Supplement to

Estimating Time Preferences from Budget Set Choices Using Optimal Adaptive Design

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Contents

A Studies Using Convex Time Budget Design

The following table lists of studies using Convex Time Budget design. As a first step, we used Web of Science and Google Scholar to identify all articles that cited Andreoni and Sprenger (2012a). This produced a list of about 400 papers which were then narrowed down to 30, including 16 published articles. In the next step, we used Google Scholar and the Social Science Research Network (SSRN) to search for keywords "convex time budget," which returned a list of about 140 papers but all the relevant papers within that set had already covered in the first step. [1]

The column *# budgets* indicates the total number of questions each subject completed during the study, and the column *# points* indicates the number of feasible options on each budget. The column *Set* $\mathcal{Q}$ is Fixed if all subjects in the study faced the same set of questions (order can be randomized across subjects) and Random if the set of questions was independently and randomly generated for each subject in the study. The column *Budget line* indicates whether the experimental interface presented two-dimensional budget lines.

[1] We performed our initial data collection in January 2016.

Table A.1: Experiments with CTB design.

Study	Location	Object	# budgets	# points	Set $\mathcal{Q}$	Budget lines	Interface
Alan and Ertac (2015)	Classroom (Turkey)	Gifts	4	6	Fixed	Yes	Physical
Alan and Ertac (forthcoming)	Classroom (Turkey)	Gifts	4	6	Fixed	Yes	Physical
Andreoni and Sprenger (2012a)	Laboratory (US)	Money	45	101	Fixed	No	Input box
Andreoni and Sprenger (2012b)	Laboratory (US)	Money	84	101	Fixed	No	Paper and pencil
Andreoni et al. (2015)	Laboratory (US)	Money	24	6	Fixed	No	Paper and pencil
Angerer et al. (2015)	Classroom (Italy)	Gifts	1	6	Fixed	No	Paper and pencil
Ashton (2015)	Laboratory (US)	Money	55	101	Fixed	No	Slider
Augenblick et al. (2015) [main]	Laboratory (US)	Money	20	NA	Fixed	No	Slider
Augenblick et al. (2015) [main]	Laboratory (US)	Effort	20	NA	Fixed	No	Slider
Augenblick et al. (2015) [replication]	Laboratory (US)	Money	18	NA	Fixed	No	Slider
Augenblick et al. (2015) [replication]	Laboratory (US)	Effort	18	NA	Fixed	No	Slider
Balakrishnan et al. (2015)	Laboratory (Kenya)	Money	48	NA	Fixed	No	Slider
Barcellos and Carvalho (2014)	Survey (ALP)	Money	6	NA	Fixed	No	Input box
Blumenstock et al. (forthcoming)	Field (Afghanistan)	Money	10	3	Fixed	No	Paper and pencil
Bousquet (2016)	Laboratory (France)	Money	40	21	Fixed	No	Input box
Brocas et al. (2016)	Laboratory (US)	Money	45	11	Fixed	No	Paper and pencil
Bulte et al. (2016)	Field (Vietnam)	Money	20	NA	Fixed	No	Paper and pencil
Carvalho et al. (2016a)	Survey (ALP)	Money	12	NA	Fixed	No	Number entry
Carvalho et al. (2016b)	Field (Nepal)	Money	4	3	Fixed	No	Paper and Pencil
Cheung (2015)	Laboratory (Australia)	Money	84	101	Fixed	No	Paper and pencil
Choi et al. (2015) [lab]	Laboratory (US); Survey (CentER)	Money	50	NA	Random	Yes	Point and click
Clot and Stanton (2014)	Field (Uganda)	Money	10	3	Fixed	No	Paper and pencil
Clot et al. (2017)	Field (Uganda)	Money	15	3	Fixed	No	Paper and pencil
Giné et al. (2018)	Field (Malawi)	Money	10	21	Fixed	No	Physical
Hoel et al. (2016)	Laboratory (Ethiopia)	Money	6	6	Fixed	No	Physical
Janssens et al. (2017)	Field (Nigeria)	Money	10	11	Fixed	No	Paper and pencil
Kuhn et al. (2017)	Laboratory (France)	Money	45	17	Fixed	No	Input box
Lindner and Rose (2017)	Laboratory (Austria)	Money	24	6	Fixed	No	Radio button
Liu et al. (2014)	Laboratory (China/Taiwan)	Money	10	301	Fixed	No	Paper and pencil
Lührmann et al. (2018)	Classroom (Germany)	Money	21	4	Fixed	No	Paper and pencil
Miao and Zhong (2015)	Laboratory (Singapore)	Money	56	101	Fixed	No	Paper and pencil
Rong et al. (2016)	Laboratory (US)	Money	36	101	Fixed	No	Paper and pencil
Sawada and Kuroishi (2015)	Field (Japan/Philippines)	Money	24	5	Fixed	No	Paper and pencil
Shaw et al. (2014)	Laboratory (US)	Money	28 or 36	101	Fixed	No	Number entry
Slonim et al. (2013)	Classroom (Australia)	Money	6	6	Fixed	No	Paper and pencil
Stango et al. (2016)	Survey (ALP)	Money	24	101	Fixed	No	Number entry
Sun and Potters (2016)	Laboratory (Netherlands)	Money	35	NA	Fixed	No	Slider
Sutter et al. (2018)	Classroom (Italy)	Gifts	1	6	Fixed	No	Paper and pencil
Yang and Carlsson (2015)	Field (China)	Money	10	21	Fixed	No	Paper and pencil

B Background on the EC^2 Criterion

In this appendix, we provide a short theoretical background on the Equivalence Class Edge Cutting (EC^2) criterion proposed originally in Golovin et al. (2010).

