INFLUENCES ON DELAY AND PROBABILITY DISCOUNTING IN HUMANS

By

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To Sara. This document exists only because of your love, care, and tolerance for my seafaring. I hope I can someday give you the opportunities you have given me.

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Discounting refers to the devaluation of an event or outcome based on some characteristic of that event or outcome. For example, delay discounting refers to a reduction in value of receiving an outcome (e.g., $1000) as the delay to receiving the outcome increases, and probability discounting refers to a reduction in value of an outcome as the probability the outcome will occur decreases. Previous research has found that the rate an individual devalues an outcome based on delay or probability is associated with the presence of clinical symptomatology considered impulsive or risky (e.g., drug abuse). However, many impulsive or risky clinical behaviors result in more than one outcome that each occurs with some delay and some probability. For example, smoking a cigarette results in (1) immediate and certain physiological effects of nicotine, and (2) delayed and uncertain negative impacts to health. Researchers have yet to parametrically examine discounting in these situations, likely because current methods are impractical for studying these complex choices. In Experiment 1, we extended an efficient measure of monetary delay discounting to measure monetary probability discounting. In Experiment 2, we extended the methods from Experiment 1 to measure discounting of money that is delayed and probabilistic. Importantly, the methods in

Experiments 1 and 2 produced similar measures of choice as longer, traditional methods. In Experiment 3, we measured discounting where each response resulted in two delayed and probabilistic amounts of money. In addition, we quantitatively described how the delay, probability, and amount of each outcome interact to influence choice. Results indicated the probability of the second outcome has greater influence on rates of discounting compared to the delay to the second outcome. When the first outcome was a gain and the second a loss, increasing the probability of the loss decreased rates of discounting the first outcome (i.e., increased preference for the larger-later alternative). When the first outcome was a gain and the second a gain, increasing the probability of the second gain increased rates of discounting the first outcome (i.e., increased preference for the smaller-sooner alternative). These results highlight how human choice is influenced by the interaction of relative value and valence of multiple outcomes that follow a single response. Finally, a multiplicative model best described discounting of two, delayed-and-probabilistic outcomes. This suggests the value of two outcomes interact to influence rates of discounting. In addition, the same model described discounting well regardless of whether the two outcomes were gains, or one outcome was a gain and one outcome was a loss. The structure of the multiplicative model provides a novel conceptualization of gain-loss interactions.

CHAPTER 1
INTRODUCTION

Discounting

Choice is omnipresent. Every day, organisms continuously choose how and when to meet their basic needs, how and when to interact with other organisms, and how and when to move about the world. Often, these choices result in a change to the environment surrounding the organism. That is, a specific environmental outcome reliably follows many choices. For over 100 years, researchers have sought to understand precisely how the characteristics of these outcomes influence the future likelihood the same choice is made (e.g., Thorndike, 1898). This dissertation focuses on three characteristics of an outcome known to influence choice: delay, probability, and amount.

The influence of delay, probability, and amount on choice has been studied empirically for decades (e.g., Mazur, 1987; Rachlin, Raineri, & Cross, 1991). Historically, researchers have been interested in isolating the effects of one or two of these dimensions on choice. For example, researchers have studied how people make choices when the delay to a large amount of money is greater than the delay to a smaller amount of money (e.g., Mazur, 1987). Relatedly, researchers have examined how preference for the smaller-sooner outcome changes as the amount of the larger-later outcome is changed (e.g., Green, Myerson, & McFadden, 1997). The general observations have been that the value of an outcome decreases systematically as delay increases (i.e., delay discounting; see Odum, 2011 for review) or probability decreases (i.e., probability discounting; see McKerchar & Renda, 2012 for review). In addition, increasing the amount gained from each choice will decrease delay discounting and increase probability discounting (e.g., Green, Myerson, Oliveira, & Chang, 2013; Myerson, Green, & Morris, 2011). But, if the outcomes are losses, then changing the amount has little-to-no effect on delay or probability discounting (e.g., Green, Myerson, Oliveira, & Chang, 2014).

Several quantitative models have been developed to precisely describe how each of these variables impact the value of outcomes and the choices organisms make. Early delay discounting research compared how well an exponential model of discounting from standard economic theory (Samuelson, 1937) described and predicted choice relative to a hyperbolic model (Mazur, 1987). Both models describe choice behavior in discounting tasks well. However, preference reversals are a common observation when people choose between two options with varying delays. Preference reversals occur when an organism with demonstrated preference for a smaller-immediate reinforcer switches, or reverses, their preference to a larger-delayed reinforcer as the delay to both reinforcers increases (e.g., Ainslie & Herrnstein, 1981; Green, Fisher, Perlow, & Sherman, 1981). The hyperbolic model predicts preference reversals whereas the exponential model does not (e.g., McKerchar, Green, Myerson, Pickford, Hill, & Stout, 2009). Thus, the hyperbolic model is the favored quantitative description of delay discounting by most researchers.

The hyperbolic model of delay discounting can be written as:

$$V = \frac{A}{(1 + k\mathrm{D})}. \qquad \text{(Equation 1)}$$

Here, *V* refers to the current value of the outcome, *A* refers to the undiscounted amount of the outcome (e.g., $100), *D* refers to the delay until the organism contacts the outcome, and k is a free parameter that describes the rate the value of the undiscounted amount decreases as a function of the delay to its receipt.

Quantitative models describing the influence of probability on choice have also been studied. Shortly after the hyperbolic equation was proposed for delay discounting, Rachlin and colleagues (1991) extended the hyperbolic function to describe how probability influences choice. The hyperbolic model of probability discounting can be written as:

$$V = \frac{A}{(1 + h\theta)}. \qquad \text{(Equation 2)}$$

In this equation, V and A refer to the certain value and undiscounted amount of the outcome; θ refers to the odds against the outcome occurring and is calculated as $(1-p)/p$, where p is the probability the outcome will occur; and h is a free parameter that describes the rate the value of the outcome reduces as a function of the odds against its occurrence. Similar to delayed outcomes, the hyperbolic form of a probability discounting equation has been found to describe choice well and account for preference reversals with probabilistic outcomes (McKerchar & Renda, 2012). For probability discounting, preference reversals refer to the common observation that organisms preferring a smaller-less-uncertain reinforcer will switch to prefer the larger-more-uncertain reinforcer as the probability to both reinforcers decreases (e.g., Allais Paradox; Allais 1953).

Central to using discounting equations is understanding what the estimated free parameters indicate (i.e., k and h). As the rate of discounting increases, k and h get larger. As the rate of discounting decreases, k and h get smaller. A steep rate of delay discounting (large k) indicates the organism is less likely to wait for the larger-later outcome (i.e., more impulsive). A shallow rate of delay discounting (small *k*) indicates the organism is more likely to wait for the larger-later outcome (i.e., less impulsive). A steep rate of probability discounting (large *h*) indicates the organism is less likely to choose the larger-uncertain outcome (i.e., more risk averse), and a shallow rate of probability discounting (small *h*) indicates the organism is more likely to choose the larger-uncertain outcome (i.e., more risk seeking). Importantly, measures of *k* and *h* differ for each individual (Odum, 2011; McKerchar & Renda, 2012).

Influences on Discounting

With the general discounting framework taking shape, researchers began to study how different variables impact rates of delay and probability discounting within an individual. In addition to outcome amount and valence (gain or loss) mentioned above, people also show different rates of discounting depending on the commodity under consideration. Consumable delayed commodities, like food and alcohol, tend to be discounted more steeply than non-consumable commodities like money (e.g., Odum & Rainaud, 2003; Robertson & Rasmussen, 2018). Steeper delay discounting also occurs when the outcome is contacted directly compared to when the decision is made for someone else (e.g., Rachlin & Jones, 2008; Ziegler & Tunney, 2012). Finally, the language used to describe the outcomes will also influence rates of discounting within individuals (framing effects; e.g., DeHart & Odum, 2015; Hohle, & Teigen, 2018).

Researchers have also studied how variables that differ between individuals correlate with rates of discounting. Of particular interest are findings that healthy and unhealthy behaviors correlate with rates of discounting. For example, smokers tend to have higher delay discounting rates than non-smokers (e.g., Bickel, Odum, & Madden, 1999). But, previous smokers that are now abstinent do not differ from non-smokers in rates of delay discounting (e.g., Bickel et al., 1999). Compared to control groups, higher rates of delay discounting have also been observed for individuals who engage in risky sexual behavior (Jones & Sullivan, 2016), abuse other pharmacological agents (e.g., alcohol – Lim, Cservanka, & Ray, 2017; cocaine – Mitchell, Weiss, Ouimet, Fuchs, Morgan, & Setlow, 2014; heroine – Kirby, Petry, & Bickel, 1999), are obese (e.g., Schiff et al., 2016), are sedentary (e.g., Sweeney & Culcea, 2017), or display other behavioral addictions (e.g., pathological gambling – Dixon, Marley, & Jacobs, 2003; internet gaming addiction – Wang, Wu, Wang, Zhang, Du, & Dong, 2016).

The above between-subject correlations suggest that individuals with clinical levels of unhealthy behavior tend to place greater value on smaller-sooner reinforcers compared to non-clinical controls. Importantly, this differential valuation framework highlights methods to improve rates of healthy behavior in individuals that currently engage in unhealthy behavior. For example, applying this approach to current smokers would suggest the value of delayed improvement to health by stopping smoking is too low to compete with the immediate reinforcement contacted from smoking (or similarly, the aversive consequences associated from delayed negative impact to health fail to compete with relatively immediate withdrawal symptoms). If clinicians add value to the healthy behavior that contacts larger-later reinforcers (e.g., offering immediate incentives for being abstinent), then this will increase the value and likelihood of engaging in the healthy behavior. In addition, the delay discounting framework suggests the amount of value that needs to be added to the healthy alternative will differ based on individual rates of discounting.

Some interventions have been developed that directly attempt to increase the value of the healthy behavioral alternative. For example, contingency management is an intervention where incentives are offered for verified abstinence from using pharmacological agents (e.g., Bigelow, Stitzer, & Liebson, 1984) or increasing amounts of physical activity (e.g., Petry, Andrade, Barry, & Byrne, 2013). Many of these researchers have sought to capitalize on the delay discounting framework by increasing the immediacy that incentives are provided following healthy behavior and the probability the individual will get caught engaging in unhealthy behavior (e.g., Dallery, Glenn, & Raiff, 2007). This approach has been relatively successful compared to previous interventions for unhealthy behavioral patterns (e.g., Davis, Kurti, Skelly, Redner, White, & Higgins, 2016; Kurti & Dallery, 2013). Nevertheless, everyday choices of whether to engage in healthy or unhealthy behaviors are likely to be influenced by many different variables that dynamically change over time. That is, choice in everyday situations is likely to involve complex interactions of multiple influential variables – which have yet to be researched explicitly.

Discounting and Daily Choices

We can begin exploring complexity in everyday choice by considering a simplified situation wherein a regular smoker chooses whether or not to smoke. The two options under consideration are: (1) smoke, OR (2) engage in some other behavior (i.e., abstain). Each one of these response options will result in multiple outcomes that are delayed and probabilistic. Smoking will result in: (a) immediate and certain physiological effects of nicotine, and (b) delayed and uncertain negative health outcomes. Abstaining will result in: (a) immediate and certain withdrawal symptoms, and (b) delayed and uncertain positive health outcomes. To further understand, predict, and control choice in these situations, researchers would benefit from understanding how multiple delayed and probabilistic outcomes interact to influence choice.

Delayed and Probabilistic Outcomes

To begin working toward the complexity of everyday choices, researchers have explored human choice when outcomes are delayed and probabilistic. In addition, many of these researchers have sought to quantitatively describe choice in these settings because such quantitative descriptions precisely state how delay and probability interact to influence choice. Generally, there have been two broad approaches to understand choice when outcomes are both delayed and probabilistic.

The first approach to studying delayed and probabilistic outcomes has sought to determine if delay is reducible to probability, or if probability is reducible to delay. Stated differently, this approach has sought to determine if delay and probability represent different aspects of a single behavioral trait (e.g., impulsivity/self-control; Green & Myerson, 1996; Rachlin, Logue, Gibbon, & Frankel, 1986; Myerson & Green, 1995). Experiments examining the reducibility hypothesis have demonstrated statistically that delayed outcomes may influence choice through uncertainty (e.g., Benzion et al., 1989), and that probability can be reduced to a delay equivalent (Rachlin et al., 1986, 1991; Rachlin & Raineri, 1992; Yi, de la Piedad, & Bickel, 2006).

The second approach maintains that delay and probability are unique psychophysical influences on choice (Green & Myerson, 2004). This approach stems from experimental results that are incompatible with a reducibility assumption. These include: (1) the absence of a correlation between delay and probability discounting (e.g., Ohmura, Takahashi, Kitamura, & Wehr, 2006; Olson, Hooper, Collins, & Luciana, 2007; Reynolds, Richards, Horn, & Karraker, 2004); (2) the different impact of outcome amount on rates of discounting (e.g., Ostaszewski, Green, & Myerson, 1998); and (3) differences in discounting gains vs. losses for delayed and probabilistic outcomes (e.g., Myerson, Baumann, & Green, 2017; c.f., Mitchell and Wilson, 2010). Subsequently, an underlying assumption of the quantitative analyses throughout this dissertation is that delay and probability are nonreducible influences on choice in discounting contexts.

The nonreducible approach has primarily sought to characterize how the value of an outcome differs when it is delayed and probabilistic, compared to only delayed, or only probabilistic. The goals are often to determine precisely how delay and probability interact and whether one is more salient in affecting choice. Thus far, results have been mixed with some researchers observing that delay seems to be more salient than probability (e.g., Blackburn & El-Deredy, 2013) and others finding that probability seems to be more salient than delay (e.g., Vanderveldt, Green & Myerson, 2015; Weatherly, Petros, Jónsdóttir, Derenne, & Miller, 2015). Through this research, several structures of quantitative models have been derived to describe how delay and probability interact to impact choice.

The first structure for a quantitative model describing the influence of delay and probability on choice could be called an independent model. That is, delay is assumed to influence the value of an outcome independently from the probability of the outcome, and vice versa. Examples of independent models are the subtractive models proposed by Ho and colleagues (1999) and Killeen (2009). Each of these models assumes the value of an outcome is a combination of the reduced outcome value from the delay to its occurrence minus the reduced outcome value from the probability it will occur. The primary difference between the model proposed by Ho and colleagues (1999) and Killeen (2009) are the location of sensitivity parameters. Ho et al.'s subtractive model includes two amount sensitivity parameters – one for delay and one for probability – whereas Killeen's subtractive model includes two exponential psychophysical scaling parameters for the denominators in equations 1 and 2 – one for delay and one for probability.

The second structure for a quantitative model describing the influence of delay and probability on choice could be called an interactive model. Here, the influence of delay on outcome value depends on the probability of the outcome, and vice versa. This interaction typically takes the form of multiplying the influence of delay by the influence of probability, and then reducing the nominal amount of the outcome by that combined value. This interaction could come in a variety of forms. For example, one could simply multiply Equation 1 by Equation 2 (e.g., Ho et al., 1999). Alternatively, one could reduce the amount of the outcome by a single denominator that includes the denominators of equations 1 and 2 multiplied by each other (e.g., Vanderveldt et al., 2015).

Only one known study has directly compared independent and interactive models (Vanderveldt et al., 2015). At both the group and individual level, the interactive, multiplicative model described the obtained indifference points better than the independent, subtractive model. Despite this explicit comparison of interactive and independent models, it should be noted that other researchers have not observed a statistical interaction between delay and probability leading them to conclude that delay and probability combine independently (e.g., Keren & Roelofsma, 1995 – Experiment 2).

