Comparing Models of Intertemporal Choice: Fitting Data from Lewis and Fischer 344 Rats [1]

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Abstract

Formal comparisons of delay discounting models have been conducted using data from humans, with only one study comparing delay discounting data by controls and pathological gamblers. This is the first study using data from nonhuman animals to compare models of intertemporal choice. For each model fitting the impulsive choices of Lewis (LEW) and Fischer (F344) rats, the Akaike's (1973) information criterion (AIC) and its corresponding AIC weight were computed. The main goal was to show that AIC weights are easy to compute and simplify the interpretation of results generated by single-parameter and dual-parameter models of intertemporal choice. Segments of a published data set (Aparicio, Elcoro, & Alonso-Alvarez, 2015) were used to compare five models of intertemporal choice. All models nicely fitted the data of the LEWs and F344s at the group and individual levels of analysis. Formal comparisons based on AIC weights, evidence ratios of Aikaike weights, and normalized probabilities revealed that Mazur's (1987) hyperbolic-decay model is the best and most parsimonious model fitting the group and individual data from LEWs and F344s, followed by Samuelson's (1937) exponential discounted utility function.

Key words: *Delay discounting models, Lewis, Fischer 344, AIC weights, rats*

Resumen

Comparaciones formales entre modelos de elección inter-temporal han usado datos de humanos y solo hay un estudio en el que jugadores compulsivos fueron comparados con un grupo control. Este estudio es el primero que utiliza datos de animales para comparar modelos de elección inter-temporal. Para cada modelo que ajustó datos de las elecciones impulsivas de las ratas Lewis (LEW) y Fischer 344 (F344), se calculó el criterio de información de Aikake (AIC; 1973) y su peso respectivo. El objetivo fue mostrar que el peso del AIC es fácil de computar y simplifica la interpretación de los resultados generados por modelos de elección inter-temporal que estiman uno o dos parámetros libres para ajustar los datos. Utilizando segmentos de datos publicados (Aparicio, Elcoro, & Alonso-Álvarez, 2015), se hicieron comparaciones entre cinco modelos de elección inter-temporal. A niveles de análisis de grupo e individuo, todos los modelos ajustaron los datos de las ratas LEW and F344. Comparaciones formales basadas en pesos del AIC, razón de proporción y probabilidad normalizada mostraron que el mejor y más parsimonioso modelo para ajustar los datos de individuos y grupos de ratas LEW y F344 es el modelo hiperbólico de descuento temporal de Mazur (1987), seguido por el modelo de descuento de utilidad temporal de Samuelson (1937).

Palabras clave: *Modelos, elección inter-temporal, Lewis, Fischer 344, peso de AIC, ratas.*

Choices between consequences separated in time (intertemporal choice) are faced every day by humans and nonhuman animals in a variety of settings, attracting the attention of research in economics

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(Frederick, Loewenstein, & O'Donoghue, 2002), cognitive neuroscience (Peters & Buchel, 2011; Sellitto, Giaramelli, & di Pellegrino, 2011), and psychology (Green & Myerson, 2004). In this research, the term delay discounting refers to the phenomenon that humans and nonhuman animals discount the value of reinforcers over time (Miedl, Peters, & Buchel, 2012). For example, in situations arranging a choice between two reinforcers differing in amount and delay, subjects choose the smaller-sooner reinforcer (SSR) even when it has lower objective value than the larger-later reinforcer (LLR). Similarly, in choice situations arranging two reinforcers differing in probability, subjects choose the more certain reinforcer discounting the value of the less certain reinforcer (e.g., Green & Myerson, 2004; McKerchar, Green, Myerson, Pickford, Hill, & Stout, 2009).

Models of delay discounting estimate the shape of the discounting function relating the value of reinforcer to delay (Killeen, 2009; Rachlin, 2006), or connecting it to the inter-reinforcer-interval (Green, Myerson, & Macaux, 2005; Kable & Glimcher, 2010). To measure quantitative aspects of the discounting function, researchers use procedures adjusting the time to the LLR or the amount of the SSR (e.g., Green, Myerson, Shah, Estle, & Holt, 2007; Mazur, 1987; Rachlin, Raineri, & Cross, 1991). In these procedures, the degree to which the value of reinforcers decays with increasing delay is well described by Mazur's (1987) hyperbolic-decay model as follows:

$$V = \frac{A}{1 + kD} \qquad (1)$$

Where V is the reinforcer value, A is reinforcer amount, D is the reinforcer delay, and k is a free parameter estimating how fast the value of the LLR decays with increasing D. The hyperbolic-decay model accurately describes data obtained from humans (e.g., Myerson & Green, 1995; Rachlin, et al., 1991) and nonhuman animals (e.g., Aparicio, Hughes, & Pitts, 2013; Farrar, Kieres, Hausknecht, de Wit, & Richards, 2003; Green, et al., 2007; Helms, Reeves, & Mitchell, 2006; Madden, Bickel, & Jacobs, 1999; Mazur, 2012; Richards, Mitchell, De Wit, & Seiden, 1997; Stein, Pinkston, Brewer, Francisco, & Madden, 2012; Woolverton, Myerson, & Green, 2007), and it does so with a single free parameter (k).

The hyperbolic-decay model, however, estimates the degree of discounting as a function of the delay, showing that the discounting of the LLR is steeper in the intervals of the near future than in those of the far future. This phenomenon termed decreasing impatience (Ebert & Prelec, 2007) is at odds with Samuelson's (1937) exponential discounted utility model sustaining that the effect of a given delay is autonomous of the point in time when it occurs, formally expressed as follows:

$$V = A * \exp{(-kD)} \qquad (2)$$

Equation 2 predicts time-consistent preferences or normative exponential discounting. Evidence against this prediction comes from studies showing preference reversals or time-inconsistent preferences in humans and nonhuman animals (Ainslie & Haendel, 1983; Green, Fisher, Perlow & Sherman, 1981; Green, Fry, & Myerson, 1994). This phenomenon has been termed dynamic inconsistency (Thaler, 1981), the common difference (Lowenstein, & Prelec, 1992), or non-stationary effect (Miedl, et al., 2012).

When goodness of fit is used to compare and contrast Equations 1 and 2, R^2 values show that the former model accounts for a greater proportion of variance than the latter (Green & Myerson, 2004; Kable, & Glimcher, 2010; McKerchar et al., 2009; Myerson & Green, 1995; Yi, Landes, & Bickel, 2009). The problem with Equation 1 is that it tends to over-estimate discounted values at short delays and under-estimate discounted values at long delays, generating poor fits (low values of R^2) to data of delay discounting from humans (Green & Myerson, 2004; McKerchar et al., 2009; Odum, Baumann, &

Rimington, 2006). To account for a greater proportion of the variance, some researchers expand criteria to exclude problematic datasets (Johnson & Bickel, 2008). Others claim that more than one parameter is required to adequately describe delay discounting in humans (McKerchar et al., 2009; Takahashi, Oono, & Radford, 2008). As a result, more flexible models of delay discounting have been proposed (Bleichrodt, Rohde, & Wakker, 2009). One alternative to Equations 1 and 2 is Myerson and Green's (1995) hyperboloid model:

$$V = \frac{A}{(1+kD)^s} \qquad (3)$$

Equation 3 raises the denominator to a power *s*, representing a special case of the generalized hyperbola (Loewenstein & Prelec, 1992). It has two free parameters, one to estimate the rate of discounting (*k*) and a second free parameter (*s*) estimating individual differences in the scaling of delay and/or amount (e.g., Green, et al., 1994; Myerson & Green, 1995). With two free parameters, the hyperboloid model adequately describes discounting in humans accounting for more proportion of the variance than Equation 1 (e. g., Green, Myerson, & Ostaszewski, 1999; Myerson & Green, 1995; Simpson & Vuchinich, 2000). The complexity of the hyperboloid model (i.e., using two instead of one free parameter) is justified by showing that the free parameter *s* deviates significantly from 1.0 when describing discounting in humans (Myerson & Green, 1995; McKerchar et al., 2009).

A different two-free-parameter discounting model is Rachlin's (2006) power function of hyperbolic discounting:

$$V = \frac{A}{(1+kD^s)} \qquad (4)$$

It raises only D to a power of *s*, corresponding to hyperbolic discounting with power-scaling of objective time (McKerchar, Green, & Myerson, 2010). Equation 4 was derived from Stevens's (1957) psychophysical power law and is comparable to Mazur's (1987) hyperbolic-decay model; it fits the data of delay, probability, and memory discounting. Rachlin (2006) asserted that the power function of hyperbolic discounting is consistent with the generalized matching law (Baum, 1974), maximizing accounts of choice (Rachlin, Green, Kagel, & Batalio, 1976), and common utility functions assuming constant elasticity of substitution (Kagel, Batalio, & Green, 1995). Equation 4 is said to be a special instance of an early discounting-by-intervals function giving 0-s delay to the SSR (Read, 2001). It has, however, the same limitation that Equation 3, that is, Equation 4 can't explain preference reversals or time inconsistence preferences.

In order to account for time-inconsistent preferences (Ainslie & Haendel, 1983; Green et al., 1981; Green & Myerson, 1994) or dynamic inconsistency (Thaler, 1981), Ebert and Prelec (2007) proposed a constant sensitivity (CS) discounting function:

$$V = A * exp(-(aD)^b) \qquad (5)$$

Where *a* estimates the level of impulsiveness and *b* sensitivity to time. Note that when $b = 1.0$, Equation 5 reduces to exponential discounting; the parameter *b* regulates the power-scaling of time (Killeen, 2009), resembling other functions with scaling exponent (Green & Myerson, 2004; Yi et al., 2009; McKerchar et al., 2009). In Equation 5 small values of the parameter *b*, symbolized as ($b<<1$), account for cases where all forthcoming LLR are down-weighted in similar way relative to the immediate present (i.e., a present-future dichotomy heuristic); large values of *b*, indicated as ($b>>1$), account for cases when

LLR are not discounted up to a given delay after which they are all discounted in similar way (i.e., an extended-present heuristic; Peter, Miedl, & Büchell, 2012).

Comparisons of delay discounting models have been conducted (McKerchar et al., 2009; Myerson, & Green, 1995; Rachlin, 2006; Takahashi et al., 2008) pursuing a parsimonious model capable to explain delay discounting data across species, reinforcers (real and hypothetical), and settings. With few exceptions (Peters et al., 2012; Takahashi et al., 2008), attempts to compare intertemporal models focused on goodness of fit (R^2 values) looking for the model accounting for the greatest proportion of the variance (e.g., McKerchar et al., 2009; Myerson & Green 1995; Rachlin, 2006). The analysis of R^2 values to compare delay-discounting models, however, has two drawbacks. One is that it confounds goodness of fit (R^2) with discounting rate (k); this is a problem because these parameters are positively correlated, high vales of k result in high vales of R^2. A second drawback is over-fitting; models using two free parameters generate greater R^2s than those using only one free parameter, prompting unfair comparisons (Peters et al., 2012).