In order to model Bayesian active learning with noisy observations, Golovin et al. (2010) introduced the *Equivalence Class Determination problem*, in which the set of hypotheses $\mathcal{H}$ is partitioned into ℓ *equivalence classes* $\mathcal{H}^1, \ldots, \mathcal{H}^\ell$ such that $\bigcup_{i=1}^{\ell} \mathcal{H}^i = \mathcal{H}$ and $\mathcal{H}^i \cap \mathcal{H}^j = \varnothing$ for all $i \neq j$. These equivalence classes essentially bin together all the predictions made by a particular hypothesis with the noise incorporated, called *noisy copies* of the hypothesis. Intuitively speaking, this is like simulating choices with noise and labeling it according to the data-generating hypothesis. It would therefore be easier to understand the rest of this section by looking at the set of hypothesis $\mathcal{H}$ not as the set of all combinations of parameters but as the set of all possible observations when we exhaustively ask questions in $\mathcal{Q}$, i.e., $\mathcal{H} = \mathcal{X}^{\mathcal{Q}}$ in this case. In order to avoid confusion, let h_n^i denote the n-th noisy copy in the i-th equivalence class $\mathcal{H}^i$ to which original hypothesis h_i belongs. In creating noisy copies of hypothesis h_i, we distribute $\Pr[h_i]$ uniformly over $\mathcal{H}^i$.

The objective of learning is to identify in which class $\mathcal{H}^i$ the true hypothesis lies in (rather than to identify what the true hypothesis is). Let

$$\mathcal{E} = \bigcup_{1 \leq i < j \leq \ell} \{\{h, h'\} : h \in \mathcal{H}^i, h' \in \mathcal{H}^j\} \tag{B.1}$$

denote the set of *edges* consisting of all pairs of hypotheses belonging to distinct classes. A question q asked under true hypothesis h *cuts* edges

$$\mathcal{E}_q(h) = \{\{h', h''\} : h'(q) \neq h(q) \text{ or } h''(q) \neq h(q)\}, \tag{B.2}$$

where $h(q), h''(q), h''(q) \in \mathcal{X}$ are shorthand representations of (noisy) responses to question q by hypotheses h, h', h''. Now a weight function $w : \mathcal{E} \to \mathbf{R}_+$ by $w(\{h, h'\}) = \Pr[h] \cdot \Pr[h']$ for any $\{h, h'\} \in \mathcal{E}$. With slight abuse of notation, the weight function is extended to sets of edges $\mathcal{E}' \subseteq \mathcal{E}$ by $w(\mathcal{E}') = \sum_{\{h,h'\} \in \mathcal{E}'} w(\{h, h'\})$. Now, a function ϕ on the pair of questions asked up to round r and true hypothesis, $(\boldsymbol{q}_r, h)$, is defined as the weight of the edges cut

$$\phi(\boldsymbol{q}_r, h) = w\left(\bigcup_{q \in \{q_1, \ldots, q_r\}} \mathcal{E}_q(h)\right) \tag{B.3}$$

and the EC^2 informational value is defined as the expected reduction in weight of the edges cut

$$\Delta^*_{\mathrm{EC}^2}(q|\boldsymbol{x}_r) = \mathbf{E}_{\mu_r(\cdot|\boldsymbol{x}_r)}[\phi((\boldsymbol{q}_r, q), h) - \phi(\boldsymbol{q}_r, h)]. \tag{B.4}$$

Golovin et al. (2010) proved that the EC^2 informational value function $\Delta^*_{\mathrm{EC}^2}$ is *strongly adaptively monotone* and *adaptively submodular* (Golovin and Krause, 2010, 2011; Krause and Golovin, 2014). The first property, strong adaptive monotonicity, says that $\phi((\boldsymbol{q}_r, q), h) \geq \phi(\boldsymbol{q}_r, h)$ holds (i.e., "adding new information never hurts"). The second property, adaptive submodularity, says that $\Delta^*_{\mathrm{EC}^2}(q|\boldsymbol{x}_{r'}) \geq \Delta^*_{\mathrm{EC}^2}(q|\boldsymbol{x}_r)$, where $\boldsymbol{x}_{r'}$ is a subvector of $\boldsymbol{x}_r$, holds (i.e., "adding information earlier helps more"). Golovin and Krause (2011) proved that an adaptive question selection rule that myopically ("greedily," in their word) maximizes $\Delta^*_{\mathrm{EC}^2}$ could achieve near-optimal performance.

Since it can be challenging to keep track of the equivalence classes, Golovin et al. (2010) proposed an approximation of $\Delta^*_{\mathrm{EC}^2}$. Note that the weight between any two equivalence classes $\mathcal{H}^i$ and $\mathcal{H}^j$ is given by

$$w(\mathcal{E}_{ij}) = \sum_{h^i \in \mathcal{H}^i, h^j \in \mathcal{H}^j} \Pr[h^i] \cdot \Pr[h^j] = \sum_{h^i \in \mathcal{H}^i} \Pr[h^i] \sum_{h^j \in \mathcal{H}^j} \Pr[h^j] = \Pr[h_i] \cdot \Pr[h_j] \tag{B.5}$$

where $\mathcal{E}_{ij} = \{\{h_i, h_j\} : h \in \mathcal{H}^i, h \in \mathcal{H}^j\}$ is the set of edges connecting classes $\mathcal{H}^i$ and $\mathcal{H}^j$. The last equality follows since we distributed $\Pr[h_i]$ equally over all noisy copies in $\mathcal{H}^i$. The total weight is thus given by

$$\sum_{1 \leq i < j \leq \ell} w(\mathcal{E}_{ij}) = \left(\sum_{i=1}^{\ell} \Pr[h_i]\right)^2 - \sum_{i=1}^{\ell} \Pr[h_i]^2 = 1 - \sum_{i=1}^{\ell} \Pr[h_i]^2, \tag{B.6}$$

which in turn motivates the form of EC^2 informational value Δ_{EC^2} in equation (1).

