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DISCOUNTING OF DELAYED AND PROBABILISTIC LOSSES OVER A WIDE RANGE OF AMOUNTS

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Abstract

The present study examined delay and probability discounting of hypothetical monetary losses over a wide range of amounts (from \$20 to \$500,000) in order to determine how amount affects the parameters of the hyperboloid discounting function. In separate conditions, college students chose between immediate payments and larger, delayed payments and between certain payments and larger, probabilistic payments. The hyperboloid function accurately described both types of discounting, and amount of loss had little or no systematic effect on the degree of discounting. Importantly, the amount of loss also had little systematic effect on either the rate parameter or the exponent of the delay and probability discounting functions. The finding that the parameters of the hyperboloid function remain relatively constant across a wide range of amounts of delayed and probabilistic loss stands in contrast to the robust amount effects observed with delayed and probabilistic rewards. At the individual level, the degree to which delayed losses were discounted was uncorrelated with the degree to which probabilistic losses were discounted, and delay and probability loaded on two separate factors, similar to what is observed with delayed and probabilistic rewards. Taken together, these findings argue that although delay and probability discounting involve fundamentally different decision-making mechanisms, nevertheless the discounting of delayed and probabilistic losses share an insensitivity to amount that distinguishes it from the discounting of delayed and probabilistic gains.

Keywords

delay discounting; probability discounting; losses; amount; hyperboloid; behavioral economics; humans

Many everyday situations involve choosing between outcomes that differ in amount as well as in the delay until their occurrence or the likelihood of their occurrence. Such choices are important not just because of their consequences for people's lives but also because of their theoretical implications. Perhaps in recognition of the important life consequences of individuals' choice behavior, there is a rapidly growing literature on differences in the degree to which various groups of people (e.g., substance abusers, the elderly) discount the value of delayed or probabilistic outcomes (Madden & Bickel, 2010). From an individual-differences perspective, researchers are seeking to understand the extent to which an

individual's tendency to discount the value of outcomes that are delayed or probabilistic reflects a single underlying trait (e.g., impulsivity) or whether multiple traits are involved. In addition, there is a growing interest in how individuals make such choices, perhaps in recognition that the processes involved reflect fundamental decision-making mechanisms (e.g., Green & Myerson, 2013; van den Bos & McClure, 2013). Of course, these different lines of research can have important implications for each other: Understanding how choices are made can clarify why it is that different individuals make different choices, and understanding how individuals differ can provide clues as to whether different types of choices involve the same or different processes.

Most previous research on discounting has focused on choices involving positive outcomes (gains or rewards), and in particular on how gains are discounted when they are delayed. Such behavior is well described by a hyperboloid discounting function:

$$V = A / (1 + bX)^s, \quad (1)$$

where V is the subjective value of a delayed reward, A is the amount of that reward, X is the delay until its receipt, b is a rate parameter that describes how rapidly the reward loses its value as the delay increases, and the exponent, s , reflects the psychophysical scaling of amount and delay (Green & Myerson, 2004). The same equation (with X as the odds against receiving a reward) also describes the discounting of probabilistic gains, although the interpretation of the exponent in such cases appears to be different (Myerson, Green, & Morris, 2011).

Despite the fact that the discounting of delayed gains and the discounting of probabilistic gains are both well described by the same equation, there are significant differences between the two kinds of discounting. One robust difference concerns the effect of the amount of reward: Larger delayed gains are discounted less steeply than smaller delayed gains, whereas larger probabilistic gains are discounted more steeply than smaller ones. In addition, the amount of delayed reward affects the rate parameter (b) of the discounting function but not the exponent (s), whereas the opposite is true for probabilistic rewards—amount affects the exponent of the discounting function but not the rate parameter (Myerson et al., 2011; Green, Myerson, Oliveira, & Chang, 2013). Moreover, an individual's tendency to steeply discount delayed gains is, at best, only weakly correlated with his or her tendency to steeply discount probabilistic gains (e.g., Chapman, 1996; Myerson, Green, Hanson, Holt, & Estle, 2003; Olson, Hooper, Collins, & Luciana, 2007), a result that strongly suggests that there is more than one “impulsivity” underlying tendencies toward making impatient or risky choices. Taken together, these findings suggest that despite some important similarities, there are fundamental differences between delay and probability discounting, at least when the outcomes involved are positive.