Summary. A handful of studies have begun to analyze how human choice is affected when the outcomes under consideration are both delayed and probabilistic. Within these experiments, some researchers have sought to reduce delay and probability to a single ‘impulsivity’ trait. Because of several contradictory empirical findings, other researchers have assumed delay and probability are nonreducible. Many of these experiments have also quantitatively described choice in these contexts to determine whether delay and probability interact or independently influence choice; and, whether delay or probability is more salient within the choice context. Results have been mixed across the few studies seeking answers to these questions.

Multiple Delayed and Probabilistic Outcomes

In addition to the several influences on human discounting covered thus far, two studies have sought to examine how multiple outcomes that result from a single response will influence choice. These experiments have examined how choice is influenced when two outcomes, with different delays, result from a single response; or, how choice is influenced when two outcomes, with different delays and probabilities, result from a single response.

Loewenstein and Prelec (1993) studied choice when two delayed outcomes resulted from a single response. In their study, participants initially chose between a dinner at a fancy French restaurant or dinner at a local Greek restaurant. Participants who chose the fancy French restaurant (86% of the sample) were then asked to choose between:

(a) Dinner at the French restaurant on Friday in 1 month.

(b) Dinner at the French restaurant on Friday in 2 months.

The majority (80%) chose the sooner dinner – option (a). Next, the same participants were presented with a choice between:

(a) (Dinner at French restaurant on Friday in 1 month) + (Dinner at Greek restaurant on Friday in 2 months).

(b) (Dinner at French restaurant on Friday in 2 months) + (Dinner at Greek restaurant on Friday in 1 month).

By adding dinner at the Greek restaurant to the choice context, more participants chose the later French dinner – option (b). These data suggest the addition of a second delayed outcome to the choice context will influence preference compared to when delayed outcomes are considered in isolation. Most participants chose increasingly preferred outcomes over time rather than a shorter delay to the most preferred outcome. This finding was replicated in a second experiment where Loewenstein and Prelec asked participants about three and five different delayed events – each with a different outcome (e.g., fancy lobster dinner, eat at home), with the outcomes occurring in different sequences, but with identical delays to the occurrence of each outcome in the sequence (e.g., 1^{st} outcome now, 2^{nd} outcome in 1 week, 3^{rd} outcome in 2 weeks).

Keren & Roelofsma (1995) replicated and extended the findings from Loewenstein and Prelec (1993) involving two delayed outcomes. In addition to two delayed outcomes, they were interested in how choice might be impacted when both outcomes were delayed and probabilistic. In their Experiment 4, participants made choices involving the same two delayed outcomes involving different dinners at restaurants. But, they also indicated each dinner would occur with a probability of 60%. Similar to Loewenstein and Prelec (1993), they found preference reversed at the group level when both outcomes resulting from a single choice were only delayed. But, when all outcomes occurred with a probability of 0.60, preference did not reverse, and most participants chose the sooner, more preferred French dinner regardless of whether the Greek dinner was included.

The above series of experiments demonstrate that the presence of multiple outcomes resulting from a single response influence human choice. Specifically, preference for delayed outcomes differed depending on whether a single response resulted in one or two outcomes – but, only if the outcomes were certain. Preference for delayed outcomes was similar with one or two outcomes if all options occurred with a probability of 0.60.

Remaining Questions. Several limitations in the above research leave gaps in our understanding of how multiple delayed and probabilistic outcomes interact to influence choice. The above experiments by Loewenstein and Prelec (1993) and Keren and Roelofsma (1995) showed *that* the addition of multiple delayed and probabilistic outcomes will influence choice. However, these experiments used outcomes of unknown value (i.e., dinners), only one delay combination to the outcomes (1 and 2 months), and only two probability values for the outcomes (1.0 and 0.6). Researchers will have to examine combinations from a range of delays and a range of probabilities to understand precisely how delay and probability discounting are affected by the presence of a second delayed and probabilistic outcome.

The purpose of the three experiments discussed here is threefold. Experiment 1 sought to extend methods for efficiently measuring rates of delay discounting to methods that measure rates of probability discounting. Experiment 2 sought to combine these methods and examine choice where a single outcome resulting from a response was both delayed and probabilistic. We then compared the data from Experiment 2 to recent research using more traditional methods to measure discounting of outcomes that are delayed and probabilistic. Experiment 3 extended the methods from Experiment 2 by adding a second delayed and probabilistic outcome to each choice option. Thus, Experiment 3 sought to measure how rates of discounting a delayed and probabilistic outcome changes as a function of a range of different delays and a range of different probabilities to a second outcome. Lastly, we sought describe these changes quantitatively.

CHAPTER 2
EXPERIMENT 1

Introduction[1]

Many choices often involve outcomes that differ in delay, probability, and magnitude. For example, engaging in physical activity may result in immediate discomfort and delayed, but uncertain, positive health outcomes. Abstaining from physical activity may result in immediate more enjoyable experiences and delayed, but uncertain, negative health outcomes. Similar differences in the delay, probability, and magnitude of beneficial and adverse outcomes may occur for many health-related behaviors such as diet, sexual behavior, and substance use.

Typically, only one or two of the above dimensions are manipulated within an experiment (e.g., Bruce et al., 2015; McKerchar et al., 2009; McKerchar & Renda, 2012; Ritschel et al., 2015). For instance, many researchers have examined how the value of an outcome is affected by the delay its receipt (see Odum, 2011 for review). Similarly, others have examined how the value of an outcome is affected by the probability it occurs (see McKerchar & Renda, 2012 for review). As noted above, the robust observation is that the value of an outcome reduces as a function of increasing delay and decreasing probability; and, the rate that outcome value changes is described well by a hyperbolic equation (Equations 1 & 2).

Several patterns of discounting have been commonly observed when examining how delay, probability, and amount influence the value of an outcome. When humans consider outcomes that are gains, increasing the amount of the outcome will change

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[1] Experiment 1 was published in a 2016 issue of *Behavioural Processes*, Volume 131, pages 15-23. doi:10.1016/j.beproc.2016.08.002

rates of discounting (i.e., the magnitude effect). Delay discounting tends to decrease as the amount is increased (e.g., Green, Myerson, & McFadden, 1997), and probability discounting tends to increase as the amount is increased (e.g., Green, Myerson, & Ostaszewski, 1999; Yi & Bickel, 2005). In contrast, when humans consider outcomes that are losses, increasing the amount of the outcome tends to have little impact on delay or probability discounting (e.g., Estle, Green, Myerson, & Holt, 2006; Green, Myerson, Oliveira, & Change, 2014). Despite the absence of a theoretical account for these observations, the direction of magnitude effect for gains and the absence of a magnitude effect for losses provide standards for evaluating new methods to measure discounting.

One challenge to evaluating choice when each response option becomes more complex is the length of procedures. For example, Du and colleagues (2002) used a common adjusting amount procedure to measure delay discounting using seven different delays to an outcome occurring. At each delay, the participant made 6 choices which equated to 42 total response trials. Using a similar adjusting amount procedure, Vanderveldt and colleagues (2015) measured discounting of delayed and probabilistic outcomes across a range of 5 delays and 5 probabilities. Here, the total number of responses for each participant increased to 125 as 5 choices were presented at each of the 25 delay-probability combinations. If one wants to examine the effects of two outcomes that follow a single response, and with each outcome being delayed and probabilistic, then the total number of responses required by each participant would be 3,125 (125 trials for the delayed and probabilistic first outcome x 5 delays of the second outcome x 5 probabilities of the second outcome). The duration required to administer such large numbers of trials may place practical limitations on researchers as well as lead to participant fatigue and decreased response quality. As a result, more efficient methods are needed to measure how multiple delayed and probabilistic outcomes influence discounting.

One more efficient procedure to measure delay discounting was used by Koffarnus and Bickel (2014). This procedure determines the delay at which the value of an outcome reduces by half (i.e., effective delay of 50%; ED_{50}). To determine ED_{50}, an immediate option is fixed at half the amount of a delayed alternative (e.g., \$50 now vs. \$100 in 3 weeks). The delay to the larger alternative is then adjusted for five trials based on the participant's response on each trial. Importantly, the delay following the final adjustment (i.e., ED_{50}) provides the delay discounting parameter from the hyperbolic equation for that participant (i.e., *k* – Equation 1; Yoon & Higgins, 2008). Koffarnus and Bickel (2014) demonstrated that the *k* parameter obtained by this adjusting delay procedure is similar to the *k* parameter obtained when Equation 1 is fit to multiple indifference points from an adjusting amount procedure. Lastly, participants in their study completed several versions of the 5-trial adjusting delay procedure. Each version replicated a different effect from the discounting literature – including the magnitude effect. Thus, the 5-trial adjusting delay procedure seems to be a valid method for measuring delay discounting of gains.

The goal of Experiment 1 was to extend the 5-trial adjusting delay gain procedures to outcomes that are delayed losses, probabilistic gains, and probabilistic losses. We also compared rates of discounting from each of these 5-trial tasks to rates of discounting obtained from traditional adjusting amount procedures.

Methods

Participants. We recruited 212 participants from the Psychology participant pool at the University of Florida. Participant age averaged 19.09 (range 18-22) and 68% self-identified as female. Each participant was randomly assigned to complete tasks involving delayed losses, probabilistic gains, or probabilistic losses. All outcomes were hypothetical money of varying amounts.

Procedure. Delayed Loss. Participants assigned to the delayed loss condition completed three different discounting tasks. One task was the more traditional adjusting amount task with a larger-later outcome value of $1000. The second task was a 5-trial adjusting delay task with a larger-later outcome value of $1000. Finally, participants completed a 5-trial adjusting delay task with a larger-later outcome value of $10. This combination of tasks allowed us to determine whether similar rates of delay discounting of losses would be observed between adjusting amount and adjusting delay tasks; and, if the absence of a magnitude effect would be observed between the adjusting delay tasks of different amounts. Participants made a choice on each trial by responding to the question, "Would you prefer losing $(amount) immediately or $1000/$10 in (delay)?"

Participants completed the traditional adjusting amount task for seven different delays. We assessed delays of 1 week, 1 month, 4 months, 8 months, 1 year, 5 years, and 10 years. When assessing preference at a delay (e.g., 1 month), the first trial always began by presenting participants with a choice between losing "$500 immediately" or "$1000 in 1 month." Following each choice, the amount of the immediate option increased if the immediate option was chosen or decreased if the delayed option was chosen. The amount of the delayed alternative remained at $1000 for all trials. The amount that the immediate option adjusted after each trial was $250, $125, $62.50, $31.25, and $15.63 following the first through fifth trials, respectively. All amounts were rounded to the nearest whole dollar for ease of presentation. The amount of the immediate alternative following the final adjustment was considered the indifference point for that participant at that particular delay.

We used an identical version of the 5-trial adjusting delay task as Koffarnus and Bickel (2014). Table 2-1 shows the 31 potential delays (i.e., indices 1-31) and the corresponding trial number that each delay might be presented to a participant. For all choice trials in the 5-trial adjusting delay tasks, the amount of the immediate option remained fixed at half the value of the delayed option. Participants completed two 5-trial adjusting delay tasks. One with response options of $500 vs. $1000 and one with response options of $5 vs. $10.

The 5-trial adjusting delay tasks ran as follows. The participant started by making a choice between the smaller-immediate option and the larger-later option delayed by 3 weeks (Table 2-1, index 16, trial 1). Following each choice, the delay to the larger-later option increased if the immediate option was chosen or decreased if the delayed option was chosen. The delay that the larger-later option adjusted after each trial was 8, 4, 2, and 1 index following the first through fourth trials, respectively. For example, if the participant chose the immediate option on the first trial, then the delay to the larger-later loss would increase from 3-weeks (index 16, trial 1) to 2-years (index 24, trial number 2). If the participant chose the delayed option on the first trial, then the delay to the larger-later loss would decrease from 3-weeks (index 16, trial 1) to 1-day (index 8, trial

Index	Delay Choice	Trial No.	ED_{50} (days) if last choice is:		*k* if last choice is:	
			Immediate	Delayed	Immediate	Delayed
1	1 hour	5	0.05893	0.0417	17.0	24.0
2	2 hours	4				
3	3 hours	5	0.1444	0.1021	6.93	9.79
4	4 hours	3				
5	6 hours	5	0.3062	0.2041	3.27	4.90
6	9 hours	4				
7	12 hours	5	0.7071	0.4330	1.41	2.31
8	1 day	2				
9	1.5 days	5	1.732	1.225	0.577	0.816
10	2 days	4				
11	3 days	5	3.464	2.450	0.289	0.408
12	4 days	3				
13	1 week	5	8.573	5.292	0.117	0.189
14	1.5 weeks	4				
15	2 weeks	5	17.15	12.12	0.0583	0.0825
16	3 weeks	1				
17	1 month	5	43.05	25.28	0.0232	0.0396
18	2 months	4				
19	3 months	5	105.4	74.56	0.0095	0.0134
20	4 months	3				
21	6 months	5	210.9	149.1	0.0047	0.0067
22	8 months	4				
23	1 year	5	516.5	298.2	0.0019	0.0034
24	2 years	2				
25	3 years	5	1265	894.7	0.0008	0.0011
26	4 years	4				
27	5 years	5	2310	1633	0.0004	0.0006
28	8 years	3				
29	12 years	5	5368	3579	0.0002	0.0003
30	18 years	4				
31	25 years	5	9131	7748	0.0001	0.0001

Table 2-1. The referencing index number, delay presented with the specific choice, the trial number a given delay could be presented at, and the resulting delays with corresponding *k* parameter. *Note.* ED_{50} = Effective Delay 50%.

Would you prefer…

Trial Number	Index Number	Losing… or	Losing…
1	16	$500 Immediately	$1000 in 3 Weeks
2	24	$500 Immediately	$1000 in 2 Years
3	20	$500 Immediately	$1000 in 4 months
4	22	$500 Immediately	$1000 in 8 months
5	21	$500 Immediately	$1000 in 6 months
	Final *k* Parameter	0.004741	

Index Number	Losing… or	Losing…
16	100% Chance of $500	50% Chance of $1000
8	100% Chance of $500	76% Chance of $1000
12	100% Chance of $500	63% Chance of $1000
14	100% Chance of $500	57% Chance of $1000
13	100% Chance of $500	60% Chance of $1000
Final *h* Parameter	1.410096	

Figure G-1. Example adjustments of choice alternatives in the 5-trail adjusting delay loss (left) and 5-trial adjusting probability loss (right) tasks. The trial number represents the order of choice presentation. The index number corresponds to the index listing in Table 2-1 (delay discounting) or in Table 2-2 (probability discounting). Circled alternatives represent the choice made by a hypothetical participant leading to the presented choice index in the following trial. The final parameter represents the rate at which the value of $1000 reduces as a function of increasing delay (k) or increasing odds against (h).

number 2). Figure G-1 shows an example for how the delay adjustments would occur for a hypothetical participant based on their particular sequence of choices. The left side of Figure G-1 displays an example for the 5-trial adjusting delay task.

The option chosen on the fifth trial was used to determine rate of discounting (k). If the immediate option was chosen on the fifth trial, k was calculated by dividing 1 by the geometric mean of the delay at the fifth trial and the delay at the index immediately below it (Table 2-1). For example, consider a participant who chose the immediate option on the final trial at index 21 (Fig. G-1). The final delay would be 6 months (183 days). The index immediately below it is 8 months (243 days). The geometric mean of 183 and 243 is 210.87. Dividing 1 by 210.87 equals 0.0047 – which is the value listed in the column labeled "k if last choice is: immediate" of Table 2-1. This method allows each participant to reach 1 of 32 potential indifference delays that are approximately logarithmically spread between 1 hour and 25 years.

