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Using crowdsourcing to compare temporal, social temporal, and probability discounting among obese and non-obese individuals ★

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Abstract

Previous research comparing obese and non-obese samples on the delayed discounting procedure has produced mixed results. The aim of the current study was to clarify these discrepant findings by comparing a variety of temporal discounting measures in a large sample of internet users ($n = 1163$) obtained from a crowdsourcing service, Amazon Mechanical Turk (AMT). Measures of temporal, social-temporal (a combination of standard and social temporal), and probability discounting were obtained. Significant differences were obtained on all discounting measures except probability discounting, but the obtained effect sizes were small. These data suggest that larger- N studies will be more likely to detect differences between obese and non-obese samples, and may afford the opportunity, in future studies, to decompose a large obese sample into different subgroups to examine the effect of other relevant measures, such as the reinforcing value of food, on discounting.

Keywords

Obesity; Decision making; Temporal discounting; Social discounting; Probability discounting; Crowdsourcing

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Introduction

Obesity is a major public health problem that impacts approximately 36% of American adults (CDC, 2013). Several conceptualizations of obesity suggest that the failure of self-control, sometimes called impulsivity or executive dysfunction, plays a major role in the genesis and maintenance of weight control problems (Epstein, Salvy, Carr, Dearing, & Bickel, 2010). Specifically, the immediate impulse to consume food prevails over the future health goals, which can be obtained by engaging in fewer and smaller bouts of eating. From behavioral and neuroeconomic perspectives, this failure of self-control results from normal learning mechanisms being commandeered by the pathological processing of food rewards, further this dysfunction becomes exacerbated over time (Bickel et al., 2007). These pathological valuations may distort decision making by altering the regulatory balance between two neurobehavioral decision systems, resulting in an over-valuation of immediate commodities (e.g., food), and an under valuation of longer-term commodities (e.g., improved health) (Bickel, Jarmolowicz, MacKillop, et al., 2012; Bickel, Jarmolowicz, Mueller, & Gatchalian, 2011; Carr, Daniel, Lin, & Epstein, 2011). Importantly, delay discounting, which measures the decline in the value of a reinforcer as a function of the delay to its receipt, reflects the regulatory balance between impulsive (i.e., limbic and paralimbic areas) and executive (prefrontal cortex) neurobehavioral systems (Bickel et al., 2007). Individuals suffering from a variety of behavioral disorders (e.g., drug addiction, pathological gambling, etc.) excessively discount delayed rewards, suggesting that excessive discounting may function as a trans-disease process (Bickel, Jarmolowicz, Mueller, Koffarnus, & Gatchalian, 2012).

Delay discounting has been shown to be an index of food reinforcement (Epstein et al., 2010), and this is true on both the physiological and behavioral level, however the few studies that have used delay discounting to research the eating behavior of obese subjects have produced inconclusive results. Physiologically, discounting in those who engage in excessive hedonic eating is thought to be a manifestation of systemic dopaminergic dysfunction (see Appelhans, 2009, for a review). Further, activity in regions of the prefrontal cortex that were more active on difficult delayed discounting trials were predictive of weight gain (within the next two years) in obese subjects (Kishinevsky et al., 2012), however a follow-up study on this same group of subjects failed to find a correlation between current BMI measures and discounting (Stoeckel, Murdaugh, Cox, Cook, & Weller, 2013). Behaviorally, discounting has been shown to be an index of excessive eating and resulting poor health across a number of different dimensions. Obese women, but not men, were shown to discount more than normal weight women, normal weight men, and obese men (Weller, Cook, Avsar, & Cox, 2008). Likewise, obese adolescent smokers have been found to discount more than normal-weight smokers (Fields, Sabet, Peal, & Reynolds, 2011). Similarly, normal-weight adolescents discount less than overweight and obese adolescents, and overweight adolescents discount less than obese adolescents (Fields, Sabet, & Reynolds, 2013). Obese and overweight women with greater discounting order more high-energy foods, and consumed more calories, when eating away-from home meals, but this is not true of meals prepared at home (Appelhans et al., 2012). Finally, both male and female subjects with higher percent body fat have greater discounting for food rewards (Hendrickson &

Rasmussen, 2013; Rasmussen, Lawyer, & Reilly, 2010), but only female participants with higher percent body fat show greater discounting for monetary rewards (Rasmussen et al., 2010).