C Implementation Details

The background computation engine (hereafter simply called engine) for our adaptive experiment design is written in Java (version 8). The engine first reads a configuration file which specifies: (i) parameters for the design space; (ii) model classes and parameter values in each class; (iii) a stopping criterion (maximum number of question or posterior threshold); and (iv) the algorithm for question selection (EC^2, fixed, or random). It then constructs the set $\mathcal{Q}$ of all possible questions (each of which consists of several options), prepares a prior belief μ_0, calculates utility value of each option in each question under each hypothesis $U_h(x)$, and calculates the probability of choosing each option in each question under each hypothesis $\Pr[X|h]$. Those components need to be assembled and stored in the memory only *once* at the beginning of the experiment. This part may take time depending on the sizes of $\mathcal{Q}$ and $\mathcal{H}$ as well as the computational power of the hardware running the engine itself. However, we avoided this issue and achieved a seamless experiment by running this part of the calculation in background while experimental subjects are reading the instructions.

The user interface (GUI) for experimental subjects is written in HTML, JavaScript (AngularJS), and CSS (Compass). The engine and the GUI are then communicated with PHP API—the GUI receives parameters for the question to be displayed from the engine, and returns subjects' responses to it. Sample screenshots for our time preference survey are presented in Appendix G.

For our simulation exercises and the online experiments, we set up on-demand instances on Amazon's Elastic Compute Cloud. [2] After experimenting with several types of instances we settle to use Linux operating system on `m3.2xlarge`, which has eight virtual central processing units (vCPUs), 30 GB memory, and 2×80 GB SSD storage. [3]

[2] This is also called "EC2" in the community. In order to distinguish it from our EC^2 algorithm, we make "Amazon" explicit and call it "Amazon EC2."

[3] Other instance types, such as `c3.2xlarge` and `c4.2xlarge`, also perform well.

D Prior for Quasi-Hyperbolic Discounting Parameters

We describe how we construct a data-driven prior for quasi-hyperbolic discounting model. We follow the econometric approaches proposed in Andreoni and Sprenger (2012a) and apply it to choice data from three experiments using CTB (Andreoni and Sprenger, 2012a; Andreoni et al., 2015; Augenblick et al., 2015).

Consider a quasi-hyperbolic discounting with a constant relative risk aversion (CRRA) utility function of the form (6):

$$U(c_t, c_{t+k}) = \frac{1}{\alpha}(c_t + \omega_1)^\alpha + \beta^{\mathbf{1}\{t=0\}}\delta^k \frac{1}{\alpha}(c_{t+k} + \omega_2)^\alpha,$$

where δ is the per-period discount factor, β is the present bias, α is the curvature parameter, and ω_1 and ω_2 are background consumption parameters. Maximizing (6) subject to an intertemporal budget constraint

$$(1+\rho)c_t + c_{t+k} = B,$$

where $1+\rho$ is the gross interest rate (over k days) and B is the budget, yields an intertemporal Euler equation

$$\frac{c_t + \omega_1}{c_{t+k} + \omega_2} = \left(\beta^{\mathbf{1}\{t=0\}}\delta^k(1+r)\right)^{\frac{1}{\alpha-1}}.$$

Andreoni and Sprenger (2012a) proposed two methods for estimating parameters (α, β, δ). The first one estimates the parameters in the log-linearized version of the Euler equation

$$\log\left(\frac{c_t + \omega_1}{c_{t+k} + \omega_2}\right) = \frac{\log\beta}{\alpha - 1} \cdot \mathbf{1}\{t=0\} + \frac{\log\delta}{\alpha-1} \cdot k + \frac{1}{\alpha-1} \cdot \log(1+r) \tag{D.1}$$

using two-limit Tobit regression in order to handle corner solutions under an additive error structure. The second one estimates the parameters in the optimal demand for sooner consumption

$$\begin{aligned} c_t^* = &\left(\frac{1}{1 + (1+r)(\beta^{\mathbf{1}\{t=0\}}\delta^k(1+r))^{1/(\alpha-1)}}\right)\omega_1 \\ &+ \left(\frac{(\beta^{\mathbf{1}\{t=0\}}\delta^k(1+r))^{1/(\alpha-1)}}{1 + (1+r)(\beta^{\mathbf{1}\{t=0\}}\delta^k(1+r))^{1/(\alpha-1)}}\right)(B + \omega_2) \end{aligned} \tag{D.2}$$

using Nonlinear Least Squares (NLS). In either case, parameters (α, β, δ) are recovered via nonlinear combination of estimated coefficients.

We take choice datasets from three recent experiments using CTB, Andreoni and Sprenger (2012a), Andreoni et al. (2015), and Augenblick et al. (2015), and estimate parameters (α, β, δ) for

