Published in final edited form as:
Exp Clin Psychopharmacol. 2010 December ; 18(6): 546–552. doi:10.1037/a0021739.

Hypothetical Intertemporal Choice and Real Economic Behavior: Delay Discounting Predicts Voucher Redemptions During Contingency-Management Procedures

Warren K. Bickel, PhD[a], **Bryan A. Jones, PhD**[a], **Reid D. Landes, PhD**[b], **Darren R. Christensen, PhD**[c], **Lisa Jackson, JD RN**[a], and **Michael Mancino, MD**[a]

[a]University of Arkansas for Medical Sciences, Department of Psychiatry, Center for Addiction Research, 4301 W. Markham St. #843, Little Rock, AR 72205-7199, United States

[b]University of Arkansas for Medical Sciences, Department of Biostatistics, 4301 W Markham, #781, Little Rock, AR 72205-7199, United States

[c]University of Melbourne, Problem Gambling Research and Treatment Centre, Melbourne, Victoria 3010, Australia

Abstract

Delay discounting rates are predictive of drug use status, the likelihood of becoming abstinent, and a variety of health behaviors. Rates of delay discounting may also be related to other relevant behaviors associated with addiction, such as the frequency at which individuals redeem contingency management voucher earnings. This study examined the discounting rates of 152 participants in a buprenorphine treatment program for opioid abuse. Participants received up to 12 weeks of buprenorphine treatment combined with contingency management. Participant's drug use was measured via urine specimens submitted 3 times a week. Successive negative urine specimens were reinforced with increasing amounts of money. After each negative urine specimen, a participant could either redeem his or her earnings or accumulate it in an account. Analysis of the frequency of redemptions showed that participants with higher rates of delay discounting at study intake redeemed their earnings significantly more often than participants with lower rates of discounting. Age and income also predicted redemption rates. We suggest that delay discounting rates can be used to predict redemption behaviors in a contingency management treatment program and that these findings are consistent with the recent theory of the competing neurobehavioral decision systems.

Keywords

delay discounting; opioid; contingency management; impulsivity; competing neurobehavioral decision systems

Correspondence concerning this article should be addressed to Warren K. Bickel, Center for Addiction Research, University of Arkansas for Medical Sciences, 4301 W. Markham St. #843, Little Rock, AR 72205. Tel.: +1 501 526 8437; fax: +1 501 526 7816. WBickel@uams.edu.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

Discounting of delayed reinforcers refers to the decrease in the behavioral effects of a reinforcer as a function of the delay to its receipt (Logue, 1988); that is, the value of a delayed reinforcer is reduced or considered to be worth less compared to the value of an immediate reinforcer. Indeed, the discounting of delayed rewards is intuitive to the extent that most individuals would prefer a reinforcer (e.g., $1,000) now rather than that same reinforcer at some later point (Kirby, 1997). The degree of discounting can be considered a measure of the continuum between impulsivity and self-control (see Bickel et al., 2008, for an alternative view).

The typical procedure used in delay-discounting experiments is to present subjects with a choice between a constant larger-later reward (e.g., $1,000 delivered in one year) and a changing an immediate reward. The magnitude of the immediate reward is adjusted after each response to make the relative value of each alternative subjectively equivalent (e.g., Green, Fry, & Myerson, 1994). This point of equivalence is the *indifference point* for that particular delay interval. When indifference points are obtained for a variety of delays, an *indifference curve* may be plotted. Indifference curves permit empirical determination of the shape of the discounting function and the rate at which delayed rewards are discounted by an individual. Mazur’s (1987) hyperbolic discounting model proposed that the devaluation of delayed rewards is proportional to their delay (Ainslie & Haslam, 1992); that is, for each unit of time that constitutes the delay to delivery, the reward’s present value decreases by an increasingly smaller proportion (Kirby, 1997). The hyperbolic model is

$$Y=(1+k\mathrm{D})^{-1} \quad \text{Equation 1}$$

where *Y* is the indifference point, expressed as a proportion of the larger option delayed by *D* days, and *k* is the discounting rate. As *k* increases, immediate options are chosen more frequently.

Greater discounting has been demonstrated among various groups of addicted populations (Bickel & Marsch, 2001). For example, compared to matched controls, greater discounting was shown among alcohol-dependent individuals (Bjork, Hommer, Grant, & Danube, 2004; Dom, D'haene, Hulstijn, & Sabbe, 2006; S. H. Mitchell, Reeves, Li, & Phillips, 2006; Petry, 2001), cocaine-dependent individuals (Coffey, Gudleski, Saladin, & Brady, 2003; Heil, Johnson, Higgins, & Bickel, 2006; Kirby & Petry, 2004), methamphetamine-dependent individuals (Hoffman, et al., 2006), opioid-dependent individuals, and tobacco cigarette smokers (Baker, Johnson, & Bickel, 2003; Bickel, Odum, & Madden, 1999; S.H. Mitchell, 1999; Odum, Madden, & Bickel, 2002). Interestingly, greater monetary discounting is also associated with individuals who have problems gambling, who are obese, or who regularly view erotica (Petry, 2001; Weller, Cook III, Avsar, & Cox, 2008). When individuals with drug addiction are compared to individuals without addiction or with less drug use, the addicted individuals generally discount delayed reinforcers more (Johnson, Bickel, & Baker, 2007; Vuchinich & Simpson, 1998). These results have been confirmed with the discounting of both real and hypothetical monetary rewards (Baker, et al., 2003; Johnson & Bickel, 2002). Moreover, direct comparisons of real and hypothetical rewards have been corroborated using both behavioral and neural correlates (Bickel, Pitcock, Yi, & Angtuaco, 2009).

