Time Discounting and Behavior

John-Henry Pezzuto

University of Chicago

Table of Contents

Abstract

Previous studies comparing delay discounting with various behaviors have often produced conflicting results or have not been confirmed by multiple sources. Furthermore, since discount rates are calculated using different methods, which includes those commonly used in the literature (hyperbolic, quasi-hyperbolic, exponential -- as well as with lesser known methods like discount factors and patience scores), it is sometimes difficult to compare effect sizes across studies. This study calculates discount rates for 800 Amazon MTurk subjects and offers confirmatory evidence for the wide variety of behaviors previously studied (e.g., exercise, BMI, substance). Ridge regression was utilized to limit covariance, and it was found that larger amounts of money and the unconventional patience model were best connected with behavior.

Keywords: Delay discounting, behavior, hyperbolic, exponential, quasi-hyperbolic, factor, patience.

Time Discounting and Behavior

Delay discounting, also known as time discounting or temporal discounting, is a procedure which involves asking subjects whether they would prefer an immediate smaller reward, or a larger reward at a later time. When subjects choose the smaller but more immediate reward over the later but larger reward, this indicates that subjects discount the value of the larger reward because of time. More broadly, delay discounting exists in multiple domains where subjects have a choice of giving up immediate gratification in order to pursue a better future outcome, including scenarios such as healthy eating, which may require giving up delicious desserts now so that your body can enjoy other foods with more nutrients; exercising, which may be uncomfortable at the moment, but leads to greater health down the line; or when to begin collecting social security payments, since the payments increase gradually the longer you wait to begin collecting. The differences in how subjects value rewards over time in different domains then makes for interesting comparisons about participant behavior. Because delay discounting can be used as an indicator of how rapidly a reward loses value over temporal distance and as an index of ability to delay gratification, delay discount rates can roughly be seen as an estimate of a participant's impulsivity and patience and, as such, has been linked with various "impulsive" behaviors such as smoking or binge drinking (MacKillop et al., 2011). The link between behavior and delay discounting will be discussed in depth.

In humans, delay discounting studies are mostly done with a series of hypothetical[1] binary monetary choices or via a matching method. In the binary choices method, subjects answer an assortment of questions about whether they would prefer a smaller sum of money now or a larger amount of money over time (e.g., choose between $10 now or $30 in one month). The matching method allows the subject to select their own amount for a delayed large reward (e.g., "how many dollars in one month would make you indifferent to $10 today?"). Each of these methods are converted to a discount rate using a number of different methods described in more detail below. Previous research on the matching method and the binary choice method has tested both methods in a within-subjects design and found that the matching method yields lower discount rates than the binary choice method, possibly because binary choices creates demand characteristics that make subjects feel obliged to discount given the option (Read & Roelofsma, 2003). Delay discounting has been used in a wide variety of situations including animal subjects [e.g., pigeons deciding how long to wait for larger but later amounts of food; rats waiting for more water (Green et al., 2007)], and hedonistic items (e.g., 1 cigarette now or 2 cigarettes in an hour).

In this paper I will use the binary choice method as it has been shown to be easier for subjects to understand and is better at predicting behavior (Hardisty et al., 2011). I hold the delayed reward constant (known as a fixed delayed reward) and ask about a series of ascending[2] immediate rewards. When using the binary choice method, the point at which a subject makes the switch from the later larger reward to the sooner smaller reward is

[1] Previous literature regarding delay discounting found no difference between hypothetical rewards and actual rewards, although most of this work has been confined to small amounts (Johnson & Bickel, 2002; Lagorio & Madden, 2005; Madden, Begotka, Raiff, & Kastern, 2003)

[2] Some previous research has indicated that ascending choice order has been shown to affect discount rates in a way that makes subjects appear less patient (Hardisty et al., 2011).

commonly called the indifference point or simply the switch point. The indifference point can be more accurately thought of as the point at which the subject sees the rewards of being roughly equal in value and is therefore indifferent between the two options (so if someone prefers $30 in a month to $10 now, but $12 now to $30 in a month, I can think of their indifference point as approximately $11 -- because the subject would equally enjoy the sooner but smaller amount and the later but larger amount). Subjects who answer the questions in an inconsistent fashion (i.e., without a single indifference point), are most commonly excluded from analysis, although in this paper I will also include these subjects in a measure of patience.

