Online Appendix: Not for Publication

A Replication and Reconciliation with Pre-Analysis Plan

In this section we report the methodology and corresponding analyses from earlier versions of this paper (https://papers.ssrn.com/sol3/papers.cfm?abstractid=3170670 and https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3589906) as specified in the pre-registration plan of our replication study (https://www.socialscienceregistry.org/trials/3124). The key difference is that while our approach in the present version of the paper relies on a mixed-logit methodology following a suggestion of an anonymous referee, our previous approach employed standard logit methods. All our previous results are closely in line with those obtained using the new methodology. Here we provide a summary of the central exercises conducted in prior versions of the manuscript. For the complete analysis please see https://papers.ssrn.com/sol3/papers.cfm?abstractid=3170670 and https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3589906.

A.1 Stage 1: Identifying Gain-Loss Attitudes

Our previous methodology relied on the same preference statements that we introduced in Section 4.1, but focused only on the liking preference statements. As noted in the main text, the liking data indicate both a substantial endowment effect and potential differences in utility across objects. We construct a simple structural model of the liking preference statement based upon standard random utility methods (McFadden, 1974) with the objective of capturing the source of both of these features: gain-loss attitudes and differences in intrinsic utility for the two objects.

Consider an individual endowed with X that is asked to provide ratings statements for both X and Y. Under the KR model, an individual evaluates their endowment, X, based upon $U(X, 0|X, 0)$. Given that the agent is endowed with X and is uninformed of the possibility of confiscation at the time of the ratings, they plausibly evaluate Y based upon $U(0, Y|X, 0)$. With standard logit shocks, ϵ_X and ϵ_Y, the parameters associated with these KR utilities are easily estimated. We assume subjects will provide a higher rating for their endowed object, X, if

$$U(X, 0|X, 0) + \epsilon_X > U(0, Y|X, 0) + \epsilon_Y + \delta,$$

where δ is a discernibility parameter which accounts for the fact that the goods may be given identical ratings (for use of such methods, see, e.g., Cantillo et al., 2010). Similarly, subjects provide a higher rating for the alternative object, Y, if

$$U(0, Y|X, 0) + \epsilon_Y > U(X, 0|X, 0) + \epsilon_X + \delta,$$

and provide the same rating if the difference in utilities falls within the range of discernibility,

$$|U(X, 0|X, 0) + \epsilon_X - (U(0, Y|X, 0) + \epsilon_Y)| \leq \delta.$$

Under the functional form assumptions of section 2 with $\eta = 1$, for someone endowed with object X, we obtain familiar logit probabilities for the ranking of ratings $R(X)$ and $R(Y)$,

$$\begin{aligned}
P(R(X) > R(Y)) &= \frac{\exp(U(X, 0|X, 0))}{\exp(U(X, 0|X, 0)) + \exp(U(0, Y|X, 0) + \delta)} = \frac{\exp(X)}{\exp(X) + \exp(2Y - \lambda X + \delta)} \\
P(R(Y) > R(X)) &= \frac{\exp(U(0, Y|X, 0))}{\exp(U(0, Y|X, 0)) + \exp(U(X, 0|X, 0) + \delta)} = \frac{\exp(2Y - \lambda X)}{\exp(X + \delta) + \exp(2Y - \lambda X)} \\
P(R(X) = R(Y)) &= 1 - P(R(X) > R(Y)) - P(R(Y) > R(X)),
\end{aligned}$$

where the intrinsic utility values, X and Y, the discernibility parameter δ, and the gain-loss parameter, λ, are the desired estimands.[27] We normalize one of the good's values to be $Y = 1$, and estimate the remaining parameters via maximum likelihood.

Table A1 provides aggregate estimates of intrinsic utilities, λ and δ, separately for each pair of goods in both the initial study and our replication. In each case we find aggregate support for loss aversion, $\lambda > 1$, though less pronounced in our replication study.

Table A1: **Prior Analysis: Aggregate Parameter Estimates**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Initial Study				*Replication Study*			
	Est.	(Std. Err.)	Est.	(Std. Err.)	Est.	(Std. Err.)	Est.	(Std. Err.)
	Pair 1		*Pair 2*		*Pair 1*		*Pair 2*	
Gain-Loss Attitudes:								
$\hat{\lambda}$	1.56	(0.14)	1.29	(0.12)	1.18	(0.15)	1.12	(0.13)
Utility Values:								
$\hat{X}_1$ *(Pen Set)*	0.63	(0.05)			0.66	(0.06)		
$\hat{Y}_1$ *(USB Stick)*	1	-			1	-		
$\hat{X}_2$ *(Picnic Mat)*			0.84	(0.05)			1.05	(0.07)
$\hat{Y}_2$ *(Thermos)*			1	-			1	-
Discernibility:								
$\hat{\delta}$	0.55	(0.06)	0.45	(0.05)	0.45	(0.06)	0.62	(0.07)

Notes: Maximum likelihood estimates. Robust standard errors in parentheses.

[27] For someone endowed with the alternative object, Y, these same probabilities are

$$
\begin{aligned}
P(R(X) > R(Y)) &= \frac{\exp(U(X,0|0,Y))}{\exp(U(X,0|0,Y)) + \exp(U(0,Y|0,Y) + \delta)} = \frac{\exp(2X - \lambda Y)}{\exp(Y + \delta) + \exp(2X - \lambda Y)} \\
P(R(Y) > R(X)) &= \frac{\exp(u(0,Y|0,Y))}{\exp(U(0,Y|0,Y)) + \exp(U(X,0|0,Y) + \delta)} = \frac{\exp(Y)}{\exp(Y) + \exp(2X - \lambda Y + \delta)} \\
P(R(X) = R(Y)) &= 1 - P(R(X) > R(Y)) - P(R(Y) > R(X)).
\end{aligned}
$$

