Allocentric effort decision making : a neuroeconomic investigation

Fitzgerald, Sean

2018

Fitzgerald, S. (2018). Allocentric effort decision making : a neuroeconomic investigation. Doctoral thesis, Nanyang Technological University, Singapore.

http://hdl.handle.net/10356/74800

https://doi.org/10.32657/10356/74800

Allocentric Effort Decision Making: A Neuroeconomic Investigation

Sean Joseph Fitzgerald

Nanyang Business School – Division of Strategy, Management, and Organization

A thesis submitted to the Nanyang Technological University
in fulfilment of the requirement for the degree of
Doctorate of Philosophy

2018

Acknowledgements

First and foremost, I'd like to acknowledge the exceptional support and guidance from George Christopoulos. Not only has he been an emphatically positive role model in how to conduct good research, but his generosity and flexibility in helping me throughout the PhD process have been far more than I could have ever asked for. I am grateful for his Homeric patience and willingness to choose the risky option of supervising a former art auctioneer.

As anyone educated in culture science knows, it takes a village to raise a researcher, and this work would not be possible without the support and guidance of Prof. Ying-Yi Hong and my colleagues at the CSI and NTU-NBS. Special thanks are in order for my fellow researchers Wei Jie Yap, Elliot Chan, Tenace Setor, and the research assistants who enabled me to conduct work from abroad, and those who assisted me at every step in the PhD process: Karen, Nisha, and Bee Hua. Likewise, I am indebted to my hosts at the Virginia Tech Carillion Research Institute who helped make the fMRI study possible especially Prof. Brooks King-Casas, Prof. Pearl Chiu and Riley Palmer.

Finally, I am most grateful for the love and support of my parents without whom I would never had been able to begin this undertaking and certainly would never have come close to finishing. Their support has been immeasurable and unconditional, to which I can only say thank you.

Finally, I'd like to say thanks to my friends, editors, and impromptu therapists: Sabita, Sam, Arthur, Billy, Will, Mike, Tenace, and Lukas.

Table of Contents

Summary

Decisions often require tradeoffs between costs and benefits, such as effort and reward. Prior findings show that decision makers discount the subjective value of a rewarding option as the effort required to obtain it increases. The mechanisms of discounting when the decision maker is also the recipient of the outcome ("egocentric" decision making) are known. However, in many cases, the decision maker decides for someone else, with the decision outcomes delivered entirely to another person ("allocentric" decision making). Implementing a neuroeconomics approach, the present thesis examines the mechanisms of allocentric decisions in the domain of effort discounting across three different levels: behavioral, computational, and neural descriptions of a single phenomenon. Behavioral results showed that making allocentric, as compared to egocentric, effort decisions shifts preferences toward smaller effort, smaller reward options. Computational modeling revealed that differential weighting of effort discounting parameters adequately explained choice differences between allocentric and egocentric decisions. Furthermore, neural activation patterns examined using functional magnetic resonance imaging in brain regions associated with value and reward (the prefrontal cortex and striatum) along with regions associated with theory of mind and social cognition (the temporoparietal junction, posterior cingulate cortex, and angular gyrus) reflected allocentric option valuation, choices, and estimated computational modeling parameters. Together, the research presented in this thesis describes allocentric effort decisions as a discriminant phenomenon, provides computational modeling of how allocentric decision makers value the tradeoff between effort and compensation, and offers physiological evidence of the related cognitive processes.

Definitions & Abbreviations

Decision making (DM) – the process of evaluating options and choosing a preferred option

Decision maker – the agent choosing the preferred option

Options – potential outcomes that would result from a decision if chosen

Choice – the act or result of selecting a preferred outcome

Outcome – the consequential action(s) or event(s) mandated by a choice. Outcomes can be costly, beneficial, uncertain, or conditional. Furthermore, outcomes may contain bundled events representing combinations of costs and benefits.

Social DM – decisions that have outcome externalities beyond the decision maker.

Sociocentric DM – a type of social decision making where the tangible outcomes are shared by the decision maker and one or more other agents. These types of decisions may be interactive or non-interactive.

Allocentric DM – a type of social decision making where the tangible outcomes are bestowed to an agent other than the decision maker. There may be social externalities, such as reputation and accountability that affect the decision maker.

Egocentric DM – decision making where the outcomes are wholly incurred by the decision maker

Accountability - the state or belief of needing to justify or explain one's thoughts, feelings, or actions to one or more agents.

Neuroanatomy:

Anterior (a)- forward portion of a neural region. Forward refers to the x-axis dimension with anterior being closer to a standing person's face.

Posterior (p)- rear portion of a neural region. Rear refers to the x-axis dimension with posterior being closer to a standing person's back of the head.

Ventral (v)- Underneath portion of a neural region. Underneath, inferior, or lower refers to the y-axis dimension with ventral being closer to the chin

Dorsal (d)- Upper portion of a neural region. Upper, superior or greater refers to the y-axis dimension with dorsal being closer to the crown

Medial (m)- Inner portion of a neural region. Inner refers to the z-axis dimension with medial being closer to the center of the brain.

Lateral (r, l)- Outer portion of a neural region. Outer refers to the z-axis dimension with lateral being closer to the exterior of the brain. There are two lateral aspects, denoted left and right. Left and right are labeled from the perspective of the brain from posterior to anterior.

fMRI – functional magnetic resonance imaging

ROI – region of interest

PFC – prefrontal cortex

ACC – anterior cingulate cortex

PCC – posterior cingulate cortex

SMA – supplementary motor area

TPJ – temporoparietal junction

List and Location of Figures

1 Introduction & Literature Review

1.1 Aim and Research Question

This thesis presents research collectively aimed at understanding the cognitive processes associated with decisions where an agent other than the decision maker receives the outcomes – referred to here as allocentric decisions. The research focuses exclusively on decisions that require the recipient to exert effort and actively participate to earn monetary compensation. To fully explore the mechanisms underpinning these decisions, allocentric choices are examined at the levels of behavioral phenomena, computational cognitive modeling, and neural activity. The connection of these three levels brings a fuller picture of allocentric decision making into view. Allocentric choices are contrasted with egocentric choices to establish the discriminant cognition responsible for the evaluation of allocated outcomes. Furthermore, allocentric decisions are examined under the moderation of social accountability to compare the dissociable social presence of an observer from an active recipient.

1.2 Motivation

Decisions are ever-present. They are integral to free-market capitalism, efficacious democracy, Information Era social interactions, and many other facets of modern life. Trading time, effort, and ability in exchange for goods, services, and social capital requires decision making processes, either consciously or unconsciously. The reader is currently engaged in an autological example of a tradeoff decision: choosing to continue reading this introduction may result in the benefits of learning new information, but at the cost of wading through pretentious meta-examples.

Decisions are not only common, but necessary and important. The passage of time and a competitive natural environment impose scarcity constraints that force all organisms to make tradeoffs, sacrificing one scarce resource for another. Organisms flourish despite these constraints by making decisions. Decision making is the process of weighing and selecting from possible outcomes. Organisms must choose a location to search for food or when to flee from danger, who to mate with, and many other decisions crucial to both individual and species survival. While decision making is not unique to humans, due to the aforementioned resource constraints, the scope of this thesis pertains only to human decision making.

Humans make important decisions with more extensive consequences than individual survival. As social animals, humans can organize themselves into groups capable of incredible and unique feats of social will: erecting monuments, waging war, and voyaging to the moon. Yet much of decision making research examines independent choice behavior in a social vacuum whereby the decision maker alone receives the outcomes – both benefits and costs – of his or her own decision. However, humans embedded in social networks allocate or bestow decision outcomes to other agents, social groups make decisions that impact rival or allied groups, leaders make decisions for followers, and partners make decisions for each other. Furthermore, such decisions are often unilateral. For example, politicians create laws and policies governing individuals in socioeconomic classes and geo-political regions to which they do not belong. Parents must make health and lifestyle choices for their children, and only later will children reciprocate. Medical proxies and doctors choose between risky surgical procedures and lifetime symptom management, each with crucial quality of life implications for an incapacitated patient. Understanding distal social decisions is only growing in significance as an increasingly connected and specialized Network Society emerges through the rise of digital new media, neo-tribal affiliations, and rapid communication methods (Castells, 2011; Dijk, 2012; Maffesoli, 1995). Using technology, the scope of social decisions is growing as information can now be transmitted from around the globe, aggregated, and mobilized into high-impact outcomes with ever-increasing speed.

In the workplace, social decisions are intrinsic to the nature of organizations. Organizing human agents for a single purpose requires coordination, direction, and specialization afforded by a hierarchical structure where decision makers direct agents other than themselves. For example, CEOs and managers make strategic decisions that influence individuals throughout and beyond their firm with employees, customers, and stakeholders all sharing the outcomes. Employees may even be assigned tasks by managers in another country, despite being organizationally and geographically distant. Social influence can affect more than the outcome incurred by the recipients. Social pressure can operate as non-economic control measures as well. For example, CEOs make strategic decisions on behalf of stakeholders, but may face pressure from the general public or community stakeholders who are not directly affected by the choice if the decision is unpopular. Firms with inappropriate hiring practices or those that source materials unjustly may be the subject of social media campaigns or in-person protests.

Management scholars have identified the importance of social actors in management decisions. The framework for identifying the roles in managerial social decision making have been codified in Agency Theory and the principal-agent problem (Eisenhardt, 1989; Jensen & Meckling, 1976). A principal-agent problem exists when an agent acts on behalf of the principal, but is compelled by personal preference to act against the desires of the principal thus creating a conflict of interest. Much of agency theory scholarship concerns itself with egocentric interests and governance such as risk attitudes, compensation, and performance. Recently, scholars have expanded their scope to investigate how agents and principals evaluate actions embedded in social contexts (Wiseman, Cuevas-Rodríguez, & Gomez-Mejia, 2012). Two important types of social influences are apparent in decision making: 1) the social relationship between the decision maker and the decision recipients and 2) the greater impact of outcomes embedded in existing social networks. Decisions may or may not reflect on the decision maker's reputation or social standing. Often, the complexity of real world human social networks makes it difficult to distinguish the effects of one type of social influence from another. For example, a mid-level manager must make decisions for her employees and justify these decisions to her supervisor. Assigning additional tasks to the employee will please the supervisor with cost savings afforded from the additional labor efficiency, but negatively strain the employee. If the other employees hold the decision maker accountable, this will negatively affect the relationship between management and employees. These two relationships – one with the supervisor and one with the employee - may present simultaneous, competing interests manifested through social relationships.

To study the effects of social influence on decision making, scientific rigor is needed to specify what is meant by a social interaction, behavior, or influence. Behavioral choice experiments offer several key advantages for studying social interactions using human participants in a controlled environment. Experimental controls limit potential confounds inherent in the study of social decision making. For example, to control the identity of a decision recipient, experiments may use a confederate to receive the decision outcomes, recruit specific participant pairings such as friends or coworkers, or anonymize the recipient altogether. Each design has specific benefits for studying social decisions. Studying specific participant pairings can lead to comparison between relationships, while using a common confederate or anonymous other disentangles decision preferences from relationship effects.

Furthermore, choice experiments have proven useful for understanding and comparing the underlying mechanisms of decision making. Are the decision processes for evaluating potential losses the same as potential gains (Kahneman & Tversky, 1979)? Under what conditions is known risk the same as unknown risk (Curley, Yates, & Abrams, 1986)? Is waiting for money the same as working for money (Sugiwaka & Okouchi, 2004)? The various components of such decisions have been investigated using well-designed experiments. As researchers push to integrate findings from behavioral choice experiments into existing management theory, the field has grown to include experimental findings of interest to both management scholars and practitioners (Larraza-Kintana, Wiseman, Gomez-Mejia, & Welbourne, 2007; Martin, Washburn, Makri, & Gomez-Mejia, 2015; Wiseman & Gomez-Mejia, 1998). The research presented in this thesis follows in this vein focusing on decisions that managers commonly face in practice.

Organizational decision makers face several important types of decisions including whether to make risky investments, when to launch a new product, or how to allocate human resources. To do so, decision makers must calculate the value of potential outcomes and choose the best option for the organization. The process of valuation is complex and dependent not only on external stimuli such as choice options, but also the decision maker's past experiences and preferences. How choice options are valued is an important mechanistic question for researchers, yet little is known about how decision makers value options for another agent. To delve into the cognitive mechanisms responsible for valuation on behalf of another agent requires examining multiple aspects of the decision process in conjunction. The neuroeconomic approach to decision research utilizes multiple methods that complement strengths and weaknesses of each other. In combining multiple methods of study, individual layers of choice behavior can coalesce to provide a holistic understanding of decision making as a complex information processing system (Glimcher, 2004; Glimcher & Fehr, 2013). Using economic theory, computational modeling, and neuroimaging, the research presented in this thesis aims to provide a robust initial exploration of social decision making. Given the recent emergence of neuroeconomics as an integrated field, a brief overview and history is provided in the following section.

1.3 Neuroeconomic Approach to the Study of Decision Making

The neuroeconomic approach to investigating decision making is a multilevel, interdisciplinary approach aimed at understanding the cognitive processes of decision making. Neuroeconomics describe decision making as a complex information system following a model developed by the neuroscientist David Marr (Marr & Vision, 1982). According to Marr, a tri-level model describes the processing of information commonly referred to as the computational-, algorithmic-, and implementation-level descriptions of a system (Glimcher, 2004). The computational-level describes the root purpose of a system defining its goals and serves as a guiding principle of functionality. The algorithmic-level describes how an information system accomplishes its computational purpose and organizes itself. The implementation-level describes the physical manifestations of the functions necessary to achieve the computational purpose per the algorithm. This approach has led to advancement in the holistic understanding of decision making (Fehr & Camerer, 2007; Rangel, Camerer, & Montague, 2008).

The study of each level requires a unique toolset while neuroeconomics provides the organization to integrate information from these disparate methods. The computational level relies on economic theory that has been validated with robust behavioral validation to serve as the driving organizing force of an investigation. Theory and behavior phenomenon are closely intertwined as one cannot exist without the other. Algorithm-level understanding stems from representing logical frameworks that can explain behavior while abiding robust computational principles. Cognitive computational modeling borrowed from psychology creates testable hypotheses of latent mechanisms and constructs. Finally, implementation-level explanations rely on the physical manifestations of cognition in the brain. The following sections highlight some of the theories and methods used in a neuroeconomic approach and explicate the reasoning behind their application to decision making.

The computational-level relies in economic theory. Traditionally, researchers have viewed human decision making through an economic lens where decision makers are economic agents attempting to find benefit from scarce resources while minimizing associated costs. Economic theory describes decision makers as rational agents with consistent and well-defined preferences. Axioms are economic rules that define a series of choices as rational. For example, if a decision maker prefers a block of cheese to a bottle of wine, this person would not later trade the block of cheese for a bottle of wine. This staple of rational decision theory is known as the Weak Axiom of Revealed Preference (Samuelson, 1938).

When agents are rational, repeated decisions between one choice option and several others can reveal value estimates of a choice option's value. This method of eliciting preferences through repeated choices is essential for testing economic theory using real human decisions. Economic decision experiments use human participants’ choice behavior in controlled environments to test choice theory predictions. Choice options can be consumable goods, money, events, actions, or any combination of these presented as a bundle. Importantly, even uncertain choice options have value (Von Neumann & Morgenstern, 2007). This is an important caveat for incentivizing participants in choice experiments. Not every decision must necessarily reflect a certain reward, but real money incentives are important, particularly for reducing socially-desirable responses (C. F. Camerer, Hogarth, Budescu, & Eckel, 1999; V. L. Smith & Walker, 1993). Choice experiments also rely on the assumption that more money is always better based on the assumption that money has a positive, monotonic utility function. Importantly, economic theories can fall into one of two groups: descriptive (positive) or prescriptive (normative). Rational choice theory and expected utility theory are prescriptive theories that dictate what an individual’s preferences should be by establishing a formalized rule set for choice behavior. Using these basic assumptions, rational choice theory can classify an immense number of decision situations as rational or irrational.

A rational actor is one that exhibits preferences consistently across choices. In social decision making, this becomes complicated. However, in a "social vacuum", a rational person making an allocentric decision would attempt to perfectly match outcomes with the preference of a recipient. Having no information about the recipient's preferences, the decision maker might attempt to minimize cognitive dissonance (Festinger 1957) about her own preferences by assuming the recipient shares her preferences identically. In this case, a rational actor would exhibit no differences between egocentric and allocentric decisions ceteris paribus. However, a decision maker's self-perception may alter this assumption. A decision maker that wants to preserve a self-image of being unique, risk-seeking, or exceptionally hard-working relative to others, may adjust allocentric decisions to keep this self-image intact and reduce cognitive dissonance.

However, rational choice theory is not without criticism. One critique is rational choice theory only aims to describe and assess choice behavior and not choice mechanisms resulting in a black-box explanation of decision making. When viewing decisions through a strictly economic lens, the decision maker is a self-interested, utility-maximizing agent. While early economic models have been robust in describing general patterns in choice behavior, early experimental evidence has shown the assumptions of rational choice theory do not hold in certain contexts. Probing the limits of standard economic theory through experiments produced a new wave of decision insight and extensions to theory under the label of behavioral economics.

If economic theory postulates that rational decision makers always choose $10 over $2, behavioral economics asks the question "when is $2 more valuable than $10?". Pioneering studies showed that certain cost factors influence decision makers' perception of outcomes in ways that are not predicted by rational choice theory, but are not "irrational" in the lay sense. Several important examples come from the work of Daniel Kahneman and Amos Tversky and their exploration of choice heuristics and biases that lead decision makers to reverse their established preferences. For example, framing the same choice option as either a potential gain or a potential avoidance of loss can revert risk averse decisions into risk seeking decisions (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Another important bias occurs when subsequent decisions are influenced by perceived default choices or initially presented options. These two examples, known as framing effects and anchoring bias respectively, exemplify how individual decision makers are sensitive to context and experience. Biases such as these are more than theoretical quirks, they have real impacts in the market (C. F. Camerer, 2004). For example, the endowment effect is a bias where individuals require more compensation for a good in their possession than they would pay to acquire the good (Carmon & Ariely, 2000; Thaler, 1980). Endowment effects describe an intrinsic disequilibrium that when extrapolated to a market breaks fundamental economic tenets that supply and demand converge at a common price. Choice behavior influences trade markets and shows individual decision makers can hold inconsistent preferences for the same economic good.

Preferences for a choice option reflect a decision maker's valuation of that option. However, understanding how an individual creates internal valuations is beyond the capabilities of rational choice theory and the computational-level. The algorithmic-level description of decision making focuses on how decision making occurs with regards to constructs and cognitive mechanisms. Cognitive mechanisms of decision making are internal, mental processes by which a decision maker (1) evaluates choice options and assigns each option a subjective value before (2) comparing potential options and selecting the action or decision outcome (Glimcher, 2008; Rangel et al., 2008). Option valuation integrates the costs and benefits of a potential outcome into a subjective value representation of that choice option. In many choice studies, the benefits are monetary rewards, but can also be consumption goods like movies (Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007), lottery entries (Christopoulos, Tobler, Bossaerts, Dolan, & Schultz, 2009), or arousing images (Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010). Examples of common cost factors include risk, ambiguity, lost time, compensation, or effort. In many neuroeconomic stimuli presentations, a cost factor is paired with a reward to create bundled choice options with cost and reward varying orthogonally. To choose between these options, decision makers must evaluate the tradeoff between cost and reward.

Option selection requires comparison of available options. This is straightforward when comparing like one-attribute options ($2 vs. $10 or 1 apple vs 2 apples), but becomes more complicated when choice options are multi-attribute (1 large, red apple vs. 1 small, green apple), bundles (a $2 cost in exchange for 1 apple vs. a $3 cost in exchange for 2 oranges) or conditionally dependent on other events (a 50% chance to win $5 vs. a 10% chance to $50). Researchers have theorized that comparison relies on a common representation of options (Levy & Glimcher, 2012; Ruff & Fehr, 2014). How a decision maker cognitively represents options and uses comparison strategies falls outside the purview of economics. The shift from describing choice outcomes to describing internal decision processes mirrors psychology as field shifting from behaviorism to the cognitive revolution. Neuroeconomics borrows the methods of computational cognitive modeling from psychology to link cognitive representation with decision behavior.

Computational models represent latent cognitive processes with estimated parameters (Sun, 2008). The models are validated by their ability to explain and predict behavioral choice data. A prime example of this approach comes from discounting models. Discounting models are mathematical algorithms representing how the rewards of a potential decision outcome devalue as a cost factor increases. The discounting model estimates the subjective value for each possible outcome. By comparing multiple valuation models to the same data set, computational modeling is an efficient way to simultaneously compare many hypotheses about cognitive processes associated with valuation. The estimated values of all possible outcomes are weighted against each other to determine “the winner” or highest-value option. A prolific algorithm for comparing choice options is the SoftMax decision rule which compares exponentiated subjective value ratios. The ratio, which is standardized between 0 and 1, reflects the probability that a decision maker will choose a particular option from a set of all possible options. The model’s predicted choices are validated via comparison with real behavioral choices.

However, computational modeling also has notable weaknesses. Representing “unknown cognitive processes” with parameters is convenient, but as with all modeling techniques, is only an estimation and is susceptible to misappropriation or misapplication. For example, overfitting occurs when a model too closely mirrors a sample data set and results in a model that is not generalizable to the population. An overabundance of free parameters could reflect complex cognitive processes or simply random data. To prevent this, several measures must be taken. Models should be validated across multiple participants' choices and ideally across multiple choice scenarios. It is also important to compare multiple models using an information criterion that accounts for the number of parameters used to preferentially retain more parsimonious models. Additionally, it is important that cognitive models reflect physical processes described at the implementation-level. In Marr's tri-level framework, the physical processes should reflect these abstract algorithms in function and form.

For cognitive processes, the physical manifestation exists in the brain. Tracing variance in model predictions across neural activity provides validation and context to model parameters. Likewise, variance in specific parameters can be linked to specific neural processes. Cognitive processes are localized both spatially and temporally in the brain. Cognitive models can provide *a priori* hypotheses about neural responses to stimuli and, in turn, be informed by neural correlates. Biological evidence does more than simply cross-validate cognitive modeling predictions. Understanding underlying biological processes has provided insights into decision making behavior (Bossaerts & Murawski, 2015; Saez, Set, & Hsu, 2014). A recent example of this bottom-up approach, discovering whether the brain uses universal or context-specific reward signals is a generative finding that expands economic theories of substitute goods into substitute utility. Analysis of neurotransmitter differences in the brain has shown correlation with learning rates and strategy formation in competitive social games (Set et al., 2014).

Another important neurologically driven theory is that of the "social brain". The Social Brain Hypothesis stems from evolutionary anthropology and refers to a distinct brain region or network functionally dedicated to interactions with other agents (Dunbar, 2003, 2009; Dunbar & Shultz, 2007). The existence of such a region underlies theories of social and cultural evolution in humans and helps to explain the extraordinary social intricacies of human society. Group selection theories posit that cohesive groups may be more successful at fending off threats making group survival the aggregated level at which evolutionary selection occurs rather than the individual (Grafen, 1984; J. M. Smith, 1964; Wilson, 1975). Adapting a social brain, cultivating culture, and establishing social norms may be coevolutionary threads in the fabric of humans' success. For example, how a decision maker manages relationships with others and how each agent contributes to essential effort tasks like gathering food or constructing shelter has larger scale implications for the efficiency and success of that population. Understanding the role of the social brain in decision making is crucial for developing further theory and insights into social behavior.

Overall, these three approaches – behavioral economic, cognitive, and neurological – lean on each other to form a stronger and more complete understanding of phenomena. This interdisciplinary triangulation spawned the field of neuroeconomics that aims to improve holistic understanding of decision making. The field has made great strides studying the mechanisms underpinning choices and the environmental contexts that can influence these choices. Important environmental contexts that have already been alluded to are social contexts. The next section reviews prior literature in social decision making and winnows this broad concept into discrete concepts using established frameworks.

1.4 Social Decision Making

Social decisions require selection from outcomes that entail externalities for agents other than the decision maker. These outcomes can be both tangible, like monetary rewards, or intangible, like social standing or prestige. Social decisions necessitate a relationship between decision makers and outcome recipients, often pitting the preferences of the individual at odds with social norms, cultural tenets, or the greater, common good. However, the “common good” and adherence to social norms do not have discrete representation like money or consumption goods. Rather these intangible outcomes are valued subjectively in the perception of the parties to the decision. A decision maker can be assumed to have full knowledge of her own preferences, but cannot fully comprehend the preferences of decision recipients. The inherent uncertainty between local and global social values creates tension between the decision maker and other agents. This tension between an individual decision maker and the social recipients of the decision outcomes is reflected in The Fundamental Social Dilemma:

"All social relationships involve the repeated dilemma … of identifying and contributing effort and personal resources to a social or organizational entity to accomplish goals and better outcomes and a self-identity that incorporates a broader social meaning than could ever be achieved alone. On the other hand, identification with and sacrifice for a group, organization, or society can limit individual freedom of action, invite exploitation, and open the door to rejection and loss of identity." (Lind, 2002)

The Fundamental Social Dilemma represents the broad-scope and dynamic relationship between an individual agent (or decision maker) and the social environment in which he or she operates. Social relationships can moderate decision making in several ways. For example, the relationship between the decision maker and recipient(s), the visibility or transparency of the interaction between them, or the type of decision being made can all impact the decision process. When considering social moderators, two primary mandates for investigation emerge: (1) contrasting how social decision making differs from non-social decision making and (2) understanding the social contexts and influences that affect decision mechanisms. The following section addresses these two mandates using established conceptual frameworks to identify and parse key aspects of social decisions and subsequently tailor the broad domain of social decision making to a specific and focused research theme.

Foremost, social decisions require discriminant validity from non-social decisions. There may exist mechanistic differences between social and non-social decisions. Recent research has shown that social and non-social decisions likely leverage many of the same neural mechanisms when comparing the value of choice options regardless of the identity of the decision recipient (Dunne & O'Doherty, 2012; Nicolle et al., 2012; Zaki & Ochsner, 2011). These findings support an "extended common currency" theory that not only are different types of decision outcomes comparable such as gambles and certain outcomes, but also decisions that target different recipients (Ruff & Fehr, 2014). However, this does not preclude the social brain hypothesis entirely. The social brain may leverage existing decision-making pathways in the brain to evaluate latent social outcomes. Differences could also arise from the computational algorithms for ascribing value to options may differ in form or carry different weights to account for social factors. For example, a decision maker may be primarily motivated to choose a job based on monetary compensation because she is the recipient of that choice attribute; however, when choosing between charities to make a monetary donation, the amount of the donation requested may be a secondary concern to the charity's cause. In this way, social factors moderate how decisions are made while still conforming to an extended common currency. To rigorously investigate these differences in social valuation processes, appropriate frameworks are required for classifying social influences and contexts.

Organizing the myriad types of social influences on valuation requires a descriptive framework. Researchers have identified three levels of social valuation: 1) the value of the outcomes to the decision recipients, 2) the value of the decision recipients to the decision maker, and 3) the value of the outcomes to cultural and social norms and the role it plays in "reinforcing social constellation"

(Ruff & Fehr, 2014). For comparison between social and non-social decisions, the value of outcomes to the decision recipients is an accessible starting point, as both social and non-social decisions can evaluate similar outcomes without affecting other mechanisms. Additionally, the subjective value of options can be readily compared when decisions use monetary rewards because they have the same initial, objective value. Thus, the research presented in this thesis focuses on differences in valuation of tangible outcomes when the recipient of those outcomes changes.

Another key aspect of social decision making is identifying and controlling aspects of the relationship between decision maker and the recipient(s) of the decision outcomes. To this end, a behavioral definition for decisions provides concrete labels based on the possible combinations of decision maker and outcome recipient relationship. This thesis employs a tripartite theory that identifies (1) egocentric, (2) sociocentric, and (3) allocentric decisions. Figure 1.1 presents a visual description of each type of decision using effort and money outcomes.

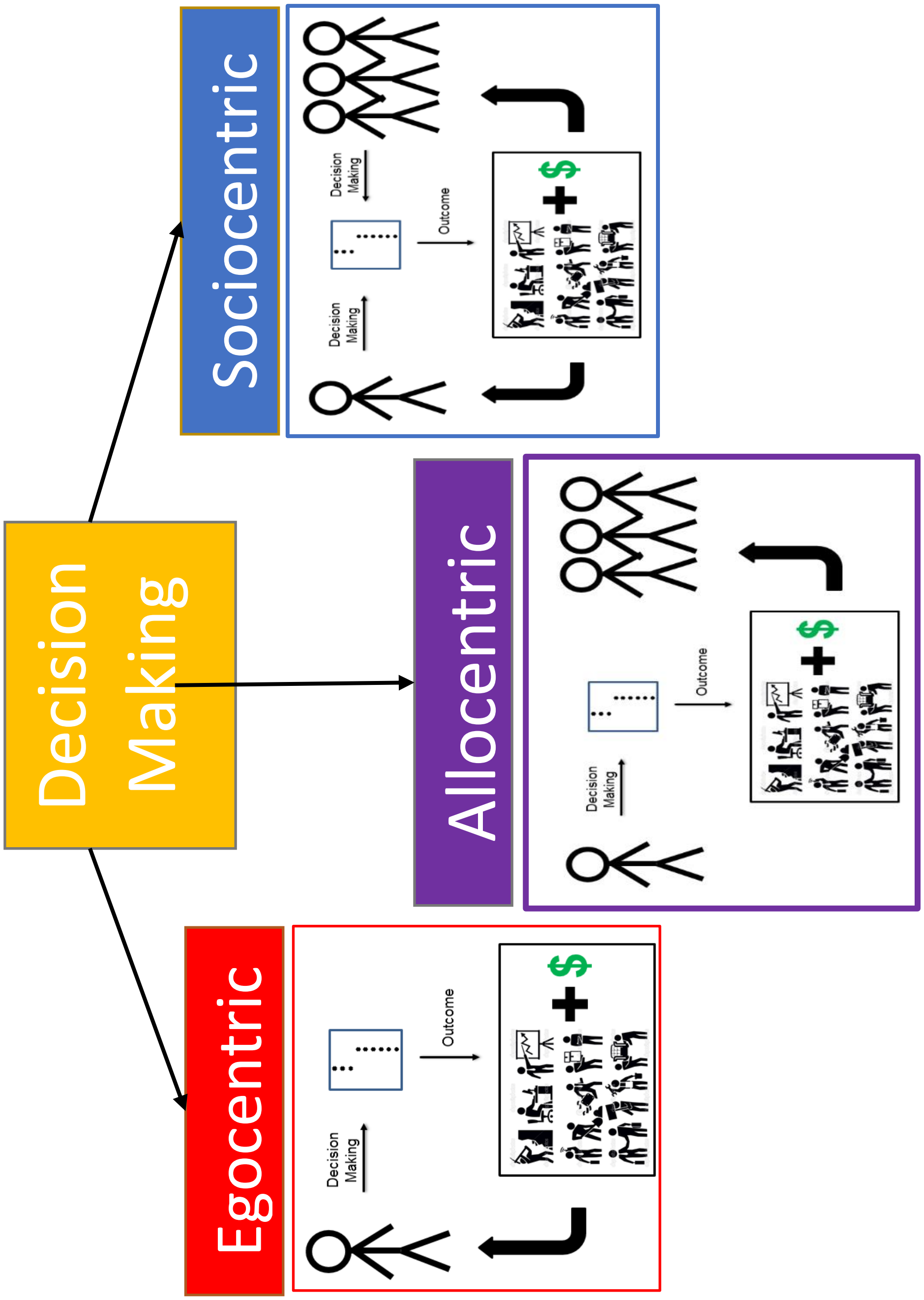

Figure 1.1: Tripartite Model of Decision Making

Egocentric decisions are made by a single agent as decision maker who receives the entirety of the outcomes. Egocentric decisions are usually, but not necessarily, private and made by an individual independent of outside influence or oversight. However, recent research has highlighted the important role of social advice in these decisions (Bonaccio & Dalal, 2006; Brooks, Gino, & Schweitzer, 2015; Harries & Harvey, 2000; L. Kray & Gonzalez, 1999). Most neuroeconomic research has investigated egocentric decision processes.

Sociocentric decision outcomes affect both the decision maker and others either simultaneously or iteratively. This type of decision making has been well studied within the framework of behavioral game theory, which provides a strong theoretical understanding of strategic interactions between players in a rule-based system (C. Camerer, 2003). In laboratory experiments, social decisions are often operationalized through behavioral games where players (participants, confederates, or computers) interact with each other to maximize real outcomes, often exchanged for monetary compensation. The outcomes can be rewarding or costly depending on the game design and choices made by participants. Games can also be iterative, played repeatedly with the same participants, or single-shot where the all outcomes are resolved after one round of play and new participants enter the game for the next round.

Many considerations and assumptions go into the design of a game to ensure it reflects social interaction outside of the laboratory. Any given game has several different forms and by tweaking the parameters of the game's design, researchers can test different hypotheses. For example, the scenario may be zero-sum where no player can receive a higher outcome without another player receiving a lower income, or payouts can be based on chance or cooperative behavior. Another design consideration is if the payout structure is known for all players (a "perfect information" scenario) or limited in a controlled way for some or all players. Repeating the game for multiple iterations with the same partner can lead to instrumental reputation building and signaling behavior while changing partners on every iteration can affect choice behavior (Fehr & Camerer, 2007; Glimcher & Fehr, 2013).

Each of these design parameters can be modified to reflect real social interaction phenomenon. Research using behavioral games has made vast strides in understanding the role of trust in investing, bargaining and negotiation strategies, and individual differences in cooperative and competitive behavior (Fehr & Camerer, 2007; Fehr & Fischbacher, 2004; Güth, Schmittberger, & Schwarze, 1982; Lave, 1960; Van Lange, De Bruin, Otten, & Joireman, 1997). Loaning money to another agent as an investment has been modeled to reflect trust (Berg, Dickhaut, & McCabe, 1995). Behaviors related to fairness and punishment have been modeled in the third-party dictator game where one agent unilaterally splits a monetary gift between herself and another recipient (Fehr & Fischbacher, 2004). Additionally, within each game paradigm, the individual parameters can be varied orthogonally to determine the unique effect parameters. For example, payout rates for each outcome can be adjusted to determine the effect of monetary incentive on choice behavior. The return on investment for the trustee can be altered to determine the degree to which the loan is a prosocial act to help another or an egocentric investment decision.

Yet, direct comparison between egocentric and sociocentric decisions does not adequately disentangle the relationship between social and egocentric influences. Another class of decision is needed to isolate decision makers from tangible, egocentric outcomes. In sociocentric decisions, a decision maker's personal stake in the outcomes is directly correlated with the social outcomes for others making it difficult to parse the valuation mechanisms of outcomes for others against outcomes for the self. For example, many behavioral games used to study social decisions involve splitting a common pool of reward money between the decision maker and another agent (the decision recipient). This is common practice in the dictator's game where the decision maker has unilateral power to share a reward pool, but economic incentive to hoard the entire payoff (Kahneman, Knetsch, & Thaler, 1986). The dictator's game compares egocentric economic incentive with social desirability, norm adherence, and reputation-building incentives. To study the impact of norms on game behavior, researchers manipulate the conditions of the game by affected the rules and relationships between the players. For example, one prominent study manipulated the social distance, a measure of relatedness, between players to determine the changes in sharing decision outcomes (Hoffman, McCabe, & Smith, 1996). However, this is fundamentally different from decisions for another person whereby the decision maker has no monetary stake in the outcome, relying strictly on social motivations to determine a choice for another.

Allocentric decisions are unilateral social decisions, where the decision maker is materially removed from the outcomes that are bestowed entirely to other agents. Other researchers have posited that social decisions can be either interactive or non-interactive (Utevsky & Huettel, 2015). For example, a marketing team deliberating over how to best implement an ad strategy uses a different decision-making process from a military leader administering battle commands to subordinates. The team likely engages each other through iterative communication which is one of many critical channels of social influence and has been shown to impact decision outcomes (Ellingsen & Johannesson, 2008; Johannesson & Persson, 2000). Allocentric decision making differs from sociocentric choices through the separation of outcome incentive from social influence. This separation allows for analysis of social influence and social outcome allocation independent of monetary incentive.

Allocentric recipients are either individuals or groups that neither share nor reciprocate decision outcomes with the decision maker. Such a unilateral relationship limits the potential confound of future material gain through signaling and instrumental reputation building (“you scratch my back, I’ll scratch yours” and “she’s a good person so therefore deserves a larger payoff”). The foil to this is allocentric decisions inherently amplify the ambiguity of the choice; even if a decision maker has perfect information of all possible decision outcomes, she does not have perfect knowledge of the recipients’ preferences for these outcomes. How decision makers cope with unknown preferences of a decision recipient when evaluating choice options remains unknown.

Despite the ambiguity, allocentric decisions remain commonplace. Decision makers use internal and external cues, contextual clues, learned strategies, and cultural norms for guidance. Notably, allocentric decision making does not mean the complete removal of relationship influence from decision making. There are intrinsic rewards inherent in social interaction. For example, a decision maker may still feel some empathy for the recipient or kinship, and indirectly feel generous by bestowing a positive outcome. Other aspects such as feelings of responsibility, control, or dominance, may influence how a decision maker values potential options (Pratto, Sidanius, Stallworth, & Malle, 1994). For example, a mid-level manager may decide differently when choosing outcomes for employees under her supervision compared to outcomes for her own supervisor. Identifying aspects of social relationships and their effects on allocentric decisions is a crucial component of understanding overall social decision making.

Furthermore, the circumstances that place a decision maker in the position to choose for another agent are important contextual factors that may affect the relationship between decision maker and recipient, or influence choice outcomes. Researchers have identified three important circumstances for consideration (Harvey, Twyman, & Harries, 2006). Proxy decision makers are requested by decision recipients because the decision maker possesses expertise or resources (including proximity to a location where decisions will take place) that the recipients cannot provide. Legal counsel is frequently closer to an allocentric decision than advice. Unlike advice or consultation, allocentric decisions are not weighted with another agent's own preferences – they are always enforced. Surrogate decisions are made for recipients who are incapable of deciding for themselves. Medical patients often require surrogate decision makers to make crucial treatment decisions. These decisions are often made by next of kin or established surrogates who know the patient well enough to make somewhat informed decisions in the event of an emergency. Finally, executive decisions are imposed on the recipient and reflect political and organizational decisions that are not directly requested by the recipient (Harvey et al., 2006). The difference between executive and surrogate decisions is crucial and reflects an implicit power hierarchy of the decision maker over the recipient. To protect decision recipients from decision makers who do not take their preferences into account, organizations use control mechanisms to balance this power imbalance. The research presented in this thesis focuses on executive decisions due to their prominence in managerial settings. Control mechanisms and their implementation for executive decision making are discussed in section 1.5.3.

Allocentric decision makers may use different cognitive strategies. Such strategies would be conscious schemas accounting for the inherent ambiguity of another agent's preferences. These strategies are reflective of different cognitive processes for evaluating decision outcomes. Two easily identifiable strategies follow a "would" vs "should" dichotomy (Fernandez-Duque & Wifall, 2007; Harvey et al., 2006). A decision maker can (1) choose an optimal outcome in line with a preset criteria, heuristic, or social norms thereby choosing what the recipient "should" choose in this situation or (2) choose the outcome that best coalesces with the recipient's preferences based on any information gathered beforehand or a cognitive model of the recipient's preferences. This second strategy selects an option based on what the recipient "would" choose in an identical choice and is also known as preference prediction or a simulation perspective in the literature (Faro & Rottenstreich, 2006; Hsee & Weber, 1997; Tunney & Ziegler, 2015).

Another cognitive difference in allocentric decisions may reside in how a decision maker represents decision recipients. One method for approximating another agent's preferences may be anchoring on a decision maker's own preferences and adjusting based on perceived similarity to the decision recipient. This strategy relies on a form of social discounting or appraisal of social distance. Research has shown that genetic coefficients of relatedness may approximate this social distance (Ziegler & Tunney, 2012). On the other hand, preferences may be internally simulated and represented as distinct from the decision maker's own (Tunney & Ziegler, 2015). Which strategy a decision maker ultimately uses may reflect individual differences or be determined by external factors. Given that these strategies are latent, both possibilities are considered without *a priori* hypotheses.

The environmental context of an allocentric decision is also an important factor. While laboratory studies induce an artificial social environment, there are likely effects that carryover from the external environment and an agent's prior experience. Chief among these is culture. Culture is the shared knowledge networks used by agents in social contexts mediated by social cognition (Y. Hong

& Chiu, 2001). This dynamic, constructivist view of culture describes a bilateral relationship between an agent's internal cognition and external environment resulting in a combined effect on an agent's behavior. The role of culture is inherent and intertwined with allocentric decision making as culture dictates social norms. Norms are the behavioral standards shared and enforced by a community (Chudek & Henrich, 2011). Norms provide a means for strangers to interact and engage, scripted responses or default behaviors in response to others, and guidelines for moral development in a particular culture. For example, an agent embedded in a culture valuing pride and honor is more likely to present aggressive responses to perceived threats (D. Cohen, Nisbett, Bowdle, & Schwarz, 1996). Further evidence from behavioral game experiments shows that cooperation, reputation, and punishment play varying roles in different cultures with some cultures even punishing excessively prosocial deviations from perceived norms (Herrmann, Thöni, & Gächter, 2008). The knowledge of norm-enforcement plays a role in executive allocentric decisions, mollifying the power imbalance. Cultural-cognitive constructs like guilt or shame may play a moderating role in executive allocentric abuses by creating feelings of pre-decision accountability (Y.-Y. Hong & Chiu, 1992).

The next section reviews prior findings in the literature as they pertain to egocentric and allocentric differences in decision valuation.

1.5 Literature Review

1.5.1 Allocentric vs. Egocentric Decision Making

Allocentric decision making has been shown to differ from egocentric decisions in several types of choices. In laboratory studies, experiments utilize tradeoff decisions to assess differences in choice behavior. Most studies are concerned with the tradeoff between risk or loss aversion and monetary reward. A burgeoning literature has emerged examining allocentric temporal discounting and allocentric consumer choices. The following sections review these studies based on decision types while highlighting important contextual factors and experimental design considerations of allocentric – egocentric differences.

When considering uncertain or risky options, decision makers predict others will prefer riskier options than themselves. Many studies require participants to make binary choices between receiving a certain amount of money or a 50-50 gamble for double-or-nothing payout. These choices can be framed as earning an amount of money or avoiding a monetary loss. In one of the first studies to directly measure allocentric – egocentric differences, four experiments placed participants into groups deciding for either unknown classmates, unrelated strangers, or themselves and their friends (Hsee and Weber 1997). The results showed egocentric decision makers were more risk averse than they predicted strangers to be. Stated another way, decision makers expected others to choose uncertain options more often than they would choose for themselves.

This early study highlights important contextual factors including the identity of the decision recipient playing a crucial role in allocentric decision making. Interestingly, the risk preference discrepancy was observed when presenting choice options for both gains and losses of imagined monetary reward but only when the recipient was an imagined stranger. While choices were incentivized for prediction accuracy, the actual choice options were hypothetical, using large sums of money. Additionally, these were preference predictions and not enforced choice outcomes, inferring a potential bias towards the cognitive strategy of “would” decisions.

Studies investigating risk taking decisions for others, as opposed to preference prediction, have used similar binary choices between imagined monetary rewards however decisions were framed as for another person rather than a prediction of their behavior (Stone et al. 2002). One option was an uncertain gamble and the other option was a certain monetary reward. In one experiment, the choice options were a gamble with outcomes of a large monetary payoff or nothing vs. a certain amount of money equal to the expected value of the gamble. Across fifteen trials, choices were made with varying probability of winning the gamble and adjusted expected value amounts. Choices were made for the decision maker to collect the outcomes either privately, with a partner watching or for a partner to receive who was present in the room. Analysis was conducted by comparing the number of gambles selected. The data show no difference between risky decision counts for public allocentric decisions, private egocentric decisions, and public egocentric decisions. The null result held for the second study when decisions were made about the probability of a skill task compared with a dice game for real money payouts instead of abstract gambles for imagined payouts. The contrasting evidence in allocentric predictions compared with egocentric action reflects the lack of understanding of allocentric-egocentric differences and the importance of clear study design and rigorously controlled experimental conditions including how the decision outcomes are implemented and the identity of the recipient.

In contrast, risk aversion differences are apparent when decision makers choose real monetary options for anonymous fellow laboratory participants. Using a multiple price list comparison task (Holt & Laury, 2002) and a computer-simulated sealed auction game to elicit risk attitudes, researchers have observed differences in behavioral choice patterns and estimated risk aversion (Chakravarty, Harrison, Haruvy, & Rutström, 2011). While both allocentric and egocentric decision makers were risk averse compared to risk-neutral model predications, the allocentric decisions were significantly less risk averse. The studies were conducted using a within-participants design, meaning participants acted as both egocentric and allocentric decision makers. Within-participants designs strengthen the power of the study by controlling for individual risk attitudes. While this study provides reinforcing evidence for risk aversion differences between egocentric and allocentric decision making, the differences appear dependent on how decision stimuli are framed or presented to participants.

How decisions are framed is an important consideration in decision making research. If stimuli explicitly refer to a cognitive strategy for selecting or evaluating options, it may bias participants in favor or against the highlighted strategy. For example, passive viewers of a confederate participant engaging in a risky card-playing game were asked what the confederate should do on the next turn - either take further risk or retire with the already won monetary earnings? The participants who viewed the confederate chose not to continue playing the risky game where participants who played the game themselves preferred the risk of continued play (Fernandez-Duque & Wifall, 2007). This effect persisted even when a follow-up experiment split participants into two groups with one group asked what *should* the player do next and the other asked what *would* the player do next. Both *should* and *would* groups exhibited similar choice patterns with both being less risk averse than the decisions of participants playing the game.

When making risky decisions, another important contextual factor is how the decision stimuli are framed. Framing effects refer to how the presentation of choices can alter decision making (Kahneman & Tversky, 1979). Prior research has shown that framing effects interact with differences in egocentric and allocentric decision making (Ziegler and Tunney 2015). When choice options were presented as monetary gains, allocentric decision makers were less risk averse compared to egocentric decision makers. When choices were presented as avoiding further losses, allocentric decisions were more risk averse compared to egocentric decisions. Notably, the framing effect had a larger effect size on egocentric decisions, but both frames significantly affected decisions for either outcome recipient.

Risky decisions with regards to monetary gains and losses are common in management, but differences in allocentric and egocentric risk taking have been observed in other domains. Using social scenario decisions to study risk, researchers found the similar patterns of risk aversion in egocentric and allocentric decisions, but only when the decisions were considered “low-impact” and posed no lasting negative consequences (Beisswanger et al. 2003). Examples of the risky social scenarios used in this task include speaking to a stranger at a party or making romantic advances – common situations for the university undergraduate student participants. The stimuli used in this study were poised as choosing for a close, same-sex friend (allocentric) or taking independent action (egocentric). Their results show increased frequency of risky choices in both advice giving and executive allocentric decision making. However, differences in risk taking disappear if the choice outcomes contain high-impact decisions like disease or familial shame. The researchers also observed self-reports from participants stating that they weighed potentially negative outcomes more when making egocentric decisions. The negative outcomes are less emotionally salient when they impact other agents, creating a difference in emotional state or empathy gap (Boven, Loewenstein, Dunning, & Nordgren, 2013; G. Loewenstein, 2005). The empathy gap explanation is powerful and provides clear predictions for explaining decision making phenomenon such as risk aversion, but is not a comprehensive theory for all allocentric-egocentric decision differences.

Avoiding losses at the expense of foregoing equivalent gains is a robust decision phenomenon known as loss aversion (Kahneman, Knetsch, & Thaler, 1991; Tversky & Kahneman, 1991). An empathy gap explanation predicts that egocentric decisions would show greater loss aversion than allocentric decisions because the egocentric loss is more emotionally salient. There is mixed evidence that deciding for other agents reduces loss aversion, particularly when considering domain-specific choices and different types of stimuli. Researchers conducting an experimental study in Denmark showed reduced loss aversion with a multiple price list task, but notably not pure risk aversion, when deciding for others. Four choice conditions were used in the study to provide a range of contrasts including egocentric, shared outcome, hypothetical, and pure allocentric choices. Analysis was conducted using structural equation modeling controlling for gender, age, education, cognitive ability, and cognitive reflection (Andersson, Holm, Tyran, & Wengström, 2014). The researchers found an overall 8% increase in expected returns when deciding for others due to the increase in loss-neutral decision making based on expected value returns.

Researchers using alternative stimuli presentations of uncertain monetary gambles found similar results in a student population. In three decision tasks, participants made both egocentric and allocentric decisions, but exhibited reduced loss aversion when deciding for others (Mengarelli, Moretti, Faralla, Vindras, & Sirigu, 2014). The researchers solicited a willingness-to-pay response from participants to determine how much compensation was necessary for a ticket to a lottery with known odds. The willingness-to-pay measure provides an explicit, continuous indicator of loss-aversion compared to implicit estimations from repeated decisions. Additionally, the experiment design controlled for the identity of the decision recipient for all allocentric choices by utilizing an anonymous confederate in another room and providing decision makers with no information on risk preferences. This is crucial and separates risk attitude prediction from decision making.

Anonymity is an important consideration in allocentric decision making. Early research on bargaining behavior utilized anonymous participants to control for the intricacies inherent in human social relationships (Siegel & Fouraker, 1960). Recent research utilizing the dictator's game has also found evidence that anonymity between players influences decisions (G. Charness & Gneezy, 2000). When player names were known, the amount split from a reward pool was greater on average and contained a higher number of even (50-50 reward distribution) splits. When players remained anonymous, the amounts split were significantly reduced with more 100-0 splits of the reward pool.

Loss aversion can be operationalized without monetary choice outcomes (Tversky & Kahneman, 1991). When choice options present physically harmful or dangerous outcomes, loss aversion or harm aversion differences in allocentric decision making become ambiguous. In a scenario choice task, student participants felt they were more likely than other college students to get out of a taxi driven by a drunk driver (G. F. Loewenstein, Weber, Hsee, & Welch, 2001).

This decision came at the cost of having to walk a large distance home. The scenario presents a tradeoff that is difficult to interpret as participants must choose between ambiguous, potential harm or certain effort and time cost.

In a binary choice study using the subjective value of money to measure harm aversion, decision makers could forego monetary gains to avoid large painful shocks for either themselves or another participant. Another participant was used as the other agent in the study introduced through a "blind" handshake. The results show different estimates of valuation for another's pain compared to the decision maker's pain. Decision makers required a high money reward for causing others pain and a lower price threshold for their own self-inflicted shocks (Crockett, Kurth-Nelson, Siegel, Dayan, & Dolan, 2014).

Real world risky scenarios often involve harm and loss. Poignant, but common examples come from the medical field when doctors and family members must make treatment decisions for incapacitated patients. A meta-analysis of risk perception studies showed that doctors only had 66% success rate at predicting their patient's medical preferences (Shalowitz, Garrett-Mayer, & Wendler, 2006). Such decisions can have life-altering consequences such as hours of arduous physical rehabilitation or risky surgery. Research has shown allocentric decision makers may have different preferences from the patients who receive medical care. In a large online study, participants were asked to imagine themselves as a patient, doctor deciding for a patient, director of a hospital deciding for many patients, or as a parent deciding for their sick child. While taking on their given role, they chose whether to engage in treatment that mollified the probability of death from the flu or a slow growing cancer. All allocentric roles were more likely to choose treatment compared to the egocentric role (Zikmund-Fisher, Sarr, Fagerlin, & Ubel, 2006).

Another medical decision study using more nuanced treatment decisions finds similar differences. In hypothetical decision scenarios investigating various treatment attributes, student participants were significantly more likely to choose treatment when making executive allocentric decisions for a loved one compared to both egocentric and choosing the treatment the loved one would want (Raymark, 2000). Treatment scenarios varied by attributes like mental and physical functioning, financial constraints, and pain. Interestingly, the attributes were not weighted differently by the participants who took on the role of executive allocentric decision makers akin to doctors.

Such divergence in preferences is not specific to lay participants. In a study comparing doctors and lay decision makers, doctors showed greater egocentric-allocentric difference when considering risky treatments. Treatments varied in time to regain full health (immediately or after some delay) with changing probabilities of success. Doctors were much more risk averse when making allocentric decisions for their patients (Garcia-Retamero & Galesic, 2012). Additionally, very few doctors predicted the risk preferences of their patients. These conflicts can create tension in the doctor-patient relationship and negatively impact the perceived success of medical treatment.

Differences between egocentric and allocentric decisions are apparent, but inconsistent across several choice types. When making decisions between monetary gambles, social action, and medical treatments, the broader context of the choice may be as important as the choice outcomes. Social context of decisions is important for understanding allocentric decisions. As such, researchers have proposed a social values theory of risk that relies on the value society places on safety, harm, and success (Stone, Choi, de Bruin, & Mandel, 2013). While egocentric perception of risk may be represented as affective changes (G. F. Loewenstein et al., 2001), allocentric decisions must rely on a recipient conveying their risk preference emotions to the decision maker. Researchers have found a link between individual differences in empathy and allocentric risk attitude prediction (Faro & Rottenstreich, 2006). A corroborating study found that both long term and new partners could accurately predict valuations of consumer goods and medical health states better than unfamiliar pairs of participants (Tunney & Ziegler, 2015). Such findings highlight how social relationships can moderate differences between allocentric and egocentric decisions either through signaling or experience.

However, preference signaling is not always possible for distant or anonymous decision recipients. In the absence of direct signaling, social norms dictate the approach to risk and loss for specific choice domains. To provide evidence for this theory, social relationship decisions that involved shame and embarrassment as possible loss outcomes were directly compared with choices that result in physical harm (Stone et al., 2013). Allocentric choices in these two domains were significantly different from each other and the corresponding egocentric decisions. Importantly, differences in choice behavior between contexts was not driven by differences in risk preference prediction.

In addition to the choice domain, the specific relationship between decision maker and recipient can influence how decisions are made. In a dictator's game study with millionaire participants, greater differences in wealth between the decision maker and recipient lead to increased donation in a dictator's game. While the dictator's game is not a purely allocentric decision because of egocentric monetary incentives, it is notable that nearly half of the wealthy participants gave away all their potential earnings - an unusually generous behavior pattern in the dictator's game (Smeets, Bauer, & Gneezy, 2015). When paired with other millionaires as decision recipients, participants were far less generous. Furthermore, when recipients held some power in the decision and could accept or reject the proposed monetary split (known as the ultimatum game), millionaire participants reduced their donations to less wealthy recipients. This shows evidence that decision makers may take socioeconomic status into consideration when making allocentric choices.

Social relationships also influence allocentric decisions when making temporal discounting valuations. Evidence for reduced temporal discounting in allocentric decisions was found (Albrecht, Volz, Sutter, Laibson, & von Cramon, 2011). This difference was replicated but only when making decisions for an unrelated and unknown recipient. Temporal discounting differences between egocentric and allocentric decisions disappear when deciding for genetically or socially similar recipients (Ziegler & Tunney, 2012).

As noted earlier, predicting the risk preferences of unknown others has been shown to differ from egocentric risk preferences (Hsee & Weber, 1997). When deciding for unknown others, decision makers may rely more on social norms to make acceptable decisions rather than attempt to mentally simulate the preferences of an unknown person or anchor to their own preferences. However, a known recipient such as a friend or significant other can be mentally simulated with some confidence based on learned preferences or extrapolations from experience with the other that supersedes the information provided by social norms. Lived experience may override social default positions in allocentric decisions.

In addition to dyad-level differences in relationships, individual differences in a decision maker's cognition can also affect how allocentric decision makers value options. Using online survey platforms and experiments, four studies found evidence for cognitive moderators when comparing paying to improve one's own life or the life of another individual. The studies identified construal level, regulatory focus, and power as significant constructs of interest in allocentric decisions (Polman, 2012).

While moderators of egocentric-allocentric differences have been explored, mediating and mechanistic differences are less well understood. While this area of the literature is underdeveloped, there is some evidence for cognitive differences between egocentric and allocentric decision processes. Specifically, the processes of option valuation may function differently in allocentric decisions. Early studies examining the relative importance of choice option attributes reflect this difference, but little work has been built around these findings. In one business scenario choice, participants chose to sell or lease out an inherited business either for themselves or for two hypothetical owners who disagree (Borreson 1987). In addition to the between-groups choice, participants ranked the hypothetical attributes of the choice outcome such as the ability to pay off debts, buying a better home, uncertain future income from leasing, and difficulties associated with leasing, based on how persuasive each attribute was to making the decision. The attributes were ranked differently between the egocentric and allocentric groups. Buying a new home in the future was more persuasive to the egocentric group, while concerns over the uncertain income during the leasing period were more important for allocentric decision makers.

Another attribute weighting difference was found when participants were asked to give career advice. When giving advice, two studies showed differences in job attribute weighting between advice giving and egocentric decision making (L. Kray & Gonzalez, 1999). The attributes of choice options were presented as job characteristics including salary, job satisfaction, and location. Egocentric decision makers weighed all attributes relatively evenly compared to allocentric advice givers who emphasized primary attributes like satisfaction. The findings were replicated in students making a choice of study major given incoming budget cuts. Participants recommended others stay with the major despite the funding cuts more often than they chose to continue with their major.

Using a similar attribute weighting paradigm, Kray found that advisors are more likely to choose options based on agreement with social norms rather than personal preference (L. J. Kray, 2000). Additionally, advisors felt less post-decision regret than egocentric decision makers. No significant differences were found between the allocentric and egocentric groups in the effort taken to evaluate choices. These findings point to a norm-driven response rather than anchoring and adjustment or empathy gap explanation for differences in decision processes. The authors of these studies note that advice giving is not identical to allocentric decision making due to framing or motivational differences between the two roles. However, moderating influences like social conformity and accountability may curb these differences.