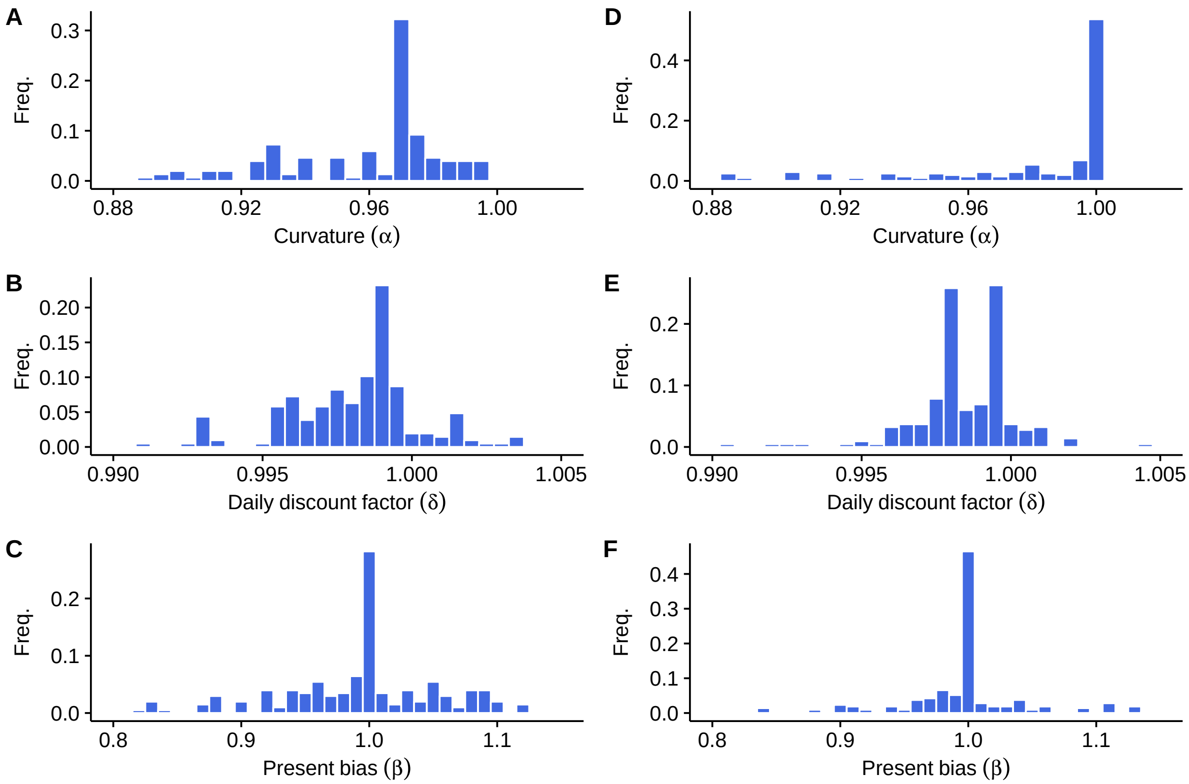

FIGURE D.1: Distributions of estimated parameters (α, β, δ) from Tobit regression (panels A-C in the left column) and NLS (panels D-F in the right column).

each individual subject. [4] We prepare two sets of estimates: the first one uses two-limit Tobit regression and sets background consumption levels at $(\omega_1, \omega_2) = (\$5, \$5)$, and the second one uses NLS approach assuming no background consumption. [5]

Figure D.1 shows histograms of estimated parameters from two estimation methods (Tobit for panels A to C and NLS for panels D to F), pooling three dataset together. The x-axes are trimmed to reduce the visual effects of outliers while covering at least 70% of the data points. NLS estimates suggest preferences that are closer to linear consumption utility and no present bias compared to those implied by Tobit estimates.

The summary statistics of estimated parameters in Table D.1 clearly reveal that estimates (α in particular) have outliers. Therefore, we apply Tukey's (1977) boxplot approach to detect and

[4] Augenblick et al. (2015) assume no heterogeneity in utility curvature α in their individual-level parameter estimation.

[5] The assumption of $(\omega_1, \omega_2) = (\$5, \$5)$ has been used in Augenblick et al. (2015). In all of the three experiments, there were minimum payments of \$5 at each payment date.

Table D.1: Quantiles of estimated parameters (before removing outliers).

Parameter	Method	N	Min	Percentile									Max
				10%	20%	30%	40%	50%	60%	70%	80%	90%	
Curvature (α)	Tobit	232	-14641.04	0.2892	0.7825	0.8540	0.9097	0.9372	0.9620	0.9713	0.9713	0.9793	3966.00
Discount factor (δ)	Tobit	232	0.9323	0.9934	0.9961	0.9970	0.9979	0.9986	0.9991	0.9991	0.9997	1.0017	1.2641
Present bias (β)	Tobit	232	0.0350	0.8838	0.9463	0.9746	0.9991	1.0000	1.0000	1.0327	1.0650	1.1191	268.513
Curvature (α)	NLS	230	-859.077	0.8406	0.9225	0.9603	0.9803	0.9957	0.9983	0.9983	0.9993	0.9994	0.9999
Discount factor (δ)	NLS	230	0.8883	0.9962	0.9974	0.9982	0.9982	0.9984	0.9991	0.9996	0.9997	1.0003	1.2334
Present bias (β)	NLS	230	0.0000	0.9039	0.9649	0.9843	0.9999	1.0008	1.0032	1.0041	1.0100	1.0661	1.5951

Table D.2: Quantiles of estimated parameters (after removing outliers).

Parameter	Method	N	Min	Percentile									Max
				10%	20%	30%	40%	50%	60%	70%	80%	90%	
Curvature (α)	Tobit	194	0.6644	0.8049	0.8706	0.9145	0.9326	0.9593	0.9713	0.9713	0.9726	0.9817	0.9941
Discount factor (δ)	Tobit	202	0.9926	0.9957	0.9964	0.9973	0.9981	0.9986	0.9991	0.9991	0.9993	1.0003	1.0031
Present bias (β)	Tobit	199	0.8448	0.9231	0.9571	0.9769	1.0000	1.0000	1.0000	1.0141	1.0466	1.0780	1.1693
Curvature (α)	NLS	206	0.8756	0.9162	0.9537	0.9767	0.9926	0.9983	0.9983	0.9987	0.9993	0.9994	0.9999
Discount factor (δ)	NLS	207	0.995	0.9971	0.9977	0.9982	0.9982	0.9985	0.9991	0.9996	0.9997	1.0000	1.0019
Present bias (β)	NLS	170	0.9348	0.9695	0.9811	0.9986	0.9999	1.0008	1.0009	1.0041	1.0041	1.0100	1.0450

remove outliers. This approach makes no distributional assumptions nor does it depend depend on mean or standard deviation. Let Q_1 and Q_3 denote the first and third quartile, respectively. The difference between the third and first quartiles, $Q_3 - Q_1$, is called *inter-quartile range (IQR)*. Tukey (1977) defined *fences* as the boundaries of the interval

$$F = [Q_1 - 1.5 \cdot IQR, Q_3 + 1.5 \cdot IQR].$$

An observation is an *outlier* if it is outside the interval F. The summary statistics after removing outliers detected by this approach is shown in Table D.2 and the effects of this procedure are graphically represented (as changes in the shapes of boxplots) in Figure D.2. From this point forward, we focus only on estimates from Tobit regression since they cover wider range than those from NLS.

