blank-space lottery.

⁵³ A design error with one of the items meant that from an original 10 items, 9 items were left for some of the analysis.

For the 2x3 Matching task, a variable was created from the elicited indifference values (for the blank space) that was weighted by value which made the two options equivalents in terms of EV. Specifically,

$$MatchingIndex = \frac{(indifference\ value - EVequivalence\ value)}{EVequivalence\ value}$$

To illustrate with example in Figure 2.8d,

$$MatchingIndex = \frac{(indifference\ value - 800)}{800}$$

An index value above (below) zero indicates greater convexity (concavity) of preferences over differences between received and forgone outcomes.

Otherwise, the potential regret variables (e.g., *RegretDiff*, *ReliefRegret*) were constructed as in study 1.

2.4.4 Incentivisation

For the second study, the incentivisation procedure was amended: participants were told that one-out-five participants would be randomly selected and paid an AUD\$ amount equal to the points earned on one randomly selected choice they made. The AUD\$ amount was calculated as points divided by 20, so that 1 point = \$0.05 AUD. Participants also received course credit for participating in the research. Entering this incentive scheme was voluntary due to ethics requirements: 56 (45%) of participants chose to enter by provide their email at the end of the survey.

Figure 2.8 Additional choice tasks in study 2: examples of negative items in WOF (panel a) and 2x2 Matrices (b) tasks, and additional 2x4 Matrices (c) and 2x3 Matching (d) tasks

Please choose between



Please choose between

b

	1 to 25	26 to 100
Action A	- 210	0
Action B	- 140	-70

Please choose between

c

	1 to 25	26 to 50	51 to 75	76 to 100
Action A	300	0	100	200
Action B	0	100	200	300

Please tell us what number of points for the empty space in B that would make you **indifferent between Action A and Action B**

d

	1 to 33	34 to 66	67 to 99
Action A	800	400	0
Action B	400	0	

2.5 Study 2: Results

2.5.1 Behavioural regret aversion and self-report regret

As in study 1, a series of models (probit) were estimated predicting choices as a function of *RegretDiff* and *RegretRelief*, interacted with Self-report regret. The results for these models are displayed in Table 2.8.

There was no statistical evidence of Self-report regret moderating regret aversion. For the WOF task, there was a consistent and significant pattern of regret aversion: the probability of choosing an option was negatively associated with the relative potential regret of the option. Similarly, the relief relative to regret of an option was positively associated with choosing that option for the 2x2 Matrices task.

For the 2x3 Matrices and 2x4 Matrices, the option with a higher regret difference (smaller relief difference) was more likely to be chosen, and this effect was stronger for 2x4 Matrices relative to 2x3 Matrices. This suggested a concave Q-function characterised participants on average. Moreover, the 2x4 Matrices were designed to be more sensitive to detecting the functional shape, which may explain why the effect was stronger for this task. Finally, there did appear to be a main effect for Self-report regret.

In Figure 2.9, the marginal effects for regret variables are displayed for each task separately and according to whether the participants fell below the 25th Quantile or above the 75th Quantile on Self-report regret. There did not appear to be any notable difference depending on group, and results largely agreed with the results in study 1. The exception was for the WOF task (Figure 2.9a): it appeared that scoring higher on Self-reported regret was associated with a lack (non-significance) of regret aversion, a surprising finding.

For the WOF task the effect of potential regret on choice probabilities was smaller than study 1, likely owing to the use of negative items: separately calculating marginals for only negative outcome items revealed much weaker effects. This aligns with suggestions in the literature that loss-only lotteries may be less effective in eliciting regret effects.

Overall, the findings of study 2 regarding the role of potential regret in shaping choices overlapped well with the findings of study 1.

Regret function convexity (versus concavity) over regret magnitudes was also explored by calculating an average *MatchingIndex* score across items for each participant. This calculation was based on indifference values provided during the 2x3 Matching task. This variable reflected whether indifference values were above or below the value that would yield equivalent EVs for option A and B. A value below zero indicated convexity and value above zero concavity. Given the conceptual overlap of the 2x3 Matrices, the 2x4 Matrices and the 2x3 Matching tasks, Figure 2.10 shows their distributions together. For the 2x3 Matrices and 2x4 Matrices, an ordinal variable was created that captured how often a participant avoided the highest regret option (chose the high relief option) and therefore indicated convexity: values above (below) 5 indicated greater convexity (concavity).⁵⁴ Self-report regret is also included in Figure 2.10 for comparison.

Distributions indicated that the behavioural regret aversion and Self-report regret variables were roughly bell-shaped (some skew), and there was variability in regret-related preferences. For the *MatchingIndex* the value 0 tended to occur frequently, indicating most participants entered a value for the blank spot in the matrices that made the two options equivalent in EV (which could be inferred to mean a linear Q-function, agreeable responding or disinterest in the task). Otherwise, responses were distributed indicating both convexity (negative values) and concavity (positive values) characterised participant's regret functions. Correlations were calculated between these variables, but none were significant. This suggests that for study 2, behavioural elicitation of regret curvature yielded evidence of both convexity and concavity but failed to find any notable overlap across measures. The reason for this is unclear but puts into question the utility of the 2x3- and 2x4 Matrices and 2x3 Matching task for capturing regret-preferences.

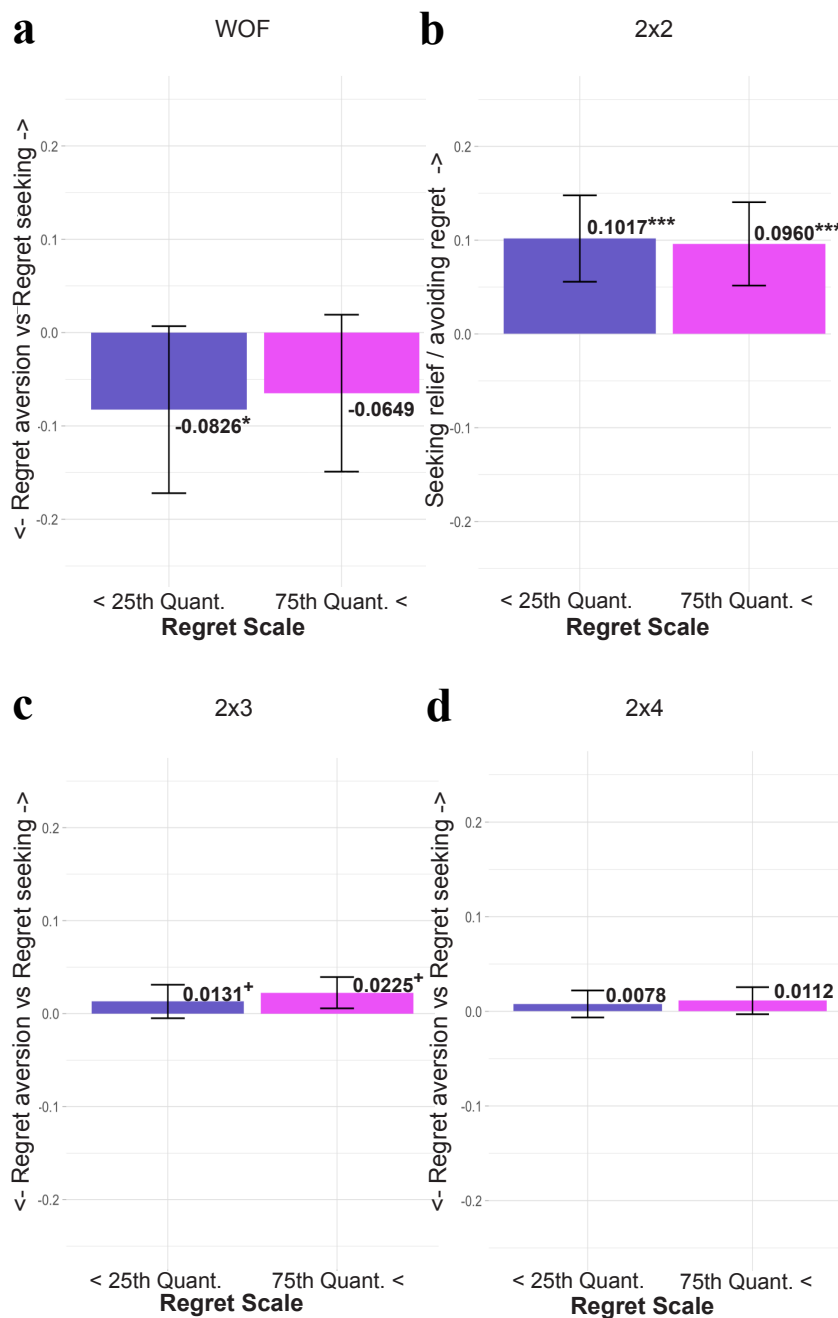
⁵⁴ For 2x4 Matrices, it is technically 4.5 not 5 because due to a design error only 9 items were included.

Table 2.8 Choices regressed on constructed regret variables and Self-report regret

	WOF (1)	WOF (2)	2x2 (1)	2x2 (2)	2x3 (1)	2x3 (2)	2x4 (1)	2x4 (2)
Intercept	0.408*** (0.009)	-1.025*** (0.033)	-0.204*** (0.005)	0.450*** (0.014)	0.221*** (0.009)	-0.720*** (0.026)	0.735*** (0.009)	-3.972*** (0.050)
EV difference	1.361*** (0.123)	1.361*** (0.123)						
Disappointment difference	-0.072 (0.053)	-0.073 (0.053)						
Regret diff (A-B)	-0.256*** (0.052)	-0.405* (0.164)						
Regret diff (A-B) by Self-report regret		0.009 (0.009)						
Regret/relief diff (A-B)			0.282*** (0.034)	0.273** (0.096)				
Regret/relief (A-B) by Self-report regret				0.001 (0.005)				
Regret Diff (A-B)					0.048** (0.015)	0.051 (0.042)	0.055*** (0.012)	0.075* (0.036)
Regret diff (A-B) by Self-report regret						-0.000 (0.002)		-0.001 (0.002)
Self-report regret		0.056*** (0.002)		-0.025*** (0.001)		0.036*** (0.001)		0.181*** (0.002)
Number Obs.	2728	2728	1736	1736	1240	1240	1116	1116
Participants (N)	124	124	124	124	124	124	124	124
Choices items	22	22	14	14	10	10	9	9
Log-likelihood	-1682	-1681	-1089	-1089	-729	-729	-624	-624
AIC	3618	3619	2427	2429	1708	1710	1498	1499
BIC	4368	4375	3109	3117	2349	2356	2125	2131

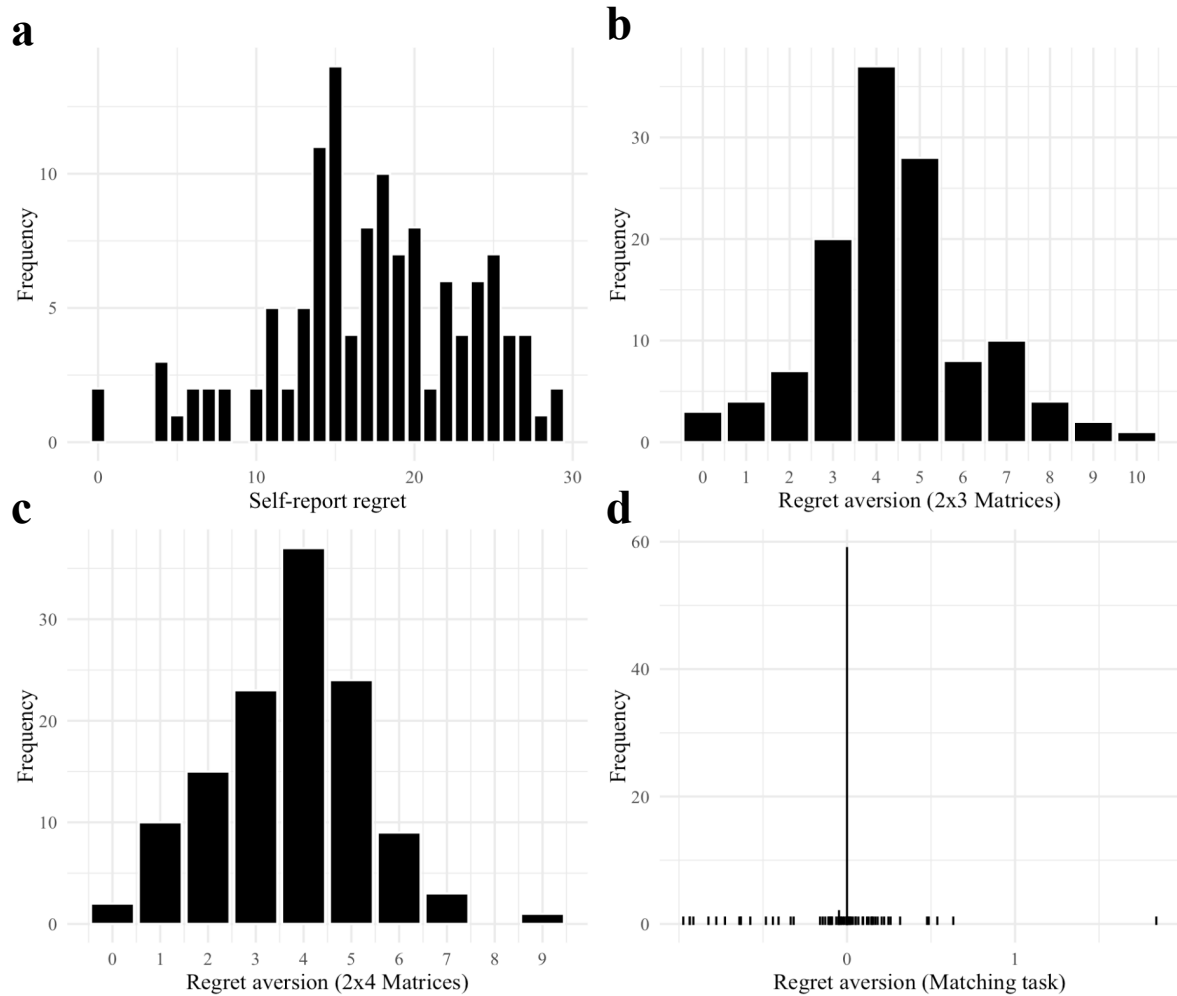
Note. Probit 'link' function used to model choices (chose option A over B) as a function of regret variables constructed from task stimuli and 'Self-report regret' (Schwartz et al., 2002 questionnaire). 'WOF' refers to choice on Wheel of Fortune task, '2x2' for 2x2 Matrices task, '2x3' for 2x3 Matrices task and '2x4' for 2x4 Matrices task (one item excluded due to a design error). For WOF, 2x3- and 2x4 Matrices, 'Regret diff (A-B)' is the max potential regret of option A minus option B; for 2x2 Matrices 'Regret/relief diff (A-B)' is the relief and regret for option A minus option B (a higher value indicated more relief over regret). Coefficients reflect change in 100s of points of regret variable (i.e., scaled variables). Models denoted as 'FE' include participant (dummy) fixed effects. For models involving interaction terms, the fixed effect (factor level) for one of the participants (ID = 124) caused a singularity and was automatically excluded when estimating the final models. Standard errors in parentheses. All models use clustered heteroskedasticity-robust errors (Stata method). Model fit summaries - Log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) - are from models that do not apply robust covariance matrix. For non-FE models, Wald-tests were calculated: all overall models were statistically significant ($p < 0.001$) except model '2x4 (2)' when a Wald-test could not be calculated. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2.9 Marginal effect capturing the effect of potential regret on behaviour (study 2)



Note. Panels refer to (a) WOF task, (b) 2x2 Matrices, (c) 2x3 Matrices and (d) 2x4 Matrices. Panels show AME from Probit models predicting choices from the relative potential regret (*RegretDiff* for WOF, 2x3 Matrices and 2x4 Matrices tasks) or potential regret relative to relief of options (*RegretRelief* for the 2x2 Matrices task). Marginals displayed separately by Self-report regret score (Schwartz et al., 2002 questionnaire) quantiles: participants falling below the 25th Quantile compared with participants falling above the 75th Quantile. Cluster-robust standard errors (non-marginal) were applied for *p-values*; however, error bars represent 95% confidence intervals based on AME estimates. Fixed effects not applied. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 2.10 *Distribution of self-report and constructed regret variables*



Note. Panel (a) shows Self-report regret (Schwartz et al. 2002 questionnaire), (b) ordinal variable capturing number of times a participant chose the option with lower maximum regret on the 2x3 Matrices task (10 choice items), (c) number of times a participant chose the option with lower maximum regret on the 2x4 Matrices task (9 choice items) and (d) the indifference score (i.e., Matching index) calculated from the 2x3 Matching task (from 9 choice items).

2.5.2 Post-decisional affect ratings and self-report regret

Panel model diagnostic tests indicated unobserved time and participant effects, and support for a fixed effects model. Appendix 2.C, Figure 2.C.1 shows there was evidence of heteroskedasticity, while residuals appeared normally distributed. There was visual evidence of mild serial correlation and tests indicated serial correlation of a higher order but not first-order. Unit-root tests indicated a stationary stochastic process.

As seen in Table 2.9, regret scenario feedback was a robust predictor of negative affect ratings across tasks. The only exception being for WOF negative-outcome choice items, for which there was no statistically significant effect of feedback. However, this subset of items was also fewer in number than the positive items (6 versus 16). Nevertheless, regret scenario was also a weaker predictor for negative relative to positive items on the 2x2 Matrices, where 7 items were used for both positive and negative outcome items. Model fit indices across positive and negative items indicated that the regression model was a worse fit for negative items.

There was evidence that Self-report regret increased the post-decisional affect experienced in regret feedback scenarios: the interaction term was significant and negative for both 2x3- and 2x4 Matrices. While the interaction term coefficients were also negative for WOF and 2x2 tasks, these were not statistically significant.

Appendix 2.F, Table F.1 shows that reporting 'true' to the social desirability question was not associated with magnified affect ratings. Rather social desirability appeared to weakly attenuated ratings following relief feedback for WOF items and regret feedback for 2x3 Matrices.

Overall, these results point to affect ratings being robustly negative after feedback scenarios involving regret; and mixed evidence regarding whether greater Self-report regret magnified this effect.

Table 2.9 Ratings regressed on task stimuli, feedback scenario and Self-report regret – WOF, 2x2-, 2x3- and 2x4- Matrices tasks separately

	WOF (positive)	WOF (negative)	2x2 (positive)	2x2 (negative)	2x3	2x4
Received outcome	13.148*** (1.518)	12.286*** (2.290)	12.602*** (1.401)	10.948*** (2.056)	2.587*** (0.371)	2.483*** (0.340)
Alternative outcome	-1.608 (1.657)	0.924 (1.950)	-1.053 (1.740)	-1.769 (1.170)	-0.475 (0.293)	-0.764** (0.292)
Regret Scenario dummy	-17.528* (7.278)	-10.996 (7.101)	-23.016** (8.668)	-17.618+ (9.487)	-18.207* (7.216)	-13.659* (6.829)
Regret Scenario dummy by Self-report regret	0.044 (0.385)	-0.280 (0.419)	-0.221 (0.438)	-0.006 (0.562)	-0.727+ (0.393)	-0.846* (0.347)
Relief Scenario dummy	4.083 (4.531)	1.821 (8.465)				
Relief Scenario dummy by Self-report regret	0.453+ (0.254)	0.162 (0.486)				
Number Observations	1984	744	868	868	1240	1240
Participants (<i>N</i>)	124	124	124	124	124	124
Choices items	16	6	7	7	10	10
R ²	0.48	0.35	0.53	0.38	0.57	0.52
Adjusted R ²	0.44	0.20	0.44	0.27	0.52	0.46
AIC	21237	7916	8977	9185	12977	12867
BIC	31523	10725	12475	12684	18627	18517

Note. Individual- & time-fixed effects models regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario and total Self-report regret (Schwartz et al., 2002 questionnaire). Results dis-aggregated across Wheel of Fortune ('WOF') task, 2x2 Matrices task ('2x2'), 2x3 Matrices task ('2x3') and 2x4 Matrices task ('2x4'). Models denoted 'positive' show results for only positive stimuli items and models denoted 'negative' show results for only negative stimuli items. For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2, 2x3 and 2x4 data, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario. All panels were balanced. Standard errors in parentheses; all models apply cluster-robust standard errors of type HC1. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R² applies to non-robust estimates. *F*-tests of overall model significance were calculated for non-robust models: all models were statistically significant ($p < 0.0001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.5.3 Post-decisional affect ratings and behavioural regret aversion

As in study 1, the effect of post-decisional ratings and task stimuli (received outcomes, forgone outcomes and feedback scenario) on subsequent regret aversion was investigated. The results are displayed for the tasks separately in Table 2.10. While for the WOF task there was no significant effect of affect ratings; for the two matrices tasks, more negative affect ratings post feedback predicted a higher chance of choosing the option with less regret subsequently (models denoted 1). However, once outcomes and feedback were accounted for, the effect reversed (models denoted 2). In these models, for matrices tasks, experiencing a regret scenario (received < forgone) was a strong predictor of choosing the option with less regret subsequently. However, this was not the case for the WOF task, where feedback scenario was non-significant in the final model (3); suggesting effects differed by display method. In the context of matrices, affect ratings may have accounted for the regret-inducing aspects of feedback (models denoted 1) because when feedback was accounted for the sign reversed (models 2). Received and forgone outcomes (*ceteris paribus*) differed in the direction of coefficients by task design (WOF versus matrices). Overall, post-decisional behaviour appeared to depend on the stimuli associated with feedback in different ways according to task display (echoing results in study 1). It appeared the relative difference per se (feedback dummy variable) was more likely to prompt regret aversion in the matrices task, perhaps owing to the correlated nature of prospects. Finally, there was no evidence of Self-report regret scores modifying the association between regret scenario and regret aversion. Overall, this suggested mixed evidence for regret-related behaviour being influenced by preceding affect ratings, outcomes or feedback scenario; an no evidence that perceived regret proneness moderated the influence of experimental regret elicitation on subsequent choices.

Table 2.10 Dependent variable: chose option with less potential regret, regressed on preceding period's affect ratings, outcomes, feedback scenario or Self-report regret interactions (WOF, 2x3 Matrices and 2x4 Matrices tasks)

	WOF (1)	WOF (2)	WOF (3)	2x3 (1)	2x3 (2)	2x3 (2)	2x4 (1)	2x4 (2)	2x4 (2)
Intercept	-0.105*	-0.186*	-0.085	-0.105*	-4.257***	-4.192***	-0.150***	-32.626***	-33.145***
	(0.041)	(0.088)	(0.252)	(0.044)	(0.212)	(0.256)	(0.042)	(1.375)	(1.283)
Ratings (previous period)	-0.000	-0.002	-0.002	-0.005***	0.007***	0.007**	-0.008***	0.013**	0.013*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.005)	(0.005)
Received outcome (previous period)		-0.166+	-0.172+		0.803***	0.803***		10.351***	10.403***
		(0.095)	(0.096)		(0.033)	(0.033)		(0.399)	(0.327)
Foregone outcome (previous period)		0.325***	0.332***		-0.793***	-0.794***		-10.342***	-10.391***
		(0.092)	(0.093)		(0.033)	(0.033)		(0.381)	(0.294)
Regret Scenario (previous period)		-0.304*	-0.227		8.183***	8.217***		64.657***	65.607***
		(0.154)	(0.329)		(0.329)	(0.417)		(2.455)	(2.123)
Relief Scenario (previous period)		0.327*	0.188						
		(0.138)	(0.281)						
Regret Scenario (previous period) by Self-report regret			-0.005			-0.002			-0.038
			(0.017)			(0.015)			(0.030)
Relief Scenario (previous period) by Self-report regret			0.009						
			(0.016)						
Number Obs.	1240	1240	1240	1240	1240	1240	1116	1116	1116
Participants (N)	124	124	124	124	124	124	124	124	124
Choices items	10	10	10	10	10	10	9	9	9
Log-likelihood	-855	-840	-839	-839	-386	-385	-736	-85	-84
AIC	1714	1692	1696	1681	781	785	1476	180	183
BIC	1724	1722	1742	1691	807	821	1486	205	218

Note. Probit 'link' function used to model choices (chose option A over B) as a function of previous choice's outcome ('previous period') variables. The variables were affect ratings (VAS) given post-feedback, received outcome, forgone outcome, feedback scenario; and total Self-report regret (Schwartz et al., 2002 questionnaire) interaction effects. Models named 'WOF' are choices on the Wheel of Fortune task, '2x3' are choices on the 2x3 Matrices task and '2x4' are for choices on the 2x4 Matrices task. Coefficients on received and forgone outcome reflect change in 100s of points (i.e., scaled variables). Due to computational difficulties, fixed effects were not included. Standard errors in parentheses. For models '2x4 (2)' and '2x4 (3)', estimation returned the warning that fitted probabilities were numerically 0 or 1 for some observations. All models use clustered heteroskedasticity-robust errors (Stata method). Model fit summaries - Log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) - are from models that do not apply robust covariance matrix. For non-FE models, Wald-tests were calculated: models 'WOF (2)', 'WOF (3)', '2x3 (1)', '2x3 (2)', '2x4 (1)' and '2x4 (2)' were statistically significant ($p < 0.05$); while overall model significance for models '2x3 (3)' and '2x4 (3)' could not be estimated. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.6 Discussion

The findings of this paper challenge the notion that regret is a one-dimensional construct. There was mixed evidence of overlap across self-reported regret, behavioural regret aversion, and affect ratings after experimental regret elicitation (feedback). Specifically, there was almost no evidence that self-report regret – one’s perceived tendency or proneness to experience regret during decision-making - was associated with behavioural choice patterns, specifically, regret aversion. The only exception was in study 1, where higher self-report regret was positively associated with behaviour indicative of convex regret curvature (as predicted by Regret theory). Moreover, there was mixed evidence that negative affect (as inferred from ratings following feedback on choices) subsequently prompted regret aversion: this was observed for matrices tasks but not the WOF task. Contrasting these findings, there was relatively strong evidence for a positive association between self-reported regret and experiencing more negative affect following regret feedback. The effect was relatively consistent across tasks and statistically robust – suggesting a conceptual link across methodologies reliant on self-report. As discussed further below, findings highlight methodological and conceptual caution must be shown when investigating the role of regret in economic decision-making.

As noted, there was little evidence of convergent validity across self-report and behavioural measures of regret, while there was overlap across self-report methods. This separability of regret according to measures method echoes findings for other decision-making constructs: self-control measures have been argued to reflect further separable concepts by Allom et al. (2016), who also note self-control has shown historically low correlations across self-report and behavioural measures (e.g., $r = 0.10$ in meta-analysis by Duckworth and Kern (2011)). Similarly, for risk-preferences, the overlap between self-report (ratings of statements regarding one’s willingness to take risk) and behaviour measures (e.g., percentage of risky choices) was identified as low in a recent meta-analysis; the meta-analytic correlation reported by Bagaïni et al. (2025) was $r = 0.15$ across 460,333 respondents. The correlation across self-report (‘propensity’) measures was nearly three times that, $r = 0.41$.

There are multiple possible explanations for why self-report regret did not overlap with behaviourally measured regret. A person may simply be generally unable to form veridical insights into their decision-making tendencies. Or a person who is very good at anticipating

and avoiding regret may therefore not tend to experience (nor report) regret. While plausible, these explanations seem extreme considering human psychology. A more likely explanation is that, although overlap may exist, the anticipatory computations that drive regret-averse behaviour are not captured well enough by many self-report questionnaires. The Schwartz et al. (2002) scale was selected from amongst published scales for pertaining most proximally to the point of choice. Further, the wording of two items, “*Whenever I make a choice...*” arguably could be interpreted as relating to anticipatory processes. Nevertheless, the scale pertains primarily to post-choice, or retrospective regret. As noted in a review by Zeelenberg and Pieters (2007), anticipatory and retrospective regret are distinguishable, the former potentially a more cognitive rather than emotional computation. If the self-report scales conversely tap into retrospective and emotional aspects of regret, this may further explain the finding that self-reports were predictive of participants subjective affect ratings in the current study. Future research involving self-report measures of regret proneness may seek to better describe the process of anticipation - indeed, the very first psychometric scale measuring anticipated regret as a general tendency was recently developed (Fergus & Hiraoka, 2025).⁵⁵ This 6-item scale showed high correlations with the Schwartz scale ($r = 0.61$, similar to that found across self-reports in study 2) but not so high as to make it redundant, suggesting the comparative computations captured by these scales are associated but different. While a scale more targeted at anticipatory regret may clarify the findings herein, the near absent association between self-report and behaviour in the current study warrants further consideration. One would expect that even though differing, a tendency to engage in comparative computations after choice (retrospective) would have some association with tending to do so before choice (anticipatory).

Additional reasons for low correlations across different measurement methods (and indeed why this might be expected) are discussed in Wennerhold and Friese (2020). They suggest self-report measures may better capture the ‘central tendency’: aggregates of many instances of behaviour, and across domains or contexts. Even though the regret scale items were selected for asking about decision-making specifically, the perceptions it gauges may better reflect such a central tendency. Conversely, behavioural tasks, such as the ones applied in the current study, may not capture domain-general tendencies. That is, self-report regret may still

⁵⁵ Regrettably, not identified in time to be included in the current research (identified by Claude, Anthropic). In Fergus and Hiraoka (2025), their scale was compared to the Schwartz et al. (2002) scale to test for convergent validity.

characterise a person's typical decision-making behaviour (i.e., their tendencies), even if there is poor overlap with behaviour in specific (experimental) contexts.

Related to this points, Dang et al. (2020) argue that low correlations between behavioural and self-report measure of the (purportedly) same construct may be due to the tasks being designed so as to measure *different response processes*: self-reports are designed to prompt participants to reflect on general tendencies, hence subjective judgement; while behavioural tasks measure responses to uncommon stimuli in highly controlled situations, and often with the aim of limiting between-participant variance while enhancing within-participant variance. The results of the current paper provides some nuance to this point: while self-report regret and behavioural regret were relatively un-associated (i.e., agreeing with Dang et al. (2020)'s point); it did appear participants could form accurate perceptions (in their self-reports) about how regretful they would feel upon receiving feedback experimentally designed to elicit regret (their affect ratings), given these were correlated.

To the author's knowledge, the studies herein are the first to explore the nature of regret applying an interdisciplinary set of methodologies that span self-reported and behavioural measures. The results of the current study speak to the importance of examining constructs for their consistency across methods that rely on self-knowledge versus methods used for inferring the influence of decisional variables from behaviour. This highlights the importance of using multiple measures (Bagai et al., 2025), and to be mindful of what decision-making phenomena a measure may actually capture. As noted, further work is needed to understand which measures capture which aspects of regret (e.g., retrospective vs anticipatory, or affective vs cognitive), and this requires convergent validity studies to incorporate not just self-report psychometrics but also behavioural measures.

Regarding Regret theory, tests of regret curvature - convexity versus concavity of the Q -function - provided mixed results. There appeared to be notable heterogeneity in curvature based on participants' choices: some participants avoided the option with the highest possible regret (or chose the highest relief option), indicating convexity; while many participants exhibited the opposite pattern, indicating concavity. Moreover, only in study 1 was there an association in the expected direction between self-report regret and greater convexity. Otherwise, measures of regret curvature failed to overlap (study 2). It may be that the methods designed to test for curvature were not sensitive enough, or that choices were simply

too noisy (due to other factors). This could explain why in study 1, with a larger sample size, there was a weak association between self-reported regret and regret aversion but not in study 2. Future studies may seek to clarify this with either larger samples or utilising other methodologies found in the literature to test for convergent validity (e.g., the “trade-off” method used in Bleichrodt et al., 2015). However, the results of the current study are not surprising seen in context of past literature: past studies suggest there is notable individual variation in whether behaviour accords with Regret theory (Andersson et al., 2023; Birnbaum & Diecidue, 2015; Birnbaum & Schmidt, 2008; Bleichrodt et al., 2010; di Cagno & Hey, 1988; Somasundaram & Diecidue, 2017). Birnbaum and Diecidue (2015) and Birnbaum and Schmidt (2008) found that there was generally little evidence of intransitive choices that would be expected from Regret theory; in the latter, only a small (single-digit) percentage of participants did exhibit intransitivity. Bleichrodt et al. (2010)’s results indicate up to 1/3 may evidence concavity (not convexity). Nevertheless, as in Bleichrodt et al. (2010), the majority of subjects in Somasundaram and Diecidue (2017) evidenced regret aversion.

Notwithstanding the tenuous associations across measurement methods and mixed results regarding Regret Theory; in general, there was strong evidence that potential regret influenced decision-making. The WOF task, displaying prospects in a manner used across several previous studies in neuroeconomics, appeared useful for identifying behaviour that was contingent on counterfactual outcomes. The task was also useful for inducing post decisional affect (regret) ratings. This was also the case for the more novel 2x2 Matrices task, designed in a manner that emphasised state-dependence for both prospects (i.e., making these correlated). Thus, tasks involving state-dependent, correlated, prospects are a useful tool when seeking to understand regret experimentally. Indeed, results suggested that the matrices display (relative to WOF) were particularly effective at inducing post-decisional affect ratings (i.e., negative following regret-inducing feedback). As for subsequent choice, it appeared the features most likely to predict regret aversion differed across tasks: for the WOF task, it was outcomes (received and forgone); while for the matrices, it was the feedback scenario per se (received < forgone). While speculative, this could be linked to variation in state-dependence: the WOF task involved uncorrelated prospects, meaning participants may have been less swayed by feedback because, say, choosing option A over B, was not *as* deterministically linked (a high outcome on B was less directly coupled to choice due to B being determine by its own random process). For matrices, receiving a negative outcome for B was less variably linked to one’s choosing A.

The studies herein extend on past findings by showing that while a higher forgone outcome was associated with more negative affect ratings, as in past studies (e.g., (Lin et al., 2006)), it appeared the overall context (feedback scenarios capturing both received and forgone outcomes) was more strongly associated with ratings. Additionally, study 2 results suggest that negative stimulus values (outcomes) were less effective at inducing the intended post-decisional affect. This agrees with previous observations that positive stimuli may be more effective (e.g., Zeelenberg et al (1996)).