Understanding how norms influence valuation processes is of paramount importance to organizations with executive allocentric decision makers. Making decisions based on norms may result in suboptimal policies or outcomes if decision makers do not adhere to them, choose to ignore them in a culture of poor oversight and accountability, or are not uniform across the organization. The stability and consistency of decision preference norms is worth noting as several studies have found evidence that information becomes distorted differently between egocentric and allocentric decisions (Polman, 2010). In a restaurant selection task, decision makers rated neutral restaurant attributes such as location and menu iteratively until they made a choice. After making the choice, they again rated attributes they had either viewed prior or had not seen. The already viewed stimuli were rated higher after the choice for egocentric decision makers, while the new attributes were rated higher for allocentric decision makers. This difference in information evaluation implies a review process or post-hoc distortion on behalf of egocentric decision makers. Early studies comparing allocentric and egocentric choices showed no difference in feelings of regret, which might otherwise be associated with post-decision information distortion (Stone, Yates, & Caruthers, 2002). Mechanisms that force an allocentric decision maker to review choices may be useful in reducing the difference between allocentric and egocentric decisions. Control mechanisms are further reviewed in section 1.5.3.

Further study is needed to help understand the mechanisms underpinning egocentric-allocentric choice differences and the domains and social contexts that moderate egocentric-allocentric differences. The next section specifically addresses a new choice domain that has yet to be studied with regards to allocentric-egocentric decision differences and may inform the current understanding of allocentric decision making.

1.5.2 Effort Decision Making

Human and animal model decision makers prefer outcomes with lower effort costs, *ceteris paribus* (Hull, 1943). Effort costs arise inherently when decision makers act, both in the process of deciding and in manifesting outcomes (V. L. Smith & Walker, 1993). As effort costs increase, a decision maker’s valuation of an option decreases or discounts. Given that all actions require effort and all decisions result in action selection, understanding the mechanisms by which a decision maker values effort is important for understanding overall choice mechanisms.

Investigations into effort discounting harken back to the tradition of behaviorism in psychology. Using animal models and reinforcement schedules, animals would prefer options for food requiring fewer lever presses (Solomon, 1948). In humans, cognitive effort is also a consideration in decision making. Economics generally equates physical and mental effort as both serve as generic costs (Camerer and Hogarth 1999). In a series of six, rigorous experiments, results showed that cognitive effort in the form of task switching and executive function also caused decision makers to discount the value of choice outcomes despite minimal physical effort (Kool, McGuire, Rosen, & Botvinick, 2010). Very rarely is cognitive ("physical") effort disambiguated into specific subcomponents such as sustained duration ("endurance") and difficulty or complexity ("strength"). Lay evidence exists for this separation. In willingness-to-pay experiment, participants exhibited a higher willingness to pay for household items that could be purchased preassembled, combining both the time to completion and the complexity of the task (Soman, 2004). Anyone who has spent an afternoon toiling with a toolset and poor instructions can affirm such generalized frustrations and tests of both mental and physical endurance. Formally, cognitive or mental effort is defined as "the mediator between the characteristics of a target task and available information processing capability and the fidelity of information-processing operations actually performed" (Shenhav et al., 2017). Generally, effort discounting tasks require either or both of active physical and mental engagement to obtain a reward. This permits a tradeoff comparison of subjective values (Shenhav et al., 2017; Westbrook & Braver, 2015; Westbrook, Kester, & Braver, 2013).

The research presented in this thesis extends research on effort discounting by focusing on decisions that compare tradeoffs between effort and money for another agent. The aim is to better understand how effort is valued when deciding about one's own effort compared to the effort of another. Little is known about how another agent's effort is valued by an allocentric decision, however there is evidence that social factors are important in the valuation of effort. Market differences exist when effort compensation involves social rewards (Heyman & Ariely, 2004). When asking students to assist with a friend's residential move in a hypothetical scenario experiment, researchers found that participants were more likely to help when more money was offered. However, when compensated with candy (a display of friendship) participants were always willing to help to a high degree. Interestingly, when the monetary value of the candy was presented to the participants, their responses mirrored those of participants who were offered cash. The researchers replicated these findings for cognitive effort using an intentionally boring computer task and increasingly difficult puzzles. The presence of monetary compensation elicits a market framework where decision makers began to value the degree of their efforts, while social compensation elicited high effort at all levels of compensation. This establishes an avenue for separation between social valuations of effort distinct from pure monetary incentives. However, this study only investigated egocentric valuations of effort.

Prior research has shown allocentric decision making differs from egocentric decision when choice outcomes are passive outcomes like uncertain gambles and hypothetical scenarios but very few with outcomes that require the active participation from choice recipients. Allocentric decision making studies have utilized several paradigms where the net result is a lump sum transferred to the recipient. In most studies, the decision recipient does not directly experience costs as a decision outcome - painful shocks in a harm aversion study being a notable exception (Crockett et al., 2014). If decision makers believe the final allocentric outcomes of their decisions will always be an aggregate monetary payout for another participant (only differing in magnitude of the payout), this may differ from assigning a costly penalty that requires the actions of the outcome recipient. A monetary gift still represents a gift; however, assigning tasks may be valued as social or market transactions with each having a different decision process (Heyman & Ariely, 2004).

Many decision outcomes in a management setting require active participation from the decision recipient(s). For example, strategic decisions made by upper management create departmental shifts or revamped operation practices that must be learned and enacted by employees. While the pervasiveness of passive choice paradigms is understandable from the standpoint of experimental design logistics, choice options that require effort on the part of the recipients may be evaluated differently compared to options that require the recipient's effort and attention and deserve attention. Yet, because the literature on allocentric effort decision making is scant, the next section reviews research relevant to the study of egocentric effort valuation to cultivate understanding of study design considerations and moderating influences on effort discounting behavior. Focus is given to effort tasks that are feasible in an fMRI environment. The specific constraints of this environment are discussed in further detail in chapter 4.

Effort discounting has been operationalized in several tasks that isolate either physical or mental effort. The most common task used in human effort discounting studies is the hand grip strength task utilized in prior research of self-control (Muraven, Baumeister, & Tice, 1999). Several studies have shown that when choosing between option bundles of rewards magnitudes paired with a proportional requirement to squeeze a lever at some percentage of maximum strength, decision makers discount the value of the reward by the amount of effort required. Rewards in these tasks can vary from straightforward monetary payouts (Hartmann, Hager, Tobler, & Kaiser, 2013; Klein-Flügge, Kennerley, Saraiva, Penny, & Bestmann, 2015; Mitchell, 2004) to erotic images (Prévost et al., 2010). The handgrip task is useful because it can be completed in a neuroimaging scanner between decision trials and outcomes can be resolved immediately after being chosen.

Cognitive effort decisions have been operationalized in neuroimaging experiments through memorization and attention tasks. A common memory task is an n-back task where participants must match a remembered symbol on a card while flipping through a deck of cards. Participants chose between difficult or easy n-back task. The easier task required remembering symbols from one card beforehand while the harder task required participants to remember several cards of symbols. Larger payouts were given when matching in the more difficult effort task but the reward payout was varied based to titrate a participant's indifference point or the amount of money that makes the two options subjectively equivalent in value (Westbrook et al., 2013).

Other researchers have used a task switching paradigm inside a neuroimaging scanner to induce cognitive effort (Botvinick, Huffstetler, & McGuire, 2009). Participants were subjected to different levels of effort for the same pay in a block design experiment. In the low effort block, the task required no switching and was a monotonous matching task. In the high effort block, participants had to alternate between matching colors and numbers in various patterns.

Another research group utilized a visual search task where participants learned eight possible combinations of effort and reward presented with a two-dimensional stimulus before engaging in the effort task (Croxson, Walton, O'Reilly, Behrens, & Rushworth, 2009). The effort task required participants to move a trackball mouse to hover over visual targets with higher effort trials requiring more target matches. The use of a symbolic choice stimulus to represent both the monetary payout and the effort simultaneously allowed the researchers to study simultaneous presentation of value.

However, these tasks are relatively abstracted from common behaviors. Gauging performance on an unfamiliar task adds a degree of complication when investigating allocentric decision making because decision makers may not know the physical capabilities of the decision recipients who must perform the task in addition to their preferences. To isolate only the effects of effort preferences, a relatively common and consistent task is beneficial. Additionally, effort in the modern work environment is unlikely to be pure physical exertion or immobile mental exertion, but more likely both physically repetitive and mentally engaging. The effort typing task fits this niche better than others given that most university students are practiced typists. Researchers have shown effort discounting behavior when participants must type a list of words in reverse character order (Libedinsky et al., 2013; Massar, Libedinsky, Weiyan, Huettel, & Chee, 2015). The size of the word list provides a quantifiable measure for effort and can rewarded at variable wage rates (dollars per word typed successfully). Additionally, the typing task requires precision, but is simple enough that it can be completed by even sleep deprived participants. Choices can be made while inside a neuroimaging scanner with outcomes resolved after the decision trials to prevent excessive movement while inside the scanner (Massar et al. 2015).

One important, but understudied moderator of effort is supervision. Supervision is the act or process of critically watching, inspecting, or directing a course of action. Research shows that supervision can negatively impact effort decisions (G. B. Charness, 1999, p. 199). In a behavioral experiment, participants were randomly paired and assigned roles in each round of the experiment. The roles were employer and employee where a wage rate for a task on each round was determined from a mutually visible public bingo ball drawing (chance) or by a private dictation from the head experimenter relayed through the employer. The employer then chose effort tasks for the employee based on this information. Third party regulation of wage rate from the experimenter negatively impacted the amount of effort performed by the employee. This finding runs counterintuitive to the underlying premise of management and challenges the common expectation that supervision improves employee performance. The next section reviews supervision in the form of accountability and its effects on decision making.

1.5.3 Accountability

Professional decisions rarely occur in a social vacuum. Outside of the controlled confines of a laboratory, decision makers act in an environment with other agents who can perceive, judge, and respond to actions. In executive allocentric decision making, an inherent power imbalance exists between decision makers and decision recipients. Deciding unilaterally and without assent creates a relationship prone to abuse. To prevent abuse and reduce preference prediction errors, regulations are implemented by agents, institutions and governments, and culture. Regulations can be corrective like punitive fines or preventative like the permission of an authority figure. Accountability is the belief that an agent will need to justify his or her beliefs, thoughts, feelings, or actions to another (Lerner and Tetlock 1999) and ties preventative regulation to social norms.

Allocentric decisions are subject to judgment of agents in the social environment – either in person or digitally via social media. Visibility is crucial and the information age helps accountability agents to hold decision makers to standards and helps outcome recipients to receive more equitable decisions. Additionally, accountability can be enforced by social watchdogs, government agencies, or whistleblowers. Accountability is crucial in organizations who embed accountability in the very structure of hierarchies with terms like “supervisor”. While there are many avenues for accountability to be enforced, control is only effective if it alters behavior.

Classic social psychology studies have shown that social presence can influence judgment and decision-making behavior (L. Festinger, 1954; Leon Festinger, 1950). Festinger showed that experiment participants were willing to conform to obviously incorrect judgements of line length when confederates espoused incorrect beliefs. The propensity of individuals to conform to social norms is a robust phenomenon that clearly displays the influential power of social contexts over behavior. Interacting with other agents imbues behavior with additional consequences in social standing or group cohesion. Thus, successful agents must consider ramifications of their actions beyond their egocentric outcomes.

Furthermore, agents can be influenced by social contexts without interacting with other agents. By merely being observed, agents exhibit changes in behavior and task performance (Zajonc, 1965). Audience effects have been widely documented in studies where individuals perform well-learned tasks above expectations (social facilitation) and falter on novel or complex tasks (social inhibition) while in the presence of others. Social evaluation can reinforce participants' understanding of social norms when they are isolated from real world interaction in laboratory experiments.

One formalized method for social evaluation that has real world implications is accountability. The presence of accountability manipulations has been shown to induce cognitive and behavioral changes in decision makers. Research has shown that accountability can reduce the influence of biases in judgment and decision making by altering attenuation to information and complexity of thought in judgment processing (Lerner & Tetlock, 1999). Philip Tetlock, a pioneer in formally investigating the effects of accountability on judgment and decision processes, found evidence that accountability promotes "complex and vigilant information processing" and reduces overweighting of initial information also known as a primacy effect. An earlier experiment consisted of a hypothetical legal case with participant's deciding on guilt or innocence of the defendant (Tetlock, 1983). Before reading any information, decision makers were informed that their choices would either be confidential, require justification via interview with the experimenter, or neither and were subjected to an interview without warning. The stimuli consisted of equal numbers of anecdotes suggesting the guilt or innocence of the defendant presented in blocks with a counterbalanced order between participants. Those participants who knew they would be held accountable for their judgments updated their judgment using information presented later in the experiment and were better able to recall earlier information compared to participants who were not held accountable or not given prior knowledge of their accountability.

The relationship between accountability and increased awareness of information is robust and well replicated. The effect of accountability even persists when experiments present decision makers with irrelevant information resulting in judgments influenced by unrelated facts (Tetlock & Boettger, 1989). In two hypothetical scenarios, participants made predictions about a student's academic performance and a patient's diagnosis. Participants who were instructed that they would justify their choices at the end of the experiment were influenced by information unrelated to student performance when making their judgments. Presenting irrelevant information to accountable decision makers resulted in judgments akin to those made by participants shown contradicting information.

Another bias thought to be affected by the presence of accountability is the sunk-cost bias. The sunk-cost bias arises when individuals have committed resources in prior time periods that are not recoverable and "double down" or continue with a course of action in hopes of breaking even or recovering some of the lost value rather than ignoring the lost resources in favor of future earnings (Arkes & Blumer, 1985; Staw, 1976). Prior losses create attachment to a choice option, making the decision maker commit further to a suboptimal choice. In four experiments using a hypothetical business investment scenario, researchers found that participants who had to explain their choices about whether to continue with a costly project or withdraw at cost were more likely to withdraw in favor of greater long-term payouts (Simonson & Nye, 1992). However, accountable decision makers were not more consistent in their choices.

Accountability can also influence chosen options such as consumption preferences for consumer goods or risk preferences. Researchers investigating consumer good choices for others found a stronger preference for bundles containing a larger variety of products when decision makers were held accountable (Choi, Kim, Choi, & Yi, 2006). Results from their experiment showed that making allocentric consumer choices increases variety-seeking choice. The tendency to choose variety options was enhanced when decision makers were asked to write down reasons why they made their choices to be passed along to the decision recipient.

Additionally, the presence of social observers was found to increase charitable donations in decision makers (Izuma, Saito, & Sadato, 2010). Experiment participants chose to give a small donation to a charity or pocket the money themselves either privately or in the presence of two, gender-balanced observers. Participants more frequently donated the money when observed. Earlier research shows that observation may not even be necessary to elicit this effect. Researchers conducted a double-blind dictator's game study where participants were anonymized both from each other (decision maker and recipient) and from the experimenters (Hoffman, McCabe, Shachat, & Smith, 1994). They found decreased reward pool allocations when participants were double-blind compared to single-blind between participants despite the experimenters holding no power to alter the choices or affect the outcomes. Double blind decision makers were significantly more likely to keep the entire reward pool for themselves.

The perception that others are evaluating choices can affect how a decision maker evaluates uncertain choice options. Researchers observed that decision makers under the auspices of social evaluation significantly reduced their preference for ambiguous choice options (Curley et al., 1986). Participants were made to choose between two lotteries of varying ambiguity either in front of a group of participants or after all other participants had left the laboratory. Perceived social evaluation was the only effective moderator of ambiguity aversion in a series of experiments testing various ambiguity aversion moderators.

Accountability also moderates loss aversion decisions (Vieider, 2009). Participants in the choice experiment stated the amount of money that could possibly be won in a gamble to make them indifferent between possibly losing money in that gamble or earning no money for certain. This indifference point elicitation method provides estimates of loss aversion with larger amounts reflecting a greater aversion to loss. The between-participants design had one group of participants make these choices privately while others had to write their name and email on paper and were told they would be interviewed about their choices after the experiment. The accountable participants exhibited decreased loss aversion. This result was repeated in a similar experiment where participants chose between a certain amount of money or a gamble with possibilities of a loss-gain pairing, smaller gain-larger gain pairing, or larger loss-smaller loss pairing (Pahlke, Strasser, & Vieider, 2012). Only the mixed loss-gain pairing showed differences between participants who were held accountable for their choices and those who remained anonymous. No difference between groups was observed in risk preference for pure gains or pure loss gamble stimuli.

However, results from a behavioral investment game have shown accountability can affect risk aversion (Pollmann, Potters, & Trautmann, 2014). In this within-participants design, investments were made both egocentrically and allocentrically and investments accrued over several rounds. Allocentric decisions showed reduced risk aversion in their investments. Yet, when allocentric decision makers were held accountable for their choices or the outcomes of their decisions, they shifted to more risk averse choices. The reduction in loss aversion resulted in accountable participants deciding for others more similarly to how they would decide for themselves.

Many choice experiments operationalize accountability by requiring participants to justify their decisions or decision-making processes. For example, decision makers may engage with the decision recipient or a third-party observer directly. In some designs, the outcome recipient can communicate directly to the decision maker or engage in costly punishment retaliation such as in the ultimatum game. Researchers found that giving recipients the ability to respond to payment allocation in the dictator's game with a handwritten letter significantly affected the decision makers' choices. Decision makers distributed money more generously, following the pattern of distribution as when recipients held the power to reject unfair offers (Ellingsen & Johannesson, 2008). Decision makers were informed they would receive feedback from the recipient prior to making the decision. However, accountability in organizations is often less formal.

One common form of accountability is a verbal report or interview explaining a decision or the cognitive process that lead to a decision. To operationalize accountability in an ecologically valid way and still maximize its effects, the research presented hereafter uses an interview paradigm implemented in pioneering studies (Tetlock, 1983; Tetlock & Boettger, 1989) and replicated recently in the allocentric decision making study by Pahlke et al. (2012). This interview paradigm aims to maximize the effect of accountability along five dimensions: accountability stems from a 1) third party of 2) sufficient and reasonable authority with 3) valid interest in the decision and required both 4) outcome and process accountability. Perhaps most importantly, the interview and its criteria were 5) made known to participants prior to making any decisions (Lerner and Tetlock 1999). There was no punishment or consequential retribution available to the regulator in any study, only the effect of pre-decision accountability was of interest.

Both culture and gender have been found to play a role in the effects of accountability. Researchers studying negotiation in China and the US found that in-group identity of partners led to positive effects of accountability, as if social norms only applied to partners who shared the same culture (Liu et al. 2011). Recent research has shown that when participants made food choices from menu items for another person, European Canadians engaged in less post-decisional justification compared with Japanese and Asian Canadian participants (Hoshino-Browne et al., 2005). Cultural constructs like shame and guilt reflect an inherent cultural attitude towards accountability by concerning agents with the perceptions of their actions to others (Hong and Chiu 1992). To mitigate effects of cultural interaction, the research assistants in each experiment were from the participants' home culture.

Furthermore, researchers have found gender interaction effects in implementing accountability (Brandts & Garofalo, 2012). Particularly in gender-crossed interactions, male participants were strongly affected by females holding them accountable. The studies in this thesis utilize a third-party agent introduced as the Head Experimenter to conduct interviews. The gender and cultural background of the Head Experimenter were masked in the instructions for all tasks and not explicitly mentioned by research assistants.

1.6 Summary

The following research utilized a neuroeconomic framework to investigate how decision makers value another agent's effort. Employing a tripartite framework of investigation into decision phenomenon, cognitive modeling of decision processes, and neural localization of cognitive processes, the research investigates two aspects of social choice. The first is the presence of another agent as a decision outcome recipient. The second is the presence of an agent as third-party regulator holding the decision maker accountable.

The neuroeconomic approach leverages unique methodologies to empirically investigate a phenomenon at each level of analysis. Economic theory predicts behavioral choice based on a decision maker's interest in maximizing egocentric rewards. This establishes a baseline for comparison with pure allocentric choice. Computational cognitive models describe choice behavior with respect to latent processes. Comparison of prediction accuracy and process typology between experimental conditions aims to clarify the structure of the information processing algorithm. Finally, fMRI scanning of real time decisions allows for localization of the dynamic processes associated with decision making.

The decisions of interest are executive allocentric decisions for an anonymous fellow participant. Decisions are unilateral (non-reciprocated) and double-blind anonymous. All decision outcomes are bundles of monetary reward and active effort on the part of recipient whether it be the decision maker or another agent. Repeated decisions allow for tracking the decrease in subjective value as effort increases.

Regulation by accountability takes the form of an interview with the head experimenter. The interview imposes pre-decision accountability that requires justification to an interested party with authority over the scenario to maximize the hypothesized effects. The interviewer's identity is anonymized to control for gender and culture effects which are outside the purview of this research.

2 Behavioral Investigation of Allocentric – Egocentric Differences in Effort Discounting Decisions

2.1 Motivation

The initial step in investigating allocentric effort decisions is to describe allocentric behavior by discriminating it from egocentric decision making. Differences in chosen outcomes between egocentric and allocentric decisions given the same input stimuli imply different underlying mechanisms. Given that effort is a cost factor, decision makers have no incentive to choose larger effort options unless paired with a comparable reward or incentive. However, when effort options are paired with a form of compensation, comparing the choices between options of varying effort amounts becomes a feasible method for gauging differences in effort valuation.

The two experiments in this chapter provide evidence that laboratory participants make different decisions for other agents than for themselves. Using tradeoff decisions between effort and compensation as choice stimuli, the experiments employ a binary choice design to investigate effort discounting behavior both between and within participants. Effort compensation tradeoffs force decision makers to choose the option that simultaneously minimizes effort costs while maximizing compensation. Independently, these attributes have opposite effects on preferences, and when combined create options that have similar objective values. For example, one choice option has a large monetary compensation coupled with a large monetary cost, while the other is a smaller option both in terms of effort required and compensation earned by the recipient.

Each option has a similar ratio of cost to compensation, but subjectively these options differ to the decision maker and to the decision recipient. The decision makers in these experiments must choose one, and only one, option as the outcome and thus reveal their subjective valuations for these options.

This research offers a two-fold contribution to the literature by (1) exploring behavioral differences in effort decisions in an allocentric decision context, and (2) exploring a potential moderator of egocentric-allocentric differences in accountability.

The first experiment used a between-groups design to establish behavioral differences in choice behavior. The second experiment provides within-participants evidence that this difference is robust and intrinsic to decision making processes as opposed to the manipulation of the prior experiment. Additionally, the choice options used in the decision task did not hinge on knowing another person's strength or intelligence to determine capability. The typing task selected here combines physical and mental effort in a familiar and accessible form. Almost all university students are expected to type efficaciously, which reduces ambiguity from a decision maker when choosing a task for another participant without knowing his or her capabilities. Prior to the present work, this typing task has only been used in egocentric decisions (Libedinsky et al., 2013; Massar et al., 2015). Thus, these experiments also test a potentially effective method for dissociating effort discounting differences in allocentric decisions.

2.2 Hypotheses

Behavioral choice differences between egocentric and allocentric decisions are expected for two reasons: 1) allocentric decisions present an empathy gap for decision makers and 2) given the ambiguity of the decision recipient's preferences, decision makers may rely on social norms rather than their own preferences to make choices. Past research has investigated egocentric-allocentric differences across a variety of domains finding varying support for an empathy gap in decision making. The empathy gap is an extension of the risk-as-feelings hypothesis and refers to differences in choice outcomes caused by differences in the affective state of a decision maker not matching that of the recipient. In empathy gap scenarios, a decision maker is unable to fully realize the cost or benefit of a decision outcome because the outcomes are not salient (Beisswanger et al., 2003; Loewenstein et al., 2001; Wray & Stone, 2005). This is in line with moral hazard explanations of the principal-agent problem where the agent is only incentivized by personal gain and only acts on this incentive. This explanation predicts no clear difference between egocentric and allocentric decisions, as no emotional cues, preferences, or response information are provided to the decision maker about the recipient. Furthermore, the decision maker receives the same compensation for participating no matter which decision is made.

An alternative hypothesis stems from socially accepted norms. Social and cultural norms act as a default or shorthand when engaging with new individuals. Social norms reflect the value a society places on domain-specific default behavior (Stone et al., 2013). For example, assigning effort to another may culturally constitute an inconvenience, harm, trust, or duty. The do-no-harm principle (Baron, 1995) predicts that decision makers will attempt to minimize inconvenience or harm to another, which would lead to steep discounting behavior. However, an egocentric decision maker may believe monetary rewards compensate for effort resulting in a less steep discounting rate. If the inconvenience caused by an assigned effort task is weighted more than the monetary reward in option valuation, an allocentric decision maker is unlikely to choose larger effort options. This scenario is a logical extension of many findings in cognitive psychology that show the weight of negative events is greater than positive ones (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). A decision maker would then prefer to minimize the effort assigned to others, even if this is not in line with her personal preferences.

A complimentary perspective in response to allocentric preference ambiguity comes from the concept of illusory superiority. Illusory superiority is the implicit cognitive bias that individuals believe themselves as better-off-than-average (Hoorens, 1993). This would imply that decision makers believe they are more capable than those they are deciding for and can outperform them in the typing task. Such over-estimating decision makers would likely minimize effort assigned to another to confirm this belief and reduce cognitive dissonance.

As the number of potential social factors is immense, the research presented here is basic and agnostic about the direction of the effect allocentric decision making will have on choice preferences and discounting behavior.

These initial studies only aim to establish the presence of a behavioral discrepancy between egocentric and allocentric effort discounting. The hypothesis is as follows:

H_0 = Allocentric decision outcomes will not differ from egocentric decision outcomes

H_{1A} = Allocentric decisions will result in less effort discounting than egocentric decisions

H_{1B} = Allocentric decisions will result in more effort discounting than egocentric decisions

2.3 First Experiment

2.3.1 Participants

98 participants were recruited from a university student population in Singapore (54 = N_{female}; M_{age} = 22). 26 participants were removed from analysis for having less than 5% variation in choice preferences or multiple failed catch trials, resulting in 37 participants in the egocentric ("Self") group and 35 participants in the allocentric ("Other") group. Participants were compensated for their time with $5 for the half-hour study duration plus the addition two averaged choices either made by themselves ("Self" group) or a participant before them ("Other" group). The mean additional compensation for the Self group was an additional $6.58 for typing 22 additional words. The mean additional compensation for the Other group was $6.52 for typing 7 additional words.

2.3.2 Methods

Participants were scheduled in group sessions, but responded independently in isolated, soundproof rooms using a computer. To incentivize participants to make decisions as accurately as possible, a random subset of decisions was resolved for real monetary and effort outcomes for each participant. In allocentric conditions, participants resolved outcomes from a prior participant and made choices for a future participant in a “pay-it-forward” design (M. H. Jung et al. 2014).

Each participant was randomly allocated to one of two groups. The Self group made egocentric decisions, whereas the Other group made allocentric decisions for a future participant in the study. After providing written consent, participants then viewed instructions explaining the typing task being assigned in the upcoming decisions and the recipient of the decision outcomes along with a small sample of the typing task to prove comprehension.

All participants underwent 75 decision trials, including three “catch” trials where one choice option was superior regardless of discounting. On each trial, participants chose between two bundles with each consisting of a variably sized effort task and compensation for completing that task (Figure 2.1); an example option pair would be choosing to type 0 words for $1 or 30 words for $5. Choices presented in the trials were identical between the two groups.

The 72 non-catch trials, consisted of 36 pairs of choice options repeated – once offered with an effortless reference option and once offered with a 50-word increase. The smaller effort, smaller reward option was held constant across trials - 0 words for $1.5 with a low reference option or 50 words for $1.5 in the high effort option. The larger-effort, larger-reward option varied orthogonally from 10-40 words for $4-10 when paired with effortless reference option or 60-90 words for $4-10 with the high reference option. Table 2.1 presents a representative subset of the stimuli used in the first experiment.

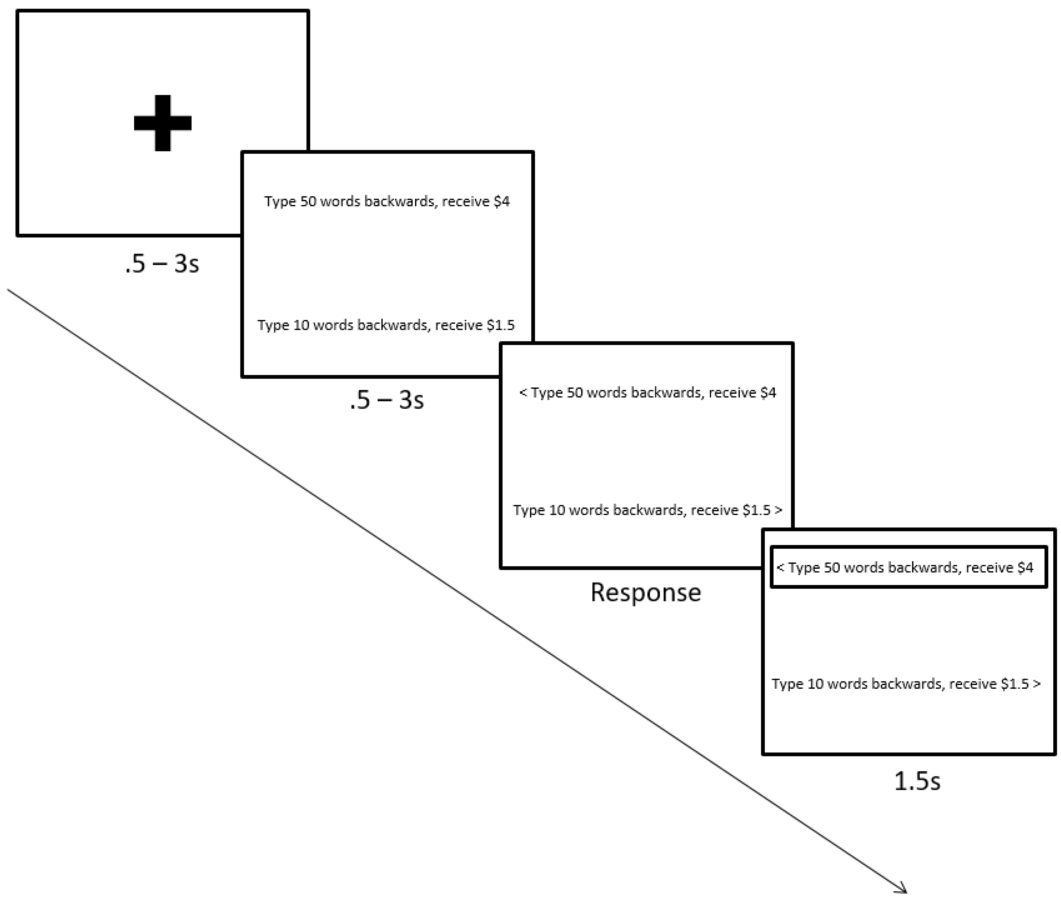

Figure 2.1: Sample trial from the within-participants experiment

Table 2.1: Sample choice stimuli from the between-participants experiment

Smaller Compensation	Smaller Effort	Larger Compensation	Larger Effort	Effort Reference Option
1.5	50	4	80	High
1.5	50	5	80	High
1.5	50	6	80	High
1.5	50	7	80	High
1.5	50	8	80	High
1.5	50	10	80	High
1.5	50	4	85	High
1.5	50	5	85	High
1.5	50	6	85	High
1.5	50	7	85	High
1.5	50	8	85	High
1.5	50	10	85	High
…	…	…	…	…
1.5	0	4	30	Low
1.5	0	5	30	Low
1.5	0	6	30	Low
1.5	0	7	30	Low
1.5	0	8	30	Low
1.5	0	10	30	Low
1.5	0	4	35	Low
1.5	0	5	35	Low
1.5	0	6	35	Low
1.5	0	7	35	Low
1.5	0	8	35	Low
1.5	0	10	35	Low
…	…	…	…	…

Choice options were presented randomly on either the top or bottom of the computer screen. Participants indicated their choice by pressing the arrow key matching the direction of the arrow next to their chosen option. The arrow directions were randomized on each trial to prevent automatic responses (Mullette-Gillman, Leong, & Kurnianingsih, 2015). After indicating their choice, participants received confirmation of their input with a black box surrounding their choice.

The effort task assigned by the decision outcomes was a typing task adapted from prior effort discounting studies (Lebidinsky et al 2013; Massar et al. 2016). After all choice trials, participants typed a list of words in reverse-letter order. If the decision recipient made a mistake, he or she was made to repeat the word. The size of the list was determined by averaging the outcomes from two choices made by either that participant or by another participant's allocentric choice. The computer randomly generated a list of words from a predetermined set which was identical for all participants. Figure 2.2 shows an example of the recipient's perspective of the typing task.

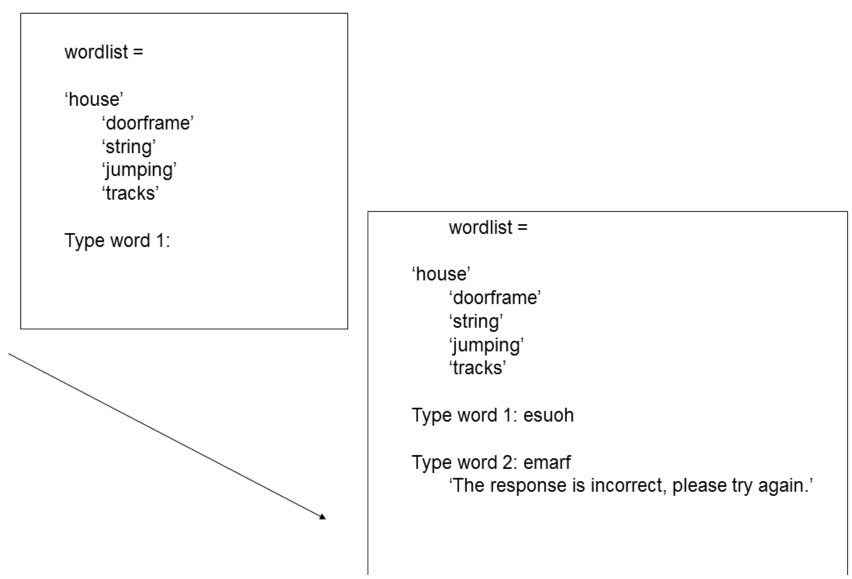

Figure 2.2: Example of the typing task

2.3.3 Results

2.3.3.1 Main Effects of Option Stimuli (Effort and Compensation) on Choice Behavior

To ensure participants were sensitive to changes in the option stimuli (effort and compensation amount), choice behavior was analyzed in relation to the large options' monetary value and effort value. Given that the monetary value and the effort of the larger option were varied independently, these option characteristics are shown in segregated analyses.

Figure 2.2: Figure 2.2 and Figure 2.3 show the mean proportion of choosing the smaller effort option (y-axis) as a function of the monetary compensation (Figure 2.3) or the effort required (Figure 2.4) of the larger alternative option (x-axis). In Figure 2.4¸ the effort is presented as a proportion of the maximum effort for an easier comparison between reference options.

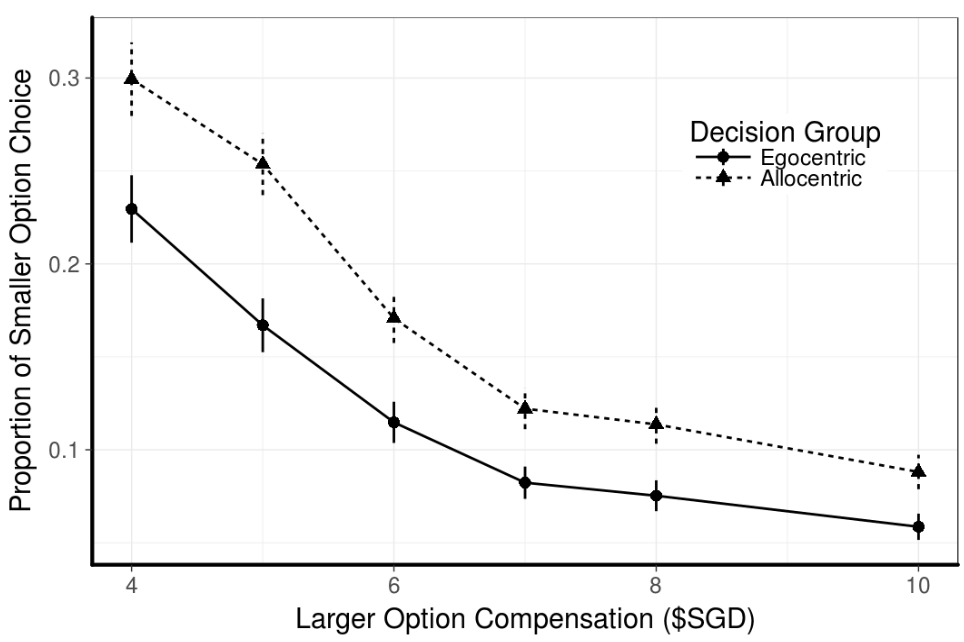

Figure 2.2: Choice proportions across Compensation

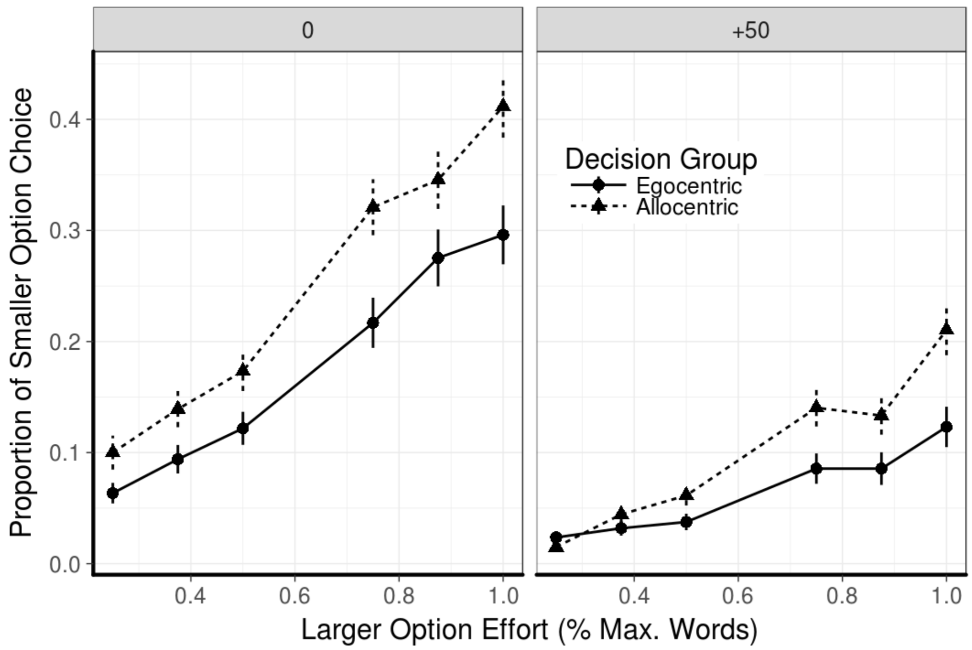

Figure 2.3: Choice proportions across effort split by reference option

To formally test these relationships, the proportion of smaller effort choices was regressed against compensation and effort in a linear model. Statistical analysis indicates that participants were sensitive to both compensation and effort. Linear regression shows a significant effect of both larger option compensation and effort in independently predicting the number of lower effort choices. Table 2.2 presents the results of the regression. Results show a negative main effect of the larger option's value on choosing the smaller effort/reward option. As the monetary value of the larger option increases, it becomes the more attractive option and the proportion of smaller effort choices decreases. Conversely, increasing the effort of the larger option makes it less attractive, resulting in a positive increase in lower effort choices. Both main effects in the linear regression are significant ($p < 0.001$).

Table 2.2: Linear Model Predicting Low Choice by Small Effort/Reward Option

Predictor	β	Std. Error	*p-value*	
Intercept	0.184	0.015	<0.001	***
Compensation	-0.031	0.001	<0.001	***
Effort	0.280	0.013	<0.001	***

*Significance codes: p<= 0.001 ***, p<= 0.01 **, p<= 0.05 **

2.3.3.2 Effort Reference Option Effects

The effects of the two effort reference options (0 and +50 words) were examined to ensure that effort discounting was reliable across ranges of effort, including effortless choices. Furthermore, it is important to dissociate effects of the effort reference option from allocentric-egocentric differences. Figure 2.4 shows the proportion of choices for each option across groups and effort reference option. Participants made smaller effort choices more frequently when the reference option was 0 words ($Mean_0 = 0.213$) than when the reference option was 50 words ($Mean_{50} = 0.083$) regardless of the outcome recipient. Similarly, participants making allocentric decisions more often chose the smaller effort option ($Mean_{Allocentric} = 0.175$) than those making egocentric choices

(Mean$_{Egocentric}$ = 0.121). However, the relative proportions of choice between the allocentric and egocentric groups are similar across reference option trials.

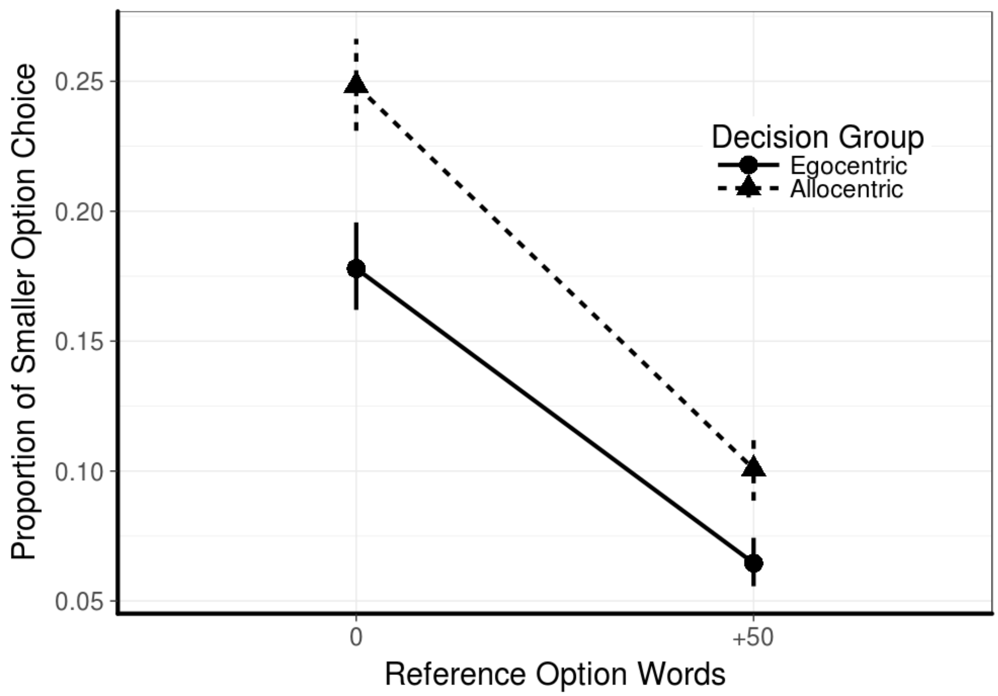

Figure 2.4: Choice proportion between groups and reference options

A generalized linear model (GLM) using a logistic link function shows that binary choice behavior is affected by the reference option, but does not interact with decision group. GLM estimations show that choice behavior is significantly affected by the reference option scaling and group manipulation ($p < 0.001$ for both), but the two predictors show no interaction effect ($p = 0.725$). Full GLM results are shown in Table 2.3.

.

Table 2.3: *GLM Predicting Smaller Effort Choice*

Predictor	β	Odds Ratio	SE	p-value	
Intercept	-2.673	0.069	0.111	<0.001	***
Allocentric Group	0.485	1.624	0.146	<0.001	***
Reference Option = 0	1.143	3.136	0.133	<0.001	***
Group x Reference Option	-0.062	0.940	0.175	0.725	

*Significance codes: p<= 0.001 ***, p<= 0.01 **, p<= 0.05 **

2.3.3.3 Effect of Group on Choice

To compare the effect of group manipulation on choice behavior across simultaneous changes to the effort and compensation of the larger option, a wage rate was calculated. A combined Words per Dollar (WpD) rate was calculated per the following:

$$WpD = \frac{Larger\ Option\ Effort - Smaller\ Option\ Effort}{Larger\ Option\ Compensation}$$

The WpD rate of the larger option is always in reference to the alternative smaller option. The choices were normalized by taking the difference between high and low effort (in words) and standardized by the compensation of the larger option. Compensation was constant across all smaller options and therefore irrelevant for determining the reference wage rate.

The proportion of low effort choices was aggregated for each level of unique value of WpD rate. WpD values ranged from 1.176 to 16 with mean =

5.672 and median = 4.661 showing a slight positive skewed in the distribution. The distribution skew was by design as pilot studies showed choice preferences converge as WpD rate increases.

Since there was no evidence of an interaction effect between group and reference option, we continue our analysis using combined, standardized data from both high and low effort reference option trials. Figure 2.6 shows the mean proportion of smaller effort choices as points with +/- 1 SE on the y-axis for each larger option's WpD rate on the x-axis. Comparison of the points shows an overall effect of allocentric decision making on choice. Allocentric choices resulted in the more frequent selection of smaller effort options compared to egocentric choices. Another GLM was fit to the collapsed choice data with WpD rate, and group as predictor variables using the combined reference option data. Figure 2.6 shows the GLM predicted probability of choosing a smaller effort option overlapped onto the mean choice data. Comparing the predicted probability curves, WpD rate had a strong effect on choice, mirroring the independent stimuli effects seen before. The higher the WpD rate of the larger option, the more likely a participant would choose the lower effort alternative regardless of who would receive the outcome.

Group manipulation between egocentric and allocentric decisions had a significant effect on both the intercept and slope of the model, with allocentric decisions showing increased smaller effort choices across all levels of WpD rate, with this effect increasing as WpD increases ($p = 0.014$). This suggests participants making allocentric choices were more sensitive to the WpD rate of the larger option. Full results from the GLM are shown in Table 2.3.

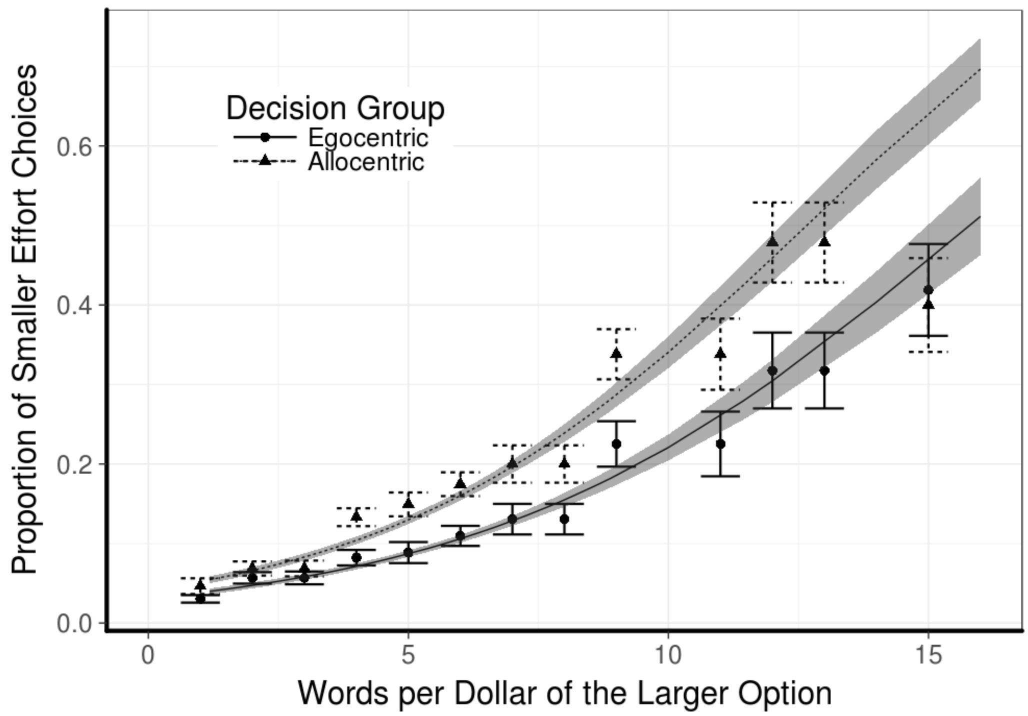

Figure 2.5: Mean Choice proportions across WpD with overlay of GLM predicted probabilities

Table 2.3	GLM Predicting Choice of Smaller Effort/Reward Option				
Predictor	β	Odds Ratio	SE	*p-value*	
(Intercept)	-3.438	0.015	0.058	<0.001	***
Allocentric Decision Group	0.289	1.335	0.079	<0.001	***
WpD	0.218	1.243	0.009	<0.001	***
WpD x Allocentric	0.031	1.032	0.013	0.014	*

*Significance codes: p<= 0.001 **, p<= 0.01 **, p<= 0.05 **

2.3.3.4 Discounting Behavior Analysis

To formally compare discounting behavior, a more precise method is needed than a wage rate; this is because there can be two sources of the same wage rate. For example, a low effort task coupled with low compensation will have a similar wage rate as a high effort task with high compensation, but these combinations are unlikely to have equivalent subjective value. To remedy this, discounting behavior analysis requires a function that represents value monotonically across one dimension (choice attribute). Effort discounting represents the change in subjective value across effort levels. Indifference points were used to represent the value at which a decision maker is ambivalent between the constant smaller option and the larger option. Indifference points reveal an estimate of a participant's subjective value for the larger effort option and were estimated independently for each participant at each unique level of effort.

A logistic regression was fit predicting choice, a binary dependent variable, across all values of compensation at a given effort level. The indifference point is the monetary value (on the x-axis) where the predicted choice probability (y-axis) equals 0.5. In a one-predictor regression, the indifference point can be estimated by the negative inverse ratio of the intercept estimate divided by the slope estimate (Moscatelli, Mezzetti, & Lacquaniti, 2012):

$$IndifferencePoint = \frac{-\beta intercept}{\beta slope}$$

For effort levels where all choices were identical, the indifference point was set to the minimum or maximum compensation value +/- 1 standard deviation. The indifference points were then standardized by the smaller option value. To compare the indifference points across reference options, we used a standardized percent of maximum effort measure:

$$Effort = \frac{LargerOptionWords - SmallerOptionWords}{MaximumOptionWords - SmallerOptionWords}$$

For example, if the effort reference option was 50 words and the larger option was 80, the effort would be 0.75 ($\frac{80-50}{90-50}$). If the reference option was 0 and the larger option was 20, the effort would be 0.5 ($\frac{20-0}{40-0}$).

The mean subjective values for each level of effort in each condition are plotted in Figure 2.6 with +/- 1 SE error bars. Comparison of indifference points for each level of effort by Wilcoxon Rank Sum test are presented in Table 2.4.

Table 2.4 Indifference Point Comparison between Groups

Effort	0	25%	37.5%	50%	75%	87.5%	100%
Wilcox Rank Sum Test p-values	NA	0.99	0.35	0.30	0.01**	0.09	0.07

*Significance codes: p<= 0.001 **, p<= 0.01 **, p<= 0.05 **

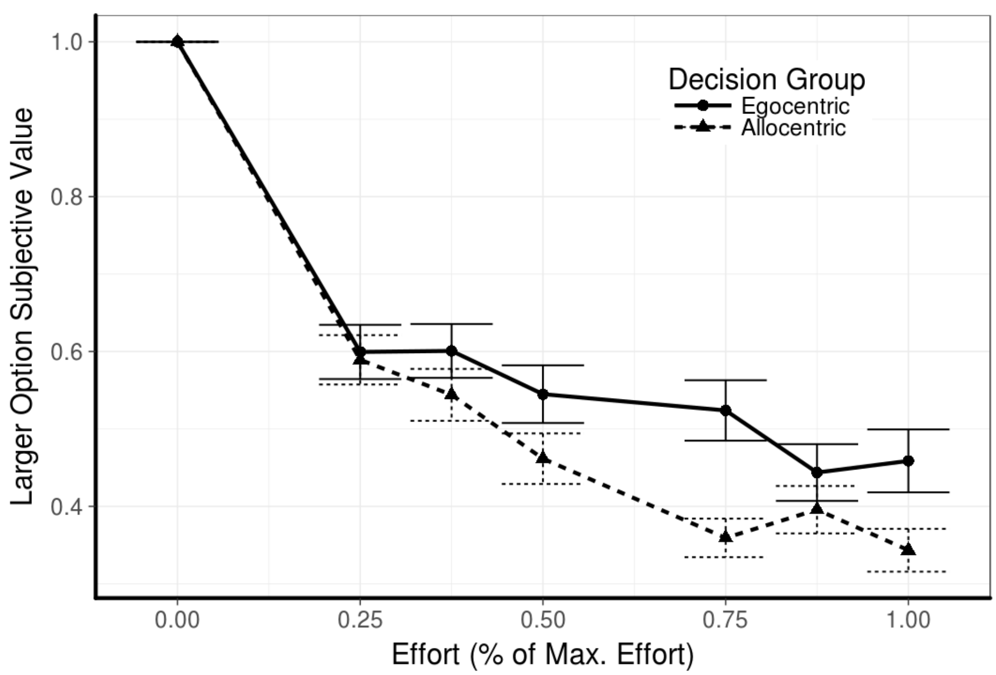

Figure 2.6: Mean indifference point estimates by group

For a model-free analysis of discounting behavior across the effort domain, the area under the curve (AUC) was estimated for each subject and compared between conditions (Myerson, Green, & Warusawitharana, 2001). By comparing discounting rates rather than indifference point estimates, these results reflect overall trends in effort valuation which are less susceptible to erroneous key press entry and are more easily interpreted and generalized across trials. Each participant's indifference points were calculated independently for each effort reference frame and then in a combined data set that included both the high and low reference frames standardized as the difference between the options' effort levels. The AUC was computed using trapezoidal approximation. Allocentric decisions showed a lower median AUC than egocentric decisions ($AUC_{Allocentric} = 0.39$, $AUC_{Egocentric} = 0.43$). Comparison of AUC values between conditions shows a statistical trend difference (Wilcoxon statistic = 482.5, $p = 0.064$).

2.3.4 Discussion

The results here provide evidence that differences in choice behavior and effort discounting exist between allocentric and egocentric decision makers when choosing between variably-sized effort tasks completed for monetary compensation. Both effort and compensation had significant, independent effects on choice outcomes.

The effects of the effort reference option mirror prior literature on decision making distortions with zero-cost options (Shampanier, Mazar, & Ariely, 2007). The zero-cost option is analogous to the effortless reference option and was preferable to non-zero cost option in both groups. However, there was no interaction effect with group manipulation, the main variable of interest.

Participants exhibited choice differences between groups. The egocentric decision group made more high effort choices than the allocentric group. GLM estimations show this difference increases as the WpD rate of the larger option increases. Indifference point estimation show statistical trends that support this finding, but only one indifference point showed a statistically significant difference at 75% of maximum effort.

The indifference point analysis combined with the GLM fit both show consistent evidence that participants in the allocentric condition discounted compensation by effort more than egocentric decision makers. The difference in AUC shows allocentric decision makers discounted the subjective value of choice options by effort more than egocentric decision makers across the entire effort range. Further investigation is needed to determine if the effect of allocentric decision context is robust or an artifact of the group manipulation. The second experiment controls for the effort preferences of the decision maker by utilizing a within-participants design.

2.4 Second Experiment

2.4.1 Motivation

The second experiment serves the dual purposes of replicating the initial findings using a within-participants design and investigating a potential moderator of allocentric and egocentric differences in social accountability. As noted in the introductory chapter, accountability is an ecologically valid moderator of decision making. Professional decisions rarely occur in the absence of accountability to prevent fraud and malpractice. By definition, allocentric decisions take place in a social environment and therefore are often subject to judgment of the recipients or third-party viewers. Additionally, both accountability and allocentric decision making are often used to curb egocentric biases by using social pressures to curb desires in favor of social norms. The following experiment investigates accountability from a third-party regulator as a potential moderator of allocentric decisions.

2.4.2 Accountability

Accountability is a state where an individual must justify beliefs, attitudes or behaviors to another (Lerner & Tetlock 1999). Accountability has been shown to affect attenuation to information and complexity of thought in decision making processing (Tetlock & Boettger, 1989). More recent work shows accountability can moderate robust decision-making phenomenon such as loss aversion, risk aversion, and sunk-cost bias (Pahlke, Strasser, & Vieider, 2012; Pollmann et al., 2014; Simonson & Nye, 1992). Similar findings show when investing for others, participants exhibited less risk and loss aversion, but this difference was mitigated when decision recipients could reward the decision maker (Pollmann et al. 2014). Using interview paradigms from Tetlock's early studies (1983; 1985) and replicated in Pahlke et al. (2012), this experiment attempts to maximize perceptions of accountability. Based on review and recommendation from the literature, the interview was presented to the participants as a request from a third party of authority who had valid interest in the decision – the head experimenter – and required both outcome and process accountability.

Participants were made aware of the requirements for accountable decisions before making any choices.

2.4.3 Participants

86 undergraduate students (55 female; $Mean_{Age} = 21$) from a Singapore university were recruited. 10 participants had less than 5% variation in choice preferences or multiple failed catch trials (n = 76). Participants were recruited via an internal database and compensated $5 SGD for their time plus the average of an outcome chosen by themselves and one outcome chosen by another participant. The mean added compensation was $5.73 for typing an additional 16.35 words.

2.4.4 Procedure

This experiment utilized a within-participants design conducted in a laboratory environment. All participants made identical decisions in each of three conditions. The first two conditions were similar to the first experiment where participants made choices for themselves (Self) or another participant (Other: No Accountability or ONA). The recipient was an anonymous participant who did not reciprocate decisions and was double-blind anonymous to the decision maker. The third condition was identical to the ONA condition, but required justification of the choice during an interview with the head experimenter (Other: Social Accountability or OSA). Participants were informed prior to any decision making that during the post-hoc interview, choices from randomly selected trials would need to be explained to the head experimenter. The interview was conducted after all decisions were made, but before outcomes were resolved.

Figure 2.7: Stimuli for indicating the condition of the upcoming trial

After giving written, informed consent, participants made 81 binary decisions independently via computer including three catch trials. Participants first identified the condition of the upcoming trial presented via one of three indicator images on screen, shown in Figure 2.7. After confirmation of the condition on the computer, participants chose between two bundles of effort and compensation similar to the first experiment (Figure 2.8). One bundle was a constant, small effort-small reward option (10 words for $1.5 SGD). The other option was a larger effort – larger reward option with option stimuli varying orthogonally between $4-$10 and 20-50 words. The experiment operationalized effort using the same typing task as the prior experiment and trials were presented in random order with regards to effort, compensation, and condition.

