Cognitive and Neural Mechanisms of Contextual Influences on Consumer Choice

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
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ABSTRACT

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Abstract

Financial decision-making in a complex and dynamic world poses many challenges including which information to use, how to filter out distractions, and how to arrive at a decision strategy that balances effort and accuracy in the face of imperfect information and cognitive constraints. Traditional financial education methods that provide more information to consider and thus require expending additional time and energy have had limited efficacy in improving long-term decision-making capacity. The research presented here takes a different approach by exploring the influence of context on the construction of value to elucidate mechanisms in consumer choice that underlie individual differences in decision-making. This approach uses computational modeling to identify the component parts of decision-making, eye tracking to measure attentional processes and information gathering strategies during choice, and functional neuroimaging (fMRI) to characterize how social networks modulate value representations in the brain. Characterizing the underpinnings of decision-making can help pinpoint which individual differences in the decision process lead to different choices. The research presented reveals that patience in intertemporal choice results from rapid, attribute-wise comparison of amounts with minimal attention paid to time information, whereas impatience results from slower integration of time and amount within options. Furthermore, measuring attention in purchasing behavior shows that

budget size can influence the value of items through a comparison process with price. Finally, a public social context influences motivation for rewards for self but does not affect motivation to earn for charity. This mechanistic approach to understanding value construction and evidence accumulation in choice can help offer strategies grounded in human cognition for people to better adapt to their financial situation, hopefully increasing the likelihood of longer-term impact.

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1. Introduction

1.1 Challenges in consumer decision-making

Decision-making in the real world is complex, involving large amounts of information, external influences, and constraints. It is impossible to perfectly integrate all information and filter out all extraneous influences during decision-making, and human brains have evolved to navigate such environments by simplifying choice to make it tractable within the constraints of our biology. These heuristic strategies can be helpful in many situations but may also cause decision-making to go awry in other situations. Indeed, a survey by the Federal Reserve found that 44% of adults in the U.S. could not come up with $400 to cover an emergency expense (Board of Governors of the Federal Reserve System, 2017). Although some of this crisis in savings is due to low wages, gaps in the social safety net, and predatory business practices, some of it may also be due to decision-biases and a lack of financial literacy (Bertrand, Mullainathan, & Shafir, 2006; Madrian et al., 2017). Traditional financial literacy education approaches have shown limited impact on changing long-term financial behavior (Fernandes, Lynch, & Netemeyer, 2014). Therefore, understanding the mechanisms underlying financial and consumer choices is important for elucidating when decision-making goes awry and how different contexts or approaches can lead to different choices. Characterizing the mechanisms of choice can help identify specific components within the choice process that can shift the resulting choice without necessarily increasing the time or effort involved. This makes it more likely that strategies developed will be adopted by individuals for longer-term behavioral change or implemented by policy-makers as low-cost, effective interventions.

In the research presented here, I focused on exploring the mechanisms of consumer choice through the lens of value construction—how context influences the representation and computation of value—within three facets of decision-making. First, I examine the underlying processes of intertemporal choice. Intertemporal choices involve tradeoffs between immediate and future gratification. In financial decision-making these involve decisions between spending smaller amounts of money available sooner and saving in order to have larger amounts of money available later. Many people prioritize immediate spending over future savings or make different spending decisions right after compared to right before a pay period, whereas others may save too much and not spread their consumption effectively over their lifespan (Lempert & Phelps, 2015; Mani, Mullainathan, Shafir, & Zhao, 2013).

Second, I examine purchasing decisions that can undermine savings goals. Many factors influence impulse purchasing, but here I focus on the processes involved in mental accounting through budgets. People construct cognitive divisions in how they consider their money and make decisions relative to these categories for spending and savings (Thaler, 1985; Thaler, Kahneman, & Tversky, 2000). Examining how these cognitive mental accounts influence valuation of items and purchasing decisions can explain in which contexts mental accounting is adaptively employed as a self-control device, and when it may be used to justify impulse purchasing.

Finally, an important influence on decision making that interacts with all other types of choices is social context. We do not make choices as purely independent agents; rather, our communities and our social surroundings impact the types of choices we make (Akerlof & Kranton, 2010; Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010; Cascio, Scholz, & Falk, 2015; Lee & Harris, 2013). In particular, we may have different motivations when making choices in private compared to making the same choice in public with others watching (Izuma, 2012). In this final study, I explore how social context interacts with self-interested and prosocial motivations.

In studying the mechanisms of intertemporal choices, purchasing choices, and prosocial motivations, I have used a variety of methods to reveal the interplay between preferences, attention, and decision context in the construction of value. The goal of this work is to use neuroscience and cognitive process-measures to better characterize the choice process in complex decision-making paradigms with multiple attributes and social pressures.

1.1.2 Consumer decision-making as a tool to understand contextual modulation of value in neuroscience

Decision neuroscience has built on concepts from economics and psychology to try to understand how value is represented in the brain. Value-based decision making builds on experiences, preferences, and context, and more complex paradigms such as those developed from studies of consumer decision-making can help elucidate these influences in value construction (Javor, Koller, Lee, Chamberlain, & Ransmayr, 2013; Plassmann, Venkatraman, Huettel, & Yoon, 2015; Smidts et al., 2014). Furthermore, looking at individual differences in subjective valuation and decision processes can help develop a framework for understanding general mechanisms of choice as well as how different approaches can lead to different outcomes.

1.1.3 Neuroscience and process measures inform consumer decision-making

In addition to the benefits of studying more complex context in the brain, a mechanistic approach is valuable to better understanding behavior. Studying the processes of choice bypasses assumptions about decision approaches in idealized or simplified settings and reveals which information people actually use, what comparisons they make, and how value is represented within the biological constraints of our brains. This is important for developing better models of human behavior (Plassmann et al., 2015). For example, neural firing constraints are important for understanding decision biases such as reference dependence (Louie & De Martino, 2013; Louie, Glimcher, & Webb, 2015). Furthermore, process-tracing techniques that measure attention and information gathering can pinpoint where in the decision process interventions or different strategies would be most likely to shift behavior.

1.2 Construction of value in consumer choices

1.2.1 Value and choice in context

Early models of decision-making sought to understand how choices were made by creating models based on principles of how decisions should ideally be made. Decision problems were abstracted to assume full (simplified) information, and follow axioms including stable preferences, transitivity, and independence to maximize utility (Von Neumann & Morgenstern, 1944). This approach assumed that values for options were pre-determined and then could be accessed, with the highest option being chosen (Samuelson, 1937). This was an explicit simplification used to determine basic principles with the acknowledgement that research on human behavior might eventually be necessary to inform these theories. For example, as noted by Von Neumann and Morgenstern, "should the need for the application of different principles arise…This would itself constitute a major revolution" (p.4, Von Neumann & Morgenstern, 1944). Indeed, since that time, many of these axioms have been shown to be violated in real world decision-making behavior and leading to the emergence of behavioral decision science to address the gap between theory and human behavior. Research in decision science has found that value computations depend on the goals of the decision-maker, the method of eliciting preferences, the available choice set, and the framing of options (Slovic, 1995; Tversky & Simonson, 1993). Elucidating the circumstances under which these axioms are violated has led to new approaches to studying decision-making behavior that are predicated on the idea that preferences are not stable, but values for options are learned through experience, change with the information considered, and are susceptible to irrelevant alternatives and other contextual influences such as social pressures of conformity, reputation, and identity (Akerlof & Kranton, 2010; Engelmann & Hein, 2013).

Behavioral decision research has focused on understanding violations of traditionally-defined rationality in favor of understanding how people actually make choices when faced with complex environments and computational constraints (Payne, 1998; Simon, 1955). This approach has provided evidence that preferences and values are not simply revealed through choice, but are constructed during the process of choice through comparisons of the relative value of the options presented with influences of attention and context (Payne, 1998; Payne, Bettman, & Johnson, 1992; Simon, 1955; Vlaev, Chater, Stewart, & Brown, 2011). This is not to say that people do not have any internal preferences; people are able to learn reward associations through experience and rank options relative to one another. Rather the research indicates that irrelevant anchors, decisions frames, or different comparison processes can shift valuations (Ariely, Loewenstein, & Prelec, 2003; Kahneman & Tversky, 1984; Payne, 1998). For example, framing decisions as losses or gains can changes risk preferences, buying or selling an item changes its perceived value, irrelevant (never-chosen) options in a choice set can invert preferences, and social information such as popularity of an option shift choices

(Engelmann & Hein, 2013; Huber, Payne, & Puto, 1982; Kahneman et al., 1991; Kahneman & Tversky, 1979, 1984; Tversky & Simonson, 1993).

Simplified models do not capture all of behavior because people cannot know or incorporate all options, probabilities, and information available and simulate all possible outcomes while also functioning adaptively in rapidly changing contexts. Instead, we use more efficient heuristic strategies that limit the amount of information considered and work within our cognitive constraints to navigate our environment (Gigerenzer & Gaissmaier, 2011). Heuristics encompass a range of strategies other than simply evaluating the value of each option and choosing the one with the highest value; these include differentially weighting attributes, focusing on the best attribute, eliminating options that don't meet minimal criteria, and attribute-wise comparisons, among others (Gigerenzer & Gaissmaier, 2011; Payne, 1998). However, although in some cases heuristic approaches may trade off effort and accuracy, there are also situations in which selectively using information can actually improve decisions compared to more complex models (Gigerenzer & Gaissmaier, 2011; Wübben & Wangenheim, 2008). Moreover, our cognitive strategies enable us to adapt to various environments and make choices in the face of large quantities of incomplete information, so studying these mechanisms can lead to better predictions of choice.

1.2.2 Value in the brain

The cortico-basal ganglia dopaminergic system, including the ventral tegmental area (VTA), ventral striatum (VS), and ventromedial prefrontal cortex (vmPFC), is an important target for understanding motivation, including the production of value signals that feed into motivated action and decision-making (Haber & Knutson, 2010). A large body of work has centered on the role of VTA, VS, and prefrontal cortical interactions in computing value and decisions. The VTA is the source of the neurotransmitter dopamine to the circuit (Ballard et al., 2011; Schultz, Carelli, & Wightman, 2015; Schultz, Dayan, & Montague, 1997; Tobler, Fiorillo, & Schultz, 2005). Dopamine plays an important role in motivated behavior and detecting reward contingencies through prediction error learning (Aarts, van Holstein, & Cools, 2011; Knutson, Adams, Fong, & Hommer, 2001; Knutson, Fong, Bennett, Adams, & Hommer, 2003; Schultz et al., 1997). Research implicates the VTA and the VS in reward anticipation and prediction error-updating and the vmPFC in contextual integration and outcome evaluation of reward (Bartra, McGuire, & Kable, 2013; Carter, MacInnes, Huettel, & Adcock, 2009; Chib, Rangel, Shimojo, & O'Doherty, 2009; Fareri & Delgado, 2014; Frank & Claus, 2006; Haber & Knutson, 2010; Kable & Glimcher, 2007; Knutson et al., 2003; Knutson, Westdorp, Kaiser, & Hommer, 2000; Levy & Glimcher, 2012; Pignatelli & Bonci, 2018; Shohamy, 2011; Smith & Huettel, 2010). All regions are involved in representing value signals of many modalities, including food, money, and social reward (Bhanji & Delgado, 2014; Chib et al., 2009; D. S. Fareri & Delgado, 2014; Levy & Glimcher, 2012). In consumer choice, the orbitofrontal cortex and more generally the medial prefrontal cortex has been implicated in willingness to pay or desire to purchase (Hare, Doherty, Camerer, Schultz, & Rangel, 2008; Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Padoa-Schioppa & Assad, 2006; Plassmann, O'Doherty, & Rangel, 2007; Platt & Plassmann, 2013; Tusche, Bode, & Haynes, 2010). Moreover, while the ventral striatum has been generally implicated in saliency and value, the vmPFC has been shown to be modulated by other information, such as price, feedback, and threats of punishment or sanctions (Knutson, Rick, Wimmer, & Prelec, 2008; Makwana, Gron, Fehr, & Hare, 2015; Murayama et al., 2013). Nevertheless, all of these regions are highly sensitive to contextual manipulations including the relative value of the offered options and social information, suggesting that they incorporate information from many other networks in the brain to construct an abstracted value of an option or action. Further understanding how value is represented and modulated by context in the brain can help explain decision biases and strategies in behavior.

1.2.3 Context modulates value representation in the brain

1.2.3.1 Value normalization

Divisive normalization is an important principle of neuroscience that extends from sensory perception to valuation and can explain behavioral decision approaches such as reference dependence (Louie & Glimcher, 2012). Neural firing rates occur within a limited range due the physical constraints of action potentials. This means that all stimuli that can be perceived must be represented within a limited firing range. In order to most efficiently represent a large range of environmental stimuli, the brain to adapts firing rates according to the context, expanding or contracting representations depending on the distribution of stimuli in the environment in order to use the full range of firing rates for a given context. For example, in visual perception, gray squares of equal luminance may look either extremely bright against a dark background or very dark against a light background because neural firing will adjust to the range on screen and represent luminance relative to that baseline (Louie & Glimcher, 2012). This normalization of firing rate based on context is also observed in the representation of value in the brain. Dopamine neurons in the midbrain, striatal neurons, and orbitofrontal neurons have all been shown to respond differently to the same reward depending on the distribution of rewards. For example whether the alternative options are higher or lower-value affects neural firing (Burke, Baddeley, Tobler, & Schultz, 2016; Cromwell, Hassani, & Schultz, 2005; Engelmann & Hein, 2013; Kobayashi, Carvalho, & Schultz, 2010; Tobler et al., 2005; Tremblay & Schultz, 1999; Wimmer, Li, Gorgolewski, & Poldrack, 2018). More recently these findings of contextual adaptation have been formalized in a divisive normalization framework (Khaw, Glimcher, & Louie, 2017; Louie & Glimcher, 2012; Louie et al., 2015; Louie, Khaw, & Glimcher, 2013). This suggests that value is not represented as an absolute quantity, but rather is represented relative to the distribution of other options, or to a reference point or expectation.

1.2.3.2 Contextual effects in consumer choice

This understanding of neural coding of value can help explain many of the contextual effects on choice in the heuristic and behavioral decision-making literature. For example normalization explains why irrelevant alternatives matter; this is because they shift the distribution of options and thus influence the value representation of the considered options (Louie et al., 2013). Moreover, expectations and framing can create reference points in valuation. For example, telling participants how much a bottle of wine cost influenced their stated enjoyment and their value representation in the OFC (Plassmann, O'Doherty, Shiv, & Rangel, 2008). Value normalization can also explain gain-loss asymmetry in prospect theory in which people are risk averse in the gain domain, but risk seeking in the loss domain, even with the same objective outcomes (Kahneman & Tversky, 1979; Tymula & Plassmann, 2016; Woodford, 2012). People code gains and loss relative to the reference point given by the decision frame. Normalization also explains more general reference dependence in decision-making in other framing effects such as in the endowment effect, in which buying versus selling an item lead to very different valuations (De Martino, Kumaran, Holt, & Dolan, 2009; Knutson, Wimmer, et al., 2008; Louie & De Martino, 2013). Value normalization may also account for anchoring effects. For example, irrelevant values have been shown to anchor willingness to pay, but only when they are within a reasonable range (Ariely et al., 2003; Tymula, Woelbert, & Glimcher, 2016). This may be because in comparing potential bids to anchors, those anchors constrain or influence the distribution of values considered. However, anchors that depart drastically from experienced value can have the opposite effect on valuation, so prior experiences and preferences can impose limits on the contextual effects on valuation (Gneezy, Gneezy, & Lauga, 2014). Neural findings support the existence of context dependency in the representation of value, but the influence of context may occur through multiple channels based on other networks in the brain that interact with valuation systems.

1.2.4 Social context in valuation and choice

Many decisions are made in social contexts, from strategically making decisions based on our expectations of others' reactions to learning from social information about an option. Humans are social creatures and we value social rewards such as friendly, smiling faces and social acceptance and cooperation, and these rewards are processed in overlapping regions with monetary and food rewards, including the striatum and vmPFC (Bhanji & Delgado, 2014; Bonini et al., 2011; Davey, Allen, Harrison, Dwyer, & Yu, 2010; Fareri & Delgado, 2014; Izuma, Saito, & Sadato, 2008; Korn, Prehn, Park, Walter, & Heekeren, 2012; Lin, Adolphs, & Rangel, 2012; Smith, Clithero, Boltuck, & Huettel, 2013). People also care about what happens to others. These other-regarding preferences for benefits to friends and charity also activate overlapping regions with rewards for self, although this can vary with the identity of the reward recipient (Braams et al., 2014; Engelmann & Hein, 2013; Fareri, Niznikiewicz, Lee, & Delgado, 2012; Harbaugh, Mayr, & Burghart, 2007; Mobbs et al., 2009; San Martín, Kwak, Pearson, Woldorff, & Huettel, 2016).

In addition to social rewards for self and others, social contexts can influence decision-making. Many social interactions require decision-making about how to engage, in which strategic thinking about the responses of others impacts the value of choice or actions (Camerer & Hare, 2014; Chang, Smith, Dufwenberg, & Sanfey, 2011; Fareri, Chang, & Delgado, 2012; Li, Xiao, Houser, & Montague, 2009; Rilling & Sanfey, 2011; Sanfey, 2007; Sanfey, Rilling, Aronson, Nystrom, & Cohen, 2003). Finally, social context can also exert a large impact on valuation even when making decisions for oneself. Social information can influence our own valuation of items through conformity or in advice-taking, and choices may change when being observed because of motivations to impress others or to build a positive reputation, and internalized social norms such as fairness may shape valuation of options (Berns, Capra, Moore, & Noussair, 2010; Campbell-Meiklejohn et al., 2010; Izuma, 2012; Izuma & Adolphs, 2013; Izuma, Saito, & Sadato, 2010; Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009; Knoch, Schneider, Schunk, Hohmann, & Fehr, 2009; McDonald & Crandall, 2015; Mobbs et al., 2015; Ruff, Ugazio, & Fehr, 2013; Spitzer, Fischbacher, Herrnberger, Grön, & Fehr, 2007; Stallen, Smidts, & Sanfey, 2013; Zaki, Schirmer, & Mitchell, 2011). Social information modulates valuation in the striatum and vmPFC. However, other regions in the brain that respond to social context and pressures can inform the value of social actions and update based on learned social information (Ruff & Fehr, 2014).

Social contexts that require mentalizing activate a common network of regions, including the TPJ and dmPFC. These regions enable a representation of others' minds (Dufour et al., 2013; Koster-Hale & Saxe, 2013; Saxe, Moran, Scholz, & Gabrieli, 2006). The TPJ exists at the convergence of attention, memory, and social streams, and it may harness these processes for constructing contexts and enabling predictions in complex environments (Bzdok et al., 2013; Carter & Huettel, 2013; Decety & Lamm, 2007). In particular, these processes may feed into the ability of the TPJ to recognize relevant social agents and predict their goals, beliefs, and desires (Koster-Hale & Saxe, 2013; Van Overwalle, 2009). The TPJ is involved in predicting others' reactions in competitive contexts in which people must strategize about others' goals and intentions (Carter, Bowling, Reeck, & Huettel, 2012; Griessinger & Coricelli, 2015; Santiesteban, Banissy, Catmur, & Bird, 2012). TPJ activity also increases for altruistic choices when there is a high cost to altruism or when the recipient is socially distant, suggesting activity facilitates incorporating others' outcomes into value processing (Morishima, Schunk, Bruhin, Ruff, & Fehr, 2012; Strombach, Weber, et al., 2015). The TPJ is implicated in thinking not only about others' goals and intentions, but also in thinking about what others' think of us including predictions about how our actions may affect our reputation (Izuma, 2012). It is implicated in considering others' expectations of us, such as choosing not to cheat a fellow player in a trust game or to follow social norms to avoid sanctions (Chang et al., 2011; Makwana et al., 2015).

However, knowing the social norms required to build a good reputation and behaviorally executing choices that follow this knowledge may require multiple processes. The dorsolateral prefrontal cortex (dlPFC) is implicated in executive functions including cognitive control, behavioral monitoring, and action selection (Hare, Camerer, & Rangel, 2009). In social contexts, the right dlPFC enables people to choose the socially normative choice, especially when it goes against self-interest (Baumgartner, Knoch, Hotz, Eisenegger, & Fehr, 2011; Knoch, Gianotti, Baumgartner, & Fehr, 2010; Knoch et al., 2009). Transcranial magnetic stimulation (TMS), which interferes with dlPFC function, reduces rejections of unfair offers in favor of self-interested choices despite no difference in unfairness perception. Furthermore, TMS reduces dlPFC-vmPFC connectivity that typically accompanies rejections, suggesting that without dlPFC input supporting the value of social norm enforcement, the vmPFC values the self-interested option over rejection (Baumgartner et al., 2011; Knoch et al., 2009). In addition, dlPFC activity is involved in reputation-building. The dlPFC responds more during decisions with the threat of punishment for selfish action, and this activity correlates with the behavioral adaptation to punishment threat (Spitzer et al., 2007). Furthermore, TMS to the dlPFC reduces the ability to build a good reputation, suggesting that the temptation to defect undermines the long-term strategy of cooperation to earn more from a good reputation (Knoch et al., 2009). All of this suggests that the dlPFC plays a role in integrating context into valuation to enable socially appropriate choices.

1.2.5 Measuring contextual modulations of value with fMRI

Neuroimaging using functional magnetic resonance imaging (fMRI) is particularly useful for measuring contextual influences on value. fMRI is non-invasive and thus can be used to study the brain regions involved in human decision-making in complex contexts. fMRI can provide a measure of activity across the entire brain which enables the investigation of both reward regions and exploration of which other regions might be involved in modulating reward. Finally, the whole-brain view the fMRI provides enables the modeling of functional connectivity changes that relate to task context, helping to elucidate how networks in the brain communicate to construct value.

1.3 Attention during information gathering modulates value

Attention allows organisms to focus on behaviorally relevant stimuli in the environment. Selectively attending to a specific stimulus enhances the perception of that stimulus and dampens the processing of non-attended stimuli, reducing distraction. In navigating complex environments, attention can be harnessed to prioritize reducing uncertainty and locating rewarding stimuli in order to promote survival (Tatler, Hayhoe, Land, & Ballard, 2011). Because of the important role of attention in adaptively navigating the environment, it is a critical component of valuation and decision-making

(Orquin & Mueller Loose, 2013). Prior research has found that overt attention interacts with valuation in an interdependent way in which preferences can drive attention, but incidental attention can also bias evidence accumulation in a way that influences preferences and choice.

1.3.1 Reward associations influence attention

Attention is drawn toward reward. People and other animals prefer to look at ethologically relevant, rewarding stimuli, and will even give up other rewards to look at rewarding images (Deaner, Khera, & Platt, 2005; Smith et al., 2013). Moreover, simply learning to associate a cue or a spatial location with reward can drive attention. This can facilitate faster responding when reward aligns with task goals, but orienting to reward can also occur even when the reward association is no longer relevant and distracts from the current task (Anderson, Laurent, & Yantis, 2011; Chelazzi et al., 2014; Gottlieb, Hayhoe, Hikosaka, & Rangel, 2014; Leong, Radulescu, Daniel, DeWoskin, & Niv, 2017; Peck, Jangraw, Suzuki, Efem, & Gottlieb, 2009). This may be particularly relevant in situations of dysfunctional reward associations, such as attentional capture by cues that induce craving in addiction (Aarts et al., 2011). This provides evidence that preferences and reward associations can be strong drivers of attention.

1.3.2 Attention modulates valuation

Incidental attention can also bias evidence accumulation toward the attended option, with mere exposure increasing the likelihood of choosing an option or rating it more highly (Bird, Lauwereyns, & Crawford, 2012; Shimojo, Simion, Shimojo, & Scheier, 2003). Thus, more salient options or options that are viewed for longer will bias evidence accumulation toward that option, even at very short timescales (Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Shimojo et al., 2003). If the option-value is positive, choice will be biased toward the option that is attended more, whereas if option-value is negative, choice will be biased away from the attended option (Armel, Beaumel, & Rangel, 2008). One way in which this phenomenon manifests is the gaze cascade effect, in which people look more at the eventually chosen option as time progresses. This effect can happen because people look more at the preferred option, but it can also occur even if attention is randomly allocated, suggesting that changing looking patterns exogenously can influences choice (Mullett & Stewart, 2016).

1.3.3 Selective attention frames the decision process

Attention can also be used to narrow the scope of attributes processed in complex multi-attribute environments. Selective attention can simplify choice by prioritizing the relevant attributes and reducing the effect of irrelevant ones (Hayhoe & Ballard, 2005; Leong et al., 2017; Orquin & Mueller Loose, 2013; Simon, 1955). Attention may be driven by a purposeful top-down strategy, such as avoiding looking at a dessert menu to reduce temptation. Specific goals can be used to determine the relevance of information in the choice process through the interaction of fronto-parietal attention networks and the basal ganglia (Corbetta & Shulman, 2002). However, attention can also be co-opted by bottom-up salience such as bright packages in a display that draw attention (Bourgeois, Neveu, Bayle, & Vuilleumier, 2017; Corbetta & Shulman, 2002). Features including color, surface size, number of options, and position all affect bottom-up saliency and may be employed in marketing to increase the likelihood of purchase.