The information criterion index (AIC; Akaike, 1974) is an alternative method to compare models of intertemporal choice. It takes into account both goodness of fit and the number of free parameters that need to be estimated in order to attain that fit. To avoid the over-fitting problem, the AIC penalizes the model using more parameters and gives the lowest index to that estimating less parameters to fit the same data set, allowing fair comparisons of multiple non-nested models. In practice, using raw AIC values to accept one model (the preferred model) is difficult because most of the times the differences in raw AIC values are not substantial among models. Errors in interpretations when choosing a model can be avoided by transforming raw AIC values into AIC weights (Akaike, 1978, 1979; Bozdogan, 1987; Burnham & Anderson, 2002).

One aim of the present study is to show that AIC weights simplify the interpretation of the results generated by five prevalent models of delay discounting using a different number of free parameters. Another goal is to compare these models using sections of a published data set (Aparicio, Elcoro, & Alonso-Alvarez, 2015) produced by Lewis (LEW) and Fischer 3444 (F344) rats choosing between two reinforcers differing from one another in the amount and delay to delivery (SSR vs. LLR). This is important because formal comparisons of delay discounting models have been conducted using data from humans, usually college students (e.g., McKerchar et al., 2009; Myerson, & Green, 1995; Rachlin, 2006; Takahashi et al., 2008); and only one study compared discounting data from human controls and pathological gamblers (Peters et al., 2012). To our knowledge, the present paper is the first study using the data from nonhuman animals to formally compare delay discounting models. A final objective is demonstrating that Mazur's (1987) hyperbolic-decay model is the preferred model (i.e., parsimonious model); even though in the present study all five models of delay discounting fitted the data of the LEW and F344 rats.

Method

Subjects

Sixteen experimentally naïve (8-LEWs and 8-F344) male rats of approximately 122 days old at the beginning of the experiment, served as subjects. Animals were placed on a regimen of food restriction with post-session feedings of approximately 10 g of Purina® Lab Chow and housed separately in plastic cages with water permanently available in a temperature-controlled colony room providing 12:12 hr light/dark cycle (lights on at 0600).

Apparatus

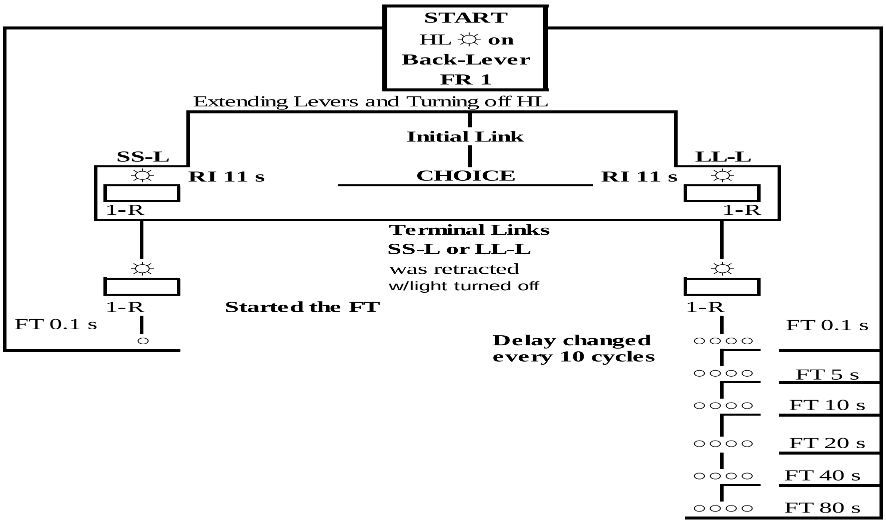
Eight identical operant chambers for rats (Coulbourn E10-11R TC), measuring 29.5 cm long, 25.0 cm wide, and 28.5 cm high, were used. Each operant chamber was equipped with two retractable levers (E23-17RA) mounted on the intelligence panel, 7.0 cm above the floor and 2.5 cm from its respective left and right sidewall. Above each retractable lever (3.5 cm) was a white 24-V DC stimulus light (H11-03R). A third nonretractable lever (H21-03R) was centered on the back wall of the chamber and mounted 6.0 cm above the floor. All levers required a force of approximately 0.25 N to operate. A food dispenser (H14-23R) centered between the retractable levers, 2.0 cm above the floor, delivered 45-mg grain pellets (BioServ®) into a receptacle 3.0 cm wide and 4.0 cm long. A 24-V DC houselight (H11-01R) centered on the back wall, 2.0 cm below the ceiling, provided ambient illumination. A continuous white noise was presented on 2.6 cm x 4.0 cm speaker (H12-01R) connected to white noise generator (E12-08); the speaker was installed on the back wall, 1.0 cm from the left sidewall and 6.5 cm from the house light. Coulbourn Instruments® software and interfacing equipment, operating at .01-s resolution, were used to program the experimental events and record the data.

Procedure

The general procedure has been described into detail elsewhere (Aparicio et al., al 2015; Aparicio, Hughes, & Pitts, 2013); it was a concurrent chains procedure arranging choices in the initial link between 1-food and 4-food pellets that were delivered in the terminal links, the former (SSR) with a 0.1-s delay and the latter (LLR) with a delay that varied within each session (0.1, 5, 10, 20, 40, or 80 s). The delays to LLR delivery were manipulated in ascending, descending, and random order of presentation in conditions lasting 105 sessions each. Figure 1 summarizes the concurrent chains procedure. A single response on the back lever turned off the houselight (HL) and extended the levers into the chamber (SS-L and LL-L) with the lights above them turned on, signaling the initial link where two random interval schedules (RI) concurrently arranged entries to the terminal links (one every 11 seconds on average). One RI 11-s schedule was associated with the SS-L and the other with the LL-L lever, setting up an approximately equal number of left and right terminal link entries (Alsop & Davison, 1986; Stubbs & Pliskoff, 1969). When a terminal link entry was set up in a given lever, SS-L or LL-L, one response on that lever initiated the terminal link retracting the opposite lever and turning off the light above it; a second response on the still extended lever (SS-L or LL-L) started a fixed-time schedule (FT), but that lever was not retracted to avoid signaling the delay to the reinforcer's delivery. The terminal link delivering the SSR (1-food pellet) was associated with the left SS-L and the terminal link delivering the LLR (4-food pellets) with the right LL-L. These relations applied for half of the rats within each strain and were reversed for the other half of the rats (the SSR was associated with the right lever and the LLR with the left lever).

The delay to the SSR was a FT 0.1 s and that to the LLR a FT that every 10 cycles took on different value (0.1, 5, 10, 20, 40, or 80 s). Each cycle ended with the reinforcer's delivery, LLR or SSR; the lever that produced it was retracted and the light above it turned off. A new cycle began with the HL turned on (see Figure 1). The completion of 10 cycles produced a 1-minute blackout, separating the previous delay to the LLR from a different delay to be active for the next 10 cycles. Responses on the back lever were not effective during the blackout, and the levers were retracted from the chambers with the lights above them turned off. Sessions ended after 60 cycles were completed or 60 minutes elapsed, whichever occurred first.

Figure 1. Concurrent chains procedure.



Data Analysis

A selected data set from a previous study (Aparicio et al., 2015) was re-analyzed and used for data analysis. It consisted of the last 15 days of the data collected in each condition where the delays to the LLR were varied in ascending, descending, and random order. For each individual LEW and F344 rat, the number of initial-link responses emitted on the SS-L and LL-L levers was counted separately for each delay to LLR and aggregated across sessions of the same condition. Computations obtained for the individuals of the same strain, were used to calculate the group's average of responses on the SS-L and LL-L levers. These calculations in turn were used to compute the corresponding proportions of LL choice (LL / (LL + SS)) for the individuals and the average of each group. Equations 1 to 5 which were entered manually into Origin (version 8.5) as user-defined equations, providing nonlinear curve fitting to the proportions of LL choice of the individual LEW and F344 rats and the averages of their corresponding groups. It should be noted that in all equations the parameter *A* was free to vary; meaning that it was not assumed to be 100% LL choice at the y-intercept. Except for Equation 5 that used *a* to estimate the level of impulsiveness, Equations 1 to 4 used *k* to estimate the rate of delay discounting.

Results

For the ascending, descending, and random presentation order of delay conditions, the left panels of Figures 2 to 4 plot the groups' means of the proportions of LL choice as a function of delay to LLR, and the right panels the resulting R^2s of the best fits to these data points using Equations 1 to 5. The top panels show the data of the LEWs and the bottom panels those of the F344s. The solid, dash, dash-dot dot, short dot, and short-dash dot lines are the best fits to data points of the LEWs and F344s using Equations 1 to 5, respectively.

Figures 2 to 4 show that the groups' means of the proportion of LL choice decreased as a function of the increasing delay to the LLR. Delay discounting functions show that all equations fitted the groups' data of the LEW and F344 rats, accounting for most proportion of the variance in LL choice that occurred as a function of within session changes in delay to the LLR. In the Appendix A, the resulting parameters of Equations 1-5 (y-intercept (A), *k*, *a*, *s*, *b*, and R^2) for the data of the groups are listed in Table 1, and those corresponding to the individual LEW and F344 rats in Tables 2 to 7.

Figure 2. For the ascending presentation order of delays condition, the proportion of choice as a function of delay in seconds to LLR (left graphs). The circles stand for the data of the LEWs and squares for data of the F344. Solid, dash, dash-dot dot, short dot, and short-dash dot lines are the best fits using Equations 1 to 5, respectively. The right panels show R^2 values generated by Equations 1 to 5.

