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Money Earlier or Later? Simple Heuristics Explain Intertemporal Choices Better Than Delay Discounting Does

Keith M. Marzilli Ericson[1,2], John Myles White[3], David Laibson[2,4], and Jonathan D. Cohen[3,5]
[1]School of Management, Boston University; [2]National Bureau of Economic Research, Cambridge, Massachusetts; [3]Department of Psychology, Princeton University; [4]Department of Economics, Harvard University; and [5]Princeton Neuroscience Institute, Princeton University

Abstract
Heuristic models have been proposed for many domains involving choice. We conducted an out-of-sample, cross-validated comparison of heuristic models of intertemporal choice (which can account for many of the known intertemporal choice anomalies) and discounting models. Heuristic models outperformed traditional utility-discounting models, including models of exponential and hyperbolic discounting. The best-performing models predicted choices by using a weighted average of absolute differences and relative percentage differences of the attributes of the goods in a choice set. We concluded that heuristic models explain time-money trade-off choices in experiments better than do utility-discounting models.

Keywords
delay of gratification, decision making, heuristics, judgment, open data

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People make many decisions with both short-term and long-term consequences. For example, smoking a cigarette has the immediate benefit of averting nicotine withdrawal and the long-term risk of lung cancer. Decisions involving consequences at different points in time are referred to as intertemporal choices (for a review, see Frederick, Loewenstein, & O'Donoghue, 2002).

The primary theoretical paradigm that has been used to explain intertemporal choice is the theory of delay discounting (Ainslie, 1975; Frederick et al., 2002), which assumes that the greater the delay in receiving the rewards, the more the rewards are discounted. The rate at which delayed consequences lose value is referred to as a *discount rate*. Discount rates are sometimes used as a measure of impatience.

There are several well-known models of delay discounting, including the classic economic model of exponential discounting, which assumes a constant discount rate (Samuelson, 1937), and the more recent hyperbolic-discounting model, which assumes that discount rates decline as time to delivery increases (Ainslie, 1975). A large body of research has measured discount rates to characterize individual differences in impatience (e.g., Kirby, Petry, & Bickel, 1999; Shamosh et al., 2008).

With delay-discounted utility, intertemporal preferences are modeled with a discount function, $D(t)$, and a utility (or value) function, $u(x)$. The utility function translates rewards (e.g., $1 or a serving of food) into units of value; for a particular individual, 20 servings of food may not be 20 times as valuable as a single serving. The discount function measures how that unit of utility decays if it is delivered at a time delay of t periods. The total value of a reward, x, at a particular time, t, is calculated by multiplying the discount function and the utility function.

The canonical experimental task used to measure discount functions is an intertemporal-choice task in which individuals choose between a smaller, earlier monetary

Corresponding Author:
Keith M. Marzilli Ericson, School of Management, Boston University, 595 Commonwealth Ave., Boston, MA 02215
E-mail: kericson@bu.edu

reward and a larger, later monetary reward. We refer to such tasks as *money-earlier-or-later* (MEL) tasks. MEL tasks are typically assumed to directly measure a decision maker's discount function (Frederick et al., 2002). However, the results of MEL tasks reveal several empirical regularities that cannot be easily accounted for by theories of delay discounting. For example, an extensive body of research has found that individuals are more impatient (per unit of time) for shorter time horizons than for longer ones (Ainslie, 1975; Laibson, 1997; Loewenstein & Prelec, 1992; Prelec, 2004)—a finding that cannot be explained by simple exponential discounting.