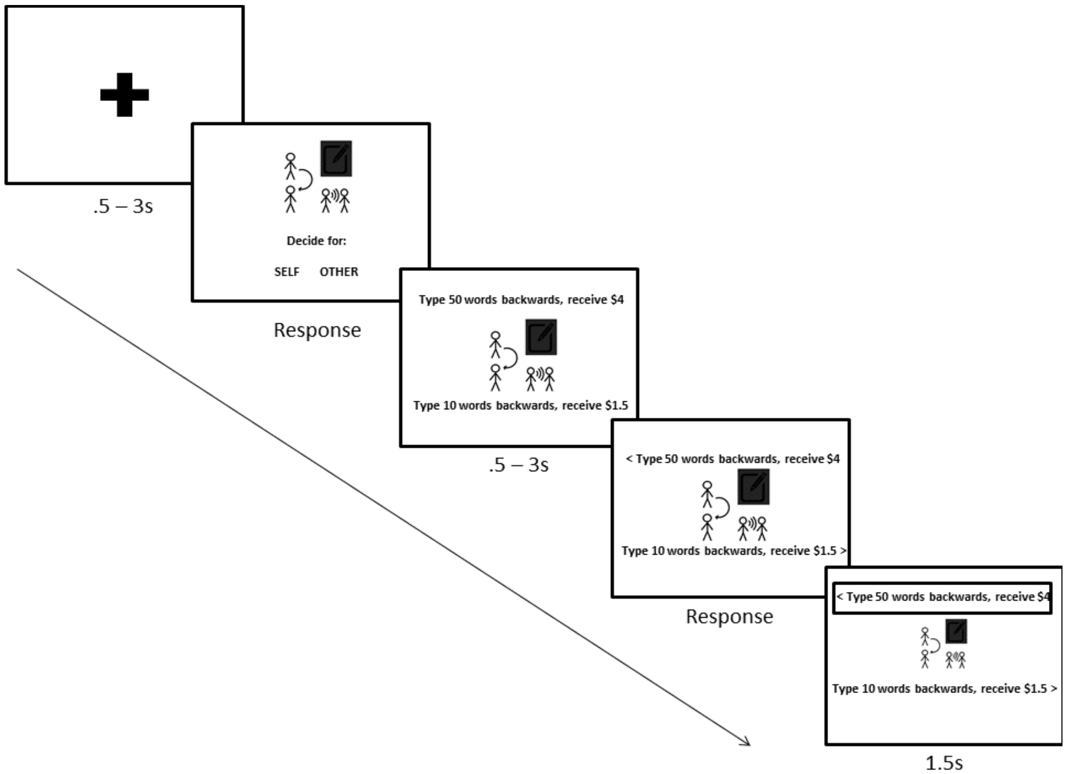

Figure 2.8: Sample trial from the between-participants experiment

2.4.5 Results

2.4.5.1 Main Effects of Option Stimuli (Effort and Compensation) on Choice Behavior

The stimuli for this design were examined using linear regression to demonstrate main effects of both the compensation and effort parameters on the probability of choosing the low effort option. Similar to the findings in the first experiment, the large option value has a negative effect on choosing the smaller option ($p < 0.001$) and the large options' effort cost has a positive main effect ($p < 0.001$), indicating that participants were sensitive to both effort and compensation manipulations. For full results, see Table 2.5. Figure 2.9 presents the smaller effort choice proportion across all levels of effort (x-axis) with +/-1 SE bands. Figure 2.10 shows the same dependent variable across all levels of monetary compensation (x-axis).

Table 2.5 Linear Model Predicting Choice of Smaller Effort/Reward Option

Predictor	β	Odds Ratio	SE	*p- value*	
Intercept	0.233	0.028	8.322	<0.001	***
Compensation	- 0.095	0.003	- 31.071	<0.001	***
Effort	0.022	0.001	41.514	<0.001	***

*Significance codes: p<= 0.001 ***, p<= 0.01 **, p<= 0.05 **

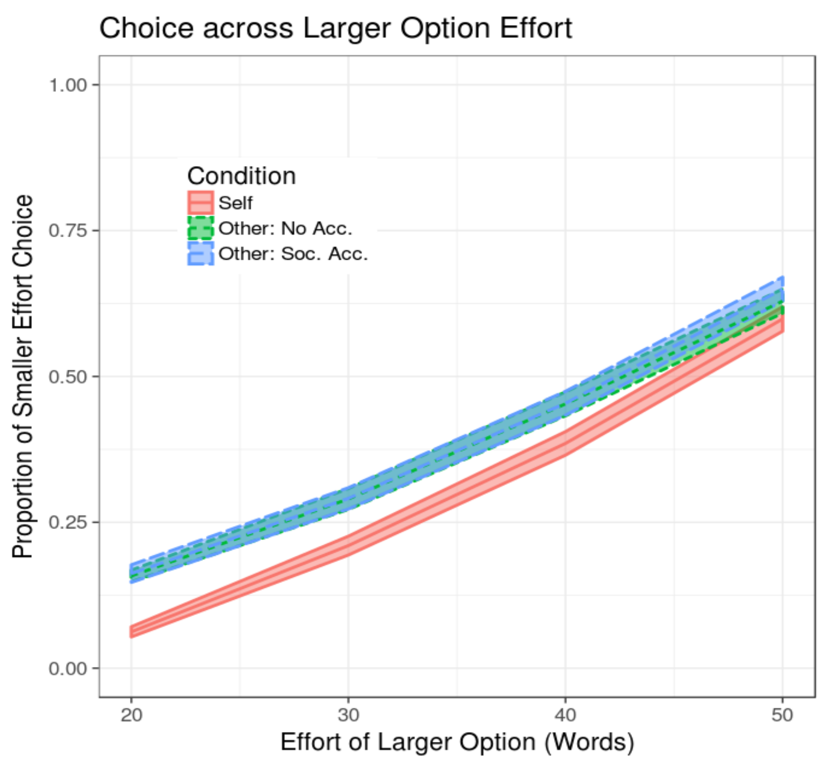

Figure 2.9: Choice outcomes vary as the effort of the larger option increases

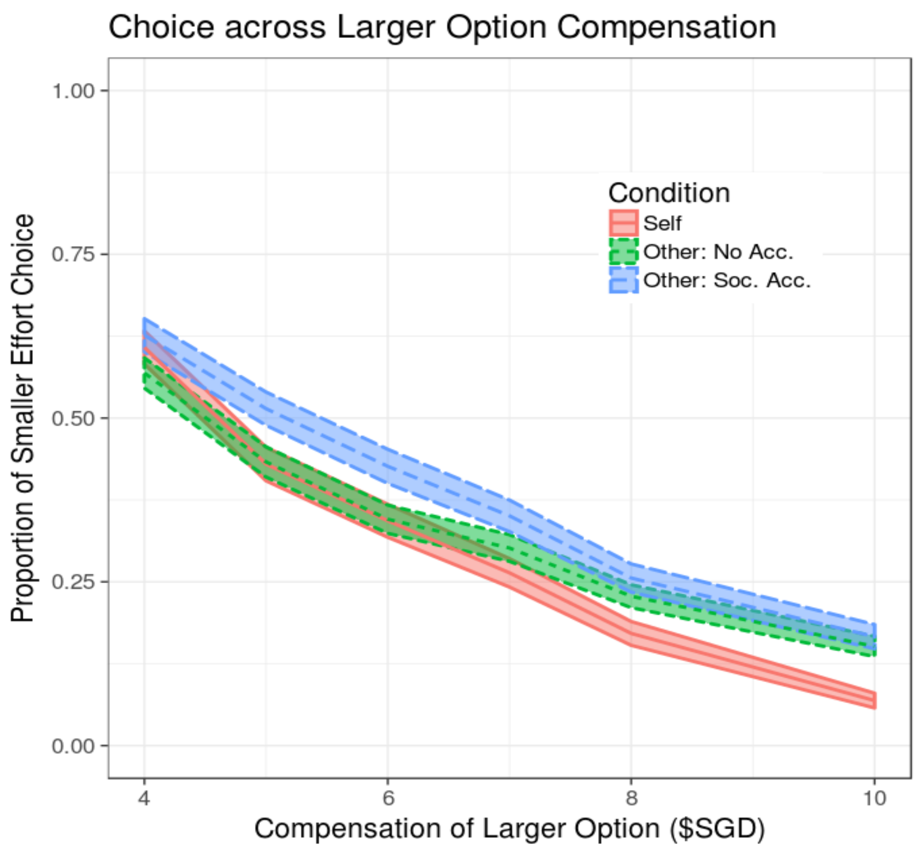

Figure 2.10: Choice outcomes vary with the compensation of the larger option

2.4.5.2 Main Effect of Condition on Choice

To compare the value of the combined bundle of effort and money, WpD Rate was computed as before. The proportion of low effort choices was calculated for each WpD rate and plotted by condition in Figure 2.11. A GLM was fit to the data using the Other: No Accountability condition as the reference category to allow likewise comparison for each alternative condition (decision recipient and accountability respectively). Both WpD rate and condition are significant predictors of choice with egocentric decisions less likely to result in lower effort outcomes than allocentric choices at all levels of WpD Rate ($p < 0.001$ Self Condition). However, allocentric decisions under accountability did not significantly differ from allocentric decisions without accountability ($p = 0.102$).

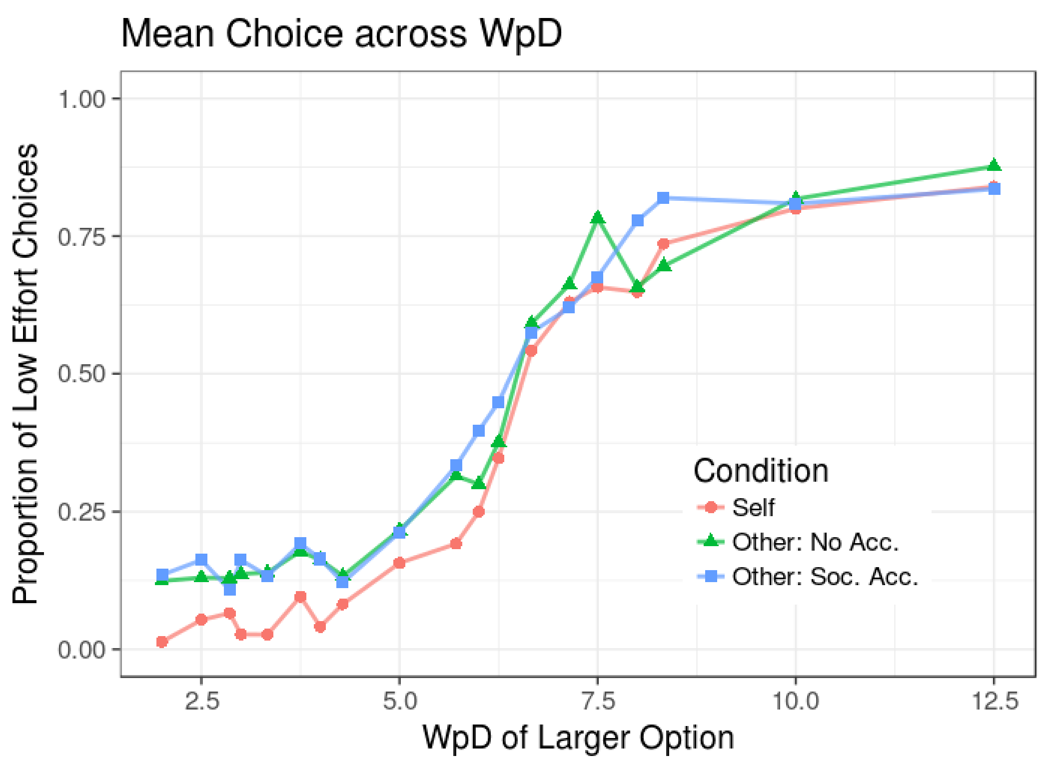

Figure 2.11: Choice varies as the WpD rate increases

Table 2.6 GLM Predicting Choice by WpD and Condition

Predictor	β	Odds Ratio	SE	z-value	*p-value*	
(Intercept)	-3.525	0.029	0.081	-43.330	<0.001	***
WpD Rate	0.508	1.662	0.016	32.670	<0.001	***
Self	-1.643	0.193	0.158	-10.377	<0.001	***
Other: Social Acc. (OSA)	-0.224	0.799	0.137	-1.637	0.102	
WpD x Self	0.203	1.224	0.027	7.484	<0.001	***
WpD x OSA	0.043	1.044	0.025	1.738	0.082	

*Significance codes: p<= 0.001 ***, p<= 0.01 **, p<= 0.05 **

2.4.5.3 Mixed Effects Modeling

Traditional GLM does not distinguish variance in the dependent variable attributed to differences between participants from variance attributed to trial-level predictors. Parsing these effects is important. Each decision maker may possess different typing abilities or contain other forms of unexplained heterogeneity that may bias the effect size estimate well beyond the experimental design of randomized sample selection. For example, one participant may think she is an excellent typist compared to the average student while another may think he is very poor. Furthermore, one participant may use different cognitive strategies when evaluating options, leading to systematic differences in option selection. Variance attributable to between-participants effects, also known as individual differences, is considered more specifically in chapter 3, while the current analysis hones findings related to the effects of condition and trial-level predictors.

To control for interpersonal differences post-hoc, a mixed-effects GLM (GLMM) was fit to allow for observations within-participants to covary in terms of both intercept (mean condition differences) and slope (WpD rate x condition interaction) (Baayen, Davidson, & Bates, 2008). This method of analysis helps to isolate the effect of condition across the sample and makes results more generalizable to the population level (Moscatelli et al., 2012). The model fits grouping-level parameter estimates (in this case the group of observations are linked to one participant) using maximum-likelihood estimation from the lme4 package for R (Bates, Mächler, Bolker, & Walker, 2014). Unlike in two-step hierarchical regression, grouping-level parameters are estimated simultaneously with observation-level (choice-level) predictor estimates.

To ensure the best fit to the data, three nested models were compared. The initial fixed-effects only GLM, a random-slope model, and a random slope and intercept (referred to hereafter as a "crossed") model were compared using the Akaike Information Criterion (AIC). Of the three models, the crossed model exhibited the lowest AIC. A likelihood ratio test shows the improvement in the model fit is significant between the two mixed-effects models, justifying the need for a crossed-model. Full results are presented in Table 2.7.

Table 2.7 Model Comparison Likelihood Ratio Test

Model	df	AIC	Chi^2	p-value
Fixed Effects Only	6	14200.710		
Random Intercept	7	9114.434	9100.4	
Crossed (Random Intercept and Slope)	9	7070.555	7052.6	<0.001***

*Significance codes: p<= 0.001 ***, p<= 0.01 **, p<= 0.05 **

The random effects of the crossed model are variance estimates of each participant (intercept) and the participant by WpD rate interaction (slope). Strong evidence for random effects can be seen in Figure 2.12 which shows the standardized variance estimate for each participant with respect to the grand mean (black vertical line). The blue and red colored participants show deviations from the grand mean that are significantly different using a two-tailed t-test.

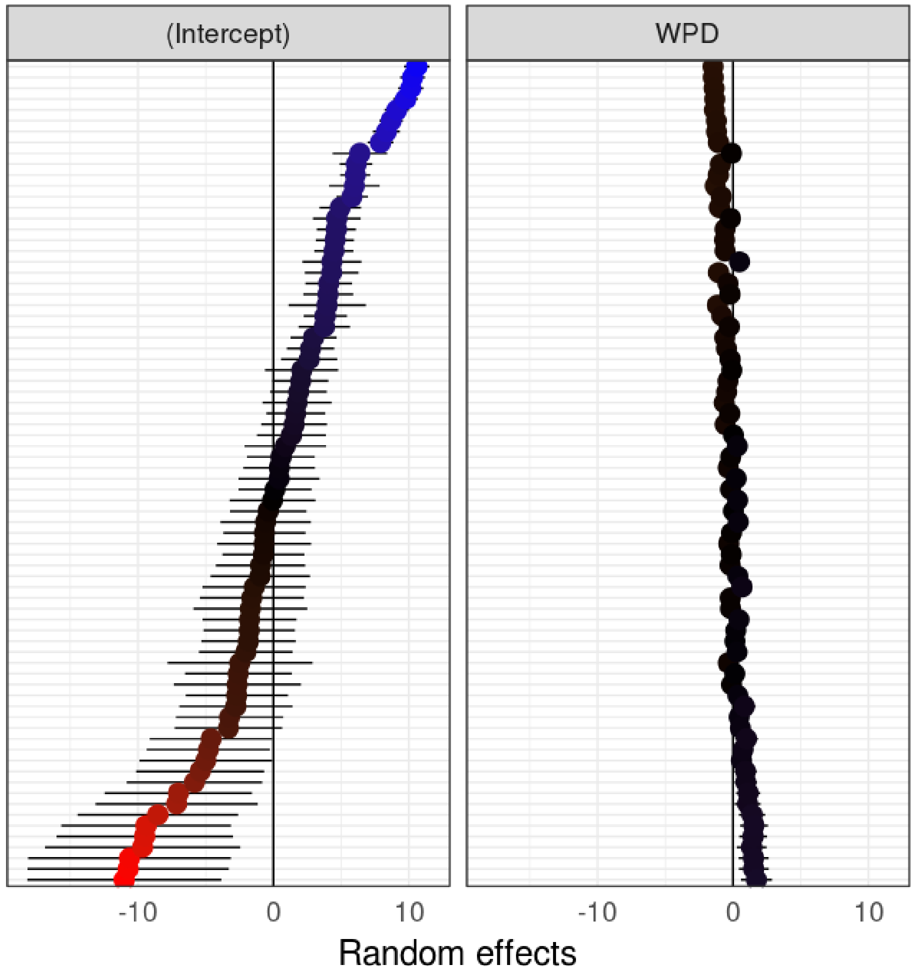

Figure 2.12: Random effects estimates and 95% CI for each participant in the crossed model

The fixed effects of interest are the same as with the prior GLM model, with independent and interaction effects of WpD rate and condition used as predictors of choice behavior. The model presents a similar shape to the GLM (Figure 2.11), but with additional power due to bootstrapped sampling of parameters over 5000 iterations. Using the Other: No Accountability condition as the reference category, the model shows significant differences between Self and Other conditions both as a main effect and interaction across WpD rate ($p < 0.001$ for both). No differences were observed between the two Other conditions or the interaction with WpD rate ($p_{OSA} = 0.490$, $p_{OSAxWpD} = 0.345$ respectively). Table 2.8 shows the full results of the GLMM while Figure 2.13 shows the predicted probabilities of choosing the smaller effort option for each condition as WpD increases.

Table 2.8 Results of the Crossed GLMM Predicting Choice

Predictor	β	Odds Ratio	SE	z-value	p	
(Intercept)	-8.141	0	0.745	-10.929	< 0.001	***
WpD	1.222	3.394	0.113	10.759	< 0.001	***
Self	-2.515	0.081	0.201	-12.499	< 0.001	***
Other: Soc. Acc. (OSA)	-0.126	0.882	0.182	-0.690	0.490	
WpD x Self	0.296	1.344	0.034	8.608	< 0.001	***
WpD x OSA	0.031	1.031	0.033	0.944	0.345	

Significance codes: p<= 0.001 ***, p<= 0.01 **, p<= 0.05 *

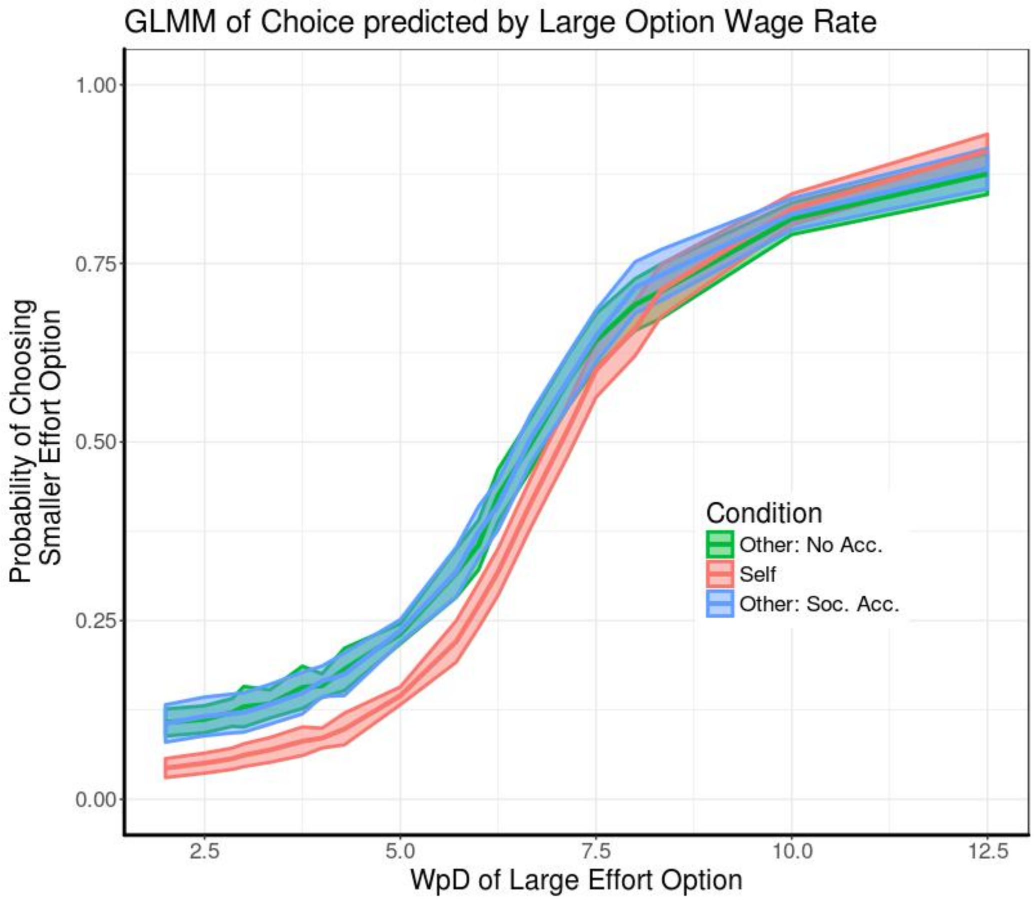

Figure 2.13: Fixed effects of the crossed model predicting choice by WpD and Condition

2.4.5.4 Discounting Behavior Analysis

To investigate discounting behavior, indifference points were estimated for all levels of effort within each subject and condition. The standardized subjective value across effort levels is shown in Figure 2.14. The larger effort option in the egocentric condition exhibits higher subjective value than in the allocentric conditions. AUC analysis confirms similar results to the findings from experiment one ($Mean_{Self}$ = 0.379, $Mean_{ONA}$ = 0.345, $Mean_{OSA}$ = 0.352). One-way ANOVA of

AUC by Condition shows significant differences between conditions ($F = 3.826$, $p = 0.023$). Pairwise Wilcoxon sign-rank tests confirms that allocentric-egocentric differences drive this effect, while there are no significant differences in the effect of accountability ($p_{Self\text{-}ONA} = 0.0003$, $p_{Self\text{-}OSA} = 0.0018$, $p_{ONA\text{-}OSA} = 0.4076$).

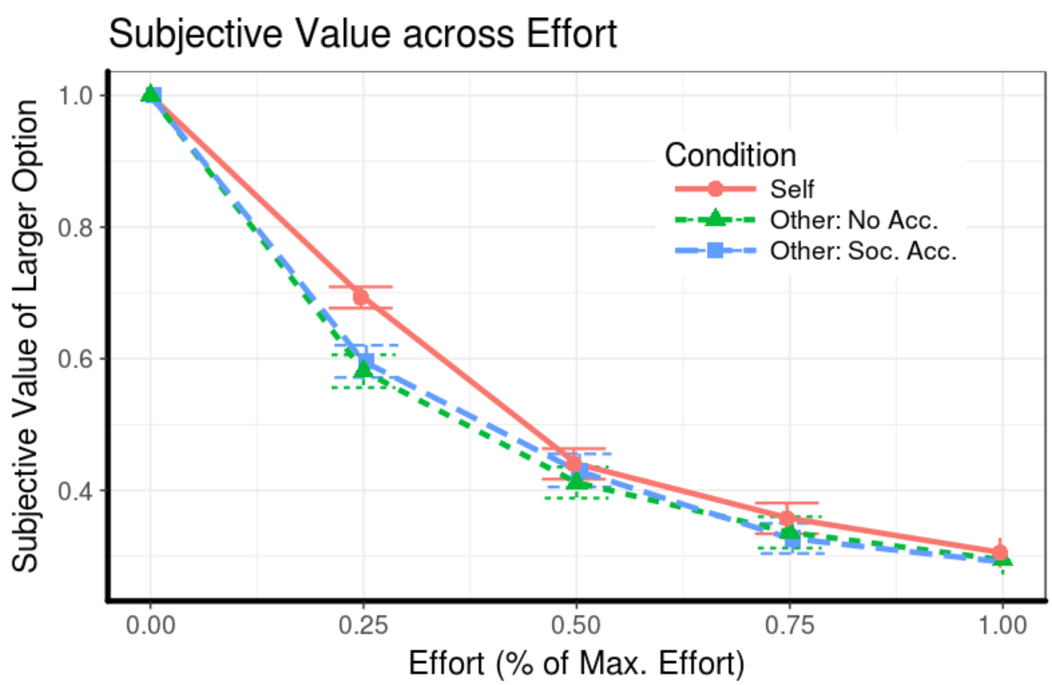

Figure 2.14: Mean indifference points by condition for each unique effort level

2.4.6 Discussion

The results from the second experiment showed evidence for allocentric-egocentric differences in effort decision making. These results confirm the findings from the first experiment. Choice differences were observed using mixed-effects modeling of all three conditions to increase the internal validity of the analysis. The mixed-effect model showed significant differences between egocentric and both allocentric conditions while controlling for between-participants' variance.

Analysis of effort discounting behavior was conducted indifference point estimation and AUC analysis. Comparison of AUC between conditions showed that choice differences are related to how decision makers value an option based on the effort required to obtain it.

2.5 Conclusion

In two behavioral choice studies, effort discounting behavior was observed in both egocentric and allocentric conditions when making decisions determining the effort and compensation of a typing task. Furthermore, both the within- and between- participants designs produced effort discounting behavior. The results of the stimuli validation provide evidence that the typing task is adequate for eliciting discounting behavior.

The behavioral experiments presented here show a robust difference between allocentric and egocentric decision making, both within- and between-participants. Participants in these experiments discounted the monetary compensation of choice outcomes more when considering another person's effort compared with their own. Stated another way, egocentric decision makers exhibited reduced effort discounting compared to allocentric decision makers. Findings from both experiments support hypothesis H_{1B}.

Furthermore, social accountability, a moderator of interest, did not affect allocentric decision making. This was an unexpected finding given prior research. Social accountability neither exacerbated nor reduced the effect of deciding for another. While difficult to interpret a null result, it is noteworthy that both allocentric conditions exhibited similar results, which reinforces the robust effect of egocentric-allocentric differences. Whether the lack of an effect of accountability is due to poor operationalization or the effect size being dwarfed by the relatively larger effect of egocentric-allocentric differences is unknown and merits further investigation. Decision making studies using similar operationalizations of accountability have found effects on loss aversion and risk taking, but it may be such that accountability does not play a large roll in effort discounting decisions particularly.

Overall, the behavioral evidence accrued in these studies requires a deeper understanding of the cognition underlying these choice outcomes. Different methods are required to understand the underlying cognitive mechanisms of the observed allocentric-egocentric choice differences. Decision makers may have given more weight to the attribute of compensation in egocentric decisions than allocentric ones, as predicted by the empathy gap explanation. Conversely, decision makers may have weighted the allocentric effort more than egocentric effort as predicted by the do-no-harm principle. The results are agnostic about these underlying mechanisms. Furthermore, it may be that both theories are correct and used by different decision makers.

To advance understanding of this phenomenon, more specific models of cognition are needed to test hypotheses of latent cognitive processes.

3 Computational Cognitive Modeling of Effort Discounting

3.1 Introduction

Understanding the cognitive mechanisms driving differences between egocentric and allocentric decisions requires modeling latent processes. Computational models mimic the internal “black box” calculations of the brain responsible for valuing each option and selecting the one with highest value. Models can describe both the representation of the available choice options and the means of comparison for option selection. Computational modeling is important for comparing hypothesized latent processes between individuals, groups, or with other forms of discounting behavior. In addition to identifying and describing the mechanisms underlying allocentric effort decision making processes, computational cognitive modeling results can be compared with individual measures to investigate individual differences in decision making.

Identifying an explicit model how effort discounts value is beneficial for two primary reasons: specificity and generalizability. One reason is that an explicit modeling approach allows for comparison of multiple models on the same data set which provides an opportunity to test theoretical differences in model construction. Using goodness of fit measures, multiple models can be compared independently even when fit to the same underlying data. Goodness-of-fit measures assess the ability of the models to explain behavioral choice data. Each model can test different assumptions about the latent mechanisms involved in decision making and therefore provide implicit testing of hypotheses. For example, four candidate models are used in this chapter, but they can grouped along two dimensions. Comparing each dimension results in a theoretical test without requiring new data collection.

The second reason is that models are easily generalized to other data. Upon determination of the best fitting model for one data set, identical fitting methods and parameters can be replicated and tested on new data sets to evaluate a model's robustness between experiments, manipulations, or participant samples. Theoretical assumptions drive this cross-validation strategy by grouping data by manipulation or sample while not explicitly modeling these differences. For instance, imposed experimental manipulations are used to segregate the data into sets (train-test splits) rather than modeling marginal effects of conditions from the average (such as in logistic regression analysis). This method allows the model to retain parsimony while allowing for cross-sample comparison.

Another method of analysis is to fit the same model between data sets but allowing the parameters to be estimated freely and independently for each data set. Parameter estimates can then be compared between participants, experiments, manipulations, or conditions. Parameter comparison is more specific than the goodness-of-fit comparison as parameters may explicitly correlate with theoretical cognitive constructs. For example, when modeling learning behavior, one parameter may distinguish between participants' overall learning rate while another parameter estimates models task difficulty. Comparing the parameter differences provides evidence for which aspect of the cognitive mechanism is responsible for behavioral differences. The following investigation in this chapter utilizes both goodness-of-fit and parameter comparison strategies.

While prior computational models have successfully represented learning and reward (Daw, O'Doherty, Dayan, Seymour, & Dolan, 2006; John P. O'Doherty, Dayan, Friston, Critchley, & Dolan, 2003), risk aversion (Tversky & Kahneman, 1992), and temporal discounting (Ainslie, 1975; Laibson, 1997), computational modeling can be a controversial as it relies on estimations of latent cognitive processes that are not directly observed and are heavily influenced by theoretical assumptions. Furthermore, models are prone to overfitting where representations of random variance in the data become modeled instead of true signal. To prevent overfitting, models should be estimated with large samples and ideally across multiple data sets. Fitting a model using different choice scenarios helps establish test-retest reliability. Additional measures to prevent overfitting include selecting parsimonious models that exhibit good fit to the data while using the fewest number of free parameters possible. Comparing multiple models using an information criterion that accounts for the number of parameters is crucial when determining the best representation of latent cognitive processes.

Even the best models are only approximations of cognitive computations, and are often contentious in the literature. Computational models of effort discounting behavior are not widely agreed upon (Hartmann et al., 2013; Klein-Flügge et al., 2015). Several competing models and theoretical conflicts currently exist to explain effort discounting phenomena. They differ in generalizability between effort tasks and may not separate the differential effects of mental and physical effort. As of writing, no models have been formalized for effort decisions related to the typing task used in this thesis.

Two important theoretical questions arise when reviewing the current discourse on effort discounting models:

(1) What is the relationship between the cost of effort and the value of its outcomes in computing subjective value? Is the relationship additive or multiplicative?

(2) What is the shape of the effort discounting function and what does that imply about value computation of extreme effort values?

Each question merits further development. The first question is arguably more straightforward as it can be reduced to a purely quantitative concern of model fit. Per common currency theories of decision making, benefits and costs must be combined when decision makers cognitively represent choice options (Levy & Glimcher, 2012). The overall or subjective value of a simple, single-cost/single-benefit choice option can be mathematically expressed in many ways. Additive computational models involve a linear comparison between the amount of effort and the amount of reward where one term (usually the cost) has been scaled and subtracted from the objective value of the reward. Stated another way, the subjective value of these two attributes (effort cost and benefit) are computed independently and compared in the same scale through addition/subtraction of like terms where the effort cost has been weighted by estimated parameters.

A common alternative, is a multiplicative comparison where a lumped subjective value of the entire option arises from more complex computation. The reward is standardized by the effort cost which is scaled by a discounting parameter. Comparison between additive and multiplicative models can be tested with goodness of fit comparison to determine which is a better fit for the choice data.

The second question reflects a theoretical argument and requires further explication in the form of an analogy. Imagine lifting weights. Lifting more weight at the gym always requires more effort (or “work” technically speaking in Newtonian physics). However, as the weight becomes heavier there will be a threshold where the weightlifter cannot perform the task regardless of effort applied. This upper limit of strength may differ between individuals, but it exists for some amount of weight for every human. Conversely, there are relatively small amounts of effort that are essentially “effortless” to even a weak person. Per cognitive miser theories, the cognitive cost of computing how to evaluate such effort may be more than the effort cost itself (Shenhav et al., 2017). Assuming these analogies hold in the typing task, the discounting function should show no change in subjective value for these extremely low or high levels of effort, but variable change in between. However, such extremes may or may not exist in the scope of effort levels used in the task. Limits of strength and endurance are different for each subject based on their capabilities and highly dependent on how a researcher chooses to operationalize effort. This makes “off-the-shelf” model fitting risky without prior knowledge of discounting behavior in the specific task used. The model must be contingent on the task and rooted in assumptions made based on data. To minimize issues from improper assumptions, several models were fit to the data using competing and diverse assumptions to determine the best-fitting model.

Taking into consideration these issues, four models were selected from the current effort discounting literature to fit to behavioral choice data from chapter 2. Each model reflects a unique computation for how decision makers create a cognitive representation of value for a given choice option. The candidate models are the hyperbolic model, parabolic model, sigmoidal model, and the two-parameter flexible power model (referred to hereafter as “power model” for simplicity).

All four of these models can be characterized based on two dimensions. The first dimension is the number of parameters freely estimated. The power model and sigmoidal model estimating two free parameters (denoted as *k* and *p*) while the hyperbolic model and parabolic model estimate only one parameter (denoted as *k*). The number of estimated parameters reflects the flexibility of the model and its ability to fit different shapes of discounting curves, with two parameters being more flexible than one. The second dimension is how the models combine effort and reward. The power model and parabolic model use additive combination while the hyperbolic and sigmoidal use multiplicative combination. The second dimension reflects the shape of the discounting function and the assumptions made at extreme values of effort. The combination of these dimensions creates a unique model representing different cognitive processes. The implications of each model are discussed below.

The hyperbolic model is a standard discounting model borrowed from temporal discounting literature (Ainslie, 1975) where the value of a reward decreases (or is discounted) as the time between choice and reward delivery increases. When a reward requires 0 effort, there is no discounting and the subjective value is equivalent to the listed value of the reward ($5 has a subjective value of $5 or 1 cookie is worth 1 cookie). The relationship is monotonically decreasing across all values of effort greater than 0. The rate of discounting is represented by one estimated parameter known as the *k* value. Graphically, the *k* value refers to the steepness of the function's slope. The combination of reward and cost is multiplicative in this model and represent immediate discounting of all effort with decreased discounting at higher marginal effort. The hyperbolic model has successfully captured even irregular behavioral patterns such as preference reversals in prior behavioral choice experiments (Kirby & Herrnstein, 1995). Figure 3.1 shows how the hyperbolic subjective value estimates vary across effort levels as the *k* parameter changes.

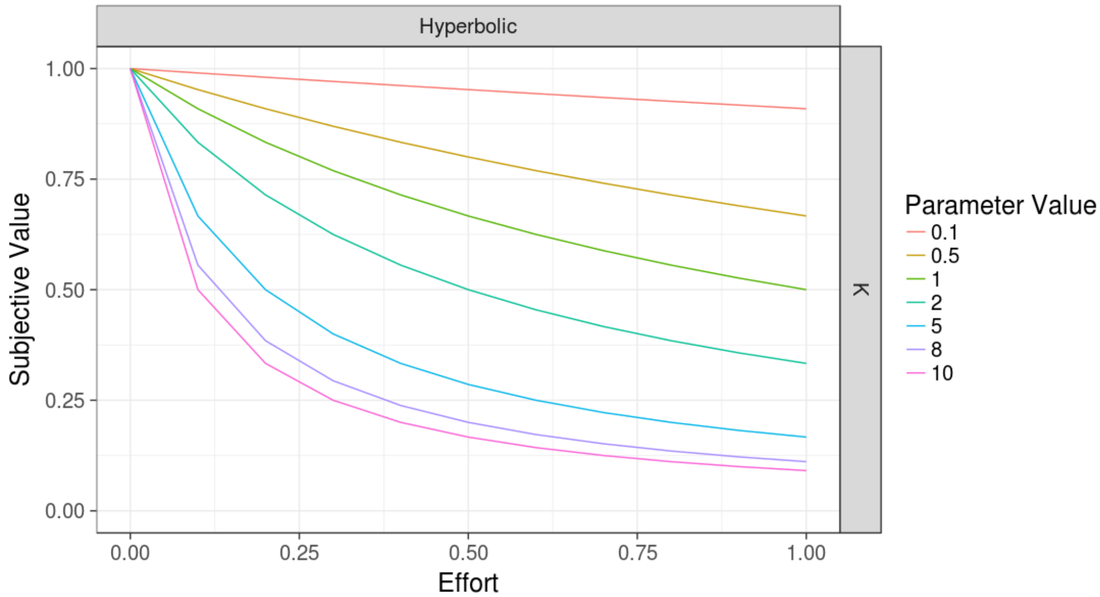

Figure 3.1: Hyperbolic Model Simulations

The parabolic model is an additive function that models the opposite theoretical pattern: flat initial discounting that gives way to steep discounting at larger amounts of effort (Hartmann et al., 2013). This model represents steep discounting past a threshold level of effort and effortlessness at low levels of effort. Cost and reward are additive in this model and only effort costs are modulated by the lone discounting rate parameter raised to the power of 1.2. The discounting rate in this model likewise controls the steepness of the model and how soon effort begins to discount value. Figure 3.2 shows how the parabolic subjective value estimate varies across effort levels as the *k* parameter changes.

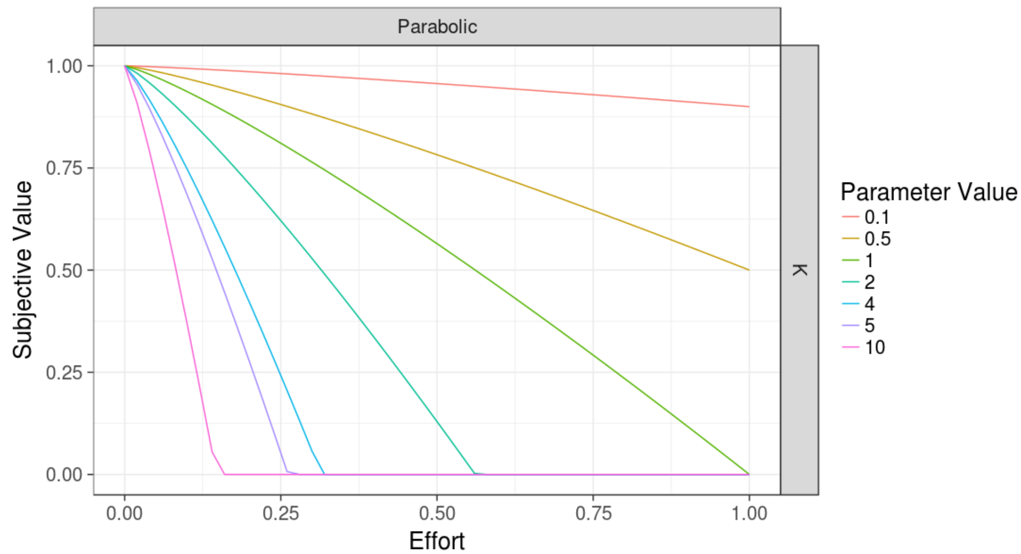

Figure 3.2: Parabolic Model Simulations

The third model is the sigmoidal model (Klein-Flügge et al., 2015) which fits two parameters to the data. The first parameter is analogous to the discounting rate in the prior models, again labeled as the *k* value. Larger values of *k* reflect increasingly steep discounting behavior. The second parameter is the *p*-threshold which represents the effort level of the lone inflection point in the curve. Values of *p* indicate the effort level where discounting is steepest and correlates with the threshold of effortlessness before discounting begins. By dissociating these parameters, the sigmoidal model is more flexible and allows for both shapes of discounting function at the cost of an extra degree of freedom. shows the change in subjective value across effort levels as each parameter is varied independently. Figure 3.3 shows simulated subjective values when the *k* parameter is varied and p = 0.5. Figure 3.4 shows simulated subjective values when the *p*-threshold parameter is varied while k = 5.

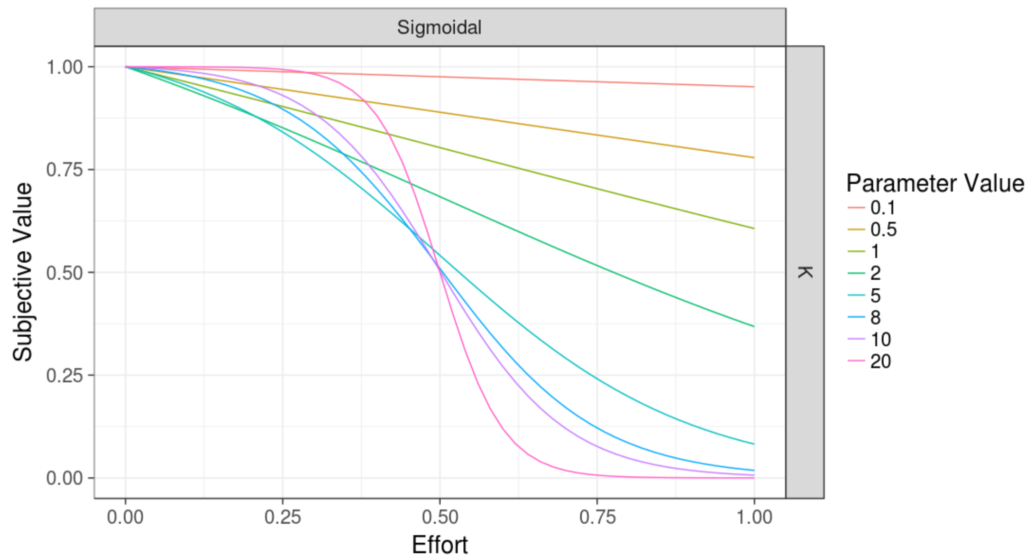

Figure 3.3: Sigmoidal k value simulations

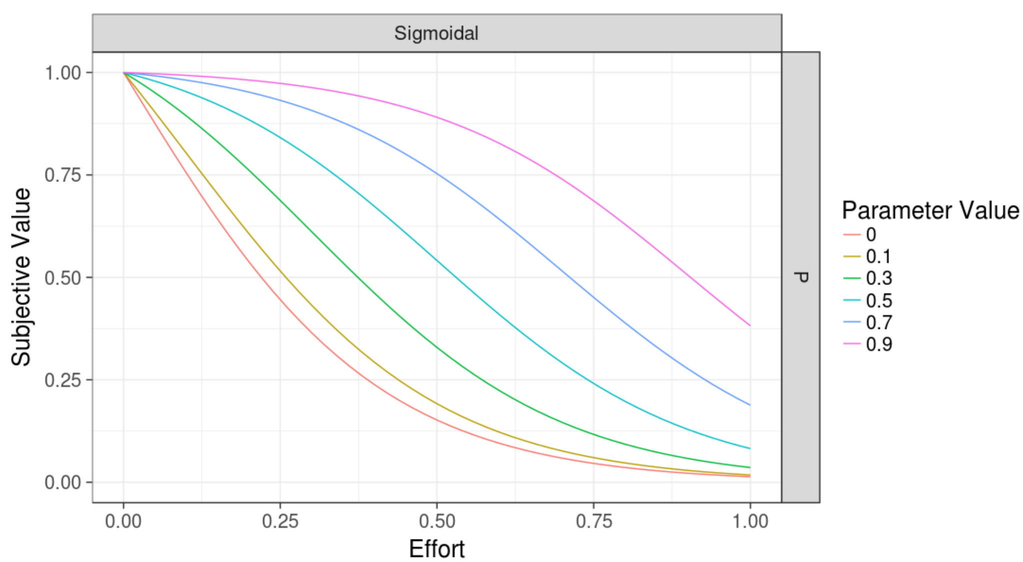

Figure 3.4: *Sigmoidal* p *value simulations*

The sigmoidal model is a multiplicative model but should be noted that a two-parameter power function can also be fit to the data as an additive combination of reward and cost. The same study posited a more general form referred to as "the flexible two-parameter power model" using a simpler additive combination of effort and value (Klein-Flügge et al., 2015). This model is similar in form to the parabolic model, but estimates the power of the discounting function rather than defaulting to a prior set value based on the scale of the effort task. Figure 3.5 and Figure 3.6 show the change in subjective value across effort levels as each parameter is varied independently. When the k parameter is varied, p is fixed at 2; when the p parameter is varied, k is fixed at 5.

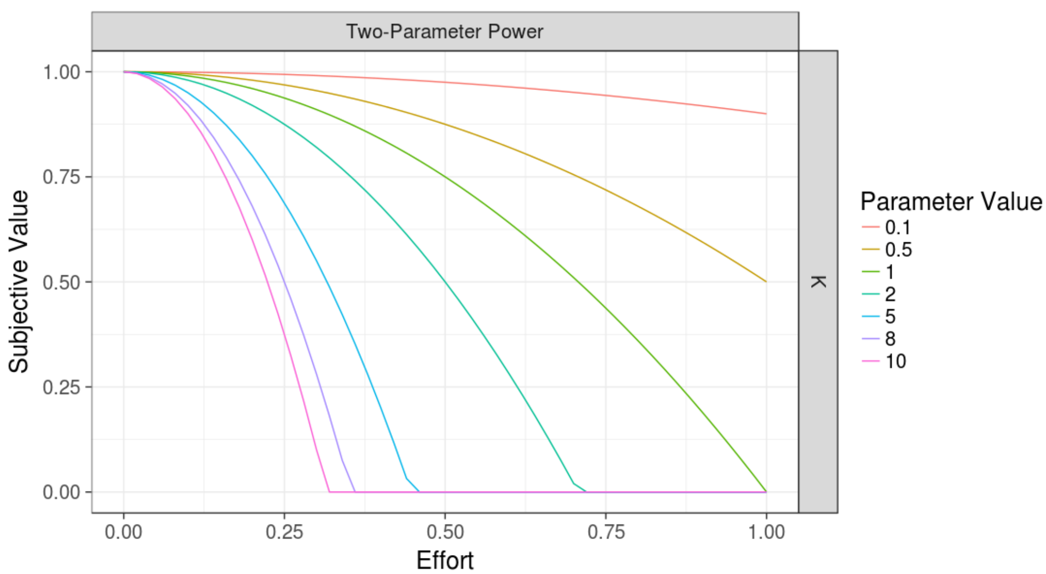

Figure 3.5: Power model k simulations

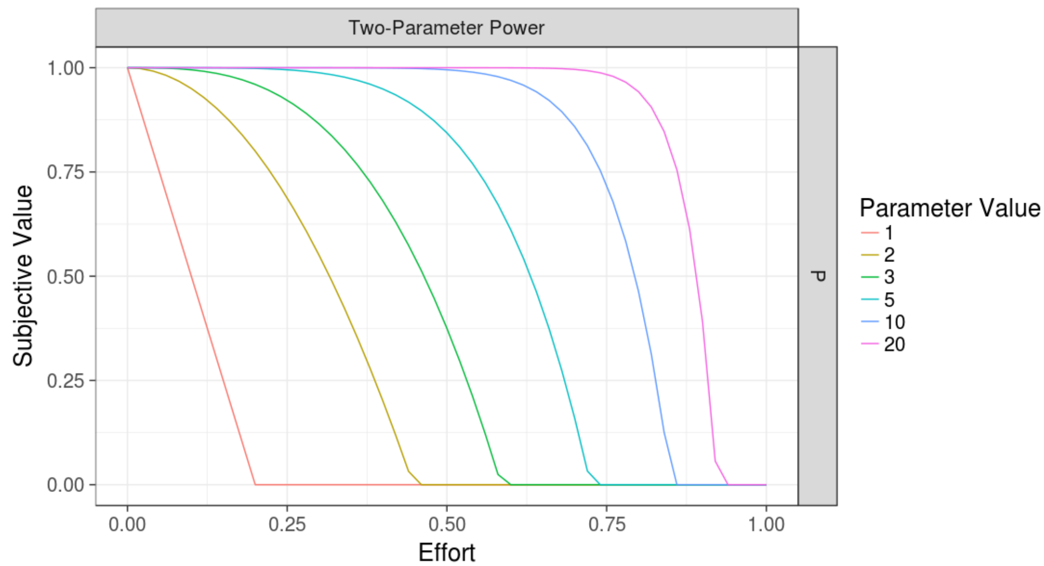

Figure 3.6: Power model p simulations

Each model represents a unique set of assumptions about how effort discounts the value of a monetary reward. These assumptions are best viewed in the shape of the curve created when plotting subjective value across effort levels. If the domain of choice options contains "effortless" levels of typing, then the curve is initially flat for low values of effort. If participants find the effort task impossible at high levels of effort, the discounting curve should decrease sharply to zero before reaching maximum effort. Naturally, all model curves are monotonically decreasing as effort increases. For purposes of comparison, all four models were plotted in Figure 3.7 using representative parameters to provide contrast in the shape of each model.

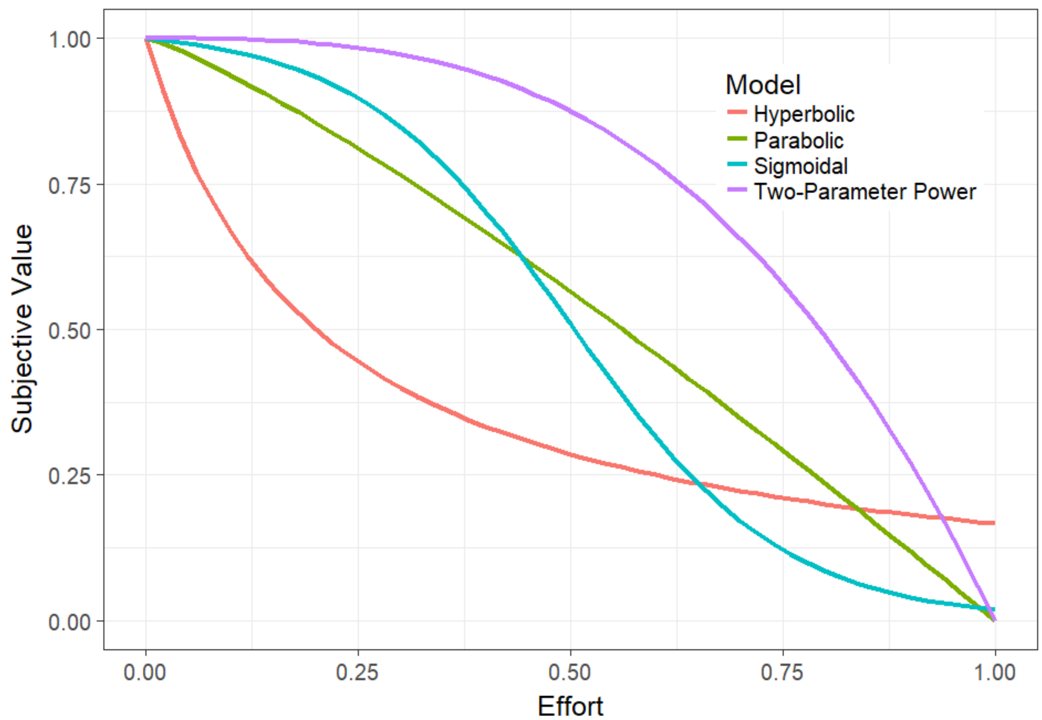

Figure 3.7: Representative discounting models

3.2 Motivation

The primary motivation of this chapter is to determine an appropriate model for representing effort discounting behavior when decision outcomes result in the typing task. As of writing, no formal models have been proposed for such decisions with prior investigations using model-free analysis. Identifying the best fitting model allows for interpretations of how decision makers value the effort required to perform this task.

A secondary motivation is to compare egocentric and allocentric effort discounting. One method is to determine if the best fitting model for egocentric decisions is the same as allocentric decisions. If the best fitting models are the same, then estimated parameters can be compared between egocentric and allocentric decisions to investigate differences in how decision makers weight option attributes. Differences in parameter weights provide evidence for differences in cognitive valuation mechanisms. For instance, allocentric decision makers may undervalue a decision recipient's effort compared to egocentric decisions.

A tertiary motivation is to use parameter estimates to explore individual differences in how decision makers discount effort. This approach is particularly important for the within-participants design where a participant's choices can be compared against themselves, effectively holding the neural basis responsible for valuation constant. “The Computer” (for lack of a better term) is held constant, providing more power to the analysis and reducing noise from interpersonal differences. Additionally, individual-level shifts in discounting behavior can be compared with self-reported measures from social-psychological scales and decision-making strategy questionnaires. The investigation of individual differences is a direct response to prior literature which calls for greater understanding of allocentric shifts in decision making (Andersson et al., 2014)

3.3 Methods

Computational models were fit to the behavioral choice data from chapter 2. The subjective value equations Table 3.4 were fit to the data, where the inputs to the model are the effort and value of a choice option and the output is the subjective value. Parameters were estimated to minimize the deviance between subjective value from actual choice outcomes.

Table 3.4: *Computational Discounting Models*

Model	Num. of Parameters	Subjective Value Equation
Hyperbolic	1	$SV = \frac{Value}{1 + k * Effort}$
Parabolic	1	$SV = Value - k * Effort^{1.2}$
Sigmoidal	2	$SV = Value\left(1 - \frac{\left(\frac{1}{1 + e^{-(k*Effort-p)}} - \frac{1}{1 + e^{k*p}}\right) * 1}{e^{k*p}}\right)$
Power	2	$SV = Value - k * Effort^{p}$

To estimate the parameters of each model, two fitting methods were used: (1) fitting inverse indifference points as estimates of subjective value and (2) fitting model predictions against raw choice responses through a SoftMax decision function. Both methods fit parameters with non-linear maximum likelihood estimation (MLE) across standardized effort levels. Normalized effort levels refer to the number of words needed to be typed backwards in a given option taken as a difference over the maximum number of words in the option set:

$$Normalized\ Effort_{Large} = (Effort_{Large} - Effort_{Small}) / Effort_{Maximum}$$

$$Normalized\ Effort_{Small} = (Effort_{Small} - Effort_{Small}) / Effort_{Maximum} = 0$$

The indifference points estimation method relies on the indifference points estimated in chapter 2 as estimations of subjective value. Indifference points were estimated from a logistic regression of compensation amount predicting choice outcomes grouped by level of effort. The following equation shows the simplified form where β_0 is the intercept parameter and β_i is the parameter of the compensation level from the logistic regression:

$$SV_{IndifferencePoint} = \frac{Compensation(\$)_{smaller}}{\frac{\beta_0}{\beta_i}}$$

The indifference points across each unique level of effort were fit with each discounting model to estimate parameters and assess fit. Parameters were estimated using nonlinear curve fitting minimizing the sum of squared errors.

The second fitting method utilizes SoftMax estimation of choice probabilities. SoftMax estimation is a typical decision model for selection of one categorical option in machine learning (Jacobs, Jordan, Nowlan, & Hinton, 1991; MacKay, 1992) and has been applied to neuroeconomic studies (Daw et al., 2006). This method differs from indifference point estimation because it uses the entirety of choice outcome data rather than a collapsed summary measure. The SoftMax decision function estimates the probability of option selection given a set of option values. The probability of a decision maker choosing option A is based on the relative value of option A compared to all other options. When values are nearly equal, the probability of choosing either option approaches 0.5. Figure 3.8

shows a simulated function and choices based on two possible options (labeled here as option A and option B).

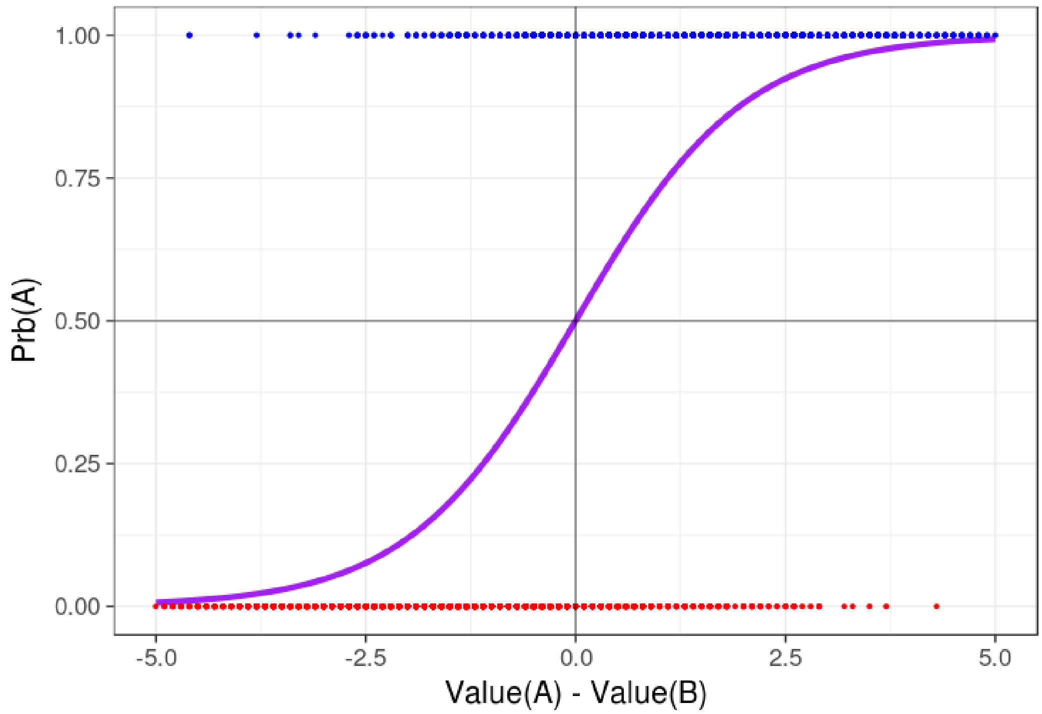

Figure 3.8: Simulated SoftMax function predicting the probability of choosing option A as the difference in value of choice options increases

The SoftMax function returns a probabilistic representation of choice that allows for noise in the data where decision makers choose options that do not have the maximum subjective value. This means each trial in a given choice experiment is treated as an independent observation and all choice options are explicitly represented in fitting, even those trials that are incoherent with model predictions. A further advantage of the SoftMax function is option value can be represented using any discounting model or model-free valuations. The SoftMax function compares the subjective values of whole options rather than individual attributes and does not dictate assumptions on how individual attributes of the choice option are valued. Modeling the entire bundle of choice attributes is a boon for analytic versatility and allows for comparison of all four discounting models while controlling for selection process. To estimate discounting model parameters, the discounting models are nested within the SoftMax decision function and optimized with respect to a cost function.