Probabilistic Loss. Participants randomly assigned to the probabilistic loss condition also completed three discounting tasks. The tasks included an adjusting amount task with a larger-uncertain amount of $1000, a 5-trial adjusting probability task with a larger amount of $1000, and a 5-trial adjusting probability task with a larger amount of $10. Participants made a choice on each trial by responding to the question, "Would you prefer a 100% chance of losing $(amount) or a (percent) chance of losing $1000/$10?"

The traditional adjusting amount task was completed for seven different probabilities. We assessed probabilities of 95%, 80%, 50%, 25%, 10%, and 1%. When assessing preference at a probability (e.g., 25%), the first trial always began by presenting participants with a choice between "100% chance of losing $500" or "25% chance of losing $1000." Following each choice, the amount of the certain option increased if the certain option was chosen or decreased if the uncertain option was chosen. The amount of the uncertain alternative remained at $1000 for all trials. The amount the certain option adjusted after each trial was $250, $125, $62.50, $31.25, and $15.63 following the first through fifth trials, respectively. All amounts were rounded to the nearest whole dollar to ease choice presentation. The amount of the certain alternative following the final adjustment was considered the indifference point for that participant at that particular probability.

We modified the 5-trial adjusting delay task from Koffarnus & Bickel (2014) for participants assigned to the probability loss condition. Table 2-2 shows the 31 potential probabilities a participant could experience (i.e., indices 1-32) as well as the trial number they could contact that probability. We adjusted the probability to the uncertain

Index	Uncertain Choice	Odds Against	Trial No.	EP_{50} (%) for Loss Group if last choice is: Certain	Uncertain	*h* if last choice is: Certain	Uncertain
1	99%	0.0101	5	0.0205	0.0101	48.7442	99.4987
2	96%	0.0417	4				
3	92%	0.0870	5	0.1037	0.0602	9.6460	16.6132
4	89%	0.1236	3				
5	86%	0.1628	5	0.1826	0.1418	5.4765	7.0499
6	83%	0.2048	4				
7	79%	0.2658	5	0.2897	0.2333	3.4515	4.2857
8	76%	0.3158	2				
9	73%	0.3699	5	0.3981	0.3418	2.5117	2.9260
10	70%	0.4286	4				
11	66%	0.5152	5	0.5500	0.4699	1.8180	2.1282
12	63%	0.5873	3				
13	60%	0.6667	5	0.7092	0.6257	1.4101	1.5981
14	57%	0.7544	4				
15	53%	0.8868	5	0.9417	0.8179	1.0619	1.2226
16	50%	1.0000	1				
17	47%	1.1277	5	1.2226	1.0619	0.8179	0.9417
18	43%	1.3256	4				
19	40%	1.5000	5	1.5981	1.4101	0.6257	0.7092
20	37%	1.7027	3				
21	34%	1.9412	5	2.1282	1.8180	0.4699	0.5500
22	30%	2.3333	4				
23	27%	2.7037	5	2.9260	2.5117	0.3418	0.3981
24	24%	3.1667	2				
25	21%	3.7619	5	4.2857	3.4515	0.2333	0.2897
26	17%	4.8824	4				
27	14%	6.1429	5	7.0499	5.4765	0.1418	0.1826
28	11%	8.0909	3				
29	8%	11.500	5	16.6132	9.6460	0.0602	0.1037
30	4%	24.000	4				
31	1%	99.000	5	99.0000	48.7442	0.0101	0.0205

Table 2-2. The referencing index number, probability presented with the specific choice, corresponding odds against, the trial number a given probability could be presented at, and the resulting certainties with corresponding *h* parameter. The certain and uncertain columns reverse when the outcomes are gains. *Note:* EP_{50} = Effective Probability 50%.

outcome in a similar manner to the 5-trial adjusting delay task. That is, if the larger-uncertain loss was chosen, the probability of that loss was increased on the next trial. If the smaller-certain loss was chosen, the probability of the larger-uncertain loss decreased on the next trial. We adjusted the probability to the larger-uncertain loss by 25%, 12.5%, 6.25%, 3.13%, and 1.56% following the first through fifth trials, respectively. All probabilities were rounded to the nearest percent to ease presentation. Finally, *h* was calculated in an identical manner as described above based on whether the last choice was the certain or uncertain option. Figure G-1 shows an example for how the probability adjustments would occur for a hypothetical participant based on their particular sequence of choices. The right side of Figure G-1 displays an example for the 5-trial adjusting probability task.

Probabilistic Gain. Participants randomly assigned to the probabilistic gain group also completed three different discounting tasks. One adjusting amount probability discounting task with a larger-uncertain amount of $1000, one 5-trial adjusting probability task with a larger amount of $1000, and one 5-trial adjusting probability task with a larger amount of $10. All tasks and manner of calculating *h* for the probabilistic gain group were identical to the tasks and manner of calculating *h* for the probabilistic loss group – with one exception. Adjustments to the probability following each choice were opposite to the direction of adjustments made in the probabilistic loss group. Choosing the larger-uncertain option resulted in an increase in the amount of the certain option (adjusting amount task) or a decrease in the probability of the larger-uncertain option (5-trial adjusting probability tasks).

Task Order. Participants completed all adjusting amount tasks in both an ascending and descending order. That is, the adjusting amount procedure would occur with the delayed outcome at 1 week, then at 1 month, etc. (ascending order). Once the indifference points were obtained for the ascending order, the participant would complete the same adjusting amount procedures at the different delays, but beginning with a delay of 10 years, then at 5 years, etc. (descending order). For each delay, we used the average amount of the ascending and descending indifference points as the final indifference point for each participant. The order of ascending and descending tasks was random for each participant. In addition, the order of the adjusting amount task and 5-trial adjusting delay or adjusting probability tasks was random for each participant.

Data Exclusion Criteria. We used an algorithm for eliminating nonsystematic delay discounting responses published by Johnson and Bickel (2008). For this experiment, these criteria were (1) less than $100 indifference point amount between the shortest and longest delay, or largest and smallest probabilities, assessed in the adjusting amount task; or (2) $200 or greater increase in indifference point amount from one delay to the next longer delay, or from one probability to the next smaller probability, in the adjusting amount task. We chose this algorithm because research suggests this algorithm excludes fewer cases than the R^2 method and is uncorrelated with log k values (White, Redner, Skelly, & Higgins, 2015). Forty of the 212 participants met one of the criteria above and all data sets from those participants were removed from the analysis (i.e., the remaining 172 participants were used for the analysis).

Data Analysis. We estimated discounting parameters for each participant by fitting Equations 1 and 2 to the indifference points obtained from the adjusting amount task. Parameter estimation was conducted using Microsoft Excel Solver Add-In for Microsoft Excel 2013. In turn, the estimated discounting parameter for the adjusting amount task was used to obtain the approximate delay wherein the value of the outcome reduced by 50% (i.e., ED_{50}, EP_{50}). ED_{50} and EP_{50} values were compared across the different discounting tasks using a Pearson's product-moment correlation coefficient and a paired samples *t*-test.

Results and Discussion

Table 2-3 shows the average ED_{50} (in months) and the average EP_{50} (in probability) for each task. We found significant correlations between the ED_{50} obtained from the adjusting amount task and the ED_{50} obtained from the 5-trial adjusting delay task for losses of \$1000 ($r = 0.60$, $p < 0.001$). We also observed significant correlations between EP_{50} values obtained from the adjusting amount tasks and the 5-trial adjusting probability task for losses and gains of \$1000 (losses – $r = 0.54$, $p < 0.001$; gains – $r = 0.55$, $p < 0.001$). In addition, we did not observe a difference in the distribution of EP_{50} values for probabilistic gains ($t_{38} = 0.75$, $p = 0.46$) or for probabilistic losses ($t_{67} = 1.14$, $p = 0.26$). However, we did observe a difference between the distribution of ED_{50} values for delayed losses ($t_{62} = 2.39$, $p = 0.02$). Although the absolute values of ED_{50} differed, the results of the correlation analysis suggest the relative difference in ED_{50} was similar between the two discounting tasks.

We next compared the effects of magnitude on discounting delayed and probabilistic outcomes to further test the validity of the 5-trial adjusting delay and

	Task	Mean (σ^2) ED_{50} (Months) or EP_{50} (p)	Pearson Correlation	Student's t
Delayed Losses	Adjusting Amount $1000	52.49 (23.20)	0.60*	---
	5-Trial Adjusting Delay $1000	31.16 (10.57)		1.67
	5-Trial Adjusting Delay $10	41.56 (20.99)	---	
Probabilistic Losses	Adjusting Amount $1000	0.51 (0.04)	0.54*	---
	5-Trial Adjusting Delay $1000	0.48 (0.05)		1.32
	5-Trial Adjusting Delay $10	0.43 (0.06)	---	
Probabilistic Gains	Adjusting Amount $1000	0.34 (0.03)	0.55*	---
	5-Trial Adjusting Delay $1000	0.36 (0.02)		4.00*
	5-Trial Adjusting Delay $10	0.47 (0.03)	---	

Table 2-3. Mean and 95% confidence interval of discount parameters for each task. Pearson correlations and paired student's *t*-test values for comparison between discounting tasks. Asterisks indicate a statistically significant comparison at $^*p < 0.001$.

probability tasks. Consistent with previous research (e.g., Estle, Green, Myerson, & Holt, 2006; Green, Fry, & Myerson, 2014), we observed a significant difference in EP_{50} of gains across different amounts ($t_{38} = 4.00$, $p < 0.001$), and we did not observe an effect of magnitude on ED_{50} of losses ($t_{62} = 1.67$, $p = 0.38$) or EP_{50} of losses ($t_{68} = 1.32$, $p = 0.19$). It should be noted that previous comparisons of the magnitude effect in discounting typically compare log-transformed discounting parameters. When conducting this more typical analysis, we did observe a significant difference in log-transformed *k* parameters ($t_{62} = 3.35$, $p = 0.001$) and *h* parameters for gains ($t_{38} = 3.76$, $p < 0.001$), but not for *h* parameters for losses ($t_{68} = 1.56$, $p = 0.12$).

Delay discounting of losses were the only magnitude comparison that was inconsistent with previous research. However, Green and colleagues (2014) observed no difference in rates of discounting delayed losses over a much wider parametric range of magnitudes ($20 to $500,000). For the two amounts most similar to the amounts used in the present study (i.e., $20 and $3,000), they did observe a difference in *k*s despite no functional relation between magnitude and *k* across the full range of magnitudes. Therefore, it is possible the magnitude effect observed in the current study was an artifact of the narrow range of magnitudes we used.[2] Overall, assessing the effects of pharmacological or behavioral interventions using 5-trial tasks is likely to yield similar outcomes to those using adjusting amount tasks.

The primary goal of Experiment 1 was to determine if 5-trial adjusting delay and 5-trial adjusting probability tasks offer an efficient method to analyze more complex choice situations. When the results from Experiment 1 are combined with the results from Koffarnus and Bickel (2014), 5-trial adjusting delay tasks appear to be useful toward this end. Additionally, the results from Experiment 1 suggest that 5-trial adjusting probability tasks provide an accurate and efficient method to include probability discounting in more complex choice situations. Thus, Experiment 2 sought to take one step further in the direction of increasingly complex choice situations by extending 5-trial adjusting delay and adjusting probability tasks to monetary gains and losses that are delayed and probabilistic.

[2] In fact, a follow-up experiment revealed just that. Similar rates of delay discounting of losses were observed across a wider range of amounts (see *Appendix A*). In this follow-up experiment, participants completed three adjusting amount tasks and seven adjusting delay tasks across amounts ranging from $10 to $10,000.

CHAPTER 3
EXPERIMENT 2

Introduction[3]

Researchers have approached assessment of delayed and probabilistic outcomes in a variety of ways (see Chapter 1). Those maintaining a separate influence of delay and probability within the underlying assumptions of quantitative descriptions have observed three patterns. First, probability seems to affect the value of a commodity to a greater extent than delay (Keren & Roelofsma, 1995; Vanderveldt et al., 2015; Weatherly et al., 2015; c.f., Bialaszek et al., 2015). In other words, the value of a delayed and probabilistic commodity changes little across increasing delays. But, the value of a delayed and probabilistic commodity changes systematically across decreasing probabilities. Second, delay and probability interact multiplicatively to reduce the value of a commodity (Vanderveldt et al., 2015). That is, the change in value of a delayed and probabilistic commodity is best described by dividing the outcome amount by the product of the denominator of Equation 1 and the denominator of Equation 2. This contrasts with an additive description where Equation 1 is subtracted from Equation 2 to describe the value of a delayed and probabilistic commodity. Third, a magnitude effect is not observed for delayed and probabilistic outcomes (Vanderveldt et al., 2015).

To compare the results from Experiment 2 with previous research, we assessed probability discounting across several delays, and delay discounting across several probabilities. To do this, we used the hyperbola-like delay and probability discounting

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[3] Experiment 2 was published in a 2016 issue of *Behavioural Processes*, Volume 131, pages 15-23. doi:10.1016/j.beproc.2016.08.002

functions (Green et al., 1994). The hyperbola-like delay (Equation 2) and probability (Equation 3) discounting equations can be written as:

$$V = \frac{A}{(1 + k\mathrm{D})^{s_d}}, \qquad \text{(Equation 3)}$$

$$V = \frac{A}{(1 + h\theta)^{s_p}}. \qquad \text{(Equation 4)}$$

Equations 3 and 4 differ from the hyperbolic equations used in Experiment 1 through an added *s* parameter (s_p for probability and s_d for delay). The *s* parameter is a nonlinear scaling constant of sensitivity to changing delay (Equation 2) or to changing probability (Equation 3), and is based on power laws from psychophysical research (see Vanderveldt, Oliveira, & Green, 2016 – for overview). The *s* parameter is often added to discounting models of human choice because the value of a commodity tends to level off (i.e., flatten) at long delays and high odds against. Values of *s* that are less than 1.0 account for such flattening. Values of 1.0 for *s* cause Equations 3 and 4 to reduce to the hyperbolic Equations 1 and 2, respectively.

To compare the results from Experiment 2 with previous research, we also assessed the hyperbolic additive (Equation 5) and hyperbolic multiplicative (Equation 6) discounting models from Vanderveldt et al. (2015). These models can, respectively, be written as:

$$V = A - A\left(1 - \frac{1}{(1 + k\mathrm{D})^{s_d}}\right) - A\left(1 - \frac{1}{(1 + h\theta)^{s_p}}\right), \qquad \text{(Equation 5)}$$

$$V = \frac{A}{([(1 + k\mathrm{D})^{s_d}] * [(1 + h\theta)^{s_p}])}. \qquad \text{(Equation 6)}$$

In both equations, *V*, *A*, *k*, *h*, *D*, θ, s_p and s_d represent the same discounting parameters and variables noted above. The main difference between Equations 5 and 6 is whether the influence of delay and probability on the amount of the commodity are independent (Equation 5) or dependent (Equation 6) on the level of the other dimension. In other words, the difference is whether delay influences the amount of a commodity in the same manner regardless of the probability the outcome will occur (Equation 5). Or, if delay influences the amount of a commodity differently, depending on the probability it will occur (Equation 6). The same holds for the influence of probability on commodity value across Equations 5 and 6.

Experiment 2 sought to extend the 5-trial adjusting delay and adjusting probability tasks from Experiment 1 to assess outcomes that were both delayed and probabilistic. In addition, we also examined whether the absence of a magnitude effect would be observed using the 5-trial adjusting delay and probability tasks.