In conclusion, findings from the two experimental studies comprising this chapter align with a large literature conferring importance on regret as a decisional emotion. This held for regret as an anticipatory influence on behaviour, while regret manipulations also appeared to shape post-decisional affective states. While participants' perceptions regarding their tendency or proneness to experience regret correlated with affective states, there was little overlap with behavioural measures of regret aversion based on their choices. Regret as a decisional construct may therefore not overlap well across self-reported versus behavioural methods, indicating these capture distinct phenomena influencing economic decision-making.

Appendix 2.A

Calculation showing the implied regret function convexity when choices favour the option that is regret minimising / relief maximising.

Table A.1 *Three-outcome prospects identifying regret aversion (holding EU, EV and disappointment constant)*

	State $j = 1$	State $j = 2$	State $j = 3$
Action (choice) 1	450	850	50
Action (choice) 2	50	450	850

Applying the example of choosing between Action 1 and 2 in Table 2.2 (from the main text), and assuming linear utility $u(x) = x$, then the two prospects can be summarised as,

Action A: $1/3(450) + 1/3(850) + 1/3(50)$ and

Action B: $1/3(50) + 1/3(450) + 1/3(850)$, if

Next if

$$\begin{aligned}
 & \textit{Action A} < \textit{Action B} \\
 & \rightarrow \\
 & Q(450 - 50) + Q(850 - 450) + Q(50 - 850) \\
 & < Q(50 - 450) + Q(450 - 850) + Q(850 - 50) \\
 & \rightarrow \\
 & Q(400) + Q(400) + Q(-800) < Q(-400) + Q(-400) + Q(800) \\
 & \rightarrow \\
 & Q(400) + Q(400) - Q(-400) - Q(-400) < -Q(-800) + Q(800) \\
 & \rightarrow \\
 & \text{because it is assumed } Q(z) = -Q(-z) \\
 & \rightarrow \\
 & Q(400) + Q(400) + Q(400) + Q(400) < Q(800) + Q(800) \\
 & \rightarrow \\
 & 2(Q(400) + Q(400)) < 2(Q(800)) \\
 & \rightarrow \\
 & Q(400) + Q(400) < Q(800) \\
 & \rightarrow \\
 & Q(\cdot) \text{ is convex}
 \end{aligned}$$

Appendix 2.B

Summary of total points, comprehension questions and FOSD-violations from study 1 and study 2.

Participants completed comprehension questions before the Wheel of Fortune (WOF) task, 2x2 Matrices task and 2x3 Matching task. The frequencies of correct responses for both study 1 and study 2 are displayed in Figure 2.B.1. Across the three WOF comprehension questions, in study 1: 3 (1.6%) participants got all answers incorrect, while 152 (78.4%) got all three answers correct; in study 2: the frequencies were 3 (2.4%) all incorrect and 95 (76.6%) all correct. For the 2x2 Matrices, in study 1: 9 (4.7%) participants got all three answers incorrect, while 116 (60.1%) got all answers correct; in study 2 the frequencies were: 6 (4.8%) all incorrect, while 66 (53.2%) all correct (about 7% lower than study 1). For the Matching task in study 2, 2 (1.6%) got all questions incorrect and 64 (51%) got all three questions correct. Overall, there was evidence that participants comprehended the tasks.

One item was embedded in each of the WOF and 2x2 Matrices tasks testing for First Order Stochastic Dominance (FOSD)-violating choices. In study 1: on the WOF, 166 (85.57%) of participants chose the non-dominated option (i.e., showing rationality); while on the 2x2 Matrices task, 169 (87.11%) chose the non-dominated option. In study 2: 103 (83.1%) chose the non-dominated option on the WOF task, and 111 (89.5%) chose the non-dominated option on the 2x2 task.

Given only a very small number of participants had notable difficulty with the comprehension tasks or violated FOSD, the full sample was retained for analysis in both studies. This avoided interfering with the natural variation within the samples.

For both study 1 and study 2, the total points earned by each participant across the tasks were distributed normally, as seen in Figure 2.B.2. Total points earned were uncorrelated with Self-report regret.

Figure 2.B.1 Frequency of correct comprehension questions answers. For study 1 (a) WOF task and (b) 2x2 Matrices task; for study 2 (c) WOF task, (d) 2x2 Matrices task and (e) 2x3 Matching task

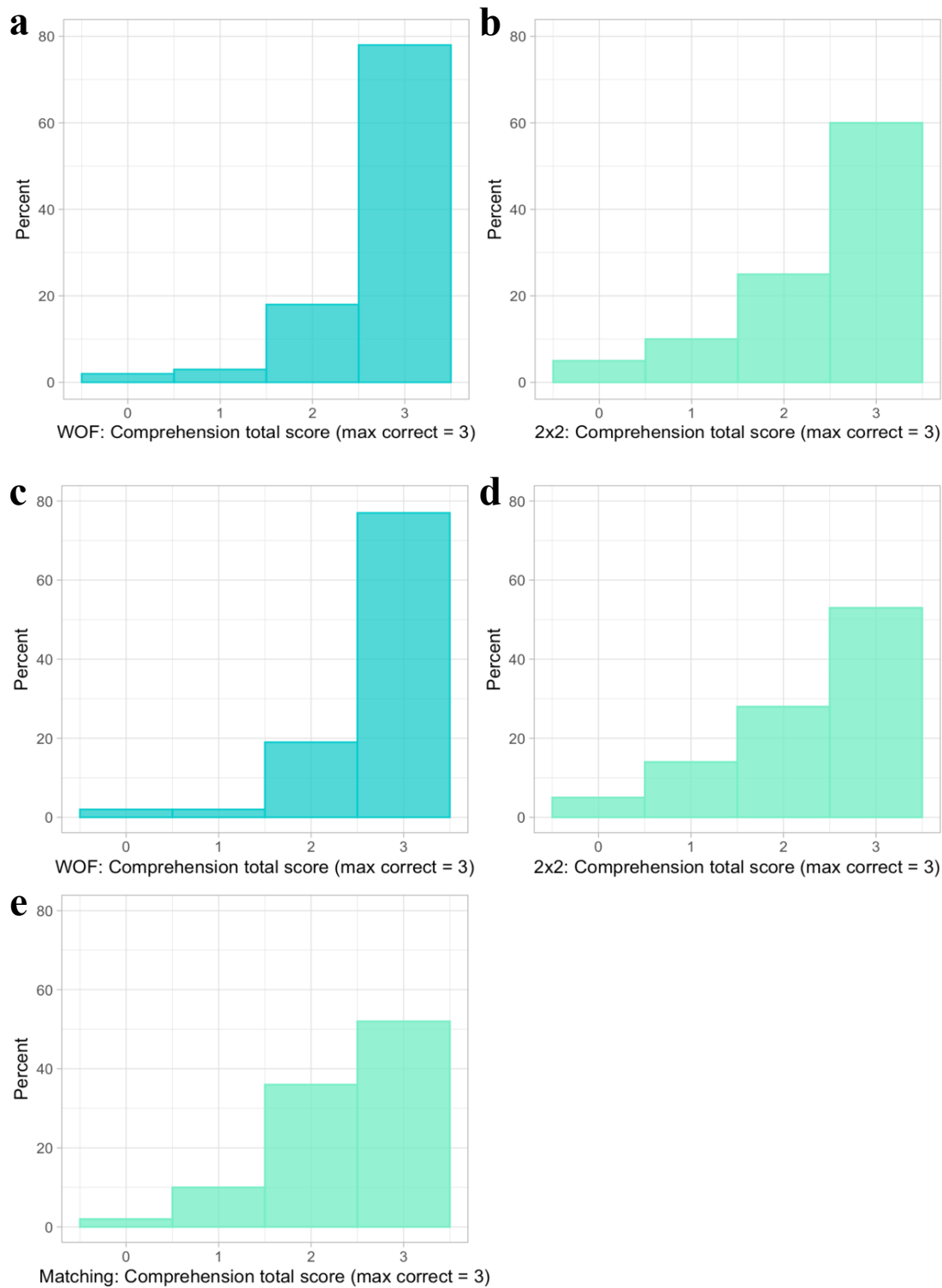
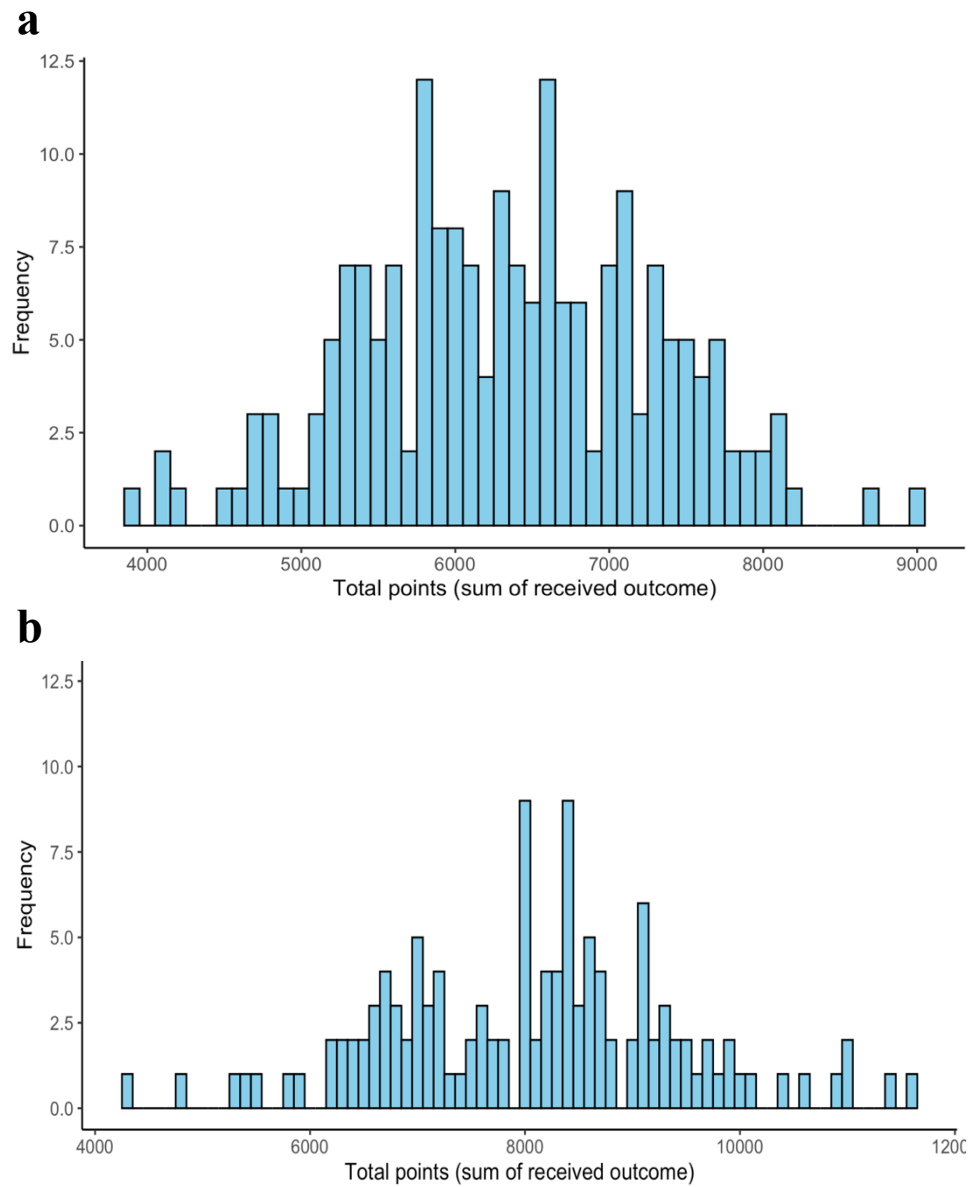
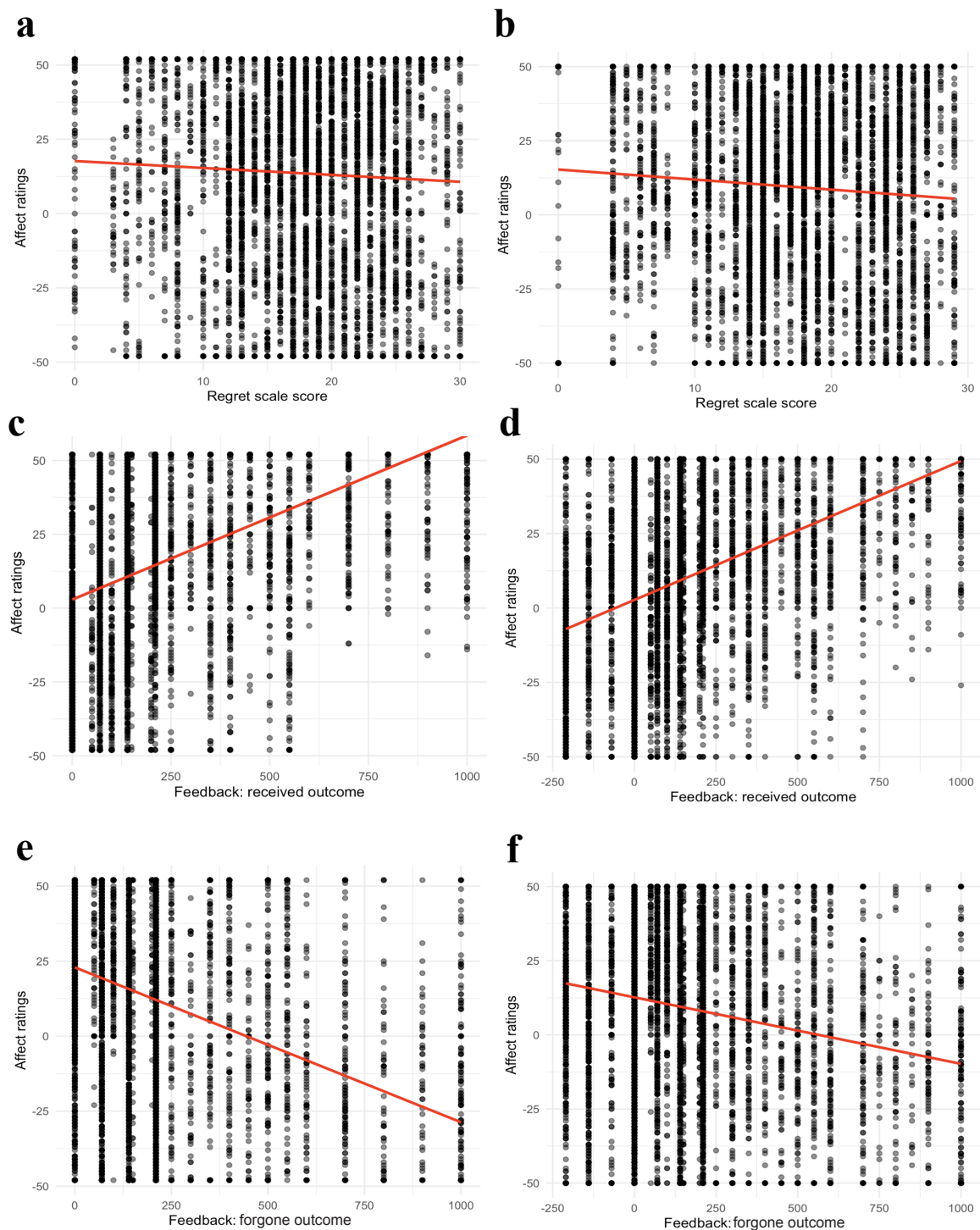


Figure 2.B.2 Frequency of total points earned by each participant. Panel (a) shows for study 1 (across 33 choice items) and (b) shows for study 2 (across 56 choice items, excluding 2x3 Matching task)



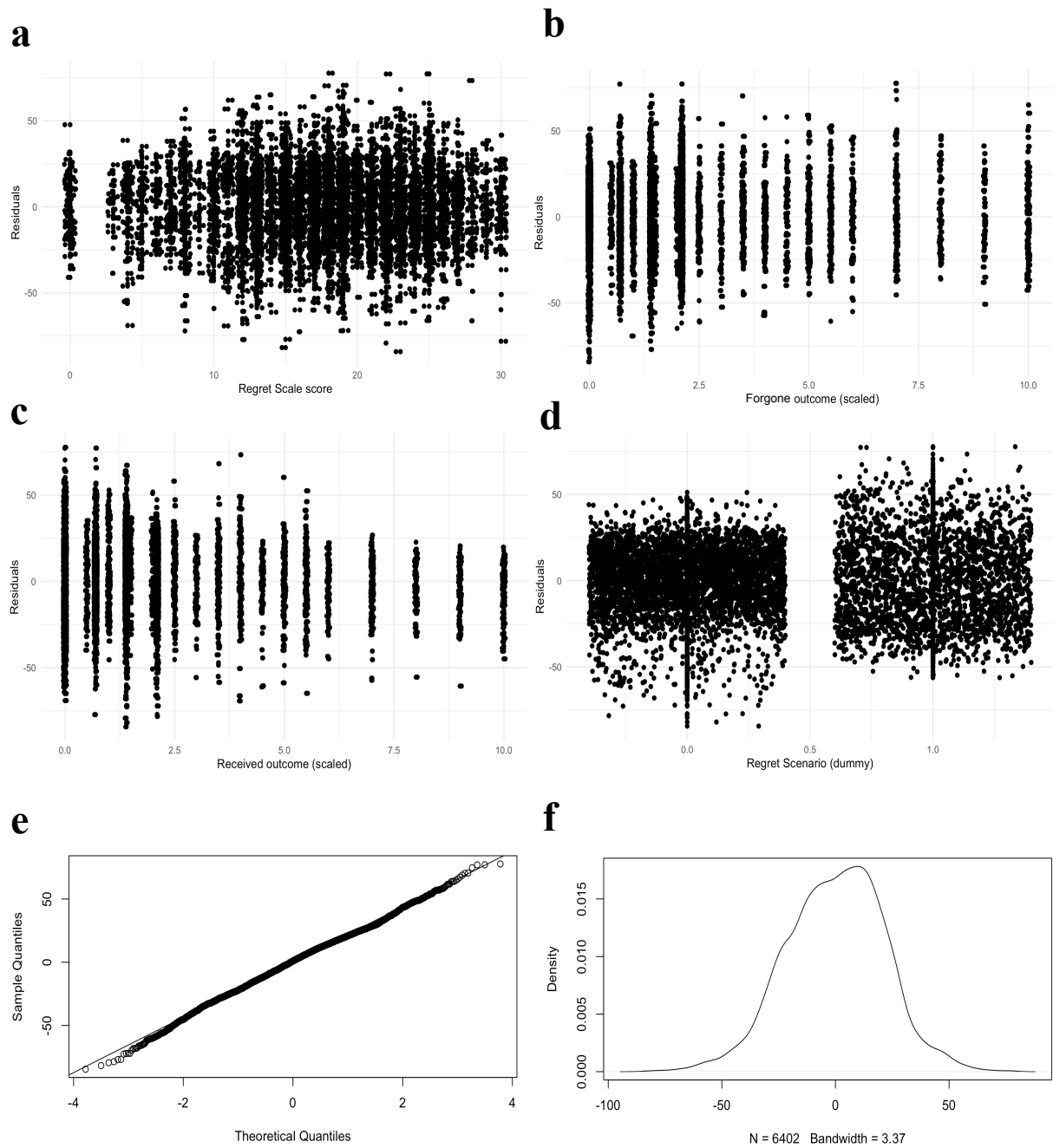
Appendix 2.C

Figure 2.C.1 Scatterplots for heteroskedasticity diagnosis of affect ratings



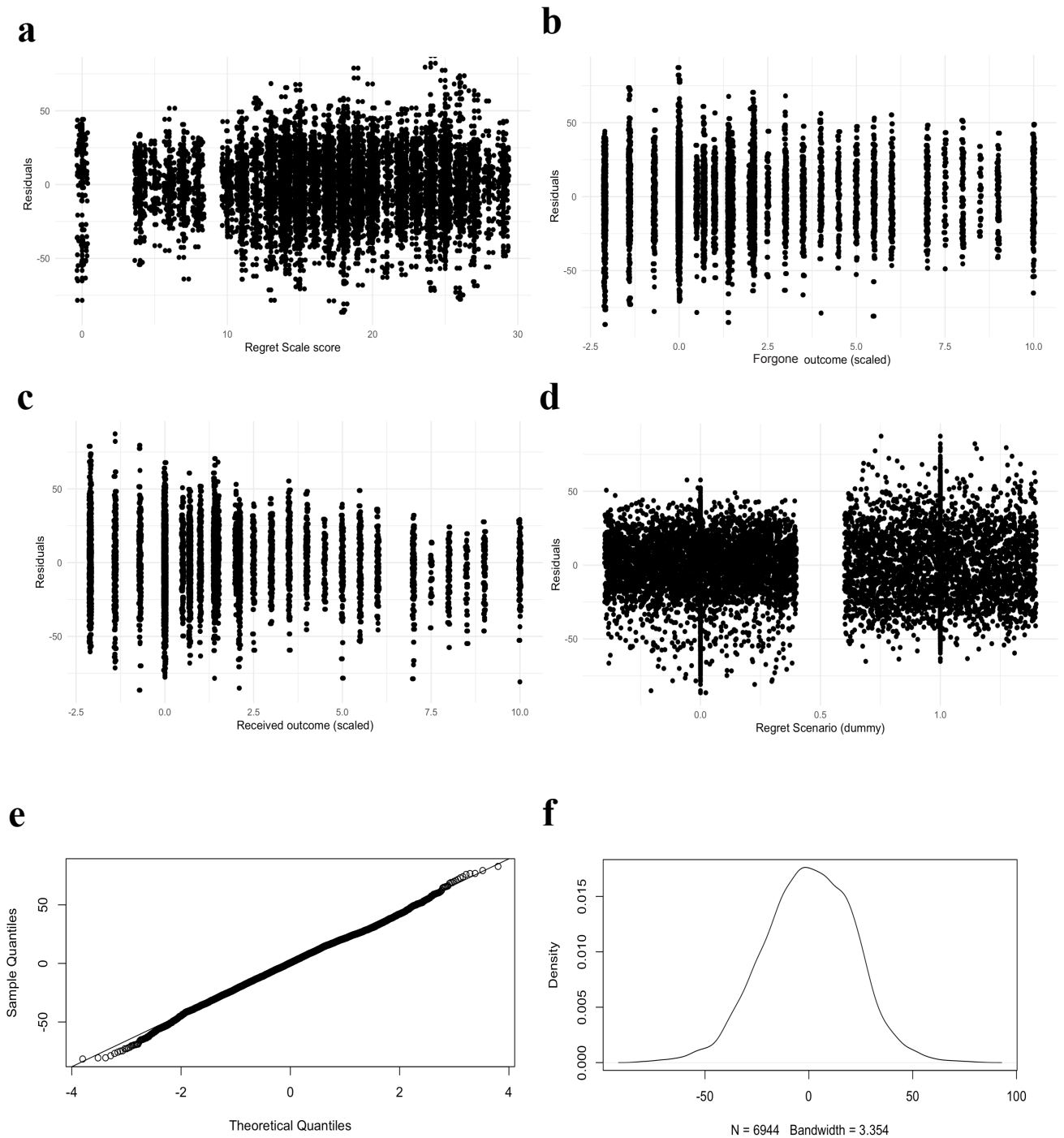
Note. Fixed effect (panel) models in study 1: Affect ratings by (a) Self-reported regret scale score (Schwartz et al., 2002 questionnaire), (c) received outcome and (e) forgone outcome. For study 2: Affect ratings by (b) Self-reported regret scale score, (d) received outcome on choice item and (f) forgone outcome on choice item.

Figure 2.C.2 Residual scatterplots, Q-Q plot and density plots from panel model of affect ratings (fixed effects) in study 1



Note. Panels (a) shows scatterplot for Self-reported regret scale score (Schwartz et al., 2002 questionnaire), (b) scatterplot for Forgone outcome, (c) scatterplot for Received outcome, (d) Scatterplot for regret scenario dummy variable, (e) Q-Q Plot comparing residuals to theoretical quantiles and (f) density plot of residuals

Figure 2.C.3 Residual scatterplots, Q-Q plot and density plots from panel model of affect ratings (fixed effects) in study 2



Note. Panels (a) shows scatterplot for Self-reported regret scale score (Schwartz et al., 2002 questionnaire), (b) scatterplot for Forgone outcome, (c) scatterplot for Received outcome, (d) scatterplot for regret scenario dummy variable, (e) Q-Q Plot comparing residuals to theoretical quantiles and (f) density plot of residuals.

Appendix 2.D

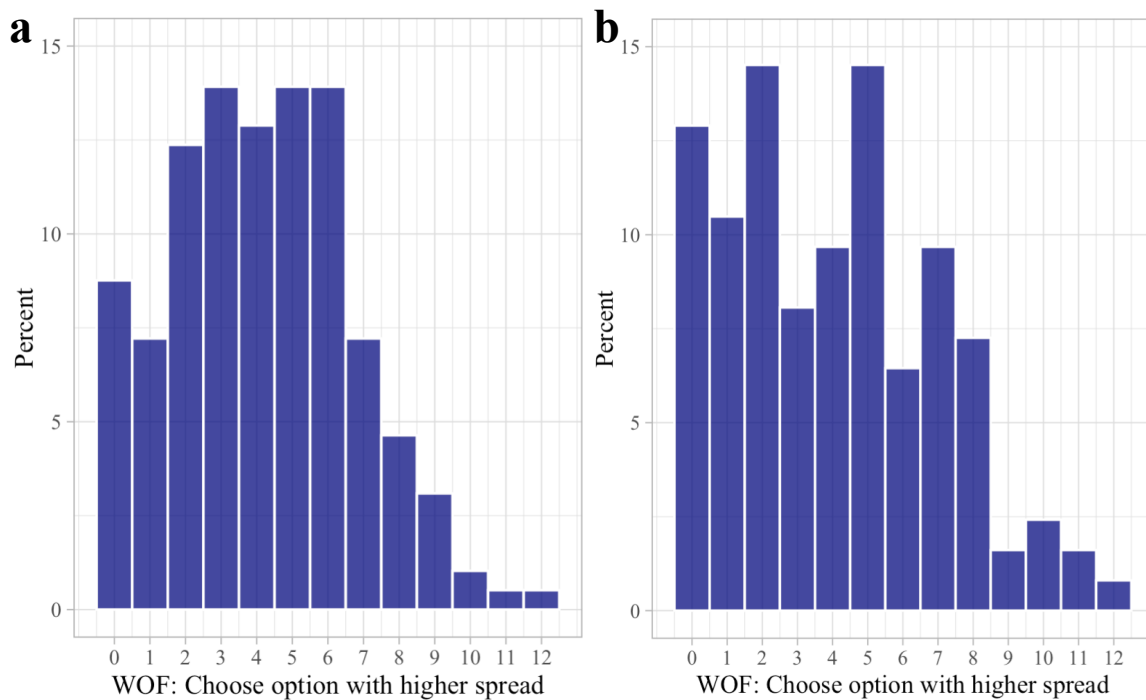
Table D.1. *Affect ratings post-feedback regressed on task stimuli, feedback scenario and Self-report regret - random-effects, fixed-effects & pooled OLS for comparison*

	FE (1)	FE (2)	FE (2-robust)	FE (3)	FE (3-robust)	RE (1)	RE (2)	RE (2-robust)	RE (3)	RE (3-robust)	Pooled (3)	Pooled (3) (robust + controls)
Intercept						8.952*** (1.233)	21.238*** (2.368)	21.238*** (3.383)	13.822*** (3.293)	13.822** (4.651)	17.971*** (4.686)	16.963** (5.611)
Received outcome	8.340*** (0.223)	3.903*** (0.219)	3.903*** (0.262)	3.459*** (0.218)	3.459*** (0.258)	7.773*** (0.198)	3.407*** (0.201)	3.407*** (0.229)	2.866*** (0.202)	2.866*** (0.222)	1.866*** (0.177)	1.872*** (0.178)
Alternative outcome	-5.120*** (0.220)	0.266 (0.227)	0.266 (0.231)	1.052*** (0.230)	1.052*** (0.239)	-5.711*** (0.195)	-0.273 (0.211)	-0.273 (0.232)	0.425* (0.214)	0.425+ (0.238)	-0.653** (0.207)	-0.667** (0.210)
Regret Scenario dummy		-26.083*** (1.863)	-26.083*** (5.394)	-19.210*** (2.945)	-19.210*** (5.582)		-25.592*** (1.859)	-25.592*** (5.489)	-19.505*** (2.939)	-19.505*** (5.674)	-18.612** (6.079)	-18.551** (6.060)
Regret Scenario dummy by Self-report regret		-0.746*** (0.093)	-0.746** (0.286)	-0.458** (0.153)	-0.458 (0.294)		-0.766*** (0.093)	-0.766** (0.289)	-0.482** (0.153)	-0.482 (0.298)	-0.602+ (0.320)	-0.611+ (0.320)
Relief Scenario dummy				10.470*** (2.875)	10.470** (3.752)				9.738*** (2.870)	9.738** (3.736)	8.574* (3.945)	8.743* (3.915)
Relief Scenario dummy by Self-report regret				0.352* (0.150)	0.352+ (0.194)				0.346* (0.150)	0.346+ (0.193)	0.337 (0.206)	0.320 (0.205)
Number Obs.	6402	6402	6402	6402	6402	6402	6402	6402	6402	6402	6402	6369
Participants (<i>N</i>)	194	194	194	194	194	194	194	194	194	194	194	193
Choices items	33	33	33	33	33	33	33	33	33	33	33	33
R ²	0.348	0.506	0.506	0.522	0.522	0.339	0.497	0.497	0.513	0.513	0.482	0.482
Adjusted R ²	0.324	0.488	0.488	0.505	0.505	0.339	0.497	0.497	0.512	0.512	0.481	0.481
AIC	59517	57735	70069	57529	69855	59784	58014	70792	57823	70593	59008	58709
BIC	59537	57769	111819	57576	111591	59811	58061	114057	57884	113844	59069	58810

Note. Individual- & time- fixed effects, random effects and pooled OLS models, regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario and total Self-report regret (Schwartz et al., 2002 questionnaire). Results for data aggregated across Wheel of Fortune (WOF) task, 2x2 Matrices task and 2x3 Matrices task. For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2 and 2x3 data, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario. 'FE' refers to fixed effects models, 'RE' random effects models, and 'Pooled' pooled OLS. For pooled model, controls ('controls.') were dummy capturing female gender status (vs other), age, dummy capturing country of birth is Australian (vs other), dummy capturing if income is above median of sample (vs not); and two dummies if i) unemployed or ii) student - relative to the following as dummy: full-time employed, self-employed, part-time employment, retired, volunteer, carer, home duties or other. Standard errors in parentheses; models denoted '-robust' apply cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R² applies to non-robust estimates. F-tests (or χ^2 -test for RE) of overall model significance were calculated for non-robust models: all models were statistically significant ($p < 0.0001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix 2.E

Figure 2.E.1 Frequency of participants choosing the WOF task option with the higher spread (risk) in outcomes: (a) study 1 and (b) study 2.



A colleague noted that the incentivisation used in study 1 - paying participants based on whether they were the top 5 participants with the most total points – could prompt participants to choose options to maximise points relative to others rather than according to their preferences. In study 2, participants were incentivised by being told 5 of them would be chosen at random, and for those, one option would be chosen at random for payment. To see if incentivisation approach produced differences in behaviour, the frequency of times participants chose a WOF option with a higher outcome spread is shown in Figure 2.E.1, for study 1 and study 2. By ‘spread’ is meant the difference between the two outcomes: for example, for option A (say 210 points - 0 points) versus for option B (say 140 points – 70 points). Option A has the higher number of points possible but also with a risk of a lower outcome. Scores in Figure 2.E.1 ranged from 0 to 12 as there were 12 items with difference in spread. There was no notable visual difference in participants choosing a higher spread (risk) option in study 1 relative to study 2, as seen in Figure 2.E.1. For both studies there was evidence of a greater frequency of participants choosing the option with a lower spread.

Appendix 2.F

Table F.1 Ratings regressed on task stimuli, feedback scenario and Self-report regret – WOF, 2x2, 2x3 and 2x4 Matrices tasks separately, accounting for social desirability

	WOF (positive)	WOF (negative)	2x2 (positive)	2x2 (negative)	2x3	2x4
Received outcome	12.967*** (1.542)	12.317*** (2.242)	12.623*** (1.381)	10.873*** (2.044)	2.653*** (0.375)	2.475*** (0.344)
Alternative outcome	-1.322 (1.649)	1.066 (1.855)	-1.044 (1.746)	-1.860 (1.181)	-0.400 (0.290)	-0.752** (0.290)
Regret Scenario dummy	-7.081 (8.447)	-14.742 (9.193)	-11.709 (10.429)	-13.949 (12.361)	-2.594 (9.952)	-1.325 (10.663)
Regret Scenario dummy by Self-report regret	-0.205 (0.466)	0.253 (0.573)	-0.784 (0.530)	0.059 (0.733)	-1.758*** (0.464)	-1.367** (0.498)
Relief Scenario dummy	-5.109 (7.244)	-19.515* (9.327)				
Relief Scenario dummy by Self-report regret	1.182** (0.428)	1.356** (0.487)				
Regret Scenario dummy by SDS	-17.058 (12.816)	5.004 (12.535)	-18.622 (14.953)	-5.478 (17.892)	-24.897+ (13.406)	-19.342 (13.344)
Relief Scenario dummy by SDS	13.816 (8.526)	32.350* (14.168)				
Regret Scenario dummy by Self-report regret by SDS	0.396 (0.695)	-0.806 (0.773)	0.926 (0.792)	-0.113 (1.063)	1.646* (0.684)	0.814 (0.662)
Relief Scenario dummy by Self-report regret by SDS	-1.083* (0.505)	-1.831* (0.809)				
Number Observations	1984	744	868	868	1240	1240
Participants (<i>N</i>)	124	124	124	124	124	124
Choices items	16	6	7	7	10	10
R ²	0.48	0.35	0.53	0.34	0.57	0.52
Adjusted R ²	0.43	0.20	0.44	0.27	0.51	0.46
AIC	21196.8	7895.5	8967.6	9175.7	12951.2	12852.5
BIC	31459.7	10685.8	12456.5	12664.6	18591.5	18492.8

Note. Individual- & time-fixed effects models regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario, total Self-report regret (Schwartz et al., 2002 questionnaire) and 'SDS' = Social Desirability Scale. SDS scored with single T/F question where '1' vs '0' indicated a tendency to accept another's opinion even if it disagreed with one's own. Results dis-aggregated across Wheel of Fortune ('WOF') task, 2x2 Matrices task ('2x2'), 2x3 Matrices task ('2x3') and 2x4 Matrices task ('2x4'). Models denoted 'positive' show results for only positive stimuli items and models denoted 'negative' show results for only negative stimuli items. For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2, 2x3 and 2x4 data, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario. All panels were balanced. Standard errors in parentheses; models denoted '- Robust' apply cluster-robust standard errors of type HC1. *F*-tests of overall model significance were calculated for non-robust models: all models were statistically significant ($p < 0.0001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chapter 3. Depressive symptoms and self-reported versus behavioural regret during decision-making

Abstract

Depression has been linked to regret, an important decisional emotion that can shape evaluation and economic decision-making. However, most of this literature pertains to self-reported regret in the form of perceived tendencies or proneness towards regret. In contrast, decision-making studies have yielded mixed evidence: it is unclear if regret aversion and affective responses following regret are moderated by depressive symptoms. To clarify, two large samples were recruited to complete various decision-making tasks eliciting regret, and questionnaires measuring self-reported regret and depressive symptoms. Results indicated self-reported regret proneness was robustly associated with depressive symptoms. However, there was no evidence of depressive symptoms being associated with reporting more or nor less negative affect following regret feedback. Furthermore, there was at best weak/mixed evidence of depressive symptoms being associated with regret aversion. Anhedonia appeared to blunt responsiveness to the potential regret/relief of an option during (one) experimental decision-making task. And there was some descriptive statistical evidence of non-linear patterns of regret aversion across depression severity. However, depressive symptoms generally did not moderate the behavioural effects of regret during decision-making. Findings highlight the importance of delineating constructs across measurement method when exploring economic decision-making in the context of depression.

