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The Neural Representation of Value and individual Differences in Human Intertemporal Choice

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Abstract

Intertemporal choices, or decisions that involve tradeoffs between rewards and time, are ubiquitous in our daily lives. The tendency to devalue, or discount, future rewards has been linked to maladaptive long-term health and financial outcomes. Despite their broad clinical relevance, individual differences in discounting preferences are poorly understood. In this thesis, we make progress on the understanding of the neural basis of these decisions and factors that affect individual differences. The first two chapters focus on neurobiology. Chapter 2 investigates the decision-related variables that best explain the observed patterns of BOLD activity in ventromedial prefrontal cortex (VMPFC) and ventral striatum (VS) during intertemporal choice. We find that these regions carry different signals and likely contribute to different stages of the choice process. Across the brain, we find four kinds of value-responsive regions, each carrying different combinations of value-related signals. Next, we examine whether we can predict participants' choices from any or all of these groups of regions, and find that we can predict choice from most value-responsive regions, with interesting exceptions. In Chapter 3, we identify a novel brain predictor of individual differences in discounting. When participants are making judgments about how far away some number of days feels, discount rates, measured a week later, can be predicted from how VMPFC and VS respond as a function of temporal distance. This difference in the basic response to delayed time intervals could be a target for interventions aiming to reduce discount rates. In the final chapter, we find several behavioral manipulations that are able to reduce discount rates persistently and to a significant degree. We find that there is a general lack of knowledge about the normative strategy in the monetary discounting task, and that providing information about this strategy - to accept all delayed offers that provide higher interest rates than one could obtain elsewhere - reduces discounting significantly, for at least one month. Information about peers' strategies for making these decisions also reduces discounting. Taken together, this work advances our understanding of individual differences in discounting and further suggests interventions that could be used to reduce discounting.

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ABSTRACT

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Intertemporal choices, or decisions that involve tradeoffs between rewards and time, are ubiquitous in our daily lives. The tendency to devalue, or discount, future rewards has been linked to maladaptive long-term health and financial outcomes. Despite their broad clinical relevance, individual differences in discounting preferences are poorly understood. In this thesis, we make progress on the understanding of the neural basis of these decisions and factors that affect individual differences. The first two chapters focus on neurobiology. Chapter 2 investigates the decision-related variables that best explain the observed patterns of BOLD activity in ventromedial prefrontal cortex (VMPFC) and ventral striatum (VS) during intertemporal choice. We find that these regions carry different signals and likely contribute to different stages of the choice process. Across the brain, we find four kinds of value-responsive regions, each carrying different combinations of value-related signals. Next, we examine whether we can predict participants' choices from any or all of these groups of regions, and find that we can predict choice from most value-responsive regions, with interesting exceptions. In Chapter 3, we identify a novel brain predictor of individual differences in discounting. When participants are making judgments about how far away some number of days feels, discount rates, measured a week later, can be predicted from how VMPFC and VS respond as a function of temporal distance. This difference in the basic response to delayed time intervals could be a target for interventions aiming to reduce discount rates. In the final chapter, we find several behavioral manipulations that are able to reduce discount rates persistently and to a significant degree. We find that there is a general lack of knowledge about the normative strategy in the monetary discounting task, and

that providing information about this strategy – to accept all delayed offers that provide higher interest rates than one could obtain elsewhere – reduces discounting significantly, for at least one month. Information about peers' strategies for making these decisions also reduces discounting. Taken together, this work advances our understanding of individual differences in discounting and further suggests interventions that could be used to reduce discounting.

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CHAPTER 1 - Introduction

Delay discounting

Measurement and meaning of discount rates

Many of the decisions we make in our daily lives involve tradeoffs between rewards and time. For example, we must decide how much of our earnings to spend now and what to save for retirement; whether to eat appetizing and rich desserts or to refrain in favor of healthier foods; whether to smoke a cigarette for the immediate satisfaction or to quit and keep our physical health intact. These types of decisions, with outcomes occurring at different points in time, are referred to as intertemporal choices. When making these decisions, humans and other animals tend to devalue, or discount, rewards to be received in the future (Ainslie and Haslam, 1992; Frederick et al., 2002; Green and Myerson, 2004; Soman et al., 2005; Kalenscher and Pennartz, 2008).

A task often utilized in laboratory studies of human intertemporal choice is a monetary delay discounting paradigm which asks subjects to repeatedly choose between receiving smaller amounts of money immediately (or soon) or larger amounts of money at a later date (Kirby and Maraković, 1995). Participants who are willing to wait into the future for delayed rewards have low discount rates, and those who strongly prefer immediate rewards have high discount rates. In the absence of manipulations, discount rates have been shown to be a very stable behavior within individuals, on the timescale of weeks (Senecal et al., 2012), months (Ohmura et al., 2006) and even years (Kirby, 2009).

Despite this consistency within individuals, there is wide variability in preferences between individuals. This discounting task, then, lends itself to investigations of individual differences. Preferences on this type of monetary delay discounting task are not an isolated laboratory behavior. Years of research into individual differences in discounting have yielded myriad reasons why this behavior is important. Impatience on this style of laboratory questionnaire is related to drug use and addiction (Kirby et al., 1999; Bickel and Marsch, 2001);

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smoking (Audrain-McGovern et al., 2004; Chabris et al., 2008); pathological gambling (Petry, 2001a; Reynolds, 2006); obesity (Epstein et al., 2010); low exercise & high BMI (Chabris et al., 2008); and a lack of creditworthiness (Meier and Sprenger, 2012). On the other hand, more patient, far-sighted performance on delay discounting tasks has been related to higher intelligence (Shamosh and Gray, 2008; Burks et al., 2009); life satisfaction and subjective health (Becker et al., 2012); and academic and social performance in children and adolescents (Mischel et al., 1988; Duckworth and Seligman, 2005). The goal of this thesis is to further the understanding of the neural basis for these tradeoffs, and particularly what drives these individual differences, to inform successful interventions.

A normative solution

An element unique to the monetary discounting task is that there is a normative solution. The normative strategy is to compare the interest rate offered implicitly by each choice pair to the interest rates one has access to outside of the experiment (Fisher, 1930; Read, 2004). If a subject could borrow the smaller amount of money on offer, wait for the larger payoff, and then be able to repay this loan plus interest and still make a profit, then the larger later option is the better choice, whether the subject intends to spend the money immediately or not.

Despite this normative solution, most studies of delay discounting observe discount rates much higher than market interest rates, some even in the range of several hundred percent per year (Thaler, 1981; Ainslie and Haslam, 1992; Coller and Williams, 1999; Frederick et al., 2002; Reynolds, 2006; Chabris et al., 2008). A number of factors could contribute to higher-than-normative discount rates; some of these, which imply non-normative discounting, are described below (see *individual differences*). It is also possible that people do discount according to the normative strategy, but have normatively relevant reasons to discount more highly. For example, the normative strategy depends on the interest rates available to each individual in their personal finances. If participants are credit constrained, or do not have investment opportunities available, they would be justified in accepting only immediate options. Selecting the option of waiting for a delayed payment also indicates an implicit level of trust both in the experimenter and the future. If

participants felt that either the receipt of the delayed payment, or their place in the future in general, contained an element of risk, then they would be justified in demanding a higher rate of return for waiting (Benzion et al., 1989; Keren and Roelofsma, 1995; Dasgupta and Maskin, 2005; Bommier, 2006; Halevy, 2008; Gerber and Rohde, 2010). Chapter 4 of this dissertation explores a lack of understanding of the normative strategy as a contributor to high discount rates, through an online survey and several laboratory experiments, and finds evidence that this is a factor in high discount rates.

Several mathematical models have been put forth to describe discounting behavior. The earliest was the discounted utility model, proposed by Samuelson (1937). The discounted utility model takes an exponential form, and involves just one free parameter to describe the steepness of the discounting function. The shape of this function dictates that the rate of discounting is equivalent across all future time intervals. Despite the simplicity of this model, and the convenient normative predictions it makes, it fails to capture the nuances of empirically observed behavior. Individuals do tend to discount shorter time intervals more steeply than longer ones (Thaler, 1981; Prelec and Loewenstein, 1991). A model with a hyperbolic form captures this behavior pattern while still using a single free parameter to describe discounting steepness, and outperforms the normative exponential model in predicting behavior in humans (Rachlin et al., 1991; Kirby and Maraković, 1995; Green et al., 1997; Kirby and Finch, 2010), primates (Kim et al., 2008), rodents (Richards et al., 1997), and pigeons (Mazur, 1987). Models with additional parameters have been proposed to explain variations in discount rates due to contextual or framing effects (Laibson, 1997; Read, 2001; Scholten and Read, 2006); however, the hyperbolic form is generally preferred in neuroeconomics, for its simplicity and good fit to behavior.

Individual differences

Despite the clear clinical relevance of delay discounting, there are relatively few manipulations that are known to affect discount rates, nor are there clear links to trait-like individual differences. The chapters in this thesis make progress on this both through behavioral experiments and in the search for individual differences in the brain.

The most commonly reported manipulations of discount rates are contextual and framing effects, such as phrasing choices in terms of interest rates (Coller and Williams, 1999; Read et al., 2005a), presenting exact dates of delayed payment receipt rather than delay durations (Read et al., 2005b), and cuing future planned events or scenarios in addition to delay durations (Peters and Büchel, 2010a; Benoit et al., 2011). It has also been shown that discounting for gains is less than discounting for losses (Green and Myerson, 2004), and that discounting is steeper for lower amounts of money than for very large amounts (Kirby and Maraković, 1995; Myerson and Green, 1995; Green et al., 1997).

The effects described above could be grouped under the category of "state" effects (Peters and Büchel, 2011), in that they are temporary changes dependent on the presentation of the task. Fewer "trait", or more permanent, differences in discounting have been identified. For example, older adults discount less steeply than younger adults, and individuals with a high base income level discount less steeply than those with very low income (Green et al., 1994; 1996; 1999). Discount rates have also been reported to be negatively related to some measure of intelligence, such as IQ, education level, or scholastic achievement (Kirby et al., 2005; Shamosh and Gray, 2008; Burks et al., 2009). Reports of correlations with personality variables, such as impulsivity, are inconsistent.

Other effects concern individuals' perception of the future. The perception of time and temporal distance differs within individuals, and may effect discount rates (Kim and Zauberman, 2009; Zauberman et al., 2009). One study finds framing effects of relative temporal distance on discount rates (Kim and Zauberman, 2013). Several studies have found that people who feel more connected, or similar to, their future selves are lower discounters (Ersner-Hershfield et al., 2009a; 2009b; Bartels and Rips, 2010; Mitchell et al., 2011); this finding has also been linked to differences in brain activity. Chapter 3 of this thesis looks further for individual differences in the brain, by investigating individuals' responses to the future as a potential predictor of discount rates.

Neural basis of valuation and value-based choice

Understanding how preferences are represented and choices are executed in the brain could elucidate other potential targets for investigating individual differences. This neural process of value-based decision making can be broken down into several steps. The decision maker must be able to understand what the possible options are and evaluate them, select the higher valued option and execute the necessary action to obtain it, and evaluate and learn from the outcome of the decision (Rangel et al., 2008; Kable and Glimcher, 2009). The latter component of this schema, which requires outcomes to be experienced during the course of the task, are the topic of the subfield of reinforcement learning (Rangel et al., 2008; Balleine and O'Doherty, 2009; Niv, 2009; Schultz, 2010). The decision making tasks described herein do not involve experienced outcomes and will therefore focus heavily on the first two components of this process.

Neuroanatomy of reward

Although much of the brain can be responsive to the value of stimuli and events, a core set of regions is central to value-based decision making. The seminal finding by Olds and Milner (1954, 1956) that rats will work to electrically self-stimulate the nucleus accumbens initiated the examination of the neuroanatomy of the reward system. Since then, evidence from across species and research modalities has converged on a coherent model of reward processing, at the core of which is a cortico-basal ganglia circuit involving the ventral striatum, orbitofrontal cortex, and midbrain dopamine neurons (Hikosaka et al., 2008; Haber and Knutson, 2010).

Dopaminergic neurons in the substantia nigra send extensive inputs both to other basal ganglia structures, including the striatum, and to cortical regions, including orbitofrontal and medial prefrontal cortices. The striatum consists of the caudate, putamen, and nucleus accumbens. The nucleus accumbens, and the ventral portion of the striatum more broadly, are reciprocally connected primarily with the orbital and medial prefrontal cortices, and with the anterior cingulate (Haber and Knutson, 2010). While all of the striatum is responsive to reward, it is this ventral portion with the nucleus accumbens that is most strongly related to the value of

possible goods; the dorsal portion of the striatum is more linked to action selection during choice execution (Hikosaka et al., 2008).

The orbitofrontal cortex (OFC) contains the most ventral portion of the prefrontal cortex, and the area of OFC which overlaps with the medial wall of the prefrontal cortex is termed the ventromedial prefrontal cortex (VMPFC). Although the lateral OFC is most often linked to value representation in non-human primates, it is the ventromedial region that responds to reward in humans (Wallis, 2011). The OFC and VMPFC receive strong dopaminergic innervation, as well as inputs from many cortical regions, and indirect input from the ventral striatum (through the thalamus). In addition, the OFC is the only part of the prefrontal cortex that receives input from every sensory modality (Carmichael and Price, 1995), making this an ideal location for integrating all aspects of value.

Human neuroimaging experiments demonstrate that ventral striatum and ventromedial prefrontal cortex are involved in the valuation of primary rewards such as preferred food, drinks, odors, and touch (Kringelbach et al., 2003; Rolls et al., 2003; Grabenhorst et al., 2007; McClure et al., 2007); secondary rewards such as money and trinkets (Knutson, 2005; Delgado, 2007; Chib et al., 2009); and more abstract rewards such as social approval and cooperation (Sanfey et al., 2003; King-Casas et al., 2005; Fehr and Camerer, 2007; Montague and Lohrenz, 2007). This is supported by results in the primate literature demonstrating, using single-unit recordings, that neurons in these regions can represent the subjective value of choice options in a number of tasks (Wallis and Miller, 2003; Samejima, 2005; Padoa-Schioppa and Assad, 2006; Lau and Glimcher, 2007; Rolls et al., 2008).

Subjective value representation

Decades of evidence support the claim that the evaluation, comparison, and selection of choice options are done in the space of subjective, rather than objective, values. This allows for the comparison of choice options across distinct domains (Rangel et al., 2008; Kable and Glimcher, 2009). The measure of value that the brain represents, then, reflects not just the

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objective characteristics of any choice option, but a composite obtained from a weighted combination of the relevant objective features of the option.

Experiments that aim to correlate brain activity with subjective value can obtain estimates of value in a number of ways. Subjective value can be inferred from the choices subjects make between stimuli, or assessed more explicitly by asking subjects to rate some positive feature of the stimuli (pleasantness, liking) or to provide an amount of money they would be willing to pay to obtain the stimulus. Quantitative meta-analyses of the large literature on this topic have found that the ventromedial prefrontal cortex and ventral striatum reliably reflect value on a subjective scale (Levy and Glimcher, 2012; Bartra et al., 2013; Clithero and Rangel, 2013).

Subjective value representations have been examined in a wide variety of tasks. For example, activity in the ventral striatum and ventromedial prefrontal cortex reflects the potential values of risky gambles, and scales with subjective measures of loss aversion (Tom et al., 2007). The ventromedial prefrontal cortex also reflects the monetary value that hungry subjects place on preferred foods (Plassmann et al., 2007) and the value of potential food choices, integrating health and preference ratings (Hare et al., 2009; 2011a; Hutcherson et al., 2012). Some studies have looked at reward representation of different categories of goods within the same individual, and found large overlap regions (Chib et al., 2009; FitzGerald et al., 2009; Basten et al., 2010). A number of studies have shown that the ventral striatum and ventromedial prefrontal cortex represent subjective value during intertemporal choice tasks (McClure et al., 2004; Kable and Glimcher, 2007; McClure et al., 2007; Ballard and Knutson, 2009; Peters and Büchel, 2009; Pine et al., 2009; Kable and Glimcher, 2010). If a region tracks subjective value, rather than objective value, then its activity should correlate with the objective values that go into the subjective estimate, but be better accounted for by the subjective variable. Several papers do this comparison directly, and do report higher correlations of VS and VMPFC activity with subjective value than objective values such as probability, amount, delay, or expected value (Kable and Glimcher, 2007; Peters and Büchel, 2009). Confirming the importance of ventromedial prefrontal cortex in value estimation, humans and monkeys with lesions to this region make less consistent

value-based choices, particularly when options are close in value (Fellows and Farah, 2007; Noonan et al., 2010; Camille et al., 2011; Kennerley and Walton, 2011; Glascher et al., 2012).

The ventromedial prefrontal cortex and ventral striatum contain a representation of value even when participants are performing an orthogonal task, and are not explicitly asked to judge how much they like something (Lebreton et al., 2009; Tusche et al., 2010; Smith et al., 2011). For example, Lebreton et al (2009) asked participants to view a series of images and judge the age of the objects or faces shown in those images. After the scan, participants were asked to make choices between the stimuli. Despite performance of an orthogonal task during viewing, VMPFC still contained a reliable correlate of the pleasantness ratings that were obtained later. Several other studies find that neural activity in these regions while participants are judging stimuli (on qualities related to value) can predict choices made later (Tusche et al., 2010; Levy et al., 2011).

It is also possible to predict differences in discounting from neural responses to different tasks that may tap into components of the discounting process. For example, high discounters exhibit a higher VS response to unpredicted rewards (Hariri et al., 2006). Differential responses in VMPFC to judgments of oneself in the present compared to the future also predict discount rates (Ersner-Hershfield et al., 2009b; Mitchell et al., 2011). In Chapter 3 we investigate a more basic neural predictor of discount rates, and find a differential pattern of response in VMPFC and VS for high and low discounters while participants are merely evaluating future time intervals. This suggests an interesting new target for behavior change.

Value-based decision making

As described above, the process of value-based decision-making requires the evaluation, comparison, and selection of choice options. While work in the field of neuroeconomics has largely converged on an understanding of where subjective value is represented in the brain, the question of how and where decisions are made between these representations is still under debate (Rushworth et al., 2009; Wallis and Kennerley, 2010; Rushworth et al., 2012; Summerfield and Tsetsos, 2012).

Given the strong relationship between subjective value and activity in the ventral striatum and ventromedial prefrontal cortex, early summaries of work in neuroeconomics concluded that these regions were primarily responsible for evaluating choice options (it should be noted that these regions are also crucial for aspects of learning, although it is not discussed here; c.f. Balleine and O'Doherty, 2009; Schultz, 2010). The functions of action selection and execution have been posited to belong to the dorsolateral and parietal cortices, and perhaps also to the anterior cingulate cortex (Kable and Glimcher, 2009; Kennerley and Walton, 2011). However, as the field progresses in experimental design and methodology, these labels have become less clear.

One aspect of this is that it seems possible for choices to be made both in the space of *goods* or of *actions*. While both models agree that the evaluation of choice options takes place in OFC/VMPFC, the goods-based model posits that decisions are made between these abstract value representations, and then translated to a motor response by regions such as the anterior cingulate and posterior parietal cortices (Padoa-Schioppa, 2011). The action-based model, on the other hand, proposes that these abstract value representations for each choice option are translated to potential actions, and that decisions are made in the space of these differently valued action plans (Rangel et al., 2008). While it is evident that the brain can make decisions in either schema, the question of whether these possible mechanisms are used in parallel, or somehow selected depending on the choice situation, is an open debate.

Value-based decision making requires a number of different variables to be computed, which are often highly correlated with one another, and occurring very close together in time (Behrens et al., 2007; Hare et al., 2008; Wallis and Kennerley, 2010). Because of the frequently high correlation between these variables, and the lack of rigor in comparing them in the same experiments, it is sometimes unclear what variables best explain brain activity in a given brain region.

One region for which the literature has mixed findings is the ventromedial prefrontal cortex. This region has been found to correlate not only with the values of possible choice options

(Kable and Glimcher, 2007; Hare et al., 2008; Chib et al., 2009; Kable and Glimcher, 2010), but also with the value of the option that is ultimately chosen (Blair et al., 2006; Glascher et al., 2009; Wunderlich et al., 2009; 2010; Barron et al., 2013), and with measures of the difference in value between the choice options (Boorman et al., 2009; FitzGerald et al., 2009; Basten et al., 2010; Philiastides et al., 2010; Rolls et al., 2010; Lim et al., 2011; Hare et al., 2011b; De Martino et al., 2012; Hunt et al., 2012; 2013). Within this mix of reports, interpretations of the findings also differ. One school of thought posits that choices between goods are made within VMPFC, and that the true pattern of activity resolves to the chosen option (Padoa-Schioppa and Assad, 2006; Hunt, 2008). Another possibility is that VMPFC truly represents the value of whatever option is being attended, and that this valuation signal is translated to action plans downstream of VMPFC (Lim et al., 2011; Hare et al., 2011b). Resolution between these models will require careful examination of model assumptions, and likely methods other than fMRI. However, Chapter 2 contributes to this discussion with a careful analysis of disambiguated decision variables, and examines which variable(s) best explain activity in several value-related brain regions.

Research aims

The goal of this dissertation is to examine neural and behavioral factors that affect valuation and choice during intertemporal decision making. The first chapter contributes to the debate about the differentiation of valuation versus choice by making an important statistical point about localization of certain decision-related variables, and identifying which brain regions can predict choices. The next two chapters provide insight into underlying individual differences in intertemporal decision making, first identifying a neural predictor of differences in discount rates, and second using a set of behavioral experiments to explore factors that change discount rates. Both chapters provide potential targets for discounting interventions.

We begin, in Chapter 2, with an fMRI study of intertemporal choice. Despite a consistent understanding of what regions in the brain respond to subjective value, there is a lack of consensus on where and how choices are made, and even on precisely what signals should be

generated by a choice process. Several prominent theories have made competing claims about the choice process being associated with specific variables in particular brain regions. However, most studies stop once they have found regions that correlate with their putative decision signals, rather than looking for discriminative evidence that their model of interest *best* describes activity in a given region. In this chapter, we separate several decision variables of interest, and examine which variables best explain activity in value-related regions. We find a dissociation between the combinations of decision-related signals carried by four different sets of regions. While we replicate some of the predictions of each of two prominent models, neither perfectly describes the data. Additionally, we examine whether regions that represent different combinations of decision variables are differentially predictive of participants' choices.

In Chapter 3, we move from the prediction of choices to the prediction of individual differences. Here we ask whether we can predict delay discounting from neural activity during a task about the perception of time, in which participants make judgments about how far away some number of days feels. Regions crucial to the representation of subjective value, the ventral striatum and ventromedial prefrontal cortex, carry representations during temporal judgments that predict delay discount rates obtained in a separate task. This builds on previous work identifying correlations between discounting and performance of other tasks, and provides insight into individual differences in discounting.

Chapter 4 is a series of behavioral studies that further investigate contributing factors to higher than normative discount rates, including lack of awareness or understanding of the normative strategy. We find that when asked what factors are important considerations when making intertemporal choices, most participants do not spontaneously cite the crucial elements of the normative strategy. Two studies find that providing participants with information about the normative strategy significantly reduces discount rates, even after a delay period of about one month. These studies together suggest that a contributor to variable discount rates is not just time preferences, but also knowledge about relevant considerations when making decisions.

CHAPTER 2 – Neural differentiation of subjective value and value comparison during intertemporal choice in humans

Abstract

In the neuroeconomics literature, a reliable finding is that BOLD activity in the ventromedial prefrontal cortex (VMPFC) and ventral striatum (VS) is correlated with the subjective value of choice options during value-based decision making. However, in many studies, subjective value (the overall value of all options offered) is highly correlated with other decision-related variables. Here we design a delay discounting task that can distinguish several of these variables, and find that while activity in VS is best explained by subjective value, activity in VMPFC represents the chosen (maximally valued) option. In the whole brain, we find distinct groups of regions that represent different combinations of these variables: ventral striatum and anterior and posterior cingulate cortices reflect subjective value; the amygdala and temporoparietal junction reflect value comparison (the difference in value between the choice options); and dorsomedial and lateral prefrontal and lateral parietal cortices multiplex subjective value and response-related (reaction time) signals. Furthermore, we find that choices can be predicted from activity in most of these value-related regions, except for those that only reflect value comparison. These findings are the first to carefully disambiguate these decision variables and examine which best explain brain activity.

Introduction

Theories of decision making from several disciplines posit that in making a choice, the brain must be able to estimate the value of the available options on a generalized, subjective scale, compare them, and select and execute the higher valued option (Rangel et al., 2008; Kable and Glimcher, 2009). Much work in neuroeconomics has looked for neural correlates of the variables that would carry this information. The ventromedial prefrontal cortex (VMPFC) and

ventral striatum (VS) in particular are frequently cited as representing value signals during

decision making, and recent meta-analyses confirm that these two regions in particular carry

domain general signals of subjective value (Levy and Glimcher, 2012; Bartra et al., 2013; Clithero

and Rangel, 2013).

While it is well established that VMPFC and VS are crucial for value-based decision

making, there is a lack of consistency in the dissociation of signals carried by these regions. The

process of value-based decision making involves the computation of several crucial variables,

which are often highly correlated and occurring close together in time, making their

disambiguation difficult. Compounding this challenge, there has been little emphasis on

estimating what the brain response is and examining what variables best capture it; rather,

previous work tends to test single models, without examining multiple variables, or allowing them

to compete in the same model.

Here we examine two particular variables of interest. One of these is the overall value, on

a participant-specific subjective scale, of the choice options on offer, referred to here as

subjective value. Another is a measure of the difference between the offered options on this

subject-specific scale, defined herein as *value comparison*. While many studies have

demonstrated a correlation between activity in VMPFC and VS and subjective value (Kable and

Glimcher, 2007; Hare et al., 2008; Chib et al., 2009; Kable and Glimcher, 2010), a number of

studies have also found a link between VMPFC activity and the value of the chosen option (Blair

et al., 2006; Glascher et al., 2009; Wunderlich et al., 2009; 2010; Barron et al., 2013), and value

comparison, or some construct of the difference in value between the choice options (Boorman et

al., 2009; FitzGerald et al., 2009; Basten et al., 2010; Philiastides et al., 2010; Rolls et al., 2010;

Lim et al., 2011; Hare et al., 2011b; De Martino et al., 2012; Hunt et al., 2012; 2013).

Identifying the pattern of BOLD activity in these regions, and the decision variable(s) that

best explain this activity, could help to distinguish between different models of how value-based

choice is executed. Several models have been put forth that make different predictions about

BOLD activity in VMPFC and VS. For example, one class of models posits that the VMPFC is the

location of an attractor-network-based decision process that involves competition between representations of the two options. In this model, the VMPFC should carry a signal of the comparison between choice options (Hunt et al., 2012) . Other models propose that while VMPFC does carry the value signals that are the input to a comparison process, comparison and choice selection is executed elsewhere; in this schema, VMPFC should track subjective value of attended items (Lim et al., 2011).

Here, we disambiguate subjective value and value comparison, using a carefully designed human delay discounting task. In this task, participants make decisions between smaller monetary rewards that are available immediately and larger rewards available after some time delay. The discount rate, a measure of preference for immediate versus delayed rewards, is estimated from these choices, and can be used to calculate the subject-specific discounted value (subjective value) of each choice option seen during the task. Human fMRI studies using discounting tasks have found reliable BOLD activation in VMPFC and VS that correlates with the subjective value of choice options (Kable and Glimcher, 2007; Ballard and Knutson, 2009; Peters and Büchel, 2009; Pine et al., 2009; Kable and Glimcher, 2010). However, previous work in intertemporal choice has either not modeled multiple decision variables, such as both subjective value and value comparison, or has reported very high correlations between these variables (Kable and Glimcher, 2007; 2010), making them impossible to differentiate reliably.

We first perform a directed region of interest analysis of activity in VMPFC and VS, and find that BOLD activity in VS tracks only the subjective value signal, while BOLD activity in VMPFC tracks a combination of subjective value and value comparison signals. In an exploratory whole-brain analysis, we find three additional groupings of regions representing different combinations of these signals. Subjective value is represented positively in the ventral striatum, and posterior and anterior cingulate cortices. Value comparison is positively correlated with activity in the amygdala and temporoparietal junction. A third set of regions, including the dorsomedial and dorsolateral prefrontal cortices and lateral parietal cortex, correlate positively with subjective value and negatively with value comparison, which mirrors the effect of reaction

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time. Additionally, we find that activity in these subgroups of value-related regions is differentially predictive of choice – regions that track response demands are most predictive, and those that track value comparison least so.

Materials and methods

Participants. Thirty-three participants were recruited from the University of Pennsylvania and surrounding community. All participants were compensated for their time at each session, and received additional payment based on their decisions in the delay discounting task. All participants were consented in accordance with the procedures of the Institutional Review Board of the University of Pennsylvania.

A total of 33 participants were collected in two samples. After exclusions, the first sample consisted of 10 subjects, of whom 6 were female, and all were right-handed. The average age of this sample was 22 years (SD=2.5yrs). The second sample consisted of 17 subjects, of whom 10 were female and 13 were right-handed. The average age of this sample was 22 years (SD=3.8yrs).

In the first sample, subjects were pre-selected to be in the median 20% of the population on a discounting questionnaire. All subjects saw the same stimuli, and completed three days of scanning while completing the discounting task. In the second sample, subjects were pre-screened to establish a baseline discount rate, but were not excluded based on initial screenings. Choice stimuli for their single scanning session were tailored for each individual, according to this baseline discount rate.