Relatively little is known, however, about the discounting of negative outcomes (losses or payments) despite their obvious importance, both theoretically and in terms of their role in everyday choice situations, although two things seem clear. First, as in the case of positive outcomes, the discounting of delayed losses and the discounting of probabilistic losses both can be described by Equation 1, and second, also as in the case of positive outcomes, an

exponent with a value less than 1.0 typically provides the best fits to data at both the individual and group levels (Estle, Green, Myerson, & Holt, 2006; Ostaszewski & Karzel, 2002). What is unclear is how amount affects the discounting of delayed losses, with some studies reporting amount effects similar to those observed with gains (Chapman, 1996; Ostaszewski & Karzel, 2002; Thaler, 1981) and other studies reporting no effect of amount on the discounting of losses (Baker, Johnson, & Bickel, 2003; Estle et al., 2006; McKerchar, Pickford, & Robertson, 2013; Mitchell & Wilson, 2010). One study even reported that small losses showed negative discounting rates (i.e., individuals would choose to pay more now rather than pay less later), whereas larger losses were associated with positive discounting rates (Hardisty, Appelt, & Weber, 2012). Greater consensus exists with respect to probability discounting of losses, with several studies reporting little or no effect of amount (Estle et al., 2006; Mitchell & Wilson, 2010; Ostaszewski & Karzel, 2002). The present study attempts to clarify the relation between amount of loss and degree of discounting by examining the discounting of both delayed and probabilistic losses over a much wider range of amounts than previously studied.

Moreover, the effects of amount of loss on the rate parameter and on the exponent of the hyperboloid discounting function have not been examined previously. Mitchell and Wilson (2010) did not fit their data with a discounting function. Ostaszewski and Karzel (2002) fitted their data with a hyperboloid function but used a model in which the exponent was held constant across all delayed and probabilistic amounts based on the untested assumption that the value of the exponent of the function is independent of amount. Finally, Estle et al. (2006) examined the effects of amount on the exponent but did not report the results for the rate parameter. The present study is the first to examine how both parameters of the hyperboloid discounting function are affected by amount of delayed and probabilistic loss.

Perhaps surprisingly, given the importance (both theoretically and with respect to applied issues) of the relative independence of delay and probability discounting when gains are involved, no studies have examined the correlation between delay and probability discounting when the outcomes are losses. The present study is the first to address this issue, which is important from the perspective of the growing interest in determining how many “impulsivities” there are (Green & Myerson, 2013).

Thus, the present study had three goals. First, we wished to examine how amount of loss affects delay and probability discounting using a much wider range of amounts than has been studied previously. Recently, Green et al. (2013) and Myerson et al. (2011) have taken this approach with regard to the discounting of delayed and probabilistic gains, and the results established similarities and differences between delay and probability discounting that were only suggested by the results of previous studies that used a much narrower range of amounts. Second, we wished to examine how amount of loss affects both the rate parameter and the exponent of the hyperboloid discounting function, an issue that has not been addressed in previous studies. In our recent research on the discounting of delayed and probabilistic gains, the use of a wide range of amounts revealed clear differences in how the parameters of the hyperboloid function behave, and these differences, in turn, yielded insights into the mechanisms underlying delay and probability discounting, at least when the outcomes involved are gains. The present study uses this same approach to examine how

amount affects the parameters of the delay and probability discounting functions when losses, rather than gains, are involved. Third and finally, given the relative independence of the tendency toward steep discounting of delayed and probabilistic rewards, we sought to assess the extent to which a tendency to steeply discount delayed losses predicts a tendency to steeply discount probabilistic losses (and vice versa), and whether these tendencies represent the same or separate “impulsivity” traits.

Method

Participants

Fifty undergraduate students (21 males and 29 females, mean age = 20.7 years) were recruited from the Washington University Department of Psychology’s human subject pool and received course credit for their participation.

Procedure

Participants were tested individually in a quiet room. The computer-administered discounting tasks presented participants with a series of choices between two hypothetical payments. In the delay discounting task, choices were between a smaller amount of money to be paid immediately and a larger amount to be paid after a delay. In the probability discounting task, choices were between a smaller amount of money to be paid for sure and a larger amount to be paid with a given probability.