Key words: *regret, economic, depression, anhedonia, decision-making, counterfactual*

3.1 Introduction

The way depressive symptoms manifest as computational-, information- and reward-processing differences has received increasing attention (Bishop & Gagne, 2018; Foland-Ross & Gotlib, 2012; Gotlib & Joormann, 2010; Halahakoon et al., 2020; Huys et al., 2021; Mukherjee et al., 2023). A *decision-theoretic* account of depression holds promise for integrating such research (Huys et al., 2015), and may help clarify the links between clinical symptoms and disorder-related disadvantage, including impacts on economic decision-making. On a societal level, Major Depressive Disorder (MDD) cost the global community 49.4 million disability-adjusted life-years in 2020 (Santomauro et al., 2021); and depression is linked to social and occupational impacts (Godard et al., 2012; Gutiérrez-Rojas et al., 2020). A few decision-theoretic concepts have received particular attention for their potential to explain decision-making in depression, as evidenced by recent systematic reviews: *reward processing* (Halahakoon et al., 2020), *loss aversion* (Prospect theory) (Sediyaama et al., 2020), and *risk preferences* (Lu et al., 2024). Although this literature suggests that depressive symptoms and mood disorders can influence decision-making and reward-contingent behaviour, findings across studies have been mixed (e.g., for risk preferences).

An under-investigated facet of decision-making in depression is *regret*. Regret arises when one becomes aware that *the reward of one's chosen action or option is worse than that of the action one didn't choose*. Importantly, there is evidence that reporting a proneness towards experiencing regret or tending to consider better hypothetical alternatives (*upwards counterfactual thought*) is empirically associated with depressive symptoms (Broomhall & Phillips, 2018; Broomhall et al., 2017; Markman & Miller, 2006; Roese et al., 2009). Although regret is an aversive affective state, regret may be a useful during decision-making as a signal for corrective action (Epstude & Roese, 2008; Kahneman & Tversky, 1982; Roese, 1997). However, in depression, a greater tendency towards entertaining upwards counterfactuals and regret may indicate exaggerated and maladaptive tendencies, leading to persistent and unhelpful negative affective experiences. These may constitute a disorder-specific risk factor, particularly when there is little opportunity for enacting corrective change to one's situation (Epstude & Roese, 2008). Conversely, encouraging *down-ward counterfactual thought* ("I could have done worse") has been found to reduce negative affect (Johnson et al., 2012; Parikh et al., 2021). These proposed regret-related dynamics align with a recent theoretical proposal that depressive symptoms may be associated with maladaptive

reference points, that become incongruent with one's true context (Rigoli et al., 2021; Zavlis et al., 2024). Indeed, regret may be understood as a reference-dependent concept, as regret arises when one's received outcome is compared unfavourably to a forgone outcome, which acts as a reference point. This reference-dependent nature of regret, and particularly how the anticipation of regret may shape preferences, or *anticipatory regret*, is emphasised in seminal economic models of individual choice (Bell, 1982; Loomes & Sugden, 1982, 1987).

While regret may help explain decision-making in depression, a meta-analysis by Broomhall et al. (2017) highlights that regret has almost exclusively been investigated using self-report measures. The author of this chapter could only identify four published studies (Chase et al., 2010; Eryilmaz et al., 2014; Feng et al., 2015; Zheng et al., 2021), and one unpublished study (Chowdhury, 2020), that investigated whether regret during decision-making was linked to depressive symptoms. The results of these studies were mixed. In a task involving choices between two lotteries, Chase et al. (2010) found attenuated regret ratings in depressed individuals relative to controls when they received feedback that the received outcome was lower than the forgone outcome. The effect was greater for those with greater self-report apathy (a symptom closely related to anhedonia). On another lottery task used with a sample of healthy individuals, Eryilmaz et al. (2014) found less sustained activity in the striatum (typically associated with reward processing) of those with higher depression scores when feedback on choices was gratifying: such that it should lead to *relief* (chosen outcome > outcome foregone). In a group of individuals with and without MDD, Chowdhury (2020) found that higher self-reported depression scores were associated with less sensitivity to potential regret when making choices between option. Specifically, less avoidance of options with greater potential regret (i.e., *regret aversion*), but intact sensitivity to disappointment. For those with higher depressive symptoms, subjective affect ratings were also attenuated following feedback designed to elicit regret (although there were no MDD-group differences), as well as relief. A small potential challenge to interpretation in Chowdhury (2020) and Chase et al. (2010) is the use of the word "Disappointed" as verbal anchors for their rating scales.

The decision-making studies above suggest mood disorder may be associated with a blunted regret response. However, these findings conflict with the positive meta-analytic association between depression and self-reported regret (Broomhall et al., 2017). Moreover, an experimental study by Zheng et al. (2021) failed to find a significant difference between those

with MDD and controls on neither regret nor relief ratings using a lottery task. They argued their results suggested intact, normal, experience of regret and relief in depression.

Decision-making studies involving patient samples (i.e., MDD vs controls) are an important step towards understanding perturbation owing to extreme depressive symptoms. However, experiments involving non-clinical samples are also warranted, as these may clarify whether findings are generalisable more broadly. Practically, larger samples of this type are also more likely to yield the appropriate statistical power for more subtler analyses (note that across studies cited above, the sample sizes were arguably small: 18, 20, 38, 46 and 50).

Overall, despite strong empirical links across self-report measures, the association between regret and depressive symptoms during decision-making remains unclear. An increased tendency towards experiencing regret may explain maladaptive behaviours during depressive moods, potentially providing clues to why depression is associated with suboptimal socio-economic outcomes. Conversely, blunting of normal regret during depressive symptoms may also be maladaptive, as regret likely plays a corrective role for improving decision quality (Epstude & Roese, 2008; Kahneman & Tversky, 1982; Roese, 1997; Zeelenberg & Pieters, 2007).

Herein, I aim to clarify whether regret manifests differently in decision-making when a person is experiencing depressive symptoms. A rich set of methods involving self-report measures and behaviourally decision-making tasks are applied towards this aim. This project builds on a rich literature within economics and neuroeconomics applying regret to understand individual decision-making (Bell, 1982; Bleichrodt & Wakker, 2015; Braun & Muermann, 2004; Camille et al., 2004; Coricelli et al., 2005; Giorgetta et al., 2013; Lin et al., 2006; Loomes & Sugden, 1982; Tsiros & Mittal, 2000). To comprehensively test the link between regret and depressive symptoms – including a focus on symptom severity groupings, non-linearities and accounting for confounding factors with sufficient statistical power - a large sample was gathered from a non-clinical population. Findings might therefore be generalised to economic decision-making in the context of sub-clinical depressive symptoms. Indeed, even sub-clinical symptoms of depression can be majorly disruptive (Gotlib & Hammen, 2014).

3.2 Methods

3.2.1 Participants

318 students were recruited from a large metropolitan Australian university who completed the experiment online, including all the decision-making tasks in full. Data were pooled from two similar studies: 194 recruited from February to May 2025 and 124 recruited from September to December 2025.⁵⁶ Overall, the two samples were comparable on demographics. The self-reported gender of the sample was: 77.7% female, 20.8% male and 1.6% non-binary, transgender, intersex, other, or ‘prefer not to say’. The age distribution of the sample was mean: 23, median: 19, SD: 8.7, and range: 18 to 64.

3.2.2 Procedure

Recruitment occurred via a university-administered research participation platform, and the study materials were administered online using Qualtrics. It was a requirement for the students to complete the task on a laptop or stationary computer for proper stimulus display. Participants were first provided brief information summarising the focus of the study. Then participants completed a consent form, followed by the questionnaires and then experimental tasks. Detailed instructions were provided and comprehension questions were administered (see General appendix D and E). The full experimental survey was expected to take ca. 45-60 min to complete.

Participants received course credit for participating in the research. Moreover, to incentivise decision-making, participants could choose to enter a draw for a reward based on their performance. For the first sample, participants were told that the 5 individuals with the highest total points would receive a gift card worth 50 AUD when the study finished. Total points were not displayed during the experiment to avoid “wealth effects”. For the second sample, incentivisation was amended to focus on rewarding individual choices: participants were told that one-out-five participants would be randomly selected and paid an AUD\$

⁵⁶ These two samples are described in detail in Chapter 2, studies 1 and 2, respectively. Hence, information is not repeated in this chapter. The samples were pooled for greater statistical power when investigating the role of depressive symptoms and regret on economic decision-making.

amount equal to the points earned on one randomly selected choice item. The AUD\$ amount was calculated as points divided by 20, so that 1 point = \$0.05 AUD.⁵⁷

3.2.3 Variables

Three decision-making tasks⁵⁸ were applied to gauge the influence of regret - including sensitivity to potential regret and relief, and regret aversion - during decision-making:

3.2.3.1 *Wheel of Fortune task*

The ‘Wheel of fortune’ (WOF) task completed first, involved a choice between two options A or B. After a choice was made, a screen showing the outcome for the chosen option (‘partial feedback’ condition) was followed by a screen showing the outcomes for the chosen *and* forgone options (‘full feedback’ condition). The task was designed according with tasks used in several regret studies (Camille et al., 2004; Camille et al., 2010; Chowdhury, 2020; Coricelli et al., 2005; Gillan et al., 2014; Giorgetta et al., 2013; Zheng et al., 2021). Participants were provided partial feedback for only a subset of choices to increase comprehension of the difference between received and forgone outcomes. Only affect ratings following full feedback were analysed.

3.2.3.2 *2x2 Matrices task*

Next, participants completed the 2x2 Matrices which differed from the WOF task in that outcomes across the two options were correlated: there were only two possible “states of the world”, ‘green’ or ‘blue’. The WOF also had two states, but the chosen option could have a blue outcome while the forgone option could have a green or blue outcome. Choice-contexts with correlated states (2x2 Matrices) imply the counterfactual outcomes are more directly linked to one’s actions (A or B) and are a common way to conceptualise regret in economics (Bell, 1982; Bleichrodt & Wakker, 2015; Loomes & Sugden, 1982).

⁵⁷ As part of a larger project, the plan to test the hypothesis that regret would be associated with depression symptoms was pre-registered on 10/31/2025 under the OSF. However, the specific methodologies to be used and more detailed hypothesis tests (pertaining to self-reported, behavioural and post-decisional regret) were updated subsequently and described in a second pre-registration on 08/30/2025. The second registration occurred after collection of the first sample and preliminary analysis, but before collection of the second sample. The first and second registrations are accessible via the following links: <https://osf.io/7xwd2/overview> and <https://osf.io/c4wap/overview>.

⁵⁸ These 3 tasks represent a subset of the tasks described in Chapter 2 and which were completed by all participants in both studies (i.e., allowing pooling of their data). As the tasks are described and illustrated in Chapter 2, figures are not re-displayed in Chapter 3.

3.2.3.3 2x3 Matrices task

Finally, the 2x3 Matrices task was similar to the 2x2 Matrices task but involving three possible states of the world. The task was designed to keep constant the expected value (EV), potential disappointment and risk of each option, while ensuring one option had a higher potential maximum regret. This method for separating out regret effects has been noted in past literature (Bleichrodt & Wakker, 2015; Loomes & Sugden, 1982; Zeelenberg et al., 1996).

Depressive symptoms were measured with the following questionnaires:

3.2.3.4 Patient Health Questionnaire

The Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001) is commonly applied in research settings. The last item on suicidal ideation was excluded; the PHQ-8 and PHQ-9 scores are highly correlated (Kroenke et al., 2009). The PHQ-8 is scored on a 4-point scale: 0 = 'Not at all', 1 = 'Several days', 2 = 'More than half the time' and 3 = 'Nearly every day'. Cronbach's alpha was comparable across samples: 0.86 and 0.84, indicating good internal consistency for the measure.

3.2.3.5 Depression, Anxiety and Stress Scale

The 21-item Depression, Anxiety and Stress Scale (DASS-21; Lovibond & Lovibond, 1995) is also frequently used in research and in clinical practice; and allowed for a robustness check of results with an additional mood scale. The DASS21 is scored on a 4-point scale: 0 = 'Never', 1 = 'Sometimes', 2 = 'Often' and 3 = 'Always'. The DASS-21 comprises three sub scales, each totalling 7 items, that measure depressive symptoms, anxiety symptoms and stress symptoms. Cronbach's alpha was comparable across samples on the depressive symptoms scale, 0.88 and 0.89.

Including DASS21 anxiety and stress scales was partly motivated by past research indicating anxiety and general distress may be associated with regret and counterfactual thought (Parikh et al., 2021; Roese et al., 2009). Additionally, 4 questions assessing state-anxiety were included from the State-Trait Anxiety Inventory (Spielberger et al., 1983).

One's perceived tendency or proneness to experience regret was measured with the following questionnaires:

3.2.3.6 Regret Scale (Schwartz)

The 5-item self-report *Regret Scale* (Schwartz et al. 2002) was designed to measure a person's self-perceived tendency to experience regret in the context of decision-making. Questions are rated on a scale from 1 = *completely disagree* to 7 = *completely agree* (one question is reverse scored). Cronbach's alpha was comparable across samples, 0.78 and 0.82.

The Regret Scale (Schwartz) was used across both samples. Additionally, in the second sample, the following scales were included:

3.2.3.7 Counterfactual Thinking for Negative Events Scale

The 16-item *Counterfactual Thinking for Negative Events Scale* (CTNE, Rye et al., 2008) comprehensively measures the self-perceived tendency to experience i) non-referent upward counterfactuals (e.g., 'I feel sad when I think about how much better things could have been'), ii) non-referent down-ward counterfactuals (e.g., 'I think about how much worse things could have been'), iii) self-referent- upward counterfactuals (e.g., 'I think about how much better things would have been if I had acted differently') and iv) other-referent upward counterfactuals (e.g., 'If another person (or other people) had not been so inconsiderate, things would have been better'). Down-wards counterfactuals were not analysed. The scale is rated from 1 = *Never* to 5 = *Very Often*. Cronbach's alphas were, respectively, 0.83, 0.82, 0.77 and 0.84.

3.2.3.8 Regret Scale (Roese)

The 6-item *Regret Scale* (Roese et al., 2009) assesses a general tendency to entertain regret in life and has been found to be elevated in depression. An example question is 'I regret a lot of my actions.'. Questions are rated on a 5-point scale: 1 = *Strongly agree* to 5 = *Strongly disagree* (inc. 3 reverse-scored questions). Cronbach's alpha was 0.73.

3.2.3.9 Regret vignette

A single vignette-question (adapted from Tsiros & Mittal, 2000) was included that described a hypothetical person who made a poor purchase of a laptop. The question asked: ‘Paul is regretful for having chosen (*the laptop brand*)’ and was rated: 1 = *Strongly disagree* to 7 = *Strongly agree*. This vignette-question was administered to see if participants with depressive symptoms were more likely to rate others as more prone to regret.

3.2.4 Modelling

3.2.4.1 Variables

A pattern of avoiding options where there was a greater chance of regret was defined as *regret aversion*. To measure regret aversion, *potential-regret* variables were constructed from the stimulus (outcomes and probabilities) associated with each task. These variables were then incorporated in models predicting choices, applying statistical methods to infer their effect on behaviour.⁵⁹

The following variables were created for each task to statistically capture behaviour contingent on potential regret:

- For WOF task: $Regret\ Diff = Max\ Regret\ (A) - Max\ Regret\ (B)$, which reflects the difference in maximum potential regret for option A over B (a higher value implied greater potential regret for option A over B).
- Variables capturing maximum disappointment difference (*Dissapointment Diff*) and expected value difference (*EVDiff*) were also created.
- For 2x2 Matrices task: $RegretReliefDiff = RegretRelief\ (A) - RegretRelief\ (B)$, reflects the difference between regret/relief associated with choosing an option (e.g., A over B). Meaning a higher value implied greater potential relief than regret for option A over B.
- For 2x3 Matrices task: $Regret\ Diff = MaxRegret(A) - MaxRegret(B)$, reflects the difference between the maximum possible regret associated with option A over that of option B; meaning a higher value implied greater potential regret for option A over B.

⁵⁹ A full description of variable creation has not been repeated here, given this was described in Chapter 2.

Post-decisional affect ratings were gauged with a visual analogue scale (VAS). These ratings ranged from -48 to 52 in the first sample (owing to a coding mistake), and -50 to 50 for the second sample. Numeric values were not displayed to participants, so this difference was not perceptible. Negative values indicated regret (ratings towards a simple image of a frowny face) and positive values indicated relief (towards a smiley face).

3.2.4.2 Choice model

For the WOF task, the probability of choosing option A over B, p , was modelled as,

$$\ln\left(\frac{p}{(1-p)}\right) = X\beta \text{ where,}$$

$$X\beta = \beta_0 + \beta_1 EVDiff + \beta_2 Dissapointment Diff + \beta_3 Depression + \beta_4 Regret Diff + \beta_5 (Regret Diff * Depression)$$

The coefficients β_5 is the coefficient of interest: a significant interaction effect meant that higher depression scores moderated the effect of potential regret by increasing its effect during choice. A logit link function was used across models, where $g(\cdot)$ represents a logit link function.⁶⁰

In models applied to choices during 2x2 Matrices, neither *EVDiff* nor *Dissapointment Diff* EV were included to avoid multicollinearity, given how *RegretRelief* was calculated. For the 2x3- Matrices task, neither the EV nor disappointment were included as predictors because these are identical across the two options.

All models were estimated with robust standard errors cluster at the individual level to account for correlations within individuals' responses. Models were estimated with and without fixed effects (FE) to account for unobserved individual-specific effects on choice. For FE models, the fixed effect for several participants (the coefficients on their ID as a factor variable) could not be estimated correctly or were excluded (e.g., due to singularity); however, no choice observations were excluded as a result.

⁶⁰ In Chapter 3 the logit function was used as the chapter was being prepared for submission to a general science journal and where the logit function appears more commonly applied (e.g., based on previous regret studies).

3.2.4.3 Econometric approach: affect ratings

To capture the effect of task stimuli and depressive symptoms on affective ratings, the following model was estimated via panel OLS,

$$\begin{aligned} \text{Affect ratings}_{it} = & \alpha_i + \lambda_t + \beta_1 \text{received}_{it} + \beta_2 \text{forgone}_{it} + \beta_3 \text{Feedback}_{it} + \\ & \beta_4 (\text{Feedback}_{it} * \text{Depression}_i) + \\ & X'_{it} \delta + \epsilon_{it} \end{aligned}$$

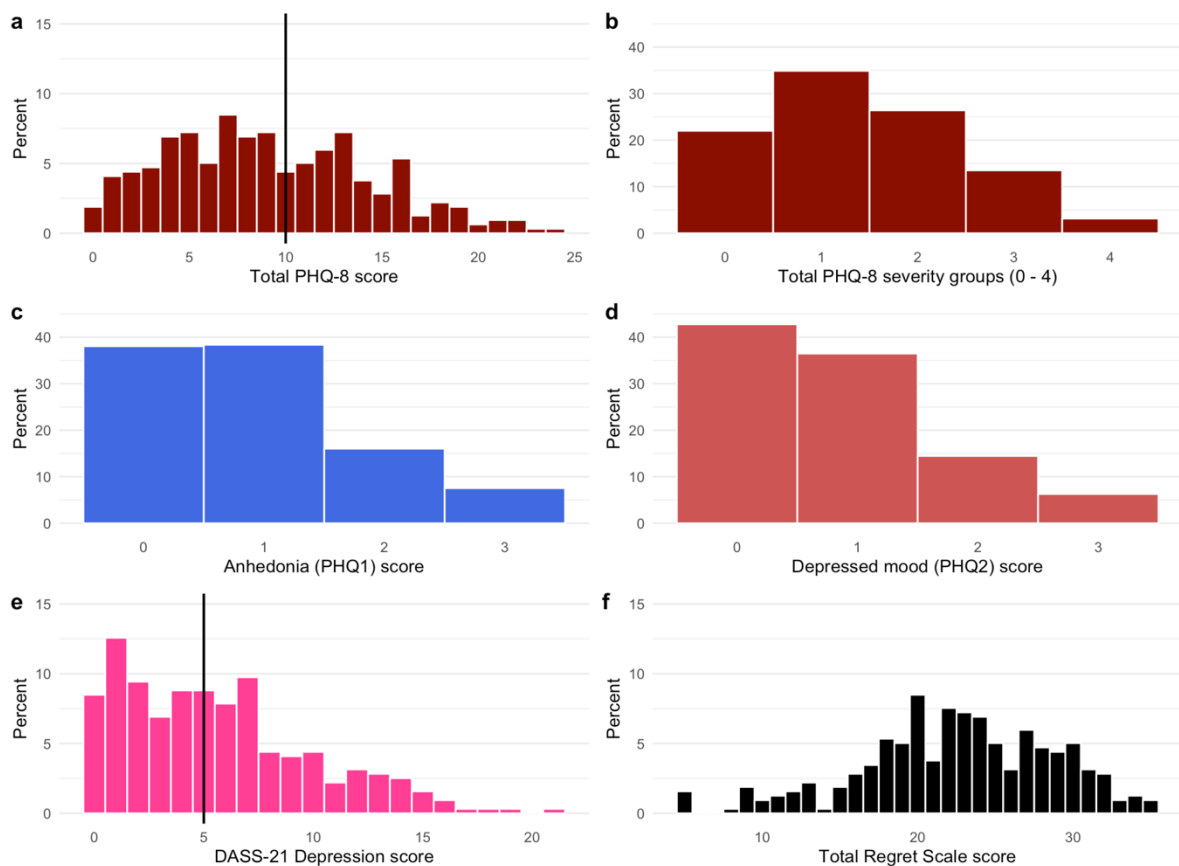
Where α_i is a participant-fixed effect, λ_t is a time/choice-item-fixed effect, received_{it} is the received outcome, forgone_{it} is the foregone outcome (of the non-chosen option), and Feedback_{it} is the feedback scenario dummy: *regret* (received < forgone) vs *relief* (received > forgone). For the WOF task, neutral (received = forgone) was the baseline comparison group. The interaction term coefficient on $\text{Feedback}_{it} * \text{Depression}_i$, β_4 , captures the moderating effect of depressive symptoms. When models included both received outcomes, forgone outcomes and feedback scenario; it implied that the coefficients on outcomes capture the effect of these, while the relative difference between them is held fixed and captured by feedback scenario coefficient(s). The model thus allowed for separating out the effect of regret as the coefficient on the dummy variable, β_3 . Some models were elaborated to include Depression_i as a quadratic term. Moreover, for some models, Depression_i depression was instead interacted with the forgone outcome to capture a moderating influence on the referent value (i.e., $\text{forgone}_{it} * \text{Depression}_i$).

Diagnostics checks indicated the presence of unobserved time- and participant- fixed effects, while a fixed effects model was preferred over a random effects model. However, results for random effects models and pooled OLS were also reported for comprehensiveness. There was evidence of heteroskedasticity, so final models were estimated with robust standard errors clustered at the participant level. Residuals appeared normally distributed. There was evidence of mild serial correlation (first and higher order) from visual inspection and a statistical test. Finally, unit-root tests indicated a stationary stochastic process as required for OLS.

3.3 Results

3.3.1 Distributions of depressive symptoms

Figure 3.1a shows the distribution of total PHQ-8 scores, indicating a significant percentage of participants scored in the higher range, and above the cut-off 10 (solid black line) indicative for identifying potential MDD (Kroenke et al., 2001). Figure 3.1b shows that approximately 3% of participants fell in the most severe (4) range of depressive mood. Two key diagnostic symptoms of MDD are also highlighted: anhedonia (item PHQ1, 'little interest or pleasure in doing things', Figure 3.1c) and depressed mood (item PHQ2, 'feeling down, depressed or hopeless', Figure 3.1c). While most participants reported these symptoms occurring 'Not at all' (0) or 'Several days' (1), about 20% reported symptoms occurring at least as often as 'More than half the days' (3). The distribution for the DASS21, the additional mood scale, is displayed in Figure 3.1e: a notable percentage of participants scored above the 'Normal' range cut-off 5 (solid black line). Finally, scores on the Regret scale (Schwartz) were distributed so as to indicate a broad range of self-reported regret proneness within the sample (Figure 3.1f).

Figure 3.1 *Distribution of depressive symptoms and self-reported regret*

Note. Panel (a) shows total Patient Health Questionnaire (8-items; PHQ-8) scores for the sample. The black line is cut-off (10) used to screen for the presence of MDD. (b) Shows severity groupings by total score for the PHQ-8: 0 = Minimal (< 5), 1 = Mild (5 to < 10), 2 = Moderate (10 to < 15), 3 = Moderately severe (15 to < 20), and 4 = Severe (> 20). (c) Shows the percent of participants reporting *anhedonia* (PHQ1 from PHQ-8) by severities: 0 = ‘Not at all’, 1 = ‘Several days’, 2 = ‘More than half the time’ and 3 = ‘Nearly every day’. (d) Shows the frequency for reporting *feeling depressed* (PHQ2). (e) Shows total scores on the Depression, Anxiety and Stress Scale (21-item, DASS-21), depression sub scale (7 items). The scale is scored: 0 = ‘Never’, 1 = ‘Sometimes’, 2 = ‘Often’ and 3 = ‘Always’. The black line reflects the cut-off between ‘Normal’ and ‘Mild’-or-higher severity. (f) Shows the distribution of the 5-item self-report Regret scale (Schwartz), which is scored on a 7-point scale (1 = *completely disagree*, 7 = *completely agree*).

3.3.2 Self-reported regret by depressive symptoms

To compare with past literature, simple OLS regressions were estimated of Regret scale (Schwartz) scores regressed on the different depressive symptom measures. The associations were positive for total PHQ-8 scores ($\beta = 0.37, p < 0.001$), DASS21 Depression scores ($\beta = 0.31, p < 0.001$), anhedonia ($\beta = 0.24, p < 0.001$) and feeling depressed ($\beta = 0.22, p < 0.001$). As robustness checks, the following covariates were included: stress, anxiety, state anxiety (somatic symptoms); and dummies capturing demographic and socio-economic variables. Heteroskedasticity-robust standard errors were applied. The coefficient on total PHQ-8 was smaller but remained significant, $\beta = 0.22, t = 2.79, p < 0.01$. This is comparable to the average effect size identified in Broomhall et al. (2017): $r = 0.2, p < 0.001$. The overall regression model was also significant, $F(10, 303) = 8.8, p < 0.0001$, explaining 22% of the variance in Self-report regret ($R^2 = 0.22$). However, for the other measures, the associations were not robust: for DASS21, $p = 0.15$; for PHQ1, $p = 0.23$; and for PHQ2, $p = 0.57$. Overall, the association between depressive symptoms and the Regret scale was relatively strong (see Appendix 3.2, Table A.1 for further information on models).

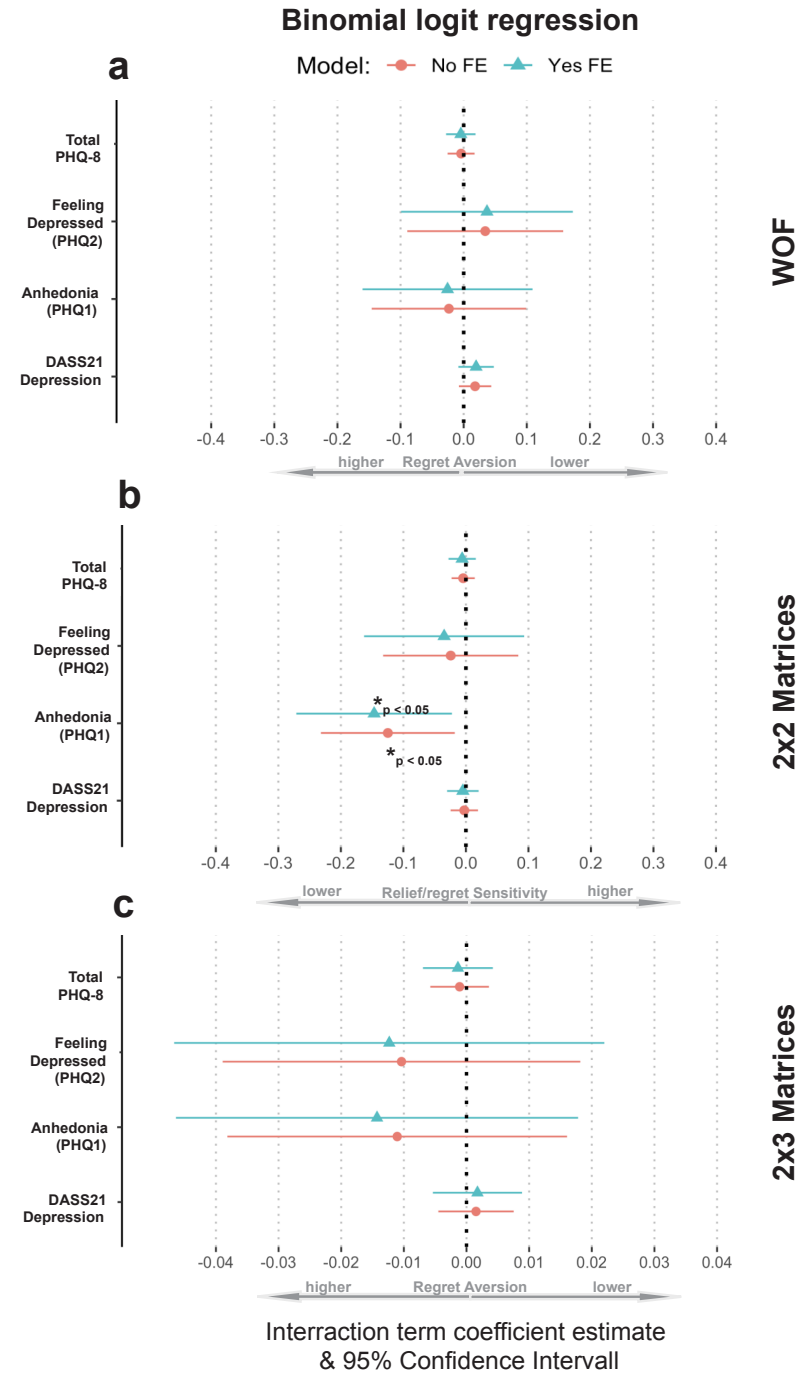
3.3.3 Behavioural regret aversion by depressive symptoms

Regret aversion was evident if participants avoided options with higher potential regret (during WOF and 2x3 Matrices tasks), or similarly, regret sensitivity by choosing options with a positive balance between potential regret and relief (i.e., regret/relief during 2x2 Matrices task). Importantly, the association between regret aversion (sensitivity) and depressive symptoms was tested with an interaction term between the two: the size and significance of the interaction coefficient captured this relationship.

Figure 3.2 shows the interaction terms for each of the three tasks across depression measures. Overall, results indicated that experiencing depressive symptoms was neither associated with a consistently greater nor lower regret aversion. The exception was for the 2x2 Matrices task, where reporting greater anhedonia was associated with a reduced sensitivity to the regret/relief of options (Figure 3.2 b).

Figure 3.2 Interaction term coefficients: regret aversion and depressive symptoms

Note. Panels (a), (b) and (c) display coefficients and 95% Confidence Intervals (CI) from binomial logit regressions. The dependent variable was individual choices (chose option A over B). Panel (a): for the Wheel of Fortune (WOF) task, a variable was defined capturing the potential *regret difference* between option A and B. Panel (b): for the 2x2 Matrices, a variable capturing the difference in regret and relief for each option was created. Panel (c): for the 2x3 Matrices, a variable capturing the maximum regret of option A minus B was calculated. Across (a), (b) and (c), the aforementioned regret variables were interacted with total PHQ-8, feeling depressed, anhedonia or total DASS21 Depression scores, separately. The interaction term coefficients are displayed such that the x-axis indicates whether the coefficient estimates suggested a higher or lower aversion or sensitivity to regret. Models with and without fixed effects denoted ‘Yes FE’ or ‘No FE’, respectively. Standard errors were clustered on the individual. For WOF, the expected value difference and potential disappointment difference of each option A and B were controlled for.



