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Decision Making in Older Adults: A Comparison of Delay and Probability Discounting Across

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by

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ABSTRACT OF THE DISSERTATION

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The value of an outcome is affected both by the delay until its receipt (delay discounting) and by the likelihood of its receipt (probability discounting). The discounting framework has greatly aided in modeling and understanding decision-making, particularly in the areas of impulsivity, but these findings have overwhelmingly been based on research with young adults. In three experiments, the current study extended the discounting framework by examining choice by older adults. Experiments 1 and 2 found that both young and older adults discounted delayed outcomes and probabilistic outcomes and that their choices were well-described by the same hyperboloid model. Both young and older adults also showed magnitude effects with delayed rewards, reverse magnitude effects with probabilistic rewards, and no systematic effect of amount with delayed or probabilistic losses. In Experiment 3, in which choice was more complex and involved rewards that were both delayed and probabilistic, a multiplicative hyperboloid model in which delay and probability interacted to affect the subjective value of an outcome, described choice well for both young and older adults. Across the three experiments, some differences across young and older adults emerged. Older adults in Experiment 1, for example, showed a magnitude effect for delayed gains only up to $3,000, whereas young adults

continued to show a magnitude effect for much larger amounts. Experiments 1 and 2 revealed differences in the degree of delay, but not probability discounting, after income was controlled, such that older adults discounted delayed rewards less steeply than young adults. Finally, in Experiment 3, older adults tended to show greater risk-aversion than young adults when outcomes were both delayed and probabilistic. In spite of the age differences observed, there was remarkable consistency in discounting across young and older adults. The results of the current study suggest that although there are quantitative age differences in decision making, choice appears qualitatively similar across age groups.

Chapter 1: Introduction

When outcomes vary along one dimension only, choice is relatively easy: People usually prefer a reward that is larger rather than smaller, immediate rather than delayed, and certain rather than probabilistic. Most of the choices people make every day, however, are more complex and involve trade-offs among preferences. For example, people often make the choice whether to have dessert after dinner or to forgo dessert every night and ultimately live healthier; whether to go out with friends or to study in order to get a good grade on next week's exam; whether to purchase several small items or to save in order to purchase a larger, more desired item in the future. Consider the choice between receiving $10 right now and waiting a year to receive $50. Most people prefer $50 to $10, but also prefer an immediate reward to a delayed reward. So, too, in the choice between receiving a guaranteed $10 or a 30% chance of receiving $50, people prefer certainty over taking a risk, but also prefer more to less money. Choice becomes even more difficult as the number of dimensions further increases, for example, when the reward alternatives differ with respect to amount, delay, and probability of receipt, potentially pitting one's preferences for larger, sooner, and more certain against each other.

1.1 The Discounting Framework

One approach to studying choice of delayed and probabilistic outcomes is the discounting framework. Although in the example above $50 is nominally five times greater than $10, many people nonetheless choose the immediate or certain outcome, despite its being a smaller amount. In such cases, it is said that the delayed or probabilistic option has less subjective value than the immediate or certain option. *Delay discounting* is defined as the decrease in the subjective value of an outcome as the time until its occurrence increases, and *probability discounting* is defined as the decrease in subjective value as the likelihood of an occurrence decreases (Rachlin, Raineri, & Cross, 1991). Discounting theory argues that people do not make choices between the objective values of outcomes but rather between the subjective values of outcomes, and that they choose the outcome with the higher subjective value.

Many economists and others who study intertemporal and risky choice have proposed that preferences are relatively stable across different contexts and time. A leading model of decision making was an exponential discount function (Samuelson, 1937):

$$V = Ae^{-bX}, \tag{1}$$

where V is the subjective value of a future (or probabilistic) reward, A is the objective amount, b is the discounting rate parameter, and X is either the delay (for delay discounting) or odds-against receipt of a reward (for probability discounting). Note that for probability discounting the odds against receipt of a reward equals $(1-p)/p$, where p is the probability of reward. The exponential model assumes that, for intertemporal choices, preference should remain constant across time. Some researchers, however, have challenged the view that preferences are stable.

Rachlin and Green (1972) presented pigeons with choices between a 2-sec presentation of food available after a relatively short delay, and a 4-sec presentation of food available after a longer delay. When both outcomes were relatively distant in time (e.g., a delay of 10 and 14 sec, respectively), each pigeon overwhelmingly preferred the larger, later reward. As the delay to both rewards decreased (e.g., to 2 and 6-sec delays, respectively), each pigeon's preference reversed to the smaller, sooner reward (see also Ainslie & Herrnstein, 1981; Green, Fisher, Perlow, & Sherman, 1981). As with pigeons, humans also show reversals in preference (Green, Fristoe, & Myerson, 1994; Holt, Green, Myerson, & Estle, 2008). Students who decide during the week to study for an upcoming test over the weekend may reverse their preference Friday night, choosing instead to go out with friends. Preference reversals occur because the subjective value of the smaller reward increases more rapidly than that of the larger reward as the delay to both is reduced.

To account for preference reversals, alternatives to the exponential function have been proposed. A hyperboloid function has been shown to provide a superior and more theoretically consistent description of both intertemporal and probabilistic choice (Green, Myerson, & Ostaszewski, 1999a; Rachlin et al., 1991):

$$V = A/\,(1 + bX)^{s}, \qquad (2)$$

where V, A, X, and b are the same as in Equation 1. In delay discounting, s is a free parameter that accounts for the nonlinear scaling of amount and delay, and determines how quickly the tail of the discounting function asymptotes. In probability discounting, it is assumed that the s parameter corresponds to a decision weight, similar to what Kahneman and Tversky (1979) proposed in prospect theory (Myerson, Green, & Morris, 2011).

1.1.1 Delay and Probability Discounting as Distinct Processes. The hyperboloid function describes both intertemporal and risky decision making well, which makes the discounting framework an appealing means by which to study choice and, specifically, to examine the relation between delayed and probabilistic choice. One issue within the discounting literature, and more broadly within the fields of decision making and behavioral ecology, has been whether delay and probability involve the same underlying processes and, in particular, whether they both are forms of impulsivity (Benzion, Rapoport, & Yagil, 1989; Prelec & Loewenstein, 1991; Rachlin et al., 1991). The behaviors of 'acting without foresight', 'seeking immediate gratification', and 'taking risks' all might be considered impulsive. Rachlin et al. suggested that delay discounting is the fundamental process and that probability merely is a function of the wait time until a win during repeated gambles. In contrast, others (e.g., Green &

Myerson, 1996) have argued that probability discounting is the more fundamental process because there is a greater implicit risk of not receiving an outcome with longer delays than with immediate or shorter delays.

According to either perspective, a single process is thought to underlie both delay and probability discounting. The parallelism between intertemporal and risky decision making has been discussed for years in the behavioral economics literature (e.g., Mischel & Grusec, 1967; Quiggin & Horowitz, 1995). Prelec and Loewenstein (1991) point out the corresponding violations of rational decision making theories in intertemporal and risky choice. For example, people tend to value certain outcomes disproportionally more in comparison to probabilistic outcomes (termed the *certainty effect*) and value immediate outcomes disproportionally more in comparison to delayed outcomes (termed the *immediacy effect*).

One advantage of the discounting framework is that the use of parallel procedures and analyses allows for unconfounded comparisons of delay and probability discounting. Despite the appearance of a single process, evidence from the discounting literature suggests that delayed and probabilistic choice are fundamentally different processes. If the same underlying process were responsible for both delay and probability discounting, then a strong negative correlation between the degree of delay and probability discounting would be expected. A person who is unable to wait for a reward (a high degree of delay discounting) should also be more risk-taking (a low degree of probability discounting). Contrary to this expectation, the correlation between degree of delay and probability discounting are often weak and typically positive (Estle, Green, Myerson, & Holt, 2006; Holt, Green, & Myerson, 2003; Mitchell, 1999; Mitchell & Wilson, 2010).

Similarly, if the same underlying process underlies delay and probability discounting, then any manipulation should affect delayed and probabilistic choice in similar ways. In contrast, most variables (e.g., inflation: Ostaszewski, Green, & Myerson, 1998; smoking cessation: Yi & Landes, 2012) have been shown to affect delay and probability discounting in different ways. The most well-studied of these differences is the opposite effect that amount of reward has on the degree of delay and probability discounting. Larger delayed rewards are discounted proportionally less steeply than smaller delayed rewards (*the magnitude effect*). At a delay of 12 months, Raineri and Rachlin (1993) found that a $10,000 reward was subjectively worth approximately 75% of its nominal amount. By contrast, at the same delay a $100 reward was subjectively worth only 58% of its nominal value: The $100 was discounted more steeply (i.e., it lost subjective value more quickly) than the $10,000 reward. In contrast to delay, larger probabilistic rewards are discounted <u>more steeply</u> than smaller probabilistic rewards (*the reverse magnitude effect*). Green et al. (1999) found that when the chance of receiving a reward was 70%, $200 decreased to 54% of its nominal value, $5,000 decreased to 45%, and $100,000 reward decreased to 36%. Interestingly, Green, Myerson, Oliveira, and Chang (2013) also found that the degree of discounting of delayed rewards generally decreases as the amount increases but the degree of discounting leveled off around $50,000. No such asymptote was observed with probability discounting, even when reward amounts were as large as $10 million (Myerson et al., 2011).

Reward amount also differentially affects the parameters of the hyperboloid function (Eq. 2) for delay and probability discounting (Estle et al., 2006; Green et al., 2013; Myerson et al., 2011). For delay discounting, the discounting rate parameter, b, decreases as the reward amount increases, whereas the exponent, s, does not systematically vary with amount. In contrast, for probability discounting, b does not systematically vary with amount, whereas s

increases as reward amount increases. If delay and probability involved the same underlying process, then it would be expected that amount would affect them in similar ways. The finding that amount affects both the degree of discounting and the behavior of the parameters in different ways is strong evidence that delay and probability involve at least some distinct and separate processes (for a review, see Green & Myerson, 2013).

1.1.2 Comparison of Choice Between Gains and Between Losses. The discounting framework also allows an evaluation of choice for gains and for losses using the same procedures and analyses. Although the vast majority of discounting experiments have examined rewards (gains), many of the choices people make involve delayed or probabilistic losses. For example, when deciding to buy insurance, people are faced with the decision either to pay an immediate cost for an insurance premium or to risk the possibility of paying a larger bill in the future. Just as preference reversals occur with delayed gains, so too, preference reversals occur when a common delay is added to a smaller, sooner and a larger, later loss (Holt et al., 2008), and decision making involving delayed and probabilistic losses is well-described by a hyperboloid function (Estle et al., 2006; Ostaszewski & Karzel, 2002).

One difference in how people make choices that involve gains and choices that involve losses is the g*ain-loss asymmetry* (sometimes referred to as the *sign effect*). When amount and commodity are held constant, both delayed and probabilistic gains are discounted more steeply than delayed and probabilistic losses, respectively (Benzion et al., 1989; Estle et al., 2006; Kahneman & Tversky, 1979; Thaler, 1981). That is, a given amount of a gain (e.g., receiving $100) will lose subjective value more rapidly as it is delayed in time (or made less certain) than would an equivalent amount of a loss (i.e., having to pay $100). With regard to probability, this finding is consistent with another model of decision making, prospect theory, which predicts that people are risk-averse in the domain of gains, but risk-seeking with potential losses (Kahneman & Tversky, 1979).

Although amount has opposite effects on the degree to which delayed and probabilistic gains are discounted, amount has little or no systematic effect on the discounting of either delayed or probabilistic losses (Estle et al., 2006; Holt et al., 2008; McKerchar, Pickford, & Robertson, 2013; Mitchell & Wilson, 2010; Ostaszewski & Karzel, 2002; Yi & Landes, 2012). Across a wide range of amounts, Green, Myerson, Oliveira, and Chang (2014) found that for both delayed and probabilistic losses, the degree of discounting and the value of the free parameters in the hyperboloid function did not vary systematically as a function of amount. Recently, Myerson, Baumann, and Green (in press) also found that, at least for delayed losses, individual differences in discounting may not only vary quantitatively but may vary qualitatively. Although most people tended to choose the larger, later loss as the delay increases (what Myerson et al. termed "loss-averse"), there is a group of people who actually become more likely to choose the immediate loss as the delay to the larger loss increased. These "debt-averse" individuals also showed more self-control with gains: They were more likely to choose the larger, delayed reward than were other participants. The presence of debt-averse individuals suggests that much research still is needed in order to understand how individuals make choices involving losses.

1.2 Discounting and Impulsivity

The study of discounting not only is important from a theoretical standpoint; many researchers have pointed to its relation with impulsivity disorders. Cigarette smokers (Mitchell, 1999), alcoholics (Petry, 2001), and opium addicts (Kirby, Petry, & Bickel, 1999) all discount delayed rewards more steeply than controls, implying that addicts behave more impulsively than non-addicts (for a review of delay discounting and addictions, see MacKillop et al., 2011). Furthermore, substance abusers discount their drug of addiction more steeply than monetary rewards (Madden, Petry, Badger, & Bickel, 1997). Discounting also is related to non-drug impulsive behaviors like disordered eating (Manwaring, Green, Myerson, Strube, & Wilfley, 2011; Rasmussen, Lawyer, & Reilly, 2010) and gambling (Petry & Madden, 2010). Interestingly, there is some evidence that degree of discounting is a predictor of later self-control problems (Audrain-McGovern et al., 2009; Carroll, Anker, Mach, Newman, & Perry, 2010; Yoon et al., 2007). The strong relation between degree of discounting and impulse-control problems adds support for the argument that discounting may be an underlying trait reflecting an individual's degree of 'impulsivity' (Odum, 2011).

1.3 Discounting and Aging

One understudied area within the discounting framework is how decision making, including self-controlled and impulsive choice, varies across the lifespan. Of direct relevance to the current proposal is whether the same model of decision making can account for choice across age groups and whether young and older adults discount outcomes at similar or dissimilar rates. Why might decision making change across the lifespan? One prominent view is that because cortical brain structures develop and deteriorate across the lifespan, behavior also would change. Various regions of the brain appear to be related to discounting (Scheres, de Water, & Mies, 2013). Regions of prefrontal cortex (e.g., dlPFC, OFC, mPFC) appear to be of particular importance in intertemporal choices (Kable & Glimcher, 2007; McClure, Laibson, Loewenstein, & Cohen, 2004). Indeed, the frontal cortex is one of the last brain regions to become fully developed during adolescence yet is among the first to show impairment in older adults (Casey, Giedd, & Thomas, 2000; Daigneault, Braun, & Whitaker, 1992; Raz et al., 1997).

In addition to cortical brain changes, people encounter different life and learning experiences throughout the lifespan. During development, from childhood through adolescence, children undergo many environmental changes (e.g., school, first jobs, etc.) that tend to encourage self-control and discourage impulsive choice, yet they also encounter many risky situations for the first time (e.g., learning to drive, experience with drugs, etc.). As people age through mid-life and older adulthood, experience with delayed and probabilistic outcomes increases (Samanez-Larkin et al., 2011). Indeed, Romer, Duckworth, Sznitman, and Park (2010) found that individual differences in self-control could not be completely explained by changes in brain structure, and that life experiences contribute to self-controlled and impulsive decision making.

1.3.1 Impulsivity and Risk-taking in Children and Adolescents. Most research on impulsive and risky decision making across the lifespan has focused on childhood and adolescence. Both Scheres et al. (2006) and Olson, Hooper, Collins, and Luciana (2007) found that younger children tended to discount delayed rewards more steeply than adolescents, consistent with the hypothesis that self-control develops during these years as prefrontal regions of the brain fully mature (Casey et al., 2000). Interestingly, de Water, Cillessen, and Scheres (2014) and Whelan and McHugh (2009) found that young adults tended to discount delayed rewards less steeply than did adolescents, suggesting a continuation of the development of self-control beyond typical brain development correlated with these processes.

In contrast, risky decision making appears to change very little or not at all as children develop into adolescence and early adulthood (de Water et al., 2014; Olson et al., 2007; Rakow & Rahim, 2010; Scheres et al., 2006). However, Rakow and Rahim noted that small but significant differences in risky choice were observed when comparisons were made between very young children (e.g., 5 and 6 years old) and young adults (e.g., 21 years old). In addition, although not significant, de Water et al. found that young adults (e.g., 18-27 years) consistently chose the risky option less often than did adolescents (e.g., 12-17 years). These findings suggest that risky decision making may have a different developmental trajectory than delayed choice, and that differences may continue to be observed when comparisons are made between younger and older adults.

1.3.2 Delayed Choice by Older Adults. The findings that self-controlled choice develops throughout childhood and adolescence are consistent both with theories of frontal cortical development and with environmental changes that occur during this time. However, it also must be emphasized that environmental and brain structures change throughout the lifespan, not only during early development. Discounting has been examined to a far lesser extent in the latter part of the lifespan. Nonetheless, a few studies have found that older adults tend to discount delayed rewards less steeply than do younger adults, suggesting self-control continues to change as one ages (Green, Fry, & Myerson, 1994; Harrison, Lau, & Williams, 2002; Jimura et al., 2011; Whelan & McHugh, 2009).

The lower rates of discounting observed in older adults could not be accounted for by the fact that as one ages, the same amount of time represents a smaller and smaller percentage of one's life. A 20-year old adult, for example, might substantially discount a reward that is delayed five years because five years is equal to a quarter of one's life; in contrast, a 70-year old adult might discount the same reward less steeply because five years is a relatively smaller percentage of one's life. Green, Myerson, and Ostaszewski (1999b), however, found that when comparing the subjective value of a reward at a delay equal to approximately 10% of one's life (i.e., 1 year in children, 2 years in young adults, and 7 years in older adults), discounting still was steepest for children and shallowest for older adults. Importantly, the hyperboloid function (Eq. 2) provided a good description of delay discounting across all age groups, and all age groups showed a magnitude effect such that larger delayed amounts were discounted less steeply than smaller amounts (Green, Fry, et al., 1994; Green, Myerson, Lichtman, Rosen, & Fry, 1996; Whelan & McHugh, 2009). The results from these early studies suggest that although there are quantitative differences in decision making across the lifespan, decision making might not be fundamentally different as people age.

Although a few studies have compared delay discounting of gains in young and older adults, a systematic evaluation is warranted. Of the experiments that have evaluated discounting in older adults, only one or two amounts were studied. However, interesting effects have been observed in young adults when a wider range of amounts was examined. Young adults, for example, show a clear magnitude effect with small reward amounts, but their degree of discounting tends to level off at larger amounts (Estle et al., 2006; Green et al., 2013). Although a few studies have evaluated the parameters of the hyperboloid in older adults (Green et al., 1999b; Whelan & McHugh, 2009), none has systematically evaluated their behavior across a range of amounts. Green et al. (1999b) found with amounts of $1,000 and $10,000, that the *s* parameter generally was larger than 1.0 in older adults, but not in young adults; however, other studies have not replicated this result (Jimura et al., 2011; Whelan & McHugh, 2009). In young adults, the parameter *s* has been shown to change unsystematically with amount whereas the parameter *b* tends to decrease with amount until it eventually levels off. The relatively few amounts studied in older adults, and the different delays used across studies, makes a conclusion about these effects in older adults difficult. Furthermore, there is evidence that some of the observed age effects might have been driven exclusively by effects of income (e.g., Green et al., 1996; Westbrook, Kester, & Braver, 2013).

Research on choice involving delayed losses across the lifespan is even more limited than that with delayed gains. Both Löckenhoff, O'Donoghue, and Dunning (2011) and Halfmann, Hedgcock, and Denburg (2013) examined discounting of delayed losses across different age groups, and found that degree of discounting did not significantly vary as a function of age. However, in both studies, very small amounts and delays were used. The largest delay used in Löckenhoff et al. (2011) and Halfmann et al. (2013) was 6 months and 1 month, respectively, and the largest amount of the delayed loss used was $8 and $72, respectively. Differences in the discounting of losses across age groups might not become apparent until much longer delays and wider range of amounts are examined.

Furthermore, recall that Myerson et al. (in press) found that some individuals were debt-averse, rather than loss-averse, and that debt-averse individuals also tended to discount delayed gains less steeply. If older adults do discount delayed rewards less steeply than younger adults (e.g., Green, Fry, et al., 1994), then there also might be a higher proportion of debt-averse individuals in an older adult population. Löckenhoff et al. (2011) evaluated anticipated valence when having to make a delayed payment. Interestingly, whereas for young adults a loss increased in its degree of positivity as it was delayed, delaying a loss had little effect on affective valuation in middle-aged or older adults. Outside of discounting, there is some evidence that as people age, their motivation switches more from accruing gains to that of preventing losses (Depping & Freund, 2012), suggesting that older adults might be more willing than young adults to choose smaller, immediate losses (i.e., discount less steeply) when longer delays are evaluated, and that age differences in the loss domain might be more pronounced than they are in the gain domain.