Methods

Participants. Ninety-seven undergraduate students were recruited from the Psychology participant pool at the University of Florida. Average participant age was 18.78 (range 18-22) and 73.58% self-identified as female. Forty-three participants completed all tasks using delayed and probabilistic hypothetical monetary losses. The remaining 54 participants completed all tasks using delayed and probabilistic hypothetical monetary gains.

Procedure. Delayed and Probabilistic Losses. All participants completed three discounting tasks. The first task was an adjusting amount task wherein each response option resulted in one delayed and probabilistic outcome. Here, the larger-delayed-uncertain option was always $1000. The second and third tasks were 5-trial adjusting delay and probability tasks with larger-delayed-uncertain amounts of $1000 or $10.

Participants made a choice on each trial by responding to the question, “Would you prefer a 100% chance of losing $(amount) immediately, or a (percent) chance of losing $1000/$10 in (delay)?”

The adjusting amount task resulted in 25 indifference points resulting from combinations of 5 delays and 5 probabilities. The delays used were 0 months (immediate), 1 month, 6 months, 2 years, and 5 years. The probabilities used were 100%, 80%, 40%, 25%, and 10%. We adjusted the amount of the smaller-immediate-certain option in the same way as the loss condition from Experiment 1 (i.e., smaller amount decreased if larger option chosen and increased if smaller option chosen). Participants completed a single adjusting amount task at a larger-delayed-uncertain amount of $1000.

We combined the 5-trial adjusting delay and adjusting probability tasks from Experiment 1 (i.e., 10 total trials). These tasks adjusted the delay or probability to the outcome in a similar manner as described in Experiment 1. In addition, the smaller-immediate-certain outcome was fixed at half of the amount of the larger-delayed-uncertain outcome (i.e., $500 vs. $1000; $5 vs. $10). The primary difference for Experiment 2 was that each response option resulted in losing hypothetical money at a delay and with a probability.

Figure G-2 shows an example of the 5-trial adjusting delay and probability tasks. Half of the participants were exposed to the delay adjusting before the probability adjusted. These participants were initially asked if they would prefer a 100% chance of losing $500 immediately, or a 100% chance of losing $1000 in 3 weeks. The delay to the larger

Trial Number	Index Number	Option A	OR	Option B
1	16	100% Chance of LOSING $500 Immediately		100% Chance of LOSING $1000 in 3 weeks
2	8	100% Chance of LOSING $500 Immediately		100% Chance of LOSING $1000 in 1 day
3	12	100% Chance of LOSING $500 Immediately		100% Chance of LOSING $1000 in 4 days
4	14	100% Chance of LOSING $500 Immediately		100% Chance of LOSING $1000 in 1.5 weeks
5	13	100% Chance of LOSING $500 Immediately		100% Chance of LOSING $1000 in 1 week

Final *k* parameter = 0.117

Delay of "1 week" used for adjusting probability

6	16	100% Chance of LOSING $500 in 1 Week		50% Chance of LOSING $1000 in 1 week
7	24	100% Chance of LOSING $500 in 1 Week		24% Chance of LOSING $1000 in 1 week
8	20	100% Chance of LOSING $500 in 1 Week		37% Chance of LOSING $1000 in 1 week
9	18	100% Chance of LOSING $500 in 1 Week		43% Chance of LOSING $1000 in 1 week
10	19	100% Chance of LOSING $500 in 1 Week		40% Chance of LOSING $1000 in 1 week

Final *h* parameter = 0.625727

Figure G-2. Example adjustments of choice alternatives in the 5-trial adjusting delay then adjusting probability task. The trial number represents the order of choice presentation. The index number corresponds to the index listing in *Tables 2-1* and *2-2*. Circled options represent the choice made by a hypothetical participant leading to the presented choice index in the following trial. The final parameter represents the rate at which the value of losing $1000 reduced as a function of increasing delay (*k*) and increasing odds against (*h*).

option adjusted over five trials based on each participant response while the probability remained fixed at 100%. The delay on the fifth trial was used as the delay for the five trials where the probability adjusted. For instance, if the delay on the fifth trial was 1 week, the first trial for the adjusting probability section (i.e., 6th overall trial) would ask the participant to choose between a "100% chance of losing $500 in 1 week" or a "50% chance of losing $1000 in 1 week." The probability of the larger option would then adjust over five trials based on each participant response while the delay to both alternatives remained fixed at 1 week. The other half of the participants completed the adjusting probability section before the adjusting delay section. The probability adjusted over the first 5-trials and the probability on the fifth trial was used for both response options during the adjusting delay sections (i.e., trials 6-10).

Delayed and Probabilistic Gains. Participants assigned to the gains condition completed the same three discounting tasks as the delayed and probabilistic loss group. The only difference in tasks were the direction of the adjustment following each response made by a participant. Selecting the smaller option resulted in the amount of the smaller option decreasing (adjusting amount task) or the delay/probability of the larger option decreasing/increasing (5-trial adjusting delay and probability tasks). Selecting the larger option resulted in the amount of the smaller option increasing (adjusting amount task) or the delay/probability of the larger option increasing/decreasing (5-trial adjusting delay and probability tasks). These adjustments were identical to the adjustments used in Experiment 1 and, for the adjusting amount task, identical to the adjustments used by Vanderveldt et al. (2015).

Task Order. The 25 delay and probability combinations were randomly presented to participants. We interspersed the 5-trial adjusting delay and probability tasks among the 25 delay and probability combination tasks.

Data Analysis. We did not remove any participants from the analyses. We estimated discounting parameters in several ways. We first fit equations 3-6 to individual and group median indifference points by estimating all four discounting parameters using Microsoft Excel Solver Add-In for Microsoft Excel 2013. This allowed us to compare: delay vs. probability salience; and additive and multiplicative models. Subsequently, we could compare our results with previous research (Vanderveldt et al., 2015).

We also sought to compare data from the adjusting amount tasks with data from the 5-trial adjusting delay and probability tasks. The 5-trial tasks do not allow for estimation of a sensitivity parameter. Therefore, we also estimated *k* and *h* parameters for the adjusting amount task with the *s* parameter in equations 3 and 4 set to 1.0. The estimated discounting parameters were then used to obtain the delay and probability where the value of the outcome reduced by 50% (i.e., ED_{50}, EP_{50}). ED_{50} and EP_{50} values were compared across the different discounting tasks using a Pearson's product-moment correlation coefficient and a paired samples *t*-test.

Results and Discussion

Figure G-3 shows the fits of Equations 3 and 4 to the group median indifference points from the adjusting amount tasks. The left panels show the hyperbola-like delay discounting model (Equation 3) for indifference points at each probability. The right panels show the hyperbola-like probability discounting model (Equation 4) for indifference points at each delay. The top panels of Figure G-3 are for participants in the delay and probability loss group. The bottom panels of Figure G-3 are for participants in the delay and probability gains group.

The results for both gain and loss groups are similar to those observed by previous researchers studying delayed and probabilistic outcomes. Delay discounting was observed at higher probabilities (100%, 80%, and 40%). But, increasing the delay had little-to-no effect on the value of $1000 when the probability was low (25% and 10%). In contrast, rates of probability discounting were steep across all delays, and increasing the delay had a small-to-minimal effect on probability discounting. Overall, the results support previous research that probability is more salient than delay in the

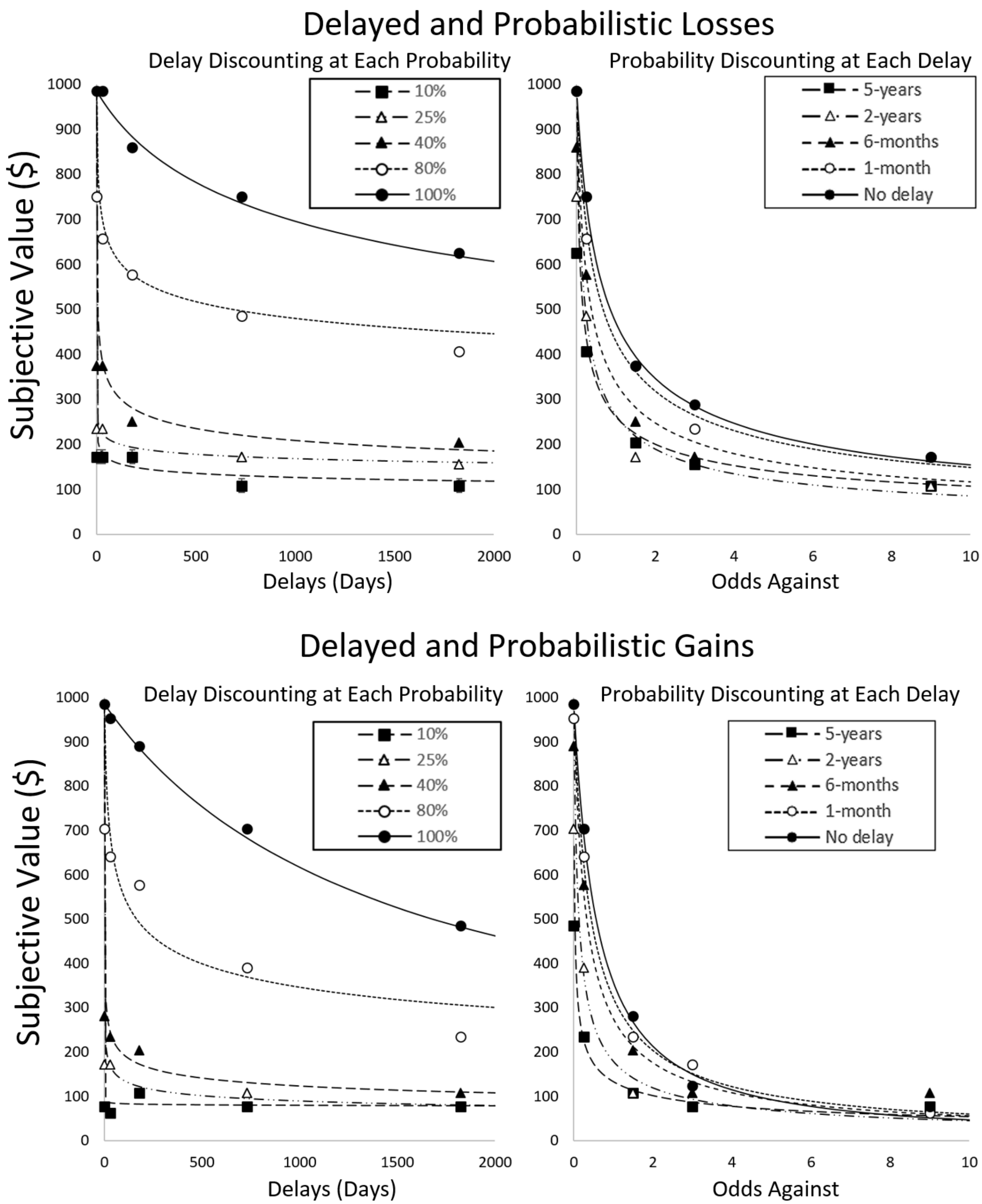

Figure G-3. Median indifference points and best fitting curves from Equation 3 (left panels) and Equation 4 (right panels) for Experiment 2. The upper panels are delayed and probabilistic losses. The lower panels are delayed and probabilistic gains.

choice context when hypothetical monetary gains are delayed and probabilistic (Vanderveldt et al., 2015; Weatherly et al., 2015). In addition, the results of this study extend the greater salience of probability over delay to hypothetical monetary losses.

Figure G-4 shows the results of fitting the multiplicative and additive models to group median indifference points from the adjusting amount task. The left panel shows the fits of the additive equation (Equation 5). The right panel shows the fits of the multiplicative equation (Equation 6). Top panels show model fits for participants who completed adjusting amount tasks with hypothetical monetary losses. The bottom panels show model fits for participants in the delayed and probabilistic gains group.

The additive model (Equation 5) accounted for 96% of the variance for monetary losses (top left panel) and 91% of the variance for monetary gains (bottom left panel). In addition, the additive model predicted a negative value for monetary gains at long delays and low probabilities. This could be interpreted that the participant would prefer to lose money in such a choice context rather than gain money at a long delay and with a low probability. This does not make logical sense and further questions the accuracy of the additive model.

The multiplicative model (Equation 6) accounted for 99% of the variance for monetary loss (top right panel) and gain (bottom right panel) groups. When compared to the additive model fits, the superior fit of Equation 6 suggests that delay and probability interact to influence the value of hypothetical monetary outcomes. Higher VAC of the multiplicative equation compared to the additive equation replicates previous research comparing these models for hypothetical monetary gains (Vanderveldt et al., 2015). In

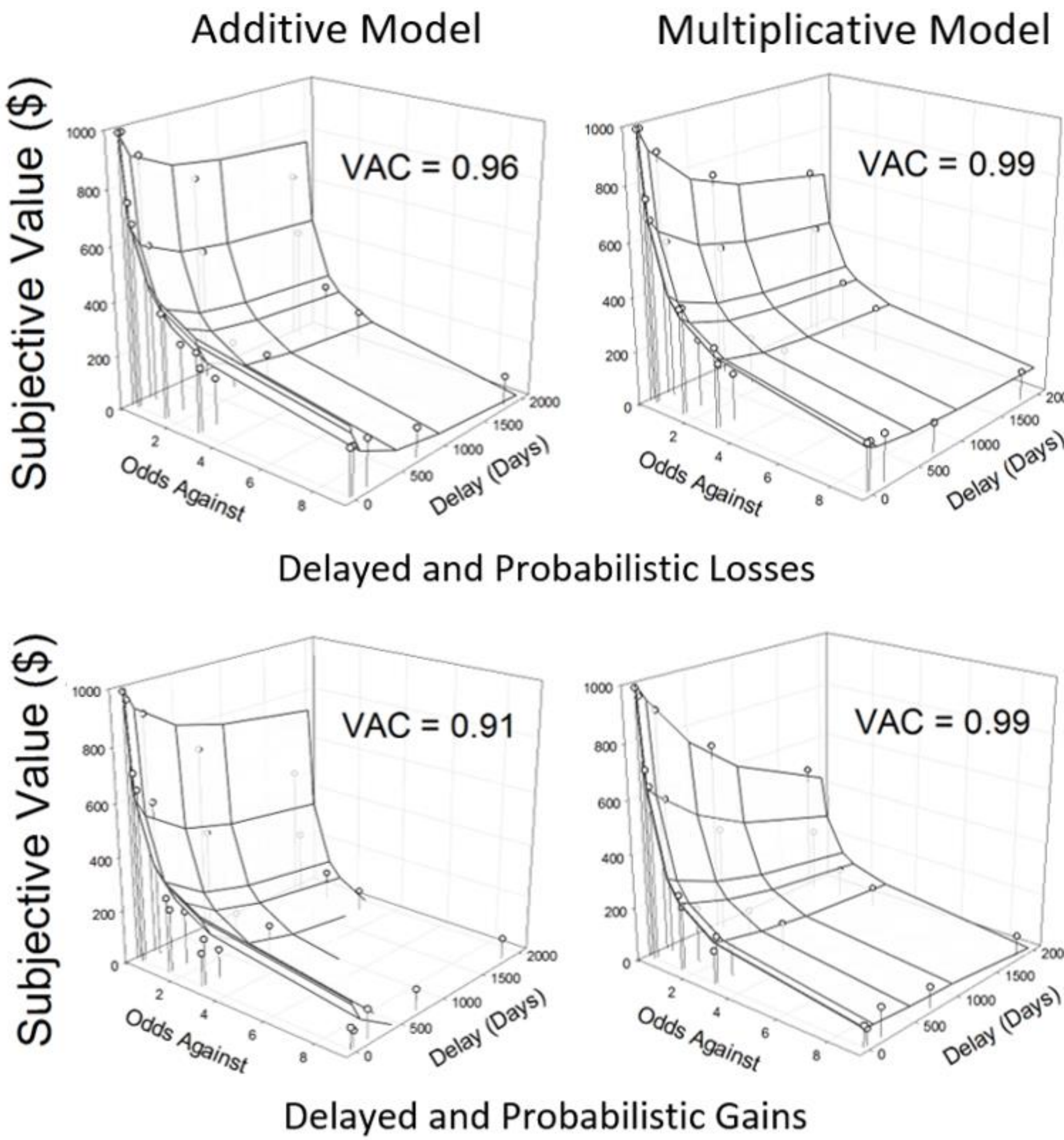

Figure G-4. Median indifference points and best fitting curves from Equation 5 (left panels) and Equation 6 (right panels) for Experiment 2. The upper panels are delayed and probabilistic losses. The lower panels are delayed and probabilistic gains.

addition, the results of Experiment 2 extend these findings to delayed and probabilistic hypothetical monetary losses.