The study of discounting in the obese so far has not examined a relatively new variant of the delayed discounting procedure referred to as social temporal discounting (Bickel, Jarmolowicz, Mueller, Franck, et al., 2012; Bickel, Jarmolowicz, Mueller, Gatchalian, & McClure, 2012; Bickel, Jarmolowicz, Mueller, Koffarnus, et al., 2012; Charlton et al., 2013). Social temporal discounting provides a measure of the decline in value of a reinforcer that will be distributed to a group of individuals (including the participant) as a function of the delay to the reinforcer's receipt (Bickel, Jarmolowicz, Mueller, Franck, et al., 2012). This procedure presents participants with choices between a reinforcer that will be evenly distributed among a group of unspecified individuals (including the participant) now vs. a larger reward to be shared among that same group later (i.e., "we now" vs. "we later"; Charlton et al., 2013). Comparison of standard delay discounting (i.e., "me now" vs. "me later") and social temporal discounting among college students resulted in greater preference for the delayed option (less discounting) in the social temporal option relative to preference in the standard discounting procedure. Moreover, a study examining temporal discounting, social temporal discounting, and a combination of standard temporal discounting and social temporal discounting (i.e., "me now" vs. "we later") in problem drinkers showed comparable results to controls on the extent of discounting on social temporal and the combination discounting task, while smokers discounted significantly more on all forms of discounting relative to controls (Bickel, Jarmolowicz, MacKillop, et al., 2012; Bickel, Jarmolowicz, Mueller, Franck, et al., 2012; Bickel, Jarmolowicz, Mueller, Gatchalian, et al., 2012; Bickel, Jarmolowicz, Mueller, Koffarnus, et al., 2012). Thus, whether social temporal discounting engenders more or less preference for the delayed option is, in part, dependent on the population under study.

In this study, we obtained a large sample of participants ($n = 1181$) by using Amazon's Mechanical Turk (AMT). AMT, a crowdsourcing service, permits researchers to post tasks or questions which are then answered by a potential participant pool of more than 500,000 potential research volunteers to complete (The Economist, 2012). This participant pool is considerably more diverse than typical university-based samples (Buhrmester, Kwant, & Gosling, 2011; Jarmolowicz, Bickel, Carter, Franck, & Mueller, 2012; The Economist, 2012), and studies using AMT as a source of participants have replicated previously reported findings (Bickel, Jarmolowicz, Mueller, Franck, et al., 2012; Sprouse, 2011). The present study used AMT to collect data from a large sample to clarify the extent of differences in temporal, social temporal discounting, combination of standard and social temporal discounting, and probability discounting between obese and control participants.

Materials and methods

Participants

Individuals ($N = 1181$) from across the United States of America took a 198-item questionnaire about health behaviors, sociality, and monetary decision-making through the AMT crowdsourcing service. To access the survey, individuals had to be registered with

AMT, be at least 18 years old, and successfully complete at least 90% of their previous Human Intelligence Tests (HITs). Before participating, participants were provided with an overview of the study. Implied consent was obtained from participants when they indicated they understood the description and wished to continue. Participation was anonymous with no personally identifiable information collected. This study protocol was approved by the Virginia Tech's Institutional Review Board.

Participants who either did not report both height and weight or failed to provide plausible values of height and weight were excluded from further analysis. Additionally, 5 subjects who reported ages below 18 were excluded. This permitted 1163 subject records to be available for analysis. Of these, 55.6% were female and all participants were between the ages of 18–82 (*Median* = 28).

Procedures

Individuals accessed the questionnaire online as a HIT entitled “Decision Making Study.” They were then asked to read a description of the study and indicate that they read and understood that material. Participants were given \$2.50 upon submission of the questionnaire and were given an additional bonus of \$2.50 if their responses were eligible for data analysis. An individual's data was excluded from the analysis if he/she did not indicate understanding of the instructions or did not complete 80% of the survey questions. Additionally, individuals were excluded from analysis if the survey was completed in less than 800 s or if answers to any of the discounting measures reflected unvarying response patterns, suggesting an absence of thoughtful consideration of survey questions. Finally, individuals who did not provide their height and/or weight, provided implausible values for either, were removed from the analysis as these are prerequisites for computing one's body mass index (BMI) and obesity status.