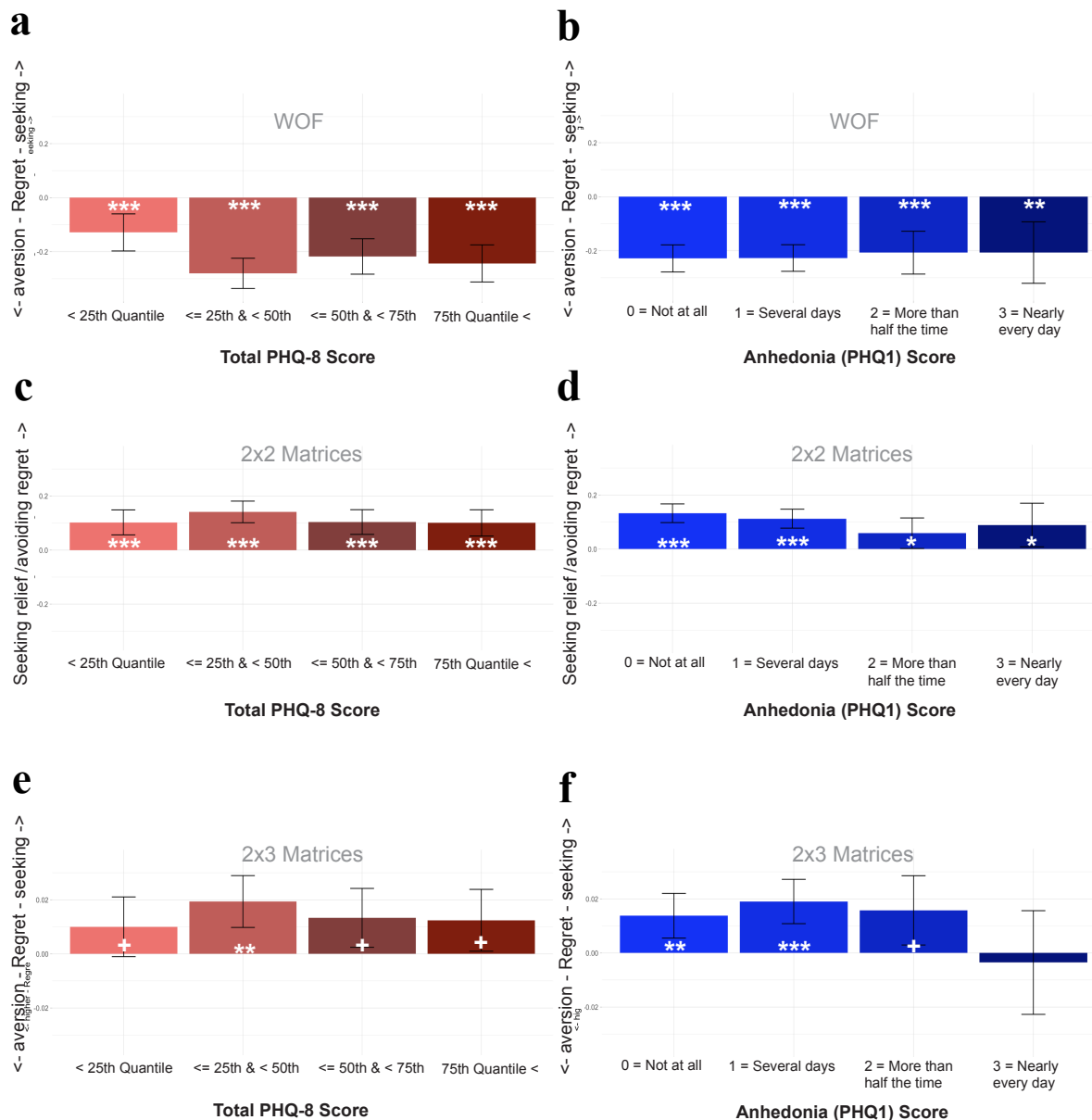
To visually identify potential non-linearities in behavioural regret aversion (sensitivity) across depression severity; marginal effects were computed for regret variables predicting choices separately for total depression severity groupings. These are displayed in Figure 3.3. PHQ-8 total scores were quartered by quantile: below 25th quantile (scoring below 5 or ‘Minimal’ severity), between 25th and 50th (scoring 5 to below 9, or ‘Mild’ severity), between 50th and 75th (scoring 9 to below 12, roughly ‘Moderate’ severity) and above the 75th Quantile (scoring above 12, ‘Moderately severe’ to ‘Severe’). Marginals were also computed for participants delineated by severity levels of anhedonia (PHQ1 scores). Anhedonia was chosen for further analysis given the interest anhedonia (apathy) has been shown in the literature, and the significant interaction effect identified above.

While regret and regret/relief was predictive of behaviour across groupings, there was visual indications of non-linear effects according to mood severity. For PHQ-8 scores, participants falling in the 25th to 50th Quantile showed the strongest regret aversion on the WOF and 2x2 Matrices task. However, results from the 2x3 Matrices task suggested this group choose options with the higher maximum regret. This counter-intuitive finding, which also held in general across the sample, was weaker for the groups with the most severe scores (scores above 50th quantile). A potential reason for the pattern of choosing the option with maximum regret is that these options also always involved two smaller options with higher relief. These may have weighed more heavily on preferences. For anhedonia, a similar pattern was found for 2x3 Matrices, although those experiencing the highest severity (frequency) of anhedonia did evidence neither clear regret seeking nor aversion. Moreover, anhedonia appeared to reduce the sensitivity to relief-regret during choices on the 2x2 Matrices task. These results speak to the importance of disaggregated analysis across symptoms and methods.

Formal tests of non-linearity were applied: the aforementioned logistic models changed to i) include quadratic terms for PHQ-8, anhedonia, and feeling depressed; and ii) include dummies by PHQ-8 total score quantiles, and dummies by severity levels for anhedonia and feeling depressed. These models did not yield significant coefficient effects (at alpha 0.05) indicative of non-linear effects; however, a single exception was a significant dummy coefficient ($p < 0.01$) for anhedonia severity level 2 relative to baseline, indicating lower sensitivity to regret/relief on the 2x2 Matrices task.

Overall, while there was some (mainly descriptive) evidence of non-linear effects owing to depression severity, and greater anhedonia significantly reduced relief/regret sensitivity; there were otherwise little statistically significant nor visually marked differences in behavioural regret aversion (sensitivity) according to the severity of depressive symptoms.

Figure 3.3 Marginal effects across total PHQ-8 scores and anhedonia (PHQ1) severity



Note. Panels display Average Marginal Effects (AME) from binomial logit models predicting choices (choosing A over B). The same regret difference variables described in Figure 3.2 were used in modelling regret aversion/sensitivity, however, depressive symptoms scores were not included (nor interaction terms). Results are shown for total PHQ-8 scores (a, c, e) separated into four quantile groups: 1) below 25th, 2) between the 25th and 50th, 3) between the 50th and 75th, and 4) above the 75th quantile. Results are shown for anhedonia (b, d, f) severity levels: 0 ('Not at all') to 3 ('Nearly every day'). Estimates indicated the change in probability of choosing option A over B for a 100-point change in the regret and relief-regret difference variables. Cluster-robust standard errors were applied. Estimates are without fixed effects given sample sub-setting reduced within group n . Significance is based on cluster-robust standard errors from probit model (non-marginal) coefficient estimates. Error bars represent 95% confidence intervals based on AME estimates. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.3.4 Affect ratings post-feedback by depressive symptoms

Affect ratings by depressive symptom scores are displayed for inspection in Figure 3.4. There was little visual evidence of an any association: Figure 3.4a shows affect ratings as a function of total PHQ-8 scores and the difference between received minus forgone outcomes. While ratings appeared more positive when the relative points received was higher, depression scores did not appear to markedly moderate this association. Figure 3.4b displays regression slopes of the association between total PHQ-8 scores and affect ratings. Both linear and cubic functions (to capture non-linearities) are included, and are delineated by feedback scenario: regret, relief or neutral. Figures for the DASS-21 depression scale were similar and are displayed in Appendix 3.A, Figure 3.A.1.

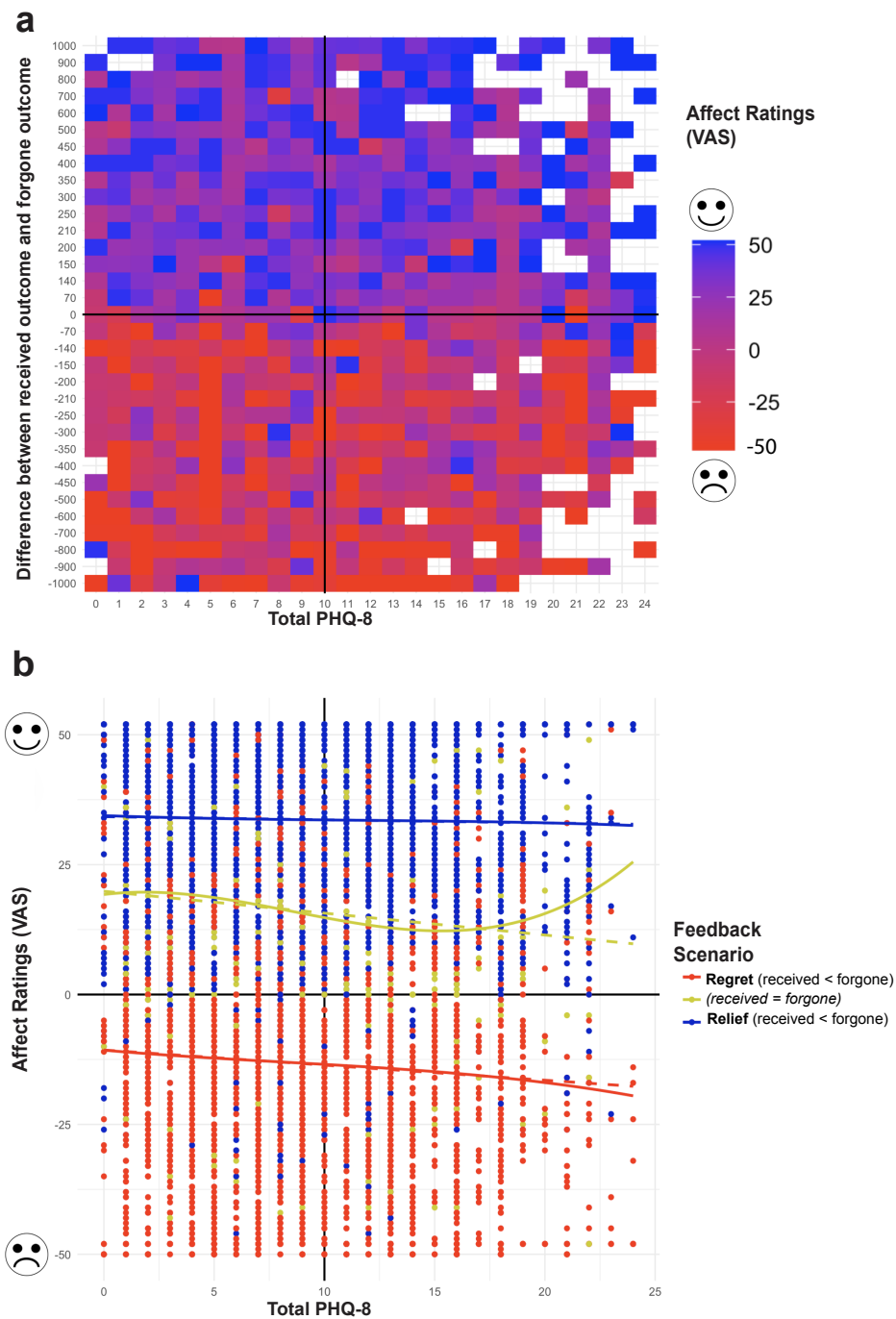
The associations between affect ratings and depressive symptoms were tested with hierarchical fixed and random effects models (with pooled OLS displayed for comparison). As reported in Table 3.1, in the simple model ‘FE (1)’, a higher received outcome was associated with more positive affect ratings, and a higher forgone outcome was associated with lower ratings. However, once the feedback scenario dummy variable (regret over relief, or regret over neutral) was accounted for, this effect became weaker for received outcomes, and either non-significant or reversed for forgone outcomes. This is likely owing to feedback scenario dummies capturing the relative magnitude between received and forgone outcomes per se. The coefficients on feedback scenario indicated regret was associated with markedly lower affect ratings. Conversely, relief was associated with higher ratings, albeit with about half the strength.

Importantly, there was little evidence to suggest depressive symptoms measured as total PHQ-8 scores moderated the effect of regret or relief feedback on ratings. While there were small associations in the expected direction detected for models FE (2) and FE (3), these became non-significant with robust model specification. There was also no evidence of non-linearities (quadratic) associations, seen in models FE (4). This final model accounted for about 50% of the variance in ratings, suggesting participants’ reported affect was largely in responses to task stimuli. Results were not notably different for models replacing the PHQ-8 with DASS-21 Depression scores, anhedonia nor feeling depressed (see Appendix 3.A, Table A.2). Although not displayed, models were also estimated including both anhedonia and feeling depressed together - with and without quadratic interaction terms. This was done for

FE, RE and pooled (inc. controls) models, and applying robust standard errors. There were no statistically significant coefficients on either of these depression symptoms, suggesting that the preceding results were not due to potential omitted variable bias.

Whether depressive symptoms moderated the effect of counterfactual outcomes on affect ratings was investigated with a series of FE, RE and pooled OLS models. Ratings were regressed on the alternative outcome (that was not received), interacted with either total PHQ-8 scores, anhedonia, feeling depressed, or both of the latter two. This analysis was restricted only to ratings when received outcomes were lower than alternative outcomes, so as to focus on regret specifically. While both the received outcome and the alternative outcomes were independently positively and negatively associated with ratings, respectively, all interaction term coefficients were statistically non-significant and small. Thus, regression models yielded no support for depressive symptoms moderating the effect of counterfactual referents on post-decisional affect.

Figure 3.4 *Affect ratings according to depressive symptoms and outcome feedback*



Note. Panel (a) shows affect ratings made with the visual analogue scale (VAS) according to the difference between the received and forgone outcomes (provided as feedback to participants post choice), and by Total PHQ-8 scores. This heatmap indicates whether ratings were more positive (blue) or negative (red). The vertical solid black line at Total PHQ-8 cut off 10 is commonly used to identify potential MDD. The horizontal solid black line is at the point indicating received outcomes equalled forgone outcomes (i.e., neither regret nor relief). Panel (b) shows affect ratings by Total PHQ-8 scores and slopes reflecting simple linear (dashed) and polynomial (solid) models of this association. Ratings and slopes are delineated according to whether ratings occurred following feedback scenarios involving regret, relief or neither (neutral) – latter only for WOF task.

Table 3.1 Affect ratings post-feedback regressed on received outcomes, forgone outcomes, feedback (regret, relief, neutral) and depressed mood (total PHQ-8 score) with interaction effects - Fixed-effects, with Random-effects & pooled OLS for comparison.

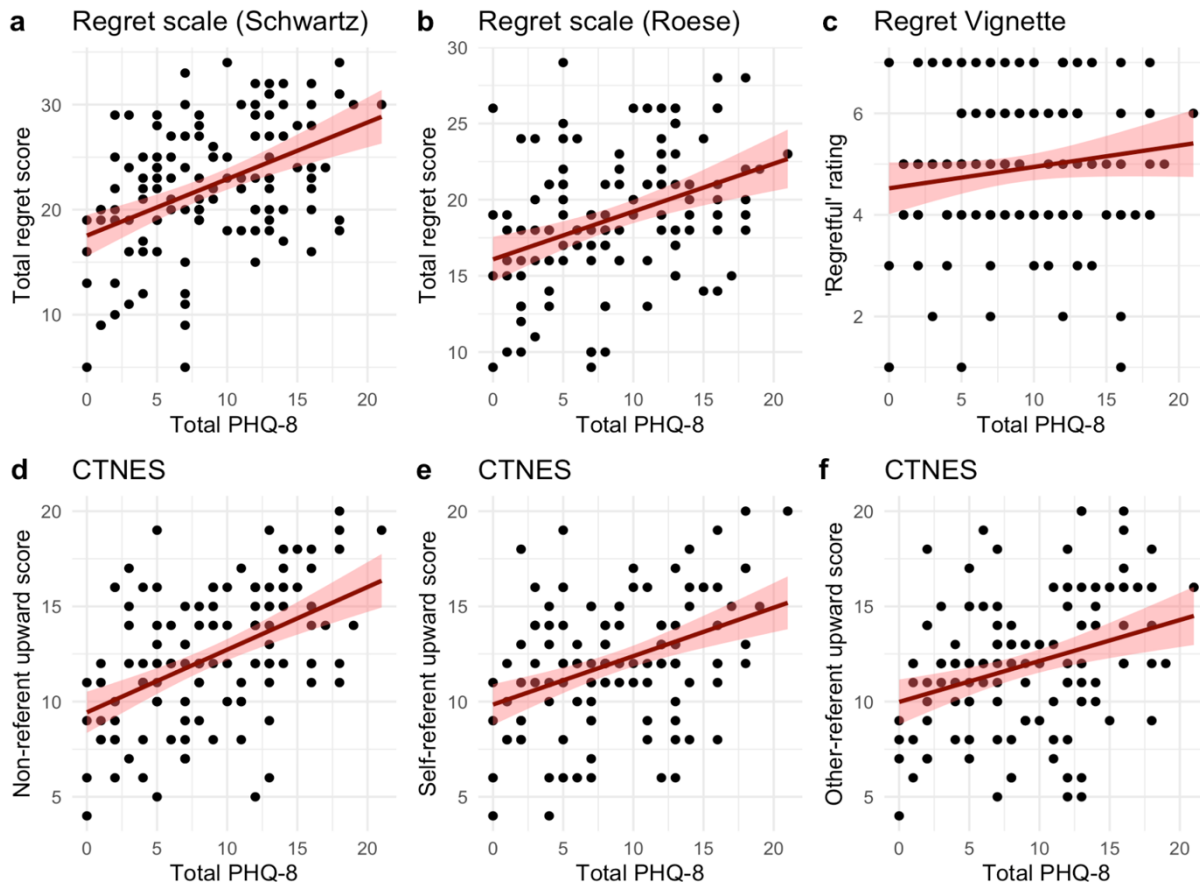
	FE (1)	FE (2)	FE (2-robust)	FE (3)	FE (4)	FE (3-robust)	RE (3-robust)	Pooled (3-robust)
Intercept							12.065*** (2.497)	22.971*** (4.867)
Received outcome	8.121*** (0.170)	3.936*** (0.169)	3.936*** (0.212)	3.437*** (0.168)	3.435*** (0.168)	3.437*** (0.203)	2.939*** (0.178)	1.859*** (0.139)
Alternative outcome	-4.729*** (0.167)	0.221 (0.174)	0.221 (0.189)	1.171*** (0.177)	1.170*** (0.177)	1.171*** (0.195)	0.615** (0.194)	-0.603*** (0.166)
Regret Scenario dummy		-34.942*** (1.040)	-34.942*** (2.948)	-25.832*** (1.559)	-27.685*** (2.309)	-25.832*** (3.010)	-26.576*** (3.024)	-28.832*** (3.199)
Regret Scenario dummy by PHQ8 score (sqrd)		-0.169* (0.086)	-0.169 (0.284)	0.067 (0.141)	0.581 (0.492)	0.067 (0.301)	0.080 (0.302)	0.133 (0.320)
Relief Scenario dummy				14.249*** (1.521)	12.271*** (2.248)	14.249*** (2.041)	13.352*** (2.049)	11.333*** (2.149)
Relief Scenario dummy by PHQ8 score (sqrd)				0.289* (0.139)	0.838+ (0.480)	0.289 (0.187)	0.303 (0.190)	0.331 (0.202)
Relief Scenario dummy by PHQ8 score (sqrd)					-0.028 (0.023)			
PHQ8 score							-0.369+ (0.219)	-0.413 (0.261)
Number Obs.	10494	10494	10494	10494	10494	10494	10494	10362
Participants (N)	318	318	318	318	318	318	318	314
Choices items	33	33	33	33	33	33	33	33
R ²	0.335	0.483	0.483	0.502	0.502	0.502	0.502	0.462
Adjusted R ²	0.312	0.465	0.465	0.485	0.485	0.485	0.485	0.461
AIC	97207	94579	114849	94179	94181	114441	115577	95447
BIC	97228	94615	188450	94230	94247	188028	191690	95578

Note. Individual- & time-fixed effects ('FE'), random effects ('RE') and pooled OLS models, regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario and total depression scores measured as total PHQ-8 scores. Results for data aggregated across Wheel of Fortune (WOF) task, 2x2 Matrices task and 2x3 Matrices task. For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2 and 2x3 data, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario. For pooled ('Pooled') model, controls were a dummy capturing female gender status (vs other), age, dummy capturing country of birth is Australian (vs other), dummy capturing if income is above median of sample (vs not); and two dummies if i) unemployed or ii) student - relative to a dummy capturing: full-time employed, self-employed, part-time employment, retired, volunteer, carer, home duties or other. Controls also included the DASS21 Anxiety subscale (7-items), DASS21 Stress subscale (7-items) and STAI State anxiety (4-items). Standard errors in parentheses; models denoted '-Robust' apply cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R² applies to non-robust estimates. Overall model F-tests (for non-robust models) were significant across models ($p < 0.001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.3.5 Supplemental: depressive symptoms and self-reported regret across scales

The subset of participants (124) recruited at the second time-point completed additional self-report regret scales. Scatter-plots between total PHQ-8 scores and self-reported regret scales are displayed in Figure 3.5. These suggest depressive symptoms were positively associated with reporting regret tendencies. Table A.3 reports the results of regressions testing these relationships for both Total PHQ-8 and total DASS21 Depression scores. Coefficients on PHQ-8 total scores were positive and generally significant ($p < 0.05$ to $p < 0.001$), symptoms alone explaining about 10% to 20% of the variance in regret scales. However, there was no statistically significant relationship for the vignette question – suggesting the association between depressive symptoms and self-report regret does not extend to expecting regret in others. Results applying the DASS-21 Depression scale instead largely overlapped with those of the PHQ-8 for non-robust models, but relationships were not as robust. Overall, there was relatively strong support (echoing that reported in section 3.3.1) that self-reported depressive symptoms were positively associated with a self-reported tendency towards experiencing regret.

Figure 3.5 Self-report regret scales by depressive symptoms (PHQ-8) for subset of 124 participants



Note. Scatter plots with simple linear model of the association between regret scores and depressive symptoms (solid line) and 95% Confidence Intervals (shaded area). Panel (a) shows 5-item regret scale by Schwartz et al. (2002) capturing Self-report regret: one's perceived tendency towards experiencing regret during decision-making. Panel (b) shows 6-item regret scale by Roese et al. (2009) capturing perceptions of one's more general regret proneness in life. Panel (c) shows 1-item ratings on vignette about how regretful participants thought a hypothetical consumer would feel after making a poor purchase (Tsiros & Mittal, 2002). Panels (d), (e) and (f) are from Counterfactual Thinking for Negative Events Scale (CTNES; Rye et al., 2008): specifically, (d) 4-item upwards counterfactual cognitions, (e) 4-item upwards counterfactual cognitions about oneself and (f) 4-item upwards counterfactual cognitions pertaining to situations involving oneself and others. All scores are total scores.

3.4 Discussion

A large literature highlights anticipatory regret as influential in shaping decision-making, while post-decisional regret is theorised to play a role in optimising behaviour. Moreover, depressive symptoms have been linked to more pronounced regret, as indicated with self-reports. Therefore, identifying interactions between regret and depressive symptoms during decision-making may provide clues to understanding depression-related maladaptation. To date, few studies have tested the link between regret and depressive symptoms during decision-making, and often these have involved very small samples and provided mixed evidence. Herein, methodology was applied from across economics, neuroeconomics and psychology; and in a large enough sample to perform subtle statistical tests. Broadly, findings suggested that while reporting depressive symptoms was associated with a greater tendency towards regret based on self-reports, there was little support for a link between depressive symptoms and behavioural regret-related patterns. Depressed people were also not more nor less likely to report greater negative affect following feedback designed to elicit regret. Within the broader context of decision-making research, the notion has been put forth that the influence of depressive symptoms on evaluation and behaviour can be understood within the framework of reference-dependence. This paper suggests that there is little evidence to support regret as a decisional framework for understanding reference-dependent choice during sub-clinical depressive symptoms.

As noted, evidence has accrued appearing to support a link between greater self-reported regret proneness and depressive symptoms (Broomhall et al., 2017), and it's been proposed that normal regret may become perturbed during depressive mood (Epstude & Roese, 2008). However, the findings of this study cast doubt on the notion that depressive symptoms influence regret-related decision-making per se. The sample overall did evidence regret averse behaviour (except on one task, 2x3 Matrices) and negative affect following feedback designed to trigger regret. However, there was very little evidence that depressive symptoms either heightened nor blunted neither regret-related behaviour patterns nor post-decisional affect. Only anhedonia appeared to significantly reduce sensitivity to regret/relief, and only on one task: the 2x2 Matrices. This latter finding may be interpreted as due to anhedonia blunting the effect of anticipated regret-and-relief on choice. Given the 2x2 task incorporated anticipated relief (compared to the WOF, focused on anticipated regret), this would suggest the sensitivity to relief anticipation (arguably reward anticipation) may have been

systematically blunted in those reporting higher anhedonia. Note that actual experiences upon feedback (emotion ratings) were not associated with anhedonia (Appendix, Table A.2), meaning the effect pertained to decision-making not experiencing. Otherwise, tests for interactions between depressive symptoms and regret aversion were non-significant.

These findings are in stark contrast with the relatively robust positive associations between depressive symptoms and self-reported regret found in this study, echoing past research within psychology. This held across various measures of self-reported regret. However, the association was restricted to regret pertaining to oneself and not beliefs about whether others experienced regret - suggesting the association was not merely due to a common-method bias. Moreover, the CTNES regret scale was administered after all behavioural tasks (at the other end of the experiment relative to the remaining regret measures) yet had similar strong associations with depressive symptoms.

In the present study, there was descriptive evidence pointing to a difference in the degree of regret sensitivity across mild, moderate, and severe levels of depressive symptoms (Figure 4). Relatedly, Markman and Miller (2006) found qualitative differences in the type of regret entertained according to symptom severity: mild-to-moderate depressive symptoms associated with entertaining controllable counterfactuals (a focus on changeable aspects of situation), while those with severe symptoms focused on uncontrollable counterfactuals (less reasonable and feasible). Severity-specific regret-patterns may help explain mixed evidence in previous literature. Given many studies investigated depression as a unitary phenomenon, and compared dichotomous groupings (patients vs controls); more subtle, symptom-specific patterns may have been missed. The larger sample of the present study allowed for statistically reliable testing of effects according to the severity for specific symptoms. Indeed, anhedonia was revealed to moderate the sensitivity to the potential relief and regret during decision-making but not regret aversion *per se*. This may mean anhedonia specifically blunts the effect that counterfactual referents involving gain (i.e., relief) have on behaviour. This would seem to agree with past literature highlighting reduced reward sensitivity during anhedonia.

Previous research has indicated that self-reported and behavioural measures may capture separate concepts across decisional phenomena, such as self-control (Allom et al., 2016; Dang et al., 2020) and risk preferences (Bagañi et al., 2025). Inconsistency in depression

effects across self-report and behavioural measures of regret could therefore be attributable to these measures reflecting different phenomena. Yet, depressive symptoms were also not associated with post-decisional affect rating, a form of self-report, meaning the findings cannot be purely explained as a function of measurement method. This is a striking finding and may tentatively be owing to the influence of cognitive biases in how more depressed individuals see themselves or expect to feel. Such biases are well-documented in the form of pessimistic thinking (Alloy & Ahrens, 1987; MacLeod & Salaminiou, 2001), rumination (Nolen-Hoeksema, 1991), negative cognitive schemas (Evans et al., 2005; Renner et al., 2012), and information-processing biases (Foland-Ross & Gotlib, 2012; Gotlib & Joormann, 2010). Specifically, negative cognitive-affective states may bias individuals towards forming perceptions of themselves, including expectations of their experiences (e.g., regret proneness), that are unrealistic.

Nevertheless, a potential methodological limitation of the behavioural (decision-making) tasks was that these may better capture responses to uncommon stimuli in highly controlled situations (Dang et al., 2020), rather than domain-general tendencies (Wennerhold & Friese, 2020) that depressed individuals recognise in themselves. Indeed, self-report questions may better capture such tendencies (Dang et al., 2020; Wennerhold & Friese, 2020). Future research may clarify by applying both methodologies, along with additional ecologically valid measures, to identify which approach best captures people's non-experimental behaviour. A potential limitation with the present study is that the pooling of the results from two periods of data-collection in 2025 (to increase power) may not have been valid given the use of different incentivisation methods (and some minor variation in item presentation). However, as identified in chapter 2, the two studies showed very similar results in terms of the effect of anticipatory regret on behaviour. Moreover, as noted in Appendix 2.E, there was no clear difference in the gauge of risk-contingent behaviour across the studies. Finally, internal consistency for the relevant self-report measures (Cronbach's alphas) were near identical in the two studies. While a valid caveat, at least the evidence above does not suggest pooling to be a major limitation to the interpretation of results.

Overall, findings herein speak to the importance of exploring depressive symptomatology as a non-unitary construct that may have different effects on decision-making by symptoms type and severity. Moreover, while it is not suggested that either self-report or behavioural measures of regret are erroneous, it is important to not assume overlap across these measures.

A careful examination of both what people say and do will better reveal how decision-making differs in the context of depressive symptoms.

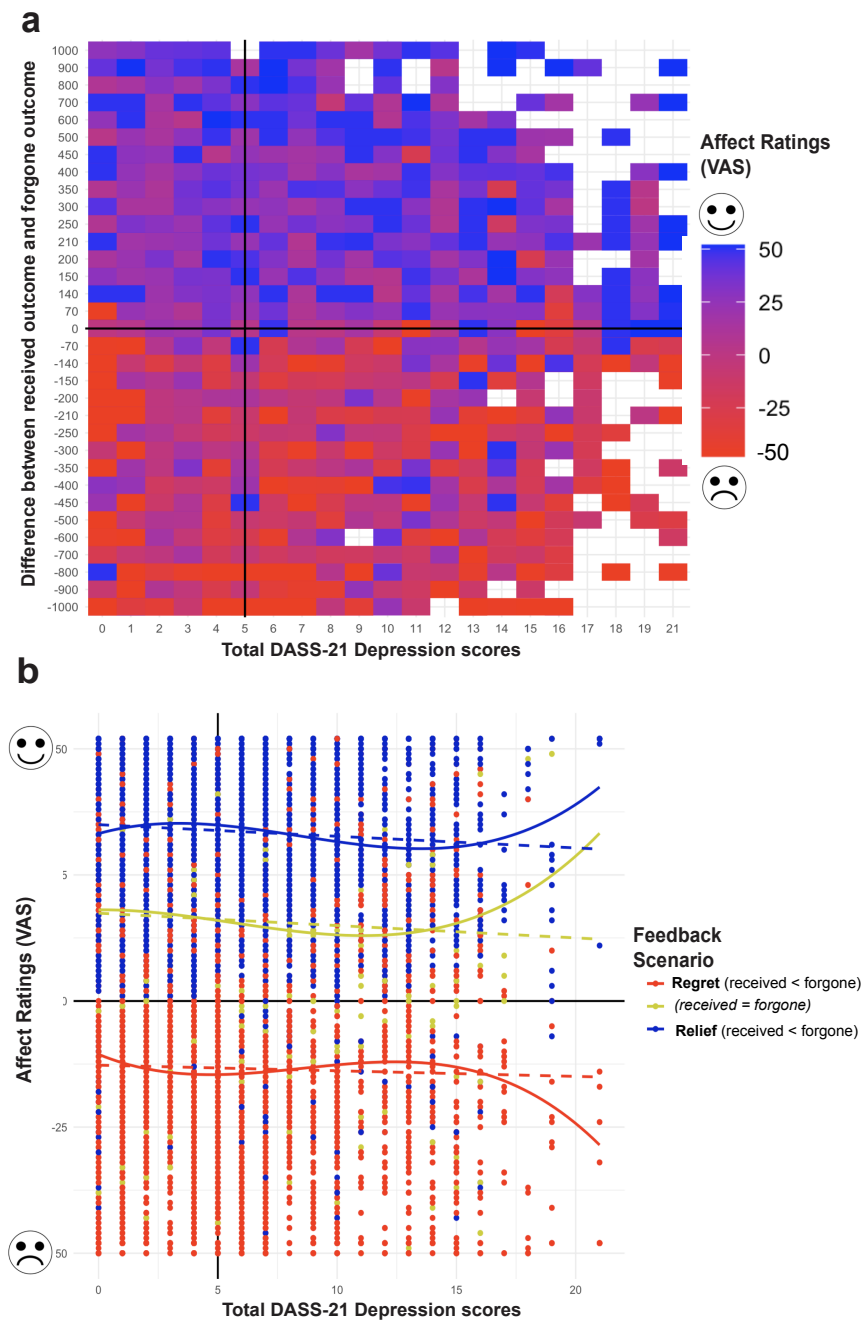
Appendix 3.A

Table A.1 Self-reported regret scale (Schwartz et al., 2002) regressed on depression scores: PHQ-8, DASS-21 Depression, anhedonia and feeling depressed – with and without controls and robust standard errors

	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	18.487*** (0.651)	18.855*** (2.840)	20.025*** (0.543)	20.060*** (2.940)	20.965*** (0.485)	19.874*** (2.872)	21.196*** (0.470)	19.876*** (2.945)
Total PHQ-8 score	0.439*** (0.062)	0.260** (0.093)						
DASS-21 Depression score			0.440*** (0.077)	0.158 (0.114)				
Anhedonia (PHQ1)					1.635*** (0.372)	0.496 (0.417)		
Feeling depressed (PHQ1)							1.532*** (0.383)	0.218 (0.407)
Participants (N)	318	314	318	314	318	314	318	314
R2	0.138	0.220	0.094	0.201	0.058	0.200	0.048	0.197
R2 Adj.	0.135	0.194	0.092	0.175	0.055	0.174	0.045	0.170
AIC	2025	1987	2041	1994	2053	1995	2056	1996
BIC	2036	2032	2052	2039	2065	2040	2068	2041

Note. Dependent variable is total Self-report regret (Schwartz et al. 2002 questionnaire), capturing one's perceived tendency to experience regret during decision-making. Models labelled '(1)' are simple regressions, and models labelled '(2)' include controls and apply robust standard errors. Coefficients are unstandardized. Controls were: the DASS21 Anxiety (7-items), DASS21 Stress (7-items) subscales, STAI State anxiety (4-items), a dummy capturing female gender status (vs other), age, a dummy capturing country of birth is Australian (vs other), a dummy capturing if income is above median of sample (vs not); and two dummies if i) unemployed or ii) student relative to a dummy reflecting: full-time employed, self-employed, part-time employment, retired, volunteer, carer, home duties or other. Full models had smaller N as 4 participants had missing values across control variables. Heteroskedasticity-robust standard errors (Stata method, i.e., HC1) in parentheses. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R^2 applies to robust estimates. Overall model F -tests were significant across models ($p < 0.001$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 3.A.1 *Affect ratings according to depressive symptoms and outcome feedback*



Note. Panel (a) shows affect ratings made with a visual analogue scale (VAS) according to the difference between the received and forgone outcomes (provided as feedback post choice) by total DASS-21 Depression scores. Vertical solid black line at total DASS-21 cut off separating Normal and Mild-or-higher symptom severity. Horizontal solid black line at point indicating received outcome equalled forgone outcome (neither regret nor relief). Panel (b) shows affect ratings by total DASS-21 Depression scores and slopes reflecting simple linear (dashed) and polynomial (solid) models of this association. Ratings and slopes are delineated according to whether ratings occurred following feedback scenarios involving regret, relief or neither (neutral) – latter only possible for WOF task.