Three participants were excluded from analysis of the first sample because of excessive head motion during the scan sessions (>5 spikes exceeding 1mm of movement, during at least 2 of their 3 sessions). In sample 2, another two participants were excluded for excessive head motion (>10 spikes exceeding 1mm of movement). Finally, one participant was excluded from the second sample because of an unusually high rate of missed trials (23%; this is 3 standard

deviations above the mean of 2.4 missed trials [SD=4.7]). This leaves a total of 10 participants in the first sample and 17 in the second sample.

One subject participated in both samples. This subject's data is included in presentations of each sample separately, but his data from the second sample has been removed for presentations of both samples combined. Thus, the analyses that combine across samples have a total of 26 unique participants.

Task description. All scanning sessions involved a monetary delay discounting task, in which participants made a series of decisions between a smaller amount of money available immediately and a larger amount of money available after a delay. The smaller-sooner amount was always $20 now, and the larger-later amount and delay were variable. Only the larger-later option was presented on screen during the choice task. At the beginning of each scanning run, participants were instructed whether to press the right or left button to accept the larger-later option on the screen or to reject it in favor of $20 now. Halfway through the task, the right-left contingency was switched; participants were explicitly told about, and shown a graphic explaining, the switch. Participants had 4 seconds to make a choice once the larger-later option appeared on the screen. After a choice was made, a feedback screen was displayed for 1 second. A checkmark was shown if the option on-screen (larger-later) was chosen, and an "X" if the option on-screen was rejected in favor of $20 now. The inter-trial interval ranged from 0 – 26 seconds, with an average of 5 seconds. If participants made a decision in less than the allotted 4 seconds, the remaining decision time was incorporated into the inter-trial interval.

In the first sample, participants were selected to be in the median 20% of the population based on a preliminary discounting questionnaire. At each session, participants made 192 choices between receiving $20 now or a larger amount at a later date. Amounts ranged from $20.50 to $50, and delays from 1 to 180 days. All participants saw the same choice pairs within a scan, but no choice pair was repeated within participants or across days. The study design in this sample included an attempt to influence discount rates before the second scanning session; however, this manipulation did not change discount rates (paired t-tests of logK between days all

ns). In the fMRI analyses presented below, discount rates from each scan day are used, rather than an overall average, and will therefore account for any slight changes in discount rates between scanning days.

In the second sample, participants were not pre-selected. However, the choice sets were tailored to each participant. These participants completed a single scanning session, during which they made 196 choices between non-repeating stimuli. The smaller-sooner option was always $20 today. The maximum delay for a larger-later amount was 190 days for all participants. The maximum larger-later amount offered after a delay was variable between participants. This amount averaged $68 (SD=$51). Tailoring of stimuli was based on the baseline screening discount rate, and was designed to reduce the correlations between the decision variables of interest (described below).

In using different selection methods in each sample, we can rule out some possible confounds. Selecting participants to be in a small range of discounting preferences allow us to keep the stimuli constant, while still reducing the correlations between our variables of interest. On the other hand, tailoring stimuli to each participant, without pre-selection, allows for direct minimization of these correlations without limiting the range of preferences in pre-selection. When analyzed separately, the two samples give very similar results (see below), indicating that our findings are not limited to specific experimental design choices.

Payments. In addition to a flat $15 per-hour payment for their participation in each scanning session, participants were paid an additional amount according to their decisions in the delay discounting task. Participants rolled dice to randomly select one of the choice trials, and were paid for the choice they made on that trial. All payments were made using pre-paid debit cards, as described previously (Kable and Glimcher, 2007; 2010). The cards have the advantage of making receipt of the delayed payment easy and reliable. If the participant chose the smaller sooner option on the selected trial, the amount was available on the card immediately after the session. If the participant chose the larger later option on the selected trial, the amount was available on the card after the appropriate number of days had passed.

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Behavioral data analysis. Discount rates in this experiment were calculated assuming a hyperbolic discounting model (Mazur, 1987), such that SV = A / (1+k*D), where SV is the subjective value of the delayed option, A is the monetary amount of the delayed option, D is the time delay in days, and k represents the individually fit discount rate. Discount rates were estimated using a logistic regression model, implemented in Matlab (Mathworks, Natick, MA). We estimated this function for each participant at each testing session. Because discount rates are not normally distributed, any statistics performed on discount rates substitute the log transform of the discount rate.

We primarily investigated two decision variables, subjective value and value comparison. Within a scanning session, for each participant, decision variables were estimated by applying the estimated discount rate to the options seen on each trial. Subjective value was taken to be the discounted value of the larger later option on each trial. Because the value of the smaller sooner option remained constant, this subjective value metric is collinear with the *overall* subjective value of both options together. Value comparison was defined as the absolute value of the difference between the smaller sooner option ($20) and the discounted value of the larger later option; this value becomes smaller as the subjective value of the larger later option approaches $20, and larger as the subjective value gets much higher or lower than $20.

Across all participants, the average correlation between subjective value and value comparison was r=-0.04 (SD=0.56). In sample 1 alone, this correlation was r=0.17; in sample 2, this correlation was r=-0.21. Given the low level of the overall correlation and the fact that the directionality of correlation is opposite in the two samples, we believe we can make conclusions about whether BOLD activity tracks one of these variables or some combination of them. In previous studies of intertemporal choice, this correlation has been much higher (r=0.8 in Kable & Glimcher 2010, r=0.75 in Kable & Glimcher 2007).

In a set of region of interest analyses, we also consider the maximally valued option. Maximum value is taken as the highest subjectively valued option – this is the subjective value of the larger later option if it is greater than $20, and $20 otherwise. The average correlation

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between maximum value and subjective value was r=0.85 (SD=0.09), and the average correlation between maximum value and value comparison was r=0.42 (SD=0.39).

Of possible interest are a parallel set of decision variables that are more dependent on trial-by-trial choice. For example, instead of the maximally valued option, one could look for representations of the option chosen on each trial. Likewise, instead of taking the value comparison metric to be the absolute value of the difference between the choice options, one could analyze the difference between the chosen and unchosen options. The variables used here are less dependent on trial-by-trial choices than on overall preferences. Both of these sets of variables are highly correlated, as participants nearly always choose the maximally valued option (chosen value vs maximum value, r=0.92; absolute value difference vs chosen minus unchosen, r=0.88). Analyses reported here do not differ significantly when using this set of parallel variables.

The estimated discount rate was also used to calculate a measure of choice consistency. Choice consistency was defined as the percentage of a participant's actual choices predicted correctly by the estimated discount rate from that same session. The choice predicted by the estimated discount rate is simply the option with the higher subjective value, according to that discount rate.

The average reaction time was 1.46 seconds (SD=0.24s). Participants were allowed 4 s to make a response, and could do so as soon as the choice was presented. On the vast majority of trials (over 99%), participants were able to make a choice in this timeframe. Across both samples, the correlation between reaction time and subjective value was 0.12 (SD=0.24). In sample 1, this correlation was r=0.04, and in sample 2, r=0.17. Across both samples, the correlation between reaction time and value comparison was r=-0.37 (SD=0.13). In sample 1, this correlation was r=-0.39; in sample 2, r=-0.35. Both of these correlations are significant in the combined sample (reaction time and subjective value, p<0.034; value comparison, p<0.0001).

MRI image acquisition. Functional and anatomical scans were collected using a 3T Siemens Trio scanner equipped with a 32-channel head coil. High resolution T1-weighted anatomical images were collected using an MPRAGE sequence (T1 = 1100ms, 160 axial slices, 0.9375 x

0.9375 x 1.000 mm, 192 x 256 matrix). T2*-weighted functional images were collected using an EPI sequence (TR = 3s, TE = 30ms, 45 axial slices, 3 x 3 x 3 mm, 64 x 64 matrix). The slice acquisition angle was 30° from the AC-PC line, in order to reduce signal dropout in regions such as orbitofrontal cortex (Deichmann et al., 2003). Each scan consisted of 168 images. In the first sample, all participants completed four scans at each of three sessions. Five trials of scanning data were lost from the final session of one participant due to experimenter error. In the second sample, all participants completed four scans at one session.

Imaging data analysis. Functional images were analyzed using VoxBo (www.voxbo.org), incorporating tools from SPM8 and AFNI. Functional images were sinc-interpolated in time to adjust for staggered slice acquisition, corrected for head motion by realigning all volumes to the first volume of the scanning session using six-parameter rigid-body transformations, and de-trended and high-pass filtered (cutoff of 126 cycles per scan, or 0.0079 Hz) to remove low frequency drift in the fMRI signal. Images were co-registered with each participant's high-resolution anatomical scan and normalized into MNI space. Normalized data were then spatially smoothed (kernel FWHM=9mm) and thresholded to remove voxels outside of the brain.

Single-participant analyses were performed using the general linear model as implemented in VoxBo. Estimation was by ordinary least squares. For participants in the first sample, the three scans were concatenated (totaling 12 runs) for analysis after preprocessing. First level models used the respective scan's discount rate for calculation of decision variables.

The first general linear model (GLM1) tested the effect of different decision variables at the onset of the trial, and included three covariates of interest. The first covariate modeled the time at which a trial began (first 100ms), when participants saw the larger-later choice option. The second and third covariates were parametric modulators of subjective value and value comparison for the choice pair in each trial. These values were all mean-centered, so the parametric modulator covariates fit the deviations from mean activity that were correlated with the respective variable across trials. Nuisance variables were included to mark run boundaries.

GLM2 included the same regressors as the first model, with an additional parametric regressor that modeled the reaction time on each trial. This regressor was also mean-centered. GLM3a included mean-centered onset time and parametric chosen value covariates. GLMs 3b and 3c built on GLM3, adding parametric regressors for either subjective value (GLM3b) or value comparison (GLM3c).

Group random-effects analyses were performed using the summary statistics approach, which tests whether the mean effect at each voxel is significantly different from zero across participants. Contrast maps were initially thresholded at $p<0.005$ (uncorrected), and the appropriate spatial extent threshold for corrected cluster-level inference at $p<0.05$ was determined for each contrast. Cluster thresholds were determined using the AlphaSim function in AFNI. Group tests were performed across both samples, as well as for each sample separately.

Region of interest analysis. We used *a priori* regions of interest from a recent quantitative meta-analysis of studies that report value-related neural signals during decision-making (Bartra et al., 2013). The regions used here were the result of a conjunction analysis looking for areas that (1) exhibit primarily positive correlations with subjective value, (2) correlate with subjective value during the experience of decision outcomes and during the decision process, and (3) correlate with subjective value across different choice modalities (i.e., money, food). The resulting regions are bilateral ventral striatum (147 voxels at 3x3x3 mm, centered on MNI coordinates -3, 10, -4) and ventromedial prefrontal cortex (137 voxels at 3x3x3mm, centered on MNI coordinates -1, 46, -7). Downloadable versions of masks from these regions can be found at (http://www.sas.upenn.edu/~mcguirej/meta-analysis.html). There are subtle differences between the masks used here and the downloadable masks, due to the downsampling process from 2mm to 3mm voxel sizes.

Prediction analysis. The prediction analysis was performed on BOLD activity that was averaged and demeaned, by run, in each region of interest. Preprocessing included smoothing, motion correction, and normalization. Because of the event-related nature of the task, the LSS procedure for beta-series correlations was used (Mumford et al., 2012) to obtain activation levels for each

trial. This method obtains each trial's activation estimate using a general linear model including a regressor for a given trial as well as a second regressor for all other trials in the set; this procedure is repeated for each trial.

Classification was implemented using logistic regression on activity from several regions of interest. The regions of interest used in the prediction analysis were defined based on the contrasts of GLM1. In each region, the area under the curve (AUC) of the regression and beta values on the brain activity predictor were estimated. The most basic classification included only an intercept term and the brain activity betas (resulting from the LSS procedure) in the logistic regression. Subsequent models also included the subjective value of the later option, or the amount and delay of the later option on each trial.

In all cases, the classification model was run separately for each subject. The significance values presented in Table 1 for AUC are the result of a signed-rank test of all subjects' AUC values against 0.5 (chance level), and in Table 2, significance values for beta coefficients are the result of a signed-rank test of all subjects' beta values against 0.

Results

Behavioral data. Discount rates were estimated for each participant using a hyperbolic model. The average discount rate was k=0.014 (in sample 1, k = 0.012; in sample 2, k = 0.015). See Figure 1 for distribution of discount rates across both samples. On average, 91% (SD = 4.5%) of choices were consistent with the estimated discount rates during the scans (sample 1, 91%; sample 2, 90%).

Region of interest analysis: Dissociation of subjective value and value comparison. We performed a region of interest analysis to examine the BOLD response particularly in VS and VMPFC, and explore what quantity best explains their responses. We used the results of a recent meta-analysis of value-related neural signals during decision making (Bartra et al., 2013) to define these regions of interest, displayed in Figure 2A. Average beta coefficients across both samples, extracted from GLM1, are plotted in Figure 2B. While only subjective value is above 0 in

VS, both subjective value and value comparison signals are present in VMPFC. There is a significant interaction between the average coefficients for subjective value and value comparison in these two regions (p<0.006, repeated-measures ANOVA), but not a significant difference between the two variables within VMPFC. Figures 2C and 2D show this result in samples 1 and 2, respectively, with interactions trending towards significance for sample 1 (p<0.083) and significant for sample 2 (p<0.033).

GLM2 adds a parametric reaction time covariate to GLM1. Reaction time coefficients in these regions are not above zero, meaning that activity in these two regions does not scale significantly with reaction time. The addition of reaction time does not reduce any other coefficients to zero, and the interaction term remains moderate (p<0.067). The value comparison response in VMPFC, then, is not attributable to response demands of the task, or we should see a greater response in this area on trials for which the reaction time is shorter.

One alternate variable that could be represented in VMPFC is value relative to a subject-specific reference point, rather than value comparison. If the choice that an individual generally makes (now versus later) is taken as a reference point against which to evaluate the other option, then the value of the delayed option on a given trial will be negative when the typical choice is the now option, and positive when the typical choice is the later option. We tested this possibility with a variant of GLM1 and found that this reference-point subjective value appears to be the inverse of the original subjective value regressor, and the activity correlating with the value comparison regressor changes very little. This suggests that the response we observe in VMPFC is not due to only a value response that has a different reference point across subjects.

Another way to approach the problem of identifying which decision variables best fit neural activity is to simply extract BOLD activity from these regions of interest and compare it to several possible patterns. Figure 3A displays a plot of idealized activity patterns expected in a region that codes subjective value, value comparison, or maximum value. Three possible patterns are: linearly increasing activity with subjective value; a V shaped pattern that increases as the choice options get farther apart in value (value comparison); or activity that increases linearly with

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subjective value of the later option once this is greater than $20, and remains a flat line at $20 when the subjective value of the later option is less than $20 (maximum value). Figures 3B and 3C plot the actual patterns of activity in the VMPFC and VS regions of interest, respectively, and bin trials by subjective value (bin width = $5). Because stimuli were tailored to individual participants in the second sample, and discount rates did vary in the first sample, the range of subjective values varies across participants. As shown in Figures 3C and 3E, activity in VMPFC in each sample is relatively flat until the indifference point, and then increases with the subjective value of the later option once this is greater than $20. This is the expected pattern of activity for a region that reflects the maximally valued choice option. Activity in VS is plotted for each sample in Figure 3B and 3D, and increases roughly linearly with subjective value.

Region of interest analysis: Maximum value. The multiplexed subjective value and value comparison signals observed in VMPFC in Figure 2 could be an indication that activity in VMPFC actually follows the pattern of the maximum valued choice option, as suggested in Figure 3. To examine this possibility further, we created three additional GLMs focusing on maximum value. GLM3a models maximum value alone, and GLMs 3b and 3c add in subjective value and value comparison, respectively. Figure 4 shows these model coefficients in the VS and VMPFC regions of interest. In fact, activity in VMPFC is better explained by maximum value when it is included in a model with value comparison, and when it is included in a model with subjective value. In VS, however, when maximum value competes directly with subjective value, neither model has a significant model coefficient. This could be due to the very high correlation between these two variables (r=0.85).

Whole brain analysis of subjective value and value comparison. Despite the importance of VS and VMPFC in value representation, these are clearly not the only regions in the brain that carry value signals. We performed a whole-brain analysis of GLM1 across both samples, with results displayed in Figure 5.

We see four different patterns of activity in this whole-brain analysis: (1) positive correlation only with subjective value, including ventral striatum (VS) and anterior and posterior

cingulate cortices (ACC, PCC), (2) positive correlation only with value comparison, including superior/medial temporal gyri (STG/MTG), temporoparietal junction (TPJ), and amygdala (AMY), (3) positive correlation with subjective value and negative correlation with value comparison, including dorsomedial and lateral prefrontal cortices (DMPFC, DLPFC), and posterior parietal cortex (PPC), and (4) positive correlation with subjective value and value comparison, exhibited only in ventromedial prefrontal cortex (VMPFC).

Separate samples. The results of analyzing subjective value and value comparison across both samples suggest that there are separable groupings of regions that represent different combinations of these variables. In Figure 6, we verify that these results still hold when the samples are analyzed separately. There are positive effects of subjective value in both samples in ventral striatum, anterior cingulate, and posterior cingulate (Figure 6A). Positive effects of value comparison are present in both samples in ventromedial prefrontal cortex (albeit non-overlapping areas), amygdala, and temporoparietal junction (Figure 6B). There are negative effects of value comparison in dorsomedial and lateral prefrontal, and lateral parietal cortices (Figure 6C). Despite some variability between samples, the results from the whole group largely replicate in each sample individually.

Reaction time. The pattern of activations in one set of regions identified above (DLFPC, PPC, and DMPFC), correlating positively with subjective value and negatively with value comparison, mirrors the pattern of reaction time correlations. One possibility, then, is that activity in these regions is entirely explained by response demands. To test this, we ran a whole-brain analysis including a parametric regressor for the reaction time on each trial, as well as regressors for subjective value and value comparison (GLM2).

As displayed in Figure 7, the activity in these three regions does correlate positively with reaction time. Even after accounting for this relation to reaction time, however, activity in these regions still scales with subjective value, but not with value comparison. This bolsters the argument that the signal carried in these regions is a multiplex of subjective value and response demands. However, not all regions responding to value comparison are better explained by

reaction time. Activity in the amygdala and TPJ scales positively with value comparison, even after accounting for reaction times.

Choice prediction. We ran logistic regressions to examine whether brain activity could predict choices made on each trial. We compared this prediction accuracy across regions of interest, and against other predictive variables. Timecourses of activity were extracted from several regions of interest in each of the four categories of response described above – VS, ACC, PCC, as regions that respond to subjective value; AMY and STS, as regions that respond to value comparison; DLPFC, PPC, and DMPFC, as regions that multiplex value and response demands; and VMPFC, the only region to respond positively to both subjective value and value comparison. The first two groups of regions were identified by the intersection of the subjective value or value comparison contrasts across samples, and the second two groups by the intersection of effects across both samples (thus, each set is identified by the overlap of 2 contrast maps). Regressions are performed on each subject separately and the distributions of performance statistics are tested against chance.

The first regression included only brain activity. We find that the area under the curve (AUC) of this regression is significantly above chance for all regions, with response related regions having higher AUCs and value comparison regions having lower AUCs (see Table 1). The second two logistic regressions examine whether brain activity can contribute to prediction above and beyond other variables related to choice. Brain activity is a significant contributor to the regression in areas that seem to multiplex value and response demands (DLPFC, PPC, DMPFC), as well as regions that respond only to subjective value (VS, PCC, ACC), and the VMPFC, but not in regions that responded only to the comparison in value (AMY, TPJ). Of these two logistic regressions, the first included two predictors, the subjective value of the later option and brain activity. The second included three, the amount and delay of the later option, and brain activity. In both cases, brain activity in the regions that multiplex subjective value and response demands regions continues to be a significant contributor to the model, as does activity in VMPFC (see Table 2).

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Discussion

While the decision making literature cites numerous examples of the localization of neural representation of variables posited to be necessary for value-based choice, few studies have carefully disambiguated these variables and searched for the best fit to BOLD activity. In this investigation, we separate two variables of interest, subjective value (the subject-specific discounted value of the choice options) and value comparison (the absolute difference in subjective value between the choice options). In a region of interest analysis, we find that ventral striatum reflects only subjective value, while ventromedial prefrontal cortex reflects a combination of both variables that is closest to the maximally valued option in the choice set.

In a whole brain analysis, we find that VMPFC is the only region where activity correlates positively with both subjective value and value comparison. Other regions often cited to be involved in valuation fall into three groups, which carry different combinations of these signals. Ventral striatum, posterior cingulate, and anterior cingulate correlate positively only with subjective value; the amygdala and temporoparietal junction correlate positively only with value comparison; and dorsolateral prefrontal, dorsomedial prefrontal, and posterior parietal cortices correlate positively with subjective value and negatively with value comparison.

The results of the prediction analysis show that these four sets of regions not only respond to different features of value, but also vary in whether they carry a signal that can predict choice. Regions that carry subjective value signals predict choice reasonably well, which follows from the fact that more highly-valued larger later choice options are more likely to be chosen over the smaller immediate reward. The value comparison signal, however, is unsigned, and should not – and does not – predict choice. The third set of regions, which respond both to subjective value and to reaction time, are reliable predictors of choice. This result is consistent with the proposal that these regions are the latest in the pathway of information, receiving information about value from downstream regions such as VMPFC (Kable and Glimcher, 2009). These patterns hold even when other variables, such as subjective value or the amount and delay of choice options, are included in the model. Performance reported here is on par with other value-

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based prediction studies, which generally involve simple preferences among goods (Knutson et al., 2007; Smith et al., 2011).

Activity in the anterior cingulate, ventral striatum, and posterior cingulate is best explained by subjective value. This subjective value map is similar to other studies of value in intertemporal choice (Kable and Glimcher, 2007; Peters and Büchel, 2009; Kable and Glimcher, 2010). While we find that a very ventral region of medial prefrontal cortex responds to both subjective value and value comparison, the more dorsal region found here (along the genual cingulate) is similar to previous subjective value reports. Interestingly, although neither of the models described above propose that these regions would carry choice signals, activity in these regions does predict choice reliably.

We find that activity in the amygdala and temporoparietal junction responds to value comparison, such that activity in these regions increases when options are farther apart in value. This pattern of activity is modeled here as value comparison, but a similar construct comes up under different names in other contexts; for example, this signal could be called the easiness of the decision, confidence in the decision, and perhaps salience of choice options. While the role of the amygdala in value-based decision making is not entirely defined, it is clear that the amygdala responds to both rewarding and aversive events and choice options (Baxter and Murray, 2002; Schultz, 2004; Hsu, 2005), and may play a role particularly in emotional or motivational salience (Anderson and Phelps, 2001; Andino and de Peralta Menendez, 2012; Cunningham and Brosch, 2012). The TPJ is classically thought of as a key player in social cognition (Saxe and Kanwisher, 2003; Frith and Frith, 2006; Saxe, 2006), but has also been implicated in the reorienting of attention (Decety and Lamm, 2007; Corbetta et al., 2008; Mars et al., 2012), and in responding to salient stimuli (Downar et al., 2002; Geng and Mangun, 2011; Kahnt and Tobler, 2013). A study of functional connectivity from the TPJ shows extensive networks throughout the brain, including with areas of ventromedial prefrontal cortex and dorsolateral prefrontal cortex (Kahnt et al., 2012; Mars et al., 2012).

There have been several competing claims about how the choice process is executed in the brain. While much primate single-unit work localizes chosen values in terms of actions to areas in the lateral parietal and dorsal prefrontal cortices (Platt and Glimcher, 1999; Dorris and Glimcher, 2004; Sugrue, 2004; Kim et al., 2008), others have found chosen value signals in VMPFC (although in the space of goods, not actions; c.f.(Padoa-Schioppa, 2011; Cisek, 2012). Recent work using human fMRI and MEG is adding to this debate. A number of recent studies have implemented a modeling approach, predicting what signals should be generated by a decision-making system, and then searching for these signals in the brain. The two prominent examples of process models are the neural circuit model (Wang, 2008; Rolls et al., 2010; Hunt et al., 2012), and variants based on the drift diffusion model (Ratcliff and McKoon, 2008; Krajbich et al., 2010; Krajbich and Rangel, 2011; Hare et al., 2011b).

The neural circuit model predicts that separate pools of neurons receive input about the value of each choice option, and that these pools compete through mutual inhibition until one reaches a choice threshold. Notably, a study using MEG and basing predictions of neural activity on the neural circuit model found that VMPFC represents the subjective value of choice items initially, but transitions to a representation of value comparison later in the trial (Hunt et al., 2012). Several fMRI and MEG studies using this modeling approach have reported correlations between BOLD activity and value comparison in VMPFC (Rolls et al., 2010; Hunt et al., 2013). A common interpretation of this is the value comparison signal in VMPFC reflects mutual inhibition of the competing choice pools, and the shift to chosen value takes place as one choice pool comes to dominate the other (Hunt et al., 2012; Rushworth et al., 2012). Choice, in this model, seems to take place in the VMPFC.

An alternative interpretation comes from work based on the drift diffusion literature. This class of decision making models, including the neural drift diffusion model (Krajbich et al., 2010; Krajbich and Rangel, 2011; Hare et al., 2011b), posits that binary choice takes place via the integration, by a single unit (often called the comparator, but also referred to as the accumulator), of signals representing the value of taking each action. These value signals are integrated over

time until a barrier is reached, at which point a decision is made. This comparator process is posited to be located in the DMPFC and/or IPS (Wunderlich et al., 2009; Basten et al., 2010; Philiastides et al., 2010; Lim et al., 2011; Hare et al., 2011b). These papers do find value comparison signals in the VMPFC, but the current interpretation is that this is a reflection of which options are visually attended, and that the true direction of the comparison signal is the value of the attended option minus the unattended option (Lim et al., 2011). In this model, while subjective values are estimated in the VMPFC, these values are passed to regions downstream (comparator regions), where choice takes place.

The results presented here are qualitatively consistent with both of these possible models. We find that activity in VMPFC is well modeled by a multiplex of value comparison and subjective value, as predicted by the neural circuit model (Wang, 2008; Hunt et al., 2012; Wang, 2012). However, we also find that activity in DMPFC and PPC is explained by value comparison (or response demands, as indexed by reaction time), as would be predicted by the neural drift diffusion model (Hare et al., 2011b). However, these activity patterns are not a perfect quantitative fit; for example, we do see the DMPFC and PPC respond to subjective value in addition to value comparison, which is not predicted by either model.

Thus, although we can identify the patterns of BOLD activity in these regions, neither of these models is a perfect predictor. This debate, then, needs to shift its focus from identifying patterns of brain activity towards finding a model that explains the responses across multiple valuation and choice-related regions. Methodology other than fMRI can add to this investigation in crucial ways, particularly by providing information about the timing of decision signals that fMRI cannot capture. The discrepancies in the literature are exacerbated by the tendency in the neuroimaging literature to design one model, look for correlates of its predicted variables, and, if any are found, to declare that this model is the correct one. More careful examination of model assumptions, and more rigorous comparison between models and their predicted variables, will be necessary to fully elucidate the neural mechanisms of choice.