Measures

All participants responded to the same questions. Items included: collection of demographic information such as height and weight, questions related to health-seeking behaviors, and health risk behaviors (e.g., alcohol and tobacco use).

Income – Participants indicated their yearly income by selecting one item from a list of 44 non-overlapping ranges (ranging from an income loss to an income of \$1,000,000 or more). The midpoint of the range in their selected item served as the measure of income.

Body Mass Index (BMI) – BMI served as a measure of body fat (Garrow & Webster, 1985) and was calculated using the following equation:

$$\text{BMI} = \left(\text{Weight}[\text{lbs}] / \text{Height}[\text{in}]^2 \right) * 703 \quad (1)$$

An adult in the United States with a BMI score between 25 and 29.9 is considered overweight, while obese adults are defined as those who have a BMI of 30.0 or above (World Health Organization, 2013). One individual reported a height and weight

combination that yielded a BMI greater than 135 and was not considered for further analysis.

Reward discounting measures—Two types of discounting rates were investigated in this procedure. Delay discounting (DD) where participants selected between a small or large (but delayed) reward and probability discounting (PD) where participants selected between a small or large (but less probable) reward. A subject's rate of discounting was quantified using a procedure based upon the Kirby method (Kirby & Marakovic, 1996; see Table 1 for a sample of this questionnaire) (see also Jarmolowicz et al., 2012). DD was further explored by incorporating a social element to the task. Participants were asked to select either the immediate or delayed reward when they would be the only one receiving it (the Me–Me condition); when they and 9 other people they did not know would evenly split the reward selected (the We–We condition); and when the subject would solely receive the small reward (if selected), but would be required to split the large reward among the group of 10 described above (the Me–We condition).

Under these four conditions participants answered 21 questions involving hypothetical receipt of monetary amounts in which they must choose either a smaller or a larger reward that was either delayed (for the three DD conditions) or less probable (for the PD condition). The 21 questions establish 20 non-overlapping ranges, from which a discounting rate parameter, $\ln(k)$ for DD or $\ln(h)$ for PD (see Mazur, 1987 for equation), was extracted. The questions were split between relatively small, medium, and large size rewards (seven questions for each grouping), and based on their responding a participant was assigned to three ranges, one for each reward size. In the case where a subject could be classified as being in two ranges for a reward size (in other words if two ranges were equally consistent based on a subject's pattern of response) then the subject's assigned k or h value was the geometric mean of the two equally plausible k or h values.

The 21 questions can be further separated into seven discrete ranks, with 2–4 questions falling into each rank (see Table 1 for the rank assignments). A subject is assigned to one of the 7 ranks based on the point at which they switch from predominately selecting the large reward to predominately selecting the smaller option. Under this classification, a subject assigned a “1” would discount little, whereas a subject assigned a “7” would exhibit considerable discounting. In the case where a subject could be classified as being in two ranks, the subject was assigned the geometric mean of the two ranks. A subject was assigned the range, rank, and corresponding $\ln(k)$ or $\ln(h)$ value most consistent with their set of answers. Note that log-transformations of the discount rate results in the data approximating a normal distribution.

Statistical analysis

Statistical analyses and graphics were produced using SAS version 9.3 and R version 2.15.3. Pearson correlation was used as a measure of association between variables that were continuous or binary. Spearman correlation was used for variables that were ordinal, including education and income. Comparisons in discounting were conducted between obese and non-obese groups using two sample t tests, and Cohen's d was used as an estimate of

effect size. Small and medium effects are typically considered to be $d = .2$ and $d = .5$ respectively.