	DASS21 (1) FE)	DASS21 (2) FE	DASS21 (2) RE	DASS21 (2) Pooled	PHQ1 (1) FE	PHQ1 (2) FE	PHQ1 (2) RE	PHQ1 (2) Pooled	PHQ2 (1) FE	PHQ2 (2) FE	PHQ2 (2) RE	PHQ2 (2) Pooled
Anhedonia (PHQ1)							-1.179 (3.286)	-1.131 (3.461)				
Anhedonia (PHQ1) (sqrd)							-0.362 (1.364)	-0.359 (1.431)				
Feeling depressed (PHQ2)											-3.754 (3.249)	-3.778 (3.420)
Feeling depressed (PHQ2) (sqrd)											1.035 (1.340)	1.231 (1.412)
Number Observations	10494	10494	10494	10362	10494	10494	10494	10362	10494	10494	10494	10362
Participants (<i>N</i>)	318	318	318	314	318	318	318	314	318	318	318	314
Choices items	33	33	33	33	33	33	33	33	33	33	33	33
R ²	0.50	0.50	0.49	0.462	0.50	0.50	0.49	0.463	0.50	0.50	0.49	0.462
Adjusted R ²	0.48	0.48	0.49	0.461	0.49	0.49	0.49	0.462	0.49	0.49	0.49	0.461
AIC	114448	114440	115565	95462	114428	114422	115572	95446	114447	114441	115566	95461
BIC	188035	188013	191657	95614	188015	187994	191664	95599	188034	188014	191658	95614

Note. Individual- & time-fixed effects ('FE'), random effects ('RE') and pooled OLS models, regressing affect ratings (VAS) given post-feedback on received outcome, forgone outcome, feedback scenario and total Self-report regret (Schwartz et al., 2002). Results for data aggregated across Wheel of Fortune (WOF) task, 2x2 Matrices task and 2x3 Matrices task. For received and alternative outcome variables, coefficients reflect change in 100s of points (i.e., scaled variables). When both Regret and Relief Scenario dummies included for WOF data, the comparison scenario is when received and alternative outcome are the same. However, for 2x2 and 2x3 data, the Relief scenario dummy is dropped, and Regret scenario is relative to Relief scenario. For pooled ('Pooled') models, controls were a dummy capturing female gender status (vs other), age, a dummy capturing country of birth is Australian (vs other), a dummy capturing if income is above median of sample (vs not); and two dummies if i) unemployed or ii) student - relative to full-time employed, self-employed, part-time employment, retired, volunteer, carer, home duties or other. Standard errors in parentheses; all models apply cluster-robust standard errors of type HC1 (random effects models applied 'arellano' method, pooled applied 'stata' method). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R^2 applies to non-robust estimates. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3 Self-reported regret scales regressed on total PHQ-8 scores and DASS-21 Depression (w/without controls)

	Schwartz	Schwartz	Roese	Roese	CTNES	CTNES	CTNES	CTNES	CTNES	CTNES	Regret	Regret
	(controls)	(controls)	(controls)	(controls)	upward	upward	upward	upward	upward	upward	vignette	vignette
					(controls)	(controls)	self	self	other	other	(controls)	(controls)
								(controls)		(controls)		
Intercept	17.531*** (1.041)	18.788*** (4.288)	16.084*** (0.797)	10.863** (3.358)	9.436*** (0.567)	7.244* (2.781)	9.844*** (0.573)	6.614* (2.593)	9.981*** (0.548)	8.567** (2.678)	4.524*** (0.279)	2.159* (1.025)
PHQ-8 depression scale	0.539*** (0.097)	0.338** (0.122)	0.314*** (0.074)	0.196* (0.093)	0.329*** (0.054)	0.183* (0.074)	0.254*** (0.056)	0.133+ (0.078)	0.215*** (0.056)	0.078 (0.084)	0.042 (0.027)	0.033 (0.034)
Participants (<i>N</i>)	124	122	123	121	124	122	124	122	124	122	124	122
R ²	0.200	0.340	0.131	0.235	0.235	0.343	0.158	0.274	0.100	0.209	0.022	0.108
Adjusted R ²	0.194	0.281	0.124	0.166	0.229	0.283	0.152	0.209	0.093	0.138	0.014	0.027
AIC	781	763	705	695	633	621	631	615	654	647	446	448
BIC	789	797	713	728	642	654	639	648	662	681	454	481
	Schwartz	Schwartz	Roese	Roese	CTNES	CTNES	CTNES	CTNES	CTNES	CTNES	Regret	Regret
	(controls)	(controls)	(controls)	(controls)	upward	upward	upward	upward	upward	upward	vignette	vignette
					(controls)	(controls)	self	self	other	other	(controls)	(controls)
								(controls)		(controls)		
Intercept	19.100*** (0.907)	21.128*** (4.531)	16.766*** (0.636)	12.404*** (3.327)	10.121*** (0.457)	8.896** (2.637)	10.551*** (0.462)	7.239** (2.460)	10.465*** (0.477)	9.437*** (2.556)	4.614*** (0.224)	2.425* (1.055)
DASS-21 Depression scale	0.569*** (0.114)	0.277 (0.172)	0.372*** (0.092)	0.201 (0.141)	0.396*** (0.057)	0.234** (0.085)	0.275*** (0.059)	0.044 (0.096)	0.253*** (0.067)	0.136 (0.110)	0.050+ (0.028)	0.035 (0.050)
Participants (<i>N</i>)	124	122	123	121	124	122	124	122	124	122	124	122
R ²	0.170	0.316	0.140	0.225	0.259	0.341	0.140	0.253	0.105	0.214	0.024	0.105
Adjusted R ²	0.163	0.255	0.133	0.155	0.253	0.281	0.133	0.185	0.098	0.143	0.016	0.025
AIC	786	767	703	697	630	621	633	618	653	646	446	448
BIC	794	801	712	730	638	655	642	652	662	680	454	482

Note. 'Schwartz' refers to the 5-item regret scale by Schwartz et al. (2002), capturing one's perceived tendency towards regret during decision-making. 'Roese' refers to the 6-item regret scale by Roese et al. (2009) capturing perceptions about one's more general regret proneness in life. 'CTNES' refers to the Counterfactual Thinking for Negative Events Scale (Rye et al., 2008), assessing i) 'upward' = upwards counterfactual cognitions, ii) 'upward self' = upwards counterfactual cognitions about oneself, and iii) 'upward other' = upwards counterfactual cognitions pertaining to others. 'Regret vignette' refers to a single Likert scaled rating made about how regretful a hypothetical consumer would feel after making a poor purchase; adapted from Tsiros and Mittal (2002). Controls were: DASS21 Anxiety subscale (7-items), DASS21 Stress subscale (7-items) and STAI State anxiety (4-items); dummy capturing female gender status (vs other), age, dummy capturing country of birth is Australian (vs other), dummy capturing if income is above median of sample (vs not); and two dummies if i) unemployed or ii) student relative to full-time employed, self-employed, part-time employment, retired, volunteer, carer, home duties or other. Heteroskedasticity-robust standard errors (Stata method) in parentheses. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). R² applies to robust estimates. Overall model *F*-tests were significant across models ($p < 0.005$), except for "Regret vignette" models ($p > 0.05$). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

General discussion

With this thesis, I hope to have contributed interdisciplinary insights to the field of economics by showing how affective states – depressive symptoms and regret – influence individual decision-making. My research has involved adapting and furthering methodology centred on reference-dependence, hopefully in interesting and novel ways. I have clarified how reference points can help explain variation in economic decision-making during depressive symptoms and the influence of regret on decision-making. My main motivations were to help address the significant societal costs of depression, and to show that economics has great potential for explaining how decision-making is influenced by affect. Below, I summarise and interpret my findings.

Across the three studies in Chapter 1, I experimentally tested whether reference point variation was associated with the severity of depressive symptoms a person was experiencing while making economic choices. Reference points were measured i) parametrically, estimated from behaviour with models of subjective value, ii) via self-report questions (i.e., stated reference points) and iii) as reward expectations inferred from simulated foraging behaviour. Higher parametric reference points were associated with more severe (frequent) anhedonia. This relatively consistent finding across studies 1 and 2, could help explain past literature indicating reduced reward salience during anhedonia, as higher reference points theoretically would be expected to generally reduce the hedonic value of reward stimuli. Moreover, parametric reference points allowed for delineating depressive symptoms based on decision-making behaviour: feeling depressed (the other main symptom of MDD) was linked to lower reference points. Study 2 indicated that stated reference points were less clearly linked to depressive symptoms, however, feeling depressed was associated with lower long-term income expectations. This suggests that the negative affective symptom of feeling depressed may exert different effects on economic decision-making compared with anhedonia. Finally, in study 3, while inference was hampered by a small sample size, results indicated that reward expectations diverged according to anhedonia versus feeling depressed. These divergences contrasted with those for parametric reference points. Thus, a model was proposed that could account for these divergences across reference points and symptoms. Additionally, the divergent results by depression symptoms were argued to potentially explain mixed findings in past depression literature. Instead of assuming depression is a

unitary construct, findings herein suggest that researchers employ both clinical populations and non-clinical populations and investigate depression at the symptom-level.

While Chapter 3 explored reference dependence in the form of regret and its association with depression; first, in chapter 2, I explored the consistency of regret across different measurement methods, during different stages of decision-making. The importance of clarifying the convergent validity of regret is high given the popularity of regret as a decisional concept in economics and other fields. I found people's self-reported perceptions about their tendency to experience regret agreed with their subsequent reported affect when exposed to regret eliciting feedback. Conversely, there was little convincing evidence that self-reported regret proneness was related to how people behaved: although the potential regret of an option influenced people's choices, and most people avoided experiencing regret, this was unrelated to their self-reported regret proneness. There was, however, some mixed evidence that more negative post-decisional affect ratings might prompt subsequent regret aversion. Overall, the findings of Chapter 2 suggested that regret may be separable into two relatively distinct concepts: self-reported regret versus behavioural regret aversion (sensitivity). This questions the convergent validity of regret, necessitating conceptual care when seeking to relate regret to other phenomena (e.g., mood symptoms).

In Chapter 3, I tested whether depressive symptoms may be associated with regret across self-report measures and behaviourally during economic decision-making. Combining the samples used in Chapter 2 meant a larger sample size could be brought to bear on statistical tests. Results indicated that experiencing depressive symptoms meant one was more likely to report regret proneness across commonly applied self-report measures. Conversely, whether one was depressed in general, or experienced specific symptoms (anhedonia versus feeling depressed), was mostly unrelated with regret averse (or sensitive) behaviour, nor with affect ratings upon feedback designed to elicit regret. The only exception was for anhedonia attenuating the effect of relief and regret combined. Overall, counterfactual outcomes were neither more nor less influential in shaping choices nor post-decisional regret as a function of depressive symptoms. At least not during experimental tasks commonly used in economics, behavioural economics and neuroeconomics to make inference about real-world behaviour. This highlights the importance of understanding what depressed people perceive relative to how they actually behave. Moreover, as emphasised in Chapter 2, regret may be separable. As such, the links between depressive symptoms and regret may depend on the type of regret

investigated. Future research may employ multiple methods spanning modalities (self-report, behavioural) and contexts to clarify this.

Regret is a reference-dependent decisional emotion: people evaluate what they could or did receive relative to counterfactual outcomes, which serves as a referent. As noted, depressive symptoms were not found to increase nor decrease the likelihood that the size of the counterfactual referent influenced choices (Chapter 3). This contrasts with the divergent associations found for reference points measured in Chapter 1. To explain this, it may be necessary to distinguish reference-dependence involving counterfactual outcomes involving regret from the behavioural reference-points examined in Chapter 1. The latter, parametric reference points and behaviourally inferred reward expectations, may involve different computational processes, with more direct links to mood states. As these are also more implicit, the findings of this study suggest that depressive symptoms may shape reference-dependent reward-processing at a ‘deeper’ or sub-conscious level. In contrast, regret likely involves more conscious comparisons. A caveat to this interpretation is, however, the strong negative link between feeling depressed and long-term income expectations; this type of expectation formation may involve different types of information-processes, biased by depression. The finding of lower reference-points while experiencing the symptom of feeling depressed (Chapter 1) may be considered together with the absent link between general depressive symptoms and feeling regret post-choice despite positive correlations between depressive symptoms and higher self-report regret proneness scales (Chapter 3): people experiencing negative affective moods may be more pessimistic (lower expectations and perceive themselves as more regret prone) *and* have blunted or attenuated subjective experiences of outcomes. Future research may delve deeper into exploring the subjective experience of rewards in those experiencing negative affect (delineating this symptom from anhedonia) by complementing self-report and behavioural methods with biological methods (e.g., neural activation of reward areas in the brain or psychophysiological measures of arousal).

As noted in the general introduction, General appendix A (below) contains a conceptual essay aimed at providing further rationale for the use of self-report for measuring affect. This chapter also summarised key points regarding the ontologically nature of affect. The essay complements the preceding experimental chapters by providing a clearer conceptual

understanding and general framework for linking moods as decisional states with empirical findings.

The findings of this thesis provide a starting point for future research. The studies in Chapter 1 are novel for quantifying reference points and applying these to explain and delineate economic decision-making across depressive symptoms. Future research may explore the origin of reference-dependent reward processing differences: for example, how longitudinal environmental (e.g., psychosocial changes) shape implicit (behavioural) reference points, and the neurobiological correlates of these. Chapter 2 is one of the first studies to explore the convergent validity of regret in decision-making. Results suggest a need for further research that clarifies the nature of regret. Relatedly, Chapter 3 points out that depressive symptoms may be specifically linked to self-reported, perceived, regret; but highlights that research must clarify whether these perceptions reflect a tendency that is behaviourally influential. Alternatively, self-reports may be shaped by information-processing biases so that depressed people's perceptions are no longer veridically linked to their behaviour.

In conclusion, depressive symptoms are prevalent and impose vast societal costs through their influences on behaviour. This thesis shows that the effects of depressive symptoms on decision-making can be understood within the research area of economics, and specifically through the lens of reference-dependence. I hope to have contributed knowledge that furthers the work of others before me, and which is a significant contribution towards improving people's wellbeing.

General appendix

Appendix A. Utilising self-reports when researching affect: a conceptual framework

Abstract

Researchers investigating affect commonly utilise people's self-reports to measure affective states; and self-reports are routinely used in clinical practice. Yet, whether self-reports actually capture anything veridically has been questioned: including whether self-reports reflect the true nature of emotions (if there is such a nature). This paper applies conceptual analysis to give a rationale for the use of self-reports. Using the emotion 'sadness' as an example, the rationale distinguishes *the folk concept* of sadness from scientifically identified (empirical) phenomena of sadness. It places importance on understanding the folk concept given its direct links to self-reports. The rationale incorporates two-dimensional semantics to explain the information-disseminating role of self-reports. The conclusion is that folk concepts of affect must be appreciated as forming part of scientific theories; only then can self-reports be cogently applied in research and clinical practice.

Key words: *affect, self-report, folk concept, two-dimensional semantics*

1 Introduction

Researchers and clinicians commonly ‘measure’ affective states with self-report scales, following a long tradition of psychometrics within psychology (Benjamin, 2005).

Researchers explore the nature of affect by linking self-report data to other empirical data – such as research associating depression with decision-making (Huys et al., 2015; Mukherjee et al., 2023) and with neurobiological activity (Kaltenboeck & Harmer, 2018). However, the measurement of psychological concepts has been criticised on philosophical grounds, argued to rely on unfounded assumptions about what is measured (Maul et al., 2016; Michell, 2008). For affect, disagreement about the nature of what is measured appears particularly pronounced: “Everyone knows what an emotion is, until asked to give a definition. Then, it seems, no one knows.” (Fehr & Russell, 1984, p. 464). Even assuming psychological measurement is valid, risks to confident inference remain (e.g., such as response biases (Brenner & DeLamater, 2016; Rosenman et al., 2011)). Perhaps it is true, therefore, as Nisbett and Wilson (1977) argue:

When people attempt to report on their cognitive processes, they do not do so on the basis of any true introspection. Instead, their reports are based on a priori, implicit causal theories, or judgments about the extent to which a particular stimulus is a plausible cause of a given response. (p.231)

Haeffel and Howard (2010) highlight the paradox that self-reports see widespread use yet are simultaneously doubted by researchers, who then tend to espouse the superiority of behavioural or biological measures. This indicates some implicit trust in self-reports, despite doubts. Even Nisbett and Wilson (1977) acknowledge that an individual has “what almost all psychologists and philosophers would assert to be “knowledge” at least quantitatively superior to that of observers concerning his emotions” (p.255). Indeed, as summarised by Haeffel and Howard (2010), i) there is greater agreement that people can report on mental content (e.g., moods, plans, attitudes and beliefs) over processes; ii) self-reports may have superior predictive power over other measurement approach when applied to moods, emotions, and psychopathology; and, importantly, iii) whether to use self-reports (or other methods) should ultimately be theoretical informed.

Against this background, a rationale is elaborated within this paper for why self-report measures of affect are valid, when grounded in an understanding of both *folk concepts* and *scientific concepts*. Emphasis is put on the former, folk-concepts, which are delineated vis-à-vis the empirical phenomena comprising scientific concepts. Moreover, *two-dimensional semantics* is applied to clarify the folk concept based on how people arguably talk about their own and others' affect. The two-dimensional framework distinguishes the role played by a person's 1) actual context and 2) their circumstance of evaluation (possible or counterfactual worlds) when explaining the referents⁶¹ or extensions of words. This is argued to address the challenge often raised that people may mean different things when using words for affective states. Throughout the paper, the emotion *sadness* (i.e., *feeling sad*) is used as an example, partly for its clinical significance and partly owing to the author's own research interests. However, the aim is to provide a conceptual rationale for the use of self-reports that remain flexibly applicable to affective states in general.

Psychometrics does appear to suffer from philosophical challenges Maul et al. (2016), and endorsing the use of self-reports does not imply an apologist stance towards these. Moreover, whether affect is quantitative (i.e., ontologically nominal, ordinal, interval or ratio) is not the question here - although it may be an important question for the field psychometrics in general (Michell, 2008). Instead, the question is: can self-reported affect (e.g., the statement "I feel sad") be taken as a measure of, by corresponding with, the actual affective state (i.e., sadness) of the person doing the reporting? Hopefully, by the concluding section most readers would answer in the affirmative. A valid rationale for the use of self-reports may help move affect from being seen as a *latent* variable to more of an *observed* variable, using the distinction in Borsboom (2008). Of his criteria, both *determination* and *causal isolation* are in this paper argued to apply to self-reported affect: that self-reported affect depends deterministically only on affective states.⁶²

In the next sections, what is meant by folk concepts and scientific concepts is elaborated. First, I attempt to describe the folk concept of sadness, followed by an explanation linking the folk concept to self-reports, partly achieved by reasoning with two-dimensional semantics.

⁶¹ 'Referent' is here not used as a decisional variable but as a word meaning referring to.

⁶² The third, *equivalent cardinality*: that the number of distinct patterns in self-reports data (e.g., how sad one says one feels) equal the strength of the affective state, is beyond the scope of this chapter to explore.

Subsequently, an account is provided of how folk concepts may be seen as constituting scientific theories of affect.

2 The folk concept and the scientific concept of sadness

Why introduce the folk concept of sadness, or the folk concept of any emotion for that matter? Can't a person's reported affect just be taken as data and then linked directly to some variable of interest (e.g., brain activity)? The answer is 'No' for three reasons i) as noted in the introduction, what self-reported affect refers to is oftentimes questioned. The *relativist* rejoinder that what I mean when I say 'I feel sad' may not be what you mean when you say 'I feel sad', still stands; ii) well-defined latent concepts, let alone observable ones, for affective states are hard to agree upon - indeed, this is an ongoing endeavour of both psychologists and philosophers (Barrett, 2022; Tappolet, 2022); and iii) the folk concept is arguably a necessary component of any theory of affect – more on this later. Thus, while research incrementally reveals the ontology of affective states (it's existence in the world), the folk concept is more directly available for understanding, making it a good initial conceptual anchor to self-reports, that is, a referent concept.

The folk concept of sadness, henceforth Sad_F (subscript 'F' for 'Folk'), can be revealed through conceptual analysis of what is "the current stereotype of ... 'whatever is happening to people in these paradigm cases.'" (Griffiths, 1997, p. 5). *Paradigm cases* may be understood as the aspects that comprise situations when most (folk) would agree a person feels sad. Similarly, Jackson (1998) proposes that "To the extent that our intuitions coincide with those of the folk, they reveal the folk theory." (p. 32). For example, there is a folk concept of red, and our word 'red' picks out the red things in the world that people give as examples of the concept (e.g., blood, stop signs, tomatoes). Our subjective experience of the colour red also makes up the concept of red to us and is linked casually to some physical aspect of the things picked out in the world. Similarly, the folk concept of tomato is red, round, and a vegetable. But wait, is a tomato a vegetable? – the science of botany tells us it is not. To the point, folk and scientific concepts are not the same.

Consider next the author's own folk-description of what 'sad' means:

the feeling that arises when one has experienced or thinks of a significant negative loss, such as a loss of someone or something meaningful.

Although this may be a good first approximation to what most people would mean with ‘sad’ (Sad_F), it is unlikely to be a good description of the ontology of sadness. The description ignores centuries of philosophical and scientific work trying to establish the true nature of emotions. This work suggests emotions have biological, somatic, motivational, evaluative, social-constructivist features; see Tappolet (2022) for a review. Indeed, Griffiths (1997) warns those who believe “they are uncovering the true nature of emotions as revealed a priori in vernacular emotion concepts. In fact, they are picking apart beliefs about emotion that have become prevalent” (p. 201). Accordingly, Scarantino and Griffiths (2011) explain criticism about the scientific utility of emotion as a natural kind category (Barrett, 2006, 2012, 2022) by arguing that although folk emotions appear to fall short, biologically basic (read scientific) concepts of emotions may, once demarcated, constitute empirically useful knowledge. It seems therefore, Sad_F stand out more clearly by contrasting it with a potential scientific concept and theory of sadness, Sad_S (subscript S’ for ‘Scientific’). In contrast to Sad_F , Sad_S could be an example of a *natural kind*, or what Griffiths (2004) prefers to call *investigative kind*, that allows for organisation of scientific discoveries. Such scientific concepts, as categories, “admit reliable extrapolation from samples of the category to the whole category, or in other words, categories which are productive objects for scientific investigation.” (Griffiths, 2013, p. 217). Vitally, this does not describe the folk concept, Sad_F on its own does not “carve nature at its joints.” (Plato’s analogy, Phaedrus, 265e). Nor should one expect this; it is not the function of folk concepts to be natural kinds. The purpose of telling a person how you feel is not to convey the ontology of sadness. A researcher using self-reports must appreciate that these self-reports do not pick out the true nature of emotion, these self-reports pick out the folk concept. Indeed, the utility of self-reports is that they reflect the folk concept. Then, once the folk concept is understood, self-reports may be used to say something about how the folk concept, Sad_F , relates to other empirical phenomena. This, in turn, may furnish the ontological, scientific, theory of sadness: meaning Sad_F will become a part of Sad_S . Of course, information about Sad_F itself is empirical data; and shows how conceptual analysis can help clarify the import empirical findings have for the meaning of concepts (Jackson, 1998). It is also worth noting that regarding Sad_F the word ‘construct’ may be more appropriate than ‘concept’, according to the distinction by (Markus, 2008). This is because the empirical properties that constitute a folk construct of emotion will differ depending on the society of interest (Barrett, 2022; Mesquita et al., 2017) (i.e., the population). Different researchers have different groups of interests, and the population may

change over time. For example, a more valid construct than ‘sadness’ may be ‘sadness in Australian young people’ (the population being ‘Australian young people’).

3 Linking self-reported sadness with the folk concept of sadness

Aggregating across the descriptive accounts of sadness given by groups of people may better capture *Sad_F*. This could pick up additional meaning, such as physiological and mental phenomena that people have in-mind. However, even aggregating will likely fall short of capturing the complexity of *Sad_F*, necessitating more sophisticated methods. Yet extensive exploration of *Sad_F* is not required to support the use of self-reports. Rather, what needs clarifying is whether *Sad_F* supports communication of sad affect via self-report. Once this is established, self-reports can be assumed to be veridically communicative. Next, it is argued that *Sad_F* does in-fact support this.

Folk, typically, do not qualify nor are required to verify their statements about sadness by elaborating on what they refer to with the word ‘sad’. Rather, we assume folk *mean* whatever *we mean* and *we think others mean* by ‘sad’. Arguably, this is an important part of the folk concept, *Sad_F*. While the following section addresses whether people need to refer to *exactly* the same experience (i.e., whether the extensions of their statements are identical); Barrett (2012) argues that emotions generally come into existence on the basis of *collective intentionality*, whereby subjective things become ontological by existing across human minds (i.e., in consensus). An attempt at explaining this process is given below for sadness. Of course, this is only a suggestion. One’s account of how words come to correspond with folk-concepts of emotion will likely vary with one’s preferred philosophical conception of emotion. Nevertheless,

Imagine a young child at their grandfather’s funeral, tearing up. Imagine the child was asked how they felt at some point and the child replies ‘disgusted’. It seems likely that the parent hearing this would be surprised and correct the child by saying something like “Disgusted? You mean you feel sad?”.

The parent’s correction may be seen as socialisation or enculturation that educates the child about the type of paradigmatic case that the word ‘sad’ refers to; a process for acquiring psychological meaning (Barrett, 2022). This response simultaneously creates a

correspondence between i) the child's use of the word 'sad', ii) the paradigm instance of loss (grandfather's death), and iii) the child's individual subjective experience of sadness. This example also underscores the arguably normative aspect of emotion (Mesquita et al., 2017): used to "construct the psychology of the young and to set up norms of behaviour" (Griffiths, 1997, p. 201). Feedback processes - linking subjective sadness, loss paradigms and the word 'sad' - constitute a paradigm-based (contrasted with definition-based) learning of *Sad_F*. That is, through repeated exposure "one [then] gets the feel for what is to count as a genuine application of the term" (Wettstein, 1989, as cited in Jackson, 1998, p. 65). Similar, though subtler, processes are probably myriad: for example, an infant attending to a parent's facial cues. Such acquisition-processes may have evolved as "The (sic) significance of events in the current environment can be very rapidly assessed by noting the assessment of those who have already lived in that environment." (Griffiths, 1997, p. 90). This notion agrees with perceptual and receptive philosophical theories of emotion (Tappolet, 2022), in the sense that emotions are not merely a signal to oneself but also to others about important environmental characteristics. As put by Barrett (2022, p. 908), the brain likely constructs "...a situated conceptual category, such as an emotion category, that is tailored to goals and functional requirements that are situation-specific.....And two people who live in the same culture will learn to construct similar situated prototypes (i.e., similar ensembles of entwined, related physical signals), allowing them to communicate efficiently and effectively.". As such, the folk concept *Sad_F* both reflects, and actively organises, what a group (society) of people refer to when using the word 'sad'. Although as noted, the referent of a word may become established in different ways for the specific individual, shared social environments constrains the meaning of *Sad_F* for the group of individuals comprising a society.

A caveat, affect has been thought of in many ways, i) socially constructed or evolutionarily given, as reviewed in Tappolet (2022); ii) *prototypical* or a *classical*, as discussed in Fehr and Russell (1984) and Scarantino and Griffiths (2011)⁶³; and iii) as either categorical or decomposable into specific affect dimensions (e.g., valence vs arousal), the nature of which has been debate since the foundations of psychology (Barrett & Bliss-Moreau, 2009). Rather than take a particular stance, they key point here is that there is good reason to believe that people within a society do *think* they talk about (at least approximately) the same thing.

⁶³ *Classical* structure means a concept, and an instance of it, can be defined and identified by a set of necessary and sufficient features. A *prototypical* definition is where an instance of a particular concept is judged on the degree to which it compares to some prototype example(s) of the concept.

“Humans automatically and effortlessly experience emotion and “detect” emotion in each other ...routinely each and every day...” (Barrett, 2012, p. 413). The next section provides a conceptual framework and rationale for this perspective on affective words, and the folk-concepts that support their use.

4 The communicative meaning of the folk concept: two-dimensional semantics

Even though affect theories either directly argue or indirectly imply emotions can be communicated, the philosopher may still argue there are not sufficient conceptual grounds for believing the statement made earlier that “...we assume people *mean* whatever *we mean* and *we think others mean* by ‘sad’”. In this section, I argue that if the folk concept is incorporated into our understanding of affect, then sameness is not required, regardless of what theory of emotion one prefers.

First, the idea of *sameness* for a subjective experience needs clarifying. It seems reasonable to suppose that people do not think of sameness in an extreme sense of *exactly the same state* when referring to subjective affect. If a person is told two people feel sad, and a follow-up question is asked: “do you think they feel *exactly* the same”, most people would probably say “no”.⁶⁴

At the other end of the extreme, it seems obvious people do assume there is meaningful overlap across two people’s feelings of sadness. If there was none, the word ‘sad’ seems unlikely to have entered use. Indeed, words for affective states likely have this feature of assumed overlap across people’s subjective states.⁶⁵ This seems evident given the tendency for affective expressions to invite a why?-question in circumstances when the affect seem out of place (e.g., as in the example of a child at the funeral). This why?-aspect speaks to the evaluative nature of emotion (Tappolet, 2022) and implies people have some semantic

⁶⁴ It is beyond the scope of this paper to discuss the nature of mental states per se; here the aim is to give a reasonable, or at least intuitive, account of how folk talk about sadness (affect) and the degree of sameness implied. Even if one insisted people referred to *exactly the same* feeling, folk and philosophers alike would have trouble agreeing on what this really means: is it possible to have the same *qualia*? If so, does it represent a functional instantiation possible in different substrates (functionalism)?

⁶⁵ The author is not aware of any commonly used word in the English language for ‘that subjective experience that *only* I can feel’, and the philosopher’s *qualia* does not appear much in common parlance.

structure (e.g., paradigm instances) for the meaning of affective words, and against which they compare the context of other people's utterances.⁶⁶

There is likely a conceptual middle ground between these two extremes: people use 'sad' without meaning exact sameness nor a complete lack of overlap regarding what different people mean by 'sad'. This is further understood by applying two-dimensional semantics.

There are many ways to apply two-dimensional semantics (Chalmers, 2008; Schroeter, Winter 2021 Edition), therefore the following description risks doing violence to certain approaches. Two-dimensional semantics allow the meaning of words to be defined as a function of both i) *the context of an utterance* or *one's actual world* (dimension 1) and ii) *the circumstance of evaluation* or *counterfactual contexts* or *possible worlds* (dimension 2). Before proceeding with sadness, illustrative examples are given that were adapted from Robinson and Braddon-Mitchell (2010), Schroeter (Winter 2021 Edition) and Braddon-Mitchell (2023).⁶⁷

The first example is a two-dimensional understanding of the meaning of the statement "I am here" (Robinson & Braddon-Mitchell, 2010). The word of interest for understanding whether the statement is true or false is 'here', the concept of which is <here> (' indicates the word, < > indicate the associated concept and "" is used for statements). In Table A.1, rows represent the evaluator's context or actual world and columns represent the counterfactual context or possible worlds⁶⁸. The evaluator's *actual world* (each row) may differ from the *possible worlds* (column) that they may be thinking of when making the statement "I am here". Therefore, whether a statement such as "I am here" is true is conditional on the actual and possible worlds. For example, imagine three *worlds*: W1, W2 and W3 that refer to three possible geographic location (Sydney, Athens, and Oslo). If the speaker's actual world/context is Sydney (row) and the possible world/counterfactual is Sydney (column), then the statement "I am here" is True (T) – as indicated in the top-left of Table A.1. For intuition, it can be helpful to imagine sitting in one's living room (actual world) and watching a travel program on the TV (counterfactual world) when making these statements (perhaps

⁶⁶ I suspect this also applies to one's own subjective affect, as when asking oneself: "why do I feel this way?".

⁶⁷ The original examples have been changed and therefore may not reflect the original meaning that the authors intended to convey.

⁶⁸ Rather than 'index', as in Robinson and Braddon-Mitchell (2010), I use 'counterfactual' and 'possible worlds'.

pointing to the location visited in the TV-program). Should actual world be Oslo (row) and possible world be Sydney (column), the statement “I am here” would be false. Notice the statement “I am here” is a-priori true when worlds coincide (the diagonal). This shows us the meaning of <here> is anchored to the context (rows) and is pivotal for determining the truth of the statement vis-à-vis counterfactual, possible worlds (i.e., circumstance of evaluation).