Figure 1. Delay discounting task and discount rate distribution. (A) The sequence of events in a trial is shown. At the start of each run, participants were reminded of the response contingencies (i.e., whether the left or right button corresponded to selecting the larger later choice option). On each trial, participants had up to 4 seconds to respond, followed by 1 second of feedback about the choice made (checkmark for accepting the onscreen option, X for rejecting it). The inter-trial interval averaged 5 sec. (B) A histogram of discount rates is shown, across both samples, with discount rates displayed on a $\log_{10}$ scale.
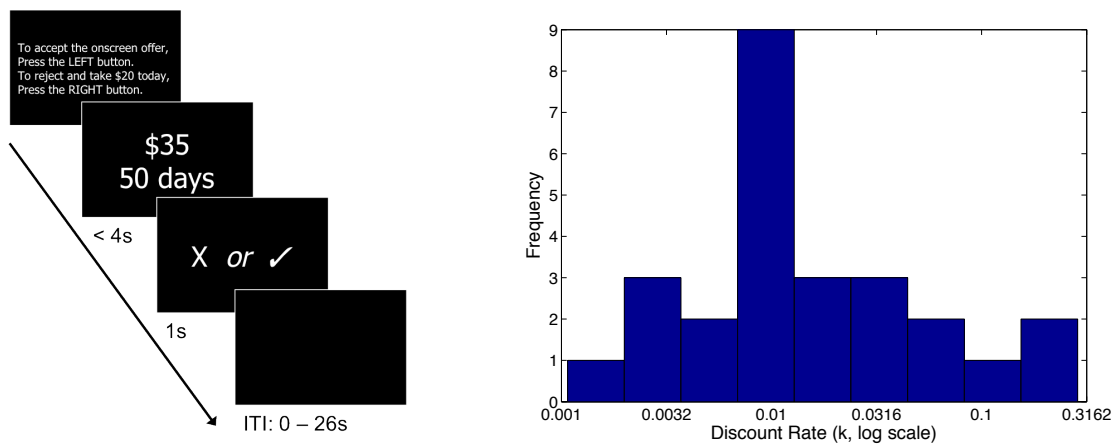
Figure 2. Analysis of subjective value and value comparison in ventromedial prefrontal cortex and

ventral striatum. (A) Regions of interest in ventromedial prefrontal cortex and striatum, from which

model coefficients of GLM1 are extracted and plotted for the analysis of both samples together

(B) and separately (sample 1 in C, sample 2 in D). Asterisks represent sign-rank tests against

zero.
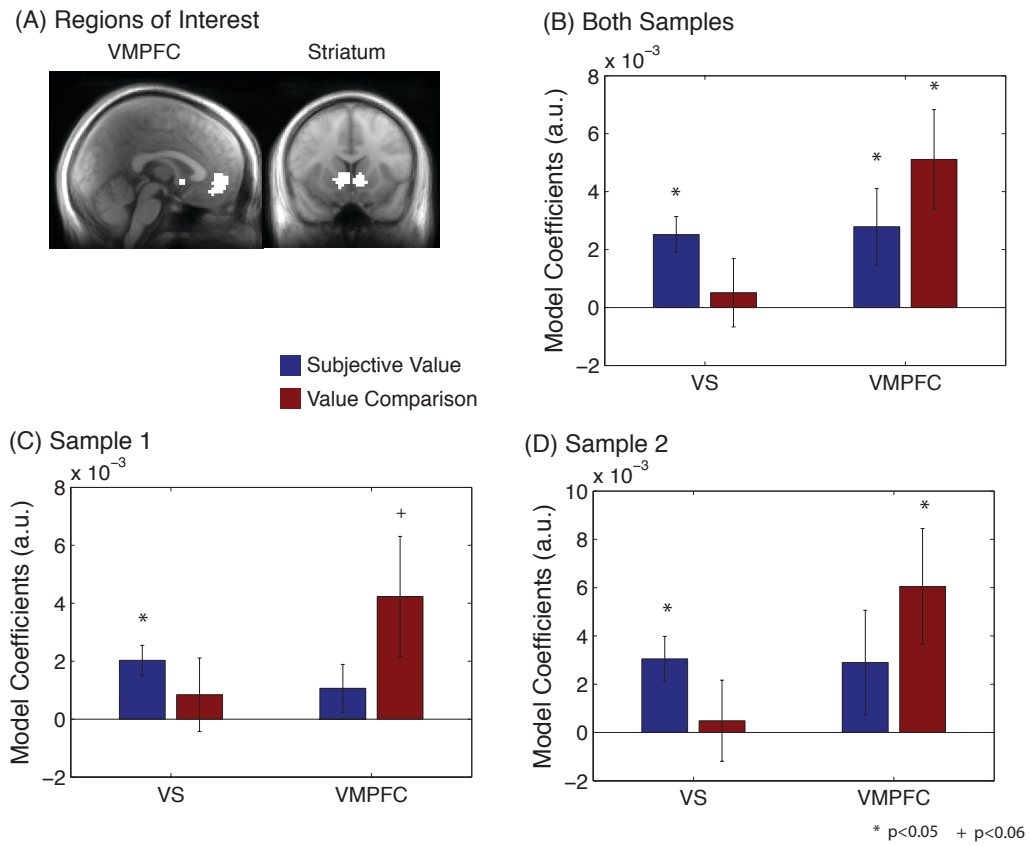
Figure 3. BOLD activity patterns in ventromedial prefrontal cortex and ventral striatum. (A) Panel A shows idealized activity patterns for three possible decision signals, subjective value (blue), value comparison (red), and maximum value (green). Panels B and D plot activity in the ventral striatum in samples 1 and 2, respectively. Panels C and E plot activity in the ventromedial prefrontal cortex in samples 1 and 2, respectively. Subjective value is binned in a range of $5. Because the range of subjective value varies across participants, only bins that include at least 25% of the sample are plotted.

(A) Idealized Activity Patterns

(B) Sample 1, Ventral Striatum

(C) Sample 1, VMPFC

(D) Sample 2, Ventral Striatum

(E) Sample 2, VMPFC
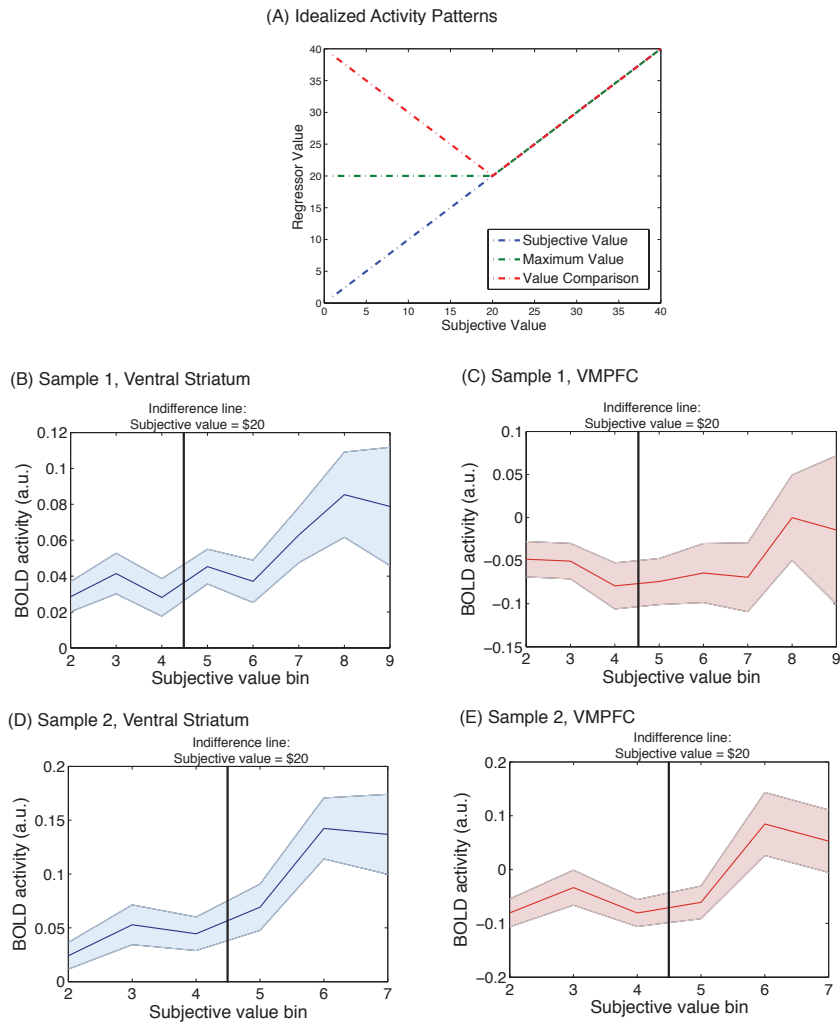
Figure 4. Analysis of maximum value in ventromedial prefrontal cortex and ventral striatum.

Model coefficients from an analysis of maximum value alone (left), maximum value with

subjective value (middle), and maximum value with value comparison (right) are plotted from the

regions of interest. Asterisks indicate significance in rank-sum tests against zero.
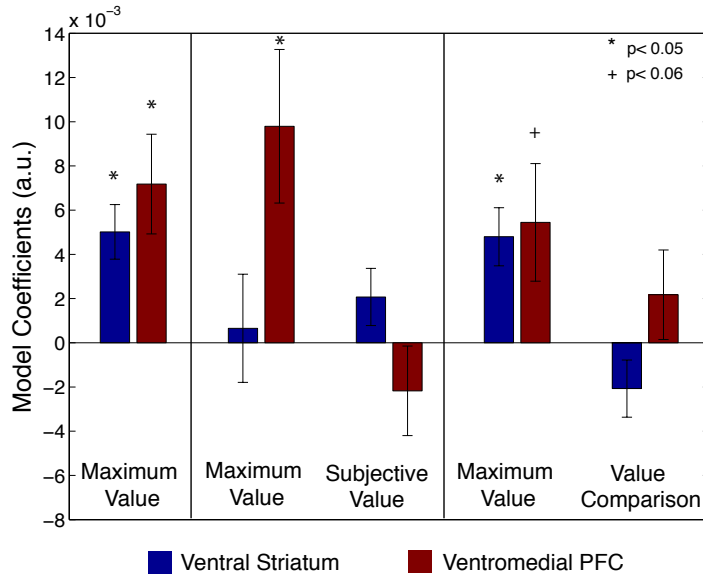
Figure 5. Whole brain analysis of subjective value and value comparison. The top panel shows the subjective value contrast, and the bottom panel the value comparison contrast, across both samples. Activity maps are thresholded at p<0.005 and cluster corrected at p<0.05.
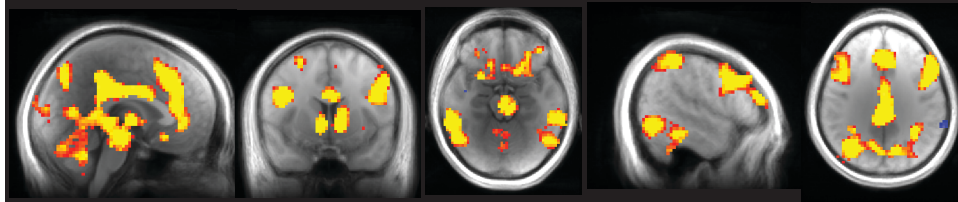
Subjective value
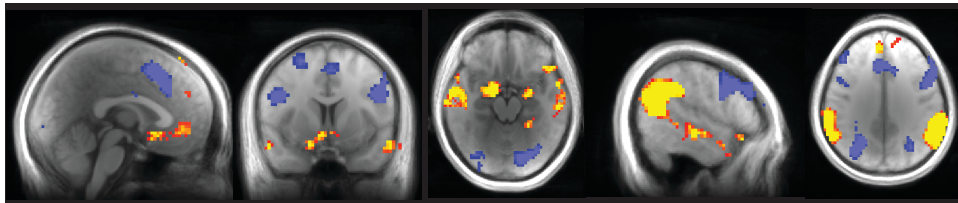
Value comparison

Figure 6. Imaging results replicate in both samples. Subjective value and value comparison contrast maps are thresholded at p<0.005 (cluster correction p<0.05) and masked. Each panel shows the overlay of contrast results from each sample separately, and their overlap. The top panel represents positive effects of subjective value; the middle, positive effects of value comparison; and the bottom, negative effects of value comparison.

Subjective Value: Positive Effects
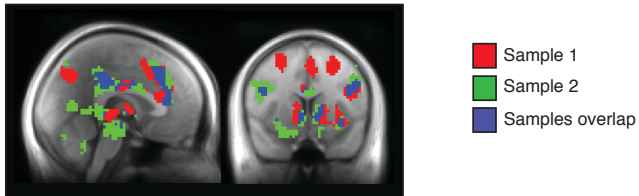
Value Comparison: Positive Effects
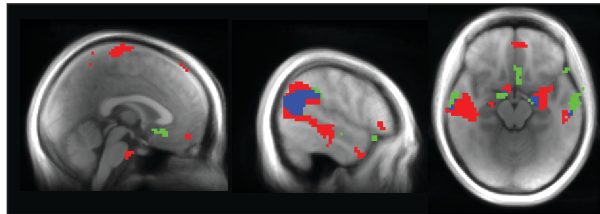
Value Comparison: Negative Effects
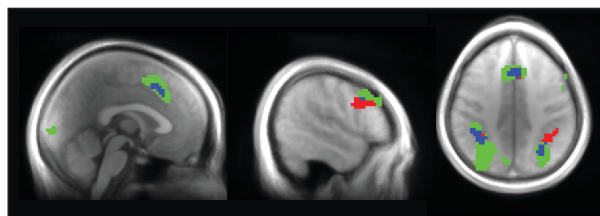
Figure 7. Whole brain analysis of value and response demands. Contrasts of subjective value (top), value comparison (middle) and reaction time (bottom) from the same model are shown, across both samples. Contrasts are thresholded at p<0.005 and cluster corrected at p<0.05.

Subjective value
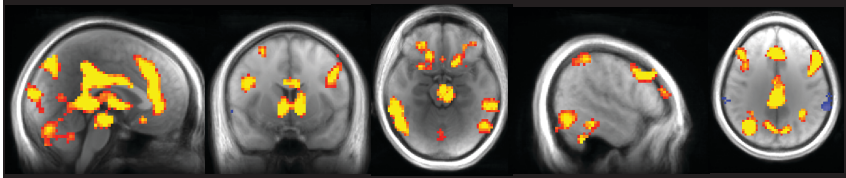
Value comparison
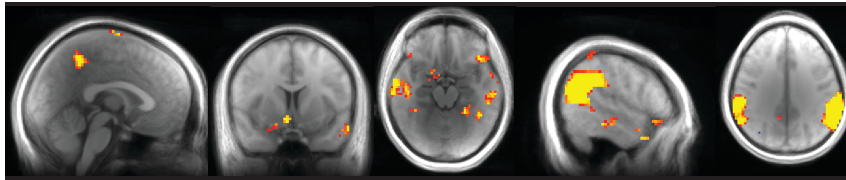
Reaction time
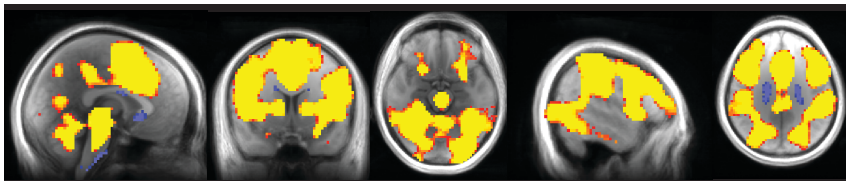
Table 1. Brain activity predicts choices. In each region of interest, logistic regression was used to

test whether brain activity could predict choices. This table displays the area under the curve

(AUC), and level of significance against chance, for each brain region tested.

Region of Interest	AUC	P Value
AMY_L	0.530	4.6E-05
TPJ_L	0.536	1.3E-05
TPJ_R	0.544	1.5E-05
VMPFC	0.598	8.3E-06
VS	0.600	8.3E-06
ACC	0.608	9.3E-06
PCC	0.613	9.3E-06
DMPFC	0.606	8.3E-06
DLPFC_L	0.600	8.3E-06
DLPFC_R	0.595	8.3E-06
DLPFC_R2	0.601	8.3E-06
PPC_L	0.600	1.2E-05
PPC_R	0.609	8.3E-06

Table 2. Brain activity predicts choices beyond objective variables. In each region of interest, logistic regression was used to test whether brain activity, alone and in combination with other objective variables, could predict choices. For each region tested, this table displays the weight (and significance) of the brain activity parameter.

ROI	Brain alone	w/ Subjective Value	w/ Amount & Delay
AMY_L	-0.041	-0.124	-0.035
TPJ_L	-0.089	-0.050	-0.348
TPJ_R	-0.067	0.142	0.098
VMPFC	1.526 **	1.207 **	0.935 *
VS	1.487 **	1.041 *	0.269
ACC	1.416 **	1.343 **	0.644 *
PCC	1.670 **	1.215 **	1.145 *
DMPFC	1.312 **	1.134 **	0.527 *
DLPFC_L	1.161 **	0.856 *	0.638 *
DLPFC_R	1.258 **	0.965 **	0.565
DLPFC_R2	1.005 **	0.894 **	0.678 **
PPC_L	1.169 **	0.761 **	0.704 *
PPC_R	1.379 **	0.928 *	0.960 *

*** p<0.001, * p<0.05*

CHAPTER 3 – Brain activity in valuation regions while thinking about the future predicts individual discount rates

Abstract

People vary widely in how much they discount delayed rewards, yet little is known about the sources of these differences. Here we demonstrate that neural activity in ventromedial prefrontal cortex (VMPFC) and ventral striatum (VS) when human subjects are asked to merely think about the future – specifically, to judge the subjective length of future time intervals – predicts delay discounting. High discounters showed lower activity for longer time delays, while low discounters showed the opposite pattern. Our results demonstrate that the correlation between VMPFC and VS activity and discounting occurs even in the absence of choices about future rewards, and does not depend on a person explicitly evaluating future outcomes or judging their self-relevance. This suggests a link between discounting and basic processes involved in thinking about the future, such as temporal perception. Our results also suggest that reducing impatience requires not suppression of VMPFC and VS activity altogether, but rather modulation of how these regions respond to the present versus the future.

Introduction

People differ in their willingness to defer immediate gratification to pursue long-term goals. These individual differences are important, because a tendency to delay gratification is associated with better educational outcomes in children and beneficial health behaviors in adults (Mischel et al., 1988; Bickel and Marsch, 2001; Duckworth and Seligman, 2005; Chabris et al., 2008). However, we know little about the source of these differences. This article links individual

differences in delay discounting to brain activity while individuals are merely thinking about future durations, in the absence of any explicit tradeoffs between immediate and delayed gratification.

Delay discounting tasks provide a measure of preference for immediate versus delayed rewards. The extent of preference for immediate rewards is captured by the discount rate, which expresses how much the subjective value of a delayed reward declines as a function of delay. Neuroimaging studies of discounting have found that BOLD activity in ventral striatum (VS) and ventromedial prefrontal cortex (VMPFC) scales with the subjective value of the options being considered (Kable and Glimcher, 2007; Ballard and Knutson, 2009; Peters and Büchel, 2009; Pine et al., 2009; Kable and Glimcher, 2010). This implies that individual differences in discounting are linked to differences in the neural sensitivities of VS and VMPFC. In high discounters, there is much greater activity in these regions for immediate compared to equally sized delayed rewards, while this difference is smaller in low discounters. Contextual manipulations that shift discount rates within an individual may involve the same mechanism, affecting BOLD activity within VS and VMPFC (Peters and Büchel, 2010a).

More recent work has suggested a link between discounting and VS or VMPFC activity in other task contexts. Hariri and colleagues have shown that higher discounters exhibit a greater VS response to unpredicted rewards (Hariri et al., 2006). Others have shown that higher discounters exhibit a greater difference in BOLD activity between judgments of oneself in the present compared to the future (Ersner-Hershfield et al., 2009b; Mitchell et al., 2011).

A more basic question is whether brain activity when individuals are merely prompted to think about the future can predict discount rates. Is there a relationship between VS and VMPFC activity and discount rates even when individuals are not explicitly evaluating present or future outcomes or judging their self-relevance? Behavioral studies have recently demonstrated the role of time perception in intertemporal choice (Kim and Zauberman, 2009; Zauberman et al., 2009), but to date, there are no neuroimaging data on this relationship. Here we show that the delay sensitivity of VS and VMPFC BOLD responses when individuals make simple value-free judgments about the subjective length of future time intervals predicts behavioral discount rates

measured ten days later. This suggests that the association between neural activity and discounting arises from a basic process involved in thinking about the future, such as judging temporal distance. Additionally, our results suggest that reducing impatience requires not suppressing VS and VMPFC activity altogether, but rather modulating how these regions respond to the present versus the future.

Materials and methods

Subjects. Forty participants (16 males and 24 females, 88% right-handed) were recruited from the University of Pennsylvania and surrounding community. Participants had a mean age of 21.75 years (SD = 3.27). All participants were compensated for their time on both of two testing days, and received an additional monetary payment based on their decisions in the discounting task. All participants were consented in accordance with the procedures of the Institutional Review Board of the University of Pennsylvania.

Tasks. All participants completed two sessions, separated by an average of 10 days (SD= 5, range = 4 to 21). Participants were told that there were two sessions involving different tasks, but they were not told the details of each task until that session began. In the first session, participants completed the temporal judgment task (see Fig. 1A). In this task, participants were asked to judge the subjective duration of a future delay interval on a visual analog scale. This scale was bounded by "very short" and "very long" (Zauberman et al., 2009). Participants were asked questions of the form, "How long do you consider the duration between today and a day in 28 days?" In each scan, participants were asked about 26 different delay durations, uniformly distributed between 14-364 days. Participants were informed beforehand about the entire range of delays they would be judging. Participants entered their judgment by moving the response bar along the scale. The response bar always appeared in the middle of the scale. Participants used two buttons to move the bar to the right and left, and a third to submit their response. Ratings were recorded in arbitrary screen units, ranging from 1-165. All participants completed four scans of this task.

In the second session, participants completed the temporal discounting task (see Fig. 1C). In this task, participants bid on delayed monetary rewards. They provided the amount of money received immediately that they felt was equivalent to receiving a larger amount after a specified delay. Participants were asked questions of the form, "I feel indifferent between receiving $75 in 28 days and receiving $? now." From trial to trial, the $75 value of the delayed amount remained constant, and only the delay varied. In each of 4 scans, participants were asked about the same 26 delays used in the temporal judgments task (i.e., between 14-364 days). Again, participants were informed beforehand about the range of possible delays. The response amount always began at $75 now. Participants entered their bid by using two buttons to increase or decrease this amount, and a third button to submit their response. The behavioral data from one scan of one subject in this task was lost due to experimenter error.

The timing of the two tasks was similar. The inter-trial interval was variable, between 0.5-13.5 seconds. In the "question period," participants saw the delay they were judging or the delayed amount they were evaluating, but could not yet enter their response. This period lasted from 3 - 5 seconds. This period terminated with the appearance of the response bar or of "$ 75 now" in the respective tasks. The "response period" began at this point and lasted until the participant submitted their response. The response period timed out after 10 seconds in both tasks, and the current location of the response bar or the immediate amount was taken as the participant's response.

Participants knew that if they did not press a button to submit their response, the value that the cursor was on when the 10-second response period ended would be taken as their response. Participants also knew that there was no penalty for not pressing the submit button. Because of this, several participants adopted a strategy of never pressing the submit button. Overall, participants did not submit a response within 10 seconds on 12% of trials in the temporal judgment task and 22% of trials in the temporal discounting task. However, these "timed out" trials appeared clearly strategic, rather than indicative of an inability to complete the task. Indeed,

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the discount rates estimated using all trials and those excluding "timed out" trials were very highly correlated, r (36) = 0.998. We therefore kept all "timed out" trials in our analyses.

Only a very small minority of "timed out" trials were the result of participants not responding on the trial at all. Across both scans, only 5 participants had any instance of not moving the cursor along the response scale at all; each of these participants made no response on only 1 out of a total of 104 trials.

Payments. In addition to a flat $15 per-hour fee for their participation, subjects were paid an additional amount according to their decisions in the time discounting task, using the Becker-DeGroot-Marschak mechanism (Becker et al., 1964). First, participants rolled a die to randomly select one of the trials. The delayed option on that trial (e.g., $75 in 28 days) and the participant's bid for that option (e.g., $70 now) were determined. The participant then rolled a die a second time to generate a random 'counteroffer.' The generation of counteroffers was such that they would be uniformly distributed between $0-$75. If the participant's bid was greater than the counteroffer, they received $75 at the delay specified. If the participant's bid was below the counteroffer, they received the counteroffer amount immediately. The payment procedure provides incentive for the participant to bid their true valuation of the delayed option. All payments were made using pre-paid debit cards, as described previously (Kable and Glimcher, 2007; 2010). These cards have the advantage of making receipt of the delayed payment easy and reliable, minimizing the effects of greater uncertainty and effort of the future reward.

Behavioral Data Analysis. Behavioral data were analyzed in MATLAB (Mathworks). In the time discounting task, we characterized the relationship between the objective delay (OT) and the participant's evaluation of $75 received after that delay (BID). We fit this relationship with the function: BID = 75 / (1 + k* OT) (Mazur, 1987). Because discount rates are not normally distributed, statistics are performed on the log-transform of the discount parameter k.

For one subject, this function could not be fit because the subject always bid $75. This subject is excluded from all analyses and figures, with one exception. This subject is included in additional analyses that use an alternative method of estimating discount rates, the area-under-

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the-curve (AUC) method (Myerson et al., 2001). We report the correlation between brain activity and discount rates estimated with both the hyperbolic k and AUC measures, and observe similar results with both sets of estimates.

To reduce the influence of possible accidental responses in the time discounting task, we excluded all trials for any delay where the range of the subject's responses spanned more than half the range of the response scale (range greater than $37.50). We excluded a total of 12 delay bins in a total of 5 subjects (maximum of 4 per subject, approximately 1% of the data). Our reported results do not differ when these trials are included.

MRI Image Acquisition. In both sessions, functional and anatomical images were collected using a 3T Siemens Trio scanner equipped with an 8-channel head coil. T2*-weighted functional images were collected using an EPI sequence (TR = 3 s, TE = 30 ms, 45 axial slices, 3 x 3 x 3 mm, 64 x 64 matrix). Each scan consisted of 150-152 images. All participants completed four scans in each session. High-resolution T1-weighted anatomical images were collected using an MPRAGE sequence (TI = 1100 ms, 160 axial slices, 0.9375 x 0.9375 x 1.000 mm, 192 x 256 matrix).

Imaging data analysis. Functional images were analyzed using VoxBo, incorporating tools from SPM2. Functional images were first sinc-interpolated in time to adjust for staggered slice acquisition, corrected for head motion by realigning all volumes to the first volume of the scanning session using six-parameter rigid-body transformations, and de-trended and high-pass filtered (cutoff of 3 cycles/scan, or 0.0066 Hz) to remove low frequency drift in the fMRI signal. Images were co-registered with each subject's high-resolution anatomical scan and normalized into MNI space. Normalized data were then spatially smoothed (kernel FWHM = 9 mm) and thresholded to remove voxels outside of the brain.

Single-subject analyses were performed using the general linear model as implemented in VoxBo. Estimation was by ordinary least squares.

Only the neuroimaging data from the temporal judgments task is discussed here. The neuroimaging data from the temporal discounting task will be addressed in a separate report,

which we have previously presented in abstract form (Kable et al., 2011). That report focuses on the similarities between activation during the bidding task we used here and the choice task used in previous studies (Kable and Glimcher, 2007; 2010).

The first model for the temporal judgments task included 15 covariates of interest. These covariates modeled activity at three different timepoints in the trial: (1) the time at which a trial began and participants saw the delay to be judged (Q_{on}); (2) the time at which the response bar appeared and the participant could begin entering their response (R_{on}); (3) the time at which the participant submitted their response (R_{off}). The first 13 regressors divided the Q_{on} periods into equally sized bins based on the objective delay being judged. Since there was a small number of trials for each delay (4), we combined consecutive rank-ordered delays (i.e., the 4 trials from the shortest delay with the 4 from the second shortest, and so on) to obtain 13 delay bins from the 26 unique objective delays presented. The last two regressors modeled all of the R_{on} periods and all of the R_{off} periods. All of these covariates were constructed by convolving a delta function at the time of each event (i.e., only the first 100 ms of each event is modeled) with an empirically estimated hemodynamic response function. This hemodynamic response function is distributed with the VoxBo software package, and was empirically estimated by Aguirre et al., 1998, from motor cortex responses during a motor performance task.

The second model for the temporal judgments task included six covariates of interest: three covariates modeling activity at Q_{on}, R_{on}, and R_{off}; and three additional parametric modulator covariates, one at each of these three timepoints in the trial. All six regressors modeled the first 100ms of each event. The first three covariates were constructed by convolving a delta function at the time of each event with an empirically estimated hemodynamic response function (Aguirre et al., 1998). These first three covariates fit the mean activity at a given point in a trial, across all trials. The parametric modulator was the objective delay being judged on that trial (OT). These values were all mean-centered and then convolved with the hemodynamic response, so the parametric modulator covariates fit the deviations from mean activity that were correlated with the objective delay across trials.

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Region of interest analysis. We used regions of interest from Bartra et al., 2013. This is a quantitative meta-analysis of studies that report value-related neural signals during decision making. The regions of interest used here were defined from an analysis of 27 studies reporting subjective value effects (increased BOLD signal for increasingly valuable rewards) at the time when subjects were evaluating the available choice options. Regions of interest in bilateral ventral striatum and ventromedial prefrontal cortex defined by this contrast are available for download (http://www.sas.upenn.edu/~mcguirej/meta-analysis.html). Slight differences in the downloadable masks and the masks used here are due to the downsampling process from 2mm to 3mm voxel sizes. The resulting regions are bilateral ventral striatum (300 voxels at 3x3x3mm, centered on MNI coordinates -6, 8, -4 on the left and 6, 10 -8 on the right) and ventromedial prefrontal cortex (609 voxels at 3x3x3mm, centered on MNI coordinates -2, 40, -8). The regions of interest used are shown in Figure 2.

Results

On each trial of the temporal judgment task, participants indicated their perceived duration of a future delay on a visual analog scale (Fig. 1A). Delays ranged from 14-364 days. In the temporal discounting task, participants indicated how much they valued a delayed gain of $75 (Fig. 1C). The delays were identical to those used in the temporal judgment task. For each subject, we fit the relationship between objective time and the person's valuation with the function: BID = 75 / (1 + k* OT), to estimate each subject's discount rate (k).

Our analyses concentrated on the link between neural responses in the temporal judgment task and delay discount rates as measured in the temporal discounting task ten days later. Previous studies of intertemporal choice have identified correlates of subjective value during decision making in ventral striatum and ventromedial prefrontal cortex (Kable and Glimcher, 2007; Peters and Büchel, 2009; Kable and Glimcher, 2010; Peters and Büchel, 2010b). We defined regions of interest in the ventral striatum and ventromedial prefrontal cortex based on a

quantitative meta-analysis that examined subjective value correlates during decision making (Bartra et al., 2013).

We used two different approaches to examine the link between neural sensitivity to delay in the time judgment task and behavior on the time discounting task. In both cases, we looked at the neural response in the temporal judgment task at the time when the participant first saw the future duration to be judged on that trial, before they could enter their response (Q_{on}). First, we split participants at the median discount rate k into two groups of high (n=20) and low (n=19) discounters. In both ROIs, we estimated the BOLD activity in the two groups at Q_{on} as a function of the delay being judged (delays were divided into thirteen bins). High discounters showed a higher response in both ventral striatum and ventromedial prefrontal cortex to short delay periods that decreased as delay lengths increased (see Fig. 2). Low discounters showed the opposite pattern, with responses increasing from short delays to long delays (Fig. 2). The estimated slopes of individual subjects in the high and low discounting groups are significantly different (VS, p=0.0026, 2-tailed t-test; VMPFC, p=0.037, 2-tailed t-test).