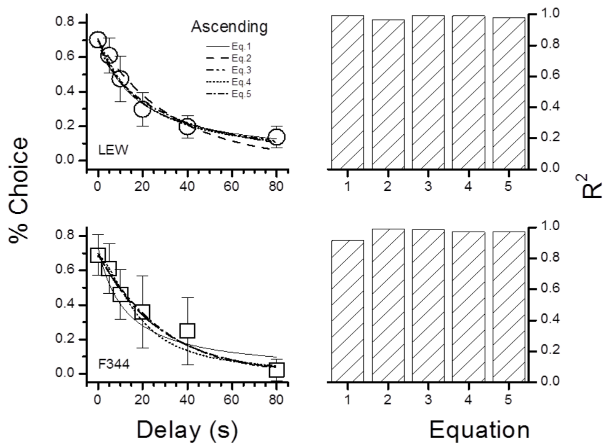
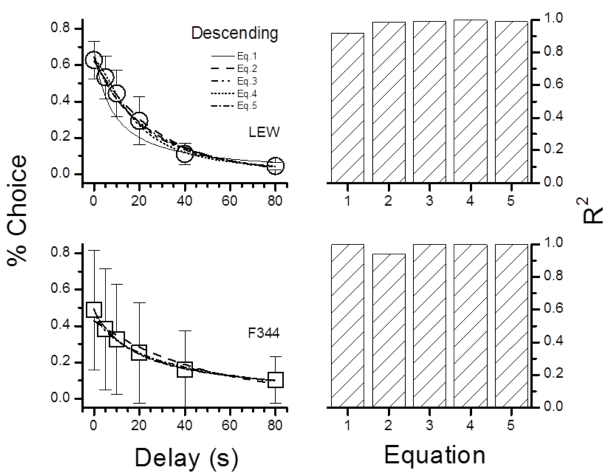


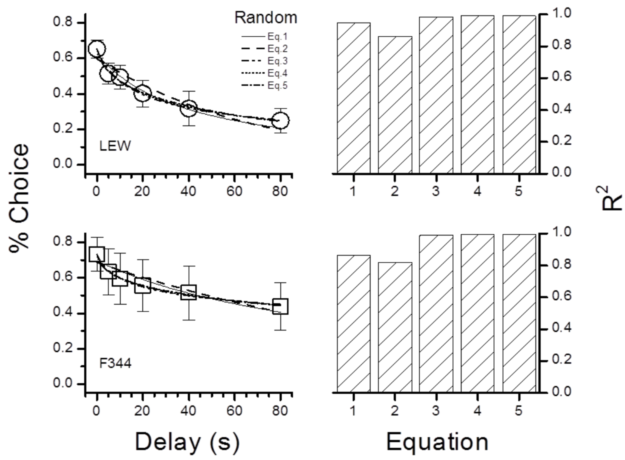
Figure 3. For the descending presentation order of delays condition, the proportion of choice as a function of delay in seconds to LLR (left graphs). Other details as in Figure 2.



The ascending condition shows that both strains produced similar discounting functions (Figure 2), with the choices of the F344s showing more variability than the choices of the LEWs across delays to LLR (compare error bars of the F344s with those of the LEWs). However, the descending and random conditions (Figures 3 and 4) show steeper discounting functions for the group data of the LEWs than for the F344s, suggesting that in these conditions the former chose more impulsively that the latter strain of rats (but see Tables 4-7). Consistent with results of the ascending condition, the F344s show more variability in the group's mean of the proportion of LL choice than the LEWs across delays to LLR of the descending and random presentation order of delay conditions.

There were no further attempts to compare here the discounting data of the LEW with those of the F344 rats; formal statistical comparisons between these strains were conducted in detail elsewhere (Aparicio et al., al 2015) analyzing the entire data set of conditions varying the presentation order of delay to LLR in ascending, descending, and random order. As in Peters et al.'s, (2012) study, the analyses of the data focused in comparing and contrasting Equations 1 to 5 with one another using the following methods: (1) comparisons of R^2s based on fits to group's data and data of the individual LEW and F344 rats; (2) Akaike's (1973) information criterion (AIC) computed for the groups and data corresponding to the individual LEWs and F344s; and (3) comparisons using raw AIC values transformed into AIC weights.

Figure 4. For the random presentation order of delays condition, the proportion of choice as a function of delay in seconds to LLR (left graphs). Other details as in Figure 2.



Comparisons based on R^2

An inspection of the right panels of Figures 2 to 4 reveals that models of intertemporal choice that estimated two free parameters to fit the groups' data of the LEW and F344 rats (i.e., Equations 3, 4, and 5), generated values of R^2 that were slightly greater than those produced by models estimating only one free parameter to fit the same data points (Equations 1 and 2). Yet, the ascending and descending conditions show that Equation 1 nicely fitted the data of the LEWs and F344s, respectively, and it did so estimating a single free parameters (*k*); note that Equation 1 generated R^2s that are comparable to those Equations 3, 4, and 5 produced for the same data. The slightly low values of R^2 that Equations 1 and 2 show for the group's data of the F344s in the random condition, and that corresponding to Equation 2 for the data of the LEWs, were more likely due to an overestimation of short delays and underestimation of long delays characterizing the fits of Equations estimating only one free parameters (McKerchar et al., 2009).

Paired comparisons of R^2 values using Wilcoxon signed rank tests (at the .05 level), indicated that the distribution of R^2s that Equation 1 generated for the data of the individual LEWs and F344s was not significantly different from that Equation 2 produced in the ascending ($Z = -.284, p = .781$) and descending ($Z = -1.215, p = .231$) conditions. In the random condition, however, the distribution of R^2s that Equation 1 generated for the data of the individual LEW and F344 rats was significantly different ($Z = 2.869, p = .002$) from that of Equation 2.

For models of intertemporal choice estimating two free parameters to fit the data (Equations 3, 4, and 5), paired comparisons of R^2 values (Wilcoxon signed rank tests) showed that the distribution of R^2s that Equation 3 generated for the data of the individual LEWs and F344s was significantly different from that Equation 4 produced in the ascending ($Z = 2.611, p = .006$) and random ($Z = -1.990, p = .044$) conditions; but it was not significantly different from that Equation 4 generated for the data of the descending condition ($Z = -1.783, p = .073$). Paired comparisons of R^2 values between Equations 4 and 5 showed significant differences in the ascending (Z = 2.404, p = .013) and descending ($Z = 2.527, p =$

.008) conditions; but distributions of R^2s were not significantly different (*Z = 1.008, p = .322*) in the random condition.

Comparisons based on AIC

The Akaike's (1973) information criterion (AIC) was computed to compare models of intertemporal choice, offering an alternative method to estimate the anticipated Kullback-Leibler (1951) discrepancy between the correct model and the prospective model. AIC minimizes this discrepancy choosing the model with the lowest likely information loss (Akaike, 1973, 1974, 1978, 1979, 1987). Accordingly, the explanatory correct and parsimonious model is selected as:

$$AIC_i = -2\log L_i + 2V_i \qquad (6)$$

Where the highest probability of the prospective model *i* (L_i) is determined by adjusting a free parameter (V_i) maximizing the likelihood that the prospective model *i* has produced the data (Wagenmakers, & Farrell, 2004).

Tables 8 and 9 show AIC values computed for model selection using group and individual data from LEWs and F344s, respectively. The first column lists the equation, the second column the number of free parameters, and columns 3 to 5 show AIC values computed for data collected in the ascending, descending, and random conditions. Because *A* was free to vary in all equations, it is one of free parameters listed in the 2nd column. Columns 6, 7, and 8 show *AIC* weights (described below) obtained by comparing the fit of Equation 1 with the fit that any other Equation provided to the group and individual data for the LEW and F344 rats in the ascending, descending, and random conditions.

Table 8. Results of AIC for model selection, using fits of the groups.

		LEW					
		AIC			**Δ (AIC)**		
Model	No. Par	Asc.	Des.	Ran.	Asc.	Des.	Ran.
Eq.1	2	4. 11	15.23	8.34	0.00	10.63	0.00
Eq.2	2	12.45	4.60	13.82	8.30	0.00	5.48
Eq.3	3	33.78	30.00	29.43	29.67	25.41	21.09
Eq.4	3	32.72	22.81	27.01	28.61	18.22	18.67
Eq.5	3	37.72	32.65	26.38	33.60	28.05	18.04
		F344					
Eq.1	2	12.66	-28.58	1.92	11.87	0.00	0.00
Eq.2	2	0.79	-6.95	3.72	0.00	21.63	1.81
Eq.3	3	30.79	0.68	15.66	30.00	29.26	13.74
Eq.4	3	34.55	0.55	9.83	33.76	29.14	7.91
Eq.5	3	30.25	7.33	8.04	29.46	35.91	6.12

The ascending condition shows that Equation 1 is the preferred model (i.e., the model with the lowest AIC value) fitting group's data (AIC = 4.11) and data of the individual LEWs (AIC = - 19.74). For the F344s in the same ascending condition, however, Tables 8 and 9 show that Equation 2 is the preferred model fitting group's data (AIC = 0.79) and data of the individual F344s (AIC = - 6.90). For both strains, the descending condition (Table 9) shows that Equation 2 is the preferred model fitting the data of individual LEWs (AIC = - 30.15) and F344s (AIC = -19.73). The same result is observed for the group's data of the LEWs (Table 8), Equation 2 (AIC = 4.60) is the chosen model; however, Equation 1

(AIC = - 28.58) was the preferred model fitting the group's data of the F344s. For both strains, the random condition (Table 8) shows that Equation 1 is the chosen model fitting the group's data (AIC = 8.34 and 1.92) and data of the individual (AIC = - 22.70 and - 20.18) LEWs and F344s, respectively (Table 9). To assess the relative performance of models, the difference in AIC between a given model and the chosen model (i.e., the model with the lowest AIC value) was computed using Equation 7 (e.g., Akaike, 1978; Burnham & Anderson, 2002).

$$\Delta_i \,(AIC) = AIC_i - \min AIC \qquad (7)$$

Table 9. Results of AIC for model selection, using fits of the individuals.

		LEW					
		AIC			**Δ (AIC)**		
Model	No. Par	Asc.	Des.	Ran.	Asc.	Des.	Ran.
Eq.1	2	-19.74	-16.68	-22.70	0.00	13.47	0.00
Eq.2	2	-17.25	-30.15	-18.35	2.50	0.00	4.35
Eq.3	3	9.10	-0.14	0.65	28.84	30.01	23.35
Eq.4	3	7.05	1.58	0.79	26.80	31.72	23.49
Eq.5	3	11.57	-2.57	1.41	31.32	14.11	24.11
		F344					
Eq.1	2	-5.64	-19.67	-20.18	1.25	0.06	0.00
Eq.2	2	-6.90	-19.73	-18.27	0.00	0.00	1.91
Eq.3	3	23.10	10.27	3,82	30.00	30.00	24.00
Eq.4	3	15.47	11.40	5.27	22.37	31.13	25.45
Eq.5	3	15.43	11.40	5.78	22.32	31.13	25.96

Tables 8 and 9 (columns 6-8) show computations of Δ_i (AIC) that confirmed the results based on AIC values; the preferred models fitting the group and individual data of LEW and F344 rats are Equations 1 and 2, showing Δ_i (AIC) = 0 in the ascending, descending, and random conditions.