Discounting rates have also been correlated with, and or predictive of, a wide variety of health-related behaviors. Two studies have demonstrated that monetary discounting is correlated with HIV-risk. In the first, Odum, Madden, Badger, and Bickel (2000) found heroin-dependent individuals who shared needles discounted money considerably more than heroin-dependent individuals who did not share needles, demonstrating that monetary discounting can distinguish HIV-risk behavior. In the second,Chesson et al. (2006) obtained an estimate of monetary discounting rates in a large sample (N = 1042) of adolescent and young adults and examined associations with risky sexual behavior. Degree of discounting was significantly associated with a variety of sexual behaviors, including ever having sex, having sex before age 16, and past or current pregnancy, again demonstrating that monetary discounting predicts risky sexual behavior and, therefore, HIV-related behavior.

Other health behaviors have been shown to be significantly associated with discounting in three more recent studies. One study measured discounting in 1,039 respondents between the ages of 24 and 65 years of age and found that high rates of discounting were negatively associated with recent participation in health screenings and health-promoting behaviors including mammography, pap smear, prostate exam, dental visits, cholesterol testing, receipt of a flu shot, and no-smoking status (Bradford, 2010). Similar associations have been obtained with other health behaviors such as exercise frequency, eating breakfast, wearing safety belts, and following physician advice (Axon, Bradford, & Egan, 2009; Daugherty & Brase, 2010).

Discounting has also been shown to be predictive of subsequent therapeutic behavior; predicting relapse to cigarette smoking among pregnant smokers, and clinical outcomes in smoking cessation programs among alcohol dependent individuals (MacKillop & Kahler, 2009; Yoon, et al., 2007). Collectively, these results suggest that excessive discounting functions as a trans-disease process (Bickel & Mueller, 2009) that may underlie a plethora of behaviors related to poor health.

In this study we extend the predictive ability of the discounting rates of delayed hypothetical money to predict real monetary behavior of individuals with opioid dependence. Specifically, we examined the utility of delay discounting measures (obtained prior to the start of treatment) for predicting whether an opioid-dependent individual earning vouchers in a contingency management (CM) clinical trial would redeem frequently or not, and for predicting the redemption rates of the individuals. Presentation of opioid- and cocaine-free urine samples resulted in the receipt of a voucher. Those vouchers could be redeemed immediately or saved and redeemed at a later time. We hypothesize that greater discounting of hypothetical monetary choices will be predictive of withdrawal of the actual money accrued in a contingency management treatment program.

Method

Participants

One hundred seventy opioid users were recruited through radio advertisement, newspaper advertisements, flyers, and physician referrals for a 12-week contingency management program (CM; vouchers accrued to participants for providing urine sample negative for opioid and cocaine metabolites) with buprenorphine maintenance. Eligibility criteria included being at least 18 years of age, DSM-IV criteria for opioid dependence, and a positive opioid urine screen. Exclusion criteria included pregnancy, active psychiatric disorders, or an unstable medical condition. For cohabitating participants, only the data from one participant per dwelling was randomly chosen to be included in the study; 18 participants were thus randomly excluded leaving 152 data-providing participants. The average age of the sample of 85 men and 67 women was 34.8 years (standard deviation (SD): 10.0 years). Subjects had a median education of 12 years (interquartile range (IQR): 12–14 years) and a median annual income of $10,160 (IQR: $275–$29,000).

Buprenorphine Treatment

At induction participants were screened for drug use by urine test and for alcohol use by breathalyzer. Participants were initially given a 6 mg dose of buprenorphine sublingually. Over the following week, the supervising physician adjusted the dose (between 6–18 mg) to minimize intoxication or withdrawal effects. Participants were paid $10 for each visit for the following week, during which time their doses were adjusted. Once the dose was stabilized, participants were randomized to one of two groups and received double doses of buprenorphine on Monday and Wednesday of each week, and triple doses each Friday until the end of the study (12 weeks) (Bickel, Amass, Crean & Badger, 1999).

For the 12 weeks of treatment, one group (n = 84) received CM paired with computer-assisted behavior therapy based on the community reinforcement approach (CM+CRA condition) (Bickel, Marsch, Buchhalter, & Badger, 2008), whilst the other group (n = 68) received CM alone (CM condition). Note that the efficacy of these treatments is presented in a separate paper (Christensen, under review). The voucher redemption habits of both groups were combined and analyzed for this paper. Finally, after the 12-week treatment period ended, participants were either referred to another treatment program or entered into a stepped detoxification program under the supervision of the study physician.