Table A.1 *Truth of statement: “I am here”*

Index Context	W1: Sydney	W2: Athens	W3: Oslo
W1: Sydney	T	F	F
W2: Athens	F	T	F
W3: Oslo	F	F	T

Schroeter (Winter 2021 Edition) provides another illustrative example of two-dimensional semantics involving the inaugural address of the person who won the 2008 presidential election.⁶⁹ The worlds being considered are where either Barack Obama (W1), Hillary Clinton (W2) or John McCain (W3) were the winners of the election. Again, for intuition, imagine sitting in one’s actual world but watching a TV program called *Possible worlds*. The statement considered is: “*the inaugural speaker in 2009 ...*”. In tables A.2 and A.3, the truth of two versions of this statement is considered.

Table A.2 *Truth of statement: “The inaugural speaker in 2009 is Barack Obama.”*

Possible/ Actual/ Counterfactual Context	W1: Barack Obama	W2: Hillary Clinton	W3: John McCain
W1: Barack Obama	T	F	F
W2: Hillary Clinton	T	F	F

⁶⁹ Who, of course, was Barack Obama. Note the inaugural speech is given the year following the election.

W3: John McCain	T	F	F
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Table A.3 Truth of statement: “The inaugural speaker in 2009 is Hilary Clinton.”

Possible/ Counterfactual Actual/ Context	W1: Barack Obama	W2: Hillary Clinton	W3: John McCain
W1: Barack Obama	F	T	F
W2: Hillary Clinton	F	T	F
W3: John McCain	F	T	F

The meaning of the expression “the inaugural speaker in 2009...” *does not* depend on the context in which it is used; rather it depends on the possible, counterfactual, circumstance of evaluation. This is because “the inaugural speaker in 2009...” refers to the very same *property*, being <the person who was the inaugural speaker in 2009>, even if one is in the actual world/context of Barack Obama being the winner of the 2008 election. Alternatively, when considering the counterfactual/possible world where Hillary Clinton won, the statement will refer to her. As Schroeter (Winter 2021 Edition) explains “This property is exemplified by different individuals at different possible worlds...(a) variety of different individuals who could instantiate the property represented by ‘the inaugural speaker’ in different circumstances” (Section 1.1.2).

It is argued below that people use ‘sad’ in a similar way to the preceding example: sadness is a property that can be had by whomever is referred to as a person that is experiencing sadness in that particular circumstance of evaluation, or, in other words, the possible subjective world. This person (with the property sadness) can be exemplified by different individuals. Hence <sad> is not context-specific. If it was, ‘sad’ could only refer to the property sadness in the person using the word (their subjective experience being considered the actual world or context).

Before proceeding to sadness, Table A.4 illustrates another popular example within philosophy, adapted from lectures by Braddon-Mitchell (2023). Suppose the concept of ‘water’ is \langle water is the actual, local, watery stuff \rangle . Then we can evaluate a statement like “Water is H_2O ” in different contexts and with different possible worlds where worlds refer to either the case where water’s molecular structure is H_2O , XYZ or H_2O -XYZ. For intuition, imagine *Twin Earth* that is exactly like our earth (and has the exact same universe) except *Twin Earth* differs in terms of the molecular structure of water there. Further, imagine you are sitting on actual earth, but Twin Earth is depicted on the TV screen. As seen in Table A.4, for this concept of water (\langle water is the actual, local, watery stuff \rangle) the context determines the truth of the statement entirely (across the columns for each row), regardless of the possible counterfactual worlds considered. This is because the concept (it’s meaning) only picks out the *local watery stuff* in the actual local context of the evaluator (your earth), which is true when the actual local watery stuff (on your earth) is H_2O .

Table A.4 Truth of statement: “Water is H_2O ”.

Actual/ Context \ Possible/ Counterfactual	W1: H_2O	W2: XYZ	W3: H_2O - XYZ
W1: H_2O	T	T	T
W2: XYZ	F	F	F
W3: H_2O -XYZ	F	F	F

I can say “I am made of water that is H_2O ” and “you are made of water that is H_2O ” and for both these statements to be true we would need to exist within the same context/world. As regards the point about sameness above: to the follow-up question, “do you mean *exactly* the same water?”, most would probably answer, “yes”. However, for statements involving ‘sad’ it’s likely different: the actual world of my subjective state of sadness does not need to pick out the exact same subjective state in you (or me during some other time), at least not as folk appear to use the word ‘sad’.

A quick recap: the key aspect of two-dimensional semantics is that it allows one to consider the meaning as a function of actual context and the counterfactual circumstance of evaluation. This reflects a *two-place function*, mapping context and counterfactual context to referents or extensions (Robinson & Braddon-Mitchell, 2010). Assuming sufficient intuition is in place, two-dimensional semantics is applied to how the word ‘sad’ is used. In tables A.5 and A.6, I propose to capture how statements involving sadness are used by folk in general, hopefully shedding light on the communicative aspect of the folk concept, Sad_F (i.e., $\langle \text{sad} \rangle$).

As before, in Table A.5 and Table A.6 rows and columns identify the actual worlds (W) and possible worlds (W) where subjective sadness either is present or is not, in either me (I) or you. The statements to be evaluated are “I feel sad” and “You feel sad”, respectively. These are statements that a lay person, researcher or clinicians seem likely to want to use for their various purposes. Accordingly, the pattern of ‘T’s and ‘F’s in the tables reflect the (arguably) common way that folk would use the word ‘sad’.

Table A.5 Truth of statement: “I feel sad”

‘T’ = true or ‘F’ = false				
Possible Actual	W1 I am feeling sad	W2 I am not feeling sad	W3 You are feeling sad	W4 You are not feeling sad
W1 I am feeling sad	True: from the context/actual world of my subjective experience where I feel sad, I refer to a possible world (circumstance of evaluation) where I feel sad → the statement is true.	... False: I refer to a counterfactual, possible world (e.g., time) where I don’t feel sad → the statement is false (i.e. <i>context-dependent</i>).	F	F
W2 I am not feeling sad	True: from the world of my subjective experience where I don’t feel sad, I refer to a world of possible subjective experience where I do feel sad → the statement is true (there)	F	F	F
W3 You are feeling sad	True: what you feel in my actual world is irrelevant to statements about my sadness in a possible world	F	F	F
W4 You are not feeling sad	T	F	F	F

Table A.6 Truth of statement: “You feel sad”

‘T’ = true or ‘F’ = false				
Possible \ Actual	W1 I am feeling sad	W2 I am not feeling sad	W3 You are feeling sad	W4 You are not feeling sad
W1 I am feeling sad	False F	F	... True: I refer to a world where you are experiencing subjective features of sadness → the statement is true (regardless of what <i>I</i> feel). T	...False: I refer to a world where you’re not sad → the statement is false. F
W2 I am not feeling sad	F	F	T	F
W3 You are feeling sad	F	F	T	F
W4 You are not feeling sad	F	F	T	F

The truthfulness of statements indicated in tables A.5 and A.6 is proposed to reflect the way that folk use words involving sadness. Specifically, the folk concept *Sad_F* is such that the truthfulness of these statements hinges on the possible counterfactual worlds, or circumstance of evaluation: the subjective sadness of the person in question. The concept is not context-dependent (i.e., centred on the subjective sadness of the person making the statement). The referents or extensions of ‘sad’ can be collapsed to: I can be sad (Table A.5, column 1) or not sad (Table A.5, columns 2-4) and you can be sad (Table A.6, column 3) or not sad (Table A.6, columns 1,2 and 4), regardless of the context (rows). Thus, *Sad_F* is such that it allows ‘sad’ to be applied across different subjective experiences, and across times (when the same individual is talking about themselves). Contrast this to the example in Table A.1, “I am here”, where the meaning of ‘here’ is determined by context: for “I am here” to be true requires that context and counterfactual world coincide. If sadness was context-dependent, the concept ‘sad’ could be something like <my sad subjective feeling now>. In this case, the context of the speaker’s feeling would entirely decide whether the statement ‘I feel sad’ was true or not: one could rightfully deny someone else was sad unless the sadness was *exactly* like ours (words for affective experience would become obsolete).

The meaning of *Sad_F* implied by Tables A.5 and A.6, appears to encompass something like <*the sad subjective experience I have at some time/place and the sad subjective experience you have at some time/place*>. This may appear self-evident (“Of course we can both feel sad!”). However, the two-dimensional analysis reflects a clearer conceptual defence against the common challenge: “how can I know what I mean when I say, ‘I feel sad’, is the same as what you mean when you say, ‘I feel sad’?” The answer is that this question misunderstands affective self-reports as referring directly to only natural kind concepts. Instead, affective self-reports refer to a folk-concepts, *ontologically subjective categories* with a *relative* stable structure owing to collective intentionality (Barrett, 2012) across speakers within a society using those words. Some processes that society-dwelling language speakers are subject to ensures a correspondence between individual subjective experiences of sadness (which can differ), the paradigm cases of loss and the word ‘sad’ (as argued in section 3). Put another way, expecting self-reports to refer to natural kind concepts would impose on these self-reports that they refer to subjective experiences that are invariant across individuals. We should not require this of folk concepts nor the words that they support the meaning of. As explained in Robinson and Braddon-Mitchell (2010):

“When we think about a Twin Earth⁷⁰ case in which some other internal state plays the functional role of pain, say, or of belief, we *don't* intuitively claim that the people on Twin Earth therefore don't experience pain or have beliefs. At least, we don't according to me. And that shows that we don't use “pain” or “belief” rigidly to name particular natural kinds, e.g. natural kinds of brain states.” (p. 34)

The view of *Sad_F* proposed above agrees with a communicative notion of emotions (Barrett, 2012). Specifically, a person's subjective *representation* of emotion may be seen somewhat like Brandom (1994)'s *representational content* (i.e., what's *in the mind* and that is said or thought *about*). Such representations play a role in communicating one's reason and assessing the reasons offered by others. Sadness, when used by ‘folk’ may be understood, partly, as forming such *reasons* that plays a role in communicating with others (and with oneself). This perspective also aligns with *perceptual* and *receptive* philosophical conceptions of emotion mentioned earlier, which emphasise both experiential (it feels like something) and intentional features (emotions represent the world in a certain way). And also explains why people appear to question their own and others' emotions when these disagree with circumstances (Griffiths, 2013; Tappolet, 2022).

The discussion above suggests that emotions can be seen as collective cognitive tools (Barrett, 2012): a species-specific adaption allowing for a broad range of social functions, such as bonding, problem-solving (Mesquita et al., 2017), communication and social influence; as well as self-regulation (Barrett, 2012). One may imagine that while language was relatively unsophisticated and information technology absent, emotions may have been pivotal for ensuring social groupings were immediately and collectively informed, particularly about social developments therein. That is, “A (sic) word for a psychological category, such as anger, might be thought of as an efficient way to communicate an entire pattern or ensemble of features without listing them individually” Barrett (2022, p. 904). The

⁷⁰ Here, ‘Twin Earth’ is taken to refer to a different ‘possible world’ not ‘other-parts-of-our-universe’. Although initially it may seem more valid to consider other people's subjective feelings are other-parts-of-our-universe, the (arguable) impossibility of inhabiting said subjective experience suggest ‘possible worlds’ may be most fitting.

view from economics may be that language is the market for words, and only words survive within language that confer some utility – for affective words, this utility is the ability to intuitively and rapidly communicate perceived features of one’s internal and external world.

Hopefully, the discussion above provides a cogent rationale for utilising self-reports that is based on understanding the communicative aspect of the folk concept. Importantly, the conceptual rationale means jettisoning the need to reveal what subjective experience *is* (or that it is the same across people) before using self-reports. This should not be interpreted as saying that people do not rely on subjective experience and introspection when answering self-reports. Rather it means that the results of their introspection, whatever it reveals, will already be anchored to the folk concept of *Sad_F*.

It is worth emphasising that the other features of *Sad_F* within a society (i.e., elaborating the meaning of the construct) is necessarily a continual and important effort. After some time, the concept is liable to change as folk usage gradually changes (take for example the word ‘gay’). Indeed, *concept creep* (Haslam, 2016) is an important consideration for both clinicians and researchers working within psychiatry (Haslam et al., 2021). This may also explain why philosophers and psychologists have struggled to pin down the meaning of affect, at least classically defined (Fehr & Russell, 1984; Scarantino & Griffiths, 2011).

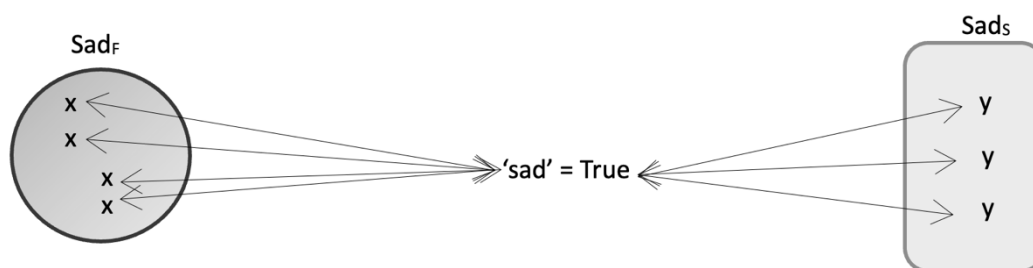
To summarise this section, *Sad_F* has been clarified through conceptual analysis, yielding a folk concept with communicative meaning. Therefore, self-reports referring to *Sad_F* can be applied meaningfully. As briefly described next, a clearer folk concept can, in turn, feature in scientific, empirical theories of sadness.

5 Linking self-reports and folk concept to other empirical phenomena of sadness

Figure A.1 illustrates the linking of empirical phenomena of scientific interest to the self-reports and therefore folk concepts. This linking is consistent with the notion of ‘entailment’ in Jackson (1998): an account of the folk concept (*Sad_F*) is entailed by an empirically informed theory of sadness (*Sad_S*) if the account of the folk concept can be told in the account and preferred terms provided by the theory and the scientific disciplines that support the theory. To the empiricist falls the difficult task of identifying which are the real distinctions in nature that are scientifically interesting and go into the scientific *schemata* of sadness (*Sad_S*).

Griffiths (1997) separates this latter form of *natural kind* – carving nature at its joint - from the social scientist’s ‘natural kind’ which focuses on the natural kinds that “societies tend to use” (p. 4) – above I have argued both will constitute the theory of sadness (emotions). Indeed, Griffiths argues that emotion must exist as a “transtheoretical identity” which allows “that an important component of meaning remains constant across radical shifts in theory. This component is the actual reality with which language users interact.” Griffiths (1997, p. 172). A well-defined folk concept may act as such an entity. This would allow people to talk about the same thing yet thoroughly disagree about what the thing they are talking about *actually is*. This seems pivotal for allowing empirical import to incrementally build our understanding of emotion.

Figure A.1 Linking features (x) of the folk concept Sad_F to phenomena (y) associated with the scientific concept Sad_S using self-reports of sadness (‘sad’)



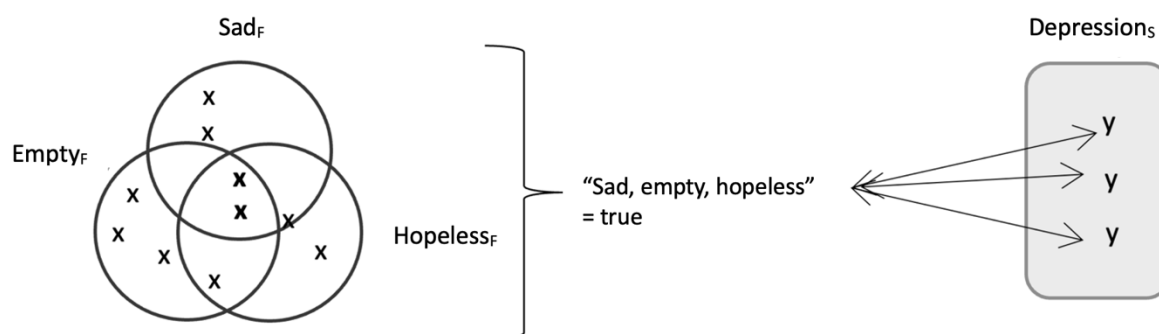
The distinction between Sad_F and Sad_S may be further appreciated through Scarantino and Griffiths (2011)’s delineation of emotion into three levels at which they may be considered *basic* concepts i) conceptual, ii) biological and iii) psychological. *Conceptually basic* emotions refer to the folk theory concepts and may be like Fehr and Russell (1984)’s *scripts* that people store in long-term memory: “The script contains prototypical causes, beliefs, physiological reactions, feelings, facial expressions, actions, and consequences.” (p. 482). Scarantino and Griffiths (2011) describe *biological basicness* with reference to the work of Ekman (e.g., Ekman (1999)) and the proposed adaptive value of emotion for enacting rapid mobilisation and communication. Biologically basic emotions have physiological, expressive, behavioural, cognitive, and experiential responses, which may be neurobiologically hardwired, yet are also “operated on” by cultural influences. Finally, *psychologically basic* emotions can only be defined when these are not blends of, nor elaborations of, other basic

emotions. Importantly, Scarantino and Griffiths (2011) make clear the risk of conflating the conceptual and the biological concepts (read Sad_F with Sad_S): “the fact that some cultures do not classify large, flightless birds with other birds is no reason for a taxonomist to exclude them from the taxon *Aves*.” (Scarantino & Griffiths, 2011, p. 449).

As noted, the researcher must be mindful that Sad_F is dynamic: gradually changing over time, and different when explored in new cultures, societies or groups. Hence, the relationship between Sad_F and Sad_S will be non-stationary: Sad_F may change to Sad_{F^*} whereby Sad_S does not correspond with Sad_{F^*} . This will necessitate further empirical work to understand the new Sad_{F^*} . Thus, empiricism is needed for pinning down folk concepts and the words linked to these, as much as for other empirical phenomena linked to sadness.

To protect against concept creep, and variability in concept understanding across individuals, self-report scales that include synonyms and overlapping words may have utility, as in the DSM-5-TR’s use of “feels sad, empty, hopeless” to identify MDD. This form of *triangulation* (Figure A.2), using multi-concept statements, may allow the researcher to capture meaning assumed shared across folk concepts (words): the set of referent concepts constituting the intersection or *core*. Because this core may dominate the meaning of the multicomponent statement, a researcher interested in measuring it will be more likely to do so with such triangulation-statements. However, theory and reason would inform the choice of component words so as to yield a core rather than disparate referents.

Figure A.2 *Triangulation: identifying concepts of empty, sad, and hopeless with self-reports utilising multiple words; then linking the core referents (bold x in intersection of Venn diagram) to phenomena (y) associated with depression*



The challenges of capturing *Sad_F* and the difficulty of relating it to *Sad_S* underscores the reciprocal relationship between conceptual analysis and empiricism. As pointed out by Jackson (1998), the referent or ‘extension’ of concepts “is in part determined by the nature of the best, true theory in which the term appears” (p.34). Jackson (1998) gives the example of whales not counting as fish because theory from “biological science told us which features were important for dividing fish from mammals-having gills” (p.35) and gave us the ‘paradigm case’ for whale, not because we settled on a list of criteria for being a fish that excluded whales. Thus, the overarching theory of sadness, as it develops through empirical discovery, will tell us which phenomena – folk and otherwise – fall under it. The penultimate section briefly explores how theories and concepts of sadness may differ and develop.

6 Elaborating on the scientific concept (theory) of sadness

The phenomena that are encompassed in a scientific concept or theory of emotions (e.g., *Sad_S*) will change with empirical discovery (Jackson, 1998; Scarantino & Griffiths, 2011). However, there is deeper disagreement in the literature about i) whether *emotions* are natural kinds; and ii) about the empirical phenomena that may be attributed to specific emotions. Regarding the former, Barrett (2006) argues that neither the category ‘emotion’ nor specific emotions (e.g., sadness, anger) are natural kinds because “our perceptual processes lead us to aggregate emotional processing into categories that do not necessarily reveal the causal structure of the emotional processing” (p. 29). A more moderate view is held by Scarantino and Griffiths (2011) who argue that although the category *emotion* holds little promise as a natural kind, certain emotions, when defined appropriately, still do. While disagreeing about whether emotions are natural kinds, the properties that natural kinds should exhibit appear agreed upon. Barrett (2006) defines natural kinds as a collection or category of things that are all the same as one another, albeit not necessarily on the surface, but equivalent in some “deep” way reflected in correlated necessary features, and given by nature not by the human mind. While different natural kinds may share features, their pattern of features must be distinctive enough to separate them and allow for inductive discoveries about them. Similarly, Scarantino and Griffiths (2011) cite Boyd’s theory of homeostatic property clusters whereby an emotion may be seen as involving “co-occurring properties and by the (‘homeostatic’) mechanisms that bring about their co-occurrence” (Boyd (1999), as cited in Scarantino and Griffiths (2011, p. 445)). While agreeing that emotions may be demarcated in the form of having correlated features and some underlying causal mechanism, these authors appear to

mainly disagree about how to interpret empirical findings. Moreover, Barrett (2012) argues for a move away from seeing emotions as traditional natural kinds to something like social kinds ('ontologically subjective categories' referred to above). This seems like a good compromise.

Many scientific accounts of affect seem to treat folk concepts as a distraction. This seems misguided. Words, concepts, and their patterns of use across a collection of minds (society) should also bear on determining the nature of affect (mood, emotions). Even more broadly, Barret (2022) espouses an anti-reductionist perspective with great potential but also (exciting) challenges. Therein, emotional meaning is understood as emergent (constructed) from, not merely moderated by, context: reflecting an entire ensemble of factors comprising the complex web of causality in which emotional experiences occur; even if, pragmatically, she says, this "will be a bitch" (p. 905).

7 Conclusions

We readily speak to others about our feelings and assume they understand what we mean. However, the use of self-reports in research and clinical practice requires a firm conceptual footing to dispel doubts about their validity. Herein, I hope to have provided a reasonable conceptual rationale for the use of self-reports. My route has been to emphasise the role of the folk concept; arguing that the folk-concept has value as the most direct referent of self-reports and clarifying its communicative meaning. Importantly, the folk concept must form a vital part of the scientific concepts (theories) of affective states; helping avoid unconstructive dualist splits between the social and what is taken to be the *natural* (e.g., the biological) (Barrett, 2012). Hopefully, I have provided cogent insights regarding the use of affective self-reports for the researchers and clinicians. In concluding, it is recommended that when using self-reports one aims to:

- Understand the folk concept: its meaning, including the paradigm cases, the way it is commonly communicated, and other aspects of how it is understood by the population of interest.
- Conceptually distinguish the folk concept from other empirical phenomena, while appreciating that a theory of emotion should incorporate the folk concept.
- Be mindful that the folk concept will necessarily change (as will scientific theory more broadly).

Although these recommendations may seem tedious, they likely prove a remedy to conceptual confusion and disagreements when working with and researching affect. In short, when someone tells you they feel sad, ask yourself, “what do folk mean by this, and what has this meaning been linked to empirically?”

Appendix B. Key instructions for behavioural tasks in Chapter 1, study 2

Unincentivised prediction

Different people will earn different amounts by participating in this study, depending on their choices and a bit of luck. Before we explain the study in more detail, we would like to understand what would be the payment that would make you indifferent between participating and not participating in a typical one-hour-long Prolific study. We are looking for an amount such that if you were to be paid less, you would prefer not to take part in the study and that if you were paid more, it would be a pleasant surprise.

Note: the answer to this question will not influence your payment in the study or any other people who complete studies on Prolific.

The amount of money that would make me indifferent between participating and not participating in a one-hour-long Prolific study is:

Task instructions and comprehension quiz

Task Instructions

You will complete tasks which provide you with a chance to earn additional money. At the end of the study, you will also complete several questionnaires.

How much will I get paid?

If you complete the study, you will receive a participation fee of **\$8 for sure**.

In addition, we will randomly select **one out of every ten** participants to receive a bonus payment. If you are one of the randomly selected participants, you will be paid one of your choices in the lottery choice task and one of your predictions in the prediction task.

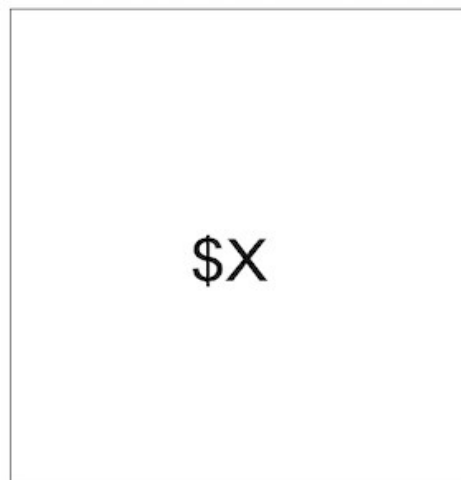
Payment will be made through Prolific.

Understanding the lottery choice task

In the lottery choice task, you will make 107 decisions between lotteries shown on the screen. There are no wrong decisions because different people have different preferences.

Understanding the sure amount display

We will show the sure amount as in the example below:



If you pick this option, you will receive \$X for sure (with 100% chance).

Understanding the lottery choice task

Understanding the lottery display

We will show lotteries as in the example below:



If you pick this lottery, you will earn one of the two dollar amounts which are written above and below the yellow-and-blue rectangle. In this case you would earn either \$Y or \$W. This means that if you pick the lottery, your outcome is not certain. You know you would get \$Y or \$W but you are not sure which one. (In the experiment, the letters will be replaced with numbers of dollars.)

The probability of receiving each amount of money is written inside the rectangle and is proportional to the size of the corresponding colored area.

- The chance with which you would receive the amount on the top (\$Y) is written in the top and yellow part of the rectangle ($p\%$)
- The chance with which you would receive the amount on the bottom (\$W) is written in the bottom and blue part of the rectangle ($(100\% - p\%)$)

In the task, the probabilities will be real numbers that will change from one decision scenario to another.

Click next to see some examples to get a better understanding.

First notice, that both lotteries above pay either \$Y or \$W.

Second, have a look at the lottery on the left only. The yellow box that indicates the probability of getting \$Y is smaller than the blue box that indicates the probability of getting \$W. This means that if you pick the lottery on the left, the chance of receiving \$Y is smaller than the chance of \$W. The precise probabilities are written inside the colored boxes – 10% chance of \$Y and 90% chance of \$W.

Third, compare the lottery on the left with the lottery on the right. In the lottery on the right, the yellow box is larger than the blue box, indicating that the chance of receiving \$Y (90%) is greater than the chance of receiving \$W (10%).

In the lottery choice task, you will choose between lotteries and sure amounts. You will indicate your choice by clicking on your preferred option and pressing next to see the next decision scenario.

Example of a decision scenario



In the above hypothetical example of a decision scenario, you can choose between:

- a lottery which pays \$Y $p\%$ of the time and \$W $100\%-p\%$ of the time (on the left), and
- receiving \$X for sure (on the right).

In the task, the amounts and probabilities will be real numbers that will change from one decision scenario to another.

You will complete sets of the lottery choice task. Then, for **one out of ten** participants, **one decision scenario** will be **randomly selected**. If this happens for you, your choice in this decision scenario will be realized for payment. Only one of your decisions made throughout the study can be selected for payment. This means that it is in your best interest to treat every decision as independent from the other choices you make. In other words, whenever you face a decision scenario, you should decide as if this is the only decision that you are making.

Payment example



Suppose that this example decision scenario was randomly selected for payment. How much would you earn?

There are two possible cases:

1. If you picked the option on the left, the computer would play the lottery. It would randomly pick a number between 0 and 100. If the number is smaller or equal to p , you would get $\$Y$, if it is larger than p , you would get $\$W$.
2. If you picked the option on the right, you would get $\$X$ for sure

Once you feel you understand each component of the visual lottery display, please click next to answer comprehension questions.

Lottery task comprehension check

You need to answer ALL three questions correctly to participate in the study. You



will have TWO attempts at each question to complete the comprehension check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#).

Consider the example decision scenario above that was randomly selected to count towards payment and select the true statement.

1. If I picked the option on the left, I will receive

- \$X for sure.
- \$Y with (100-p)% chance.
- \$W with p% chance.
- \$Y with p% chance and \$W with (100-p)% chance.

Your answer was not correct. In the scenario below, if you picked the option on the left, you would get \$Y with p% chance and \$W with 100%p% chance. The option

on the right is a lottery, represented with a yellow and blue box. The option on the right, a white box with a \$ number inside represents a sure payoff. In this case, a sure payoff of \$X.

Lottery task comprehension check

You need to answer ALL three questions correctly to participate in the study. You will have TWO attempts at each question to complete the comprehension check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#).



Let's try a similar question one more time.

Lottery task comprehension check

You need to answer ALL three questions correctly to participate in the study. You will have TWO attempts at each question to complete the comprehension check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#).



Consider the example decision scenario above that was randomly selected to count towards payment and select the true statement.

1. If I picked the option on the left, I will receive

- \$C for sure.
- \$A with 100%-p% chance.
- \$B with p% chance.
- \$A with p% chance and \$B with 100%-p% chance.

You answered question one correctly! Press next to move onto question two.

Lottery task comprehension check

You need to answer ALL three questions correctly to participate in the study.
You will have TWO attempts at each question to complete the comprehension

check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#)



Consider the example decision scenario above that was randomly selected to count towards payment and select the true statement.

2. If I picked the option on the right, I will receive

- \$X for sure.
- \$Y with (100-p)% chance.
- \$W with p% chance.
- \$Y with p% chance and \$W with (100-p)% chance.

Your answer was not correct. In the scenario below, if you picked the option on the right, you would get \$X for sure. The option on the right is a lottery, represented with a yellow and blue box. The option on the right, a white box with a \$ number inside represents a sure payoff. In this case, a sure payoff of \$X.

Lottery task comprehension check

You need to answer ALL three questions correctly to participate in the study. You will have TWO attempts at each question to complete the comprehension

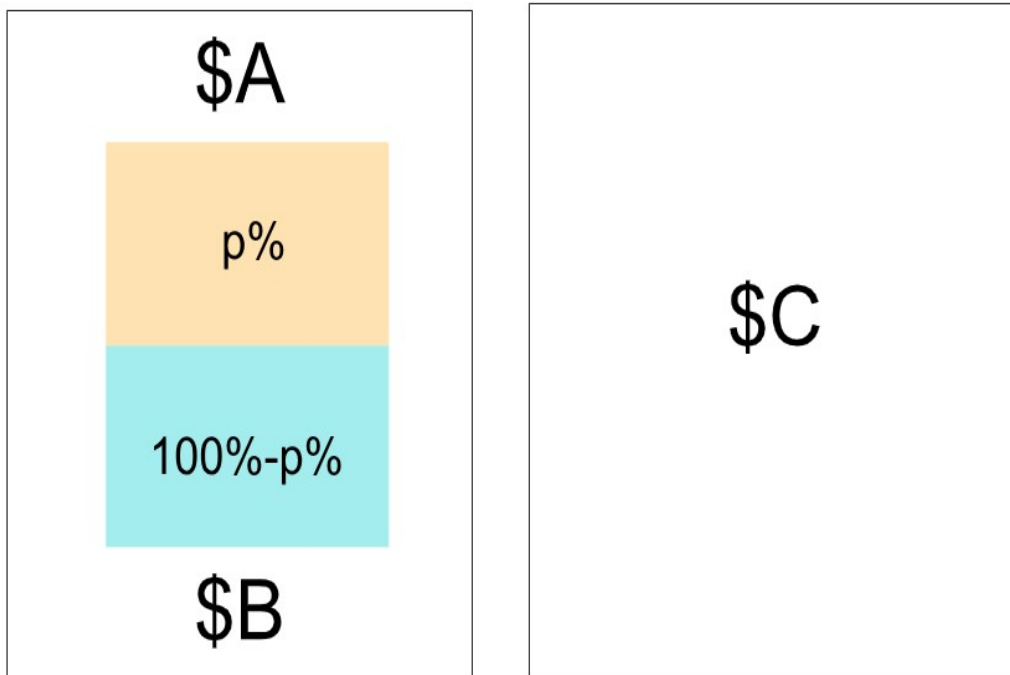
check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#).



Let's try a similar question one more time.

LOTTERY TASK COMPREHENSION CHECK

You need to answer ALL three questions correctly to participate in the study. You will have TWO attempts at each question to complete the comprehension check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#).



Consider the example decision scenario above that was randomly selected to count towards payment and select the true statement.

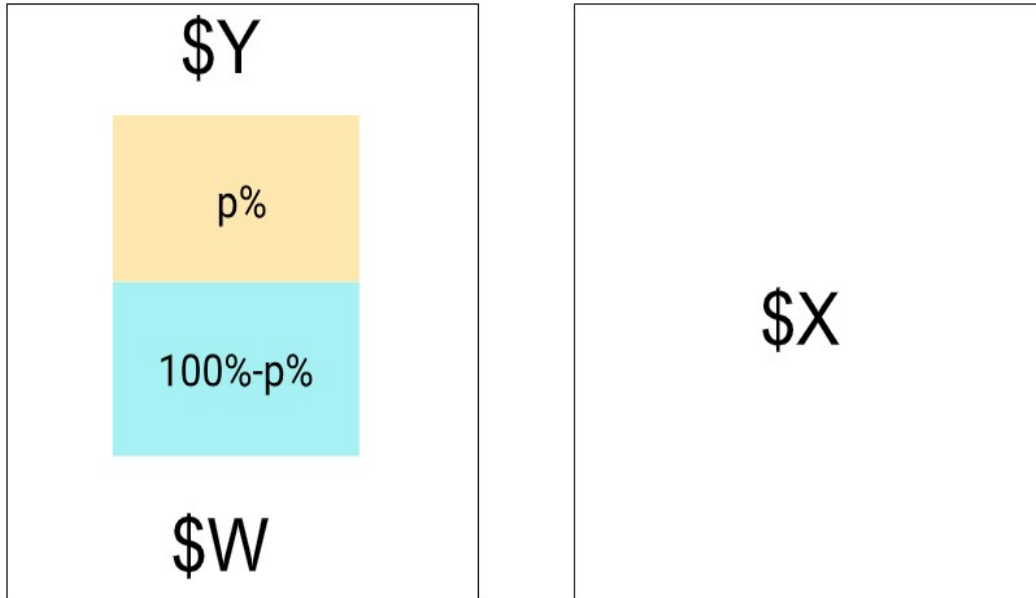
2. If I picked the option on the right, I will receive

- \$A with 100%-p% chance.
- \$B with p% chance.
- \$C for sure.
- \$A with p% chance and \$B with 100%-p% chance.