Aikaike Weights

Formal comparisons between models of intertemporal choice estimating one or two free parameters to fit the data, Aikaike weights w_i (AIC) were calculated using Equation 8 (Burnham & Anderson, 2002).

$$w_i\,(AIC) = \frac{\exp\left\{-\frac{1}{2}\Delta_i\,(AIC)\right\}}{\sum_{k=1}^{k}\exp\left\{-\frac{1}{2}\Delta_k(AIC)\right\}} \qquad (8)$$

Where $\sum w_i(AIC) = 1$. Tables 10 and 11 show the resulting Aikaike weights computed with models fitting the groups' data of the LEWs and F344s. As Wagenmakers and Farrell (2004) noted, Aikaike weights are interpreted as the likelihood that a particular model has to minimize the Kullback-Leibler (1951) discrepancy given a particular data set and the models being compared (Burnham & Anderson, 2001).

Comparisons between Equation 1 and 2 based on Aikaike weights (Table 10) reveal that hyperbolic-decay model (Equation 1) has the highest probability (1.0) of being the correct model fitting the groups' data of the LEWs and F344s (but see random condition). However, fitting the data of the LEWs in the descending and those of the F344s in the ascending condition, the model with the highest probability (1.0) of minimizing the Kullback-Leibler (1951) discrepancy is the exponential discounted utility model (Equation 2).

For the ascending, descending, and random conditions, Table 11 shows Aikaike weights comparing: (1) Equation 2 with Equations 3, 4, and 5 (rows 2-5, 6-9, and 10-13); (2) Equation 3 with Equations 4 and 5 (rows 14-16, 18-19, and 20-22); and (3) comparisons between Equation 4 and 5 (rows 23-24, 25-26, and 27-28, respectively). When comparing Equations 3, 4, or 5 with Equation 2, the latter shows the highest probability (1.0) of being correct fitting the groups' data of the LEWs and F344s across conditions (but see F344s in the random condition). For models estimating two parameters, Table 11 shows that Equation 4 has the highest probability of being correct fitting data of the LEWs and F344s in the descending (.973 and .515) and random (.770 and .948) conditions. In the ascending condition Equation 3 shows the highest probability (.867) of being correct fitting the data of the F344s and Equation 4 (.629) fitting the data of the LEWs. Comparisons of Aikake weights between Equation 4 and 5, show that the former has the highest probability of being correct fitting data of the LEWs in the ascending condition (.923) and fitting data of both strains in the descending condition (.992 and .973, respectively). For both strains the random condition shows that Equation 5 has the highest probability of being correct fitting data of the LEWs and F344s (.587 and .709, respectively).

Table 10. Akaike Weights and Residual Sum of Squares (RSS).

	LEW					**F344**				
	w (AIC)				**RSS**	**w (AIC)**				**RSS**
Asc										
Eq.1	0.9848	1.0000	1.0000	1.0000	0.5927	0.0026	0.9999	1.0000	0.9999	2.4645
Eq.2	0.0152				2.3808	0.9974				0.3408
Eq.3		3.6E-07			0.5613		1.2E-04			0.3409
Eq.4			6.1E-07		0.4701			1.8E-05		0.6382
Eq.5				5.0E-08	1.0807				1.5E-04	0.3115
Des.										
Eq.1	0.0049	0.9994	0.9780	0.9998	3.7788	1.0000	1.0000	1.0000	1.0000	0.0026
Eq.2	0.9951				0.6425	2.0E-05				0.0938
Eq.3		6.2E-04			0.2989		4.4E-07			0.0023
Eq.4			0.0220		0.0902			4.7E-07		0.0022
Eq.5				1.6E-04	0.4646				1.6E-08	0.0068
Ran.										
Eq.1	0.93929	1.0000	0.99991	0.9999	1.1987	0.7116	0.9990	0.9812	0.95523	0.4113
Eq.2	0.06071				2.9870	0.2884				0.5557
Eq.3		2.6E-05			0.2714		0.00104			0.0274
Eq.4			8.8E-05		0.1814			0.0188		0.0104
Eq.5				1.2E-04	0.1633				0.04477	0.0077

Computations of Aikaike weights for all five models fitting data of the individual LEWs and F344s are listed in Tables B1 and B2 (Appendix B), showing results consistent with those described above for models of intertemporal choice fitting the groups' data of the LEWs and F344s. The next step was to compute the evidence ratio of Aikaike weights of one model over the other and express the normalized probability that the former had to be chosen over the latter. For example, the evidence ratio of Aikaike weights between Equation 1 and 2 (see Table 10) was computed as

$$\frac{w_{Eq1}(AIC)}{w_{Eq2}(AIC)} = \frac{.984}{.015} = 64.8$$

Table 11. Results of AIC, Weights, and Residual Sum of Squares (RSS) using fits of group.

	LEW						**F344**					
	AIC	**Δ(AIC)**	**RSS**		**w(AIC)**		**AIC**	**Δ(AIC)**	**RSS**		**w(AIC)**	
Asc												
Eq.2	12.45	0.00	2.3808	1.0000	1.0000	1.0000	0.79	0.00	0.3408	1.0000	1.0000	1.0000
Eq.3	33.78	21.33	0.5613	2.3E-05			30.79	30.00	0.3409	3.1E-07		
Eq.4	32.72	20.27	0.4701		4.0E-05		34.55	33.76	0.6382		4.7E-08	
Eq.5	37.72	25.26	1.0807			3.3E-06	30.25	29.46	0.3115			4.0E-07
Des.												
Eq.2	4.60	0.00	0.6425	1.0000	0.9999	1.0000	-6.95	0.00	0.0938	0.9784	0.97706	0.99921
Eq.3	30.00	25.41	0.2989	3.0E-06			0.68	7.62	0.0023	0.0216		
Eq.4	22.81	18.22	0.0902		1.1E-04		0.55	7.50	0.0022		0.02294	
Eq.5	32.65	28.05	0.4646			8.1E-07	7.33	14.28	0.0068			0.0008
Ran.												
Eq.2	13.82	0.00	2.9870	0.9996	0.9986	0.9981	3.72	0.00	0.5557	0.9975	0.9548	0.89635
Eq.3	29.43	15.61	0.2714	0.0004			15.66	11.93	0.0274	0.0026		
Eq.4	27.01	13.19	0.1814		0.0014		9.83	6.10	0.0104		0.0452	
Eq.5	26.38	12.56	0.1633			0.0019	8.04	4.31	0.0077			0.10365
Asc			LEW						F344			
Eq.3	33.78	1.06	0.5613	0.3701	0.8771		30.79	0.37	0.3409	0.8677	0.43262	
Eq.4	32.72	0.00	0.4701	0.6299			34.55	0.63	0.6382	0.1323		
Eq.5	37.72	4.99	1.0807		0.1229		30.25	0.00	0.3115		0.56738	
Des												
Eq.3	30.00	7.19	0.2989	0.0267	0.7897		0.67555	0.12	0.0023	0.4849	0.96529	
Eq.4	22.81	0.00	0.0902	0.9733			0.55454	0.00	0.0022	0.5151		
Eq.5	32.65	9.84	0.4646		0.2103		7.32632	6.77	0.0068		0.03471	
Ran												
Eq.3	29.43	3.05	0.2714	0.2299	0.1788		15.66	7.62	0.0274	0.0513	0.02167	
Eq.4	27.01	0.63	0.1814	0.7701			9.83	1.79	0.0104	0.9487		
Eq.5	26.38	0.00	0.1633		0.8212		8.04	0.00	0.0077		0.97833	
Asc												
Eq.4	32.72	0.00	0.4701	0.9239			34.55	4.30	0.6382	0.1041		
Eq.5	37.72	4.99	1.0807	0.0761			30.25	0.00	0.3115	0.8959		
Des												
Eq.4	22.81	0.00	0.0902	0.9927			0.55454	0.00	0.0022	0.9673		
Eq.5	32.65	9.84	0.4646	0.0073			7.32632	6.77	0.0068	0.0327		
Ran												
Eq.4	27.01	0.63	0.1814	0.4217			9.82526	1.79	0.0104	0.2905		
Eq.5	26.38	0.00	0.1633	0.5783			8.03929	0.00	0.0077	0.7095		

The result in this example suggests that Equation 1 is 64.8 times is more likely to be chosen than Equation 2. Then this evidence ratio was expressed as the normalized probability that Equation 1 has to be chosen over Equation 2 as follows:

$$\frac{w_{Eq1}(AIC)}{w_{Eq1}(AIC) + w_{Eq2}(AIC)} = \frac{.984}{.984 + .015} = .985$$

Following the example, Equation 1 has a .985 probability to be the correct fitting the group's data of the LEWs. Accordingly, the evidence ratio of Aikaike weights was computed for each model of intertemporal choice taking a turn in the numerator, and then it was expressed as the normalized probability that the model had to be chosen over the other. Tables 12 and 13 display normalized probabilities computed with Aikaike weights of models fitting the data of the groups, and Tables 14 and 15 those corresponding to Aikaike weights of models fitting the data of the individual LEWs and F344s. The first column list the presentation order of delays to LLR condition, the second column uses the symbol > representing that one model was chosen over the other, the third column the number of times that model is more likely to be correct, and the forth column the normalized probability that the model had to be preferred over the other; comparable comparisons and computations for the F344s are shown in columns 5, 6, and 7 of Tables 12-15.

Table 12 shows that among models of intertemporal choice, Mazur's (1987) hyperbolic-decay model (Eq. 1) was the best model fitting the group's data of the LEWs and F344s. Only two times the exponential discounted utility model (Eq. 2) was chosen over Equation 1; when fitting group's data of the LEWs in the descending condition and those of the F344s in the ascending condition. Comparisons excluding Equation 1 show that Equation 2 is the second best model fitting group's data of the LEWs and F344s across conditions. Further comparisons of models that estimated two free parameters to fit the groups' data (Table 13), showed mixed results: (1) Ebert and Prelec's (2007) constant sensitivity discounting model (Equation 5) was the preferred model fitting data the LEWs in the random condition and those of the F344s across conditions; and (2) Rachlin's (2006) power function of hyperbolic discounting (Equation 4) was the chosen model fitting groups' data of the LEW in the ascending condition and the data of both strains in the descending condition.

Table 12. Best Model and Normalized Probability (group).