The two tasks were administered in separate sessions: On average, the number of days between the first and second sessions was 4.5 (range = 2-9 days). Twenty-six participants completed the probability discounting task first, while the other twenty-four participants completed the delay discounting task first.

At the beginning of each session, the instructions for the discounting task were read aloud by the experimenter and simultaneously were presented on the computer monitor. Three practice conditions preceded the actual experimental conditions and participants had an opportunity to ask questions, following which the experimental conditions were presented.

The instructions for the delay discounting task were as follows:

In the experiment, you will be asked to make a series of decisions about different amounts of money that you might have to PAY. For each alternative presented, we are interested in which amount you would choose to PAY if you were offered that choice for real. On each trial, two amounts of money will appear on the screen. One amount would have to be paid RIGHT NOW. The other amount would have to be paid LATER, and the screen will show you how long it will be before you have to pay this later amount. The RIGHT NOW amount of money will change after each choice. The LATER amount of money will stay the same for a group of choices.

For each alternative, indicate the option you would choose by clicking the appropriate button. THERE ARE NO CORRECT OR INCORRECT CHOICES. Although you will not actually pay the money, assume that you have sufficient funds and make your

choices as if the alternatives were real. If you change your mind about a choice, you can return to the start of that group of choices by clicking the “Reset” button on the screen.

The instructions for the probability discounting task were similar, except that “RIGHT NOW” was replaced by “FOR SURE,” “would have to be paid LATER” was replaced by “MIGHT POSSIBLY have to be paid,” and “The LATER amount” was replaced by “The POSSIBLE amount.”

The delay discounting task consisted of 42 conditions: seven amounts of delayed payment (\$20, \$250, \$3,000, \$20,000, \$50,000, \$100,000, and \$500,000) crossed with six delays (1 month, 3 months, 6 months, 1 year, 6 years, and 12 years). The probability discounting task consisted of 35 conditions: the same seven amounts used in the delay discounting task crossed with five probabilities (80, 50, 25, 10, and 5 percent chance). In each condition, an adjusting-amount procedure was used to obtain an estimate of the amount of the immediate/certain payment that was equivalent in value to the delayed/probabilistic payment (Du, Green, & Myerson, 2002).

The computer program randomly selected a delayed/probabilistic payment amount (without replacement) and then administered all 6 delay/5 probability conditions for that amount in a random order before selecting another delayed/probabilistic payment amount. The side of the computer screen on which the delayed/probabilistic payment was presented alternated randomly across conditions within a session. Each condition consisted of a series of six choice trials. On the first trial, the participant chose between paying either the delayed/probabilistic amount or half of that amount immediately/for certain. On each subsequent trial, the amount of the immediate/certain payment was adjusted based on the participant's choice on the preceding trial. Specifically, if the participant had chosen the immediate/certain payment on the previous trial, the amount of immediate/certain payment was increased; if the participant had chosen the delayed/probabilistic payment, the amount of the immediate/certain payment was decreased.

The size of the adjustment (i.e., the decrease or increase in the immediate/certain payment amount) decreased with successive choices within a condition. The first adjustment was half of the difference between the amounts of the immediate/certain and delayed/probabilistic payments presented on the first trial, and the size of each subsequent adjustment was half that of the preceding adjustment, rounded to the nearest dollar. For example, in the condition where the delayed payment was \$20,000 paid in a year, the choice on the first trial would be between “\$20,000 in a year” and “\$10,000 right now.” If the participant chose the “\$10,000 right now,” the choice on the second trial would be between “\$20,000 in a year” and “\$15,000 right now.” If the participant then chose the “\$20,000 in a year,” the choice on the third trial would be between “\$20,000 in a year” and “\$12,500 right now.” Following the sixth and last trial of each condition, the subjective value of the delayed/probabilistic payment was estimated as the amount of immediate/certain payment that would have been presented on the seventh trial.

Results

Figure 1 shows group mean relative subjective value plotted as a function of the delay until payment for each of the seven amounts, and Figure 2 shows group mean relative subjective value plotted as a function of the odds against having to pay for each of the seven amounts. Relative subjective value (i.e., subjective value as a proportion of the actual amount of the delayed payment) is used as the dependent variable in order to facilitate comparisons across different payment amounts. In each panel, the solid curve represents the hyperboloid function (Eq. 1) that best fitted the data for that amount condition. Note that relative value is positive because it is calculated by dividing the amount of the immediate or certain payment by the amount of the delayed or probabilistic payment, and dividing one negative number by another negative number yields a positive number.