1.3.3 Probabilistic Choice and Risk-taking in Older Adults. Few studies have examined probability discounting of gains and losses in older adults. Rather than examining how people value outcomes as a function of the odds of their receipt, researchers have focused on how older adults assess risk. Deakin, Aitken, Robbins, and Sahakian (2004), for example, found that older adults tended to bet a smaller amount of their allotted points than did younger adults and, moreover, were less likely to adjust their level of risk-taking as the likelihood of winning changed. Other work, however, has reported that older and younger adults make similar risky decisions (Dror, Katona, & Mungur, 1998; Zamarian, Sinz, Bonatti, Gamboz, & Delazer, 2008). Much of this work confounds gains and losses rather than examining them separately, so it is difficult to understand how gains and losses separately are evaluated. Mather et al. (2012), who did examine gains and losses separately, found that older adults were more likely than younger adults to choose a sure gain but also were more likely to take a risk in order to potentially avoid a sure loss. If motivation switches from accruing gains to preventing losses as one ages (Depping & Freund, 2012), then older adults might be much more risk-seeking than young adults in the domain of losses. In contrast, Jarmolowicz, Bickel, Carter, Franck, and Mueller (2012), who also evaluated discounting of probabilistic gains, reported no correlation between age and probability discounting rate. The sample Jarmolowicz et al. recruited, however, appeared to be overwhelmingly middle adult (median age = 28 years; interquartile range: 21 to 35 years), and it is not clear whether a similar relation would be observed when older adults are evaluated.

In addition to examining risk behavior, another important consideration is whether how a decision is made remains the same or changes across the lifespan. That is, does the same model account for decision making across domain and age? To date, there has been no assessment of the hyperboloid discounting model (Eq. 2) on older adults' probabilistic choices, and there is some evidence to suggest that different processes are involved when older and young adults make probabilistic choices. Wood, Busemeyer, Koling, Cox, and Davis (2005) argued that there were differences in how older and young adults weighted gains and losses, suggesting different ways in which they arrived at a choice. Both age groups were successful at learning the Iowa Gambling task, but each used a different strategy. Specifically, older adults were better at calculating expected payoff whereas younger adults were more biased by a negative outcome. Mata and Hertwig (2011) theorized that there might be age differences in the value function (Kahneman & Tversky, 1979) and that this accounts for differences in risky choice across age groups. It remains to be seen whether the hyperboloid function, which has been robustly shown to account for choice of both probabilistic gains and probabilistic losses in younger adults (Estle et al., 2006), accounts for such choices in older adults, and whether there are systematic changes in how probabilistic choices are made across the lifespan.

1.4 Complex, Multi-attribute Decision Making

Although it is important to understand how different processes affect the value of an outcome, many real-life choices are more complex and involve outcomes that are both uncertain and delayed in time. If one makes a financial investment, there is the possibility, but not the guarantee, that it will pay off in the future. Similarly, if one chooses to smoke cigarettes now, there is a chance of getting cancer later on. Although discounting research has provided ample understanding of how delay and probability separately affect choice, it is not immediately obvious how these two processes might combine to affect choice.

Killeen (2009) argued that the subjective value of an outcome is derived by adding the utility (e.g., amount) and the disutility (e.g., delay). Although Killeen did not specifically address discounting involving both delayed and probabilistic rewards, his theory nonetheless would imply that the disutility from both the delay and the odds-against receipt would be subtracted from the utility of the reward amount to affect the subjective value of an outcome. An additive model of the discounting of delayed and probabilistic rewards assumes that the subjective value of such rewards equals the actual amount of the reward, A, minus the subjective value lost as a function of the delay, f(D), and the subjective value lost as a function of the odds against, g(θ):

$$V = A - f(D) - g(\theta). \tag{3}$$

According to the hyperboloid discounting model, the amount by which the value of the reward is to be decreased based on the delay is equal to $f(D) = A[1 - 1/(1 + kD)^{S_d}]$, where D is the delay to a reward, k is the discounting rate parameter, and s^d the nonlinear scaling parameter for delay discounting. The amount by which it is to be decreased based on the odds against is $g(\theta) = A[1 - 1/(1 + h\theta)^{S_p}]$, where θ is the odds-against receipt of the reward, h is the discounting rate parameter, and s^p is the nonlinear scaling parameter for probability discounting. Substituting for $f(D)$ and $g(\theta)$ in Equation 3 yields:

$$V = A - A\left[1 - \frac{1}{(1 + kD)^{S_d}}\right] - A\left[1 - \frac{1}{(1 + h\theta)^{S_p}}\right].$$

Alternatively, other models of choice have suggested a multiplicative combination of value and disutility (Ho, Mobini, Chiang, Bradshaw, & Szabadi, 1999; Kahneman & Tversky, 1979). A multiplicative model of discounting suggests that subjective value is affected by the interaction between the effects of delay and the effects of probability:

$$V = A[(1 + kD)^{S_D} \times (1 + h\theta)^{S_p}]. \tag{4}$$

Vanderveldt, Green, and Myerson (2015) systematically varied both delay and probability in a combined discounting procedure. They found that delay and probability interacted, and that

Equation 4 fit the data very well. Furthermore, they also found that probability appeared to have a greater effect than delay. When a simple hyperboloid (Eq. 2) was fit to the data as a function of odds-against, it provided consistently better fits than when a simple hyperboloid was fit as a function of delay. In addition, a reverse magnitude effect with probabilistic rewards, in which larger rewards are discounted more steeply than smaller rewards, was more consistently found than a magnitude effect with delayed rewards, in which smaller rewards are discounted more steeply than larger rewards. These two findings suggested that when outcomes are both delayed and probabilistic, individuals generally become more risk-averse (i.e., discount probabilistic rewards more) and more patient (i.e., discount delayed rewards less). However, the finding that probability exerts a stronger influence than delay might have been partially due to the subjective inequality between the delays and probabilities used (e.g., a delay of 5 years might not be subjectively the same as a 10% probability of receipt). If, instead, values are used in which delay and probability are more subjectively equal, probability may no longer have such an overwhelming effect over delay.

As noted previously, several studies have used delay and probability discounting procedures as a measure of impulsivity both to identify clinical disorders and to predict success in treatment programs for clients with impulse-control disorders, such as drug or gambling addiction (e.g., see Yoon et al., 2007, for predicting postpartum smoking relapse). This line of research has primarily focused on the separate effects of delay and probability, but many real-world situations involve outcomes that are both delayed and probabilistic. It is unclear whether the degree to which an individual discounts a delayed or a probabilistic reward when evaluated separately differs from how a delayed or probabilistic reward is evaluated when they are combined. That is, how one discounts a reward that is both delayed and probabilistic might not be predictable from how one discounts a delayed reward and a probabilistic reward when evaluated separately. Research evaluating delay and probability discounting as a measure of impulsivity may overlook important differences about the relative degree of discounting when these effects are assessed simultaneously. The current experiment will determine whether standard delay and probability discounting tasks assessed separately can predict behavior on a discounting task in which the rewards are both delayed and probabilistic.

As discussed previously, older and younger adults might differ when delay and probability discounting are examined separately. In delay discounting, older adults likely discount delayed rewards less steeply than younger adults and, although there is not as much known about probability discounting in older adults, some research suggests that older and younger adults make risky choices differently (Mather et al., 2012) and that there might be age-related differences in the value function (Mata & Hertwig, 2011). If older and younger adults make different choices when outcomes are delayed and when outcomes are probabilistic, then they might weight the two dimensions differently when outcomes are both delayed and probabilistic.

1.4.1 Decision-Making Strategy and Aging. A multiplicative model is a complex way to combine dimensions of an outcome. Specifically, a multiplicative model argues that the effect that delay has on the subjective value varies depending on the odds against receiving the outcome, and that the effect of probability varies with the delay to the outcome. Although this effect was overwhelmingly found in a young adult sample (Vanderveldt et al., 2015), there is no reason to assume that such a complex decision-making model would be commonly used in an older adult sample. In the strategy literature, when faced with multi-attribute decisions, older adults tend to rely on simpler heuristics that are less cognitively demanding (Mata, Schooler, &

Rieskamp, 2007). For example, when presented with a multi-attribute choice task, two common strategies are take-the-best (TTB), in which one considers a single piece of information when making a decision, and the weighted additive rule (WADD), in which one considers and individually weights each piece of available information before making a decision. WADD is a compensatory strategy that requires more effort on the part of the decision maker, whereas TTB is a noncompensatory strategy that is less cognitively demanding.

In discounting, a multiplicative model may be more akin to a compensatory decision strategy, like WADD. In contrast, simpler discounting models, such as basing choice on only one attribute (e.g., amount, delay, or probability) or combining outcomes additively, may be more similar to a noncompensatory strategy, like TTB. In general, older adults are more likely to use noncompensatory strategies like TTB (Mata et al., 2007; Queen, Hess, Ennis, Dowd, & Grühn, 2012). In less complex environments (e.g., choice alternatives have few dimensions to consider) these strategies seem to work fine: Older and younger adults tend to make decisions of similar quality (e.g., similar expected value), despite relying on different strategies. However, as decisions become more complex, reliance on simpler strategies tends to lead to poorer quality decision making in older adults (Mata et al., 2007; Mata, von Helversen, & Rieskamp, 2010; Queen et al., 2012). In general, older adults appear to look up less information and base choices on a smaller number of dimensions (Mata et al., 2007; Queen et al., 2012; Riggle & Johnson, 1996). These findings have been replicated in a wide variety of contexts, including more ecologically valid settings such as in choosing a drug prescription plan (Hanoch, Wood, Barnes, Liu, & Rice, 2011) and evaluating political candidates (Riggle & Johnson, 1996). Findings from the strategy literature suggest that when faced with decisions in which outcomes vary in amount, delay, and probability, a multiplicative hyperboloid discounting function (Eq. 4) might not provide the best model of older adults' decision making. Simpler strategies in which outcomes combine additively (e.g., Eq. 3) or in which choice is based exclusively on one attribute are likely contenders for modeling decision making in older adults.

1.5 The Current Study

The current study extends the discounting framework to examine decision making in older adults. The research evaluated how older adults value delayed and probabilistic outcomes, whether their choices, like that of young adults, are well described by a hyperboloid discounting model, and whether fundamentally distinct processes underlie delay and probability discounting, as has been robustly observed with a young adult population.

Experiment 1 investigated discounting of delayed rewards and discounting of probabilistic rewards over a wide range of amounts. Examining behavior over a wide range of amounts allows for an assessment of the change in degree of discounting, as well as changes in the parameter values, *b* and *s*, of the hyperboloid model (Eq. 2), as a function of reward amount. As discussed previously, in delay discounting, *b* increases as amount of the reward increases, before eventually reaching asymptote. In contrast, *s* does not change systematically as a function of the amount of the delayed reward. It presently is unknown whether and how the parameters vary in an older adult population. Importantly, this experiment is the first to examine probability discounting in older adults.

Experiment 2 investigated delay and probability discounting of losses over a wide range of amounts. This experiment is the first to examine probabilistic losses in older adults and the first to examine delayed losses in older adults for large amounts and at longer delays.

Experiment 3 investigated the discounting of rewards that are both delayed and probabilistic. This experiment extends prior research by examining whether the multiplicative hyperboloid model (Eq. 4) describes choice well and whether probability affects choice to a greater extent than does delay when the values of the delays and probabilities used are more subjectively similar. In addition, this experiment tested whether standard delay and probability discounting tasks can predict behavior on a more complex decision making task in which outcomes are both delayed in time and uncertain to occur. Finally, the current experiment also is the first to assess choice in older adults in which both dimensions vary and assesses the fit of the multiplicative hyperboloid model (Eq. 4). If the model provides a good fit to older adults' choice behavior, such a finding suggests that a fundamental component is preserved in decision making throughout the lifespan. Alternatively, if another model provides a better fit (e.g., the additive hyperboloid model, Eq. 3), this suggests that older adults make multi-attribute decisions in qualitatively different ways from that of younger adults.

Chapter 2: Experiment 1

Delay and Probability Discounting of Gains

2.1 Method

2.1.1 Participants. Fifty young adult participants between the ages of 18 and 24 (mean age = 19.7; 30 Female, 20 Male) were recruited from the Washington University Department of Psychological and Brain Sciences Human Subjects Pool. Participants were tested individually in a small room with a computer and received either monetary compensation or course credit for their participation.

Fifty older adult participants over the age of 65 (mean age = 70.4; 31 Females, 19 Male) were recruited from the St. Louis community. In order to qualify to participate, older adults had to self-report no history of a neurological disorder and pass the Short Blessed Test, a screening test for dementia (Carpenter et al., 2011), with a score of less than 5. Participants were tested individually in a small room with a computer and received monetary compensation for their participation.

2.1.2 Materials and Procedure. Participants completed both a delay discounting and a probability discounting task in which they made a series of choices between two hypothetical monetary rewards. The order in which tasks were presented was counterbalanced across participants. Before the experimental trials for each task, participants received instructions and completed six practice trials consisting of two amounts and three delays/probabilities. The values used were similar, but not identical, to those used during the experimental trials.

In the delay-discounting task, participants made a series of choices between receiving an amount of money available immediately (e.g., $10 right now) and receiving a larger amount of money at a later time (e.g., $20 in 6 months). For this task, a six (amount: $20, $250, $3,000, $20,000, $50,000, $100,000) by five (delay: 1 month, 6 months, 1 year, 6 years, 12 years) within-subjects design was used. One amount was randomly selected (without replacement) and then all of the delay conditions were administered for that amount in random order.

For each amount-delay condition, participants made six choices. On the first choice, the amount of the smaller, immediate reward was half the amount of the larger, delayed reward (e.g., $1,500 in the $3,000 amount condition). For each subsequent choice in a condition, the amount of the smaller reward was adjusted based on the participant's previous choice (Du, Green, & Myerson, 2002). The size of each adjustment was half that of the preceding adjustment. For example, when the choice was between receiving $1,500 immediately and $3,000 in 6 years, if a participant chose the $1,500 immediately, then the amount of this reward was decreased to $750 on the next trial. If the participant instead chose the delayed $3,000, then the amount of the smaller reward was increased to $2,250. If the participant then chose $2,250 on the second trial, the amount of the smaller reward on the third trial was decreased to $1,875 (half of the previous adjustment). Subjective value was estimated as the amount of the smaller reward that would have been presented if there were an additional, seventh trial (Du et al., 2002). This titrating procedure converged on an immediate, certain amount of money that was approximately subjectively equivalent to the larger, delayed reward (i.e., the subjective value of the larger, delayed reward).

In the probability-discounting task, participants made a series of choices between receiving an amount of money available for certain (e.g., a 100% chance of $10) and receiving a larger amount of money that was probabilistic (e.g., a 40% chance of $20). For this task, a six (amount: $20, $250, $3,000, $20,000, $50,000, $100,000)[F1] by five (probability: 80%, 50%, 25%, 10%, 5%) within-subjects design was used. One amount was randomly selected (without replacement) and then all of the probability conditions were administered for that amount in random order. For each amount-probability condition, a titrating procedure identical to that used in the delay-discounting task was used to estimate the subjective value of each larger, probabilistic reward (i.e., the subjective value of the larger, probabilistic reward).

After completion of the delay discounting and probability-discounting tasks, participants completed a short demographic survey consisting of questions regarding education, income, and cigarette smoking status[F2].

2.2 Results

Figure 1 presents the group mean subjective values and best-fitting hyperboloid functions (Eq. 2) for young adults (left panels) and older adults (right panels). The top panels of Figure 1 show delay discounting for each of the six amounts and the best-fitting hyperboloid curves. The hyperboloid function (Eq. 2) described delay discounting of gains for each of the six amounts for both the young and older adults extremely well (all R^2s > .98; see Table 1).

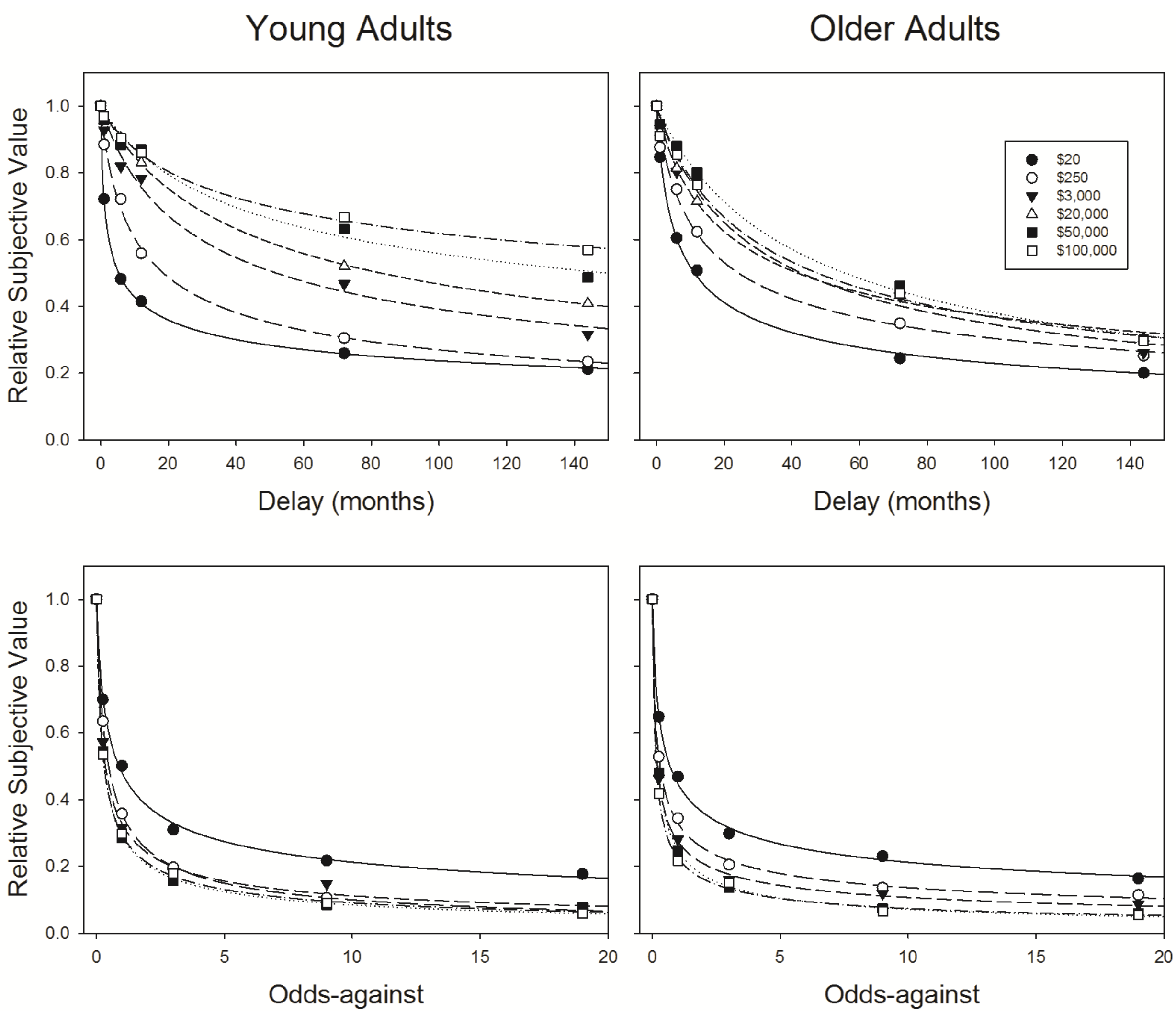

Figure 1. Mean relative subjective value for each of the six amounts and the best-fitting hyperboloid functions (Eq. 2) in young (left panels) and older (right panels) adults from Experiment 1. The top panels show delay discounting at each reward amount, and the bottom panels show probability discounting at each reward amount.

Table 1. Parameter estimates and proportion of variance (R^2) accounted for by Equation 2 as a function of delay (left panel) and as function of odds-against (right panel) for young and older adults in Experiment 1.

	Delay Discounting							Probability Discounting				
	\$20	\$250	\$3,000	\$20,000	\$50,000	\$100,000		\$20	\$250	\$3,000	\$50,000	\$100,000
Older Adults												
b	0.454	0.205	0.059	0.115	0.033	0.059	*b*	9.893	15.885	21.341	10.889	19.556
s	0.384	0.388	0.552	0.395	0.660	0.518	*s*	0.337	0.393	0.416	0.561	0.493
R^2	0.998	0.992	0.986	0.995	0.996	0.990	R^2	0.998	0.999	0.999	0.999	0.999
Young Adults												
b	2.485	0.247	0.073	0.043	0.054	0.096	*b*	6.046	4.551	8.998	8.004	8.789
s	0.261	0.403	0.443	0.456	0.315	0.203	*s*	0.376	0.600	0.485	0.562	0.534
R^2	0.999	0.996	0.988	0.998	0.986	0.997	R^2	0.998	0.999	0.998	0.999	0.999

The bottom panels of Figure 1 show probability discounting for each of the five amounts and the best-fitting hyperboloid curves as a function of odds-against receipt of reward (θ; $\theta = p/(1-p)$). As with delay discounting, the hyperboloid provided excellent fits of probability discounting for each of the five amounts for both the young and older adult groups (all R^2s > .98; see Table 1).