Calculating Discount Rates

Delay discount rates are then most commonly assessed in four ways. The first way is as a hyperbolic discounting measure given by the equation $V = A / (1 + kd)$, where V is the indifference point or subjective value, A is the delayed reward, k is the free parameter that estimates discount rate (i.e., increases in k indicate more impulsivity, and a k value of 0 indicates that the subject values the future and present exactly the same), and d is the delay.

The second approach of quantifying delay discounting is the area under the curve (AUC) method which is atheoretical (Myerson, Green, & Warusawitharana, 2001). To calculate AUC all the delays and indifference points are normalized by expressing them as a proportion of the maximum value. Each delay and indifference point pair are compared in the equation, $x_2 - x_1 [(y_1 + y_2)/2]$, where x_1 and x_2 are successive delays and y_1 and y_2 are the indifference points associated with those delays. Because I am using a fixed delayed reward, and a single time delay, a full-fledged AUC measure is not viable. Instead, I will use a nonparametric adapted version where I simply normalize the indifference points, creating a measure ranging between 0 and 1, where 0 indicates no patience at all and 1 indicates absolute patience (Bartels & Urminsky, 2011). This alternative method is called a discount factor.

The third way to assess discounting, although it is less common than the previous two methods, is the quasi-hyperbolic method (Laibson, 1997). This method distinguishes consistency of discounting from level of discounting, by assuming a higher discount factor in the first period (β), but a constant discount factor for subsequent periods (δ) (Urminsky & Zauberman, 2014). In other words, β can be thought of as a measure of present bias, while δ can be thought of as the long run discount factor (Urminsky & Zauberman, 2014). In this paper, δ is calculated as $\delta = (V_2/A)^{\wedge(1/D)}$ where V_2 is the later indifference point, and A is the larger but later amount, and D is the delay, and β is calculated as $\beta = (V_1/A)*(1/\delta^{\wedge D})$ where V_1 is the sooner indifference point.

The fourth and last method I will use to measure discount rates is the exponential method which has largely fallen out of favor in recent years compared to the hyperbolic method. The exponential rate can be thought of as a logical discount factor as it declines over time proportionately unlike the other models used. The exponential discount rate will be calculated as $r = (A/V)^{1/D} - 1$, where A is the later but larger amount, V is the indifference point and D is the total delay of the later but larger reward.

Delay Discounting, Behavior & Demographics

Delay discounting has been linked to a wide range of behaviors although some of these relationships have been linked more strongly than others. For example, previous research has examined the relationship between delay discounting and demographic variables such as gender (cf. Jarmolowicz et al., 2014; Weller, Cook, Avsar, & Cox, 2008) and age (cf.

Buono, Whiting, & Sprong, 2015; Stoeckel, Murdaugh, Cox, Cook, & Weller, 2013) but has generally returned mixed or inconclusive results. However, in domains like cognition, delay discounting seems to be well associated. A large scale meta-analysis has linked delay discounting to intelligence (Shamosh & Gray, 2008), and there is robust literature linking delay discounting with answering trick math questions correctly that require subjects to double check their intuition (Frederick, 2005). There is also robust evidence showing a link between delay discounting, credit card borrowing, and FICO scores as well (Meier & Sprenger, 2010; Meier & Sprenger, 2012).

Furthermore, there have been many studies relating delay discounting with health-related behaviors. Large scale meta-analyses have found significant relationships between delay discounting and BMI (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Emery & Levine, 2017), exercising (Sweeney & Culcea, 2017), and addictive behaviors such as smoking, drinking, and drug use (Amlung et al., 2017; MacKillop et al., 2011), though in most cases the effect is small but significant.

Lastly, there have been a large amount of “one-off” type studies which have found a significant effect in delay discounting and a behavior in a domain less commonly looked at. These include voting (Fowler & Kam, 2006), finishing your prescribed medication (Chabris et al., 2008) and dental status (Kang & Ikeda, 2015). These effects are significant, but less well documented than many of the previous behaviors, and therefore worth further examination.

This paper intends to offer a single large-scale survey looking at which types of delay discounting are genuinely associated with behavior, and in which behaviors no true relationship exists. By utilizing a relatively large sample of 800 subjects, this survey is equipped to find the small but significant effects that exist among an online population. I use Amazon MTurk workers because they have previously been shown to produce replicable results and are more representative of the population than a convenience sample of college students (Berinsky, Huber and Lenz, 2012). As previously stated, it is important to be to considerate of how the framing of the delay discounting question can affect the choices made by subjects. Binary choices will be used because it has been shown to be easiest for subjects to understand and is strongly associated with behavior (Hardisty et al., 2011). Furthermore, because studies typically only measure discount rate in a single way, comparing alternative methods of delay discounting may yield fruitful results because methods are not often compared. Thus, in this study, discount rate are measured using the factor, hyperbolic, and quasi-hyperbolic, patience, and exponential methods.