Fits of the Hyperboloid Discounting Function

As may be seen in Figures 1 and 2, the hyperboloid function provided very good fits to the group delay and probability discounting data at each amount: Across the fits to the data from the seven delayed amount conditions, the median R^2 was .927, and across the fits to the data from the seven probabilistic amount conditions, the median R^2 was .997 (see Table 1). In order to obtain a single overall measure of goodness of fit, the hyperboloid function was fitted simultaneously to the group data from all seven delayed/probabilistic amount conditions with a separate b and s parameter for each amount; the resulting R^2 for delay discounting was .928 and for probability discounting was .993. (In both figures, the dashed curves, to be discussed later, represent a hyperboloid function with a single b parameter and a single s parameter fitted simultaneously to the data for all seven amounts.)

The hyperboloid function also provided reasonably good fits to the data at the individual level. In order to obtain an overall R^2 for each participant, the hyperboloid function was fitted simultaneously to the participant's data from all seven amount conditions. This was done separately for the delay and probability discounting data. Across the 50 participants, the median overall R^2 for the delay discounting data was .694 and the median overall R^2 for the probability discounting data was .891. Fits of the hyperboloid function to data from the next-to-smallest (\$250), middle (\$20,000), and next-to-largest (\$100,000) amounts for the individuals whose overall R^2 s were at the first, second, and third quartiles for delay discounting are presented in Figure 3, and the fits to the corresponding data for probability discounting are presented in Figure 4.

Data from all 50 participants, regardless of R^2 , were included in the group means (see Figs. 1 and 2). After all, it would seem inappropriate to examine application of a model to a novel situation (i.e., the discounting of delayed and probabilistic losses) and analyze only the data from those participants whose behavior was well described by that model. We would note, however, that when we did examine the effect of amount of loss on the degree of discounting with and without data from those participants with extremely low R^2 s, the same pattern of results (described in the following section) was observed in both cases.

Effect of Amount on Degree of Discounting

There was no apparent effect of amount on the discounting of delayed losses or on the discounting of probabilistic losses at either the group or individual level. The absence of magnitude effects can be seen clearly in Figure 5, which plots the area under the (discounting) curve (AuC) as a function of amount. Following Myerson, Green, and Warusawitharana (2001), the AuC values have been normalized so as to range from 0.0, indicating maximal discounting, to 1.0, indicating no discounting. The top panels show the AuC based on the group means for delayed and probabilistic losses (left and right panels, respectively), and the bottom panels show the corresponding median individual AuCs at each amount.

Similar to what was observed at the group level and in the median individual AuCs, little or no systematic effect of amount on either delay or probability discounting of losses was observed when discounting was examined in each individual participant. The relation between degree of discounting and amount was assessed by examining the distribution of correlations between each individual's AuC and the logarithm of the amount of loss. (The logarithm of amount was used because of the increasing difference between successive amounts.) With respect to the relation between the degree of delay discounting and log amount, the 95% confidence intervals about the mean Fisher z included zero ($.190 \pm .235$), indicating that the correlation was not significant. With respect to the relation between the degree of probability discounting and log amount, the 95% confidence intervals about the mean Fisher z did not include zero ($-.218 \pm .186$). This analysis was rerun without the AuC for the \$20 probabilistic loss because, as described below, the parameter estimates for this amount were anomalous (see Table 1). When the AuC for \$20 was not included in the analysis, the mean Fisher z was $-.084 \pm .179$, indicating that for losses ranging from \$250 to \$500,000, degree of probability discounting was not significantly correlated with amount. Examination of the AuCs for the six individuals whose overall R^2 s were at the first, second, and third quartiles (and whose discounting functions were presented in Figs. 3 and 4) reveals no consistent effect of amount on the discounting of either delayed or probabilistic losses (see Fig. 6).