Several different (and complementary) extensions of the theory have been offered to account for this apparent anomaly. Some researchers have argued that decreasing impatience reflects nonlinear perceptions of time (Ebert & Prelec, 2007; Zauberman, Kim, Malkoc, & Bettman, 2009) or diminished sensitivity to delay (Scholten & Read, 2010). Other researchers have explained decreasing impatience with hyperbolic discounting, which has become the leading model of intertemporal choice in psychology. But a large accumulation of additional findings, including studies of subadditive discounting (Read, 2001), date-delay discrepancies (Read, Frederick, Orsel, & Rahman, 2005), similarity effects (Rubinstein, 1988, 2003), delay-speedup asymmetries, and query-order effects (Loewenstein & Thaler, 1989; Weber et al., 2007) suggests that intertemporal choice is not well described by either exponential or hyperbolic discounted-utility models.

Heuristics provide an alternative approach to understanding intertemporal choice behavior. Heuristics are shortcuts that afford simpler, if not optimal, solutions to a problem. In a model of decision making that we call the *intertemporal choice heuristic* (ITCH) model, decisions are made by using simple arithmetic heuristics to compare earlier and later options. This approach is consistent with a general preference for earlier rewards, without making any assumptions about the existence of an underlying discount function. In this respect, it is closely related to two other heuristic models of decision making in intertemporal choice—the difference-ratio-interest-finance-time (DRIFT) model of Read, Frederick, and Scholten (2013) and the trade-off model of Scholten and Read (2010). The ITCH model is motivated by a large literature concerning the use of heuristics in decision making, including work on attribute-based models of choice (Payne, Bettman, & Johnson, 1988; Tversky, 1972) and proportional thinking (Bordalo, Gennaioli, & Shleifer, 2012; Tversky & Kahneman, 1981). In the experiment reported here, we compared heuristic models and models that assume systematic discounting.

We aimed to show that the functional form of the ITCH model can account for a number of the anomalies reported in the literature concerning human performance in MEL tasks. In the ITCH model, decisions depend on the sum of absolute and relative percentage differences of the attributes of reward—specifically, the absolute and relative differences in money and in time. By considering both absolute and relative comparisons, the ITCH model can account for patterns of decision making that have been a challenge to explain in terms of utility and discount functions.

To make rigorous comparisons between different models used to interpret behavior in MEL experiments, we needed to collect data on MEL choices in a variety of framing conditions and use these data to conduct model comparisons. Unlike methods used in earlier studies, our use of out-of-sample evaluation methods to conduct model comparisons provided an unbiased estimate of the extent to which different models fit the empirical data collected in typical MEL tasks. To this end, we used cross-validation techniques that are now widely used for model comparison in contemporary statistics and machine learning (Arlot & Celisse, 2010; Kohavi, 1995). By conducting a quantitative, out-of-sample comparison of the fit of heuristic and discounting models to empirical data, we hoped to determine whether heuristic models are significantly better at accounting for people's intertemporal choice behavior than standard discounting models are.

ITCH Model

As suggested earlier, the ITCH model is based on psychological principles rather than economic theory. In particular, it is inspired by a large body of research in judgment and decision making that provides support for attribute-based models of choice. In attribute-based models, a decision maker weighs several distinct reasons for and against making a decision. For example, Lichtenstein and Slovic's (1971) seminal study of risky choice found that the relevant weight placed on certain attributes reliably shifts when participants make binary choices compared with when they estimate the monetary value of a gamble. Likewise, Shafir, Simonson, and Tversky (1993) described decision making in terms of reasons for and against a decision that can be used as retrospective justifications for the decision.

The ITCH model assumes that decision makers compare the two options in a typical MEL task in terms of reasons that favor choosing one or the other option. These heuristic comparisons generate a vector of arguments for and against selecting the earlier or later option. Participants construct a weighted combination of these comparisons that determines their probability of choosing each of the two options in a MEL task.

The specific heuristics used in the ITCH model involve the simplest arithmetic comparisons that can be made between the two options (e.g., subtracting one from the other, dividing one by the other) along each of the two relevant dimensions (i.e., money value and time of delivery). The application of each heuristic to a particular pair of options generates a vector of four features for that choice (i.e., the results of each simple arithmetic computation), each of which favors one option or the other. The model assumes that the final decision is made on the basis of a weighted sum of these four features. The weights can be interpreted as reflecting the attentional focus or importance (or both) placed on each heuristic comparison. The model is consistent both with individuals using all four heuristics and attaching different weights to them or as an approximation of a model in which each individual relies on only a single heuristic or subset of heuristics. The heuristics that are used are chosen probabilistically (across tasks or individuals).