This influence of attention and context on choice is stronger when option values are more uncertain and require gathering more information from the environment. For options with very strong prior knowledge or expectations, attention may matter less because preferences and strategies are more well-defined than for those with weaker internal preferences or expectations (Payne et al., 1992). For example, model-based learners' choices are not affected by the location of their last gaze, whereas model-free learners' choices are strongly modulated by the final fixation location (Konovalov & Krajbich, 2016). Furthermore, those who are more familiar with options or layout may develop more stereotyped patterns of information search and use information more selectively (Orquin & Mueller Loose, 2013). In contrast, when options and option-locations are not predictable or when people are less familiar with options, visual biases such as central or top left fixations earlier in the decision may be more likely to influence choice (Orquin & Mueller Loose, 2013; Reutskaja, Nagel, Camerer, & Rangel, 2011).

1.3.4 Patterns of information gathering both reveal and influence the decision process

In addition to prioritizing certain information in a decision, characterizing the patterns of information gathering during choice can give insight into the underlying process of choice. Early behavioral decision research focused on heuristics in decision-making with an emphasis on measuring how choice presentation and subsequent information processing influenced choice (Bettman & Kakkar, 1977; Johnson, Payne, & Bettman, 1988; Payne, Bettman, & Johnson, 1988; Payne et al., 1992; Simon, 1955). Using complex multi-attribute and multi-alternative problems with conflicting values across options allowed researchers to investigate how people simplified choices to make them more tractable. This work is predicated on the idea that decision-makers use attention to reduce working memory load, especially for difficult choices. Therefore, observing what information people look at can enable inference of the types of comparisons being made (Droll & Hayhoe, 2007).

1.3.5 Measuring attention during choice

Current methods for measuring decision processes primarily focus on mouse tracking and eye tracking. Mouse tracking can be used on any computer, and generally requires participants to hover their mouse over a box of information to reveal its contents (Johnson et al., 1988; Reeck, Wall, & Johnson, 2017). This allows researchers to examine which information is sought out and which comparisons between different types of information are made. However, it requires decision-makers to explicitly decide which information to reveal, and this may alter information gathering in certain circumstances (Glaholt & Reingold, 2011; Lohse & Johnson, 1996). Nevertheless, it also allows for more direct manipulations of processing strategies to test exogenously whether specific information gathering patterns influence choice (Reeck et al., 2017). Eye tracking is a less obtrusive, more naturalistic measure of attention in which all information is revealed on the screen and transitions between items are much faster. In addition, eye tracking movements may not always be deliberate and thus the influence of salience can be observed, measuring the interaction of stimulus-driven attention and goal-directed search. Eye tracking enables many components of the choice process to be measured including the order of information acquisition and the length of time spent looking at each piece of information. More recent research in process-tracing has used eye tracking to characterize effective heuristics and individual differences in the process of information gathering during risky choice (Kim, Seligman, & Kable, 2012; Kwak, Payne, Cohen, & Huettel, 2015; Venkatraman, Payne, & Huettel, 2014). Therefore, examining patterns of comparison in eye tracking can offer insight into the underlying decision process and reveal where in the decision process changing attentional patterns could shift choices.

1.4 Evidence accumulation in choice

The drift-diffusion model framework of decision-making is supported by both behavioral and neural data. Specifically, the data support the idea that decisions are made from the brain noisily accumulating evidence for options that must reach a boundary to trigger choice (Brody & Hanks, 2016; Gold & Shadlen, 2007; Ratcliff & McKoon, 2008; Ratcliff, Smith, Brown, & McKoon, 2016). This model was initially developed to explain binary perceptual decisions and has since been expanded to encompass value-based decision-making as well. A simple version of this model includes parameters for bias, drift rate, noise, non-decision time, and decision boundaries (Milosavljevic, Malmaud, & Huth, 2010). In a binary choice, the relative evidence for one option over another begins at 0, equidistant from the decision boundaries unless there is an *a priori* bias toward an option, in which case the bias parameter indexes that difference in starting point. Once the decision starts, evidence accumulates with noise with toward the preferred option at an average drift rate based on the relative support for one option over the other. Evidence can be represented by a relative value signal (RVS) that evolves at the drift rate (a combination of the difference in preference or strength of evidence across options and the drift slope parameter, θ) with gaussian noise, ε, centered around 0 and with constant variance:

$$RVS(t+1) = RVS(t) + \theta\,(\text{Option 1} - \text{Option 2}) + \varepsilon(t)$$

When the RVS reaches a boundary, the boundary reached is the option chosen. Boundary height determines the amount of evidence required before making a choice and can be viewed as a measure of response caution or a tradeoff between speed and accuracy (van Maanen et al., 2011). A high boundary requires more evidence accumulation and longer choices but is more likely to be accurate. Whereas a lower boundary requires less evidence and will lead to a faster choice with more potential for errors. In addition, non-decision time accounts for time not spent accumulating evidence during the process, including initial perceptual processing and motor output for choice. This model can explain both choices and response times during decision-making, as the strength of evidence or difference in value between two options can lead to a fast choice in the case of strong evidence or a much slower choice for more similar options or equivocal evidence. This form of the model uses the relative value signal (as opposed to a race model with separately evolving signals for each option) which is more in line with the neural research on normalization.

1.4.1 Neural systems underlying evidence accumulation

Initial neural support for evidence accumulation as a choice mechanism came from studies of perceptual decision-making. In one prominent paradigm, monkeys were tasked with detecting the direction of movement in a random-dot motion task with varying coherence of the dots. In this task, the objective motion coherence determines the strength evidence, and decisions are slower for lower coherence stimuli. Furthermore, the lateral intraparietal area, a region involved in action selection in decision-making, reflected evidence accumulation with increasing firing rate over time, and with a steeper increase for stronger evidence (Roitman & Shadlen, 2002; Shadlen & Newsome, 1996). Moreover, despite differing coherences and differing slopes of firing rate increase, most decisions were made when the firing rate reached a certain level, supporting the idea that choice is triggered when a (neural firing rate) boundary is reached (Roitman & Shadlen, 2002). Subsequent research found similar evidence accumulation signals across many areas of the brain, including dlPFC, frontal eye fields, superior colliculus, and striatum (Gold & Shadlen, 2007; Heekeren, Marrett, Bandettini, & Ungerleider, 2004; Kim & Shadlen, 1999). More recent work in rodents has suggested that while the parietal cortex and other regions reflects evidence accumulation, the anterior dorsal striatum is the only region that has been shown to be causally implicated in evidence accumulation (Brody & Hanks, 2016; Yartsev, Hanks, Yoon, & Brody, 2018).

Value-based decision making departs from perceptual decision making because it incorporates internal sampling of value information from learned associations and memories in addition to information in the environment. One study found evidence for hippocampal-striatal interactions during slower, more difficult choices and further found that this process has subsequent effects on value representation in the vmPFC (Bakkour, Zylberberg, Shadlen, & Shohamy, 2018). This adds further evidence that the striatum may be involved in integrating evidence accumulation across choice types, but that the evidence in different choices comes from different information sources.

1.4.2 Multi-attribute (maDDM) and time-dependent (mtDDM) drift-diffusion models

While most drift-diffusion models take in the relative value of one option compared to another, more recent models have split up the option value into separate attributes that contribute separately to an overall value. For example, these more recent models have been used to separately account for the influence of rewards for self and other in prosocial choice, for taste and health in dietary choice, and for amount and time in intertemporal choice (Dai & Busemeyer, 2014; Harris, Clithero, & Hutcherson, 2018; Hutcherson, Bushong, & Rangel, 2015). Rather than assuming integration of attributes in option-wise comparison, these models take an attribute-wise comparison approach where the relative value signal evolves according to separate attribute-wise comparisons:

$$RVS(t+1) = RVS(t) + \theta_1 (Att1_{Opt1} - Att1_{Opt2}) + \theta_2 (Att2_{Opt1} - Att2_{Opt2}) + \varepsilon(t)$$

Moreover, multi-latency models are multi-attribute models with the addition of different onsets times for each attribute into the choice process. This can account for the fact that some attributes may be processed faster than others. Indeed, mouse-tracking work has found that the relative onset of taste versus health in food choice relates to the overall proportion of healthy choices (Sullivan, Hutcherson, Harris, & Rangel, 2015).

An example of a multi-attribute time-dependent model is illustrated in Figure 1. This example models a choice between a smaller, sooner (SS) and larger, later (LL) option. The gray line represents the RVS, which starts equidistant between the two options and accumulates evidence via a noisy process. In this example, the time latency (t^*_T) occurs first, which drives evidence accumulation toward the smaller, sooner option which has the preferable, shorter time. However, when the amount latency is reached (t^*_A), information about amount enters RVS, shifting the accumulation process toward the larger, later option. This shift shows how a faster latency for one attribute can bias choice early on in the decision process. In addition, the rate at which the RVS moves, the drift rate, is determined by the value difference between the options as moderated by the attribute-specific drift slopes (i.e., the relative weighting a subject places on amount or time). Moreover, this example shows that moving the boundaries inward could have led to a SS choice due to the early evidence accumulation toward the SS option.

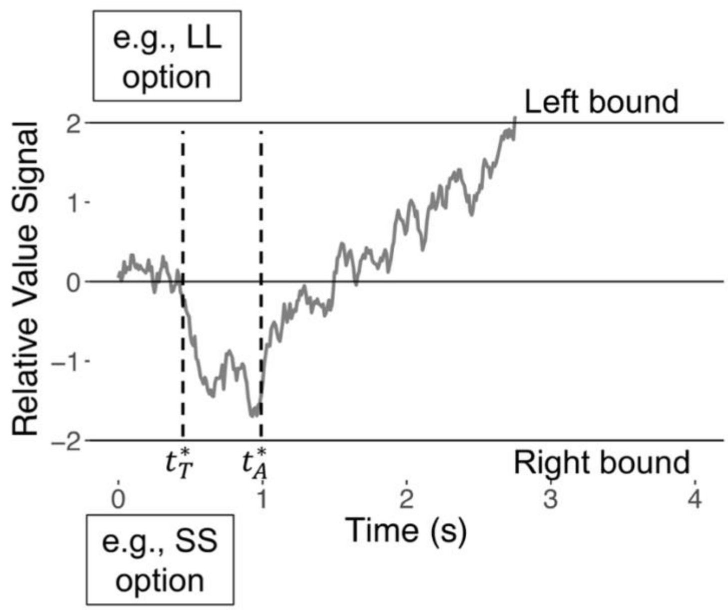

Figure 1: Attribute-wise Drift-Diffusion Model (DDM) example. This figure shows the overall form of the drift diffusion model with an example drawn from a simulated trial. The gray line represents the relative value signal (RVS), which represents the process of evidence accumulation over time; when that RVS hits a boundary, a decision is made. The RVS incorporates both the drift slopes for amount and time and the value differences between the attributes. The horizontal lines represent the decision boundaries, and the vertical lines represent the time and amount latencies.

1.4.3 Attentional Drift-Diffusion Model (aDDM)

The attentional drift-diffusion model (aDDM) incorporates attention into the value accumulation process by decrementing evidence accumulation for the non-attended information (Krajbich, Armel, & Rangel, 2010). This model makes a number of predictions that align with actual data, including that the final fixation will typically be the chosen option unless it is much worse than the alternative. This is predicted even if attention is allocated randomly, because the boundary of the option attended is more likely to be crossed than that of the non-attended option given the decrement in evidence accumulation for the non-attended option (Mullett & Stewart, 2016). This model has been extended to many types of consumer choice, including food and social choices, purchasing decisions, and choices with more than two options (Fisher, 2017; Krajbich, Hare, Bartling, Morishima, & Fehr, 2015; Krajbich, Lu, Camerer, & Rangel, 2012a; Krajbich & Rangel, 2011).

1.5 Summary and dissertation approach

The following chapters center on research that explores how attention and social motivations influence value construction in economic decision-making. I use mechanistic approaches including neuroimaging, eye tracking, and computational modeling to understand value construction in different types of value-based choice. One line of research uses computational modeling and eye tracking to characterize the patterns of information gathering that lead to individual differences in choice as applied to intertemporal choice and mental accounting. In chapter 2, I explore the mechanisms of evidence accumulation in intertemporal choice, examining how people tradeoff between smaller amounts of money available sooner and larger amounts of money available later. In order to characterize these mechanisms, I use a multi-attribute time-dependent drift-diffusion model to understand the contributions of amount and time at different points in the evidence accumulation process. In addition, I measure overt attention using eye tracking to be able to confirm the computational findings with a measure of the actual information being gathered and the comparisons being made.

In chapter 3, I focus on purchasing decisions and how mental accounting through budget size influences valuation of items. In this study, I use eye tracking to explore the factors influencing valuation including information gathered, comparisons made, and overall scan paths across individuals who modulate purchasing by budget size relative to those who do not. Furthermore, I explore the differences in information gathering when items are bought or skipped. This allows a more in-depth exploration of the mechanisms of mental accounting and how smaller, stricter budgets can constrain spending while larger budgets may enable impulse purchasing.

In a different line of investigation, in chapter 4, I explore social motivations in valuation with an emphasis on characterizing how social networks modulate value representations in the brain. More specifically, I investigate the neural mechanisms of social context during reward anticipation for self-interested and prosocial incentives. In particular, I test whether reputation motivation influences prosocial reward undermining by comparing motivated behavior and neural activity in a private context compared to a public context. I examine whether reward motivation changes across social context for rewards for self or for a charity, and whether combining self-interested and prosocial incentives in public undermines motivations for self or charity.

2. Amount and time exert independent influences on intertemporal choice

The work presented in this chapter is published: Amasino, D., Sullivan, N., Kranton, R., Huettel, S. (2019). Amount and time exert independent influences on intertemporal choice. *Nature Human Behaviour.*

2.1 Introduction

Intertemporal choices involve tradeoffs between the value of rewards and the delay before those rewards are experienced. Canonical intertemporal choice models such as hyperbolic discounting assume that reward amount and time until delivery are integrated within each option prior to comparison (Ainslie, 1975; Samuelson, 1937). An alternative view posits that intertemporal choice reflects attribute-wise processes in which amount and time attributes are compared separately (Dai & Busemeyer, 2014; Ericson, White, Laibson, & Cohen, 2015; Read, Frederick, & Scholten, 2013; Roelofsma & Read, 2000). Here, we use multi-attribute drift diffusion modeling (DDM) to show that attribute-wise comparison represents the choice process better than option-wise comparison for intertemporal choice in a young adult population. We find that, while accumulation rates for amount and time information are uncorrelated, the difference between those rates predicts individual differences in patience. Moreover, patient individuals incorporate amount earlier than time into the decision process. Using eye-tracking, we link these modeling results to attention, showing that patience results from a rapid, attribute-wise process that prioritizes amount over time information. Thus, we find converging evidence that distinct evaluation processes for amount and time determine intertemporal financial choices. Because intertemporal decisions in the lab have been linked to failures of patience from insufficient saving to addiction (Bickel, Koffarnus, Moody, & Wilson, 2014; Bulley & Pepper, 2017; Griskevicius et al., 2013; Jarmolowicz et al., 2014; Lempert & Phelps, 2015; Meier & Sprenger, 2012; Story, Vlaev, Seymour, Darzi, & Dolan, 2014), understanding individual differences in the choice process is important for developing more effective interventions.

Substantial research shows that intertemporal choices between smaller, sooner (SS) and larger, later (LL) monetary rewards can be characterized by a hyperbolic discounting function in which rewards lose value very rapidly over short delays and then more slowly over longer periods of time (Ainslie, 1975; Samuelson, 1937). A single hyperbolic discount rate (*k*) describes choices, such that a higher *k* indicates steeper discounting of future rewards and thus more impatient choices, whereas a lower *k* indicates more patient choices. Such hyperbolic option-wise models have been generally accepted for several reasons: the discount rate often relates to other measures of individual differences (Bickel et al., 2014; Jarmolowicz et al., 2014; Lempert & Phelps, 2015; Story et al., 2014), hyperbolic models account for preference reversals as rewards become more proximal in time (Ainslie, 1975), and value functions derived from hyperbolic models match well to neural data (Frederick, Loewenstein, & O'Donoghue, 2008; Kable & Glimcher, 2007; G. Loewenstein & Prelec, 1992; Mazur, 1987; Monterosso & Luo, 2010; Thaler, 1981). Yet, it is also known that directing attention toward one attribute (e.g., time) can alter decisions, perhaps by encouraging attribute-wise processing (Ebert & Prelec, 2007; Fassbender et al., 2014; Radu, Yi, Bickel, Gross, & McClure, 2011; Weber et al., 2007). Recent research into heuristic and sequential sampling models has suggested that such an attribute-wise process may better fit choice behavior (Dai & Busemeyer, 2014; Ericson et al., 2015; Read et al., 2013; Roelofsma & Read, 2000), although there remains debate about whether the form of these previous models accounts for all factors (Wulff & van den Bos, 2017).

The current experiments examine whether amount and time make independent contributions to individual differences in intertemporal choice in young adults. To support this conclusion, three conditions must be met. First, intertemporal choices should be better modeled by a combination of uncorrelated parameters for amount and time than by either of those parameters in isolation. If this condition holds, two individuals could exhibit the same intertemporal patience (i.e., the same apparent k value) through different combinations of decision weights on amount and time. Second, a model that combines amount and time parameters in an attribute-wise manner (i.e., comparing amounts to amounts and times to times) should be better matched to choice behavior than a similar option-wise model that integrates amount and time information to determine the value of each option. Third, amount and time should have distinct influences on the attentional process during choice, measured independently of choice behavior; if such attentional effects are observed, they would provide an important lever for shifting the process of choice. Our experiments provide evidence that meets all three of these conditions.

We investigated the dynamic process of intertemporal choice using multi-attribute drift diffusion modeling (DDM). This approach builds on prior work indicating that intertemporal choice – like other forms of value-guided decision making – involves a dynamic accumulation of evidence before reaching a decision threshold (Dai & Busemeyer, 2014; Rodriguez, Turner, & McClure, 2014). Expanding on other studies, our multi-attribute model introduces a separation of amount and time information in multiple parts of the decision process. Drift diffusion models split up the decision process into fundamental components that shape both choices and response times; each component provides a potential source for inter-individual variation in choice patience (White, Ratcliff, Vasey, & McKoon, 2010). A necessary component to account for differences in patience is variation in attribute-specific *drift slopes* for amount compared to time. The drift slope reflects the weight placed on an attribute during the evidence accumulation process. On a given trial, the total evidence accumulation (i.e., trial drift rate) depends on the trial-specific value differences between the two options as modulated by the subject- and attribute-specific drift slope. Because drift slopes play a dominant role in evidence accumulation, they will necessarily have a large part in driving choice and thus explaining individual differences. A steeper drift slope for amount compared to time would promote more patient choices while a steeper drift slope for time would promote more impatient choices. Nevertheless, another possible contributing mechanism is *attribute latency*, or the temporal advantage that results if one attribute is processed earlier than another. Faster latency for one attribute would initially bias choice toward the better value on that attribute before the other attribute starts influencing value accumulation (Sullivan et al., 2015). Finally, *decision bounds* represent response caution, which can manifest as a tradeoff in speed vs. accuracy (van Maanen et al., 2011). Differences in boundaries could contribute to individual differences in choice with lower bounds relating to faster, less cautious, and noisier responses, although bounds do not directly bias choice in one direction.

We adopted a multi-stage procedure for data collection, analysis, and replication (see Appendix A for manipulation checks). Our task (Figure 2) offered participants incentive-compatible choices between smaller rewards delivered that day and larger rewards delivered up to a year later. In our primary sample, options were presented vertically with amount information at the top of the screen and time information at the bottom. In our replication sample, options were presented horizontally with amount and time information location (left or right) switching halfway through the experiment. In both samples, the locations of the SS and LL options were randomized across trials. While participants performed the task, we sampled their gaze position at high temporal resolution using eye-tracking, so that we could obtain real-time assessments of information processing in advance of each decision (Fisher, 2017; Glockner & Herbold, 2011; Konovalov & Krajbich, 2016; Krajbich et al., 2010, 2012a; Orquin & Mueller Loose, 2013). We examined not only the relative gaze bias between the SS and LL options, which has been linked to overall patience in intertemporal choice (Franco-Watkins, Mattson, & Jackson, 2016), but also the pattern of eye movements between elements in the display, which can reveal variation in decision heuristics across individuals (Reeck et al., 2017; Venkatraman et al., 2014). We used choices and response times from the task to fit the drift diffusion models and gaze data from the eye tracker during choice periods to characterize gaze patterns. Successful analyses in the primary sample determined which analyses were conducted in the replication sample – and all analyses are reported in this paper, regardless of replication success.

2.2 Methods

2.2.1 Participants

2.2.1.1 Primary Sample.

We recruited 117 subjects (mean age = 21.3 years, SD = 2.3 years; 75 female). Before data collection, we established a target sample size of 100 participants. No statistical methods were used to pre-determine sample sizes, but our sample sizes are larger than those reported in previous publications (Franco-Watkins et al., 2016; Konovalov & Krajbich, 2016; Reppert, Lempert, Glimcher, & Shadmehr, 2015). Because of a data collection error with a second unrelated task completed by the same participants, we collected additional participants who completed both tasks – leading to a final sample of 117 for this experiment. Of these participants, 12 were excluded from eye tracking analyses because of poor-quality or insufficient data (subjects were excluded if in 50% or more of the eye tracking data for one or both eyes could not be identified or if their calibration was poor). All participants were recruited from the Durham, NC and Duke University communities and provided informed consent under a protocol approved by the Institutional Review Board of Duke University.

2.2.1.2 Replication Sample.

We recruited 100 subjects (mean age = 21.5 years, SD = 2.0 years; 68 female); 15 of whom were excluded from eye tracking analyses because of poor-quality or insufficient data. All recruitment, consent, and instructional procedures were identical to those of our Primary Sample.

2.2.2 Procedure

Following informed consent, participants read a brochure about financial decision making; that brochure described either a traditional information-based strategy or a social cognition strategy. Conditions were randomly assigned to subject numbers before participants signed up for the experiment. Data collection and analysis were not performed blind to the conditions of the experiments. Note that because initial analyses revealed that the strategies did not evoke differences in ITC behavior that replicated across experiments, we hereafter combine across them in all reported analyses. Participants then completed two independent economic decision-making tasks – an intertemporal choice task (reported here) and an unrelated shopping task – in randomized order. After both tasks, subjects provided open-ended feedback about the strategies they used during decision making and completed the Abbreviated Barratt Impulsivity Scale (ABIS) as a general measure of individual differences in impulsivity (Coutlee, Politzer, Hoyle, & Huettel, 2014). Because the ABIS did not correlate with intertemporal choice across samples, we do not further report on its relationship to other variables.

Participants completed 141 intertemporal choices. The SS choice was always available that day and varied between $0.50-$10 in increments of $.50, while the LL choice was always $10 but delivered between 1-365 days later (1, 7, 15, 30, 90, 180, and 365 days). All possible combinations of immediate amounts and later delays were used. In the Primary experiment (Figure 2, top row), the choice options were displayed on the left and right sides of the screen, with amount on top and time on bottom. In the Replication experiment (Figure 2, bottom row), the choice options were displayed at the top and bottom of the screen; with left-right position of time and amount information counterbalanced across the first and second halves of the experiment in blocks. The left-right (Primary) or top-bottom (Replication) order of the SS and LL options was randomized across trials.

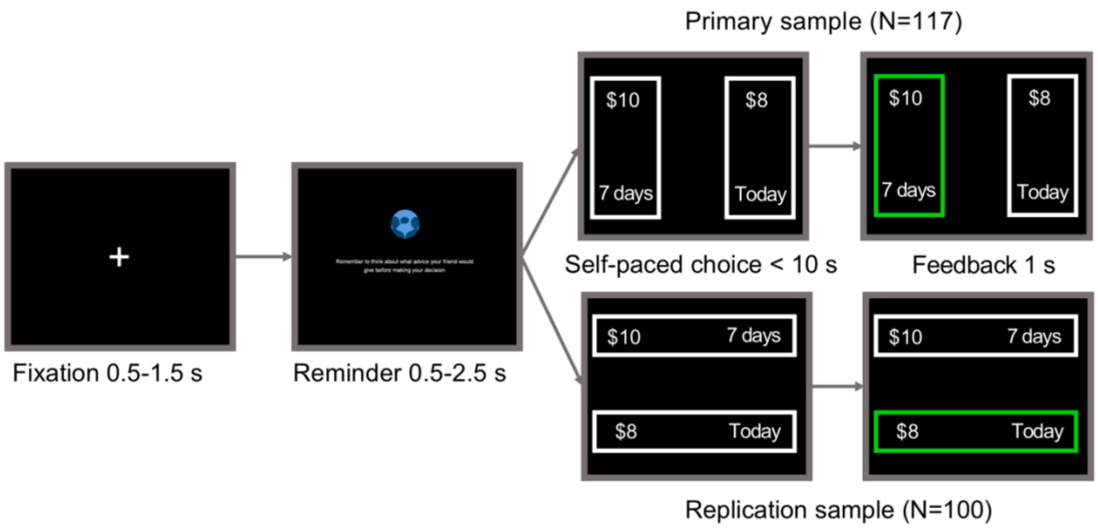

Figure 2: Intertemporal choice task. On every trial, participants saw a fixation cross followed by a reminder to follow the task instructions. Next, they viewed and made a choice between a LL and SS option and received 1s of feedback highlighting the choice made. The positions of the LL and SS options were randomized across trials. The orientation of amount and time information in the primary sample was rotated in the replication sample.