Our second approach looked at this same effect in a continuous rather than categorical manner. For each subject, we estimated the neural sensitivity to delay in both regions in the temporal judgment task. We modeled the objective delay as a parametric modulator in the temporal judgment task and took the beta coefficient on this parameter as our estimate of neural sensitivity. This provides a measure of how activity in these regions changes as a function of delay in the temporal judgment task; for example, whether activity increases or decreases as the delay judged gets longer, and how strongly it does so, in each subject. We then related this neural sensitivity to delay (from the temporal judgment task) to individual discount rates (from the behavioral measures in the time discounting task). Delay discount rates were negatively correlated with neural delay sensitivities. There was a significant linear relationship between discount rates and neural response to objective duration during the temporal judgment task in both regions (ventral striatum: $r(37) = -0.42$, $p = 0.0076$; ventromedial prefrontal cortex: $r(37) = -0.35$, $p = 0.0294$; see Fig. 3). Using the area-under-the-curve estimation of discount rates, which

allows us to include all participants, this relationship is just as strong (ventral striatum: r (38) = 0.44, p = 0.0049; ventromedial prefrontal cortex, r (38) = 0.34, p = 0.0314; note that larger AUC corresponds to less discounting). Higher discounters showed an increasingly negative relationship between BOLD activity and objective durations, while lower discounters had an increasingly positive relationship.

These data show that neural delay sensitivity can account for approximately 15% of the variance in discount rates. Given recent concerns regarding the interpretation of effect sizes in imaging experiments (Vul et al., 2009), we hasten to add that the effect sizes we estimated here are unbiased and not artificially inflated, because we carefully identified valuation regions *a priori*, based on separate data entirely. Indeed, estimating the same brain-behavior relationship in a circular manner, by using only those voxels in ventromedial prefrontal cortex and ventral striatum that show a significant across-subjects correlation, results in inflated effect size estimates (ventral striatum: r (37) = -0.51, p = 0.0008; ventromedial prefrontal cortex: r (37) = -0.51, p = 0.0009).

Discussion

We scanned forty people while they made judgments about the perceived length of future time durations, and found that brain activity during this outcome-free task was predictive of how the same individuals discounted future monetary rewards. We identified regions in ventromedial prefrontal cortex and ventral striatum where activity consistently scaled with subjective value in previous fMRI studies of decision making, and measured the delay sensitivity of these regions during the temporal judgment task. This neural sensitivity to time delays was negatively correlated with discount rates measured ten days later. Steep discounters tended to have larger neural responses when judging short delays than when judging long delays, while shallow discounters tended to have the opposite pattern. Our results show that prompting someone to think about the future, in a fairly minimal manner with no mention of outcomes, elicits brain activity that predicts discount rates. These results suggest that individual differences in the propensity to delay gratification derive from differences in basic cognitive and neural processes

engaged when one thinks about the future, rather than, or in addition to, an individual's drive towards immediate rewards and/or their ability to control that drive.

Our study builds on previous work in several ways. First, we identified regions involved in valuation *a priori*. This is critical to the claim that temporal judgments elicit activity in the *same* regions as decision making, since there is heterogeneity within valuation regions, and in general nearby anatomical regions can be implicated in different cognitive processes (Kable, 2011; Poldrack, 2011). Second, we measured the sensitivity of these regions to parametrically varying delays. This allowed us to determine that activity differences between individuals are not solely due to the response of these regions to the immediate present, but instead involve how activity in these regions varies as people consider intervals that extend farther into the future. Third, our temporal judgment task did not involve explicit choices, evaluation of rewards or future scenarios, or judgments of self-relevance. The simplicity of our task allows us to show that even very basic judgments about the future are sufficient to elicit brain activity in valuation regions that predict discount rates.

Our findings leave open the exact nature of the cognitive processes that mediate this link. The neural processes of temporal judgment and reward valuation could be directly or indirectly linked, in several ways. One possibility is that judging prospective future durations itself activates ventromedial prefrontal cortex and ventral striatum, and that the activity we observe does not explicitly or implicitly reflect valuations. Under this account, neural activity is predictive because the perception of future durations predicts discount rates. Alternatively, since the waiting duration is a necessary input for evaluating delayed rewards, judgments of future durations may be sufficient to elicit value-related neural activity, as an epiphenomenon. Another possibility is that evaluative processes are critically involved in the judgment of prospective future durations. People might directly use their evaluation of future reward as a cue for judging the length of a future duration. Or, they might imagine a specific future event when judging duration. Cues in the simulated future event might be used to judge temporal distance, and the same simulated event might also be automatically evaluated.

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Of course, these possibilities are not mutually exclusive, and the implicated cognitive processes are highly intertwined. Temporal estimates are an important factor in the evaluation of delayed rewards, and a major reason for simulating different possible futures is to evaluate whether these are desirable or not (Gilbert and Wilson, 2007). More than one of these cognitive processes might drive activation in ventromedial prefrontal cortex and ventral striatum, and these different processes may be instances of a more general function performed by these brain areas. Future experiments might use techniques that can separate neural signals that overlap spatially (e.g., adaptation or multi-voxel pattern analysis) to tease apart the component processes in this network.

Regardless of the details of the link, our results demonstrate that outcome-free temporal judgments and temporal discounting of rewards share neural processes, as would be predicted by theories that attribute some features of discounting and impulsivity more generally to properties of temporal perception (Wittmann and Paulus, 2008; Wittmann et al., 2011). Some of our previous work has focused on how the curvature of time perception can affect the *shape* of the discount function (Zauberman et al., 2009). We did not observe a similar relationship in these data, perhaps because of the smaller sample size or larger time lag between the two tasks. In contrast, these data call attention to another link we have explored recently, between the magnitude of a temporal perception and the *extent* of discounting (Kim and Zauberman, 2009; 2013). Given that the absolute perceived magnitude is difficult to measure behaviorally, because it can be confounded with scale use, the individual differences in neural delay sensitivities discovered here might provide a useful tool in further exploring this relationship.

Previous work has shown that discount rates vary widely across individuals, and that these differences are relatively stable across time (Ohmura et al., 2006; Kirby, 2009; Senecal et al., 2012). Despite this intra-individual reliability, there are surprisingly few reliable predictors of discount rates. Perhaps the strongest is cognitive ability, which is reliably associated with discount rates with an effect size of around r = -0.20 (Shamosh and Gray, 2008; Burks et al., 2009). The relationship between discount rates and self-reported personality traits is usually

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smaller than this. In this context, the 15% of the variance in discount rates that can be accounted for by neural delay sensitivities is a sizable and important effect. These data show that, avoiding the previously described bias from circular estimates (Vul et al., 2009), the correlations between BOLD activity and individual differences in behavior can be comparable to or even outperform those of standard psychometric variables.

Our results also have implications for how to enhance patient, future-oriented behavior. Much work has concentrated on the hypothesis that lateral prefrontal cortex promotes patient choices, and that (correspondingly) such choices require a greater degree of cognitive control (McClure et al., 2004; Hare et al., 2009; Figner et al., 2010; Luo et al., 2012). Some have additionally proposed that lateral prefrontal cortex acts in opposition to ventromedial prefrontal and ventral striatal regions, and that suppressing activity in these two regions promotes patient behavior. In contrast, our results show that patient individuals show a different pattern of activity in ventromedial prefrontal cortex and ventral striatum, rather than reduced activity in these regions altogether. Shallower discounters showed greater activity in ventromedial prefrontal cortex and ventral striatum when considering durations lasting farther into the future. This suggests that patient behavior might be promoted by *enhancing* activity in ventromedial prefrontal cortex and ventral striatum in response to future outcomes, relative to that for immediate outcomes. This proposal is consistent with several recent studies showing that medial prefrontal BOLD activity predicts the effectiveness of messages promoting future-oriented behavior (Falk et al., 2010; Chua et al., 2011). Given that ventromedial prefrontal cortex has been linked to a "prospective brain network" that simulates the future (Buckner and Carroll, 2007; Gilbert and Wilson, 2007; Schacter et al., 2007) and to predicting the subjective value of different possible actions during decision making (Kable and Glimcher, 2009; Rangel and Hare, 2010), these neural findings may suggest novel psychological interventions to promote the delay of gratification.

Figure 1. Temporal judgment and temporal discounting tasks. (a) The sequence of events during a trial in the temporal judgment task is shown. Participants viewed each question for 3-5s, then were given 10s to respond. Participants moved a black bar (which always appeared first in the center) along a scale from 'very short' to 'very long' to indicate their perceived duration of each delay. When a final response was submitted, the bar turned red and remained on screen for 1s. (b) Plot of subjective time ratings against objective time durations. Grey lines are individual subjects, and the black line is the mean. (c) The sequence of events during a trial in the temporal discounting task is shown. Participants viewed each question for 3-5s, and were then given 10s to respond. Bids for each trial always began at $75, and participants were able to increase and decrease the monetary amount. After pressing a button to submit their response, the text turned red and remained on the screen for 1s. (d) Plots of bids against objective durations. Grey lines are individual subjects' bids, and the black line is the mean.
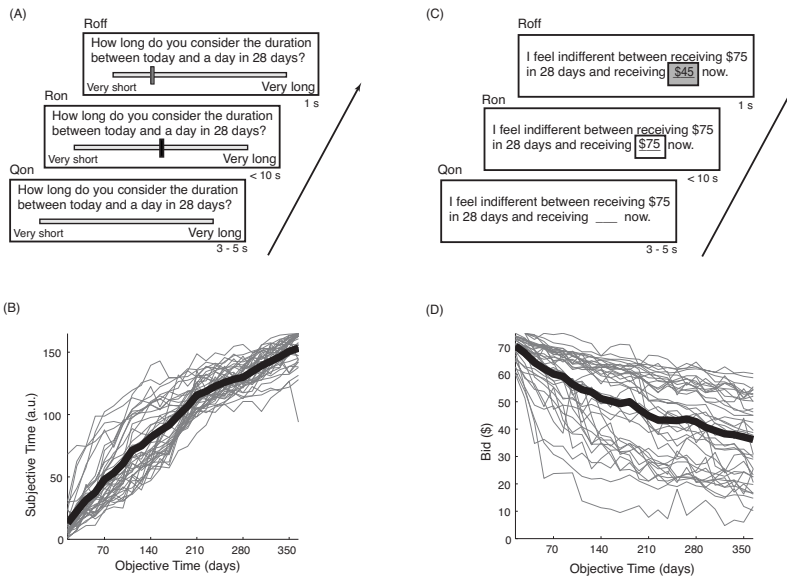
Figure 2. BOLD activity during the temporal judgment task differentiates high and low discounters. (a,c) Region of interest encompassing ventral striatum (a) and ventromedial prefrontal cortex (c), identified from previous meta-analysis (Bartra et al., 2013). (b,d) BOLD activity in the ventral striatum (b) and ventromedial prefrontal cortex (d) ROIs at question onset during the temporal judgments task is plotted based on the length of delay being judged on that trial (26 delay lengths represented in 13 bins). Participants are divided at the median into high (n=20) and low (n=19) discounters based on their behavior during the temporal discounting task. Average BOLD activity at each delay is plotted for the high (red) and low (blue) discounting groups. Light colors are standard error ranges.
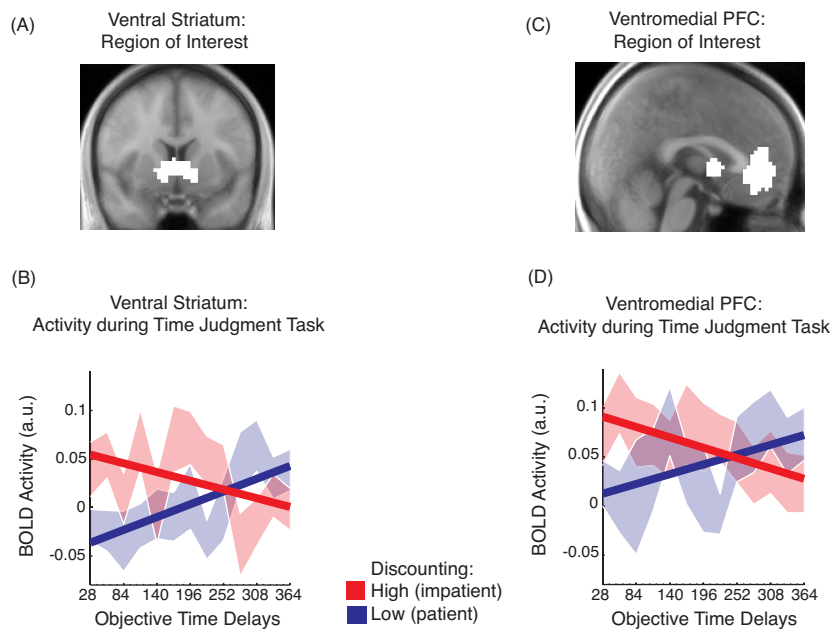
Figure 3. Individual neural delay sensitivities during temporal judgment predict delay discount rates. Individual discount rates (log scale) calculated from behavior on the temporal judgment task are plotted against individual neural delay sensitivity, or the fit of a parametric objective time modulator to neural activity in the temporal judgments task. This is plotted for activity in ventral striatum (a) and ventromedial prefrontal cortex (b).
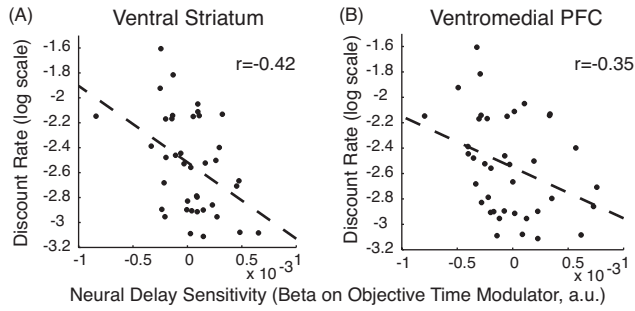
CHAPTER 4 – Normative arguments from experts and peers reduce delay discounting

Abstract

When making decisions that involve tradeoffs between the quality and timing of desirable outcomes, people consistently discount the value of future outcomes. A puzzling finding regarding such decisions is the extremely high rate at which people discount future monetary outcomes. Most economists would argue that decision-makers should only turn down rates of return that are lower than those available to them elsewhere. Yet the vast majority of studies find discount rates that are significantly higher than market interest rates (Frederick et al., 2002). Here we ask whether a lack of knowledge about the normative strategy can explain high discount rates. In an initial experiment, we find that nearly half of subjects do not spontaneously cite elements of the normative strategy when asked how people should make intertemporal monetary decisions. In two follow-up experiments, we find that after subjects read a "financial guide" detailing the normative strategy, discount rates declined by up to 85%, but were still higher than market interest rates. This decline persisted, though attenuated, for at least one month. In a final experiment, we find that peer-generated advice influences discount rates in a similar manner to "expert" advice, and that arguments focusing on normative considerations are at least as effective as others. These studies show that part of the explanation for high discount rates is a lack of knowledge regarding the normative strategy, and quantify how much discount rates are reduced in response to normative arguments. Given the high level of discounting that remains, however, there are other contributing factors to high discount rates that remain to be quantified.

1 Introduction

1.1 Background

Many of the decisions we make involve tradeoffs between the quality and timing of

desirable outcomes. What *should* people do when faced with such intertemporal tradeoffs?

Discussions of this question usually focus on *how* people should make these tradeoffs (i.e.,

exponential vs. hyperbolic discounting), rather than on *to what extent* they should discount future

rewards. A notable exception is the case of monetary rewards, where the normative argument is

that individuals should compare any intertemporal tradeoff against the other borrowing and

investment opportunities available to them.[1] In practice, this argues that the rate of discounting

ought to be similar to the current market interest rate, at least for most individuals (Fisher, 1930;

Read, 2004). For example, consider a person given a choice between receiving a smaller amount

of money at a sooner time and a larger amount at a later time. If this person could borrow the

smaller amount while waiting for the larger payoff, and if the larger amount is enough to repay this

loan plus interest and still leave the individual with a profit, then the larger, later reward is the

better choice, *regardless of when the person would want to spend the money*.

Most studies of delay discounting, however, have observed discount rates considerably

higher than market interest rates (Thaler, 1981; Ainslie and Haslam, 1992; Coller and Williams,

1999; Frederick et al., 2002; Reynolds, 2006; Chabris et al., 2008). Although most of these

studies involve explicit choices in the laboratory between monetary amounts now or in the future,

high discounting rates are also observed in field experiments where normative considerations

should be relevant, such as consumers deciding whether to spend additional money now on an

energy efficient appliance that will save them money later (Hausman, 1979; Gately, 1980;

Ruderman et al., 1987). Many studies cite discount rates in the range of several hundred percent

per year (Frederick et al., 2002 for review). In contrast, the current prime rate is around 3%

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[1] Another notable exception is discussion regarding the normative discount rate for policy evaluation, particularly in the realm of environmental policy (Baron, 2000; Baron, 2008; Horowitz, 1996; Moore & Viscusi, 1990).

(Federal Reserve). This extremely high rate of discounting is puzzling – why do people appear to diverge so dramatically from the normative strategy?

There are several possible explanations for the high discount rates observed in these experiments. One possibility is that people discount according to the normative strategy, but also have normatively relevant reasons to favor the immediate reward. For example, subjects may think that the delayed reward carries some risk: they may not trust that they will receive a delayed payment from the experimenter, or they may believe that their own future is uncertain. If subjects believe that the delayed reward is uncertain, this would warrant a greater preference for the certain immediate payment, and the observed discount rate would be higher. It is also possible that there is a knowledge gap, and that subjects either may be simply unaware of the normative strategy, or might apply it to this task incorrectly. Alternatively, people may not perceive that the normative strategy is relevant. For example, subjects might not think about these tradeoffs in terms of money, but rather in terms of the objects that could be purchased with the money(Zauberman and Lynch, 2005). If they are considering tradeoffs of non-fungible items instead of money, the normative monetary strategy is not applicable.

Determining what factors contribute to high discounting would have significant practical implications. Policy makers are often interested in what influences people's financial decisions – for example, what persuades individuals to save more for retirement or to avoid high-interest "pay-day" loans (Zhong and Xiao, 1995; Hershey and Mowen, 2000; Skiba and Tobacman, 2008). Moreover, high discount rates are also associated with addiction. Cigarette smokers (Bickel et al., 1999; Mitchell, 1999; Audrain-McGovern et al., 2004), heavy or problem drinkers (Vuchinich and Simpson, 1998; Petry, 2001b), illicit drug users (Madden et al., 1997; Kirby et al., 1999; Bickel and Marsch, 2001), and pathological gamblers (Petry, 2001a) exhibit higher monetary discount rates than normal healthy adults. A better understanding of high discount rates might further clarify the link between discounting and addiction. Information about what influences discount rates in the laboratory may therefore prove relevant to a number of issues in public health and policy-making.

1.2 Summary and main contributions

A set of four experiments was conducted to explore whether lack of knowledge of the normative strategy can explain high discount rates. We designed an online survey to poll subjects regarding their reasoning behind intertemporal decisions (Experiment 1), to determine which of several possible explanations for high discounting are most often mentioned. Although several of the possibilities mentioned above received some support, the results implied that a large fraction of subjects either were unaware of the normative strategy or were not applying it to the task appropriately. If people are not considering the normative strategy or are applying it incorrectly, then providing them with information about the normative strategy and how to apply it to the task should reduce discounting. We tested this prediction in a series of three additional experiments. Experiment 2 tested this hypothesis by providing subjects with a "financial guide" that explained the normative strategy. To reduce any demand effects, the guide emphasized what information subjects should consider, and explicitly stated that this information could lead one to be more or less patient. Providing this information significantly reduced discounting immediately after the manipulation and for at least one month, but did not lower discount rates nearly as far as the normative strategy would prescribe. Experiment 3 tested the effectiveness of a much more strongly worded version of the financial guide, which reduced discounting further, though still not as low as market interest rates. The failure of even strongly worded normative arguments to reduce discount rates to level of market interest rates led us to compare normative arguments to other approaches. In Experiment 4, arguments referencing the normative strategy were at least as effective as other potential arguments in reducing discount rates. Since this experiment used short paragraphs written by other participants, it also demonstrates that information regarding the normative strategy is effective when it does not come from the experimenter (who was blinded to the content of the paragraphs) and when it does not reference "experts".

Combined, these studies confirm that lack of knowledge about the normative strategy does contribute to high monetary discounting. Normative arguments reduce discount rates. These

interventions produce at least as large a change in discounting as other previously described manipulations of the tangibility and perceived distance of future timepoints (Peters and Buchel, 2010; Kim, 2010). On a practical level, our results suggest that education regarding normative considerations should not be dismissed as being an ineffective way to change financial decision making. However, our results also contain a puzzle, in that none of the interventions tested reduced discounting to the level that the normative strategy would prescribe. Other factors, such as transaction costs or perceptions of the future, must also contribute to high discounting, and further experiments are needed to quantify the contribution of these other considerations. In terms of practical implications, simply providing information about normative considerations alone will not reduce discounting to normative levels, so future work should investigate combining multiple arguments, tailoring arguments to individuals, and other approaches.

2. Experiment 1 – Online survey

Several factors might contribute to high levels of monetary discounting. Among them are perceived risk, thinking about consumable goods rather than money, and a lack of understanding of the normative strategy. This experiment asked subjects to describe what considerations they think are important when making intertemporal choices, to examine which, if any, of these factors are cited spontaneously.

2.1 Methods

2.1.1 Subjects

Individuals recruited through Amazon's Mechanical Turk completed a short intertemporal choice task on Qualtrics (Qualtrics Labs Inc., Provo, UT) and then responded to two question prompts. Amazon's Mechanical Turk is considered a fast and reliable source of experimental data, with results typically not differing between in-lab and online experiments (Paolacci et al., 2010; Buhrmester et al., 2011; Mason and Suri, 2011). We restricted participation to US-based participants only. Of the 151 subjects who began the survey, 93 completed it. Subjects were paid

$0.50, and the survey was estimated to take no longer than 30 minutes[2]. The average age of subjects who completed the survey was 32.5 years (SD = 12 years), and 73.6% of subjects were female. All subjects provided informed consent in accordance with the procedures of the institutional review board at the University of Pennsylvania.

2.1.2 Procedures

The temporal discounting task consisted of 51 choices. This task was modeled after the short questionnaire designed by Kirby (Kirby and Maraković, 1995). Each choice was between a smaller monetary reward received immediately and a larger monetary reward received after a delay. Choices were presented one at a time. Amounts for the smaller reward ranged from $10-$34, and amounts for the larger reward were $25, $30, or $35. Delays ranged from 1- 180 days. All subjects saw the same choices, though the choices were presented in a different random order for each subject.

In this experiment, the main variable of interest was not discount rates but rather the open-ended response questions. For this reason, subjects were only given a flat participation payment, and not paid according to their choices on the discounting questionnaire. In all other experiments, subjects were paid in an incentive-compatible manner according to one of their choices.

After completing the intertemporal choice task, each subject answered two questions: (1) "Why did you choose the way you did?" and (2) "If you had to persuade other people to make the same choices that you just did, what would you say? Include a numerical example. Please write a paragraph (8-10 sentences) explaining your answer. Minimum word count: ~180." Several pilot experiments were conducted to determine these stipulations for the second question, which was designed to produce lengthy answers containing specific examples, rather than the brief, vague explanations seen in pilot experiments.

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[2] The payment rate, as presented on the HIT, was $1 per hour. However, the average response time was 18 minutes, giving an effective rate of $1.67 per hour. The presented rate of $1 per hour is slightly lower than the estimated reservation wage ($1.38; Hornton & Chilton, 2010). The attrition rate in this study (38%) is within the range of attrition seen in other studies using MTurk (Chandler & Kapelner, 2010; Kelley, 2010; Willett et al., 2012).

2.1.3 Data analysis

Analyses focused on the second question, "If you had to persuade other people to make the same choices that you just did, what would you say?" Responses to the first question, "Why did you make the choices that you did?" were more likely to involve very specific personal considerations (i.e., receipt dates for paychecks or due bills). The second question was intentionally framed to produce general explanations and advice to others.

Responses were scored by 2 individual raters (NS, TW) on whether the writer mentioned: (1) the risk of waiting or general uncertainty about the future, (2) purchases or other things the money could be spent on, (3) the difference in money between the two options (e.g., "five more dollars"), (4) the ratio of money in the two conditions (e.g., "25% more"), and (5) opportunity costs (e.g., investing, saving, interest rates, and/or the time value of money). After rating the arguments individually first, the 2 raters agreed on categorizations by discussing points of contention.

Discount rates in this experiment were calculated assuming an exponential[3] discounting model : $SV = Ae^{-kD}$, where SV is the subjective value of the delayed option, A is the monetary amount of the delayed option, D is the time delay in days, and k represents the discount rate. A higher k value indicates steeper discounting of a delayed reward. Discount rates were estimated using a logistic regression model, implemented in Matlab (Mathworks, Natick, MA). In some cases, this regression would not be well estimated because subjects selected all immediate or all delayed rewards. To deal with this issue, we determined the lowest and highest discount rates that we could reliably estimate, and constrained our estimates to this range. In this experiment, the discount rates of four subjects were at the lowest extreme of this range, and none were at the high extreme.

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[3] Since the normative strategy involved exponential discounting, we report the fits from an exponential discount model. However, both hyperbolic and exponential models were fit to all data. The hyperbolic model fit the function: $SV = A / (1+k*D)$ 3 (Mazur, 1987). In this experiment, the fit (r^2) of exponential and hyperbolic models were not significantly different (Wilcoxon sign-rank test, p=0.3), and the results reported in the text did not differ for exponential versus hyperbolic discount rates. Note that the stimuli used were optimized for detecting differences in the rate of discounting rather than the shape of the discount function, so we refrain from interpreting comparisons between the fits of the hyperbolic and exponential model.

For purposes of comparison, subjects were split at the median (k=0.0094) into high (n=46) and low (n=47) discounters. The median discount rate was in a reasonable range compared to in-lab behavioral testing (see Experiments 2, 3, and 4). We compared the percentage of high and low discounters that mentioned each consideration using Chi square tests, and also performed a logistic regression of log-transformed discount rates on the likelihood that participants mentioned each consideration.

2.2 Results

The most frequently recommended strategy (mentioned by 58% of subjects) was to consider the difference in the two amounts being offered. Comparatively fewer subjects (37%) recommended that others consider ratios of amounts. The second highest percentage (47%) of subjects mentioned opportunity costs, such as interest rates or savings accounts. Of the five categories scored, the least frequently mentioned factors were the risk inherent in waiting into the future (16%) and items that could be purchased (29%).

To examine whether the percentages of subjects recommending these strategies differed depending on discount rate, subjects were split into two groups at the median discount rate. The largest difference between the high and low discounting groups was in mentioning opportunity costs, with the low discounting group being more likely to mention opportunity costs (62%) than the high discounting group (33%) (Chi square p=0.016). There was also a trend for the high discounting group to be more likely to mention considering differences in amounts (67% vs. 49%, Chi Square p=0.065). Roughly equal percentages of high and low discounters mentioned risk, purchases and ratios between amounts (all comparisons *ns*). See Table 1 for all percentages.

A logistic regression was performed to further explore the relationship between discount rates and the likelihood that participants would mention each consideration. There was a significant negative relationship between log-transformed discount rates and the likelihood of mentioning opportunity costs (odds ratio = 0.4, p = 0.004). There was also a moderately significant positive relationship between discount rates and mentioning future risk (odds ratio = 2.5, p = 0.051). All other models were *n.s.* Those with higher discount rates were therefore less

likely to mention opportunity costs, and more likely to mention risk inherent in waiting into the future. However, note that the overall rate of mentioning future risk is rather low (16% of respondents) compared to opportunity costs (47% of respondents).

2.3 Discussion

The responses to the online survey support some of the theoretical explanations for high discounting, but not others. First and foremost, we found substantial evidence that not all subjects consider the normative strategy to be an important element in intertemporal choices, and that those who do might be making mistakes in its application. If subjects were considering these tradeoffs normatively by comparing the interest rates available in the experiment to those available to them on the market, they should recommend that others consider relative percentages or ratios of money rather than differences in amounts. Yet we found that more subjects mentioned differences in monetary amounts than ratios, and that less than half of responders recommended comparing ratios at all. Finding that more subjects recommended paying attention to differences in amounts is in line with recent descriptive models of intertemporal choice, such as the tradeoff model (Scholten and Read, 2006). This model suggests that individuals focus on weighing attribute differences (i.e., amount or delay) between the choice options, rather than comparing their overall values.

Furthermore, if subjects were considering these tradeoffs normatively, they should mention opportunity costs. While many subjects did mention opportunity costs, there was still a considerable proportion (53%) who did *not* recommend considering the key element from a normative point of view. Opportunity costs was the category that that differed most clearly between patient and impatient subjects. Patient subjects were more likely to recommend that others consider opportunity costs than those who were relatively impatient, with 62% of patient subjects mentioning opportunity costs and only 33% of impatient subjects doing so. This suggests that those who exhibit higher discount rates may be less aware of normative considerations.