We now construct a data-driven prior over model parameters following and extending the approach taken in Wang et al. (2010).

- For α and δ, we first bin the estimates into five equiprobable bins. Let b_i, $i = 0, \ldots, 5$, denote the boundaries of those bins where b_0 is the minimum, b_5 is the maximum, and the rest correspond to quintiles of the distribution. We then take midpoints of those bins,

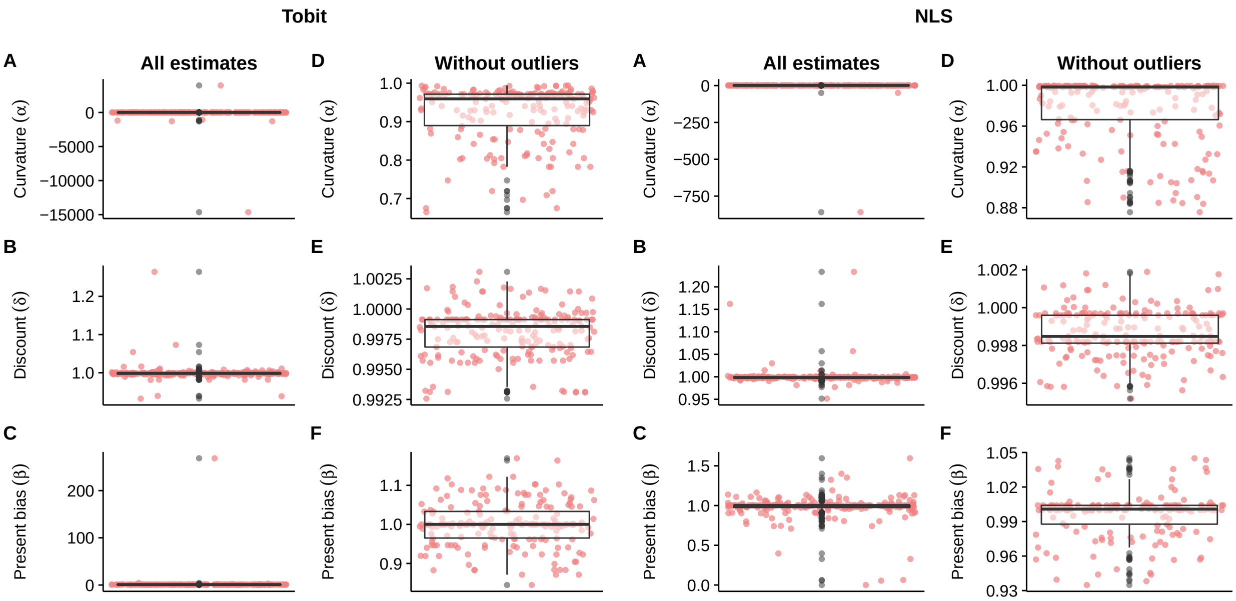

FIGURE D.2: Boxplots of parameters estimated with Tobit (left panels) and NLS (right panels). Panels A to C display all data-points while panels D to F remove outliers.

$(b_i + b_{i+1})/2$, $i = 0, \ldots, 4$, to use as discrete mass points and assign equal prior probability to each of them.

- For β, we construct a non-uniform prior to reflect the fact that the distribution of estimates has a huge mass at 1. We first bin the estimates into 10 equiprobable bins with boundaries b_i, $i = 0, \ldots, 10$ as before. We take seven midpoints β_j, $j = 1, \ldots, 7$, by:

$$\left\{ \frac{b_0 + b_1}{2}, \frac{b_1 + b_2}{2}, \frac{b_2 + b_4}{2}, \frac{b_4 + b_6}{2}, \frac{b_6 + b_8}{2}, \frac{b_8 + b_9}{2}, \frac{b_9 + b_{10}}{2} \right\}.$$

  By construction, the middle three mass points have 20% prior probability while the rest have 10% each.

This procedure yields parameter values shown in Table D.3. Assuming that three parameters are independently distributed, we obtain the prior $\mu_0(h)$ by the product of the Bayesian priors over the parameters. We call a collection of vectors $\mathbf{H} = (\mathbf{H}(\alpha), \mathbf{H}(\delta), \mathbf{H}(\beta))$ the *hypothesis space*. The set of hypotheses $\mathcal{H}$ is thus the all possible combinations of the numbers in the vectors $\mathbf{H}$ contains. We may use a notation $\mathcal{H}(\mathbf{H})$ to make the underlying hypothesis space explicit. There are 175 hypotheses under the hypothesis space presented in Table 2.

Table D.3: Data-driven prior—parameter values and their initial probabilities.