A.1.1 Individual Gain-Loss Attitudes

The aggregate estimates show evidence of loss aversion. To construct bounds for estimates of individual gain-loss attitudes, we evaluate individual choices assuming average utility and discernibility values. For example, consider an individual endowed with the pen set in Pair 1 in the initial study. At the aggregate estimates of δ and X for Pair 1, if this individual were to state a higher rating for the pen set than for the USB stick, it would imply $0.632 > 2 - \hat{\lambda} * 0.632 + 0.549$ or $\hat{\lambda} > 3.03$. Similarly, stating a higher rating for the USB stick would imply $\hat{\lambda} < 1.30$,[28] and stating the same rating implies $\hat{\lambda} \in [1.30, 3.03]$. Of these three possible cases, two demonstrate evidence of loss aversion $\hat{\lambda} > 1$, while the other case is plausibly loss neutral as $\hat{\lambda} = 1$ can rationalize the ratings.[29] In total, there exist twelve cases of endowments and relative liking statements.

Overall, in our initial study 217 subjects (35.7 percent) are categorized as loss-averse, 240 (39.5 percent) are categorized as potentially loss-neutral, and 150 (24.7 percent) are categorized as gain-loving. In our replication study, 124 subjects (29.7 percent) are categorized as loss-averse, 185 (44.4 percent) are categorized as potentially loss-neutral, and 108 (25.9 percent) are categorized as gain-loving. These are the taxonomies of individual gain-loss types used in our analysis.

A.2 Stage 2: Heterogeneous Treatment Effects

Table A2, presents linear probability models for Stage 2 behavior with dependent variable *Exchange (=1)*. Panels A and B provide separate results for our initial and replication studies. Beginning with the initial study, we find a null average treatment effect in Column (1). In Condition B, 36.5 percent of subjects choose to exchange, demonstrating a significant endowment effect relative to the null hypothesis of 50 percent exchange,

[28] To state a higher rating for the USB implies $2 - \hat{\lambda} * 0.632 > 0.632 + 0.549$ or $\hat{\lambda} < 1.30$.

[29] It may seem prima-facie surprising that providing the same rating in this case is consistent with loss aversion. The logic is simple: given that the pen set has substantially lower intrinsic utility than the USB stick, one must be loss-averse to rate them equally.

$F_{1,605} = 18.32,\ (p < 0.01)$. Probabilistic forced exchange has a null average treatment effect, increasing trading probabilities by only 0.4 percentage points on aggregate. Columns (2) through (4) conduct the same regressions separately for subjects categorized as loss-averse, loss-neutral, and gain-loving, based on their Stage 1 liking statements. Panel A of Table A2 shows a dramatic heterogeneous treatment effect. Loss-averse subjects exhibit a statistically significant endowment effect in Condition B, and grow more approximately 16 percentage points more willing to exchange in Condition F. Gain-loving subjects exhibit no endowment effect in Condition B, and grow approximately 25 percentage points less willing to exchange in Condition F. The heterogeneous treatment effect over gain-loving and loss-averse subjects of roughly 40 percentage points closely follows our theoretical development on the sign of comparative statics, and is significant at all conventional levels, $F_{1,363} = 15.76,\ (p < 0.01)$.

As detailed in the main text, we registered and conducted an exact replication in the summer of 2018 with 417 subjects, again at the University of Bonn. The registration of our pre analysis plan, including power calculations, can be found at `https://www.socialscienceregistry.org/trials/3124`. The number of subjects for the replication was guided by a requirement of 80 percent power for the 40 percentage point difference in treatment effect between gain-loving and loss-averse subjects noted above. Ex-post our initial study was slightly over-powered and the replication was thus conducted with around 400 subjects. Panel B of Table A2 provides the replication analysis analogous to that presented in Panel B. The null average treatment effect, positive treatment effect for loss-averse subjects, and negative treatment effect for gain-loving subjects are all reproduced with accuracy. Indeed, the 40 percentage point heterogeneous treatment effect in our initial study is echoed in a 37 percentage point difference between gain-loving and loss-averse subjects in our replication study.

Our replication study reproduces with precision the heterogeneous treatment effect over gain-loss types obtained in our initial study under our prior methods. Subjects classified

Table A2: **Prior Analysis: Exchange Behavior and Probabilistic Forced Exchange**

	(1)	(2)	(3)	(4)
	Dependent Variable: Exchange (=1)			
	Full Sample	Loss Averse	Loss Neutral	Gain Loving
Panel A: Initial Study				
Condition F	0.004	0.158	0.027	-0.248
	(0.034)	(0.067)	(0.066)	(0.078)
Constant (Condition B)	0.365	0.330	0.361	0.429
	(0.028)	(0.049)	(0.053)	(0.067)
R-Squared	0.000	0.025	0.001	0.072
# Observations	607	217	240	150
H_0: Zero Endowment Effect in B	$F_{1,605}$=18.32	$F_{1,215}$=12.21	$F_{1,238}$=6.85	$F_{1,148}$=1.15
	($p < 0.01$)	($p < 0.01$)	($p < 0.01$)	($p = 0.29$)
H_0: Zero Treatment Effect (F-B)	$F_{1,605} = 0.01$	$F_{1,215} = 5.64$	$F_{1,238} = 0.17$	$F_{1,148} = 10.18$
	($p = 0.90$)	($p = 0.02$)	($p = 0.68$)	($p < 0.01$)
H_0: Constant (col. 2) = Constant (col. 4)				$F_{1,363} = 1.44$
				($p = 0.23$)
H_0: Condition F (col. 2) =Condition F (col. 4)				$F_{1,363} = 15.76$
				($p < 0.01$)
Panel B: Replication Study				
Condition F	-0.010	0.206	-0.073	-0.160
	(0.044)	(0.085)	(0.075)	(0.094)
Constant (Condition B)	0.399	0.271	0.444	0.474
	(0.030)	(0.058)	(0.059)	(0.067)
R-Squared	0.000	0.045	0.005	0.027
# Observations	417	124	185	108
H_0: Zero Endowment Effect in B	$F_{1,415}$=7.97	$F_{1,122}$=15.40	$F_{1,183}$=0.89	$F_{1,106}$=0.16
	($p < 0.01$)	($p < 0.01$)	($p = 0.35$)	($p = 0.69$)
H_0: Zero Treatment Effect (F-B)	$F_{1,415} = 0.05$	$F_{1,122} = 5.79$	$F_{1,183} = 0.95$	$F_{1,106} = 2.92$
	($p = 0.83$)	($p = 0.02$)	($p = 0.33$)	($p = 0.09$)
H_0: Constant (col. 2) = Constant (col. 4)				$F_{1,228} = 5.22$
				($p = 0.02$)
H_0: Condition F (col. 2) =Condition F (col. 4)				$F_{1,228} = 8.33$
				($p < 0.01$)