Delay Discounting Procedure

During the intake visit participants completed the delay discounting computer program. This delay discounting procedure asked participants to choose between amounts of hypothetical money available immediately or later. The immediate amount changed but never exceeded the larger, later amount ($1,000). Initially, participants were offered the immediate amount at 50% of delayed amount, with subsequent amounts adjusted up or down by 50% depending on the choices made by the participant, for a total of six choices per delay. The choices were repeated six times for each of the seven selected delays (1 day, 1 week, 1 month, 6 months, 1 year, 5 years, and 25 years). The final value selected was stored as the indifference point for the particular delay. Participants completed discounting tasks for hypothetical future gains of both $1,000 and $10,000.

Contingency Management Treatment

The contingency management procedures were based on previous incentive-based treatment programs (Budney, Higgins, & Sigmon, 2003; Higgins, et al., 1991). Participants earned vouchers of increasing value contingent on negative urine analysis. Urine samples were submitted three times a week for 12 weeks on Monday, Wednesday, and Friday. Each voucher earned was worth a specified number of points, which were converted to cash at a rate of \$0.25 for each point. The initial voucher was worth 10 points, or \$2.50. Each subsequent consecutive negative urine screen increased the voucher earned by 5 points, with a bonus of 10 points earned for three consecutive negative urine tests in a row. Conversely, a positive urine screen (1) prevented participants from redeeming money that day, (2) resulted in no points being earned for that day, and (3) reset the value of the following voucher to its initial 10-point value. After a positive urine screen, if the participant presented three consecutive negative urine screens the value of the participant's voucher was returned to the amount earned prior to the positive test. Importantly, any points earned could not be lost.

Points accumulated in a "savings" account until a participant chose to redeem them. Participants were informed after each test how much they earned and how much they had accumulated. Complete abstinence earned participants a total of \$997.50 across the 12-week CM trial. After any negative urine screen, a participant could decide to redeem any amount of money that they had earned. Any amount under \$100 was paid in gift cards to local businesses; amounts \$100 and greater were paid as a check. At the end of the trial, upon request all participants could receive the remaining balance of their account as a check. Eight participants had yet to claim all their earnings at the time of writing; but this did not alter the utility of their data collected up to the end of the treatment. All earned vouchers and redemptions were recorded as data.

Data Analysis

The two primary outcomes of interest were redemption rate and redeemer type. *Redemption rate* was the percentage of times a participant redeemed earnings out of the total number of times he or she could redeem earnings; the median rate was 20.3%. *Redeemer type* indicated whether a participant was an infrequent or frequent redeemer. This dichotomization was determined by splitting the sample on the median of redemption rates. (Six participants failed to achieve even one opportunity to redeem earnings; hence these outcomes were undefined for these participants.)

A participant's discount rate, k, for each discounted amount (\$1,000 and \$10,000) was estimated by fitting the corresponding indifference points with Equation 1. Since the distribution of k estimates tends to be skewed, we transformed estimates of k with the natural logarithm [ln(k)] that normalizes the discount rates.Yi et al. (2009) found that the exponential-power model tends to better fit delay discounting data than the hyperbolic function. For this reason, we also fit the indifference points with the exponential-power function:

$$Y = \exp[-g \,\mathrm{sqrt}(D)] \quad \text{Equation 2}$$

where Y and D are as in Equation 1 (Y is the indifference point, expressed as a proportion of the larger option delayed by D days), and g is the discount rate for the exponential-power function. As with k, increases in g indicate stronger preference for immediate outcomes and the distribution of g is normalized with a logarithm transformation (we use ln(g)). Of the 289 sets of discounting data, 208 (72.0%) were better fit by the exponential-power function than the hyperbolic function (sign test of no difference: $p < 0.001$). We thus primarily report discounting results in terms of ln(g), and include ln(k) for comparison sake.

To learn whether discounting can predict *redeemer type*, we used logistic regressions that controlled for CRA therapy and individually included the log-discount rates for $1,000 and $10,000 and the average of the two (that is, one regression for each type of discount rate). In the same way, we also individually considered the predictive utility of age, income, and years of education. Finally, we included CRA and the significant demographic covariates along with each of the discounting rates to determine (*i*) whether discounting continued to predict redeemer type in the presence of demographic information and (*ii*) which discount rate ($1,000, $10,000, or the average of the two) had the strongest effect. We report conditional odds ratios (ORs) and their 95% confidence intervals (CIs). For the continuous outcome, *redemption rate*, we repeated the general strategy for redeemer type except we used linear regression in place of logistic regression. We report slope coefficients (*b*s) and their 95% CIs.

Results

The medians (and IQRs) of the amount of vouchers earned, number of withdrawals made, and number of withdrawal opportunities were $727.50 ($231.25–$997.50), 5 (2–9) withdrawals, and 32 (21–35) opportunities. Figure 1 shows the distribution of redemption rates, along with their median of 20.3 % (8.3 – 34.3).