α	0.7675	0.9016	0.9519	0.9719	0.9833		
$\mu_0(\alpha)$	0.2	0.2	0.2	0.2	0.2		
δ	0.9945	0.9972	0.9986	0.9992	1.0012		
$\mu_0(\delta)$	0.2	0.2	0.2	0.2	0.2		
β	0.8839	0.9401	0.9786	1.0000	1.0233	1.0623	1.1237
$\mu_0(\beta)$	0.1	0.1	0.2	0.2	0.2	0.1	0.1

E Additional Figures

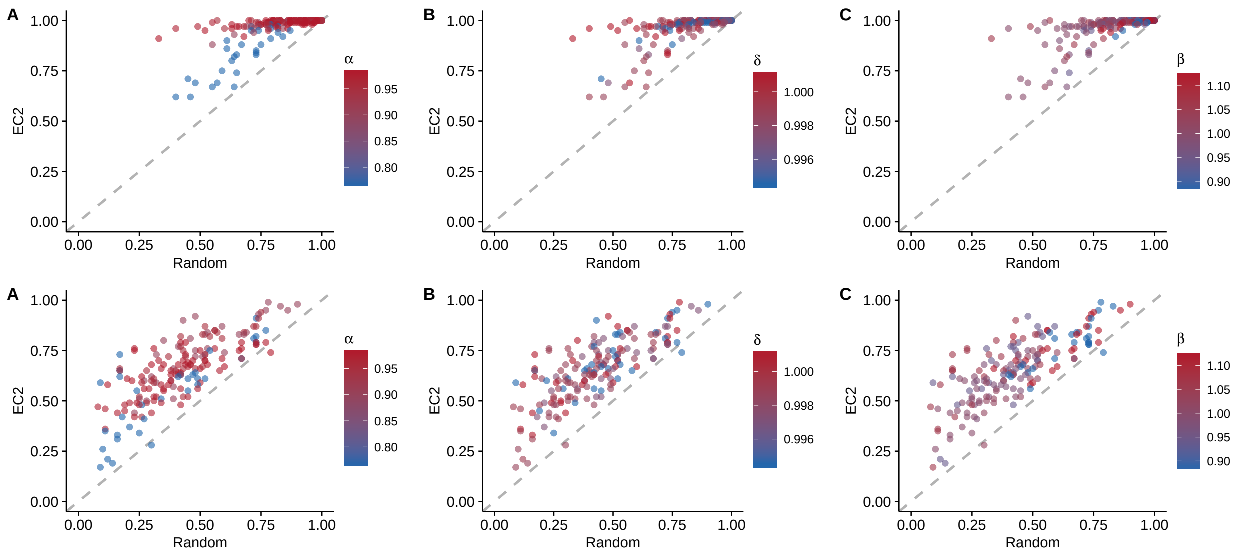

Figure E.1: "Hit rates" comparison between EC^2 and Random. The first row is from simulation with $\mathbf{H}_1$ and $\lambda = 0.04$, and the second row is with $\mathbf{H}_1$ and $\lambda = 0.18$. Each panel is color-coded by the parameter value.

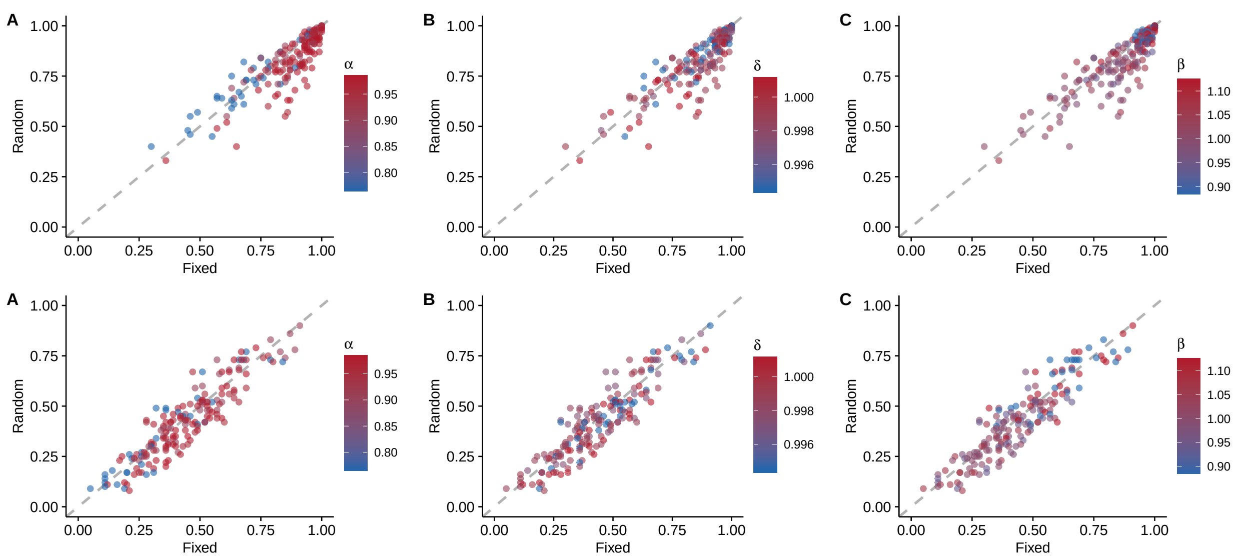

Figure E.2: "Hit rates" comparison between Fixed and Random. The first row is from simulation with $\mathbf{H}_1$ and $\lambda = 0.04$, and the second row is with $\mathbf{H}_1$ and $\lambda = 0.18$. Each panel is color-coded by the parameter value.