Notes: Ordinary least square regression. Robust standard errors in parentheses. Null hypotheses tested for 1) zero baseline endowment effect, regression (Constant = 0.5); 2) zero treatment effect (F-B); 3) Identical Condition B behavior across loss-averse and gain-loving subjects (Constant (col. 2) = Constant (col. 4)); 4) Identical treatment effects of forced exchange across loss-averse and gain-loving subjects (Forced Exchange (col. 2) = Forced Exchange (col. 4)). Hypotheses 3 and 4 tested via interacted regression with observations from columns (2) and (4).

as loss-averse respond to Condition F by increasing their willingness to exchange; subjects classified as gain-loving respond by decreasing their willingness to exchange.

B Additional Theoretical Analysis: PE and PPE

This appendix provides additional theoretical development for heterogeneity in response to probabilistic forced exchange under Personal Equilibrium (PE) and the PE refinement, Preferred Personal Equilibrium, PPE. Throughout, our maintained assumptions will be $X, Y, \lambda, \eta > 0$. We begin with the restrictions on behavior implied by PE. To begin, we focus on Condition B and a choice set consisting of pure strategy choices $\mathcal{D} = \{(X, 0), (0, Y)\}$. In this setting, there are two potential PE selections, $[\mathbf{c}, \mathbf{r}] = [(X, 0), (X, 0)]$ and $[\mathbf{c}, \mathbf{r}] = [(0, Y), (0, Y)]$. The individual can support not exchanging, $[\mathbf{c}, \mathbf{r}] = [(X, 0), (X, 0)]$, in a PE if

$$U(X, 0|X, 0) \geq U(0, Y|X, 0),$$

or

$$X \geq \frac{1+\eta}{1+\eta\lambda} Y. \tag{2}$$

Note that the smallest value of X at which the individual can support not exchanging, $\underline{X}_{B,PE} = \frac{1+\eta}{1+\eta\lambda} Y$, is inferior to Y if $\lambda > 1$. As such, loss-averse individuals with $\lambda > 1$ may be able support not exchanging X for Y even if Y would be preferred on the basis of intrinsic utility alone. This describes the mechanism by which the KR model generates an endowment effect in PE. Similarly, the individual can support exchanging, $[\mathbf{c}, \mathbf{r}] = [(0, Y), (0, Y)]$, if

$$U(0, Y|0, Y) \geq U(X, 0|0, Y),$$

or

$$X \leq \frac{1+\eta\lambda}{1+\eta} Y.$$

The highest value of X at which the agent can support exchanging, $\overline{X}_{B,PE} = \frac{1+\eta\lambda}{1+\eta} Y$, increases linearly with λ. For $\underline{X}_{B,PE} \leq X \leq \overline{X}_{B,PE}$, there will be multiple equilibria, with the agent able to support both exchanging and not exchanging as a PE.

Note that for gain-loving individuals with $\lambda < 1$ it is also possible for $\overline{X}_{B,PE} < X < \underline{X}_{B,PE}$, such that no pure strategy PE selection from the assumed $\mathcal{D}$ exists. In this region, if $\mathcal{D}$ were to include all mixtures of exchanging and not exchanging, there would be a mixed strategy PE of not exchanging with a given probability, p. Below, we provide this analysis. Figure A1 provides the pure strategy PE cutoffs associated with exchanging not exchanging in Condition B.

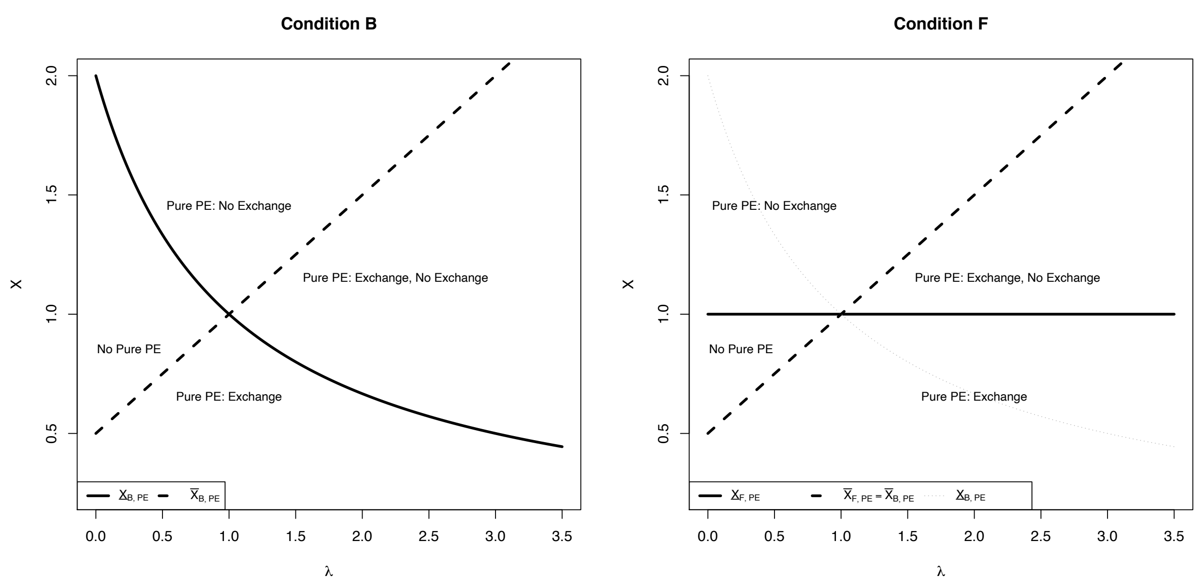

Figure A1: **Gain-Loss Attitudes and Theoretical Pure PE Strategy Thresholds**
Notes: Threshold values for pure strategy PE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