In the experiment reported here, we aimed to show that the ITCH model would provide a good fit to data from five different variants of a MEL task. The pattern of weights it assigned to the heuristics was broadly consistent across participants and task variants, which suggests that people use a stable combination of heuristics when evaluating MEL questions, irrespective of manipulations of content and context. In addition, the differences in relative weights assigned to different heuristics across task variants offers additional insights into the decision-making process, because these weights provide a mechanism for quantifying the differential importance assigned to different heuristics in different framing contexts.

The heuristics of the ITCH model implement four basic psychological principles: (a) each option is compared to a reference point (Kahneman & Tversky, 1979); (b) comparisons are performed in both absolute terms (by subtraction) and relative terms (by division; Thurstone, 1927); (c) comparisons are performed independently along the monetary and time dimensions (Lichtenstein & Slovic, 1971); and (d) the results of these comparisons are then aggregated linearly using a set of decision weights (Busemeyer & Townsend, 1993). In our model, we apply these principles to intertemporal choice, but they could also be applied to develop heuristic choice models in other domains; for example, see the heuristic model of risky choice in Mellers, Weber, Ordóñez, and Cooke (1995).

Mathematical Specification of the ITCH Model

We formalize the ITCH model (for binary choices) as follows. The ITCH model treats the dimensions of time and money symmetrically. Each of the two options is written in the form (x, t), where x is the option's monetary value and t is the time the money would be received. The probability of choosing the larger, later option, denoted $P(LL)$, in a choice between a smaller, earlier amount of money, (x_1, t_1), and a larger, later amount of money, (x_2, t_2), is expressed as

$$P\left(LL\right) = L\left(\begin{array}{l}\beta_I + \beta_{xA}\left(x_2 - x_1\right) + \beta_{xR}\dfrac{x_2 - x_1}{x^*} \\ + \beta_{tA}\left(t_2 - t_1\right) + \beta_{tR}\dfrac{t_2 - t_1}{t^*}\end{array}\right),$$

where β_I is the intercept term, R means "relative," A means "absolute," and (x^*, t^*) represents a reference point that is the arithmetic average of the two options along each dimension: $x^* = (x_1 + x_2)/2$, $t^* = (t_1 + t_2)/2$. In this equation, L is the cumulative distribution function of a logistic distribution with a mean of 0 and a variance of 1. Thus, each term of the model represents either an absolute or proportional arithmetic operation that compares the options along a particular dimension (money value and time). Each term is multiplied by a parameter, β, that represents the weight given to each heuristic in making the decision between the two choices. The weighted sum of the outcomes predicted by each heuristic then determines the probability of choosing one option or the other. This model can be fit to data from different versions of a MEL task to estimate and compare the parameters across conditions (see the Supplemental Material available online).

The ITCH model can explain the two most robust and widely observed phenomena in MEL tasks—decreasing impatience and the absolute-magnitude effect—in terms of a single, consistent set of heuristics: the simultaneous consideration of absolute and relative differences between the two options. For example, when the weight on relative time β_{tR} is negative (as in our fitted estimates), the ITCH model predicts that the probability of choosing the larger, later amount will increase as both options are delayed by an additional identical amount of time—e.g., by adding a front-end delay to both options. Such decreasing impatience (Prelec, 2004) has often been interpreted as evidence of hyperbolic discounting (Ainslie, 1975). According to the ITCH model, this is a natural consequence of including both relative and absolute differences in time: The relative difference between the timing of the two goods decreases as the earliest available option moves into the future—even as the absolute difference is held fixed.