Logistic regression was used to build and select predictive models for obesity. Candidate predictors considered included Age, Education, Gender, Income, and $\ln(k)$ from the Me–Me, Me–We, and We–We DD conditions, $\ln(h)$ from PD, and smoking status (Yes/No). 511 candidate models were fit, corresponding to all possible combinations of these candidate predictors (i.e. $2^9 - 1$ possible models), and the model with the lowest Bayesian Information Criterion (BIC) was chosen. The BIC weighs the likelihood of a given model while penalizing a model when more parameters are added. Since the penalty term in BIC includes sample size, a subset of the data ($n = 684$) was used which has no missing values in any candidate predictor or response. The concordance index (c-statistic) was calculated for the selected logistic regression model. This statistic measures the tradeoff between true positive rate and the false positive rate for predicting an obesity outcome based on the model predictions; a c-statistic of 0.5 model performance equivalent to predicting obesity by chance alone, while 1 indicates perfect predictive ability.

Results

A preliminary analysis was conducted to compare normal (BMI <25), overweight (25 ≤ BMI <30), and obese (BMI ≥ 30) individuals in terms of $\ln(k)$ and $\ln(h)$ for the four discounting measures. Discounting was modeled as a function of BMI group and model contrasts were used to compare each of these three groups. Non-obese individuals ($n = 596$) and overweight individuals ($n = 304$) were not significantly different for any of the four discounting measures (p values ranged from 0.1762 to 0.7083). Therefore these 900 participants were re-classified as the non-obese and the remaining 263 as obese (i.e., their BMI was greater than 30). Tables 2A and 2B display the demographic information (Age, Income, and Education) for these 1163 participants,

Fisher's exact test did not reveal a significant dependence between smoking status (yes/no) and obesity (p -value = .0969). However, Fisher's exact test revealed a dependence between gender and obesity ($p = 0.0199$). Among non-obese participants there were 415 males and 483 females. Among obese participants there were 100 males and 163 females. Two participants did not report gender.

The pattern of significance comparing normal and overweight to obese individuals varied. To succinctly report on differences between obese and non-obese participants, and in reflection of these preliminary findings, normal and overweight individuals were combined into a single "non-obese" group and compared with obese participants for all subsequent analysis. The four panels of Fig. 1 show mean rates of delay discounting in the Me–Me, Me–We, We–We conditions (i.e., $\ln(k)$, in panel A, B, and C, respectively) and probability discounting (i.e., $\ln(h)$, panel D), for the non-obese and obese groups (see Table 3 for average discounting values. The error bars denote one standard error of the mean. Me–Me discounting was significantly ($t_{1033} = 3.25$; $p = 0.0012$; $d = 0.24$) higher for the obese ($Mean = -4.01$) than the non-obese ($Mean = -4.28$) groups. Me–We and We–We discounting $\ln(k)$ values also exhibited significant differences between obese and non-obese groups (Me–We:

$t_{847} = 1.98, p = 0.0475, d = 0.16$ We–We: $t_{1058} = 3.39, p = 0.0007, d = 0.25$). For probability discounting rates, the obese group ($Mean = 0.90$) and non-obese group ($Mean = 0.82$) were not significantly different ($t_{968} = 1.38; p = 0.1689, d = 0.11$). These effect sizes are small by convention.

To account for the possibility that smoking status (yes/no) might explain the association between discounting and obesity (yes/no), smoking and obesity status were jointly modeled as predictors of discounting. The pattern of significance between obesity and the four discounting types was generally the same, with p -values equal to 0.0022, 0.0521, 0.0044, and 0.1629 for Me–Me, Me–We, We–We, and probability discounting, respectively. Note that the Me–We p -value in this case is slightly above the threshold which is traditionally considered to be statistically significant in this analysis. These p -values are based on partial F tests between obesity and discounting with smoking included in the model. Interaction effects between smoking and obesity were non-significant in all four of the cases.

The four panels in Fig. 2 capture the ranking scores of obese and non-obese groups, the proportion of participants at each rank who selected the smaller reward is displayed along the y-axis. These proportions were estimated by fitting to a logistic regression model, and generalized estimating equations were used to account for repeated questions within-subject. Obesity comparisons are based on a 1 degree of freedom contrast. This was done on the three different DD tasks in the Me–Me, Me–We, We–We conditions, panels A, B, and C respectively, and for the PD condition which is displayed in panel D. These two functions were significantly different according to model contrasts in the Me–Me ($\chi^2 = 9.60, p = .0019$), Me–We ($\chi^2 = 6.03, p = 0.0141$), and We–We ($\chi^2 = 12.77, p = 0.0004$) conditions. This means that, compared to the non-obese group, the proportion of obese participants who selected the smaller reward, within each rank, is significantly greater in these conditions. This, however, is not true of the PD condition as the difference between the two groups was not significant ($\chi^2 = 2.39, p = 0.1223$).