Now, consider Condition F. The potential selections for someone endowed with X are $\mathcal{D} = \{0.5(X,0) + 0.5(0,Y), (0,Y)\}$, with the first element reflecting attempting not to exchange and the second reflecting exchange, as before. The individual can support attempting not to exchange in a PE if

$$U(0.5(X,0) + 0.5(0,Y)|0.5(X,0) + 0.5(0,Y)) \geq U(0,Y|0.5(X,0) + 0.5(0,Y)),$$

or

$$X \geq Y. \tag{3}$$

Under forced exchange, the individual can support attempting to retain X in PE only on the basis of intrinsic utility values, regardless of the level of λ.

Though probabilistic forced exchange alters the PE considerations associated with not exchanging, it leaves unchanged the PE considerations associated with exchanging. The individual can support exchanging in PE if

$$U(0, Y|0, Y) \geq U(0.5(X, 0) + 0.5(0, Y)|0, Y),$$

which as before is

$$X \leq \frac{1 + \eta\lambda}{1 + \eta} Y.$$

Hence, $\overline{X}_{F,PE} = \overline{X}_{B,PE}$.

The manipulation of probabilistic forced exchange changes the PE cutoff for not exchanging from $\underline{X}_{B,PE} = \frac{1+\eta}{1+\eta\lambda} Y$ to $\underline{X}_{F,PE} = Y$. There is no longer any possibility in PE for a loss-averse individual to support keeping their object if $Y > X$. A loss-averse individual with $\lambda > 1$ and valuation $\underline{X}_{B,PE} < X < \underline{X}_{F,PE}$ moves from a position of multiple PE in Condition B, to having a unique PE to exchange in Condition F. Such an individual plausibly grows more willing to exchange when moving from Condition B to Condition F. Similarly, a gain-loving individual with $\lambda < 1$ and valuation $\underline{X}_{F,PE} < X < \underline{X}_{B,PE}$ moves from a position of no pure strategy PE in Condition B to having a unique PE of exchange in Condition F. Such an individual plausibly grows less willing to exchange when moving from Condition B to Condition F. Figure A1, illustrates these changing pure strategy PE considerations from Condition F to Condition B. The direction of these comparative statics is identical to that of our CPE analysis in the main text.

B.1 PE Mixed Strategy Analysis

To provide more complete analysis, particularly when there is no pure strategy PE, we now elaborate PE and PPE formulations when the choice set $\mathcal{D}$ includes all available mixtures of exchanging and not exchanging. For Condition B , we assume $\mathcal{D}_B = \{p \in [0,1] : p(X,0) + (1-p)(0,Y)\}$, allowing all mixtures of exchange and no exchange to be chosen. A given mixture, p, will be PE if

$$U(p(X,0)+(1-p)(0,Y)|p(X,0)+(1-p)(0,Y)) \geq$$
$$U(q(X,0)+(1-q)(0,Y)|p(X,0)+(1-p)(0,Y)) \ \forall\ q \ \in [0,1],$$

or

$$pX+(1-p)Y+p(1-p)\eta(1-\lambda)(X+Y) \geq$$
$$qX+(1-q)Y+(1-q)p\eta(Y-\lambda X)+q(1-p)\eta(X-\lambda Y) \ \forall\ q \in [0,1].$$

For a given p, let $\mathbf{q}^*(p) \equiv \{argmax_q U(q,p)\} \equiv \{argmax_q U(q(X,0)+(1-q)(0,Y)|p(X,0)+(1-p)(0,Y))\}$. The brackets indicate that $\mathbf{q}^*(p)$ may be a set. A mixture, $p \in [0,1]$, is PE if $p \in \mathbf{q}^*(p)$.

Note that

$$\begin{aligned}\frac{\partial U(q,p)}{\partial q} &= X - Y - p\eta(Y-\lambda X) + (1-p)\eta(X-\lambda Y) \\ &= (1+\eta)X - (1+\eta\lambda)Y - p\eta(1-\lambda)(Y+X)\end{aligned}$$

is constant for a given p, as $U(q,p)$ is linear in q. If $\frac{\partial U(q,p)}{\partial q} > (<)\ 0$, then it will attain a unique maximum $\mathbf{q}^*(p) = \{1\}(\{0\})$. As such, any strict mixtures, $p \in (0,1)$, for which $\frac{\partial U(q,p)}{\partial q} \neq 0$ cannot be PE. Note that this development implies that not exchanging with certainty, $p = 1$, will be PE if $\frac{\partial U(q,1)}{\partial q} \geq 0$, or

$$\begin{aligned}(1+\eta)X - (1+\eta\lambda)Y - \eta(1-\lambda)(Y+X) &\geq 0,\\ X &\geq \frac{(1+\eta)}{(1+\eta\lambda)}Y,\end{aligned}$$

which corresponds to the pure strategy threshold noted above, $\underline{X}_{B,PE}$. Similarly, exchanging with certainty, $p = 0$, will be PE if $\frac{\partial U(q,0)}{\partial q} \leq 0$, or

$$\begin{aligned}(1+\eta)X - (1+\eta\lambda)Y &\leq 0\\ X &\leq \frac{(1+\eta\lambda)}{(1+\eta)}Y,\end{aligned}$$

which corresponds to the pure strategy threshold, $\overline{X}_{B,PE}$. For values of X such that

$$\frac{(1+\eta)}{(1+\eta\lambda)}Y \leq X \leq \frac{(1+\eta\lambda)}{(1+\eta)}Y,$$

$p = 1$ and $p = 0$ will be PE.