You answered question two correctly! Press next to move onto question three.

LOTTERY TASK COMPREHENSION CHECK

You need to answer ALL three questions correctly to participate in the study. You will have TWO attempts at each question to complete the comprehension check. If you fail a question twice, you will not be able to participate in the study. If you would like to re-read the instructions, please [click here](#).



Consider the example decision scenario above that was randomly selected to count towards payment and select the true statement.

3. To increase the chance that I receive my most favored payment, I should pay attention and always select the option I prefer.

- True
- False

Lottery task comprehension check

You need to answer **ALL** questions correctly to participate in the study. You will have **TWO** attempts to complete the comprehension check. If you would like to re-read the instructions, please [click here](#).



Consider the example decision scenario above that was randomly selected to count towards payment and select the true statement.

You have answered question three incorrectly! This is your last attempt at question three. If you do not answer question three correctly on this attempt, you will not get paid.

3. To increase the chance that I receive my most favored payment, I should pay attention and always select the option I prefer.

- True
- False

You answered question three correctly!

You have passed the comprehension quiz and are now ready to continue.

Pass comprehension test

You are about to make choices in a set of 107 decision scenarios. What do you expect your average earnings per decision scenario in this set will be?

To calculate your average earnings, we will add the earnings from all your decisions in this set and divide them by the number of decision scenarios in this set.

The closer your prediction is to the correct amount, the more likely you are to earn a bonus of \$1 in the prediction task.

To determine whether you get the bonus, we use a procedure which has been used in many other studies. The closer your prediction is to your average earnings in the lottery choice task, the higher your chance of receiving \$1. Therefore, it is in your best interest to report your true belief about what you think your average earnings in the lottery choice task will be. To get detailed instructions about how the exact probability of receiving the bonus is generated, [click here](#).

I expect to earn \$ _____ on average from the lottery choice task.

You are now ready for the lottery choice task. Please press next on the bottom of the screen to start. Your task is to click on the option that you prefer.

(Post task)

You have just made choices in a set of 107 decision scenarios. What do you expect your average earnings per decision scenario in this set were?

To calculate your expected average earnings, we will add the earnings from all your decisions in this set and divide them by the number of decision scenarios in this set.

The closer your prediction is to the correct amount, the more likely you are to earn a bonus of \$1 in the prediction task.

To determine whether you get the bonus, we use a procedure which has been used in many other studies. The closer your prediction is to the correct amount, the higher your chance of receiving \$1. Therefore, it is in your best interest to report your true belief about what you think your average earnings in the lottery choice task will be. To get detailed instructions about how the exact probability of receiving the bonus is generated, [click here](#).

I expect to earn \$ _____ on average from the lottery choice task.

Appendix C. Key instructions for behavioural tasks in Chapter 1, study 3

Intro/Walkthrough

Thank you for consenting to take part in this study. The study consists of the following parts:

1. Several questionnaires and a puzzle task
2. A lottery choice task
3. An apple picking task
4. Payment and goodbye

For your participation you will receive \$15. Based on your choices in the lottery choice task or apple picking task you may receive more money. At the end of the experiment, you will toss a coin to determine whether you get paid based on your decision in the lottery task or the apple picking task.

You will get information about each task before you complete it.

Let the experimenter know if you have any questions or click next to continue.

You are about to start two tasks:

1) the lottery choice task, and 2)

the apple picking task.

Your decisions are important because they will determine your payment. There are no wrong decisions because we will ask what you prefer, and people have different preferences.

We will explain exactly how you can earn money in each task before you complete them. Please pay attention to the instructions and ask questions whenever anything is unclear because your payment depends on your decisions.

Press next to learn more.

How is my payment determined?

After you finish both tasks, you will toss a coin to determine which task you are paid for.

Additionally, for each completed session, you will receive a \$15 showup fee.

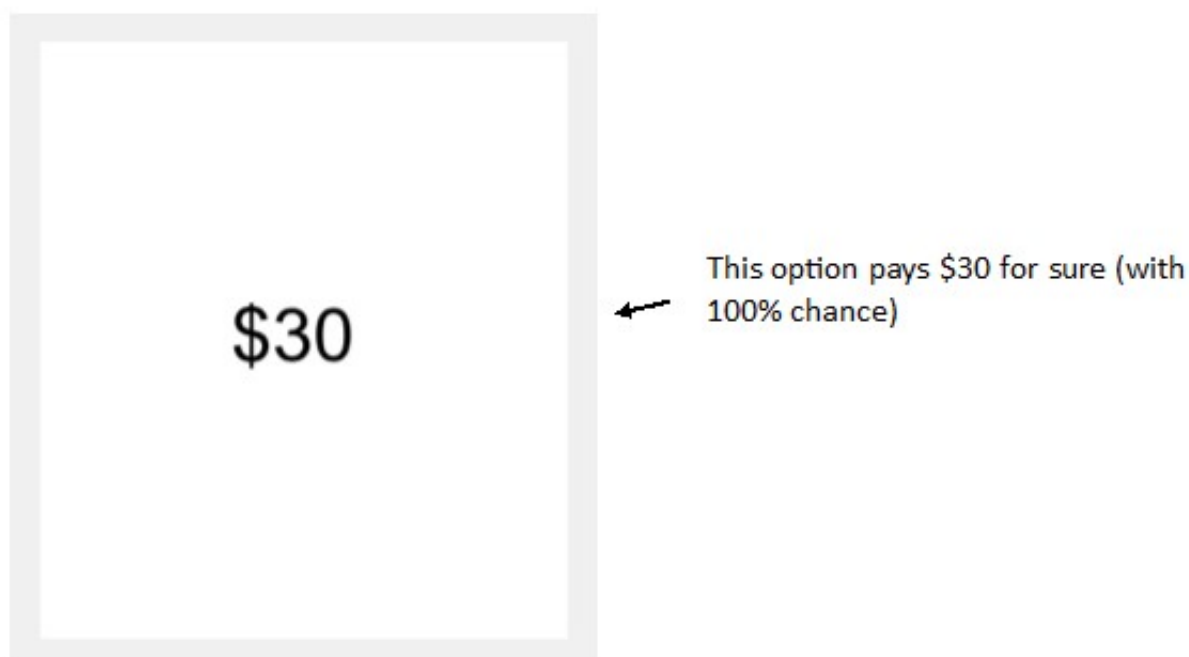
Press next to learn about the lottery choice task.

Lottery Choice Task

You will make 107 decisions between a sure amount of money and a lottery.

Understanding the sure amount display

We will show the sure amount as in the example below:

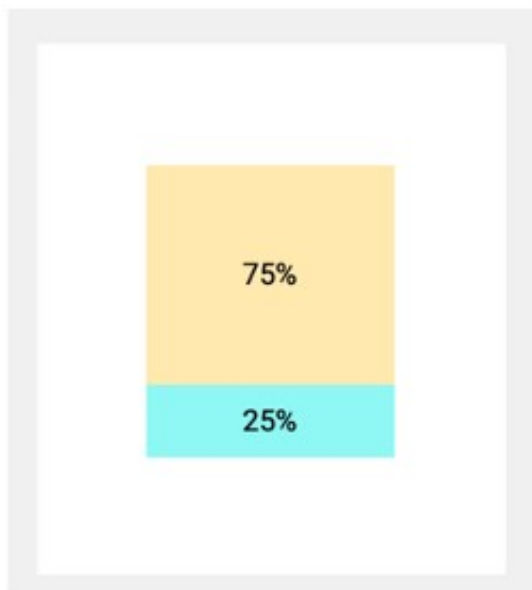


Understanding the lottery display

We made five physical bags filled with coloured chips to represent lotteries. All these bags are now in this room and you are welcome to inspect their contents if you would like.

Each bag has 100 coloured chips (some yellow and some blue). The pictures on the bags tell you how many of each colour there are.

On the computer, we will show lotteries as in the example below:



This lottery has 75 yellow chips (75%) and 25 blue chips (25%)

All five bags have different amounts of yellow and blue chips. Below are two more examples:

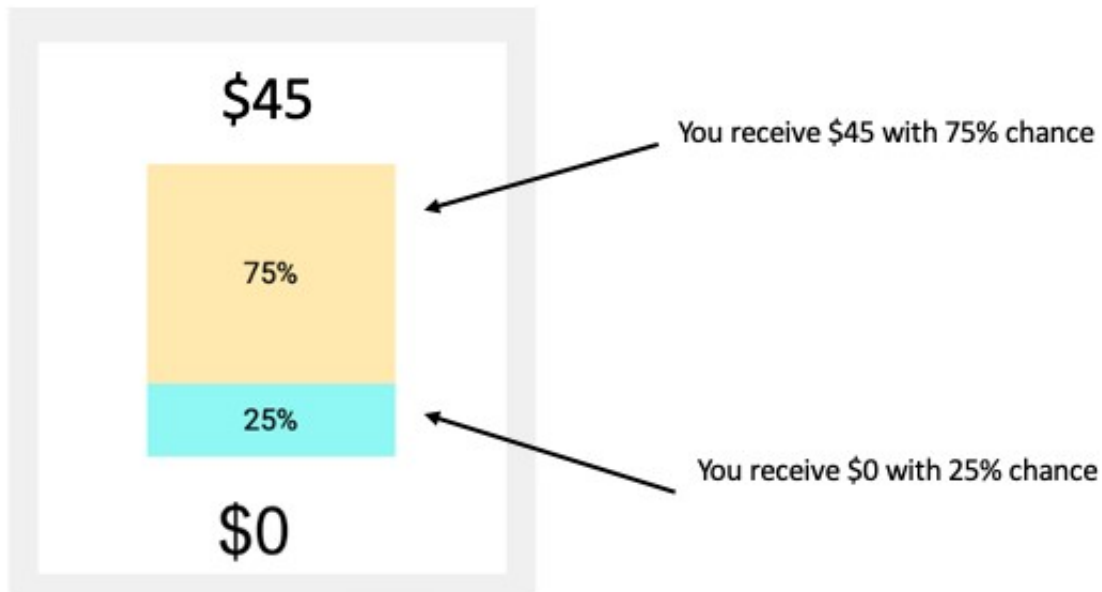


Both lotteries above contain 100 chips.

In the lottery on the left the yellow box is smaller than the blue box, indicating that there are fewer yellow (10) than blue chips (90).

In the lottery on the right the yellow box is bigger than the blue box, indicating that there are more yellow (90) than blue chips (10). If you were to pick one chip from each bag without looking. You are more likely to pick blue from the one on the left and more likely to pick yellow from the one on the right.

Above and below each lottery icon will be a number indicating an amount of money. Here is an example:



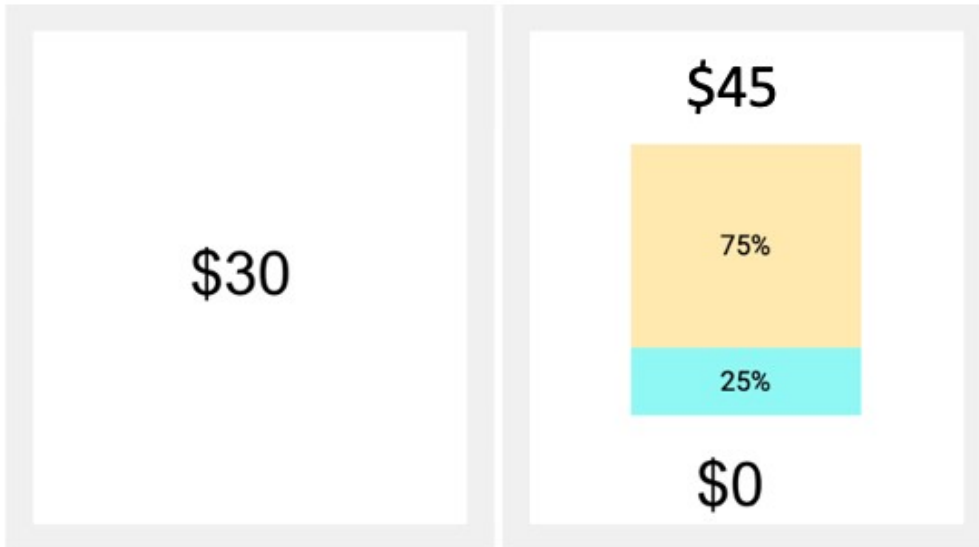
If this lottery was selected for payment, you would draw (without looking) a chip from a physical bag with 75 yellow and 25 blue chips. The colour of the chip you draw, would determine how much money you receive. If you drew a yellow chip, you would receive \$45. If you drew a blue chip, you would receive \$0.

Remember that you will draw the chip from the bag without looking so you cannot choose what colour you want to pick.

Understanding the lottery choice task

In each decision scenario, you will decide whether you prefer the lottery or sure amount of money.

Example



The picture above is just an example so you cannot make a choice.

Your task is to choose between

- 1) \$30 for sure – the option on the left
- 2) a lottery in which you would get \$45 with 75% chance and \$0 with 25% chance – the option on the right.

To indicate your decision click on the option you prefer (the option you click on will light up with a LIGHT GREEN frame around it). Once you are sure about your decision, press next to move to the next decision scenario.

Understanding the payment in the lottery choice task

After you complete the lottery task and the apple picking task, you will toss a coin to decide whether you are paid based on a choice you made in the lottery or apple picking task.

Let's suppose that you are to be paid for the lottery choice task.

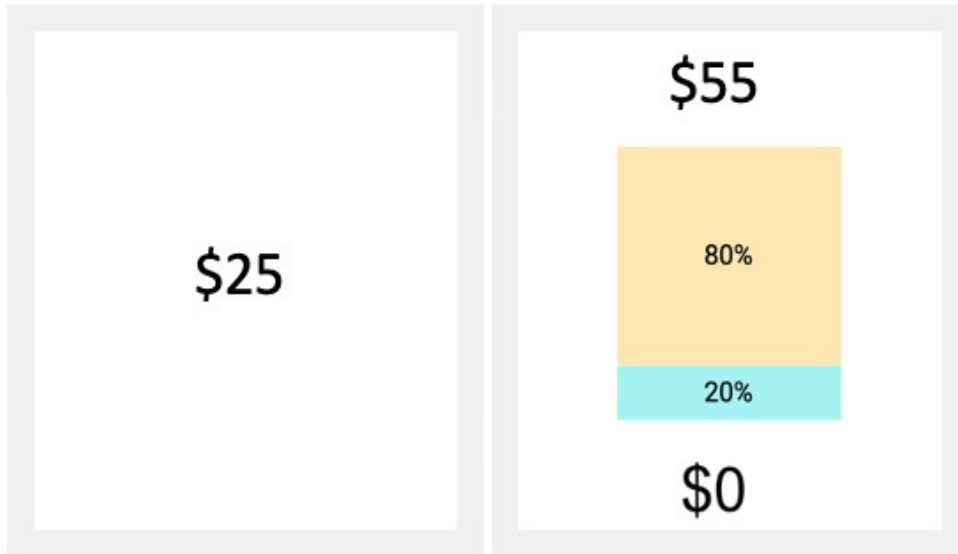
We prepared a bag with chips numbered from 1 to 107 corresponding to the number of decisions you made in the lottery choice task. At the end of the session, you will pick (without looking) one numbered chip to determine which decision scenario counts for payment.

If in the selected decision scenario, you chose the sure amount it will be added to your final payment.

If in the selected decision scenario, you chose the lottery, you will reach into the appropriate lottery bag and draw a single chip without looking. The colour of this chip will determine your additional payment.

The decisions you make in the lottery choice task do not impact your possible earnings in the apple picking task which we will explain later.

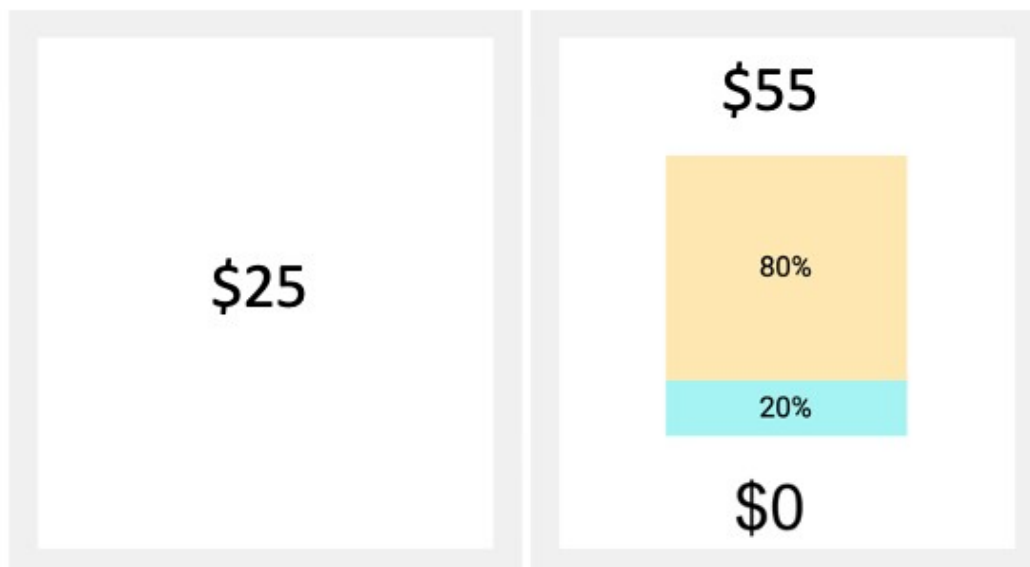
Comprehension questions



Imagine you are paid from the decision scenario above. Suppose you chose the option on the left. On top of the \$15 show up fee, you will receive...

- a. \$25 for sure
- b. \$55 with 80% chance
- c. \$25 with 80% chance
- d. \$55 with 80% chance and \$0 with 20% chance

Comprehension questions

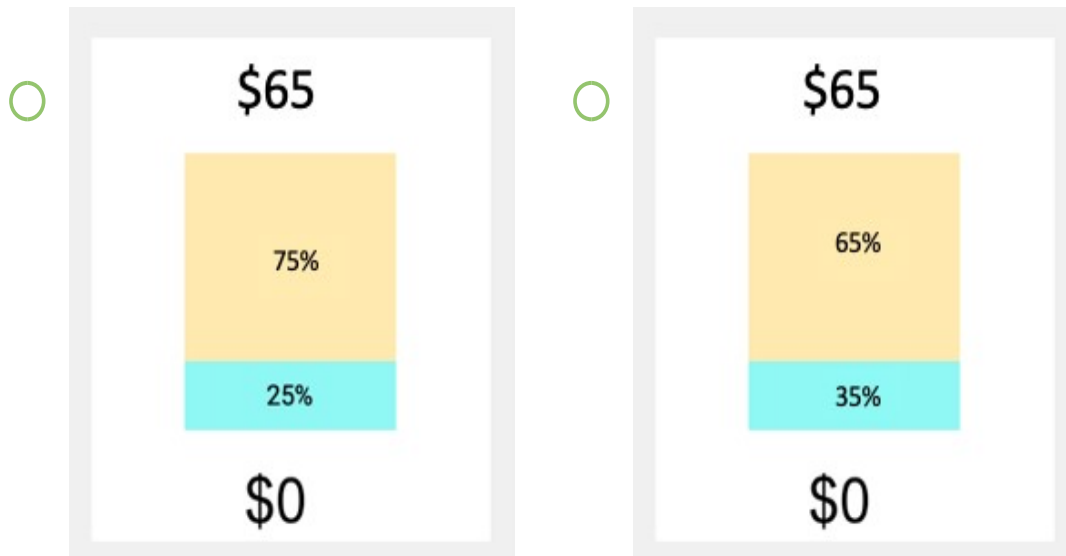


Suppose you chose the option on the right. On top of the \$15 show up fee, you will receive...

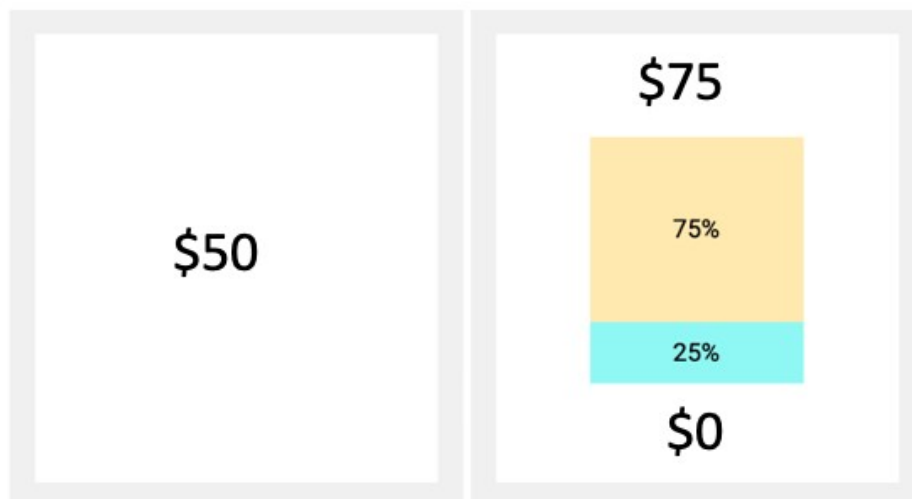
- a. \$25 for sure
- b. \$55 for sure
- c. \$25 with 20% chance
- d. \$55 with 80% chance and \$0 with 20% chance

Comprehension questions

Which lottery has higher chance of paying \$65?



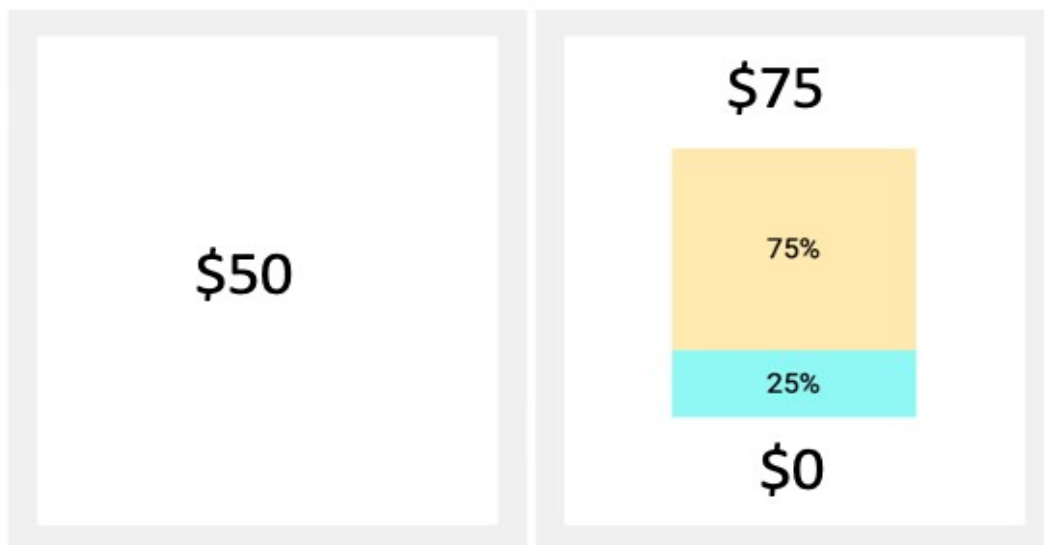
Additional comprehension questions



Imagine you are paid from the decision scenario above.
 Suppose, you chose the option on the left. On top of the \$15 show up fee, you will receive...

- a. \$50 for sure
- b. \$75 with 75% chance
- c. \$50 with 75% chance
- d. \$75 with 75% chance and \$0 with 25% chance

Additional comprehension question

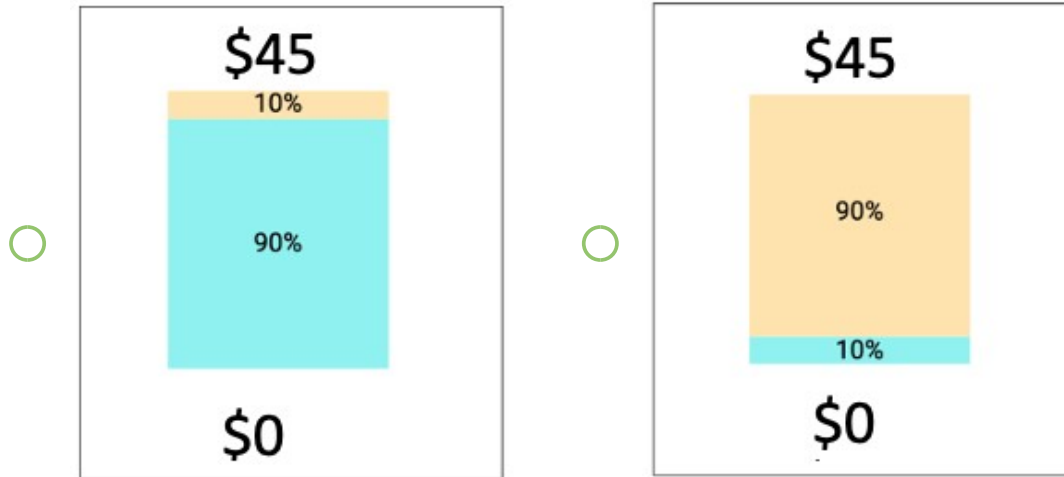


Suppose you chose the option on the right. On top of the \$15 show up fee, you will receive...

- a. \$50 for sure
- b. \$75 for sure
- c. \$50 with 25% chance
- d. \$75 with 75% chance and \$0 with 25% chance

Additional comprehension question

Which lottery has the higher chance of paying \$45?



If you have any questions, please ask the experimenter now.
If you do not have any questions, please press next to start the task.

Appendix D. Key instructions for behavioural tasks in Chapter 2, study 1

Part 2: the 3 choice and rating tasks

In this part of the study, you will be making various decisions (e.g., two options presented on the screen) and rating how you feel about the outcomes after. Your decisions are important because they partly determine the number of points you receive, and therefore, whether you are selected to receive a **\$50 electronic gift card** (if you choose to enter the draw).

Before starting each task, you will read instructions and complete comprehension questions.

For some choices your points are also determined by the outcomes that are chosen by the computer, based on probabilities (this will become clearer when you see the tasks).

There are no wrong or right answers because we will ask what you prefer and people have different preferences.

Reminder: reward from points

Across the 3 tasks (not the questionnaires) you will earn points based partly on your choices and you may be selected to receive a reward:

● At the end of our study, only **5 participants with the highest number of points** will be selected to receive a \$50 electronic gift card from JB Hi-Fi ● These gift cards will be provided via email, once data collection has stopped and the survey has been closed.

The way we will ensure the selected 5 participants receive their gift card, is to ask you to enter your email address by clicking on a link we'll provide on a separate page - on this page we will ask you to enter your email along with a randomly generated individual ID number (which we will provide you).

This is of course **entirely voluntary**: you do not need to enter your email if you prefer not to, and you will then not be part of the group of people who may be selected for the gift card (you will still receive credit for completing the study).

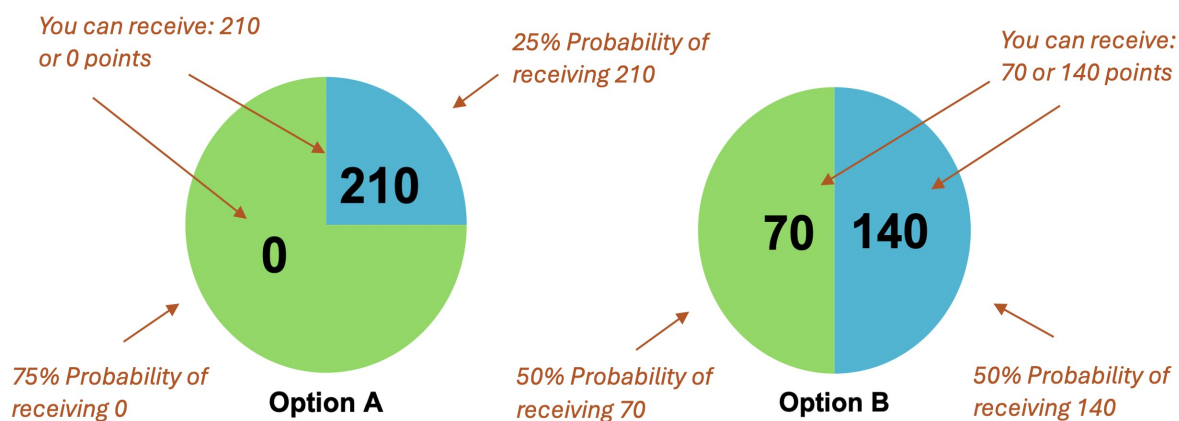
Instructions 4.1

First task: understanding the display

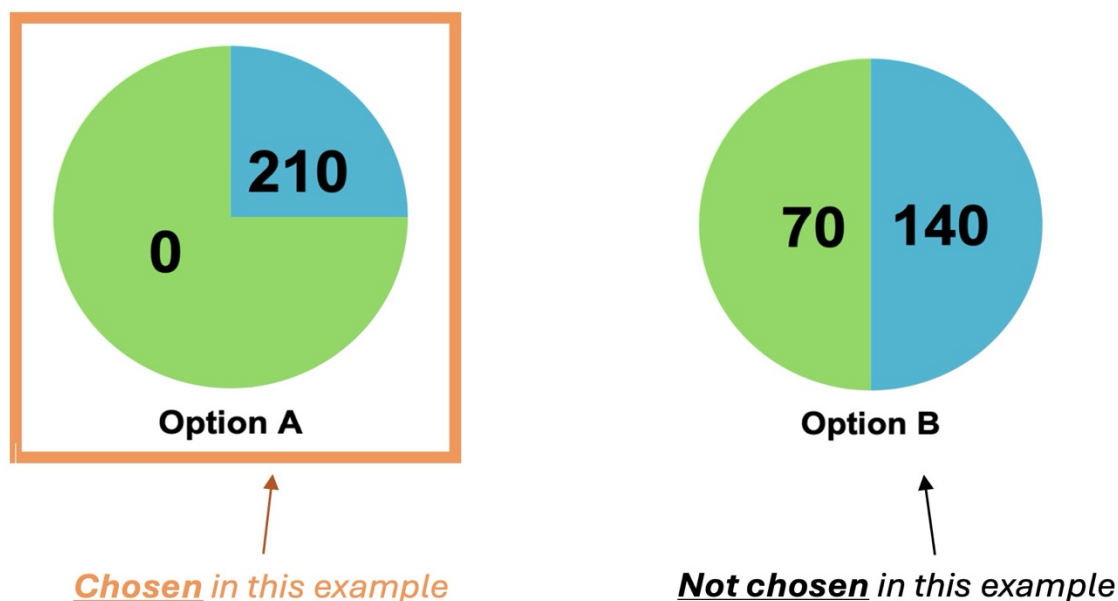
In the following task, you will see **two options – A and B**. Your task is to choose the option you prefer. Each option is a lottery that offers some probability to receive some number of points. The size of the coloured pie chart tells you the probability of receiving the number of points written inside it. Below is an example:

- **Option A** offers a 75% probability to receive 0 points and a 25% probability to receive 210 points
- **Option B** offers a 50% probability to receive 70 points and a 50% probability to receive 140 points

Please take some time to inspect the two options and the text describing each aspect.

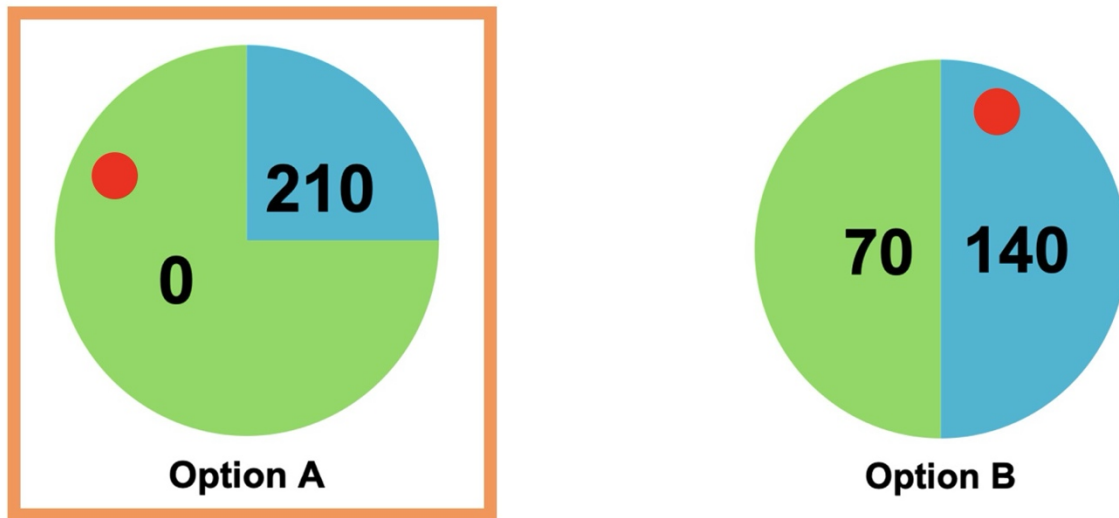


When you make a choice, **your chosen option will be highlighted** (as in the example below, where option A was chosen).

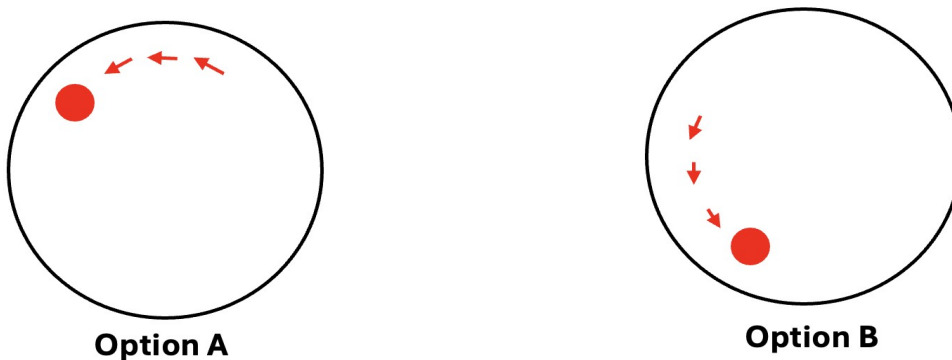


After you have made your choice, the computer will decide the outcome according to the probabilities – for the example below:

- **for option A** (the chosen option) the computer will choose 0 points with 75% chance and 210 points with 25% chance.
- **for option B** (the not chosen option) the computer will choose 70 points with 50% chance and 140 points with 50% chance.