Table 4 presents all pairwise correlations for variables collected in this study. The upper 8 blocks of rows exhibit Pearson correlations, while the lower two blocks (which reflect the ordinal variables of Education and Income) shows Spearman correlations. A number of the significant positive correlations captured are in accordance with prior findings, these include: one's highest level of Education and Income, Income and Age, BMI and Age, and Education and Age. Likewise, a high level of concordance between the different measures of discounting was expected (and captured as all six positive correlations were significant) as these variables measure similar processes.

A series of 511 candidate predictive models were fit and BIC was used as a criterion to identify the subset of variables that best predicted obesity. Variables included in the candidate list were age, education level, gender, income, $\ln(k)$ and $\ln(h)$ for the four discounting measures, and smoking status, and the 511 models included every combination of these. The model with the lowest BIC included age and Me–Me $\ln(k)$ ($BIC = 701.62$). Partial significance tests based on the regression model revealed p -values below 0.0001 for both predictors. The model had decent overall classification properties with a concordance index of 0.646. No significant lack of fit was exhibited for this model as evidenced by a non-

significant Hosmer and Lemeshow test ($\chi^2 = 7.61$, $df = 8$, $p = 0.4726$) (Hosmer & Lemeshow, 2000).

Discussion

In this study, crowdsourcing technology (i.e., AMT) was used to obtain discounting data from a large sample of obese and non-obese participants. Overall, we found that the obese discounted more than controls in temporal discounting and social temporal discounting, but not probability discounting. We also found that the best model to predict obesity as identified by BIC included age, and $\ln(k)$ from the standard (me now vs. me later) discounting procedure. This observation contributes to the recognition that those who suffer from obesity may share excessive discounting with other disorders, such as drug addiction, problematic gambling, executive dysfunction, and several different forms of impulsivity disorders (Bickel, Jarmolowicz, Mueller, Koffarnus, et al., 2012). Moreover, this is the first study to examine social temporal discounting in this population with the observation that the obese are less sensitive to social conditions in this context. Below we comment on four features of our findings.

First, the obtained difference in delay discounting rates for the obese and non-obese is consistent with the results of other studies that found higher delay discounting rates for obese samples compared to non-obese samples in some conditions (Appelhans et al., 2011; Davis, Patte, Curtis, & Reid, 2010; Epstein et al., 2010; Fields et al., 2011; Weller et al., 2008). Perhaps the prior studies that failed to find a difference used a restricted N that reduced the power of their statistical tests. In the present study, the large N allowed us to more reliably measure and determine with high statistical significance that there is a difference in delay discounting rate between obese and non-obese individuals, but that these differences are associated with relatively small effect sizes. These small effect sizes would not be reliably detectable using a reduced sample size, which may suggest a basis for the inconsistency in the previous literature (e.g., Nederkoorn, Smulders, Havermans, Roefs, & Jansen, 2006).

Second, a future direction, related to the small effect size, is to examine whether BMI is too gross a category that may obscure important sub-groups or phenotypes such as has been explored with the concept of reinforcer pathology (Bickel et al., 2011; Epstein et al., 2010). That is, those who both substantially discount future rewards and also find food more reinforcing may be a functionally different phenotype associated with a larger effect size (Best et al., 2012; Rollins, Dearing, & Epstein, 2010). Perhaps consistent with the notion of reinforcer pathology is findings that normal weight (Rollins et al., 2010), as well as obese and overweight women (Appelhans et al., 2011) whose rate of discounting was comparatively lower than the sample used in their respective studies showed a greater influence of food reward sensitivity on the amount of calories they consumed in a laboratory taste-test.