Consider the following concrete example. If the participant uses weights (0.0, 0.1, 0.1, −0.1, −0.1) and selects between \$10 today and \$20 tomorrow, then the probability of choosing the later option is

$$P\left(LL\right)=L\begin{pmatrix}0+0.1\left(20-10\right)+0.1\dfrac{20-10}{(20+10)/2}\\-0.1\left(1-0\right)-0.1\dfrac{1-0}{(1+0)/2}\end{pmatrix}=.68.$$

In contrast, if the participant selects between \$10 in 10 days and \$20 in 11 days, only the relative time term changes. The probability of choosing the later option increases to

$$P\left(LL\right)=L\begin{pmatrix}0+0.1\left(20-10\right)+0.1\dfrac{20-10}{(20+10)/2}\\-0.1\left(11-10\right)-0.1\dfrac{11-10}{(11+10)/2}\end{pmatrix}=.72.$$

ITCH also predicts that when the weight on the monetary-difference term β_{xA} is positive, multiplicatively scaling up the magnitude of the monetary amounts will make participants more likely to take the later option. This prediction, often referred to as the *absolute-magnitude effect*, has been confirmed in virtually all MEL tasks that have tested it (Loewenstein & Prelec, 1992). Using the same weights as before, (0.0, 0.1, 0.1, −0.1, −0.1), consider what happens when the stakes are scaled up by a factor of 10. The probability of choosing the later option when choosing between \$10 today and \$20 tomorrow is still 0.68. However, when choosing between \$100 today and \$200 tomorrow, only the absolute monetary-difference term changes. The probability of choosing the later option will be

$$P\left(LL\right)=L\begin{pmatrix}0+0.1\left(200-100\right)+0.1\dfrac{200-100}{(200+100)/2}\\-0.1\left(1-0\right)-0.1\dfrac{1-0}{(1+0)/2}\end{pmatrix}=.99.$$

The magnitude effect can also be generated by a concave value function for rewards (e.g., as in the trade-off model). In general, a model in which decisions are made on the basis of a combination of absolute and relative comparisons mimics the effects otherwise attributed to psychophysical curvature or diminishing marginal utility.

Moreover, by letting the intercept term β_I vary across different framing conditions, the ITCH model can also capture a large number of anomalies that can be conceptualized as presenting the same information in different frames (e.g., β_I might be higher in a task that presents time-dated payments in terms of dates rather than delays). Finally, ITCH is an example of a heuristic model that produces nonadditive discounting behavior; that is, total discounting over an interval depends on whether it is presented as one long interval or subdivided into separate intervals (for an extended discussion of a similar model, see Scholten & Read, 2010).

The ITCH model is similar to other heuristic models of MEL behavior, including both Scholten and Read's (2010) trade-off model and Read et al. (2013)'s DRIFT model. Unlike systematic discounting models, these models do not produce a discounted utility value by multiplying a discount function and utility function. Instead, like ITCH, they explain choice in terms of the sum of different factors, and this includes allowing the effects of money and time to be additively separable. However, these models differ in a few potentially important ways. ITCH includes absolute and percentage comparisons for time delay, whereas DRIFT includes only an absolute comparison. The model fits we present later suggest that the percentage comparison for time delay is statistically significant. DRIFT includes an interest-rate term and a term that captures whether the decision is framed as consumption or as investment. The trade-off model assumes concave functional forms for perceived time delay and perceived reward magnitude, which are used to account for diminishing sensitivity. In contrast, ITCH relies exclusively on simple arithmetic comparisons, which are symmetrically applied to both money and time. Our results indicate that ITCH provided a slightly better fit to the data than the alternative heuristic models. However, what is most significant—in both a statistical and a conceptual sense—is that all three heuristic models provided a substantially better fit than the current standard economic models of intertemporal decision making, which suggests that further work developing and refining heuristic models of intertemporal choice would be fruitful.