One strength of SoftMax parameter estimation is the additional free parameter for weighting the importance of the model when predicting choice outcome. This model-weight factor is known as the temperature and is also freely estimated. SoftMax decision functions estimate an additional parameter that denotes how strongly estimated subjective value affects choice outcome. Temperature estimation was conducted for all models and constrained between [0, 1]. All fitting results had suitably high temperature (>90% of Temperature estimations = 1). The SoftMax utility function follows the form:

$$P(larger) = \frac{\frac{e^{SV(larger)}}{Temp.}}{\frac{e^{SV(larger)}}{Temp.} + \frac{e^{SV(smaller)}}{Temp.}}$$

SoftMax choice predictions were compared with actual chosen outcomes to assess fit by minimizing a cross-entropy cost function. The probability of selecting the larger effort option was an arbitrary distinction as all choices used binary outcomes that were complete and mutually exclusive (probability of choosing the larger option + probability of choosing the smaller options = 1). To optimize parameter estimates, a log-likelihood cost function for binomial distribution was utilized in maximum likelihood estimation. The loglikelihood was obtained by comparing choice prediction with actual choices via the binomial cost function. The cost function penalizes incorrect model predictions based on model confidence, or the probability estimate returned by the SoftMax function. Incorrect predictions with the probability of the incorrect option approaching 1 are harshly penalized compared to model predictions that are incorrect, but less confident (where the probability of the incorrect option approaches 0.5). The log-likelihood is summed for all choices in each set space. Set space was determined by condition and participant for each fitting. The cost function follows the form below where p is the estimated probability of choosing the correct option:

$$\text{Log-Likelihood} = -\sum p * log(p) + (1-p) * log(1-p)$$

In both indifference point and SoftMax fitting methods, parameters that minimized the deviance between predicted and actual choice in each set space were retained for further analysis. For model comparison, the log-likelihood of each parameter estimation was weighted or penalized by the number of parameters estimated by the model. Model comparison was conducted using the Akaike Information Criterion or AIC (Akaike, 1974). The AIC is weighted by the number of parameters to penalize overfitting, but only provides a relative comparison of model fit, not an absolute measure. Therefore, AIC cannot be compared between the types of fitting methods because fewer observations were used to estimate the model with indifference point fitting. Lower AIC reflects a relatively better fitting model.

To clarify the following analysis, the experiments will be referenced by their design – within-participants and between-participants and the fitting approach used – indifference point or SoftMax. Choices across conditions were fit separately for the within-participants design. The following analyses lead with the within-participants design because the paired comparisons improve the power of the analysis. Between-participants design choices were also modeled and reported when appropriate to validate contrast between conditions.

3.4 Results

3.4.1 Model Fit Comparisons

Model fit comparison results were dependent upon the fitting method. AIC distributions from SoftMax fitting methods for the within-participants experiment data were compared across the four candidate computational models as well as two model-free estimations of subjective value. The model free estimates were a standardized additive (Dollars – Words) and multiplicative (Dollars / Word) combination of effort and compensation. For a baseline comparison, a SoftMax fit estimate was calculated using only compensation (no inclusion of effort costs) as the “subjective” value. This represents decision makers who are indifferent to effort and whose subjective value of an option is equivalent to the objective monetary value. The Compensation model was not reflective of the choices made in the experiment and serves as an example of a poor-fitting model.

Figure 3.9 shows the AICs for each estimation as a point with distribution density represented by a violin-plot. Better models are represented by high density grouping of lower AIC values.

Comparison of the AIC distributions shows better that multiplicative combinations of effort and compensation fit the data better when considering either computational models or model free estimations. Dollars/Word outperforms Dollars-Words as a choice predictor (Kruskal-Wallis $p < 0.001$). Furthermore, both the hyperbolic and sigmoidal models have lower AIC distribution than the additive models. Kruskal-Wallis test confirms the difference between multiplicative and additive models is significant ($\chi^2 = 774.49$, df = 5, $p < 0.001$).

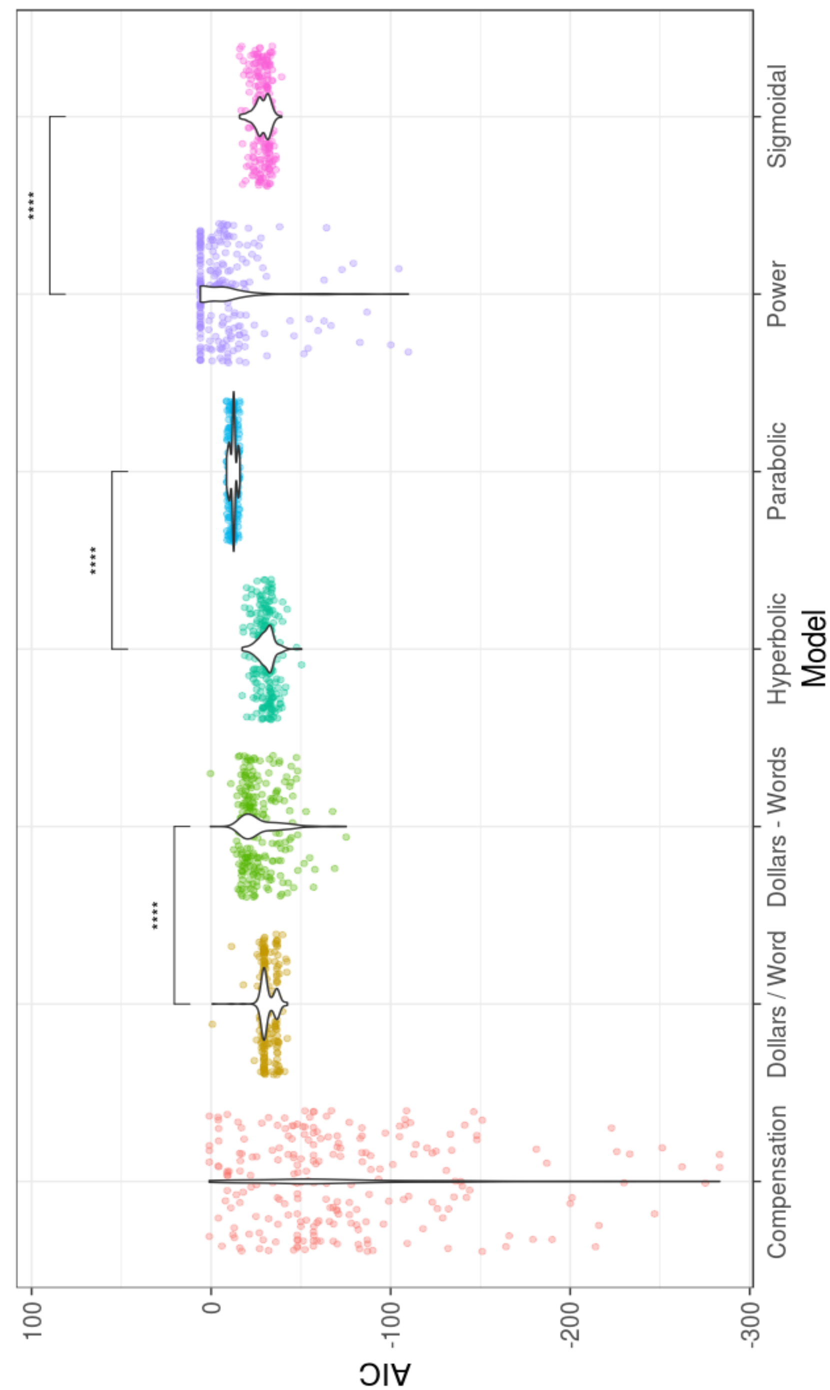

Figure 3.9: AIC distributions of SoftMax model fitting for the within-participants experiment data

Indifference point fitting resulted in similar findings for computational model fit. Figure 3.10 shows the distributions of AICs from indifference point fitting. The hyperbolic model was the best fitting with the sigmoidal model a close second. Both models were well suited to fit the data, but with the reduced number of observations used in indifference point fitting, the hyperbolic model is superior because it utilized one fewer parameter while estimating a similar discounting curve. The *k* values between sigmoidal and hyperbolic models were highly correlated (r = .95). The sigmoidal *p* parameter was not informative during indifference point fitting (>90% estimated *p* values were 0). Additive models were significantly worse at predicting indifference points, with the two-parameter power model being the worst performing model in part because of the additional parameter penalty. Again, Kruskal-Wallis test results confirm that the difference is significant amongst discounting models ($\chi^2 = 701.34$, df = 3, $p < 0.001$).

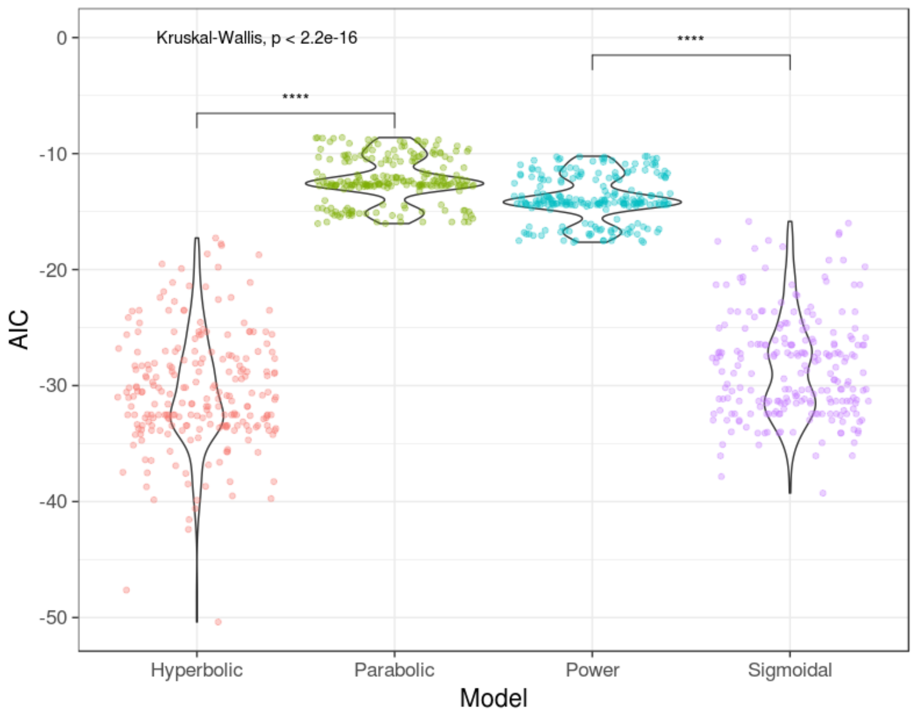

Figure 3.10: AIC distributions for models fit using indifference point estimation for the within-participants data

The data followed this pattern with hyperbolic and sigmoidal models best representing the data. Furthermore, the AIC distribution patterns hold across effort reference options, meaning that computational models can describe differences in larger and smaller effort options. The distributions of AIC by model can be seen in the boxplots in Figure 3.11. The sigmoidal model was a very close second in both effort reference frames and the combined data. Going forward, only the sigmoidal and hyperbolic models are retained with the parabolic model chosen as a contrasting point of reference.

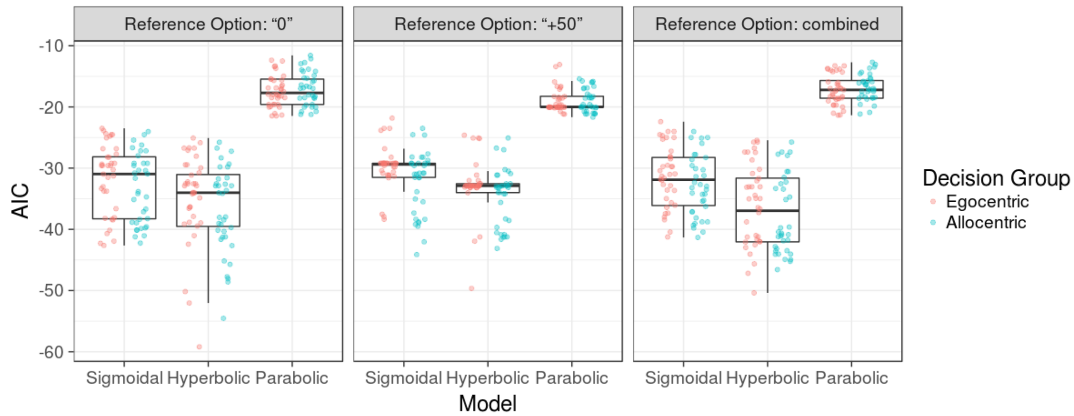

Figure 3.11: AIC distributions for models fit using SoftMax estimation for the between-participants experiment

3.4.2 Condition-wise Model Fit Comparisons

Comparing model fits between egocentric and allocentric choices shows no difference in AIC. The within-participants data set shows the sigmoidal model and hyperbolic model were the best fitting models across all three conditions. Kruskal-Wallis testing the AIC fit data for each model shows that condition does not affect model fit for either the hyperbolic ($\chi2 = 1.06$, df = 2, $p = 0.588$) or sigmoidal models ($\chi2 = 5.16$, df = 2, $p = 0.076$). Figure 3.12 shows the results of condition-wise model fits for the hyperbolic and sigmoidal discounting models.

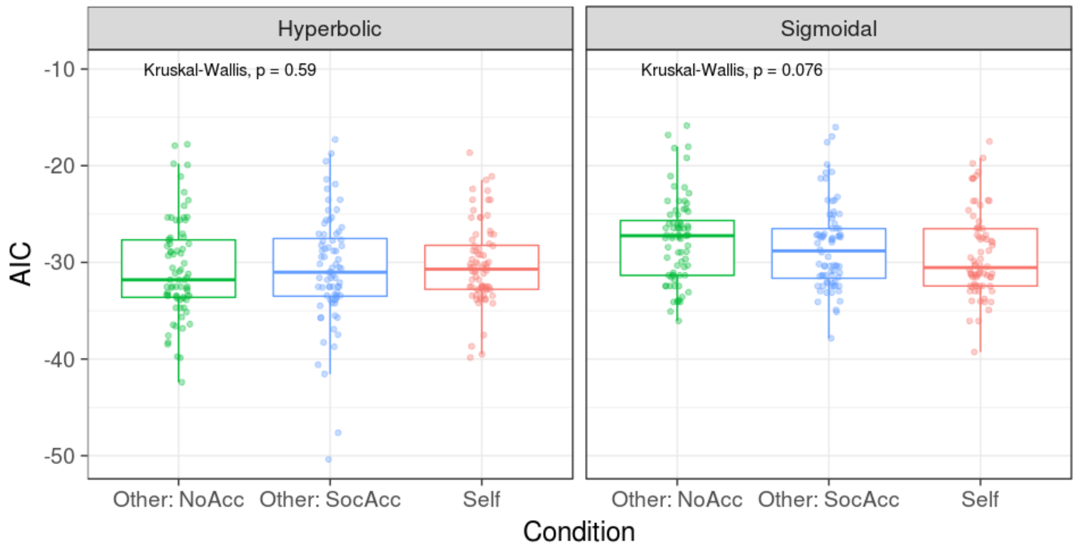

Figure 3.12: AIC distributions by condition for the two best models fit with SoftMax estimation to the within-participants experiment data

Between-participants fitting can be seen in Figure 3.11. Models fit allocentric group choices better than egocentric choices overall, yet the relative fit of the models was identical between groups. Kruskal-Wallis test shows the AIC distributions for models were not significantly different between groups ($\chi 2$ = 2.86, df = 2, p = 0.239).

3.4.3 Condition-wise Parameter Comparison

Based on the prior analyses, the hyperbolic and sigmoidal models were retained for parameter comparison. The parameter estimates from the hyperbolic and sigmoidal model were then compared across conditions, with emphasis placed on allocentric and egocentric differences. Given the similarity of parameter estimates between models in a fitting method, only the best fitting model from each fitting method was retained. The hyperbolic model parameters were compared using the indifference points data while the sigmoidal model parameters were compared when estimated via SoftMax decision function. The first comparison examines hyperbolic model *k* values between egocentric and allocentric decisions fit to the indifference point data.

Within-participants data shows that the hyperbolic *k* parameter was significantly different between egocentric and both allocentric conditions, but did not differ between accountability conditions, mirroring the model-free findings from chapter 2. Similarly, the distributions are positively skewed in all three conditions, necessitating the use of non-parametric statistical analyses. Pairwise Wilcoxon sign-rank tests confirm that *k* value differences were significant ($p_{\text{Self-ONA}} < 0.0001$, $p_{\text{Self-OSA}} = 0.0022$, $p_{\text{ONA-OSA}} = 0.4861$). The egocentric *k* values were less than either of the allocentric conditions reflecting the same pattern of discounting behavior from the between-participants design. The lower *k* value corresponds to a reduced discounting rate and the more likely selection of larger effort choices ($\text{Mean}_{\text{Self}} = 5.79$, $\text{Mean}_{\text{ONA}} = 8.16$ $\text{Mean}_{\text{OSA}} = 7.91$). Figure 3.13 shows the distribution of k values presented as a violin plot overlaid with the mean and confidence interval as boxplots.

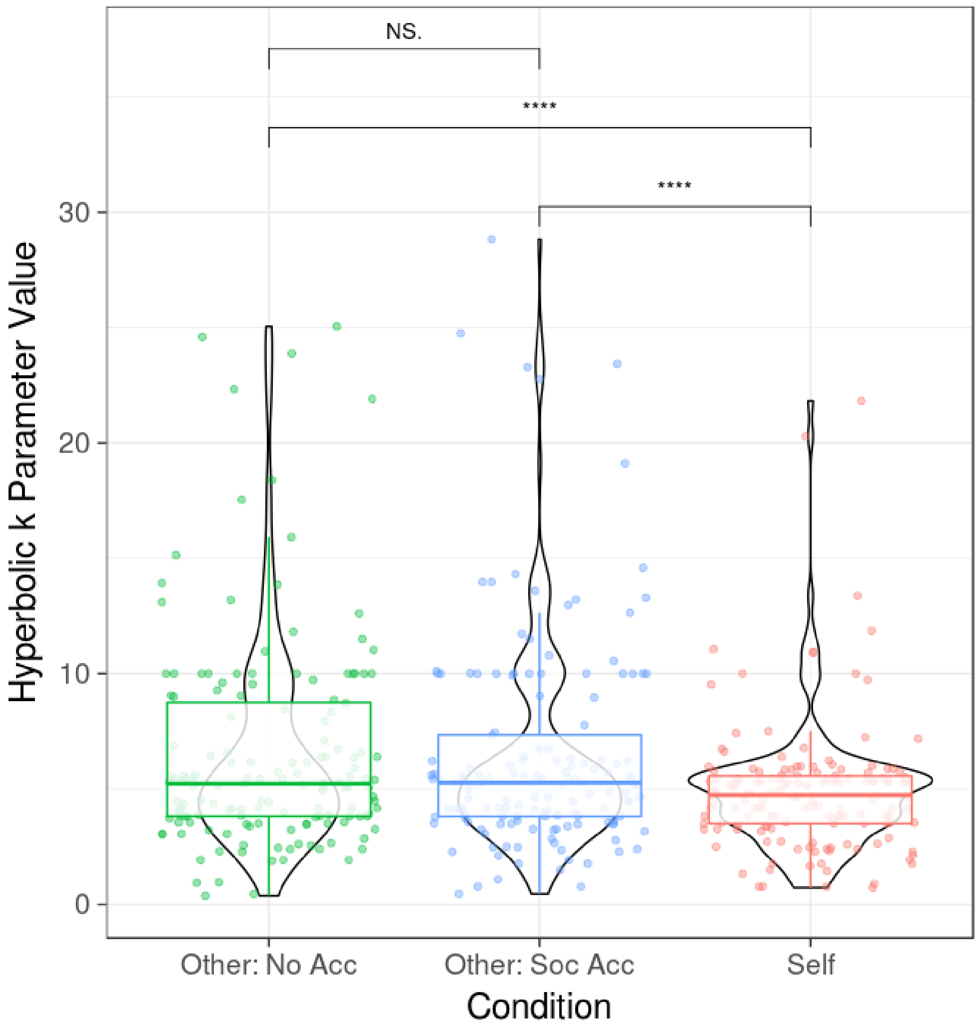

Figure 3.13: Hyperbolic model parameter distributions by condition estimated with indifference point fitting for the within-participants data

In the between-participants experiment, the indifference point fit hyperbolic model shows evidence for trend differences in *k* value between egocentric and allocentric groups. Non-parametric tests of distribution between groups confirm this for both combined and low reference option choices, while the high effort reference option choices were significantly different between groups. (Wilcoxon-Mann-Whitney test, $U_{combined}$ = 808.0 p = .071; U_{high} = 844.5, p = .025; U_{low} = 799.0, p = .089). Participants who decided for others exhibited higher k values on average than those who decided for themselves. Both distributions are positively skewed and can be seen in Figure 3.14.

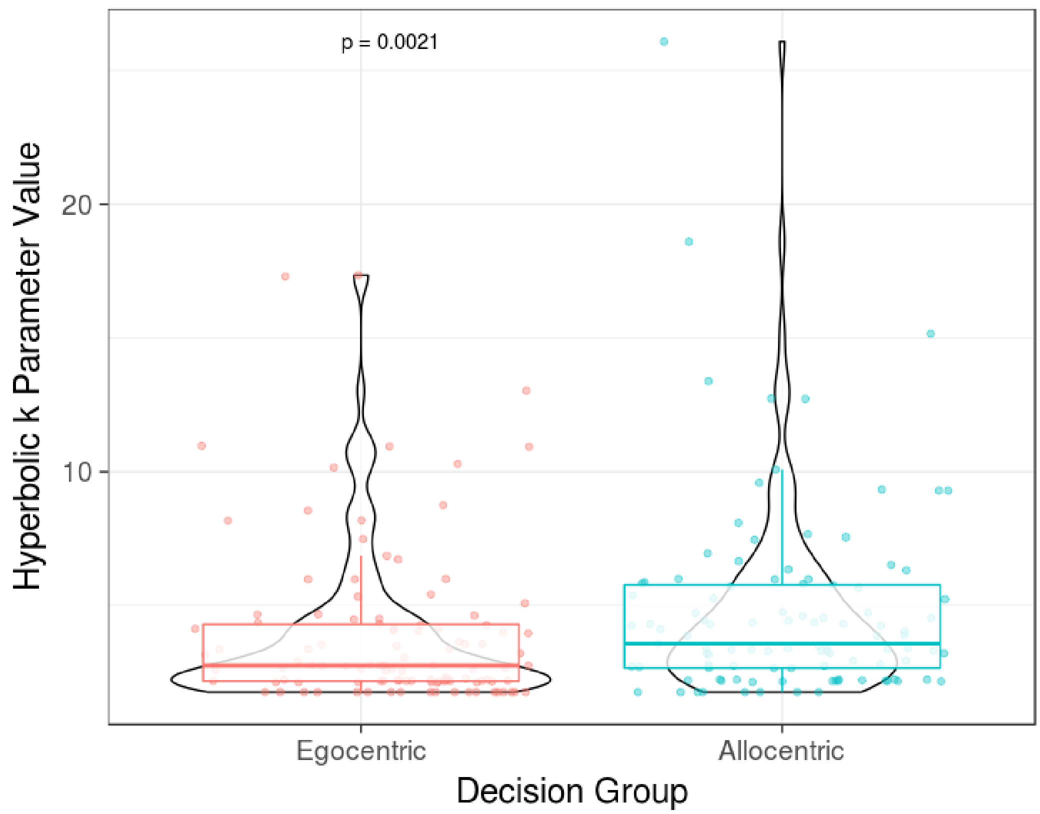

Figure 3.14: Hyperbolic model parameter estimation for the between-participants experiment

The sigmoidal model parameters were estimated with SoftMax fitting. No difference was found between conditions for either the *k* or *p* parameters. Wilcoxon sign-ranked tests for sigmoidal *k* (V= 1366, p = 0.62) and sigmoidal *p* (V = 1467, p = 0.99) parameters support the null hypothesis. However, when the sigmoidal model is fit to the indifference points, the *k* parameter shows similar egocentric-allocentric differences as the hyperbolic model. Figure 3.15 shows the estimates for all parameters using both fitting methods for the two best fitting models.

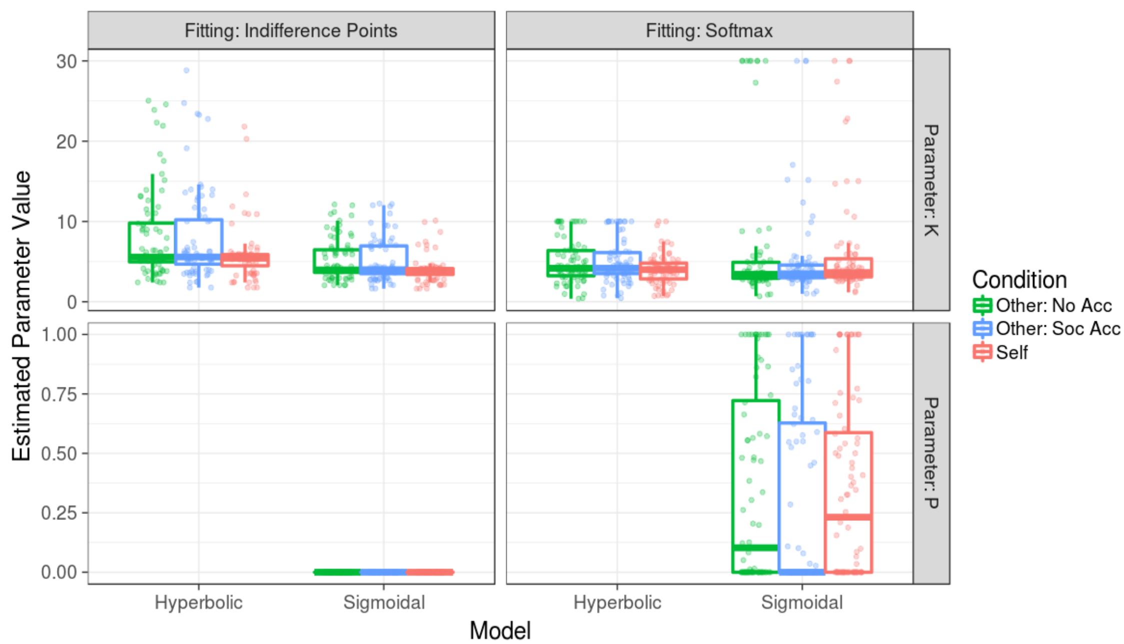

Figure 3.15: Parameter estimates of the best fitting models for each fitting method

Given that the two parameters are constrained and estimated simultaneously, the model may suffer from an unnecessary additional parameter for some participants or conditions, masking real discounting differences with increased variance for each parameter. Thus, an area under the curve (AUC) measure was calculated for the simulated discounting curves and compared between egocentric and allocentric conditions. The AUC was not significantly different between conditions, as confirmed by ANOVA (F = 0.265, p = 0.768). Figure 3.16 shows the mean and +/- 1 standard error of the AUC for both the hyperbolic model discounting curves fit to indifference points and the sigmoidal model curves fit via SoftMax estimation.

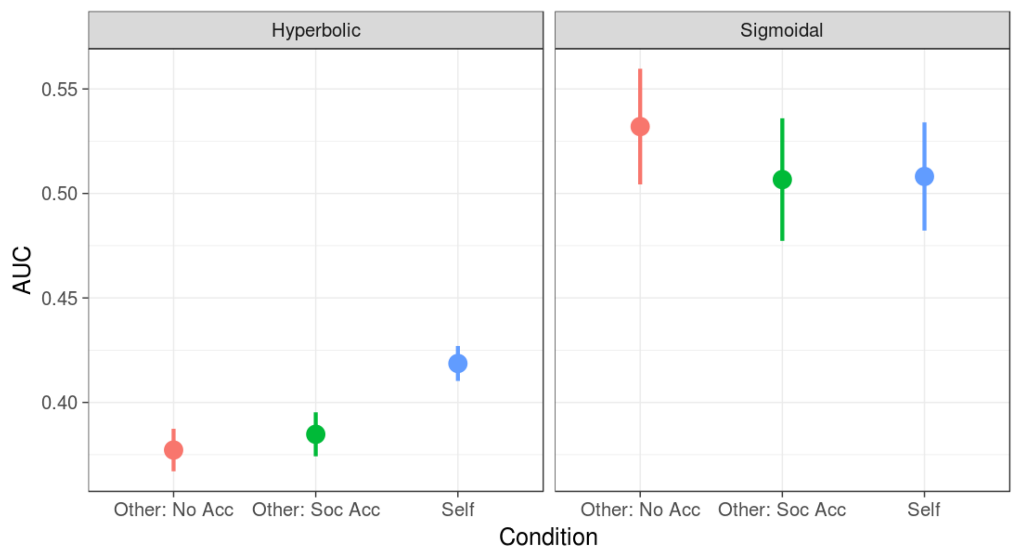

Figure 3.16: Model AUC distributions for the two best models by condition

3.4.4 Individual Differences

Individual differences in the parameter estimates were present in the data. The sigmoidal model parameter estimates captured this variance better than the hyperbolic model, resulting in a large variety of sigmoidal discounting curves. To illustrate this discounting diversity, Figure 3.17 shows each participants' discounting curves plotted for every condition. As an additional method of comparison, parameter differences were analyzed to understand individual differences in how decision makers shift their preferences between egocentric and allocentric decisions.

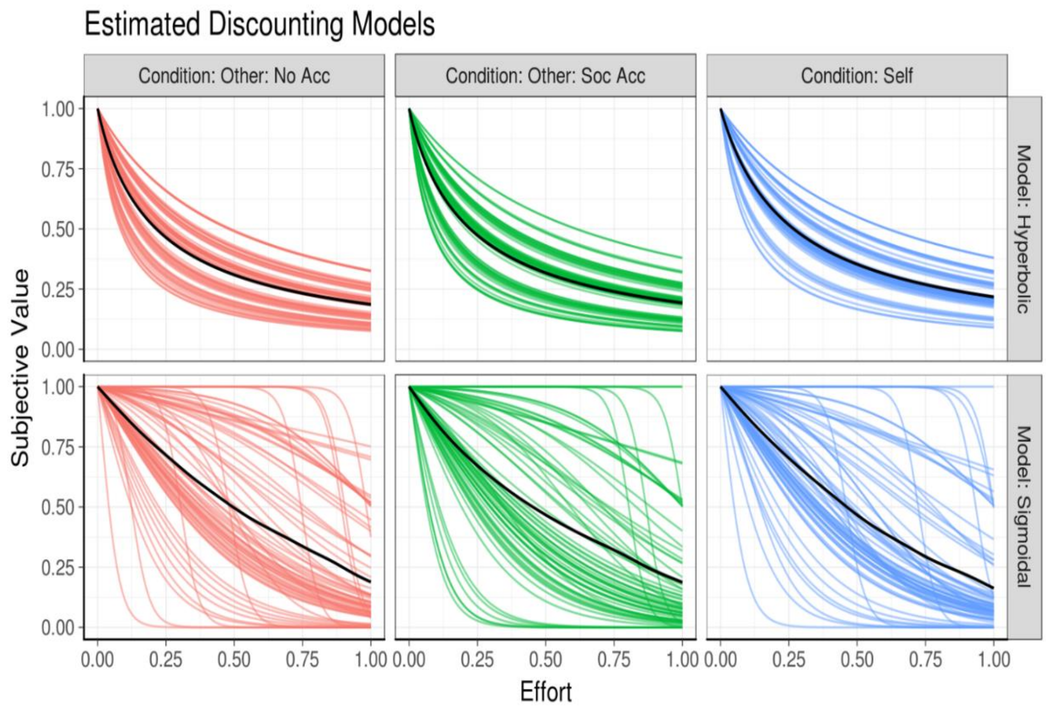

Figure 3.17: Estimated discounting curves for each participant. Hyperbolic model estimates are shown in the top row while sigmoidal model estimates are shown in the bottom row. Each column represents one condition.

To examine individual differences in allocentric-egocentric differences, the within-participants parameter estimates were used to calculate a condition-wise difference score. The difference between the egocentric condition parameter estimate and the mean of the two allocentric conditions' parameter estimate was calculated for each participant. The condition differences for each parameter are shown in Figure 3.18 and Figure 3.19 in magnitude rank order for the hyperbolic and sigmoidal models respectively. Negative scores resulted when participants discounted effort more in allocentric decisions than egocentric decisions. Positive scores reflect decision makers who discounted egocentric effort more than allocentric effort.

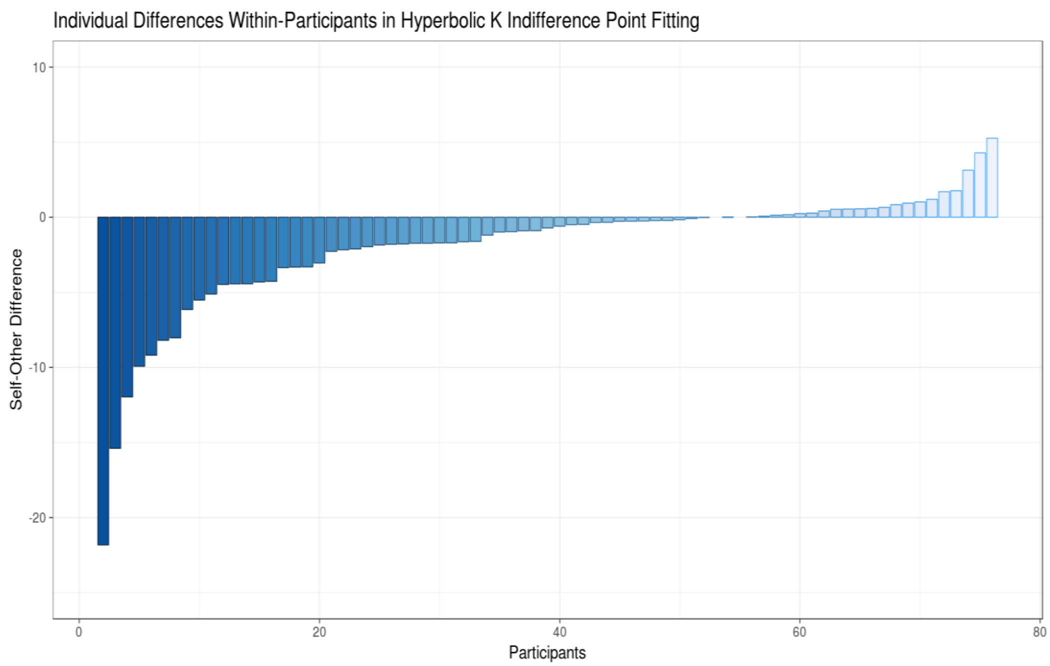

Figure 3.18: Condition difference scores of the hyperbolic k parameter estimate for each participant in the within-participants experiment.

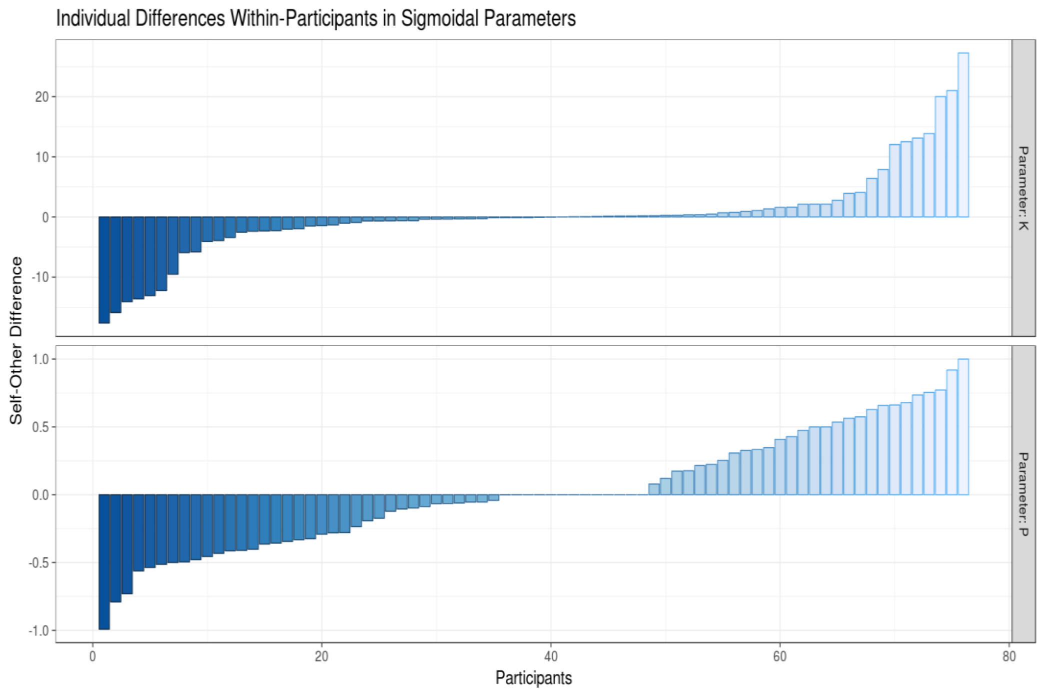

Figure 3.19: Condition difference scores of the sigmoidal model parameters for each participant in the within-participants experiment.

The differences in parameter estimates (egocentric – allocentric) were correlated with self-reported measures administered immediately following the choice trials. The measures used were aggregated scores for Social Values Orientation (SVO) and Fear of Negative Evaluation (FNE) (Murphy, Ackermann, & Handgraaf, 2011; Leary, 1983). Additionally, one-item measurements of similarity with the recipient ("How similar do you think the decision recipient is to you?" 1- very similar: 7- very dissimilar); feelings of responsibility ("I feel responsible for and accountable to" [the decision recipient during the task]; 1- absolutely disagree: 7- absolutely agree); and personal decision making strategies ("I chose what is best for" [the decision recipient during the task]; 1- absolutely disagree: 7- absolutely agree; "I chose what I think" [the decision recipient during the task] "would choose"; 1- absolutely disagree: 7- absolutely agree) were correlated with the differences in parameter estimates between egocentric and allocentric conditions. The resulting correlations are shown in Table 3.5 with significant ($p < 0.05$) positive correlations starred.

Results show that differences in hyperbolic discounting rate parameters were significantly correlated with several post-hoc measures, but not correlated with shifts in sigmoidal model discounting rate between conditions ($r = .1$, $p = 0.684$). However, the sigmoidal p shift was negatively correlated with the hyperbolic k ($r = -.3$, $p = 0.018$*). The inverse relationship is expected, as the hyperbolic model reflects increased discounting behavior with an increased discounting rate, while the sigmoidal model may reflect increased discounting behavior with a lower threshold for effort (discounting behavior can begin sooner).

To concentrate the analysis of individual differences on discounting behavior, the AUC of the estimated sigmoidal model is used as a correlate with the self-reported measures. It should be noted that AUC and all model parameters are inversely related, where a greater AUC reflects a reduced discounting rate or k parameter. Larger shifts in the hyperbolic discounting rate between egocentric and allocentric decisions were correlated with those participants who felt feelings of responsibility for the recipient ($r = .3$, $p < 0.001$) and those who reported they chose what was best for the recipient ($r =.6$, $p <$

0.001). Similar findings were observed in sigmoidal model AUC (r = -.3, p < 0.001 and r = -.5, p < 0.001 respectively).

Smaller shifts in hyperbolic k were correlated with participants who reported feeling more similar to the recipient (r = -.3, p = 0.008). There was no observed correlation in the sigmoidal model parameters or AUC with decision recipient similarity.

Egocentric-allocentric shifts in the hyperbolic k value were positively correlated with SVO responses (r = -.3, p = 0.026). Those participants who were more generous in hypothetical common-pool monetary splits exhibited increased shifts in the discounting rate, or stated another way valued allocentric effort more than egocentric effort. The opposite trend was found for sigmoidal discounting rate (r = .3, p = 0.024). However, this was accompanied by a reduction in the sigmoidal p. Sigmoidal AUC did significantly correlate with SVO (r = -.2, p = 0.045).

The strong similarity in individual differences results serve as a further check on the modeling paradigms used. Despite different estimation methods (indifference point estimation for hyperbolic model and SoftMax estimation for the sigmoidal model), both models reflected similar self-reported findings in affect, cognition, and decision-making strategy.

Table 3.5: Egocentric-Allocentric Parameter Differences Correlated with Self-Reported Measures

	Discounting Model Parameter			
	Hyperbolic *k*	Sigmoidal *k*	Sigmoidal *p*	Sigmoidal AUC
SVO	.3*	-.3*	-.2	-.2*
FNE	0	.1	0	0
Similar	-.3*	0	-.1	.2
Choose best for the recipient	.6*	-.1	-.2	-.5*
Choose what recipient would	.2	-.2	0	-.1
Feel Responsible	.4*	0	-.1	-.3*

*Significance codes: p<= 0.05 **

As an additional check on the null effect of accountability on allocentric decision making, gender effects were investigated. Research has shown that decision maker gender can moderate the effects of accountability even when the party holding the decision maker responsible is not personally known (Brandts & Garofalo, 2012). Differences in model parameter estimates between allocentric conditions were analyzed by gender. The difference in between allocentric parameter discounting rates was compared between groups using the participants' gender to segregate the groups. A two-sample t-test was conducted between gender groups and showed no significant difference (t = 0.488, p = 0.627).

3.5 Discussion

The computational modeling results presented in this chapter provide evidence for the multiplicative combination of effort and value in option comparison. Multiplicative models fit the data better than additive models, including model-free combinations of effort and value. Dollars-per-word was a better model-free predictor of choice than dollars-words in SoftMax estimation of the within-participants experiment data. Amongst computational models, both the hyperbolic and sigmoidal models fit the observed choice data better than the parabolic and power models. Indifference point fitting also supports this finding with both multiplicative models outperforming the additive models when comparing AIC distributions.

Comparing computational models, the hyperbolic and sigmoidal models were both good fits to the data. These models fit decisions in both egocentric and allocentric conditions equally well. When utilizing indifference point fitting, the reduced number of observations benefits the hyperbolic model because it uses one fewer parameter while still adequately describing the discounting behavior. When fitting with indifference points, the sigmoidal p threshold was very close to zero, implying that discounting was immediate for all levels of effort greater than 0. The lack of variance of the secondary parameter resulted in the hyperbolic model being preferred for indifference point fitting.

The sigmoidal model was more apt when SoftMax estimation was used as the extra parameter affords it additional versatility to cope with increased variance given the greater number of observations. Regardless of fitting method, both models were able to represent the shape of the discounting curve and fit egocentric and allocentric decisions better than the other two models.

The shape of the average discounting curve reflected several key findings about effort discounting in the data. Discounting behavior began at low effort levels in typing task decisions, and very little of the effort domain is considered “effortless”. At the other end of the domain, even maximum effort was perceived as feasible for the higher values of compensation. However, the higher values of effort were highly discounted in both egocentric and allocentric conditions. The discounting models estimated subjective values greater than 0 for all options. This finding was reassuring as a logical test of task-model fit.

The best fitting models did not differ between egocentric and allocentric conditions, implying that similar cognitive processes and assumptions are made when deciding for others as when deciding for oneself. However, parameter estimates differed between egocentric and allocentric choices. When the hyperbolic model was fit to the indifference point data, discounting rates were reduced when participants made egocentric decisions. The sigmoidal model, which was the best fit using SoftMax estimation, did not exhibit significant differences in *k* or *p* parameters, nor in the AUC measure. This may be a result of increased noise in the data when fitting all choices, as participants may have erroneously entered choices during the trials. Indifference point fitting used smoothed, summary statistics rather than direct choice observations, but greatly reduced the variance of the data. Another possible explanation is the two parameters were inversely related causing the overall shape of the model to change, but increasing variance in direct parameter comparison. For trial-by-trial comparison, the sigmoidal model may be of greater use, and thus both models were retained for further analysis.

Variance in parameter estimates reflected individual differences. Post-hoc measures including SVO, FNE, feelings of similarity, and the decision-making strategy of choosing what was best for the decision recipient were all correlated with parameter shifts between egocentric and allocentric decisions in the hyperbolic model. The correlation between SVO and both models' discounting rate parameters opens avenues for further exploration of sociocentric decision making correlations in the future.

3.6 Conclusion

The findings in this chapter yield both clear insights and further questions. The discounting curve for decisions about the typing task appears to follow a convex pattern with steep initial discounting based on a multiplicative combination of effort and compensation. This was found for both egocentric and allocentric decision making and coalesces well with the results from chapter 2 where the significant effect of "effortless" choice options in the between-participants study reflects steep initial discounting behavior. Both multiplicative models, the sigmoidal and hyperbolic models, allow for steep initial discounting.

Additive models, the parabolic and two-parameter power models, do not allow for steep initial discounting.

This steep initial discounting was found in both the indifference point fitting method and the SoftMax estimation method. Furthermore, models were estimated using the within-participants data that did not use an effortless reference option as stimuli (unlike the between-participants design), yet model estimates showed a similar pattern. This finding is encouraging as it shows the robustness of the cognitive computational modeling approach generally, and the models selected more specifically.

Steep initial discounting lends support to the do-no-harm principle as a potential mechanism for explaining allocentric effort discounting differences. Effort is immediately discounted for both self and others with allocentric effort discounted even further. Similarly, the do-no-harm principle is a viable mechanism for egocentric choices. The empathy gap explanation would likely present as less steep discounting at low levels of effort in egocentric decisions to obtain more compensation when effort is small, but be irrelevant when deciding for others. Thus, different discounting models would be expected for an empathy gap explanation.

However, the sigmoidal model did not show a distinction between egocentric and allocentric decisions despite the strong behavioral differences. This begs the question of the appropriate number of parameters needed to model effort discounting and if “endurance” and “strength” are independent components of effort evaluated in the typing task. However, the sigmoidal model captured a far more diverse array of discounting behavior than the hyperbolic model and was versatile enough to be the best predictor when describing subjective value and ultimately choice on a trial-by-trial basis using the SoftMax fitting method.

Individual differences in effort discounting curves naturally opens the discussion to individual-level predictors of both effort discounting and egocentric-allocentric differences. While preliminary findings show evidence that individual level predictors exist, these predictors were neither controlled for nor manipulated and only offer correlational results. However, investigating individual differences in the brain may glean more robust findings.

4 Neuroimaging Introduction and Background

4.1 Motivation

Computational models are representations of theoretical cognitive mechanisms suited to fit patterns in behavioral data. but theory can be validated by examining the physical implementations responsible for cognition. For cognition, physical reality is activity in the central nervous system, specifically in the brain (Collell & Fauquet, 2015). Neural correlates can both extend and further specify understanding of the mechanisms underpinning decision making. With modern neuroimaging methods, real time localization of neural activity can be recorded in human participants while they experience stimuli and make decisions. This chapter provides background on the current methods used in the neuroimaging of decision making coupled with a review of prior neuroimaging literature tailored to allocentric effort decisions.

4.2 Background and Methodology

The multitudinous neural regions and pathways that process stimuli and action responses transmit information at speeds of 120 m/s (432 km/h) and activate and deactivate on the order of milliseconds (Gerstner, Kreiter, Markram, & Herz, 1997). This creates an immense amount of data dispersed throughout the brain at any given time. Therefore, studying neural activity necessitates a high degree of temporal and spatial resolution. Of the available neuroimaging methods, functional magnetic resonance imaging (fMRI) is the technique best suited for the current study because fMRI scanners can detect differences in the time-scale of the decision-making task. In addition to being commonly used in neuroeconomic studies, fMRI is also preferable because it is noninvasive, does not require participants to ingest radioactive isotopes, and is relatively easy for participants to undergo with simple training, instruction, and safety briefing lasting approximately 30 minutes. Additionally, there are various established decision-making experiment paradigms that can be implemented and adapted to the current investigation. As fMRI is not yet commonly used in organizational and management research, the following sections provide brief overviews of fMRI including the underlying physics, neuroanatomy, neurophysiology, fMRI data collection, and fMRI analysis methods associated with neuroeconomic investigation of decision making.

4.2.1 Neuroimaging Background

MRI is a method for viewing static soft tissue inside an organism commonly used in medical diagnosis. Functional MRI is the dynamic imaging of changes in electromagnetic response of the soft tissue over time and has been particularly useful for researchers studying cognitive processes embedded in the brain. The brain contains multitudinous networks of soft tissue arranged in complex patterns. fMRI has unveiled the immense complexity of the neural pathways and activations underpinning cognitive phenomenon like emotion (Phan, Wager, Taylor, & Liberzon, 2002), attention (Coull & Nobre, 1998), exploration and exploitation tradeoffs (J. D. Cohen, McClure, & Yu, 2007) and even moral deliberation (Greene, Sommerville, Nystrom, Darley, & Cohen, 2001). To encompass this complexity, two separate types of scans distinguish the structure of brain regions from the active functioning of the brain. Each type of scan utilizes a different temporal resolution. The next sections follow this methodological segregation with the first section focusing on neural structure and the second on neural function. All neuroanatomical regions of interest have been italicized for clarity and ease of identification.

4.2.2 Structural Imaging and Neuroanatomy

Structural images allow visualization of the anatomy of the brain. Structural MRI provides highly detailed images of the brain in a static state. By using a prolonged scan duration, these images provide more visual detail, but lose the ability to detect signal variance from neural activity – similar to how extending the exposure time on a camera (leaving the shutter open longer than usual) produces a photo with enriched color and detail, but blurs motion.

Structural imaging reveals the complex structure of the brain evolved to store and process information. As such, the brain has many levels of organization. The basic unit of the brain is the cell. Cells in the central nervous system are highly specialized with those responsible for communication and information aggregation known as neurons. The average brain has 86 billion cells along with as many support cells, called glia, interlaced in a 1260 cm^3 fluid-filled area of the human skull (Azevedo et al., 2009; Cosgrove, Mazure, & Staley, 2007; Herculano-Houzel, 2009). Neurons communicate with each other in organized patterns producing neural tracts or pathways for rapid, aggregate signal transfer between major regions of the brain. This is analogous to smaller city roads feeding into a network of highways that link major cities. Clusters of neuronal cell bodies make up the major cities in this analogy and serve as the processing centers of the brain where incoming signals are temporally and spatially aggregated and outgoing signals originate. Cell bodies are microscopic and cannot be observed without invasive methods and specialized tools. However, with modern neuroimaging methods and computer modeling, brain regions can be compared on a visible scale.

On a visible scale, the brain is identified using large anatomically distinct regions. Lobes are the largest regions distinguished by differences in striation patterns and large fissures (*sulci*) between regions of tissue (*gyri*). The lobes contain modular regions and sub-regions of the brain. These structures are labeled and defined by their physical location, characteristics, or functionality. For example, the *substantia nigra*, Latin for “black substance”, is named for the dark stained color of the cells, and the *hippocampus*, translated from the Greek word ιπποκαμπος for seahorse, named because its slender and spiraled shape resembles a seahorse. Less uniquely shaped structures are named based on their relative location. Relative identifiers use axis-specific labeling based on the average position of a standing organism (see definitions and abbreviations for more information on terms used to navigate the brain). Additionally, four fluid-filled cavities called *ventricles* exist in the interior regions of the brain that supply nutrients and remove waste. These major structures - lobes, fissures, bulges, and ventricles - serve as guideposts when visualizing the brain and identifying localized activity.

The largest scale anatomical segmentation of the brain is the cerebrum which contains the *cortex* (“bark” from Latin) and covers the inner structures including the *basal ganglia* and *hippocampus*. The cortex is the outermost layer of the brain and can be subdivided into four lobes. From front to back (anterior to posterior), the four lobes of the brain are: 1) the frontal lobe which begins above the eyes and extends centrally, covering the top, front-half of the brain until the central sulcus, 2) the temporal lobe which extends on both sides from the rear of the brain forward underneath the frontal lobe, 3) the parietal lobe which covers the crown and posterior dorsal region of the cortex, and 4) the occipital lobe which resides ventral and posterior to the parietal lobe and temporal parietal junction.

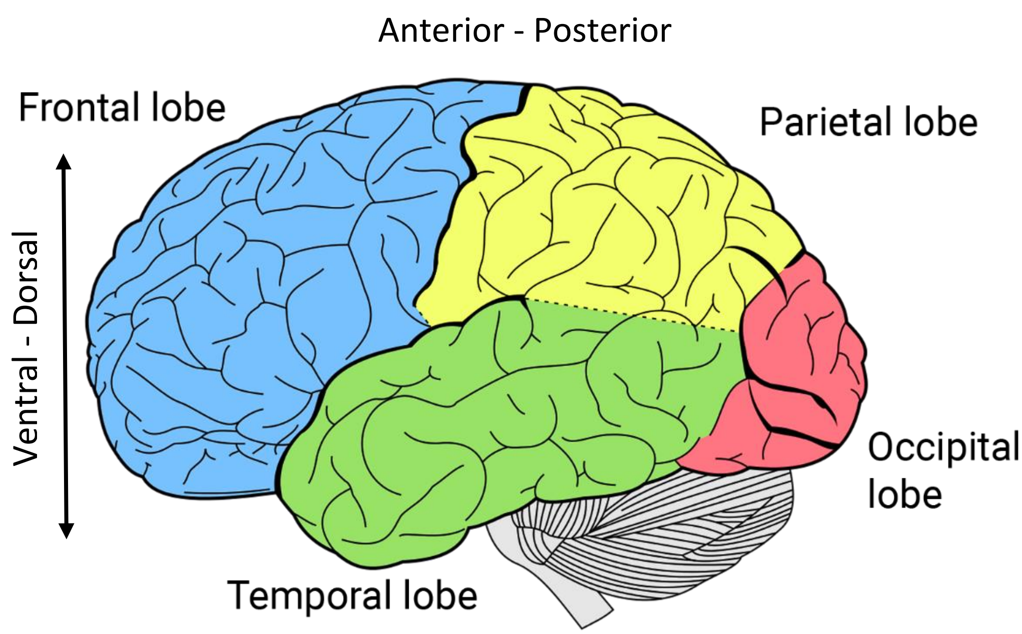

Figure 4.1: Four major lobes of the brain

Centrally located beneath the cortex is the *basal ganglia*. The basal ganglia is a collection of neural substructures resting on top of the hindbrain. These substructures include the *caudate*, *putamen*, *nucleus accumbens* presented in Figure 4.2. This region spans the midbrain regions connecting the brain stem and spine to the cortex. The basal ganglia is an important structure for linking cortical networks with pre-motor neurons in the spine and peripheral nerves that lead to muscles in the body. While anatomical distinctions are useful for navigating and orienting brain images, functional sub-region distinctions are more important for theoretical discussion of cognitive processes.

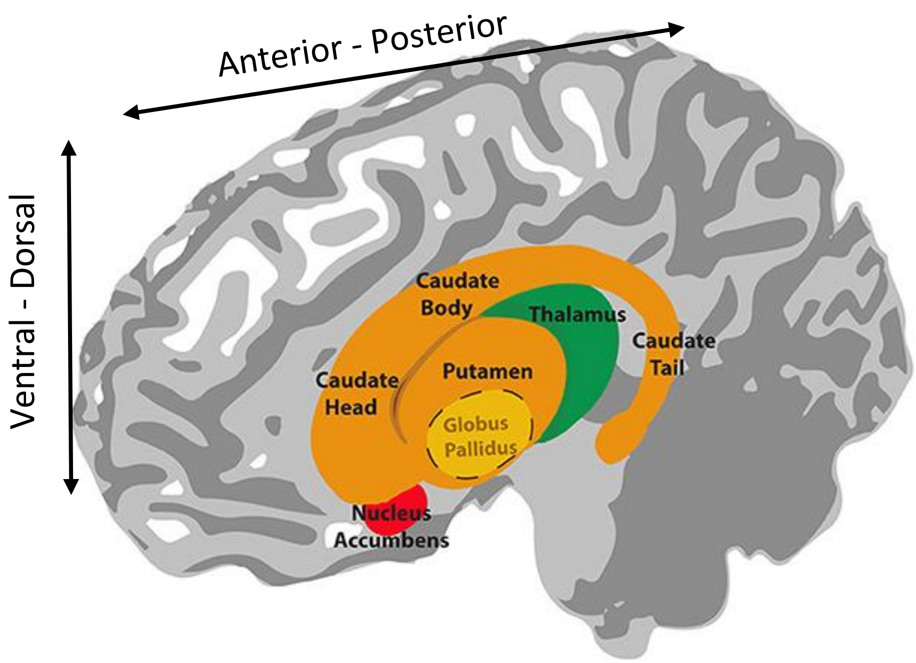

Figure 4.2: Substructures of the Basal Ganglia. Image from Lim, Fiez, & Holt, 2014

The following sections identify and describe the regions and structures of the brain that correlate with decision making, social cognition, and effort discounting processes. For the sake of organization, these regions are discussed by lobe and anatomical region.

4.2.2.1 Frontal Lobe

Beginning with the anterior portion of the cortex, the frontal lobe contains several important regions related to decision making, particularly choice option valuation and representation of social preferences. The primary regions of interest are the *prefrontal cortex* (PFC), the *anterior cingulate cortex* (ACC), and the *supplementary motor area* (SMA).