Third, significant differences between the groups were observed with the social temporal discounting procedures. Previously, we reported that smokers discounted social temporal monetary rewards more than controls, while problem drinkers did not (Bickel, Jarmolowicz,

Mueller, Franck, et al., 2012). In the present study, we report for the first time that the obese discounted social temporal monetary outcomes to a greater extent than controls. This observation supports the use of these social temporal discounting procedures as a means to understand the sensitivity of different diagnostic groups to social conditions. Whether this difference in social discounting results directly from obesity, as a result from other factors, such as the interactions with others (e.g., secondary to stigma), this profile suggests that the obese are less sensitive to social factors when considering temporally distributed choices.

Fourth, and finally, we address two potential weaknesses that could be raised with this study. One potential weakness is that this study was conducted online and was based on only self-reports. As such, we could not verify any feature of this study, including height and weight from which one's BMI and obesity status were derived. The results of several studies have been replicated with AMT, and thus far suggest that comparable results are obtained (e.g., Bickel, Jarmolowicz, Mueller, Franck, et al., 2012; Sprouse, 2011). The second potential weakness, related to the first, is that the rewards employed in the discounting tasks were all hypothetical and perhaps may not reflect the discounting of actual outcomes. Here the results of large number of studies have demonstrated the comparability of real and hypothetical temporal and probability discounting outcomes including the neural signature associated with real and hypothetical outcomes (Baker, Johnson, & Bickel, 2003; Bickel, Jarmolowicz, Mueller, Gatchalian, et al., 2012; Bickel, Pitcock, Yi, & Angtuaco, 2009; Jarmolowicz et al., 2012; Johnson & Bickel, 2002; Sprouse, 2011). Whether a similar profile of results would be obtained when real and hypothetical outcomes are compared from social temporal discounting remains an open question.

Despite the strong evidence of a connection between obesity and discounting there is evidence that a number of third variable may instead be the cause of this finding; in obese subjects, discounting maybe an index of (1) generalized impulsivity, or (2) binge-eating disorder (BED), independent of obesity. For example while no differences in discounting between obese and normal weight women have been reported, instead impulsivity on a stop-signal reaction time test showed a difference between these two groups (Nederkoorn et al., 2006). Normal weight women were found to discount less than obese women and women with BED (Davis et al., 2010). However, obese women with BED were found to have greater discounting than obese women without BED (Manwaring, Green, Myerson, Strube, & Wilfley, 2011). Elucidating how discounting characterizes obesity will require future studies that use more refined methods (e.g., the social discounting task used here) and samples (e.g. individuals suffering from binge-eating disorder).

Conclusions

In conclusion, this report provides evidence that temporal discounting and social temporal discounting are different when comparing those with obesity to controls, but that the effect size is small. As such, this study suggests a reason for the inconsistent findings observed in prior studies. Future research might consider decomposing the obese sample into different subgroups and perhaps identifying different phenotypes as indicated above (e.g., reinforcer pathology). Nonetheless, these findings support temporal discounting functioning as a trans-disease process implicated in a variety of disorders including obesity.

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Fig. 1.

Panels A, B, and C show the average logged k or h of discounting in the Me-Me, Me-We, and We-We conditions, respectively, while panel D shows probability discounting. Each panel compares the behavior of the non-obese (BMI <30) and obese (BMI ≥30) groups. Asterisk indicates a significant difference between the two groups on that measure.

Fig. 2.

Panels A, B, and C show the proportion of subjects at each rank in the Me–Me, Me–We, and We–We conditions, respectively, that selected the smaller rewards, while Panel D also shows this data, but for the probability discounting condition. See Fig. 1 for additional details.

Table 1

On the left-hand column of this table are the Delay discounting (DD) questions, and on the right are the Probability discounting (PD) questions. As there are three separated DD conditions (Me-Me, Me-We, and We-We), the X and Y portion of each question can be inter-changed in accordance with the naming conventions listed at the top of the DD portion of the table to make the questions specific to each condition.