	LEW			**F344**		
	Eq.	**Times**	**p**	**Eq.**	**Times**	**p**
Asc.	1 > 2	6.5E+01	0.98	2 > 1	3.8E+02	1.00
	1 > 3	2.8E+06	1.00	2 > 3	8.6E+03	1.00
	1 > 4	1.6E+06	1.00	2 > 4	5.7E+04	1.00
	1 > 5	2.0E+07	1.00	2 > 5	6.6E+03	1.00
Desc.	2 > 1	2.0E+02	1.00	1 > 2	5.0E+04	1.00
	2 > 3	1.6E+03	1.00	1 > 3	2.3E+06	1.00
	2 > 4	4.5E+01	0.98	1 > 4	2.1E+06	1.00
	2 > 5	6.0E+03	1.00	1 > 5	6.3E+07	1.00
Ran.	1 > 2	1.5E+01	0.94	1 > 2	2.5E+00	0.71
	1 > 3	3.6E+04	1.00	1 > 3	6.8E+02	1.00
	1 > 4	1.1E+04	1.00	1 > 4	3.8E+01	0.97
	1 > 5	7.8E+03	1.00	1 > 5	1.6E+01	0.94

Evidence ratios and normalized probabilities computed with Aikaike weights of models fitting the data of the individual LEWs and F344s are listed in Tables 14 and 15. The results are consistent with those computed for models fitting the data of the groups. Table 14 shows that the hyperbolic-decay model (Equation 1) is the best model and the exponential discounted utility (Equation 2) the second best model. When Equation 1 was excluded, comparisons revealed that the exponential discounted utility model was the second best model fitting data of the individual LEW and F344 rats.

Table 13. Best Model and Normalized Probability (group).

	LEW			**F344**		
	Eq.	**Times**	**p**	**Eq.**	**Times**	**p**
Asc.	2 > 3	4.3E+04	1.00	2 > 3	3.3E+06	1.00
	2 > 4	2.5E+04	1.00	2 > 4	2.1E+07	1.00
	2 > 5	3.1E+05	1.00	2 > 5	2.5E+06	1.00
	4 > 3	1.7E+00	0.63	5 > 3	6.5E-01	0.40
	4 > 5	5.1E+00	0.84	5 > 4	4.3E+00	0.81
	4 > 5	1.2E+01	0.92	5 > 4	8.6E+00	0.23
Desc.	2 > 3	3.3E+05	1.00	2 > 3	4.5E+01	0.98
	2 > 4	9.0E+03	1.00	2 > 4	4.3E+01	0.98
	2 > 5	1.2E+06	1.00	2 > 5	1.2E+03	1.00
	4 > 3	3.6E+01	0.97	4 > 3	1.1E+00	0.52
	4 > 5	7.6E-01	0.82	4 > 5	1.5E+01	0.94
	4 > 5	1.4E+02	0.99	4 > 5	3.0E+01	0.97
Ran.	2 > 3	2.5E+03	1.00	2 > 3	3.9E+02	1.00
	2 > 4	7.3E+02	1.00	2 > 4	2.2E+01	0.96
	2 > 5	5.3E+02	1.00	2 > 5	9.6E+00	0.91
	5 > 3	3.6E+00	0.78	5 > 3	1.9E+01	0.95
	5 > 4	1.1E+00	0.52	5 > 4	1.0E+00	0.51
	5 > 4	1.4E+00	0.58	5 > 4	2.4E+00	0.71

Table 14. Best Model and Normalized Probability (Individuals).

	LEW			**F344**		
	Eq.	**Times**	**P**	**Eq.**	**No.**	**P**
Asc.	1 > 2	3.5E+00	0.78	2 > 1	1.9E+00	0.65
	1 > 3	1.4E+06	1.00	2 > 3	1.1E+06	1.00
	1 > 4	5.1E+05	1.00	2 > 4	2.5E+04	1.00
	1 > 5	4.9E+06	1.00	2 > 5	2.5E+04	1.00
Desc.	2 > 1	8.4E+02	1.00	2 > 1	1.0E+00	0.51
	2 > 3	3.9E+03	1.00	2 > 3	1.6E+06	1.03
	2 > 4	9.2E+03	1.00	2 > 4	2.8E+06	1.00
	2 > 5	1.2E+03	1.00	2 > 5	2.8E+06	1.00
Ran.	1 > 2	8.8E+00	0.90	1 > 2	2.6E+00	0.72
	1 > 3	1.1E+05	1.00	1 > 3	1.2E+05	1.00
	1 > 4	1.1E+05	1.00	1 > 4	2.4E+05	1.00
	1 > 5	1.5E+05	1.00	1 > 5	3.1E+05	1.00

In Table 15, further comparisons between models that estimated two free parameters to fit the data show that Myerson and Green's (1995) hyperboloid model (Eq. 3) is the preferred model fitting data of both strains in the descending and random conditions. Rachlin's (2006) power function of hyperbolic discounting (Eq. 4) was the preferred model fitting data of the LEWs in the ascending condition; but Ebert and Prelec's (2007) constant sensitivity discounting model (Eq. 5) was chosen fitting data of the F344s in the ascending condition.

Discussion

The aim of the present study was to compare five prevalent models of intertemporal choice, describing the impulsive choices of LEW and F344 rats at the group and individual levels of analysis. A revealing result was that all five models of intertemporal choice nicely fitted the data of the LEWs and F344s at both levels of analysis. The techniques of maximum likelihood parameter estimation and model comparison were used to weigh and compare these models of intertemporal choice.

Consistent with findings of studies comparing models of intertemporal choice fitting delay discounting data from humans (McKerchar et al., 2009; Rachlin, 206; Myerson & Green, 1995; Takahashi et al., 2008), this study showed that dual-parameter models provide better fits to delay discounting data from nonhuman animals (R^2 was greater) than single-parameter models.

Table 15. Best Model and Normalized Probability (Individuals).

	LEW			F344		
	Eq.	Times	p	Eq.	Times	p
Asc.	2 > 3	5.3E+05	1.00	2 > 3	3.3E+06	1.00
	2 > 4	1.9E+05	1.00	2 > 4	7.2E+04	1.00
	2 > 5	1.8E+06	1.00	2 > 5	7.0E+04	1.00
	4 > 3	2.8E+00	0.74	5 > 3	4.5E+01	0.98
	4 > 5	3.3E+00	0.77	5 > 4	1.0E+00	0.50
	4 > 5	9.6E+00	0.91	5 > 4	1.0E+00	0.51
Desc.	2 > 3	3.3E+06	1.00	2 > 3	3.3E+06	1.00
	2 > 4	7.7E+06	1.00	2 > 4	5.7E+06	1.00
	2 > 5	9.7E+05	1.00	2 > 5	5.7E+06	1.00
	3 > 4	2.4E+00	0.70	3 > 4	1.8E+00	0.64
	3 > 5	9.1E-01	0.48	3 > 5	1.8E+00	0.64
	5 > 4	7.9E+00	0.89	4 = 5	1.0E+00	0.50
Ran.	2 > 3	1.3E+04	1.00	2 > 3	6.2E+04	1.00
	2 > 4	1.4E+04	1.00	2 > 4	1.3E+05	1.00
	2 > 5	2.0E+04	1.00	2 > 5	1.7E+05	1.00
	3 > 4	1.1E+00	0.52	3 > 4	2.1E+00	0.67
	3 > 5	1.3E+00	0.56	3 > 5	2.5E+00	0.71
	4 > 5	1.4E+00	0.58	4 > 5	1.3E+00	0.56

With respect to single-parameter models, the present study showed that Mazur's (1987) hyperbolic-decay model is the preferred model, and Samuelson's (1937) exponential discounted utility the second best model fitting group and individual data from LEW and F344 rats. In the ascending and random presentation order of delays conditions, Mazur's (1987) hyperbolic-decay model generated R^2s that were comparable to those that dual-parameter models (Equations 3, 4, and 5) generated fitting the data of the LEWs and F344s. At the group and individual levels of analysis, these results seem to fully support Mazur's (1987) over Samuelson's (1937) model (i.e., McKerchar et al., 2009). Nonetheless, the distribution of R^2s that Mazur's (1987) hyperbolic-decay model generated fitting the data of individual LEWs and F344s was not significantly different from that Samuelson's (1937) exponential discounted utility model generated fitting data in the ascending and descending conditions. Only for the data collected in the random condition, Mazur's (1987) model generated a distribution of R^2s that was significantly different ($Z = 2.869, p = .002$) from that Samuelson's (1937) model. Also, when delays to LLR were presented in descending order Samuelson's (1937) model performed better than Mazur's (1987) model, R^2 was consistently greater fitting the group's data of the F344s. This result suggests that Samuelson's (1937) exponential discounted utility function handled the variability in the data of the F344s better that the Mazur's (1987) model, and it is in dispute with studies questioning the efficacy of Samuelson's (1937) model to fit delay discounting data (e.g., Kirby & Herrnstein; 1995; Madden et at., 1999; Myerson & Green. 1995).

For dual-parameter models (Equations 3, 4, and 5), paired comparisons indicated no differences in R^2s between Equations 4 and 5; nor there were differences in R^2 distributions between Equations 3 and 4, replicating results obtained with humans (Rachlin, 2006). The distribution of R^2s that Equation 3 generated fitting the data of the individual LEWs and F344s, was significantly different from that Equation 4 generated for the data of the ascending and random conditions. Paired comparisons between Equations 4 and 5 also showed differences in distributions of R^2s when fitting data in the ascending and descending conditions. Consequently, the present results do not support the idea that is difficult to discriminate between dual-parameter models only on the basis of their fits to the data (Rachlin, 2006); this notion might only apply to delay discounting data from humans.

The present study used the Akaike's (1973) information criterion (AIC), offering an alternative method to estimate the anticipated Kullback-Leibler (1951) discrepancy between the correct model and the prospective model. Generally, the results showed that Mazur's (1987) hyperbolic-decay model was the preferred model (i.e., the model with the lowest AIC value) fitting the data of the LEWs and F344s in the ascending and random conditions. However, for the data collected in the descending condition, Samuelson's (1937) exponential discounted utility model was the best model fitting group's data of the LEWs and data of the individual LEW and F344 rats (see Tables 8 and 9).

To facilitate comparisons between AIC values computed for models fitting the groups' data and those computed for models fitting the data of the individual LEWs and F344s, the analysis of the results focused on the relative performance of the models, computing for each model the difference in AIC with respect to the AIC of the preferred model (e.g., Akaike, 1978; Burnham & Anderson, 2002). These computations confirmed the results based on raw AIC values; Mazur's (1987) and Samuelson's (1937), with a Δ_i (AIC) = 0, were the preferred models fitting the groups' data and data of the individual LEWs and F344s in the ascending, descending, and random conditions (see Tables 8 and 9).