Statistical tests were performed on the area under the curve (AuC) measures calculated separately for each condition. The AuC provides a theoretically neutral measure of the degree of discounting because it does not assume a particular mathematical form for the discounting function (Myerson, Green, & Warusawitharana, 2001). To calculate the AuC, indifference points are converted into proportions of the delayed or probabilistic amounts (e.g., \$20, \$250, etc.) and delays and odds against are converted into proportions of the longest delay or highest odds against examined. As a result of this normalization, AuC can range from 1.0, indicating no discounting relative to the actual amount, to 0.0, indicating complete discounting.

A 6 (delayed amount) x 2 (age) ANOVA on the delay discounting AuCs revealed a significant effect of amount, $F(5,94) = 32.50$, $p < .001$, $\eta_p^2 = .63$ but no significant age difference ($F(1,98) = 2.63$, $p = .11$). For each individual, I calculated the correlation between their delay discounting AuC and the logarithm of the delayed amounts. The logarithm of amount was used because of the large range of amounts in the present study. Individuals tended to show strong positive correlations between AuC and log amount, with an average correlation (back-transformed from the mean Fisher *z*) of .830 for young adults and .612 for older adults. Furthermore, the 95% confidence interval around the mean Fisher *z* did not include zero for both young adults (95% CI [.754, .883]) and older adults (95% CI [.478, .724]), indicating that the correlation was significant.

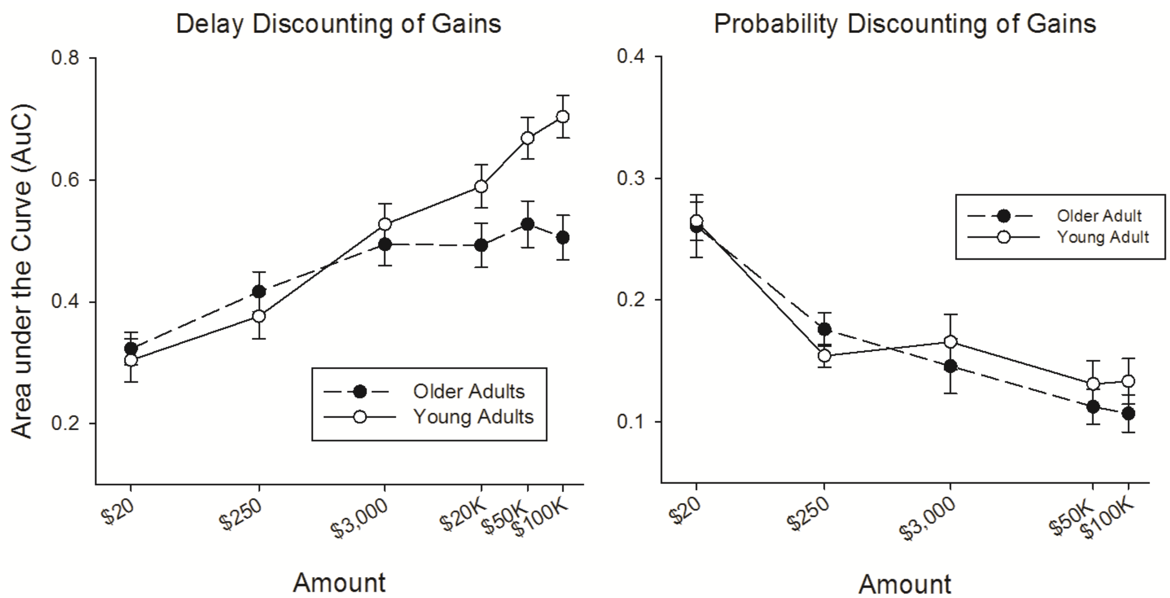

Figure 2. Mean area under the curve (AuC) and standard errors for each of the six reward amounts for delay discounting (left panel) and each of the five reward amounts for probability discounting (right panel) from Experiment 1. The closed circles show the AuC for older adults and the open circles show the AuC for older adults. Note the different scales on the y-axes and the logarithmic scaling of amount on the x-axes.

Although there was no significant age difference, there was a significant age x amount interaction, $F(5, 94) = 5.75$, $p < .001$, $\eta_p^2 = .234$. The left panel of Figure 2 presents the group mean AuCs for each delay discounting amount, and inspection of this figure suggests that the exact pattern of discounting across amounts varies between age groups. For the young adult group, there was a strong positive linear relation between the mean delay discounting AuC and log amount ($F(1,4) = 237.97$, $p < .001$) that was not significantly improved by a quadratic model ($p = .20$). In older adults, however, a quadratic trend provided a significantly better description of the relation between mean AuC and amount ($R^2 = .98$; $F(1,3) = 11.58$, $p = .04$), reflecting the fact that although the size of the AuCs initially increased with amount, it levelled off at a delayed amount of $3,000.

The right panel of Figure 2 plots the mean AuC for each probability discounting amount condition for young and older adults. A 5 (probabilistic amount) x 2 (age) ANOVA on the probability discounting AuCs revealed a significant effect of amount, $F(4, 95) = 27.54$, $p < .001$, $\eta_p^2 = .54$. There was no significant difference between age groups ($p = .65$) and no age x amount interaction ($p = .24$). For each individual, I calculated the correlation between AuC and log amount. Individuals tended to show strong negative correlations between AuC and log amount, with an average correlation (back-transformed from the mean Fisher *z*) of -.747 for young adults and -.812 for older adults. Furthermore, the 95% confidence interval around the mean Fisher *z* did not include zero for both young adults (95% CI [-.830, -.633]) and older adults (95% CI [-.871, -.729]), indicating that the correlation was significant.

Whereas in delay discounting young and older adults showed a different relation between delay AuC and log amount, the right panel of Figure 2 suggests that young and older adults displayed a similar relation between probability AuC and log amount. Indeed, a linear trend between log amount and group mean was significant for the older adult group (R^2s = .95; $F(1,3) = 54.65$, $p > .001$) and marginally significant for the young adult group ($R^2 = .75$; $F(1,3) = 9.15$, $p = .057$), and these linear relations were not significantly improved by a quadratic model in either young or older adults (both ps > .12).

In order to determine whether delay and probability discounting are fundamentally distinct processes underlying impulsivity, I conducted a principle component analysis on the AuCs followed by a factor analysis with a varimax rotation. There were two significant components extracted. The first component (Eigenvalue = 4.32) accounted for 39.27% of the variance and, as may be seen in Table 2, all of the delayed amount conditions loaded strongly on the corresponding rotated factor whereas the probabilistic amount conditions loaded weakly. The second component (Eigenvalue = 3.33) accounted for 30.32% of the variance, and the corresponding rotated factor showed the opposite pattern of loadings (see Table 2). When principle component analyses were conducted separately for young and older adults, the same two components, representing a delay discounting factor and a probability discounting factor, emerged in each group. These results strongly suggest that distinct processes underlie delay and probability discounting and that this is true in both young and older adults.

Table 2. Principle component loadings (Varimax roation) for each delayed and probabilistic amount condition in Experiment 1.

	Component 1	Component 2
Delay Discounting		
$20	0.707	0.106
$250	0.833	0.042
$3,000	0.893	-0.044
$20,000	0.920	0.081
$50,000	0.869	0.083
$100,000	0.837	0.131
Probability Discounting		
$20	0.082	0.686
$250	0.034	0.747
$3,000	0.095	0.890
$50,000	0.008	0.892
$100,000	0.101	0.819

Note. Loadings that are less than .2 are shaded in grey.

2.2.1 Parameters. Given the evidence of strong effects of amount on the degree to which both the delayed and probabilistic gains were discounted, I next sought to determine the changes in the parameters that might correspond to these effects. Figure 3 shows the values of the *b* (top panels) and *s* (bottom panels) parameters of the hyperboloid functions that best described the group mean subjective values, plotted as a function of the logarithm of the amount of delayed gain (left panels) and probabilistic gain (right panels). The young adult groups' *b* parameter was well described by a quadratic model that captured the initial decrease and the subsequent levelling off of the *b* parameter as amount increased (R^2 = .99, $F(1,3)$ = 51.86, p = .006). Although a similar pattern appears to characterize the older adult group, only a linear decrease was significant (R^2 = .79; $F(1,4)$ = 14.62, p = .02). The bottom left panel of Figure 3 depicts the log of the *s* parameter across amounts for both groups and, as may be seen, there was little or no relation between amount and *s* (both *F*s(1,4) < 2.96, both *p*s < .16) . Although the pattern for young adults suggests an inverted-U, this impression appears to be primarily driven by the parameter estimate for the largest delayed amount. It is interesting to note, that a similar curved pattern appeared in Green et al. (2013), but the pattern ultimately emerged into a “W” shape when larger amounts also were examined (see Appendix A). The similarity of the *s* parameter in the current study to that of Green et al. suggests that *s* ultimately does not systematically increase or decrease with amount.

The right two panels of Figure 3 show the parameter changes across amount for probability discounting. The value of the *b* parameter was not significantly related to the amount of probabilistic gain for either young or older adults (both *F*s(1,3) < 3.20, $p > .17$). It should be noted, however, that the probability discounting data had one less amount condition, and thus fewer data points in which to examine the trend. Both the young and older adult groups show a slight positive relation between *s* and amount. For the older adult group, there was a significant positive linear relation between log *s* and log amount ($R^2 = .89$; $F(1,3) = .89$, $p = .02$); however, this trend was not significant in young adults ($F(1,3) = 1.64$, $p = .29$).

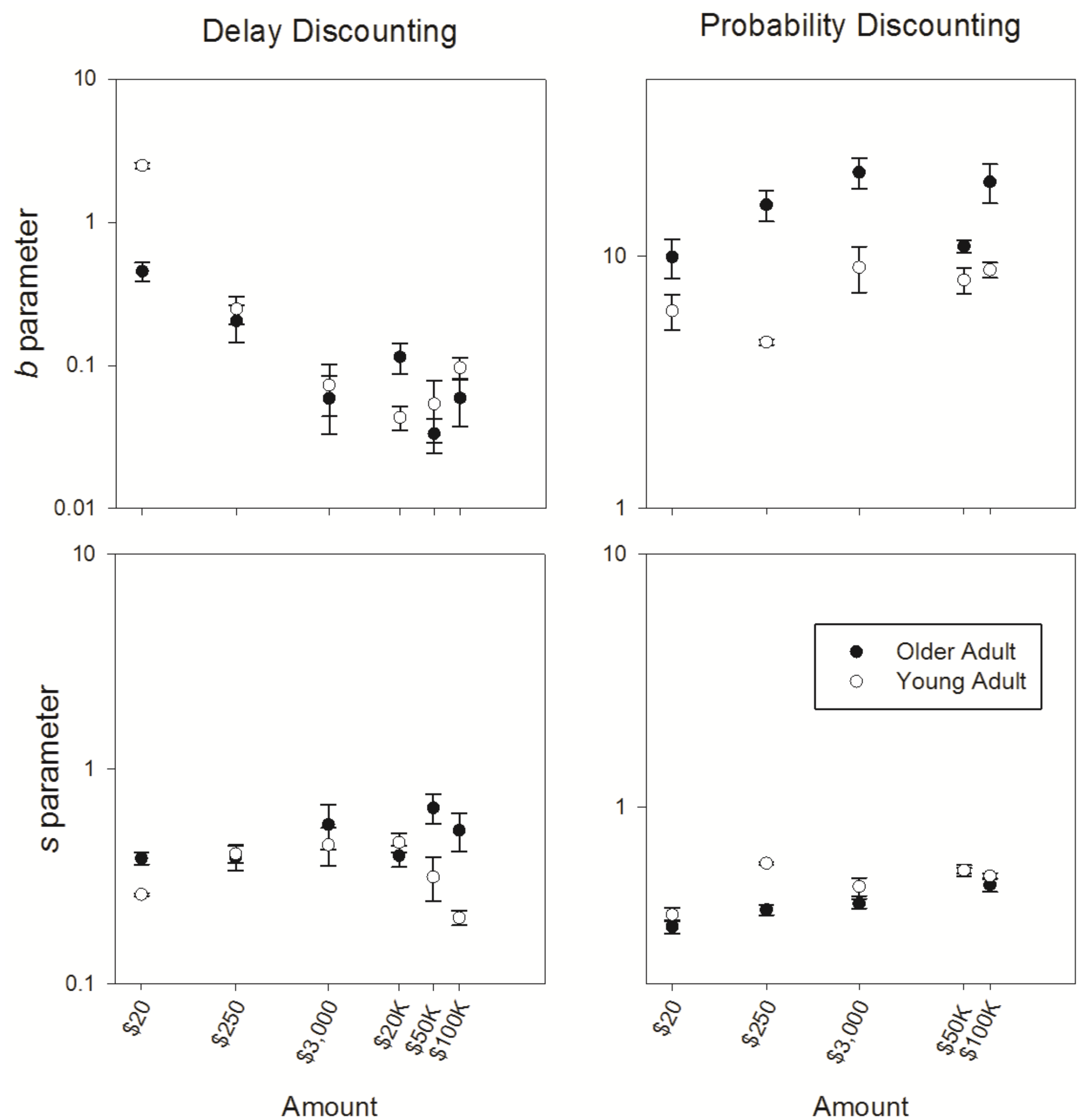

Figure 3. Mean value and the standard error for the *b* parameter (top panels) and the *s* parameter (bottom panels) when Equation 2 was fit as a function of delay (left panels) and as a function of odds-against (right panels) in Experiment 1. The closed circles show the parameter values for average older adult and the open circles show the parameter values for the average young adult.

2.2.2 Exploratory Analyses of the Effect of Income on Older Adults' Discounting. Although the self-reported income of the young adult sample was not sufficiently diverse (most Washington University undergraduates come from high-income households; Schoenberger, 2013), there was a sufficient range of reported income levels in the older adult sample. I sought to examine how income of older adults affected degree of discounting. Twelve older adult participants opted not to report their income level. This resulted in 14 individuals with a reported household income under $50,000, 15 individuals with a reported household income between $50,000 and $100,000, and 9 individuals with a reported household income greater than $100,000. Although there is not a significant effect of income for either delay nor probability discounting (both *p*s > .12), plotting the data shows evidence of trends that may not be significant due to low power. Recall that Figure 2 showed an interaction between age and amount on the degree of delay discounting, in which younger adults discounted more steeply than older adults at small amounts but this pattern reversed with larger amounts. Figure 4 shows that when the household income of older adults is considered, a more complex pattern emerges. Degree of discounting systematically decreases as income increases in older adults. Interestingly, all three income groups show a strong magnitude effect when increasing the amount from $20 to $250 and from $250 to $3,000, but the degree of discounting levels off for amounts $3,000 and greater. When the reported household income of young and older adults is comparable (i.e., income over $100,000), older adults discounted nominally less steeply at all but the largest two amounts, at which point there appeared to be no difference. Due to low number of older adults in this income bracket (*n* = 9), however, statistical comparisons of young and older adults at each amount could not be completed.

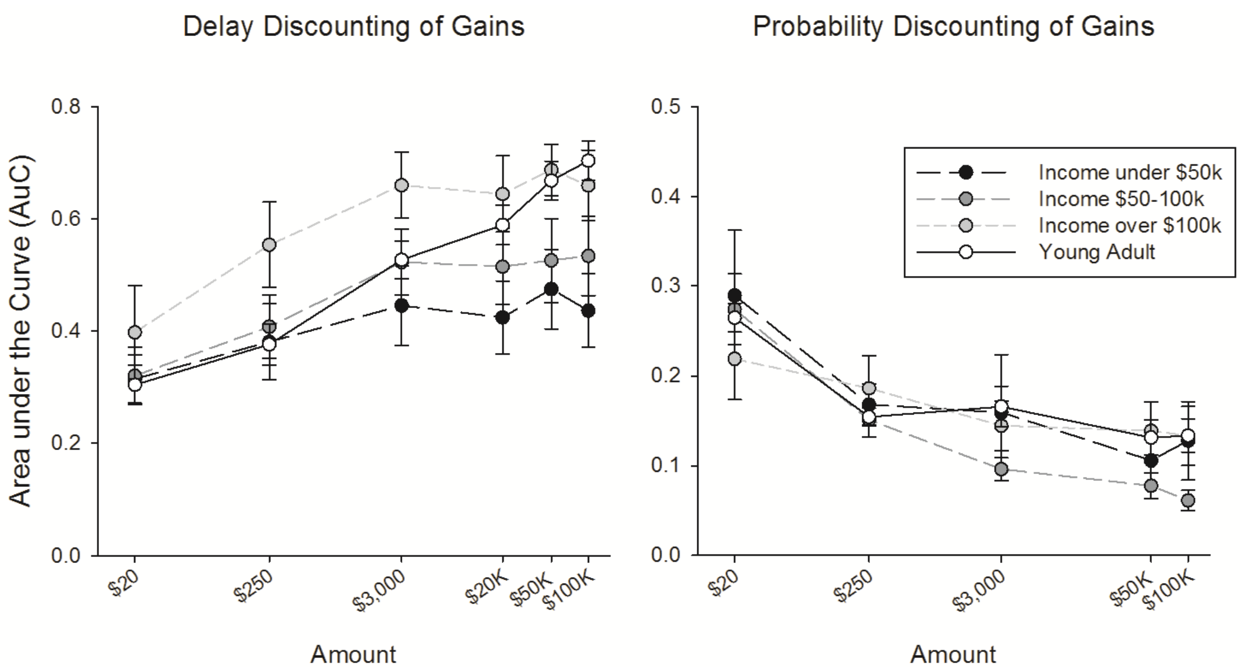

Figure 4. Mean area under the curve (AuC) and standard error at each amount for delay discounting (left panel) and probability discounting (right panels) by young adults (open circles) and each of the three older adult household income groups (closed circles) from Experiment 1. Note the different scales on the y-axes and the logarithmic scaling of amount on the x-axes.

Interestingly, for probability discounting, there appears to be no age difference and no effect of income on the degree of discounting (see right panel of Figure 4). Although the current data set is limited in the number of individuals at each income range and is lacking diverse income in the young adult sample, these exploratory analyses suggest income is a driving factor in delay, but not probability, discounting.

2.3 Discussion

Choice is a ubiquitous aspect of everyday life, but the types of decisions one faces varies widely and differ across groups. Older adults, for example, more frequently make decisions about saving throughout retirement, must weigh the risks of various health care plans, and make choices concerning their current health (e.g., compliance issues), whereas young adults are faced with a different set of decisions (e.g., whether to take a job or to delay earning more money by first obtaining a degree; whether to invest in purchasing a home or to pay a lower cost to rent; etc.). Despite the different types of decisions young and older adults may face, many of these decisions may be construed as related to issues of self-control and risk-taking. Importantly, the results of the current experiment suggest that young and older adults make intertemporal and risky decisions in fundamentally similar ways: Both young and older adults discounted delayed and probabilistic gains; for both age groups, amount reliably affected the degree of delay and probability discounting in different ways; and, the hyperboloid function provided a good model of decision making.

In spite of these strong similarities, age differences were expected. Regions of the brain associated with cognitive control (e.g., prefrontal cortex) are more likely to show structural decline (e.g., Raz et al., 1997), yet older adults also display greater emotional regulation, and both cognitive and emotional aspects appear to play a role in discounting (e.g., Kable & Glimcher, 2007; McClure et al., 2004). Indeed, in the current experiment some interesting differences in discounting did emerge between age groups. Green et al. (2013) found that young adults showed a reliable magnitude effect with delayed gains, such that larger amounts were discounted less steeply than smaller amounts (i.e., a positive relation between amount and AuC). Green et al. also observed that degree of discounting began to level off at larger amounts, such that there were negligible differences in degree of discounting as amount further increased. In the current study, young adults did not appear to show an asymptote in which amount no longer affected degree of discounting (see Figure 2). Unlike Green et al. where the largest amount examined was $10 million, the current study examined amounts ranging from $20 to $100,000. The asymptote (i.e., the lack of the relation between amount and discounting for larger amounts) observed by Green et al. becomes clearer when additional larger amounts are included. Indeed, when the data from the young adults in the current study are compared to those in Green et al. (see Appendix A), the degree of discounting is extremely similar, suggesting that an asymptote would become more apparent in young adults with additional amounts.

The current study is the first to observe that older adults show a similar pattern of discounting of delayed gains with amount. As can be seen in Figure 2, older adults showed a clear magnitude effect as amounts increased from $20 to $3,000, and that the degree of discounting did not substantially decreased with larger amounts. Interestingly, the asymptote appeared at smaller amounts than was observed with young adults. There was no significant difference in degree of discounting for any of the reward amounts between $3,000 and $100,000. All three income groups in older adults showed an asymptote at approximately the same amount (see Figure 4), suggesting this is a robust difference between young and older adults.