Participants indicated their chosen option via keyboard button press. The task was self-paced with a 10s maximum response time; most choices were much faster (primary sample: mean RT = 2.21s, SD = 0.70; replication sample: mean RT = 2.14s, SD = 0.64). Our maximum response time was well above the average response time; it was implemented to minimize extended lapses of attention and to keep participants focused on the task. At the end of the experiment, each participant received a base payment of $6 (cash) for their participation, and 1 trial was resolved for additional payment in an

Amazon gift certificate that was delivered via email at the date on that trial. We used this payment method to minimize transaction costs and risk of delivery for future rewards (Andreoni & Sprenger, 2012; George Loewenstein & Thaler, 1989; Weber et al., 2007); that is, subjects could be confident that they would receive the chosen reward on the promised date, with no additional time or effort commitment on their part.

2.2.3 Eye tracking

Tasks were presented on a Tobii T60 eye tracker, which uses an unobtrusive camera system to sample gaze position at 60hz while allowing free head motion by the participant. We established areas of interest (AOIs) around the four pieces of information present on each display; each AOI was 350 by 350 pixels within the 1280 by 1024 total resolution of the screen. Before ROI analyses (gaze indices), we preprocessed the gaze position data using a clustering algorithm that identified drifts in calibration and then shifted the centers of mass of fixation clusters into the appropriate AOIs.

2.2.4 Analysis

2.2.4.1 Modeling intertemporal value.

For each subject, we used maximum likelihood estimation to identify their temporal discounting coefficient (k) within a hyperbolic function (Equation 1).

Equation 1: $$SV = \frac{A}{1+kT}$$

In this equation, SV is the subjective value of an option for an individual, A is its amount (in dollars), T is the time until its delivery (in days), and k is the discount rate. In addition, because *k*-values are non-normally distributed, we use a natural log transformation of *k* for analysis (Fassbender et al., 2014; Kable & Glimcher, 2007; Lempert, Glimcher, & Phelps, 2015). Participants with uniformly patient choices or almost all patient choices with a few highly inconsistent choices (Primary Sample, N = 12; Replication Sample, N = 19) could not be fit by this function and were excluded from statistical analysis; on figures, their data is shown in lighter gray triangles to facilitate comparison with the other participants. Two additional participants in the replication sample had highly inconsistent choices that could not be fit to a single discount rate; those participants are excluded both from statistical analysis and from figures plotting the discount rate. Once *k* was identified for a given subject, we used its value to estimate the subjective value of the LL options on each trial, assuming a linear utility function for money over the range of values used; note that the subjective value for each SS option is equivalent to its nominal value. We chose the hyperbolic model for baseline comparison to our multi-attribute DDM as it has been shown to best fit with neural data and is widely used in relevant literature (Kable & Glimcher, 2007; Monterosso & Luo, 2010; Peters & Büchel, 2011).

2.2.4.2 Multi-attribute DDM models

To examine individual differences in the processing of amount and time information, we fit two multi-attribute DDM models for each participant, one based on attribute-wise comparison and the other on option-wise comparison.

DDMs assume that people stochastically accumulate evidence toward one choice option or the other until a relative value signal (RVS) reaches a decision boundary, triggering the execution of the choice (Milosavljevic et al., 2010; Ratcliff et al., 2016). Our computational implementation of the DDM involved the following steps. First, we model the decision as a choice between two options (i.e., left or right in the primary sample, top or bottom in the replication sample) that differ in two attributes: amount and time. We assume that the relative value signal (RVS) is unbiased and starts at 0, equidistant from the decision boundaries for the two options; this assumption is appropriate because of our randomization of options to left/right or top/down locations. Second, we estimate separate attribute latency values for amount (t_A^*) and for time (t_T^*). These values reflect the interval after the onset of the stimulus when no information is accumulating related to that attribute; both attribute latency values include perceptual and motor processing (Ratcliff & McKoon, 2008; Wiecki, Sofer, & Frank, 2013), while differences between latency values reflect a *temporal advantage* of one attribute over the other. The RVS accumulates in 10 ms time steps according to the amounts and times of each option weighted by separate drift slopes for time and amount attributes (δ_A or δ_T). All terms in the model are proportional to a stochastic error signal (ϵ_t) that is defined by a Gaussian distribution centered at 0 with standard deviation $\sigma = 0.1$.

In our *option-wise model*, equation (2), amount and time for each option are integrated in an option-wise manner similar to typical hyperbolic models. Prior to the attribute latency for a given attribute, the average over the experiment is used in place of the actual amounts or times on that trial as a scaling factor. We kept amount and time in their original scales to preserve the relative relationship between them.

Equation 2: $RVS_t = RVS_{t-1} + \frac{\delta_A \cdot A_{left}}{1+\delta_T \cdot T_{left}} - \frac{\delta_A \cdot A_{right}}{1+\delta_T \cdot T_{right}} + \epsilon_t$

Where: $A_{left}, A_{right} = \bar{A}$ if $t < t_A^*$;

$T_{left}, T_{right} = \bar{T}$ if $t < t_T^*$.

In comparison, in our *attribute-wise model*, equation (3), following an attribute-specific latency period, each attribute begins contributing to the RVS according to the difference in values. We normalized amount and time values to each be within the range [-1,1]; this allows their relative drift slopes to be directly comparable.

Equation 3: $RVS_t = RVS_{t-1} + \delta'_A(A_{left} - A_{right}) + \delta'_T(T_{left} - T_{right}) + \epsilon_t$

Where: $A_{left} - A_{right} = 0$ if $t < t_A^{*\prime}$;

$T_{left} - T_{right} = 0$ if $t < t_T^{*\prime}$.

We estimated the parameters of this model for each participant, independently, from their response time and choice data. To improve the stability of our estimation process, we excluded the 2.5% slowest and 2.5% fastest response times for each subject. We simulated each participant's data 1000 times to identify the combination of parameters that best generated their choices and response time distribution (using 8 RT bins for each subject). The two models take different forms, but both fit the same five parameters – amount latency, time latency, amount drift slope, time drift slope, and decision boundary – while holding noise and bias constant. This similarity means that model fits can be directly compared on a subject-by-subject basis. We used the Bayesian Information Criterion (BIC) to compare model fits. The equation for the criterion is BIC = -2 x log likelihood + d x log(N) where N is the number of trials completed and d is the number of parameters fit. Lower scores indicate better fit.

For all models we used a grid-search procedure with an initial common coarse grid for all subjects, followed by a finer grid search around each individual's best fitting parameters (see Supplementary methods for parameter ranges). Linear spacing was appropriate for all DDM parameters, save for drift slope in the option-wise model (which used a log spacing to as log-normalization was needed to obtain a normal distribution for the time drift slope). We did not include negative drift slopes because they do not make theoretical sense in our paradigm; that is, subjects did not prefer to receive smaller amounts of money at later times, as would be needed to generate a negative slope. We note that there are a variety of methods to solve DDMs that seek to account for a variety of psychological processes such as inconsistencies in choice, but we chose a grid search to minimize assumptions about the attentional process (Busemeyer & Diederich, 2002; Ratcliff et al., 2016; Srivastava, Feng, Cohen, Leonard, & Shenhav, 2017).

2.2.4.3 Indices of looking behavior

We derived three measures of gaze behavior from our eye tracking data. All measures were scaled to a -1 to 1 range. The *Attribute Index,* equation (4) describes the proportion of time a participant looked at the amount AOIs (compared to the total time looking at AOIs); positive values indicate more time spent looking at amounts, negative indicate more time spent looking at time AOIs.

Equation 4: $\frac{Gaze\ points\ in\ Amount\ ROIs - Gaze\ points\ in\ Time\ ROIs}{Gaze\ points\ in\ Amount\ ROIs\ +\ Gaze\ points\ in\ Time\ ROIs}$

The *Option Index,* equation (5) measures the proportion of time a participant looked at SS AOIs (again compared to the total looking time); positive values indicate looking at SS options, negative at LL (Franco-Watkins et al., 2016).

Equation 5: $\frac{Gaze\ points\ in\ Immediate\ option\ ROIs - Gaze\ points\ in\ Delayed\ option\ ROIs}{Gaze\ points\ in\ Immediate\ option\ ROIs\ +\ Gaze\ points\ in\ Delayed\ option\ ROIs}$

Finally, the *Payne Index* (Payne, 1976), equation (6), quantifies whether transitions in gaze tend to be within options (e.g., from the SS amount to the SS time; positive Payne Index) or within attributes (e.g., from the SS amount to the LL amount; negative Payne Index).

Equation 6: $\frac{Option{-}wise\ transitions\ -\ Attribute{-}wise\ transitions}{Option{-}wise\ transitions\ +\ Attribute{-}wise\ transitions}$

2.3 Results

We tested two drift diffusion models that differed in how and when amount and time information contributed to the decision process. The attribute-wise model [Equation (3)] assumes that people make direct comparisons between amounts and direct comparisons between times, whereas the option-wise model [Equation (2)] assumes that people integrate time and amount for each option before comparing options. We compared model fits using Bayesian information criterion (BIC); because both models fit the same number of parameters, here the BIC is a transformation of the negative log likelihood. Nearly all participants were better fit by an attribute-wise model (Two-sided exact binomial tests: primary sample 107/117, $p < 0.001$, 95% CI = 0.85 – 0.96; replication sample 99/100, $p < 0.001$, 95% CI = 0.95 – 1.0), and analyses reported in the following sections use parameters from that model. Moreover, the difference in fit was significantly correlated with discount rate (Figure 3) as tested by a two-tailed Pearson's product-moment correlation: primary sample $t(103) = 12.66$, $p < 0.001$, $r = 0.78$, 95% CI = 0.69 – 0.85; replication sample $t(77) = 5.56$, $p < 0.001$, $r = 0.54$, 95% CI = 0.36 – 0.68), such that more patient individuals' choices were much better fit by an attribute-wise model, while very impatient individuals' choices tended to be more similarly fit by both models.

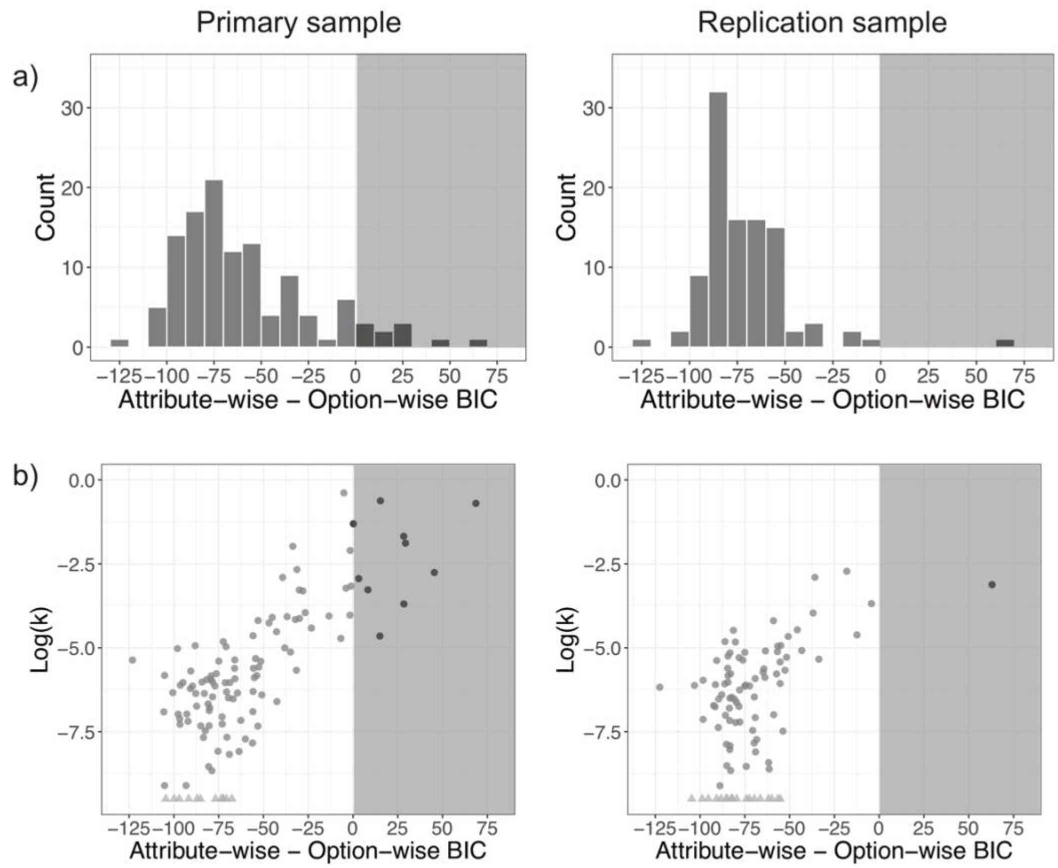

Figure 3: Attribute-wise vs. option-wise DDM model comparison using Bayesian Information Criterion (BIC). Shown are data from all participants (primary sample N = 117, replication sample N = 100); note that participants that could not be fit to a single discount rate (primary sample N = 12, replication sample N = 21) were excluded from subsequent statistical testing. a) A histogram of the difference in BIC for each participant across models showing that overall the attribute-wise model fit better. b) The difference in BIC has a positive correlation with individual discount rate, log(k). Participants with all patient choices are displayed in light gray triangles at -9.5 on the y-axis for illustrative purposes. Gray shading indicates values better fit by the option-wise model, whereas no shading indicates values better fit by the attribute-wise model (lower BIC values indicate better fit).

Because intertemporal choices involve trade-offs between two attributes – amount and time – those attributes influence choice in opposite directions; that is, an increased decision weight on time will potentiate SS choices, while an increased decision weight on amount will lead to LL choices. Within the DDM, an increased weight on one attribute would be evident in a steeper drift slope compared to the other attribute. For every participant, we used a multi-attribute DDM (see Methods) to estimate the unique drift slopes associated with amount information and with time information. We found that these two drift slopes were uncorrelated across participants (Figure 4a; Two-sided Pearson's product-moment correlations: primary sample $t(115) = 0.24$, $p = 0.81$, $r = 0.02$, 95% CI = -0.16 – 0.20; replication sample $t(98) = 0.74$, $p = 0.46$, $r = 0.07$, 95% CI = -0.12 – 0.27) indicating that amount and time make distinct contributions to the process of intertemporal choice.

As a manipulation check of the fit of the drift slopes, we examined the relationship between the difference in drift slopes for amount and time and individual differences in intertemporal choice as measured by the discount rate (Figure 4b). As expected, more patient individuals accumulated amount information at a faster rate than time information, whereas more impatient individuals accumulated time information at a faster rate than amount information (Two-sided Pearson's product-moment correlations: primary sample $t(103) = -19.14$, $p < 0.001$, $r = -0.88$, 95% CI = -0.92 – -0.83; replication sample ($t(77) = -16.22$, $p < 0.001$, $r = -0.88$, 95% CI = -0.92 – -0.82). This result confirms that the model correctly distributes weight between the amount and time parameters to predict choice. Together, these results demonstrate that patience results from the combination of two uncorrelated factors—time and amount—rather than from a single factor or a slower overall drift slope (i.e., the sum of the axes on Figure 4a). Preferences in intertemporal choice are proportional to the difference between these drift slopes but the drift slopes themselves are not correlated with each other.

While the previous section shows that attribute-specific differences in drift slope are closely connected to intertemporal choice, differences in attribute latency could amplify (or moderate) those effects. We found that the latency for amount information was shorter than that for time information overall (Two-sided Welch's paired t-test: primary sample, mean difference of 160 ms, $t(116) = -3.24$, $p = .0015$, Cohen's $d = -0.30$, 95% CI = -0.56 – -0.04; replication sample, mean difference of 325 ms, $t(99) = -7.17$, $p < 0.001$, Cohen's $d = -0.72$, 95% CI = -1.00 – -0.43), and that the difference between attribute latencies for amount and time was positively correlated with *k* values (Figure 4c, Two-sided Pearson's product-moment correlations: primary sample $t(103) = 6.21$, $p < 0.001$, $r = 0.52$, 95% CI = 0.37 – 0.65; replication sample $t(77) = 4.86$, $p < 0.001$, $r = 0.48$, 95% CI = 0.29 – 0.64). That is, people who are more patient begin accumulating amount information more quickly, while those who are less patient begin accumulating time information more quickly.

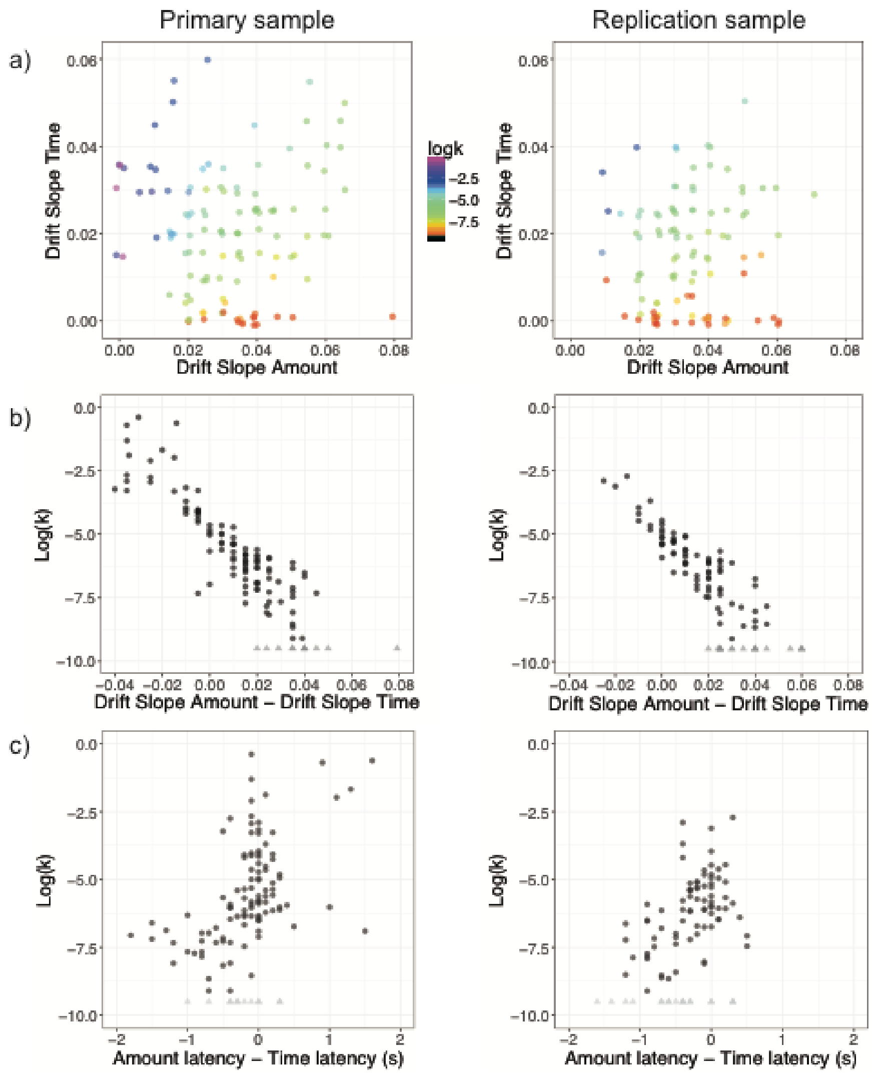

Figure 4: Patience reflects the difference in drift slopes and latencies for amount and time. Primary sample N = 117, replication sample N = 100, participants not able to be fit to a single discount rate were excluded from analyses involving the discount rate (primary sample N = 12, replication sample N = 21). a) The drift slopes for amount (x-axes) and for time (y-axes) were uncorrelated across participants. Values are jittered (.001 horizontal and vertical jitter) to reduce over-plotting. The color-map indicates the log(k) value for each participant; note that participants with similar levels of patience had different combinations of drift slopes for the two attributes. b) The difference in drift slopes was related to patience, in both samples. c) The relative attribute latency for amount and time also relates to patience. Participants with all patient choices are displayed in light gray triangles at -9.5 on the y-axis for illustration and were excluded from statistics.

Within the DDM, the decision boundary provides a measure of how much evidence is required before making a choice – and thus expanded bounds could be plausibly linked to patient intertemporal choices. However, there were no correlations between decision bounds and discount rate in either sample (Two-sided Pearson's product-moment correlations: primary sample $t(103) = -0.85$, $p = 0.40$, $r = -0.08$, 95% CI = -0.27 – 0.11; replication sample $t(77) = 0.18$, $p = 0.85$, $r = 0.02$, 95% CI = -0.20 – 0.24). We found a positive correlation between discount rate and response time such that impatient participants actually took longer to make choices than more patient participants (primary sample $t(103) = 3.49$, $p < 0.001$, $r = 0.33$, 95% CI = 0.14 – 0.49; replication sample $t(77) = 4.16$, $p < 0.001$, $r = 0.43$, 95% CI = 0.23 – 0.59. Together, these data suggest that there is no systematic relationship between patience in the intertemporal domain and the amount of evidence or speed required to make a decision; instead, individual differences in attribute-specific latency and drift slopes account for which individuals exhibit intertemporal patience.

If amount and time are uncorrelated contributors to intertemporal choice, there should be observable attentional biases toward one attribute or the other that relate to variation in drift slope. We tested this hypothesis by examining whether differences in drift slope showed a relationship with our *Attribute Index,* which quantifies relative looking time at amount versus time information (Figure 5a). There was a significant positive correlation between difference in drift slope and relative gaze in both the primary sample (two-sided Pearson's product-moment correlation: $t(103) = 6.35$, $p < 0.001$, $r = 0.53$, 95% CI = 0.38 – 0.66) and the replication sample ($t(83) = 6.05$, $p < 0.001$, $r = 0.55$, 95% CI = 0.39 – 0.69). That is, individuals direct more attention toward the attribute for which they show a higher drift slope. This could be due either to attention driving the information gathering process or to underlying preferences driving attention; the challenge in separating these explanations is considered below. We also tested whether the location of the first fixation was related to individual differences in attribute latency for amount and time and found a significant correlation in our primary sample (two-sided Kendall's rank correlation tau: $z(103) =-3.40$, $p < 0.001$, tau = -0.23, 95% CIs = -0.35 – -0.12) and in our replication sample ($z(83) = -2.16$, $p = 0.031$, tau = -0.16, 95% CIs = -0.30 – -0.03) such that those who had a faster amount latency were more likely to fixate first on amount information.

While the results from the previous sections show attribute-specific biases in decision making, they do not in themselves provide evidence that participants directly compare attribute values when making decisions. To obtain that evidence, we identified all gaze transitions in our eye-tracking data and then measured the relative proportions of attribute-based transitions (e.g., SS time to LL time) and option-based transitions (e.g., SS time to SS amount). The difference in transition probabilities is quantified by the *Payne Index*(Payne, 1976), for which positive values reflect more option-based gaze transitions. We observed a strong negative correlation between the Payne Index and the difference in attribute drift slopes: individuals with a higher drift slope for amount were indeed more likely to engage in attribute-wise comparisons, while those with a higher drift slope for time used more option-wise comparison (Figure 5b two-sided Pearson's product-moment correlations: primary sample $t(103) = -7.60$, $p < 0.001$, $r = -0.60$, 95% CI = -0.71 – -0.46; replication sample $t(83) = -5.51$, $p < 0.001$, $r = -0.52$, 95% CI = -0.66 – -0.34). Moreover, those with higher Payne Index values tended to look more at amounts than times ($t(103) = -7.80$, $p < 0.001$, $r = -0.61$, 95% CI = -0.72 – -0.47; replication sample $t(83) = -11.04$, $p < 0.001$, $r = -0.77$, 95% CI = -0.85 – -0.67). Together, these results indicate that people who make more patient choices tend to directly compare the amounts offered (and largely ignore temporal information), whereas those who are less patient tend to integrate amount and time within an option before comparing the two options.