Strict mixtures, $p \in (0,1)$, for which $\frac{\partial U(q,p)}{\partial q} = 0$, $p \in \mathbf{q}^*(p)$, as all values of q, including $q = p$, attain the maximum. For each parameter constellation, X, Y, η, λ, if there exists a candidate mixture

$$p \in (0,1) \ s.t \ p = \frac{(1+\eta)X - (1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)}$$

such a p is PE. Note that there will be at most one strict mixture PE. This strict mixture will be a proper probability provided $\frac{(1+\eta)X-(1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)} \in (0,1)$. For such a proper mixture probability to exist for $\lambda > 1$, it must be that

$$\frac{(1+\eta)}{(1+\eta\lambda)}Y < X < \frac{(1+\eta\lambda)}{(1+\eta)}Y.$$

That is, if $\lambda > 1$, both pure strategies, $p = 0$ and $p = 1$, are PE, and the required preferences are strict, there will also be a strict mixture PE. In contrast, for such a proper probability mixture to exist for $\lambda < 1$, it must be that

$$\frac{(1+\eta\lambda)}{(1+\eta)}Y < X < \frac{(1+\eta)}{(1+\eta\lambda)}Y.$$

That is, if $\lambda < 1$, and neither pure strategy, $p = 0$ or $p = 1$, are PE, there will be a strict mixture PE.

Figure A2 summarizes the PE considerations in Condition B recognizing the possibility of mixed strategy equilibria with the corresponding value of the mixture probability noted. In contrast to the pure strategy analysis of Figure A1, for $\lambda < 1$ within the bounds

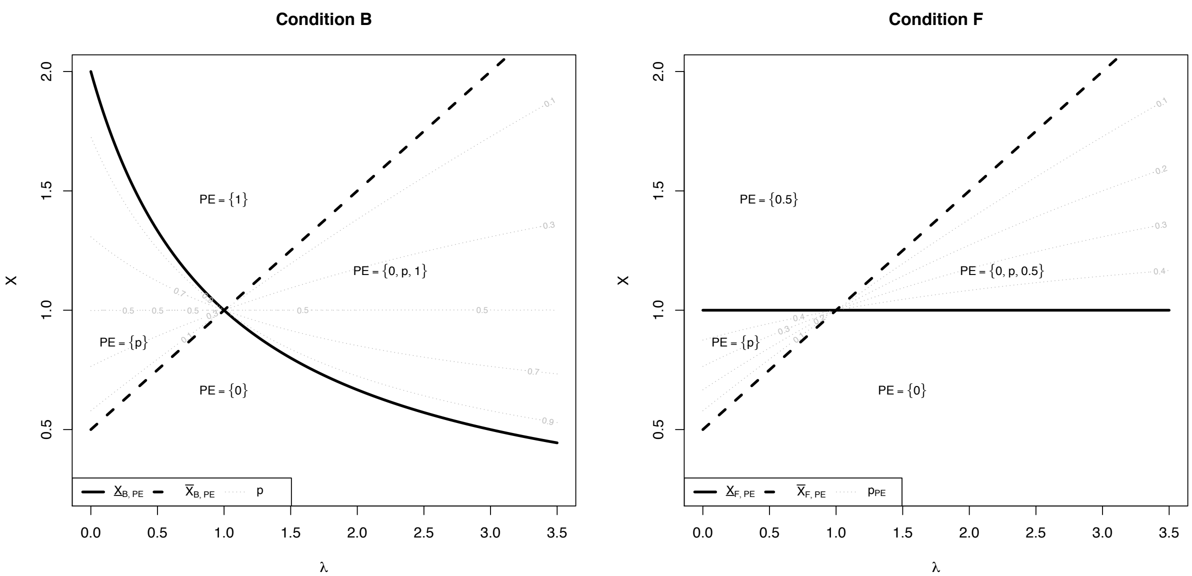

Figure A2: **Gain-Loss Attitudes and Theoretical PE Strategy Thresholds**
Notes: Threshold values for mixed strategy PE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

$\frac{(1+\eta\lambda)}{(1+\eta)}Y < X < \frac{(1+\eta)}{(1+\eta\lambda)}Y$, there is now a mixed strategy PE. Further, for $\lambda > 1$ and $\frac{(1+\eta)}{(1+\eta\lambda)}Y < X < \frac{(1+\eta\lambda)}{(1+\eta)}Y$ there are three equilibria when accounting for potential mixtures.

Having elaborated the PE restrictions for Condition B, we proceed to Condition F. Condition F alters the choice set from $\mathcal{D}_B = \{p \in [0,1] : p(X,0) + (1-p)(0,Y)\}$ to $\mathcal{D}_F = \{p \in [0,0.5] : p(X,0) + (1-p)(0,Y)\}$. This alteration induces two potential changes to the PE calculus. First, potential PE choices from Condition B may not be available in Condition F. Second, lotteries, q, that prevent a specific p from being PE may potentially be eliminated.