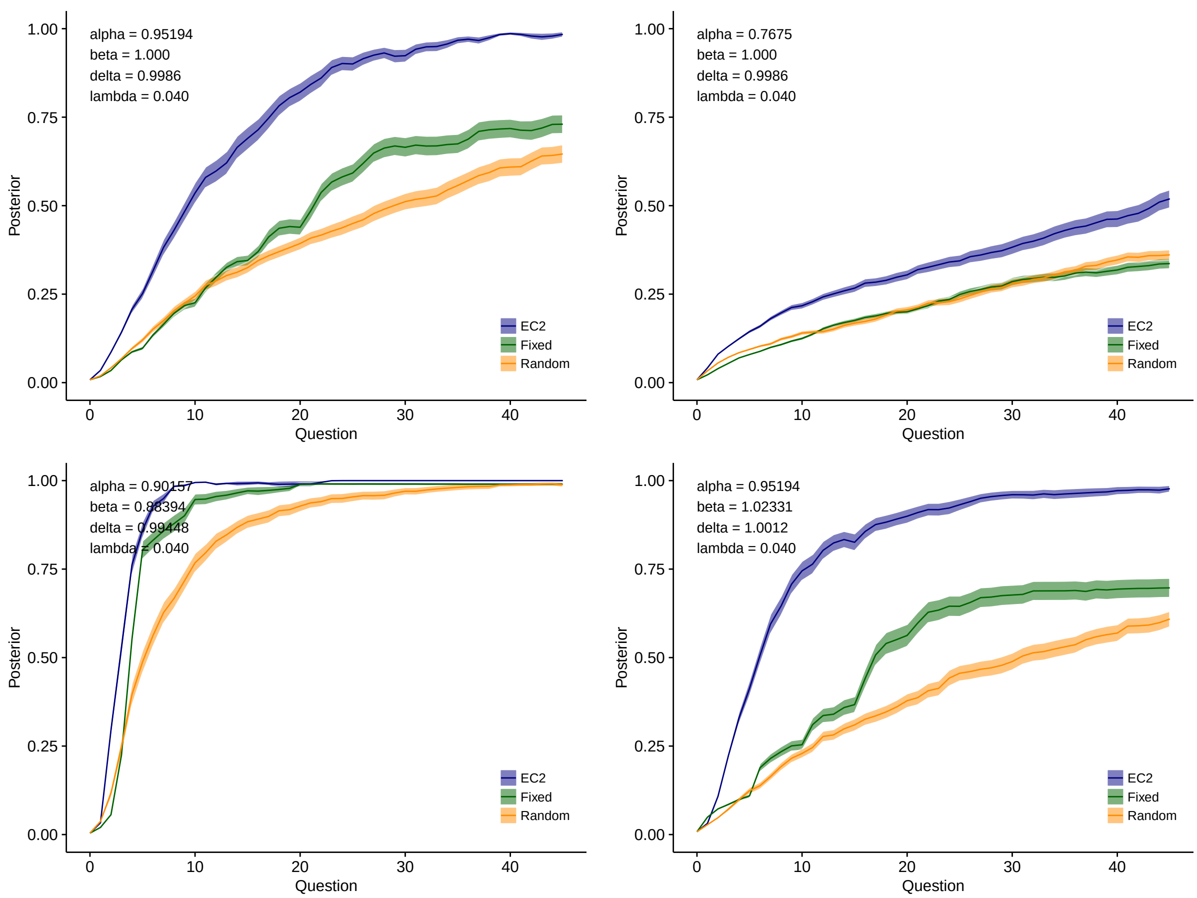

FIGURE E.3: Average posterior beliefs on true model $\bar{\mu}_r(h^0|h^9)$. Four different profiles of h^0 are examined.

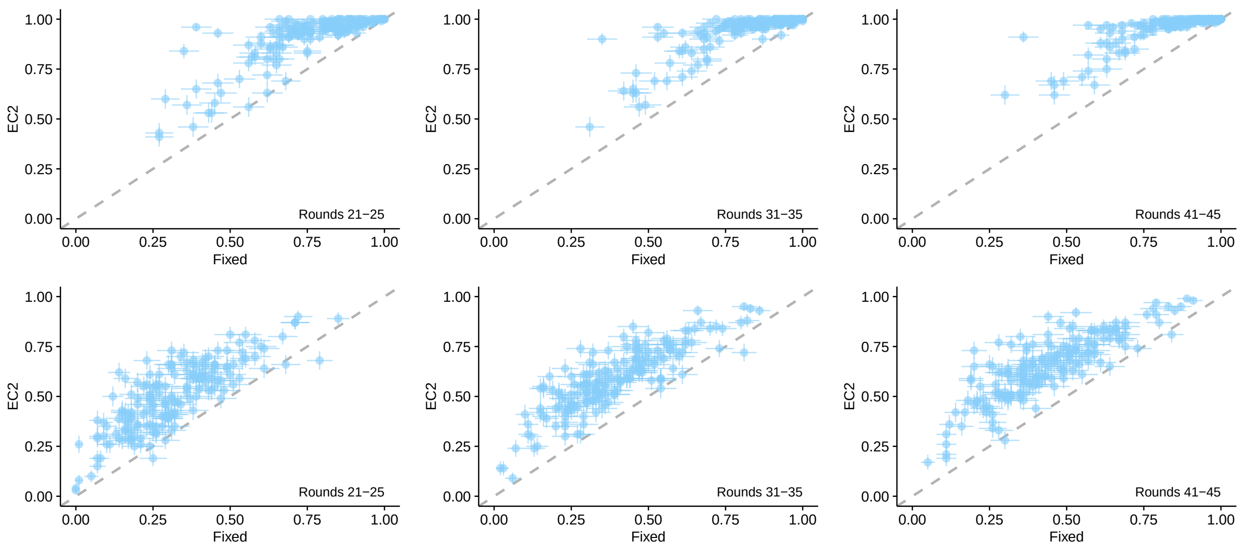

FIGURE E.4: "Hit rates" comparison between EC^2 and Fixed. The first row is from simulation with $\mathbf{H}_1$ and $\lambda = 0.04$, and the second row is with $\mathbf{H}_1$ and $\lambda = 0.18$.

F Order of Questions in Fixed Design

TABLE F.1: Order of questions for simulation.