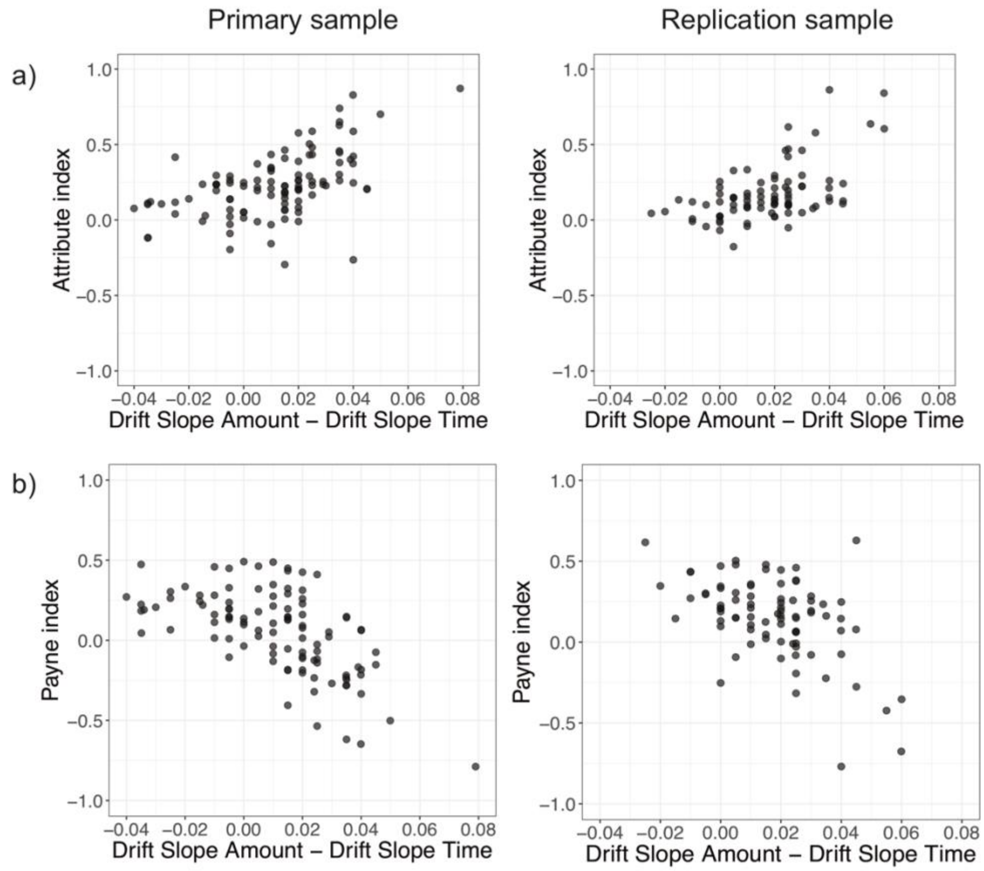

Figure 5: Differences in drift slope between amount and time attributes are reflected in measures of attention. Primary sample N = 105, replication sample N = 85 which includes all participants with sufficient eye-tracking data. a) The Attribute Index measures relative looking at amounts (index>0) versus times (index<0). Across participants, a bias toward looking at amounts was associated with a greater drift slope for amount information. b) The Payne Index measures the relative likelihood of gaze transitions within options (index>0) or between attributes (index<0). Participants who tended to make more attribute-wise transitions also showed a greater drift slope for amount information.

2.4 Discussion

Collectively, our results support the conclusion that intertemporal choices result from the combination of two distinct processes – one evaluating amount information and the other evaluating time information – that combine to shape an individual's choice patience. This conclusion follows from converging evidence drawn from choice behavior, multi-attribute drift diffusion modeling, and metrics of attention obtained using eye-tracking. Moreover, markers of the choice process (e.g., patterns of gaze transitions, latency of attribute integration) were predictive of subject-specific individual differences in patience. These markers contribute to an improved understanding of the mechanisms of intertemporal choice, which in turn could inform policy and interventions that ameliorate negative real-world outcomes (Bickel et al., 2014; Bruderer Enzler, Diekmann, & Meyer, 2014; Bulley & Pepper, 2017; Chapman, 1996; Hardisty & Weber, 2009; Jarmolowicz et al., 2014; Jimura et al., 2011; Lempert & Phelps, 2015; Meier & Sprenger, 2012; Story et al., 2014; Tsukayama & Duckworth, 2010).

Three features of our results are particularly relevant for understanding intertemporal choice. First, we show that the processing of amount information and time information have uncorrelated contributions to the choice process. While our design cannot confirm complete statistical independence, the observed lack of correlation between drift slopes for amount and time stands in contrast to other models that assume a limited capacity constraint on attention such that weights on amount and time trade-off within the decision process (i.e., sum to a constant) (Dai & Busemeyer, 2014; Diederich & Oswald, 2014). Moreover, prior work suggests that although attention can constrain processes of evidence accumulation in decision making, this bias is partial rather than absolute (Krajbich et al., 2010). We note, however, that modeling approaches like ours could miss idiosyncratic violations of independence, as could be the case if a subject adopts different choice heuristics on different trials that are mixed across trials in an overall model. Future work should extend these analysis procedures to identify potential decision heuristics, including attentionally constrained trade-offs in processing, that may be manifest in some contexts.

Second, because the pattern of gaze transitions provides an index of overt attention (Deubel & Schneider, 1996; Hoffman & Subramaniam, 1995; Krajbich et al., 2010; Krajbich, Hare, et al., 2015; Leong et al., 2017; Rehder & Hoffman, 2005), we could link parameters extracted from diffusion models to observable online behavior during the period of choice. This connects biases observed in the models (e.g., a steeper drift slope for amount information) to potential heuristics observed in eye movements (e.g., attribute-wise transitions between amounts).

Third, our large sample size and replication strategy allowed us to make strong claims about inter-individual variability in patience. We showed, for example, that the overall biases toward amount information in drift slope and latency are modulated by participants' preferences, with more patient individuals showing more bias toward amount information. While our study focused on young adults, expanding this understanding of inter-individual variability in the mechanisms of intertemporal choice will be particularly important for studies of groups characterized by excessively impatient choices (e.g. people with addiction (Bickel et al., 2014)).

Our modeling results revealed a strong bias toward an attribute-wise comparison process, rather than an integration of attributes within a choice option. Importantly, our eye tracking data indicated that this bias was not universal; there is not one best-fitting approach, but rather both attribute-wise and option-wise strategies may be employed in different contexts, with substantial individual variability. This result builds upon the similar finding (using mouse-tracking methods) from Reeck and colleagues (2017); we extend their results by showing that the attribute-wise model fits best for those at the most patient end of the spectrum whereas the option-wise model fits better for those who are less patient. Moreover, Wulff et al. (2017) have suggested that specifics of the modeling can influence the dominance of attribute-wise vs. option-wise models. Indeed, while the relationship between modeling and eye tracking is as expected, many of our participants show a small positive (option-wise) bias in their eye tracking. More research is needed to confirm the underlying psychological mechanism, particularly for participants with no extreme measurable eye tracking bias who likely look at all information on the screen. Further experiments could extend a display to include more options as has been done in risky decision-making (Böckenholt & Hynan, 1994; Schulte-Mecklenbeck, Kühberger, Gagl, & Hutzler, 2017) to explore whether clearer patterns of information gathering develop. Therefore, while the attribute-wise computational model fits better overall, individuals may still differ in the mechanisms by which they make these choices, given the clear individual differences both in choice behavior and in processes of information acquisition.

High-patience individuals showed a striking – and potentially counterintuitive – pattern of behavior. Rather than exhibiting a slow and analytic comparison process that integrated all available information, they tended to employ a heuristic strategy of directly comparing amounts and choosing the larger. In contrast, low-patience individuals showed a more balanced process of examining both amounts and times, as evident in gaze tracking and model parameters. This combination of results – with patient decisions arising from heuristics, and impatient decisions arising from a more analytic comparison process – seems counter to rational choice models. However, it echoes previous findings in other choice domains that point to the use of heuristics as a characteristic feature of effective decision making (Gigerenzer, Czeslinski, & Martignon, 1999; Gigerenzer & Gaissmaier, 2011; Kwak et al., 2015; Venkatraman, Payne, Bettman, Luce, & Huettel, 2009). Interventions to promote patience by encouraging analytic integration of outcome attributes might not be effective, accordingly. Instead, patient decisions might be nudged through interventions that encourage comparison of amounts, rather than times to delivery, which could be considered a "cost" or "penalty" (Radu et al., 2011; Wittmann & Paulus, 2008; Zhao et al., 2015). Attentional manipulations may be particularly effective for decisions involving relatively short periods of time until reward delivery; in such cases, attention toward the time component increases the number of smaller, sooner choices (Ebert & Prelec, 2007; Fassbender et al., 2014; Radu et al., 2011). While our study cannot disentangle whether attentional bias itself drives choice or whether some underlying preference drives both attentional biases and choices, research showing a positive feedback loop between attention and preference (i.e., the gaze cascade effect) suggests that even externally directing attention can influence choice (Mullett & Stewart, 2016). Future interventions could provide strong tests of the directionality of our effects by attempting to force the "patient" attentional patterns we observed.

Our results do not obviate conclusions derived from simpler models that assess individual differences in behavior. The commonly used hyperbolic model assumes a relatively steeper discount curve for immediately available rewards, while the beta-delta model explains temporal variability in discount rates through separate parameters for relatively immediate and for relatively distal rewards (Ainslie, 1975; Laibson, 1997; Mazur, 1987; McClure, Laibson, Loewenstein, & Cohen, 2004). Each of these approaches explains dynamic inconsistencies in behavior (e.g., preference reversals with the passage of time) while also being measurable through simple survey or laboratory experiments (Thaler, 1981). We emphasize that for diagnostic tests in the field or in clinical settings, such simpler measures that are restricted to choice behavior will often be preferable to the more complex models used in our analyses (Andreoni, Kuhn, & Sprenger, 2015). We use modeling and eye tracking to better understand the attentional processes underlying the mechanisms of intertemporal choice – and where those mechanisms might be incompletely specified by behavioral models (e.g., the limitations of option-wise integration, as assumed by both hyperbolic and beta-delta models). The resulting insights into mechanism could in turn generate new hypotheses for future research and provide markers that could be studied in other populations.

Because both this study and others (Lim, Penrod, Ha, Bruce, & Bruce, 2018; Sullivan et al., 2015) have found that attributes processed more rapidly have an overall advantage in choice, interventions intended to encourage patient choices could draw attention to amount information before time information (e.g., via sequential presentation or a manipulation of stimulus salience) (Armel et al., 2008; Kunar, Watson, Tsetsos, & Chater, 2017; Pärnamets et al., 2015; Shimojo et al., 2003; Tavares, Perona, & Rangel, 2017). Similarly, to facilitate attribute-wise transitions during the process of choice, amounts could be placed closer to each other and further from time information to encourage attribute-wise processing, or information could be revealed in a step-wise manner that promotes attribute comparison (Bettman & Kakkar, 1977; Jang & Yoon, 2016; Johnson et al., 1988; Kleinmuntz & Schkade, 1993; Reeck et al., 2017; Reutskaja et al., 2011; Schkade & Johnson, 1989; Schkade & Kleinmuntz, 1994). For example, Reeck et al. (2017) were able to shift strategies toward attribute-wise (or option-wise patterns) by changing the speed of revealing key information based on the transition pattern used and thus reduce (or increase) discount rates (Reeck et al., 2017). Future work should investigate what factors predict whether an individual can flexibly shift decision strategies (e.g., the pattern of information acquisition) across contexts. Also important for interventions will be extensions to impatience in other domains such as primary food rewards, health outcomes, and even environmental consequences (Bruderer Enzler et al., 2014; Hardisty & Weber, 2009; Jimura et al., 2011; Tsukayama & Duckworth, 2010).

Our sample included relatively few people at the extreme end of impatience, which limits our ability to extend our claims to all populations (e.g., individuals with pathologically impatient choices, as in addiction). We hypothesize, however, that a different heuristic, attribute-wise approach may also be utilized in extremely impatient people who compare options according to their time-to-delivery attribute instead of their amounts. If that result were observed, there would be a quadratic relationship between response time and patience. Some evidence in our data supports this hypothesis; in our larger primary sample, which has more extremely impatient individuals, this relationship is best fit by a quadratic curve. However, this conclusion must be tempered because our replication sample does not have a sufficient number of extremely impatient individuals to confirm this finding. Future experiments could test the shape of this relationship with varying stimuli and across a larger sample with people with more diverse socioeconomic backgrounds and in populations known to be at the more extreme end of impatience. Such an approach could show that extreme discounters fall along the continuum of information-gathering patterns we observed or could find that those individuals employ an entirely different pattern altogether.

Another limitation of our study is that we allowed some stimulus information to vary (SS amount and LL delay) while keeping other information constant across trials. While one might hypothesize that participants would attend primarily to information that varies across trials, our eye-tracking results show that participants still used all information on the screen and made very few diagonal transitions between the cells with variable information. This suggests that attention was not driven by novelty or salience but instead by the information carried by each attribute, similar to prior research (Lempert et al., 2015; Reeck et al., 2017). Future experiments could manipulate additional features of the display, in order to evaluate whether reported moderators of choice behavior (e.g., the magnitude of the later reward) have concomitant effects on the patterns of attention. Dai & Busemeyer (2014) found that an attribute-wise model could account for variations in stimuli such as the magnitude effect, although that conclusion about choice behavior has not yet been accompanied by process-tracing data (Dai & Busemeyer, 2014). Furthermore, it would be interesting to test how the frequency of attractive LL or SS options for a given individual's discount rate affects their attentional strategies and response times (Krajbich, Bartling, Hare, & Fehr, 2015).

Temporal discounting has a profound influence on overall well-being and life outcomes –and interventions to encourage intertemporal patience could have a significant impact in many life domains. Both behavioral work and neural findings have suggested that working memory may be involved in choosing delayed options, and that training this skill may improve choice (Bickel, Yi, Landes, Hill, & Baxter, 2011; Bjork, Momenan, & Hommer, 2009; Hare, Hakimi, & Rangel, 2014; Shamosh et al., 2008). In addition, time perception, positive episodic prospection, and concreteness of future events can influence intertemporal patience (Ersner-Hershfield, Garton, Ballard, Samanez-Larkin, & Knutson, 2009; Hershfield, 2011; Lempert, Speer, Delgado, & Phelps, 2017; Peters & Büchel, 2010; Zauberman, Kim, Malkoc, & Bettman, 2009). Finally, framing choices using default options, directing attention to options or attributes or tradeoffs can shift choices (Lempert & Phelps, 2015; Radu et al., 2011; Read, Frederick, Orsel, & Rahman, 2005; Read et al., 2013; Reeck et al., 2017; Weber et al., 2007). Our results are consistent with this last category, in that we show that factors that shape attention also influence selective parameters of the choice process – leading to more patient or impatient choices. These results could direct new interventions (e.g., modulations of attention that lead to heuristic choices) to help individuals focus more on the benefits of future rewards rather than the cost of waiting for these rewards. Through a better understanding of the underlying mechanisms of intertemporal choice, interventions that work for financial decision making could potentially be extended to improve choices across many contexts.

3. Individual differences in the use of variable budget information in consumer choices

This work was completed in collaboration with Scott Huettel and Jack Dolgin.

3.1 Introduction

Understanding how people make decisions about saving and spending behavior is crucial to improving economic well-being. A survey by the Federal Reserve found that 44% of adults in the U.S. couldn't come up with $400 to cover an emergency expense (Board of Governors of the Federal Reserve System, 2017). This may be due in large part to structural barriers impeding economic mobility, but psychological biases in decision-making such as treating small windfalls as spending money and larger windfalls as savings can also factor into choices like impulse purchasing that can affect savings over time (Bertrand et al., 2006; Madrian et al., 2017). Therefore, probing the underlying decision processes that bias choices toward saving or spending is imperative for providing people who want to change their spending habits with the tools to do so within their financial situation. In this study, we explore how budgets can be used as a mental accounting strategy in item valuation and subsequent purchasing decisions for non-necessity items. Further, we examine the individual differences in information gathering across those who modulate their purchasing decisions based on budget size and those who do not.

3.1.1 Mental accounting

One prominent and well-documented decision strategy that can influence saving and spending habits is mental accounting (Kahneman & Tversky, 1984; Thaler, 1985; Thaler et al., 2000; Tversky & Kahneman, 1981). Mental accounting is the cognitive process by which people segment money into non-fungible categories, such as separate food, rent, and entertainment budgets. Rather than integrating earnings, assets, and spending into one overall wealth calculation, people tend to experience increases or decreases in wealth relative to a reference point and code changes differently depending on their assigned "mental account" (Kahneman & Tversky, 1979; Thaler et al., 2000). Moreover, people view their assets and wealth separately from their income, where income has an outsized effect on consumption decisions (Shefrin & Thaler, 1988). The findings of mental accounting behavior suggest that people do not spread wealth across their lifespan or perfectly allocate to each category as would be expected by traditional economic theories on lifespan spending behavior (Friedman, 1957; Modigliani & Brumberg, 1954; Shefrin & Thaler, 1988; Thaler, 1990). Mental accounting better represents the typical process of savings and spending, and it can simplify choices to streamline complex decision-making, so understanding how mental accounting affects saving and spending decisions is important for framing financial decisions strategies.

Mental accounting can explain diverse spending and savings habits, both overspending and underspending relative to overall wealth. One of the pitfalls of mental accounting is that people may overspend on “exceptional” large expenses compared to those that fit into a typical category (Heath & Soll, 1996; Sussman & Alter, 2012). Further, people are better at accounting for unexpected expenses when thinking about their budget for an entire year compared to expenses on a monthly basis, likely because they focus typical expenses in their monthly estimation (Ülkümen, Thomas, & Morwitz, 2008). Mental accounting can be used to justify overspending by finding loopholes in one’s own category system (Cheema, 2006). Mental accounting may also cause people to “double” discount promotional credit, both when they initially buy an item and when they use the credit, leading to overspending compared to an equivalent discount (Cheng & Cryder, 2018). Despite these potential pitfalls, mental accounting can also be harnessed as a self-control device to limit spending (Thaler et al., 2000). People are unlikely to over-spend within a strict budget category, particularly for items that are typical of the category (Heath & Soll, 1996; Thaler et al., 2000). For example, splitting savings into two envelopes instead of one helped unbanked households save more, particularly when that money was labeled as for their children (Soman & Cheema, 2011). Mental accounting is a commonly used strategy that can help simplify choice and, depending on the categories of spending used and their flexibility, enable impulsive spending or help reduce spending (Zhang & Sussman, 2018).

3.1.2 Impulse purchasing

Another important factor that interacts with mental accounting and can undermine savings is impulse purchasing. Impulse purchasing is the act of buying something without planning, typically a non-necessity that the buyer will later regret (Rook & Fisher, 1995). Impulse purchasing can be influenced by many factors including individual differences in impulsivity or propensity toward shopping. Impulse purchasing can also be influenced by the type of item being purchased (practical vs. luxury). Furthermore, the shopping context can have a large effect, including factors such as time available, budget, promotions, and social context (Amos, Holmes, & Keneson, 2014; Beatty & Ferrell, 1998; Bhakat & Muruganantham, 2013; Inman, Winer, & Ferraro, 2009; Xiao & Nicholson, 2013; Youn & Faber, 2000). Some contextual factors such as store layouts and promotions are not controlled by the consumer, but contextual factors such as budget can be determined by the consumer and harnessed to promote savings or spending.

Mental accounting can frame budgets or perceived money available in a way that can either restrict or enable impulse purchasing. For example, windfalls—money that is not anticipated or earned—can justify impulse purchasing if relatively small or reduce spending if relatively large (Shefrin & Thaler, 1988). This is because larger windfalls are more likely to directly be integrated as assets with a very low marginal propensity to consume, whereas smaller windfalls are viewed outside of typical mental accounts and thus have a higher marginal propensity to consume. Therefore, in the face of a relatively small windfall, people are more likely to spend their windfall money on goods that are more luxurious than those they would purchase given an equivalent increase in income (Arkes et al., 1994; Milkman & Beshears, 2009; Thaler, 1985). For example, in one study, people spent more money and bought atypical, higher-quality items after receiving an online grocery coupon (Milkman & Beshears, 2009).

3.1.3 Anchoring value

Another important factor in purchasing is the construction of value when people evaluate the worth of an item. Value for an item can be elicited by asking for the maximum amount a person is willing to pay for a given item using an auction procedure that incentivizes a precise estimate, penalizing over- or under-bidding (Becker, DeGroot, & Marschak, 1964). While this procedure is useful, psychology and neuroscience research has found that people construct their value for a given item based on a combination of preferences, experience, and context. Therefore, item value is not consistent, and value can be susceptible to influences such as anchoring.

Anchoring is the process by which a random number can act as a starting point for an unrelated estimate, biasing the resulting value (Tversky & Kahneman, 1974). For example, an anchor such as the last two digits of a social security number is uninformative for valuation, but simply asking whether an item is worth more or less than the dollar value of those two digits can bias willingness to pay (WTP) toward that anchor (Ariely et al., 2003). Many studies have shown that WTP can be influenced by random anchors, particularly when they are near a person's average WTP (Ariely et al., 2003; Chapman & Johnson, 1994; Tymula et al., 2016). Furthermore, while most anchoring involves asking for a direct comparison process of the anchor and value being calculated, some researchers have even found an anchoring effect with incidental presentation, although this is sensitive to whether it is attended and its proximity to the target of valuation (Brewer & Chapman, 2002; Critcher & Gilovich, 2008; Wilson, Houston, & Etling, 1996; Wong & Kwong, 2000). For example, incidental prices within a catalogue or store can increase or decrease willingness to pay for other items in the vicinity depending on whether the anchor is high or low (Krishna, Wagner, & Yoon, 2006; Nunes & Boatwright, 2004). This has also been shown to work in marketing to influence WTP by using numbers anchors in the names of brands or products to influence their valuation (Dogerlioglu-Demir & Koças, 2014, 2015). This incidental anchoring effect seems to be stronger for items with a weaker internal reference price, and anchoring does not affect the relative value of items, but it nevertheless is an important factor in item valuation (Ariely et al., 2003; Dogerlioglu-Demir & Koças, 2014).

3.1.4 Present research hypotheses

In the research presented here, we investigate how people use budget information to inform their purchasing choices for a variety of non-necessity items. We looked at how budget size affected willingness to buy items priced near each individual's willingness to pay for that item. We also sought to better understand individual differences in the use of budget by characterizing the information gathering processes across individuals as measured by eye tracking. This research can elucidate why some people are more susceptible to mental accounting and when it can be useful to promote savings or when in backfires to enable impulse choices. Moreover, characterizing the mechanisms underlying mental accounting can be used as a starting point to generate strategies that can strengthen or weaken its effect.

In our study, participants are paid an additional bonus based on one choice from the experiment. Thus, given the mental accounting literature, we expect that budgets in this study will be treated as a small windfall and the budget size will have an influence on purchasing, particularly for items that are liked more. We test whether budget matters in choice and whether this effect is due purely to incidental anchoring by budget size or the use of the budget as a mental account:

H1a: Higher budgets increase the likelihood of purchasing, even for the same items.

H1b: There is an interaction such that higher budgets have more of an effect on purchasing for items with a higher WTP.

H1c: Anchor numbers with no direct impact on payoff but with the same values as budget do not affect purchasing behavior.

In addition to budget effects, we examine the choice processes underlying purchasing behavior and the use of budget. Response times indicate deliberation and may be longer for more difficult or more conflicted choices. Because smaller budgets constrain purchasing, people should be slower to make purchasing decisions at smaller budgets and relatively faster to choose to purchase at higher budgets. In addition, we looked at how response times related to individual differences in impulse purchasing because whichever choice is more common is likely to be faster (Krajbich, Bartling, et al., 2015).

H2a: Response times are overall faster for skipping compared to buying.

H2b: There is an interaction between purchasing and budget such that response times are slower for buying items at a lower budget compared to a higher budget.

H2c: The difference in response times to buy vs. skip correlates with purchasing rate. Those who purchase the least take much longer to buy vs. skip whereas those who purchase the most show less of a response time gap in buying vs. skipping.

Another important process measure of decision-making is eye tracking. In this study, we characterize different gaze patterns to determine which looking patterns distinguish those who use budget from those who do not.

H3: There are different overall scan paths for people who use budget more or less in their decision-making and depending on whether people buy or skip on a given trial.

H3a: People who modulate purchasing more by budget look more at the budget AOI.

H3b: People who modulate purchasing more by budget make more transitions between the budget and price AOIs.

H3c: People show different overall patterns across buying vs. skipping, with less consideration of price and budget in skip trials.

Finally, we examine not only individual differences, but also trial-level differences to explore how trial-to-trial looking patterns could influence choice. We also look at how information on the screen and choice drive looking behavior.

H4a: There is an interaction such that looking more at the budget AOI increases the effect of a higher budget on the likelihood of purchasing.

H4b: Looking more at the item AOI decreases the likelihood of purchasing (whereas looking at budget or price increases it).

H5: Buying an item leads to more looking at budget and price and less looking at the item. Higher budgets increase looking at budget when an item is bought, and higher prices increase looking at price information when an item is bought.

3.2 Methods

3.2.1 Participants

3.2.1.1 Sample size and characteristics

We chose a target sample size of 70 for our primary and replication samples from on a power analysis based on Knutson et al., 2008. We chose a target sample size of 60 in our anchoring control sample based on a power analysis of our primary sample budget effect. Our age range of interest was 18-25 as we were specifically interested in young adult financial decision-making. All participants were recruited from the Durham, NC and Duke University communities and provided informed consent under a protocol approved by the Institutional Review Board of Duke University.

3.2.1.2 Primary sample

We recruited 139 participants for our pre-survey. 76 (mean age = 21.3, SD = 2.5; 51 female) of those participants passed our eligibility criteria for the laboratory experiment. Of those 76, 71 participants had eligible eye tracking data and 5 had to be excluded for poor calibration or poor overall tracking.

3.2.1.3 Replication sample

We recruited 99 participants for our pre-survey. 56 of those participants passed our eligibility criteria for the laboratory experiment (mean age = 21.7, SD = 2.2; 41 female). Of those, 42 participants had eligible eye tracking data and 14 had to be excluded for poor overall tracking.