Methods

Subjects

Subjects were 849 workers recruited from Amazon Mechanical Turk (MTurk). Subjects were excluded from analysis if they did not complete the survey, had duplicate IP Addresses or MTurk IDs, failed a single attention check at the end of the survey, or reported not being able to read the questions in a comments section at the end of the survey. In addition, I exclude subjects who completed the survey in less than 6.5 minutes. This left us with a final sample size of 800 (531 males, 269 females) with an age range from 20 to 60. Subjects were required to answer all questions except for one section about private behavior.

Discounting Measures

A total of four different methods were used to elicit discounting, each with a 6-month delay between the sooner and the later payments. These four different methods can be divided into two categories that varied by both size of payment ($30 or $300), and delay of first payment (immediately or in 1 month). A total of 16 questions were used by each method (for a total of 64 discounting questions). Table 1 summarizes the four methods used to elicit discounting.

Once the indifference points were established, discount rates were measured via hyperbolic (k), exponential, beta-delta (quasi-hyperbolic), patience (proportion of later but larger choices), and discount factors (indifference / later but larger).

Discount rate was measured in a variety of ways, both with including all the subjects and with using only the subjects who discounted consistently. Patience scores were measured using all subjects. I created three different patience scores, which were determined by the proportion of discounting questions in which subjects chose the later but larger option. Each of the four methods I used had its own patience score, in addition to the overall patience score I created which was the average of all questions. The indifference proportion, hyperbolic, exponential, and quasi-hyperbolic measures excluded subjects who answered questions inconsistently.

Indifference (factor) was created by finding the indifference point and dividing it by the later but larger payment. This measure ranges between 0 and 1 where 0 indicates no patience at all and 1 indicates absolute patience as described in Bartels and Urminsky (2011). This was done individually for all four methods of measuring discounting, as well as for an overall measure which was an average of all four. The methods for measuring the hyperbolic and exponential discount rates were done as previously described and used for all four methods individually as well as an overall average score. I created a quasi-hyperbolic score for each set of present and future payments (for a total 2 sets) with corresponding β and δs as well as an overall score with the average of the two sets.

Demographics and Behaviors

Because of concerns with data analysis, many behaviors were dummy coded in a way that included all subjects.

Demographics: Subjects reported their age, marital status, children, political affiliation, weight in pounds, height in feet and inches, employment status, ethnicity, household income in the past 12 months, expected household income in the next 12 months, and whether English was their native language. Employment status, political affiliation, and marital status were all dummy coded. Subjects who reported having children were asked their age when their children were born. Body mass index (BMI) was calculated by dividing the weight of subjects in kilograms, by their height in meters squared.

Substance: Subjects were asked how often they vaped or used electronic cigarettes, how many cigarettes they smoke regularly, how often they drank alcohol in the last month, at what age they first started drinking alcohol, if they drink caffeine or take caffeine related supplements, how frequently they smoke marijuana, and how often they gamble. Subjects who indicated they smoked cigarettes were asked at what age they started smoking. Subjects who indicated that they drink alcohol were asked how many times they passed out from drinking alcohol.

Political Interest: Subjects were asked whether they registered to vote in the 2016 presidential election, about their interest in the 2018 midterm election, which party had the majority in Congress, whether they donated to any candidate in the 2016 election, whether they would support a one time tax to support a music program, if they would favor or oppose a government increase of the excise tax on fuel to protect the environment, and their political ideology. Subjects were coded as politically knowledgeable based on whether they could correctly answer which party has the majority in Senate. Subjects who indicated that they registered to vote were asked whether they voted, and whether they voted in the election early if their state allowed.

Law Abiding Behavior: Subjects were asked whether they had ever been arrested, how many speeding tickets they received in the last year, and how many times they were in a car accident while they were driving in the past 5 years.

Financial Management Behavior Scale: Subjects were given the full Financial Management Behavior Scale (FMS) as described in Dew and Xiao (2011). I created an overall FMS score that was an average of the questions, as well as FMS sub scores in savings, insurance, budgeting, and credit.