Model Comparisons Across Five Conditions

We conducted an experiment with five closely related conditions to compare the three heuristic models with three standard economic models—the exponential, hyperbolic, and quasihyperbolic models of discounting (Ainslie, 1975; Laibson, 1997; Samuelson, 1937). One thousand participants were recruited from Amazon.com's Mechanical Turk (http://www.mturk.com) online labor market. These participants were randomly assigned to one of five task variants. Each condition involved a MEL task that differed in money value (absolute or relative) and the framing of the two time-dated options (delay or speedup):

- Absolute money value, delay framing (e.g., \$5 today vs. \$5 plus an additional \$5 in 4 weeks)
- Relative money value, delay framing (e.g., \$5 today vs. \$5 plus an additional 100% in 4 weeks)
- Standard MEL format (e.g., \$5 today vs. \$10 in 4 weeks)

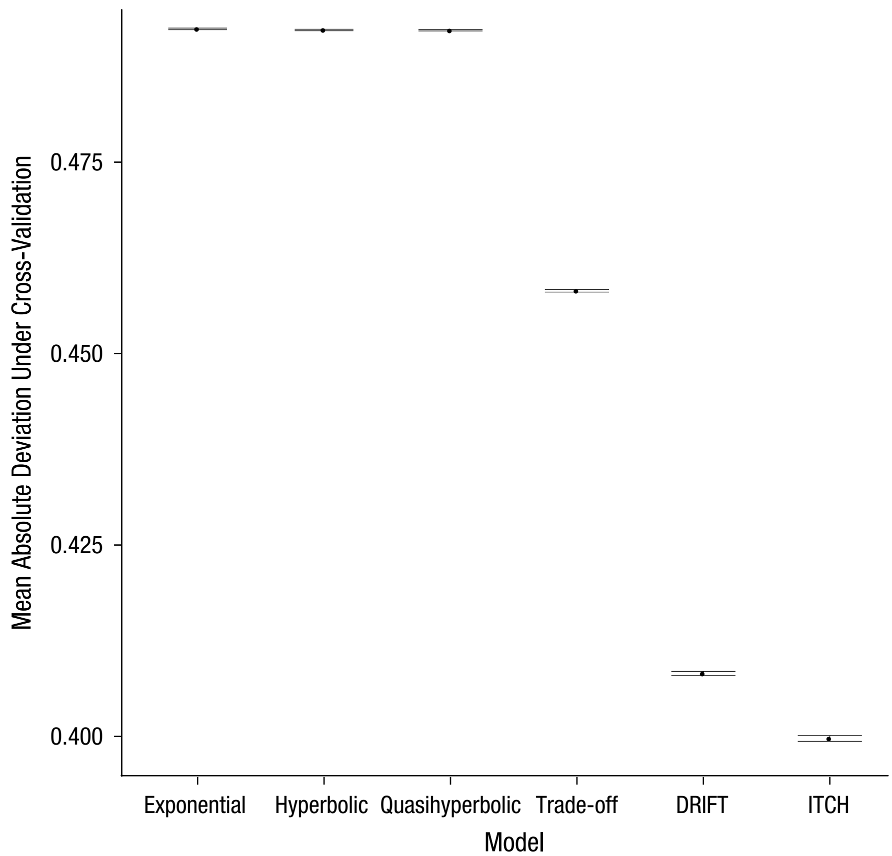

Fig. 1. The predictive accuracy of the standard and heuristic models of intertemporal choice for pooled data from all five conditions. Mean absolute deviation, a measure of error, is presented for each model. The error bars correspond to a 95% confidence interval that reflects the variability of the model-comparison results under cross-validation. DRIFT = difference-ratio-interest-finance-time; ITCH = intertemporal choice heuristic.