3.2.1.4 Anchoring control sample

We recruited 104 participants for our pre-survey, 58 of whom passed the laboratory experiment eligibility criteria (mean age = 21.2, SD = 2.2; 38 female). Of those, 55 had eligible eye tracking data and 3 had to be excluded.

3.2.2 Procedure

Participants gave informed consent followed by an online eligibility survey. Those who were eligible came into lab approximately a week after the pre-survey and decided whether to buy consumer items at a given price and budget while their eyes were being tracked. After the laboratory task, participants completed surveys including the Impulse Buying Tendency measure, the Abbreviated Barratt Impulsivity Scale (ABIS), and the Consideration of Future Consequences (CFC) survey. Participants also answered questions about their strategy in the task.

3.2.3 Task

In the eligibility pre-survey, participants bid their willingness to pay for 90 non-necessity consumer items through a Becker-DeGroot-Marschak (BDM) procedure (Becker et al., 1964). Participants were informed that the budget range would be $10-$40, but the specific budget was not specified.

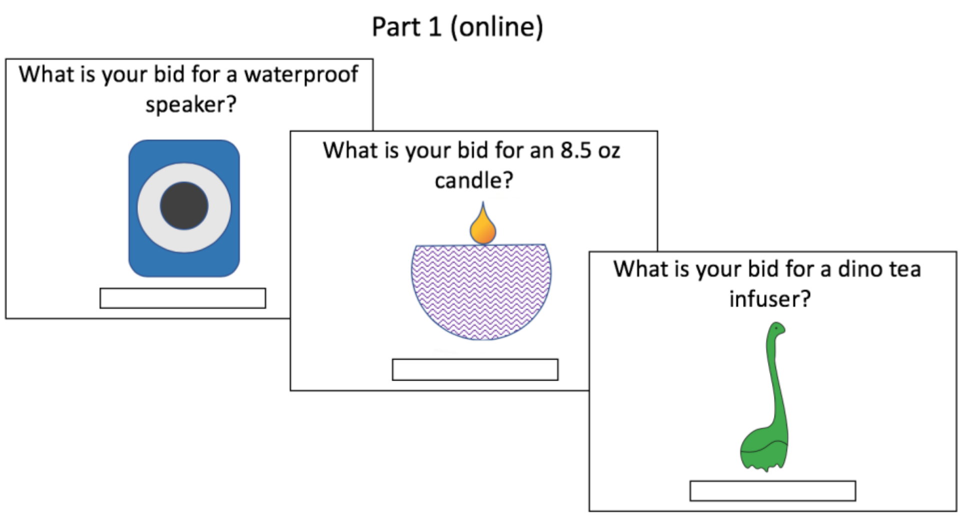

Figure 6: Variable budget pre-survey. Participants read instructions for an incentive-compatible BDM-auction. If they passed comprehension questions indicating understanding of the auction procedure, they entered their willingness to pay for 90 consumer items in an online pre-survey. Participants who had at least 30 non-zero bids continued to the lab experiment.

In the laboratory study, participants completed 120 trials, choosing on each trial whether to buy or skip an item for a given price and a given budget. The 30 items with the lowest bids from the pre-survey were dropped, and the top 60 were kept for the laboratory survey. The budgets were $10, $20, or $40. There were two rounds of the experiment with each of the 60 items seen twice. On half of the repeat trials, the items changed budget from the first to second round (half of these increased budget; half decreased) and half had the same budget. Participants were informed that the budget might change in round 2. Most items were assigned a price within $1 of the WTP, and prices did not change from the first to the second round. Items for which the WTP was over $10 were assigned a price between $8-10 as we wanted all prices to be within all budgets (less than $10). In addition, prices under $2 were randomly assigned a price from $1-$10 to ensure that participants saw a variety of prices. Participants were not told that prices would be within $1 of their WTP. Item information was always displayed in the center of the lower half of the screen. Budget and price information were spaced out in the top half of the screen, with either budget or item always on the left or right, randomized across participants.

The tasks were incentive compatible; a bonus trial was drawn from either the pre-survey or the lab study. If the pre-survey was selected, a random item, a random price from $1-10 and a random budget from $10-40 were selected. If the participant's bid was below the random price, they would just get the budget; if their bid was equal to or higher than the price, they would get the item and the leftover amount from their budget subtracting the experimental price. If a trial from the laboratory study was selected, that trial was paid out based on their choice. If they bought the item, they would get the item and leftover from the budget. If they skipped it, they would just get the budget amount.

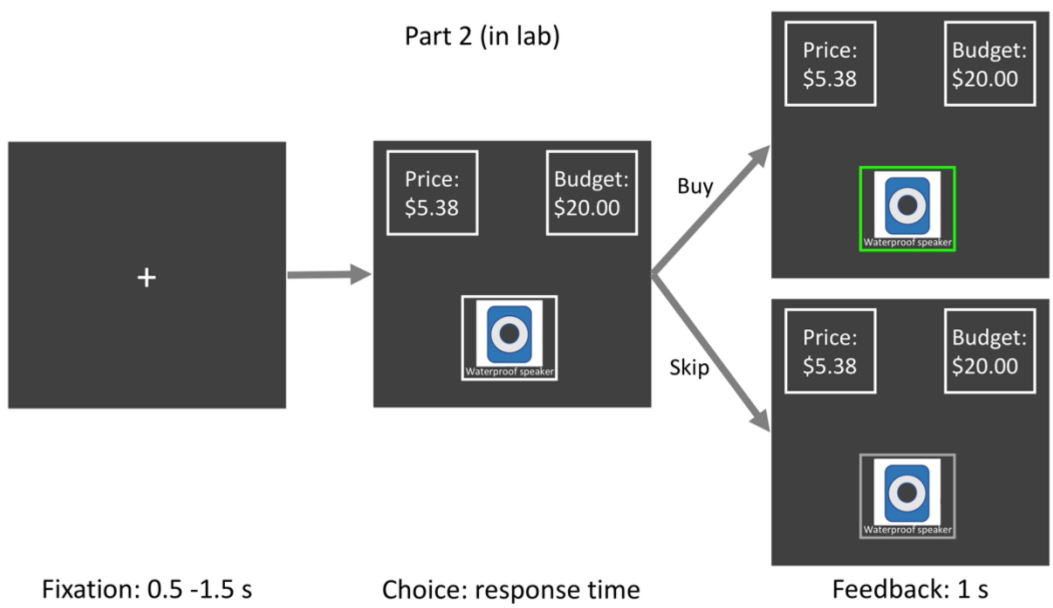

Figure 7: Variable budget eye tracking task. In part 2, participants came into the lab. In this part of the experiment, they saw 60 of the 90 items they rated from the pre-survey. For each trial, they chose whether to buy the item displayed for the given price and budget. They completed two runs of the experiment, seeing each item twice. Across runs, half of the budgets changed, but prices stayed the same.

The anchoring control experiment followed the same general procedures except that in the in-lab portion of the study budget was not indicated and instead there was a section labeled “other,” with the same values as the budget ($10, $20, or $40) but participants were told that these numbers had no effect on the outcome. Instead, they were informed that we would randomly selection a number from $10-$40 as their budget, but they wouldn't know this value until the end of the experiment. Whereas in the main budget task, budget and price were in stable positions on the screen, in this control experiment budget and price positions were randomized to the upper left or right of the screen across trials.

3.2.4 Eye tracking

We used a Tobii T60 eye tracker to collect eye gaze data. The eye tracker tracks pupil position using an unobtrusive infrared camera system without head fixation at a rate of 60 hz. We established areas of interest (AOIs) around the 3 key pieces of information present during choice (item, budget, and price). Each AOI was 346 by 346 pixels within the 1280 by 1024 total resolution of the screen.

3.2.5 Exclusion criteria

People who failed comprehension questions or bid $0 for 60 or more of the 90 items offered during the eligibility survey were not eligible for the laboratory study. Eye tracking exclusion criteria tests for poor eye tracking calibration (25% or more data points outside of AOIs during choice screen) or overall poor eye tracking (35% or more data points not identifiable by the Tobii eye tracker).

3.2.6 Analysis

We used mixed effects logistic regression to explore the effect of budget on purchasing. Our baseline model controlled for WTP and price as well as including individual intercepts. Our interaction model included an interaction between WTP and budget. To get individual differences in the effect of budget we used individual logistic regressions including budget, price, and WTP. For the effect of purchasing and budget on response time, we used a mixed effects linear regression including budget, price, WTP, and interactions between purchasing and budget and purchasing and WTP. For trial-by-trial analyses including eye tracking information we used mixed effects logistic regression to explore the effect of looking at an AOI on purchasing, separately for each AOI and including budget, price, and WTP. For trial-by-trial analyses predicting looking at AOIs, we used mixed effects linear regression splitting up trials by whether items were bought or skipped and including budget, price, and WTP.

3.2.6.1 Eye tracking indices

We calculated the proportion of time points spent looking at each AOI divided by the total fixation time in a given trial. We also calculated the proportion of gaze transitions between our AOIs relative to the total AOI transitions.

3.2.6.2 Scan path analysis

We split up scan path analysis by trials on which items were bought or skipped. The scan path analysis uses five primary steps to summarize individual average paths according to the process in (Eraslan, Yesilada, & Harper, 2016). In step 1, AOIs are coded and ranked by order in which they appear in a trial. In step 2, paths are filtered based on how frequently AOIs are viewed in all trials (with a threshold that they must be viewed in 70% of trials). In step 3, the length of viewing an AOI is compared with the length of viewing AOIs that met the threshold in step 2. AOIs that are viewed for at least as long as the minimum threshold are added. In step 4, AOIs are assigned a priority value based on the order in which they were viewed in each trial. Finally, in step 5 individual scan paths are grouped by similarity.

3.3 Results

3.3.1 Budget effect

We first investigated whether budget size affects the willingness to buy a variety of consumer items. We found that increasing budget does increase the overall proportion of items bought from ~25% for a $10 budget up to ~50% for a $40 budget (Figure 8). Moreover, budget increases the likelihood of purchasing a given item even when controlling for individual baseline purchasing rate, price, and willingness to pay in a mixed effects logistic regression (Table 1). In addition, WTP has a positive effect on purchasing, with items more likely to be purchased if they have a higher WTP. Similarly, price has a negative effect on purchasing, with relatively higher prices decreasing the likelihood of purchasing a given item.

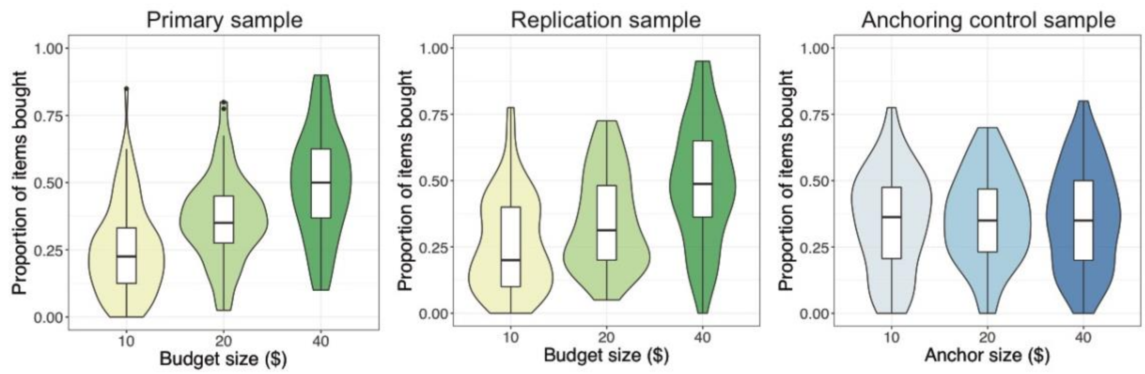

Figure 8: Purchasing rates change with budget size but not anchor size.

We tested the limits of our budget (as well as WTP and price) effects by controlling for other factors. First, because only half the items changed budgets from the first to second round of purchasing decisions, we tested this subset of items excluding those that didn't change budget. With this restricted data set, we still find that budget has an effect (Appendix B). This means that within an hour timespan, people change their willingness to buy based on a varying budget for the same items--the effect was not simply driven by different budgets on different items. In addition, we also restricted the model to items with prices within $1 of the willingness to pay. Many items were within this category, but items with very low bids or very high bids over $10 were assigned prices outside of the $1 range, so these were excluded. With this restriction to items with WTPs in this middle range (near the individual's indifference point), we still found a similar budget effect. One notable difference about this regression is that price has a much larger, negative coefficient than the baseline and item-controlled regressions, suggesting that price near WTP does indeed have a large effect on purchasing decisions.

In the replication regression including all items, the coefficient on price is small and positive, likely driven by items with a high willingness to pay above the maximum $10 price. In this restricted regression, the coefficient on price is negative for all samples, suggesting that price does have a negative effect, but that it may be masked by the effect of higher WTPs in the non-restricted sample.

Table 1: Logistic regression predicting purchasing

	Baseline: Primary	Baseline: Replication	Baseline: Anchoring	Interaction: Primary	Interaction: Replication
Fixed effects: Estimate (Std. Error)					
Intercept	-0.64*** (0.10)	-0.67*** (0.09)	-0.72*** (0.02)	-0.63*** (.010)	-0.66*** (0.13)
WTP	1.10*** (0.05)	0.79*** (0.06)	1.71*** (0.04)	1.13*** (0.05)	0.84*** (0.06)
Price	-0.22*** (0.04)	0.09* (0.04)	0.08*** (0.03)	-0.23*** (0.04)	0.06 n.s. (0.04)
Budget (Anchor)	0.51*** (0.02)	0.49*** (0.03)	0.02 n.s. (0.02)	0.51*** (0.02)	0.49*** (0.03)
WTP x Budget				0.12*** (0.03)	0.17*** (0.04)
Random effects: Variance (Std. Dev.)					
Subject ID	0.67 (0.82)	0.85 (0.92)	1.43 (1.20)	0.66 (0.81)	0.86 (0.93)
Obs., Groups	9120, 76	6720,56	6960,58	9120, 76	6720,56
BIC	10248.0	7654.2	7762.3	10243.3	7642.7

Significance is indicated by * $p < .05$, ** $p < .01$, *** $p < 0.001$

Finally, we tested whether a numerical anchor instead of budget would have a similar effect on purchasing. Seeing an incidental larger number on the screen could anchor people to a higher price and increase willingness to buy, accounting for some of the effect of budget (Critcher & Gilovich, 2008; Dogerlioglu-Demir & Koças, 2015). Alternatively, the influence of budget may be due to its mental accounting relevance such that people care about the amount left over after purchasing or the ratio of budget to price. We found no effect of our numerical anchor on the proportion of items bought, with a constant purchasing rate of ~35% for all levels of anchor. This purchasing rate suggests that participants purchased at a rate in between the extremes of the budget range. This further confirms that budget size is meaningful beyond incidental anchoring, and it is the additional relevance that causes shifts in likelihood of purchasing.

While there is an overall effect of budget, it is not clear whether there are certain items more likely to be affected by higher budgets. We investigated this by looking at the interaction of budget and willingness to pay in order to determine whether an increased budget increases the likelihood of purchasing for all items equally or for certain items more than others. If budget affects items unequally, it could be that items with a lower WTP are more likely to be bought because items with a high WTP are bought even at lower budgets. Alternatively, it could be that only items with higher WTPs are influenced by higher budgets because the lower WTP items are generally undesirable. We found a positive interaction meaning that as budget increases, there is a greater effect of WTP on purchasing likelihood. This suggests that participants were more likely to increase their willingness to buy (and, implicitly, willingness to pay) for items for which they already had a high willingness to pay. Therefore, higher WTP items that were already viewed as desirable may not have been purchased at lower budgets because of mental accounting-imposed self-control but could be viewed as more accessible at a higher budget. This result does not hold for the control analyses, which may be due to the fact that higher-value items over $10 are excluded when items are restricted to within $1 of WTP, or it could be due to reduced power in these restricted analyses.

3.3.2 Response time

To investigate the effect of budget on the decision process, we examined how response time changes as a function of budget for items that were bought or skipped. Plotting response time as a function of purchasing and budget (Figure 9) shows that a lower budget slows the decision to purchase compared to higher budgets.

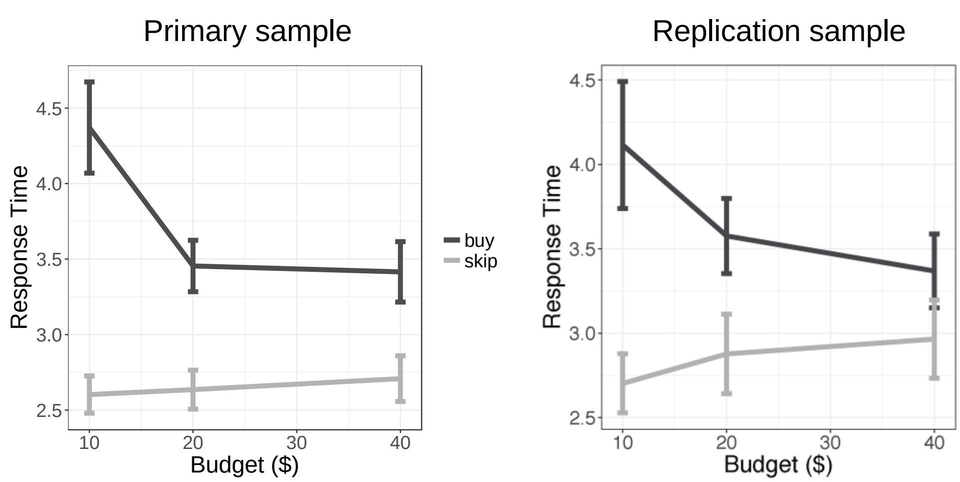

Figure 9: Response time as a function of purchasing and budget. Response times are slower to buy than to skip, but higher budgets lead to relatively faster buying decisions.

A mixed effects linear regression of response time on budget and purchasing, controlling for WTP, Price, and individual intercepts shows that higher budgets decrease response time for buying (Table 2). Overall, people are much slower to buy than to skip (t-test: buy = 3.6 s, skip = 2.6 s, t(132.6) = 4.25, p = $4.0*10^{-5}$, 95% Cl = 0.50 - 1.37; replication: t-test: buy = 3.6 s, skip = 2.8 s, t(107.1) = 2.64, p = 0.009, 95% Cl = 0.20 - 1.38), but they are faster to buy items with higher WTPs and higher budgets. This suggests that while buying is slower overall, factors including budget and desirability of the item increase the speed of the decision to purchase it.

Table 2: Linear regression of response time

	Primary	Replication
Fixed effects: Estimate (Std. Error)		
Intercept	2.26*** (0.16)	2.17*** (0.22)
WTP	0.03*** (0.005)	0.02** (0.005)
Price	$0.0003^{n.s.}$ (0.012)	0.05*** (0.015)
Budget	$0.003^{n.s.}$ (0.002)	0.006* (0.003)
Buy	1.70*** (0.12)	1.49*** (0.15)
WTP*Buy	-0.05*** (0.005)	-0.03*** (0.006)
Budget*Buy	-0.02*** (0.004)	-0.02*** (0.005)
Random effects: Variance (Std. Dev.)		
Subject ID	1.08 (2.19)	1.36 (2.26)
Obs., Groups	9120, 76	6720, 56
BIC	40506.2	30329.2

Significance is indicated by * p < .05, ** p < .01, *** p < 0.001

3.3.3 Individual differences

In addition to a main effect of budget across participants, we were interested in how individual differences in attentional patterns of information gathering related to the budget effect on purchasing. In order to examine individual differences, we ran separate logistic regressions for each participant to get their individual coefficient on budget. We then transformed this to an odds ratio which indicates the multiplicative increase in likelihood of purchasing. An odds ratio of one indicates no change, whereas an odds ratio above one indicates increasing likelihood and an odds ratio below one indicates decreasing likelihood. Most participants show a positive odds ratio confirming that increasing budget increases the likelihood of purchasing. However, there is also substantial variability indicating that the strength of this effect varied widely across individuals. We tested whether budget use related to overall purchasing rates and found no correlation ($t = -0.32$, $r(74) = -0.04$, $p = 0.75$, 95% CI = -0.26, 0.19; replication: $t = 0.81$, $r(54) = 0.11$, $p = 0.42$, 95% CI = -0.16, 0.36), suggesting that budget does not necessarily promote impulse spending or reduce it; rather, small budgets can constrain spending, but large budgets may enable spending.

We used eye tracking gaze measures as a representation of information gathering. We first examined the relationship between the use of budget behaviorally and the proportion of time spent looking at budget information. As hypothesized, there is a correlation such that people who use budget more (based on their individual budget odds ratio) are more likely to spend a greater proportion of time looking at the budget information while making their purchasing decisions ($t = 3.63$, $r(69) = 0.40$, $p = 0.0005$, 95% CI = 0.18, 0.58; replication: $t = 2.13$, $r(40)= 0.32$, $p = 0.040$, 95% CI = 0.02, 0.57) whereas those who spend a higher proportion of time looking at the item are less likely to incorporate budget into their purchasing decisions. In addition to time spent looking at the areas of interest (AOIs), we were interested in the types of information comparisons being made prior to the decision. In order to index transitions, we looked at the relative proportion of budget-price transitions compared to budget-item and item-prices transitions. We found that a greater proportion of budget-price AOI transitions (but not budget-item AOI transitions) correlated with the budget odds ratio in the primary sample, but is not significant in the replication sample ($t = 4.04$, $r(69) = 0.44$, $p = 0.0001$, 95% CI = 0.23, 0.61 ; replication: $t = 1.42$, $r(40) = 0.22$, $p = 0.16$, 95% CI = -0.09, 0.50). This result suggests that those who use budget may use a comparison process of the difference or ratio between price and budget whereas others focus more on the value of the item; however it is not fully supported.

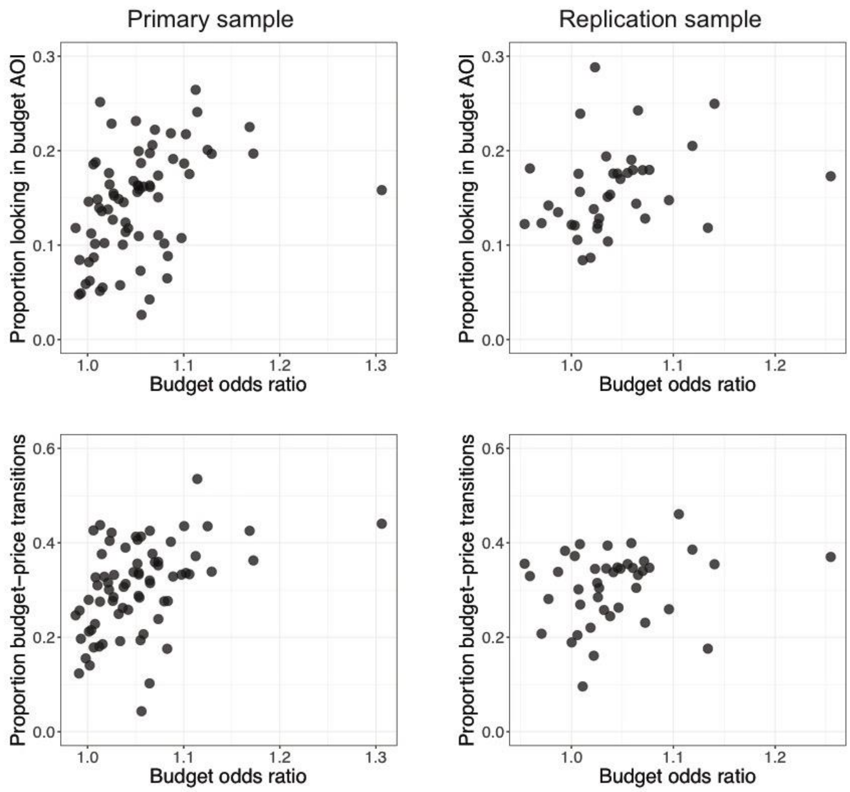

Figure 10: Correlations between budget use and eye tracking patterns. The budget odds ratio correlates with the proportion of time spent looking in the budget AOI in both samples. The budget odds ratio correlates with the proportion of budget-price transitions in the primary sample, but not in the replication sample.

We also explored more complex information about the order of information gathering using a scan path analysis to enable us to characterize differences in the dynamics within trials. We used scan path trend analysis that summarizes average scan paths for each individual, splitting up trials on which participants bought or skipped items (Eraslan et al, 2016). Figure 11 shows the results of our scan path analysis, with at least 5 participants per path in the primary sample and at least 4 participants per path in the replication sample. The color indicates average budget use and the line thickness indicates the number of participants in that group. From this scan path analysis, it is clear that on skip trials, most people start a trial looking at the item and often make their decision to skip without any further information. Others follow that by looking at price with only a subset looking at budget. For purchasing, there is a wider variety of scan paths with more information gathered overall. Most people start the trial looking at item, then diverge in their path. Of those who use budget the most, there tends to be an item to price to budget looking pattern. While this illustrates trends in behavior, we investigate trial-to-trial dynamics in more depth in the following sections.