Before evaluating the potential predictors of redemption behaviors, we provide Spearman’s rank correlations (r) of the demographic predictors with the logged discounting coefficients, ln(g), in Table 1. None of the correlations in Table 1 significantly differed from 0. The discounting coefficients coming from the $1,000 and $10,000 amounts were highly correlated: $r = 0.820$, $p < 0.001$. The only correlation that approached significance among the three demographic predictors was between age and income: $r = 0.148$, $p = 0.074$. The correlation between age and education was $r = 0.035$, $p = 0.673$, and between income and education was $r = 0.082$, $p = 0.322$.

Predictors of Redeemer Type

Controlling for CRA therapy, we determined that a person having an average discounting coefficient ln(g) that was 1-unit higher than his or her counterpart was 1.394 times more likely to be a frequent redeemer [$\chi^2_{[1]}=7.31$, p=.007; CI: (1.096, 1.774)]. This was true for the ln(g) discounting rates for both $10,000 [OR=1.453, $\chi^2_{[1]}=9.69$, p=.002; CI: (1.148, 1.838)] and $1,000 [OR=1.264, $\chi^2_{[1]}=4.02$, p=.045; CI: (1.005, 1.590)]. The results were similar when using the hyperbolic discounting parameter, ln(k);), see Table 2.

Without regard to other demographic measures, increases in age and income were each associated with decreased likelihood of being a frequent redeemer. Given the same CM treatment, the odds of being a frequent redeemer decreased by 0.647 [$\chi^2_{[1]}=5.68$, p=.017; CI: (0.452, 0.926)] as age increased 10 years, and by 0.733 [$\chi^2_{[1]}=8.86$, p=.003; CI: (0.597, 0.899)] with a \$10,000 increase in annual income. The likelihood of being a frequent redeemer dropped with each additional year of education [OR=0.919, CI: (0.801, 1.054)], but the decrease failed to statistically differ from unity ($\chi^2_{[1]}=1.46$, p=.226).

Since we found no substantial evidence that education predicts redemption type, we did not consider it in further analyses. While controlling for CRA, we entered age, income, and discount rate all into a logistic regression model of redeemer type (frequent or not). Table 3 contains the slope estimates for each of the three covariates in the multivariate logistic regressions. Increases in the discount rate for \$10,000 and decreases in annual income were jointly associated with increased odds of being a frequent redeemer; whereas the utility of age for discriminating between the two types of redeemers diminished. The same pattern of results was observed for the averaged discount rate. For the discount rate associated with \$1,000, though, there was a slight discrepancy in the above pattern: discount rates from the exponential-power model, ln(g), were not statistically significant ($\chi^2_{[1]}=3.75$, p=.053), but were for those from the hyperbolic model, ln(k) ($\chi^2_{[1]}=4.39$, p=.036).

Predictors of Redemption Rate

When examining the voucher redemption rate, we regressed the rates on each of the discounting coefficients (from discounting of \$1,000, \$10,000, and the average of the two) while controlling for CRA treatment. From the regressions, we found that the slopes associated with the average ln(g) and ln(g) for \$1,000 were not significantly different from 0 ($t_{[139]}$=1.49, p=.139 and $t_{[134]}$=0.83, p=.409, respectively), but were both in the expected direction; see Table 4. However, the slope for the \$10,000 ln(g) was significantly different than 0: for a 1-unit increase in ln(g) the redemption rate could be expected to increase 2.0 percentage points [CI: (0.0, 4.1), $t_{[137]}$=1.99, p=.049]. Results approached statistical significance when using the hyperbolic ln(k) from \$10,000; see Table 4.

Entering each of the demographics into a regression model of the redemption rate led to similar conclusions as when modeling redeemer type. Controlling for CRA condition, redemption rate was decreased by 5.6 percentage points for an increase of 10 years of age [b= −5.6, CI: (−8.9, −2.2), $t_{[139]}$=3.28, p=.001], or by 1.9 percentage points for a \$10,000 increase in annual income [b= −1.9, CI: (−3.4, −0.3), $t_{[139]}$=2.33, p=.021]. Redemption rates were estimated to decrease with increases in education, but not significantly so ($t_{[139]}$=0.81, p=.418). When we included the logged discounting rate for \$10,000, age, and income—all individually predictive of redemption rate—into one regression model, also controlling for the CRA condition, the individually estimated slopes attenuated toward zero for the three covariates. Age was found to significantly predict redemption rate [b= −4.6, CI: (−8.1, −1.2), $t_{[135]}$=2.65, p=.010], and the slope for the \$10,000 discounting coefficient tended toward significance [b=1.7, CI: (−0.3, 3.7), $t_{[135]}$=1.68, p=.092]. Income information failed to provide significantly more information about redemption rate than that already provided by the other two predictors [b= −1.2, CI: (−2.8, 0.4), $t_{[135]}$=1.47, p=.138]. Results for the \$10,000 discounting coefficient were also similar for the hyperbolic discounting coefficient: b= 0.914, CI: (−0.160, 1.989) for \$10,000 ln(k), b= −4.679, CI: (−8.176, −1.182) for age, and b= −1.190, CI: (−2.794, 0.413) for income.