The PFC is the anterior section of the frontal lobe, and is most notable for its role in executive functions like emotion regulation (Ochsner, Bunge, Gross, & Gabrieli, 2013). Famously, Phineas Gage, a mild-mannered railroad laborer, suffered damage to his prefrontal cortex when a railroad spike was launched through his skull in a construction accident. After recovering from the injury, Gage became volatile and profane while retaining motor functioning, speech, and memory (Damasio, Grabowski, Frank, Galaburda, & Damasio, 1994; Wagar & Thagard, 2004). In clinical studies of patients suffering from PFC lesions, participants exhibited learning deficiencies and fell prey to myopic choice options in decision tasks involving uncertain outcomes (Bechara, Tranel, & Damasio, 2000). Emotion and decision making appear to be intrinsically linked, particularly in choosing between risky decision outcomes (G. F. Loewenstein et al., 2001) and identifying costly choice outcomes (McGuire & Botvinick, 2010). In both the valuation and selection phases of decision making, fMRI evidence has shown activity in the PFC to be strongly associated with the value of rewards and risk in egocentric choices (Todd A. Hare, Camerer, & Rangel, 2009; Tobler, Christopoulos, O'Doherty, Dolan, & Schultz, 2009).

Social cognition may also occur in the PFC (Amodio & Frith, 2006). Patients with frontal lobe dementia exhibited difficulty inhibiting emotional responses when interacting with other agents (Plaisted KC & Sahakian BJ, 1997). A large meta-analysis of fMRI studies found that mentalizing or "Theory of Mind" ability where one agent attempts to comprehend the cognition of others strongly correlates with PFC activity (Van Overwalle & Baetens, 2009). Furthermore, empathy, a form of emotional mentalizing, has been localized to the ventromedial PFC (Saxe, 2006). The *vmPFC* is a well-studied region associated with choice option valuation in egocentric decisions, but recently has been implicated in social preference formation and inter-agent preferences (Zaki, López, & Mitchell, 2013). While evidence for social cognition and socially important behavior exist, these early findings lack specificity, particularly with regards to the identity of other social agents and the relationship between agents.

The *ACC* is located medially in the frontal lobe just posterior to the PFC and above the *corpus callosum* that connects the two hemispheres of the brain. This is an important region that has been associated with executive functions or top down cognitive processing. Cognitive modeling of this region has identified option comparison and selection through information conflict monitoring

(Botvinick, Braver, Barch, Carter, & Cohen, 2001). Evidence has also been found for encoding of decision error, task frequency in the *ACC* (Botvinick, Cohen, & Carter, 2004). Conflict management and control may be linked behaviors. Cognitive control has been associated with choice option comparison, and subjective valuation such as cost/benefit weighting for both gains and losses (Rogers et al., 2004).

Posterior and dorsal to the *ACC* is the supplementary motor area. This area is a band of neurons arcing over the top of the PFC. The *SMA* is associated with action planning and movement. Studies have shown activity in this area correlates with choices that require future physical effort (Klein-Flügge, Kennerley, Friston, & Bestmann, 2016). The *SMA* resides medially anterior to the central sulcus which marks the boundary between the end of the frontal lobe and the beginning of the parietal lobe. Figure 4.3 shows these regions of interest and their relative location in the frontal lobe.

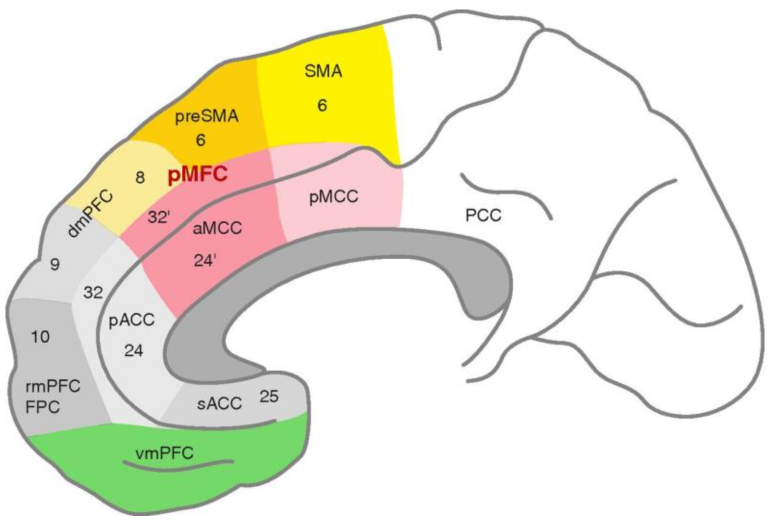

Figure 4.3: Frontal lobe regions of interest from Ullsperger, Danielmeier, & Jocham, 2014

4.2.2.2 Parietal Lobe

The parietal lobe contains the *posterior cingulate cortex* (PCC*), angular gyrus*, *precuneus*, and *temporoparietal junction* (TPJ) regions of interest. The parietal lobe has densely connected substructures that are diverse in function. Many of these regions have been associated with social behavior, decision making, and perspective taking.

The *PCC* connects the *ACC* to the rest of the parietal lobe. It is associated with new environmental stimuli, change detection, and exploration behavior (Hayden, Nair, McCoy, & Platt, 2008; Pearson, Hayden, Raghavachari, & Platt, 2009; Pearson, Heilbronner, Barack, Hayden, & Platt, 2011). The angular gyrus is posterior and bilateral to the *PCC*. Both the *PCC* and *angular gyrus* have been implicated in moral decision making where other agents receive harmful outcomes (Greene et al., 2001). In clinical studies of sociopathic participants, these regions have shown reduced activity particularly with regards to emotional perspective taking (Glenn, Raine, & Schug, 2009). The *angular gyrus and inferior parietal lobule* in general has been implicated in perception of another agent as the source of causality compared to self-induced causality (Farrer & Frith, 2002).

The *TPJ* is located ventral to the *angular gyrus* and connects the temporal lobe and parietal lobe. Like the PFC, the *right TPJ* (rTPJ) is frequently correlated with mentalizing and perspective taking from the point of view of another agent (Saxe, 2006; Van Overwalle & Baetens, 2009). The *rTPJ* in particular has been associated with representation of the self and representations of other social agents (Decety & Sommerville, 2003). A large review of 70 studies suggests the *rTPJ* is responsible or correlated with a broad spectrum of basic and complex cognition and behavior including body perception, attention, self-awareness, feelings of agency, empathy, and detecting changes in the environment (Decety & Lamm, 2007).

The precuneus and cuneus are regions with an especially dense network of neurons located anterior and medial to the angular gyrus. These regions are connected to myriad areas of the cortex and inner brain structures. The anterior portion of the precuneus has been associated with self-representation in storytelling, information processing, and self-awareness including contrasting self-representation from representation of others (Cavanna & Trimble, 2006). Figure 4.4 shows the regions of interest in the parietal lobe and their relative locations.

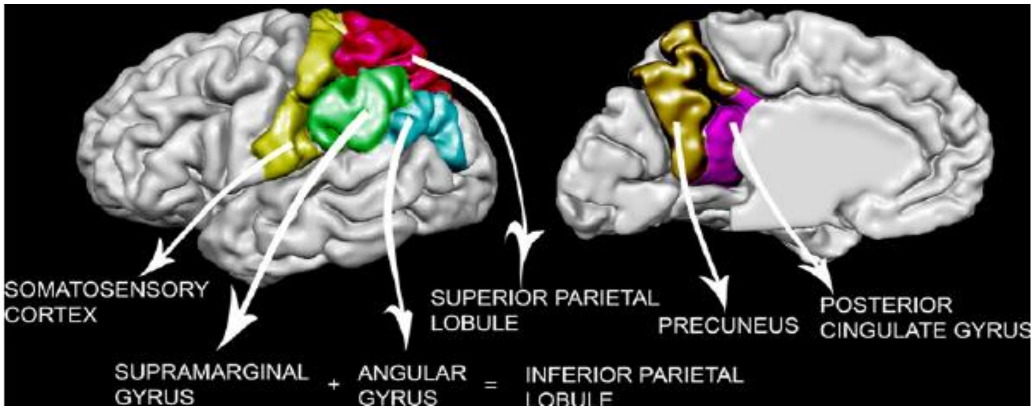

Figure 4.4: Parietal lobe regions of interest from H. I. L. Jacobs, Van Boxtel, Jolles, Verhey, & Uylings, 2012

4.2.2.3 Temporal Lobe and Basal Ganglia (mesolimbic system)

The temporal lobe is bilateral extending below the lateral sulcus from the parietal and occipital lobes towards the frontal lobe. The temporal lobes contain the *insula*, *amygdala*, and *hippocampus* substructures. The basal ganglia reside centrally between the outer cortices of the temporal lobes and into the frontal lobe. The *insula*, *amygdala*, and basal ganglia are all important structures in the limbic system which past research has shown to correlate with specific aspects decision making including cost-value computation.

Research has shown both the *amygdala* and *insula* are associated with cost factors including risk and loss. The *amygdala* contains neurons that project to the *ACC* and *PFC*, leading many researchers to consider the value encoded in these regions to reflect the potential cost of decision outcomes. The *insula* and *amygdala* are strongly associated with emotional processing, particularly negative affect (Dolan, 2002). *Insula* activity in human participants was found to correlate with unfair offers from another agent in the ultimatum game (Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003). The *insula* also showed increased activity when participants were responsible for movement of a joystick compared to another agent (Farrer & Frith, 2002). The potential for social norms and economic costs to be encoded in the same regions is an important consideration in allocentric decision studies.

While the *amygdala* and *insula* are often associated with fear, loss, and avoidance behavior, the basal ganglia are associated with positive outcomes of a decision and approach behavior. The basal ganglia are a collection of neural structures responsible for movement, learning, and reward, and are also part of the limbic system. The main sub-regions are the *ventral* and *dorsal striatum*. The *ventral striatum* includes the *nucleus accumbens*, while the dorsal striatum refers to the *caudate* and *putamen*. These regions contain many of the dopaminergic pathways involved in movement and learning associated with reward salience and reinforcement (Pessiglione, Seymour, Flandin, Dolan, & Frith, 2006). The *ventral striatum* (vStriatum) is associated with reward outcomes relative to expectations with activity that predicts reward onset and responds to erroneous predictions (T. A. Hare, O'Doherty, Camerer, Schultz, & Rangel, 2008; Kuss et al., 2013; McClure, Berns, & Montague, 2003; O'Doherty et al., 2003; Schultz, Dayan, & Montague, 1997). Neurons in the *basal ganglia* connect with lower brain structures near the spine that regulate muscles in the body. Figure 4.2 shows some of the major substructures of the basal ganglia and their relative locations.

4.2.2.4 Occipital Lobe

The occipital lobe resides at the posterior end of the brain and contains the visual cortex that receives and processes input from the optic nerves. This region has been well studied in both human and animal models and provided the foundational understanding of how networked regions in the brain operate in unison to perform higher-order functions (Marr, 1982). As such, the occipital lobe is immensely important for viewing experimental stimuli, but of little theoretical interest in investigating allocentric effort decision making. However, it is an apt transition point between anatomical distinctions of the brain and functional physiology

4.2.3 Functional Scanning and Neurophysiology

Functional scans record the dynamic activity of the brain over time. Unlike structural scans, functional scans are quick snapshots of the brain, producing images with little visual detail. However, these low-resolution images can capture signal change in relatively small time-windows throughout an experiment. When taken as a collective, these scans provide a trace of neural activity that can be used in functional analysis and statistical modeling.

While structural imaging requires knowledge of neuroanatomy, functional analysis requires an understanding of the physiology of the brain beginning with activity at the neuronal level. Neurons are specialized to rapidly communicate with each other. Neurons function by aggregate electrical signals originating from receptors residing on cell protrusions known as dendrites. The electrical signal cascades down the neuron and ultimately transforms into chemical signals (known as neurotransmitters) passed to other neurons (Jahn, 2016). Neurons receive inputs from many receptors and aggregate the signal both spatially and temporally. Receptors can detect chemical signals in the extracellular environment and alter the electrochemical gradient of the neuron in response. If the internal electrical charge reaches a threshold level, the cell chemistry of the neuron changes dramatically due to voltage-gated ion channels causing an all-or-nothing electrical signal known as an action potential. The action potential cascades down elongated protrusions from the cell body called axons. At the end of the axon, the electrical gradient change triggers the release of chemical neurotransmitters into the fluid space between neurons called a synapse. Neurotransmitters activate receptors on downstream neurons and the original signal propagates in newly activated neurons. This process is not restricted to nearby neurons only. Axons can travel large distances, propagating signals from one region of the brain to another.

A single action potential is neither a complex information carrier nor is it alone responsible for a decision or action. It is comparable to one binary switch – one bit in computer information processing. However, complex temporal and spatial patterns can emerge from aggregate action potentials that act as highly complex switches. From these temporal and spatial patterns, the brain is capable of elaborate functioning and incredible adaptability. Neurons aggregate and coordinate action potentials over time using different signal thresholds and synapse configurations to then pass information along grouped pathways or neural tracts. Importantly, these regions and pathways are dissociable in the brain and can be identified through imaging (Kanwisher, 2010).

To trace activity changes across time, fMRI analysis leverages signal changes due to the brain's natural metabolism. Neurons must actively maintain an electrochemical gradient to create action potentials. As neurons activate in response to external stimuli and internal communication, the cells metabolize oxygen to reset the electrochemical gradients disrupted by the action potential. Oxygen is delivered by blood in the circulatory system to the recently activated neurons. Changes in the blood oxygen concentrations in nearby capillaries can be recorded by the MR scanner, known as a blood oxygen level dependent (BOLD) response. BOLD response is the source of variance recorded in fMRI experiments (Ogawa, Lee, Kay, & Tank, 1990). While this is an indirect measure of neural activity, it is useful for determining both the magnitude and location of neural activity at a slower timescale than the action potentials underpinning the metabolic response (Logothetis, Pauls, Augath, Trinath, & Oeltermann, 2001). The BOLD response temporally and spatially aggregates neural activity by producing a predictable response over time, increasing in magnitude as more neurons are activated and as neurons are activated more frequently. As neurons activate more frequently, they require more oxygen to reset for the next action potential. Active regions absorb more oxygen from the surrounding blood than inactive regions. The greater the oxygen depletion, the larger the BOLD response recorded by the scanner. Figure 4.5 shows the relationship between an external stimulus and BOLD response, which can increase given a longer reaction time (temporal summation).

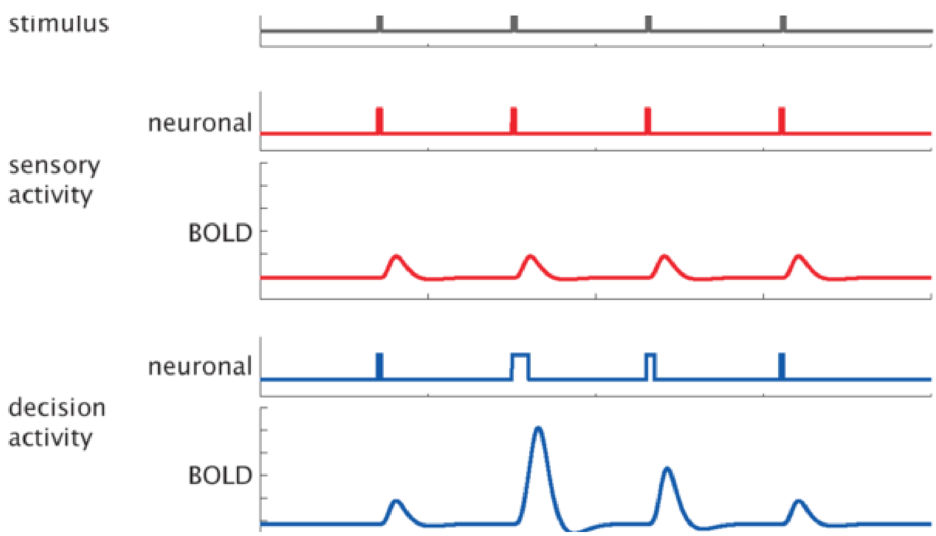

Figure 4.5: Relationship between external stimuli and BOLD response from Grinband, Wager, Lindquist, Ferrera, & Hirsch, 2008

4.2.4 fMRI Methodology

To gather images, a large and powerful electromagnet (3 Tesla used in this experiment), applies a constant magnetic field to the participant lying horizontal on a small platform inside the machine. The magnetic field forces polar molecules to align along a north-south axis. A brief radio wave pulse is then passed through the body, exciting molecules and disrupting the magnetically-enforced alignment. Molecules with differing compositions due to electronegativity, polarity, or bonding release unique energy signatures as they return to their magnetically induced resting state. The energy signatures are recorded and time-stamped by sensors around the participant. During fMRI scanning, the scanner collects data repeatedly at short intervals (approximately 2- 6 seconds in most neuroimaging studies) creating a 4-D image (or time series of 3-D images).

After participants are briefed and provide informed consent to all procedures, initial scans are taken to ensure participants are aligned in the scanner. Head movement creates artificial signal in fMRI scanning and should be minimized during the experiment. To assist with this, the participant's head is locked into position with a head guard apparatus. A second set of images are scanned using low temporal resolution, to provide a map of the participants' neural structure (structural scans). Finally, the behavioral task of the experiment commences while the scanner collects high temporal resolution scans (functional scans) of the brain. The differences between structural and

Scans are taken in k-space and undergo Fourier transformation into three-dimensional space before processing the data. The resulting planar scans represent slices of the brain that intersect to create "3D volume pixels" or voxels representing ~2mm^3 coordinates in the brain. The voxel is the basic unit of analysis in fMRI. Changes in BOLD signal are recorded for each voxel, making it imperative to fix voxel position across analysis. However, participants are in the scanner for extended periods of time and unintentionally move about due to basic metabolic functions (breathing, swallowing, or even furrowing their brow when making a difficult decision). Movements introduce random positional variance (or "noise") to the data and must be corrected to improve the signal-to-noise ratio. Additional noise arises from resting state processes in the brain, exogenous stress, and other uncontrolled for differences both within- and between-participants. These corrections take place in a multistep procedure known as preprocessing, which happens offline after data have been collected. Preprocessing is the mathematical adjustment of imaging positional data using 5 steps: realignment, coregistration, normalization, smoothing, and motion correction. Each step is described in further detail below. All steps were performed using SPM12 software (Wellcome Trust, UCL).

4.2.5 Preprocessing

The first step in preprocessing is spatial realignment. In this step, all subsequent functional scans are aligned with the first scan to correct small positional shifts and unintended motion. Six mathematical transformations are applied to the images: 3 translational shifts (one each in the x, y, and z dimension), two rotations (pitch and yaw), and a third skew transformation that shifts the left and right side of the brain in opposite directions along the same axis. This results in a twisting positional adjustment. The parameters for each realignment's magnitude are saved for each participant and input later in statistical analysis.

Next, coregistration maps the functional images to a structural image. Additionally, structural segmentation is applied to the structural images of each participant. Structural segmentation identifies and labels certain types soft tissue found in the skull to specify and validate areas of the brain to ensure the regions are grey matter rather than other types of soft tissue (Ashburner & Friston, 2005). Different types of soft tissue contain varying concentrations of water and causing different energy signatures when scanned with low temporal resolution. Four major tissue types are segregated: 1) Grey matter which contains the neuronal cell bodies, the dendrites, synapses, and the supporting glial cells and capillaries. Grey matter areas are the focus of fMRI studies as they localize where cell-to-cell communication and interaction occurs. 2) White matter are long axon tracts wrapped in a fatty lipid layer called myelin that repels water and allows the neuronal signal to propagate faster. 3) Ventricles are the four cerebral-spinal fluid (CSF) filled cavities and the cerebral aqueduct that connects them. The final soft tissue type is the 4) soft tissue layer surrounding the skull that protects the brain from physical and chemical trauma. Thin membranes are responsible for this protective layer, including the meninges and blood-brain barrier.

The third step is normalization. Normalization warps each participants' image set to fit a common image template. Images can be normalized to a template image of the brain or a mean structural image bespoke to the participants of the study. This study opted for the latter to provide a more accurate-to-sample mapping of regions of interest and functional BOLD response.

Smoothing is another step for improving signal-to-noise ratio. In this step, SPM software uses Gaussian kernel full-width half-maximum smoothing over an 6 mm^3 volume to aggregate response signals from voxels to small spatial regions. Aggregation reduces random error due to spontaneous neuron activation - present in all regions of the brain – and slight anatomical differences between participants with regards to neuron density in certain areas.

A final step of preprocessing, also used in this study, was movement artifact correction. This is an additional step to correct systematic error due to a permanent shift in the participant's head rather than mere homeostatic movements. Positional changes beyond a 3-degree rotation in pitch, yaw, or roll were marked via timestamp and all subsequent images were realigned based on the estimated rotation vector.

4.2.6 Statistical Analysis

For data analysis and statistical comparison, a hierarchical generalized linear modeling (GLM) approach is common in fMRI studies (Holmes & Friston, 1998). BOLD response across time is modeled by a Hemodynamic Response Function (HRF). The HRF serves as the dependent variable in GLM analysis and marks the replenishment of oxygen to neurons post-activation. The HRF is relatively flat when neurons are in a resting state, peaks sharply after a slight delay from stimulus time, and undershoots baseline levels slightly upon deactivation (this undershoot mirrors the theoretical refractory period of returning neurons to electrochemical equilibrium). A canonical HRF models BOLD response in each voxel over the duration of the scanning session in relation to event onsets (Friston, Josephs, Rees, & Turner, 1998). Additionally, temporal and dispersion derivatives can be modeled to improve fit and create a smoother prediction curve known as the canonical HRF. The right column of Figure 4.6 shows an example of the canonical HRF in response to a single, stimulus onset.

Estimates of the HRF are specific to conditions. For example, the HRF responses in the left column of Figure 4.6 are color coordinated based on stimulus event type. *A priori* conditions determine the type of stimulus event. The timestamp of scans associated with manipulated conditions or onscreen events are used as predictors of the HRF. GLMs estimate the HRF function for each voxel in the brain. The results are then placed over a mean or template brain image creating a statistical parametric map of the brain.

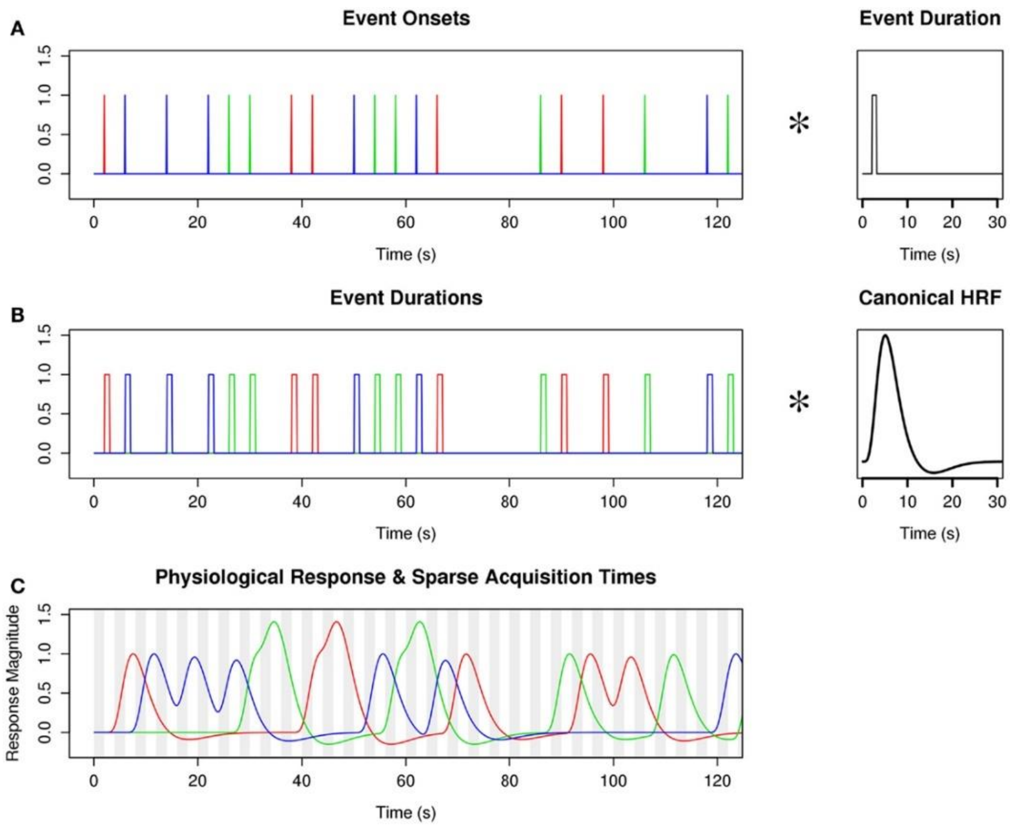

Figure 4.6: Relationship between stimulus events and HRF. The color coordination shows the specificity of the response. Temporal aggregation is reflected in increased response magnitude. Figure adapted from Perrachione & Ghosh, 2013.

Additional variables can be convolved with the HRF through parametric modulations. Parametric modulations represent variables of interest with multiple factors such as when controlling for individual differences, participant movement vectors, or the magnitude of a continuous stimuli parameter. Two examples from the effort discounting task are the variable amounts of compensation and effort of the larger choice option on each trial. The magnitude of these variables weight the mean HRF on a per-trial basis since each trial is time-stamped. Parametric modulations can be orthogonalized and therefore may be input-order dependent (Mumford, Poline, & Poldrack, 2015). Possible order effects were averted by independently computing one parametric modulation per analysis. Analyses were run iteratively with all first level analyses run, followed by independent second-level analyses.

First level GLM analysis estimates the HRF of each voxel using the same predictors independently for each participant akin to within-participants design in a mixed-effects model. The first-level GLM collapses observations across time resulting in estimates within-participants that model the effect of stimuli across all scans in each voxel. The estimates are overlaid onto an image of the brain creating a statistical parametric map (SPM) of the brain. The SPM is placed under a thresholding mask that colors voxels based on the p-values of the beta estimates. This level of analysis is computationally expensive as the number of observations is proportional to duration of scanning session multiplied by the number of voxels for each subject. Due to the sheer number of statistical tests required, many false positive results are likely. For a single whole-brain analysis with 30 participants using the scanning settings of the following experiment, approximately 50,000 single-voxel regressions are performed. Assuming a single-sample t-test for each voxel given $\alpha = 0.05$, 2,500 voxels can be expected as type-I errors. To reduce the false-positive rate while maintaining power, test-number corrections are applied by restricting the area of interest (ROI analysis), using family-wise error rate corrections (FWE), or false-discovery rate (FDR) corrections. After obtaining beta values for each voxel and each subject, second-level analysis is performed to compare the effects over time.

Second-level analysis combines the effect sizes and locations from first level analysis across all subjects to test for population-level effects. This step is less computationally intensive as the number of observations is only the number of estimated betas for each voxel for every participant. The second-level GLM results in a statistical parametric map reflecting a “grand-mean” brain. Again, a threshold mask highlights voxels with significant estimates. At this level, it is important to look for voxel groupings or regions of significance, thus clustering and *a priori* masks of regions of interest are used to improve signal-to-noise ratio and extrapolate findings.

This is a broad overview of fMRI analyses, reflecting an outline of the approach to investigating neural activity. There are myriad details and follow-up analyses available to researchers that can be applied to specific hypotheses. For example, contrasts at the second level GLM can be defined using first level contrasts, paired t-tests, ANOVA, or other techniques. Furthermore, second level estimates can be correlated with individual differences such as self-reported measures or computational model estimates (J. P. O'Doherty, Hampton, & Kim, 2007). More detailed methods used for the fMRI study in this thesis are described in chapter 5.

The next section highlights functional regions of interest in the brain through a review of prior literature related to allocentric effort valuation.

4.3 fMRI Literature Review

At the time of writing, no prior fMRI studies of allocentric effort decisions are known. However, fMRI studies have focused on allocentric decision making in other choice domains. Independently, egocentric effort discounting behavior has been examined in fMRI decision studies. As such, this review highlights these separate studies with the aim of synthesizing relevant aspects from each.

4.3.1 fMRI Studies of Allocentric Decision Making

Allocentric decisions have been studied in several choice domains including risk aversion and temporal discounting. When making choices between low and high reward/risk monetary gambles, participants have shown different risk preferences when deciding for others than when they decide for themselves and these differences correlate with neural activity (Jung, Sul, & Kim, 2013). In this experiment, participants in an fMRI scanner were presented two chance lotteries on each trial. One lottery had a reward magnitude of +10 if won and -10 if lost. The alternative option had reward magnitudes of +90/-90. The probability of winning in each lottery was the direct compliment of winning the alternative option, varying on each trial between 17-83% and 83-17% chance to win. All choices were made twice, once as allocentric decisions and once as egocentric decisions. Participants allocated the larger reward more to others than themselves when the probability of winning the larger option was lowest (17%). Conversely, participants assigned themselves the larger option more often than they gave to others when the probability of winning was the highest. Neural evidence from the twenty-three scanned participants in this study shows significant contrasts in areas associated with mentalizing. When deciding for others, regions including the *TPJ* and *dmPFC* showed increased BOLD response. Areas associated with reward and cost salience were more active when making egocentric decisions, including the *vStriatum* and *amygdala*.

An fMRI study of temporal discounting decisions shows similar results. When participants made decisions between options that required the recipient to wait for a larger reward or receive a smaller reward immediately, behavioral and neural differences were observed (Albrecht et al., 2011). Choosing between sooner, smaller rewards and later larger rewards participants who greatly discounted the value of later, larger options for themselves more often chose the delayed, larger choice for others – meaning that participants were more impatient when deciding for themselves compared to allocentric decisions. Neural activity in the twenty-eight participants shows that areas in the *anterior medial PFC*, *vStriatum*, and *pregenual ACC* exhibited greater BOLD response when immediate choice options were available for themselves, but not when both options were delayed or the immediate options were for another recipient. However, decisions with an immediate allocentric option were not distinguishable from decisions with two delayed egocentric options.

Further evidence shows that the same sub-regions of the *medial PFC* are used in choice option value comparison when making both egocentric and allocentric decisions for a confederate with different preferences from the participant. Comparisons of neural activity during decision making shows the *vmPFC* exhibited patterns of activity correlating with the discounting rate of the decision recipient. However, when participants made allocentric choices, the *dmPFC* correlated with egocentric discounting rate (Nicolle et al., 2012). Researchers have suggested that the *dmPFC* is responsible for simulated value computations irrespective of social influence, challenging prior theories of a "social brain" located in the *PFC* (Dunne & O'Doherty, 2012). While dissociable, the neural activity was inversely correlated, implying similar or related mechanisms localized to different areas. Notably, regions implicated in temporal discounting tasks are at least partially dissociable from those involved in effort discounting with studies showing different regions of activity involved in each type of decision (Massar et al., 2015).

Evidence for agent-invariant valuation in the *PFC* also comes from sociocentric decisions in a wealth distribution task (Zaki et al., 2013). Participants made choices between either an egocentric monetary reward and an allocentric monetary donation to another participant. The wealth indifference ratio between egocentric and allocentric reward was used to predict pure egocentric choice amounts and pure allocentric choice amounts. Both predictions correlated with activation in the *vmPFC*.

The idea of common valuation mechanisms across decisions is not novel. Estimations of the subjective value of charitable giving in participants asked to share a monetary reward pool with a charity institution showed activity in the *vmPFC* in twenty-two female participants (Hare et al. 2010). This area is commonly associated with subjective value of choice options in egocentric decision making (Hare et al. 2011). Overlap of subjective value mechanisms in the brain for both social and non-social outcomes is a well-supported theory, known as the "common-currency model" of decision making (Ruff and Fehr 2014). This model suggests that the neural computation of subjective value is the same irrespective of the physical properties of the choice options. Essentially, the benefits and cost valuations for apples are comparable to those for oranges.

However, the same charitable donation study also found inputs from the *anterior insula* and the *posterior superior temporal cortex* (a specific sub-region of the *TPJ*) were more active in donation decisions than in purchasing decisions (T. A. Hare, Camerer, Knoepfle, O'Doherty, & Rangel, 2010). Purchasing decisions in this study resulted in egocentric outcomes while donations provided sociocentric outcomes. Despite the donations being made anonymously by the research group on behalf of the participant, both donations and purchases were costly to the decision maker, and therefore partially egocentric. The potential for uncovering neural regions responsible for social influence in effort decision making drives the following research.

While evidence suggests egocentric and social decision making utilize similar regions in the brain, there remains evidence of unique neural inputs to these regions correlating with social elements. One important social element is the influence and relationship between social agents. Research has found behavioral evidence that participants adjusted their preference ratings for t-shirts after viewing another person's ratings (Izuma & Adolphs, 2013). Social influence depends on the identity and perceived relationship between social agents. Izuma and Adolphs also found the direction of a participant's preference adjustment depended on the identity of the other: either a fellow student (conform) or a registered sex offender (distance). Depending on the direction of the adjustment, areas in the *dmPFC* and *SMA* were activated. These preference adjustments were powerful and manifested nearly identically even after 4 months. Further studies have measured the utility of such social influence in conveying risk preferences in group decision making scenarios (Chung, Christopoulos, King-Casas, Ball, & Chiu, 2015).

Another point of evidence for social influence on valuation processes comes from social discounting research (Strombach et al., 2015). Social discounting refers to decreasing generosity of a decision maker as the outcome recipient becomes increasingly unrelated or abstract to the decision maker. Social discounting reflects a gradient between sociocentric and allocentric decision making, where close ties reflect a higher likelihood of instrumental reputation building, reward sharing, or reciprocation. In the experiment, decision makers chose between an entirely egocentric payout or social payout that was smaller for the decision maker but matched for another recipient. The results again showed egocentric value signals in the *vmPFC*, but also evidence for neural connection from the *rTPJ* when participants chose prosocial outcomes.

Correlations between activity in the *PFC* and individual differences in allocentric decision making have also been investigated. In two studies where participants chose to give money and assistance in a task, individual differences in altruistic behavior correlated with activity in the *dmPFC*, *ACC*, and parietal cortex (Waytz, Zaki, & Mitchell, 2012). Participants who gave more of their time solving logic problems for another agent's gain and shared more of a monetary pool with another agent had increased activity in the *dmPFC*, *ACC*, and parietal cortex when deciding how much money to share, but only the *dmPFC* when assisting with logic puzzles.

Prior computational models provide a role for the direct input of advice in neural option valuation (Biele, Rieskamp, Krugel, & Heekeren, 2011). However, even passive social interactions can influence valuation. Social comparisons between the "haves" and "have-nots" can impact the perceived value of rewards. A study in which two participants underwent fMRI scanning simultaneously while participating in an estimation task found evidence that reward signals in the ventral striatum differed based on the reward received by a participants' partner relative to the participant's reward (Fliessbach et al., 2007). When the participant was rewarded and the partner was not, BOLD response increased in the participant's *vStriatum*, *PFC*, *PCC*, and *angular gyrus*. When only the partner received a reward, the participant's *insula* was activated and the *vStriatum* deactivated.

The complexity of social influence in the neural mechanisms of decision making remains a challenge for neuroscience research. Social influence can be difficult to operationalize in a tightly controlled fMRI environment. While social influence can be manipulated through advice, this may differ from unstated ties established through relationships, social hierarchies, and power dynamics. However, these and other studies have made headway into a vast new area of study and laid important groundwork for future investigations into the neural processes behind allocentric decisions.

4.3.2 Effort Decision Making

The literature of studies using fMRI to investigate neural correlates of effort decision making is well established compared to that of social decision making. Here I summarize recent results from human egocentric effort decisions. These studies highlight the discriminant neurophysiology of effort discounting compared to delay discounting, neural correlates of physical and mental effort, and localization of subjective value calculations in the brain.

Discounting behavior is often operationalized with temporal delay, but effort also causes discounting behavior in decision making. While effort and delay exhibit similar behavioral choice patterns, unique neural activity drives these choice differences. Evidence comes from decisions where male heterosexual participants chose to view erotic visual stimuli. To earn the image, participants either had to wait or squeeze a handgrip lever for a time duration while inside the fMRI scanner. Using a preference-rank measure of subjective value, the researchers found disparate relationships between the subjective value of the chosen option and regions associated with reward value computation. Delay options' subjective value were positively correlated with *vStriatum* and *vmPFC* activity while effort options were associated with the *insula* and *ACC* (Prévost et al., 2010). In a similar handgrip task with money used as a reward outcome, results showed separate activity associated with learning pure reward value in the *vmPFC* and subjective value (cost-inclusive value) in the *anterior insula*, *ACC*, *PCC* (Skvortsova, Palminteri, & Pessiglione, 2014).

Using monetary rewards and the effort typing task used in the present research, research has shown distinct neural responses related to effort discounting that differ from temporal discounting (Massar et al., 2015). Subjective value of effort options was associated with activity in the *lateral PFC* and parietal cortex. Additionally, the *ACC* showed increased activity during effort trials compared to temporal delay trials. One important assumption to note is the typing task requires more cognitive or mental effort than the handgrip task.

Other studies have investigated cognitive effort decisions using different tasks. Researchers have used a visual search paradigm in which participants in the scanner had to locate objects in a varyingly crowded field of vision. Participants highlighted the located objects using a joystick in the fMRI scanner. Results showed that activity in the *dorsal ACC* and the ventral striatum correlated with the subjective value of the upcoming task where more difficult search fields were paired orthogonally with varying rewards (Croxson et al., 2009). Additionally, *SMA* activity was correlated with changes in task difficulty.

In another cognitive effort study, participants chose between two memory tasks of set difficulties (easy or hard) for varying monetary rewards. The memory task was a variation of an n-back task with either one or two dimensions of stimuli to remember. Results showed correlations between effort-modulated value and activity in the *nucleus accumbens* (a *vStriatum* sub-region), and *ACC* (Botvinick et al., 2009).

An important note is both research groups studied cognitive effort with regards to anticipation of an upcoming task. Neural structures in the basal ganglia have been associated with reward expectation. In physical effort discounting implemented with the handgrip task, anticipated effort is associated with activity in the *dACC* and *putamen*, while anticipated rewards of the chosen option were associated with ventral striatum activity (Kurniawan, Guitart-Masip, Dayan, & Dolan, 2013). This study also examined the activity associated when effort was required to prevent monetary losses. In loss-avoidance trials, effort and negative subjective value were both correlated with insula activity.

To clarify the role of effort in decision making, recent research has used computational modeling to show correlates of estimated discounting parameters (Klein-Flügge et al., 2016). The effort task used was a variable handgrip strength task coupled with either small or large monetary rewards. The researchers found a sigmoidal discounting model best fit the behavioral choice data when compared to a hyperbolic discounting model and model free expressions such as reward minus effort. In the brain, subjective value estimates from this model correlated with the *SMA*, *putamen*, and *dACC*. *SMA* and *putamen* activity were particularly associated with effort avoidance while *vmPFC* activity correlated with reward seeking decisions. *ACC* activity was associated with option comparison rather than attribute evaluation.

4.4 Summary

The brain is an immensely complex organ which research has only begun to investigate. Using rigorous neuroimaging methods, researchers have begun to probe the underlying biological processes associated with decision making. After reviewing the literature on allocentric option valuation and egocentric effort discounting decisions, several distinct regions of interest emerge. The *PFC* and *ACC* in the frontal lobe appear to control subjective valuation and choice comparison in effort decisions, while neural pathways between the *PFC* and parietal cortex, *PCC*, and *TPJ* drive social inputs into decision making. Additional regions of interest include the insula for its relationship with cost valuation and empathy, and the *vStriatum* associated with reward seeking behavior.

5 fMRI Investigation of Allocentric Effort Decisions

5.1 Motivation

The primary motivation of this research is to investigate neural correlates of allocentric effort discounting. The implementation of decision processes is reflected in the dynamic patterns of neural activity. By recording concurrent brain activity while decision makers engage in the cognitive processes of option valuation and selection, computational models can be compared with biophysiological evidence. Using neuroimaging methods, latent constructs and parameter estimates like discounting rates can be visualized in the brain through correlated activity. This provides validity for theoretical cognitive models and improved understanding of neural processes responsible for decision making.

Allocentric decisions where the outcomes require the decision recipient's effort have yet to be examined using neuroimaging methodologies. The experiment presented here investigates metabolic activity in the brain while laboratory participants chose between large effort, large reward options or small effort, small reward options for another agent. Using fMRI scanning, changes in BOLD response across the whole brain were investigated as an initial view of the processes responsible for allocentric effort discounting. Further theory-driven analysis of specific regions of interest (ROIs) were examined for more descriptive and thorough comparison of specific processes. For example, ROIs previously identified to reflect valuation processes should exhibit different activation patterns from those ROIs associated with social influence, mentalizing, or empathy.

Additionally, the research presented here investigated estimated discounting rates to determine if individual differences were reflected in region-specific activity. Localization of variance in discounting rates helps to validate the theoretical construct and computational models of an allocentric effort discounting rate. Determining a specific region or regions associated with allocentric effort discounting provides insight into how the brain is organized and how it processes social allocations. Identified regions may act as moderating afferent connections to regions responsible for option valuation or selection.

This experiment also attempts to refine the difference between two types of accountability. Accountability can be social, as described in chapter 2, where a third-party evaluator or judge enforces norms on the decision maker through an in-person interview. Accountability can also be personal and private. Self-reflection or knowledge that a decision maker must revisit the decisions in the future may utilize similar cognition without the presence of another social agent. By manipulating accountability within-participants, the experiment attempts to identify and disambiguate neural correlates of the source of accountability: either a social agent or private introspection.

5.2 Methods

5.2.1 Participants

39 participants were recruited from the general population in Virginia, USA. All participants were screened for mental illness, metal implants, drug and alcohol abuse. Participants who responded with less than 5% variance in choice preferences, failed 2 or more catch-trials, or moved excessively in the scanner

were removed during preprocessing leaving N = 29 ($Mean_{age}$ = 25.7, SD_{age} = 7.9 years; N_{female} = 16). All procedures were approved by the Virginia Tech Carillion Research Institute Institutional Review Board (VTCRI-IRB). Participants were compensated $20 for approximately 1 hour of participation plus the averaged outcome of two decisions earned by completing the typing task assigned by a previous participant. The mean added compensation was $4.38 for typing 28 additional words.

5.2.2 Task

The experiment follows a within-participants design with each participant making identical decisions in two conditions. Participants made choices in 60 decision trials and three catch trials. Catch trials were option pairs where one choice option was superior to the other irrespective of discounting rate. Decision trials were presented in pseudo-random order with each set of choice options shown twice, once in each condition. Figure 5.1 shows the progression of one decision trial.

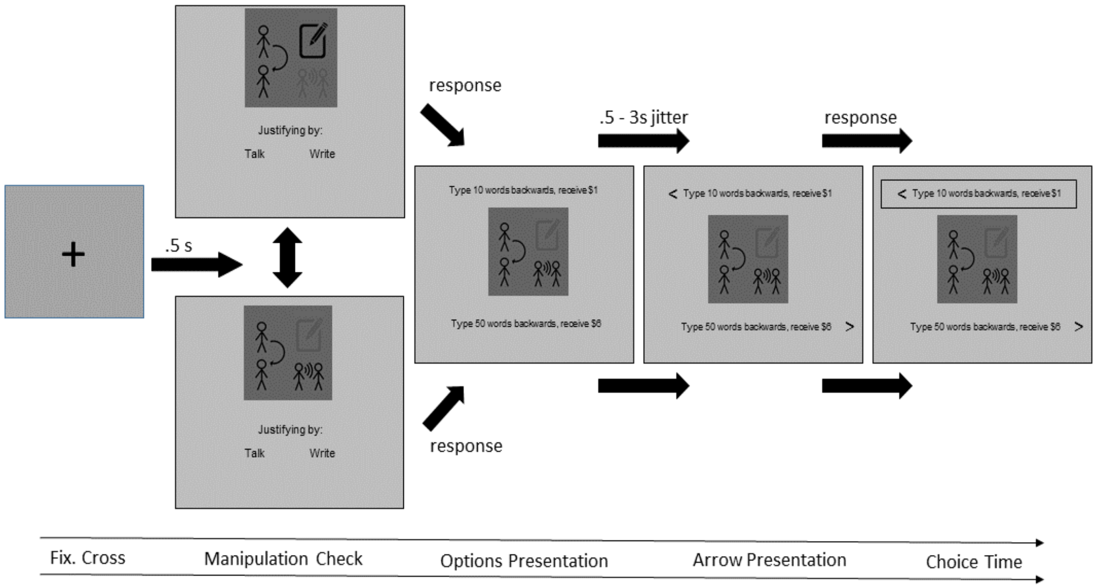

Figure 5.1: Diagram of one decision trial in the scanner. Bold arrows show the progression of visual screens viewed by the participant including durations between onset of visual stimuli and the labels for each timestamped event used in fMRI analysis.

On each trial, participants chose between two option bundles with each consisting of a variably sized effort task and compensation for completing that task. For example, a set of choice options might be choosing either to type 10 words backwards for $1 or 30 words backwards for $5. One option was always a smaller effort, smaller compensation option (referred to as the smaller option) while the other option was a variable, larger effort, larger compensation option (referred to as the larger option). The larger option varied orthogonally with regards to effort and compensation, while the smaller option remained constant on all decision trials. Larger option attributes ranged from $4 to $10 in $1 increments and 20 to 50 words in 5-word increments. The smaller option was a constant bundle of $1 for 10 words. The smaller option varied during catch trials; however, these were excluded from analysis.

Participants were informed about each of the two conditions prior to entering the scanner and were reminded prior to each decision using an indicator image. Indicator images identified the upcoming trial as requiring either written accountability or social accountability. The trial condition had to be identified and confirmed with a key press by the participant. For Written Accountability trials, participants knew they would be asked to review two randomly selected decisions for 60 seconds after the scanning session. During the 60 second review sessions, participants privately justified why they chose one option over the other in writing. The written justification was kept by the participant after the experiment and not shown to the experimenter or research assistants.

For the Social Accountability trials, two decisions were reviewed after the two Written Accountability review sessions, again in 60 second intervals. After reviewing the choices, participants were escorted to another room with a confederate acting as the head experimenter. The participants then justified the Social Accountability choices during an interview with the head experimenter.

The average of the decision outcomes from both conditions, effort and compensation, was given to the following participant in the study. After providing written consent, participants then viewed instructions for each condition and an explanation of the typing task assigned in the decision trials. Participants then completed a small sample of the typing task to prove comprehension and help them make informed decisions.

Before each trial, an indicator image appeared on screen displaying the condition of the upcoming trial. Participants then confirmed the condition of the upcoming trial as the prompt “Justify by:” appeared with the options “Write” or “Talk” below on either side. Participants confirmed using the plastic button box in their right hand. Participants received feedback only if they misidentified the condition causing a “Key Press Error” message to appear, otherwise the trial progressed as usual.

Choice options were presented randomly on either the top or bottom of the computer screen. Participants indicated their choice by pressing keys on a plastic button box with either their right index or middle finger depending on the direction of the arrow next to their preferred option. The arrow directions were randomized on each trial to prevent automatic responses and motor preparation (Mullette-Gillman et al., 2015). After indicating their choice, participants received visual confirmation of their input with a black box surrounding their choice on the screen.

Participants were then given a safety briefing and instructions pertinent to the fMRI scanning environment. Once completed and in the scanner, participants underwent two brief scanning procedures - localization and structural scanning - before completing three practice trials. Participants were permitted to ask questions and hear the instructor’s response during the practice trials. After completing the practice trials, participants began scanned trials.

The effort task assigned in these trials was the typing task used in prior effort discounting (Libedinsky et al., 2013; Massar et al., 2015) studies in this thesis. After the trials, participants typed each word from a list in reverse-letter order. If the decision recipient made a mistake, he or she was forced to attempt the same word again. The size of the list was determined by averaging the outcomes from two choices made by either that participant or by another participant's allocentric choice. The computer randomly generated a list of words for each participant from a predetermined set.

5.2.3 Behavioral Results

The proportion of smaller option choices did not differ between the two accountability conditions. Figure 5.2 shows the distribution of each participant's proportion of smaller option choice in each condition ($\text{Mean}_{\text{Written Acc.}} = 0.25$; $\text{Mean}_{\text{Social Acc.}} = 0.26$). Paired Wilcoxon signed-rank test fails to reject the null hypothesis ($V=86.5$ p-value $= 0.37$), confirming that the difference in choice behavior between conditions is not significant.

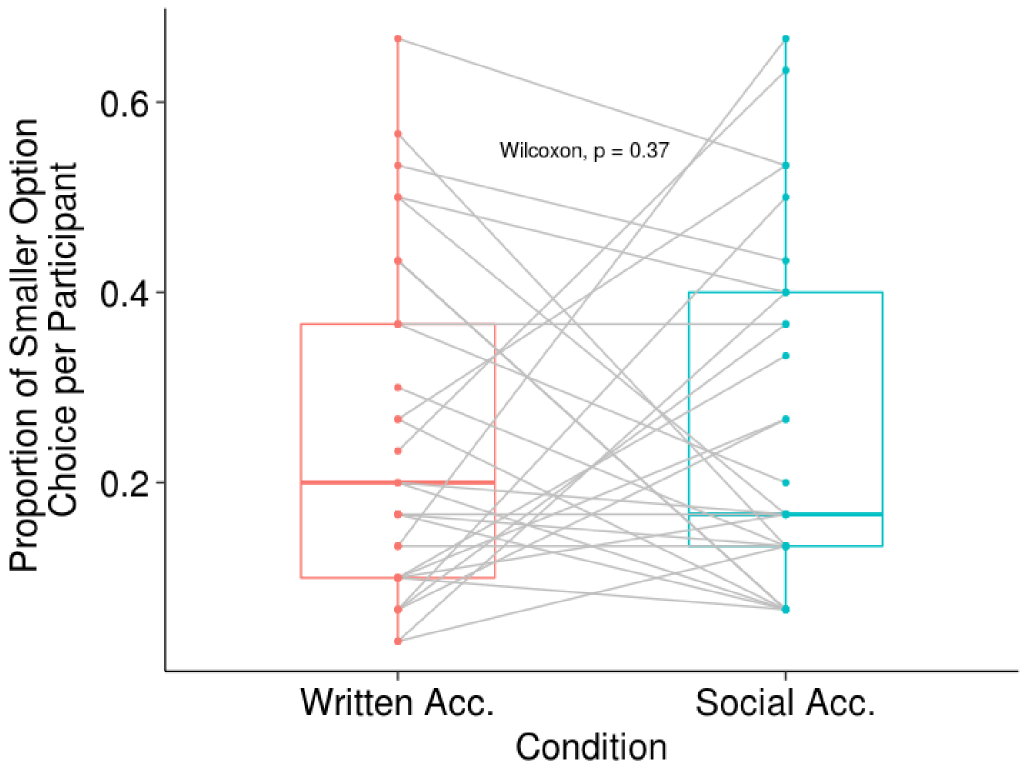

Figure 5.2: Proportion of smaller option choice for each participant in each condition.

5.3.3.2 Comparison of Reaction Times between Conditions

Reaction times between arrow presentation and choice time differed significantly between conditions. On average, participants took 0.54s longer to make Social Accountability decisions ($Mean_{Social\ Acc}$ = 2.53 s) than Written Accountability decisions ($Mean_{Written\ Acc.}$ = 2.30 s). Paired Wilcoxon signed rank tests confirms this difference is significant (V = 86, p-value = 0.011 *). Figure 5.3 shows the distribution of each participant's mean reaction time in each condition with a boxplot representing the distribution of reaction times in each condition.

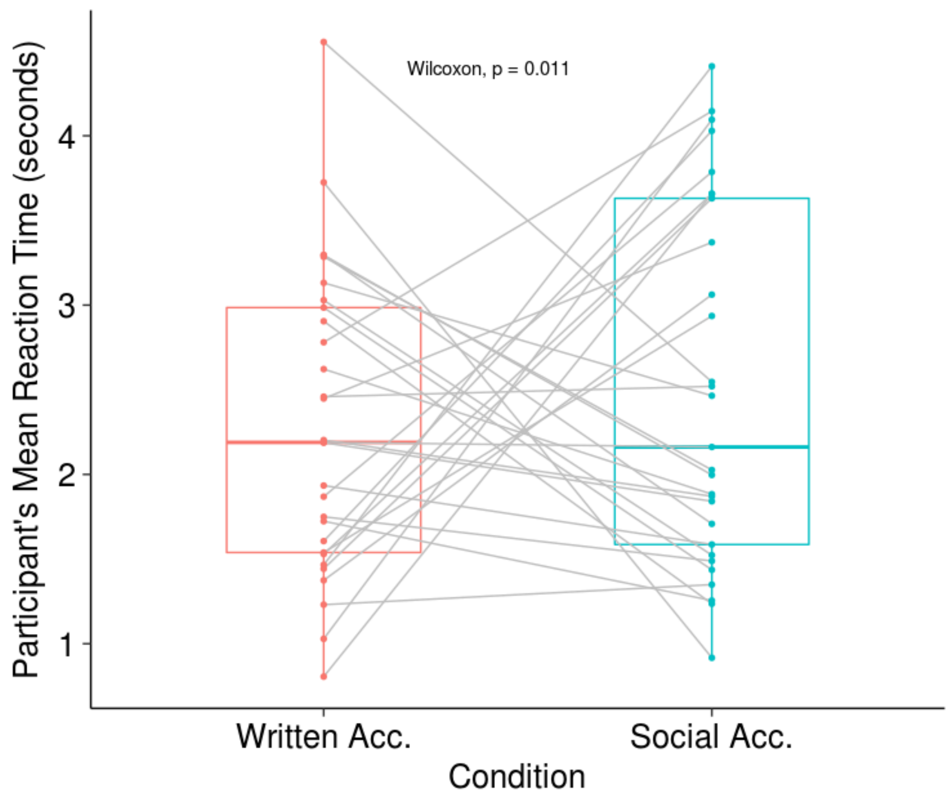

Figure 5.3: Mean reaction time for each participant in each condition.

5.3.3.3 Effect of Wage Rate on Choice

To examine choice behavior across the domain of effort, decisions were compared using a multiplicative wage rate. Wage rate was normalized by taking the difference between high and low effort amounts. A combined Word per Dollar (WpD) rate was calculated as shown:

$$WpD = \frac{Larger\ OptionWords - Smaller\ \text{Option Words}}{LargerOption\ Compensation}$$

Proportions of low effort choices were binned for each level of unique value of WpD rate. Higher WpD rate (always associated with the larger option) represents a lower value option (more effort for less compensation) and thus a higher likelihood of choosing the alternative, smaller option. Generalized linear model results confirm that WpD rate significantly affected choice proportion positively ($\beta_{WpD} > 0$, $p < 0.001$). This implies participants were discounting the value of options by effort.

The accountability manipulation did not have a significant effect on neither the intercept nor the slope of the model (p = 0. 076 and p =0.158 respectively). Full results from the GLM are shown in Table 5.6. Figure 5.4 shows the predicted probability of choosing the smaller effort option in each condition as the WpD rate increases.

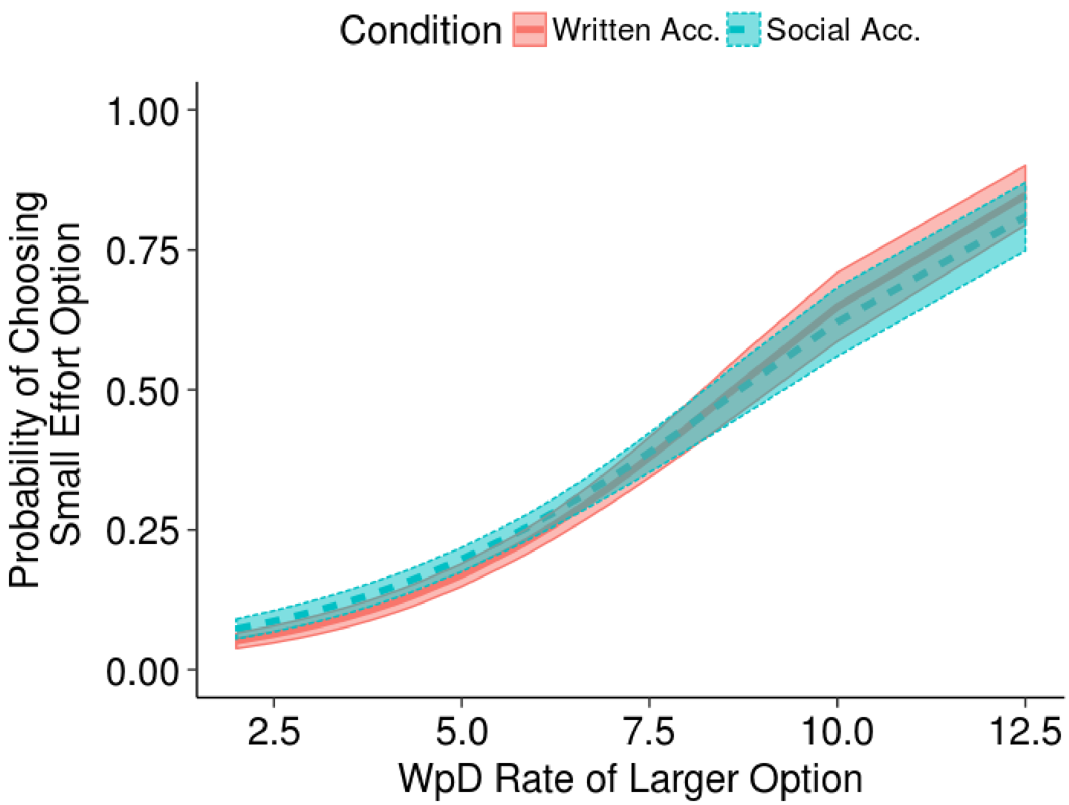

Figure 5.4: GLM of choice proportion on WpD rate.