Parameters of the Delay Discounting Function

A major goal of the present effort was to examine the effects of amount on the parameters of the hyperboloid discounting function (Eq. 1). The left panels of Figure 7 show the parameter estimates from the fits of the hyperboloid discounting function to the group mean delay discounting data depicted in Figure 1. As may be seen, neither the value of the b parameter (top left panel) nor the value of the s parameter (bottom left panel) changed systematically as the amount of delayed loss increased. The values of the b and s parameters also were not systematically related to amount of delayed loss at the individual level, although there was considerable variation among individuals. Because the distributions of b and s parameter values were both skewed, correlational analyses were conducted using the logarithms of these values. With respect to the correlation between log amount and log b , the 95% confidence interval about the mean Fisher z ($-.123 \pm .156$) included zero, indicating that the correlation was not significant. Likewise, the correlation between log amount and log s was not significant (mean Fisher $z = .091 \pm .165$).

The finding that the parameters of the hyperboloid discounting function are relatively independent of the amount of delayed loss suggests that a parsimonious hyperboloid model, one with only a single, amount-independent s parameter and a single, amount-independent b parameter, can describe the discounting of delayed losses irrespective of amount. Accordingly, we fitted a reduced model with a single exponent and a single discount rate parameter to the group mean data from all seven delayed amount conditions simultaneously. The fit of this reduced model to the group mean data is represented by the dashed curves in Figure 1. As may be seen, the reduced model (with its two free parameters) provided a good fit ($R^2 = .907$) to the delay discounting data, that was not significantly different from the fit of the full model ($R^2 = .928$) which had a separate b and s parameter for each amount (a total of 14 free parameters); $F(12, 28) < 1.0$.

Parameters of the Probability Discounting Function

The right panels of Figure 7 show the parameter estimates from the fits of the hyperboloid discounting function to the group mean probability discounting data depicted in Figure 2. As may be seen, the value of the b parameter for the \$20 probabilistic loss was higher than for larger probabilistic losses, whereas the value of the s parameter for a \$20 loss was lower than for larger losses. Importantly, neither the value of the b parameter (top right panel) nor the value of the s parameter (bottom right panel) appeared to change systematically as the amount of probabilistic loss increased from \$250 to \$500,000. These observations were confirmed statistically by examining the correlations between parameter values and the logarithms of the amounts of probabilistic loss. When the parameter estimates for the \$20 loss were not included in the analyses, the 95% confidence intervals for the correlations between log amount and log b (mean Fisher $z = -.093 \pm .175$) and between log amount and log s (mean Fisher $z = .157 \pm .169$) both included zero, indicating that neither of these correlations was significant.

Again, the finding that the parameters of the hyperboloid discounting function were relatively independent of the amount of loss suggests that a reduced model with a single s parameter and a single b parameter might describe the discounting of probabilistic losses across this range of amounts. Accordingly, as was done with the delay discounting data, we fitted a reduced model with a single exponent and a single discount rate parameter to the group mean data from all seven probabilistic amount conditions simultaneously. The reduced two-parameter model, represented by the dashed curves in Figure 2, provided a very good fit ($R^2 = .980$) to the probabilistic loss data, although the fit of the full model with its 14 free parameters (one b and one s parameter estimate for each of the seven amounts) was significantly better ($R^2 = .993$); $F(12, 21) = 3.25$, $p < .01$. With the \$20 amount excluded, however, there was no difference between the fits of the full ($R^2 = .993$) and reduced ($R^2 = .990$) models; $F(10, 18) < 1.0$. This finding indicates that with probabilistic losses, as with delayed losses, amount has little or no effect on discounting.

Analyses of Individual Differences

One approach to the question of how individuals differ in the steepness with which they discount is to look at the results of correlational and factor analyses. Table 2 presents the intercorrelations among the AuCs for the different amounts of delayed losses, and Table 3

presents the intercorrelations for the different amounts of probabilistic losses. As may be seen, these correlations were consistently strong (all r s > .57, all p s < .001) in each domain, indicating that those who steeply discounted one delayed amount discounted other delayed amounts steeply as well, and those who steeply discounted one probabilistic amount discounted other probabilistic amounts steeply.