Discussion

In this study, we examined the extent to which hypothetical discounting rates and selected demographic variables of opioid-dependent individuals were systematically related to voucher redemption for actual monetary outcomes in this clinical trial. Analysis of the discounting rates found that steeper discounting rates were related to more frequent voucher redemptions for providing drug-free urine samples in a contingency management procedure. Discounting rates for $10,000 hypothetical money showed a stronger relationship with redemption rates than the $1,000 magnitude, which exhibited the effect in the same direction but did not reach statistical significance when redemptions were treated as a continuous measure. Years of education did not predict redemption rate; however, age and income did. Younger participants were more likely to redeem their voucher earnings more frequently than older participants. Lower income was also related to more frequent redemptions. This study extends for the first time the utility of hypothetical delay discounting rates for predicting the rate of redemption of real money rewards. We will make four observations regarding these results.

First, a case can be made that frequent, small withdrawals of voucher earnings is suboptimal for two reasons. The first reason is that larger redemptions worth more than $100 were redeemed as a check and therefore convertible to cash, while smaller amounts were only redeemable as gift cards and could only be used at a local business selected at the time of redemption. Thus, the smaller, more frequent redemptions were limited to material goods or services and resulted in more constraint in the use of those financial resources, while the larger check payouts could be used to pay rent and other bills, or to purchase *any* type of goods or services. The second reason is that previous work has shown that opioid-dependent populations prefer cash over gift certificates (Amass, Bickel, Crean, Higgins, & Badger, 1996), which lends further support to the notion that accruing enough voucher earnings to redeem a check was the superior option. The findings of this study show that the degree of discounting can predict who will exhibit suboptimal behavior among a group of opioid-dependent individuals.

Second, the heterogeneity observed in discounting behavior and its consequences for redemption of voucher earnings is consistent with the recent theoretical view of addiction referred to as the competing neurobehavioral decision system. This view posits that addiction and related suboptimal behavior results from a hypoactive neural executive system and a hyperactive impulsive decision system. The function of the executive decision system, embodied in the prefrontal cortex, is to consider the future and make plans to achieve deferred goals, while the impulsive decision system, embodied in the limbic and paralimbic brain regions, is concerned with acquiring commodities that are of biological importance or that have acquired equivalent value. In another paper, we have argued that the work of McClure et al. (2004) provides neuroimaging support that an individual’s discounting behaviors are indicative of the relative control of these two brain regions (Bickel, et al., 2007). The current study extends this discourse and links discounting rates to socially important events – saving or redeeming monetary vouchers. We believe this further supports the hypothesis that competing neurobehavioral systems determine decision making behaving behavior.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

Third, the finding that age and income added to this effect is consistent with the known relationship of these variables with discounting. Prior work has etablished that the the older the individual the more they consider the future. Similar results have been obtained with income; that is, those with more income discount the future less than those with less income (Green, Myerson, Lichtman, Rosen, & Fry, 1996). The observation in our study that these variables were not correlated with discounting may have more to do with the limited range of age and income of these subjects, but they do relate to important modulators of discounting and consideration of the future.

Fourth, this work was novel and should be replicable. On this point there are at least two factors to consider in future replications. The first factor is that hypothetical discounting was employed in this study and predicted reward redemption. However, the discounting of real monetary amounts may result in greater predictive power. Certainly, the literature suggests that delay discouting of real and hypothetical monetary amounts are comparable with respect to behavior and the brain regions activated when comparing these procedures, but they might differ on prediction. The second factor regarding replication is that these results were obtained within a specific group, opioid-dependent individuals, and as such the generalizability to other groups will need to be investigated. If discounting is truly a trans-disease process then we would expect properly powered trials to find similar results.

Acknowledgments

This work was funded by NIH Grant R01DA012997, R01DA022386, R01DA024080, RR020146, T32DA022981, and 1UL1RR029884 from the National Center for Research Resources. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Center for Research Resources or the National Institutes of Health. This work was also funded by the Wilbur Mills Chair Endowment and in part by the Arkansas Biosciences Institute, a partnership of scientists from Arkansas Children's Hospital, Arkansas State University, the University of Arkansas-Division of Agriculture, the University of Arkansas, Fayetteville, and the University of Arkansas for Medical Sciences. The Arkansas Biosciences Institute is the major research component of the Tobacco Settlement Proceeds Act of 2000. Dr. Bickel is a principal of HealthSim, LLC.

References

Ainslie, G.; Haslam, N. Hyperbolic discounting. In: Loewenstein, G.; Elster, J., editors. Choice Over Time. New York: Russell Sage Foundation; 1992. p. 57-92.