Order	Delay discounting survey		Probability discounting survey	
	Choice presented	k	Choice presented	h
4	\$34 tonight, for X, or \$35 in 43 days, for Y	0.0007	\$34 for sure, or a 57% chance of getting \$35	0.039
15	\$53 tonight, for X, or \$55 in 55 days, for Y	0.0007	\$53 for sure, or a 45% chance of getting \$55	0.031
7	\$83 tonight, for X, or \$85 in 35 days, for Y	0.0007	\$83 for sure, or a 65% chance of getting \$85	0.045
20	\$27 tonight, for X, or \$30 in 35 days, for Y	0.0032	\$27 for sure, or a 65% chance of getting \$30	0.206
9	\$48 tonight, for X, or \$55 in 45 days, for Y	0.0032	\$48 for sure, or a 55% chance of getting \$55	0.178
12	\$65 tonight, for X, or \$75 in 50 days, for Y	0.0031	\$65 for sure, or a 50% chance of getting \$75	0.154
8	\$21 tonight, for X, or \$30 in 75 days, for Y	0.0057	\$21 for sure, or a 25% chance of getting \$30	0.143
16	\$47 tonight, for X, or \$50 in 60 days, for Y	0.0055	\$47 for sure, or a 40% chance of getting \$50	0.043
14	\$30 tonight, for X, or \$35 in 20 days, for Y	0.0083	\$30 for sure, or an 80% chance of getting \$35	0.667
10	\$40 tonight, for X, or \$65 in 70 days, for Y	0.0089	\$40 for sure, or a 30% chance of getting \$65	0.268
3	\$67 tonight, for X, or \$85 in 35 days, for Y	0.0077	\$67 for sure, or a 65% chance of getting \$85	0.499
18	\$50 tonight, for X, or \$80 in 70 days, for Y	0.0086	\$50 for sure, or a 30% chance of getting \$80	0.257
11	\$25 tonight, for X, or \$35 in 25 days, for Y	0.016	\$25 for sure, or a 75% chance of getting \$35	1.2
2	\$40 tonight, for X, or \$55 in 25 days, for Y	0.015	\$40 for sure, or a 75% chance of getting \$55	1.125
19	\$45 tonight, for X, or \$70 in 35 days, for Y	0.0159	\$45 for sure, or a 65% chance of getting \$70	1.032
21	\$16 tonight, for X, or \$30 in 35 days, for Y	0.025	\$16 for sure, or a 65% chance of getting \$30	1.625
6	\$32 tonight, for X, or \$55 in 20 days, for Y	0.0359	\$32 for sure, or a 80% chance of getting \$55	2.875
17	\$40 tonight, for X, or \$70 in 20 days, for Y	0.0375	\$40 for sure, or a 80% chance of getting \$70	3
5	\$15 tonight, for X, or \$35 in 10 days, for Y	0.1333	\$15 for sure, or a 90% chance of getting \$35	12
13	\$24 tonight, for X, or \$55 in 10 days, for Y	0.1292	\$24 for sure, or a 90% chance of getting \$55	5.167
1	\$30 tonight, for X, or \$85 in 14 days, for Y	0.131	\$30 for sure, or an 86% chance of getting \$85	11.26

Table 2**A**

Summary statistics for age and income. Mean and standard deviation are reported for age. Median and interquartile range are reported for income owing to a high skew in the income distribution (overall sample skew = 2.66 for income).

Demographics: Summary statistics	All subjects (<i>n</i> = 1163)	Non-obese (<i>n</i> = 900)	Obese (<i>n</i> = 263)
Age (years): Mean; standard deviation	31.64; 11.25	30.78; 11.17	34.57; 11.06
Income (dollars): Median; (interquartile range)	23750; (9000–48750)	23750; (7000–48750)	23750; (11000–48750)

B

The highest level of education attained by subject in these three groups.

Highest education level: by % in category	All subjects (<i>n</i> = 1163)	Non-obese (<i>n</i> = 900)	Obese (<i>n</i> = 263)
Less than highschool diploma or GED	1.81	1.44	3.04
High school diploma or GED	10.58	10.44	11.03
Some college	33.96	33.11	36.88
Associates degree	8.77	8.44	9.89
Bachelors degree	31.13	31.89	28.52
Advanced degree (e.g. Masters or Doctorate)	13.76	14.67	10.65

Table 3

Summary statistics for untransformed and logged k and h values for all subject (3A) and the separate groups (3B). Here, logKDD stands for the log of k for traditional delayed discounting (or the Me–Me conditions), logKMW stands for the log of k of the Me–We discounting condition, logKSD stand for the log of social discounting (of the We–We condition), and logHPD stands for the log of h for the probability condition.