Previous studies that have compared young and older adults' discounting of delayed gains reported that older adults tended to discount delayed rewards less steeply than did young adults (e.g., Green, Fry, et al., 1994; Harrison et al., 2002; Jimura et al., 2011; Whelan & McHugh, 2009). Overall, the results of the current study replicated previous findings, but the relation between age and degree of discounting appears to be more complex than previously described. Young and older adults discounted delayed rewards at similar rates when the amount was small, but young adults discounted less steeply than older adults when the amount was larger. This effect was largely dependent on a second variable: Household income. The relative degree of discounting of young adults and older adults differed depending on the household income older adults reported (see Figure 4). Interestingly, when comparing young adults to older adults of comparable household income (i.e., household income over $100,000), older adults discounted nominally less steeply at all but the largest two amounts, at which point there were no discernable differences.

The current study replicated previous findings (Green et al., 1996; Westbrook et al., 2013) that found income to play a substantial role in delay discounting, but unlike previous studies, the current study found an effect of age above and beyond that of income. Green et al., for example, reported that upper-income young adults and upper-income older adults discounted delayed rewards at similar rates. One reason for why the results of the current study diverged from Green et al. might be the age range that comprised the young adult group. In the current study, young adult participants were between the ages of 18 and 24, with a mean age of approximately 20 years. In contrast, Green et al. recruited a young adult sample with a mean age of approximately 33 years. For many people, there are many significant life changes between the ages of 20 and 30, and some personality theories have argued that personality tends to become relatively stable by age 30 (Costa & McCrae, 1988). Indeed, when Whelan and McHugh (2009) compared delay discounting in three age groups (mean ages 14, 46, and 73), they found no difference between the two older groups. The results from the current study suggest that age does have an effect on discounting, even when controlling for income, and that future research should consider both age and income when evaluating delay discounting.

The finding that young adults discounted delayed rewards more steeply than older adults of comparable income, although consistent with prior research, contrasts with the socioemotional selectivity theory of aging (Carstensen, Issacowtiz, & Charles, 1999). Socioemotional selectivity theory argues that when time is perceived as more limited, goals shift from acquisition of knowledge (future-oriented goals) to emotion regulation (e.g., maximizing positive emotions; present-oriented goals). Because time horizons generally decrease with age (e.g., Löckenhoff &

Carstensen, 2004), socioemotional selectivity theory would predict that older adults would discount delayed gains *more* steeply than young adults. One explanation for the inconsistency of this prediction with the current results may be that older adults in the current experiment generally were in good health (all older adult participants had to pass a screening test for dementia) and most individuals were within five years of our minimum required age of 65 years (median age = 69). Lindbergh, Puente, Gray, MacKillop, and Miller (2014) found that older adults with mild cognitive impairment discounted delayed rewards significantly more steeply than healthy controls, suggesting that older adults with mild cognitive impairment may have a shorter period and thus place more value on present-oriented goals.

Whereas amount has little additional effect on the degree of delay discounting at larger amounts, Myerson et al. (2011) observed a consistent reverse magnitude effect (i.e., negative relation between amount and AuC) with probabilistic gains, even with amounts up to $10 million. The current study observed a negative linear relation between mean probability discounting AuC and log amount for both young and older adults and, furthermore, that this relation was not significantly improved by a quadratic model. It is of interest to note, however, that although older adults showed a clear reverse magnitude effect at all amounts, young adults did not. Young adults discounted $20 significantly less steeply than $250 and $3,000 (both *p*s < .001), but $250 and $3,000 were not significantly different from each other. Although not significant, young adults also discounted both $50,000 and $100,000 less steeply than the two moderate amounts ($250 and $3,000), whereas there was no difference in discounting between $50,000 and $100,000 (mean difference = .002). That is, young adults discounted $20 less steeply than the two moderate amounts ($250 and $3,000), which subsequently were discounted less steeply than the two largest amounts ($50,000 and $100,000).

In contrast to delay discounting, little prior research has directly measured probability discounting in both young and older adults. Mather et al. (2012) did compare choice for probabilistic gains and found that older adults were more likely than young adults to choose a certain gain (i.e., older adults were more risk-averse in the domain of gains) whereas Jarmolowicz et al. (2012) found no correlation between degree of probability discounting and age. The results of the current study are consistent with those of Jarmolowicz et al. in that there was no difference in probability discounting as a function of age. The results of the current study also are consistent with other studies that compared probabilistic choice in young children and adults (de Water et al., 2014; Olson et al., 2007; Rakow & Rahim, 2010; Scheres et al., 2006). When comparing young children, adolescents, and young adults, risky decision-making appears to change very little. Although the degree of probability discounting did not systematically differ between young and older adults, inspection of the parameter values, *b* and *s* (see Figure 3), suggest small, but reliable differences. Older adults generally showed larger values of *b* and marginally smaller values of *s* than young adults, suggesting that despite similar degrees of probability discounting, young and older adults may be making these decisions in different ways (see section 5.1 Future Directions for further discussion).

The current study also is the first to systematically evaluate different income brackets on probability discounting as a function of different amounts. As with age, there was no systematic difference across income groups. Jarmolowicz et al. (2012) reported no correlation between probability discounting and income when evaluating a limited range of incomes (median = $23,749; IQR: $6,999-$46,249) that are lower than that of the current study. The similar results from both studies suggests that income does not have any discernable effect on degree of probability discounting of gains.

The finding that both age and income have no systematic effect on the discounting of probabilistic gains is consistent with some work that finds several variables influence degree of delay discounting but do not influence degree of probability discounting (e.g., Estle, Green, Myerson, & Holt, 2007; Ostaszewski et al., 1998; Yi & Landes, 2012), suggesting that probability discounting is less sensitive than delay discounting to manipulations (see also Vanderveldt et al., 2015). The finding that age, income, and amount all affected delay and probability discounting in distinct ways also is further evidence that there are separate processes involved in the discounting of delayed and probabilistic rewards (Green & Myerson, 2013). If the same process was underlying both delay and probability discounting, then a strong negative correlation should be observed. The large number of amounts studied for both delay and probability discounting permitted the use of more advanced analyses in the current experiment. The principle components analyses revealed two distinct factors that corresponded to delay and probability. Importantly, the same two factors were observed for both young and older adults when analyzed separately. The current study is the first to empirically evaluate the relation between delayed and probabilistic choice in older adults, and the results suggest that delay and probability discounting remain distinct processes across different age groups.

Chapter 3: Experiment 2

Delay and Probability Discounting of Losses

The results of Experiment 1 found that a hyperboloid model described discounting of delayed and probabilistic gains in both young and older adults; however, age-related differences were observed in the degree of delay, but not probability, discounting of gains. Experiment 2 investigated whether similar age similarities and differences are observed in choices involving losses. There have been relatively few studies comparing discounting of losses in young and older adults, and most were limited in the values of the delays, probabilities, and amounts that were examined. As Experiment 1 demonstrated, age differences in the degree of discounting can change dramatically across amounts (see Figures 2 and 4) and delays (see Figure 1). Furthermore, some researchers have suggested that older adults may be more motivated than younger adults to prevent losses (Depping & Frued, 2012), and the positivity effect in older adults may lead to less attention to negative information (e.g., losses; Mather & Carstensen, 2005). Both of these findings suggest that age differences in discounting might be larger in the domain of losses. Experiment 2 investigated delay and probability discounting over a wide range of amounts, and is the first experiment to systematically study probabilistic losses in older adults and delayed losses in older adults for larger amounts and at longer delays.

3.1 Method

3.1.1 Participants. Fifty young adult participants between the ages of 18 and 30 (mean age = 21.1; 36 Female, 14 Male) were recruited from the Washington University Department of Psychological and Brain Sciences Human Subjects Pool. Participants were tested individually in a small room with a computer and received either monetary compensation or course credit for their participation.

Fifty older adult participants over the age of 65 (mean age = 70.1; 34 Females, 16 Male) were recruited from the St. Louis community. In order to qualify to participate, older adults had to self-report no history of a neurological disorder and pass the Short Blessed Test, a screening test for dementia (Carpenter et al., 2011), with a score of less than 5. Participants were tested individually in a small room with a computer and received monetary compensation for their participation.

3.1.2 Materials and Procedure. Participants completed both a delay discounting and a probability-discounting task using hypothetical payments (i.e., losses). The order in which the tasks was presented was counterbalanced across participants. Before the experimental trials for each task, participants received instructions and completed six practice trials consisting of two amounts and three delays/probabilities. The values used were similar, but not identical, to those used during the experimental trials.

In the delay-discounting task, participants made a series of choices between hypothetically paying an amount of money immediately (e.g., pay $10 right now) or paying a larger amount of money at a later time (e.g., pay $20 in 6 months). For this task, a six (amount: $20, $250, $3,000, $20,000, $50,000, and $100,000) by five (delay: 1 month, 6 months, 1 year, 6 years, 12 years) within-subjects design was used. An amount was randomly selected (without replacement) and then all of the delay conditions were administered for that amount in random order.

An adjusting amount procedure was used to estimate the subjective value of the larger, delayed loss. The titrating procedure was similar to that used in Experiment 1, with the only difference being the direction of the adjustment. For example, when the choice was between paying $1,500 immediately and paying $3,000 in 6 years, if a participant chose to pay the $1,500 immediately, the amount of this payment was increased to $2,250. If the participant instead chose to pay the delayed $3,000, the amount of the immediate, smaller payment was decreased to $750. If the participant then chose the $750 on the second trial, the amount of the smaller payment on the third trial was increased to $1,125 (half of the previous adjustment).

In the probability-discounting task, participants made a series of choices between paying a hypothetical amount of money for certain (e.g., a 100% chance of paying $10) or taking the chance of paying a larger amount of money (e.g., a 40% chance of paying $20). For this task, a six (amount: \$20, \$250, \$3,000, \$20,000, \$50,000, and \$100,000)[F3] by five (probability: 80%, 50%, 25%, 10%, 5%) within-subjects design was used. For each amount-probability condition, a titrating procedure identical to that used in the delay-discounting task was used to estimate the subjective value of each probabilistic, larger loss.

After completion of the delay discounting and probability-discounting tasks, participants completed a short demographic survey consisting of questions regarding education, income, and cigarette smoking status.

3.2 Results

Figure 5 presents the group mean subjective values and best-fitting hyperboloid functions (Eq. 2) for young adults (left panels) and older adults (right panels).

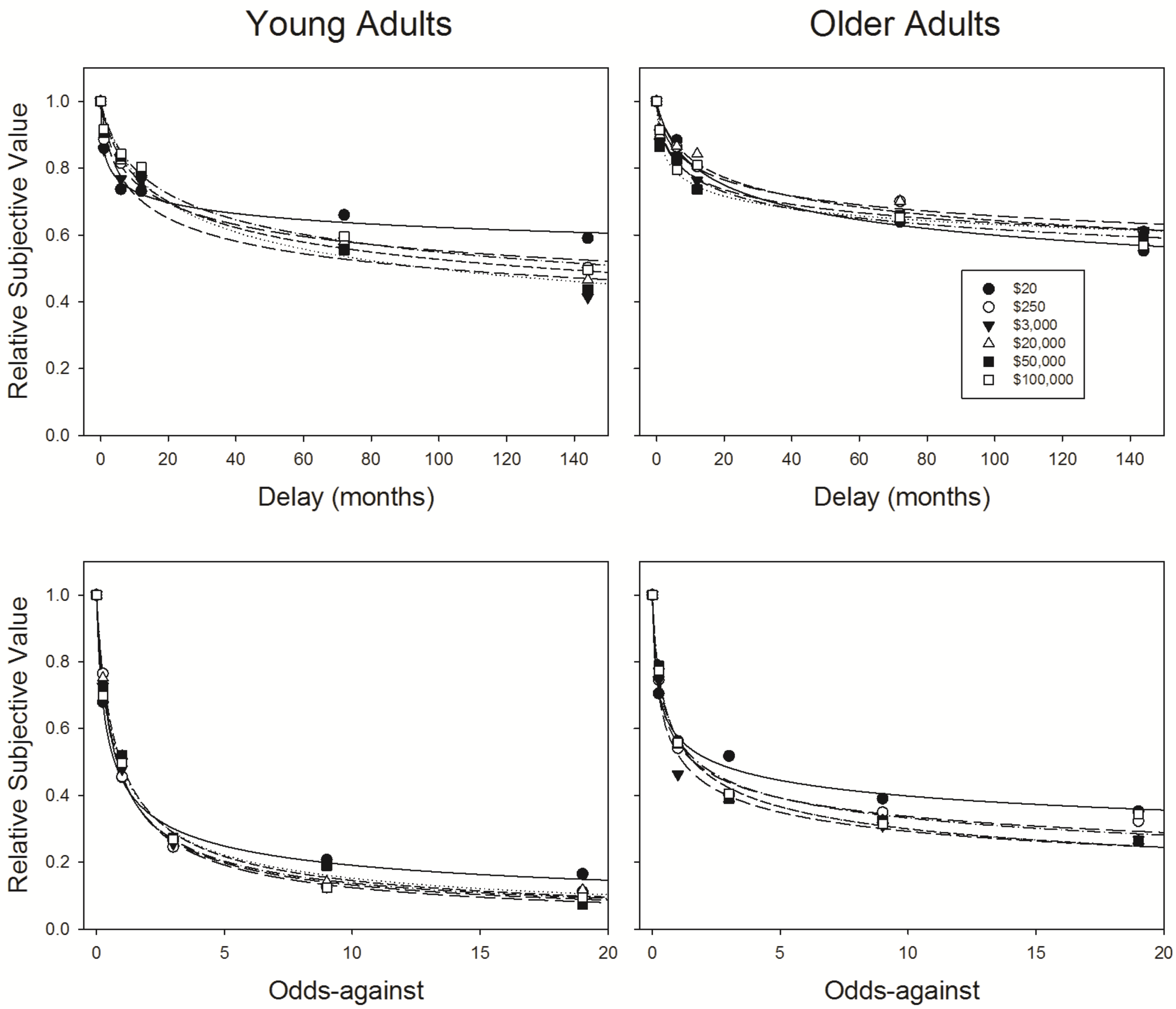

Figure 5. Mean relative subjective value for each of the six amounts and the best-fitting hyperboloid functions (Eq. 2) in young (left panels) and older (right panels) adults from Experiment 2. The top panels show delay discounting of a loss at each amount, and the bottom panels show probability discounting of a loss at each amount.

The top panels of Figure 5 show delay discounting for each of the six amounts and the best-fitting hyperboloid function. The hyperboloid function described delay discounting of losses for each of the six amounts for both the young and older adults well (all R^2s > .93; see Table 3). The bottom panels of Figure 5 show probability discounting of losses for each of the six amounts for young adults and five amounts for older adults, and the best-fitting hyperboloid fit as a function of odds-against receipt of the loss. As with delay discounting, the hyperboloid provided excellent fits of probability discounting of losses at each amount for both young and older adults (all R^2s > .98; see Table 3).

Table 3. Parameter estimates and proportion of variance (R^2) accounted for by Equation 2 as a function of delay (left panel) and as function of odds-against (right panel) for young and older adults in Experiment 2.

	Delay Discounting							Probability Discounting					
	$20	$250	$3,000	$20,000	$50,000	$100,000		$20	$250	$3,000	$20,000	$50,000	$100,000
Older Adults													
b	0.288	0.739	1.373	0.370	3.316	0.933	*b*	30.090	13.129	11.203	--	5.863	9.264
s	0.151	0.097	0.092	0.121	0.079	0.106	*s*	0.161	0.223	0.260	--	0.295	0.243
R^2	0.953	0.975	0.992	0.936	0.975	0.972	R^2	0.994	0.992	0.987	--	0.995	0.983
Young Adults													
b	8.493	0.539	0.573	0.270	0.175	0.225	*b*	6.964	2.154	2.500	2.138	2.534	2.762
s	0.070	0.148	0.171	0.192	0.239	0.190	*s*	0.389	0.670	0.621	0.620	0.575	0.591
R^2	0.987	0.975	0.941	0.976	0.984	0.983	R^2	0.997	0.998	0.999	0.997	0.993	0.995

The left panel of Figure 6 plots the mean AuC for each delay discounting amount condition for young and older adults. A 6 (delayed amount) x 2 (age) ANOVA on the delay discounting AuCs revealed no significant effect of amount on delay discounting ($F(5, 94) = 1.24$, $p = .30$). To further investigate the relation between amount and AuC, I calculated for each individual the correlation between their delay discounting AuCs and the logarithm of the delayed amounts. The average individual correlation (back-transformed from the mean Fisher *z*) between AuC and log amount was -.082 for young adults and .115 for older adults, but the 95% confidence intervals around the mean Fisher *z* included zero for both young (95% CI [-.322, .167]) and older (95% CI [-.142, .358]) adults. Thus, the correlation between AuC and log amount was not significantly different from zero, indicating no relation between degree of discounting and amount of delayed loss.

The ANOVA also revealed no significant effect of age ($F(1,98) = 1.95$, $p = .17$) and no interaction between age and amount ($F(5, 94) = 1.46$, $p = .21$). Although there was no significant effect of age, it is clear from the left panel of Figure 6 that older adults consistently discounted delayed losses marginally less steeply than younger adults at most amounts.

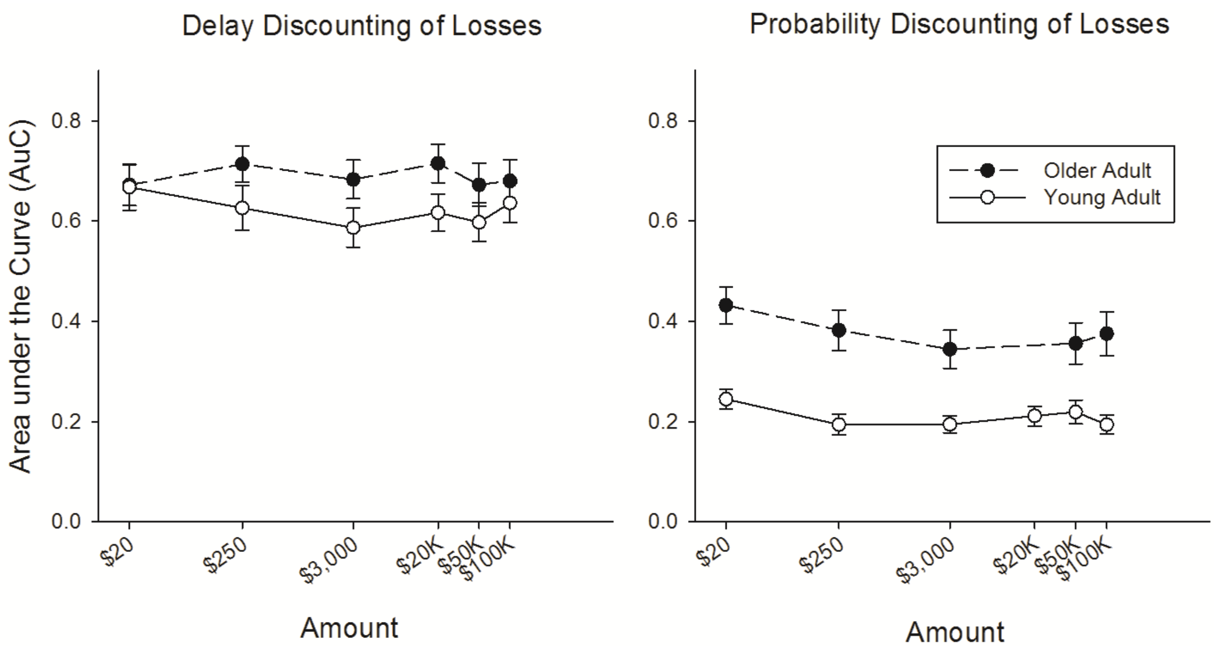

Figure 6. Mean area under the curve (AuC) and standard error for each of the six loss amounts for delay discounting (left panel) and each of the five loss amounts for probability discounting (right panel) from Experiment 2. The closed circles show the AuC for older adults and the open circles show the AuC for older adults. Note the different scales on the y-axes and the logarithmic scaling of amount on the x-axes.

The right panel of Figure 6 plots the mean AuC for each probability discounting amount condition for young and older adults. A 5 (probabilistic amount) x 2 (age) ANOVA on the probability discounting AuCs revealed a significant effect of amount on probability discounting ($F(4,94) = 4.34$, $p = .003$, $\eta_p^2 = .16$). Bonferroni-corrected pairwise comparisons suggest that the effect of amount was disproportionately driven by the shallow discounting observed at the smallest amount, \$20 (see right panel of Figure 6). Indeed, \$20 was significantly different from \$250 ($p = .05$) and from \$3,000 ($p = .001$). No other pairwise differences were significant. For each individual, I calculated the correlation between their probability discounting AuC and log of the probabilistic amount. There was a wide range of individual correlations between AuC and log amount, with an average (back-transformed from the mean Fisher *z*) of -.135 for young adults and -.173 for older adults. The 95% confidence intervals around the mean Fisher *z* included zero for both young (95% CI [-.360, .105]) and older (95% CI [-.420, .096]) adults, indicating that the correlation between degree of probability discounting and loss amount was not significant. Interestingly, when \$20 was removed from the correlational analyses, the average back-transformed correlation between probability discounting AuC and log amount reversed to a slight positive relation for older adults (.150; CI [-.111, .393]) and to near zero for young adults (.016; CI [-.182, .213]). The results suggest that there was no systematic effect of amount on probability discounting of losses.