Table 5.6*: GLM Predicting Choice of Smaller Effort/Reward Option*

Predictor	β	Odds Ratio	SE	*p*	
(Intercept)	-3.797	0.022	0.202	<0.001	***
WpD	0.441	1.554	0.031	<0.001	***
Social Accountability	0.491	1.634	0.276	0.076	
WpD x Soc. Acc.	-0.061	0.941	0.043	0.158	

Significance codes: p<= 0.001 **, p<= 0.01 **, p<= 0.05 *

5.3.3.4 Discounting Behavior

To formally compare discounting behavior between conditions, indifference points for each subject were estimated at each level of effort. Procedures for calculating indifference points followed those from the second experiment in chapter 2 which utilized a similar within-participants design. Indifference points reflect the value at which a decision maker is ambivalent between the constant smaller option and the larger option at a given effort level, thereby revealing an estimate of a participant's subjective value for the larger effort option.

A logistic regression was fit predicting choice, across all values of compensation for each unique value of effort. The indifference point was the compensation where the predicted choice probability of choosing either option equals 0.5. For effort levels where all choices were identical, the indifference point was set to the minimum or maximum compensation value +/- 1 standard deviation. The indifference points were then standardized by the smaller option value. To compare the indifference points across reference options, we used a standardized percent of maximum effort measure:

$$Effort = \frac{LargerOptionWords - SmallerOptionWords}{MaximumLargerOptionWords}$$

The mean subjective value for each level of effort in each condition are plotted in Figure 5.5 with +/- 1 SE error bars. The indifference points did not significantly differ between conditions ($p_{25,50,\,60,\,75,\,100}$ = 0.13, 0.94, 0.20, 0.95, 0.91 respectively).

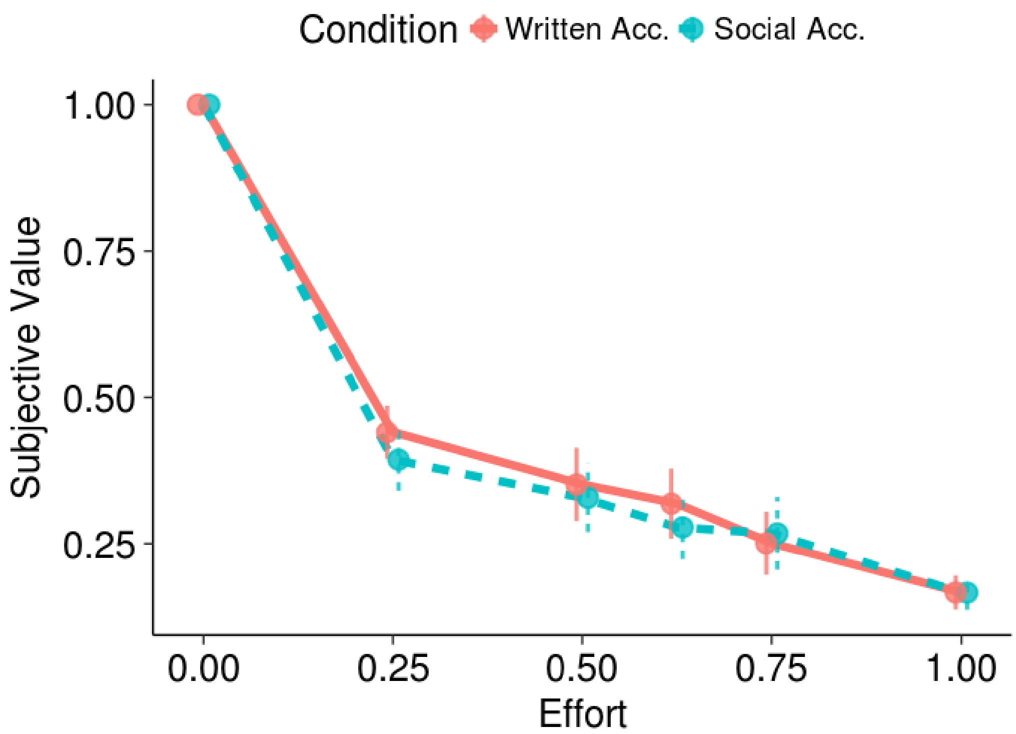

Figure 5.5: Indifference points estimates across normalized values of effort

5.2.4 Computational Modeling Results

Both the hyperbolic and sigmoidal computational models from Chapter 3 were fit to the behavioral data. The hyperbolic model was fit to the indifference points estimated in section 5.2.3. The sigmoidal model was fit using SoftMax estimation method described in chapter 3 to the raw choice data from every trial. Each participant and condition was modeled separately regardless of modeling method. Figure 5.6 shows the estimated discounting curves for each participant. The sigmoidal model represents more diverse discounting shapes than the hyperbolic model, though both retain monotonically decreasing subjective value estimates.

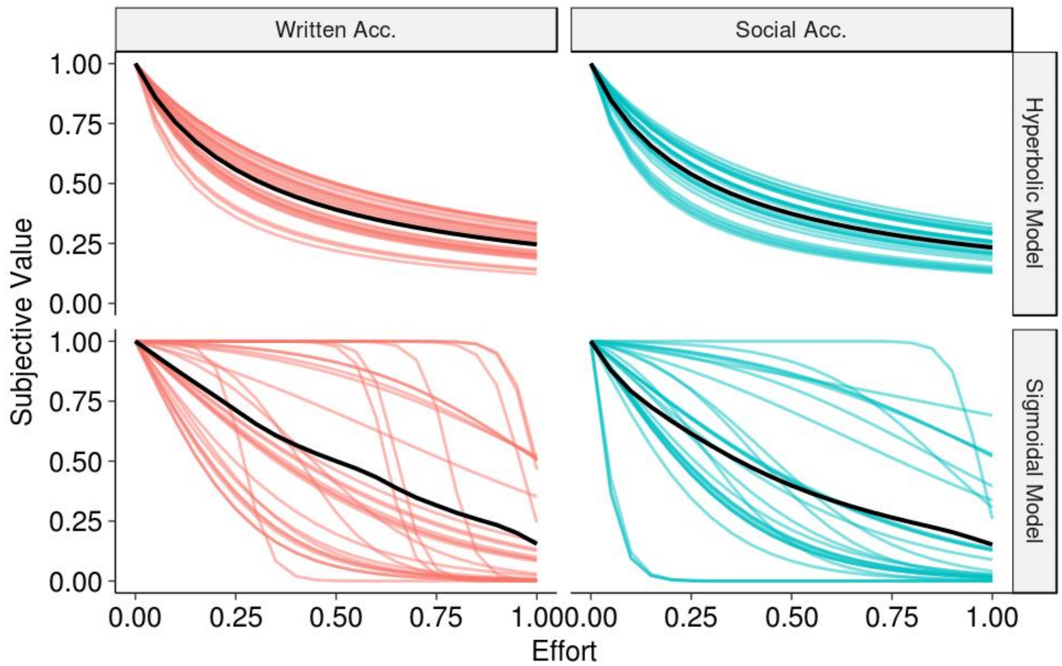

Figure 5.6: Estimated discounting curves. The top row shows hyperbolic models of discounting estimated by fitting the indifference points while the bottom row shows the sigmoidal models estimated with the SoftMax function.

Comparison between conditions was conducted using area under the curve (AUC) to standardize the methods given the different number of parameters in each model (Myerson, Green, & Warusawitharana, 2001). The AUC was computed using trapezoidal approximation across 100 subjective value estimates between [0,1]. Figure 5.7 shows the AUC distributions for each model by condition. The estimate for each participant is plotted as a point, while the box represents the mean +/- 1 SE. Results show decreased AUC in the Social Accountability condition ($Mean_{Hyp.}$ = 0.44; $Mean_{Sig.}$ = 0.45) compared to the

Written Accountability condition ($Mean_{Hyp.}$ = 0.45; $Mean_{Sig.}$ = 0.52) implying increased discounting for socially accountable decisions in both models. However, neither model exhibited a significant difference in AUC. Paired Wilcoxon tests failed to reject the null hypothesis for both models (W_{Hyp} = 276, p = 0.10; W_{Sig} = 282, p = 0.17).

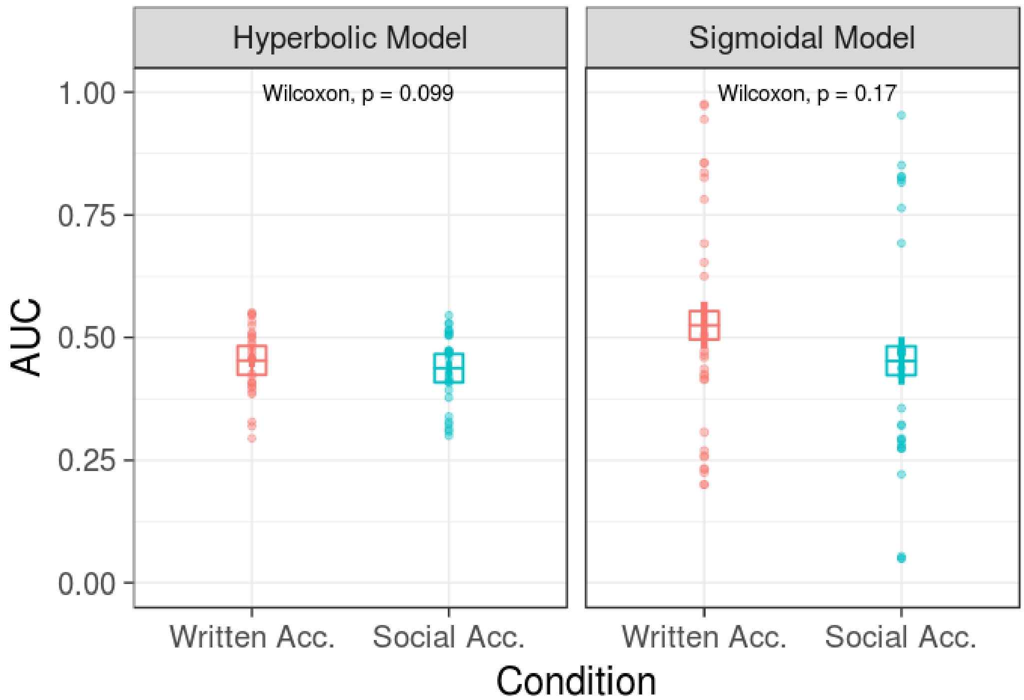

Figure 5.7: AUC distributions by model and condition

5.2.5 fMRI Analysis Methods

5.2.5.1 Preprocessing of imaging data

Images were acquired using a 3T Siemens Tim Trio with scanner settings of repetition time (TR) = 2s, TE = 30 ms, and flip angle = 90 degrees; resulting in voxels 3.2 × 3.2 × 3.2 mm in size. The structural scan was acquired using a high-resolution scanning (TR = 1200 ms, with spatial resolution of 1 × 1 × 1 mm). Images were preprocessed using SPM12 (Wellcome Department of Imaging Neuroscience, London, UK), using default values unless otherwise specified. Images were realigned within subjects, normalized to a mean structural image, segmented based on soft tissue structure, and smoothed with a 6 mm^3 volume FWHM Gaussian kernel. Movement artifact correction threshold was set to 1.6 or any movements more than 2.5 standard deviations from mean position. Analyses were conducted using a hierarchical GLM specifying both within- and between-participants effects.

5.2.5.2 First level GLM

Preprocessed fMRI data were analyzed in an event-related analysis using two-level GLM. The first level GLM fit BOLD response used predictors of two timing events within each trial. The first timing event was the onset of option presentation. The second timing event was the onset of arrow presentation. Using the arrow presentation timestamp rather than the choice timestamp reduces noise associated with neural activity related to motor control and action planning (Mullette-Gillman et al., 2015). Event onset times were used to align image data with predictors when constructing the first level model. A canonical hemodynamic response function (HRF) was modeled along with temporal and dispersion derivatives (Henson, Rugg, & Friston, 2001). Six positional regressors specific to each participant were convolved with the first level model to account for spatial registration of the images.

Given that reaction times differed significantly between the two conditions, when modeling contrasts between written and social accountability, a variable epoch model was used based on the durations of the timing events to improve power and consistency of the model (Grinband et al., 2008).

For analysis of specific trial-level variance in neural activity, parametric modulators were convolved in first level models individually to prevent multicollinearity. Three parametric modulations of attributes of the larger option were modeled: 1) Magnitude of compensation (the amount of money), 2) magnitude of effort (number of words), 3) the wage rate of the option represented as dollars per word. Two additional parametric modulators were used to investigate correlations between computational models and neural activity: 1) the hyperbolic model estimate of subjective value of the larger option and 2) the sigmoidal model estimate of subjective value of the larger option. The values for the parametric modulator were convolved with all basis functions, but only the canonical HRF for the parametric modulator was used in second level analyses.

The first level GLM resulted in whole brain SPMs generated for each participant showing the relationship between BOLD response and the predictor variables over the duration of the scanning session. First level predictors included trial level events used for binary labelling. For example, decision outcome (larger or smaller option), trial condition (social or written accountability), or a median split of the larger option's effort attribute (greater or lesser effort magnitude). The results are visualized by the t-test statistics either by comparing an individual predictor β using a one-sample t-test (null hypothesis $\beta = 0$) or by creating a contrast map using comparisons within-participants. All following analyses utilized paired t-test contrasts at the first level. First level t-statistics for each voxel represented the difference in BOLD signal between trial types (choice, condition, or effort magnitude).

5.2.5.3 Second level GLM

Second level analyses tested the effects of predictors between-participants across all voxels. The second level analysis reported utilized the paired t-statistics from the first level GLM in a one-sample t-test for each voxel. Given that all first level tests were paired t-tests, the second level analysis identifies paired contrasts that are significantly different from 0. Each second level test has observations equal to the number of participants, resulting in an SPM representing the estimated BOLD response of all participants' brains.

Several methods for second level comparison exist with respect to the number and type of timing events, trial comparisons, parametric modulations, and individual differences. Regardless of comparison test used, it is paramount that comparisons are established *a priori* to prevent inappropriately loose conclusions drawn from noisy data without a concrete hypothesis. In this study, paired t-test comparisons were established between binary labels given by the participants' choices, a median split on the effort magnitude of the larger option, and the imposed condition manipulation on each trial. All second level analyses were only compared at the same timing event – either at time of stimulus option presentation or arrow presentation to retain parsimony in analysis.

Whole brain analyses were conducted using the results of the second level GLM. Thresholding of the SPMs was based on cluster extent and strict *p* values ($p < 0.001$ as recommended by Woo, Krishnan, & Wager, 2014). Analyses were conducted using single contrasts to minimize clusters of ancillary and random BOLD response. Each contrast was modeled independently. Three contrasts were used: 1) the choice on each trial (smaller vs. larger option), 2) the relative magnitude of the larger option's effort on each trial (greater than median effort vs. less than or equal to the median effort), and 3) the accountability condition on each trial.

5.2.5.4 Regions of Interest (ROIs)

Specific analyses of allocentric valuation were conducted using *a priori* ROIs and parametric modulation of effort, compensation, and wage rate. ROI analysis was used because it controls the number of comparisons and enforces theoretical hypotheses (Poldrack, 2007). ROI analysis was conducted by restricting the second level analysis to voxels contained within the coordinates of a region-specific mask. The voxel-level statistics from the first-level GLM were averaged across the region for each participant. The mean ROI activation for each participant were tested using a one-sample t-test where $H_0 : t_{second\ level} = 0$.

ROIs were identified in chapter 4 based on a review of the literature relating to allocentric decision making and egocentric effort discounting. ROIs considered were the *anterior cingulate cortex* (ACC), the *dorsal medial* and *ventral medial prefrontal cortex* (dmPFC and vmPFC), *posterior cingulate cortex* (PCC), *angular gyrus*, *precuneus*, *cuneus*, *right temporoparietal junction* (rTPJ), *supplementary motor area* (SMA), and sub-regions of the *basal ganglia* including the *ventral striatum* (vStriatum), *putamen*, *pallidum*, and *caudate*. All ROIs were identified using the WFU pick-atlas toolbox (Maldjian, Laurienti, Kraft, & Burdette, 2003) with aal mapping (Tzourio-Mazoyer et al., 2002) except for the rTPJ which was identified with a 15mm-radius sphere centered at the coordinates x = 54, y = -44, z = 18 based on a recent meta-analysis linking the region to social dilemmas and theory of mind (Krall et al., 2015). An inclusive mask was created based on the coordinates of each ROI which was then used to constrain the voxels used for second level analysis. All images of spatial representation of BOLD response were overlaid on a mean structural image from the 29 participants retained for analysis.

5.2.6 fMRI Results

5.2.6.1 Choice Outcome Contrast

Trials were labeled based on the participants' choices (smaller vs. larger option). At the time of choice option presentation during trials where participants chose the larger effort option, BOLD response was greater in the rTPJ, left *angular gyrus*, middle ACC. Only the rTPJ (MNI x = 60, y = -46, z = 5) survived FWE correction (p_{FWE} = 0.038). Figure 5.8 shows the extent of the BOLD response in the rTPJ overlaid onto the mean structural image of all participants.

ROI analysis showed no significant differences in BOLD response based on participants' choices at time of option presentation. Likewise, when participants chose the smaller effort option, no clusters showed a significant increase in BOLD response.

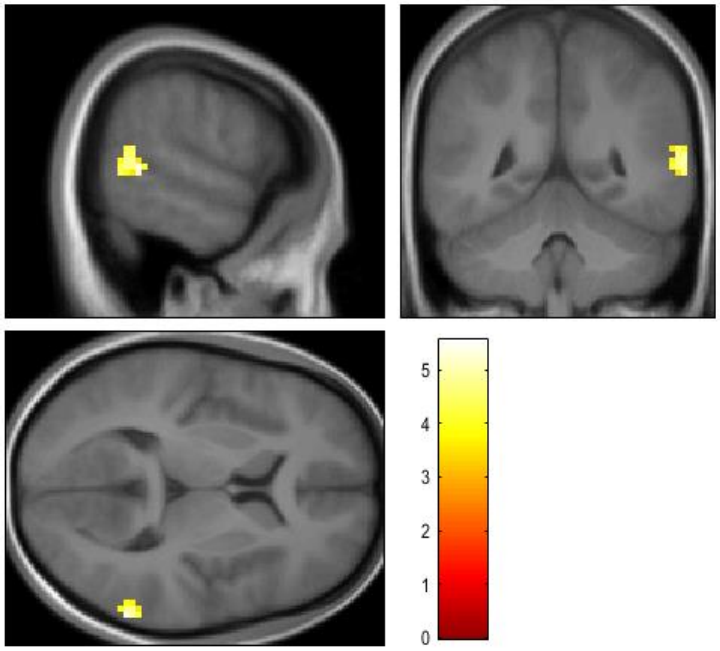

Figure 5.8: Increased activation near the rTPJ at option presentation on trials where larger effort option was chosen. Image displayed at p = 0.001 uncorrected threshold with k > 20 contiguous voxels; the rTPJ was significant at p_{FWE} = 0.038.

At the time of arrow presentation when participants chose the larger effort option compared to when they chose the smaller option, BOLD response was significantly greater in the dmPFC (MNI x = 0, y = 29, z = 44; T= 4.20; p_{FWE} = 0.037), right angular gyrus (MNI x = 48, y = -49, z = 44; T= 4.59; p_{FWE} = 0.010), and SMA (MNI x = 48, y = 29, z = 32; T= 4.76; p_{FWE} = 0.016). These regions all survived FWE correction (p_{FWE} < 0.05).

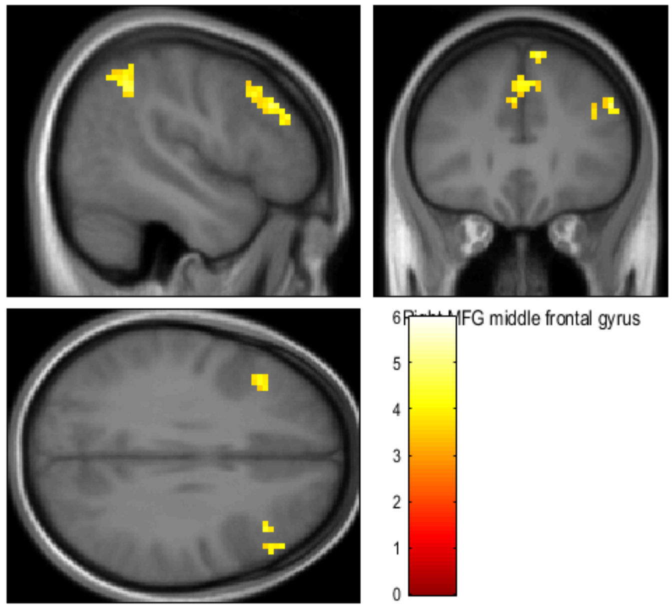

Figure 5.9 highlights the extent of the significant clusters in the *dmPFC, SMA,* and *angular gyrus*. When making smaller effort choices at time of arrow presentation, BOLD response was not significantly different from when participants chose larger options.

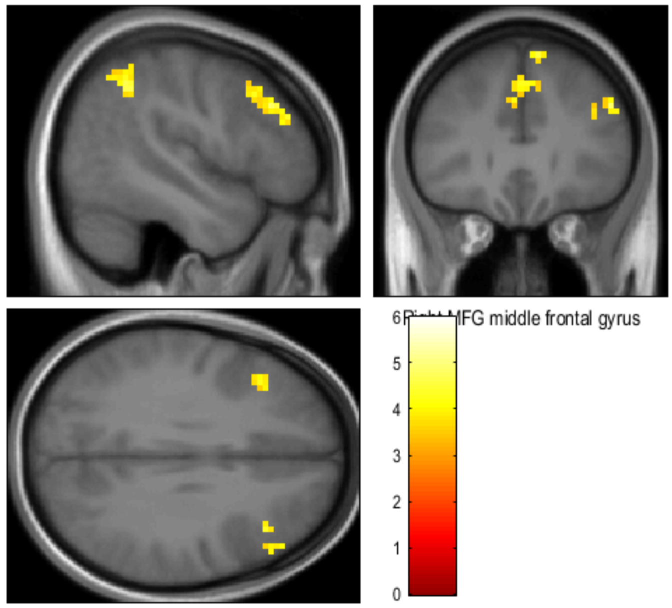

Figure 5.9: Increased BOLD response in clusters of the *right angular gyrus, dmPFC*, and *SMA* when choosing higher effort option at time of arrow presentation. Image displayed at p = 0.001 uncorrected threshold with k > 20 contiguous voxels.

ROI analysis showed increased mean BOLD response when participants chose the larger option over the smaller option in the *PCC* (p = 0.0021, 95% CI = 0.160, 0.646), *insula* (p = 0.0022, 95% CI = 0.158, 0.648), *pallidum* (p = 0.0091, 95% CI = 0.0117, 0.0751), *putamen* (p = 0.0083, 95% CI = 0.0143, 0.0884), and *striatum* (p = 0.0159, 95% CI = 0.0034, 0.0307). All ROIs showed increased activity when the larger option was chosen. Figure 5.10 shows the mean ROI response for each region.

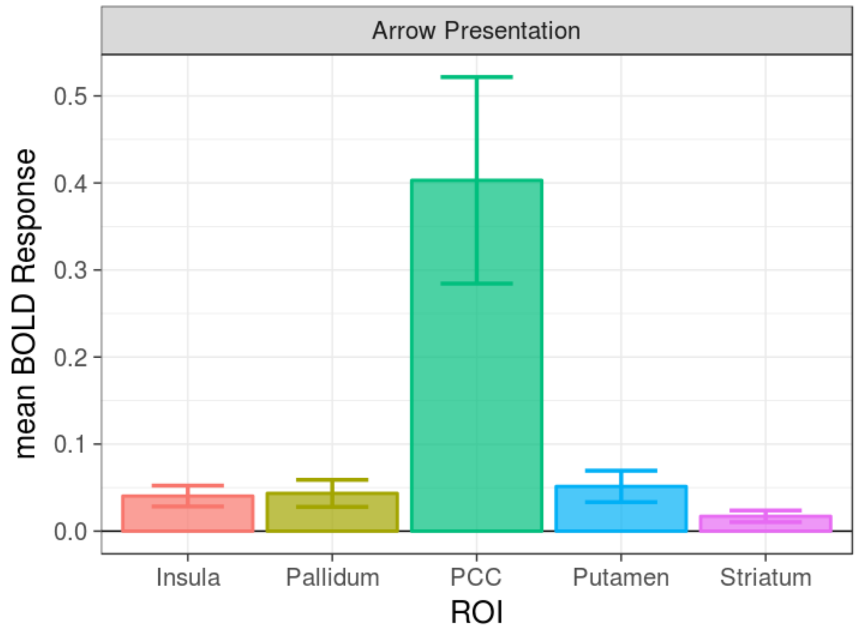

Figure 5.10: Mean ROI BOLD response +/- 1 SE during trials when participants chose the larger option rather than the smaller option at the time of arrow presentation.

5.2.6.2 Effort Magnitude Contrast

Trials were labeled based on the magnitude of the larger option's effort attribute in relation to the median effort presented (median = 35 words). For clarity, this contrast was labeled using "high effort magnitude" to refer to trials greater than the median and "low effort magnitude" for trials less than or equal to the median to avoid confusion with "larger" and "smaller" choice options which refer to the set of bundles of effort and compensation on each trial. Importantly, comparison of effort magnitude was based strictly on the stimuli values presented and not the behavior of the participant. By imposing a median split to label trials, this contrast helps to strengthen the signal-to-noise ratio of BOLD response on trials where effort discounting was more pronounced.

At the time of option presentation on trials when the larger effort option was greater than the median effort, whole-brain analysis showed increased BOLD response in the regions of the *precuneus* (MNI x = 0, y = -64, z = 35; T= 4.67; p_{FWE} = 0.002). Figure 5.11 shows the locations of increased BOLD response.

When effort stimuli presented were less than or equal to the median, scans at the time of option presentation, no significant difference was observed in whole brain analysis.

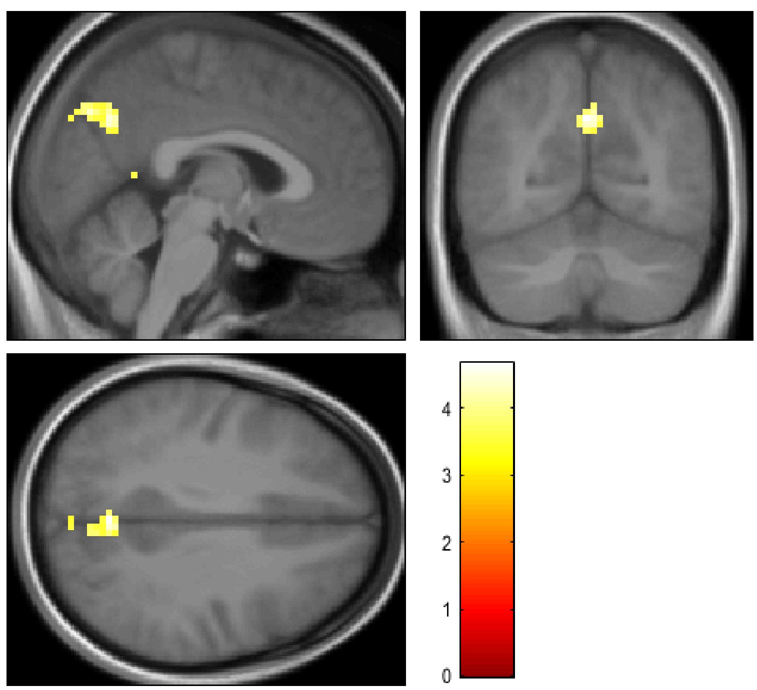

Figure 5.11: Precuneus BOLD response on trials of high effort magnitude compared to low effort magnitude at the time of option presentation. Image displayed at $p < 0.001$ uncorrected, $k > 20$ contiguous voxels; the *precuneus* was significant at p_{FWE} = 0.002.

At the time of arrow presentation, whole-brain analysis showed no significant increases in BOLD response in high effort magnitude trials compared to low effort magnitude trials. However, at the time of choice arrow presentation on low effort magnitude trials, the *precuneus* (MNI x = 6, y = -52, z = 8; T = 6.90; p_{FWE} = 0.004), *vACC* (MNI x = 3, y = 47, z = 5; T= 4.72; p_{FWE} < 0.001), *vmPFC* (MNI x = -9, y = 35, z = -7; T = 5.40; p_{FWE} < 0.000), and *left angular gyrus* (MNI x = -42, y = -70, z = 32; T= 5.33; p_{FWE} = 0.007) showed significantly increased BOLD response compared with high effort magnitude trials. Figure 5.12 shows the locations and extent of activation of the *precuneus*, *vACC*, and *vmPFC*.

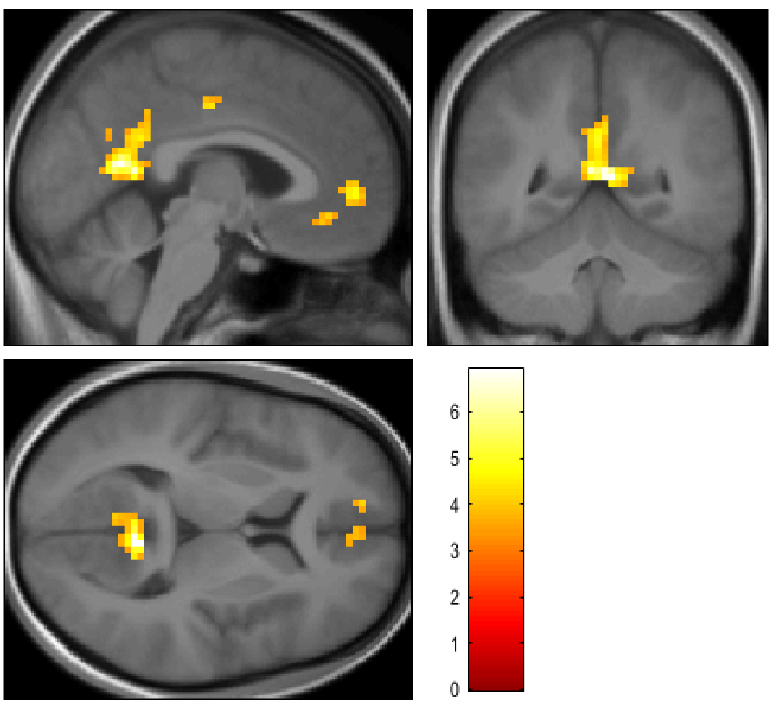

Figure 5.12: *Precuneus*, *vACC*, and *vmPFC* activity when choice arrows were presented on trials where the larger option effort was less than or equal to the median effort. Activity of the left angular gyrus not shown. Image displayed at p < 0.001 uncorrected, k > 20 contiguous voxels.

ROI analysis was conducted for this contrast at both event times. At the time of option presentation, the *precuneus* (p = 0.0074, 95% CI = 0.1454, 0.8553) exhibited increased mean BOLD response on trials with high effort magnitude compared to trials of low effort magnitude. At the time of arrow presentation, the *angular gyrus* (p = 0.0219, 95% CI = -0.1412, -0.012), *pallidum* (p = 0.0426, 95% CI = -0.0447, -0.0008), *putamen* (p = 0.0207, 95%CI = -0.0574, -0.0051), and *striatum* (p = 0.0392, 95% CI = -0.0176, -0.0004) all exhibited decreased mean BOLD response during high effort magnitude trials compared to low effort trials.

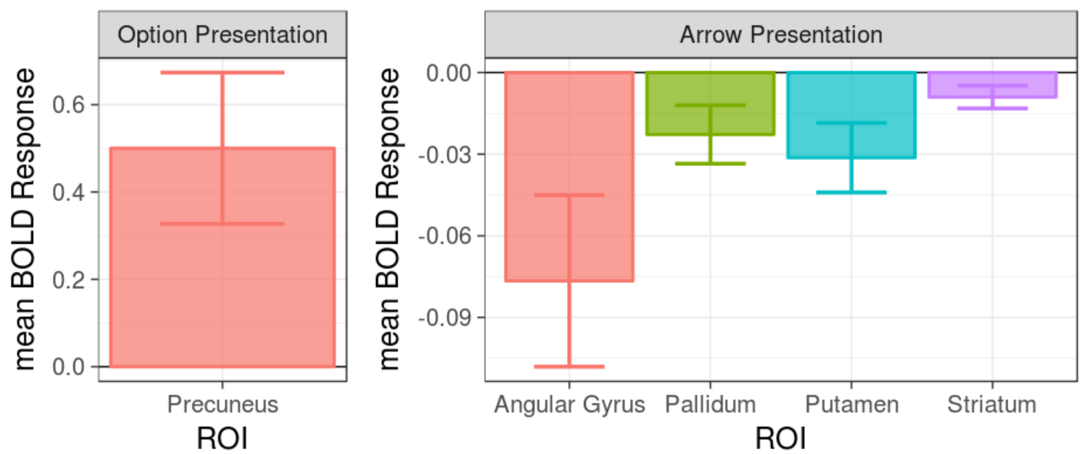

Figure 5.13: Mean BOLD response in ROIs during high effort magnitude trials compared to low effort magnitude trials.

5.2.6.3 Social vs. Written Accountability Contrast

Comparison was conducted between trials labeled based on the condition manipulation (social vs. written accountability). Both social and written accountability trials were presented identically between conditions, creating a balanced design with regards to number of observations. However, due to differences in reaction time between conditions, a variable epoch model was fit to the fMRI data to scale the response according by reaction time of each trial. Whole brain analysis did not reveal significant differences between accountability conditions at either option presentation or arrow presentation event time.

ROI analysis showed evidence of increased mean BOLD response in the *SMA* (*p* = 0.0474, 95% CI = 0.0014, 0.2255) and *TPJ* (*p* = 0.0344, 95% CI = 0.0031, 0.0745) during social accountability trials compared to written accountability trials at the time of option presentation. At the time of arrow presentation, the *precuneus* showed decreased activity (*p* = 0.0301, 95% CI = -0.3389, -0.0185) during social accountability trials compared to written accountability trials at the time of option presentation. Figure 5.14 shows the results of the ROI analysis.

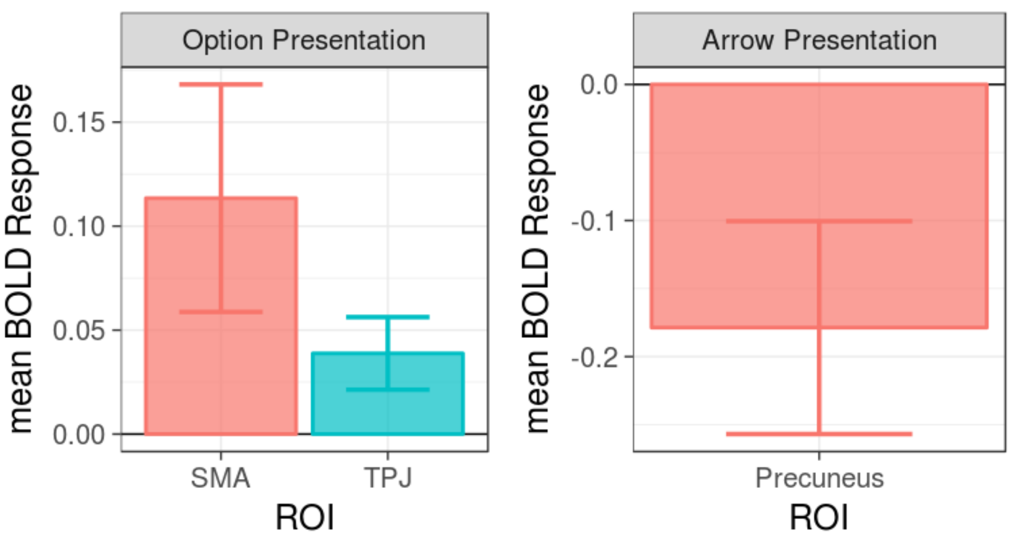

Figure 5.14: ROI results comparing social accountability trials compared to the written accountability condition with significant differences in mean BOLD response. Results shown with +/- 1 SE from the mean.

5.2.6.4 Analysis of parametric modulation (first level correlation)

5.2.6.4.1 Compensation

Analysis of parametric modulation was conducted with ROI analysis. Compensation amount varied on each trial in the larger option. The compensation value was convolved with the first level GLM. Second level results are presented to show first level correlation across participants.

At the time of option presentation, ROI analysis of voxels in the *striatum* (T = 4.25; p_{FWE} = 0.047; peak activation at x = 24, y = 8, z = -4) exhibited increased response as compensation increased. ROIs did not exhibit differences in mean BOLD response. Figure 5.15 shows the significantly different voxels in the *striatum.* No ROIs exhibited significant results at the time of arrow presentation.

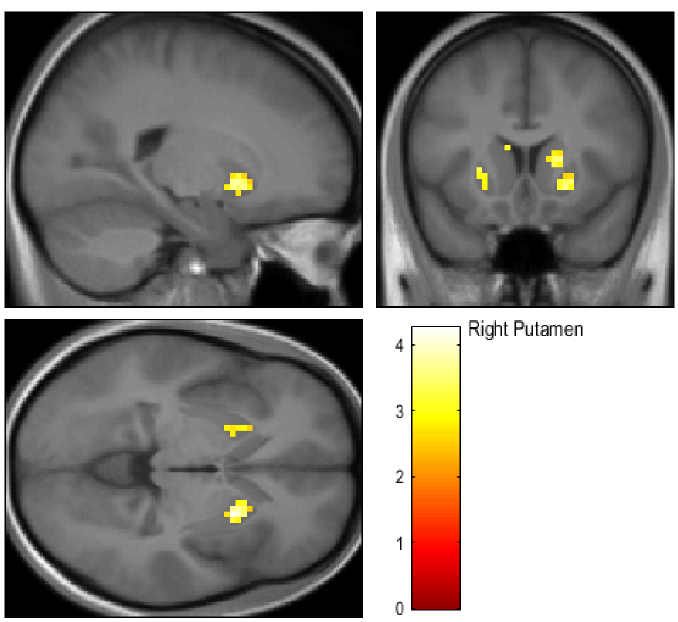

Figure 5.15: Parametric modulation of compensation shows increased BOLD response bilaterally in the striatum at the time of option presentation. Image

displayed with a threshold of p = 0.001 for visualization with $k > 10$ contiguous voxels.

5.2.6.4.2 Effort

At the time of option presentation, voxels in the posterior and dorsal *precuneus* (peak activation at T = 4.37; p_{FWE} = 0.001; x = 12, y = -37, z = 53) showed significantly increased BOLD response as the effort of the larger option increased. Figure 5.16 shows the extent of the activation. Figure 5.18 shows the small effect size of this difference is due to small variance between participants.

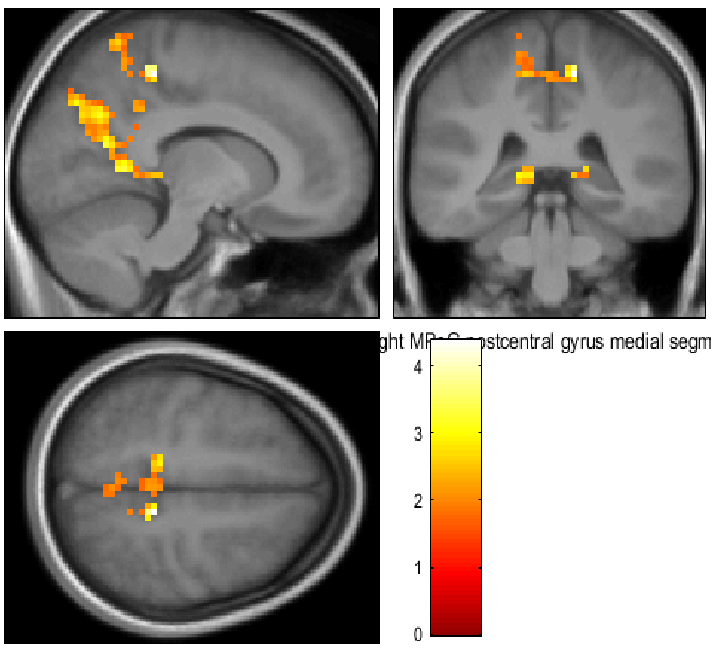

Figure 5.16: BOLD response in the precuneus increased with the effort of the larger option at the time of choice option presentation. Image displayed with a threshold of p = 0.001 and k > 20 contiguous voxels for visualization.

At the time of arrow presentation, no significant increases in BOLD response were detected. However, significant decreases in BOLD response were detected in the *ACC* (T = 5.68; p_{FWE} = 0.002; peak activation at x = -6, y = 50, z = -1), *PCC* (T = 4.99; p_{FWE} = 0.005; peak activation at x = -3, y = -52, z = 26), and ventral *precuneus* (T = 4.37; p_{FWE} = 0.001; peak activation at x = 12, y = -37, z = 53) as effort increased. Figure 5.17 shows the extent of significant BOLD response reductions as effort increases. Figure 5.18 presents the mean BOLD response of each ROI in relation to increasing effort of the larger option.

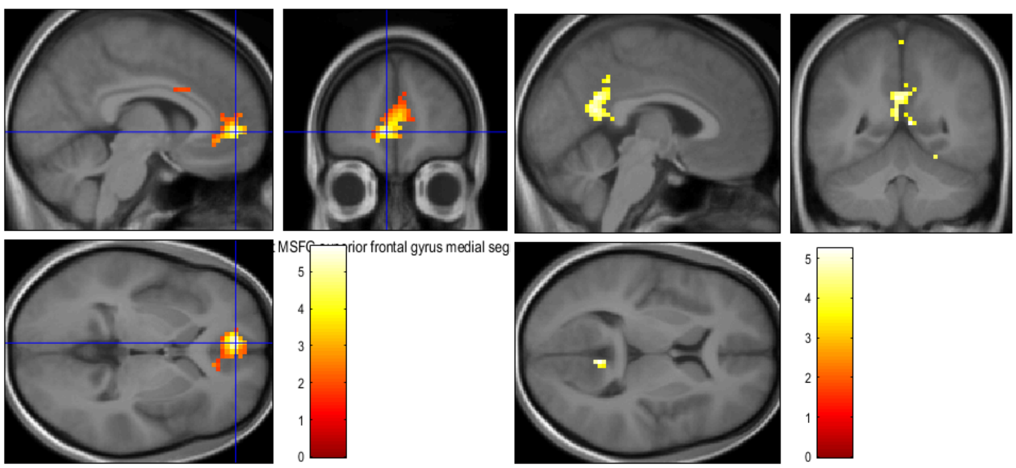

Figure 5.17: The left image shows the extend of ACC activity negatively correlating with increasing effort. The right image displays the same results for the PCC, and precuneus. Both images displayed with threshold of p = 0.001 and k > 20 contiguous voxels for visualization.

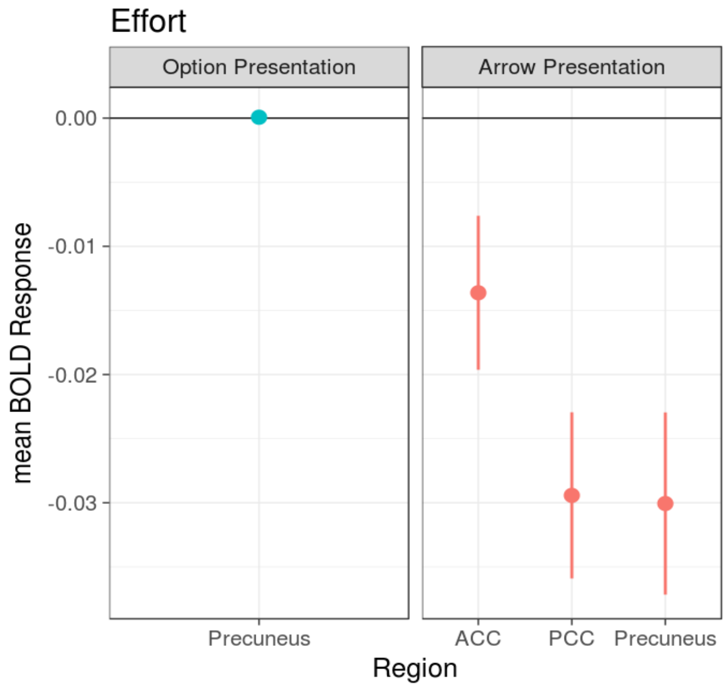

Figure 5.18: Mean +/- 1 SE of BOLD response from each ROI in relation to increasing effort of the larger option.

5.2.6.4.3 Dollars per Word

Dollars per word (DpW) ratios were calculated for the larger option on each trial and convolved with the canonical HRF as a parametric modulator. Dollars per word was used to ensure consistent orientation across analyses with increasing subjective value increasing with DpW. ROI analysis was conducted with emphasis placed on regions that have been associated with value computation. These areas include the *ACC*, *vStriatum*, and *vmPFC*.

At the time of option presentation, results showed increased BOLD response in the *ACC* and *PFC*, but these voxels did not survive FWE correction. Significant decrease in BOLD response in the *cuneus* (T = 5.99; p_{FWE} = 0.001;

peak activation at x = 6, y = -85, z = 23) occurred as DpW increased. Figure 5.19 shows the extent of the significant BOLD response at the second level.

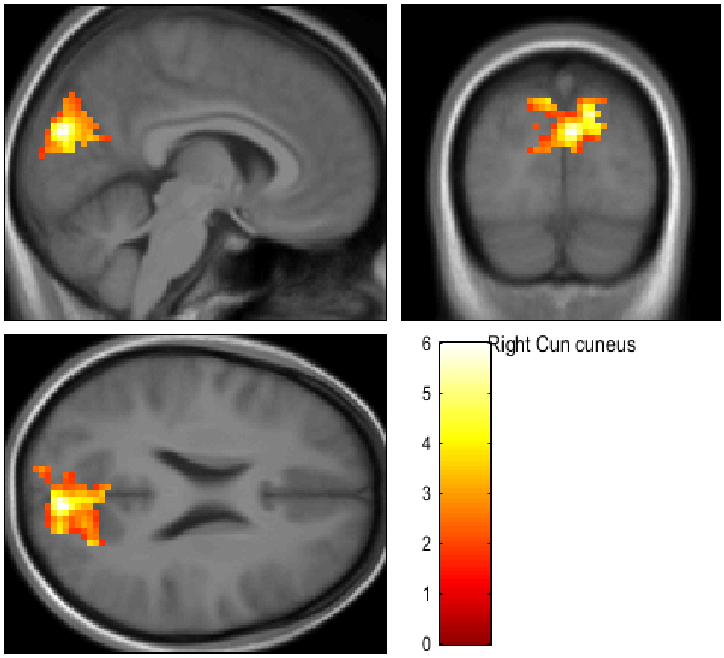

Figure 5.19: Decreased activation in the cuneus at time of option presentation when Dollars per Word of the larger option increased. Image displayed with threshold of $p = 0.001$ and $k > 20$ contiguous voxels for visualization.

At the time of arrow presentation, BOLD response in the *SMA* was negatively correlated with DpW, but did not survive correction. ROIs in the parietal cortex showed increased BOLD response as DpW increased. The *cuneus* ($T = 6.71$; $p_{FWE} < 0.001$; peak activation at x = 9, y = -82, z = 26), *PCC* ($T = 6.31$; $p_{FWE} = 0.001$; peak activation at x = 12, y = -46, z = 26), and *precuneus* ($T = 5.95$; $p_{FWE} = 0.003$; peak activation at x = 0, y = -49, z = 65) showed significant increases in BOLD response at the time of arrow presentation. Figure 5.20 shows the extent of the increased BOLD response in the parietal cortex. Figure

5.21 shows the effect of DpW on mean BOLD response in the ROIs with significant response. For this analysis, the regions of the parietal cortex were grouped.

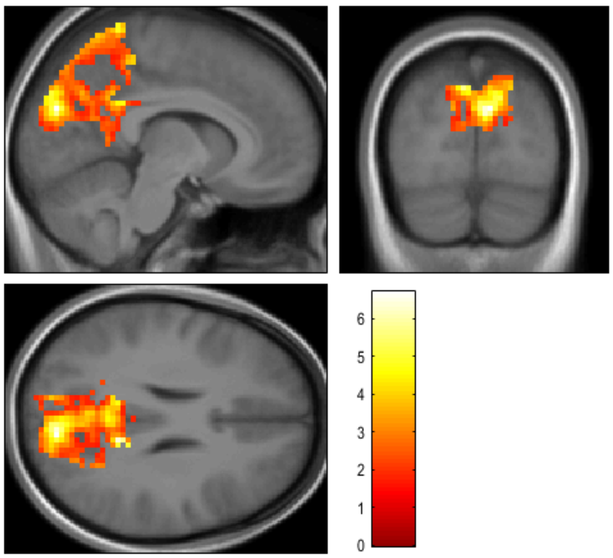

Figure 5.20: Increased BOLD response in the parietal cortex as Dollars per Word increased at time of arrow presentation. Image displayed with threshold at p = 0.001 and k > 20 contiguous voxels for visualization.

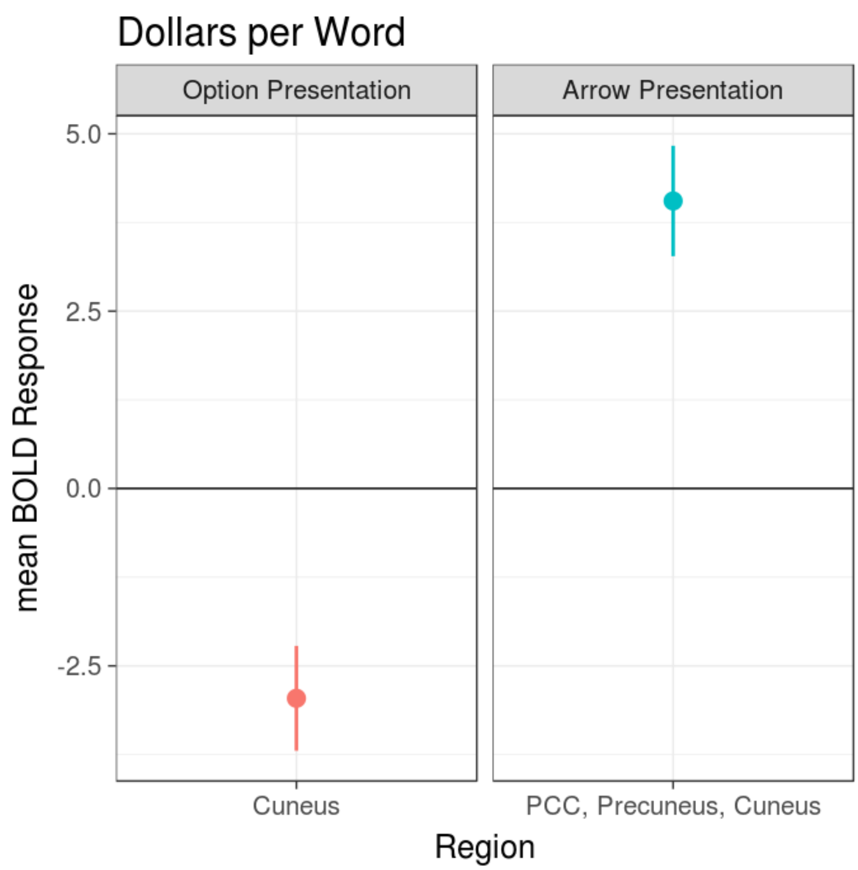

Figure 5.21: Mean +/- 1 SE of BOLD response from each ROI in relation to increasing DpW of the larger option.

5.2.6.4.4 Hyperbolic model estimate of larger option subjective value

The hyperbolic model was estimated for each participant and used to create a point estimate of subjective value of the larger option on each trial. The subjective value estimate was used as the parametric modulator at the first level. At time of option presentation, BOLD response in the *ACC* and *vmPFC* was positively correlated with hyperbolic subjective value, but did not survive FWE correction. A decrease in BOLD response was found bilaterally in the *angular gyrus*; however, only the left *angular gyrus* (T = 4.74; $p_{FWE} < 0.049$; peak activation at x = -45, y = -58, z = 38) survived correction. In the medial parietal lobe, a cluster in the *precuneus* (cluster-level $p_{FWE} < 0.001$; peak activation T = 4.77; $p_{FWE} = 0.077$; x = 12, y = -37, z = 53) also exhibited reduced BOLD response with increasing hyperbolic subjective value estimates of the larger option. Figure 5.22 shows the extent of significant BOLD responses in both the *angular gyrus* and *precuneus*.

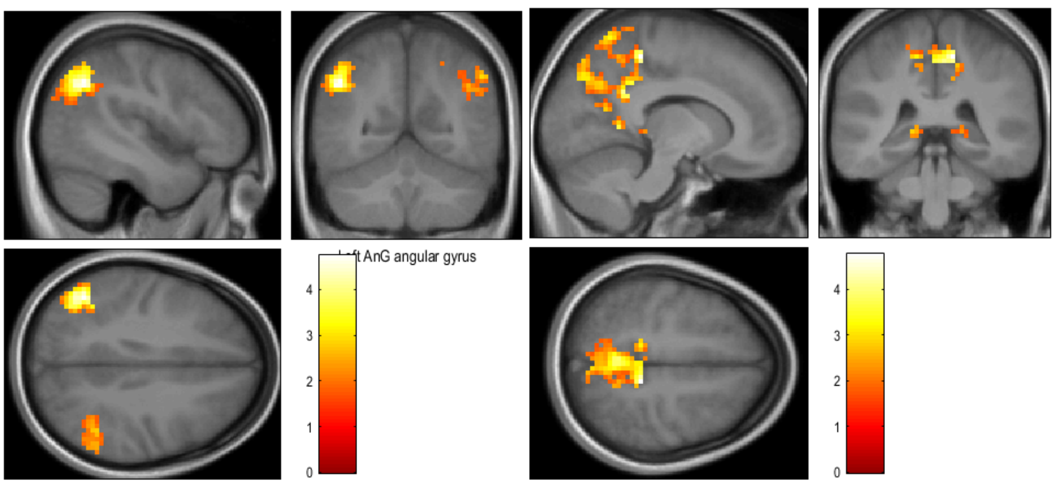

Figure 5.22: The left image shows the extent of significant BOLD response in the left angular gyrus. The right image shows the extent of activation in the precuneus. Both images show decreased BOLD response with increasing subjective value of the larger option as estimated by the hyperbolic model. Images displayed with thresholds at p = 0.001 uncorrected with extent of k> 20 voxels.

At the time of arrow presentation, the SMA showed a negatively correlated BOLD response, but did not survive FWE correction. The *dorsal precuneus* (T = 5.87; $p_{FWE} = 0.004$; peak activation at x = 0, y = -49, z = 65), *PCC* (T = 5.48; $p_{FWE} = 0.001$; peak activation at x = 12, y = -46, z = 26), *left angular gyrus* (cluster-level $p_{FWE} < 0.05$; peak activation T = 4.56; $p_{FWE} = 0.059$; peak activation at x = -42, y = -76, z = 29), *and cuneus* (T = 6.37; $p_{FWE} < 0.001$; peak activation at x = 9, y = -82, z = 38) all showed significant response with increasing hyperbolic model estimates of subjective value and survived correction. Figure 5.23 shows the spatial extent of the activation of each ROI while Figure 5.24 shows the mean BOLD response.

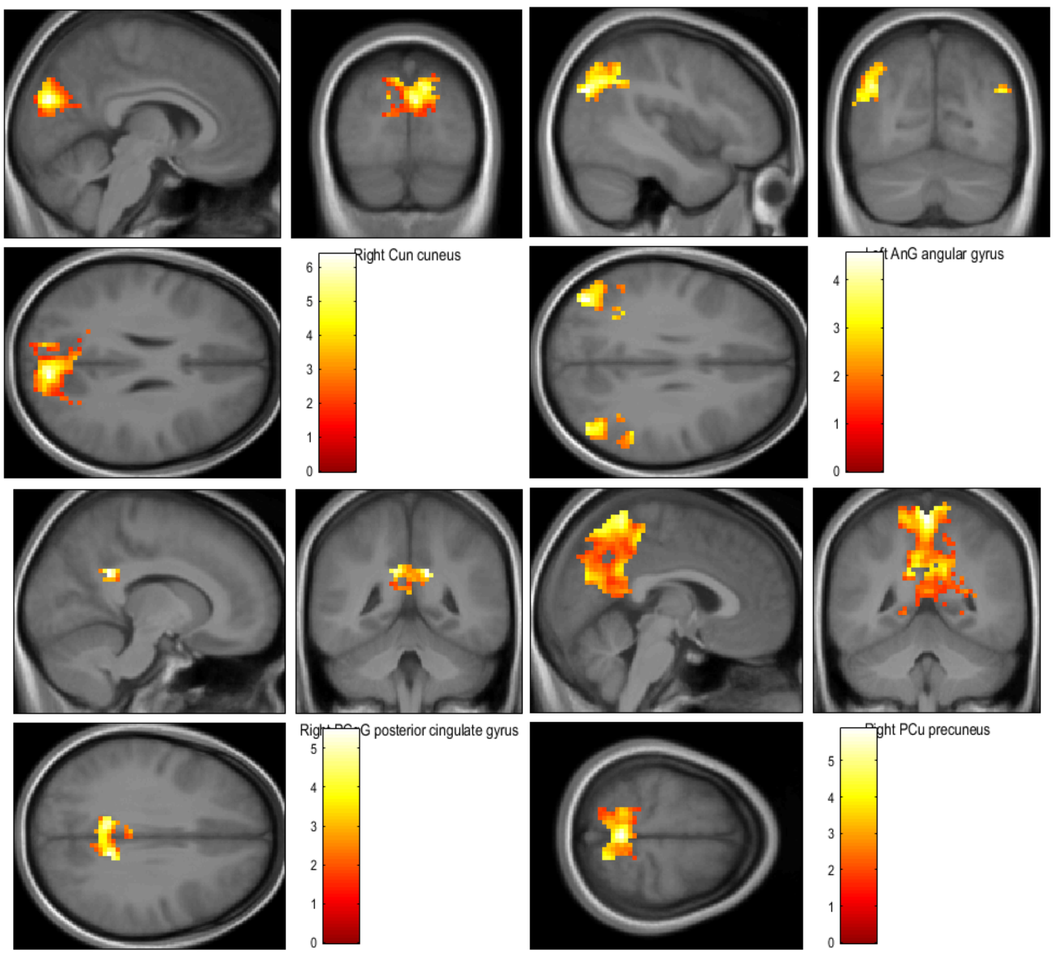

Figure 5.23: BOLD response in the parietal cortex as hyperbolic model estimates of the subjective value of the larger option increase. In clockwise order from the top left, images display significant response in the *cuneus,* bilateral *angular* gyrus, *precuneus,* and *PCC.* All images displayed with threshold at p = 0.001 and k > 20 contiguous voxels.