#	t	k	a_t	a_{t+k}
1	0	21	0.18	0.18
2	0	21	0.17	0.18
3	0	21	0.16	0.18
4	0	21	0.15	0.18
5	0	21	0.14	0.18
6	0	35	0.18	0.18
7	0	35	0.17	0.18
8	0	35	0.16	0.18
9	0	35	0.15	0.18
10	0	35	0.14	0.18
11	0	42	0.18	0.18
12	0	42	0.17	0.18
13	0	42	0.16	0.18
14	0	42	0.15	0.18
15	0	42	0.14	0.18
16	7	21	0.18	0.18
17	7	21	0.17	0.18
18	7	21	0.16	0.18
19	7	21	0.15	0.18
20	7	21	0.14	0.18
21	7	35	0.18	0.18
22	7	35	0.17	0.18
23	7	35	0.16	0.18
24	7	35	0.15	0.18
25	7	35	0.14	0.18

#	t	k	a_t	a_{t+k}
26	7	42	0.18	0.18
27	7	42	0.17	0.18
28	7	42	0.16	0.18
29	7	42	0.15	0.18
30	7	42	0.14	0.18
31	28	21	0.18	0.18
32	28	21	0.17	0.18
33	28	21	0.16	0.18
34	28	21	0.15	0.18
35	28	21	0.14	0.18
36	28	35	0.18	0.18
37	28	35	0.17	0.18
38	28	35	0.16	0.18
39	28	35	0.15	0.18
40	28	35	0.14	0.18
41	28	42	0.18	0.18
42	28	42	0.17	0.18
43	28	42	0.16	0.18
44	28	42	0.15	0.18
45	28	42	0.14	0.18

Table F.2: Order of questions for AMT experiment.

#	t	k	a_t	a_{t+k}
1	0	14	1.03	1.03
2	0	14	1.03	1.06
3	0	14	1.03	1.09
4	0	14	1.03	1.12
5	0	21	1.03	1.03
6	0	21	1.03	1.06
7	0	21	1.03	1.09
8	0	21	1.03	1.12
9	0	35	1.03	1.03
10	0	35	1.03	1.06
11	0	35	1.03	1.09
12	0	35	1.03	1.12
13	14	14	1.03	1.03
14	14	14	1.03	1.06
15	14	14	1.03	1.09
16	14	14	1.03	1.12
17	14	21	1.03	1.03
18	14	21	1.03	1.06
19	14	21	1.03	1.09
20	14	21	1.03	1.12

G Survey Instructions and Interfaces

After AMT workers accept the HIT and click on the link to our study website, they first enter their AMT worker IDs. They then see instructions for the experiment. The blue texts represent variables which depend either on the parameters the experimenter sets (PARTICIPATION-FEE, TOKENVALUE, and ALLOCATION) or on the day subjects participated in the experiment (DATE)

— Page 1 —

Welcome!

In this survey, you will be asked 20 questions about choices over how to allocate money between two points in time, one time is "earlier" and one is "later." Both the earlier and later times may vary across questions. Please read the instructions in the following pages carefully.

Important: These questions are not designed to test you—there are no "correct" or "incorrect" answers.

Those questions are all hypothetical scenarios but are designed to study how you make decisions. The payment for completion of this HIT is $PARTICIPATION-FEE.

How It Works

Please imagine the following hypothetical scenario.

For each question:

- Divide 100 tokens between two payment dates.
- Two dates: "earlier payment" and "later payment", with potentially different payoffs per token.
- Pick favored allocation of tokens with slider.

As you will see, there is a trade-off between the sooner payment and the later payment. As the sooner payment goes down, the later payment goes up (and vice versa). Therefore, all you have to do in each question is to select which combination of sooner AND later payment you prefer the most by moving the slider to that location.
The sample question below is similar to the ones you will see today. This example shows:

- The choice to divide 100 tokens between the earlier payment on DATE1 and the later payment on DATE2.
- The calendar indicates today by a RED box, the earlier payment date by an ORANGE shade, and the later payment date by a BLUE shade.
- The table at the bottom of the screen indicates:
  - Each token allocated to DATE1 is worth $TOKENVALUE1.
  - Each token allocated to DATE2 is worth $TOKENVALUE2.
- If you were to allocate ALLOCATION1 tokens to DATE1 and ALLOCATION2 tokens to DATE2, you would receive $OUTCOME1 on DATE1 AND $OUTCOME2 on DATE2.

<Calendar and table are displayed here>

How to Use the Slider

Please imagine the following hypothetical scenario.

You can allocate 100 tokens between two payment dates using the slider. The table will be updated instantly once you move the slider, showing current allocations of tokens and their implied payment amounts.

The slider controls how many tokens you would like to allocate to the "early payment date." The allocation to the "later payment date" will be automatically calculated and displayed on the table.

- The initial location of the slider will be randomly selected in each question.
- You need to activate the slider by clicking on the pointer or anywhere on the line. After its color changes to darker green, you can move the slider.

To familiarize yourself with the interface, please move the slider and check how the table would respond.

<Calendar, table, and slider are displayed here>

— Page 4 —

Your Hypothetical Earnings

Please imagine the following hypothetical scenario.

After finishing all questions, the computer will randomly pick one of the questions you were asked about to determine your earnings. Your decision in the selected question determines the amount you will receive on the early date and the later date, which will be displayed on the screen.

Important: All questions are equally likely to be selected. This rule implies that it is in your best interest to treat each decision as if it could be the one that determines your earnings.

Your Actual Earnings
When you are finished, you will receive a Completion Code that you must enter in the box below to receive credit for participation. The payment for completion of the HIT is $PARTICIPATION-FEE.

Even though your decisions will not add to your final earnings, please take the problems presented seriously.

— Page 5 —

Important

- Payment dates may change between questions. Make sure to check the calendar and the table when a new question starts.
- The value of tokens for each date may change between questions. Make sure to check the table when a new question starts.
- Once you hit the PROCEED button, you cannot change your decision. You cannot go back to previous pages, either. Note also that you CANNOT change the question by refreshing the browser once it is displayed.
- The initial position of the slider will be randomly selected in each question.
- You can always read the instructions by clicking the “Need help?” button at the top-right corner of the browser.

Figure G.1: Sample screenshot of the interface.

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