At the individual level, Wilcoxon Signed-Rank Tests were used to compare how well the multiplicative and additive models described participant indifference points in

Experiment 2. Similar to the results at the group level, Equation 6 accounted for more variance than the additive model for monetary losses ($z = 5.73$, $p < 0.001$) and for monetary gains ($z = 5.17$, $p < 0.001$). Delayed and probabilistic outcomes combine multiplicatively to influence the value of hypothetical monetary outcomes.

Table 3-1 shows the average ED_{50} (in months) and the average EP_{50} (in probability) for each task. We found significant correlations between the ED_{50} and EP_{50} values obtained from the adjusting amount task and the 5-trial adjusting delay and probability task for delayed and probabilistic losses of $1000 ($ED_{50}$ – $r = 0.58$, $p < 0.001$; EP_{50} – $r = 0.53$, $p < 0.001$). We also observed significant correlations between the ED_{50} and EP_{50} values obtained for delayed and probabilistic gains at $1000 ($ED_{50}$ – $r = 0.42$, $p = 0.017$; EP_{50} – $r = 0.25$, $p = 0.037$). In addition, we did not observe a difference in EP_{50} values across the different tasks for losses or gains (losses – $t_{42} = 1.30$, $p = 0.20$; gains – $t_{53} = 1.04$, $p = 0.30$). In contrast, ED_{50} values were longer in the adjusting amount tasks compared to the 5-trial adjusting delay and probability tasks for losses and gains (losses – $t_{42} = 7.21$; $p < 0.001$; gains – $t_{53} = 3.03$; $p = 0.004$). Similar to Experiment 1, the absolute values of ED_{50} again differed between adjusting amount tasks and 5-trial adjusting delay and probability tasks. Despite this absolute difference, the correlation analysis suggests the relative difference in ED_{50} remained constant.

We also compared the effects of magnitude on discounting delayed and probabilistic outcomes. For delayed and probabilistic gains, increasing the magnitude of the outcome resulted in a greater ED_{50} (shallower discounting; $t_{53} = 4.65$, $p < 0.001$), but no difference in EP_{50} ($t_{53} = 0.08$, $p = 0.94$). It is unclear exactly how these findings fit with previous research. Vanderveldt and colleagues did not observe an overall

	Task	Mean (σ^2) EP_{50} (Months) or EP_{50} (p)	Pearson Correlation	Student's t
Delayed & Probabilistic Losses	Adjusting Amount \$1000 ED_{50}	116.88 (510.29)	0.58***	0.82
	5-Trial Adjusting Delay \$1000 ED_{50}	77.04 (104.60)		
	5-Trial Adjusting Delay \$10 ED_{50}	54.52 (111.98)		
	Adjusting Amount \$1000 EP_{50}	0.50 (0.03)	0.53***	0.37
	5-Trial Adjusting Probability \$1000 EP_{50}	0.45 (0.04)		
	5-Trial Adjusting Probability \$10 EP_{50}	0.47 (0.06)		
Delayed & Probabilistic Gains	Adjusting Amount \$1000 ED_{50}	402.64 ($3x10^7$)	0.42**	4.65***
	5-Trial Adjusting Delay \$1000 ED_{50}	39.78 (37.13)		
	5-Trial Adjusting Delay \$10 ED_{50}	9.30 (17.99)		
	Adjusting Amount \$1000 EP_{50}	0.41 (0.05)	0.25*	0.08
	5-Trial Adjusting Probability \$1000 EP_{50}	0.45 (0.06)		
	5-Trial Adjusting Probability \$ EP_{50}	0.44 (0.05)		

Table 3-1. Mean and 95% confidence interval of discount parameters for each task. Pearson correlations for comparison between discounting tasks. Asterisks indicate statistical significance. *$p < 0.05$. ** $p < 0.01$. ***$p < 0.001$.

difference in *k* or *h* parameters for delayed and probabilistic gains of different amounts. However, they fit a hyperbola-like multiplicative equation to 25 indifference points obtained from adjusting amount tasks. Thus, it is unclear how their results may have differed had a hyperbolic multiplicative equation (i.e., Equation 6) been used for their analyses. Finally, we did not observe a magnitude effect on ED_{50} or EP_{50} for delayed and probabilistic losses (ED_{50} – $t_{42} = 1.14$, $p = 0.26$; EP_{50} – $t_{42} = 0.60$, $p = 55$).[4]

[4] As in Experiment 1, we also examined the magnitude effect using more traditional comparisons of log-transformed discounting parameters. Results were mixed. Similar to analyses of ED_{50} and EP_{50}, we observed a magnitude effect with *k* for gains ($t_{53} = 2.97$; $p = 0.005$), and we did not observe a magnitude effect with *h* for losses ($t_{42} = 1.46$; $p = 0.15$). In contrast to analyses of ED_{50} and EP_{50}, we observed a magnitude effect with *h* for gains ($t_{53} = 4.98$, $p < 0.001$), and we did observe a magnitude effect with *k* for losses ($t_{42} = 4.53$; $p < 0.001$). Similarly, Pearson's correlations with the log-transformed *k* and *h* parameters were: loss-*k* = 0.54**; loss-*h* = 0.40***; gain-*k* = 0.16; gain-*h* = 0.49***.

In sum, Experiment 2 replicated previous research that probability seems to be more salient than delay when a commodity is gained at a delay and with a probability less than 1.0 (Vanderveldt et al., 2015; Weatherly et al., 2015). The results of Experiment 2 extend this observation to delayed and probabilistic hypothetical monetary losses. As noted by Vanderveldt et al. (2015), it is possible the greater salience of probability was an artifact of the range of delays, probabilities, and amounts used in Experiment 2. To test this hypothesis, these authors discussed an experimental arrangement where the range of delays and probabilities are extended such that the decrease in outcome value for an immediate reward at the smallest probability is equivalent to the outcome value for a certain reward at the longest delay. If probability does have greater salience than delay, one would expect little-to-no change in rates of delay discounting as the probability of the outcome decreased (i.e., results similar to Experiment 2 and Vanderveldt et al., 2015). But, if increased salience of probability were a methodological artifact, one would expect changes in the value of the outcome based on longer delays regardless of the probability of the outcome.

We also replicated previous research comparing additive and multiplicative models of delayed and probabilistic gains (Vanderveldt et al., 2015). The multiplicative model (Equation 6) provided a superior description of obtained indifference points from the adjusting amount task at both the group and individual level. Similarly, Equation 6 provided a significantly better description of delayed and probabilistic losses. Delay and probability interact to influence the value of hypothetical monetary outcomes.

The primary goal of Experiment 2 was to determine if 5-trial adjusting delay and probability tasks offer an efficient method to analyze choice situations where outcomes are delayed and probabilistic. The results suggest 5-trial adjusting delay and probability tasks provide similar measures of discounting delayed and probabilistic outcomes in 115 fewer trials. Thus, Experiment 3 sought to take one step further toward increasingly complex choice by extending 5-trial adjusting delay and probability tasks to choices where each response option resulted in two delayed and probabilistic outcomes.

CHAPTER 4
EXPERIMENT 3

Introduction[5]

Human behavior often leads to more than one outcome, with each outcome occurring at a different delay and probability. For example, a regular smoker who chooses to smoke a cigarette will experience the relatively immediate physiological effects of nicotine, as well as delayed and uncertain adverse impacts to health. Likewise, a regular smoker who chooses to abstain will likely experience immediate uncomfortable withdrawal symptoms, as well as delayed and uncertain positive health outcomes. Multiple outcomes resulting from a single response might occur for many different health related behaviors such as diet, physical activity, other pharmacological use, and risky sexual behaviors.

A discounting framework has been used to study the influence of delayed and probabilistic outcomes on choice (see Chapter 1). Typically, this research has focused on quantitative descriptions of how outcome value is influenced by delay or by probability (see McKerchar & Renda, 2012; & Odum, 2011 for reviews). A smaller number of researchers have examined quantitative descriptions of outcome value when the outcome is delayed and probabilistic (see Chapter 3). Those maintaining the separate psychophysical effects of delay and probability have observed that probability is more salient in the choice context than delay. In addition, changes in delayed and probabilistic outcome value have been described well by a multiplicative equation for both gains (Vanderveldt et al., 2015) and losses (Chapter 3). More precisely, the

[5] Portions of Experiment 3 are *in press* in *Behavioural Processes, 153,* 84-91. doi:10.1016/j.beproc.2018.05.012

amount of an outcome is reduced through division by the product of the denominators in Equations 1 and 2 (i.e., Equation 6). Superior fits of Equation 6 suggest that delay and probability interact to influence the value of an outcome compared to models assuming delay and probability influence outcome value independently (e.g., Equation 5).

Researchers have yet to parametrically assess even more complex choice scenarios. For instance, it is unknown how preference for a smaller-immediate-certain option changes if each discrete response results in an additional outcome that is also delayed and probabilistic. Similarly, it is unknown how preference for the larger-delayed-uncertain alternative might be impacted if each discrete response results in an additional outcome that occurs at a delay and with probability. Understanding how multiple outcomes interact to influence choice would likely be beneficial toward understanding health-related choices such as the smoking example above.

The valence of each outcome becomes important when quantitatively describing discounting when each response option leads to multiple outcomes. For example, the regular smoker has to choose between smoking and abstaining. Smoking results in (1) immediate and certain physiological effects of nicotine and (2) delayed and uncertain adverse impact to health. Abstaining leads to (1) immediate and certain withdrawal symptoms and (2) delayed and uncertain positive impact to health. Here, both response options lead to a gain or pleasurable state (e.g., nicotine, improved functioning due to health) as well as a loss or aversive state (e.g., loss of functioning due to disease, withdrawal symptoms). That is, each response option leads to one gain and one loss. But, the signs of multiple outcomes resulting from a single behavior could involve other outcome combinations such as two gains or two losses.

One goal of Experiment 3 was to parametrically assess discounting when each discrete response led to two outcomes. Two different two outcome combinations were assessed: gain-loss and gain-gain. To manipulate these variables efficiently, we extended the methods from Experiment 2 by adding a second outcome to each response option (details below in methods section). This allowed us to measure ED_{50} (and *k* indirectly) and EP_{50} (and *h* indirectly) as a function of parametric changes in the delay and probability of a second outcome.

A second goal of Experiment 3 was to quantitatively describe discounting involving two delayed and probabilistic outcomes. Equation 6 described *one* delayed and probabilistic outcome. Describing *two* delayed and probabilistic outcomes should therefore involve two Equation 6s – one for each outcome in a response option. We assumed an interaction between the influence of both outcomes on choice based on two previous replications of model comparisons (Vanderveldt et al., 2015; Chapter 3). That is, we assumed the value of one commodity is influenced by its delay and probability, as well as the amount, delay, and probability of the second outcome that will occur from the same response. Combining two Equation 6s while maintaining the interaction between delay and probability could occur in many ways. One way to combine two Equation 6s is:

$$V = \frac{A_1}{\left(1 + \frac{(k_1 D_1)}{\left(\frac{1}{A_2} + k_2 D_2\right)}\right)\left(1 + \frac{(h_1 \theta_1)}{\left(\frac{1}{A_2} + h_2 \theta_2\right)}\right)}. \qquad \text{(Equation 7)}$$

Here, all parameters are the same as in previous Chapters. The addition of subscripts *1* and *2* refer to the first and second outcomes, respectively. Equation 7 predicts that the reduction in value of the first outcome depends on its value relative to the value of the second outcome. This assumption is made by dividing the influence of delay and probability to the first outcome (k_1D_1 and $h_1\theta_1$) by the value of the second delayed and probabilistic outcome $\left(\frac{1}{A_2}+\ k_2D_2\right)$ and $\left(\frac{1}{A_2}+\ h_2\theta_2\right)$.

In sum, Experiment 3 sought to measure changes in ED_{50} and EP_{50} across a range of delays and probabilities to a second outcome. The valence of the first outcome was the same for both groups, but the valence of the second outcome differed between groups. One group completed tasks where the first outcome was a gain and the second a loss (gain-loss). A second group completed tasks where the first outcome was a gain and the second a gain (gain-gain). Finally, we examined how well Equation 7 described the obtained data.

Methods

Participants. Seventy-six participants were recruited from the Psychology participant pool at the University of Florida. The average participant age was 18.60 years (range, 18-25) and 74% self-identified as female. Participants first completed a discrete choice procedure where each response option resulted in one delayed and probabilistic outcome. Next, participants completed a discrete choice procedure where each response option resulted in two delayed and probabilistic outcomes. For ease of presentation, the gain-loss combination group will be used to describe each procedure.

Procedure. Discrete choice with one outcome per option. The purpose of this task was to generate direct measures of ED_{50} and EP_{50} for gaining \$1000 and for losing \$1000 in isolation. These measures were later used as the second outcome value amounts to fit Equation 7 to data obtained from the discrete choice task with two outcomes per option.

The discrete choice tasks with one outcome per option were identical to the tasks used in Chapter 3. Participants made repeated choices between a smaller-immediate-certain amount of money and a larger-delayed-uncertain amount of money. Throughout the task, the smaller amount remained fixed at half of the larger amount. For example, participants were initially asked to choose between:

(a) 100% chance of gaining $500 immediately

OR

(b) 100% chance of gaining $1000 in 3 weeks.

In this choice, Option (a) results in *one outcome* of $500, with a delay of zero (immediate), and a probability of 100%. Option (b) also results in *one outcome* of $1000, with a delay of 3 weeks, and a probability of 100%.

Similar to Experiment 2, we adjusted the delay to option (b) for the first 5 trials based on each participant response. Delays would decrease if the immediate option were chosen and the outcomes were gains but increase if the outcomes were losses. The final delay on the fifth trial was used as the delay to both response options while the probability adjusted for 5 trials (i.e., trials 6-10). The probability would increase if the certain option were chosen and the outcomes were gains but decrease if the outcomes were losses. As with Experiment 2, Figure G-2 shows how choices might be presented. Tables 2-1 and 2-2 show the 31 potential delays, probability, and trial number each delay or probability might be presented to a participant. Participants always began at 3 weeks for the delay adjustments and at 50% for the probability adjustments. Similar to

Experiment 2, the index adjusted by 8, 4, 2, and 1 following the 1st through 4th delay adjustments and the 6th through 9th probability adjustments.

Discrete choice with two outcomes per option. The two-outcome gain-loss tasks were designed to be analogous to many problematic health behaviors. For example, participants were asked to choose between:

(a) (100% chance of getting $500 immediately) + (75% chance of losing $1000 in 6 months)

OR

(b) (50% chance of getting $1000 in 3 weeks) + (100% chance of losing $500 immediately)

In this choice, Option (a) results in *two outcomes*. One outcome was $500, with a delay of zero (immediate), and a probability of 100%. The second outcome is $1000, with a delay of 6 months, and probability of 75%. Option (b) also results in *two outcomes*. One outcome is $1000, with a delay of 3 weeks, and a probability of 50%. The second outcome is $500, with a delay of zero (immediate), and probability of 100%. Note that the first outcomes for options (a) and (b) are similar to the one-outcome tasks. A second outcome has just been added to the choice frame for each option.