In Condition F, a given mixture $p \in [0, 0.5]$ will be PE if

$$U(p(X,0) + (1-p)(0,Y)|p(X,0) + (1-p)(0,Y)) \geq$$
$$U(q(X,0) + (1-q)(0,Y)|p(X,0) + (1-p)(0,Y)) \;\forall\; q \;\in [0, 0.5].$$

As before $U(q,p)$ is linear in q, and so a boundary strategy of attempting to keep one's object, $(p = 0.5)$ will be PE if

$$\begin{aligned}\frac{\partial U(q,0.5)}{\partial q} = (1+\eta)X - (1+\eta\lambda)Y - 0.5\eta(1-\lambda)(Y+X) \geq 0 \\ (1+0.5\eta(1+\lambda))X \geq (1+0.5\eta(1+\lambda))Y \\ X \geq Y,\end{aligned}$$

which corresponds to the pure strategy threshold, $\underline{X}_{F,PE}$. Similarly, exchanging with certainty, $p = 0$, will be be PE if

$$\begin{aligned}\frac{\partial U(q,0)}{\partial q} = (1+\eta)X - (1+\eta\lambda)Y \leq 0 \\ X \leq \frac{(1+\eta\lambda)}{(1+\eta)}Y,\end{aligned}$$

which corresponds to the pure strategy threshold, $\overline{X}_{F,PE} = \overline{X}_{B,PE}$.

Again strict mixtures, $p \in (0, 0.5)$, for which $\frac{\partial U(q,p)}{\partial q} = 0$, $p \in \mathbf{q}^*(p)$, as all values of q, including $q = p$, attain the maximum. For each parameter constellation, X, Y, η, λ, if there exists a candidate mixture

$$p \in (0, 0.5) \; s.t \; p = \frac{(1+\eta)X - (1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)}$$

such a p is PE. Note that there will be at most one strict mixture PE. This strict mixture will be a proper probability and within the choice set provided $\frac{(1+\eta)X-(1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)} \in (0, 0.5)$. For such a proper mixture probability to exist for $\lambda > 1$, it must be that

$$Y < X < \frac{(1+\eta\lambda)}{(1+\eta)}Y$$

That is, if $\lambda > 1$, both pure strategies, $p = 0$ and $p = 0.5$, are PE, and the required preferences are strict, there will also be a strict mixture PE. In contrast, for such a proper probability mixture to exist for $\lambda < 1$, it must be that

$$\frac{(1+\eta\lambda)}{(1+\eta)}Y < X < Y.$$

That is, if $\lambda < 1$, and neither pure strategy, $p = 0$ or $p = 0.5$, are PE, there will be a strict mixture PE.

Figure A2 summarizes the PE considerations in Condition F recognizing the possibility of mixed strategy equilibria with the corresponding value of the mixture probability noted. Moving from Condition B to Condition F all mixed strategy PE with $p \in (0.5, 1)$ are eliminated from the choice set. Individuals with $\lambda > 1$ and multiple equilibria, $PE = \{0, p > 0.5, 1\}$ in Condition B have a unique $PE = \{p = 0\}$ in Condition F. Such individuals may exchange less than 100 percent of the time in Condition B and do so 100 percent of the time in Condition F, growing more willing to exchange. In contrast, individuals with $\lambda < 1$ and a unique $PE = \{p > 0.5\}$ in Condition B, have a unique $PE = \{p = 0.5\}$ in Condition F. Such individuals would attempt to retain their object less than 100 percent of the time in Condition B and would do so 100 percent of the time in Condition F, growing less willing to exchange. This analysis highlights exactly the intuition laid out with our prior pure strategy analysis and that for the CPE concept. We next turn to PPE analysis to select among multiple PE selections.

B.1.1 Preferred Personal Equilibrium Analysis

Where there exist multiple PE selections, the KR model is equipped with an equilibrium selection mechanism, *Preferred Personal Equilibrium* (PPE). PPE selects among PE values on the basis of ex-ante utility. Having elaborated the PE values in the Figure A2, it is straightforward to identify the selection, p, with the highest value of $U(p(X,0)+(1-p)(0,Y)|p(X,0)+(1-p)(0,Y)) = pX+(1-p)Y+p(1-p)\eta(1-\lambda)(X+Y)$. In the case of Condition B, there is a region of multiplicity for $\lambda > 1$ where the set of $PE = \{0, p \in (0,1), 1\}$. In this region it is clear that not exchanging, $p = 1$, will yield higher ex-ante utility than exchanging ,$p = 0$, if

$$X > Y.$$

If $X > Y$, $p = 1$ will also yield higher ex-ante utility than any PE mixture $p \in (0,1)$ as all mixtures will both lower intrinsic utility (as $X > Y \rightarrow X > pX + (1-p)Y \forall p \in (0,1)$) and expose the individual to the overall negative sensations of gain loss embodied in the term $p(1-p)\eta(1-\lambda)(X+Y) < 0$ for $\lambda > 1$. Following this logic, in Condition B, multiplicity is resolved via PPE by selecting either $p = 1$ if $X > Y$ or $p = 0$ if $X < Y$.