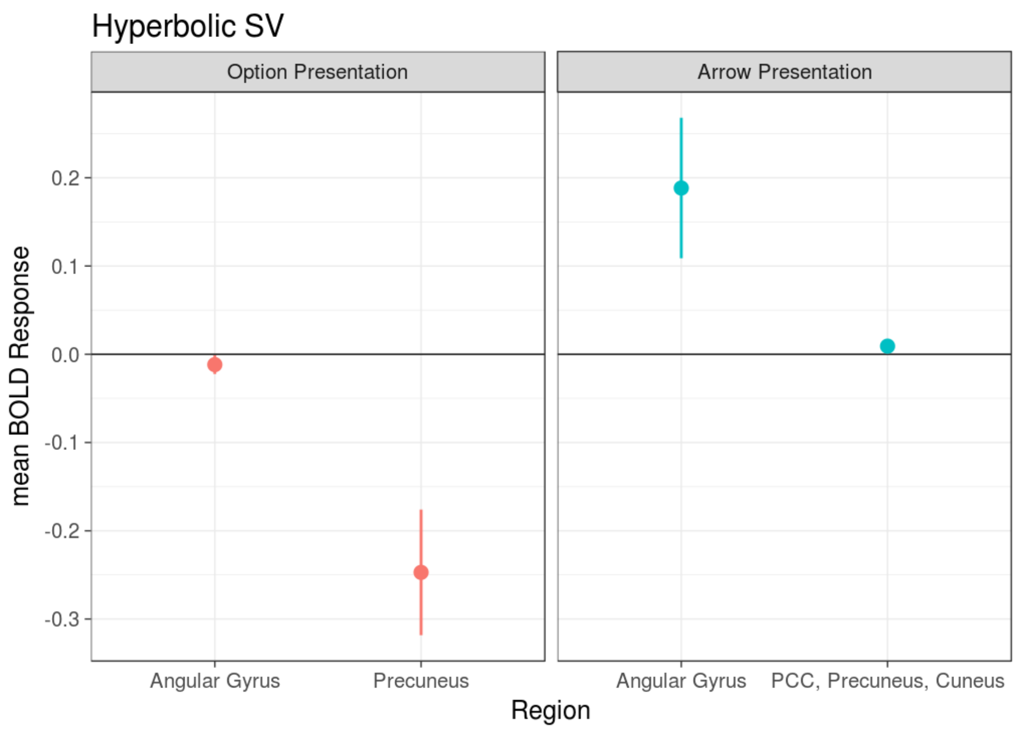

Figure 5.24: Mean BOLD response from each ROI in relation to increasing subjective value of the larger option as predicted by the hyperbolic model with +/-1 SE shown.

5.2.6.4.5 Sigmoidal model estimate of larger option subjective value

The sigmoidal model was used to calculate subjective value estimates for the larger effort option using the fitting results from SoftMax estimation. The subjective values were convolved with the canonical HRF as a parametric modulator in the first level GLM. Second level results are reported.

At the option presentation time, no significant increase in BOLD response was identified in any ROI. Inverse response patterns were observed in both the *ACC* (T = 4.89; p_{FWE} = 0.019; peak activation at x = 6, y = 44, z = 5) and *PCC* (T = 4.51; p_{FWE} = 0.016; peak activation at x = 6, y = -49, z = 29) whereby activation increased as sigmoidal model subjective value estimates decreased. Figure 5.25 shows the spatial extent of the activation.

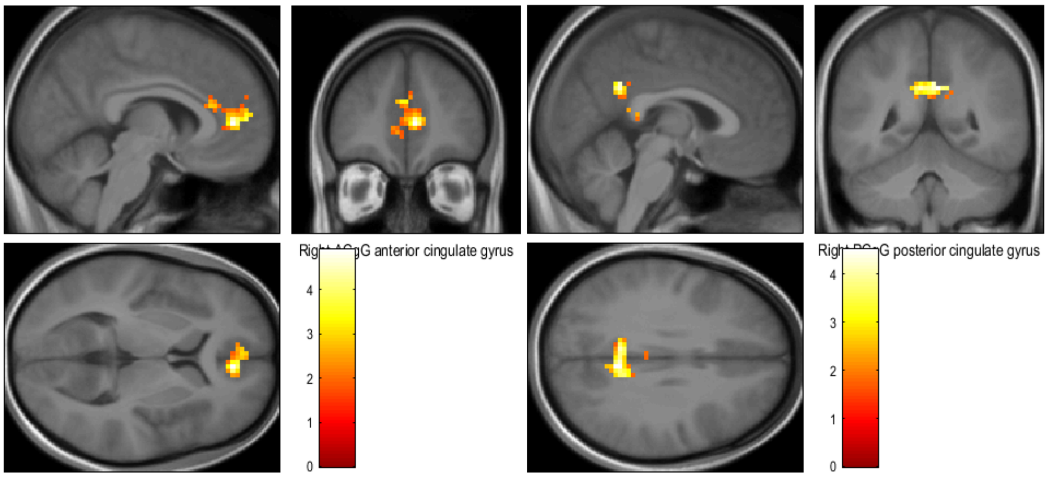

Figure 5.25: Extent of decreased BOLD response in ACC and PCC as the sigmoidal model estimate of the subjective value of the larger option increases at the time of option presentation. Images displayed with threshold set to p = 0.001 and k > 20 contiguous voxels.

At the time of arrow presentation, BOLD response to increasing sigmoidal subjective value estimates were detected in the *ACC* (cluster-level p_{FWE} = 0.002; peak voxel activation T = 3.97; p_{FWE} = 0.14; peak activation at x = 6, y = 53, z = 14)*, precuneus* (T = 5.33; p_{FWE} = 0.017; peak activation at x = 3, y = -49, z = 29)*, and cuneus* (T = 4.61; p_{FWE} = 0.038; peak activation at x = 6, y = -82, z = 23). The *PCC, angular gyrus* and *vStriatum* were also positively correlated, but did not survive FWE correction.

Figure 5.26 shows the extent of activity in the *ACC* and parietal cortex. Figure 5.27 presents the mean activation from ROIs of the sigmoidal model estimate parametric modulator.

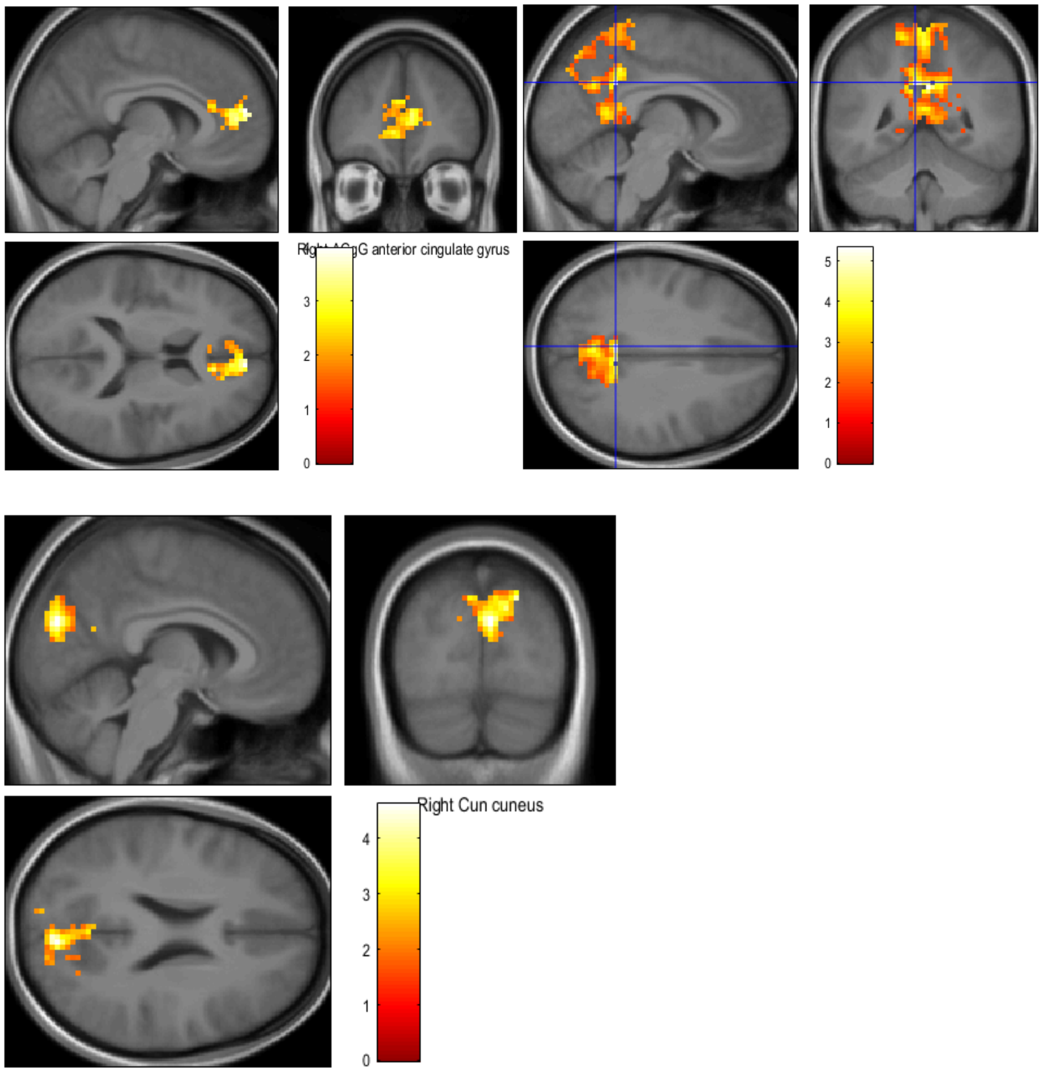

Figure 5.26: Extent of activation in response to increasing subjective value of the larger option as estimated by the sigmoidal model. Top left image shows the *ACC*¸ top right shows the *precuneus*¸ and the bottom left image shows the *cuneus.* All images displayed with thresholds at p = 0.001 and k > 20 contiguous voxels.

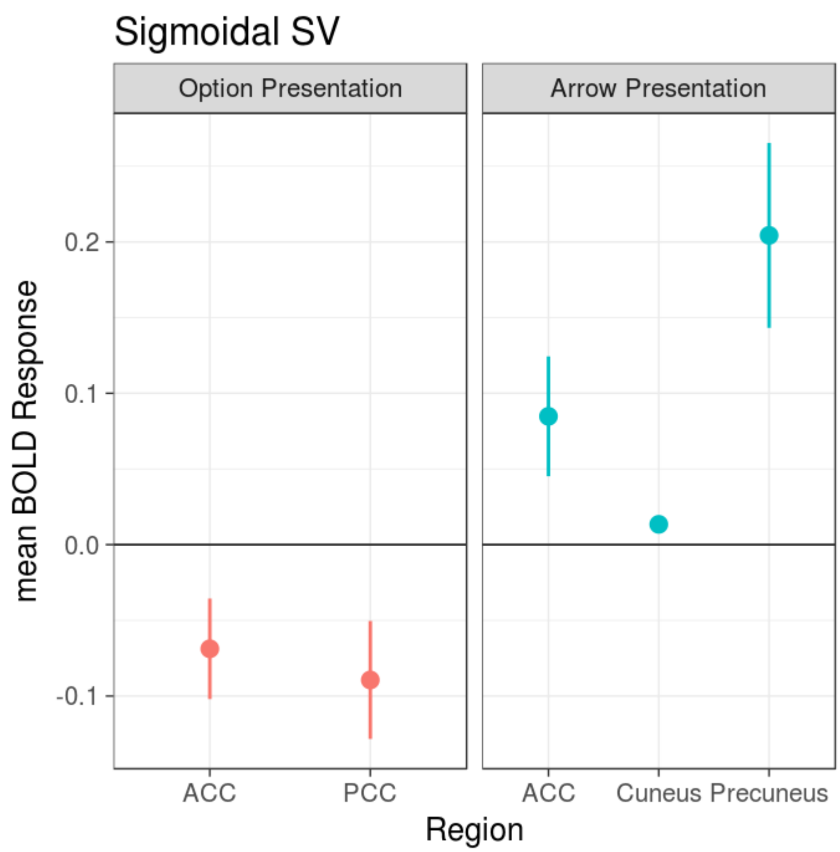

Figure 5.27: Mean +/- 1 SE of BOLD response from each ROI in relation to increasing subjective value of the larger option as estimated by the sigmoidal model.

5.2.6.5 BOLD responses associated with individual differences in discounting behavior

To investigate individual differences in discounting behavior in the brain, regression analyses were conducted using model parameter estimates and area under the curve values for each participant (Kable & Glimcher, 2007; Klein-Flügge et al., 2016). These values were entered as correlates in the second level GLM predicting voxel BOLD response by choice outcome. Both time events, option and arrow presentation were tested and each correlate was tested independently. Only the hyperbolic model k parameter and sigmoidal model p parameter exhibited significant correlations, reported below.

5.2.6.5.1 Hyperbolic K

Recall that in the hyperbolic model, participants with a smaller discounting rate estimate attribute greater subjective value to larger effort options. At time of option presentation, hyperbolic k parameter estimates were negatively correlated with BOLD response in four regions of interest: the *right caudate* in the *basal ganglia* (cluster-level p_{FWE} = 0.004; peak voxel activation T = 4.26; p_{FWE} = 0.102; peak activation at x = 12, y = -1, z = 20), the *dmPFC* (cluster-level p_{FWE} = 0.001; peak voxel activation T = 4.25; p_{FWE} = 0.573; peak activation at x = -9, y = 29, z = 44), and the *right ventrolateral PFC* (cluster-level p_{FWE} = 0.001; peak voxel activation T = 4.04; p_{FWE} = 0.728; peak activation at x = -30, y = 44, z = -10). Figure 5.28 shows the spatial location of BOLD response, while Figure 5.30 shows the correlation between Hyperbolic k values and peak voxel BOLD response for the given region in each participant.

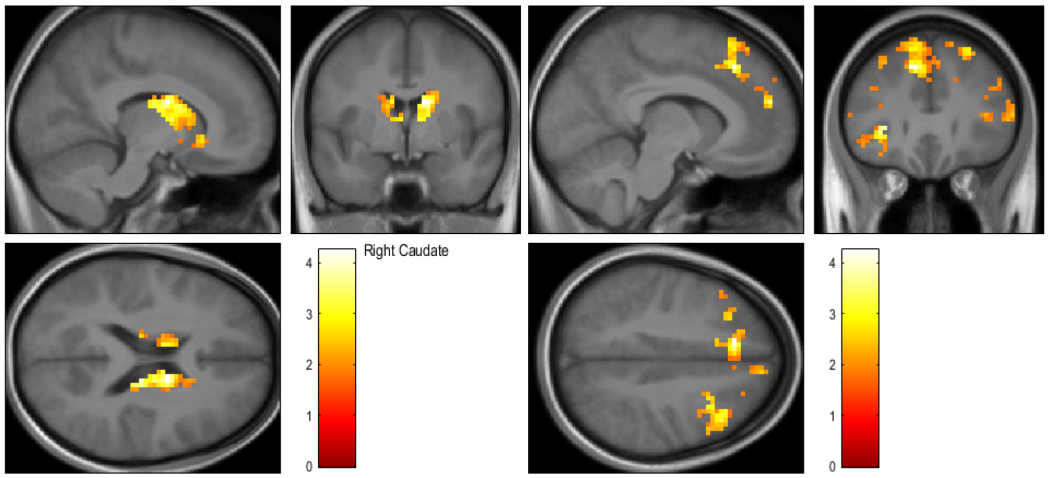

Figure 5.28*:* Extent of significant voxels from the *basal ganglia* (left image), particularly the right *caudate*, and *dmPFC* (right image) shows BOLD response correlates with hyperbolic k parameters across participants. Images displayed with threshold at p = 0.001 and k > 20 contiguous voxels.

At the time of arrow presentation, the *ACC* (T = 5.59; p_{FWE} = 0.003; peak activation at x = 15, y = 44, z = 5) and left *insula* (T = 5.04; p_{FWE} = 0.007; peak activation at x = -36, y = 17, z = -10) exhibited negative correlation between BOLD response and hyperbolic k values. Figure 5.29 shows the spatial extent of significant BOLD response, while Figure 5.30 shows the correlation between Hyperbolic k values and mean voxel response for each region for each participant.

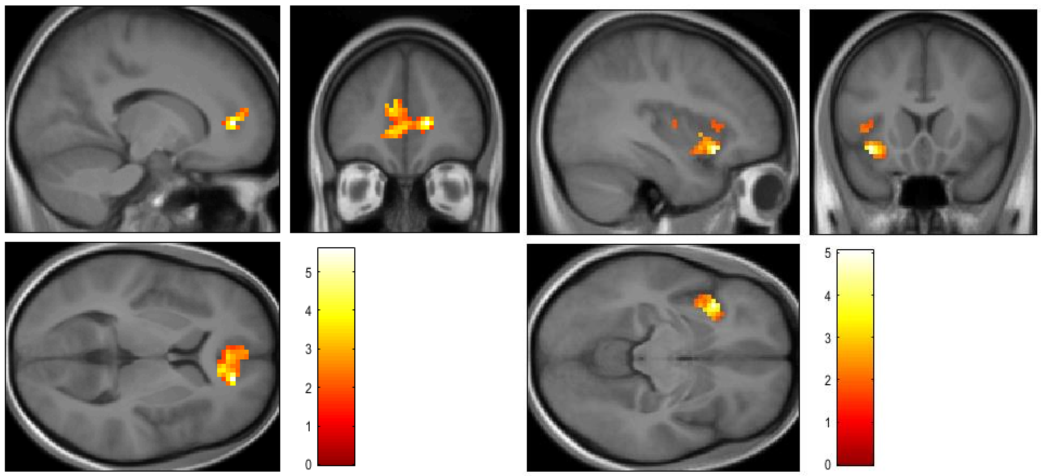

Figure 5.29: Extent of significant correlation with hyperbolic k at time of arrow presentation. Left image presents the *ACC* while the right shows *left insula.* Images displayed with threshold at p = 0.001 k > 20 contiguous voxels.

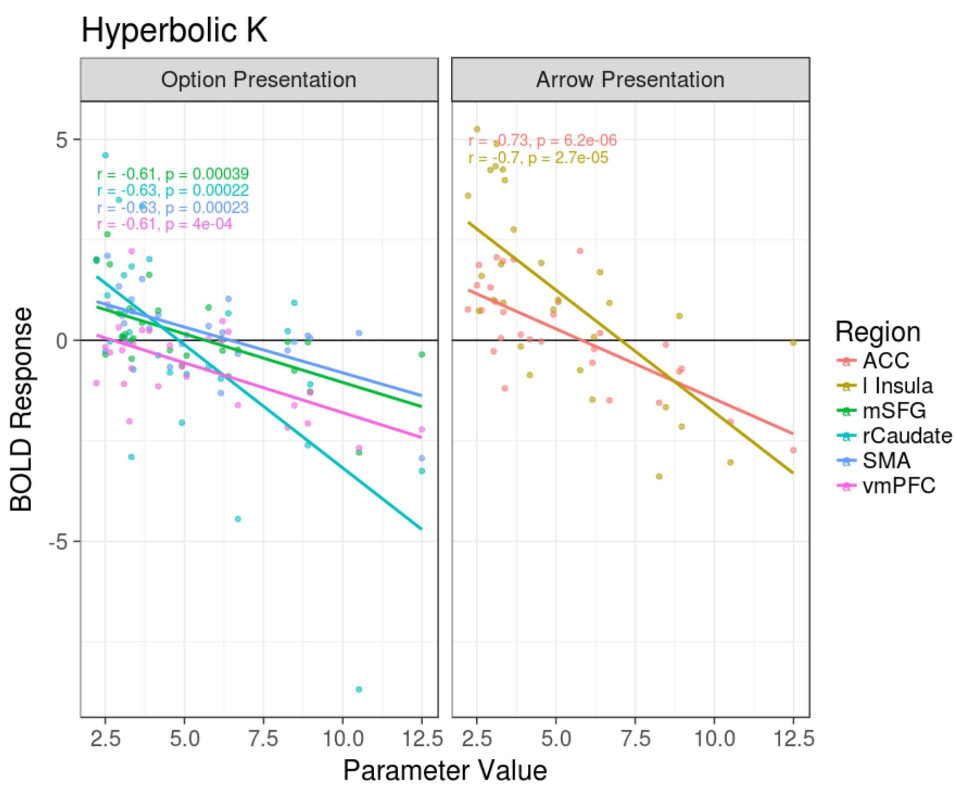

Figure 5.30: Correlation between BOLD response (y-axis) and hyperbolic k parameter

5.2.6.5.2 Sigmoidal P

In the sigmoidal model, participants with a smaller p parameter begin discounting at lower effort values than participants with a larger p parameter. The sigmoidal p is an estimate of the inflection point of the discounting curve. Positive correlation with sigmoidal p could imply a region is involved with the inhibition of discounting mechanisms. Similarly, a negative correlation could imply a region is involved with discounting or positively correlates with discounted option selection. However, it is important to note this analysis was performed at the second level and contrasts differences between participants. As such, it is unreasonable to make a claim about a specific or global neural mechanism.

At time of option presentation, sigmoidal p parameter estimates were negatively correlated with BOLD response in the *dlPFC* (cluster-level p_{FWE} = 0.008; peak voxel activation T = 4.19; p_{FWE} = 0.457; peak activation at x = 27, y = 41, z = 29), including the *mSFG (*a region in the *dmPFC)* (T = 5.04; p_{FWE} = 0.007; peak activation at x = -36, y = 17, z = -10), and *precuneus* (cluster-level p_{FWE} = 0.001; peak voxel activation T = 3.67; p_{FWE} = 0.587; peak activation at x = 15, y = -40, z = 44). Figure 5.31 shows the spatial location of BOLD response, while

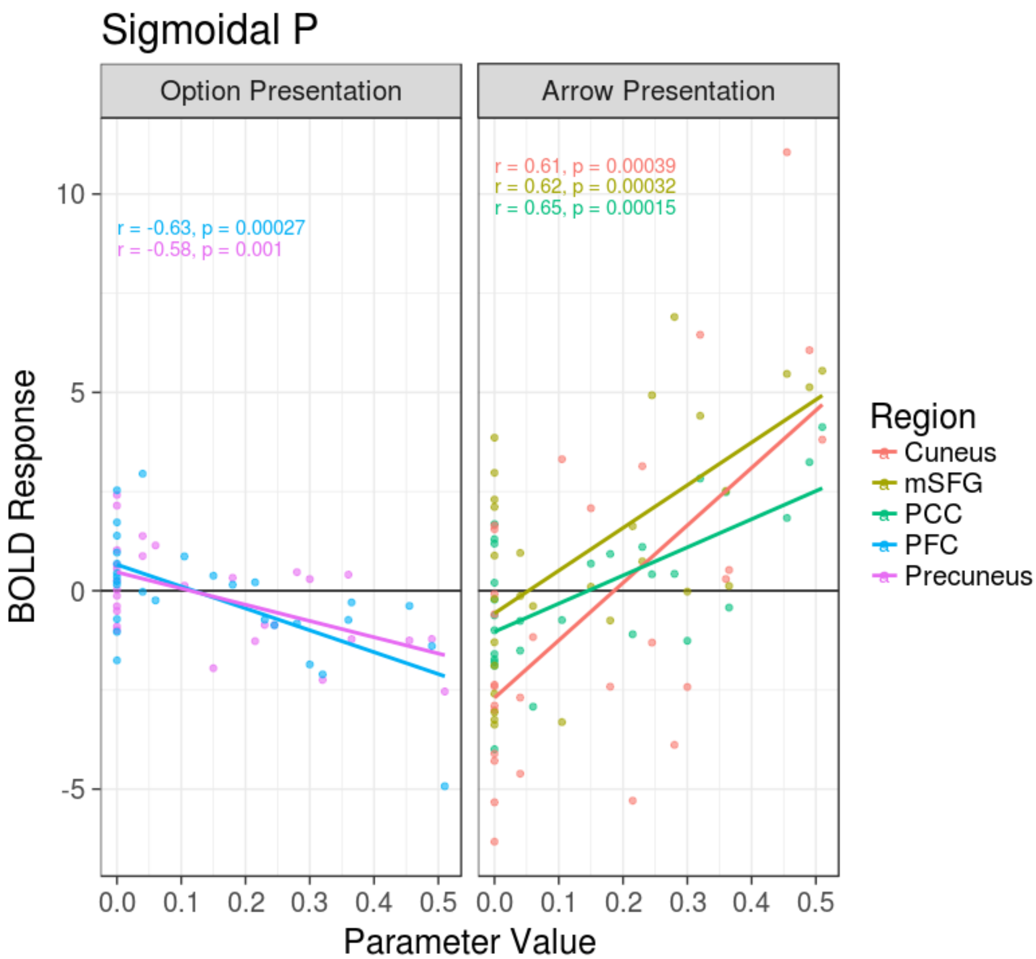

Figure 5.33 shows the correlation between Sigmoidal p parameter values and peak voxel response for the given region.

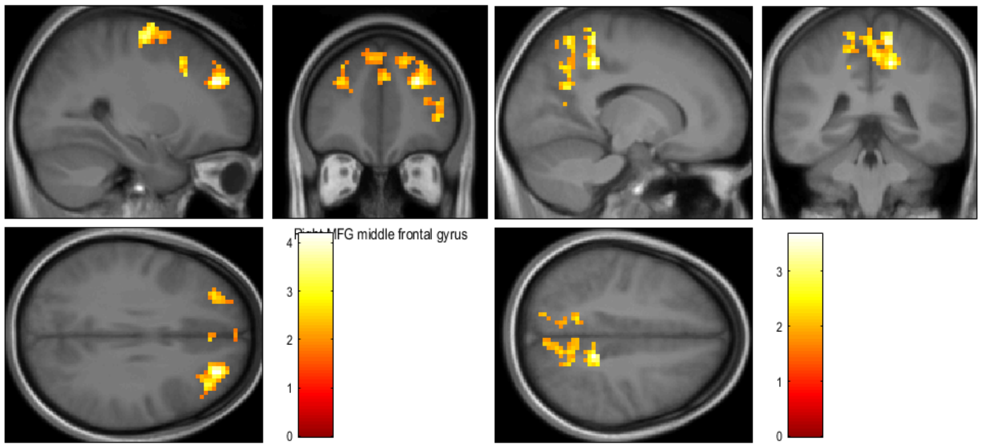

Figure 5.31: Extent of significant, negative correlation with sigmoidal p-parameter at time of option presentation. Left image shows BOLD response in the *dPFC* while the right image shows *precuneus.* Images displayed with threshold at p = 0.001 and k > 20 contiguous voxels.

At the time of arrow presentation, the *PCC* (cluster-level $p_{FWE} < 0.001$; peak voxel activation T = 4.42; $p_{FWE} = 0.200$; peak activation at x = -6, y = -46, z = 29), *cuneus* (cluster-level $p_{FWE} < 0.001$; peak voxel activation T = 3.71; p_{FWE} = 0.61; peak activation at x = -6, y = -79, z = 41), and *mSFG (dmPFC)* (cluster-level $p_{FWE} = 0.001$; peak voxel activation T = 4.12; $p_{FWE} = 0.692$; peak activation at x = 0, y = 35, z = 35) were positively correlated with sigmoidal p-parameter values. Figure 5.32 shows the spatial location of BOLD response.

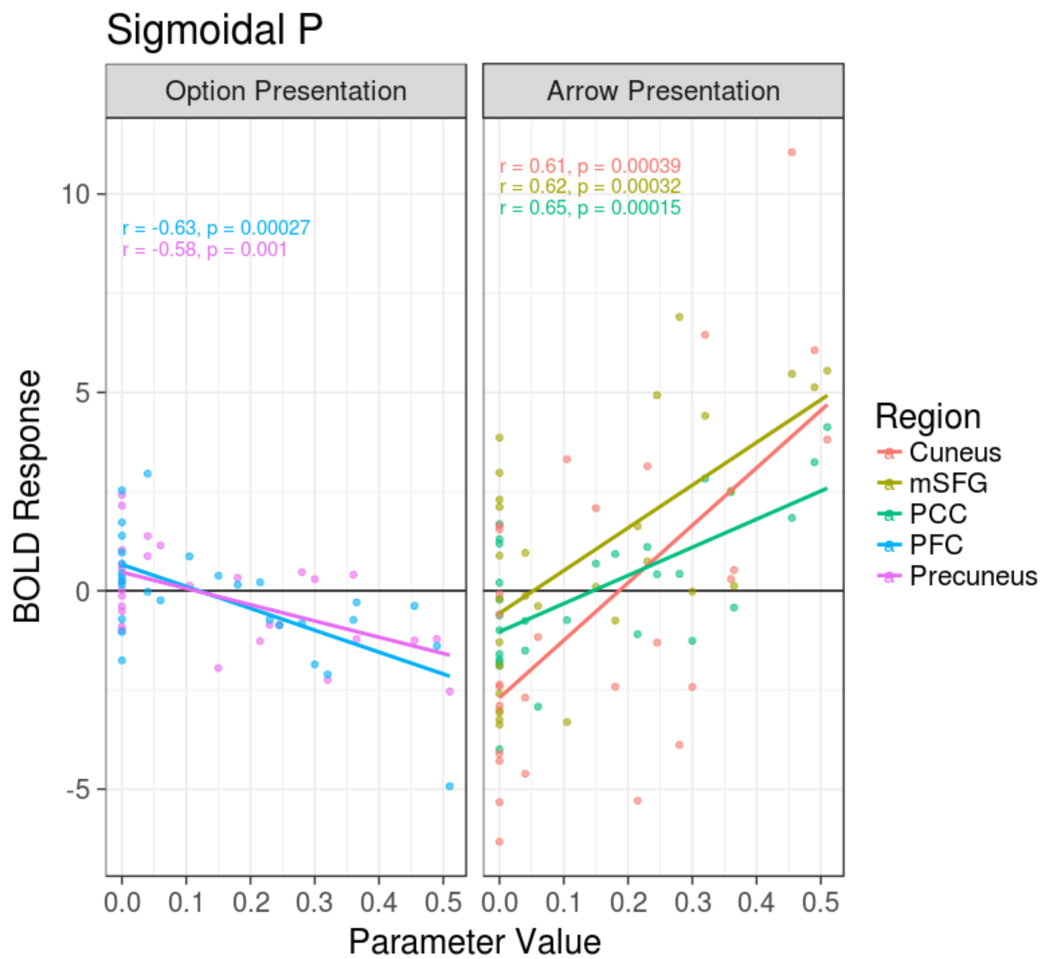

Figure 5.33 shows the correlation between parameter values and mean BOLD response for the given region.

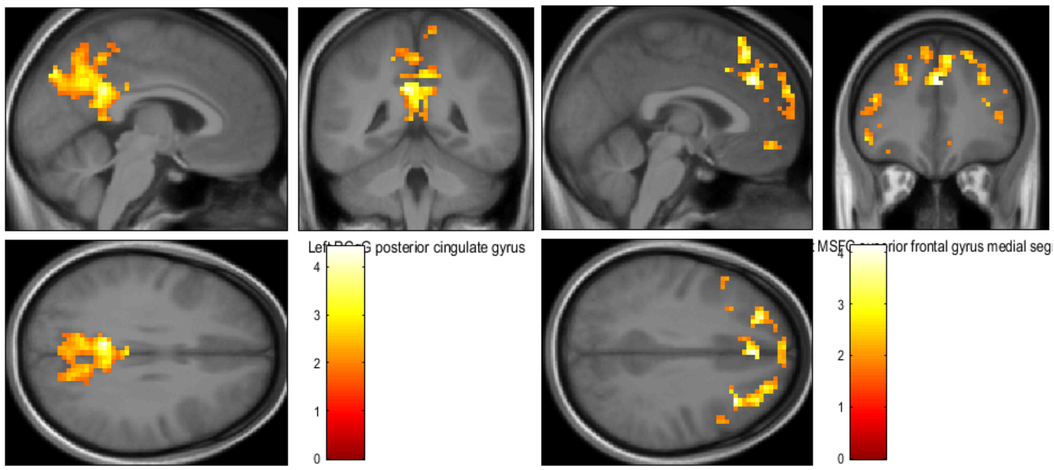

Figure 5.32: Extent of significant correlation with sigmoidal p at time of arrow presentation. Left image presents activity in the *PCC and cuneus* while the right shows *the PFC.* Images displayed with threshold at p = 0.01 uncorrected and k > 20 contiguous voxels for visualization purposes.

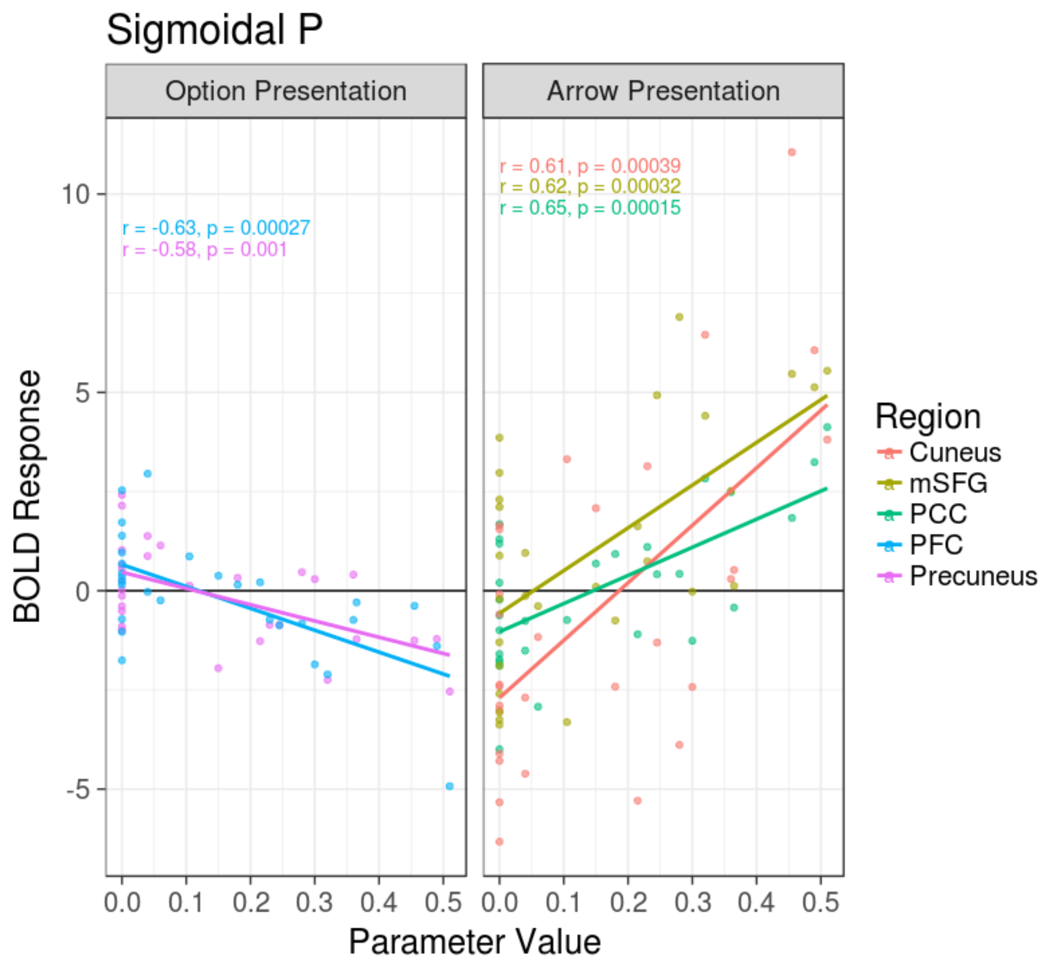

Figure 5.33: Correlation between BOLD response and sigmoidal p-parameter color coded for each ROI.

5.3 Discussion

Given the number of analyses presented in this chapter, the discussion has been segmented into three parts. The first part discusses the findings from the paired contrasts and parametric modulation analyses. Neural correlates of different choice options and valuation are highlighted. The second part discusses the BOLD response correlated with individual differences in discounting parameters. These are the most exciting findings of the analysis and present the interlink between computational modeling and fMRI methods. The third part discusses the results of the accountability manipulation between written and social accountability.

5.3.1 Neural Correlates of Choice and Discounting Behavior

The study in this chapter investigated the neurophysiological responses of decision makers who chose either a larger effort, larger compensation option or smaller effort, smaller compensation option for another participant. Of primary interest was to investigate regions of the brain where the BOLD response correlated with decision behavior and estimations of subjective valuation on behalf of another agent. Behavioral results of the GLM showed participants were sensitive to changes in effort and compensation amounts in the larger option, and the change in the ratio of these attributes significantly affected the chosen outcome. Additionally, the behavioral findings aligned with results from chapters 2 and 3.

Neural correlates of valuation were observed through whole brain contrast between trials where participants chose the larger option over the smaller option. Significant increases in the BOLD response in the *basal ganglia* (*striatum, pallidum, and putamen*), were detected when decision makers chose the larger option. These regions have been shown to respond to increasing reward magnitudes which is likely due to the increased compensation of the larger option. Further evidence stems from the parametric modulation analysis of compensation, where regions in the *basal ganglia* showed increased BOLD response as the larger option compensation amount increased.

Conversely, the *insula* which has been shown to respond to increased cost exhibited an increased BOLD response when decision makers chose the larger option. However, in conjunction with increased activity in the parietal cortex such as in the *PCC* and *precuneus* which was observed here, prior research has shown the insula and parietal cortex are linked with information seeking behavior that is relevant to rewards (Furl & Averbeck, 2011).

Regions in the parietal lobe including the *precuneus*, *cuneus*, and *PCC* were repeatedly found to reflect value in parametric modulation analyses. Egocentric valuation has often been implicated in the domain of the *ACC*, vm*PFC*, and *vStriatum*; however, the findings from this chapter suggest more dispersed neural activity may be involved in allocentric valuation. Research has shown the parietal cortex and medial temporal cortex may represent decision making goals (like maximizing value for another person) and project into the *striatum* which encodes value (Schultz, 2000). The *PCC*, *cuneus*, *precuneus*, and *angular gyrus* in the parietal cortex all exhibited significant changes in BOLD response in parametric modulation analyses of DpW, and model estimates of subjective value.

Furthermore, when examining the effort magnitude contrast, BOLD response in the *vmPFC* and *vACC* were significantly increased on trials of low effort magnitude compared to high effort magnitude. When both choice options were similar in effort, these regions exhibited increased activity. Both the *vmPFC* and *vACC* have been heavily implicated in valuation processes. One possible explanation is that an executive level goal or heuristic such as “always minimize effort for another” acts as an overriding or suppressive directive to valuation mechanisms when options are easily dissociated, but fails when the choice options are more similar. When comparing similar options, value computation is required. Such a model would support and extend a do-no-harm principle explanation of allocentric decision making. Parametric modulation analyses of effort and compensation supports this idea. As effort of the larger option increased, reduced BOLD response in the *ACC* was observed. Additionally, increased BOLD response in the parietal cortex was observed on trials with high effort magnitude. *PCC* and *angular gyrus* are particularly robust in the parietal cortex and have shown increased response when decision makers choose harmful outcomes for others (Greene et al., 2001).

While the pattern of interaction between parietal cortex regions and PFC was observed, a clear mechanism for the interplay between these regions is not apparent. BOLD response in the parietal cortex was inconsistent between option presentation and arrow presentation time events. Similarly, the relationship between regions in the PFC and parietal cortex is correlational, indirect, and subject to a third variable explanation (or in this case, a third ROI that promotes activation in both the PFC and parietal cortex). More detailed functional mapping of the pathways connecting these regions is an important future direction.

5.3.2 Individual Differences in Model Parameter Estimates Correlated with ROI BOLD Response

Individual differences in model parameters correlated with variation in ROI BOLD response. This was an important finding both for understanding allocentric valuation and for validating the computational models used. ROI regions of the *ACC*, *basal ganglia*, *dmPFC*, and *insula* correlated with individual differences in estimated discounting rates in the hyperbolic model. When participants had a high discounting rate, regions associated with subjective valuation exhibited decreased BOLD response. High discounting rates reflect participants that discounted value more steeply due to effort, reflected in reduced activity in ROIs associated with reward especially the *ACC* and *rCaudate* in the *basal ganglia*. Notably, *insula* response followed a similar pattern despite being hypothesized to reflect cost or devaluation.

Conversely, when participants had higher sigmoidal p parameter estimates, and thus greater subjective valuations over effort, regions in the *PFC* and *posterior parietal cortex* exhibited greater BOLD response. Variations in the p parameter correlated with parietal cortex activity which supports the prior findings that a regulatory link may exist between the parietal cortex and valuation mechanisms in the *PFC*. A threshold may dictate an individual-specific level of effort that determines option sets to be evaluated by traditional valuation mechanisms in the *vmPFC* and *ACC* and those options that can be selected by alternative mechanisms in dispersed regions.

5.3.3 Effects of Social Accountability Condition

Behavioral results showed no difference in choice behavior between the two accountability conditions, written and social. Indifference points analysis and computational modeling showed no difference between accountability conditions in how options were valued. Behavioral results from GLM analysis of the effect of WpD on choice showed significant effect of option value on choice, but no effect of condition. The null effect of accountability replicated findings from chapters 2 which also showed no significant effect of accountability on choice or discounting behavior.

Yet, reaction times differed significantly between these two conditions, with participants taking slightly longer to make socially accountable decisions. The difference in reaction times is encouraging with participants taking more time to respond to decisions subject to review and public justification compared to privately made allocentric decisions. Participants may have considered the manipulation in social accountability conditions, resulting in longer reaction times. Prior research has shown that individuals choosing pro-social outcomes exhibit increased reaction times compared to selfish decisions (Kuss et al., 2015).

Whole brain fMRI analysis showed no significant differences between the conditions. While accountability effects were not observed behaviorally, ROI analysis of the mean BOLD response between the two conditions revealed the *TPJ*, *precuneus*, and *dmPFC* exhibited significant differences depending the condition of the trial. Given the robust activity of the *precuneus,* the increased activity of the *SMA* and *TPJ* corresponding to social accountability is a more interesting initial finding. The *SMA* has been implicated in egocentric effort discounting rates (Klein-Flügge, Kennerley, Friston, & Bestmann, 2016) while the *TPJ* has been shown to reflect choice outcomes in this study and social perspective taking in others (Saxe & Kanwisher, 2003). Both regions showed reduced BOLD response in the social accountability trials. This would theoretically resemble a shift toward more egocentric-like decision making with reduced effort discounting and reduced perspective taking. However, further study is needed to assess the role these regions play in cognitive representation of accountability and if alternative operationalization of accountability can magnify this effect, resulting in behavioral modulation.

5.4 Conclusion

The findings from this chapter establish initial neural correlates of allocentric effort decisions. Further comparisons between allocentric decisions in other choice domains and using alternative effort tasks are necessary to provide a more robust understanding of the underlying cognitive processes responsible for allocentric effort decision processes. Furthermore, studies testing specific mechanisms are needed to elucidate the differences between neural correlates and process pathways. Studying neural causation requires proof through “double dissociation” and often relies on small samples of clinical participants with brain injuries or lesioned animal models.

The absence of an effect of accountability condition on choice behavior is notable, but the presence of an effect on reaction time due to the accountability manipulation supports the idea that accountability was considered by the participants but may not be effective in altering allocentric effort decisions. Given that accountability can be operationalized in several ways and from different sources, further study is needed to explore accountability in different contexts and using different operationalizations. Organizations that expend resources to enforce accountability on executive decision makers have a vested interest in these findings.

The neurological validation of discounting models for allocentric effort decisions was an important contribution of this study. Computational models are the central cream filling of this thesis that binds the disparate empirical findings of behavioral choice studies and neurophysiological activity. Individual differences in parameter estimates correlated with expected regions of interest even when utilizing model free whole brain analysis. Furthermore, the valence of the associated activity could be interpreted using computational model assumptions. These results extend evidence that the hyperbolic and sigmoidal models of effort discounting are useful tools for mapping latent discounting cognition and allocentric effort valuation.

An important finding across all fMRI results is the prominent role of the parietal cortex. The *PCC, precuneus, cuneus,* and *angular gyrus* were implicated in parametric modulation analyses and individual differences analyses. These regions are dense in cell bodies and heavily interconnected with each other and other regions of the brain. Given that the medial parietal lobe connects with diverse regions and neural tracts, it is possible that these areas integrate signals from other regions of the brain and do not represent unique cognitive functions but rather an amalgamation of several processes. Prior findings have shown regions in the PFC and midbrain correlate with valuation. It is possible the parietal cortex could integrate these signals with information from social cues, inhibit or enhance these processes given a social context, or otherwise modulate the inputs and outputs of the valuation process. Further study is needed to investigate the exact mechanisms involved with these regions to elucidate their role in allocentric decision making.

6 Conclusion

6.1 Assessment of research aims and review of findings

The overarching aim of the thesis was to provide a description of allocentric decision making in the domain of effort choice outcomes. The experimental design was effective at eliciting effort discounting behavior in allocentric decisions similar to prior studies of egocentric decisions (Libedinsky et al., 2013; Massar et al., 2015). Using choice experiments where participants made effort decisions, this thesis investigated allocentric decision making across three levels in the style of the neuroeconomic approach outlined in chapter 1.

First, allocentric decisions were shown to be behaviorally dissociable from egocentric decisions when decision makers chose between different sized typing tasks and their corresponding compensation. Choice differences reflected differences in effort discounting between egocentric and allocentric decisions. The distinction between egocentric and allocentric decisions persisted regardless if the recipient of the decision outcomes was manipulated within- or between-participants.

Second, computational models with multiplicative combinations of effort and compensation resulted in better model fit than additive combinations. Specifically, the hyperbolic and sigmoidal models were found to be the best fit to the data as discounting began at low levels of effort in the choice task. The same computational models best represented both allocentric and egocentric decisions. However, allocentric decisions exhibited increased discounting rates of effort relative to egocentric decisions in the hyperbolic model. The sigmoidal model was better apt to representing individual differences in discounting.

Third, neural correlates of allocentric effort discounting were found in several regions of interest including the PFC, ACC, basal ganglia, insula, rTPJ, and parietal cortex. Activity in these regions correlated with participant behavior, variations in stimuli, and individual differences in model parameter estimates. Choice differences were reflected in the BOLD response of the rTPJ, a region associated with theory of mind and social cognition. Regions associated with value (the basal ganglia and PFC) exhibited BOLD response that increased with compensation and decreased with increased effort. Importantly, regions in the parietal cortex (cuneus, precuneus, PCC, and angular gyrus) were also correlated with value. Furthermore, the activity in the parietal cortex correlated with the estimated sigmoidal p-parameter across individuals. Given that the sigmoidal p-parameter acts as a threshold indicator that reflects the level of effort where a decision maker begins to discount value, the parietal cortex may be responsible for modulating the value mechanisms in the PFC responsible for discounting behavior. Such findings open avenues for further explorations of the neural mechanisms connecting these regions.

An additional aim was to investigate the effects of accountability on allocentric decisions as a possible moderator of egocentric-allocentric differences. Accountability was implemented via an in-person interview with the head experimenter. Contrary to the hypothesis, accountability did not have a moderating effect on choice behavior large enough to be detected. Null effects of accountability on allocentric effort discounting persisted even when pairwise conditions in the fMRI study controlled for self-reflection and the additional effort of reviewing past choices. Reaction times did differ significantly between social accountability and private, written accountability in the fMRI study, but choice outcomes were nearly identical. ROI analysis showed differential BOLD response in the precuneus, TPJ, and SMA between social accountability trials and written accountability trials. The decreased response in the TPJ and SMA during social accountability trials compared to private, written accountability trials suggest that social cognition and effort cost considerations (respective to each ROI) may be influenced by accountability, and warrant further investigation.

6.2 Current findings in relation to prior literature

Allocentric effort discounting is a novel phenomenon in the decision-making literature. However, allocentric temporal discounting findings are comparable, using the same binary choice paradigm of combined monetary reward and cost options. Making allocentric decisions has been shown to decrease temporal discounting rates compared to egocentric discounting rates (Albrecht et al., 2011; Ziegler & Tunney, 2012). In contrast, studies in this thesis found allocentric effort discounting decisions were better modeled with higher discounting rates compared to egocentric decisions. This difference may be due to the requirement of the decision recipient's participation, the aversion to imposing a task on another individual, or increased salience of monetary reward in egocentric decisions.

One explanation supported by the findings here is the do-no-harm principle (Baron, 1995). This principle suggests that assigning the tedious typing task is akin to causing harm or inconvenience to another. Decision makers' aversion to assigning another person an effortful task may outweigh the benefits of providing an opportunity for another to earn monetary rewards. For comparison, when temporal delay is the cost associated with a monetary reward, increased discounting is not observed, as no participation is required on behalf of the decision recipient. Additionally, this coalesces with the findings from chapter 2 where effort reference option was found to have a significant effect on choice in both egocentric and allocentric conditions; whereas matching designed temporal discounting studies using two-period delay designs have shown an interaction effect between decision recipient (egocentric vs. allocentric) and reference option (immediate-delay vs. delay-longer delay options) (Albrecht, Volz, Sutter, Laibson, & von Cramon, 2011). Illusory superiority would predict decision makers to view themselves as more patient than others, which is contrary to the observed behavior. The do-no-harm principle may not apply to temporal discounting behavior as waiting may not be considered "harm" on the recipient, while effort discounting studies impose a cost in terms of time, attention, and exertion.

Another explanation may stem from the salience of immediate egocentric monetary rewards which would explain the shift in favor of larger rewards in effort discounting and smaller, sooner rewards in temporal discounting. While temporal and effort discounting have been shown to be dissociable (Klein-Flügge et al., 2015; Massar et al., 2015; Prévost et al., 2010), such a "greed-primacy" hypothesis is supported by findings in other choice domains. Prior studies of egocentric risk decisions have shown mounting pressure to succeed influences decision making. Participants chose increasingly risky choice options as the number of opportunities to meet reward goals decreased (Kolling, Wittmann, & Rushworth, 2014). External circumstances may have evoked a similar salience of egocentric reward in the effort studies used in chapter 2 which would explain the reduced egocentric discounting rate observed.

Evidence from other fields supports the pattern of egocentric-allocentric differences found in the two behavioral experiments. Research shows participants from a gender-specific negotiation game argue for higher salaries for others than they are willing to accept themselves in a salary negotiation game (Amanatullah & Morris, 2010). This implies participants value the effort of others more than their own. Similarly, third party non-forgiveness studies show that participants are more likely to work for the forgiveness of others than for their own wrongs (Green, Burnette, & Davis, 2008). These findings coalesce with the evidence provided here in that rather than discounting their own effort, decision makers likewise value the effort of others more. This provides a further evidence against an empathy gap explanation and in favor of the do-no-harm principle. An empathy gap explanation derives primacy from personal reward, in which case the women would be valuing themselves equally, or participants would be working to expunge their own shame just as fervently. The do-no-harm principle would require additional compensation for others. Further study is necessary to specify the mechanisms responsible for egocentric-allocentric differences.

Computational modeling results favored selection of the hyperbolic and sigmoidal models. Of the models tested, the hyperbolic model was the best fit when fitting the indifference points. While the parabolic model has been shown in prior literature to be a good fit for indifference point fitting in effort discounting (Hartmann, Hager, Tobler, & Kaiser, 2013), the implementation of the physical effort task likely placed more emphasis on duration endurance than the typing task. When using SoftMax fitting, the sigmoidal model was the best fit to the data, similar to prior effort discounting studies that used physical effort tasks (Klein-Flügge, Kennerley, Saraiva, Penny, & Bestmann, 2015).

Neural findings coalesced with prior literature. ROIs in the limbic system were associated with allocentric reward (compensation) and cost (effort) including the basal ganglia, ACC, and insula. Furthermore, parietal cortex activity was robust across all analyses, which was expected given participants were making allocentric effort decisions in both conditions. The PCC and angular gyrus have shown increased activity in intrapersonal decisions that result in harm to another (Greene et al., 2001), further supporting the do-no-harm explanation. BOLD activity in these regions correlated with the estimated parameters in both sigmoidal and hyperbolic discounting models between subjects. This provides strong evidence supporting the computational models selected in chapter 3.

Prior literature showed that social accountability, when operationalized through an interview, increased complexity of thought in decision makers (Lerner & Tetlock, 1999). Social accountability was hypothesized to influence allocentric decision making by encouraging consideration of another agent's possible preferences and, assuming a decision maker's egocentric preferences are known, more easily expressed, and thus easier to justify, aligning egocentric and allocentric preferences. However, no effects of accountability on choice behavior were observed in two experiments.

Overall, the three research approaches point to a difference in cognition between allocentric and egocentric effort discounting. While the decision mechanisms may be the same (or very similar), as evidence by the same models best predicting choice outcomes, the effort is likely weighted differently when it is for another person than for oneself. Neural regions commonly associated with valuation in egocentric decision-making studies, were correlated with the value of the larger effort/larger compensation option when making allocentric decisions. However, there were additional regions that correlated with differences in discounting parameters between participants in the PCC and dmPFC which may be responsible for varying sensitivity to social agents. Furthermore, individual differences in sensitivity to social agents were correlated with SVO, feelings of responsibility, and self-reporting the intent to choose what was best for the recipient. The evidence supports a do-no-harm interpretation of allocentric effort discounting where effort is steeply discounted for others as an inconvenience, but evaluated in a transactional cost-benefit analysis method by egocentric decision makers. This claim is subject to the limited evidence provided by these studies. The limitations are discussed further in the following section.

6.3 Limitations

The experiments used in this study were limited by design with regards to the relationship between decision maker and recipient. Double blind allocentric decisions were used to preserve the anonymity of both decision maker and recipient. Outside of the laboratory, single-blind allocentric decisions may be more common and may have differential effects on effort choices. For instance, given an increasing reliance on digital communication, agents may be knowable through an online identification, but this identity may be manifested for ulterior motives or uncorrelated to the person's true preferences. Thus accountability, as was enacted here, needed to be more than simply a name, but action that tied the decision maker to the outcome.

Furthermore, only one type of accountability and one effort task was used in these experiments. The design of these studies was an intentional tradeoff to allow comparison between studies coherent with a multilevel, neuroeconomic approach. The tradeoff improved the internal validity and rigor of the research presented here at the cost of study variety and ecological robustness. However, some extrapolations from the laboratory findings are discussed in the next section.

6.4 Managerial implications

As modern firms move toward contingent short-term labor based on projects and contracts (a "gig-economy"), wage rates and effort allocation are increasingly important factors for attracting and rehiring employees. How managers choose to position job availabilities will be a large predictor of successful hiring solutions, successful HR managers, and ultimately better usage firm-level human resources. The research presented here has implications for how managers allocate effort.

Within firms, the allocation of employee effort is required to produce outputs and services. Assigning effort tasks amongst teams and team members is integral to an organization’s success. Doing so in an efficient manner allows firms to operate more effectively and reduces wasted resources. This research shows that managers and project team leaders may overestimate their own abilities or underestimate the effort of team members. Conversely, managers may overvalue underperforming team members or undervalue their own efforts. This may create strain on managers or team relations. Oftentimes, firms expend resources to enforce accountability on managers to reduce agency problems and moral hazard. However, at least in the domain of effort decisions, accountability here showed no effect on allocentric effort decisions. While it is difficult to draw any conclusions from null results, resources used to ensure accountability, may be better freed for other operational needs.

A third implication is at a strategic level. Effort at a firm level is related to production costs. Firm directors engaged in bidding against competitors to earn contract work may undervalue their own firm’s efforts or overvalue rival firms’ efforts when competing for production contracts. Assessing the value of a rival’s production costs and comparing this to a firm’s own production costs may alter how strategic managers make competitive bids or if they choose to compete at all. Further study is needed to expand the scope of this work and to improve the ecological validity of these findings.

6.5 Future Directions

Future aims and extensions of this research include the expansion of stimuli used. Allocentric effort discounting differences from egocentric decisions may be different based on the type of effort task used - purely physical, purely cognitive, or mixed effort. Dissociating these effects, particularly neurologically, poses a challenge that is ripe for neuroeconomic approaches.

Similarly, parsing the ways in which decision maker – decision recipient relationships influence effort discounting is a paramount extension of this research. The role of social distance in moderating allocentric effort discounting has not yet been explored. Temporal discounting research has shown social distance is an important moderator of allocentric discounting rates (Strombach et al., 2015; Ziegler & Tunney, 2012). However, findings in this thesis have shown divergence from the temporal discounting literature with regards to the effect of allocentric decision making on egocentric discounting rates. Determining if and how social distance moderates allocentric effort discounting is an important gap in the literature, both for understanding allocentric decision making and its relationship with temporal discounting mechanisms.

Broadening the investigation of accountability is also an important future direction. While a third-party regulator did not influence choice behavior in these studies, accountability may be impactful when operationalized in other ways. Accountability directly to the decision recipient or third-parties in the decision maker's social network may exhibit significant impact on allocentric decision makers. Decision makers may wish to maintain a certain social standing with these agents and alter choices to pander to the preferences of the agent holding the decision maker accountable. Emphasizing reputation building may be a stronger mechanism of accountability than the authority of the head experimenter used in these studies.

A necessary and intrinsic addendum to the roles that social distance, sources of accountability, and social relationships play in allocentric decision making can more generally be represented by the role culture plays in setting the social environment and the assumptions made about other agents. Individuals from different cultures ascribe to different social norms that may influence egocentric-allocentric differences or the potential for moderating effects of accountability. Cultures may impose effects on cognition via social norms that dictate the acceptability of certain decisions for others, such as choosing what is best for them compared to their preference. For example, cultures high in collectivism may exhibit reduced egocentric-allocentric differences in effort discounting if members are making decisions for a fellow in-group member but exacerbated differences when deciding for an out-group member compared to decision makers from an individualistic culture. Additionally, a decision maker's accountability may change with context and culture. Decision makers from cultures that place a greater value on conformity to social norms may be affected by accountability more when they are identifiable to known others and may be subjected to shame or guilt than cultures that are looser regarding norms of conformity (Gelfand et al., 2011). The behavioral studies in chapter 2 were conducted in Singapore while the fMRI study was conducted in the United States. Both samples exhibited effort discounting in the task, but the data themselves are not directly comparable due to the different designs and stimuli used. Delving into the myriad effects of culture on allocentric decisions likely holds vast reserves of untapped knowledge.