The ANOVA also revealed a significant effect of age ($F(1, 98) = 18.79$, $p < .001$, $\eta_p^2 = .16$) and no significant interaction between age and amount ($F(4, 95) = .84$, $p = .50$) on the probability discounting of losses. As can be seen in the right panel of Figure 6, older adults discounted probabilistic losses less steeply than young adults, suggesting older adults are more risk-averse in the domain of losses. That is, older adults were willing to pay a large amount for certain in order to avoid the risk of paying an even larger amount. In contrast, the amount that young adults reported willing to pay for certain in order to avoid the risk was much smaller.

Bonferroni-corrected pairwise comparisons revealed these age differences were significant at each of the five amounts (all *p*s < .01).

In order to determine whether delay and probability discounting involve fundamentally distinct processes in the domain of losses, I conducted a principle component analysis on the AuCs followed by a factor analysis with a varimax rotation. As with Experiment 1, there were two significant components that emerged corresponding to delay and probability discounting. The first component (Eigenvalue = 4.99) accounted for 45.32% of the variance and, as may be seen in Table 4, all of the delayed amount conditions loaded strongly on the corresponding rotated factor whereas the probabilistic amount conditions all loaded weakly. The second component (Eigenvalue = 3.296) accounted for 35.62% of the variance, and the corresponding rotated factor showed the opposite pattern of loading (see Table 4). When principle component analyses were conducted separately for young and older, the same two components, representing a delay discounting factor and a probability discounting factor, emerged in each age group.

Table 4. Principle component loadings (Varimax roation) for each delayed and probabilistic amount condition in Experiment 2.

		Component	
		1	2
Delay Discounting			
	$20	0.696	0.037
	$250	0.853	0.031
	$3,000	0.868	0.160
	$20,000	0.896	0.132
	$50,000	0.873	0.128
	$100,000	0.887	0.024
Probability Discounting			
	$20	0.079	0.813
	$250	0.012	0.892
	$3,000	0.090	0.927
	$50,000	0.157	0.863
	$100,000	0.089	0.892

Note. Loadings that are less than .2 are shaded in grey.

3.2.1 Parameters. Experiment 1 showed that the value of the hyperboloid parameters changed systematically across reward amounts. I next determined whether the same effect occurred in the domain of losses. Figure 7 plots the values of the *b* (top panels) and *s* (bottom panels) parameters of the hyperboloid functions that best described the group mean subjective values, plotted as a function of the logarithm of the amount of the delayed loss (left panels) and probabilistic loss (right panels). The top left panel of Figure 7 suggests that the value of the *b* parameter may increase slightly as a function of amount for older adults but decrease slightly as a function of amount for young adults. In older adults, the linear trend between log *b* and log amount was not significant ($F(1,4) = 1.83$, $p = .24$), but in young adults, a negative linear trend was significant ($R^2 = .82$; $F(1,4) = 18.38$, $p = .01$). As can be seen in Figure 7, this trend might have been exaggerated by the unusually high value of *b* at $20 (8.493) compared to the value at the five other amounts (.175 to .573). However, this trend remained just significant, when the *b* associated with $20 was removed from analyses ($F(1,3) = 10.37$, $p = .049$).

In older adults a linear trend between log *s* and log amount was not significant ($F(1,4) = 1.84$, $p = .25$), suggesting that the *s* parameter did not appear to systematically change across amounts. Although a similar pattern seems to capture the young adult group, a linear trend was significant in young adults ($R^2 = .82$; $F(1,4) = 18.21$, $p = .01$). Once again, this trend may have been primarily driven by the unusual value of *s* at $20 (.07) compared to the other five amounts (.15 to .24). When the *s* associated with $20 was removed, this trend no longer was significant ($p = .08$).

In probability discounting, there was a significant linear relation between log *b* and log amount in older adults ($R^2 = .82$; $F(1,3) = 13.47$, $p = .04$) and a significant quadratic trend in young adults ($R^2 =.88$; $F(2,3) = 10.50$, $p = .04$), suggesting that log *b* appears to be slightly negatively related to amount for both young and older adults. It can be observed in Figure 7, however, that these effects might again be driven by the unusual behavior at \$20, particularly for young adults. Indeed, trends were no longer significant in either age group when the *b* parameter associated with \$20 was removed (*p*s > .22). Interestingly, for young adults, the correlations with log amount actually reversed direction to become positive, giving even further evidence of the unsystematic effect of the parameters across loss amount. For both young and older adults, a linear relation between log *s* and log amount was not significant (both *F*s < 7.70, both *p*s > .07).

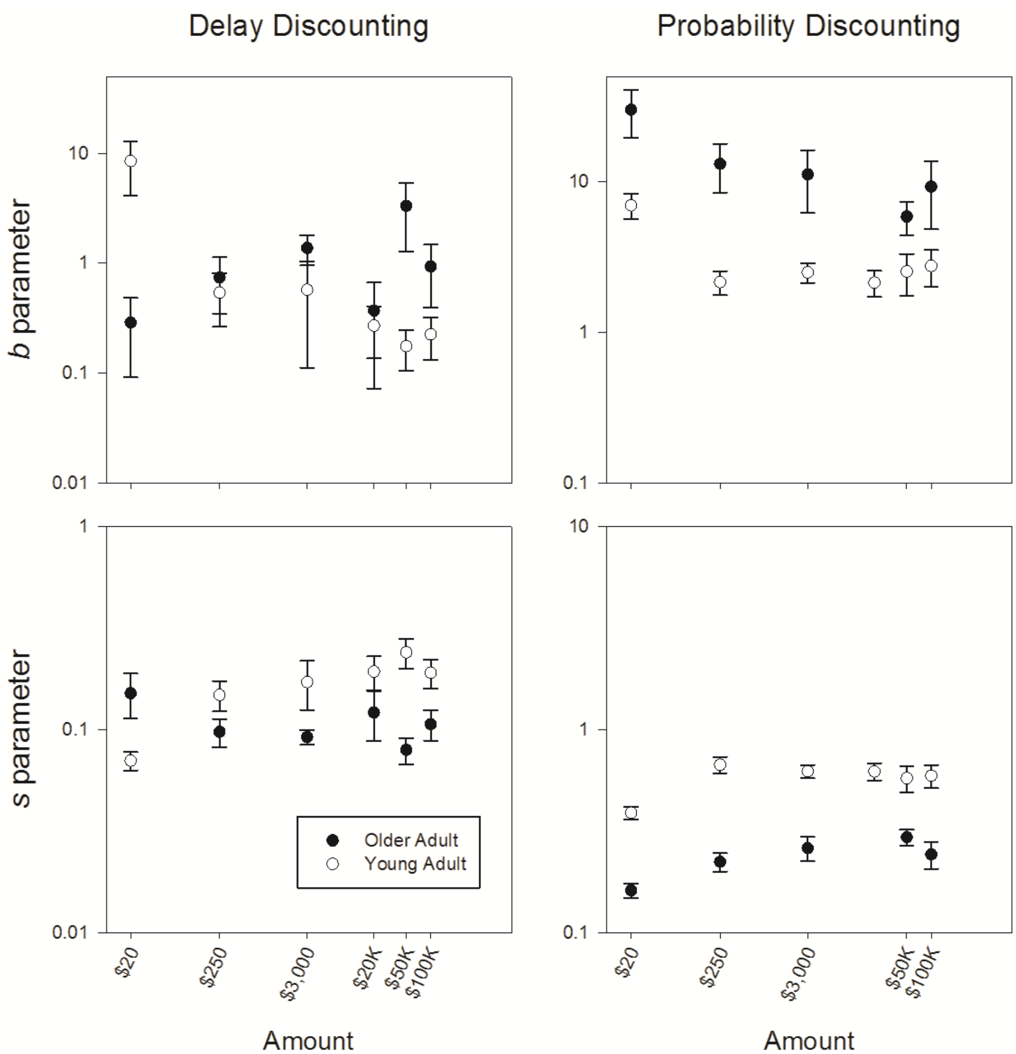

Figure 7. Mean value and the standard error for the *b* parameter (top panels) and the *s* parameter (bottom panels) when the Equation 2 was fit as a function of delay (left panels) and as a function of odds-against (right panels) in Experiment 2. The closed circles show the parameter values for average older adult and the open circles show the parameter values for the average young adult.

3.2.1 Exploratory Analyses of the Effect of Income on Older Adults' Discounting. As with Experiment 1, I sought to determine whether household income affects degree of discounting. Six participants opted not to report their income level. This resulted in 16 older adults with a reported household income under \$50,000, 29 older adults with a reported household income between \$50,000 and \$100,000, and 8 older adults with a reported household income over \$100,000. Although there is not a significant effect of income for either delay or probability discounting (both Fs < 1.0, $p > .60$) and no interaction between income and amount (both Fs $<$ 1.22, $p > .26$), plotting the data shows evidence of trends that may not be significant due to low power. The top panel of Figure 8 first suggests a slight interaction across incomes such that individuals with reported incomes of less than \$50,000 show a slight decrease in delay discounting AuC as amount increases from \$20 to \$3,000 and then stabilizes; in contrast, for those with reported incomes greater than \$50,000, the degree of discounting is relatively unchanged. This slight interaction leads to an orderly difference across incomes from amounts \$3,000 and greater such that degree of discounting decreases (AuC increases) as income increases across each amount.

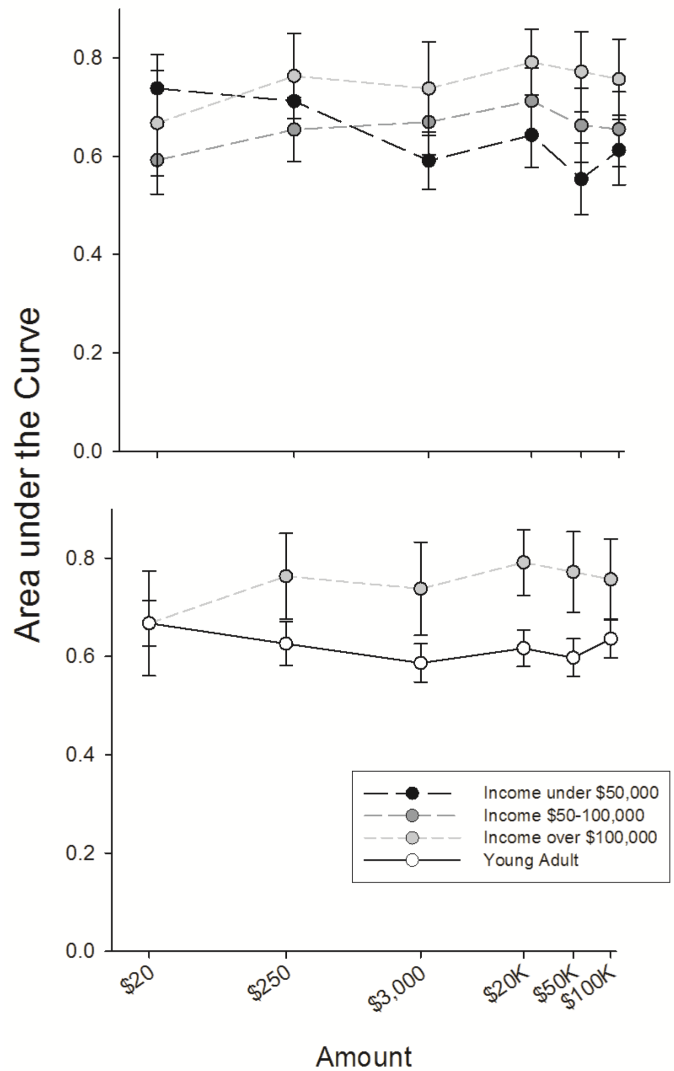

Figure 8. Mean area under the curve (AuC) and standard error at each amount for delay discounting of a loss by young adults (open circles) and each of the three older adult household income groups (closed circles) from Experiment 2. The top panel compares the three income groups in older adults and the bottom panel compares the young adults to older adults with a reported household income greater than $100,000. Note the logarithmic scaling of amount on the x-axes.

When age is considered in tandem with income, a more complex picture emerges. Recall that young and older adults did not differ on their discounting of delayed losses (Figure 6). However, when comparing young adults to an older adult sample of approximately the same household income (i.e., greater than $100,000), there is a clear difference in degree of discounting delayed losses. The bottom panel of Figure 8 compares young with older adults of comparable household incomes. Older adults discounted delayed losses nominally less steeply than young adults at all but the smallest amount. Due to low number of older adults in this income bracket (*n* = 8), however, statistical comparisons of young and older adults at each amount could not be completed.

In probability discounting, there appears to be little difference in individuals who make less than $100,000 (see Figure 9). However, individuals with incomes reported to be greater than $100,000 appear to discount probabilistic losses significantly more than those with household incomes under $100,000. That is, those with larger household incomes are more risk-taking and are less willing to pay a smaller amount for certain to avoid the risk of paying a larger amount. When age is considered, young adults (solid line in Figure 9) discount more steeply than all individuals with household incomes under $100,000, again suggesting more risk-taking by young adults. However, young adults do not appear to differ from older adults making reporting a household income greater than $100,000. Thus, the effect of degree of discounting probabilistic losses appears to be driven more by income than by age.

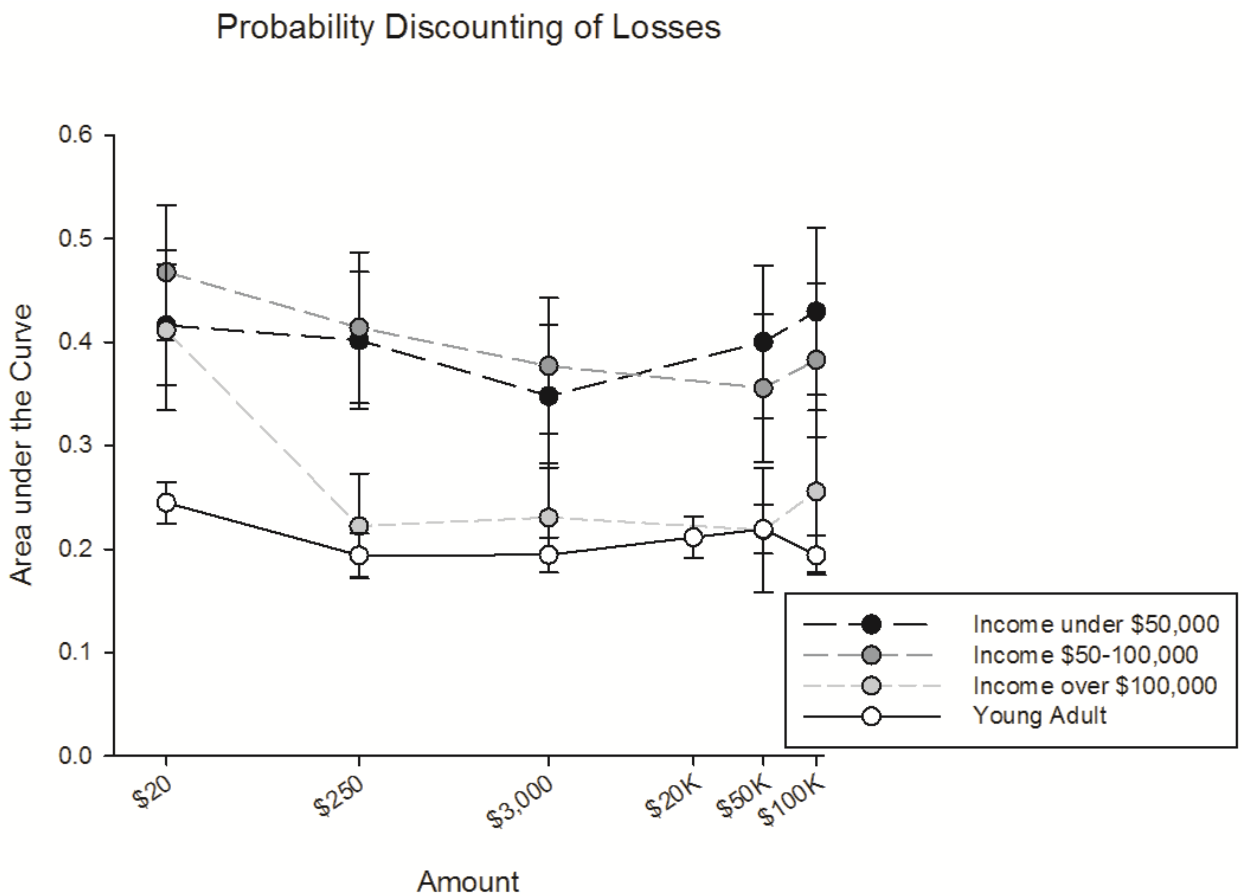

Figure 9. Mean area under the curve (AuC) and standard error at each amount for probability discounting of a loss by young adults (open circles) and each of the three older adult household income groups (closed circles) from Experiment 2. Note the logarithmic scaling of amount on the x-axis.

3.3 Discussion

As with the discounting of gains observed in Experiment 1, the results from Experiment 2 found that both young and older adults discounted delayed and probabilistic losses and that a hyperboloid function provided a good model of decision making involving losses, but unlike Experiment 1, the current experiment found that amount had no systematic effect on degree of discounting.

Previous findings with young adults reported no systematic effect of amount on the discounting of either delayed or probabilistic losses (e.g., Estle et al., 2006; Green et al., 2014;

Holt et al., 2008; McKerchar et al., 2013; Mitchell & Wilson, 2010; Ostaszewski & Karzel, 2002; Yi & Landes, 2012). The current experiment replicated these results in young adults and extended this finding to an older adult sample. In contrast to the results of Green et al. (2014), however, changes in the parameters as a function of amount were observed in the current experiment. Significant trends were observed in young adults for the *b* and *s* parameters of the hyperboloid fit as a function of delay, and were observed in both age groups for the *b* parameter of the hyperboloid fit as a function of odds-against. These trends, however, appeared to be inflated by the $20 amount (see Figure 7), as most of these trends became insignificant when that amount condition was removed. Interestingly, Green et al. also reported differences in the degree of discounting $20 compared to the other amount conditions, at least for probability discounting. As in the current study, Green et al. observed larger *b* parameter values and smaller *s* parameter values for the probabilistic $20 loss in young adults as compared to other amounts. Thus, in spite of the significant trends observed in the current study, the behavior of the parameters generally showed no systematic changes with amounts greater than $20 for both young and older adults, replicating the results of Green et al.

The effect of amount appears to have little effect on the degree of discounting and the hyperboloid parameters when choice involves losses, and this is true for both young and older adults. In spite of these similarities, some differences across age groups were observed. To date, only two previous studies (Halfmann et al., 2013; Löckenhoff et al., 2011) compared delay discounting of losses across age groups, and both reported no difference in discounting as a function of age. The current work generally replicated this finding, but it was observed that older adults discounted delayed losses nominally less steeply (i.e., had larger AuC values) than young adults (see Figure 6). Although not significant, both Löckenhoff et al. and Halfmann et al.

reported trend levels in which older adults discounted less steeply than young adults, consistent with the results observed in the current experiment. The current study illuminated this finding by including household income as an additional variable. When the family household incomes of young and older adults were comparable, young adults reliably discounted more steeply than older adults of the same income bracket. This finding suggests that earlier reports that young and older adults do not differ in their degree of discounted delayed loss may have been concealed by the effects of income.

As with delayed gains, there were reliable age differences in the discounting of delayed losses above and beyond that of household income. If these results are replicated, they suggest that older adults are more willing to pay an immediate cost in order to avoid a delayed, larger payment, providing support for the theory that motivation in older adults changes from acquiring gains to minimizing losses (Depping & Freund, 2012). In contrast, in the terms of Myerson et al. (in press), there may be a larger percentage of debt-averse older adults than in a young adult sample. That is, rather than a change in motivation to minimize losses, older adults may be more likely to show a different systematic relation between delay and subjective value of a loss than do young adults. Whereas most individuals show discounting of losses such that they are increasingly more likely to choose to pay later as the delay increases, debt-averse individuals show the opposite pattern: They are more likely to pay the immediate payment when the delay to the larger payment is long rather than short. The current study used a different methodology than that of Myerson et al. and so individuals could not be classified into groups of debt-averse and loss-averse. However, if this finding holds, it suggests that young and older adults may differ not only in their degree of delay discounting, but that their decision making concerning delayed losses is qualitatively different.