Figure G-5 provides an example of adjustments to response options based on hypothetical participant responding. Identically to the one-outcome gain task, we adjusted the delay to the first outcome of option (b) for the first 5 trials based on participant response. Delays decreased if Option (a) was chosen and increased if Option (b) was chosen. The final delay on the fifth trial was again used as the delay to the first outcome of both options while the probability adjusted for the first outcome of

Trial Number	Index Number	Option A	Option B
1	16	100% Chance of GETTING $500 Immediately WITH A 75% Chance of LOSING $1000 in 6 months	50% Chance of GETTING $1000 in 3 weeks WITH A 100% Chance of LOSING $500 Immediately
2	8	100% Chance of GETTING $500 Immediately WITH A 75% Chance of LOSING $1000 in 6 months	50% Chance of GETTING $1000 in 1 day WITH A 100% Chance of LOSING $500 Immediately
3	12	100% Chance of GETTING $500 Immediately WITH A 75% Chance of LOSING $1000 in 6 months	50% Chance of GETTING $1000 in 4 days WITH A 100% Chance of LOSING $500 Immediately
4	14	100% Chance of GETTING $500 Immediately WITH A 75% Chance of LOSING $1000 in 6 months	50% Chance of GETTING $1000 in 1.5 weeks WITH A 100% Chance of LOSING $500 Immediately
5	13	100% Chance of GETTING $500 Immediately WITH A 75% Chance of LOSING $1000 in 6 months	50% Chance of GETTING $1000 in 2 weeks WITH A 100% Chance of LOSING $500 Immediately

Final k parameter = $1/ED_{50} = 1/17.15 = 0.058 = k$

Delay of "2 weeks" used for adjusting probability

6	16	100% Chance of GETTING $500 in 2 weeks WITH A 75% Chance of LOSING $1000 in 6 months	50% Chance of GETTING $1000 in 2 weeks WITH A 100% Chance of LOSING $500 Immediately
7	24	100% Chance of GETTING $500 in 2 weeks WITH A 75% Chance of LOSING $1000 in 6 months	24% Chance of GETTING $1000 in 2 weeks WITH A 100% Chance of LOSING $500 Immediately
8	20	100% Chance of GETTING $500 in 2 weeks WITH A 75% Chance of LOSING $1000 in 6 months	11% Chance of GETTING $1000 in 2 weeks WITH A 100% Chance of LOSING $500 Immediately
9	18	100% Chance of GETTING $500 in 2 weeks WITH A 75% Chance of LOSING $1000 in 6 months	17% Chance of GETTING $1000 in 2 weeks WITH A 100% Chance of LOSING $500 Immediately
10	19	100% Chance of GETTING $500 in 2 weeks WITH A 75% Chance of LOSING $1000 in 6 months	21% Chance of GETTING $1000 in 2 weeks WITH A 100% Chance of LOSING $500 Immediately

Final h parameter = $1/EP_{50} = 1/4.29 = 0.23 = h$

Figure G-5. Example adjustments of choice alternatives in the discrete choice task with two outcomes per option. The trial number represents the order of choice presentation. The index number corresponds to the index listing in *Tables 2-1* and *2-2*. Circled options represent the choice made by a hypothetical participant leading to the presented choice index in the following trial. The final parameter represents the rate at which the value of gaining $1000 reduces as a function of increasing delay (*k*) or increasing odds against (*h*).

Option (b) (i.e., trials 6-10). The probability increased if Option (a) was chosen but decreased if Option (b) was chosen. Finally, the final delay and probability adjustments to the first outcome of Option (b) were used as measures of ED_{50}, EP_{50}, *k*, and *h.*

Participants completed nine tasks involving discrete choices with two outcomes. We parametrically varied the delay and probability of the second outcome for Option (a) across the nine tasks. This allowed us to determine how the delay and probability of the second outcome influenced discounting of the first outcome. Delays assessed were immediate, 6 months, and 2 years. Probabilities assessed were 100%, 75%, and 45%. The second outcome for Option (b) remained at a “100% chance of losing $500 immediately” throughout all nine tasks. Participants completed these nine tasks in a random order.

Group Differences. Participants were randomly assigned to one of two groups. All discrete choice with one outcome per option tasks were identical across the two groups. The difference between groups involved the valence of the second outcomes in options (a) and (b) during the discrete choice with two outcomes per option tasks. Participants assigned to the gain-loss group completed discounting tasks as described above and shown in Figure G-5. Participants assigned to the gain-gain group completed discrete choice with two outcomes per options where all outcomes were gains.

Data Analysis. We obtained 11 measures of ED_{50} and EP_{50} for each participant. Two of these were from the discrete choice with one outcome per option tasks – one for gaining $1000 and one for losing $1000. The remaining 9 measures were obtained from the discrete choice with two outcomes per option tasks. For each group, we used IBM SPSS Statistics 24 to conduct a repeated measures ANOVA to compare the nine ED_{50}

and EP_{50} values from the discrete choice with two outcomes per option tasks. However, these comparisons only indicate how discounting the first outcome changed as a function of the second outcome. These comparisons do not indicate how the first and second outcomes combine to influence choice. We fit Equation 7 to understand the interaction between the two outcomes.

Fitting Equation 7 required three steps. First, we first calculated *k* and *h* for gaining \$1000 and *k* and *h* for losing \$1000 in the discrete choice with one outcome per option tasks. This was accomplished in the same manner as Experiment 2 (i.e., using tables 2-1 and 2-2). Second, individual *k* and *h* parameters from the one outcome task were inserted as k_2 and h_2 in Equation 7. As an example, the probabilistic value of the second outcome in Equation 7 is represented by:

$$\left(\frac{1}{A_2} + h_2\theta_2\right). \qquad \text{(Equation 8)}$$

If the amount of the second outcome (A_2) was \$1000, the participant discounted losing \$1000 at a rate of h = 2.93, and the probability of the second outcome was 75%, then Equation 8 would be: $\left[\left(\frac{1}{1000}\right) + (2.93)\left(\frac{1-0.75}{0.75}\right)\right]$ = 0.98. This same process was used to calculate the value of the second outcome based on the delay and inserted into Equation 7 (i.e., $\frac{1}{A_2} + k_2D_2$). Finally, with the delay and probability values of the second outcome known, the final step was estimating the two remaining free parameters from Equation 7 using Microsoft Excel Solver Add-In for Microsoft Excel 2013 (i.e., k_1 and h_1). This process was then repeated for the remaining eight second outcome combinations.

Results and Discussion

Figure G-6 shows average ED_{50} (left panels) and EP_{50} (right panels) values from the discrete choice tasks with two outcomes per option for each group. Each panel displays nine values – one value for each of the delay and probability outcome combinations for the second outcome (*x*-axis).

First, we conducted a 2 (outcome combination) x 3 (delay to 2^{nd} outcome) x 3 (probability of 2^{nd} outcome) mixed-model ANOVA on ED_{50} and EP_{50} values. Outcome combination (gain-loss, gain-gain) was the between-groups variable. Delay and probability to the second outcome were the within-group variables. We observed a significant difference in ED_{50} and EP_{50} values based on the outcome combination that participants experienced (ED_{50} – $F(1, 74) = 32.53$, $p < 0.001$, $\eta^2 = 0.31$; EP_{50} – $F(1, 74) = 65.33$, $p < 0.001$, $\eta^2 = 0.47$). These results suggest that the effect of a second outcome on discounting depends on whether the first and second outcomes are opposite valence (gain and loss) or the same valence (both gains).

Delay Discounting. Next, we conducted 3 (delay to 2^{nd} outcome) x 3 (probability of 2^{nd} outcome) repeated measures ANOVAs on ED_{50} values for each group. When both outcomes were the same valence (gain-gain; upper left panel Fig G-6), increasing the delay to the second outcome had no effect on ED_{50} ($F(1.97, 68.86) = 1.15$; $p = 0.32$; $\eta^2 = 0.03$). In contrast, decreasing the probability of the second outcome resulted in a longer average ED_{50} (shallower delay discounting; $F(1.03, 35.96) = 28.37$; $p < 0.001$; $\eta^2 = 0.45$). Lastly, delay and probability to the second outcome did not interact to influence ED_{50} for the first outcome ($F(2.07, 72.26) = 0.59$; $p = 0.56$; $\eta^2 = 0.02$).

The above findings of delay discounting with two similar outcomes are consistent with previous research. Specifically, previous research examining discounting of one delayed and probabilistic outcome found that the probability of either outcome impacts rates of delay discounting more than the delay to the outcome (Vanderveldt et al., 2015;

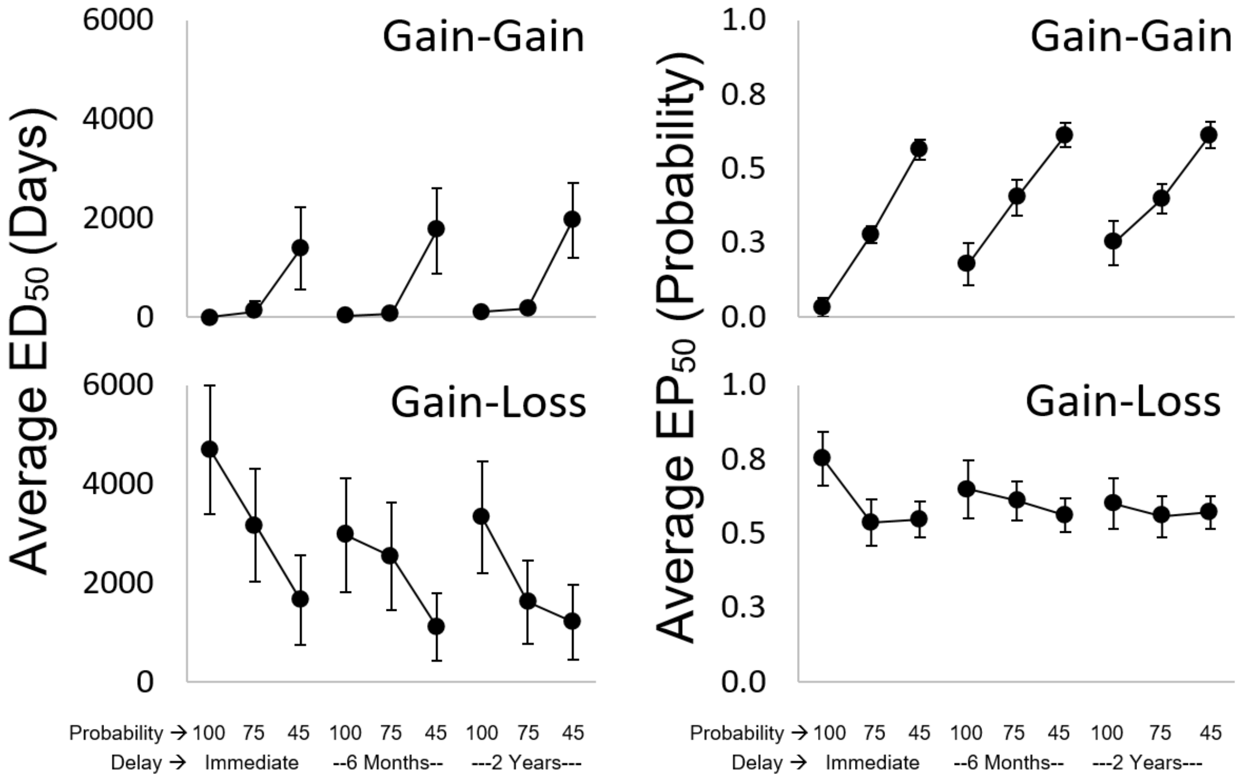

Figure G-6. Average ED_{50} (left panels) and EP_{50} (right panels) values for participants assigned to each group in Experiment 3. The listed delay and probability (*x*-axis) refer to the delay and probability of the second outcome. Error bars represent 95% confidence intervals.

Experiment 2). Experiment 3 suggests the probability of either outcome in a two-outcome choice frame impacts rates of delay discounting more than the delay to either outcome.

A different pattern for delay discounting was observed when the outcomes were opposite in valence (gain-loss; lower left panel Fig. G-6). Increasing the delay to the second outcome led to a shorter average ED_{50} for the first outcome (steeper delay discounting; $F(1.72, 67.20) = 5.51$; $p = 0.009$; $\eta^2 = 0.12$). Decreasing the probability of the second outcome also resulted in a shorter average ED_{50} ($F(1.55, 60.56) = 17.38$; $p < 0.001$; $\eta^2 = 0.31$). Lastly, delay and probability of the second outcome did not interact to influence delay discounting for the first outcome ($F(4, 156) = 1.31$; $p = 0.27$; $\eta^2 = 0.03$).

These are the first known measures of delay discounting when each response option results in one gain and one loss. Adding a second, immediate, and certain loss to the choice frame resulted in a longer average ED_{50}. That is, participants were willing to wait longer to gain $1000 if choosing a smaller-immediate-certain gain also resulted in a larger-immediate-certain loss. But, as the delay to the loss increased and probability decreased, ED_{50} became shorter. This makes logical sense. If behaving impulsively to gain something also results in an immediate and certain loss, then preference is likely to shift away from the impulsive response and toward a more self-controlled response. However, as the delay to potential loss increases and the probability decreases, participant preference shifts toward the impulsive option.

Probability Discounting. We also conducted 3 (delay to 2^nd^ outcome) x 3 (probability of 2^nd^ outcome) repeated measures ANOVAs on EP_{50} values for each group. When outcomes had the same valence (gain-gain; upper right panel Fig. G-6), increasing the delay to the second outcome led to a higher average EP_{50} (shallower probability discounting; $F(2, 70) = 27.60$; $p < 0.001$; $\eta^2 = 0.44$). Similarly, decreasing the probability of the second outcome resulted in a higher average EP_{50} ($F(1.71, 59.76) = 249.20$; $p < 0.001$; $\eta^2 = 0.88$). Lastly, delay and probability to the second outcome interacted to influence EP_{50} ($F(4, 140) = 3.82$; $p = 0.006$; $\eta^2 = 0.10$).

The above findings extend the results of previous research examining probability discounting of one delayed and probabilistic outcome (Vanderveldt et al., 2015; Experiment 2) to two delayed and probabilistic outcomes. Specifically, decreasing the probability of the second outcome influenced the value of the outcome more than increasing the delay to the second outcome. However, we also found that changing the delay to the second outcome impacted rates of probability discounting. This differs from one outcome research where delay had minimal effect on probability discounting (Vanderveldt et al., 2015; Experiment 2). Thus, delay and probability of additional outcomes that result from a single response seem to impact probability discounting for the first outcome.

Probability discounting of the first outcome was less affected by the delay and probability of the second outcome for the gain-loss group (lower right panel Fig. G-6). Increasing the delay to the second outcome did not influence EP_{50} ($F(2, 78) = 1.27$; $p = 0.29$; $\eta^2 = 0.03$). But, decreasing the probability of the second outcome did reduce EP_{50} ($F(1.45, 56.71) = 7.63$; $p = 0.003$; $\eta^2 = 0.16$). Lastly, delay and probability to the second outcome interacted to influence EP_{50} for the first outcome ($F(4, 156) = 5.18$; $p = 0.001$; $\eta^2 = 0.12$).