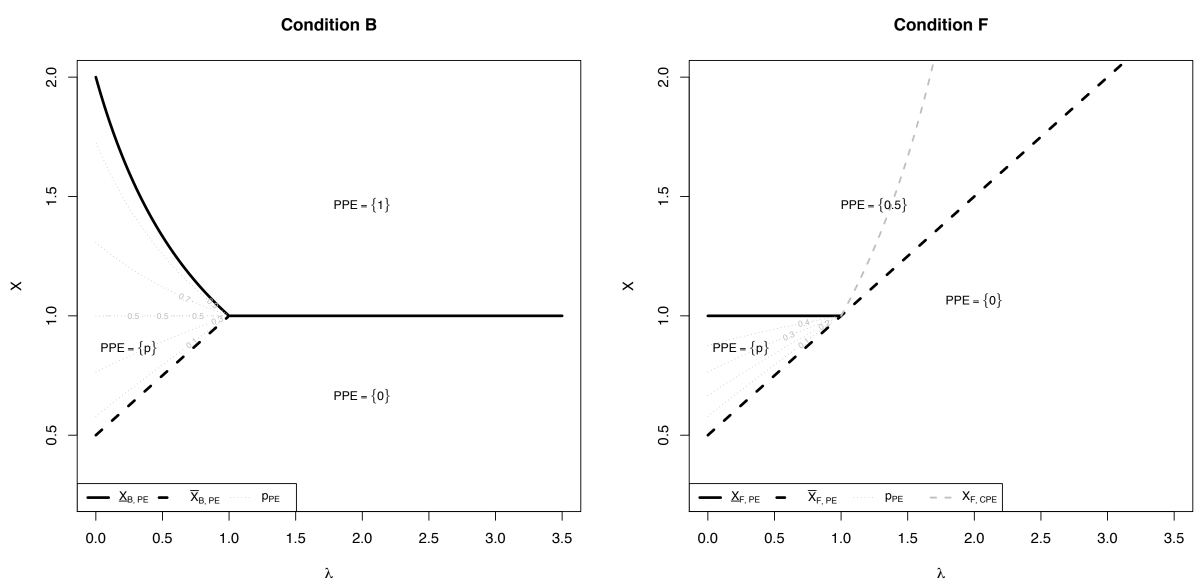

Figure A3: **Gain-Loss Attitudes and Theoretical PPE Strategy Thresholds**
Notes: Threshold values for PPE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

Similarly, in Condition F, there is a region of multiplicity for $\lambda > 1, Y < X < \frac{(1+\eta\lambda)}{(1+\eta)}Y$ where the set of $PE = \{0, p \in (0, 0.5), 0.5\}$. Note that for $\lambda > 1$, if $X < \frac{(1+\eta\lambda)}{(1+\eta)}Y$, then $X < \frac{(1+0.5\eta(\lambda-1))}{(1+0.5\eta(1-\lambda))}Y = \frac{(1+\eta\lambda-0.5\eta(\lambda+1)}{(1+\eta-0.5\eta(\lambda+1))}$. That is, in this region of multiplicity, X is below the $X_{F,CPE}$ cutoff noted in the main text. Hence, we know that exchanging, $p = 0$, yields higher ex-ante utility than attempting not to exchange, $p = 0.5$, in this region. It suffices to check which of the remaining PE selections $\{0, p = \frac{(1+\eta)X-(1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)} \in (0, 0.5)\}$ provide higher utility. For this key mixture,

$$
\begin{aligned}
p &= \frac{(1+\eta)X - (1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)} \\
(1-p) &= \frac{\eta(1-\lambda)(Y+X)}{\eta(1-\lambda)(Y+X)} - \frac{(1+\eta)X - (1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)}
\end{aligned}
$$

The PPE selection will be $p = 0$ provided

$$
\begin{aligned}
Y &> pX + (1-p)Y + p(1-p)\eta(1-\lambda)(X+Y) \\
Y &> X + (1-p)\eta(1-\lambda)(X+Y) \\
Y &> X + \left[\frac{\eta(1-\lambda)(Y+X)}{\eta(1-\lambda)(Y+X)} - \frac{(1+\eta)X - (1+\eta\lambda)Y}{\eta(1-\lambda)(Y+X)}\right]\eta(1-\lambda)(X+Y) \\
Y &> X + [\eta(1-\lambda)(Y+X) - (1+\eta)X + (1+\eta\lambda)Y] \\
Y - (1+\eta\lambda)Y - \eta(1-\lambda)Y &> X + \eta(1-\lambda)(X) - (1+\eta)X \\
-\eta Y &> -\eta\lambda X \\
X &> \frac{1}{\lambda}Y,
\end{aligned}
$$

Which is satisfied as $X > Y$ and $\lambda > 1$ in this region.

Figure A3 summarizes the PPE considerations in Conditions B and F recognizing the possibility of a mixed strategy PPE with the corresponding value of the mixture probability noted. Also graphed in Figure A3 is the relevant CPE cutoff for $\lambda > 1$ in Condition F to reinforce both that in the region of multiplicity exchanging, $p = 0$, yields higher ex-ante utility than attempting not to exchange, $p = 0.5$, and that the restrictions on behavior differ meaningfully between CPE and PPE. Nonetheless, both solution concepts share the same directional comparative statics that individuals with $\lambda > 1$ should grow more willing to exchange moving from Condition B to Condition F, while individuals with $\lambda < 1$ should grow less-so.

C Estimation Strategy

In this appendix, we provide the likelihood formulation for our mixed-logit methodology to estimate heterogeneity in gain-loss attitudes and utilities. There are three relative preference statements that subjects provide in Stage 1: relative wanting statements, relative liking statements, and hypothetical choice. Let $i = 1, ..., N$ represent the index for subjects, and let $\{w, l, h\}$ represent the index of the three preference statements, referring to (w)anting, (l)iking, and (h)ypothetical choice, respectively. Let $w, l \in \{-1, 0, 1\}$ correspond to providing a higher rating for the alternative object, providing equal ratings for both objects, and providing a higher rating for the endowed object, respectively. Let $h \in \{-1, 1\}$ correspond to hypothetically choosing the alternative object or the endowed object, respectively.

We begin by presenting a standard logit formulation and then extend to the mixed logit case. Let $G(\cdot)$ represent the CDF of the logistic distribution. For each individual there are three potential probabilities associated with the three potential wanting ratings for those endowed with X, $Prob_{w_i,X}$,

$$
\begin{array}{llr}
Prob_{w_i,X} = & G((1+\lambda) - 2\frac{Y}{X} - \delta_X) & if\ w_i = 1 \\
Prob_{w_i,X} = & G(2\frac{Y}{X} - (1+\lambda) - \delta_X) & if\ w_i = -1 \\
Prob_{w_i,X} = & 1 - G((1+\lambda) - 2\frac{Y}{X} - \delta_X) - G(2\frac{Y}{X} - (1+\lambda) - \delta_X) & if\ w_i = 0,
\end{array}
$$

and three for those endowed with Y, $Prob_{w_i,Y}$,

$$\begin{array}{rcl} Prob_{w_i,Y} = & G(2-(1+\lambda)\frac{Y}{X}-\delta_X) & if\ w_i=-1 \\ Prob_{w_i,Y} = & G((1+\lambda)\frac{Y}{X}-2-\delta_X) & if\ w_i=1 \\ Prob_{w_i,Y} = & 1-G(2-(1+\lambda)\frac{Y}{X}-\delta_X)-G((1+\lambda)\frac{Y}{X}-2-\delta_X) & if\ w_i=0. \end{array}$$