In contrast, none of the correlations between the AuC for a given delayed loss amount and the AuC for the corresponding probabilistic loss was significant (median r = .074, median p = .609), indicating that the steepness with which individuals discounted delayed losses did not predict the degree to which they discounted probabilistic losses (or vice versa). The independence of delay and probability discounting is also clearly evident in the results of factor analyses of the AuC data from the 7 delayed and 7 probabilistic amount conditions (see Table 4). Principal components analysis revealed only two components with Eigenvalues greater than 1.0, and these two components together accounted for 84.2% of the variance. A subsequent analysis using Varimax rotation revealed one factor on which only the delayed loss conditions loaded strongly (all loadings > .76) and a second factor on which only the probabilistic loss conditions loaded strongly (all loadings > .88). The strength of these loadings may be contrasted with the very weak loadings (all loadings < .13) of the probabilistic loss conditions on the first (delay) factor and of the delayed loss conditions on the second (probability) factor.

Discussion

The current study examined the discounting of a wide range of amounts of delayed losses and probabilistic losses. At each of the amounts studied, which ranged from \$20 to \$500,000, the hyperboloid discounting model (Eq. 1) provided an excellent description of both the delay and probability discounting data at the group level, and a good description at the individual level. In contrast to what is observed with gains, there was no evidence that the degree to which either a delayed or a probabilistic loss was discounted was systematically affected by the magnitude of the loss. The parameters of the discounting functions also were unaffected by the amount of loss, and consistent with this result, hyperboloid models with only one (amount-independent) rate parameter and a single (amount-independent) exponent described the discounting of delayed and probabilistic losses.

The present study is the first to examine the discounting of delayed and probabilistic losses across such a broad range of amounts (i.e., more than four orders of magnitude) and the first to examine the effects of amount of loss on both parameters of the delay and probability discounting functions. In our recent studies of the discounting of delayed and probabilistic gains (Green et al., 2013, and Myerson et al., 2011), the use of a wide range of amounts revealed clear differences in how amount of gain affected the degree of discounting and the parameters of the hyperboloid function. This approach yielded important insights into fundamental differences in the mechanisms underlying the discounting of delayed and probabilistic gains. In contrast, amount had little or no effect on the degree to which either delayed or probabilistic losses were discounted. The present findings replicate those of two previous studies that examined discounting of both delayed and probabilistic losses (Estle et

al., 2006; Mitchell & Wilson, 2010; cf. Ostaszewski & Karzel, 2002), albeit over much narrower ranges, and are the first to establish that over a very broad range, the values of both the rate parameter and the exponent of the hyperboloid function remain relatively unchanged. These findings, in turn, led us to evaluate the fits of reduced (two-parameter) discounting functions. For both delayed and probabilistic losses, a hyperboloid model with a single (amount-independent) rate parameter, and a single (amount-independent) exponent provided a very good description of the data from all of the amount conditions studied (see the dashed curves in Figs. 1 and 2).

The discounting framework (Green & Myerson, 2004) highlights the importance of using the same form of mathematical function to compare different kinds (e.g., delay and probability) of discounting as well as the discounting of different types of outcomes. Within this framework, differences in magnitude effects have provided insights into the similarities and differences in the mechanisms underlying discounting. Most notably, the fact that larger amounts of delayed reward are discounted less steeply than smaller amounts, whereas larger amounts of probabilistic rewards are discounted more steeply than smaller amounts, strongly suggested that different mechanisms were involved (Green, Myerson, & Ostaszewski, 1999; Myerson et al., 2003). Examination of the effects of amount on the parameters of the (hyperboloid) discounting function subsequently revealed that amount of delayed reward affects only the rate parameter (e.g., Green et al., 2013) whereas amount of probabilistic reward affects only the exponent (Myerson et al., 2011), suggesting that in the case of delayed rewards, the exponent is a psychophysical scaling parameter, which by its nature is amount-independent, whereas in the case of probabilistic rewards, the exponent reflects an amount-dependent probability weighting factor.

The present study applied the same strategy to the problem of delayed and probabilistic losses. In contrast to what is observed with gains, amount of loss had little or no systematic effect on either the degree of discounting or the parameters of the discounting function. Taken together with the results of previous studies, the present findings provide evidence that at least three different kinds of discounting may be distinguished based on how they are affected (or not) by the amount of the outcome whose value is being discounted: the discounting of delayed gains, the discounting of probabilistic gains, and the discounting of losses, both delayed and probabilistic.