Variable	N	Mean	Std. dev.	Skewness	
3A					
kdd	1163	0.06	0.12	3.12	
kmw	1163	0.03	0.08	5.11	
ksd	1163	0.03	0.09	5.01	
hpd	1163	4.96	4.89	1.29	
logKDD	1163	−4.13	1.61	−0.06	
logKMW	1163	−5.32	1.95	0.06	
logKSD	1163	−4.76	1.53	0.05	
logHPD	1163	1.14	0.99	−0.21	
Group	Variable	N	Mean	Std. dev.	Skewness
3B					
Non-obese	kdd	900	0.06	0.12	3.26
	kmw	900	0.03	0.09	4.97
	ksd	900	0.03	0.09	4.80
	hpd	900	4.83	4.83	1.35
	logKDD	900	−4.21	1.62	−0.04
Obese	logKMW	900	−5.32	1.94	0.10
	logKSD	900	−4.83	1.58	0.13
	logHPD	900	1.11	1.00	−0.26
	kdd	263	0.07	0.14	2.73
	kmw	263	0.03	0.08	5.75
	ksd	263	0.03	0.07	5.99
	hpd	263	5.41	5.09	1.12
	logKDD	263	−3.84	1.54	−0.08
	logKMW	263	−5.29	1.95	−0.07

Group	Variable	N	Mean	Std. dev.	Skewness
3B	logKSD	263	-4.53	1.33	-0.23
	logHPD	263	1.25	0.97	-0.03

Table 4

All pairwise correlations for variables collected in this study. (A) Exhibits Pearson correlations, while (B) reflects Spearman correlations. Here, logKDD stands for the log of k for traditional delayed discounting (or the Me–Me conditions), logKMW stands for the log of k of the Me–We discounting condition, logKSD stand for the log of social discounting (of the We–We condition), and logHPD stands for the log of h for the probability condition.

	Gender	Age	BMI	logKDD	logKMW	logKSD	logHPD
(A) Pearson correlation coefficients							
Gender	r	1	0.17757	0.02333	0.03491	0.00412	0.19644
	p -Value		<.0001	0.4271	0.2346	0.8884	0.9532
	n		1161	1161	1161	1161	1161
Age		0.17757	1	0.17874	−0.0466	−0.0709	−0.0183
		<.0001		<.0001	0.1124	0.0155	0.5325
		1161	1163	1163	1163	1163	1163
BMI		0.02333	0.17874	1	0.12151	0.05809	0.10929
		0.4271	<.0001		<.0001	0.0476	0.0002
		1161	1163	1163	1163	1163	1163
logKDD		0.03491	−0.0466	0.12151	1	0.48785	0.74305
		0.2346	0.1124	<.0001		<.0001	<.0001
		1161	1163	1163	1163	1163	1163
logKMW		0.00412	−0.0709	0.05809	0.48785	1	0.54165
		0.8884	0.0155	0.0476	<.0001		<.0001
		1161	1163	1163	1163	1163	1163
logKSD		0.00172	−0.0183	0.10929	0.74305	0.54165	1
		0.9532	0.5325	0.0002	<.0001	<.0001	<.0001
		1161	1163	1163	1163	1163	1163
logHPD		0.19644	0.11417	0.0245	0.1967	0.10644	1
		<.0001	<.0001	0.4038	<.0001	<.0001	
		1161	1163	1163	1163	1163	1163
(B) Spearman correlation coefficients							
Income	r	0.02708	0.47085	0.07071	−0.1212	−0.0784	−0.0857
							0.02286

(B) Spearman correlation coefficients									
	p-Value	n	Gender	Age	BMI	logKDD	logKMW	logKSD	logHPD
Education	0.3566	<.0001			0.0159	<.0001	0.0074	0.0035	0.4361
	1161	1163			1163	1163	1163	1163	1163
	0.00811	0.3071			-0.0445	-0.1625	-0.081	-0.1051	-0.0874
	0.7825	<.0001			0.129	<.0001	0.0057	0.0003	0.0028
	1161	1163			1163	1163	1163	1163	1163