Accordingly, the differences in AIC were used to estimate for each model the relative probability of being correct; and the obtained relative probabilities, in turn, were normalized to compute Aikaike weights (e.g., Burnham & Anderson, 2002). Again, these results showed that Mazur's (1987) model, with probability of 1.0 of minimizing the Kullback-Leibler (1951) discrepancy, was the correct model fitting the data of the LEWs and F344s. Only two times, Samuelson's (1937) exponential discounted utility function qualified as the second best model fitting the data of the LEWs in the descending condition and those of the F344s in the ascending condition (see Table 10). Computations of Aikaike weights allowed the comparisons of dual-parameter models, confirming that Rachlin's (2006) power function of hyperbolic discounting has the highest probability of being the correct fitting the groups' data of the LEW in the ascending condition and the data of both strains in the descending condition (Table 11). However, Myerson and Green's (1995) hyperboloid model yielded the highest probability of being the correct model fitting the data of the F344s in the ascending condition, and Ebert and Prelec's (2007) constant sensitivity model the highest probability of being correct fitting the data of the LEWs. Further comparisons between Rachlin's (2006) and Ebert and Prelec's (2007) models showed mixed results, with the former getting the highest probability of being correct fitting the data of the LEWs and F344s in the ascending and descending conditions and Ebert and Prelec's (2007) model with the highest probability of being the correct model fitting the data of the LEWs and F344s in the random condition.

The analysis of the results concluded with the computations of evidence ratios of Aikaike weights, assessing how much evidence ratios support one model over the other model. Resulting evidence ratios and normalized probabilities confirmed findings described above. Generally, Mazur's (1987) hyperbolic-decay model was the best model fitting groups' data and data of the individual LEW and F344 rats, and Samuelson's (1937) exponential discounted utility function was the second best model fitting data of both strains (Tables 12 and 13). Further comparisons between models estimating two free parameters to fit the data showed that Myerson and Green's (1995) hyperboloid model was the best model fitting data of both strains in the descending and random conditions. Rachlin's (2006) power function of hyperbolic discounting performed better than Myerson and Green's (1995) hyperboloid model fitting data of the LEWs in the ascending condition, and Ebert and Prelec's (2007) constant sensitivity discounting model fitting data of the F344s in the ascending condition.

In conclusion, the present study showed that Mazur's (1987) hyperbolic-decay model is the best and most parsimonious model fitting the group's data and data of the individual LEW and F344 rats. The results showed that Aikaike weights are easy to compute and agree with the idea that they facilitate formal comparisons between single-parameter and dual-parameter models of intertemporal choice (Wagenmakers et al., 2004). Aikaike weights are interpreted as the probability that each model has to minimize the Kullback-Leibler (1951) discrepancy, providing a relative index to compare competitive models. Some researchers believe, however, that AIC is too generous tending to select excessively complex models (Kass & Raftery, 1995). Others claim that AIC is not a consistent in situations where the number of observations grows very large (Bozdogan, 1987). One alternative to the AIC is the Bayesian information criterion (BIC) to select models (Burnham & Anderson, 2002; Kass & Raftery, 1995). Future research will be needed to determine a suitable way to use of Aikaike weights to choose between models of intertemporal choice fitting delay discounting data by human and nonhuman animals.

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Appendix A

Table 1.
Resulting parameters and analyses of fits using Equations 1 to 5.

		A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Ascending									
Eq.1	LEW	0.712	0.016	0.058	0.007			0.148	**0.991**
	F344	0.736	0.089	0.082	0.034			0.616	**0.916**
Eq.2	LEW	0.696	0.031	0.030	0.005			0.595	**0.963**
	F344	0.700	0.028	0.036	0.004			0.085	**0.988**
Eq.3	LEW	0.711	0.019	0.046	0.030	1.160	0.484	0.187	**0.988**
	F344	0.700	0.037	0.000	0.009	4.6E+03	5.0E+06	0.114	**0.984**
Eq.4	LEW	0.708	0.017	0.039	0.020	1.120	0.143	0.157	**0.990**
	F344	0.680	0.051	0.007	0.009	1.738	0.385	0.213	**0.971**
Eq.5	LEW	0.720	0.031	0.032	0.005	0.695	0.148	0.360	**0.978**
	F344	0.680	0.051	0.007	0.009	1.738	0.385	0.213	**0.971**
Descending									
Eq.1	LEW	0.686	0.098	0.121	0.038			0.945	**0.918**
	F344	0.486	0.007	0.049	0.002			6.4E-04	**0.998**
Eq.2	LEW	0.624	0.032	0.036	0.002			0.161	**0.986**
	F344	0.429	0.032	0.021	0.003			0.023	**0.938**
Eq.3	LEW	0.647	0.030	0.010	0.008	4.655	2.820	0.100	**0.991**
	F344	0.488	0.009	0.054	0.010	0.942	0.088	0.001	**0.998**
Eq.4	LEW	0.621	0.016	0.009	0.003	1.669	0.083	0.030	**0.997**
	F344	0.488	0.009	0.054	0.010	0.942	0.088	0.001	**0.998**
Eq.5	LEW	0.648	0.041	0.040	0.006	0.885	0.107	0.155	**0.987**
	F344	0.488	0.009	0.054	0.010	0.942	0.088	7.5E-04	**0.998**
Random									
Eq.1	LEW	0.628	0.024	0.025	0.005			0.300	**0.945**
	F344	0.696	0.024	0.009	0.002			0.103	**0.865**
Eq.2	LEW	0.599	0.033	0.014	0.003			0.747	**0.862**
	F344	0.686	0.026	0.007	0.002			0.139	**0.817**
Eq.3	LEW	0.654	0.016	0.130	0.056	0.389	0.081	0.090	**0.983**
	F344	0.733	0.010	0.272	0.107	0.157	0.023	0.009	**0.988**
Eq.4	LEW	0.664	0.016	0.084	0.022	0.682	0.068	0.060	**0.989**
	F344	0.751	0.009	0.084	0.014	0.481	0.038	0.003	**0.995**
Eq.5	LEW	0.677	0.018	0.013	0.001	0.504	0.054	0.054	**0.990**
	F344	0.760	0.010	0.003	0.000	0.395	0.031	0.003	**0.997**

Table 2.
Resulting parameters for the LEWs in the Ascending condition.

Model	Rat	A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Eq.1	L201	0.780	0.057	0.043	0.011			0.004	0.931
	L202	0.805	0.069	0.064	0.018			0.006	0.922
	L203	0.740	0.055	0.074	0.017			0.003	0.948
	L204	0.631	0.022	0.146	0.015			0.000	0.989
	L205	0.732	0.040	0.033	0.007			0.002	0.936
	L206	0.761	0.048	0.043	0.010			0.003	0.946
	L207	0.684	0.032	0.050	0.008			0.001	0.969
	L208	0.766	0.052	0.102	0.021			0.003	0.959
Eq.2	L201	0.754	0.030	0.026	0.003			0.002	0.974
	L202	0.774	0.064	0.038	0.008			0.006	0.911
	L203	0.712	0.039	0.043	0.006			0.002	0.965
	L204	0.598	0.061	0.078	0.018			0.004	0.902
	L205	0.680	0.055	0.018	0.005			0.006	0.823
	L206	0.732	0.034	0.026	0.003			0.002	0.964
	L207	0.639	0.047	0.027	0.006			0.004	0.906
	L208	0.737	0.058	0.059	0.011			0.004	0.938
Eq.3	L201	0.757	0.040	0.002	0.011	14.373	8.2E+01	0.002	0.965
	L202	0.796	0.076	0.027	0.044	1.884	2.320	0.006	0.913
	L203	0.725	0.045	0.017	0.024	3.009	3.514	0.002	0.965
	L204	0.635	0.023	0.205	0.086	0.819	0.179	0.000	0.989
	L205	0.753	0.044	0.089	0.074	0.552	0.236	0.002	0.945
	L206	0.744	0.042	0.009	0.017	3.344	5.118	0.002	0.960
	L207	0.684	0.041	0.052	0.043	0.977	0.507	0.002	0.958
	L208	0.759	0.056	0.053	0.054	1.569	1.115	0.003	0.955
Eq.4	L201	0.730	0.022	0.005	0.003	1.628	0.175	0.001	0.990
	L202	0.775	0.063	0.018	0.020	1.428	0.341	0.004	0.940
	L203	0.706	0.031	0.017	0.010	1.496	0.191	0.001	0.984
	L204	0.637	0.027	0.177	0.061	0.925	0.121	0.001	0.987
	L205	0.754	0.054	0.060	0.045	0.835	0.193	0.002	0.931
	L206	0.723	0.029	0.009	0.006	1.460	0.193	0.001	0.982
	L207	0.679	0.041	0.042	0.028	1.055	0.189	0.002	0.960
	L208	0.746	0.047	0.043	0.030	1.322	0.239	0.002	0.968
Eq.5	L201	0.745	0.043	0.026	0.003	1.072	0.199	0.002	0.967
	L202	0.790	0.093	0.037	0.010	0.871	0.294	0.008	0.888
	L203	0.719	0.056	0.043	0.007	0.932	0.209	0.003	0.955
	L204	0.700	0.071	0.098	0.031	0.472	0.108	0.001	0.975
	L205	0.770	0.076	0.018	0.005	0.573	0.181	0.003	0.905
	L206	0.737	0.051	0.026	0.004	0.964	0.207	0.003	0.952
	L207	0.691	0.060	0.028	0.006	0.692	0.175	0.003	0.933
	L208	0.765	0.079	0.058	0.014	0.762	0.220	0.005	0.932

Table 3.
Resulting parameters for the F344s in the Ascending condition.