Financial Behaviors: Subjects were asked whether they had an extended warranty on their smart phone, how much wealth they accumulated compared to their friends, how many months they would be able to sustain themselves if they lost their current stream of income, what percent of their income they save, how many times they were charged a late fee for making a credit card payment after the deadline, if they used a cash or payday lending service in the past 5 years, whether they prefer to spend more for environmentally sustainable goods, what their actual amount of savings is, and what their actual amount of debt is.

Health Behavior: Subjects were asked how often they finished their prescriptions, if they had eaten at a fast-food or pizza restaurant in the last 2 months, what their dental status is, how often they exercised in the past month for at least half an hour, if they received a vaccination in the last 12 months, and what percent of the time they wash their hands after using the bathroom.

Leisure Behavior: Subjects were asked how much they binge when watching television, whether they participate in "extreme" sports, how many times they were in physical fights outside of contact sports, whether they purchase designer or luxury goods, whether they exhibit shopping anxiety, and how many times a day they check online social media and other websites.

Cognitive Reflections Test: Subjects were given a 3-item Cognitive Reflection Test. An overall score between 0 and 3 was also given to subjects based on how many questions they answered correctly.

Private Behavior: In this section, subjects had a choice not to answer any question. The first question subjects were asked was whether they had ever had sexual intercourse. Conditional on saying yes, subjects were asked whether their first time was before or after the age of 16, if they had ever been unfaithful to a partner, whether they had more than 1 partner in the previous 6 months, and whether they engage in sex under the influence of alcohol or other drugs.

Exclusion Criteria: subjects who answered any of the continuous questions with an answer greater than the mean +3 standard deviations were excluded from analysis. All continuous questions were capped at 0 as a minimum answer.

Analysis

Because of concerns about collinearity, ridge regression was used to create a model that reduced variance. Ridge regression reduces variance by imposing constant lambda and beta constraint to the regression system, to minimize the penalized sum of squares. Participants were split into a test (30%) and training group (70%). Lambda was estimated by selecting the log lambda that offered the lowest mean squared error. Additionally, each participant was categorized into a discount rate model, by feeding them into each of the ridge regression models. This allowed us to categorize subjects by which model offered the lowest sum of squares error.

Results

The results indicate speedup large future factor consistent is best predicted by behavior, followed closely with overall patience, speedup patience, and the average of all the factors. The R squared values of each participants are shown in Table 2. Taking into consideration the top 5 models, the exponential models also do fairly well, although they are spread across the board. Likewise, the larger amounts of money seem more predictive of behavior. The future payments are generally ahead of the present payments. The quasi-hyperbolic model does not perform as well as other models.

In regards to the participant best fit into the models, the Patience model seems to perform well, clearly better than the other models, with about 100 subjects being categorized. This is 27 more subjects than the Average model which trails with about 73 subjects. We also see a pick up in the quasi-hyperbolic in this part of our analysis. The implications of these findings are discussed in more detail in the following discussion section. Results are summarized in Figure 1.

Discussion

The results consistently indicate that large sums of money are better predictors of behavior than smaller sums of money, and that receiving the first payment of future time period is slightly more predictive than receiving the first sum at a present time period. These two findings are congruent with the theory put forth by Thaler and Shefrin (1981) as well as Thaler's (1981) confirmatory study showing that discounts are inversely correlated with the amount of money. By increasing the wait time for the first payment, subjects are able to exercise more self-control, because the benefits are not immediate. It is unusual however that our exponential model does so well, because it is rarely used in modern discounting literature. Because the exponential model is consistent over periods of time, as compared to the hyperbolic model which decreased quickly initially but then steadies off, it is generally accepted that people do not get suddenly irrational. One explanation for this phenomena was that our sample had many highly impulsive people, with about 13% of participants choosing an immediate gratification option with the highest opportunity cost. This could be due to subjects not understanding our questionnaire well, a confounding variable such as drug addiction among subjects, or because of limitations within our attention check.

In regards to our model fitting, we find that the Patience score leads significantly, followed by the Average Score, and the Average Consistent score. Interestingly, the patience score is rarely used in discounting literature, and furthermore is a non-parametric model. Correlations with patience scores and behavior could therefore be a fruitful area for further literature to study. Likewise the Average and Average Consistent scores, are also non-parametric models as well. The beta-delta model performs better in this test than in our ridge regression test. This implies that the beta-delta model may not be able to predict behavior well, but may be more consistent with how people actually act in the real world. Although, the beta-delta model has recently fallen out favor as well, it may still be a valid model to consider using for further research.