Amass L, Bickel WK, Crean JP, Higgins ST, Badger GJ. Preferences for clinic privileges, retail items and social activities in an outpatient buprenorphine treatment program. Journal of Substance Abuse Treatment. 1996; 13(1):43–49. [PubMed: 8699542]

Axon RN, Bradford WD, Egan BM. The role of individual time preferences in health behaviors among hypertensive adults: A pilot study. Journal of the American Society of Hypertension. 2009; 3(1):35–41. [PubMed: 20409943]

Baker F, Johnson MW, Bickel WK. Delay discounting in current and never-before cigarette smokers: Similarities and differences across commodity, sign, and magnitude. Journal of Abnormal Psychology. 2003; 112(3):382–392. [PubMed: 12943017]

Bickel WK, Marsch LA. Toward a behavioral economic understanding of drug dependence: Delay discounting processes. Addiction. 2001; 96:73–86. [PubMed: 11177521]

Bickel WK, Marsch LA, Buchhalter AR, Badger GJ. Computerized behavior therapy for opioid-dependent outpatients: A randomized controlled trial. Experimental and Clinical Psychopharmacology. 2008; 16(2):132–143. [PubMed: 18489017]

Bickel WK, Miller ML, Yi R, Kowal BP, Lindquist DM, Pitcock JA. Behavioral and neuroeconomics of drug addiction: Competing neural systems and temporal discounting processes. Drug and Alcohol Dependence. 2007; 90S:S85–S91. [PubMed: 17101239]

Bickel WK, Mueller ET. Toward the study of trans-disease processes: A novel approach with special reference to the study of co-morbidity. Journal of Dual Diagnosis. 2009; 5(2):131–138. [PubMed: 20182654]

Bickel WK, Odum AL, Madden GJ. Impulsivity and cigarette smoking: Delay discounting in current, never, and ex-smokers. Psychopharmacology. 1999; 146(4):447–454. [PubMed: 10550495]

Bickel WK, Pitcock JA, Yi R, Angtuaco EJC. Congruence of BOLD response across intertemporal choice conditions: fictive and real money gains and losses. J. Neurosci. 2009; 29(27):8839–8846. [PubMed: 19587291]

Bickel WK, Yi R, Kowal BP, Gatchalian KMC. Cigarette smokers discount past and future rewards symmetrically and more than controls: is discounting a measure of impulsivity? Drug Alcohol Depend. 2008; 96(3):256–262. [PubMed: 18468814]

Bjork JM, Hommer DW, Grant SJ, Danube C. Impulsivity in abstinent alcohol-dependent patients: Relation to control subjects and type 1-/type 2 like traits. Alcohol. 2004; 34(2–3):133–150. [PubMed: 15902907]

Bradford WD. The association between individual time preferences and mental health maintenence habits. Medical Decision Making. 2010; 30:99–112. [PubMed: 19675322]

Budney, AJ.; Higgins, ST.; Sigmon, SC. Contingency management in the substance abuse treatment clinic. In: Rotgers, F.; Morgenstern, J.; Walters, S., editors. Treating substance abuse: Theory and technique. New York: Guilford Press; 2003.

Chesson HW, Leichliter JS, Zimet GD, Rosenthal SL, Bernstein DI, Fife KH. Discount rates and risky sexual behavior among teenagers and young adults. Journal of Risk and Uncertainty. 2006; 32(3): 217–230.

Coffey SF, Gudleski GD, Saladin ME, Brady KT. Impulsivity and rapid discounting of delayed hypothetical rewards in cocaine-dependent individuals. Experimental and Clinical Psychopharmacology. 2003; 11(1):18–25. [PubMed: 12622340]

Daugherty JR, Brase GL. Taking time to be healthy: Predicting health behaviors with delay discounting and time perspective. Personality and Individual Differences. 2010; 48:202–207.

Dom G, D'haene P, Hulstijn W, Sabbe B. Impulsivity in abstinent early- and late-onset alcoholics: differences in self-report measures and a discounting task. Addiction. 2006; 101(1):50–59. [PubMed: 16393191]

Green L, Myerson J, Lichtman D, Rosen S, Fry A. Temporal discounting in choice between delayed rewards: The role of age and income. Psychology and Aging. 1996; 11(1):79–84. [PubMed: 8726373]

Heil SH, Johnson MW, Higgins ST, Bickel WK. Delay discounting in currently using and currently abstinent cocaine-dependent outpatients and non-drug-using matched controls. Addictive Behaviors. 2006; 31(7):1290–1294. [PubMed: 16236455]

Higgins ST, Delaney DD, Budney AJ, Bickel WK, Hughes JR, Foerg F, et al. A behavioral approach to achieving initial cocaine abstinence. American Journal of Psychiatry. 1991; 148(9):1218–1224. [PubMed: 1883001]

Hoffman WF, Moore M, Templin R, McFarland B, Hitzemann RJ, Mitchell SH. Neuropsychological function and delay discounting in methamphetamine-dependent individuals. Psychopharmacology (Berl). 2006; 188(2):162–170. [PubMed: 16915378]

Johnson MW, Bickel WK. Within-subject comparison of real and hypothetical money rewards in delay discounting. Journal of the Experimental Analysis of Behavior. 2002; 77(2):129–146. [PubMed: 11936247]

Johnson MW, Bickel WK, Baker F. Moderate drug use and delay discounting: A comparison of heavy, light, and never smokers. Experimental and Clinical Psychopharmacology. 2007; 15(2):187–194. [PubMed: 17469942]

Kirby KN. Bidding on the future: Evidence against normative discounting of delayed rewards. Journal of Experimental Psychology: General. 1997; 126:54–70.