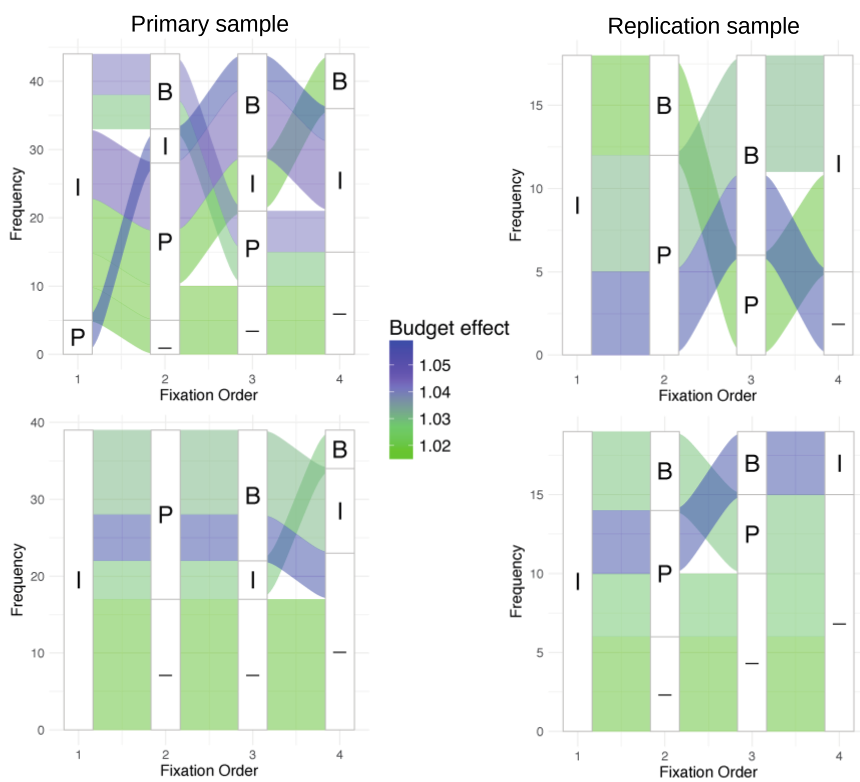

Figure 11: Scan path analyses separated by "buy" trial in the top row and "skip" trials in the bottom row. The AOIs are represented with "I" for item, "B" for budget and "P" for price. Color indicates the budget odds ratio.

We were interested in trial-level effects of attention on behavior. In order to examine this, we include the proportion of looking at an AOI in a trial-level logistic regression predicting purchasing (Table 3). We found that looking at the budget AOI increases purchasing, and there is an interaction such that more looking at the budget AOI enhances the budget effect. This means that looking more at higher budgets increases purchasing. In addition, looking at the price AOI has a positive effect on purchasing, but the interaction price and price AOI is negative for the primary sample, suggesting that looking at price has less of a positive effect for higher prices. This effect is not present in the replication sample, possibly because price has a positive effect on purchasing in the full sample (not restricted to prices within $1 of WTP). Finally, looking at the item AOI decreases the likelihood of purchasing. The negative effect of the item AOI may come from trials in which participants look only at an item and skip it compared to items that are more thoroughly considered including investigating price and budget information.

Table 3: Logistic regression predicting purchasing

	Budget AOI: Primary	Budget AOI: Replication	Item AOI: Primary	Item AOI: Replication	Price AOI: Primary	Price AOI: Replication
Fixed effects: Estimate (Std. Error)						
Intercept	-0.64*** (0.09)	-0.68*** (0.08)	-0.64*** (0.09)	-0.68*** (0.15)	-0.64*** (0.09)	-0.69*** (0.08)
WTP	1.07*** (0.05)	0.82*** (0.06)	1.08*** (0.05)	0.82*** (0.07)	1.08*** (0.05)	0.81*** (0.06)
Price	-0.20*** (0.05)	0.09* (0.04)	-0.21*** (0.04)	0.09[n.s.] (0.05)	-0.22*** (0.04)	0.09* (0.04)
Budget	0.51*** (0.03)	0.45*** (0.03)	0.51*** (0.03)	0.46*** (0.03)	0.52*** (0.03)	0.46*** (0.03)
Budget AOI	0.15*** (0.03)	0.12*** (0.04)	-	-	-	-
Budget x Budget AOI	0.20*** (0.03)	0.21*** (0.03)	-	-	-	-
Item AOI	-	-	-0.10*** (0.03)	-0.12*** (0.03)	-	-
Price AOI	-	-	-	-	0.17*** (0.03)	0.18*** (0.03)
Price x Price AOI	-	-	-	-	-0.08** (0.03)	0.02[n.s.] (0.03)
Random effects: Variance (Std. Dev.)						
Subject ID	9592.3	0.90 (0.95)	0.56 (0.75)	0.89 (0.94)	0.56 (0.75)	0.89 (0.94)
Obs., Groups	9592.3	5040,42	8520,71	5040,42	8520,71	5040,42
BIC	9592.3	5728.6	9663.9	5759.7	9635.1	5753.3

In addition to using looking information to predict purchasing decisions, we were interested in how the characteristics of the on-screen information and resulting purchasing decisions affected looking behavior on a trial by trial basis. Splitting trials by items that were purchased or skipped, we explored how WTP, price, and budget affected looking at each AOI (Table 4). Budget size had a positive effect on looking at budget for "buy" trials but a negative effect on looking at budget for "skip" trials, likely because people failed to look at budget as much on skip trials. In addition, WTP and budget size had a negative effect on looking at the item AOI for buy trials. This suggests that on "buy" trials with higher budgets, participants explored more information, reducing the proportion of looking time at the item AOI. Finally, price has a positive effect on looking at the price AOI, particularly when participants subsequently skip the item. This suggests that people may have considered price more thoroughly when it was higher and higher prices may have been a deterrent to purchasing. These findings support the idea that a higher WTP for an item increased exploration of other factors on the screen, and budget and price values did influence how much time people spent considering them in their decision making.

Table 4: Linear regression predicting looking at AOIs (Primary sample)

	Budget AOI Buy	Budget AOI Skip	Item AOI Buy	Item AOI Skip	Price AOI Buy	Price AOI Skip
Fixed effects: Estimate (Std. Error)						
Intercept	0.14*** (0.010)	0.13*** (0.009)	0.63*** (0.018)	0.61*** (0.016)	0.16*** (0.010)	0.15*** (0.009)
WTP	0.00001n.s. (0.0002)	0.0006* (0.0003)	-0.0009* (0.0004)	-0.0008n.s. (0.0004)	0.0005* (0.0002)	0.0007* (0.0003)
Price	0.0005n.s. (0.0009)	0.001n.s. (0.0008)	-0.004* (0.002)	-0.005*** (0.001)	0.002* (0.001)	0.004*** (0.0008)
Budget	0.0005*** (0.0001)	-0.0003** (0.0001)	-0.0008*** (0.0002)	0.0007*** (0.0002)	0.0002n.s. (0.0002)	-0.0003* (0.0001)
Random effects: Variance (Std. Dev.)						
Subject ID	0.05 (0.10)	0.06 (0.10)	0.10 (0.17)	0.12 (0.17)	0.05 (0.10)	0.06 (0.11)
Obs., Groups	3135,71	5385,71	3135,71	5385,71	3135,71	5385,71
BIC	-5411.5	-9034.7	-2046.2	-3337.1	-5075.0	-8110.7

Significance is indicated by * $p < .05$, ** $p < .01$, *** $p < 0.001$

3.4 Discussion

In this study, we show that there is an overall effect of budget on purchasing, with people purchasing more under higher budgets. We find that higher budgets in mental accounting can be used to justify higher spending even for non-necessity items, whereas lower budgets lengthen the decision process when people do choose to buy and also reduce overall purchasing. Despite this robust budget effect, there are large individual differences in the patterns of information gathering and in the use of budget. People who look more at budget and make more transitions between budget and price information are more likely to modulate their decisions by budget size. However, using a budget does not guarantee reduced spending—small mental budgets can help constrain spending and impulse purchasing, but larger mental budgets may invite or encourage frivolous spending.

We interpret the budget effect as mental accounting in which the budget size influences purchasing based on a comparison of budget and price. For example, because of diminishing marginal utility, spending \$5 from a \$10 budget may be perceived as a larger expense than spending \$5 from \$40 budget. Lab bonus money likely fits into the category of “small windfalls” with a higher marginal propensity to consume compared to income or larger windfalls, so we may find a larger effect than would be seen for income-based budgets (Arkes et al., 1994; Shefrin & Thaler, 1988). However, the budget values used are not outside of the range of many people’s budgets outside of the lab, and this controlled setting allows us to explore how mental accounting can be used to restrict or justify impulse purchasing. Moreover, even outside of the lab, when spending their own income, people use mental accounting to create their own budgets categories when shopping (Stilley, Inman, & Wakefield, 2010; Thaler, 1990). This adds to the literature suggesting that people can use mental accounts as a self-control device to shift their valuation of a product. One caveat of our findings is that we did not measure other financial factors such as socio-economic status. Monetary amounts from \$10-\$40 may have a very different meaning to people depending on their SES and this may drive their use of budget (Bertrand, Mullainathan, & Shafir, 2004; Shah, Shafir, & Mullainathan, 2015). Future studies should test whether the use of budget is stronger or weaker depending on socioeconomic status and other contextual factors that may enter into the decision process.

An alternative interpretation of our results could be that people enter the experimental setting expecting to leave with a certain amount of money and this constrains their purchasing at lower budgets. Participants may have an expectation of how much cash or leftover money they want from participating and anchor to that leftover target value. While we cannot entirely rule out this possibility, our study design employed four strategies to try to avoid this problem. First, people were paid a baseline amount and everything beyond this was framed as a bonus, so that base payment would be received no matter their purchasing choices. Second, the price of the item was always within the budget, so higher budgets never affected the ability to buy the item. Third, to reduce temporal discounting in the tradeoff between items and money, we paid the money portion of the bonus two days after the experiment so that it would arrive at the same time as an item ordered via Amazon. In this way, money did not offer a more immediate option than the item. Finally, all money was paid in Amazon gift cards rather than cash to reduce transaction costs and to reduce the immediacy of the ability to use that money. People are more likely to purchase luxury or hedonic items with a gift card compared to cash, so paying in Amazon gift cards may put people in a more purchasing-oriented mindset to help avoid them focusing on keeping a certain amount (Helion & Gilovich, 2014).

Importantly, we do not find that our budget effect results from incidental numerical anchoring. While budget has an influence on the process of value construction as evidenced by its influence on the decision to purchase, simply seeing a larger or smaller number on the screen does not affect purchasing rates. Indeed, part of this may be because people were not asked to compare that number to how much they would pay for an item or otherwise encouraged to make any direct comparisons (Ariely et al., 2003). Nevertheless, prior studies have found that numbers in the brand or product name can influence valuation if they are near typical price values (Dogerlioglu-Demir & Koças, 2014, 2015). This accords with other studies that show that WTP is most susceptible to anchors within a range near the average value (Ariely et al., 2003; Tymula et al., 2016). However, this effect is found most strongly for items with lower familiarity, as those are likely more susceptible to environmental influences due to the lack of other information to determine value (Dogerlioglu-Demir & Koças, 2015). This prior research poses an interesting future question for budgets—does familiarity with or uncertainty about a product affect the influence of budget size on willingness to pay for the item?

We also use a process-level exploration of the mechanisms underlying mental accounting and budget use. Measuring how attention and information gathering influence choice is important for understanding how consumers make purchasing choices and for developing more effective nudges to shift the evaluation process. The patterns we found in attention and choice process were based on individual differences, which could be due to differences in preferences for using budget or differences in decision-strategy, or a combination. Therefore, it is important test whether externally imposing the process differences we find can shift the use of budget and by how much. For example, we could reveal information serially, starting with budget, draw attention to budget (e.g., put it in a more central location, make it larger), or position budget and price closer together on the screen to facilitate direct comparisons. This can test whether budgets can affect choices even if people's baseline budget use is different.

We explored trial-level influences of looking at budget, price, and item on purchasing behavior. Attentional drift diffusion modeling (aDDM) research suggests that looking at the item will increase the likelihood of purchasing because it supports evidence accumulation in favor of the item whereas looking at the price will decrease purchasing likelihood because it is a cost rather than benefit of purchasing (Krajbich, Lu, Camerer, & Rangel, 2012b). In contrast, we find that looking relatively more at budget and price both increase the likelihood of purchasing whereas looking more at the item decreases it. However, the addition of budget in our task as well as using prices near WTP may change the decision approach. In addition, a neuroimaging study of price vs. item primacy found that when an item is seen first, people make a liking judgement whereas when price is seen first, people evaluate whether the product is worth the price

(Karmarkar, Shiv, & Knutson, 2015). The item primacy decision process could account for our finding that looking more at budget and price increases the likelihood of purchasing. Because most people look at the item first, their decision process may be oriented toward evaluating liking such that they skip the item if they are not interested but examine price and budget if they are interested and more likely to buy. This is further supported by shorter response times for "skip" trials compared to "buy" trials. While we kept the location of budget information consistent for a given participant in order to allow them to develop information gathering patterns, it would be interesting to see how changing the location of all information on the screen across trials would affect which information is seen first and subsequent use of budget and price information.

Mental accounting outside of the lab occurs in more complex environments with multiple competing items and a budget that must last for a set period of time. Therefore, expanding an eye tracking approach towards more complex paradigms and realistic decisions could prove fruitful for understanding the mechanisms of mental accounting and developing more effective interventions. For example, looking at the effect of budget on purchasing bundles of items, or examining how people keep track of serially buying items within one budget is important for understanding the decision-making process that occurs while shopping or planning spending over the course of a month (Shaddy & Fishbach, 2017; Ülkümen et al., 2008).

It is also important to examine the process by which people create budget categories and fit purchases into these categories to look at individual differences in strict vs. flexible budget categories (Cheema, 2006). Furthermore, looking more directly at how spending and savings mental accounts interact is relevant for understand how mental accounts can help and hurt savings. Prior studies show that mental accounting can influence savings accounts, and that people may take on high interest debt instead of using savings, resulting in higher interest payments than necessary (Hershfield, Sussman, Brien, & Bryan, 2015; Prelec & Loewenstein, 1998; Sussman & O'Brien, 2016; Ülkümen & Cheema, 2011). Outside of the monetary domain, mental accounting may also play a role in other decisions such as food choices or time allocation (Basil, Basil, & Deshpande, 2009; Rajagopal & Rha, 2009; Soman, 2001).

Moreover, mental accounting is not the only factor in impulse purchasing. Budgets should be examined in combination with other factors that are relevant in impulse-purchasing, such as time pressure, social context, the physical presence of items, advertising, and promotions (Bushong, King, Camerer, & Rangel, 2010; Friese, Wänke, & Plessner, 2006; Jeffrey & Hodge, 2007; Kocher & Sutter, 2006; Luo, 2005; Reutskaja et al., 2011; Shukla & Banerjee, 2014). Eye tracking can help elucidate the extent of influence of these competing pressures.

We find that budgets frame the decision to purchase, and attention to budget and comparisons of price and budget enhance the effect of budget on purchasing. This finding suggests that budgets can be used as a tool to push people to save more or spend more, depending on budget size. This can help people spread consumption more evenly to enjoy the money that they do have and overcoming extreme savings or limit impulse purchasing and extreme spending (Lempert & Phelps, 2015; Rick, Cryder, & Loewenstein, 2008). Furthermore, budget size will matter most if budget is salient and attended to, so emphasizing budget when it is helpful for adhering to financial goals will be useful, while making budget less salient if it conflicts with long-term goals will help improve saving and purchasing choices.

4. Reputation motivation in motivated prosocial and self-interested behavior

This work was completed in collaboration with Alan Sanfey at the Donders Centre for Cognitive Neuroimaging at the Radboud University in Nijmegen, the Netherlands.

4.1 Introduction

While monetary incentives are a widely used and important method of increasing motivation for a rewarded behavior, in some cases they cases can backfire and reduce motivation for a given behavior. Research in both psychology and economics has converged on a counterintuitive phenomenon termed crowding out or reward undermining: contrary to the assumption that more incentives lead to increased motivation, monetary and social incentives can compete such that monetary incentives undermine prosocial motives (Bénabou & Tirole, 2006; Frey, 2012; Gneezy, Meier, & Rey-Biel, 2011). For example, paying volunteers a token amount to help at a soup kitchen may actually decrease their effort compared to no payment. Empirically, this reduction in prosocial motivation with monetary incentives is seen in blood donation, survey responses, donations, and effort in raising money for charity—all behaviors in which paying people small amounts diminishes their motivation compared to no reward (Ariely, Bracha, & Meier, 2009; Beretti, Figuières, & Grolleau, 2011; Newman & Jeremy Shen, 2012).

One possible reason why reward undermining occurs is the desire to signal altruistic pro-social motives when reputation is at stake. While it may seem that compensation for helping one's community would be a bonus, payment can reduce the efficacy of prosocial image signaling in public because there is an aversion to mixing prosocial acts and monetary reward. Mixing incentives could imply that self-interested desire for money is the major or sole motivation behind prosocial action (Ariely et al., 2009; Bénabou & Tirole, 2006; Kosfeld & Neckermann, 2010). Indeed, we often assume the worst in others when there is potential for mixed motivations. This is seen in the Knobe effect, where no credit is assigned for an incidental positive effect, but blame is assigned for an incidental negative effect (Knobe, 2003). It is also found that mixing altruism and self-interest is often viewed as worse than or equally bad as self-interest alone (Newman & Cain, 2014). In line with this hypothesis, motivation has been shown to rebound with the opportunity to donate the monetary reward earned toward a similar charitable cause (Beretti et al., 2011; Mellstrôm & Johannesson, 2008). Thus, incentives that imply self-interest may reduce or eliminate prosocial recognition, particularly in public contexts.

Despite behavioral evidence of reward undermining, the neural mechanisms of reputation-based reward undermining have not been explored. There are many contexts in which reward undermining can occur, including the introduction and removal of a reward during an intrinsically-rewarding or enjoyable task. However, the unique impact of social context and reputation has not been explored in reward undermining. In the research presented here, we examine the impact of public and private contexts where reward for self and charity appear separately and in combination on neural responses to reward. We seek to bridge research on social norms and reputation with the findings from reward undermining to develop a neural reputation-based reward undermining framework.

4.1.1 Neural correlates of motivation and reward

Reward, motivation, and decision-making engage the cortico-basal ganglia dopaminergic system, a network of regions including the ventral tegmental area (VTA) in the midbrain, ventral striatum (VS) and ventromedial prefrontal cortex (vmPFC) (Haber & Knutson, 2010). Together, these regions support learning about reward and feedback, representing value, and motivating action. In particular, research implicates the VS in reward anticipation and updating reward representations in response to prediction errors, and the vmPFC has been shown to be involved in evaluating outcomes and integrating context into value representations (Bartra et al., 2013; Chib et al., 2009; Knutson et al., 2001; Knutson et al., 2000; Levy & Glimcher, 2012; Shohamy, 2011; Smith et al., 2013). Value is represented as a common currency in these regions across domains (Clithero & Rangel, 2013; Kable & Glimcher, 2009; Smith et al., 2013). In order to represent such diverse rewards, this network incorporates contextual information from other brain regions to construct the value of an option or action.

4.1.2 Neural mechanisms of reputation

Social contexts are often highly salient and influence value construction in impactful ways. Shifting from a nonsocial to a social context can invert preferences and alter information processing strategies. Studies exploring the neural representation of reputation found that both VS and mPFC respond to both money and reputation, and being observed can shift preferences (Izuma, 2012; Izuma et al., 2008, 2010). One study found that the VS responded more strongly to self-reward under anonymous conditions, but more strongly to charity reward while being observed, changing its representation of value based on social context (Izuma et al., 2010). These studies have examined the influence of reputation on the value of reward for self as compared to charity, but they did not characterize the interactions of social and value neural circuits and did not directly explore reward undermining. In order for preferences to change with context, there must be a modulation of value from networks processing social context, and connectivity between these regions has been shown to underlie these behavioral shifts (Hare, Camerer, Knoepfle, & Rangel, 2010; Rilling, King-Casas, & Sanfey, 2008; Smith et al., 2013; Strombach, Weber, et al., 2015).

One critical component of social processing is reasoning about other agents' minds and incorporating that into valuation. This "theory of mind" (ToM) or mentalizing requires thinking about others' goals, intentions, and desires (Deen, Koldewyn, Kanwisher, & Saxe, 2015; Koster-Hale & Saxe, 2013; Saxe et al., 2006). A network including the temporal-parietal junction (TPJ) and dorsal medial prefrontal cortex (dmPFC) has been implicated in this social process. The TPJ has been shown to be involved in thinking not only about others goals and desires, but also in thinking strategically about what others think of us, including predictions about how our actions may affect our reputation (Carter et al., 2012; Carter & Huettel, 2013; Izuma, 2012). It is implicated in considering other's expectations of us, such as choosing not to cheat a fellow player in a trust game (Chang et al., 2011). It has also been found that connectivity between the vmPFC and TPJ occurs in social contexts when people are trying to strategically avoid punishment (Makwana et al., 2015). Thus, TPJ may signal the shift from an anonymous to an observed context in which reputation is important and enable strategic reasoning.

Reasoning about the social norms required to build a good reputation and behaviorally executing the choices that will lead to a good reputation are likely separate processes. While the TPJ may be important in reasoning about other's minds, previous studies have shown that the dorsolateral prefrontal cortex (dlPFC) is involved in building a good reputation by integrating social norms into valuation, especially when these norms go against self-interest. More generally, the dorsolateral prefrontal cortex (dlPFC) is implicated in executive functions including cognitive control, behavioral monitoring, and action selection that enables contextually appropriate responses. In social contexts, this means that the dlPFC is involved in social norm following and enforcement including building a good reputation. For example, when people reject unfair offers or avoid the threat of social sanctions as punishment, dlPFC activity is observed (Sanfey et al., 2003; Spitzer et al., 2007). Moreover, interfering with dlPFC activity using transcranial magnetic stimulation (TMS) reduces the ability to build a good reputation. Instead, temptation to defect and gain immediate reward gratification is chosen over preserving the long-term value of a good reputation (Knoch, Pascual-Leone, Meyer, Treyer, & Fehr, 2006; Knoch et al., 2009). Finally, TMS reduces dlPFC-vmPFC connectivity that typically accompanies norm enforcement, suggesting that without dlPFC input, norm enforcement is not integrated into the valuation process in the vmPFC (Baumgartner et al., 2011; Izuma, 2012; Knoch et al., 2006, 2009). All of this suggests that the dlPFC plays a role in enabling contextually appropriate social behavior. While this research is important for understanding social norm following, it primarily examines social norm enforcement in direct social interactions, whereas reputation-based norm enforcement is less well characterized.

4.1.3 Neural mechanisms of reward undermining

In line with the contextual integration of context in reward valuation, many studies have looked at how reward responses change in response to context (De Martino et al., 2009; Loewenstein, 1988; Plassmann et al., 2008; Tymula et al., 2016). Moreover, a few studies have examined how value circuitry responds to reward undermining. One type of reward undermining occurs through a competition between intrinsic and extrinsic incentives in which people are paid (or not) to do an enjoyable activity. These studies have a three-period structure in which there are two groups doing intrinsically enjoyable activities. Neither group is paid in the first period, one group is paid in the second period, and neither group is paid in the third period. This allows researcher to examine how reward affects performance both while reward is given and after removal. Most studies find a behavioral reduction in motivation for those who were paid after payment removal compared to those who were never paid (Bénabou & Tirole, 2003; Deci, Koestner, & Ryan, 1999; Ryan & Deci, 2000).

In this type of reward undermining, neural studies have shown an increase in activity during the rewarded time period in dopaminergic reward regions including the midbrain and striatum, and in executive control regions including the lateral prefrontal cortex (Albrecht, Abeler, Weber, & Falk, 2014; Murayama, Matsumoto, Izuma, & Matsumoto, 2010; Strombach, Hubert, & Kenning, 2015). However, there have been mixed results in whether people showed a reduction in motivation compared to baseline after rewards were removed, with two of the three studies finding decreased performance and neural activation. In addition, one study found a decrease in vmPFC during the reward period that persisted after reward removal (Strombach, Hubert, et al., 2015). In contrast to monetary incentives, verbal affirmations as rewards increased striatal and midbrain activity in the period after rewards were no longer applied (Albrecht et al., 2014). All of these neural studies find evidence for dopaminergic midbrain and striatal reward responses being involved in the response to reward and in some cases the removal of reward. They also suggest there is a role for the prefrontal cortex in subjective valuation. However, none of these studies look at when rewards immediately backfire (as opposed to after removal), only one examines social motivations, and none of them explore how connectivity with these reward regions changes as a function of context. Therefore, there is a large gap in understanding that more varied paradigms and more complex neural analyses can address.

4.1.4 Intersection of reputation motivation and reward undermining

In this study, we investigate how social and value circuitry interact in the unique context of reputational reward undermining when monetary and social incentives compete. In particular, we examine how mixing incentives for oneself and charity influences motivation in private vs. public contexts. Integrating insights from prior behavioral reward undermining with neural findings on reward valuation, undermining, and reputation, suggests that reward-related regions including the VS and vmPFC are modulated by social context. Moreover, the TPJ and dlPFC are likely important for modulating reward representations to enable social norm following. Thus, this research expands the literature by exploring the neural mechanisms underlying the interaction of social and self-interested motivations in social settings.