A second strategy for identifying different kinds of discounting that has been used successfully in the context of the discounting framework focuses on individual differences in the degree of discounting. More specifically, we sought to determine, first, how reliably the degree of discounting is being measured and how consistently individuals discount delayed and probabilistic losses. This was accomplished by examining how well the degree to which individuals discount one delayed loss amount predicts their discounting of other delayed loss amounts and how well the degree to which individuals discount one probabilistic loss amount predicts their discounting of other probabilistic loss amounts. Second, and more importantly, we sought to determine whether the degree to which individuals discounted delayed losses predicts the degree to which they discount probabilistic losses. The answer to this question, which has not been addressed in previous

studies, is of considerable theoretical significance because it bears on the fundamental issue of how many “impulsivities” there are (Green & Myerson, 2013).

The results of the present study provide clear answers to these questions. First, the degree to which an individual discounted one amount of delayed loss was highly predictive of the degree to which he or she discounted all other amounts of delayed loss. So, too, the degree to which an individual discounted one amount of probabilistic loss was highly predictive of the degree to which he or she discounted all other amounts of probabilistic loss. The strong correlations between different amounts observed with delayed losses and with probabilistic losses (see Tables 2 and 3) argue for the reliability with which degree of discounting is being measured and the consistency of individuals’ choice behavior.

Second, despite both the consistency with which individuals discount different amounts of either delayed or probabilistic loss and the reliability with which their discounting was measured, the degree to which individuals discounted a given amount of delayed loss was uncorrelated with the degree to which they discounted the same amount of probabilistic loss. This result is consistent with the results of previous studies examining the relation between the delay and probability discounting of gains (e.g., Myerson et al., 2003) and suggests that different traits underlie the discounting of delayed and probabilistic outcomes (Green & Myerson, 2013). Further evidence that the tendency to discount delayed losses is independent of the tendency to discount probabilistic losses is provided by the finding that, when subjected to factor analysis, delay and probability discounting measures loaded almost exclusively on separate factors (see Table 4). Thus, from an individual differences perspective, the discounting of delayed and probabilistic monetary losses represent separate kinds of discounting, despite the fact that in both cases, the degree of discounting and the parameters of the discounting function are apparently unaffected by the amount of loss involved.

The present study is the first to examine the relation between the discounting of delayed losses and the discounting of probabilistic losses from an individual differences perspective. However, previous studies have examined the relation between the discounting of delayed gains and losses, as well as the relation between the discounting of probabilistic gains and losses. With respect to the discounting of delayed gains and losses, the results of several studies are consistent in showing positive correlations when the outcomes involve money (Chapman, 1996; Estle et al., 2006; Mitchell & Wilson, 2010), although not necessarily for other types of outcomes (e.g., health; Chapman, 1996). With respect to the discounting of probabilistic gains and losses, the results are somewhat mixed in that although only negative correlations have been reported, they were usually not statistically significant (Mitchell & Wilson, 2010; Shead, Callan, & Hodgins, 2008; Shead & Hodgins, 2009; Tversky & Kahneman, 1992).

The present findings with losses and those of previous studies with gains reveal that, from an individual differences perspective, the discounting of delayed and probabilistic monetary outcomes are relatively independent, regardless of whether the outcomes are gains or losses. Thus, delay and probability discounting appear to represent fundamentally different kinds of impulsivity, perhaps better termed impatience and risk-taking. Interestingly, the discounting

of delayed monetary gains and losses are positively correlated, whereas the discounting of probabilistic gains and losses are at best very weakly (negatively) correlated. These findings suggest that whereas there may be only one kind of impatience (at least when money is involved), there may be two different kinds of risk-taking, one that concerns the risk of not winning anything and another that concerns the risk of losing something.

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Fig. 1.

Relative subjective value as a function of delay. Each panel depicts the group mean subjective values at different delays for a different amount of delayed loss. Solid curves represent the hyperboloid discounting model (Eq. 1) fitted to the data from each amount condition separately; dashed curves represent a reduced hyperboloid discounting model fitted to the data from all of the amount conditions simultaneously.

Fig. 2.

Relative subjective value as a function of odds against. Each panel depicts the group mean subjective values at different odds against for a different amount of probabilistic loss. Solid curves represent the hyperboloid discounting model (Eq. 1) fitted to the data from each amount condition separately; dashed curves represent a reduced hyperboloid discounting model fitted to the data from all of the amount conditions simultaneously.

Fig. 3.