Kirby KN, Petry NM. Heroin and cocaine abusers have higher discount rates for delayed rewards than alcoholics or non-drug-using controls. Addiction. 2004; 99(4):461–471. [PubMed: 15049746]

Logue AW. Research on self-control: An integrating framework. Behavioral and Brain Sciences. 1988; 11(4):665–709.

NIH-PA Author Manuscript
NIH-PA Author Manuscript

MacKillop J, Kahler CW. Delayed reward discounting predicts treatment response for heavy drinkers receiving smoking cessation treatment. Drug and Alcohol Dependence. 2009; 104(3):197–203. [PubMed: 19570621]

Mazur, JE. An adjusting procedure for studying delayed reinforcement. In: Commons, ML.; Mazur, JE.; Nevin, JA.; Rachlin, H., editors. Quantitative analysis of behavior. Vol. Vol. 5. Hillsdale, NJ: Erlbaum; 1987. p. 55-73.

McClure SM, Laibson DI, Loewenstein G, Cohen JD. Separate neural systems value immediate and delayed monetary rewards. Science. 2004; 306(5695):503–507. [PubMed: 15486304]

Mitchell SH. Measures of impulsivity in cigarette smokers and nonsmokers. Psychopharmacology. 1999; 146(4):455–464. [PubMed: 10550496]

Mitchell SH, Reeves JM, Li N, Phillips TJ. Delay discounting predicts behavioral sensititation to ethanol in outbred WSC mice. Alcoholism: Clinical and Experimental Research. 2006; 30(3):429–437.

Odum AL, Madden GJ, Badger GJ, Bickel WK. Needle sharing in opioid-dependent outpatients: Psychological processes underlying risk. Drug and Alcohol Dependence. 2000; 60(3):259–266. [PubMed: 11053760]

Odum AL, Madden GJ, Bickel WK. Discounting of delayed health gains and losses by current, never- and ex-smokers of cigarettes. Nicotine & Tobacco Research. 2002; 4(3):295–303. [PubMed: 12215238]

Petry NM. Pathological gamblers, with and without substance use disorders, discount delayed rewards at high rates. Journal of Abnormal Psychology. 2001; 110(3):482–487. [PubMed: 11502091]

Vuchinich RE, Simpson CA. Hyperbolic temporal discounting in social drinkers and problem drinkers. Experimental and Clinical Psychopharmacology. 1998; 6(3):292–305. [PubMed: 9725113]

Weller RE, Cook EW III, Avsar KB, Cox JE. Obese women show greater delay discounting than healthy-weight women. Appetite. 2008; 51(3):563–569. [PubMed: 18513828]

Yi R, Landes RD, Bickel WK. Novel models of intertemporal valuation: Past and future outcomes. Journal of Neuroscience, Psychology, & Economics. 2009; 2(2):102–111.

Yoon JH, Higgins ST, Heil SH, Sugarbaker RJ, Thomas CS, Badger GJ. Delay discounting predicts postpartum relapse to cigarette smoking among pregnant women. Experimental and Clinical Psychopharmacology. 2007; 15(2):176–186. [PubMed: 17469941]