4.2 Methods

4.2.1 Participants

A total of 38 healthy, right-handed participants (mean age = 21.9, SD = 2.6; 27 women) completed this study. Participants were pre-screened to rule out any metal or neurological conditions. Participants gave written informed consent in accordance with the local ethics committee. Data from 7 participants were excluded due to excessive motion (>1.5 mm framewise displacements multiple times during multiple runs).

4.2.2 Procedure

Participants participated in a modified monetary incentive delay (MID) task while in the MRI scanner. They completed a practice run during their anatomical scan to reduce learning during the actual task and to estimate their starting reaction time (Knutson et al., 2001, 2000). After the scanner portion, participants answered questions about their motivations to earn for themselves and charity as well as their motivation to be rated as generous.

4.2.2 Task

At the start of the experiment, participants chose their preferred charity from a list of eight charities benefitting causes including international development, humanitarian and disaster relief, and the environment. Next, participants played a modified monetary incentive delay (MID) task in which they could earn points by pressing a button quickly enough in response to a target shape (white square). Prior to seeing the target, participants were given a cue indicating how many points they could earn for themselves, their chosen charity, both, or neither (Knutson et al., 2001, 2000, 2003). Participants could earn 0, 1, or 10 points for themselves, charity, or both and they saw all possible combinations of point values for self and charity. In addition, public and private conditions were grouped into blocks to examine the effect of social context on motivation to earn for self and charity. In the public condition, participants were informed that they would be rated and ranked on their generosity by others based on their earnings for self and charity after the study was completed. They knew that they would receive these rankings by email after the entire study was completed. In addition, they were informed that the experimenter could see their performance on a trial to trial basis during public trials. For private trials, participants were informed that neither the experimenter nor anyone else would watch their performance or rate their earnings. In all, participants complete 360 trials across 4 runs, with each run containing 2 blocks –1 public block and 1 private block, counterbalanced. Reward combinations were randomly presented within a run, with each possible combination of points totaling 40 trials, split across public and private blocks.

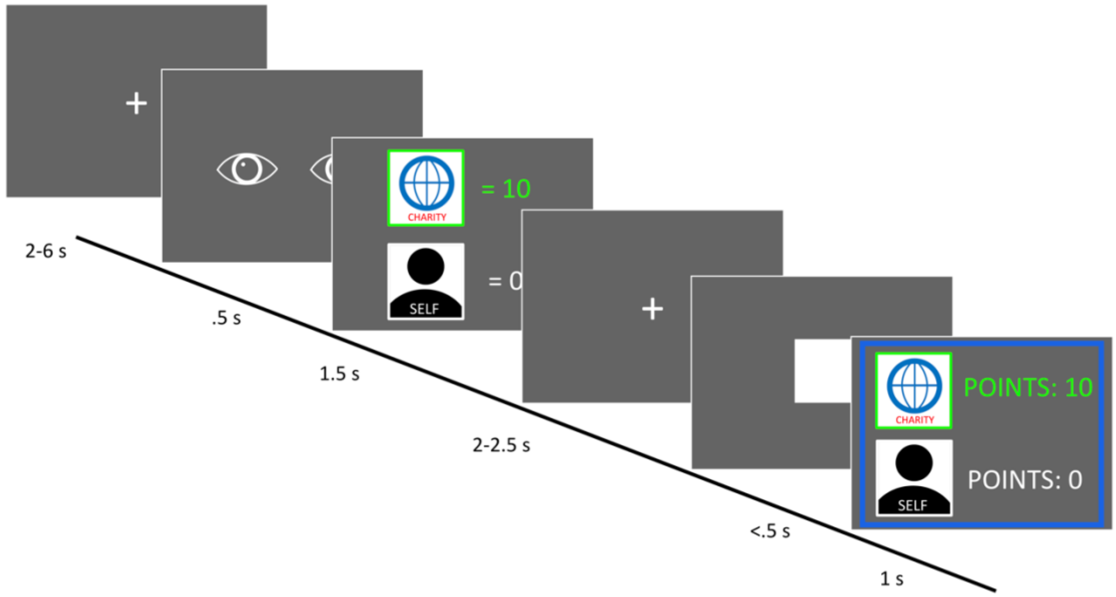

Figure 12: Participants saw a cue indicating the trial type (public or private). Next, a cue indicating the point values for self and charity was displayed followed by a variable duration of fixation. When the target white square appeared, participants had to respond as quickly as possible and their response time determined whether the cued points were earned.

On each trial, participants first saw a brief cue indicating the block type—public or private. Public trials were indicated with eyes whereas private trials were indicated with a mask. Next, participants saw a cue indicating the possible points they could earn for themselves and charity on that trial. For this cue, the color of the text and image border reinforced the point value, with white for 0 points and bright green for 10 points. Then, a fixation cross was displayed for a random amount of time between 2-2.5 seconds before the target white square appeared briefly. If participants pressed a button quickly enough while the target was still onscreen, they earned the cued points. The target display time was titrated to each participant to give an ~66% success rate by using the practice run as a starting point and updating on each trial. After the practice run, independent thresholds were used for each trial type on 60% of trials and a generic threshold based on all trial types was used on 40% of trials. Finally, participants saw the outcome of the trial, with points earned on each trial for themselves and the charity displayed (Fig. 12). If participants were fast enough on a given trial, the point information was framed by a blue rectangle, whereas if they were too slow, it was framed by a white rectangle. Participants were paid €19 plus a bonus for themselves and a bonus donation to their chosen charity based on their task performance. The bonuses were determined from a randomly drawn subset of trials across public and private conditions and point values to avoid experimenter knowledge of their total performance in the private condition.

4.2.3 MRI acquisition

Whole brain imaging data were collected on a Siemens Magnetom Skyra MRI scanner with a 32 channel head coil. We ran a localizer followed by a T1 MPRAGE image with isometric 1 mm^3 voxels. Functional data were collected using an EPI multiband (simultaneous slices), multi-echo sequence (TR = 1.5s, TEs = 12.4, 34.3, 56.2 ms; isotropic voxel size = 2.5 mm, flip angle = 75, FOV = 210 mm, 51 slices of 84 X 84, multiband factor = 3).

4.2.4 MRI preprocessing

Raw imaging data were converted to NIfTI files and formatted to the "Brain Imaging Data Structure" (Gorgolewski & Poldrack, 2016) with the BIDScoin toolkit (Zwiers, 2019). MRI data were preprocessed using fMRIprep 1.2.6-1 (Esteban et al., 2018, 2019) which is based on Nipype 1.1.7 (Gorgolewski, Burns, Madison, Clark, & Halchenko, 2011; Gorgolewski et al., 2018). Through the fMRIPrep pipeline, the anatomical T1-weighted image was corrected for inhomogeneity with N4BiasFieldCorrection (Tustison et al., 2010), skull-stripped using antsBrainExtraction.sh with the OASIS template, and co-registered with nonlinear antsRegistration to the ICBM 152 Nonlinear Asymmetrical template version 2009c (Fonov, Evans, Mckinstry, Almli, & Collins, 2009), all using ANTs 2.2.0. Fast (Zhang, Brady, & Smith, 2001) was used for brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM).

The fMRIPrep pipeline was also used to preprocess the four BOLD runs for each subject. A reference volume and a skull-stripped reference volume were generated with custom fMRIPrep methods. Head motion was estimated using mcflirt (Jenkinson, Bannister, Brady, & Smith, 2002), FSL 5.0.9. Because this was multi-echo data, a mono-exponential signal decay model was fit with log-linear regression based on the number of echoes with reliable signal in each voxel to estimate at T2* map to optimally combine across the echoes (Posse et al., 1999). The T2* map was also used as a reference that was co-registered to the T1w using flirt with boundary-based registration. The BOLD data was transformed based on head-motion estimation, susceptibility distortion correction, and co-registration to the anatomical T1w and standard space MNI152NLin2009cAsym in one step using antsApplyTransforms with Lanczos interpolation.

4.2.5 fMRI analysis

FSL 6.0.0 FEAT was used for GLM analyses. First level analyses included high-pass temporal filtering (Gaussian-weighted least-squares line fitting with sigma = 50.0s) and smoothing using a 5 mm full-width-half-maximum Gaussian kernel. GLMs examined reward anticipation activity for self and charity in the public and private conditions. Regressors were made for the anticipation period after reward cues and before the target appeared for all trials, with separate regressors for each trial type (all possible combinations of 0, 1, and 10 points for charity and self) and separately for public and private conditions. In addition, control regressors included the outcome period (split by hit or miss) and confounds from fMRIPrep (6 motion parameters, 6 parameters from aCompCor (Behzadi, Restom, Liau, & Liu, 2007), and a regressor to exclude TRs with frame-wise displacements of >0.5 mm). First-level GLM analyses examined the contrast between reward (1 or 10 points) for self and no reward for self in public and private separately. This reward versus no reward contrast was also applied to reward anticipation for charity, separated by the public and private conditions. These first four analyses were used to test for reward anticipation responses in the brain. In addition, a double subtraction contrast compared neural reward anticipation responses to public versus private conditions (and private versus public conditions) in separate contrasts for charity and self. Time-series statistical analysis was carried out using FILM with local autocorrelation correction (Woolrich, Ripley, Brady, & Smith, 2001). Second level analyses averaged across participant runs using fixed effects with zero variance random effects in FLAME (Beckmann, Jenkinson, & Smith, 2003; Woolrich, Behrens, Beckmann, Jenkinson, & Smith, 2004). Third level analyses averaged across participants using mixed effects FLAME 1, with non-parametric thresholding of images using clusters determined by $Z > 3.1$ and a (corrected) cluster significance threshold of $P = 0.05$ (Worsley, 2001).

4.3. Results

4.3.1 Behavioral results

We examined how reaction times changed in response to reward cues for self, charity, and the interaction of reward with condition. The behavioral variable of interest was reaction time across conditions. Faster reaction times can indicate higher motivation for reward. Using repeated-measures mixed-effects ANOVA, we modeled the effect of reward for self and reward for charity as factors (Table 5; Figure 13). In addition, we modeled the interaction of reward size and condition (public or private). Increasing reward for self and increasing reward for charity both decrease reaction time, with negative coefficients for high reward for self ($t(8480) = -2.40$, $B = -0.0023$, $SE = 0.0014$, $p =$

0.016) and charity ($t(8480) = -4.13$, $B = -0.0040$, $SE = 0.0010$, $p < 0.001$). In addition, we were interested in how the public and private conditions would interact with reward motivation for self and charity. Reputation motivation predicts that reward for self would be more motivating in private compared to public, whereas motivation for charity might be more motivating in public than private. We find that reward motivation for self is indeed higher in private compared to public (interaction: $t(8475) = 2.33$, $B = 0.0045$, $SE = 0.0019$, $p = 0.020$), with a positive interaction term suggesting that participants are slower to respond to high reward for themselves in public compared to private. However, there is no difference in reaction time for charity across conditions, suggesting that motivation for charity is maintained across public and private conditions. Charities were selected from a range of options by participants, so even in private there may have been a strong prosocial motivation to earn for charity. Finally, reputational reward undermining would predict that mixed incentives for self and charity would contribute to motivation additively in the anonymous condition, but that monetary reward for self would undermine charitable motivations in the observed condition. We do not find a significant interaction between self, charity, and the public condition, possibly because there is not enough power given our limited sample size and modeling reward levels separately.

Table 5: Mixed effects ANOVA of reaction time.

Fixed effects: Estimate (Std. Error)		
	Effect of reward	Interaction of reward and context
Intercept	0.24*** (0.0045)	0.24*** (0.0046)
Self 1	-0.0001 n.s. (0.0010)	0.0006 n.s. (0.0014)
Self 10	-0.0023* (0.0014)	-0.0046*** (0.0014)
Charity 1	-0.0018 n.s. (0.0010)	-0.0028* (0.0014)
Charity 10	-0.0040*** (0.0010)	-0.0041** (0.0014)
Public	-	-0.0018 n.s. (0.0019)
Self 1 X Public	-	-0.0015 n.s. (0.0020)
Self 10 X Public	-	0.0045* (0.0019)
Charity 1 X Public	-	0.0021 n.s. (0.0020)
Charity 10 X Public	-	0.0002 n.s. (0.0019)
Random effects: Variance (Std. Dev.)		
Standard deviation: Intercept (residual)	0.03 (0.04)	0.03 (0.04)
Obs., Groups	8522,38	8522, 38
BIC	-32060.8	-32027.7

Significance is indicated by * p < .05, ** p < .01, *** p < 0.001

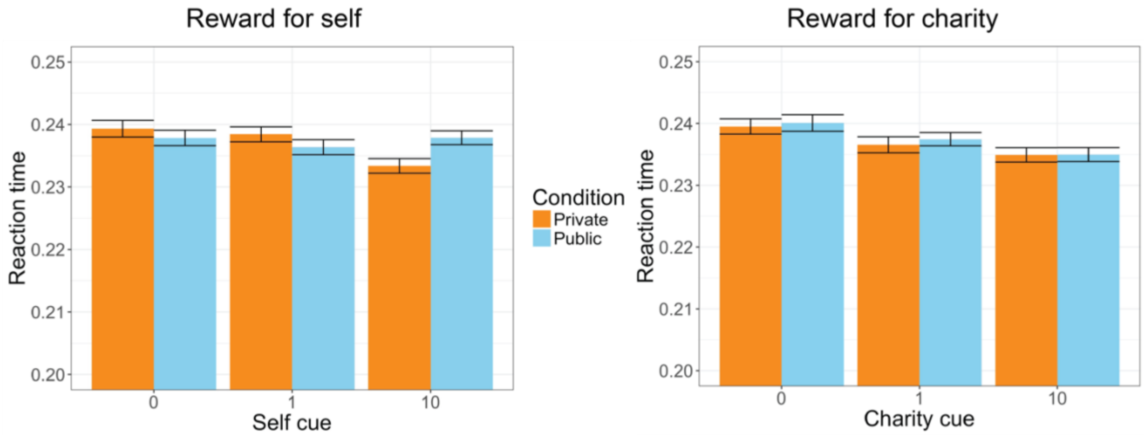

Figure 13: Reaction times to reward cues for self and charity, split by public and private condition. Reaction time becomes faster as self-reward increases in private, but not in public. Reaction time becomes faster as charity-reward increases across both the public and private conditions.

4.3.2 Imaging results

4.3.2.1 Reward anticipation of reward for self

Our first contrasts of interest were those examining reward anticipation activity by contrasting cued reward with no reward. Reward anticipation contrasts for self-interested incentives were examined separately for the public and private conditions. In the contrast of reward compared to no reward for self in the public condition, we find a large response in many regions of the brain, including ventral striatum and thalamus, bilateral insula, and cingulate gyrus in addition to the frontal pole, occipital cortex, cerebellum, and parietal regions (Figure 14a; see Table 6 for list of peak activations). We find a very similar reward anticipation response for the contrast of reward compared to no reward for self in the private condition (Figure 14b, Table 7). This confirms that there is a robust reward anticipation response in the brain regardless of social context. Next, to compare the reward response across social context conditions, we examined a contrast of reward anticipation response in public and private conditions (public > private and private > public). A contrast of public compared to private reward anticipation responses for oneself did not yield any significant clusters of activation. The opposite contrast of private compared to public reward anticipation responses showed a bilateral cluster of activation a temporal-occipital region (Figure 3c, Table 8).

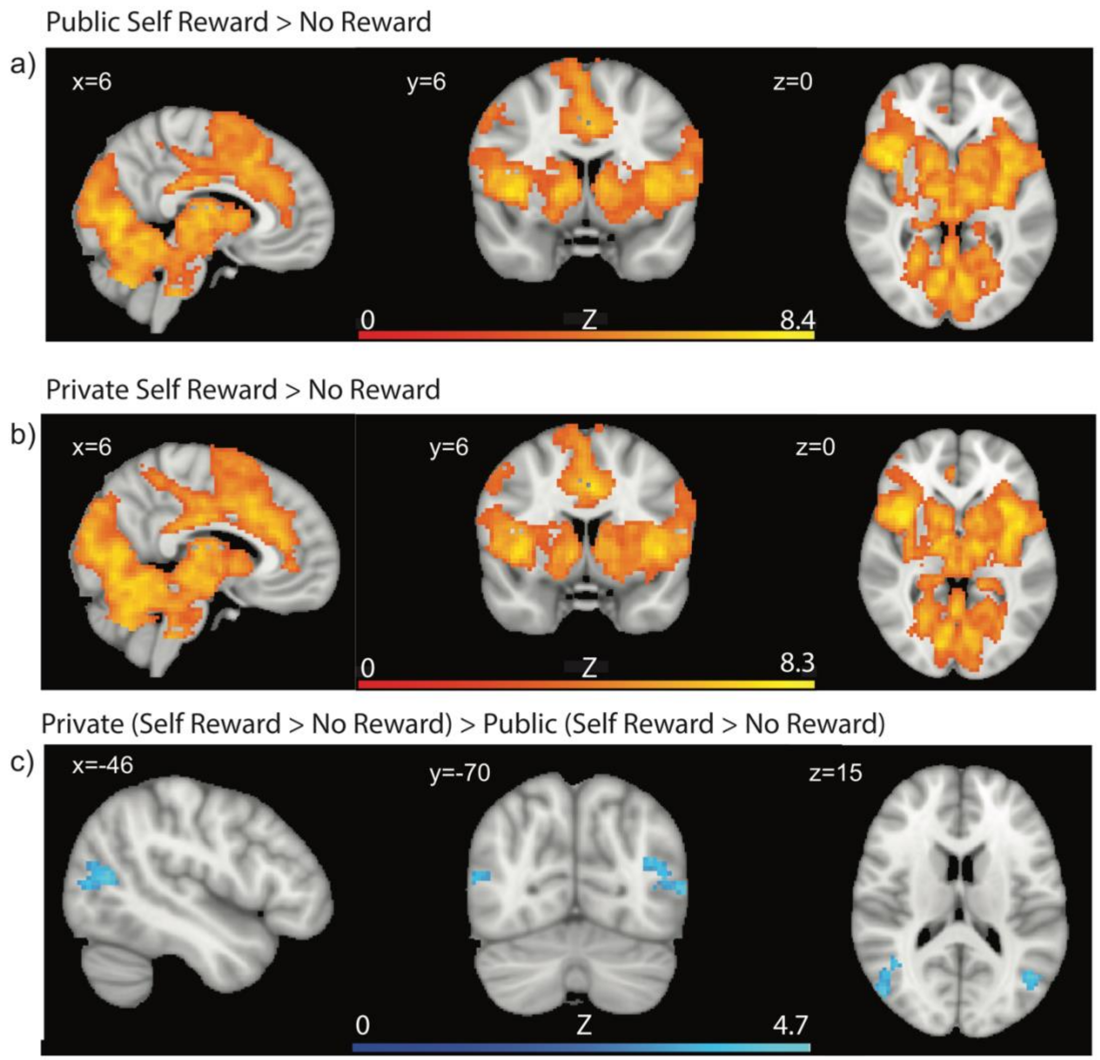

Figure 14: Reward anticipation for self. A contrast of reward anticipation of rewards for self compared to no reward reveals similar activity in the public and private conditions, with activation in the striatum, insula, cingulate, and other regions. A contrast of reward anticipation in the private compared to public condition reveals activity at the intersection of the temporal and occipital lobes.

Table 6: Peak activations of reward anticipation for self in the public condition

Contrast	Region (Hemisphere)	Cluster	Cluster size	MNI coordinates (x, y, z)	Peak z-stat
Self reward > No reward (Public)	Intracalcarine cortex	4	30030	(12, -82, 5)	8.4
				(-9, -90, 5)	8.1
	Bilateral Insula	4		(42, 8, -1)	8.2
				(-34, -10, 2)	7.9
				(-31, 13, 5)	7.9
				(-14, -17, 7)	7.9
	Thalamus	4		(64, -35, 42)	7.0
	Supramarginal gyrus	3	1326	(64, -35, 35)	6.4
				(54, -35, 52)	6.2
				(64, -40, 27)	6.0
				(64, -20, 22)	5.8
				(49, -30, 27)	5.3
				(54, 1, 37)	5.2
	Premotor cortex	2	247	(37, 1, 62)	5.0
				(52, -2, 52)	4.2
				(37, -15, 35)	3.6
				(47, -5, 57)	3.6
				(54, 6, 45)	4.8
	Middle frontal gyrus	2		(-36, 48, 35)	4.4
				(-36, 43, 32)	4.3
	Frontal pole	1	69	(-44, 56, 15)	4.2
				(-39, 41, 25)	3.3
				(-44, 46, 27)	3.2
				(-44, 46, 27)	3.2

Table 7: Peak activations of reward anticipation for self in the private condition

Contrast	Region (Hemisphere)	Cluster	Cluster size	MNI coordinates (x, y, z)	Peak z-stat
Self reward > no reward (Private)	Intracalcarine cortex	2		(12, -80, 5)	8.3
	Insula	2		(42, 11, -1)	8.3
	Cerebellum	2	34638	(2,-57, -6)	8.0
				(14, -65, -23)	7.9
				(-11, -85, 5)	7.9
	Cingulate gyrus	2		(-4, 8, 37)	7.7
	Dorsolateral prefrontal cortex	1		(-36, 43, 32)	4.5
				(-41, 43, 27)	4.5
	Frontal Pole	1	178	(-41, 56, 15)	4.1
				(-44, 51, 20)	4.1
				(-41, 46, 22)	4.0
				(-31, 53 20)	3.7

Table 8: Peak activations of reward anticipation for self for a contrast of the private condition compared to the public condition

Contrast	Region (Hemisphere)	Cluster	Cluster size	MNI coordinates (x, y, z)	Peak z-stat
Public (self reward > no reward) > Private (self reward > no reward)	Bilateral temporal-occipital cortex	2	183	(-46, -65, 12)	4.7
				(-56, -67, 7)	4.5
				(-39, -70, 22)	4.3
				(-49, -75, 10)	4.0
				(-61, -57, 7)	3.4
		1	63	(49, -75, 15)	4.3
				(42, -57, 15)	4.1
				(49, -62, 15)	3.8
				(54, -60, 10)	3.4
				(44, -67, 20)	3.2

4.3.2.2 Reward anticipation of reward for charity

Next, we examined reward anticipation for rewards to charity across the public and private conditions. The first contrast examined the difference in response to reward compared to no reward for charity in the public condition (Figure 15 a, Table 9). Similarly to reward anticipation for oneself, we find a large response across the brain to reward anticipation for charity. The contrast examining the difference in response to reward compared to no reward for charity in the private condition also shows a large and similar reward anticipation response (Figure 15b, Table 10). Both of these reward anticipation contrasts including activity in the ventral striatum, thalamus, bilateral insula, and cingulate gyrus. In addition, we also find activity peaks in the frontal pole, occipital cortex, cerebellum, and parietal cortex (Figure 15a, 15b; Tables 9,10 for a list of peak activations). This suggests that charity activates a reward anticipation response similar to the reward anticipation response for self. Finally, we also tested reward anticipation differences across the public and private conditions for charity. A contrast of public compared to private reward anticipation responses for charity showed significant clusters in the occipital lobe (Figure 15c, Table 11). The opposite contrast for reward anticipation in private compared to public for charity did not have any significant clusters.