These are the first known measures of probability discounting when each response option results in one gain and one loss. Participants were more willing to choose the safe, smaller gain when choosing the safe, smaller gain had a low probability of leading to a loss. But, as the probability of a loss increased, participants were more willing to choose the riskier gain even though the riskier gain also involved a small, but certain, loss. This again makes logical sense. If choosing a less risky option results in an immediate and certain loss, then preference is likely to shift away from the less risky option and toward the riskier option. However, as the probability of the loss decreases, participant preference shifts back toward the smaller-sooner-certain gain.

Interaction Between Delay and Probability. Although described separately above, all choices made in this experiment occurred within the context of different delays and probabilities for two different outcomes. Figure G-7 provides a visual example for the systematic patterns observed at this more complex level of interacting influences when both outcomes had the same valence (gain-gain). Each individual panel in Figure G-7 shows how a range of delays and probabilities influence the value of gaining $1000 (the first outcome in the choice frame) as a function of a fixed delay and probability to gaining an additional $1000 (the second outcome in the choice frame). To generate these figures, the group median *k* and *h* parameters obtained in each discrete choice task with two options were entered into Equation 6 to produce estimated values across a range of delays (0 to 2 years) and a range of odds against (0 to 9).

Participants were more impulsive, but less risky, when an immediate, certain and similar valence outcome was added to the choice frame (upper left panel in Fig. G-7). That is, they chose “Option A” almost exclusively. As the delay to the second outcome increased (moving down columns in Fig. G-7), participants became slightly less impulsive and more risky (shallower rates of delay and probability discounting). Similarly, as the second outcome probability decreased (moving across rows in Fig. G-7), participants became less impulsive and riskier. Again, this pattern makes sense. Adding a large, immediate, and certain gain to an impulsive and less-risky choice will increase the likelihood it is chosen. But, as the second outcome delay increases and

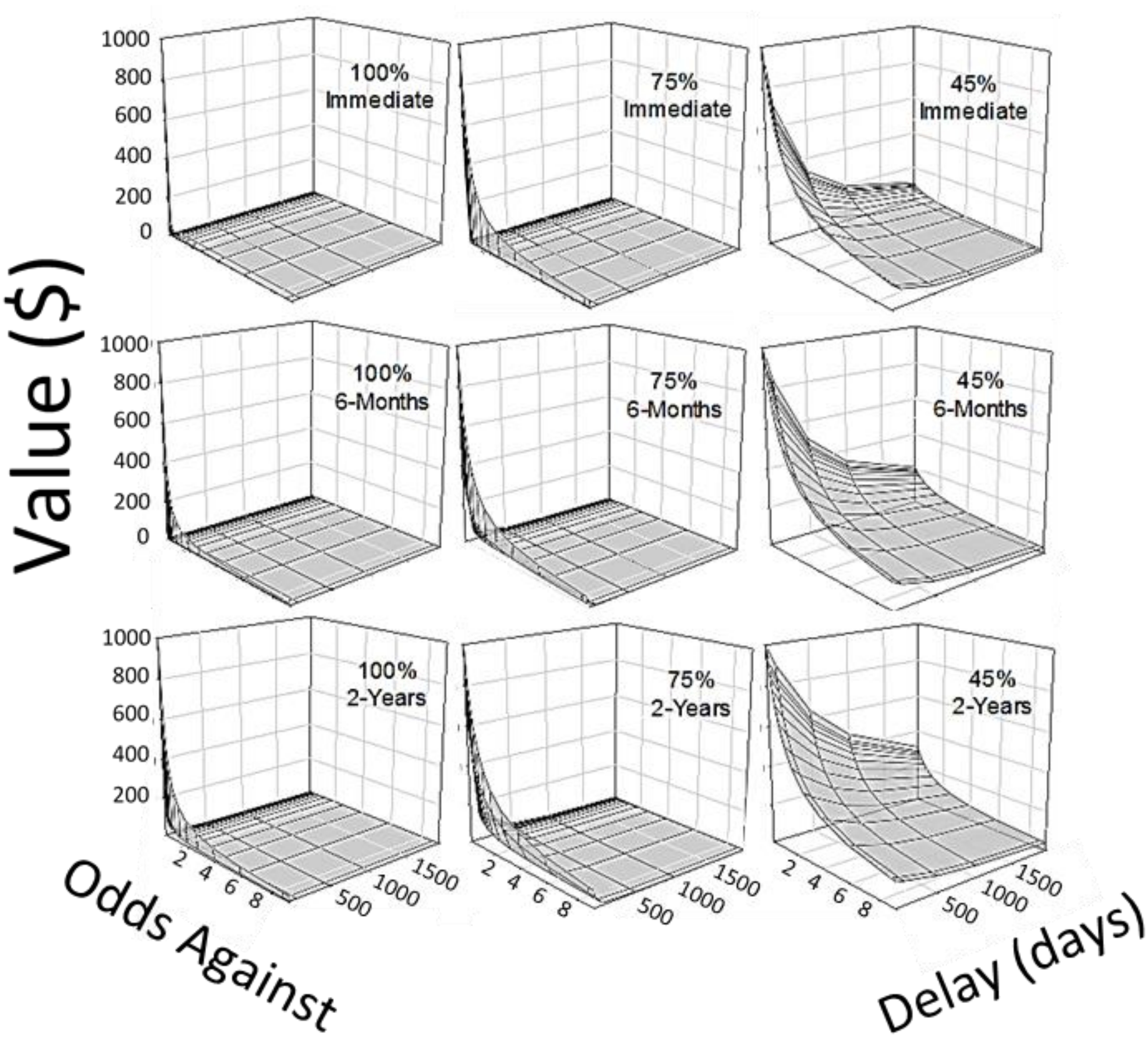

Figure G-7. Curves obtained from using median GG group *k* and *h* parameters in Equation 6 for participants in Experiment 3. The probability and delay in each plot are the probability and delay to the second outcome.

probability decreases, preference shifts away from this option because it has less overall value.

Figure G-8 provides a visual example for the opposite systematic pattern observed when one outcome was a gain and the second was a loss. Participants were less impulsive and riskier when the impulsive and safer option also resulted in an immediate and certain large loss (upper left panel in Fig. G-8). That is, participants

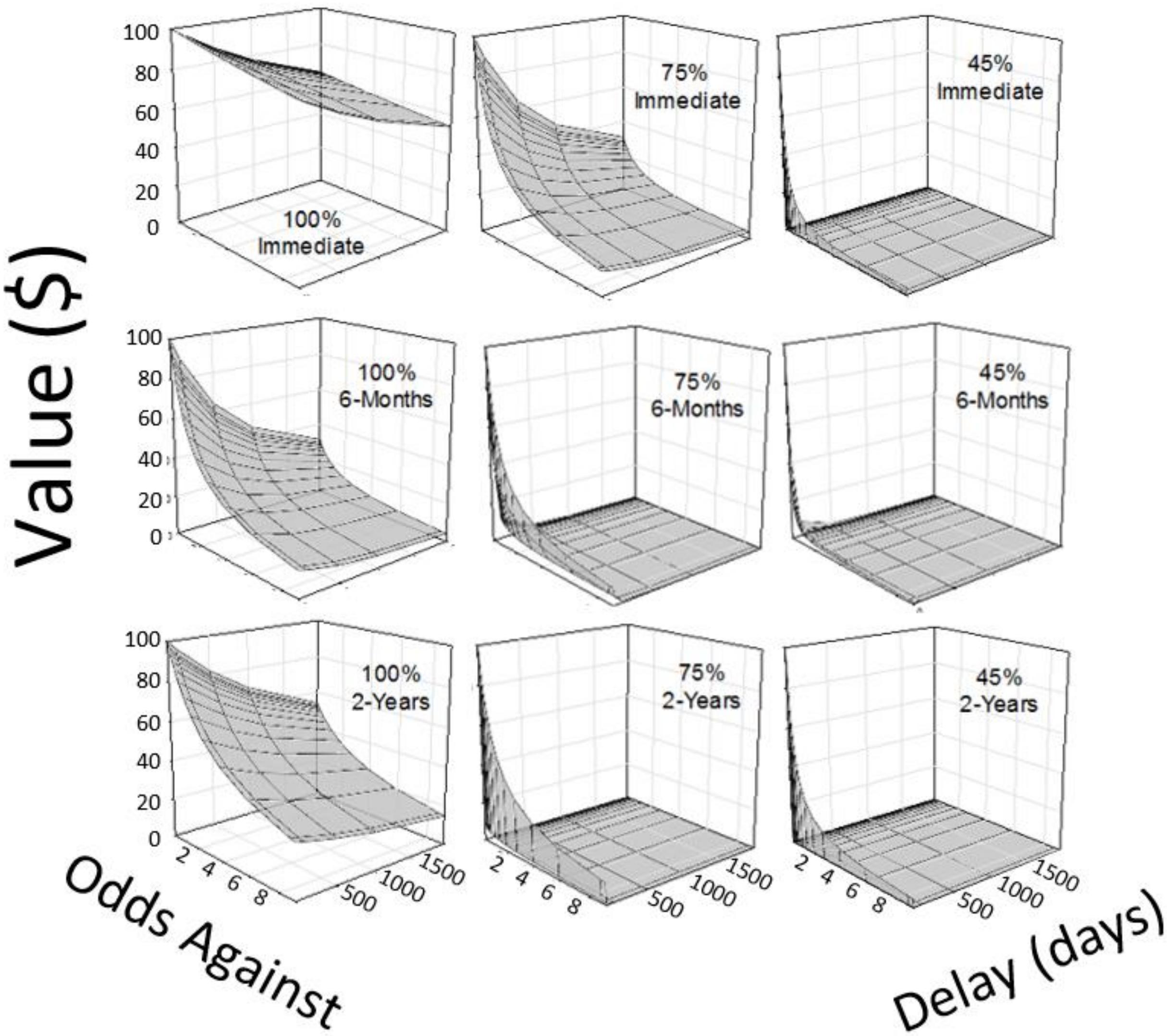

Figure G-8. Curves obtained from using median GL group *k* and *h* parameters in Equation 6 for participants in Experiment 3. The probability and delay in each plot are the probability and delay to the second outcome.

chose "Option B" primarily. However, as the delay to the second outcome increased (moving down columns in Fig. G-8) or the second outcome probability decreased (moving across rows in Fig. G-8), participants became more impulsive and less risky (e.g., chose "Option A" almost exclusively when the second outcome was 45% chance delayed by 2 years – lower right panel Fig. G-8). Again, this pattern makes sense. If an impulsive and less risky gain also results in an immediate and certain large loss, then preference shifts away from that option. But, as the delay increases and probability decreases for that large loss, preference slowly shifts back toward the impulsive and less risky option.

In sum, previous research suggests that organisms discount the value of an outcome based on its delay and probability. Experiment 3 indicates that the rate an organism discounts an outcome also depends on the presence, sign, delay, and probability of other outcomes that result from the same choice. Furthermore, the change in value of an outcome based on the presence, delay, and probability of a second outcome is systematic and thus can be modeled mathematically.

Model Fit. Table 4-1 shows the R^2 values when Equation 7 was fit to individual participant data in Experiment 3. Equation 7 described discounting of two delayed and probabilistic options well across all nine, discrete choice with two outcomes per option tasks. Median R^2 values were near 1.00 for nearly all delay and probability combinations across outcome groups – the one exception was a median VAC of 0.79 when the second outcome probability was 100%, the delay was immediate, and the second outcome a loss.

It makes sense that the likelihood someone chooses a response option will depend on the delay, probability, amount, and valence of all outcomes that result from that response. In addition, choice in health behavior situations, which were used as a model for this experiment, also follow these patterns. Smoking a cigarette, for example, could be considered most analogous to the lower right panel in Figure G-8. Smoking results in the immediate and certain effects of nicotine but also the likelihood of delayed, yet uncertain, negative health outcomes. In this instance, the value of the delayed and

First Outcome	Probability, Delay of Second Outcome	Second Outcome	
		Gain	Loss
Gain	100%, Immediate	1.00 (-0.38, 1.00)	0.79 (0.11, 1.00)
	75% Immediate	0.99 (-0.69, 1.00)	0.99 (-0.69, 1.00)
	45%, Immediate	0.97 (-0.32, 1.00)	0.99 (-1.98, 1.00)
	100%, 6 Months	1.00 (0.37, 1.00)	0.99 (0.80, 1.00)
	75%, 6 Months	1.00 (-0.02, 1.00)	1.00 (-0.70, 1.00)
	45%, 6 Months	0.99 (-1.16, 1.00)	1.00 (-3.08, 1.00)
	100%, 2 Years	1.00 (-0.22, 1.00)	0.99 (0.94, 1.00)
	75%, 2 Years	1.00 (0.04, 1.00)	1.00 (-0.78, 1.00)
	45%, 2 Years	0.99 (0.77, 1.00)	1.00 (-3.23, 1.00)

Table 4-1. Median (Min, Max) R^2 values for Equation 7 when fit to individual participant indifference points for the nine, second outcome delay and probability conditions.

uncertain loss has little impact on choice and the individual is likely to almost exclusively choose the immediate and certain gain of nicotine.

Perhaps more importantly, the good fits of Equation 7 suggest we can quantify the delay, probability, and amount of aversive consequences from smoking (i.e., second outcome in “Option A”) that would shift people toward healthier alternatives (choosing “Option B”). Alternatively, we may be able to quantify the delay, probability, and amount of alternative reward needed (i.e., first outcome in “Option B”) to counteract the immediate and certain experience of withdrawal (i.e., second outcome in “Option B”). To get to such practical application of the model, future research will need to examine outcome amounts and commodities that more closely resemble the health behavior of interest.

Equation 7 also suggests a novel conceptualization of gain-loss interactions. Several quantitative models have incorporated gains and losses in the same equation by assigning them positive and negative values, respectively (e.g., matching law –

Critchfield et al., 2003; prospect theory – Kahneman & Tversky, 1979). In these models, multiple gains and losses that result from a single response option will sum to an overall value. Experienced gains or reinforcers increase or strengthen the overall value through addition, whereas experienced losses or punishers reduce or suppress the overall value through subtraction. But, this can produce problematic quantitative predictions of behavior if the amount or rate of losses/punishers is greater than the amount or rate of gains/reinforcers because summing the values would produce a negative number (Klapes, Riley, & McDowell, 2018). Quantitative sums of negative value predict negative behavior (which is illogical) or removal of those data from the quantitative analysis (which reduces the scope of the model).

Equation 7 circumvents this issue by structuring gain-loss interactions differently. Instead of assigning gains/reinforcers a positive value and losses/punishers negative value, outcome value in Equation 7 is defined by its magnitude of influence on behavior. Only more or less behavior can be allocated to a response option. Equation 7 can never predict a negative value for an option because gains and losses are in a ratio instead of subtracting one from the other. By using a ratio form, value approaches zero by increasing the amount or rate of losses/punishers relative to gains/reinforcers. Future research will have to determine if the present quantitative conceptualization of gain-loss interaction is useful in the prediction and control of behavior.

One limitation of Experiment 3 is that the method used to fit Equation 7 did not account for the bidirectional relationship of the two outcomes. The focus of data collection, model fit, and analysis was the first outcome in Options A and B. We obtained a measure of discounting only for the first outcome and then estimated how the first outcome was discounted relative to a fixed value of the second outcome. This fixed value was taken from the results of the discrete choice with one outcome per option task. The good model fits of Equation 7 suggest the value of the first outcome is relative to the amount, delay, and probability of the second outcome. But, the structure of Equation 7 also suggests the value of the second outcome is dependent on the amount, delay, and probability of the first outcome. That is, the parameter estimates for both outcomes should change based on the presence, amount, delay, and probability of the other outcome. The method used in Experiment 3 for data collection, model fit, and analysis did not incorporate this bidirectional relationship. Future research on discounting in complex choice scenarios will need to determine how researchers can practically measure and quantitatively describe how two outcomes are discounted simultaneously, rather than focusing on a single outcome.