6.6 Conclusion

The neuroeconomic methods used here provide evidence that decision makers in a social context value effort differently than isolated, egocentric decision makers. This was shown using allocentric-egocentric contrasts in behavior and computational modeling and fMRI correlates of allocentric decision making processes. To stress, the research presented here are initial steps into the study of allocentric effort discounting and allocentric effort decisions more generally. The research provides an exploratory basis for generating more specific hypotheses testing more concrete mechanisms and moderators responsible for this decision phenomenon.

The research presented here contributes to the understanding of effort discounting by identifying useful computational models for future study of the phenomenon. Additionally, it provides evidence that egocentric and allocentric effort are valued differently, with allocentric decisions requiring more compensation for effort. Individual differences in effort discounting correlate with the endorsement of “should” type decision strategies, feelings of responsibility for the decision recipient, and social values orientation. Finally, the fMRI findings point to a need for further study of regions in the parietal cortex and *posterior cingulate cortex* which are not commonly associated with the valuation mechanisms of the *vStriatum* and *vmPFC*. Future investigation into the mechanism relating these regions could yield important results for understanding how humans evaluate outcomes for social agents. This thesis was performed in the anticipation of future study and to establish a foundation for future work in allocentric effort discounting.

Appendix A: fMRI Results Tables

Choice Outcomes Contrast - Option Presentation

Region	cluster p(FWE-corr)	cluster p(FDR-corr)	cluster equivk	cluster p(unc)	Coordinates x	y	z
right TPJ	0.038	0.03	36	0.002	60	-46	5
left Angular Gyrus	0.344	0.162	17	0.025	-48	-64	20
mid. Cingulate Gyrus	0.657	0.243	11	0.063	9	20	29
ACC	0.719	0.243	10	0.075	-9	47	20

Choice Outcomes Contrast - Arrow Presentation

Region	cluster p(FWE-corr)	cluster p(FDR-corr)	cluster equivk	cluster p(unc)	Coordinates x	y	z
Middle Frontal Gyrus (PFC)	0.016	0.032	41	0.001	48	29	32
					45	38	26
					48	20	38
r Angular Gyrus	0.01	0.032	45	0.001	48	-49	44
					42	-46	50
					45	-46	35
	0.068	0.054	29	0.004	18	23	56
					9	29	59
					21	17	62
Middle Frontal Gyrus	0.042	0.041	33	0.002	33	56	2
					45	50	8
	0.505	0.336	13	0.038	-39	-70	-31
	0.628	0.345	11	0.054	39	26	29
Superior Frontal Gyrus	0.037	0.041	34	0.002	0	29	44
					-3	29	35
	0.628	0.345	11	0.054	-39	23	29

Effort Magnitude Contrast - Option Presentation

Region	cluster p(FWE-corr)	cluster p(FDR-corr)	cluster equivk	cluster p(unc)	Coordinates x	y	z
Precuneus	0.002	0.004	60	0	0	-64	35
					3	-73	38
					-6	-82	38
rTPJ	0.16	0.116	22	0.009	54	-28	8
					42	-28	11
Cerebellum	0.69	0.469	10	0.063	15	-58	-13
PCC	0.074	0.077	28	0.004	12	-55	2
					6	-49	8
r Postcentral Gyrus	0.69	0.469	10	0.063	33	-31	56

Region	cluster p(FWE-corr)	cluster p(FDR-corr)	cluster equivk	cluster p(unc)	Coordinates x	y	z
Precuneus	0.002	0.004	60	0	0	-64	35
					3	-73	38
					-6	-82	38
rTPJ	0.16	0.116	22	0.009	54	-28	8
					42	-28	11
Cerebellum	0.69	0.469	10	0.063	15	-58	-13
PCC	0.074	0.077	28	0.004	12	-55	2
					6	-49	8
r Postcentral Gyrus	0.69	0.469	10	0.063	33	-31	56

Effort Magnitude Contrast - Arrow Presentation

Region	cluster p(FWE-corr)	cluster p(FDR-corr)	cluster equivk	cluster p(unc)	Coordinates x	y	z
Precuneus and PCC	0	0	250	0	6	-52	8
					-3	-58	14
					0	-49	26
vACC	0	0	134	0	-9	35	-7
					-9	44	-4
					3	47	5
left Angular Gyrus	0.007	0.009	51	0	-42	-70	32
					-51	-67	29
	0.468	0.296	14	0.036	0	-19	41
	0.097	0.086	27	0.006	-15	26	44
	0.258	0.18	19	0.017	48	-70	35
					45	-64	26
	0.291	0.182	18	0.02	-51	-28	26
					-45	-22	23
	0.582	0.307	12	0.05	42	-25	14
	0.086	0.086	28	0.005	21	-73	-7
					15	-58	-16
					21	-64	-7
	0.157	0.121	23	0.01	-12	59	26
	0.582	0.307	12	0.05	-9	-61	-16
	0.582	0.307	12	0.05	24	38	44
	0.708	0.371	10	0.07	36	-7	59
	0.644	0.336	11	0.059	-30	-73	-16
					-24	-67	-10

Compensation - Option Presentation

Region	cluster	cluster	cluster	peak	Coordinates		
	p(FWE-corr)	p(FDR-corr)	equivk	T	x	y	z
r Putamen	0.047	0.119	9	4.25	24	8	-4
l Putamen	0.209	1	2	3.72	-24	11	2
r Caudate	0.162	1	3	3.53	18	14	8
l Putamen	0.281	1	1	3.46	-21	5	-10

Effort - Option Presentation

Region	cluster	cluster	cluster	peak	Coordinates		
	p(FWE-corr)	p(FDR-corr)	equivk	T	x	y	z
Precuneus	0.001	0.203	928	4.37	12	-37	53
				3.9	3	-52	32
				3.87	0	-46	38

Effort - Arrow Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
ACC	261	0.002	0.009	5.68	-6	50	-1
		0.048	0.019	4.47	9	32	17
		0.758	0.331	2.78	9	35	2
PCC	227	0.005	0.021	4.99	-3	-52	26
		0.045	0.042	4.02	-6	-43	14
		0.115	0.089	3.56	-9	-37	32
Precuneus	1539	0.021	0.054	5.24	6	-52	8
		0.041	0.054	4.99	-3	-52	26
		0.043	0.054	4.97	-3	-55	17

DpW - Option Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
Cuneus	688	0.001	0.008	5.99	6	-85	23
		0.004	0.009	5.45	15	-85	32
		0.063	0.028	4.42	-6	-82	38

DpW - Option Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
Cuneus	2254	0	0.008	6.71	9	-82	26
PCC		0.001	0.008	6.31	12	-46	26
d Precuneus		0.003	0.008	5.95	0	-49	65

Hyperbolic SV - Arrow Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
l Angular Gyrus	290	0.036	0.049	4.74	-45	-58	38
		0.375	0.089	3.68	-42	-67	44
		0.417	0.092	3.61	-51	-70	26
r Angular Gyrus	234	0.342	0.089	3.74	48	-73	29
		0.812	0.26	3	51	-64	29
		0.816	0.26	2.99	45	-52	41
Precuneus	1310	0.077	0.156	4.77	12	-37	53
		0.211	0.156	4.32	-3	-79	38
		0.224	0.156	4.29	3	-64	17

Hyperbolic SV - Arrow Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
PCC	181	0.001	0.007	5.48	12	-46	26
		0.006	0.01	4.91	-9	-46	29
		0.039	0.032	4.08	0	-52	26
Cuneus	623	0	0.003	6.37	9	-82	26
		0.001	0.003	6.05	-6	-82	38
		0.186	0.067	3.87	-12	-85	26
dorsal Precuneus	1719	0.004	0.025	5.87	0	-49	65
		0.011	0.025	5.48	12	-46	26
		0.021	0.035	5.24	-6	-82	41
l Angular Gyrus	293	0.059	0.115	4.56	-42	-76	29
		0.288	0.176	3.83	-42	-64	35
		0.489	0.177	3.48	-42	-55	35

Sigmoidal SV - Option Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
ACC	240	0.019	0.05	4.89	6	44	5
		0.042	0.05	4.56	3	53	11
		0.292	0.098	3.57	12	38	11
	16	0.756	0.356	2.81	-9	26	29
		0.985	1	2.05	-3	17	29
	1	0.97	0.578	2.2	-9	35	-10
PCC	91	0.016	0.047	4.51	6	-49	29
		0.044	0.06	4.05	-6	-49	29
		0.346	0.308	2.95	-3	-43	14
	1	0.878	1	1.93	-9	-37	32
	2	0.915	1	1.8	-3	-31	29
	1	0.928	1	1.74	-6	-37	5

Sigmoidal SV - Arrow Presentation

Region	cluster equivk	peak p(FWE-corr)	peak p(FDR-corr)	peak T	Coordinates x	y	z
ACC	286	0.14	0.325	3.97	6	53	14
		0.368	0.325	3.42	9	32	17
		0.389	0.325	3.39	6	47	8
Precuneus	1315	0.017	0.111	5.33	3	-49	29
		0.028	0.111	5.13	-6	-49	32
		0.276	0.145	4.19	-12	-55	17
Cuneus	366	0.038	0.07	4.61	6	-82	23
		0.051	0.07	4.51	15	-85	32
		0.111	0.07	4.16	21	-79	41

Hyperbolic K Individual differences - Option Presentation

Region	cluster equivk	peak p(FWE-corr)	peak p(FDR-corr)	peak T	Coordinates x	y	z
rCaudate (Basal Ganglia)	481	0.102	0.155	4.26	12	-1	20
		0.165	0.155	4.01	15	-19	20
		0.19	0.155	3.93	-6	5	-1
	21	0.614	0.162	3.16	-15	-19	23
	2	0.682	0.196	3.05	-21	11	26
	2	0.996	1	1.96	15	14	-13
	1	0.997	1	1.92	-6	23	5
	4	0.998	1	1.88	24	23	11
	4	0.998	1	1.84	-12	20	-7
SMA	1325	0.573	0.399	4.25	-9	29	44
mSFG		0.721	0.399	4.05	15	44	29
vmPFC		0.728	0.399	4.04	30	44	-10
	187	0.999	0.399	3.15	51	23	8
		1	0.4	2.94	48	17	17
		1	0.455	2.65	45	26	29

Hyperbolic K Individual differences - Arrow Presentation

Region	cluster equivk	peak p(FWE-corr)	peak p(FDR-corr)	peak T	Coordinates x	y	z
ACC	367	0.003	0.021	5.59	15	44	5
		0.066	0.104	4.36	-9	38	23
		0.092	0.104	4.2	-9	47	17
	8	0.935	0.674	2.37	6	50	23
	2	0.995	1	1.84	-3	32	-1
left Insula	104	0.007	0.011	5.04	-36	17	-10
		0.288	0.216	3.31	-39	5	-4
		0.818	1	2.4	-42	14	5
	2	0.976	1	1.82	-36	-10	8

Sigmoidal P Individual differences - Option Presentation

Region	cluster equivk	peak p(FWE-corr)	peak p(FDR-corr)	peak T	Coordinates x	y	z
Precuneus	663	0.587	0.515	3.67	15	-40	44
		0.608	0.515	3.64	-12	-52	47
		0.814	0.515	3.33	12	-40	59
	25	0.949	0.515	3	6	-43	14
		1	0.773	2.2	-3	-49	11
	24	0.986	0.515	2.77	-18	-73	35
		0.996	0.515	2.61	-21	-64	32
dPFC	537	0.457	0.322	4.19	27	41	29
		0.924	0.322	3.46	33	23	35
		0.993	0.322	3.1	36	38	29
	145	0.902	0.322	3.51	27	-10	62
		1	0.395	2.67	21	5	62
		1	0.406	2.59	15	2	50
	260	0.915	0.322	3.48	-21	-4	53
		0.993	0.322	3.09	-27	-4	68
		0.994	0.322	3.08	-45	14	38
	86	0.959	0.322	3.34	-24	56	26

Sigmoidal P Individual differences - Arrow Presentation

Region	cluster	peak	peak	peak	Coordinates		
	equivk	p(FWE-corr)	p(FDR-corr)	T	x	y	z
PCC	1125	0.2	0.395	4.42	-6	-46	29
		0.537	0.395	3.81	6	-61	38
Cuneus		0.61	0.395	3.71	-6	-79	41
	8	0.963	0.395	3.03	3	-88	26
	13	1	0.542	2.37	18	-97	14
	5	1	0.604	2.27	-18	-67	62
	2	1	1	2.1	12	-52	8
	2	1	1	1.97	27	-67	26
	1	1	1	1.74	24	-85	14
mSFG (PFC)	791	0.692	0.441	4.12	0	35	35
		0.732	0.441	4.07	33	23	35
		0.96	0.441	3.62	-6	29	50
	145	0.916	0.441	3.75	-27	41	32
		1	0.441	2.83	-24	50	23
		1	0.611	2.31	-30	41	20
	43	0.991	0.441	3.41	-33	11	44
		1	0.441	3.11	-33	14	59
		1	0.441	2.84	-15	14	68
	239	0.991	0.441	3.41	-36	26	-13
		0.994	0.441	3.37	-51	23	14
		1	0.441	2.82	-48	14	5
	82	0.994	0.441	3.37	27	-4	71
		0.995	0.441	3.36	27	-7	62

7 References

Ainslie, G. (1975). Specious reward: A behavioral theory of impulsiveness and impulse control. *Psychological Bulletin*, *82*(4), 463–496. https://doi.org/10.1037/h0076860

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Albrecht, K., Volz, K. G., Sutter, M., Laibson, D. I., & von Cramon, D. Y. (2011). What is for me is not for you: brain correlates of intertemporal choice for self and other. *Social Cognitive and Affective Neuroscience*, *6*(2), 218–225. https://doi.org/10.1093/scan/nsq046

Amanatullah, E. T., & Morris, M. W. (2010). Negotiating gender roles: gender differences in assertive negotiating are mediated by women's fear of backlash and attenuated when negotiating on behalf of others. *Journal Of Personality And Social Psychology*, 98(2), 256–267. https://doi.org/10.1037/a0017094

Amodio, D. M., & Frith, C. D. (2006). Meeting of minds: the medial frontal cortex and social cognition. *Nature Reviews. Neuroscience*, *7*(4), 268–277. https://doi.org/10.1038/nrn1884

Andersson, O., Holm, H. J., Tyran, J.-R., & Wengström, E. (2014). Deciding for Others Reduces Loss Aversion. *Management Science*, 141223041315002. https://doi.org/10.1287/mnsc.2014.2085

Arkes, H. R., & Blumer, C. (1985). The psychology of sunk cost. *Organizational Behavior and Human Decision Processes*, *35*(1), 124–140.

Ashburner, J., & Friston, K. J. (2005). Unified segmentation. *NeuroImage*, *26*(3), 839–851. https://doi.org/10.1016/j.neuroimage.2005.02.018

Azevedo, F. A. C., Carvalho, L. R. B., Grinberg, L. T., Farfel, J. M., Ferretti, R. E. L., Leite, R. E. P., … Herculano-Houzel, S. (2009). Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain. *The Journal of Comparative Neurology*, *513*(5), 532–541. https://doi.org/10.1002/cne.21974

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language*, *59*(4), 390–412. https://doi.org/10.1016/j.jml.2007.12.005

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2014). Fitting Linear Mixed-Effects Models using lme4. *ArXiv:1406.5823 [Stat]*. Retrieved from http://arxiv.org/abs/1406.5823

Bechara, A., Tranel, D., & Damasio, H. (2000). Characterization of the decision-making deficit of patients with ventromedial prefrontal cortex lesions. *Brain*, *123*(11), 2189–2202.

Berg, J., Dickhaut, J., & McCabe, K. (1995). Trust, reciprocity, and social history. *Games and Economic Behavior*, *10*(1), 122–142.

Biele, G., Rieskamp, J., Krugel, L. K., & Heekeren, H. R. (2011). The Neural Basis of Following Advice. *PLoS Biology*, *9*(6). https://doi.org/10.1371/journal.pbio.1001089

Bonaccio, S., & Dalal, R. S. (2006). Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. *Organizational Behavior and Human Decision Processes*, *101*(2), 127–151. https://doi.org/10.1016/j.obhdp.2006.07.001

Bossaerts, P., & Murawski, C. (2015). From behavioural economics to neuroeconomics to decision neuroscience: the ascent of biology in research on human decision making. *Current Opinion in Behavioral Sciences*, *5*, 37–42. https://doi.org/10.1016/j.cobeha.2015.07.001

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*(3), 624.

Botvinick, M. M., Cohen, J. D., & Carter, C. S. (2004). Conflict monitoring and anterior cingulate cortex: an update. *Trends in Cognitive Sciences*, *8*(12), 539–546. https://doi.org/10.1016/j.tics.2004.10.003

Botvinick, M. M., Huffstetler, S., & McGuire, J. T. (2009). Effort discounting in human nucleus accumbens. *Cognitive, Affective & Behavioral Neuroscience*, *9*(1), 16–27. https://doi.org/10.3758/CABN.9.1.16

Boven, L. V., Loewenstein, G., Dunning, D., & Nordgren, L. F. (2013). Changing Places: A Dual Judgment Model of Empathy Gaps in Emotional Perpsective Taking. In

Advances in Experimental Social Psychology (Vol. 48, pp. 117–171). Elsevier. https://doi.org/10.1016/B978-0-12-407188-9.00003-X

Brandts, J., & Garofalo, O. (2012). Gender pairings and accountability effects. *Journal of Economic Behavior & Organization*, *83*(1), 31–41. https://doi.org/10.1016/j.jebo.2011.06.023

Brooks, A. W., Gino, F., & Schweitzer, M. E. (2015). Smart People Ask for (My) Advice: Seeking Advice Boosts Perceptions of Competence. *Management Science*, *61*(6), 1421–1435. https://doi.org/10.1287/mnsc.2014.2054

Camerer, C. (2003). *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton University Press.

Camerer, C. F. (2004). Prospect theory in the wild: Evidence from the field. *Advances in Behavioral Economics*, 148–161.

Camerer, C. F., Hogarth, R. M., Budescu, D. V., & Eckel, C. (1999). The effects of financial incentives in experiments: A review and capital-labor-production framework. In *Elicitation of Preferences* (pp. 7–48). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-94-017-1406-8_2

Carmon, Z., & Ariely, D. (2000). Focusing on the forgone: How value can appear so different to buyers and sellers. *Journal of Consumer Research*, *27*(3), 360–370.

Castells, M. (2011). *The Rise of the Network Society: The Information Age: Economy, Society, and Culture*. John Wiley & Sons.

Cavanna, A. E., & Trimble, M. R. (2006). The precuneus: a review of its functional anatomy and behavioural correlates. *Brain*, *129*(3), 564–583. https://doi.org/10.1093/brain/awl004

Chakravarty, S., Harrison, G. W., Haruvy, E. E., & Rutström, E. E. (2011). Are you risk averse over other people's money? *Southern Economic Journal*, *77*(4), 901–913.

Charness, G. B. (1999). RESPONSIBILITY AND EFFORT IN AN EXPERIMENTAL LABOR MARKET. Retrieved from http://www.escholarship.org/uc/item/7x98w91h

Charness, G., & Gneezy, U. (2000). What's in a Name? Anonymity and Social Distance in Dictator and Ultimatum Games. *Department of Economics, UCSB*. Retrieved from http://escholarship.org/uc/item/57q360q6

Choi, J., Kim, B. K., Choi, I., & Yi, Y. (2006). Variety-seeking tendency in choice for others: Interpersonal and intrapersonal causes. *Journal of Consumer Research*, *32*(4), 590–595.

Christopoulos, G. I., Tobler, P. N., Bossaerts, P., Dolan, R. J., & Schultz, W. (2009). Neural Correlates of Value, Risk, and Risk Aversion Contributing to Decision Making under Risk. *Journal of Neuroscience*, *29*(40), 12574–12583. https://doi.org/10.1523/JNEUROSCI.2614-09.2009

Chudek, M., & Henrich, J. (2011). Culture–gene coevolution, norm-psychology and the emergence of human prosociality. *Trends in Cognitive Sciences*, *15*(5), 218–226. https://doi.org/10.1016/j.tics.2011.03.003

Chung, D., Christopoulos, G. I., King-Casas, B., Ball, S. B., & Chiu, P. H. (2015). Social signals of safety and risk confer utility and have asymmetric effects on observers' choices. *Nature Neuroscience*, *18*(6), 912–916. https://doi.org/10.1038/nn.4022

Cohen, D., Nisbett, R. E., Bowdle, B. F., & Schwarz, N. (1996). Insult, aggression, and the southern culture of honor: An" experimental ethnography.". *Journal of Personality and Social Psychology*, *70*(5), 945.

Cohen, J. D., McClure, S. M., & Yu, A. J. (2007). Should I stay or should I go? How the human brain manages the trade-off between exploitation and exploration. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1481), 933–942. https://doi.org/10.1098/rstb.2007.2098

Collell, G., & Fauquet, J. (2015). Brain activity and cognition: a connection from thermodynamics and information theory. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00818

Cosgrove, K. P., Mazure, C. M., & Staley, J. K. (2007). Evolving Knowledge of Sex Differences in Brain Structure, Function and Chemistry. *Biological Psychiatry*, *62*(8), 847–855. https://doi.org/10.1016/j.biopsych.2007.03.001

Coull, J. T., & Nobre, A. C. (1998). Where and When to Pay Attention: The Neural Systems for Directing Attention to Spatial Locations and to Time Intervals as Revealed by Both PET and fMRI. *Journal of Neuroscience*, *18*(18), 7426–7435.

Crockett, M. J., Kurth-Nelson, Z., Siegel, J. Z., Dayan, P., & Dolan, R. J. (2014). Harm to others outweighs harm to self in moral decision making. *Proceedings of the National Academy of Sciences*, 201408988. https://doi.org/10.1073/pnas.1408988111

Croxson, P. L., Walton, M. E., O'Reilly, J. X., Behrens, T. E. J., & Rushworth, M. F. S. (2009). Effort-Based Cost–Benefit Valuation and the Human Brain. *The Journal of Neuroscience*, *29*(14), 4531–4541. https://doi.org/10.1523/JNEUROSCI.4515-08.2009

Curley, S. P., Yates, J. F., & Abrams, R. A. (1986). Psychological sources of ambiguity avoidance. *Organizational Behavior and Human Decision Processes*, *38*(2), 230–256.

Damasio, H., Grabowski, T., Frank, R., Galaburda, A. M., & Damasio, A. R. (1994). The return of Phineas Gage: clues about the brain from the skull of a famous patient. *Science*, *264*(5162), 1102–1105.

Daw, N. D., O'Doherty, J. P., Dayan, P., Seymour, B., & Dolan, R. J. (2006). Cortical substrates for exploratory decisions in humans. *Nature*, *441*(7095), 876–879. https://doi.org/10.1038/nature04766

Decety, J., & Lamm, C. (2007). The Role of the Right Temporoparietal Junction in Social Interaction: How Low-Level Computational Processes Contribute to Meta-Cognition. *The Neuroscientist*, *13*(6), 580–593. https://doi.org/10.1177/1073858407304654

Decety, J., & Sommerville, J. A. (2003). Shared representations between self and other: a social cognitive neuroscience view. *Trends in Cognitive Sciences*, *7*(12), 527–533. https://doi.org/10.1016/j.tics.2003.10.004

Dijk, J. van. (2012). *The Network Society*. SAGE Publications.

Dolan, R. J. (2002). Emotion, Cognition, and Behavior. *Science*, *298*(5596), 1191–1194. https://doi.org/10.1126/science.1076358

Dunbar, R. I. M. (2003). The Social Brain: Mind, Language, and Society in Evolutionary Perspective. *Annual Review of Anthropology*, *32*(1), 163–181. https://doi.org/10.1146/annurev.anthro.32.061002.093158

Dunbar, R. I. M. (2009). The social brain hypothesis and its implications for social evolution. *Annals of Human Biology*, *36*(5), 562–572. https://doi.org/10.1080/03014460902960289

Dunbar, R. I. M., & Shultz, S. (2007). Evolution in the Social Brain. *Science*, *317*(5843), 1344–1347. https://doi.org/10.1126/science.1145463

Dunne, S., & O'Doherty, J. P. (2012). Choosing for Me or Choosing for You: Value in Medial Prefrontal Cortex. *Neuron*, *75*(6), 942–944. https://doi.org/10.1016/j.neuron.2012.09.005

Eisenhardt, K. M. (1989). Agency Theory: An Assessment and Review. *The Academy of Management Review*, *14*(1), 57. https://doi.org/10.2307/258191

Ellingsen, T., & Johannesson, M. (2008). Anticipated verbal feedback induces altruistic behavior. *Evolution and Human Behavior*, *29*(2), 100–105.

Faro, D., & Rottenstreich, Y. (2006). Affect, Empathy, and Regressive Mispredictions of Others' Preferences Under Risk. *Management Science*, *52*(4), 529–541.

Farrer, C., & Frith, C. D. (2002). Experiencing Oneself vs Another Person as Being the Cause of an Action: The Neural Correlates of the Experience of Agency. *NeuroImage*, *15*(3), 596–603. https://doi.org/10.1006/nimg.2001.1009

Fehr, E., & Camerer, C. F. (2007). Social neuroeconomics: the neural circuitry of social preferences. *Trends in Cognitive Sciences*, *11*(10), 419–427.

Fehr, E., & Fischbacher, U. (2004). Third-party punishment and social norms. *Evolution and Human Behavior*, *25*(2), 63–87. https://doi.org/10.1016/S1090-5138(04)00005-4

Fernandez-Duque, D., & Wifall, T. (2007). Actor/observer asymmetry in risky decision making. *Judgment and Decision Making*, *2*(1), 1–8.

Festinger, L. (1950). Informal social communication. *Psychological Review*, *57*(5), 271.

Festinger, L. (1954). A Theory of Social Comparison Processes. *Human Relations*, *7*(2), 117–140. https://doi.org/10.1177/001872675400700202

Fliessbach, K., Weber, B., Trautner, P., Dohmen, T., Sunde, U., Elger, C. E., & Falk, A. (2007). Social Comparison Affects Reward-Related Brain Activity in the Human Ventral Striatum. Science, 318(5854), 1305–1308. https://doi.org/10.1126/science.1145876

Friston, K. J., Josephs, O., Rees, G., & Turner, R. (1998). Nonlinear event-related responses in fMRI. *Magnetic Resonance in Medicine*, *39*(1), 41–52. https://doi.org/10.1002/mrm.1910390109

Garcia-Retamero, R., & Galesic, M. (2012). Doc, what would you do if you were me? On self-other discrepancies in medical decision making. *Journal of Experimental Psychology. Applied*, *18*(1), 38–51. https://doi.org/10.1037/a0026018

Gelfand, M. J., Raver, J. L., Nishii, L., Leslie, L. M., Lun, J., Lim, B. C., … Arnadottir, J. (2011). Differences between tight and loose cultures: A 33-nation study. *Science*, *332*(6033), 1100–1104.

Gerstner, W., Kreiter, A. K., Markram, H., & Herz, A. V. M. (1997). Neural codes: Firing rates and beyond. *Proceedings of the National Academy of Sciences*, *94*(24), 12740–12741.

Glenn, A. L., Raine, A., & Schug, R. A. (2009). The neural correlates of moral decision-making in psychopathy. Retrieved from http://repository.upenn.edu/cgi/viewcontent.cgi?article=1058&context=neuroethics_pubs

Glimcher, P. W. (2004). *Decisions, uncertainty, and the brain: The science of neuroeconomics*. MIT press.

Glimcher, P. W. (2008). Choice: Towards a Standard Back-pocket Model. In *Neuroeconomics: Decision Making and the Brain* (1st ed., Vol. Ch. 32, pp. 501–519).

Glimcher, P. W., & Fehr, E. (2013). *Neuroeconomics: Decision making and the brain*. Academic Press.

Grafen, A. (1984). Natural selection, kin selection and group selection. *Behavioural Ecology: An Evolutionary Approach*, *2*, 62–84.

Green, J. D., Burnette, J. L., & Davis, J. L. (2008). Third-Party Forgiveness: (Not) Forgiving Your Close Other's Betrayer. *Personality and Social Psychology Bulletin*, *34*(3), 407–418. https://doi.org/10.1177/0146167207311534

Greene, J. D., Sommerville, R. B., Nystrom, L. E., Darley, J. M., & Cohen, J. D. (2001). An fMRI investigation of emotional engagement in moral judgment. *Science*, *293*(5537), 2105–2108.

Grinband, J., Wager, T. D., Lindquist, M., Ferrera, V. P., & Hirsch, J. (2008). Detection of time-varying signals in event-related fMRI designs. *NeuroImage*, *43*(3), 509–520. https://doi.org/10.1016/j.neuroimage.2008.07.065

Güth, W., Schmittberger, R., & Schwarze, B. (1982). An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization*, *3*(4), 367–388.

Hare, T. A., Camerer, C. F., Knoepfle, D. T., O'Doherty, J. P., & Rangel, A. (2010). Value Computations in Ventral Medial Prefrontal Cortex during Charitable Decision Making Incorporate Input from Regions Involved in Social Cognition. *Journal of Neuroscience*, *30*(2), 583–590. https://doi.org/10.1523/JNEUROSCI.4089-09.2010

Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. *Science*, *324*(5927), 646–648. https://doi.org/10.1126/science.1168450

Hare, T. A., O'Doherty, J., Camerer, C. F., Schultz, W., & Rangel, A. (2008). Dissociating the Role of the Orbitofrontal Cortex and the Striatum in the Computation of Goal Values and Prediction Errors. *Journal of Neuroscience*, *28*(22), 5623–5630. https://doi.org/10.1523/JNEUROSCI.1309-08.2008

Harries, C., & Harvey, N. (2000). Taking advice, using information and knowing what you are doing. *Acta Psychologica*, *104*(3), 399–416.

Hartmann, M. N., Hager, O. M., Tobler, P. N., & Kaiser, S. (2013). Parabolic discounting of monetary rewards by physical effort. *Behavioural Processes*, *100*, 192–196. https://doi.org/10.1016/j.beproc.2013.09.014

Harvey, N., Twyman, M., & Harries, C. (2006). Making decisions for other people: The problem of judging acceptable levels of risk. In *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research* (Vol. 7).

Hayden, B. Y., Nair, A. C., McCoy, A. N., & Platt, M. L. (2008). Posterior Cingulate Cortex Mediates Outcome-Contingent Allocation of Behavior. *Neuron*, *60*(1), 19–25. https://doi.org/10.1016/j.neuron.2008.09.012

Henson, R., Rugg, M. D., & Friston, K. J. (2001). The choice of basis functions in event-related fMRI. *NeuroImage*, *13*(6), 149. https://doi.org/10.1016/S1053-8119(01)91492-2

Herculano-Houzel, S. (2009). The Human Brain in Numbers: A Linearly Scaled-up Primate Brain. *Frontiers in Human Neuroscience*, *3*. https://doi.org/10.3389/neuro.09.031.2009

Herrmann, B., Thöni, C., & Gächter, S. (2008). Antisocial punishment across societies. *Science*, *319*(5868), 1362–1367.

Heyman, J., & Ariely, D. (2004). Effort for payment a tale of two markets. *Psychological Science*, *15*(11), 787–793.

Hoffman, E., McCabe, K., Shachat, K., & Smith, V. (1994). Preferences, property rights, and anonymity in bargaining games. *Games and Economic Behavior*, *7*(3), 346–380.

Hoffman, E., McCabe, K., & Smith, V. L. (1996). Social distance and other-regarding behavior in dictator games. *The American Economic Review*, *86*(3), 653–660.

Holmes, A. P., & Friston, K. J. (1998). Generalisability, random Effects & population inference. *Neuroimage*, *7*, S754.

Holt, C. A., & Laury, S. K. (2002). Risk Aversion and Incentive Effects. *The American Economic Review*, *92*(5), 1644–1655.

Hong, Y., & Chiu, C. (2001). Toward a paradigm shift: From cross-cultural differences in social cognition to social-cognitive mediation of cultural differences. *Social Cognition*, *19*(3: Special issue), 181–196.

Hong, Y.-Y., & Chiu, C.-Y. (1992). A study of the comparative structure of guilt and shame in a Chinese society. *Journal of Psychology*, *126*(2), 171.

Hoshino-Browne, E., Zanna, A. S., Spencer, S. J., Zanna, M. P., Kitayama, S., & Lackenbauer, S. (2005). On the cultural guises of cognitive dissonance: the case of easterners and westerners. *Journal of Personality and Social Psychology*, *89*(3), 294.

Hsee, C. K., & Weber, E. U. (1997). A fundamental prediction error: Self–others discrepancies in risk preference. *Journal of Experimental Psychology: General*, *126*(1), 45.

Hull, C. L. (1943). Principles of Behavior (Appleton-Century-Crofts, New York). *Google Scholar*.

Izuma, K., & Adolphs, R. (2013). Social Manipulation of Preference in the Human Brain. *Neuron*, *78*(3), 563–573. https://doi.org/10.1016/j.neuron.2013.03.023

Izuma, K., Saito, D. N., & Sadato, N. (2010). Processing of the incentive for social approval in the ventral striatum during charitable donation. *Journal of Cognitive Neuroscience*, *22*(4), 621–631.

Jacobs, R. A., Jordan, M. I., Nowlan, S. J., & Hinton, G. E. (1991). Adaptive Mixtures of Local Experts. *Neural Computation*, *3*(1), 79–87. https://doi.org/10.1162/neco.1991.3.1.79

Jahn, R. (2016, September 21). How neurons talk to each other. Retrieved June 30, 2017, from https://www.mpg.de/10743509/how-neurons-talk-to-each-other

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Jung, D., Sul, S., & Kim, H. (2013). Dissociable Neural Processes Underlying Risky Decisions for Self Versus Other. *Frontiers in Neuroscience*, *7*. https://doi.org/10.3389/fnins.2013.00015

Kable, J. W., & Glimcher, P. W. (2007). The neural correlates of subjective value during intertemporal choice. *Nature Neuroscience*, *10*(12), 1625–1633. https://doi.org/10.1038/nn2007

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). Fairness and the Assumptions of Economics. *The Journal of Business*, *59*(4), S285–S300. https://doi.org/10.2307/2352761

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias. *Journal of Economic Perspectives*, *5*(1), 193–206. https://doi.org/10.1257/jep.5.1.193

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263–291.

Kanwisher, N. (2010). Functional specificity in the human brain: A window into the functional architecture of the mind. *Proceedings of the National Academy of Sciences*, *107*(25), 11163–11170. https://doi.org/10.1073/pnas.1005062107

Kirby, K. N., & Herrnstein, R. j. (1995). Preference Reversals Due to Myopic Discounting of Delayed Reward. *Psychological Science (0956-7976)*, *6*(2), 83–89.

Klein-Flügge, M. C., Kennerley, S. W., Friston, K., & Bestmann, S. (2016). Neural Signatures of Value Comparison in Human Cingulate Cortex during Decisions Requiring an Effort-Reward Trade-off. *The Journal of Neuroscience*, *36*(39), 10002–10015. https://doi.org/10.1523/JNEUROSCI.0292-16.2016

Klein-Flügge, M. C., Kennerley, S. W., Saraiva, A. C., Penny, W. D., & Bestmann, S. (2015). Behavioral Modeling of Human Choices Reveals Dissociable Effects of Physical Effort and Temporal Delay on Reward Devaluation. *PLoS Comput Biol*, *11*(3), e1004116. https://doi.org/10.1371/journal.pcbi.1004116

Knutson, B., Rick, S., Wimmer, G. E., Prelec, D., & Loewenstein, G. (2007). Neural Predictors of Purchases. *Neuron*, *53*(1), 147–156. https://doi.org/10.1016/j.neuron.2006.11.010

Kolling, N., Wittmann, M., & Rushworth, M. F. S. (2014). Multiple Neural Mechanisms of Decision Making and Their Competition under Changing Risk Pressure. *Neuron*, *81*(5), 1190–1202. https://doi.org/10.1016/j.neuron.2014.01.033

Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision making and the avoidance of cognitive demand. *Journal of Experimental Psychology: General*, *139*(4), 665–682. https://doi.org/10.1037/a0020198

Krall, S. C., Rottschy, C., Oberwelland, E., Bzdok, D., Fox, P. T., Eickhoff, S. B., … Konrad, K. (2015). The role of the right temporoparietal junction in attention and social interaction as revealed by ALE meta-analysis. *Brain Structure & Function*, *220*(2), 587–604. https://doi.org/10.1007/s00429-014-0803-z

Kray, L., & Gonzalez, R. (1999). Differential weighting in choice versus advice: I’ll do this, you do that. *Journal of Behavioral Decision Making*, *12*(3), 207–218.

Kray, L. J. (2000). Contingent weighting in self-other decision making. *Organizational Behavior and Human Decision Processes*, *83*(1), 82–106.

Kurniawan, I. T., Guitart-Masip, M., Dayan, P., & Dolan, R. J. (2013). Effort and Valuation in the Brain: The Effects of Anticipation and Execution. *The Journal of Neuroscience*, *33*(14), 6160–6169. https://doi.org/10.1523/JNEUROSCI.4777-12.2013

Kuss, K., Falk, A., Trautner, P., Elger, C. E., Weber, B., & Fliessbach, K. (2013). A reward prediction error for charitable donations reveals outcome orientation of donators. *Social Cognitive and Affective Neuroscience*, *8*(2), 216–223. https://doi.org/10.1093/scan/nsr088

Kuss, K., Falk, A., Trautner, P., Montag, C., Weber, B., & Fliessbach, K. (2015). Neuronal correlates of social decision making are influenced by social value orientationâ€”an fMRI study. *Frontiers in Behavioral Neuroscience*, *9*. https://doi.org/10.3389/fnbeh.2015.00040

Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *The Quarterly Journal of Economics*, *112*(2), 443–478. https://doi.org/10.1162/003355397555253

Larraza-Kintana, M., Wiseman, R. M., Gomez-Mejia, L. R., & Welbourne, T. M. (2007). Disentangling compensation and employment risks using the behavioral agency model. *Strategic Management Journal*, *28*(10), 1001–1019. https://doi.org/10.1002/smj.624

Lave, L. B. (1960). An Empirical description of the Prisoner’s Dilemma game.

Lerner, J. S., & Tetlock, P. E. (1999). Accounting for the effects of accountability. *Psychological Bulletin*, *125*(2), 255–275. https://doi.org/10.1037/0033-2909.125.2.255

Levy, D. J., & Glimcher, P. W. (2012). The root of all value: a neural common currency for choice. *Current Opinion in Neurobiology*, *22*(6), 1027–1038. https://doi.org/10.1016/j.conb.2012.06.001

Libedinsky, C., Massar, S. A. A., Ling, A., Chee, W., Huettel, S. A., & Chee, M. W. L. (2013). Sleep Deprivation Alters Effort Discounting but not Delay Discounting of Monetary Rewards. *SLEEP*. https://doi.org/10.5665/sleep.2720

Lim, S.-J., Fiez, J. A., & Holt, L. L. (2014). How may the basal ganglia contribute to auditory categorization and speech perception? *Frontiers in Neuroscience*, *8*, 230. https://doi.org/10.3389/fnins.2014.00230

Lind, E. A. (2002). Fairness Heuristic Theory:Justice Judgments as Pivotal Cognitions in Organizational Relations. In J. Greenberg (Ed.), *Advances in Organizational Justice* (p. 61). Stanford University Press.

Loewenstein, G. (2005). Hot-cold empathy gaps and medical decision making. *Health Psychology*, *24*(4S), S49.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, *127*(2), 267.

Logothetis, N. K., Pauls, J., Augath, M., Trinath, T., & Oeltermann, A. (2001). Neurophysiological investigation of the basis of the fMRI signal. *Nature*, *412*(6843), 150–157. https://doi.org/10.1038/35084005

MacKay, D. J. (1992). The evidence framework applied to classification networks. *Neural Computation*, *4*(5), 720–736.

Maffesoli, M. (1995). *The Time of the Tribes: The Decline of Individualism in Mass Society*. SAGE.

Maldjian, J. A., Laurienti, P. J., Kraft, R. A., & Burdette, J. H. (2003). An automated method for neuroanatomic and cytoarchitectonic atlas-based interrogation of fMRI data sets. *NeuroImage*, *19*(3), 1233–1239. https://doi.org/10.1016/S1053-8119(03)00169-1

Marr, D., & Vision, A. (1982). A computational investigation into the human representation and processing of visual information. *WH San Francisco: Freeman and Company*, *1*(2).

Martin, G., Washburn, N., Makri, M., & Gomez-Mejia, L. R. (2015). Not all Risk Taking is Born Equal: The Behavioral Agency Model and CEO’s Perception of Firm Efficacy.

Human Resource Management, *54*(3), 483–498. https://doi.org/10.1002/hrm.21624

Massar, S. A. A., Libedinsky, C., Weiyan, C., Huettel, S. A., & Chee, M. W. L. (2015). Separate and overlapping brain areas encode subjective value during delay and effort discounting. *NeuroImage*, *120*, 104–113. https://doi.org/10.1016/j.neuroimage.2015.06.080

McGuire, J. T., & Botvinick, M. M. (2010). Prefrontal cortex, cognitive control, and the registration of decision costs. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(17), 7922–7926. https://doi.org/10.1073/pnas.0910662107

Mengarelli, F., Moretti, L., Faralla, V., Vindras, P., & Sirigu, A. (2014). Economic Decisions for Others: An Exception to Loss Aversion Law. *PLoS ONE*, *9*(1), e85042. https://doi.org/10.1371/journal.pone.0085042

Mitchell, S. H. (2004). Effects of short-term nicotine deprivation on decision-making: Delay, uncertainty and effort discounting. *Nicotine & Tobacco Research*, *6*(5), 819–828. https://doi.org/10.1080/14622200412331296002

Moscatelli, A., Mezzetti, M., & Lacquaniti, F. (2012). Modeling psychophysical data at the population-level: The generalized linear mixed model. *Journal of Vision*, *12*(11), 26.

Mullette-Gillman, O. A., Leong, R. L. F., & Kurnianingsih, Y. A. (2015). Cognitive Fatigue Destabilizes Economic Decision Making Preferences and Strategies. *PLOS ONE*, *10*(7), e0132022. https://doi.org/10.1371/journal.pone.0132022

Mumford, J. A., Poline, J.-B., & Poldrack, R. A. (2015). Orthogonalization of Regressors in fMRI Models. *PLOS ONE*, *10*(4), e0126255. https://doi.org/10.1371/journal.pone.0126255

Muraven, M., Baumeister, R. F., & Tice, D. M. (1999). Longitudinal improvement of self-regulation through practice: Building self-control strength through repeated exercise. *The Journal of Social Psychology*, *139*(4), 446–457.

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the Experimental Analysis of Behavior*, *76*(2), 235–243. https://doi.org/10.1901/jeab.2001.76-235

Nicolle, A., Klein-Flügge, M. C., Hunt, L. T., Vlaev, I., Dolan, R. J., & Behrens, T. E. J. (2012). An Agent Independent Axis for Executed and Modeled Choice in Medial Prefrontal Cortex. *Neuron*, *75*(6), 1114–1121. https://doi.org/10.1016/j.neuron.2012.07.023

Ochsner, K. N., Bunge, S. A., Gross, J. J., & Gabrieli, J. D. E. (2013). *Rethinking feelings: An FMRI study of the cognitive regulation of emotion*. https://doi.org/10.4324/9780203496190

O'Doherty, J. P., Dayan, P., Friston, K., Critchley, H., & Dolan, R. J. (2003). Temporal Difference Models and Reward-Related Learning in the Human Brain. *Neuron*, *38*(2), 329–337. https://doi.org/10.1016/S0896-6273(03)00169-7

O'Doherty, J. P., Hampton, A., & Kim, H. (2007). Model-Based fMRI and Its Application to Reward Learning and Decision Making. *Annals of the New York Academy of Sciences*, *1104*(1), 35–53. https://doi.org/10.1196/annals.1390.022

Ogawa, S., Lee, T.-M., Kay, A. R., & Tank, D. W. (1990). Brain magnetic resonance imaging with contrast dependent on blood oxygenation. *Proceedings of the National Academy of Sciences*, *87*(24), 9868–9872.

Pearson, J. M., Hayden, B. Y., Raghavachari, S., & Platt, M. L. (2009). Neurons in Posterior Cingulate Cortex Signal Exploratory Decisions in a Dynamic Multioption Choice Task. *Current Biology*, *19*(18), 1532–1537. https://doi.org/10.1016/j.cub.2009.07.048

Pearson, J. M., Heilbronner, S. R., Barack, D. L., Hayden, B. Y., & Platt, M. L. (2011). Posterior cingulate cortex: adapting behavior to a changing world. *Trends in Cognitive Sciences*, *15*(4), 143–151. https://doi.org/10.1016/j.tics.2011.02.002

Perrachione, T. K., & Ghosh, S. S. (2013). Optimized Design and Analysis of Sparse-Sampling fMRI Experiments. *Frontiers in Neuroscience*, *7*. https://doi.org/10.3389/fnins.2013.00055

Pessiglione, M., Seymour, B., Flandin, G., Dolan, R. J., & Frith, C. D. (2006). Dopamine-dependent prediction errors underpin reward-seeking behaviour in humans. *Nature*, *442*(7106), 1042–1045. https://doi.org/10.1038/nature05051

Phan, K. L., Wager, T., Taylor, S. F., & Liberzon, I. (2002). Functional Neuroanatomy of Emotion: A Meta-Analysis of Emotion Activation Studies in PET and fMRI. *NeuroImage*, *16*(2), 331–348. https://doi.org/10.1006/nimg.2002.1087

Plaisted KC, & Sahakian BJ. (1997). Dementia of frontal lobe type--living in the here and now. *Aging & Mental Health*, *1*(4), 293–293.

Pollmann, M. M. H., Potters, J., & Trautmann, S. T. (2014). Risk taking by agents: The role of ex-ante and ex-post accountability. *Economics Letters*, *123*(3), 387–390. https://doi.org/10.1016/j.econlet.2014.04.004

Polman, E. (2010). Information distortion in self-other decision making. *Journal of Experimental Social Psychology*, *46*(2), 432–435. https://doi.org/10.1016/j.jesp.2009.11.003

Polman, E. (2012). Self–other decision making and loss aversion. *Organizational Behavior and Human Decision Processes*, *119*(2), 141–150.

Prévost, C., Pessiglione, M., Météreau, E., Cléry-Melin, M.-L., & Dreher, J.-C. (2010). Separate Valuation Subsystems for Delay and Effort Decision Costs. *The Journal of Neuroscience*, *30*(42), 14080–14090. https://doi.org/10.1523/JNEUROSCI.2752-10.2010

Rangel, A., Camerer, C., & Montague, P. R. (2008). A framework for studying the neurobiology of value-based decision making. *Nature Reviews Neuroscience*, *9*(7), 545–556. https://doi.org/10.1038/nrn2357

Raymark, P. H. (2000). Accepting or Rejecting Medical Treatment: A Comparison of Decisions Made for Self Versus Those Made for a Significant Other1. *Journal of Applied Social Psychology*, *30*(11), 2409–2436. https://doi.org/10.1111/j.1559-1816.2000.tb02443.x

Rogers, R. D., Ramnani, N., Mackay, C., Wilson, J. L., Jezzard, P., Carter, C. S., & Smith, S. M. (2004). Distinct portions of anterior cingulate cortex and medial prefrontal cortex are activated by reward processing in separable phases of decision-making cognition. *Biological Psychiatry*, *55*(6), 594–602. https://doi.org/10.1016/j.biopsych.2003.11.012

Ruff, C. C., & Fehr, E. (2014). The neurobiology of rewards and values in social decision making. *Nature Reviews Neuroscience*, *15*(8), 549–562. https://doi.org/10.1038/nrn3776

Saez, I., Set, E., & Hsu, M. (2014). From genes to behavior: placing cognitive models in the context of biological pathways. *Decision Neuroscience*, *8*, 336. https://doi.org/10.3389/fnins.2014.00336

Samuelson, P. A. (1938). The empirical implications of utility analysis. *Econometrica, Journal of the Econometric Society*, 344–356.

Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., & Cohen, J. D. (2003). The Neural Basis of Economic Decision-Making in the Ultimatum Game. *Science*, *300*(5626), 1755–1758. https://doi.org/10.1126/science.1082976

Saxe, R. (2006). Uniquely human social cognition. *Current Opinion in Neurobiology*, *16*(2), 235–239. https://doi.org/10.1016/j.conb.2006.03.001

Schultz, W., Dayan, P., & Montague, P. R. (1997). A neural substrate of prediction and reward. *Science*, *275*(5306), 1593–1599.

Set, E., Saez, I., Zhu, L., Houser, D. E., Myung, N., Zhong, S., … Hsu, M. (2014). Dissociable contribution of prefrontal and striatal dopaminergic genes to learning in economic games. *Proceedings of the National Academy of Sciences*, *111*(26), 9615–9620. https://doi.org/10.1073/pnas.1316259111

Shalowitz, D. I., Garrett-Mayer, E., & Wendler, D. (2006). The Accuracy of Surrogate Decision Makers: A Systematic Review. *Archives of Internal Medicine*, *166*(5), 493–497. https://doi.org/10.1001/archinte.166.5.493

Shampanier, K., Mazar, N., & Ariely, D. (2007). Zero as a Special Price: The True Value of Free Products. *Marketing Science*, *26*(6), 742–757. https://doi.org/10.1287/mksc.1060.0254

Shenhav, A., Musslick, S., Lieder, F., Kool, W., Griffiths, T. L., Cohen, J. D., & Botvinick, M. M. (2017). Toward a Rational and Mechanistic Account of Mental Effort. *Annual Review of Neuroscience*, *40*(1). https://doi.org/10.1146/annurev-neuro-072116-031526

Siegel, S., & Fouraker, L. E. (1960). *Bargaining and group decision making: Experiments in bilateral monopoly*. New York, NY, US: McGraw-Hill.

Simonson, I., & Nye, P. (1992). The effect of accountability on susceptibility to decision errors. *Organizational Behavior and Human Decision Processes*, *51*(3), 416–446. https://doi.org/10.1016/0749-5978(92)90020-8

Skvortsova, V., Palminteri, S., & Pessiglione, M. (2014). Learning To Minimize Efforts versus Maximizing Rewards: Computational Principles and Neural Correlates. *Journal of Neuroscience*, *34*(47), 15621–15630. https://doi.org/10.1523/JNEUROSCI.1350-14.2014

Smeets, P., Bauer, R., & Gneezy, U. (2015). Giving behavior of millionaires. *Proceedings of the National Academy of Sciences*, *112*(34), 10641–10644. https://doi.org/10.1073/pnas.1507949112

Smith, J. M. (1964). Group selection and kin selection. *Nature*, *201*, 1145–1147.

Smith, V. L., & Walker, J. M. (1993). Monetary Rewards and Decision Cost in Experimental Economics. *Economic Inquiry*, *31*(2), 245–261. https://doi.org/10.1111/j.1465-7295.1993.tb00881.x

Solomon, R. L. (1948). The influence of work on behavior. *Psychological Bulletin*, *45*(1), 1–40. https://doi.org/10.1037/h0055527

Soman, D. (2004). The effect of time delay on multi-attribute choice. *Journal of Economic Psychology*, *25*(2), 153–175. https://doi.org/10.1016/j.joep.2003.09.002

Staw, B. M. (1976). Knee-deep in the big muddy: A study of escalating commitment to a chosen course of action. *Organizational Behavior and Human Performance*, *16*(1), 27–44.

Stone, E. R., Choi, Y., de Bruin, W. B., & Mandel, D. R. (2013). I can take the risk, but you should be safe: Self-other differences in situations involving physical safety. *Judgment & Decision Making*, *8*(3).

Stone, E. R., Yates, A. J., & Caruthers, A. S. (2002). Risk Taking in Decision Making for Others Versus the Self1. *Journal of Applied Social Psychology*, *32*(9), 1797–1824. https://doi.org/10.1111/j.1559-1816.2002.tb00260.x

Strombach, T., Weber, B., Hangebrauk, Z., Kenning, P., Karipidis, I. I., Tobler, P. N., & Kalenscher, T. (2015). Social discounting involves modulation of neural value signals by temporoparietal junction. *Proceedings of the National Academy of Sciences*, 201414715. https://doi.org/10.1073/pnas.1414715112

Sugiwaka, H., & Okouchi, H. (2004). Reformative self-control and discounting of reward value by delay or effort1. *Japanese Psychological Research*, *46*(1), 1–9. https://doi.org/10.1111/j.1468-5884.2004.00231.x

Sun, R. (2008). *The Cambridge Handbook of Computational Psychology*. Cambridge University Press.

Tetlock, P. E. (1983). Accountability and the Perseverance of First Impressions. *Social Psychology Quarterly*, *46*(4), 285–292. https://doi.org/10.2307/3033716

Tetlock, P. E., & Boettger, R. (1989). Accountability: a social magnifier of the dilution effect. *Journal of Personality and Social Psychology*, *57*(3), 388.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, *1*(1), 39–60.

Tobler, P. N., Christopoulos, G. I., O'Doherty, J. P., Dolan, R. J., & Schultz, W. (2009). Risk-dependent reward value signal in human prefrontal cortex. *Proceedings of the National Academy of Sciences*, *106*(17), 7185–7190. https://doi.org/10.1073/pnas.0809599106

Tunney, R. J., & Ziegler, F. V. (2015). Surrogate utility estimation by long-term partners and unfamiliar dyads. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00315

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, *106*(4), 1039–1061.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297–323. https://doi.org/10.1007/BF00122574

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., … Joliot, M. (2002). Automated Anatomical Labeling of Activations in SPM Using a Macroscopic Anatomical Parcellation of the MNI MRI Single-Subject Brain. *NeuroImage*, *15*(1), 273–289. https://doi.org/10.1006/nimg.2001.0978

Utevsky, A. V., & Huettel, S. A. (2015). Social Decision Making. In A.W. Tonga (Ed.), *Brain Mapping: an Encyclopedic Reference* (Vol. 3, pp. 231–234). Academic Press.

Van Lange, P. A., De Bruin, E., Otten, W., & Joireman, J. A. (1997). Development of prosocial, individualistic, and competitive orientations: theory and preliminary evidence. *Journal of Personality and Social Psychology*, *73*(4), 733.

Van Overwalle, F., & Baetens, K. (2009). Understanding others' actions and goals by mirror and mentalizing systems: A meta-analysis. *NeuroImage*, *48*(3), 564–584. https://doi.org/10.1016/j.neuroimage.2009.06.009

Vieider, F. M. (2009). The effect of accountability on loss aversion. *Acta Psychologica*, *132*(1), 96–101. https://doi.org/10.1016/j.actpsy.2009.05.006

Von Neumann, J., & Morgenstern, O. (2007). *Theory of games and economic behavior (commemorative edition)*. Princeton university press.

Wagar, B. M., & Thagard, P. (2004). Spiking Phineas Gage: A Neurocomputational Theory of Cognitive-Affective Integration in Decision Making. *Psychological Review*, *111*(1), 67–79. https://doi.org/10.1037/0033-295X.111.1.67

Waytz, A., Zaki, J., & Mitchell, J. P. (2012). Response of Dorsomedial Prefrontal Cortex Predicts Altruistic Behavior. *Journal of Neuroscience*, *32*(22), 7646–7650. https://doi.org/10.1523/JNEUROSCI.6193-11.2012

Westbrook, A., & Braver, T. S. (2015). Cognitive effort: A neuroeconomic approach. *Cognitive, Affective, & Behavioral Neuroscience*, 1–21. https://doi.org/10.3758/s13415-015-0334-y

Westbrook, A., Kester, D., & Braver, T. S. (2013). What Is the Subjective Cost of Cognitive Effort? Load, Trait, and Aging Effects Revealed by Economic Preference. *PLoS ONE*, *8*(7), e68210. https://doi.org/10.1371/journal.pone.0068210

Wilson, D. S. (1975). A theory of group selection. *Proceedings of the National Academy of Sciences*, *72*(1), 143–146.

Wiseman, R. M., Cuevas-Rodríguez, G., & Gomez-Mejia, L. R. (2012). Towards a Social Theory of Agency. *Journal of Management Studies*, *49*(1), 202–222. https://doi.org/10.1111/j.1467-6486.2011.01016.x

Wiseman, R. M., & Gomez-Mejia, L. R. (1998). A Behavioral Agency Model of Managerial Risk Taking. *Academy of Management Review*, *23*(1), 133–153. https://doi.org/10.5465/AMR.1998.192967

Woo, C.-W., Krishnan, A., & Wager, T. D. (2014). Cluster-extent based thresholding in fMRI analyses: Pitfalls and recommendations. *NeuroImage*, *91*, 412–419. https://doi.org/10.1016/j.neuroimage.2013.12.058

Zajonc, R. B. (1965). *Social facilitation*. Research Center for Group Dynamics, Institute for Social Research, University of Michigan Ann Arbor.

Zaki, J., López, G., & Mitchell, J. P. (2013). Activity in ventromedial prefrontal cortex co-varies with revealed social preferences: evidence for person-invariant value. *Social Cognitive and Affective Neuroscience*, nst005. https://doi.org/10.1093/scan/nst005

Zaki, J., & Ochsner, K. (2011). You, me, and my brain: Self and other representations in social cognitive neuroscience. *Social Neuroscience: Toward Understanding the Underpinnings of the Social Mind.* Retrieved from http://dept.psych.columbia.edu/~kochsner/pdf/Zaki_Ochsner_Self-Other_Chapter_final.pdf

Ziegler, F. V., & Tunney, R. J. (2012). Decisions for Others Become Less Impulsive the Further Away They Are on the Family Tree. *PLoS ONE*, *7*(11), e49479. https://doi.org/10.1371/journal.pone.0049479

Zikmund-Fisher, B. J., Sarr, B., Fagerlin, A., & Ubel, P. A. (2006). A matter of perspective: Choosing for others differs from choosing for yourself in making treatment decisions. *Journal of General Internal Medicine*, *21*(6), 618–622. https://doi.org/10.1111/j.1525-1497.2006.00410.x