In addition, the percentage of high discounting responders (33%) that mentioned opportunity costs suggests that these responders might not have considered opportunity costs accurately. This was directly evident in some individuals' responses. For example, one subject stated, "Would you rather have $19 now or $23 in 55 days. It's pretty simple. Why would I wait almost 2 months more for 4 extra dollars? I could make more money with the $19 now and turn it into a profit by using it for something else to invest in." In this case, a 141% annual interest rate was implied. Since such rates of return are unlikely, especially for any large percentage of the population in the US, these statements suggest that some subjects were not accurately calculating interest rates. This raises another possible factor contributing to high discounting, which is that even when people are aware of normative considerations, they may not be able to apply them correctly to the task at hand.

These findings regarding the importance of knowledge about normative considerations are potentially related to individual differences in discounting. While the associations between discounting and personality traits are generally low, stronger correlations have been found between discounting and cognitive ability (Hirsh et al., 2008; Shamosh and Gray, 2008; Burks et al., 2009). One potential explanation for this association involves the awareness of and ability to implement the normative strategy. Individuals of higher cognitive ability may be more likely to be exposed to normative arguments about opportunity costs, for example through schooling, and may be better able to accurately calculate interest rates in order to apply normative considerations correctly.

In contrast to the above findings, we did not find as strong evidence for two alternative hypotheses about the explanation for high discounting: that subjects were concerned about the risk or uncertainty involved in a delayed payment or that subjects were considering consumable goods – items that could be purchased with the money rather than the money itself. Although there is a positive relationship between discount rates and the likelihood of mentioning risk, only a minority of subjects mentioned risk as a consideration.

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One limitation of this experiment is that the question we asked subjects, "if you had to persuade other people to make the same choices that you just did, what would you say," might not provide the most accurate picture regarding the reasons subjects made the choices they did, especially if subjects do not have conscious access to the reasons for their choices. This question does provide an accurate picture of what subjects consider compelling arguments, since subjects' explicit goal was to be persuasive. In this respect, it is interesting that opportunity costs, which are normatively relevant, are the factors mentioned most often in favor of low discounting. We designed the next experiment to see whether exposure to this argument can reduce discount rates.

3. Experiment 2 – Financial guide and interest rate instruction session

If lack of knowledge is an important contributor to high discount rates, explicitly informing subjects about the normative argument should reduce discounting. In Experiment 2, some subjects were asked to read a 'financial guide,' which explained what information people should consider normatively. This guide focused on what information people should consider, specifically opportunity costs, rather than on what they should choose. It provided examples where these considerations would warrant more choices of the delayed reward and examples where these considerations would warrant fewer choices of the delayed reward, so as to not directly imply that subjects should become either more or less impatient. To address the possibility that subjects might already know this information but mistakenly underestimate the returns offered in the experiment, some subjects viewed examples of the interest rates implied between choice options. The effects of the guide and the interest-rate examples were examined individually and together, in a 2x2 design.

3.1 Methods

3.1.1 Subjects

Eighty individuals from the University of Pennsylvania community participated in this experiment, with 20 individuals in each of 4 experimental conditions. The mean age was 22.2

years (SD=5.3 years), and 66% of subjects were female. Students made up 80% of the subject pool; 17.5% of subjects were employed full-time and 2.5% were unemployed. All subjects provided written informed consent in accordance with the procedures of the institutional review board at the University of Pennsylvania.

All subjects were asked to return about one month after their first session for a second session. Of the original 80 subjects, 70 (mean age = 22.3 years, SD=5.5 years; 69% female; 84% students, 16% employed) were willing to return for a second session roughly one month after the first (average delay = 30 days, SD=5.1 days).

3.1.2 Intertemporal choice task

The temporal discounting task consisted of 102 choices. Subjects completed the task 3 times (two sets at the first session, and one set at the second session), with new choices each time. The task was presented in E-Prime (Psychology Software Tools, Pittsburgh, PA), but was otherwise as described in Experiment 1.

At each session, subjects were informed that they would be paid according to their choice on one randomly selected trial, in addition to a show-up payment of $10. Subjects received payments via debit card (Kable and Glimcher, 2007; 2010) regardless of whether the randomly selected trial involved an immediate or delayed payment. For delayed payments, the incentive payment did not become available on the card until after the delay period.

At session 1, 37.5% of payments were immediate, and the average immediate payment was $23.36. The average delayed payment was $29.47, and the average delay was 26 days. At session 2, 51.25% of payments were immediate, and the average immediate payment was $25.54. The average delayed payment was $30, and the average delay was 30 days. By the date of their second appointment, 89% of subjects had already received an incentive payment from the experimenter. Whether or not a payment had been successfully received before the second appointment did not affect the degree of change in discount rates (see below).

3.1.3 Procedures

At session 1, subjects first completed 2 practice trials, followed by 102 trials of the intertemporal choice task. After completing this first set of choices, subjects underwent one of the four experimental manipulations and then immediately completed the second set of 102 choice trials. At session 2, approximately one month later, subjects returned to the lab and completed the third set of 102 choice trials. The second session was run by a different experimenter, and no mention was made of the manipulation seen at the first appointment. Discount rates were calculated separately for each 102-item set.

3.1.4 Financial guide

The financial guide outlined in detail the elements of the normative decision strategy, but did not explicitly recommend that subjects become more or less impatient. The key aspect of the normative strategy is that the subject should not turn down a rate-of-return from the experimenter that outperforms what the subject could achieve outside of the experiment. The text emphasized that choosing in accordance with the normative strategy does not require changing one's preferences regarding consumption. Subjects could "have it both ways," such that if they strongly preferred to spend the smaller amount immediately, they could borrow that amount from another source while waiting for the larger amount, and might be able to make a profit after repaying the loan. If they could do so, then the larger, delayed option would be the better choice regardless of their preferences regarding consumption. Alternatively, if subjects would prefer to make the most money possible, they should consider whether investing the amount of money available immediately would yield a higher amount at the end of the delay period than the delayed option offers. If their potential investment would be worth more than the delayed option, then the immediate option would be the better choice. To aid in comparison, a figure included in the guide illustrated the increasing value of money when invested at several different interest rates (or, comparably, the increasing amount owed after borrowing money at several different interest rates).

The guide also emphasized that the normative strategy depends on individual circumstances. Some subjects may not have a credit card, an interest-bearing bank account, or

other convenient ways to borrow and invest money. If subjects prefer having money to spend today, and do not have other borrowing opportunities, then they might justifiably accept a smaller, immediate option that others with borrowing opportunities would reject. Similarly, if they prefer a larger amount of money, but do not have any investment opportunities, then they might justifiably accept a larger, later payment that others with investment opportunities would reject.

See Appendix for the full guide.

3.1.5 APR manipulation / interest rate instruction

For the APR (annual percentage rate) manipulation, subjects first read a short definition of APR. They then were presented with 51 choice pairs that they had previously seen. For each pair, subjects were presented with the original choice options, the implied interest rate (APR) between them, and the option they had chosen previously. Subjects were not given the opportunity to change their choices, but were asked to simply pay attention to the screen. The APRs ranged from 7% to 9000%.

3.1.6 Data analysis

Discount rates were estimated separately for each set of questions, and calculated as in Experiment 1[4]. Two subjects had discount rates estimated at the lower bound of the range, and none at the upper bound. Because discount rates are not normally distributed, all statistics in this experiment were performed on the log-transform of the discount parameter k. The average discount rates reported are transforms of the mean log discount rate. Error bars in Figure 1 are calculated as within-subject standard error (Morey, 2008).

Because of the large variability in discount rates across the population, between-group differences are difficult to detect. There was not a between-treatments difference in discount rates in this experiment. A multivariate ANOVA on each timepoint showed a nonsignificant effect of the guide at both timepoints after the manipulations (immediately after, $F(1,69) = 0.504$, $p = 0.48$; one month later, $F(1,69) = 1.785$, $p = 0.186$). However, discount rates within participants are very

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[4] Except for the first and third timepoints of the guide only and control conditions, the exponential discounting model provided a significantly better fit than the hyperbolic model (Wilcoxon sign-rank test, $p < 0.05$). The results reported in the text do not differ for exponential versus hyperbolic discount rates.

reliable without intervention (see test-retest reliability below), so within-subject analyses are both justified and more powerful. Analyses of this experiment and those following will use within-subject comparisons.

3.2 Results

3.2.1 Session 1

The four different experimental conditions were (1) reading the financial guide alone ("Guide"); (2) reading the financial guide and viewing the APR manipulation ("Guide+APR"); (3) viewing the APR manipulation alone ("APR"); and (4) viewing neither the guide nor the APR manipulation ("control"). At session 1, subjects in all conditions performed the delay discounting task twice.

A repeated measures ANOVA used the log transform of discount rates as the dependent variable, the first and second choice sets as the within-subjects factor, and dummy variables coding whether participants saw the financial guide and the APR manipulation as between-subjects factors. The results indicated a significant 2-way interaction between choice sets and exposure to the financial guide ($F(1,76)=10.707$, $p=0.002$). There was not a significant 2-way interaction between choice sets and exposure to the APR manipulation ($F(1,76)=0.004$, $p=0.947$), or a significant 3-way interaction between choice sets, exposure to the financial guide, and exposure to the APR manipulation ($F(1,76)=0.371$, $p=0.545$). Thus, only the financial guide had a significant impact on behavior.

Because we did not observe a significant effect of the APR manipulation, the four manipulations are collapsed into two groups below. The subjects who read the financial guide showed a significant reduction in discount rates, moving from a mean of $k=0.0093$ to $k=0.0061$ (t-test on log transform, $p<0.0001$). Those who did not read the guide showed no significant change in discount rates, with the mean moving from $k=0.0074$ to $k=0.0071$ (t-test on log transform, $p=0.44$).

Since subjects in the control condition did not see either manipulation, we were able to obtain a measure of the test-retest reliability of our task. Discount rates did not change

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significantly in this condition, with the average for the first test at k=0.0054 and for the second test at k=0.005 (t-test on log transform, p=0.84). Test-retest reliability, measured as the correlation between the log-transformed discount rates at the two tests, was 0.956. This demonstrates that, without intervention, discount rates in this task are consistent within individuals, on a given day.

3.2.2 Session 2 – One month later

All subjects in Experiment 2 were asked to return roughly one month after the first appointment. At this time, they completed the delay discounting task with a different experimenter, with no mention made of their previous appointment. Of the 20 subjects in each condition, the following numbers returned one month later: 16 from the Guide condition; 20 from the Guide+APR condition; 16 from the APR condition; and 18 from the Control condition.

A repeated measures ANOVA used the log-transformed discount rates as the dependent variable, the three choice sets as the within-subjects factor, and dummy variables coding exposure to the financial guide and APR manipulation as between-subjects factors. The results indicated a significant 2-way interaction between choice sets and exposure to the financial guide ($F(2,132)=9.303$, p=0.001). There was no significant 2-way interaction between choice sets and exposure to the APR manipulation ($F(2,132)=0.222$, p=0.75), or 3-way interaction between choice sets, exposure to the financial guide and exposure to the APR manipulation ($F(2,132)=0.117$, p=0.844).

Again, because we did not observe a significant effect of the APR manipulation, the four manipulations are collapsed into two groups below. For subjects who read the financial guide at the first appointment, the average discount rate decreased immediately after the manipulation. One month later, the average discount rate showed a non-significant increase relative to immediately after reading the guide (from k=0.0061 immediately after to k=0.0072 one month later; t-test on log transform, p=0.147) and remained significantly lower than before reading the guide (from k=0.0093 before to k=0.0072 one month later; t-test on log transform, p=0.032). This demonstrates that there was an effect of the financial guide that lasted for at least one month. Although there was a trend for some rebound in discount rates one month after the manipulation,

discount rates were still significantly lower than at the first, naïve test. See Figure 1 for average discount rates across time.

We also observed higher discount rates one month later in subjects who did not receive the financial guide, relative to the second test (t-test on log transform, p=0.002). This was not attributable to whether subjects had received immediate or delayed payments from session 1. Examined across all subjects, payment category (immediate payment or delayed payment received before second session, vs delayed payment received after second session) did not have a significant effect on the degree of change in discount rates (difference in log k) from sets 2 to 3 (ANOVA, F(2,69)=1.556, p=0.217) or from sets 1 to 3 (ANOVA, F(2,69)=0.591, p=0.445). The significant reduction of discounting that we observed in subjects who did read the guide was in the opposite direction of the drift observed in those who did not read the guide, so if anything, this finding suggests that the above results underestimate the effects of the guide.

3.3 Discussion

This experiment used a 2x2 design to examine the effects of providing information regarding the normative strategy (the financial guide) and the implied interest rates in the choices the subjects face (the APR manipulation). If subjects discount highly because they are unaware of the normative strategy, reading the financial guide should reduce discounting. Results from this experiment indicate that this is in fact true for many subjects. Subjects who read the guide exhibited a significant 35% reduction in discounting. This effect lasted at least one month, with discount rates remaining 23% lower one month later.

Viewing the APR manipulation did not have a significant effect on discounting. It could be that the information in the guide provided enough clarification about interest rates for any subjects who were unclear, and that viewing the APR manipulation alone was not enough information to change behavior. Our results suggest that misunderstanding interest rate calculations was not a major contributor to high discount rates in this experiment.

Although the financial guide reduced discounting significantly, it did not lower discount rates nearly as far as the normative strategy would prescribe. The average discount rate of the

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subjects who read the financial guide was equivalent to an annual interest rate of about 320%.
However, the financial guide employed a neutral tone and provided no general recommendation
that subjects become more or less impatient. This neutral wording was used to eliminate any
possibility of experimenter demand effects, but it might also have obscured an understanding of
the normative argument. To rule out the possibility that the extremely high discount rates that
remain in this experiment are due to people still not fully understanding the normative argument
or its implications, we performed the next experiment, which uses a very strongly worded guide
that makes explicit recommendations for what to choose.

4. Experiment 3 – Prescriptive financial guide

In this experiment, we tested whether a more strongly worded argument could reduce
discounting further than the manipulations described in Experiment 2. Here the guide emphasized
that because most delayed choices yield very high rates of return and most subjects do have
flexible financial opportunities, the normative strategy, in the case of the choice options presented
here, is to almost always choose the delayed reward. We were interested in whether or not, when
the argument is put in strongest possible terms, people would reduce their discounting to the level
of market interest rates.

4.1 Methods

4.1.1 Subjects

Twenty individuals from the University of Pennsylvania and surrounding community
participated (75% female; 70% students, 20% employed, 10% unemployed). The mean age was
26 years (SD = 10.7). All subjects were asked to return roughly one month after their first
appointment for a second session. Of the original 20 subjects, 17 (82% female; 76% students,
12% employed, 12% unemployed; mean age 26, SD = 11.6) were willing to return for a second
session (average delay = 30 days, SD = 6 days). All subjects provided written informed consent
in accordance with the procedures of the institutional review board at the University of
Pennsylvania.

4.1.2 Intertemporal choice task

The temporal discounting task consisted of 51 choices. Subjects completed the task 3 times (two sets at the first session, and one set at the second session). The particulars of the task and payment are otherwise identical to Experiment 2.

At session 1, the average payment was $27.45. Forty-five percent of these payments were immediate (average $25.44) and 55% were delayed (average $29.09). For delayed payments, the average delay was 53.5 days. At session 2, the average payment was $25.18. Thirty-five percent of those payments were immediate (average $18.60) and 65% were delayed (average $31.00). For delayed payments, the average delay was 53.2 days.

4.1.3 Procedures

Subjects first completed 2 practice trials, followed by 51 trials of the intertemporal choice task. Then subjects read the financial guide and immediately afterward completed the second set of 51 intertemporal choices. One month later, subjects returned to complete the third set of 51 intertemporal choices. This session was run by a different experimenter, with no mention made of the guide read at the previous session. Discount rates were calculated separately for each set of 51 trials.

4.1.4 Financial guide

Like the financial guide used in Experiment 2, this guide outlined in detail the normative decision strategy, that subjects should not turn down a rate-of-return from the experimenter that outperformed what they could obtain outside the experiment. The guide also presented scenarios that allowed the subject to "have it both ways," making the most profit from the experiment while still spending or saving money according to their personal preferences.

However, unlike the balanced argument in Experiment 2, which emphasized that the normative strategy could lead to different subjects making different decisions in this task, the guide in this experiment strongly emphasized that in most cases, the normative strategy would lead subjects to make more patient choices. The guide pointed out that because most of the larger, delayed options in this experiment yielded very high returns, the best strategy was almost

always to choose the delayed option. The guide explained that since the rate of return from most of the choices in the experiment was higher than what is available on the market, a simple way to implement the "best strategy" was to always accept the larger amount of money. It then described the more sophisticated approach of comparing subjects' own borrowing and investment opportunities to the interest rates offered in the experiment. Assuming that all subjects had such financial opportunities, the larger, later option was almost always the more valuable choice given the range of options offered in these experiments. For example, if subjects chose all delayed options offering an annual rate of return greater than the current prime rate (3%), they would select the delayed option 100% of the time in this experiment. Even if subjects only chose the delayed option when it offered a rate of return greater than 20%, they would still select the delayed option 82% of the time in this experiment.

This presentation of the normative strategy did make some generalizations, both about the choices offered (that they had high returns) and about the personal finances of the subjects. In some ways, then, it may not have been the fairest representation of the normative argument. However, since the goal of this experiment was to test for the strongest possible effect, we erred on the side of overstating the normative argument.

See Appendix for the full guide.

4.1.5 Data analysis

Discount rates in this experiment were calculated as in Experiment 1^5. Three subjects had discount rates estimated at the lower bound of the range, and none at the upper bound. Again, statistical analyses were performed on the log-transformed discount rate, and the average discount rates reported are transforms of the mean log discount rate. Error bars in Figure 2 are calculated as within-subject standard error, as in Morey (2008).

4.2 Results

4.2.1 Session 1

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[5] There were no significant differences between fit of the exponential and hyperbolic models in this experiment (Wilcoxon sign-rank test, all p > 0.3), and the results reported in the text do not depend on whether exponential or hyperbolic rates are used.

Discount rates (k) were calculated for each subject (n=20) from their choices before and immediately after reading the guide at session 1. There was an 85% decrease in discount rates after reading the guide (t-test on log transform, p<0.0002). The average discount rate declined from k = 0.008 to k = 0.0012. Discount rates did not cluster around the discount rate illustrated in the guide (k = 0.0005, suggesting that overall, subjects did not simply implement the illustrated decision rule. Very few subjects (n = 2) selected all the delayed options immediately after reading the guide[6], suggesting that subjects also did not follow the simpler version of the decision rule put forth in the guide, which was to always take the larger amount of money.

4.2.2 Session 2 – One month later

Subjects were asked to return roughly one month after their first session and were tested by a different experimenter, with no reminder of the guide read at session 1. For these subjects (n=17), discount rates were calculated from choices on the third set of discounting questions and compared to the two sets from the first session. A repeated-measures ANOVA showed a significant change in discount rates over time (F(2,32)=16.46, p<0.0001).

The average discount rate at the second session, approximately one month after reading the guide, was k = 0.003. This discount rate was significantly higher than immediately after reading the guide (k = 0.0012; t-test on log transform, p=0.009). However, this discount rate was also significantly lower than before any intervention (k = 0.008; t-test on log transform, p=0.013). Thus, although subjects were steeper discounters one month after reading the guide, they still discounted significantly less than before reading the guide. See Figure 2 for average discount rates over time.

4.3 Discussion

When subjects read a financial guide including not only an explanation of the normative strategy but also specific recommendations to choose more delayed options, we observed an even stronger immediate reduction in discount rates. There was an 85% decrease in discount rates in Experiment 3, compared to a 35% decrease in Experiment 2. As seen in Experiment 2,

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[6] A third subject chose all delayed options only at the one-month timepoint.

the effect of the financial guide persisted for at least one month; discount rates remained significantly lower at the one-month timepoint than at the original test.

Interestingly, the rebound in discount rates from immediately after reading the guide to one month later was reliable in this experiment, whereas it was not reliable in Experiment 2. This difference in the degree of rebound is significant (repeated-measures ANOVA with discount rates as within-subjects factor and experiment as between-subjects factor; $F(1,51)=10.69$, $p=0.002$). One possibility is that the larger decline in discount rates in this experiment provides more opportunity for discount rates to rebound. Another possibility is that the guide used in this experiment induced strong experimenter demand effects, which account for much of the larger observed decline in discount rates, and that the rebound in discount rates one month later reflects the reduction of these effects with a new experimenter.

The observed reduction in discount rates did not occur because subjects chose to follow either of the suggested decision rules. The financial guide suggested that the "simplest version of the best strategy" was to always choose the larger, later option. However, very few subjects (2 out of 20) adopted this strategy after reading the guide; nearly all continued to select a mixture of immediate and delayed rewards. The guide also described an implementation of the "sophisticated version of the best strategy," assuming a 20% annual interest rate. Again, there was no clustering of subjects around this discount rate.

Immediately after reading the guide, the average discount rate was equivalent to an APR of about 48%. This APR is not completely outside a reasonable realm: taking into account possible penalties and late fees, the interest rate on a credit card could approach this level. However, this APR is not as low as typical market interest rates. Even with a very strongly worded, clear, and understandable argument for the normative strategy, and the possible presence of demand effects, the average individual still did not shift to discount at the level of typical market interest rates.

These results show that normative arguments, while effective, still do not lead people to discount at the level of market interest rates. This raises the question of whether normative

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arguments are more or less effective at changing discounting than other possible arguments. We conducted the next experiment to begin exploring this question. We also manipulated the source and framing of the arguments presented, to test whether information needs to come from an authority to be effective.

5. Experiment 4 – Peer-generated advice

Experiment 4 examined whether the source and framing of information presented affected discount rates. In contrast to the materials presented in Experiments 2 and 3, the advice presented to subjects in Experiment 4 was written by other participants, rather than by the experimenter. These paragraphs varied on two dimensions – whether they encouraged subjects to be more patient or more impatient (argument type), and the content of the argument. Two arguments (one patient, one impatient) relied on reasoning about financial opportunity costs, as required by the normative strategy, while two arguments encouraged subjects to engage in episodic future thought and imagine how they might use the money now or in the future.

5.1 Methods

5.1.1 Subjects

Sixty-four individuals from the University of Pennsylvania and the surrounding community participated in this study, with 16 people in each of the four experimental conditions. The mean age was 21 years (SD=2.17 years) and 62.5% of the subjects were female. The majority of the participants (91%) were students, with the remaining individuals being either employed full-time (6%) or unemployed (3%). All subjects provided written informed consent in accordance with the procedures of the human subjects review board at the University of Pennsylvania.

Each subject received a set show-up payment of either $5 or $10, depending on whether they participated only in this 30 min. study (44% of subjects) or this study and an additional, unrelated 30 min. study. Additional winnings were then determined based on participant's responses in the choice trials. Seventy percent of the payments were immediate, with the

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average immediate reward being $24.36. The other thirty percent of the payments were delayed, with an average delayed reward of $28.95 and an average delay of 45 days.

5.1.2 Procedures

The task and payment details are as described in Experiment 3. Subjects completed two practice trials, followed by 51 intertemporal choice trials. They saw one of four experimental manipulations, and then completed the second set of 51 choice trials. All four experimental manipulations required participants to read one of the four peer-generated paragraphs, selected at random (experimenter blinded), and then to rate the paragraph's persuasiveness and helpfulness (Likert scale, with 1 being not persuasive/helpful and 5 being extremely persuasive/helpful). Subjects were told that after completing some monetary decisions, they would be viewing one of several possible paragraphs that were written by other people who had completed the same experiment. They were asked to read the paragraph carefully, as they would be asked to rate the persuasiveness and helpfulness of the paragraph later. They were also informed that the experimenter did not know which of the paragraphs they would be reading.

5.1.3 Peer-generated advice paragraphs

The paragraphs were taken from participants' responses to the second question in Experiment 1, "If you had to persuade other people to make the same choices that you just did, what would you say?" The list of 93 original arguments was narrowed down to 44 paragraphs by selecting the strongest and most coherent arguments. An additional 8 paragraphs were taken from a similar survey of University of Pennsylvania students enrolled at the Wharton school. These 52 paragraphs were then rated by another set of 278 participants through online surveys; 170 participants were recruited through Amazon's Mechanical Turk, and 108 from the University of Pennsylvania's psychology department subject pool. The survey asked participants to complete a short delay discounting task and then to read ten randomly selected paragraphs, and (1) indicate if the paragraph would have made them more likely to take the "now" option (i.e. more impatient), the "later" option (i.e. more patient), or neither, and (2) rate the strength of the argument from 1 to 5 (5 being the strongest).

The arguments that received the highest ratings were then sorted according to whether they advised patience or impatience, and by whether they utilized primarily financial reasoning or prospective thought. For example, the "impatient prospective" paragraph includes, "Imagine that you are worried about paying your electric bill, the baby sitter, the dentist for your child. The economy is tanking, half your peers have lost their jobs this month. … A smaller amount of money given today…provides a financial cushion and a margin of security." The "patient financial" paragraph includes, "I know the numbers are small, but think about it this way – would you rather have $20,000 today or $22,000 three months from now? …If you annualize the return, that would be a 40% return per year! If you took the $20,000 today and put it in a savings account, (earning about 1%) in three months you would only have $20,050. The difference is $1950!" See Appendix for the full paragraphs.

The four experimental conditions were paragraphs that encouraged patience using predominantly prospective thought (patient-prospective), encouraged patience using financial reasoning (patient-financial), encouraged impatience using prospective thought (impatient-prospective), and encouraged impatience using financial reasoning (impatient-financial). One of the highest-rated paragraphs was chosen from each condition, such that the final 4 paragraphs did not significantly differ on argument strength in the initial rating surveys. The lengths of the paragraphs were also roughly equal, from 193 to 233 words.

5.1.4 Data analysis

Discount rates were estimated separately for each set of questions, and calculated as in Experiment 1[7]. In this experiment one subject was at the upper bound and one at the lower bound of the estimation range. As above, statistical analyses were performed on the log-transformed discount rate, and the average discount rates reported are transforms of the mean

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[7] Exponential and hyperbolic fits did not differ at the first measurement of this experiment (Wilcoxon sign-rank test, p = 0.98), but exponential fits were significantly better at the second measurement (Wilcoxon sign-rank test, p=0.002). In this case, all the results reported in the text but one do not depend on which model is used. The exception is the analysis of change in the group viewing "impatient" arguments, as noted in footnote 8.

log discount rate. Error bars in Figure 3 are calculated as within-subject standard error, as in Morey (2008).

As in Experiment 2, a between-groups ANOVA was conducted on discount rates immediately following the manipulation. In this experiment, there is a significant group effect of argument type ($F(1,64)=7.124$, $p=0.01$); after the manipulation, participants who read the patient paragraphs were significantly more patient than those who read the impatient paragraphs. There was no significant effect of argument content ($F(1,64)=0.323$, $p=0.572$), or an interaction ($F(1,64)=0$, $p=0.99$). However, as discussed in Experiment 2, within-subject analyses of discount rates are both justified and more powerful, and are therefore the focus of the results section below.

5.2 Results

Subjects in all conditions performed the delay discounting task twice. After completing the task once, subjects read one of the four peer-generated paragraphs, rated the paragraph on its persuasiveness and helpfulness, and then completed the task a second time. A repeated-measures ANOVA using the log transform of discount rates from the first and second set as the within-subjects factor and the argument type (patient or impatient) and content (financial reasoning or prospective thought) as between-subjects factors indicated a significant relationship between discount rate tests and the patience condition ($F(1,60)=23.8$; $p<0.0001$). The average discount rate of subjects viewing patient arguments decreased from $k=0.0111$ to $k=0.0056$ (t-test on log k, $p<0.0001$), while the discount rates of subjects viewing impatient arguments increased, although less reliably, from $k=0.0126$ to $k=0.0153$ (t-test on log k, $p=0.057$)[8]. There was no significant effect of argument content ($F(1,60)=0.717$, $p=0.401$), and no significant interaction between argument type and content ($F(1,60)=0.463$, $p=0.5$).

The analysis above indicates that the argument type (patient or impatient) did have a significant effect on behavior, but does not ask whether patient or impatient arguments were more effective. To address this, a repeated-measures ANOVA was performed using adjusted log-

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[8] Using hyperbolic fits, this increase in discount rates for impatient arguments does reach significance at p=0.02.

transformed discount rates, such that change in discount rates was signed in the same direction for the patient and impatient conditions. Because this analysis is done on log-transformed discount rates, these discount rates and changes are normally distributed. The within-subjects variable was the adjusted discount rate, and the between-subjects variables were the argument type and content conditions. There was a significant effect of argument type ($F(1,60)=7.517$, $p=0.008$), with those in the patient condition having a larger change in discount rates than those in the impatient condition. There was no effect of argument content ($F(1,60)=0.463$, $p=0.5$), and no significant interaction between argument type and content ($F(1,60)=0.717$, $p=0.401$). The patient paragraphs, then, changed behavior more drastically than the impatient paragraphs, but the degree of change was not affected by the content of the argument.

To examine whether argument conditions affected persuasiveness and helpfulness ratings differently, a multivariate ANOVA was performed using argument type and content as between-subjects factors. The average persuasiveness and helpfulness ratings are in Table 2. The ANOVA indicated a significant effect of argument type on persuasiveness ratings ($F(1,63)=25.97$, $p<0.0001$) and a moderately significant effect on helpfulness ratings ($F(1,63)=4.059$, $p=0.048$), with "impatient" paragraphs being rated as more persuasive and helpful than "patient" paragraphs. There was also a significant effect of content type on persuasiveness ratings ($F(1,63)=8.609$, $p=0.005$), with "prospective" paragraphs being rated as more persuasive than "financial" paragraphs, but not on helpfulness ratings ($F(1,63)=2.283$, $p=0.136$). There was no significant interaction between ratings, argument type, and argument content for persuasiveness ($F(1,63)=0.024$, $p=0.878$) or helpfulness ($F(1,63)=0.063$, $p=0.802$). Average ratings can be found in Table 2.