Model	Rat	A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Eq.1	F101	0.715	0.066	0.068	0.020			0.005	0.923
	F102	0.887	0.085	0.081	0.025			0.008	0.923
	F103	0.919	0.106	0.045	0.018			0.014	0.861
	F104	0.781	0.204	0.044	0.040			0.054	0.557
	F105	0.635	0.070	0.068	0.024			0.006	0.868
	F106	0.507	0.053	0.120	0.038			0.003	0.924
	F107	0.683	0.135	0.069	0.044			0.020	0.648
	F108	0.705	0.134	0.024	0.019			0.029	0.535
Eq.2	F101	0.682	0.035	0.038	0.005			0.002	0.971
	F102	0.846	0.054	0.045	0.007			0.004	0.960
	F103	0.892	0.053	0.027	0.005			0.005	0.951
	F104	0.785	0.150	0.030	0.016			0.038	0.686
	F105	0.610	0.077	0.041	0.013			0.009	0.792
	F106	0.493	0.027	0.068	0.009			0.001	0.976
	F107	0.592	0.117	0.027	0.015			0.025	0.574
	F108	0.693	0.104	0.016	0.008			0.024	0.623
Eq.3	F101	0.684	0.045	0.001	0.016	4.3E+01	7.4E+02	0.002	0.962
	F102	0.858	0.068	0.008	0.026	6.040	17.043	0.005	0.949
	F103	0.892	0.070	0.000	0.015	4.9E+03	1.4E+07	0.007	0.935
	F104	0.785	0.195	0.000	0.050	1.0E+04	1.8E+08	0.051	0.581
	F105	0.635	0.086	0.066	0.113	1.027	1.090	0.007	0.824
	F106	0.494	0.033	0.002	0.026	35.864	4.8E+02	0.001	0.968
	F107	0.718	0.168	0.248	0.675	0.517	0.626	0.025	0.564
	F108	0.693	0.142	0.000	0.042	7.3E+03	1.4E+08	0.032	0.497
Eq.4	F101	0.676	0.049	0.014	0.015	1.509	0.331	0.003	0.959
	F102	0.846	0.066	0.019	0.020	1.495	0.341	0.005	0.955
	F103	0.838	0.069	0.002	0.005	1.841	0.582	0.007	0.934
	F104	0.673	0.026	0.000	0.000	11.075	48.710	0.002	0.983
	F105	0.625	0.083	0.038	0.056	1.206	0.454	0.007	0.836
	F106	0.478	0.024	0.015	0.011	1.806	0.284	0.001	0.983
	F107	0.734	0.211	0.183	0.373	0.706	0.576	0.025	0.569
	F108	0.591	0.047	0.000	0.000	10.436	1.1E+02	0.009	0.859
Eq.5	F101	0.684	0.050	0.038	0.006	0.987	0.215	0.002	0.962
	F102	0.856	0.076	0.045	0.009	0.942	0.243	0.005	0.948
	F103	0.847	0.059	0.026	0.004	1.306	0.329	0.005	0.956
	F104	0.671	0.023	0.027	4.9E+05	3.9E+01	4.0E+09	0.002	0.987
	F105	0.641	0.118	0.038	0.017	0.681	0.342	0.010	0.766
	F106	0.486	0.033	0.068	0.009	1.131	0.244	0.001	0.971
	F107	0.768	0.292	0.044	0.048	0.454	0.428	0.024	0.583
	F108	0.589	0.047	0.016	0.038	8.449	46.172	0.009	0.860

Table 4.
Resulting parameters for the LEWs in the Descending condition.

Model	Rat	A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Eq.1	L201	0.867	0.073	0.065	0.018			0.006	0.934
	L202	0.476	0.027	0.118	0.020			0.001	0.975
	L203	0.594	0.032	0.089	0.015			0.001	0.974
	L204	0.665	0.081	0.085	0.032			0.007	0.890
	L205	0.621	0.061	0.074	0.023			0.004	0.920
	L206	0.743	0.090	0.039	0.017			0.011	0.835
	L207	0.662	0.052	0.046	0.013			0.003	0.927
	L208	0.723	0.066	0.088	0.025			0.005	0.933
Eq.2	L201	0.835	0.019	0.038	0.002			0.001	0.994
	L202	0.455	0.013	0.064	0.004			0.000	0.992
	L203	0.565	0.016	0.049	0.003			0.000	0.992
	L204	0.652	0.038	0.051	0.007			0.002	0.970
	L205	0.602	0.020	0.044	0.004			0.001	0.989
	L206	0.730	0.049	0.025	0.005			0.004	0.934
	L207	0.639	0.022	0.028	0.003			0.001	0.983
	L208	0.698	0.019	0.050	0.003			0.000	0.993
Eq.3	L201	0.836	0.024	0.000	0.007	1.2E+03	2.4E+05	0.001	0.992
	L202	0.465	0.006	0.025	0.007	3.1E+00	7.6E-01	0.000	0.999
	L203	0.577	0.010	0.018	0.008	3.3E+00	1.1E+00	0.000	0.997
	L204	0.652	0.048	0.000	0.021	3.4E+03	4.8E+06	0.003	0.959
	L205	0.602	0.025	0.000	0.011	2.0E+03	9.7E+05	0.001	0.985
	L206	0.730	0.064	0.000	0.017	5.1E+03	1.7E+07	0.006	0.912
	L207	0.639	0.028	0.000	0.009	1.1E+03	3.7E+05	0.001	0.977
	L208	0.698	0.024	0.000	0.010	1.6E+03	5.0E+05	0.001	0.991
Eq.4	L201	0.803	0.023	0.008	0.004	1.674	0.154	0.001	0.993
	L202	0.459	0.005	0.041	0.005	1.398	0.043	0.000	0.999
	L203	0.571	0.014	0.032	0.009	1.351	0.095	0.000	0.995
	L204	0.606	0.017	0.003	0.002	2.198	0.221	0.000	0.994
	L205	0.572	0.009	0.006	0.002	1.841	0.099	0.000	0.998
	L206	0.655	0.019	0.000	0.000	2.815	0.448	0.001	0.988
	L207	0.608	0.024	0.004	0.003	1.726	0.249	0.001	0.983
	L208	0.672	0.028	0.011	0.007	1.698	0.219	0.001	0.987
Eq.5	L201	0.819	0.020	0.037	0.002	1.115	0.086	0.000	0.995
	L202	0.468	0.012	0.064	0.004	0.851	0.065	0.000	0.996
	L203	0.581	0.015	0.050	0.003	0.860	0.063	0.000	0.996
	L204	0.618	0.029	0.052	0.004	1.462	0.239	0.001	0.985
	L205	0.582	0.016	0.044	0.002	1.227	0.112	0.000	0.994
	L206	0.666	0.030	0.026	0.002	1.952	0.457	0.002	0.976
	L207	0.626	0.028	0.028	0.003	1.115	0.165	0.001	0.980
	L208	0.684	0.021	0.050	0.003	1.131	0.107	0.000	0.994

Table 5.
Resulting parameters for the F344s in the Descending condition.

Model	Rat	A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Eq.1	F101	0.798	0.073	0.064	0.019			0.006	0.922
	F102	0.981	0.089	0.058	0.017			0.009	0.920
	F103	0.878	0.045	0.010	0.003			0.004	0.838
	F104	0.105	0.008	0.024	0.006			0.000	0.923
	F105	0.326	0.028	0.159	0.041			0.001	0.925
	F106	0.250	0.017	0.207	0.042			0.000	0.970
	F107	0.301	0.029	0.171	0.050			0.001	0.910
	F108	0.136	0.035	0.008	0.013			0.003	-0.045
Eq.2	F101	0.773	0.030	0.038	0.004			0.001	0.983
	F102	0.951	0.038	0.035	0.004			0.002	0.980
	F103	0.873	0.033	0.008	0.001			0.003	0.894
	F104	0.096	0.008	0.013	0.003			0.000	0.840
	F105	0.300	0.050	0.078	0.030			0.003	0.719
	F106	0.243	0.006	0.106	0.006			0.000	0.996
	F107	0.278	0.047	0.085	0.033			0.002	0.720
	F108	0.136	0.032	0.007	0.008			0.003	-0.036
Eq.3	F101	0.774	0.038	0.000	0.012	8.4E+02	2.1E+05	0.002	0.977
	F102	0.951	0.049	0.000	0.011	9.5E+02	2.9E+05	0.003	0.973
	F103	0.873	0.048	0.000	0.016	2.5E+03	1.3E+07	0.004	0.859
	F104	0.137	0.053	0.298	0.656	3.7E-01	1.5E-01	0.000	0.952
	F105	0.347	0.006	1.484	0.403	0.383	0.029	0.000	0.998
	F106	0.245	0.005	0.025	0.015	4.816	2.474	0.000	0.998
	F107	0.325	0.023	2.072	2.111	0.364	0.091	0.000	0.980
	F108	0.136	0.046	0.000	0.117	1.4E+03	3.6E+07	0.004	-0.381
Eq.4	F101	0.738	0.015	0.005	0.002	1.803	0.123	0.000	0.997
	F102	0.907	0.021	0.005	0.002	1.786	0.141	0.001	0.995
	F103	0.827	0.015	0.000	0.000	2.277	0.367	0.001	0.978
	F104	0.197	0.214	0.471	1.226	0.472	0.300	0.000	0.952
	F105	0.414	0.029	0.787	0.171	0.485	0.046	0.000	0.997
	F106	0.241	0.002	0.053	0.005	1.590	0.041	0.000	1.000
	F107	0.409	0.109	0.991	0.694	0.455	0.131	0.000	0.980
	F108	0.289	4.1E+06	1.503	3.6E+07	0.000	--	0.004	-0.667
Eq.5	F101	0.753	0.035	0.038	0.004	1.176	0.175	0.001	0.983
	F102	0.925	0.044	0.035	0.003	1.194	0.187	0.002	0.981
	F103	0.829	0.017	0.010	0.001	1.887	0.326	0.001	0.975
	F104	0.054	0.024	0.000	2.8E+04	3.909	1.2E+08	0.002	-1.964
	F105	0.669	0.158	1.630	2.205	0.190	0.039	0.000	0.996
	F106	0.246	0.007	0.108	0.006	0.902	0.082	0.000	0.996
	F107	0.768	0.646	6.373	33.334	0.163	0.098	0.000	0.980
	F108	0.314	0.074	6.969	--	0.000		0.004	-0.667

Table 6.
Resulting parameters for the LEWs in the Random condition.