- Absolute money value, speedup framing (e.g., $10 in 4 weeks vs. $10 minus $5 today)
- Relative money value, speedup framing (e.g., $10 in 4 weeks vs. $10 minus 50% today)

The use of conditions framing the choices as involving delay or speedup parallels the order manipulations used in the studies by Weber et al. (2007). Participants were assigned to one framing condition. They then answered 25 randomly generated MEL questions designed to span a large range of money amounts and delays (for more information, see the Supplemental Material available online).

To compare models, we used a cross-validation approach in which each model was fit to one subset of our data and then tested on another subset of data. To generate many training data sets and test data sets, we randomly subsampled 75% of the data as a training data set and 25% as a test data set; we repeated this subsampling procedure 100 times. Cross-validation provides an unbiased method for comparing the predictive power of models with different numbers of parameters, which is necessary in our case because all of the heuristic models have more parameters than some of the discounting models with which they were compared (Kohavi, 1995). Cross-validation is a type of out-of-sample analysis. In contrast, standard measures of model fit applied within a sample (e.g., the calculation of R^2 values) do not provide reliable indicators of the generalizability of fitted models.

In all five conditions, the three heuristic models (ITCH, DRIFT, and trade-off) outperformed all of the standard delay-discounted utility models of intertemporal choice in predicting participants' choices. The specification for each model is listed in the Supplemental Material. Within the heuristic class, the ITCH model outperformed the trade-off and DRIFT models. We fit the model to the training data and tested it on the testing data for that condition. In Table S1 in the Supplemental Material, results are presented separately for each experimental condition. (Note that estimating parameter separately by condition thus lets model parameters vary by condition, capturing generalizations of each model that would let parameters differ between delay and speedup and between absolute and relative frames.)

Because relative model performance was similar across conditions, in Figure 1 we present a pooled

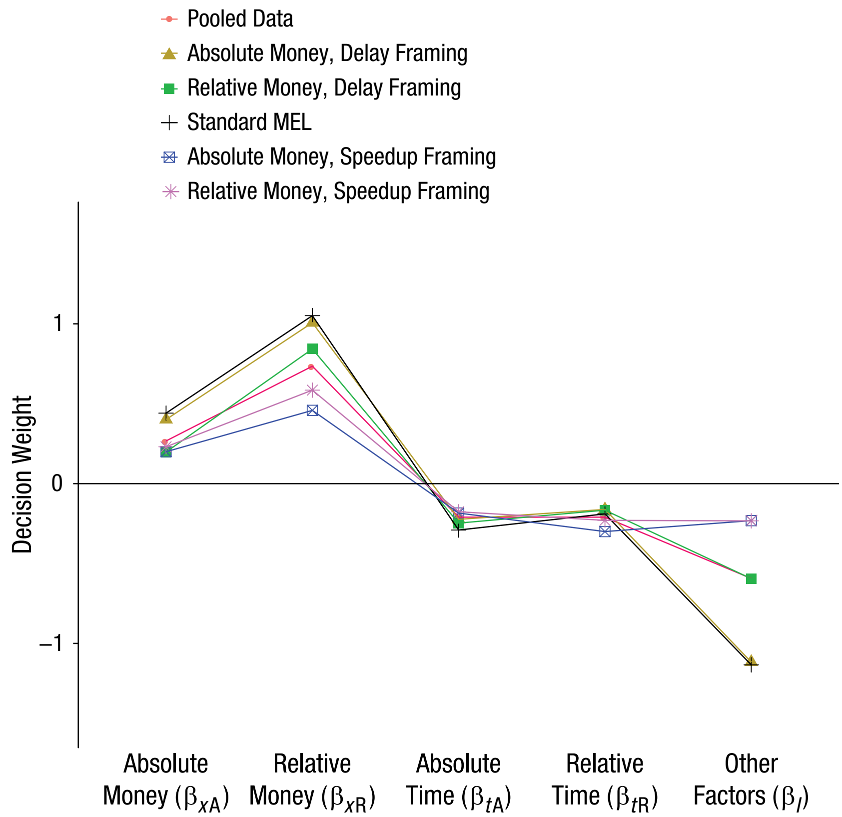

Fig. 2. Decision weights for the money-earlier-or-later (MEL) tasks. Six sets of decision weights are shown: one for each experimental condition, plus a sixth set estimated using the pooled data from all conditions. To make decision weights more readily comparable, we *z*-scored all inputs.

analysis of model performance. In this analysis, for each cross-validation subsample, we estimated one set of model parameters on the training data pooled from all five experimental conditions and then assessed the fit on the pooled testing data.