Persuasiveness ratings were not significantly correlated with the absolute percent change in discount rates ($r=0.136$, one-tailed $p=0.142$), though helpfulness ratings were ($r=0.277$, one-tailed $p=0.013$).

5.3 Discussion

In Experiment 4, we asked whether peer-generated advice could change discount rates. Participants read advice that suggested patience or impatience, and utilized financial reasoning or prospective thought. We observed that discount rates could be significantly increased or decreased depending on the type of advice (patient or impatient) read. This was true for participants who read either advice emphasizing financial reasoning or advice emphasizing prospective thought.

The reduction in discounting resulting from peer advice emphasizing financial reasons for patience was of comparable size to the reduction observed in Experiment 2, which utilized a neutral presentation of the normative strategy. The effects seen in our previous experiments, then, do not depend either on the source of the advice or on the particulars of the message. The financial reasoning paragraphs used here conceptually resembled the normative argument as presented in Experiments 2 and 3, but did not include all the particulars. Presenting some elements of the normative strategy in the form of advice from others is enough to reduce discounting. Again, however, normative arguments do not reduce discounting to anything near the level of market interest rates.

Interestingly, patient advice emphasizing financial reasoning and patient advice emphasizing prospective thought reduced discounting to a similar degree. Further experiments could utilize more than one exemplar for each category, to confirm these observed differences, or lack thereof, between advice types. Although the advice emphasizing financial reasoning and normative considerations was rated least persuasive, it was not any less effective than the advice relying prospective thought. This is noteworthy, given that opinions about the efficacy of normative instruction are often pessimistic.

We were able to shift discount rates not only towards increased patience, but also towards increased impatience. In the impatient condition, as well as in the patient condition, there was no difference between the participants who read paragraphs using financial reasoning and paragraphs relying on prospective thought. The fact that advice mentioning financial opportunity

costs had the potential to *increase* discount rates, and to do so with equal effectiveness to advice relying on prospective thought, highlights the fragility of people's understanding of the normative strategy.

However, we did observe that the "patient" paragraphs caused significantly greater change in discount rates than the "impatient" paragraphs (50%, compared to 21%). This is despite the fact that the patient arguments were rated as less persuasive and less helpful than the impatient arguments. It appears, then, that although impatient arguments are effective at changing behavior and are rated as more persuasive and helpful, patient arguments are still significantly more effective in changing behavior.

6. General discussion

In experimental studies of intertemporal choice, people generally discount the value of monetary rewards at a rate that far exceeds the market interest rate (Frederick et al., 2002; Reynolds, 2006). This set of experiments shows that one important factor contributing to high rates of discounting is a lack of understanding of the normative strategy, and that providing information regarding the normative strategy results in sustained reductions in discounting. These experiments also demonstrate that providing such information is not enough to reduce discounting to levels near those of market interest rates. Below we discuss the potential remaining reasons for high discounting, and the implications of these findings for designing more effective interventions to reduce discounting.

In an online survey (Experiment 1), only half of the responders spontaneously referred to opportunity costs – interest rates, investments, etc. - as a factor to be considered when making intertemporal choices. The other half of the responders, then, did not mention the most important consideration from a normative point of view. Of those who did refer to opportunity costs, about a third were high discounters, suggesting that many who mentioned this strategy may not have been using it appropriately. These results suggest that many people are unaware of the

normative strategy or how it applies to this task, and that some who try to apply the normative strategy do so inappropriately, perhaps because of incorrect estimates of interest rates.

To examine whether addressing these knowledge gaps would reduce discounting, the next experiment (Experiment 2) tested the effects of learning about the normative strategy and/or about interest rates. People who learned about the normative strategy and how to apply it to the task exhibited lower discount rates, suggesting that not all subjects could (or did) apply the normative strategy spontaneously. This reduction in discounting was not temporary, and lasted for at least a month. However, although discounting was significantly reduced, observed discount rates were still very impatient relative to market interest rates. As demonstrated in Experiment 3, even using strong prescriptive language and providing simple heuristics, which made the normative strategy clear, did not reduce discount rates to the level of market interest rates. Finally, Experiment 4 compared the effect of the normative argument to that of other arguments. Arguments that referenced normatively relevant factors (financial opportunity costs) and those encouraging subjects to engage in episodic future thought were similarly effective at changing discount rates. Normative arguments, while perhaps not being any more effective than other arguments, are at least not any less effective. It was also possible to convince people to become more impatient, even when referencing financial opportunity costs. However, arguments in favor of greater patience resulted in shifts that were proportionally larger and more reliable.

Two previous studies reported results related to these findings. Coller and Williams (1999) showed that providing APY comparisons between available market options and the choices in the experiment decreased discount rates by 30%. Similarly, Read et al. (2005) found that framing choices as between taking a smaller amount of money now or investing it at a given interest rate reduced discount rates by up to 57% (Read et al., 2005a). Here we did not show the APR of each choice, but rather provided examples of different APRs as part of an explicit normative argument about why rates of return should be relevant to the discounting task. In addition, discount rates were measured both immediately after subjects were given this information as well as one month later, to determine whether any observed changes were lasting.

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Across three experiments, we found similar or steeper reductions in discounting (35 - 85%) than

Coller and Williams (1999) and Read et al. (2005), and demonstrated that these reductions

persisted (at 23 - 61%) for at least one month.

Though providing normative instruction did reduce discount rates, even with the strongest

possible wording in Experiment 3, discount rates still remained above market interest rates. This

set of experiments quantifies how much lack of knowledge about the normative argument

contributes to high discount rates. There are several other possible contributing factors to high

discount rates, which remain to be further explored and quantified. While the simplest explanation

might be that subjects simply ignore normative considerations, it is worth also considering

potential normative reasons for the continued high rates of discounting.

One possibility is that subjects felt that the future payment was associated with some

degree of inherent risk (Benzion et al., 1989; Keren and Roelofsma, 1995; Dasgupta and Maskin,

2005; Bommier, 2006; Halevy, 2008; Gerber and Rohde, 2010). If subjects did not trust that they

would receive the delayed payment from the experimenter, whether due to a default on the part of

the experimenter or some other unexpected event, then they would be justified in demanding a

greater rate of return. However, in Experiment 1 we saw that only 16% of responders

spontaneously mentioned risk as a consideration in their choices. Additionally, if risk were a factor

in increasing discount rates, we would have expected a difference in discount rates at the month

time point between subjects who had already received a delayed payment and those who had

not. This was tested in Experiment 2, and no effect was apparent. Risk considerations alone do

not seem to be able to account for the high levels of discounting that remained in our

experiments.

Another possibility is that subjects may have been credit-constrained. The expectation

that discount rates should be near market interest rates assumes that subjects have borrowing

opportunities available. It seems unlikely that this would not be the case in the university

undergraduate population that we tested. The most likely major source of credit for these subjects

is a credit card. Taking into account possible penalties and late fees, the interest rates on credit

cards could approach 50% annually, which is close to the median discount rate we observed immediately after subjects read the guide in Experiment 3. Discount rates in Experiments 2 and 4 were larger this, though. So credit constraints alone seem unlikely to account for the high levels of discounting that remained in our experiments.

A third possibility is that subjects could have expected their baseline levels of consumption to have increased by the end of the delay period, making the future reward relatively less valuable (Frederick et al., 2002; Gerber and Rohde, 2010). Rather than being impatient, then, subjects were being (overly) optimistic. This possibility merits some consideration, though it is unclear why many of our subjects (university students) would have expected a large change in consumption in such a short timeframe (at most six months).

A final possibility is that subjects faced transaction costs in implementing the normative strategy. Subjects might have perceived borrowing money from another source to require a greater amount of effort (for example, remembering their credit bill, not losing the experiment payment card over the course of several months, etc.) and felt that this additional effort was not worth the marginal gain in earnings. If there were transaction costs, subjects could have been licensed to discount according to when they wanted to consume. This explanation would predict that subjects would be more likely to move towards the normative strategy for larger monetary amounts, since the marginal gain would then outweigh any transaction costs. Future research should test this possibility.

The considerations described above are all normative reasons why subjects might continue to discount at a high rate. However, it is also possible that subjects in our experiments simply ignored normative considerations altogether, or weighed them along with other factors. These other factors might suggest different interventions from the ones used here, which might prove more successful at changing discount rates. Two other potential factors are concreteness and perceived temporal distance.

The way people consider time-money tradeoffs could be affected by the relative concreteness of the present versus the future (Trope and Liberman, 2003; Malkoc and

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Zauberman, 2006; Rick and Loewenstein, 2008). Immediate events tend to be more concrete, more tangible, and easier to imagine, while delayed events tend to be more abstract, more intangible, and harder to imagine. This suggests that manipulations that change the way people construe future events could change discount rates, if these make the receipt of future payments more tangible. The "prospective" arguments in Experiment 4 provide an example of one way to manipulate the tangibility of the future. The prospective argument encouraging patience described potential future situations in which individuals would enjoy having an additional amount of money, or regret having accepted a smaller amount of money sooner.

Peters and Buchel (2010) also found that increasing the tangibility of the future reduced discount rates. In their study, intertemporal choices were accompanied by a reference to an event the subject had planned for that date (e.g., "vacationing in Paris"). They observed a modest decrease (22%) in discount rates when future reward dates were accompanied by a reference to a discrete future event.

Another potential factor is perceived temporal distance. People who perceive the future reward as closer should be more patient than those that perceive it as farther away. Kim (2010) manipulated temporal distance by having subjects read facts framed to reduce ("the average lifespan is 80 years") or enhance ("the human brain begins to deteriorate at age 40") the relative temporal distance to a delayed reward. Those in the latter condition discounted at a significantly higher rate.

However, while manipulations of tangibility or perceived temporal distance do affect discount rates, none of these effects are larger than those we demonstrated here with normative arguments. An important question for future research is whether combining different kinds of arguments or tailoring arguments to specific individuals results in any larger effects on discounting, since normative information is not the entire solution.

Another important question for future research is how generalizable the effects we observed are. Although not complete reductions, Experiments 2 and 3 demonstrate that the effects we observed persist on the same experimental task for at least a month. But would

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similar manipulations also affect behavior outside the laboratory environment? Would these effects transfer from a discounting task to other decision contexts where interest rates or opportunity costs are normatively relevant (such as a consumer's decision whether to purchase an more expensive yet energy-efficient appliance)?

One potential concern is the extent to which our results might be affected by experimenter demand effects (Nichols and Maner, 2008). Throughout these experiments, we took systematic measures to mitigate this concern. First, our subjects were motivated to reveal their true preferences, since the choices in all of our experiments were incentive-compatible and had real monetary consequences, which were substantial relative to typical subject payments. If subjects were changing their behavior based on expectations alone, they were "paying" to do so. Further, in Experiment 2, the financial guide was carefully written to not privilege patient shifts over impatient shifts. It focused on *how* subjects should think about their choices rather than *what* they should choose. In Experiment 4, the arguments were explicitly labeled as being generated by other participants. Subjects knew that there were multiple experimental conditions and that the experimenter was blinded to their condition assignment, so it was more difficult to infer what the experimenter expected in each condition. Demand effects might be a factor in Experiment 3. However, the primary aim of Experiment 3 was to examine whether the strongest possible manipulation could reduce discount rates to the level of market interest rates, regardless of the reason for this shift. It is noteworthy that even here, despite the clear recommendations made in the guide, subjects did not follow either of the choice rules that were explicitly suggested to them.

In the field, there is inconsistent evidence about the effectiveness of financial education, including attempts to encourage retirement savings in the workplace and efforts to impart general financial knowledge to high school and college students (Bernheim and Garrett, 2003; Mandell, 2006; Borden et al., 2007; Martin, 2007). Although many studies report that financial education changes people's intentions regarding spending or investing, fewer studies are able to measure whether altered intentions do actually carry through to changes in behavior (Choi et al., 2004; Lusardi and Mitchelli, 2007; Lusardi, 2008). Several authors claim that given the inconsistent

evidence and high cost, financial education should not be continued in its current forms; however, reviews of the topic note greater success when interventions are targeted to a very specific behavior and point in time (Fox et al., 2005; Mandell, 2006; Hathaway and Khatiwada, 2008; Lusardi, 2008; Willis, 2008). Interventions like ours, that address a specific type of choice immediately before people make those choices, are among the more successful.

It will undoubtedly disappoint and surprise some that providing normative arguments did not reduce discount rates to the level of market interest rates. However, normative arguments did induce changes that are at least as large, if not larger, than those seen with other manipulations. Given these findings, efforts to reduce discounting should not ignore normative instruction, though more effective interventions might combine normative and other arguments, or tailor arguments to the specific individual. On a practical level, the type of manipulation tested here may prove useful, even if the effects are time- and context-limited. Many financial decisions, such as allocating retirement funds or taking out a loan, are made largely at one point in time, and are already subject to the social influences of experts. Changing the information and advice provided at the time of these choices can have profound practical impacts on decision-making.

Figure 1 – Discount rates before and after reading financial guide

Average discount rates (on log scale) at each of three timepoints, grouped by whether or not participants read the financial guide. Error bars are calculated for the within-subject comparison, as described by Morey (2008).
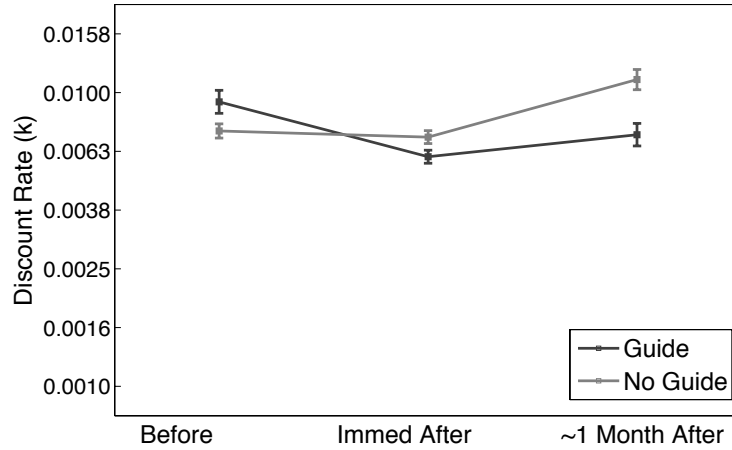
Figure 2 – Discount rates before and after reading prescriptive financial guide

Average discount rates (on log scale) at each of three timepoints. Error bars are calculated for the within-subject comparison, as described by Morey (2008).
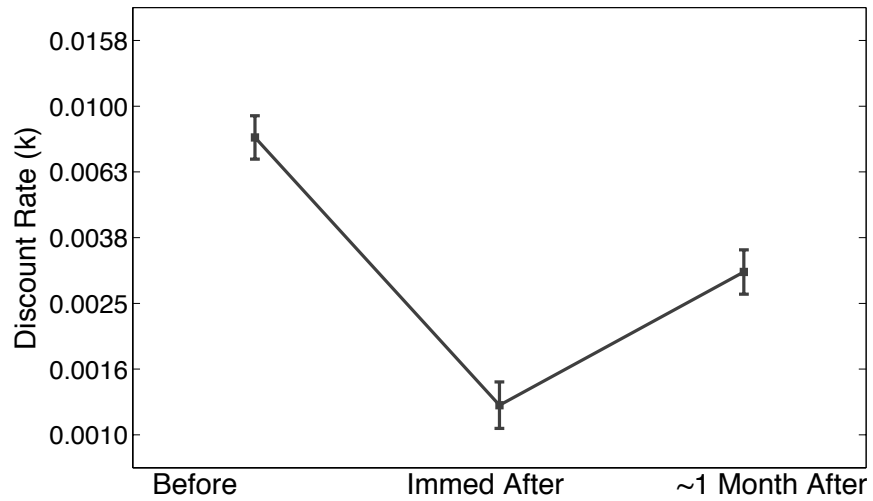
Figure 3 – Discount rates after reading peer-generated advice

Average discount rates (on log scale) grouped by content and type of advice paragraph read.

Error bars are calculated for the within-subject comparison, as described by Morey (2008).
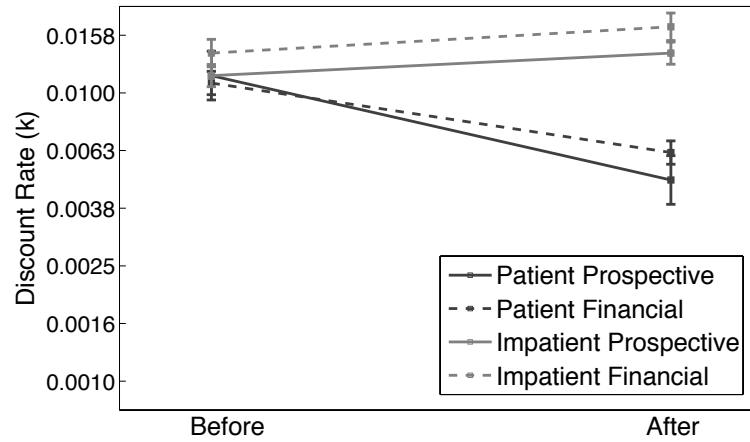
Table 1 – Survey response category percentages

	Future risk	Other purchases	Monetary differences	Money %s or ratios	Investing, saving, etc.
Overall	16%	29%	58%	37%	47%
High discounters	22%	26%	67%	39%	33%
Low discounters	11%	32%	49%	34%	62%

Table 2 – Average argument ratings

	Persuasiveness	Helpfulness
Patient-financial	2.69 (SD=0.7)	2.88 (SD=0.96)
Patient-prospective	3.31 (SD=1.01)	2.44 (SD=1.15)
Impatient-financial	3.75 (SD=0.86)	3.31 (SD=1.01)
Impatient-prospective	4.31 (SD=0.6)	3.00 (SD=0.82)

CHAPTER 5 – General discussion

Many of the choices in our daily lives involve intertemporal tradeoffs. This thesis furthers the understanding of the neurobiology of this type of decision (Chapter 2), the neural basis of individual differences in discounting preferences (Chapter 3), and behavioral interventions that change discounting preferences (Chapter 4). In Chapter 2, we contribute to the neuroimaging literature on choice by carefully separating several value-related decision variables, and examining which variables are the best fit to brain activity in several value-responsive brain regions. Chapter 3 focuses on the prediction of individual differences from brain activity in two particular regions, and finds that high and low discounters show opposite neural response patterns while judging time delays. This neural response to time judgments provides one potential intervention target to reduce discounting, and Chapter 4 suggests another intervention target, knowledge and understanding of the economic normative strategy for the monetary delay discounting task.

Neural mechanisms of choice

Process models

Recent research in economic decision-making has begun to apply the process models developed in the perceptual decision making literature to value-based choices (Basten et al., 2010; Philiastides et al., 2010; Krajbich and Rangel, 2011; Hare et al., 2011b; Hunt et al., 2012). Despite their similar goals, decision-making research in the economic and perceptual domains has largely evolved separately. Traditionally the analysis of perceptual decision making has involved more detailed process models of choice execution than has the economic field, but this has begun to shift towards shared ideas between the two literatures (Summerfield and Tsetsos, 2012).

There are two dominant variations on process models in value-based decision-making. One is based on the drift diffusion model, in which information about choice options, and their

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difference in value, is integrated over time by a single unit until a decision bound is reached (Bogacz, 2007; Ratcliff and McKoon, 2008; Hare et al., 2011b). The other, based on recurrent neural network models (Wang, 2002; 2008; 2012), assumes that there are separate but mutually inhibitory pools of neurons representing the value of each choice option, and that these pools compete until one comes to dominate the other and a choice is made.

While such a model-based approach should be beneficial for improving our understanding of economic choice, one problem is translating predictions of activity at a single neuron level, which is what is often measured in perceptual decision making, to predictions at the level of BOLD activity. Predictions of these models depend on whether the BOLD signal is presumed to reflect activity only until a decision bound is reached (Basten et al., 2010) or also includes activity after a decision has been reached (Rolls et al., 2010). These assumptions generate opposite predictions about response levels (Hunt et al., 2012; Summerfield and Tsetsos, 2012). Models based on the drift diffusion literature have tended to build in the assumption that an integrator or comparator region will reflect activity until the decision bound, and predict that such a region will show increased activity as choice options grow closer together in value (Hare et al., 2011b). On the other hand, models based the recurrent neural network model include the high steady-state activity after a decision bound has been reached, and predict that a decision region will show decreased activity as choice options grow closer together in value (Rolls et al., 2010; Hunt et al., 2012; Wang, 2012). This discrepancy in model predictions has led to contradictory reports in the literature.

Differentiable decision variables

Given this discrepancy in model predictions, a more basic question to ask is what decision variables best explain activity in value-responsive brain regions. One region with particularly contested function is the ventromedial prefrontal cortex. Previous work has largely looked for correlates of only one of several possible variables, without comparing more than one variable in the same dataset or ensuring that possible decision signals are decorrelated. In the VMPFC, some studies have reported signals correlating with the overall value of choice options

(Kable and Glimcher, 2007; Hare et al., 2008; Chib et al., 2009; Kable and Glimcher, 2010), others with the value of the chosen option (Blair et al., 2006; Glascher et al., 2009; Wunderlich et al., 2009; 2010; Barron et al., 2013), and still others with some measure of the difference between the options (Boorman et al., 2009; FitzGerald et al., 2009; Basten et al., 2010; Philiastides et al., 2010; Rolls et al., 2010; Lim et al., 2011; Hare et al., 2011b; De Martino et al., 2012; Hunt et al., 2012; 2013).

In Chapter 2, we disambiguate several possible decision signals through careful design of an intertemporal choice task. We find that BOLD activity in VS is best explained by subjective value, and that activity in VMPFC by a combination of subjective value and value comparison. This multiplex of value signals corresponds to a representation of the maximally valued option (which is nearly always the chosen option).

Even within studies that note the representation of the same variable, interpretations differ. For example, some interpret the presence of chosen value signals in VMPFC as support for the resolution of choices between goods within VMPFC (Padoa-Schioppa, 2011; Hunt et al., 2012). Others claim that VMPFC represents the option that is visually attended, and that because we spend more time attending the option we will ultimately choose, this chosen value signal is an artifact (Krajbich et al., 2010; Lim et al., 2011). However, this particular interpretation cannot explain the results in Chapter 2. In the discounting task from Chapter 2, participants saw only the larger later option visually displayed onscreen, and compared that to a constant smaller sooner option that was not shown. According to a strict interpretation of the latter model, the best explanation of activity in VMPFC should be subjective value, and we find that this is not the only variable represented. It is possible, perhaps, that the VMPFC focuses attention (in a less visual, and more cognitive sense) on the option that will guide behavior.

It has been suggested that at a finer timescale, activity in VMPFC includes a transition between value representations (Hunt et al., 2012). Using MEG, Hunt et al. (2012) found that activity in VMFPC shifted from a representation of the overall subjective value of choice options to a representation of the difference between choice options. These two signals are precisely what

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we observe in Chapter 2. This is the signature of a region that executes choice, as predicted at the single-neuron level by recurrent neural network models (Wang, 2012). Future work should emphasize methodology other than fMRI to make use of more detailed timecourse information, and establish precisely what signals are carried by different value-responsive regions.

Overlapping functions of ventromedial PFC and ventral striatum

In Chapter 2, we find that VMPFC and VS carry different combinations of value-related decision signals. While activity in VS correlates positively with subjective value, activity VMPFC correlates positively both with subjective value and with value comparison. This suggests that these two regions perform different, though potentially overlapping, functions during value-based choice. In Chapter 3 we report what may appear to be a contradictory result, that activity in both regions during a time judgment task shows the same relationship with individual differences in behavior on an intertemporal choice task. It should be noted that under many conditions, these two regions do show similar patterns; dissociating activity patterns in these regions in Chapter 2 required careful design of choice stimuli.

If subjective value representation is the link to discounting preferences through activity during time judgments, then it follows that discount rates can be predicted from both regions, since both carry subjective value signals. Because VMPFC also carries additional information about value comparison, the signal relating to discounting preferences could be diluted relative to that in VS. Accordingly, we find that the correlation between VS activity and discount rates is higher (although not significantly so) than the correlation between VMPFC activity and discount rates.

Neural representation of value

Research over the past several decades has shown that across many types of choice, the representation of value on a domain-general scale can be localized to the VMPFC and VS (Levy and Glimcher, 2012; Bartra et al., 2013; Clithero and Rangel, 2013). The consistency of this finding across participants, laboratories, and task types supports the idea that these regions are

the "final common pathway" for value during decision making. As observed in Chapter 2, these regions may reflect slightly different aspects of this final calculation of value under certain conditions, but do both share this generalized subjective value representation.

It could be the case that while this generalized value representation is held in VMPFC and VS, different brain regions contribute to this representation depending on choice strategies or scenarios. In Chapter 4, we find evidence that there is heterogeneity in what strategies participants use when making delay discounting choices. The first study in Chapter 4 shows the variability in spontaneously generated explanations for how discounting decisions should be made. Despite this variability in decision strategies on this particular monetary discounting task, which is likely present in the participants of Chapter 2 as well, we find a subjective value map in Chapter 2 that is consistent across subjects and with reports from other task types (Bartra et al., 2013). A possible explanation for this is that although VMPFC and VS represent the subjective values on which choice is based, there could be individual differences in how this value representation is computed. Further work could explore individual differences in strategies and recruitment of brain regions contributing to valuation.

Dorsolateral prefrontal cortex and self-control

A popular early proposal in the neuroimaging of delay discounting was that separate groups of brain regions respond to choices that involve only delayed options and to those that involve one immediate and one delayed option (McClure et al., 2004; 2007). These studies found that regions such as the striatum and ventromedial prefrontal cortex responded more strongly on trials containing an immediate option, while fronto-parietal regions responded equally across all trial types. The interpretation of this finding was that these two sets of regions compete for the selection of immediate versus delayed rewards.

Further work has refuted this idea. Generally the immediately available rewards are more subjectively valuable, and therefore show greater activation in valuation regions. When this is taken into account, it is evident that VMPFC and VS respond to the subjective value of both

immediate and delayed choices (Kable and Glimcher, 2007; Peters and Büchel, 2009; Pine et al., 2009; Peters and Büchel, 2011). In Chapter 2, we also find that increased activity in both VMPFC and DLPFC is predictive of choosing delayed rewards. If it was the case that VMPFC always responded more strongly to immediate reward options, we should observe the opposite relationship.

A number of studies have promoted variants on the hypothesis that a source of individual differences in discounting is the ability to exert cognitive control, and that this is upheld in the brain through the lateral prefrontal cortex (McClure et al., 2004; Hare et al., 2009; Figner et al., 2010; Hare et al., 2011a; Luo et al., 2012). Some work suggests that the DLPFC interacts with the construction of value representation, such that the DLPFC modulates the representation of value directly in VMPFC and VS. Several prominent examples are studies in which participants are asked to use self-control in their choices, for example to make choices while thinking about the "taste" or "health" qualities of different foods (Hare et al., 2009; 2011a). These studies find higher activity in DLPFC, and increased connectivity with VMPFC, on trials in which participants employ self-control, as well as lowered VMPFC activity to the items targeted for self-regulation. Other studies have looked for a causal relationship between DLPFC activity and decision-making. One report shows somewhat reduced discounting after TMS in DLPFC (Figner et al., 2010). Changes in preferences after the inhibition of DLPFC have been reported in the domains of probabilistic and social decision- making (Knoch and Fehr, 2007), and food choices and cravings (Fregni et al., 2008; Camus et al., 2009). However, the laterality and directionality of these effects are inconsistent.

This literature has led to the proposal that to increase patient decision making, an overall upregulation in the activity of the DLPFC is needed, to thereby decrease the value placed on immediately available rewards by the VMPFC. The results of Chapter 3 indicate that the proposed pattern of overall upregulation of DLPFC and downregulation of VMPFC is too simplistic. We found that patient individuals show different patterns of activity in VMPFC and VS than higher discounters, rather than decreased activity in these regions overall. This suggests,

then, that patient behavior is more likely to be promoted by enhancing activity in these regions selectively in response to far-future outcomes, and relatively reducing activity to near-future outcomes.

Functions of the medial prefrontal cortex

The ventromedial prefrontal cortex has long been considered crucial for valuation and decision-making, but this region, and the medial prefrontal cortex more generally, is involved in many other aspects of cognition. The results of Chapter 3, demonstrating a relationship between behavioral manifestations of delay discounting and brain activity during a time judgment task unrelated to intertemporal choice, beg the question of what the general role of medial prefrontal cortex could be that encompasses all of these functions.

Much work has linked activity in medial prefrontal cortex, among other regions, with episodic future thought, or prospection (Schacter et al., 2008; Szpunar, 2010; Schacter et al., 2012). Activity in MPFC also increases when people imagine positive rather than negative future events (Sharot et al., 2007; D'Argembeau et al., 2008). In addition to this shared neural substrate, prospection has been behaviorally linked to discounting. Two recent studies have found that linking specific events to the receipt date of a delayed reward, and encouraging participants to imagine these events, reduces discounting (Peters and Büchel, 2010a; Benoit et al., 2011). In one, events on participants' calendars were matched to the dates of delayed options in a discounting task, such that each larger-later option was linked with a personally relevant event (Peters and Büchel, 2010a). This presentation of choice options did reduce discounting. Similarly, another study asked participants to either imagine particular scenario matched to the larger-later option (i.e., spending $40 in a pub in 30 days), or just estimate what the money could buy during that episode (Benoit et al., 2011), and found that the imagining condition also reduces discount rates.