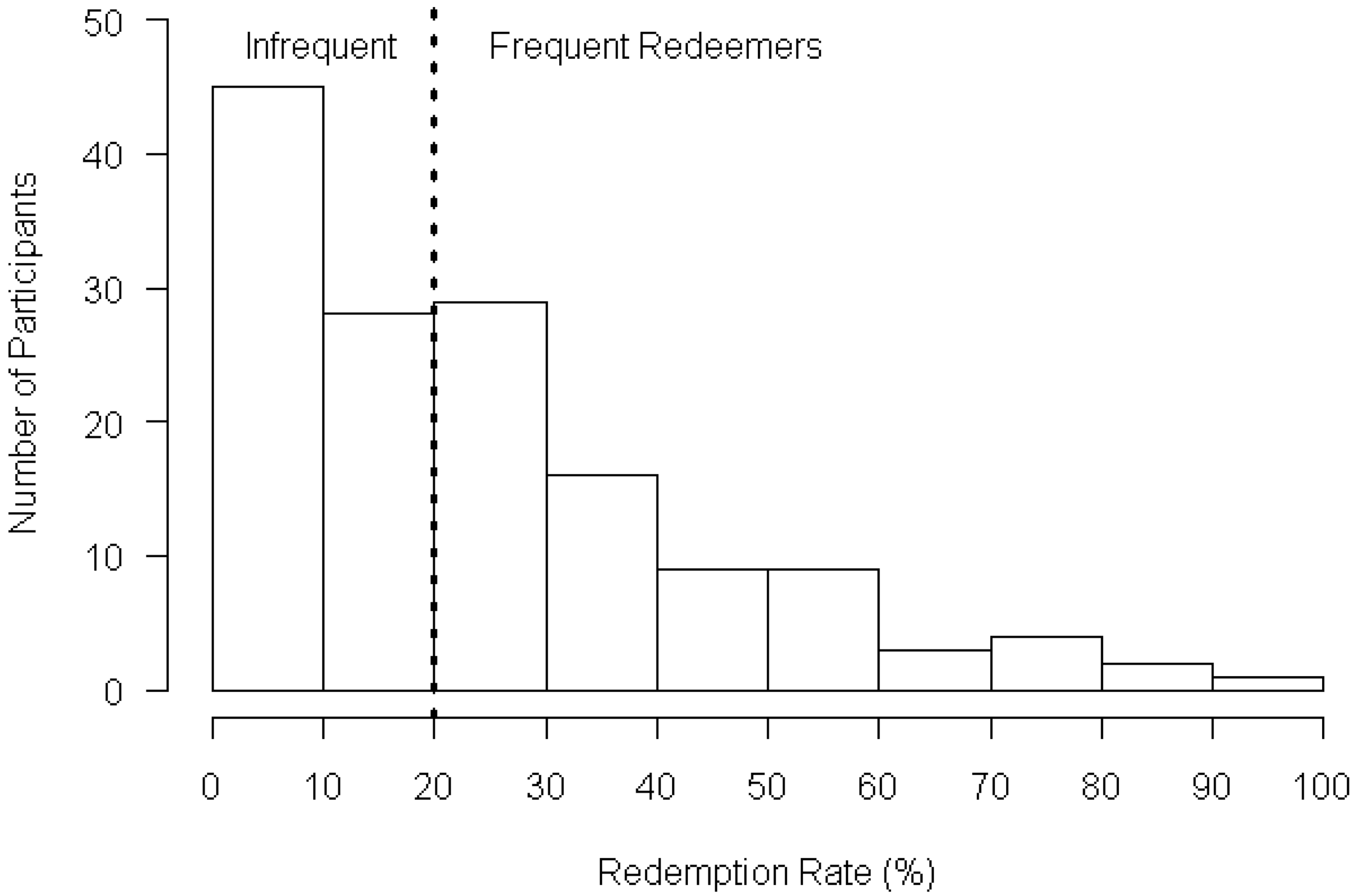

Figure 1.

Distribution of redemption rates. Redemption rate describes the number of redemptions divided by the number of opportunities the participant had to redeem. The dotted line at the median redemption rate of 20.3% defines the redeemer type: infrequent (below the line) or frequent (above the line).

Table 1

Rank Correlations of Logged Discounting Coefficients, ln(*g*), with Three Demographic Predictors

(Rank correlations)	Age	Income	Education
$1,000 ln(*g*)	−.091	.000	−.067
$10,000 ln(*g*)	−.072	−.091	−.127*
Average ln(*g*)	−.089	−.031	−.085

*Smallest observed $p = 0.125$

NIH-PA Author Manuscript

NIH-PA Author Manuscript

Table 2

Estimated Odds Ratios (ORs) for Three Discounting Rates (Hyperbolic ln(*k*)s)

Discounting Rate	OR	95% CI	*p*-value
$1,000 ln(*k*)	1.143	(1.013, 1.289)	0.306
$10,000 ln(*k*)	1.237	(1.089, 1.405)	0.001
Average ln(*k*)	1.204	(1.059, 1.368)	0.005

Table 3

Odds Ratios (95% CIs) for Predictors in Multivariate Models of Redeemer Type (CIs containing 1 are not significant at 0.05)

Discounting Rate		Discounting	Income	Age
$1,000	ln(*g*)	1.260 (0.997, 1.592)	0.765 (0.619, 0.946)	0.734 (0.492, 1.096)
	ln(*k*)	1.142 (1.009, 1.293)	0.764 (0.617, 0.946)	0.736 (0.492, 1.100)
$10,000	ln(*g*)	1.409 (1.109, 1.790)	0.766 (0.617, 0.952)	0.750 (0.506, 1.111)
	ln(*k*)	1.217 (1.068, 1.389)	0.768 (0.618, 0.955)	0.746 (0.503, 1,109)
Average	ln(*g*)	1.368 (1.070, 1.750)	0.759 (0.613, 0.939)	0.726 (0.494, 1.068)
	ln(*k*)	1.193 (1.046, 1.361)	0.758 (0.612, 0.940)	0.726 (0.493, 1.069)

Table 4

Estimated Slopes (95% CIs) of Discounting Rates When Predicting Redemption Rate

Discounting Rate		*b*	95% CI	*p*-value
$1,000	ln(*g*)	0.893	(−1.241, 3.026)	0.409
	ln(*k*)	0.515	(−0.616, 1.646)	0.370
$10,000	ln(*g*)	2.033	(0.008, 4.057)	0.049
	ln(*k*)	1.099	(−0.003, 2.202)	0.051
Average	ln(*g*)	1.647	(−0.541, 3.835)	0.139
	ln(*k*)	0.883	(−0.290, 2.055)	0.139