Acknowledgements

Special thanks to Professor Oleg Urminsky for his excellent guidance, support, and for being an overall wonderful advisor, and to Rick Evans and Benjamin Soltoff for their encouragement and everlasting patience

References

Amlung, M., Petker, T., Jackson, J., Balodis, I., & MacKillop, J. (2016). Steep discounting of delayed monetary and food rewards in obesity: a meta-analysis. *Psychological Medicine*, *46*(11), 2423–2434. https://doi.org/10.1017/S0033291716000866

Amlung, M., Vedelago, L., Acker, J., Balodis, I., & MacKillop, J. (2017). Steep delay discounting and addictive behavior: a meta-analysis of continuous associations: Delay discounting and addiction. *Addiction*, *112*(1), 51–62. https://doi.org/10.1111/add.13535

Bartels, D. M., & Urminsky, O. (2011). On Intertemporal Selfishness: How the Perceived Instability of Identity Underlies Impatient Consumption. *Journal of Consumer Research*, *38*(1), 182–198. https://doi.org/10.1086/658339

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating Online Labor Markets for Experimental Research: Amazon.com's Mechanical Turk. *Political Analysis*, *20*(3), 351–368. https://doi.org/10.1093/pan/mpr057

Buono, F. D., Whiting, S. W., & Sprong, M. E. (2015). Comparison of temporal discounting among obese college students and obese adults. *Behavior Analysis: Research and Practice*, *15*(2), 139–147. https://doi.org/10.1037/bar0000015

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., & Taubinsky, D. (2008). *Individual Laboratory-Measured Discount Rates Predict Field Behavior* (Working Paper No. 14270). National Bureau of Economic Research. https://doi.org/10.3386/w14270

Emery, R. L., & Levine, M. D. (2017). Questionnaire and behavioral task measures of impulsivity are differentially associated with body mass index: A comprehensive meta-analysis. *Psychological Bulletin*, *143*(8), 868–902. https://doi.org/10.1037/bul0000105

Fowler, J. H., & Kam, C. D. (2006). Patience as a Political Virtue: Delayed Gratification and Turnout. *Political Behavior*, *28*(2), 113–128. https://doi.org/10.1007/s11109-006-9004-7

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives*, *19*(4), 25–42.

Green, L., Myerson, J., Shah, A. K., Estle, S. J., & Holt, D. D. (2007). Do Adjusting-Amount and Adjusting-Delay Procedures Produce Equivalent Estimates of Subjective Value in Pigeons? *Journal of the Experimental Analysis of Behavior*, *87*(3), 337–347. https://doi.org/10.1901/jeab.2007.37-06

Hardisty, D. J., & Weber, E. U. (2009). Discounting future green: money versus the environment. *Journal of Experimental Psychology. General*, *138*(3), 329–340. https://doi.org/10.1037/a0016433

Jarmolowicz, D. P., Cherry, J. B. C., Reed, D. D., Bruce, J. M., Crespi, J. M., Lusk, J. L., & Bruce, A. S. (2014). Robust relation between temporal discounting rates and body mass. *Appetite*, *78*, 63–67. https://doi.org/10.1016/j.appet.2014.02.013

Johnson, M. W., & Bickel, W. K. (2002). Within-subject comparison of real and hypothetical money rewards in delay discounting. *Journal of the Experimental Analysis of Behavior*, *77*(2), 129–146. https://doi.org/10.1901/jeab.2002.77-129

Kang, M.-I. (2015). Present-biased preference and human health behavior: A mini review. *Quality in Primary Care*, *23*(6).

Lagorio, C. H., & Madden, G. J. (2005). Delay discounting of real and hypothetical rewards III: Steady-state assessments, forced-choice trials, and all real rewards. *Behavioural Processes*, *69*(2), 173–187. https://doi.org/10.1016/j.beproc.2005.02.003

Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *The Quarterly Journal of Economics*, *112*(2), 443–478. https://doi.org/10.1162/003355397555253

MacKillop, J., Amlung, M. T., Few, L. R., Ray, L. A., Sweet, L. H., & Munafò, M. R. (2011). Delayed reward discounting and addictive behavior: a meta-analysis. *Psychopharmacology*, *216*(3), 305–321. https://doi.org/10.1007/s00213-011-2229-0

Madden, G. J., Begotka, A. M., Raiff, B. R., & Kastern, L. L. (2003). Delay discounting of real and hypothetical rewards. *Experimental and Clinical Psychopharmacology*, *11*(2), 139–145. https://doi.org/10.1037/1064-1297.11.2.139

Meier, S., & Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, *2*(1), 193–210.