The self-reflection literature provides another tie between MPFC and discounting. Cortical midline structures, particularly the MPFC, are more active when people are making judgments or

thinking about themselves as opposed to others (Denny et al., 2012). Two recent studies have found links between perceptions of the future self, discounting, and activity in VMPFC, showing that higher discounters exhibit a greater difference in BOLD activity between judgments of oneself in the present compared to the future (Ersner-Hershfield et al., 2009a; Mitchell et al., 2011). The way that people think about themselves, and in particular their future selves, has been proposed as a contributor to delay discounting. According to theories of this type, we feel psychologically closer to our future self of a day or week from now than our future self a year or decade from now, and this increasing lack of psychological closeness causes lack of concern for the future self. It has been suggested that we consider our distant selves to be "others" (Parfit, 1971; Schelling, 1984; Pronin and Ross, 2006; Pronin et al., 2007; Wakslak et al., 2008). Myopic decision making, then, could be due to the future self's interests not "belonging" to the current self, when there is tension between present and future outcomes (D'Argembeau, 2013).

Thus far, we have touched on the relationship between medial prefrontal cortex and the literatures on decision-making, prospection, and self-reflection. However, the MPFC is involved in even more task domains than these — it has also been linked to autobiographical memory, theory of mind, and the default mode network. Meta-analytic work has shown overlap of the regions identified in autobiographical memory, prospection, theory of mind, and the default mode (Spreng and Grady, 2010), and the medial prefrontal regions identified in valuation meta-analyses overlap with these other domains (Levy and Glimcher, 2012; Bartra et al., 2013; Clithero and Rangel, 2013).

An intriguing question is how to describe the general role of the medial prefrontal cortex across all of these different literatures. It has been proposed that the medial prefrontal cortex supports "the ability to mentally project oneself from the present moment into a simulation of another time, place, or perspective" (Buckner and Carroll, 2007). It is also possible that the common link is value; that much of what drives behavior, and what makes things personally relevant, is value maximization (Northoff and Hayes, 2011; Levy and Glimcher, 2012; D'Argembeau, 2013). The link we observe in Chapter 3 between discounting and time estimation

could be due to shared processes of self-projection, as in the former account — perhaps people imagine future events at a given delay both to place a value on delayed rewards and to come up with a subjective rating of time distance. In line with the latter account, it could also be the case that people who discount steeply place low, or negative, value on the future in general, and therefore are less inclined to wait for delayed rewards, and also experience thinking about the future more negatively. Future work using other imaging techniques, such as multivariate pattern analysis, and perhaps using several of these task types (prospection, valuation, self-thought) in the same participants, may be able to identify dissociations in these spatially overlapping representations.

Considerations for discounting interventions

As the field progresses in its understanding of the neural mechanisms of decision making, neuroimaging data will be able to make significant contributions towards improved behavior change interventions. Two of the chapters presented here suggest possible intervention targets. In Chapter 3 we demonstrate that individual differences in neural responses during a time judgment task are a relatively strong predictor of discount rates. These results suggest that changing the way people think about future time intervals could reduce discounting behavior. Two recent studies have touched on this possibility by associating the time duration through which participants have to wait for the larger later reward with a positive future event. Both of these studies suggest that encouraging subjects to prospectively pre-experience the delay will encourage more far-sighted decision making.

In Chapter 4, we discuss several behavioral interventions that reduce discounting. A unique aspect of the monetary version of the delay discounting task is that in economic terms, there is a normatively correct way to perform the task. The normative strategy on this task is to compare the interest rates implied in the choice pairs offered to the interest rates one can obtain outside of the experiment, and to only accept the immediate option if the interest rates obtainable outside the experiment are better. In the first few studies, we find that the majority of participants

do not spontaneously consider the economically normative strategy, and that presenting information about this strategy significantly reduces discounting for up to a month.

In line with the possibilities discussed above, we also find that encouraging prospection reduces discount rates to a similar degree as economic information. In that study, participants were asked to generate paragraphs advising others on how to make their choices on the monetary discounting task. We found that these "advice" paragraphs could be separated into four categories. Some participants encouraged more patient choices, and others impatient choices. Within this split, some arguments focused on financial reasoning, and others on prospection. For example, some "advice" paragraphs encouraged participants to think about the positive things they could do with a large amount of money in the future if they waited for the larger later reward (categorized as patient, financial). Others described scenarios in which turning down an immediate reward would lead to negative consequences, such as missing bill payments, etc (categorized as impatient, prospective). A separate set of participants read a single "advice" paragraph from one of the four categories, in between completing sets of discounting choices. Arguments that employed prospection and financial reasoning each reduced discounting, to a similar degree.

It may be the case that providing information about the normative strategy can reduce discounting by filling a knowledge gap about this particular monetary discounting task, and that changing the way participants view the future reduces discounting at a more basic and broad level. A combination of these interventions could be even more effective. Additionally, people who are higher discounters on one type of task, such as this monetary task, are more likely to be high discounters in other domains (Tsukayama and Duckworth, 2010; Odum, 2011a; 2011b). While providing economic information is an intervention specific to this particular task, interventions that focus on prospection could reduce discounting across other domains. This will be of great interest in future work.

One arena in which neuroimaging has already begun to influence real-world behavior interventions is in the smoking cessation literature. Recent work has shown that individuals'

responses in medial prefrontal cortex while they watch smoking cessation ads can predict, above and beyond traditional self-report measures, not only how likely the individual is to quit smoking, but also how well a given advertisement will do in encouraging quitting in the general population (Falk et al., 2010; Chua et al., 2011; Falk et al., 2011; 2012; Wang et al., 2013). The next generation of focus groups for public health media campaigns may come to involve not just self-report measures, but also neuroimaging. Understanding the complicated relationship between the medial prefrontal cortex and all of the factors described above will help to inform and improve behavior interventions such as these.

A broadly effective manipulation to reduce discounting would also need to demonstrate lasting effectiveness over time. In Chapter 4, we do show reduced discount rates on this particular task out to a month. Despite the evidence of discounting preferences being stable over long periods of time without intervention (Ohmura et al., 2006; Kirby, 2009; Senecal et al., 2012), it would not be the first example of an otherwise stable, trait-like variable that can be changed. For example, trait anxiety (an individual's anxiety level, as a personal characteristic) has high test-retest reliability on the timescale of years (Usala and Hertzog, 1991), but can be reduced with cognitive behavioral therapy and, for example, mindfulness training (Lipsey and Wilson, 1993; Shapiro et al., 1998).

Conclusions

The research described here focused on the neurobiology of value-based decision making and individual differences. We have furthered the understanding of how and where decision-related variables are represented in the brain, identified a novel neural predictor of individual differences in delay discounting, and tested several behavioral interventions designed to change discount rates. A detailed understanding of how and where in the brain preferences are formed and choices are made, combined with information about how to change preferences, will help future work find ways to meaningfully change these behavior patterns.

APPENDIX

Contents, from Chapter 4:

1. Experiment 2 – Financial guide
2. Experiment 3 – Prescriptive financial guide
3. Experiment 4 – Peer-generated advice

1. Experiment 2 – Financial guide

How do you decide which option you prefer?

There are several things you might think about when deciding whether you prefer to receive a larger amount of money in the future or a smaller amount of money now. However, most financial advisors would recommend that you also consider your other financial opportunities when making these decisions. They would say that the best choice for you will depend on what other opportunities you have.

Maybe you want to spend money today. Then, if given a choice between $20 now and $30 in a month, you might want to accept the $20 now because you would prefer to spend the money right away. On the other hand, maybe you want to make the most money possible in the experiment. In this case, if given a choice between $20 now and $20.50 in a year, you might want to accept the $20.50 in a year because you would prefer to receive the largest amount of money. Both of these possible goals – to spend money today and to make the most money possible – might be achieved in more profitable ways if you also considered the financial opportunities available to you outside of the experiment. That is, if you have other opportunities, you might be able to spend *more* money now *without* taking the smaller, immediate option in the experiment. Similarly, if you have other opportunities, you might be able to make *more* money overall *without* taking the larger, later payment.

You can borrow or invest money in several different ways.

In this experiment, you can think about each choice as a potential loan or investment. Choosing the smaller, immediate payment over the larger, delayed option is comparable to taking out a loan – to obtain a smaller amount of money now, you forfeit a larger amount of money later. Likewise, choosing the larger, delayed payment over the smaller, immediate option is comparable to making an investment – to obtain a larger amount of money later, you give up a smaller amount of money now.

Outside of the experiment, you might have other ways of borrowing and investing money. You could borrow money by using your credit card, getting a loan from your bank, or asking a friend for money. You could invest money by putting it in a savings account, purchasing a certificate-of-deposit, or buying stocks and bonds.

You can use interest rates to compare the choices in this experiment to your other financial opportunities.

An economist or financial advisor would recommend that you compare the opportunities offered in this experiment to the other opportunities available to you outside the experiment. You may know the interest rates that you pay on your other loans or that you earn on your other investments. To compare your choices in this experiment to your options outside the experiment, then, you can think about these choices in terms of interest rates.

The graph below might help you do this. Both borrowing and investing involve interest rates in a similar way. Each line shows, for a different interest rate, the increasing value of $20 if borrowed or invested at that rate for different lengths of time.

When you *borrow* money, you accumulate interest on the amount you borrowed until you repay the loan. One way to use this graph is to think of each line as showing how the amount of money you would have to repay after borrowing $20 grows over time. For example, the red line shows that if you borrowed $20 for a year at an annual interest rate of 20% (compounded monthly), you would have to pay back $24.39 at the end of the year. Choosing $20 now over $24.39 in a year, therefore, is like borrowing money at a 20% annual interest rate.

Likewise, when you *invest* money, you earn interest on your deposit until you withdraw the money. Another way to use the graph is to think of each line as showing how the amount of money you would earn by investing $20 grows over time. For example, the green line shows that if you invested $20 for a year at an annual interest rate of 10% (compounded monthly), you would receive $22.09 at the end of the year. Choosing $22.09 in a year over $20 now, then, is like investing money at a 10% annual interest rate.

You can "have it both ways."
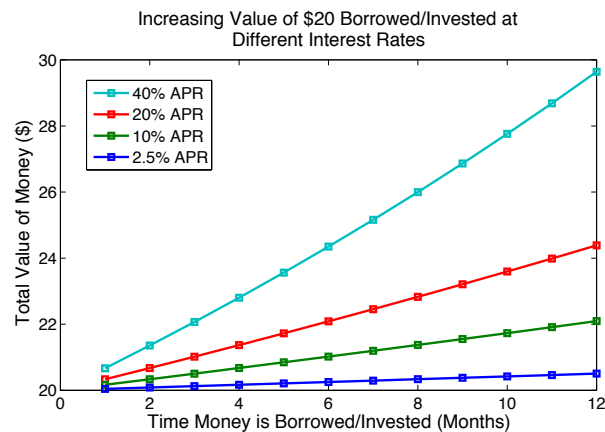
You can use interest rates to compare the choices in this experiment to your other financial opportunities. This comparison is important, because if your other financial opportunities are better, then you can "have it both ways" in this experiment.

Returning to our previous two examples will make this concrete. What if you really want to spend money now? Having other borrowing opportunities means that you could take the larger, delayed payment and still enjoy spending money right away. Given a choice between $20 now and $30 in a month, you could simply accept the smaller, immediate option and spend the money today. However, this would be like borrowing money at a high annual interest rate of 600%. You might have a credit card with a lower annual interest rate of 20%. If you do, instead of choosing to receive $20 now, you could choose $30 in a month, and still spend $20 today by charging it on your credit card. Then, when you receive the $30 from the experiment, you could pay off the charge on your credit card. At this point, you would still have an additional amount ($9.70) left over. Notice that this way you get what you want – spending the money today – and also gain additional money that you would not have had if you chose the immediate option.

Alternatively, what if you really want to make the most money possible? Having other investment opportunities means that you could take the smaller, immediate payment and still get a larger amount of money later. Given a choice between $20 now and $20.50 in a year, you might want to accept the $20.50 in a year because you prefer to receive the larger amount of money. However, this would be like investing money at a low annual interest rate of 2.5%. You might have a savings account that earns a higher annual interest rate of 5%. If you do, instead of choosing $20.50 in a year, you could choose $20 now, and put that money in your savings account. Then, in a year, you would have $21.02. At this point, you would have the $20.50 that you originally wanted, plus an additional amount ($0.52). Notice that this allows you to get what you want – the larger amount of money – and also earn additional money that you would not have had if you chose the delayed option.

Consider *your* opportunities for borrowing and investment.

All of this advice depends on your financial situation. You might not have a credit card or other convenient ways to borrow money. Even if you do have a credit card, you may have reached your credit limit or be behind on your payments. You might not have a bank account that earns interest, or other convenient ways to invest money. Obviously, if you don't have these other opportunities, then you can't use them in the ways suggested above.

This means that you might make decisions that people with different opportunities might not necessarily make. If you want money to spend today, and you do not have any other borrowing opportunities, then you might accept a smaller, sooner option that other people would reject. If you want the greatest amount of money, and you do not have any other investment opportunities, then you might accept a larger, later option that other people would reject.

Everyone is different.

Everyone will come into this experiment with a different financial situation. For some, considering your other opportunities might lead you to choose the larger, later option more frequently. For others, considering your other opportunities might lead you to choose the smaller, immediate option more often.

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Choose what is best for you.

If you think these are good recommendations for you, then you should consider your other financial opportunities when making decisions in this experiment. Remember that you will be paid according to the choice you make on one randomly selected trial, so you should choose the option on every trial that you think is truly best for you.

2. Experiment 3 – Prescriptive financial guide

You are more impatient than most participants.

When given the choice between receiving a smaller amount of money sooner or a larger amount of money later, you usually choose to receive the money as soon as possible. Most participants in our experiments are more patient—they are more willing to wait for larger amounts of money.

Your impatience is costing you money.

Because you usually choose to receive the money as soon as possible, you are likely to earn less money than other participants. You would receive the most money from us, of course, if you chose the larger amount of money regardless of the delay.

Any expert would tell you that there is a single best strategy in this experiment.

If you were to ask any expert—for example, an economist, someone working in business, or a financial advisor—all of them would tell you that there is a single best strategy in this experiment. Since the choices in our experiment involve money, which can be invested or borrowed, there is a way to definitively determine which option best achieves your goals.

The simple version of the best strategy is to always accept the larger amount of money.

As you will read below, any expert would advise you to accept the larger amount of money, as long as it is worth more than what the immediately available amount would be after investing it over the delay. Since this will almost always be the case with our delayed offers, a simple rule that is very close to the best strategy would be to choose the larger amount of money, regardless of the delay.

The sophisticated version of the best strategy takes into account the rate of return that you could earn on investments.

How should you decide which is the more valuable option in our experiment? If you were to ask any expert, they would tell you that you should approach this decision by thinking about how much the immediate payment would be worth in the future if invested at some interest rate during the given delay. If the immediate option plus the interest from its investment is larger than the delayed option, then it is the better choice; if the delayed option is larger than the immediate option plus interest, then it is the more valuable option.

Consider the example of choosing between $20 today and a larger amount of money in a year. If you were to accept the offer of $20 and invest it at the very high compounding interest rate of 20% per year, you can see from the graph that you would earn a growing amount of interest on that money every month. At the end of the year, the $20 that you invested originally will be worth $24.43. If your choice were between $20 today and $21 in a year, the immediate offer would be the more valuable one.

However, if your choice were between $20 today and $25 (or anything greater) in a year, the later amount would more valuable. Since you will probably not be able to find such a high, profitable interest rate, and since we are usually offering you much larger delayed sums than those in the graph, you are almost always better off taking the larger, delayed option in our experiment.

Optimal Decision Strategy, Considering the Increasing Value of $20 at 20% APY
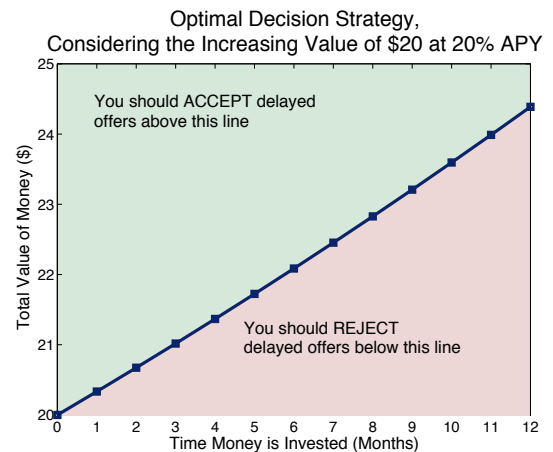
The best strategy lets you "have it both ways."

But what if you *really wanted* $20 today, rather than $25 in a year? You are *still better off* following the best strategy. In this case, you should borrow the $20 from another source, and wait for the $25 we would pay you in a year, rather than foregoing the larger offer and taking the

$20 today from us. If you had enough money, you could "borrow" $20 from your bank account at 0% interest. If not, you could borrow money from another source, for example, by taking a cash advance from a credit card. Credit cards tend to have high interest rates, up to 20% per year. Even at this high rate, though, you could borrow $20 from your card to spend today and only owe $4.38 of interest in a year. So you could borrow $20 today and spend it, then pay off your credit card when you receive the $25 from us a year from now, and still have some extra change to spare—money which you would not have had if you took the $20 from us rather than another source.

You are not required to follow this advice – your choices are up to you.

Although we believe that we have provided you with the best advice possible, your selections are still up to you. Remember that you will be paid according to the choice you make on one randomly selected trial, so you should choose the option on every trial that you truly think is best.

3. Experiment 4 – Peer-generated advice paragraphs

Patient, financial reasoning

With the rate of savings accounts today, if you are given the option of taking $20 today or $22 three months from now, you should choose the $22 three months from now. I know the numbers are small, but think about it this way...would you rather have $20,000 today or $22,000 three months from now? That is a 10% return on your money in only three months! You would not be able to do that in the stock market very easy and that would entail lots of risk! If you annualize the return, that would be a 40% return per year! If you took the $20,000 today and put it in a savings account, (earning about 1%) in three months you would only have $20,050. The difference is $1950! What would be so important that you would need to have money today and can't wait just a few months down the road to get even MORE money. The percentages are the same for the lower numbers. The amounts are guaranteed, so just take the later payment. Resist the urge to take the money today, delay your gratification and get more in the future!

Patient, prospective thought

You might as well wait to get the money. It's like putting money in the bank. Sometimes you can't touch the money for a certain period of time, but you will have more in the long run because of the interest gained. Just pretend the money isn't there at all. You will be glad you did when you are paid at the end of a few weeks. The money may come in handy when you really need it if you save it--to pay bills or save for something you've been wanting. If you get it now, you will probably just spend it on something you don't really need, like going out to a restaurant or buying something frivolous that you'll regret later. It is much better to have patience and earn a better reward than to enjoy a small amount now. Also, what it comes down to is that you get less money! Why would you settle for less today if you could simply wait a while and have much more? For example, if I were to receive $15 today rather than $30 in a month, I could spend the $15 on dinner for myself. But if I were to wait, I could take a friend to dinner or put it towards something I've been saving for. You get more, and all you have to do is wait. Waiting isn't so bad.

Impatient, financial reasoning

The stock market on average grows about 10% annually. Therefore, most of the choices there beat the average expectation of the market. However, some, like $34 now or $35 173 days later, do not even compare with what you could do if you invested in the market. While 10% in finance may be a lot, in daily activities, we experience mark ups easily exceed 10%. Thus, from an entrepreneurial or pricing standpoint, waiting more than a month for small return (eg $20 now, or $24 in 40 days) would also seem excessive. Time is money, and you could easily take the $20 and generate more than $24 in 40 days if you, for example, were able to make a cheap product and sell to your friends (like personal birthday cards), then you would obviously want the money now. For larger differences, say $10 now or $15 in 10 days, the wait is not substantial and the increase is dramatic. In situation, it would be better to wait the 10 days to get $15. Lastly, anything with a ridiculously long wait time just isn't worth it. Who would want to wait half a year to receive money that's only marginally more than what they would receive today?

Impatient, prospective thought

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Imagine that you are worried about paying your electric bill, the baby sitter, the dentist for your child. The economy is tanking, half your peers have lost their jobs this month. You may be next. You're still there because your hours were reduced. Someone is offering you money. You can take an amount today or you can take somewhat more money in a few weeks. If the payment is much larger at a much later date, the odds of being given the money are reduced. Your need for the money will also be increased. Money now can be used to pay immediate needs to prevent interest charges. It can be put in an emergency fund, something money "later" (that may never arrive or be devalued by inflation) may not provide. A smaller amount of money given today or in the next few days also provides a financial cushion and a margin of security. That cash reserve can be used to pay sudden costs (kid to ER, car repair) that might have caused over-draft charges on a checking account. That $20 extra today suddenly saves $25 in overdraft charges or late fees. $35 in six months cannot equal that value.

BIBLIOGRAPHY

Aguirre GK, Zarahn E, D'esposito M (1998) The variability of human, BOLD hemodynamic responses. NeuroImage 8:360–369.

Ainslie G, Haslam N (1992) Choice over time (Loewenstein G, Elster J, eds). New York, NY: Russell Sage Foundation.

Anderson AK, Phelps EA (2001) Lesions of the human amygdala impair enhanced perception of emotionally salient events. Nature 411:305–309.

Andino SG, de Peralta Menendez RG (2012) Coding of saliency by ensemble bursting in the amygdala of primates. Frontiers in Behavioral Neuroscience 6:1–16.

Audrain-McGovern J, Rodriguez D, Tercyak KP, Epstein LH, Goldman P, Wileyto EP (2004) Applying a Behavioral Economic Framework to Understanding Adolescent Smoking. Psychology of Addictive Behaviors 18:64–73.

Ballard K, Knutson B (2009) Dissociable neural representations of future reward magnitude and delay during temporal discounting. NeuroImage 45:143–150.

Balleine BW, O'Doherty JP (2009) Human and Rodent Homologies in Action Control: Corticostriatal Determinants of Goal-Directed and Habitual Action. Neuropsychopharmacology 35:48–69.

Barron HC, Dolan RJ, Behrens TEJ (2013) Online evaluation of novel choices by simultaneous representation of multiple memories. Nature Publishing Group 16:1492–1498.

Bartels DM, Rips LJ (2010) Psychological connectedness and intertemporal choice. Journal of Experimental Psychology: General 139:49–69.

Bartra O, McGuire JT, Kable JW (2013) The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. NeuroImage 76:1–16.

Basten U, Biele G, Heekeren HR, Fiebach CJ (2010) How the brain integrates costs and benefits during decision making. Proceedings of the National Academy of Sciences 107:21767–21772.

Baxter MG, Murray EA (2002) The amygdala and reward. Nature Reviews: Neuroscience 3:563–573.

Becker A, Deckers T, Dohmen T, Falk A, Kosse F (2012) The Relationship Between Economic Preferences and Psychological Personality Measures. Annu Rev Econ 4:453–478.

Becker GM, DeGroot MH, Marschak J (1964) Measuring utility by a single-response sequential method. Behavioral Science 9:226–232.

Behrens TEJ, Woolrich MW, Walton ME, Rushworth MFS (2007) Learning the value of information in an uncertain world. Nat Neurosci 10:1214–1221.

Benoit RG, Gilbert SJ, Burgess PW (2011) A Neural Mechanism Mediating the Impact of Episodic Prospection on Farsighted Decisions. Journal of Neuroscience 31:6771–6779.

Benzion U, Rapoport A, Yagil J (1989) Discount rates inferred from decisions: An experimental study. Management Science 35:270–284.

Bernheim BD, Garrett DM (2003) The effects of financial education in the workplace: evidence from a survey of households. Journal of Public Economics 87:1487–1519.

Bickel WK, Marsch LA (2001) Toward a behavioral economic understanding of drug dependence: delay discounting processes. Addiction 96:73–86.

Bickel WK, Odum AL, Madden GJ (1999) Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. Psychopharmacology 146:447–454.

Blair K, Marsh AA, Morton J, Vythilingam M, Jones M, Mondillo K, Pine DC, Drevets WC, Blair JR (2006) Choosing the Lesser of Two Evils, the Better of Two Goods: Specifying the Roles of Ventromedial Prefrontal Cortex and Dorsal Anterior Cingulate in Object Choice. Journal of Neuroscience 26:11379–11386.

Bogacz R (2007) Optimal decision-making theories: linking neurobiology with behaviour. Trends in Cognitive Sciences 11:118–125.

Bommier A (2006) Uncertain Lifetime and Intertemporal Choice: Risk Aversion as a Rationale for Time Discounting. International Economic Review 47:1223–1246.

Boorman ED, Behrens TEJ, Woolrich MW, Rushworth MFS (2009) How Green Is the Grass on the Other Side? Frontopolar Cortex and the Evidence in Favor of Alternative Courses of Action. Neuron 62:733–743.

Borden LM, Lee S-A, Serido J, Collins D (2007) Changing College Students' Financial Knowledge, Attitudes, and Behavior through Seminar Participation. J Fam Econ Iss 29:23–40.

Buckner RL, Carroll DC (2007) Self-projection and the brain. Trends in Cognitive Sciences 11:49–57.

Buhrmester M, Kwang T, Gosling SD (2011) Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data? Perspectives on Psychological Science 6:3–5.

Burks SV, Carpenter JP, Goette L, Rustichini A (2009) Cognitive skills affect economic preferences, strategic behavior, and job attachment. Proceedings of the National Academy of Sciences 106:7745–7750.

Camille N, Griffiths CA, Vo K, Fellows LK, Kable JW (2011) Ventromedial Frontal Lobe Damage Disrupts Value Maximization in Humans. Journal of Neuroscience 31:7527–7532.

Camus M, Halelamien N, Plassmann H, Shimojo S, O Doherty J, Camerer C, Rangel A (2009) Repetitive transcranial magnetic stimulation over the right dorsolateral prefrontal cortex decreases valuations during food choices. European Journal of Neuroscience 30:1980–1988.

Carmichael ST, Price JL (1995) Limbic connections of the orbital and medial prefrontal cortex in

macaque monkeys. Journal of Comparative Neurology 363:615–641.

Chabris CF, Laibson D, Morris CL, Schuldt JP, Taubinsky D (2008) Individual laboratory-measured discount rates predict field behavior. J Risk Uncertain 37:237–269.

Chib VS, Rangel A, Shimojo S, O'Doherty JP (2009) Evidence for a Common Representation of Decision Values for Dissimilar Goods in Human Ventromedial Prefrontal Cortex. Journal of Neuroscience 29:12315–12320.

Choi JJ, Laibson D, Madrian BC, Metrick A (2004) For better or for worse: Default effects and 401 (k) savings behavior. NBER Working Paper Series:81–126.

Chua HF, Ho SS, Jasinska AJ, Polk TA, Welsh RC, Liberzon I, Strecher VJ (2011) Self-related neural response to tailored smoking-cessation messages predicts quitting. Nature Publishing Group 14:426–427.

Cisek P (2012) Making decisions through a distributed consensus. Current Opinion in Neurobiology 22:927–936.

Clithero JA, Rangel A (2013) Informatic parcellation of the network involved in the computation of subjective value. Social Cognitive and Affective Neuroscience.

Coller M, Williams MB (1999) Eliciting individual discount rates. Experimental Economics 2:107–127.

Corbetta M, Patel G, Shulman GL (2008) The Reorienting System of the Human Brain: From Environment to Theory of Mind. Neuron 58:306–324.

Cunningham WA, Brosch T (2012) Motivational Salience: Amygdala Tuning From Traits, Needs, Values, and Goals. Current Directions in Psychological Science 21:54–59.

D'Argembeau A (2013) On the role of the ventromedial prefrontal cortex in self-processing: the valuation hypothesis. Frontiers in Human Neuroscience 7:1–13.

D'Argembeau A, Raffard S, Van der Linden M (2008) Remembering the past and imagining the future in schizophrenia. Journal of Abnormal Psychology 117:247–251.

Dasgupta P, Maskin E (2005) Uncertainty and hyperbolic discounting. American Economic Review 95:1290–1299.

De Martino B, Fleming SM, Garrett N, Dolan RJ (2012) Confidence in value-based choice. Nature Publishing Group 16:105–110.

Decety J, Lamm C (2007) The Role of the Right Temporoparietal Junction in Social Interaction: How Low-Level Computational Processes Contribute to Meta-Cognition. The Neuroscientist 13:580–593.

Deichmann R, Gottfried JA, Hutton C, Turner R (2003) Optimized EPI for fMRI studies of the orbitofrontal cortex. NeuroImage 19:430–441.

Delgado MR (2007) Reward-Related Responses in the Human Striatum. Annals of the New York Academy of Sciences 1104:70–88.

Denny BT, Kober H, Wager TD, Ochsner KN (2012) A meta-analysis of functional neuroimaging studies of self-and other judgments reveals a spatial gradient for mentalizing in medial prefrontal cortex. Journal of Cognitive Neuroscience 24:1742–1752.

Dorris MC, Glimcher PW (2004) Activity in posterior parietal cortex is correlated with the relative subjective desirability of action. Neuron 44:365–378.

Downar J, Crawley AP, Mikulis DJ, Davis KD (2002) A cortical network sensitive to stimulus salience in a neutral behavioral context across multiple sensory modalities. Journal of Neurophysiology 87:615–620.

Duckworth AL, Seligman MEP (2005) Self-discipline outdoes IQ in predicting academic performance of adolescents. Psychological Science 16:939–944.