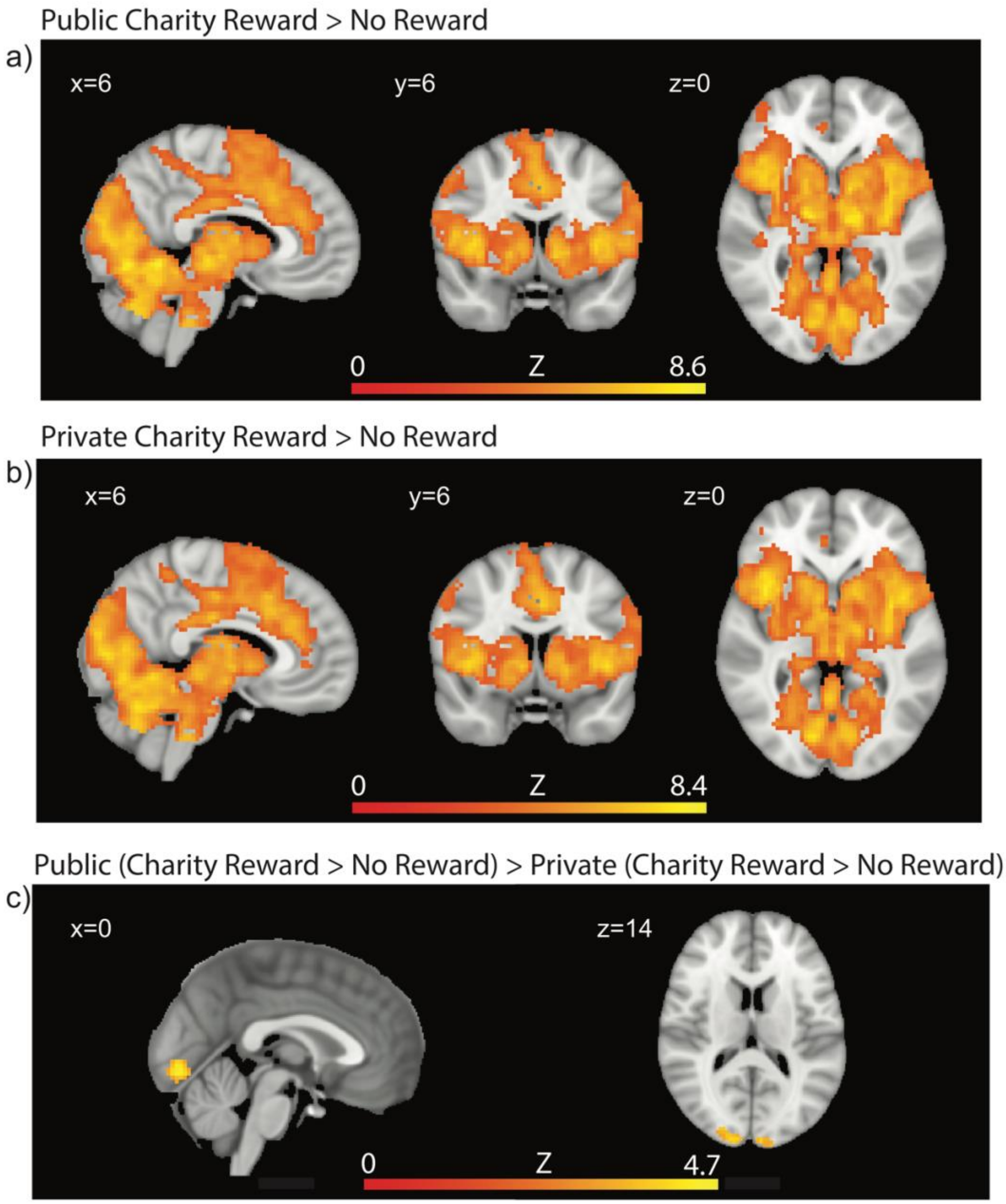

Figure 15: Reward anticipation for charity. A contrast of reward anticipation of rewards for charity compared to no reward reveals similar activity in the public and private conditions, with activation in the striatum, insula, cingulate, and other regions including occipital, parietal, and cerebellar activation. A contrast of reward anticipation in the public compared to private condition reveals activity in the occipital lobe.

Table 9: Peak activations of reward anticipation for charity in the public condition

Contrast	Region (Hemisphere)	Cluster	Cluster size	MNI coordinates (x, y, z)	Peak z-stat
Charity reward > No reward (Public)	Thalamus	2	33290	(-14, -17, 2)	8.6
	Cerebellum	2		(7, -55, -8)	8.4
				(17, -67, -21)	8.0
	Lingual gyrus	2		(9, -74, -11)	8.4
	Intracalcarine cortex	2		(-11, -87, 5)	8.2
				(12, -80, 5)	8.1
	Middle temporal gyrus	1	44	(-51, -62, 7)	3.9
				(-51, -55, 7)	3.4

Table 10: Peak activations of reward anticipation for charity in the public condition

Contrast	Region (Hemisphere)	Cluster	Cluster size	MNI coordinates (x, y, z)	Peak z-stat
Charity reward > No reward (Private)	Cerebellum	5	29811	(-1, -60, -6)	8.4
				(22, -52, -28)	8.0
				(4, -65, -26)	7.9
	Intracalcarine cortex	5		(12, -80, 5)	8.2
				(-11, -87, 5)	8.0
	Insula (R)	5		(42, 13, -3)	8.1
	Supramarginal gyrus	4	1197	(59, -20, 22)	6.3
				(62, -35, 40)	6.2
				(54, -37, 52)	5.9
				(64, -35, 32)	5.8
				(57, -27, 25)	5.5
				(49, -35, 45)	5.4
	Frontal pole	3	353	(42, 51, 17)	5.4
				(42, 46, 15)	5.4
				(29, 48, 22)	5.1
	Middle temporal gyrus	2	179	(-49, -60, 10)	5.2
				(-44, -52, 7)	4.4
	Lateral Occipital cortex	2		(-39, -77, 10)	4.7
	Frontal Pole	1	61	(-31, 53, 20)	4.2

Table 11: Peak activations of reward anticipation for charity for a contrast of the public condition compared to the private condition

Contrast	Region (Hemisphere)	Cluster	Cluster size	MNI coordinates (x, y, z)	Peak z-stat
Public (charity reward > no reward) > Private (charity reward > no reward)	Occipital cortex	3	123	(12, -97, 10)	4.6
				(19, -92, 12)	4.1
				(17, -97, 17)	4.1
				(22, -90, 17)	3.9
	Intracalcarine cortex	2	114	(-1, -85, -6)	4.7
				(2, -92, -6)	4.4
	Occipital pole	1	45	(-6, -100, 15)	3.9
				(-14, -102, 12)	3.8
				(-9, -97, 20)	3.7

4.4 Discussion

Elucidating the conditions and mechanisms underpinning social reward undermining is important for understanding how to encourage pro-social behavior, such as volunteering, donating, and contributing to shared societal resources. Applied research has shown that monetary incentives may decrease pro-social behavior such as canvassing for charity, and that fines can sometimes actually increase anti-social behavior such as littering and picking children up late from daycare (Gneezy & Rustichini, 2000b, 2000a). Therefore, investigating the impact of reputation motivation on behavior, and exploring the undermining of social motivations by monetary incentives can help provide clearer targets for behavioral change. In this study, we examine how social context affects motivation for self and charity, separately and combined. We find that people are motivated to earn for themselves and for charity overall. Moreover, we find that participants are equally motivated to earn for charity in public or private, but that they are less motivated to earn for themselves in the public condition when reputation is at stake. This suggests that there is some effect of reputation in public, where there is a motivation to appear less self-interested, but that this does not interfere with prosocial motivations.

This study's design departed from prior reputation and reward undermining studies in order to be better adapted for neuroimaging, and these differences may have had an impact on the findings. First, participants did not make explicit choices in this task. We were interested in measuring motivation and effort rather than choice as many prior crowding out and undermining studies measured behavioral change in response to a given incentive structure without making the choices explicit, (Ariely et al., 2009; Gneezy & Rustichini, 2000b; Heyman & Ariely, 2004; Murayama et al., 2010) although this departs from previous work using neuroimaging to examine reputation (Izuma et al., 2010). Moreover, the trial structure of fMRI and the need to minimize movement, makes many effortful tasks difficult to perform in that setting because they either take too much time or require physical effort. The MID task structure was chosen to measure motivation and to reduce experimenter demand; because the participant's ultimate goal is the same on every trial—simply to press the button as fast as possible when the target appears, there is no pressure to make a different choice due to context. However, this also means that participants may feel less responsible or accountable for their choices and may weaken the effect since participants do not control the distribution of point values and are not making direct tradeoffs between reward for themselves and charity.

In addition to the task structure, the design was within-subjects and participants experienced both the public and private condition and separate and combined rewards for self and charity. Most undermining studies use between-subjects designs that allow for separate evaluation (only one reward scheme is considered by each participant) compared to joint evaluation in which the participants view all possible combinations of incentives. These design choices may reduce the effect of combining self-interested and prosocial compared to separating each condition across participants. Nevertheless, our finding of differences in motivation for reward for oneself across conditions suggests that these changes did not eliminate all reputation motivation. However, our findings indicate that financial incentives for self may not be effective in increasing prosocial actions in public settings, but also don't directly interfere with them.

One other confound in the study is that it was advertised with the possibility of earning money for oneself and charity, so it is possible that it attracted people who were relatively more prosocial than the general population. This may have affected their consistent high motivation for charity and may not capture the full spectrum of individual differences in the response to incentives for self and charity. However, after the task, participants rated their perception of the charity they chose and their motivation for the rewards for self and charity as well as their motivation to build a positive reputation, so any differences that do exist within the range of motivations across the participants included can be accounted for within the analyses.

Our neural findings show an overall strong response to reward across conditions. We find activity in the primary neural region of interest in reward anticipation, the ventral striatum. We also find activity extending into the thalamus, cingulate cortex, insula, and frontal pole, and occipital lobe all of which have been found in prior reward anticipation studies (Carter et al., 2009; Clithero, Reeck, Carter, Smith, & Huettel, 2011; Knutson et al., 2001). While cerebellar activity is less commonly reported in reward anticipation, the first MID anticipation research study found cerebellar activity, and recent animal research has implicated cerebellar activity in representing reward anticipation (Knutson et al., 2001; Wagner, Kim, Savall, Schnitzer, & Luo, 2017). It is surprising that the only difference in activity across public and private is found in the occipital lobe. This may be due to the approach of using a whole-brain contrast rather than a region of interest (ROI) approach because the threshold for significance is much higher. Because of the strong a priori hypothesis of ventral striatal involvement in reward anticipation, an important next step is to look at the level of activation in the ventral striatum across conditions. Previous studies showed a higher level of activity in reward anticipation for self compared to charity in private, but also showed that in public this relationship reversed such that reward response to charity was higher than that for self (Carter et al., 2009; Izuma et al., 2010). This suggests that a more sensitive

ROI approach may find modulation of reward anticipation for self and charity across the public and private conditions. In addition to an ROI approach, there may be different connectivity across conditions that a simple contrast does not reveal. Instead, a psychophysiological interaction (PPI) analysis using the ventral striatum as a seed region could elucidate differences in connectivity that may influence the strength of motivation and incorporate reputation in the public condition.

In conclusion, we find a behavioral effect of reputation on motivation for incentives for oneself, with the public condition reducing motivation to earn for oneself, but we do not find an effect of the public condition on motivations to earn for charity. Moreover, we find a robust effect of reward anticipation for self and for charity across conditions, but further ROI analyses of the ventral striatum are needed to characterize more sensitive differences in motivation across conditions. Furthermore, connectivity analyses can help elucidate the shift in inputs to the ventral striatum reward anticipation response across the public and private conditions to better understand how reputation motivation is implemented in the brain.

5. Conclusions

The studies presented each chapter address the ways in which value is constructed based on context using different paradigms in consumer choice. In one line of research, I use eye-tracking and computational modeling to characterize the patterns of information gathering that lead to individual differences in choice. I have applied these techniques to intertemporal choice (chapter 2) and mental accounting (chapter 3) to better understand how to shift behavior by modulating attentional patterns. Second, I examine social motivations that influence choice but are often ignored in traditional financial education settings. I explore how social networks modulate value representations in the brain (chapter 4). In particular, I investigate the interaction of monetary incentives for self and charity, with a focus on how money for oneself can conflict with the motivation to build a prosocial reputation in public settings.

5.1 Chapter summaries

Chapter 2 provides evidence that in intertemporal choice, many people use attribute-wise comparisons of amounts and times separately, rather than integrating them in the choice process. This is captured in a multi-attribute time-dependent drift diffusion model in which drift slopes for amount and time are uncorrelated, but combine to predict patience or impatience—with higher drift slopes on amount relating to patience and higher weights on time relating to impatience. Moreover, we also find that the relative onset of time versus amount into the evidence accumulation process relates to choice. While amount enters the process earlier on average, the difference between amount and time (which correlates with the proportion of first fixations to amount vs. time) also relates to patience. In contrast, decision bounds are not different across groups, so there is no evidence that impatient choices are the result of less deliberation or noisier responses. Finally, eye tracking data accord with computational findings, showing that people look relatively more at the attribute that has a higher drift slope in their drift diffusion model. In addition, there are individual differences in the patterns of information gathering in the eye tracking data, with more patient participants exhibiting more attribute-wise comparisons and more impatient participants using more integrative option-wise comparisons. The culmination of this evidence suggests that both the timing of when information about amount or time enters the choice process and the attention directed to a given attribute can influence the valuation of the options and therefore choice. This unifies prior work that behaviorally directed attention to one attribute over the other, and future work can build on this framework to help people develop strategies of information processing to help them meet their financial goals.

Chapter 3 focuses on a different type of valuation by looking at how attributes including price, willingness to pay, and budget contextualize the decision to purchase or skip an item. I find that budget size affects willingness to buy items within a price range near a pre-determined WTP, even when all item prices are below all given budgets.

Moreover, we show evidence that this effect is not simply due to anchoring to a larger number on the screen. Furthermore, we find a greater influence of budget size on items with higher bids suggesting that increased budgets do not uniformly increase valuation across all items, but rather do so for items that are already preferred. Despite an overall budget effect, there are individual differences in the use of budget, and our eye tracking data reveals that those who do use budget tend to look at budget more and make more comparisons between budget and price information, A combination of scan path analyses and trial to trial regressions show that people tend to look at items first to determine their interest and skip very quickly if they are not interested in that item. Typically participants only gathered information about price and budget when they were considering it after looking at the item and before making a final choice. Finally, the use of budget does not relate to overall purchasing rates, as those who use budget buy less for $10 budgets and buy more for $40 budgets rather than more overall. This suggests that budget size can be used as a mental accounting strategy to reduce impulse purchasing by adjusting the valuation of the item within the set budget.

In chapter 4, I examine social contextual modulation of valuation using neuroimaging rather than process tracing through computational modeling or attention. This paradigm tests reward anticipation responses to reward for self and charity in public and private contexts to explore how social context modulates the motivation for oneself and for charity. I find evidence that the public context reduces self-interested motivations behaviorally, but that there is no difference in charitable motivations across context. Moreover, I do not find an interaction between self-interested and charitable motivations across contexts, suggesting that while context matters for motivation for self, this does not undermine prosocial motivations. In the brain, I find strong reward responses for self-interested incentives and charitable incentives that span large value networks in the brain, including the striatum, insula and cingulate cortex. However, a simple contrast of public compared to private or private compared to public conditions does not show a large contextual difference in whole-brain activation other than occipital activity. However, the ventral striatum was an a priori region of interest and future analyses will look directly and signal change in this region across conditions to get a more sensitive measure of differences in motivation for self and charity. Moreover, future work will use the striatum as a seed region for connectivity to explore how the driving inputs to reward anticipation may change for self and charity across contexts.

5.2 Future directions

This work has broader implications for decision making outside of the lab. Probing the underlying processes of choice for decisions such as intertemporal choice and mental accounting can be instrumental in providing people with the tools to make better decisions within their financial situation. However, short-sighted decision-making by people experiencing financial hardship and poverty is often due in part to larger structural and contextual factors that constrain people's options to few or no "good" choices, and the constraints of poverty may also alter decision-making approaches. Savings and spending decisions interact with socioeconomic constraints in which seemingly anomalous choices may be adaptive for that specific context, whereas others may be maladaptive responses to constraints (Bertrand et al., 2004; Haushofer & Fehr, 2014; Mcguire & Kable, 2013; Shafir, 2017; Shah, Mullainathan, & Shafir, 2012). For example, intertemporal choices are influenced by socioeconomic status and some of this can be attributed to social trust and life history (Griskevicius et al., 2013; Mcguire & Kable, 2013; Michaelson, de la Vega, Chatham, & Munakata, 2013; Prabhu, Weber, Chafik, Jachimowicz, & Munrat, 2017). Other research shows that people experiencing poverty are less susceptible to certain decisions biases, such as irrelevant context effects, while studies of other contexts such as scarcity shifts attention in ways that increase susceptibility to debt (Shah et al., 2015; Shah et al., 2012). Therefore, examining the interaction of external structural factors imposed by poverty in combination with a mechanistic understanding of attentional patterns in individual decision-making to ground mechanistic work in more realistic contexts is an important future step.

Moreover, it is important to characterize the boundaries of mechanistic laboratory research when extended to field settings with low income populations in order to test whether these laboratory findings (largely from undergraduates in developed countries) generalize or differ across contexts. In addition to examining attention and process-based mechanisms, further exploration of social influences on decision-making will be helpful in future work on contextual valuation. For example, many savings and lending approaches in developing countries use social-group based commitments, and understanding the mechanisms involved is important to developing better interventions (Bryan, Karlan, & Nelson, 2010). More generally, investigating social influences in decision-making, including how identity, reputation, and group affiliation interact to modulate choices can help build more comprehensive models of human decision-making (Huettel & Kranton, 2012; Lee & Harris, 2013).

5.3 Conclusion

Value is constructed during decision making, and factors such as attention and social influence can affect this construction of value. Individual differences in the decision process in intertemporal choice, including attribute-wise versus option-wise comparison, the relative onset of amount versus time information, and the attention paid to these attributes during information gathering relates to intertemporal patience. Individual differences in the use of budget information and the comparison of budget and price relates to the strength of budget modulation of value, both to decrease item value under lower budgets and to increase value under higher budgets relative to a pre-determined WTP. Finally, a public social context can induce reputation motivations that reduce motivation to earn for oneself, but not for charity. These findings further our understanding of the mechanisms of value construction that influence consumer choice.

Appendix A

We examined how trial-to-trial variation in subjective value (SV) – as fit by the hyperbolic discounting model – influenced choices, response times, and gaze fixations. As expected, choices followed a logistic shape, such that the proportion of choices to the higher-SV option increased with increasing relative SV. Additionally, trials that had relatively greater differences in SV were associated with faster response times and fewer fixations, while trials where SV was more matched between the options had longer response times and a higher number of fixations. All effects observed in the first sample were replicated in the second sample. We conclude from these manipulation checks that our task had appropriate psychometric properties. While the hyperbolic model may not be the true choice generating process, it explained participants' choices and response times well, and we use it as a comparison to our multi-attribute DDM.

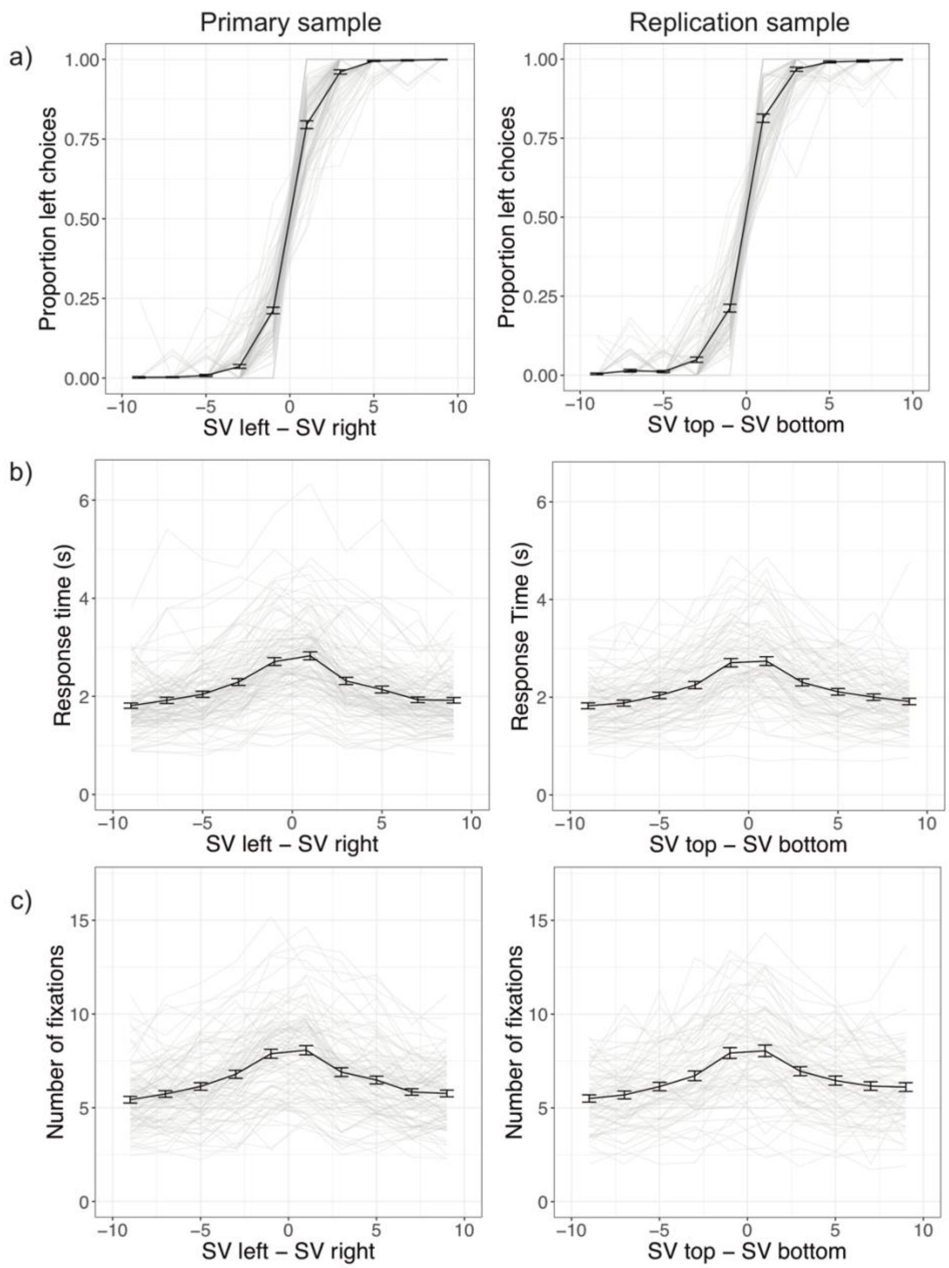

Figure 16: Subjective value (SV) corresponds to (a) choices, (b) response time, and (c) eye tracking gaze fixations. Panels (a) and (b) exclude participants not able to be fit to a single discount rate, leaving primary sample N = 105 and replication sample N = 79. Panel (c) excludes participants not able to be fit to a single discount rate or who had insufficient eye-tracking data for analysis, leaving primary sample N = 93 and replication sample N = 68. Light gray lines represent individual subjects; darker lines represent group mean values; error bars are SEM.

Appendix B

Regressions on subsets of the variable budget data are presented below. The first model, "Changing budget," uses the half of items that changed budget across runs of the lab task, and finds a similar budget effect to the full sample. The second regression "Prices within $1 of WTP" uses items that were priced within $1 of the subjects' bids from the online pre-survey. This shows that for a restricted price range, the coefficient on price is negative as expected when controlling for WTP.

Table 12: Mixed effects logistic regression of purchasing

	Changing budget	Changing budget (replication)	Prices within $1 of WTP	Price within $1 of WTP (replication)	Anchoring prices within $1 of WTP
Fixed effects: Estimate (Std. Error)					
Intercept	-0.66*** (0.10)	-0.69*** (0.14)	-0.85*** (0.11)	-0.96*** (0.15)	-1.01*** (0.16)
WTP	0.98*** (0.06)	0.66*** (0.09)	1.13*** (0.14)	0.87*** (0.16)	1.04*** (0.18)
Price	-0.23*** (0.05)	0.27*** (0.06)	-1.01*** (0.14)	-0.65*** (0.16)	-0.67*** (0.18)
Budget (Anchor)	0.44*** (0.03)	0.40*** (0.04)	0.53*** (0.03)	0.50*** (0.04)	0.04 n.s. (0.04)
Random effects: Variance (Std. Dev.)					
Subject ID	0.63 (0.79)	0.95 (0.97)	0.76 (0.87)	1.12 (1.06)	1.33 (1.15)
Obs., groups	4584, 76	3360,56	4993, 75	3888, 54	3660, 56
BIC	5244.4	3889.2	5787.4	4394.3	4085.1

Significance is indicated by * $p < .05$, ** $p < .01$, *** $p < 0.001$

The replication sample AOI regressions are presented below.

Table 13: Linear regression predicting looking at AOIs (Replication sample)

	Budget AOI Buy	Budget AOI Skip	Item AOI Buy	Item AOI Skip	Price AOI Buy	Price AOI Skip
Fixed effects: Estimate (Std. Error)						
Intercept	0.14*** (0.013)	0.15*** (0.013)	0.62*** (0.020)	0.58*** (0.021)	0.17*** (0.013)	0.17*** (0.013)
WTP	-0.0001 n.s. (0.0003)	0.0003 n.s. (0.0003)	-0.0001 n.s. (0.0005)	-0.0007 n.s. (0.0005)	-0.0001 n.s. (0.0003)	0.0008* (0.0003)
Price	0.0002 n.s. (0.0014)	0.002 n.s. (0.001)	-0.003 n.s. (0.002)	-0.0004 n.s. (0.002)	0.003* (0.001)	0.002 n.s. (0.001)
Budget	0.0008*** (0.0002)	-0.0004* (0.0002)	-0.001*** (0.0003)	0.0008** (0.0003)	0.0003 n.s. (0.0002)	-0.0004* (0.0002)
Random effects: Variance (Std. Dev.)						
Subject ID	0.05 (0.11)	0.07 (0.13)	0.07 (0.18)	0.11 (0.19)	0.05 (0.11)	0.07 (0.12)
Obs., Groups	1843,42	3197,42	1843,42	3197,42	1843,42	3197,42
BIC	-2817.2	-4306.0	-1007.1	-1236.4	-2689.1	-4207.5

Significance is indicated by * $p < .05$, ** $p < .01$, *** $p < 0.001$

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Biography

Dianna attended Macalester College, earning her B.A. in Neuroscience with a minor in Economics in the spring of 2013. She began her PhD at Duke University in the Cognitive Neuroscience Admitting Program in the Fall of 2013. She was awarded an NSF graduate research fellowship in 2014 and officially joined Scott Huettel's lab in the Fall of 2014. Dianna joined the Department of Neurobiology in the Spring of 2015. In the summer of 2018, she received an NSF GROW fellowship and visited the lab of Dr. Alan Sanfey at Radboud University Nijmegen.

<u>Publications</u>

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