There is limited prior work on the discounting of probabilistic losses that addresses the influence of age, but Mather et al. (2012) reported that older adults were more likely than younger adults to take a risk in order to avoid a sure loss. In contrast, older adults in the current study discounted losses significantly less steeply than young adults, suggesting, instead, that older adults are more willing to pay a smaller loss in order to avoid the risk of paying a larger loss. That is, older adults instead are *less* likely to take a risk in order to avoid a sure loss. When the reported household income is considered, however, it becomes clear that the degree of discounting probabilistic losses is driven more by income than by age. Older adults who reported household incomes of less than $100,000 discounted probabilistic losses less steeply than older adults who reported incomes greater than $100,000, indicating that higher-income older adults were more willing to take the risk of paying more in order to avoid a sure loss. Interestingly, there was no difference between older adults with household incomes greater than $100,000 and the young adult sample with a comparable socio-economic status. The results suggest that household income, rather than age, might be affecting the probability discounting of losses.

Unlike the discounting of delayed and probabilistic gains, amount had little effect on the degree of discounting delayed or probabilistic losses. On the surface, this could suggest that a single process might underlie decision-making involving losses. However, the current results made clear that other variables, specifically age and household income, affected delay and probability discounting of losses in distinctive ways. So, too, a principle components analysis revealed two distinct factors, one corresponding to the delay discounting measures and the other corresponding to the probability discounting measures, and this finding was replicated when young and older adults were examined separately. The results suggest that there is little correspondence in how people make decisions concerning delayed losses and probabilistic losses, providing additional support for their being distinct processes.

The current study did not compare discounting of gains and losses within the same individuals, so it is not clear whether there is a relation between the discounting of delayed gains and delayed losses and between probabilistic gains and probabilistic losses. Mitchell and Wilson (2010) reported a positive correlation between the discounting of delayed gains and delayed losses. They also reported a weak, but nonsignificant negative correlation between the discounting of probabilistic gains and probabilistic losses, and Shead and Hodgins (2009) found a significant negative correlation between the discounting of probabilistic gains and probabilistic losses. However, when comparing the results of the current experiment to that of Experiment 1, gains and losses appear to be at least somewhat distinct. Amount affected degree of discounting for both delayed gains and probabilistic gains, but had no systematic effect on degree of discounting delayed losses and probabilistic losses. Income had a clear effect on the discounting of delayed gains but little effect on the discounting of delayed losses, whereas income had little effect on the discounting of probabilistic gains but an effect on the discounting of probabilistic losses. Interestingly, age seemed to affect gains and losses in similar ways: When controlling for reported household income, older adults discounted delayed gains and losses less steeply than young adults, but there was no difference between young and older adults in the discounting of probabilistic gains and losses. Because the current study did not compare gains and losses within the same individuals, these results should be interpreted with caution.

Chapter 4: Experiment 3

Discounting Rewards that are Both Delayed and Probabilistic

Whereas Experiments 1 and 2 focused on choice involving tradeoffs between two attributes (i.e., amount and delay/probability), Experiment 3 investigated more complex choice that involved rewards that were both delayed and probabilistic. Previous research reported that delay and probability interacted to affect the subjective value of an outcome (Vanderveldt et al., 2015), but a multiplicative model may not be the best descriptor of complex choice by older adults (e.g., Mata et al., 2007). Furthermore, Experiment 1 found that, when income was equated, older adults discounted delayed gains less steeply than young adults, but there was no systematic age difference in the discounting of probabilistic gains. The results of Experiment 3 will help determine whether these age differences in delay and probability discounting hold in more complex choice situations.

Vanderveldt et al. (2015) reported that when outcomes were both delayed and probabilistic, probability appeared to have a stronger influence than delay on the subjective value of a reward. However, the values of the delays, probabilities, and amounts used in Vanderveldt et al., although commonly used in discounting experiments, led to a degree of probability discounting that was far steeper than the degree of delay discounting. It is unknown whether the finding that probability had a far greater influence than delay when outcomes were both delayed and probabilistic was an artifact of the values used. The current experiment investigated whether the findings of Vanderveldt et al. replicated when degrees of delay and probability discounting, when evaluated separately, were approximately equal and when the degree of delay discounting was greater than that of probability discounting. Because degree of delay discounting and degree of probability discounting are uncorrelated (e.g., Green & Myerson, 2013; Mitchell & Wilson, 2010; see also, Experiment 1), values that would lead to all participants having similar rates of delay and probability discounting cannot be obtained. Rather, in the current experiment, the values of the delays, probabilities, and the amount were chosen so that I could reliably obtain a proportion of individuals who discounted delay more steeply than probability (Delay-Steeper discounters), a proportion of individuals who discounted probability more steeply than delay (Probability-Steeper discounters), and a proportion of individuals who discounted delay and probability at approximately equal rates (Even discounters).

To determine the values that would be used in the current experiment, I conducted a pilot study in which participants completed both a standard delay discounting and a standard probability discounting task, with the procedure being similar to that of Experiment 1. Across conditions, the values of the delays, probabilities, and amount of the larger reward were varied. For each participant, I compared their degrees of delay and probability discounting. To compare degree of discounting, I found the difference in the area under the curve (AuC) between delay discounting and probability discounting. I categorized degree of delay discounting and degree of probability discounting as approximately equal if the difference between the delay discounting AuC and the probability discounting AuC was less than 0.1. This criterion was chosen because examination of the indifference points showed good correspondence (i.e., indifference points for delay and probability discounting were overlapping or alternated between being higher and lower). The final values chosen for this experiment led to a reliable proportion of Delay-Steeper, Probability-Steeper, and Even discounters. Therefore, with these values I am able to examine how outcomes that are both delayed and probabilistic are discounted when their discounting, when evaluated separately, is approximately equal and when one is discounted more steeply than the other.

4.1 Method

4.1.1 Participants. Fifty young adult participants between the ages of 18 and 22 (mean age = 19.4; 34 Female, 16 Male) were recruited from the Washington University Department of Psychological and Brain Sciences Human Subjects Pool. Participants were tested individually in a small room with a computer and received either monetary compensation or course credit for their participation.

Fifty older adult participants over the age of 65 (mean age = 70.6; 36 Females, 14 Male) were recruited from the St. Louis community. In order to qualify to participate, older adults had to self-report no history of a neurological disorder and pass the Short Blessed Test, a screening test for dementia (Carpenter et al., 2011), with a score of less than 5. Participants were tested individually in a small room with a computer and received monetary compensation for their participation.

4.1.2 Materials and Procedure. Participants first completed standard delay and standard probability discounting tasks, similar to those described in Experiment 1. Before each task, participants received instructions and completed two practice trials. Five delays to the larger reward (1 month, 6 months, 1 year, 3 years, and 5 years) and one amount of the delayed reward ($96) were used for the delay-discounting task. Five probabilities (98%, 85%, 70%, 50%, and 40%) and one amount of the probabilistic reward ($96) were used for the probability-discounting task. Values were chosen based on the pilot data described previously. The order in which the delay and probability tasks was presented was counterbalanced across participants. Within each task, each delay/probability was randomly presented (without replacement). For each delayed/probabilistic reward, a titrating procedure identical to that described in Experiment 1 was used to estimate the subjective value of each delayed/probabilistic reward.

Participants next completed a combined discounting task in which they made choices between a small, immediate and certain reward and a larger, delayed and probabilistic reward. Before the experimental trials, participants received instructions and completed six practice trials. In the combined delay and probability discounting task (hereafter referred to as the *combined discounting task*), participants made a series of choices between two hypothetical amounts of money: One amount could be received immediately and was guaranteed whereas the other amount was larger, but might be both delayed in time and probabilistic in its receipt. For example, a participant might be asked to choose between receiving a 100% chance of $24 right now and a 70% chance of receiving $96 in 6 months.

In the experimental trials, six delays (0 [immediate], 1 month, 6 months, 1 year, 3 year, and 5 years), six probabilities, (100% [certain], 98%, 85%, 70%, 50%, and 40%), and one amount of the larger, delayed and probabilistic reward ($96) were used. These values were chosen based on the pilot data described previously and were identical to those used in the standard delay and standard probability discounting tasks. Each condition consisted of a unique combination of a delay and a probability. When the probability was 100%, the procedure reduced to that of the standard delay discounting task and when the delay was 0, the procedure reduced to that of the standard probability discounting task. The combination of a 0 delay and 100% probability was not used, creating a total of 35 conditions. For each condition, participants completed six trials, and the titrating procedure was used to converge on an indifference point in which the small, immediate and certain reward was approximately subjectively equal to the larger, delayed and probabilistic reward (i.e., the subjective value of the larger, delayed and probabilistic reward).

The delay-probability conditions were blocked either by delay or by probability. Blocking condition was counter-balanced across participants. For half of the participants (the block-by-probability group), the first block of conditions involved the $96 reward available with a probability of 100% (a standard delay discounting task), and the delays within that block were presented in random order. The five subsequent blocks each involved one of the five other probabilities (98%, 85%, 70%, 50%, and 40%). These blocks were randomly presented to participants, and within each block the delays were presented in random order. For the other half of the participants (the block-by-delay group), the first block of conditions involved the $96 reward available immediately (a standard probability discounting task), and the probabilities within that block were presented in random order. The five subsequent blocks each involved one of the five other delays (1 month, 6 months, 1 year, 3 year, and 5 years). These blocks were randomly presented to participants, and within each block the probabilities were presented in random order.

4.2 Results

There was no main effect of blocking group ($F(1, 96) < 1.0$, $p = .94$), and therefore all subsequent analyses were conducted across these groups. Figure 10 presents the group mean subjective values of young adults (top panels) and older adults (bottom panels) from all of the conditions, plotted first as a function of delay (left panels) and then as a function of odds-against (right panels). In the left panels, the six curves correspond to delay discounting, each at a different probability.

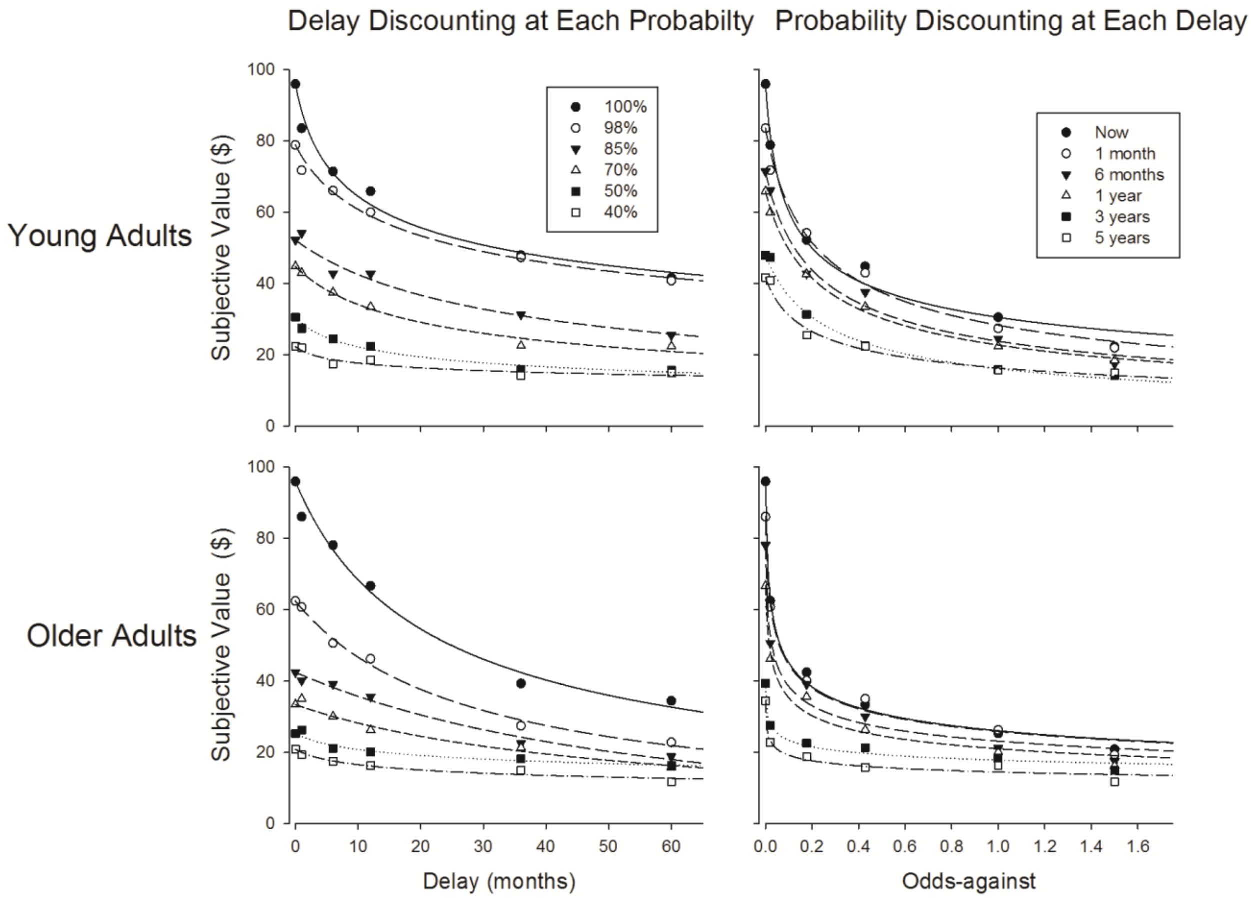

Figure 10. Mean subjective value the best-fitting hyperboloid functions (Eq. 2) in young (top panels) and older (bottom panels) adults from Experiment 3. The left panels show delay discounting at each probability, and the right panels show probability discounting at each delay.

Each curve in the left panels was obtained by fitting the hyperboloid function (Eq. 2) as a function of delay, but with *A* equal to the immediate equivalent at the specified probability estimated during the combined discounting task. For example, when describing the delay discounting of a reward with an 85% probability (closed triangles in the left panels of Figure 10), *A* in Equation 2 was set to the subjective value of an immediate 85% chance of a reward ($52.26 for young adults and $42.48 for older adults). Similarly, in the right panels, the six curves correspond to probability discounting each at a different delay. Each curve in the right panels was obtained by fitting the hyperboloid function (Eq. 2) as a function of the odds-against, but with *A* equal to the certain equivalent at the specified delay estimated during the combined discounting task. For example, when describing the probability discounting of a reward available in 1 month (see open circles in the right panels of Figure 10), *A* in Equation 2 was set to the subjective value of a 100% chance of a reward available in 1 month ($83.58 for young adults and $86.10 for older adults).

The hyperboloid model provided excellent fits of delay discounting at each probability (R^2s = .92 - .99), and of probability discounting at each delay (R^2s =.97 - .99). As can be seen in the left panels of Figure 10, for both young and older adults delay discounting was most evident when the probability of a reward was high (e.g., 100% and 98%). However, the effect of delay on degree of discounting weakened as the probability of a reward decreased. In contrast, the right panels of Figure 10 show steep probability discounting, even as the delay of receipt increased.

In order to evaluate potential differences in discounting between age groups, I used the area under the curve (AuC) measure. Figure 11 compares the area under the delay discounting curves at each probability (left panel) and the area under the probability discounting curves at each delay (right panel) for young and older adults. A 6 (probability) x 2 (age) ANOVA on the delay discounting AuCs revealed a significant effect of probability ($F(5, 94) = 66.96$, $p < .001$, $\eta_p^2 = .78$), reflecting the fact that the degree of delay discounting decreased continuously as a function of the probability of receiving the reward. A linear trend of probability was significant ($F(1, 98) = 345.73$, $p < .001$, $\eta_p^2 = .78$), implying that the delay discounting AuCs decreased as probability of receipt decreased. Although the main effect of age was marginally significant ($F(1, 98) = 3.51$, $p = .06$, $\eta_p^2 = .04$), this must be considered in light of the significant age x probability interaction ($F(5, 94) = 5.72$, $p < .001$, $\eta_p^2 = .23$). As can be observed in the left panel of Figure 11, initial decreases in probability of receipt (e.g., 98% and 85%) led to a greater degree of delay discounting by older adults than by young adults. Specifically, older adults discounted delayed rewards significantly more steeply than young adults when the probability of receipt was 98% (p <.001) and marginally less steeply when the probability was 85% (p = .053), but young and older adults did not differ in their degree of delay discounting when the probability was lower (all ps > .20). It is interesting to note that there was not a significant age difference when the probability of receipt was 100% (p = .38), despite older adults discounting delayed rewards more steeply than young adults when the probability of receipt was reduced to 98%. So, too, older adults showed a large difference in delay discounting between the 100% and 98% conditions, but there was relatively little difference between these conditions for young adults. Bonferroni-corrected pairwise comparisons revealed that whereas older adults discounted delayed rewards more steeply when the reward had a 98% compared to 100% chance of receipt (p < .001), there was no difference between these two probabilities in young adults (p < .05). This finding suggests that older adults may show a larger certainty effect, in which individuals tend to overweight outcomes that are available with certainty, compared to outcomes that are only probabilistic in their receipt (Kahneman & Tversky, 1979). That is, older adults are more risk-averse than young adults, even with marginal decreases probability.

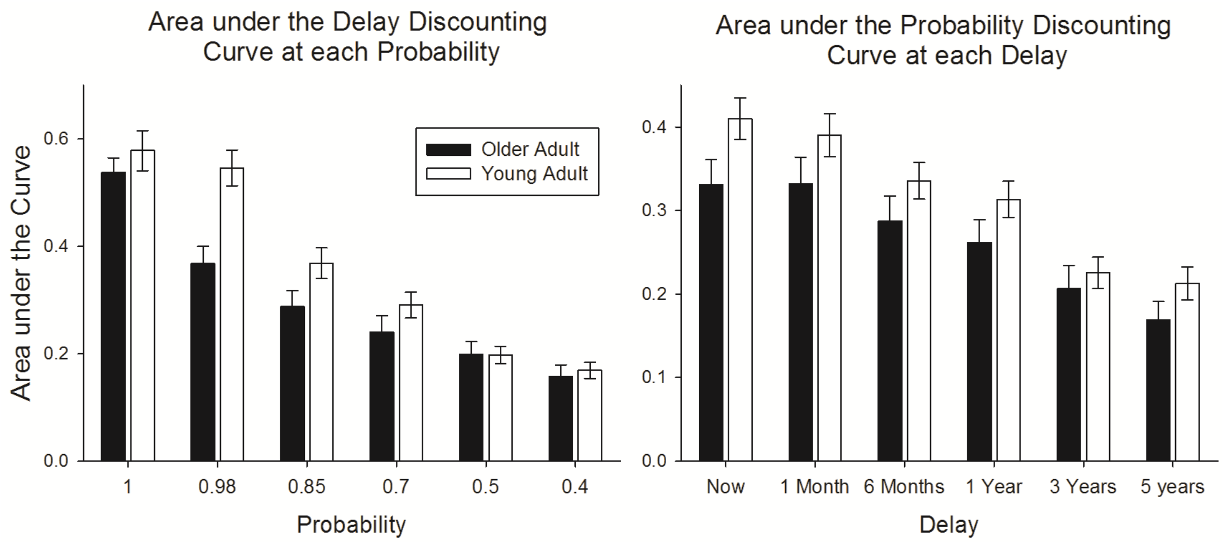

Figure 11. Mean area under the curve (AuC) and standard error for delay discounting at each probability (left panel) and probability discounting at each delay (right panel) in Experiment 3. The filled bars represented the average older adult and the open bars represent the average young adult. Note the different scales on the y-axes.

A 6 (delay) x 2 (age) ANOVA on the probability discounting AuCs revealed a significant effect of delay ($F(5, 94) = 30.88$, $p < .001$, $\eta_p^2 = .62$), suggesting that the degree of probability discounting changed as a function of the delay to receiving the reward. There was a significant linear trend of delay ($F(1, 98) = 155.84$, $p < .001$, $\eta_p^2 = .61$), indicating an orderly decrease in probability discounting AuC as delay increased. There was not a significant overall effect on age on probability discounting ($F(1,98) = 2.37$, $p = .13$), and no interaction between delay and age ($F(5, 94) = 1.06$, $p = .39$), indicating that the effect of delay on probability discounting was similar for young and older adults.

In order to examine whether delay and probability interact, as predicted by a multiplicative model but not by an additive model, a 2 (age) x 6 (delay) x 6 (probability) repeated-measures ANOVA was conducted on the obtained subjective values. Planned contrasts revealed a significant interaction between delay and probability ($F(25, 74) = 13.45$, $p < .001$, $\eta_p^2 = .82$) but importantly, there was no three-way age x delay x probability interaction ($F(25, 74) = 1.37$, p = .15), indicating that the two-way interaction was consistent across age groups[F4]. As noted previously, this interaction can be observed in the left panel of Figure 10, in which delay appears to have a stronger effect when the probability of receipt is very high than when it is lower.