Relative subjective value as a function of delay for three individual participants. The left column presents data from the participant for whom the R^2 for the hyperboloid model (Eq. 1) fitted to all of the delayed amounts was at the first quartile; the center column presents data from the participant whose R^2 was at the second quartile; the right column presents data from the participant whose R^2 was at the third quartile. The top, middle, and bottom rows present data from the \$250, \$20,000, and \$100,000 amount conditions. Solid curves represent fits of the hyperboloid discounting model.

Fig. 4.

Relative subjective value as a function of odds against for three individual participants. The left column presents data from the participant for whom the R^2 for the hyperboloid model (Eq. 1) fitted to all of the probabilistic amounts was at the first quartile; the center column presents data from the participant whose R^2 was at the second quartile; the right column presents data from the participant whose R^2 was at the third quartile. The top, middle, and bottom rows present data from the \$250, \$20,000, and \$100,000 amount conditions. Solid curves represent fits of the hyperboloid discounting model.

Fig. 5.

Area under the Curve (AuC) as a function of amount of delayed (left column) and probabilistic (right column) loss. The top panels present the AuCs for the group mean data presented in Figures 1 and 2, and the bottom panels present the median of the individual AuCs for each delayed and probabilistic amount condition.

Fig. 6.

Area under the Curve (AuC) as a function of amount of delayed (left column) and probabilistic (right column) loss for the six individual participants whose data are depicted in Figures 3 and 4.

Fig. 7.

Values of the parameters of the hyperboloid discounting function (Eq. 1) as a function of amount of delayed (left column) and probabilistic (right column) loss. The top panels present the values of the rate parameter (b) and the bottom panes present values of the exponent (s) estimated based on fits to the group mean data presented in Figures 1 and 2.

Table 1

Parameters and goodness of fit measures (R^2) for the hyperboloid discounting function (Eq. 1) fitted to the group means for each delayed and probabilistic payment amount.

Amount	Delayed Losses			Probabilistic Losses		
	<i>b</i>	<i>s</i>	R^2	<i>b</i>	<i>s</i>	R^2
\$20	2.189	0.069	0.966	12.151	0.274	0.997
\$250	2.736	0.073	0.927	3.133	0.416	0.999
\$3,000	1.211	0.088	0.853	2.692	0.467	0.999
\$20,000	2.730	0.062	0.916	2.414	0.465	0.993
\$50,000	3.176	0.063	0.927	3.159	0.414	0.980
\$100,000	1.656	0.074	0.970	2.062	0.529	0.999
\$500,000	2.162	0.064	0.967	2.137	0.486	0.987

Table 2

Intercorrelations among the Areas under the Curve (AuCs) for the different amounts of delayed loss.

Amount	Delayed Losses					
	\$20	\$250	\$3,000	\$20,000	\$50,000	\$100,000 \$500,000
\$20		.804	.719	.583	.575	.599 .572
\$250			.848	.819	.751	.789 .764
\$3,000				.855	.879	.844 .845
\$20,000					.874	.867 .748
\$50,000						.878 .847
\$100,000						.856
\$500,000						

Note. All correlations are significant; all $ps < .001$

Table 3

Intercorrelations among the Areas under the Curve (AuCs) for the different amounts of probabilistic loss.

Amount	Probabilistic Losses					
	\$20	\$250	\$3,000	\$20,000	\$50,000	\$100,000
\$20		.835	.842	.823	.727	.772
\$250			.889	.810	.798	.872
\$3,000				.846	.835	.882
\$20,000					.852	.859
\$50,000						.866
\$100,000						
\$500,000						

Note. All correlations are significant; all $ps < .001$

Table 4

Factor loadings (Varimax rotation) for the different delayed and probabilistic amount conditions.

Loss Amount	Delay Factor	Probability Factor
Delayed \$20	.762	-.034
Delayed \$250	.914	.027
Delayed \$3,000	.953	-.001
Delayed \$20,000	.915	.075
Delayed \$50,000	.926	.035
Delayed \$100,000	.926	.093
Delayed \$500,000	.891	.111
Probabilistic \$20	.125	.888
Probabilistic \$250	-.049	.940
Probabilistic \$3,000	.096	.947
Probabilistic \$20,000	.097	.927
Probabilistic \$50,000	.037	.905
Probabilistic \$100,000	.059	.942
Probabilistic \$500,000	-.066	.957