Model	Rat	A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Eq.1	L201	0.602	0.054	0.034	0.011			0.004	0.826
	L202	0.662	0.043	0.026	0.007			0.003	0.911
	L203	0.580	0.041	0.027	0.008			0.003	0.873
	L204	0.695	0.021	0.041	0.004			0.001	0.986
	L205	0.595	0.051	0.011	0.005			0.005	0.608
	L206	0.589	0.040	0.042	0.010			0.002	0.925
	L207	0.553	0.025	0.009	0.002			0.001	0.831
	L208	0.696	0.031	0.019	0.004			0.002	0.929
Eq.2	L201	0.545	0.059	0.016	0.006			0.008	0.678
	L202	0.644	0.029	0.017	0.002			0.002	0.946
	L203	0.539	0.046	0.014	0.004			0.005	0.763
	L204	0.657	0.032	0.023	0.003			0.002	0.951
	L205	0.577	0.049	0.008	0.003			0.006	0.547
	L206	0.553	0.048	0.023	0.006			0.004	0.844
	L207	0.545	0.024	0.007	0.002			0.002	0.818
	L208	0.664	0.038	0.012	0.003			0.004	0.853
Eq.3	L201	0.680	0.017	0.693	0.270	0.261	0.032	0.000	0.990
	L202	0.644	0.039	0.000	0.012	2.7E+02	5.2E+04	0.002	0.928
	L203	0.642	0.021	0.377	0.176	0.283	0.047	0.000	0.982
	L204	0.691	0.025	0.031	0.019	1.230	0.524	0.001	0.983
	L205	0.733	0.052	4.714	7.910	0.112	0.029	0.001	0.956
	L206	0.593	0.051	0.055	0.068	0.839	0.625	0.003	0.903
	L207	0.595	0.040	0.222	0.328	0.176	0.095	0.001	0.823
	L208	0.733	0.027	0.112	0.068	0.369	0.103	0.001	0.969
Eq.4	L201	0.739	0.030	0.299	0.063	0.454	0.046	0.000	0.994
	L202	0.622	0.035	0.003	0.004	1.584	0.388	0.002	0.944
	L203	0.671	0.024	0.183	0.045	0.526	0.057	0.000	0.990
	L204	0.684	0.024	0.028	0.012	1.115	0.120	0.001	0.986
	L205	0.972	0.338	0.635	0.607	0.213	0.104	0.001	0.961
	L206	0.588	0.054	0.040	0.042	1.014	0.284	0.003	0.901
	L207	0.606	0.047	0.072	0.068	0.530	0.207	0.001	0.866
	L208	0.744	0.033	0.070	0.033	0.685	0.113	0.001	0.968
Eq.5	L201	0.815	0.051	0.030	0.007	0.278	0.037	0.000	0.994
	L202	0.636	0.043	0.017	0.003	1.083	0.286	0.002	0.930
	L203	0.704	0.030	0.017	0.002	0.358	0.042	0.000	0.993
	L204	0.697	0.040	0.024	0.003	0.754	0.131	0.001	0.967
	L205	1.169	0.670	0.039	0.189	0.120	0.093	0.001	0.963
	L206	0.602	0.073	0.023	0.007	0.660	0.240	0.004	0.866
	L207	0.610	0.049	0.004	0.002	0.452	0.186	0.001	0.879
	L208	0.758	0.041	0.010	0.002	0.514	0.103	0.001	0.964

Table 7.
Resulting parameters for the F344s in the Random condition.

Model	Rat	A	SE-A	k/a	SE-k	s/b	SE-s	Chi-Sqr	R^2
Eq.1	F101	0.639	0.026	0.018	0.003			0.001	0.936
	F102	0.856	0.017	0.007	0.001			0.001	0.945
	F103	0.874	0.023	0.005	0.001			0.001	0.869
	F104	0.670	0.030	0.006	0.002			0.002	0.722
	F105	0.617	0.047	0.006	0.003			0.005	0.430
	F106	0.576	0.050	0.022	0.008			0.004	0.803
	F107	0.614	0.048	0.003	0.003			0.006	0.108
	F108	0.606	0.035	0.011	0.003			0.003	0.771
Eq.2	F101	0.613	0.032	0.011	0.002			0.003	0.865
	F102	0.847	0.019	0.005	0.001			0.001	0.921
	F103	0.872	0.020	0.004	0.001			0.001	0.899
	F104	0.663	0.030	0.005	0.001			0.002	0.692
	F105	0.606	0.045	0.005	0.002			0.006	0.375
	F106	0.548	0.046	0.013	0.004			0.005	0.766
	F107	0.610	0.047	0.003	0.002			0.006	0.087
	F108	0.588	0.036	0.007	0.002			0.004	0.684
Eq.3	F101	0.666	0.027	0.083	0.058	0.402	1.4E-01	0.001	0.961
	F102	0.882	0.017	0.059	0.036	0.235	7.2E-02	0.000	0.974
	F103	0.872	0.028	0.000	0.016	1.0E+03	3.6E+06	0.001	0.866
	F104	0.743	0.037	1.056	1.647	9.1E-02	3.5E-02	0.001	0.870
	F105	0.755	0.059	8.289	17.283	0.079	0.019	0.000	0.961
	F106	0.616	0.069	0.144	0.240	0.365	0.269	0.005	0.784
	F107	1.360	1.6E+04	7.3E+05	1.5E+11	0.056	0.029	0.001	0.852
	F108	0.649	0.036	0.172	0.196	2.2E-01	9.7E-02	0.001	0.888
Eq.4	F101	0.674	0.031	0.056	0.031	0.723	0.132	0.001	0.960
	F102	0.889	0.018	0.026	0.011	0.688	0.098	0.000	0.978
	F103	0.841	0.011	0.000	0.000	2.289	0.469	0.000	0.970
	F104	0.785	0.082	0.146	0.125	0.326	0.155	0.001	0.898
	F105	1.513	2.158	1.426	3.522	0.113	0.106	0.000	0.959
	F106	0.624	0.080	0.084	0.105	0.673	0.304	0.004	0.795
	F107	2.7E+03	4.3E+07	4.2E+03	6.8E+07	0.056	0.208	0.001	0.852
	F108	0.662	5.5E-02	0.075	7.2E-02	0.552	0.215	0.002	0.857
Eq.5	F101	0.685	0.038	0.010	0.002	0.549	0.122	0.001	0.954
	F102	0.892	0.019	0.003	0.001	0.602	0.093	0.000	0.978
	F103	0.842	0.010	0.008	0.001	2.062	0.416	0.000	0.972
	F104	0.798	0.096	0.001	8.9E-04	0.266	1.5E-01	0.001	0.902
	F105	3.051	12.240	6.4E+04	5.6E+06	0.042	0.103	0.000	0.958
	F106	0.632	0.090	0.013	0.006	0.517	0.257	0.004	0.805
	F107	4.816	78.673	2.0E+11	1.0E+14	0.027	0.216	0.001	0.830
	F108	0.673	0.069	0.004	0.003	0.430	0.207	0.002	0.844

Appendix B

Table B1.
Akaike Weights and Residual Sum of Squares (RSS), using fits of the individuals.

	LEW					F344				
Asc	w (AIC)				RSS	w (AIC)				RSS
Eq.1	0.7771	1.0000	1.0000	1.0000	0.0111	0.3484	1.0000	1.0000	1.0000	0.1166
Eq.2	0.2229				0.0169	0.6517				0.0946
Eq.3		5.5E-07			0.0092		5.7E-07			0.0946
Eq.4			1.5E-06		0.0065			2.6E-05		0.0265
Eq.5				1.6E-07	0.0139				2.7E-05	0.0263
Des.										
Eq.1	0.0012	0.9997	0.9999	0.9991	0.0186	0.4931	1.0000	1.0000	1.0000	0.0113
Eq.2	0.9988				0.0020	0.5069				0.0112
Eq.3		2.6E-04			0.0020		3.1E-07			0.0112
Eq.4			0.0001		0.0026			1.8E-07		0.0135
Eq.5				8.6E-04	0.0013				1.8E-07	0.0135
Ran.										
Eq.1	0.8981	0.99999	0.99999	0.99999	0.0068	0.7223	1.0000	1.0000	1.0000	0.0103
Eq.2	0.1019	8.5E-06			0.0140	0.2777				0.0142
Eq.3			7.9E-06		0.0022		6.2E-06			0.0038
Eq.4					0.0023			3.0E-06		0.0049
Eq.5				5.8E-06	0.0026				2.3E-06	0.0053

Table B2.
Results of AIC, Weights, and Residual Sum of Squares (RSS) using fits of individuals.

			LEW						F344			
Asc	AIC	Δ(AIC)	RSS		w(AIC)		AIC	Δ(AIC	RSS		w(AIC)	
Eq.2	-17.25	0.00	0.0169	1.0000	1.0000	1.0000	-6.90	0.00	0.0946	1.0000	1.0000	1.0000
Eq.3	9.10	26.35	0.0092	1.9E-06			23.10	30.00	0.0946	3.1E-07		
Eq.4	7.05	24.30	0.0065		5.3E-06		15.47	22.37	0.0265		1.4E-05	
Eq.5	11.57	28.82	0.0139			5.5E-07	15.43	22.32	0.0263			1.4E-05
Des.												
Eq.2	-30.15	0.00	0.0020	1.0000	1.0000	1.0000	-19.73	0.00	0.0112	1.0000	1.0000	1
Eq.3	-0.14	30.01	0.0020	3.0E-07			10.27	30.00	0.0112	3.1E-07		
Eq.4	1.58	31.72	0.0026		1.3E-07		11.40	31.13	0.0135		1.7E-07	
Eq.5	-2.57	27.58	0.0013			1.0E-06	11.40	31.13	0.0135			1.7E-07
Ran.												
Eq.2	-18.35	0.00	0.0140	0.9999	0.9999	1.0000	-18.27	0.00	0.0142	1.0000	1.0000	0.99999
Eq.3	0.65	19.00	0.0022	0.0001			3.82	22.08	0.0038	1.6E-05		
Eq.4	0.79	19.14	0.0023		7.0E-05		5.27	23.54	0.0049		7.7E-06	
Eq.5	1.41	19.76	0.0026			0.0001	5.78	24.05	0.0053			6.0E-06
Asc												
Eq.3	9.10	2.05	0.0092	0.2643	0.7748		23.10	7.68	0.0946	0.0216	0.0211	
Eq.4	7.05	0.00	0.0065	0.7357			15.47	0.05	0.0265	0.9785		
Eq.5	11.57	4.52	0.0139		0.2252		15.43	0.00	0.0263		0.9789	
Des												
Eq.3	-0.14	0.00	0.0020	0.7021	0.2288		10.27	0.00	0.0112	0.6375	0.6375	
Eq.4	1.58	1.71	0.0026	0.2979			11.40	1.13	0.0135	0.3625		
Eq.5	-2.57	-2.43	0.0013		0.7712		11.40	1.13	0.0135		0.3625	
Ran												
Eq.3	0.65	0.00	0.0022	0.5172	0.5940		3.82	0.00	0.0038	0.6745	0.7279	
Eq.4	0.79	0.14	0.0023	0.4829			5.27	0.14	0.0049	0.3255		
Eq.5	1.41	0.76	0.0026		0.4060		5.78	0.76	0.0053		0.2721	
Asc												
Eq.4	7.05	0.00	0.0065	0.9054			15.47	0.05	0.0265	0.4943		
Eq.5	11.57	4.52	0.0139	0.0946			15.43	0.00	0.0263	0.5057		
Des												
Eq.4	1.578	4.15	0.0026	0.1118			11.40	0.00	0.0135	0.5000		
Eq.5	-2.57	0.00	0.0013	0.8882			11.40	0.00	0.0135	0.5000		
Ran												
Eq.4	0.79	0.00	0.0022	0.5773			5.27	0.00	0.0049	0.5635		
Eq.5	1.41	0.62	0.0023	0.4227			5.78	0.51	0.0053	0.4365		