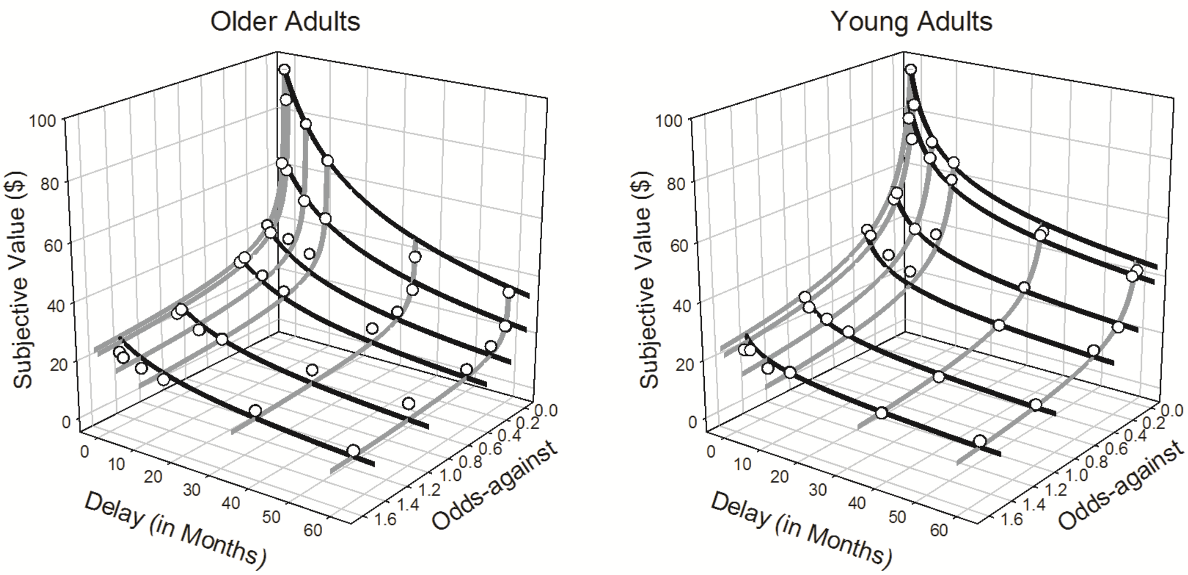

Figure 12. Three-dimensional plots of the mean subjective value and the best-fitting curves as predicted by the multiplicative discounting model (Eq. 4) for older adults (left panel) and young adults (right panel) in Experiment 3.

Given that delay and probability interacted, I next fit the multiplicative hyperboloid model (Eq. 4) to the group mean subjective values, separately for young and older adults. As can be observed in Figure 12, the multiplicative hyperboloid model provided an excellent fit to the data for both young and older adults (both R^2s > .97). The top row of Table 5 (i.e., Entire Age Group) shows the fits and the obtained parameter values of the multiplicative hyperboloid model. To determine whether simpler versions of the multiplicative model would provide similar fits, the group data were fit with a reduced model that had two rate parameters but no exponent (k and h only; Ho et al., 1999). Adding additional free parameters to a model always increases the variance accounted for. Therefore, differences between nested models like those just described often are compared using incremental-*F* tests to assess whether the increase in the explained variance is significantly greater than what would be expected simply because of the additional free parameters. The four-parameter model explained significantly more variance than the two-parameter model in both young and older adults (both Fs(2, 32) > 57.20, both ps < .001). The results suggest that discounting of outcomes that are both delayed and probabilistic is best described by the multiplicative combination of separate hyperboloid delay and probability discounting functions, each with its separate rate parameters (k and h) and exponents (s_d and s_p).

Table 5. Parameter estimates and proportions of variance (R^2) accounted for by the multiplicative discounting model (Eq. 4) in Experiment 3. The multiplicative hyperboloid was fit separately for young (left panel) and older adults (right panel) and for each of the three discounting subgroups (Even, Steeper-Probability, and Steeper-Delay) in each age group.

	Young Adults					Older Adults				
	k	s_d	h	s_p	R^2	k	s_d	h	s_p	R^2
Entire Age Group	0.356	0.238	16.894	0.385	0.979	0.070	0.590	248.773	0.219	0.975
Even-Discounting Sub-Group	0.510	0.245	5.835	0.749	0.946	0.061	0.765	144.915	0.256	0.963
Steeper-Probability Sub-Group	0.127	0.234	52.661	0.280	0.967	0.041	0.633	417.376	0.254	0.989
Steeper-Delay Sub-Group	0.400	0.256	14.785	0.370	0.974	0.126	0.487	94.977	0.178	0.903

Another goal of this experiment was to determine whether standard delay and probability discounting predicted discounting on the combined discounting task, in which rewards were both delayed and probabilistic. In order to evaluate the predictive power of the standard discounting tasks, I first fit the hyperboloid function (Eq. 2) to the standard delay discounting and standard probability discounting data, when evaluated separately, in order to obtain parameter values for each (see the Entire Age Group row of Table 6). The hyperboloid provided excellent fits for both young and older adults to the standard delay discounting and probability discounting data (all R^2s > .96). The obtained parameter values then were substituted into the multiplicative hyperboloid model (Eq. 4). Thus, the parameters of Equation 4 were fixed (i.e., no free parameters). The fixed-parameter multiplicative model then was fit to the combined discounting data. Given there were no free parameters, the multiplicative model provided a good fit to the data for both young (R^2 = .81) and older adults (R^2 =.92), suggesting that standard delay and probability discounting tasks can be used to predict discounting when outcomes are both delayed and probabilistic. Although the fixed-parameter model provided a good fit to the data, it is important to note that the free-parameter model, in which four parameters were free to vary, did provide a significantly better fit for both young adults (both Fs(4, 32) > 16.32, both ps < .001).

Table 6. Proportions of variance (R^2) accounted for by the parameter-fixed multiplicative discounting model (Eq. 4) in Experiment 3. The four parameters in Equation 4 were fixed to the values obtained when the hyperboloid (Eq. 2) was fit to standard delay and probability discounting when evaluated separately. The multiplicative hyperboloid was fit separately for young (left panel) and older adults (right panel) and for each of the three discounting subgroups (Even, Steeper-Probability, and Steeper-Delay) in each age group.

	Young Adults					Older Adults				
	k	s_d	h	s_p	R^2	k	s_d	h	s_p	R^2
Entire Age Group	0.637	0.333	17.147	0.335	0.809	0.129	0.580	90.942	0.238	0.923
Even-Discounting Sub-Group	0.553	0.375	16.917	0.440	0.813	0.132	0.664	128.059	0.204	0.893
Steeper-Probability Sub-Group	0.106	0.313	36.450	0.326	0.953	0.026	1.028	115.152	0.294	0.943
Steeper-Delay Sub-Group	0.667	0.458	6.183	0.417	0.584	0.878	0.396	15.343	0.296	0.573

4.2.1 Subgroup Analyses. The degree of delay discounting and degree of probability discounting are not approximately equal within individual. Although some individuals might show approximately equal discounting rates, others might discount probability more steeply than delay, and others might discounting delay more steeply than probability. Furthermore, choice when outcomes are both delayed and probabilistic might depend on how delay and probability separately are discounted. To evaluate whether discounting of rewards that are both delayed and probabilistic is different depending on how one separately discounts delayed rewards and probabilistic rewards, individuals were divided into one of three subgroups (Probability-Steeper, Delay-Steeper, and Even discounters) depending on their relative degree of standard delay and probability discounting, when these were evaluated separately. Participants were placed into subgroups based on the procedure described in the pilot study (i.e., delay discounting AuC - probability discounting AuC). For young adults, this procedure resulted in 10 Even discounters (a difference in delay and probability discounting AuCs of less than .1), 13 Probability-Steeper discounters, and 27 Delay-Steeper Discounters. For older adults, this procedure resulted in 15 Even discounters, 21 Probability-Steeper discounters, and 14 Delay-Steeper discounters.

A multiplicative model assumes that delay and probability interact to affect the degree of discounting, and this finding was observed in both young and older adults when the entire sample was observed together. However, if individuals differ in the way in which they separately discount delayed and probabilistic rewards, the model that best describes their combined discounting also might differ. A 6 (delay) x 6 (probability) x 3 (subgroup) x 2 (age) ANOVA was conducted on the subjective values. An interaction between delay and probability still was observed ($F(25, 70) = 12.80$, $p < .001$, $\eta_p^2 = .82$), but importantly, a three-way interaction between subgroup, delay, and probability was not observed ($F(50, 142) = 1.00$, $p = .48$), suggesting that all three subgroups showed the interaction between delay and probability**[F5]**. Although there was not a significant main effect of subgroup ($F(2, 94) = 1.46$, $p = .24$), this variable interacted with both delay and probability (both Fs(10, 182) > 2.09, both ps < .03, both η_p^2s > .10), suggesting that the extent to which delay and probability are discounted when outcomes are both delayed and probabilistic differed across the three subgroups. There was not a significant age x subgroup interaction ($F(2, 94) = 1.62$, $p = .20$), suggesting the young and older adults in each subgroup behaved similarly.

The results of the ANOVA found that for each subgroup, delay and probability interacted. To determine if a multiplicative model still provided a good description of the discounting of delayed and probabilistic rewards for each subgroup, Equation 4 was fit separately to the mean subjective values of each subgroup, separately for young and older adults. As can be observed in the bottom three rows of Table 5, the multiplicative hyperboloid model described the discounting of rewards that are both delayed and probabilistic well in each subgroup for both young adults and older adults.

Next, I determined whether standard delay and probability discounting could predict discounting on the combined discounting task in each subgroup. As with the entire-group data, the hyperboloid (Eq. 2) provided a good fit to the separate standard delay and standard probability discounting data for both young and older adults in each of the three subgroups (median R^2 = .98). The obtained parameter values then were substituted into the multiplicative hyperboloid model (Eq. 4), and each fixed-parameter model then was fit to the combined discounting data for each corresponding subgroup and age group. The bottom three rows of Table 6 display the parameter values used in the fixed multiplicative model and the fits of this model for each age and subgroup. Given there were no free parameters, the fixed multiplicative model accounted for a large percentage of variance for both young and older adults in each subgroup. However, there were considerable differences in the variance accounted for across subgroups. For both young and older adults in the Probability-Steeper subgroup, the fixed-parameter model accounted for a similar amount of variance as the model with four free parameters (compare Tables 5 and 6). However, the fixed-parameter model accounted for substantially less variance in the Even discounting subgroup and even less in the Delay-Steeper subgroup.

One possible explanation for this difference is that the subgroups discount rewards differently when delay and probability discounting are measured separately and when these conditions are presented intermixed in the combined discounting task. Recall that the standard conditions (e.g., $36 now vs. $96 in 1 month; 100% of $36 vs. 50% chance of $96) were presented both in the standard task and intermixed in the combined discounting task. One way to test whether degree of discounting changes when presented separately and intermixed is to compare these conditions. Figure 13 shows the area under the curve (AuC) for the delay (dark bars) and probability (light bars) discounting conditions when presented separately in the standard task and when presented intermixed in the combined discounting task for each of the three subgroups for young (top panels) and for older adults (bottom panels). Whereas the relative degree of discounting did not differ much between tasks for the Probability-Steeper subgroup, the degree of discounting changed between tasks for the Even and Delay-Steeper subgroups.

In the Delay-Steeper subgroup, the degree of delay discounting is steeper than the degree of probability discounting in the separate standard tasks (this is how individuals were placed into this subgroup). This relation changed, however, when the conditions were intermixed in the combined discounting task, such that the degree of delay discounting decreased and the degree of probability discounting increased. In the Even subgroup, the two degrees of discounting are approximately equal in the separate standard tasks, but the degree of probability discounting was greater than that of delay when the conditions were intermixed. Importantly, these findings are relatively consistent across both young and older adults. These results suggest that regardless of the relative degree of delay and probability discounting when assessed separately, probability appears to be discounted to a relatively greater degree than delay when outcomes are both delayed and probabilistic.

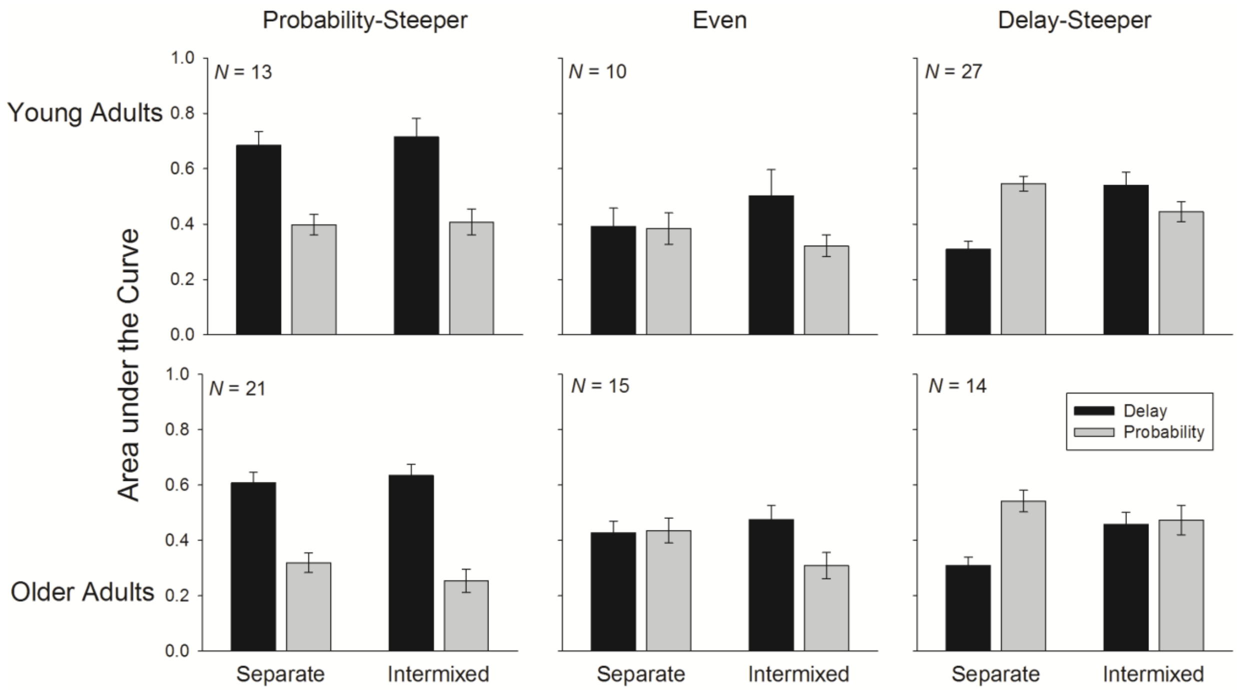

Figure 13. Mean area under the curve (AuC) and standard error for the standard delay discounting (dark bars) and standard probability discounting (grey bars) when evaluated separately and intermixed in the combined discounting task. The right panels correspond to individuals who discount probability more steeply than delay when evaluated separately (Probability-Steeper subgroup); the middle panels correspond to individual who discount delay and probability approximately the same when evaluated separately (Even subgroup); the left panels correspond to individual who discount delay more steeply than probability when evaluated separately (Delay-Steeper subgroup).

4.3 Discussion

The results of Experiment 3 replicated Vanderveldt et al. (2015) and, importantly, extended the findings to older adults and to groups of individuals who separately discount delayed and probabilistic rewards at different relative rates. In the current experiment, delay and probability interacted to affect the subjective value of an outcome, and the discounting of rewards that are both delayed and probabilistic was well-described by the four-parameter multiplicative hyperboloid model (Eq. 4). As also was observed in Vanderveldt et al., a simpler multiplicative model with fewer free parameters was tested but performed significantly worse than the four-parameter multiplicative model. This finding gives support for separate discounting rate parameters and exponents to account for the different effects of delay and probability discounting.

This finding is not surprising given the results of Experiment 1, in which the parameters of the hyperboloid changed in distinctly different ways for delay and probability discounting as amount of reward increased, suggesting that these parameters are accounting for unique changes in discounting when delay and probability are manipulated.

The current experiment also provided support for the finding that probability is discounted more steeply than delay when outcomes are both delayed and probabilistic. As is apparent in Figure 10, there is relatively little change in subjective value as delay increases (i.e., the discounting curves are relatively flat as a function of increasing delay), especially when the probability of receipt is lower. In contrast, there is steep probability discounting, even with very long delays. It is worth noting that degree of delay discounting is greater and degree of probability discounting is slightly less than what was observed in Vanderveldt et al. (2015), suggesting that some of those findings reported were driven by the extreme values of probability used compared to that of delay. However, the lowest probability used in the current study was relatively large (40%) and yet the main findings of Vanderveldt et al. still replicated.

Additional support for the view that probability has a greater effect than delay when outcomes are combined comes from the subgroup analyses. In Vanderveldt et al. (2015), probabilistic rewards were discounted to a greater degree than delayed rewards. In the current experiment, this result is reflected in the Probability-Steeper subgroup, and indeed the results of Vanderveldt et al. were replicated in this subgroup. Importantly, even when degree of probability and degree of delay discounting was made more similar in the current experiment (Even subgroup) or when delayed rewards were discounted to a greater extent than probabilistic rewards (Delay-Steeper subgroup), the results of Vanderveldt et al. held. In all three subgroups, delay and probability interacted, the multiplicative model (Eq. 4) accounted for choice very well, and probability appeared to have a greater effect than delay when outcomes were both delayed and probabilistic. That is, regardless of how individuals discounted delayed rewards and discounted probabilistic rewards separately, when outcomes were both delayed and probabilistic, individuals discounted the outcomes in qualitatively similar ways.

Despite the similarities observed across groups, the importance of considering subgroups became clear when evaluating the predictive power of standard delay and probability discounting tasks. When using the standard delay and standard probability discounting tasks to predict choice on the combined discounting task, there was a clear difference in proportion of variance accounted for in each of the three subgroups. Whereas the standard tasks by the Probability-Steeper subgroup accounted for a large percentage of variance in the combined discounting task (and was near identical to the fit of the free-parameter model), the predictive power in the Even and Delay-Steeper subgroups was substantially poorer. Many researchers have used standard delay or standard probability discounting tasks in order to assess and predict complex behavior. The current results suggest that even though the standard tasks generally predict complex behavior well (even the worse performing group accounted for 57% of the variance), there are major caveats. At a minimum, the relative degree of delay and probability discounting must be considered.

4.3.1 Comparison of Young and Older Adults. The results of the current experiment suggest a strong correspondence in complex decision making between young and older adults. Despite the strong qualitative similarities, however, differences were observed. There was a significant age x probability interaction in degree of delay discounting (see left panel of Figure 11). More specifically, older adults discounted delayed rewards significantly more than young adults when the probability of receipt was relatively high, but not guaranteed (i.e., 98%). As can be clearly observed in Figures 10 and 11, older adults were more affected by these initial decreases in probability than were young adults. To illustrate, when a reward was available immediately, but had a 98% probability of receipt, the mean subjective value of a $96 reward for young adults was $78.90. In contrast, for older adults, the mean subjective value dropped to $62.50. This disproportionally larger decrease in subjective for older adults when rewards were not guaranteed was consistent for rewards that also were delayed in time. When the $96 was available in 1 month with an 85% chance of receipt, the mean subjective value for young adults was $54.20 whereas for older adults, the mean subjective value was only $40.20. The finding that older adults are disproportionately more affected by reductions in probability in the combined discounting task is intriguing given the results of Experiment 1, in which there were no observed age differences in probability discounting.

Although there was no significant overall effect of age on probability discounting at each delay (see right panel of Figure 11), it is worth noting, that in the 'Now' condition, which is equivalent to a standard probability discounting task, older adults discounted more steeply than young adults (p = .04) and nominally less steeply at all other delays. This finding again contradicts what was observed in Experiment 1, in which there was no difference between young and older adults in probability discounting of gains. These different findings might be due to the manner in which the conditions were presented. In the current experiment, these conditions were presented intermixed in the combined delay and probability discounting task, rather than evaluated separately in a standard probability discounting task, as in Experiment 1. As was made clear by the subgroup analyses, individuals often discount delayed and probabilistic rewards differently when these conditions are evaluated separately or intermixed in the combined discounting task.

Recall that in the current experiment, participants completed a standard delay and probability discounting task prior to completing the combined discounting task. When AuCs of the separate standard probability discounting were compared, there was no significant effect of age (*t*(98) = -1.703, p = .092), replicating the results of Experiment 1. This finding is the first piece of evidence to suggest that young and older adults might discount probabilistic rewards differently, but only in more complex choice situations in which multiple attributes vary. It also adds support to the finding that individuals discount rewards differently when standard delay and probability discounting tasks are measured separately than when measured within the combined discounting task.