A **red ball** will show which outcome was the result. Imagine this is *as if there is a ball spinning around*, and that the computer decides where it lands. That is, **where the red balls 'lands' will determine the points** for the option you chose (points you get) and for the option you did not choose (points you don't get).



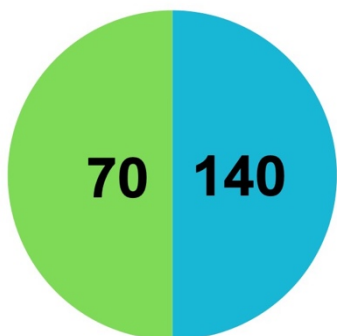
Importantly, the outcome for option A and option B are **independent**: the computer can randomly decide one part of circle A for the red ball in A to land in, but choose another part of circle B for the red ball in B to land in.

The computer will determine the outcome (where the red ball lands) **randomly**, according to the probabilities.

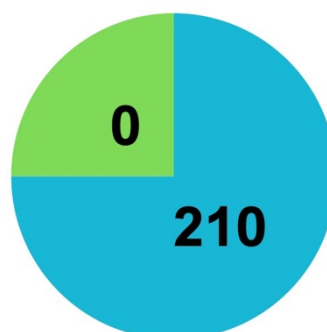
- If the ball lands **in the blue area**, the **outcome is the points in the blue area**.

- If the ball lands **in the green area**, the **outcome is the points in the green area**.

A larger area means a higher probability that that outcome is selected by the computer - this means a higher chance that you will get that outcome. Below, in *option A*, there is a higher chance of 210 points (**blue area**) than of 0 points (**green area**). In *option B*, there is an equal chance of 140 points (**blue area**) and of 70 points (**green area**).



Option A



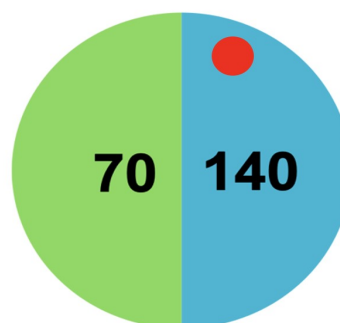
Option B

Y

our outcome is **0 points!** the outcome you **didn't get** is **140 points**



Option A



Option B

In the example above, **option A gave 0 points** – this is what the person will get because they selected A. Had they instead selected the other **option B**, they would have received **140 points**.

After making your choice, we will show you **the number of points that was the result for your choice** and **the number of points that was the result for the option you did not choose** (the points you didn't get). Then you will be asked to rate how you feel about the outcomes, using a slider like the one shown below - you click on the slider and move it to reflect how you feel about the outcome.

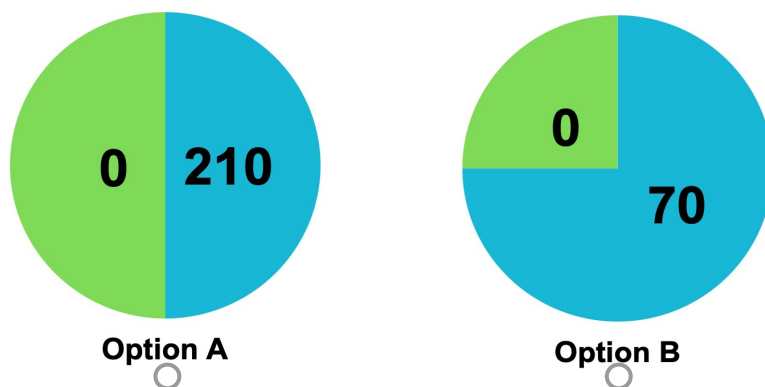
Rate how you feel about this outcome:



Instructions 4.2.1

Now let's try some comprehension questions to see if you understand the study.

Please click on the option that offers a 75% probability of receiving 70 points and 25% probability of receiving 0 points.

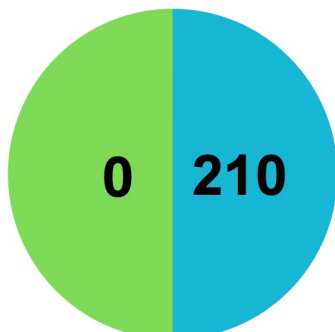


Instructions 4.2. Correct

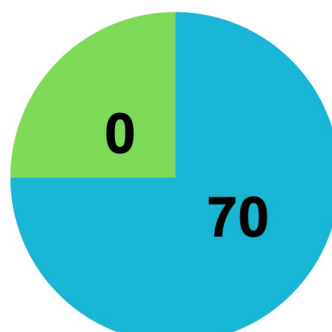
Correct!
please continue

Instructions 4.2.Incorrect

That is not quite right, if you selected option B, and this decision-scenario is chosen for payment, there is a 75% probability of receiving 70 points and 25% probability of receiving 0 points.



Option A

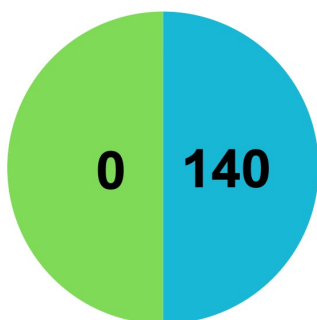


Option B

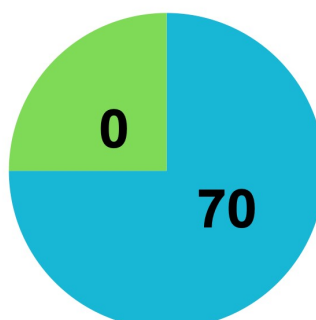
please continue

Instructions 4.3

Next comprehension question: please click on the option that offers a 50% probability of receiving 140 points and 50% probability of receiving 0 points.



Option A



Option B

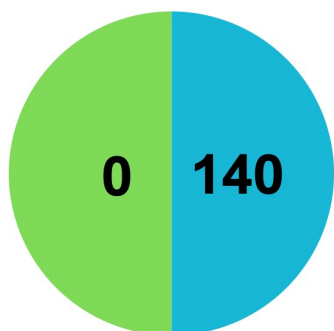


Correct!
please continue

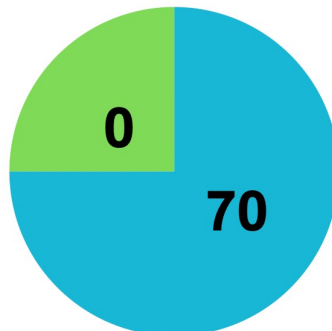
Instructions 4.3.Correct

Instructions 4.3.Incorrect

That is not quite right, if you selected option A, and this decision-scenario is chosen for payment, there is a 50% probability of receiving 140 points and 50% probability of receiving 0 points.



Option A

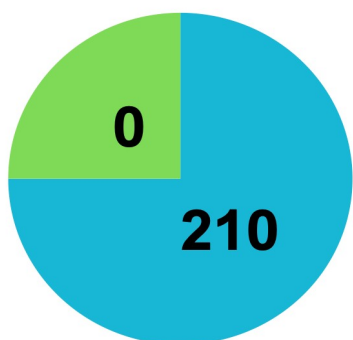


Option B

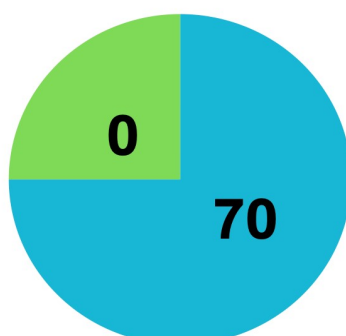
please continue

Instructions 4.4

In the example below, **If option A was selected**, then you could receive (pick the



Option A



Option B

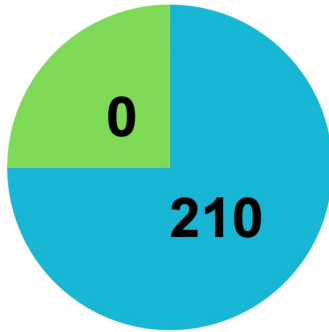
- 70 points for sure
- 210 points with 50% chance
- 0 points for sure
- 210 points with 75% chance
correct answer?

Instructions 4.4. Correct

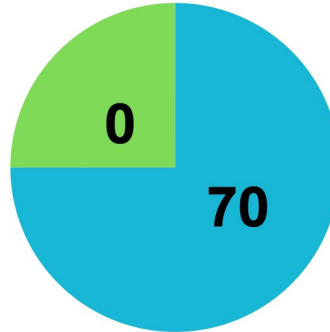
Correct!
please continue

Instructions 4.4.Incorrect

That is not quite right, if you selected option A, and this decision-scenario is chosen for payment, there is a 75% probability of receiving 210 points (and 25% probability of receiving 0 points).



Option A



Option B

please continue

Instructions 4.5

The task will now begin!

Remember, your decisions are important because they will determine how many points you receive. There are no correct decisions because we will ask what you prefer, and people have different preferences.

Reminder: reward from points

Across the 3 tasks (not the questionnaires) you will earn points based partly on your choices and, if you choose to participate in the draw, you may be selected to receive a reward:

- At the end of our study, only **5 participants with the highest number of points** will be selected to receive a \$50 electronic gift card from JB Hi-Fi ●
- These gift cards will be provided via email, once data collection has stopped and the survey has been closed.

The way we will ensure the selected 5 participants receive their gift card, is to ask you to enter your email address by clicking on a link we'll provide on a separate

page - on this page we will ask you to enter your email along with a randomly generated individual ID number (which we will provide you).

This is of course **entirely voluntary**: you do not need to enter your email if you prefer not to, and you will then not be part of the group of people who may be selected for the gift card (you will still receive credit for completing the study).

BreakTwo

You may take a short break, if you wish, then proceed to the next task.

Instructions 5.1

Next task: understanding the display

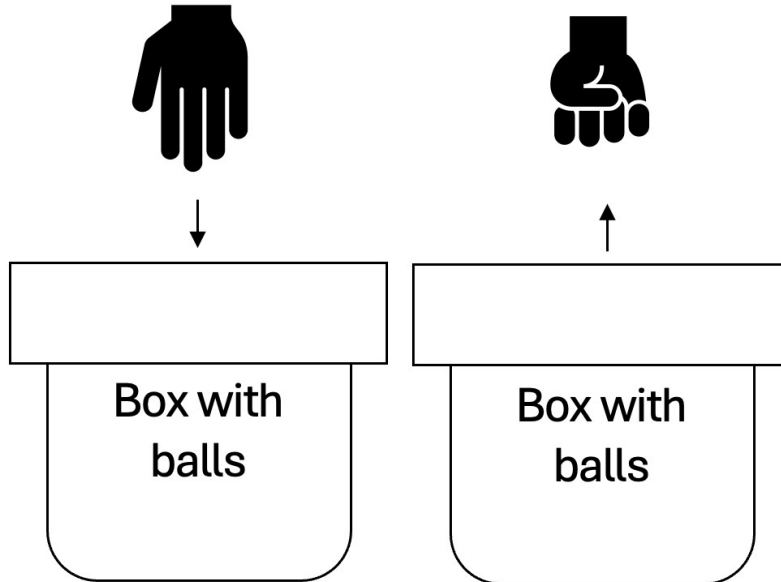
In this task, **you will choose between two actions – A and B** – as seen below. Each of the two actions offer a chance to receive some number of points. Imagine that the outcome is decided by **drawing one ball from a box containing 100 balls**: in this example,

- **balls 1 to 25 are coloured blue (25% of the balls),**
and
- **balls 26 to 100 are coloured green (75 % of the balls).**

The colour of the ball that is drawn by the computer determines the outcome of your action (A or B).

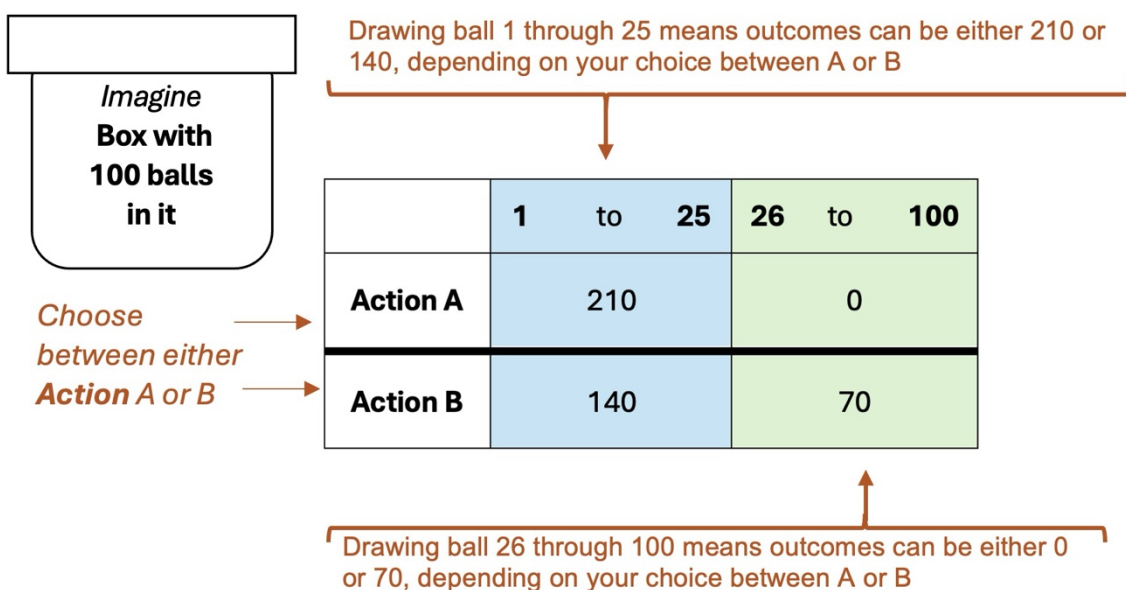
	1 to 25	26 to 100
Action A	210	0
Action B	140	70

Imagine it is as if there is a hand that picks a ball out of a box of balls that can have different colours. The computer decides which colour is drawn. The **colour of the ball that is drawn will determine the points** for the option you chose (points you get) and for the option you did not choose (points you don't get).



The more balls of one color in a box, the higher the chance this is the color ball that will be drawn randomly by the computer program. In the example below, there are **25 blue balls (ball 1 to 25)** and **75 green balls (ball 26 to 100)**,

- **Action A** offers a 25 out of 100 chance to receive **210** points and a 75 out of 100 chance to receive **0** points
- **Action B** offers a 25 out of 100 chance to receive **140** points and a 75 out of 100 chance to receive **70** points



When you make a choice, **an orange box will appear around your selected action** (as in the example below, where action A was selected). In the example below, **the selected ball was green**, and having chosen action A gave a prize of 0 points, while action B would have given a prize of 70 points. Notice the **color ball** that was selected is highlighted with a box the same color (e.g., here **green box**).

Was chosen in this example →

Was not chosen in this example →

	1 to 25	26 to 100
Action A	210	0
Action B	140	70

After making your choice, we will show you **the number of points that was the result for your choice** and **the number of points that was the result for the option you did not choose** (the points you didn't get). Then you will be asked to rate how you feel about the outcomes, using a slider like the one shown below.

Rate how you feel about this outcome:



Instructions 5.2.1

Now let's try some comprehension questions to see if you understand the experiment.

Please click on the action that offers a 75% (75/100) chance of receiving 70 points and a 25% (25/100) chance of receiving 0 points

	1 to 75	76 to 100	<input type="radio"/>
Action A	70	0	<input type="radio"/>
Action B	0	210	

Action A

Action B

Instructions 5.2. Correct

Correct!
please continue

Instructions 5.2.Incorrect

That is not quite right, if you selected option A, and this decision-scenario is chosen for payment, there is a 75% probability of receiving 70 points and 25% probability of receiving 0 points.

	1 to 75	76 to 100
Action A	70	0
Action B	0	210

please continue

Instructions 5.3.1

Please click on the action that offers a 50% (50/100) chance of receiving 210 points and a 50% (50/100) chance of receiving 0 points

	1 to 50	51 to 100	
Action A	140	0	<input type="radio"/> Action A
Action B	210	0	<input type="radio"/> Action B

Instructions 5.3.Incorrect

That is not quite right, if you selected option B, and this decision-scenario is chosen for payment, there is a 50% probability of receiving 210 points and 50% probability of receiving 0 points.

	1 to 50	51 to 100
Action A	140	0
Action B	210	0

please continue

Instructions 5.3.Correct

Correct!

please continue

Instructions 5.4.1

If action B was selected, you could receive (pick the correct answer):

	1 to 25	26 to 100
Action A	140	0
Action B	0	210

- 210 points for sure
- 25% chance of 140 points
- 75% chance of 0 points
- 75% chance of 210 points

Instructions 5.4.Correct

Correct!
please continue

Instructions 5.4.Incorrect

That is not quite right, if you selected option B, and this decision-scenario is chosen for payment, there is a 75% probability of receiving 210 points and 25% probability of receiving 0 points. *please continue*

	1 to 25	26 to 100
Action A	140	0
Action B	0	210

Instructions 5.5

The task will now begin.

Remember, your decisions are important because they will determine the amount of points you receive. There are no wrong decisions because we will ask what you prefer, and people have different preferences.

Instructions 6.1

Next part: understanding the display

In this part of the task, **you will again choose between two actions – A and B** – as seen below. Each of the two actions offer a chance to receive some number of points. Now, imagine that the outcome is decided by **drawing one ball from a box containing 99 balls**:

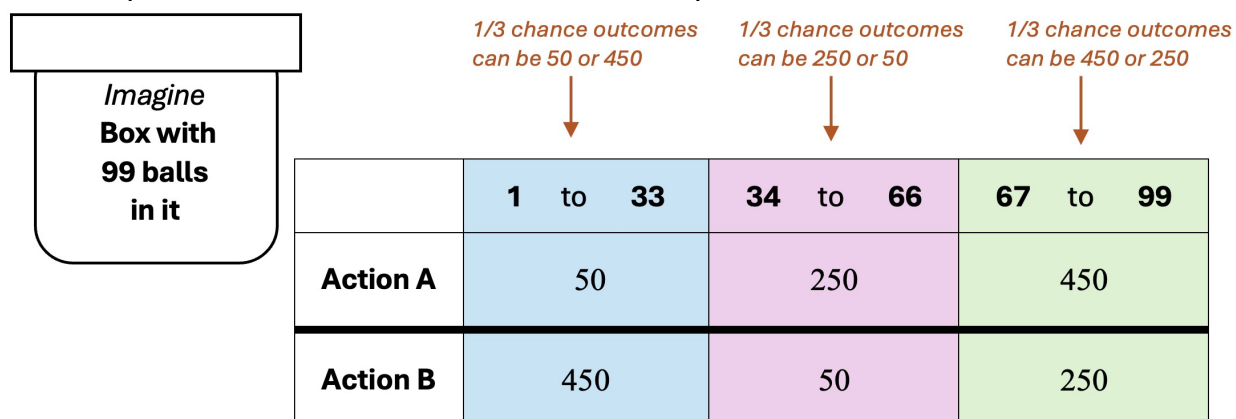
- **balls 1 to 33 are coloured blue, or one-third (1/3) of the balls**, and
- **balls 34 to 66 are coloured purple, or one-third (1/3) of the balls**,
- **balls 67 to 99 are coloured green, or one-third (1/3) of the balls**.

The colour of the ball that is drawn by the computer determines the outcome of your action (A or B).

	1 to 33	34 to 66	67 to 99
Action A	50	250	450
Action B	450	50	250

The more balls of one color in a box, the higher the chance this is the color ball that will be drawn randomly by the computer program. **There will always be: 33 blue balls (ball 1 to 33), 33 purple balls (ball 34 tot 66) and 33 green balls (ball 67 to 99)** - in the example below:

- **Action A** offers a 1/3 chance to receive 50 points, a 1/3 chance to receive 250 points, and a 1/3 chance to receive 450 points
- **Action B** offers a 1/3 chance to receive 450 points, a 1/3 chance to receive 50 points, and a 1/3 chance to receive 250 points



When you make a choice, **an orange box will appear around your selected action**. In the example below, action A was selected and **the selected ball was purple**, resulting in a prize of 250 points. Had action B been selected instead, the prize would have been 50 points. Notice the **color ball** that was selected is highlighted with a box the same color (e.g., here **purple box**).

	1 to 33	34 to 66	67 to 99	
Was <i>chosen</i> in this example →	Action A	50	250	450
Was <i>not chosen</i> in this example →	Action B	450	50	250

After making your choice, we will show you **the number of points that was the result for your choice** and **the number of points that was the result for the option you did not choose** (the points you didn't get). Then you will be asked to rate how you feel about the outcomes, using a slider like the one shown below.

Rate how you feel about this outcome:



Instructions 6.2

The task will now begin.

Remember, your decisions are important because they will determine the amount of points you receive. There are no wrong decisions because we will ask what you prefer, and people have different preferences

Appendix E. Key instructions for behavioural tasks in Chapter 2, study 2

Across the decision-making tasks (not the questionnaires) you will earn points based on your choices, and you **may be selected to receive a bonus reward**:

- At the end of our study, **5 participants** will be randomly selected to receive a **bonus payment**.
- The bonus payment - **in Australian dollar (AUD)** - will be based on **one of the decision-making choices you've made**. This one choice will be **randomly selected** from all the choices you've made across the decisionmaking tasks.
- The decision-making tasks involve choices where **you can earn points** the bonus **payment will be based on the number of points** received on the selected choice.
- The bonus payment in dollars (AUD) will be equal to: **the points divided by 20**, that is **points / 20** so that **1 point = \$0.05 AUD**. So for example,
 - if you receive 100 points this equals $100/20 = \$5$ (AUD) bonus payment
 - if you receive 200 points this equals $200/20 = \$10$ bonus payment if
 - you receive 400 points this equals $400/20 = \$20$ bonus payment, and so on.
- **If you are one of the 5 randomly selected participants**, this bonus payment in dollars will be transferred to your **bank account**, once data collection has been completed.

The way we will ensure the 5 randomly selected participants receive their bonus payment is to ask you to enter your email address by clicking on a link we'll provide on a separate page at the end of the survey - on this page we will ask you to enter your email and a randomly generated individual ID number (which we will provide you).

If you are one of the 5 individuals randomly selected to receive a bonus payment, we will contact you via email to ask for your bank account information so that the bonus

payment can be transferred - once data collection has stopped and the survey has been closed.

This is of course **entirely voluntary**: you do not need to enter your email if you prefer not to, and you will then not be part of the group of people who may be selected for the bonus payment (you will still receive credit for completing the study).

Instructions 6.3

In this example, a hypothetical person chose action B, and the computer picked a **purple ball**, resulting in the outcomes below for action A and B. Please click on the word you think best would describe how this person may feel:

A **purple ball** was drawn! **Your outcome** is **50 points!**
the outcome you **didn't get** is **250 points**

	1 to 33	34 to 66	67 to 99
Action A	50	250	450
Action B	450	50	250

Instructions 6.4

Understanding the display: 4 outcomes

In the following task, you will see two actions – A and B - but there will be **four possible outcomes for each action** (choice) you chose. Each of these outcomes have a $\frac{1}{4}$ chance of occurring, that is 25% probability for each. Specifically, there is a:

- **$\frac{1}{4}$ chance that a blue ball will be drawn,**
- **$\frac{1}{4}$ chance that a purple ball will be drawn,**
- **$\frac{1}{4}$ chance that a green ball will be drawn,**
- **$\frac{1}{4}$ chance that a yellow ball will be drawn**

As before, before, your task is to choose the action you prefer.

Instructions 8.1

Next part: understanding the display

In this task, you will see the **potential payoffs of two actions – A and B** – as below. Each of the two actions offer a chance to receive some number of points.

This task is **similar** to the tasks you just completed but a **little different** also:

- notice the empty/blank space **highlighted with a red circle** for how much action B pays if a purple ball is picked.

1/3 chance outcomes can be 800 or 400
1/3 chance outcomes can be 400 or 0
1/3 chance outcomes can be 0 or (points to be decided)

	1 to 33	34 to 66	67 to 99
Action A	800	400	0
Action B	400	0	○

Your task is to **tell us how many points you would need to be in the empty space (red circle)** for you to be **indifferent** between action A or action B. **Indifferent** means not preferring one over the other (i.e., valuing the actions A and B the same). Across the decision scenarios, the empty spot may be in a different place and you are to tell us **the number of points that leaves you indifferent between choosing Action A or Action B.**

Press continue to learn more about this task.

Task procedure (continued)

As in the previous tasks, actions A and B will be played out and the rewards will be based on what color ball is drawn out of the box.

However! Please tell us the points that will make you feel indifferent between actions A and B, because the **computer will also randomly select a number of its own for the empty space** in action B (a random number between 0 and 2000 points):

- **If the points selected by the computer for the empty space in action B is lower than the points you entered for the empty space in action B**, it means that the computer's value makes Action B less valuable to you, so you would prefer Action A more than Action B (because you were indifferent before with your own value). So you then receive Action A and whatever is the outcome for action A.

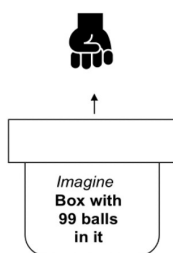
- If the points selected by the computer for the empty space in action B is **higher** than the points you entered for the empty space in action B, it means that the computer's value makes Action B more valuable to you, so you would prefer Action B more than Action A (because you were indifferent before with your own value). So you receive Action B and whatever is the outcome for action B.

This procedure ensures that it's best for you to tell us the true number of points that makes you indifferent between Action A and Action B.

In the **hypothetical example below**, the number of points that were selected by the computer was **820**.

This means that if a ball is drawn from the Box with 99 balls, the following outcomes are possible:

- **Action A** offers a 1/3 chance to receive 800 points, a 1/3 chance to receive 400 points, and a 1/3 chance to receive 0 points
- **Action B** offers a 1/3 chance to receive 400 points, a 1/3 chance to receive 0 points, and a 1/3 chance to receive 820 points



	1 to 33	34 to 66	67 to 99
Action A	800	400	0
Action B	400	0	820

Notice that, ultimately, the outcome that is filled in the blank space in the end is that selected by the computer.

In general,

- If the **number of points selected by the computer** for the blank space in an Action is **higher** than **your number of points** for that blank space, then **you get that Action and the outcome for that** (e.g., Action A in the example below).
- If the **number of points selected by the computer** for the blank space in an Action is **lower** than **your number of points** for that blank space, then **you get the other Action and the outcome for that** (e.g., Action B in the example below).

	1 to 33	34 to 66	67 to 99
Action A	0	0	250
Action B	0	250	500

If the value selected by you and the value selected by the computer is exactly the same, then the computer will randomly pick one of the two Actions (A or B) for you.

This procedure means that if you lie about the true number of points that make you indifferent, you might end up getting an outcome that you prefer less.

As in the previous tasks, the choice (Action) you receive and the points you get, become one of the choices/outcomes that could be randomly selected for a bonus payment; if you are one of the 5 randomly selected participants.

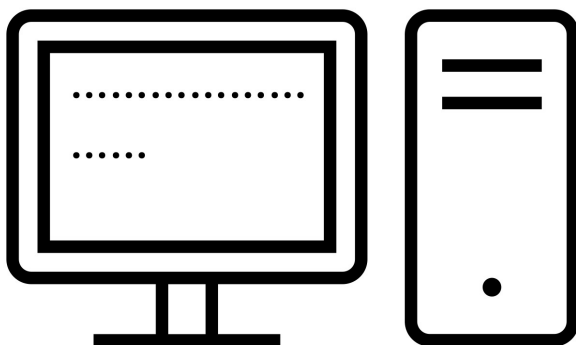
Next, you will do some practice and comprehension questions.

Instructions 8.2

Practice example 1

Using the box below - please tell us what number of points for the empty space in B that would make you **indifferent between Action A and Action B (so you value these the same)**

	1 to 33	34 to 66	67 to 99
Action A	900	450	50
Action B	450	50	<input type="text"/>



The value selected by the computer was:

Instructions 8.2.1

Because the points you selected for the empty space in Action B was higher than that selected by the computer for the empty space in B, **you receive Action A and the outcome of A**

Instructions 8.2.2

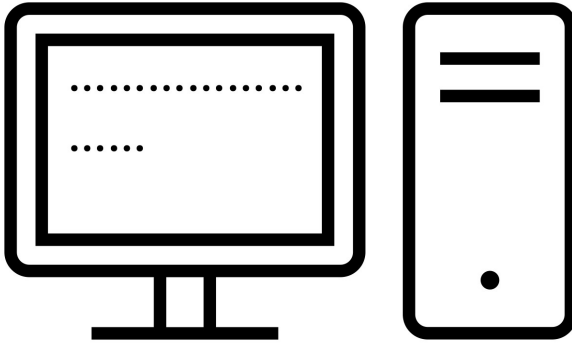
Because the points you selected for the empty space in Action B was lower than that selected by the computer for the empty space in B, **you receive Action B and the outcome of B**

Instructions 8.3

Practice example 2

Using the box below - please tell us what number of points for the empty space in B that would make you **indifferent between Action A and Action B (value these the same)**

	1 to 33	34 to 66	67 to 99
Action A	600	200	0
Action B	200	0	<input type="text" value="0"/>



The value selected by the computer was:

Instructions 8.3.1

Because the points you selected for the empty space in Action B was higher than that selected by the computer for the empty space in B, **you receive Action A and the outcome of A**

Instructions 8.3.2

Because the points you selected for the empty space in Action B was lower than that selected by the computer for the empty space in B, **you receive Action B and the outcome of B**

Instructions 8.4.1

Comprehension Question part 1

	1 to 33	34 to 66	67 to 99
Action A	520	200	0
Action B	200	0	

In this example, what are the possible outcomes for Action A?

- 200, 0 and (empty)
- 520, 200 and 0
- 520 and 200

Instructions 8.4.1. Correct

Correct!

please continue

Instructions 8.4.1. Incorrect

	1 to 33	34 to 66	67 to 99
Action A	520	200	0
Action B	200	0	

That is not quite right, the possible outcomes for Action A are 520, 200 and 0.

Instructions 8.4.2

Comprehension Question part 2

	1 to 33	34 to 66	67 to 99
Action A	520	200	0
Action B	200	0	

In this example, what is the chance that the empty (to be filled-in) outcome for Action B will be selected?

- one-third (1/3)
 chance 50%
 chance zero
 (0) chance

Instructions 8.4.2. Correct

Correct! please continue

Instructions 8.4.2. Incorrect

	1 to 33	34 to 66	67 to 99
Action A	520	200	0
Action B	200	0	

That is not quite right, there is a one-third (1/3) chance that the empty (to be filled-in) outcome for Action B will be selected is.

Instructions 8.4.3

Comprehension Question part 3

	1 to 33	34 to 66	67 to 99
Action A	520	200	0
Action B	200	0	0

If you said **1500 points for the empty spot in Action B** and the **computer picked the value 1750 for the empty spot in Action B** - then you would... (*pick the right answer to finish the sentence*)

- receive the outcome for Action B
- receive the outcome for Action A

Instructions 8.4.3. Correct

Correct! please continue

Instructions 8.4.3. Incorrect

	1 to 33	34 to 66	67 to 99
Action A	520	200	0
Action B	200	0	0

That is not quite right, if the value you selected for the empty space in Action B is lower than the computer's value; it means that, with the computer's value, you prefer Action B over Action A for sure, therefore **you receive Action B and the outcome for Action B.**

Instructions 8.5

A frequently asked question is:

Can I get a better outcome by choosing a number that is larger or smaller than my real preference?

No. If you choose an amount that is different from your true preferences, you run the risk of not receiving your preferred lottery. Let's consider an example:

Suppose that you are **truly indifferent** between Action A and Action B for **400 points** in the blank space in B. But,

Scenario 1 - You misreport by providing a larger number, saying you are indifference at 450 points. We will therefore infer that you prefer Action B to Action A for any value for the empty space larger than 450 points. Say now the computer draws 420 points for the blank space in B. You will get Action A, however, you are **worse off** because your true preference would be Action B (given your true indifference was at 400 points).

Scenario 2 - You misreport by providing a smaller number, saying you are indifference at 370 points. We will therefore infer that you prefer Action B to Action A for any value for the empty space larger than 370 points. Say now the computer draws 390 points for the blank space in B. You will get Action B, however, you are worse off because your true preference would be Action A (given your true indifference was at 400 points).

In conclusion, if you misreport the amount that you choose, you run the risk of being worse-off than if you had chosen the true amount. You should take the time to carefully consider what amount makes you feel indifferent between Action A and Action B.

That concludes the instructions and practice section, the task will now start.

Remember, each time you will be asked to tell us **how many points out of 0 to**

2000 you would put in the empty spot to make you indifferent between Action A and Action B.

The empty space can be in Action A or Action B in the next choices, your task will always be to tell us what value makes you indifferent between Action A and Action B.

For the rest of this segment we do not show you what the outcomes are; however, each of the outcomes will be played out and your points will be based on your choices and the random number selected by the computer.

Please tell us a value based on your own preference, as there are no correct or incorrect answers – people have different preferences.

Instructions 4.6

Understanding the display: negative amounts

Before continuing the decision-making tasks, **we will offer you 250 points now to keep for the duration of the experiment**. At the end of the experiment, if you are one of the 5 randomly selected participants to receive a bonus payment, these 250 points count towards the bonus payment (are in addition to one of the randomly selected choices).

However, if one of your randomly selected choices leads to negative points (losing points), this will be **subtracted from the 250 points**.

Across the next few choice you will see two options – A and B - but the outcomes will include **negative amounts** this time. These **negative amounts mean that the outcome you receive will be subtracted** from your 250 points.

As before, your task is to choose the option you prefer.

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