CHAPTER 5
GENERAL DISCUSSION

All organisms make a myriad of daily choices. Many environmental variables likely interact dynamically to affect each choice point. In addition, many changes to the environment and the organism are likely to result from each choice the organism makes. Researchers interested in improving the choices people make will need to measure and describe how multiple variables interact to influence choice, and what variables are most influential and practical to target for intervention.

Precisely measuring and describing choice in complex settings is not an easy task. Isolating a single variable in an experimental setting can sometimes be challenging. Isolating two variables for parametric analysis can be even more challenging but is required for studying complex choice situations. Practically studying complex choice can be accomplished by extending existing methods for studying one independent variable to study two independent variables (e.g., Vanderveldt et al., 2015). However, this requires exponentially increasing resources (e.g., time, money). In contrast, one could develop more efficient procedures to measure the effect of an independent variable (e.g., Koffarnus & Bickel, 2014). This subsequently requires less resources when multiple independent variables are combined to examine complex choice.

Choosing which complex choices to study is another decision that has to be made. This is likely to be a somewhat arbitrary decision based on researcher preference. But, one constraining parameter could be social importance. One could further narrow the range of topics studied by focusing on choices that play a daily role in the health and well-being of humans.

This dissertation sought to move forward our basic understanding of complex choice, advance practical methods to isolate and measure the influence of multiple independent variables on choice, and focus on one complex choice situation of societal importance. Specifically, many health behaviors involve choice between behavior that results in an immediate and certain outcome, but also a delayed and uncertain outcome. The primary goal of this dissertation was to measure and describe choice in these complex choice situations. To do this, existing methodological constraints had to be resolved before this question could be asked.

The purpose of Experiment 1 was to extend efficient methods to measure discounting of delayed gains to other variables known to influence choice in isolation. We found that the more efficient measures provided similar estimates as traditional tasks for delayed discounting of losses, probability discounting of gains, and probability discounting of losses. In turn, the results of Experiment 1 allowed us to take one step closer to the complex discounting situations that were the target of this dissertation.

The purpose of Experiment 2 was to examine discounting situations where the outcomes were delayed and probabilistic. Previously, parametric measurement of the interaction between delay and probability had primarily been accomplished through longer adjusting amount tasks (e.g., Vanderveldt et al., 2015; Weatherly et al., 2015). Experiment 2 found that: the same pattern of interaction between delay and probability is observed for losses; probability seems to be more salient than delay; and, the discounting models for delay and probability can be combined multiplicatively to describe discounting of delayed and probabilistic outcomes (i.e., Equations 1 and 2 combine to Equation 6). Experiment 2 also found that the efficient methods to measure discounting from Experiment 1 (i.e., examining delay in isolation, and probability in isolation) could be combined to provide similar measures of discounting when the response options are more complex (i.e., examining the interaction between delay and probability). Whereas the traditional adjusting amount task required 125 choice trials, the more efficient methods required only 10 trials. This practically opened the door to the primary goal of this dissertation – to measure and describe choice when each response results in two delayed and probabilistic outcomes.

Experiments 1 and 2 also contribute to the discounting literature on types of discounting. Several authors have suggested there are three types of discounting: discounting of delayed gains, discounting of probabilistic gains, and discounting of losses (e.g., Green et al., 2014). This argument is supported by the different effect of outcome magnitude on choice. Experiment 1 further supports that discounting of probabilistic gains is different than discounting of probabilistic losses. We observed steeper discounting of probabilistic gains when the magnitude increased. But, we observed no magnitude effect for probabilistic losses. Similarly, humans tend to discount delayed gains more steeply than delayed losses, and probabilistic losses more steeply than gains (e.g., Mitchell & Wilson, 2010). This finding was replicated in Experiments 1 and 2 suggesting participants continue to discount gains more steeply than losses when the outcomes are both delayed and probabilistic.

Finally, Experiment 3 examined discounting when two delayed and probabilistic outcomes result from each option in a choice set. Importantly, Experiment 3 is the first known study to parametrically examine discounting where gains and losses are considered within the same task. The structure of this choice setting could have taken a number of forms. We designed the choice scenario to be analogous to many everyday health behaviors where each response option results in an immediate and certain outcome, but also a delayed and uncertain outcome. To do this, we used the same methods from Experiment 2, but we added a second outcome to the choice frame.

We found that the delay, probability, and valence (gain or loss) for both outcomes interact to influence value in Experiment 3. That is, the rate that a delayed and probabilistic outcome is discounted will depend on the delay, probability, and valence of any other outcome that results from the same response. This interaction occurred in logical ways. For example, adding a larger-immediate-certain loss shifted preference away from the ‘impulsive choice’ (the smaller-immediate-certain gain). But as the probability and delay to the loss decreased, preference shifted back toward the smaller-immediate-certain gain.

That all outcomes in a choice context influence value is not a novel finding. Arguably the field of behavioral economics focuses on studying how different variables within a context interact to influence commodity value and behavior (Dhami, 2016). Nevertheless, Experiment 3 contributes to the discounting literature in several ways. First, the results from Experiment 3 provide novel evidence that probability seems to be more salient for two-outcome monetary combinations. These results add to a small, but growing, literature where probability seems to influence discounting to a greater degree than delay (Experiment 2; Vanderveldt et al., 2015; Weatherly et al., 2015). Together, the results of these experiments suggest manipulating the probability of outcomes might lead to greater changes in preference for smaller-sooner-certain outcomes compared to changing delay.

Second, we also extended previous quantitative descriptions of discounting to two delayed and probabilistic outcomes. Previous research had found that models structured with delay and probability interacting were superior to models assuming delay and probability combine additively (Experiment 2; Vanderveldt et al., 2015). As a result, we fit an interactive model to data obtained in Experiment 3 (Equation 7). The interactive model described choice well across all outcome combinations with median individual VACs near 100% for all but one task. Thus, Experiment 3 contributes to the discounting literature by providing an initial description for how two delayed and probabilistic outcomes might interact to influence value.

Third, Equation 7 also suggested a novel conceptualization of gain-loss interactions. Previous quantitative models of gain-loss interactions denote gains and losses as positive and negative, respectively. Equation 7 assigns positive values to gains and losses but places them into a ratio form. This different conceptualization may make sense if one assumes value directly relates to behavior because behavior, and thus value, could never be negative.

There are many future directions that stem from Experiments 1-3. First, future research could examine discounting of multiple outcomes that differ in amount. Many outcome combinations resulting from non-laboratory choices are of different amount. For example, the overall value gained from smoking a cigarette is seemingly much less than the overall value of loss that would occur from developing lung cancer. The data in Experiment 3 suggest there is a delay and probability wherein further delay and probability to a second loss no longer influences value (e.g., when the large loss was delayed by 6 months and occurred at a probability of 75% – Fig. G-8). Similarly, the influence of adding a second gain only started to differentially influence value beyond 2 years and below 75%. However, Experiment 3 examined discounting when the outcomes were equivalent in amount. Future research could examine if the delay and probability wherein the second outcome no longer influences first outcome value differs when the first outcome is significantly smaller, or larger, than the second outcome.

A second area of future research is to examine how discounting with multiple outcomes changes across different commodities. We examined hypothetical money as the outcomes. But, many health choices do not involve money directly (e.g., diet, physical activity). Furthermore, the commodities that result from a single response are likely to be different across the multiple outcomes. If smoking, physiological effects of nicotine are likely to be different than impaired lung function and health. If abstaining, withdrawal symptoms are different than the money a smoker could gain if they are taking part in contingency management programs where monetary incentives are offered for abstinence (e.g., Petry, 2000). It is unclear that examining multiple commodities would lead to structural changes in Equation 7. However, some researchers have advocated for adding a scaling parameter to incorporate different commodities in the same equation (e.g., Miller, 1976). Future research could examine if additional commodity scaling parameters are needed, or if allowing different *k* and *h* values across commodities while maintaining the commodity's objective amount is sufficient.

A third area for future research is to continue modifying these procedures to more closely mimic ongoing choice contexts from everyday settings. For example, organisms often do not make a choice and then wait the entire delay to the outcome.

Organisms continue to make choices, consume commodities, and interact with their environment. Relative to this experiment, how might the opportunity to continue responding during a wait period impact preference? How might preference shift immediately after experiencing the larger and delayed loss (e.g., Baum & Davison, 20014; Davison & Baum, 2002)? If every response for the smaller-sooner-certain gain results in a larger-delayed-uncertain loss, will preference switch away from this alternative only once it is too late and the number of losses one will experience is insurmountably costly (e.g., terminal cancer from a lifetime of smoking)? Or, can the researcher implement preventive measures before it becomes too late? These, and other, experiments would allow researchers to test and refine quantitative models that describe choice in complex settings as well as procedures that may improve the rate at which people choose healthy behaviors that pay off in the long run.

CHAPTER 6
CONCLUSION

These experiments extended research on 5-trial adjusting delay tasks for monetary gains (Koffarnus & Bickel, 2014) to delay discounting of losses, probability discounting of gains, and probability discounting of losses (Experiment 1). These more efficient methods resulted in measures of ED_{50} and EP_{50} similar to longer adjusting amount tasks. The results of combining these methods for outcomes that are delayed and probabilistic also were promising (Experiment 2). The 5-trial adjusting delay and probability tasks provided relatively similar measures of ED_{50} and EP_{50} as adjusting amount tasks – in 115 fewer trials. We also found the multiplicative model published by Vanderveldt and colleagues (2015; Equation 6) described delayed and probabilistic hypothetical monetary losses better than an additive model (Equation 5). Finally, we extended these methods and quantitative descriptions one step further by examining discounting of two delayed and probabilistic outcomes (Experiment 3). We observed systematic and intuitive changes in rates of discounting that depended on the delay, probability, and valence of the second outcome. These data were also described well by an interactive model where the value of one outcome depends on the value of the second (Equation 7). This suggests the value of two delayed and probabilistic outcomes interact to influence the value of money. Perhaps, most importantly, the methods advanced in this dissertation open the door for practically studying discounting in more complex scenarios in future research.

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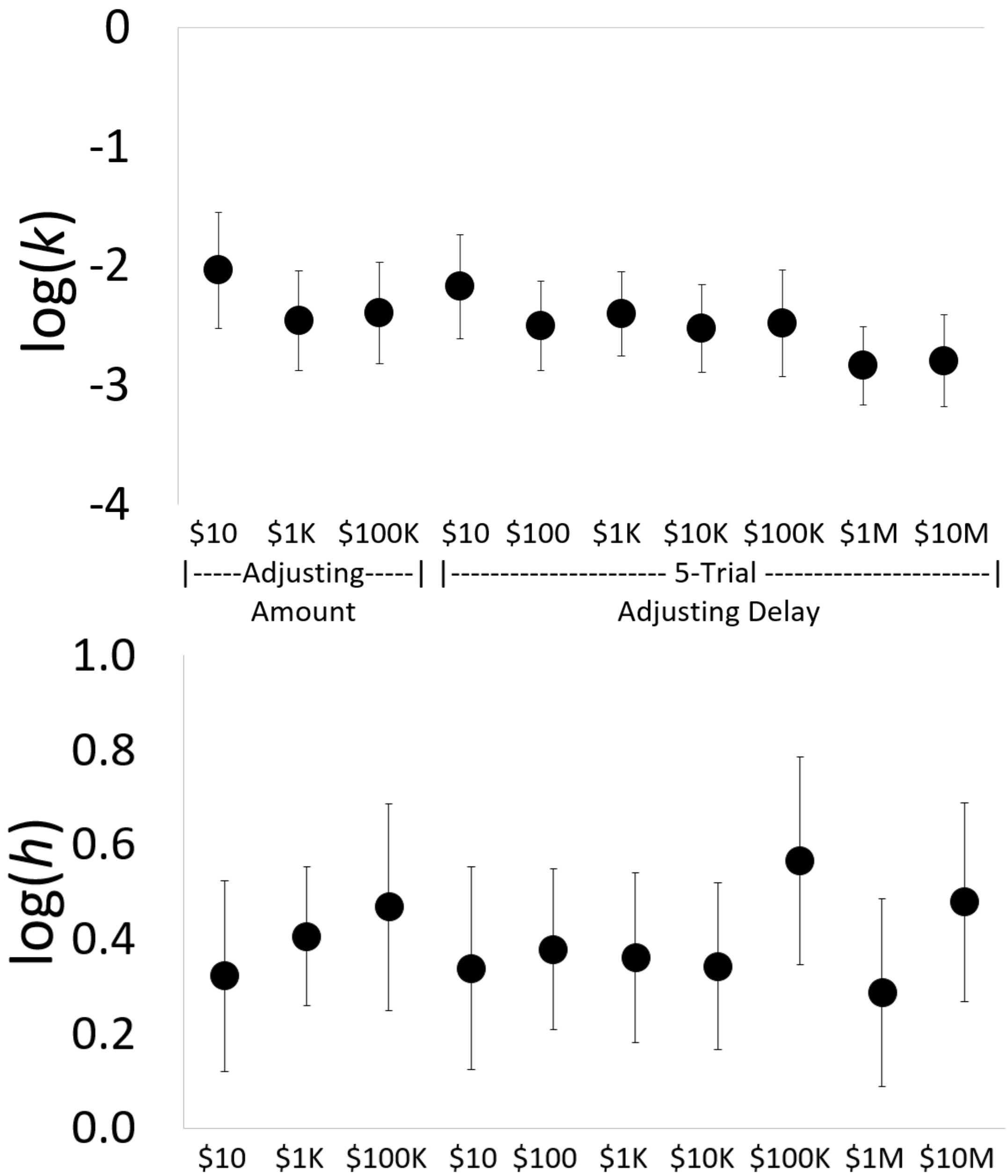
BIOGRAPHICAL SKETCH

David J. Cox received a Bachelor of Science in Psychology from Arizona State University in 2008. He then received a Master of Science in Bioethics in 2010 from a joint program between Union Graduate College and the Mt. Sinai School of Medicine. David then received a Graduate Certificate in Applied Behavior Analysis (ABA) from the University of North Texas in 2011 and became a Board Certified Behavior Analyst in 2011. David worked clinically in ABA agencies for individuals with Autism Spectrum Disorders and related developmental disabilities from 2006 through 2014 before transitioning to the PhD program in Behavior Analysis within the Department of Psychology at the University of Florida. Here, David began conducting basic human operant research on choice behavior, verbal behavior, and quantitative analyses. These remain the primary focus of his research interests today. David completed his Master's Equivalency in May of 2016, Qualifying Examinations in November of 2017, and Ph.D. in August of 2018. Finally, he has accepted a National Institute on Drug Abuse postdoctoral fellowship at the Johns Hopkins University Behavioral Pharmacology Research Unit.

APPENDIX A
DISCOUNTING LOSSES OVER A WIDE RANGE OF MONETARY AMOUNTS



Measures of delay (top panel) and probability (bottom panel) discounting across a wide range of amounts. A two-way repeated measures ANOVA indicated no effect of task type or outcome amount for delay discounting of losses (p = 0.88 and 0.08, respectively) or probability discounting of losses (p = 0.67 and 0.09, respectively). In addition, rates of discounting also were significantly correlated between the 5-trial and adjusting amount tasks at all three equivalent magnitudes for delay ($10 - r = 0.46; $1000 - r = 0.47; $100,000 - r = 0.53; $p < 0.001$ for all) and probability ($10 - r = 0.49; $1000 - r = 0.47; $100,000 - r = 0.58; $p < 0.001$ for all).