Epstein LH, Salvy SJ, Carr KA, Dearing KK, Bickel WK (2010) Food reinforcement, delay discounting and obesity. Physiology & Behavior 100:438–445.

Ersner-Hershfield H, Garton MT, Ballard K, Samanez-Larkin GR, Knutson B (2009a) Don't stop thinking about tomorrow: Individual differences in future self-continuity account for saving. Judgment and Decision Making 4:280.

Ersner-Hershfield H, Wimmer GE, Knutson B (2009b) Saving for the future self: Neural measures of future self-continuity predict temporal discounting. Social Cognitive and Affective Neuroscience 4:85–92.

Falk EB, Berkman ET, Lieberman MD (2012) From Neural Responses to Population Behavior: Neural Focus Group Predicts Population-Level Media Effects. Psychological Science 23:439–445.

Falk EB, Berkman ET, Mann T, Harrison B, Lieberman MD (2010) Predicting Persuasion-Induced Behavior Change from the Brain. Journal of Neuroscience 30:8421–8424.

Falk EB, Berkman ET, Whalen D, Lieberman MD (2011) Neural activity during health messaging predicts reductions in smoking above and beyond self-report. Health Psychology 30:177–185.

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

Fellows LK, Farah MJ (2007) The Role of Ventromedial Prefrontal Cortex in Decision Making: Judgment under Uncertainty or Judgment Per Se? Cerebral Cortex 17:2669–2674.

Figner B, Knoch D, Johnson EJ, Krosch AR, Lisanby SH, Fehr E, Weber EU (2010) Lateral prefrontal cortex and self-control in intertemporal choice. Nat Neurosci:1–24.

Fisher I (1930) The theory of interest. New York 43.

FitzGerald THB, Seymour B, Dolan RJ (2009) The Role of Human Orbitofrontal Cortex in Value Comparison for Incommensurable Objects. Journal of Neuroscience 29:8388–8395.

Fox J, Bartholomae S, Lee J (2005) Building the case for financial education. Journal of Consumer Affairs 39:195–214.

Frederick S, Loewenstein G, O'Donoghue T (2002) Time discounting and time preference: A critical review. Journal of Economic Literature 40:351–401.

Fregni F, Orsati F, Pedrosa W, Fecteau S, Tome FAM, Nitsche MA, Mecca T, Macedo EC, Pascual-Leone A, Boggio PS (2008) Transcranial direct current stimulation of the prefrontal cortex modulates the desire for specific foods. Appetite 51:34–41.

Frith CD, Frith U (2006) The Neural Basis of Mentalizing. Neuron 50:531–534.

Gately D (1980) Individual discount rates and the purchase and utilization of energy-using durables: Comment. Bell Journal of Economics 11:373–374.

Geng JJ, Mangun GR (2011) Right temporoparietal junction activation by a salient contextual cue facilitates target discrimination. NeuroImage 54:594–601.

Gerber A, Rohde KIM (2010) Risk and preference reversals in intertemporal choice. Journal of Economic Behavior & Organization 76:654–668.

Gilbert DT, Wilson TD (2007) Prospection: Experiencing the Future. Science 317:1351–1354.

Glascher J, Adolphs R, Damasio H, Bechara A, Rudrauf D, Calamia M, Paul LK, Tranel D (2012) Lesion mapping of cognitive control and value-based decision making in the prefrontal cortex. Proceedings of the National Academy of Sciences 109:14681–14686.

Glascher J, Hampton AN, O'Doherty JP (2009) Determining a Role for Ventromedial Prefrontal Cortex in Encoding Action-Based Value Signals During Reward-Related Decision Making. Cerebral Cortex 19:483–495.

Grabenhorst F, Rolls ET, Margot C, da Silva MAAP, Velazco MI (2007) How Pleasant and Unpleasant Stimuli Combine in Different Brain Regions: Odor Mixtures. Journal of Neuroscience 27:13532–13540.

Green L, Fry AF, Myerson J (1994) Discounting of delayed rewards: A life-span comparison. Psychological Science 5:33–36.

Green L, Myerson J (2004) A discounting framework for choice with delayed and probabilistic rewards. Psychological Bulletin 130:769.

Green L, Myerson J, Lichtman D, Rosen S, Fry A (1996) Temporal discounting in choice between delayed rewards: the role of age and income. Psychology and Aging 11:79.

Green L, Myerson J, McFadden E (1997) Rate of temporal discounting decreases with amount of reward. Memory & Cognition 25:715–723.

Green L, Myerson J, Ostaszewski P (1999) Discounting of delayed rewards across the life span: age differences in individual discounting functions. Behavioural Processes 46:89–96.

Haber SN, Knutson B (2010) The Reward Circuit: Linking Primate Anatomy and Human Imaging. Neuropsychopharmacology 35:4–26.

Halevy Y (2008) Strotz Meets Allais: Diminishing Impatience and the Certainty Effect. American Economic Review 98:1145–1162.

Hare TA, Camerer CF, Rangel A (2009) Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. Science 324:646–648.

Hare TA, Malmaud J, Rangel A (2011a) Focusing Attention on the Health Aspects of Foods Changes Value Signals in vmPFC and Improves Dietary Choice. Journal of Neuroscience 31:11077–11087.

Hare TA, O'Doherty J, Camerer CF, Schultz W, Rangel A (2008) Dissociating the Role of the Orbitofrontal Cortex and the Striatum in the Computation of Goal Values and Prediction Errors. Journal of Neuroscience 28:5623–5630.

Hare TA, Schultz W, Camerer CF, O'Doherty JP, Rangel A (2011b) Transformation of stimulus value signals into motor commands during simple choice. Proceedings of the National Academy of Sciences 108:18120–18125.

Hariri AR, Brown SM, Williamson DE, Flory JD, de Wit H, Manuck SB (2006) Preference for Immediate over Delayed Rewards Is Associated with Magnitude of Ventral Striatal Activity. Journal of Neuroscience 26:13213–13217.

Hathaway I, Khatiwada S (2008) Do financial education programs work? Working paper:1–29.

Hausman JA (1979) Individual discount rates and the purchase and utilization of energy-using durables. The Bell Journal of Economics:33–54.

Hershey DA, Mowen JC (2000) Psychological determinants of financial preparedness for retirement. The Gerontologist 40:687–697.

Hikosaka O, Bromberg-Martin E, Hong S, Matsumoto M (2008) New insights on the subcortical representation of reward. Current Opinion in Neurobiology 18:203–208.

Hirsh JB, Morisano D, Peterson JB (2008) Delay discounting: Interactions between personality and cognitive ability. Journal of Research in Personality 42:1646–1650.

Hsu M (2005) Neural Systems Responding to Degrees of Uncertainty in Human Decision-Making. Science 310:1680–1683.

Hunt LT (2008) Distinctive Roles for the Ventral Striatum and Ventral Prefrontal Cortex during Decision-Making. Journal of Neuroscience 28:8658–8659.

Hunt LT, Kolling N, Soltani A, Woolrich MW, Rushworth MFS, Behrens TEJ (2012) Mechanisms underlying cortical activity during value-guided choice. Nature Publishing Group 15:470–476.

Hunt LT, Woolrich MW, Rushworth MFS, Behrens TEJ (2013) Trial-Type Dependent Frames of Reference for Value Comparison Diedrichsen J, ed. PLoS Comput Biol 9:1–14.

Hutcherson CA, Plassmann H, Gross JJ, Rangel A (2012) Cognitive Regulation during Decision Making Shifts Behavioral Control between Ventromedial and Dorsolateral Prefrontal Value Systems. Journal of Neuroscience 32:13543–13554.

Kable JW (2011) The cognitive neuroscience toolkit for the neuroeconomist: A functional overview. Journal of Neuroscience, Psychology, and Economics 4:63–84.

Kable JW, Glimcher PW (2007) The neural correlates of subjective value during intertemporal

choice. Nat Neurosci 10:1625–1633.

Kable JW, Glimcher PW (2009) The Neurobiology of Decision: Consensus and Controversy. Neuron 63:733–745.

Kable JW, Glimcher PW (2010) An "As Soon As Possible" Effect in Human Intertemporal Decision Making: Behavioral Evidence and Neural Mechanisms. Journal of Neurophysiology 103:2513–2531.

Kable JW, Kim BK, Senecal N, Zauberman G (2011) Heterogeneity in the neural substrates of time perception and time discounting. Interdisciplinary Symposium in Decision Neuroscience: Second Annual.

Kahnt T, Chang LJ, Park SQ, Heinzle J, Haynes JD (2012) Connectivity-Based Parcellation of the Human Orbitofrontal Cortex. Journal of Neuroscience 32:6240–6250.

Kahnt T, Tobler PN (2013) Salience Signals in the Right Temporoparietal Junction Facilitate Value-Based Decisions. Journal of Neuroscience 33:863–869.

Kalenscher T, Pennartz CMA (2008) Is a bird in the hand worth two in the future? The neuroeconomics of intertemporal decision-making. Progress in Neurobiology 84:284–315.

Kennerley SW, Walton ME (2011) Decision making and reward in frontal cortex: Complementary evidence from neurophysiological and neuropsychological studies. Behavioral Neuroscience 125:297–317.

Keren G, Roelofsma P (1995) Immediacy and certainty in intertemporal choice. Organizational Behavior and Human Decision Processes 63:287–297.

Kim BK, Zauberman G (2009) Perception of anticipatory time in temporal discounting. Journal of Neuroscience, Psychology, and Economics 2:91–101.

Kim BK, Zauberman G (2013) Can Victoria's Secret Change the Future? A Subjective Time Perception Account of Sexual-Cue Effects on Impatience. Journal of Experimental Psychology: General 142:328–335.

Kim S, Hwang J, Lee D (2008) Prefrontal Coding of Temporally Discounted Values during Intertemporal Choice. Neuron 59:161–172.

King-Casas B, Tomlin D, Anen C, Camerer CF, Quartz SR, Montague PR (2005) Getting to know you: reputation and trust in a two-person economic exchange. Science 308:78–83.

Kirby KN (2009) One-year temporal stability of delay-discount rates. Psychonomic Bulletin & Review 16:457–462.

Kirby KN, Finch JC (2010) The hierarchical structure of self-reported impulsivity. PERSONALITY AND INDIVIDUAL DIFFERENCES 48:704–713.

Kirby KN, Maraković NN (1995) Modeling myopic decisions: Evidence for hyperbolic delay-discounting within subjects and amounts. Organizational Behavior and Human Decision Processes 64:22–30.

Kirby KN, Petry NM, Bickel WK (1999) Heroin addicts have higher discount rates for delayed

rewards than non-drug-using controls. Journal of Experimental Psychology: General 128:78–87.

Kirby KN, Winston GC, Santiesteban M (2005) Impatience and grades: Delay-discount rates correlate negatively with college GPA. Learning and Individual Differences 15:213–222.

Knoch D, Fehr E (2007) Resisting the Power of Temptations: The Right Prefrontal Cortex and Self-Control. Annals of the New York Academy of Sciences 1104:123–134.

Knutson B (2005) Distributed Neural Representation of Expected Value. Journal of Neuroscience 25:4806–4812.

Knutson B, Rick S, Wimmer GE, Prelec D, Loewenstein G (2007) Neural Predictors of Purchases. Neuron 53:147–156.

Krajbich I, Armel C, Rangel A (2010) Visual fixations and the computation and comparison of value in simple choice. Nat Neurosci 13:1292–1298.

Krajbich I, Rangel A (2011) Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. Proceedings of the National Academy of Sciences 108:13852–13857.

Kringelbach ML, O'Doherty J, Rolls ET, Andrews C (2003) Activation of the human orbitofrontal cortex to a liquid food stimulus is correlated with its subjective pleasantness. Cerebral Cortex 13:1064–1071.

Laibson D (1997) Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics 112:443–478.

Lau B, Glimcher PW (2007) Action and Outcome Encoding in the Primate Caudate Nucleus. Journal of Neuroscience 27:14502–14514.

Lebreton M, Jorge S, Michel V, Thirion B, Pessiglione M (2009) An Automatic Valuation System in the Human Brain: Evidence from Functional Neuroimaging. Neuron 64:431–439.

Levy DJ, Glimcher PW (2012) The root of all value: a neural common currency for choice. Current Opinion in Neurobiology:1–12.

Levy I, Lazzaro SC, Rutledge RB, Glimcher PW (2011) Choice from Non-Choice: Predicting Consumer Preferences from Blood Oxygenation Level-Dependent Signals Obtained during Passive Viewing. Journal of Neuroscience 31:118–125.

Lim SL, O'Doherty JP, Rangel A (2011) The Decision Value Computations in the vmPFC and Striatum Use a Relative Value Code That is Guided by Visual Attention. Journal of Neuroscience 31:13214–13223.

Lipsey MW, Wilson DB (1993) The efficacy of psychological, educational, and behavioral treatment: confirmation from meta-analysis. American Psychologist 48:1181.

Luo S, Ainslie G, Pollini D, Giragosian L, Monterosso JR (2012) Moderators of the association between brain activation and farsighted choice. NeuroImage 59:1469–1477.

Lusardi A (2008) Household Saving Behavior: The Role of Financial Literacy, Information, and

Financial Education Programs. NBER:1–43.

Lusardi A, Mitchelli O (2007) Financial literacy and retirement preparedness: Evidence and implications for financial education. Business Economics 42:35–44.

Madden GJ, Petry NM, Badger GJ, Bickel WK (1997) Impulsive and self-control choices in opioid-dependent patients and non-drug-using control patients: Drug and monetary rewards. Experimental and Clinical Psychopharmacology 5:256.

Malkoc SA, Zauberman G (2006) Deferring versus Expediting Consumption: The Effect of Outcome Concreteness on Sensitivity to Time Horizon. Journal of Marketing Research 43:618–627.

Mandell L (2006) Financial literacy: If it's so important, why isn't it improving. Networks Financial Institute Policy Brief:08.

Mars RB, Sallet J, Schuffelgen U, Jbabdi S, Toni I, Rushworth MFS (2012) Connectivity-Based Subdivisions of the Human Right "Temporoparietal Junction Area": Evidence for Different Areas Participating in Different Cortical Networks. Cerebral Cortex 22:1894–1903.

Martin M (2007) A Literature Review on the Effectiveness of Financial Education. Working Paper.

Mason W, Suri S (2011) Conducting behavioral research on Amazon's Mechanical Turk. Behav Res 44:1–23.

Mazur JE (1987) An adjusting procedure for studying delayed reinforcement. In: Quantitative analysis of behavior: Vol 5. The effects of delay and intervening events on reinforcement value. (Commons ML, Nevin JE, Rachlin H, eds), pp 55–73. Hillsdale, New Jersey: Lawrence Erlbaum.

McClure SM, Ericson KM, Laibson DI, Loewenstein G, Cohen JD (2007) Time Discounting for Primary Rewards. Journal of Neuroscience 27:5796–5804.

McClure SM, Laibson DI, Loewenstein G, Cohen JD (2004) Separate Neural Systems Value Immediate and Delayed Monetary Rewards. Science 306:503–507.

Meier S, Sprenger CD (2012) Discounting Financial Literacy Time Preferences and Participation in Financial Education Programs. Journal of Economic Behavior & Organization:1–35.

Mischel W, Shoda Y, Peake PK (1988) The nature of adolescent competencies predicted by preschool delay of gratification. Journal of Personality and Social Psychology 54:687.

Mitchell JP, Schirmer J, Ames DL, Gilbert DT (2011) Medial prefrontal cortex predicts intertemporal choice. Journal of Cognitive Neuroscience 23:857–866.

Mitchell SH (1999) Measures of impulsivity in cigarette smokers and non-smokers. Psychopharmacology 146:455–464.

Montague PR, Lohrenz T (2007) To Detect and Correct: Norm Violations and Their Enforcement. Neuron 56:14–18.

Morey RD (2008) Confidence intervals from normalized data: A correction to Cousineau (2005). Tutorial in Quantitative Methods for Psychology 4:61–64.

Mumford JA, Turner BO, Ashby FG, Poldrack RA (2012) Deconvolving BOLD activation in event-related designs for multivoxel pattern classification analyses. NeuroImage 59:2636–2643.

Myerson J, Green L (1995) Discounting of delayed rewards: Models of individual choice. J Exp Anal Behav 64:263–276.

Myerson J, Green L, Warusawitharana M (2001) Area under the curve as a measure of discounting. J Exp Anal Behav 76:235–243.

Nichols AL, Maner JK (2008) The good-subject effect: investigating participant demand characteristics. The Journal of General Psychology 135:151–166.

Niv Y (2009) Reinforcement learning in the brain. Journal of Mathematical Psychology 53:139–154.

Noonan MP, Walton ME, Behrens T, Sallet J, Buckley MJ, Rushworth M (2010) Separate value comparison and learning mechanisms in macaque medial and lateral orbitofrontal cortex. Proceedings of the National Academy of Sciences 107:20547–20552.

Northoff G, Hayes DJ (2011) Is Our Self Nothing but Reward? BPS 69:1019–1025.

Odum AL (2011a) Delay Discounting: I"m a k, You"re a k. J Exp Anal Behav 96:427–439.

Odum AL (2011b) Delay discounting: Trait variable? Behavioural Processes 87:1–9.

Ohmura Y, Takahashi T, Kitamura N, Wehr P (2006) Three-Month Stability of Delay and Probability Discounting Measures. Experimental and Clinical Psychopharmacology 14:318–328.

Padoa-Schioppa C (2011) Neurobiology of Economic Choice: A Good-Based Model. Annual Review of Neuroscience 34:333–359.

Padoa-Schioppa C, Assad JA (2006) Neurons in the orbitofrontal cortex encode economic value. Nature 441:223–226.

Paolacci G, Chandler J, Ipeirotis P (2010) Running experiments on amazon mechanical turk. Judgment and Decision Making 5:411–419.

Parfit D (1971) Personal identity. The Philosophical Review 80:3–27.

Peters J, Büchel C (2009) Overlapping and Distinct Neural Systems Code for Subjective Value during Intertemporal and Risky Decision Making. Journal of Neuroscience 29:15727–15734.

Peters J, Büchel C (2010a) Episodic Future Thinking Reduces Reward Delay Discounting through an Enhancement of Prefrontal-Mediotemporal Interactions. Neuron 66:138–148.

Peters J, Büchel C (2010b) Neural representations of subjective reward value. Behavioural Brain Research 213:135–141.

Peters J, Büchel C (2011) The neural mechanisms of inter-temporal decision-making: understanding variability. Trends in Cognitive Sciences:227–239.

Petry NM (2001a) Substance abuse, pathological gambling, and impulsiveness. Drug and Alcohol

Dependence 63:29–38.

Petry NM (2001b) Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. Psychopharmacology 154:243–250.

Philiastides MG, Biele G, Heekeren HR (2010) A mechanistic account of value computation in the human brain. Proceedings of the National Academy of Sciences 107:9430–9435.

Pine A, Seymour B, Roiser JP, Bossaerts P, Friston KJ, Curran HV, Dolan RJ (2009) Encoding of Marginal Utility across Time in the Human Brain. Journal of Neuroscience 29:9575–9581.

Plassmann H, O'Doherty J, Rangel A (2007) Orbitofrontal Cortex Encodes Willingness to Pay in Everyday Economic Transactions. Journal of Neuroscience 27:9984–9988.

Platt ML, Glimcher PW (1999) Neural correlates of decision variables in parietal cortex. Nature 400:233–238.

Poldrack RA (2011) Inferring Mental States from Neuroimaging Data: From Reverse Inference to Large-Scale Decoding. Neuron 72:692–697.

Prelec D, Loewenstein G (1991) Decision making over time and under uncertainty: A common approach. Management Science 37:770–786.

Pronin E, Olivola CY, Kennedy KA (2007) Doing Unto Future Selves As You Would Do Unto Others: Psychological Distance and Decision Making. Personality and Social Psychology Bulletin 34:224–236.

Pronin E, Ross L (2006) Temporal differences in trait self-ascription: When the self is seen as an other. Journal of Personality and Social Psychology 90:197–209.

Rachlin H, Raineri A, Cross D (1991) Subjective probability and delay. J Exp Anal Behav 55:233–244.

Rangel A, Camerer C, Montague PR (2008) A framework for studying the neurobiology of value-based decision making. Nature Publishing Group 9:545–556.

Rangel A, Hare T (2010) Neural computations associated with goal-directed choice. Current Opinion in Neurobiology 20:262–270.

Ratcliff R, McKoon G (2008) The diffusion decision model: Theory and data for two-choice decision tasks. Neural Computation 20:873–922.

Read D (2001) Is time-discounting hyperbolic or subadditive? J Risk Uncertain 23:5–32.

Read D (2004) Intertemporal choice. Blackwell handbook of judgment and decision making:424–443.

Read D, Airoldi M, Loewe G (2005a) Intertemporal tradeoffs priced in interest rates and amounts: A study of method variance. Working paper LSEOR.

Read D, Frederick S, Orsel B, Rahman J (2005b) Four score and seven years from now: The date/delay effect in temporal discounting. Management Science 51:1326–1335.

Reynolds B (2006) A review of delay-discounting research with humans: relations to drug use and gambling. Behavioural pharmacology 17:651–667.

Richards JB, Mitchell SH, Wit H, Seiden LS (1997) Determination of discount functions in rats with an adjusting-amount procedure. J Exp Anal Behav 67:353–366.

Rick S, Loewenstein G (2008) Intangibility in intertemporal choice. Philosophical Transactions of the Royal Society B: Biological Sciences 363:3813–3824.

Rolls ET, Grabenhorst F, Deco G (2010) Choice, difficulty, and confidence in the brain. NeuroImage 53:694–706.

Rolls ET, McCabe C, Redoute J (2008) Expected Value, Reward Outcome, and Temporal Difference Error Representations in a Probabilistic Decision Task. Cerebral Cortex 18:652–663.

Rolls ET, O'Doherty J, Kringelbach ML, Francis S, Bowtell R, McGlone F (2003) Representations of pleasant and painful touch in the human orbitofrontal and cingulate cortices. Cerebral Cortex 13:308–317.

Ruderman H, Levine MD, McMahon JE (1987) The behavior of the market for energy efficiency in residential appliances including heating and cooling equipment. The Energy Journal 8:101–124.

Rushworth MF, Kolling N, Sallet J, Mars RB (2012) Valuation and decision-making in frontal cortex: one or many serial or parallel systems? Current Opinion in Neurobiology:1–10.

Rushworth MF, Mars RB, Summerfield C (2009) General mechanisms for making decisions? Current Opinion in Neurobiology 19:75–83.

Samejima K (2005) Representation of Action-Specific Reward Values in the Striatum. Science 310:1337–1340.

Sanfey AG, Rilling JK, Aronson JA, Nystrom LE, Cohen JD (2003) The neural basis of economic decision-making in the ultimatum game. Science 300:1755–1758.

Saxe R (2006) Uniquely human social cognition. Current Opinion in Neurobiology 16:235–239.

Saxe R, Kanwisher N (2003) People thinking about thinking people: The role of the temporo-parietal junction in "theory of mind." NeuroImage 19:1835–1842.

Schacter DL, Addis DR, Buckner RL (2007) Remembering the past to imagine the future: the prospective brain. Nature Reviews: Neuroscience 8:657–661.

Schacter DL, Addis DR, Buckner RL (2008) Episodic Simulation of Future Events: Concepts, Data, and Applications. Annals of the New York Academy of Sciences 1124:39–60.

Schacter DL, Addis DR, Hassabis D, Martin VC, Spreng RN, Szpunar KK (2012) The Future of Memory: Remembering, Imagining, and the Brain. Neuron 76:677–694.

Schelling TC (1984) Self-command in practice, in policy, and in a theory of rational choice. American Economic Review 74:1–11.

Scholten M, Read D (2006) Beyond discounting: the tradeoff model of intertemporal choice. Working paper LSEOR.

Schultz W (2004) Neural coding of basic reward terms of animal learning theory, game theory, microeconomics and behavioural ecology. Current Opinion in Neurobiology 14:139–147.

Schultz W (2010) Dopamine signals for reward value and risk: basic and recent data. Behav Brain Funct 6:24.

Senecal N, Wang T, Thompson E, Kable JW (2012) Normative arguments from experts and peers reduce delay discounting. Judgment and Decision Making 7:566–589.

Shamosh NA, Gray JR (2008) Delay discounting and intelligence: A meta-analysis. Intelligence 36:289–305.

Shapiro SL, Schwartz GE, Bonner G (1998) Effects of mindfulness-based stress reduction on medical and premedical students. Journal of behavioral medicine 21:581–599.

Sharot T, Riccardi AM, Raio CM, Phelps EA (2007) Neural mechanisms mediating optimism bias. Nature 450:102–105.

Skiba P, Tobacman J (2008) Payday loans, uncertainty and discounting: explaining patterns of borrowing, repayment, and default. Vanderbilt Law and Economics Research Paper.

Smith A, Bernheim BD, camerer C, Rangel A (2011) Neural Activity Reveals Preferences Without Choices. Working paper NBER:1–40.

Soman D, Ainslie G, Frederick S, Li X, Lynch J, Moreau P, Mitchell A, Read D, Sawyer A, Trope Y (2005) The psychology of intertemporal discounting: Why are distant events valued differently from proximal ones? Marketing Letters 16:347–360.

Spreng RN, Grady CL (2010) Patterns of brain activity supporting autobiographical memory, prospection, and theory of mind, and their relationship to the default mode network. Journal of Cognitive Neuroscience 22:1112–1123.

Sugrue LP (2004) Matching Behavior and the Representation of Value in the Parietal Cortex. Science 304:1782–1787.

Summerfield C, Tsetsos K (2012) Building bridges between perceptual and economic decision-making: neural and computational mechanisms. Front Neurosci 6:1–20.

Szpunar KK (2010) Episodic Future Thought: An Emerging Concept. Perspectives on Psychological Science 5:142–162.

Thaler R (1981) Some empirical evidence on dynamic inconsistency. Economics Letters 8:201–207.

Tom SM, Fox CR, Trepel C, Poldrack RA (2007) The Neural Basis of Loss Aversion in Decision-Making Under Risk. Science 315:515–518.

Trope Y, Liberman N (2003) Temporal construal. Psychological Review 110:403–421.

Tsukayama E, Duckworth AL (2010) Domain-specific temporal discounting and temptation.

Judgment and Decision Making 5:72–82.

Tusche A, Bode S, Haynes JD (2010) Neural Responses to Unattended Products Predict Later Consumer Choices. Journal of Neuroscience 30:8024–8031.

Usala PD, Hertzog C (1991) Evidence of differential stability of state and trait anxiety in adults. Journal of Personality and Social Psychology 60:471.

Vuchinich RE, Simpson CA (1998) Hyperbolic temporal discounting in social drinkers and problem drinkers. Experimental and Clinical Psychopharmacology 6:292.

Vul E, Harris C, Winkielman P, Pashler H (2009) Puzzlingly high correlations in fMRI studies of emotion, personality, and social cognition. Perspectives on Psychological Science 4:274–290.

Wakslak CJ, Nussbaum S, Liberman N, Trope Y (2008) Representations of the self in the near and distant future. Journal of Personality and Social Psychology 95:757–773.

Wallis JD (2011) Cross-species studies of orbitofrontal cortex and value-based decision-making. Nature Publishing Group 15:13–19.

Wallis JD, Kennerley SW (2010) Heterogeneous reward signals in prefrontal cortex. Current Opinion in Neurobiology:1–8.

Wallis JD, Miller EK (2003) Neuronal activity in primate dorsolateral and orbital prefrontal cortex during performance of a reward preference task. European Journal of Neuroscience 18:2069–2081.

Wang AL, Ruparel K, Loughead JW, Strasser AA, Blady SJ, Lynch KG, Romer D, Cappella JN, Lerman C, Langleben DD (2013) Content Matters: Neuroimaging Investigation of Brain and Behavioral Impact of Televised Anti-Tobacco Public Service Announcements. Journal of Neuroscience 33:7420–7427.

Wang X-J (2008) Decision Making in Recurrent Neuronal Circuits. Neuron 60:215–234.

Wang X-J (2012) Neural dynamics and circuit mechanisms of decision-making. Current Opinion in Neurobiology 22:1039–1046.

Wang XJ (2002) Probabilistic decision making by slow reverberation in cortical circuits. Neuron 36:955–968.

Willis LE (2008) Against Financial Literacy Education. 94 Iowa L. Rev.

Wittmann M, Paulus MP (2008) Decision making, impulsivity and time perception. Trends in Cognitive Sciences 12:7–12.

Wittmann M, Simmons AN, Flagan T, Lane SD, Wackermann J, Paulus MP (2011) Neural substrates of time perception and impulsivity. Brain Research 1406:43–58.

Wunderlich K, Rangel A, O'Doherty JP (2009) Neural computations underlying action-based decision making in the human brain. Proceedings of the National Academy of Sciences 106:17199–17204.

Wunderlich K, Rangel A, O'Doherty JP (2010) Economic choices can be made using only stimulus values. Proceedings of the National Academy of Sciences 107:15005–15010.

Zauberman G, Kim BK, Malkoc SA, Bettman JR (2009) Discounting Time and Time Discounting: Subjective Time Perception and Intertemporal Preferences. Journal of Marketing Research 46(4):543–556.

Zauberman G, Lynch JGJ (2005) Resource Slack and Propensity to Discount Delayed Investments of Time Versus Money. Journal of Experimental Psychology: General 134:23–37.

Zhong LX, Xiao JJ (1995) Determinants of family bond and stock holdings. Financial Counseling and Planning 6:107–114.