A major consistency observed across both young and older adults was that delay and probability interacted and that the multiplicative hyperboloid model provided an excellent description of choice when outcomes were both delayed and probabilistic. Given the complexity of a multiplicative model, this result may appear to be contradictory to the robust finding reported in the choice literature in which older adults use heuristics and simpler strategies of choice to a greater degree than young adults (e.g., Mata et al., 2007). Although delay and probability interact both in young and older adults, the manner in which they interact might differ. The degree to which young and older adults weight each factor, for example, might be different. Table 5 shows the free-parameter fit and parameter values of the multiplicative model (Eq. 4). As can observed, the k parameter for delay was very small for older adults (k = 0.07) compared to young adults (k = 0.356). Conversely, the h parameter for probability discounting was extremely large for older adults (h = 248.8) compared to young adults (h = 16.9). This pattern held when comparing across the three subgroups.

Research in the strategy literature has shown that older adults typically base their choices on a fewer number of dimensions in multi-attribute decisions (Mata et al., 2007; Queen et al., 2012; Riggle & Johnson, 1996). In Mata et al. (2007), for example, young and older adults made judgements about which of two diamonds was more expensive, and were provided information about several attributes for each diamond (e.g., size, clarity, color Mata et al. masked the values of the attributes so that participants had to click on each attribute to reveal its value. Using this process-tracing procedure, Mata et al. determined how many attributes an individual looked up and how often a particular attribute was examined during the decision-making process. Older adults generally searched less information before making a choice. The results of the current experiment suggest that older adults relied on probability to a greater extent than delay than did young adults. Although a different procedure was used than that of Mata et al., older adults may have used a simpler strategy by relying on information concerning the probability of receipt to a greater extent than the delay.. A follow-up experiment using a process-tracing procedure like that in Mata et al. can determine whether older adults considered probability of receipt more often than delay when making a choice, or whether the greater probability discounting observed in older adults merely reflects greater risk-aversion in complex environments.

Chapter 5: General Discussion

The discounting framework has greatly aided in modeling and understanding decision-making, particularly in the areas of impulsivity, but the findings overwhelmingly have been based on research with young adults. There has been limited research on discounting among people of different ages, with much of that work focusing on developmental changes in self-control as children progress to young adulthood. In three experiments, the current study extended the discounting framework by examining decision making in older adults. Experiments 1 and 2 found that both young and older adults discounted delayed outcomes and probabilistic outcomes and that their choices were well-described by the hyperboloid model. So, too, both young and older adults showed magnitude effects with delayed rewards, reverse magnitude effects with probabilistic rewards, and no systematic effect of amount on the discounting of delayed or probabilistic losses. In Experiment 3, in which choice was more complex and involved rewards that were both delayed and probabilistic, a multiplicative hyperboloid model in which delay and probability interacted to affect the subjective value of an outcome described choice well for both young and older adults. The results of Experiment 3 also suggested that individuals tend to become more risk-averse (i.e., discount probabilistic rewards more) and more patient (i.e., discount delayed rewards less) in these complex choice situations.

Across the three experiments, differences between young and older adults emerged. Much of the previous work in discounting examining age has compared degree of discounting, and most studies report that older adults tend to discount delayed rewards less steeply than young adults (e.g., Green, Fry, et al., 1994; Harrison et al., 2002; Jimura et al., 2011; Whelan & McHugh, 2009). When household income was considered in the current study, older adults discounted delayed rewards less steeply than young adults at all but the largest amounts, at which point there were no discernable age differences. This finding adds strong support for a reliable difference between young and older adults, but suggests that this difference is more complex and that other variables, like income, must be considered. Another consistency with previous research was the magnitude effect observed for delayed gains, in which larger amounts were discounted relatively less steeply than smaller amounts. In addition, degree of discounting levelled off with increasing amounts. For young adults in the current study, the asymptote at which degree of discounting levelled off was at rather large amounts and not easily observed given the range of amounts used (see Appendix A). For older adults, the asymptote appeared at much smaller amounts (around $3,000), and consistently was observed across income groups.

It is not clear why a magnitude effect exists when people discount delayed rewards (see Green, Myerson, & Vanderveldt, 2014 for a discussion of possible explanations of a magnitude effect); therefore, it is not immediately clear why such a difference might occur between age groups. The simplest explanation might be a ceiling effect. Older adults reliably discount less steeply than young adults. Because larger amounts are discounted at increasingly lower rates, a point is reached in which there would be no discernible difference in the degree of discounting with further increases in amount. However, as can be clearly seen in Figure 4, older adults in each income group discounted well below the maximum. In particular, individuals making under $50,000 had an asymptote at approximately 45% of the nominal value of the reward, well below the maximum. Until an explanation can be found for why humans show a magnitude effect, any differences observed across age groups might not be fully satisfying.

There has been little previous work examining age and the discounting of losses. Löckenhoff et al. (2011) and Halfmann et al. (2013) both reported no difference between young and older adults in the degree of discounting delayed losses, but Experiment 2 of the current work found this relation to be more complex. No overall significant age difference was observed, but when household income was considered, older adults reliably discounted delayed losses less steeply than young adults. Older adults may be more willing to pay an immediate cost in order to avoid a larger payment later, giving some support to the view that older adults may be more debt-averse whereas young adults may be more loss-averse (Myerson et al., in press).

Finally, although Experiment 3 showed that a multiplicative hyperboloid model described the discounting of outcomes that are both delayed and probabilistic for both age groups, the exact way in which delay and probability interacted might differ. Older adults appear to be affected by probability to a greater extent than young adults, and this effect is stronger with initial decreases from certainty (e.g., 98% and 85%) than for smaller probabilities (e.g., 40%). This result is surprising given the finding that young and older adults did not differ on a probability-discounting task given separately from the combined discounting task. Although this finding needs to be explored more, it does suggest the need to continue examining decision making within more complex choice environments. It is clear from Experiment 3 that individuals discount delayed rewards and probabilistic rewards differently when evaluated separately or in a combined discounting task in which both attributes vary (see Figure 13). There is some evidence that in less complex choice environments, the decision-making strategy used by young and older adults is similar, but as the choice situation becomes more complex, age differences become more apparent (Mata et al., 2010). In the standard probability discounting task, only amount and probability of receipt varied from trial to trial, whereas in the combined discounting task, an individual must take into account the delay, probability, and amount that change on every trial. Given most choices people make are more complex and frequently involve outcomes that are both uncertain and delayed in time, many important age differences may be overlooked when only simpler choice environments are examined. Although risk-aversion often is preferred to risk-taking, it is not always ideal to be risk-averse. The findings of Experiment 3 raise the possibility that older adults may make poorer decisions (i.e., when expected value favors taking the risky alternative) in more complex choice situations because they overweight the risks. Furthermore, the age differences observed in Experiment 3 may become even more extreme when even more complex choice environments, like those experienced in the natural environment, are examined.

5.1 Future Directions

The current series of experiments reported several novel findings in the study of discounting and age, and provided additional support for some previously reported age differences. Some of the reported findings, of course, need to be explored more fully in future research. Most evidently, the effect of household income on degree of delay and probability discounting will need more systematic analysis. Given the little prior research considering income in discounting research (viz., Green et al., 1996), it was not predicted to have a major influence on discounting in the current study. However, several differences across income groups were observed in Experiments 1 and 2, and some apparent age differences and similarities were made clear once household income was taken into consideration. The current study did not actively recruit participants from different income brackets, and the young adult sample was not diverse enough to examine income effects in young adults.

The current study was limited by the use of a two age group design. Although interesting age differences were observed across all three experiments, little is understood about the transition in decision making from young to older adulthood. There might be a gradual transition in how one makes decisions from young to older adults, or there might be a point of more abrupt change after which no further age differences are observed. Green et al. (1996), for example, observed that young and older adults differed in their degree of delay discounting, but that an intermediary adult group did not differ from older adults after income was controlled. The differences between young and older adults observed in the current study will be better understood when more intermediary age groups are examined.

The discounting of losses is just beginning to be explored and understood more clearly. Using a different procedure, Myerson et al. (in press) recently showed that individuals can vary in their discounting of delayed losses, not only quantitatively, but also qualitatively, and they identified different groups of individuals that they labeled debt-averse and loss-averse. The results of Experiment 2 suggest that there might be a higher percentage of debt-averse older adults than young adults, but future research with the procedures used by Myerson et al. will have to confirm whether this finding holds.

The results of Experiment 3 showed that when outcomes were both delayed and probabilistic, people tended to show greater probability discounting and less delay discounting. Given the novelty of this finding, it must be investigated whether the effects of probability still overwhelm those of delay in different complex choice environments. In Experiment 3, participants made choices between outcomes that were both delayed and probabilistic and outcomes that were both immediate and certain. One method in which to test the competing effects of delay and probability is to directly pit these effects against each other. Choice, for example, might be between a delayed outcome and a probabilistic outcome of the same subjective value (e.g., a 70% chance of receiving $96 now vs. a 100% chance of receiving $96 in 6 months). If, when evaluated separately, subjective value is equated for each option, then the individual should not have a preference for one outcome over the other. The results of Experiment 3, however, would suggest that when both the delay and the probability of receipt are considered, participants will discount the probabilistic reward more and the delayed option less. This effect would lead individuals to overwhelming choose the delayed reward over a probabilistic reward of the same subjective value.

Finally, expanding the current research to functional neuroimaging may reveal interesting results that are not easily observed with behavioral data alone. Experiments 1 and 2 revealed age-related differences, when income was controlled, in delay discounting but not probability discounting. What is unclear from the current study are the underlying mechanisms moderating these age differences in delay discounting and age similarities in probability discounting. The observed age similarities in probability discounting, for example, might be the result of distinct neural processes in young and older adults. Research in neuroeconomics has shown the importance of both cognitive and emotional aspects when evaluating subjective value in discounting tasks (e.g., Kable & Glimcher, 2007; McClure et al., 2004). Regions typically associated with cognitive control functions, like planning and goal maintenance, (e.g., prefrontal cortex, anterior cingulate cortex; Botvinick, Braver, Barch, Carter, & Cohen, 2001) and regions associated with emotion (e.g., amygdala, orbitofrontal cortex; O'Doherty, 2004; Seymour & Dolan, 2008) are reliably recruited during decision making tasks. Interestingly, there appear to be distinct age-related changes in brain regions associated with cognitive and emotional processes. Whereas there tends to be structural decline in older adults tend in the brain regions associated with cognitive control functions (e.g., Raz et al., 1997), older adults generally exhibit both greater structural preservation and greater activation in regions associated with emotional regulation (Nashiro, Sakaki, & Mather, 2012). Research in neuroeconomics can help unravel the effects of cognitive control and emotional regulation in probability discounting across young and older adults. Despite showing similar behavioral patterns, individuals might make these decisions in fundamentally distinct ways, with young adults relying to a greater extent on cognitive control and older adults relying to a greater extent on emotional regulation.

5.2 Conclusions

Although it is tempting to highlight the age differences observed in the current study, the remarkable consistency across young and older adults must not be understated. In Experiments 1 and 2, the hyperboloid model described both young and older adults' decision making across several different choice situations. In more complex environments, as in Experiment 3, a multiplicative model derived from the hyperboloid accounted for choices by both age groups. The effects on discounting when outcome amount was varied was similar across young and older adults for both delayed and probabilistic gains and losses. In Experiment 3, delay and probability interacted to affect subjective value of an outcome, and probability was discounted more steeply when combined with delay, regardless of how the delayed and the probabilistic rewards were discounted separately. Finally, for both young and older adults, delay and probability appeared to be distinct processes: There was little relation between how one made decisions involving delayed outcomes and how one made decisions involving probabilistic outcomes, and this did not change as a function of age.

There are many changes across the lifespan, both biological and learned, that shape how an individual makes choices. The current study certainly observed some differences in decision making across young and older adults. However, there was remarkable consistency between the age groups in the decision-making model that described their choices and in the relative independence of delayed and probabilistic choice. There undoubtedly are interesting quantitative age differences in decision making, but the results of the current study suggest that choice appears rather qualitatively similar across age groups.

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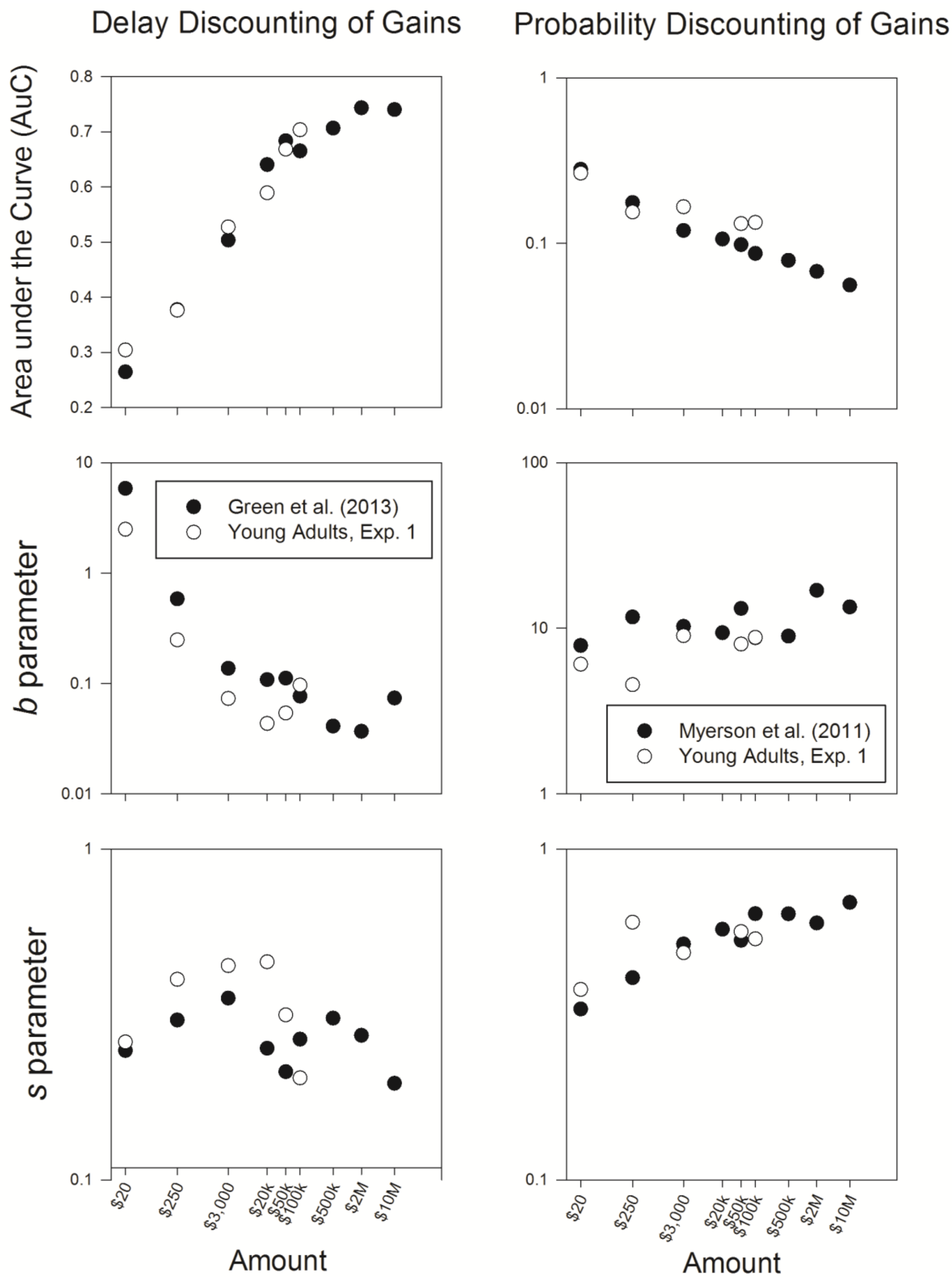
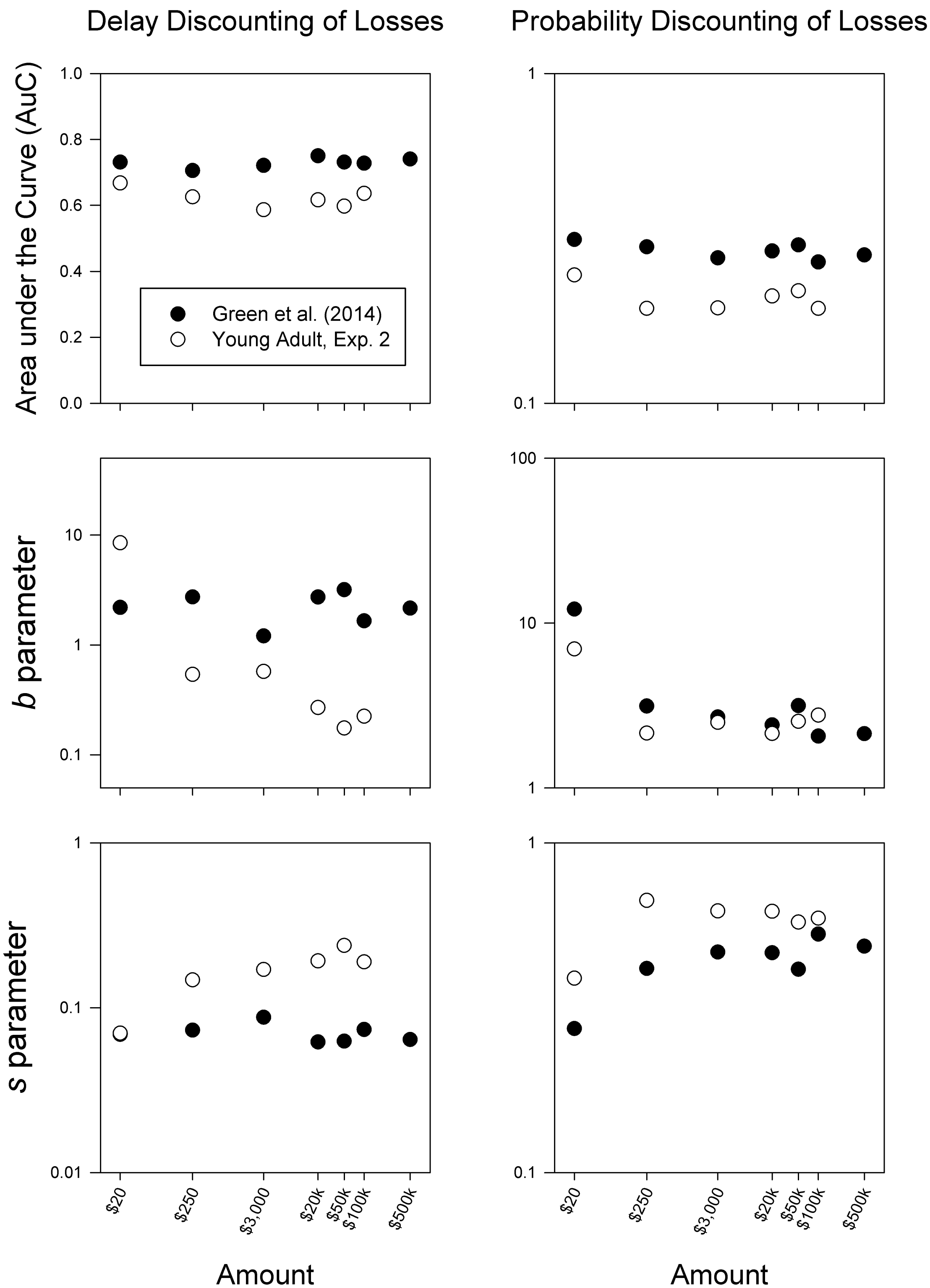
Appendix A

Comparison of Young Adult Discounting of Gains in the Current Study to Green et al. (2013; Delay Discounting) and to Myerson et al. (2011; Probability Discounting)



Appendix B

Comparison of Young Adult Delay and Probability Discounting of Losses in the Current Study to Green et al. (2014)



Footnotes

[1]An error in the program led to the $20,000 probabilistic amount condition not being presented. For the statistical analyses, this amount was not included.

[2]Smoking nicotine has reliably been shown to affect delay discounting (i.e., Yi, Mitchell, & Bickel, 2010), so a question about smoking was included on the demographic questionnaire to validate that the number of individuals who smoked did not differ across age groups. Across all three experiments, relatively few individuals in either age group reported smoking (2 young adults and 3 older adults). Therefore, this variable was not considered in any analyses.

[3]An error in the program led to the $20,000 probabilistic reward not being presented to older adults, and therefore was not included in the statistical analyses. This error was corrected for the young adults and the amount, therefore, was included in statistical analyses when appropriate.

[4]A separate ANOVA for each age group confirmed a significant interaction between delay and probability (both Fs(25, 25) > 4.6, both ps < .001, both η_p^2s > .82).

[5]A separate 6 (delay) x 6 (probability) ANOVA was conducted for the Probability-Steeper and Delay-Steeper subgroups. There was not enough participants to conduct this ANOVA for the Even subgroup. A significant interaction between delay and probability was observed for both the Probability-Steeper and the Delay-Steeper subgroups (both Fs > 3.19, both ps < .03, both η_p^2s > .89).