For the ITCH model, we found that the β decision weights for the four component heuristics were relatively stable across experimental conditions. Figure 2 plots six sets of decision weights: the weights when estimated separately in the five conditions, plus a set of weights estimated from the pooled data across all conditions (for raw numbers, see Table S3 in the Supplemental Material). Absolute time and relative time were weighted similarly, but relative money received much higher weight than absolute money; we speculate that this was due to the much wider range of money reward amounts available compared with the time delays available.

Although the magnitude of the parameters varied across fits, the pattern of decision-weight β parameters was stable across framing conditions. We tested the consistency of decision weights by computing the pairwise correlations between decision weights across the six data sets and comparing these correlations against the null hypothesis of no correlation, $t(35) = 125.977$, $p < 10^{-14}$.

The estimates imply that participants assigned a qualitatively similar pattern of relative weights to the heuristics represented by each term of the ITCH model, irrespective of manipulations of task content or context. Moreover, variations in parameter estimates across conditions capture variations between the comparisons made salient by each of the tasks. The ratios of the relative-to-absolute comparison coefficients are higher in the conditions that emphasize relative differences of money than in conditions that emphasize absolute differences in money. Because our frames always presented time delays in absolute, not relative, terms, we expected to see less variation in the coefficients for relative time. Finally, the variation in the intercept term β_I also captures differences between conditions in generalized impatience.

Discussion

To understand the anomalous decision-making behavior observed in MEL experiments, we developed an alternative account of behavior in MEL tasks—the ITCH model—that was based on basic psychological principles, including reference points and simple arithmetic comparisons. The results of our model comparisons show that both this model and the other two heuristic models provide substantially better fits to choices in MEL tasks than standard economic models of intertemporal choice that rely on a discount function.

The fit of the ITCH model demonstrated that the relative weights assigned to each of the heuristics in the model were stable across individuals and a range of conditions. Moreover, the variations in the weights across framings were themselves interpretable in terms of the relative salience of different comparisons suggested by question framing. Thus, although participants' decision-making behavior in MEL tasks may not be meaningfully described by a discount function, our findings suggest that decision making in MEL tasks nevertheless exhibits a form of psychological stability that may generalize to other tasks.

In summary, our findings raise two important points. The ability of heuristic models to predict behavior in MEL tasks suggests that for these tasks, as for many other decision-making tasks, people may apply simple heuristics to generate a response that is sufficient for their purposes rather than use a decision process that mirrors conventional economic models. The ITCH model and related models show that a weighted combination of simple heuristics can model time-money trade-offs in MEL tasks well. Future research should evaluate the usefulness of this approach for other types of intertemporal choices besides MEL, as well as for decision-making tasks in other domains (e.g., risky choice).

Author Contributions

K. M. M. Ericson, J. M. White, D. Laibson, and J. D. Cohen developed the intertemporal choice heuristic model and designed the experiment described in the article. K. M. M. Ericson and J. M. White analyzed the data. K. M. M. Ericson, J. M. White, D. Laibson, and J. D. Cohen wrote the article.

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The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Open Practices

All data have been made publicly available via Open Science Framework and can be accessed at https://osf.io/9uxve/. The complete Open Practices Disclosure for this article can be found at http://pss.sagepub.com/content/by/supplemental-data. This article has received the badge for Open Data. More information about the Open Practices badges can be found at https://osf.io/tvyxz/wiki/view/ and http://pss.sagepub.com/content/25/1/3.full.

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