Meier, S., & Sprenger, C. D. (2012). Time Discounting Predicts Creditworthiness. *Psychological Science*, *23*(1), 56–58. https://doi.org/10.1177/0956797611425931

Myerson, J., Green, L., & Warusawitharana, M. (2001). Area under the curve as a measure of discounting. *Journal of the Experimental Analysis of Behavior*, *76*(2), 235–243. https://doi.org/10.1901/jeab.2001.76-235

Read, D., & Roelofsma, P. H. M. P. (2003). Subadditive versus hyperbolic discounting: A comparison of choice and matching. *Organizational Behavior and Human Decision Processes*, *91*(2), 140–153. https://doi.org/10.1016/S0749-5978(03)00060-8

Shamosh, N. A., & Gray, J. R. (2008). Delay discounting and intelligence: A meta-analysis. *Intelligence*, *36*(4), 289–305. https://doi.org/10.1016/j.intell.2007.09.004

Stoeckel, L. E., Murdaugh, D. L., Cox, J. E., Cook, E. W., & Weller, R. E. (2013). Greater impulsivity is associated with decreased brain activation in obese women during a delay discounting task. *Brain Imaging and Behavior*, *7*(2), 116–128. https://doi.org/10.1007/s11682-012-9201-4

Sweeney, A. M., & Culcea, I. (2017). Does a future-oriented temporal perspective relate to body mass index, eating, and exercise? A meta-analysis. *Appetite*, *112*, 272–285. https://doi.org/10.1016/j.appet.2017.02.006

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics Letters*, *8*(3), 201–207.

Weller, R. E., Cook, E. W., Avsar, K. B., & Cox, J. E. (2008). Obese women show greater delay discounting than healthy-weight women. *Appetite*, *51*(3), 563–569. https://doi.org/10.1016/j.appet.2008.04.010

Zauberman, G., & Urminsky, O. (2014). *The Psychology of Intertemporal Preferences*.

Tables

Table 1

Measures of Temporal Discounting

Discounting Task	**Abbrev.**	**Sooner Payment**	**Later Payment**	**Maximum Payment**
Time Discounting Large Future	tdlf	1 month	7 months	300
Time Discounting Large Present	tdlp	Today	6 months	300
Time Discounting Small Future	tdsf	1 month	7 months	30
Time Discounting Large Present	tdlp	Today	6 months	30

Table 2

R Squared Values by Discount Method

Discounting	rsq
Speedup large future factor consistent	0.9996344
Patience	0.9977793
Speedup Patience	0.9971708
Average	0.9966355
Time discounting large future exponential	0.9957507
Time discounting large present factor consistent	0.9946626
Time discounting small future exponential	0.9941270
Time Discounting Large delta	0.9847055
Speedup large future factor consistent	0.9845331
Speedup small delta	0.9491173
Speedup small future factor consistent	0.9348571
Speedup small present factor consistent	0.9292209
Speedup large delta	0.8926612
Time discounting large present factor consistent	0.8787575
Time discounting small future factor consistent	0.8635179
Average consistent	0.8017903
Time Discounting Small delta	0.6245473
Speedup large present factor consistent	0.6082600
Speedup small future k	0.6043318
Time Discounting Small beta	0.5902292
Time discounting large future k	0.5347206
Time Discounting Large beta	0.4352749
Time discounting small future exponential	0.4098534
Time discounting small present k	0.3869942
Time discounting patience	0.2844718
Speedup large present exponential	0.2481768
Speedup small beta	0.1714597
Speedup small present exponential	0.1571541
Time discounting large future k	0.1433953
Avg k	0.0951316
Speedup large beta	0.0544742
Time discounting small present exponential	0.0185598
Speedup large future k	0.0089667
Speedup large present k	0.0030524
Speedup small future exponential	0.0024058
Speedup small present k	0.0023788
Time discounting large future k	0.0020140
Time discounting large present exponential	0.0018862
Avg exponential	0.0017285

Figure

Figure 1

Lowest Sum of Squares Error Model Match for Each Participant