Similarly, there are three potential probabilities associated with the three potential liking ratings for those endowed with X, $Prob_{l_i,X}$,

$$\begin{array}{rcl} Prob_{l_i,X} = & G((1+\lambda)-2\frac{Y}{X}-\delta_X) & if\ l_i=1 \\ Prob_{l_i,X} = & G(2\frac{Y}{X}-(1+\lambda)-\delta_X) & if\ l_i=-1 \\ Prob_{l_i,X} = & 1-G((1+\lambda)-2\frac{Y}{X}-\delta_X)-G(2\frac{Y}{X}-(1+\lambda)-\delta_X) & if\ l_i=0, \end{array}$$

and three for those endowed with Y, $Prob_{l_i,Y}$,

$$\begin{array}{rcl} Prob_{l_i,Y} = & G(2-(1+\lambda)\frac{Y}{X}-\delta_X) & if\ l_i=-1 \\ Prob_{l_i,Y} = & G((1+\lambda)\frac{Y}{X}-2-\delta_X) & if\ l_i=1 \\ Prob_{l_i,Y} = & 1-G(2-(1+\lambda)\frac{Y}{X}-\delta_X)-G((1+\lambda)\frac{Y}{X}-2-\delta_X) & if\ l_i=0. \end{array}$$

Lastly, there are two potential probabilities associated with the two hypothetical choice statements for those endowed with X $Prob_{h_i,X}$,

$$\begin{array}{rcl} Prob_{h_i,X} = & G((1+\lambda)-2\frac{Y}{X}) & if\ w_i=1 \\ Prob_{h_i,X} = & G(2\frac{Y}{X}-(1+\lambda)) & if\ w_i=-1, \end{array}$$

and two for those endowed with Y, $Prob_{h_i,Y}$,

$$\begin{array}{rcl} Prob_{h_i,Y} = & G(2-(1+\lambda)\frac{Y}{X}) & if\ w_i=-1 \\ Prob_{h_i,Y} = & G((1+\lambda)\frac{Y}{X}-2) & if\ w_i=1. \end{array}$$

Let $\mathbf{1}_X$ indicate an individual endowed with object X. A single individual's choice probability would thus be

$$L_i = (Prob_{w_i,X} \cdot Prob_{l_i,X} \cdot Prob_{h_i,X})^{\mathbf{1}_X} \cdot (Prob_{w_i,Y} \cdot Prob_{l_i,Y} \cdot Prob_{h_i,Y})^{(1-\mathbf{1}_X)},$$

and the grand log likelihood would be

$$\mathcal{L} = \sum_{i=1}^{N} log(L_i)$$

Moving from this logit formulation to our mixed logit formulation is straightforward and follows Train (2009). For estimating the heterogeneity of gain-loss attitudes, we assume that the value λ is drawn from a log-normal distribution with $log(\lambda) \sim N(\mu_\lambda, \sigma_\lambda^2)$. Let $\theta \equiv (\mu_\lambda, \sigma_\lambda^2)$, represent the parameters of this distribution, and let $f(\lambda|\theta)$ be the distribution of λ given these parameters. A single individual's choice probabilities are thus

$$L_i = \int L_i(\lambda) f(\lambda|\theta) d\lambda$$

where $L_i(\lambda)$ is the individual choice probability evaluated at a given draw of $f(\lambda|\theta)$. We construct these choice probabilities through simulation. Let $r = 1, ..., R$ represent simulations of λ from $f(\lambda|\theta)$ at a given set of parameters, θ. Let λ^r be the r^{th} simulant. We simulate L_i as

$$\check{L}_i = \frac{1}{R} \sum_{r=1}^{R} L_i(\lambda^r),$$

And these simulated probabilities replace the standard choice probabilities in the grand log likelihood to create a simulated log likelihood,

$$\mathcal{SL} = \sum_{i=1}^{N} log(\check{L}_i).$$

This simulated log likelihood is maximized to deliver estimates of μ_λ and σ^2_λ alongside the homogeneous utility ratio $\frac{X}{Y}$.

When considering heterogeneous utility, the exercise is analogous. We assume that the value $\frac{X}{Y}$ is drawn from a log-normal distribution with $log(\frac{X}{Y}) \sim N(\frac{X}{Y}, \sigma^2_{\frac{X}{Y}})$. Let $\theta' \equiv (\mu_{\frac{X}{Y}}, \sigma^2_{\frac{X}{Y}})$, represent the parameters of this distribution, and let $f(\frac{X}{Y}|\theta')$ be the distribution of $\frac{X}{Y}$ given these parameters. A single individual's choice probabilities are thus

$$L_i = \int L_i(\frac{X}{Y}) f(\frac{X}{Y}|\theta') d\frac{X}{Y}$$

where $L_i(\frac{X}{Y})$ is the individual choice probability evaluated at a given draw of $f(\frac{X}{Y}|\theta')$. We construct these choice probabilities through simulation. Let $r = 1, ..., R$ represent simulations of $\frac{X}{Y}$ from $f(\frac{X}{Y}|\theta')$ at a given set of parameters, θ'. Let $\frac{X}{Y}^r$ be the r^{th} simulant. We simulate L_i as

$$\check{L}_i = \frac{1}{R}\sum_{r=1}^{R} L_i(\frac{X}{Y}^r),$$

And these simulated probabilities replace the standard choice probabilities in the grand log likelihood to create a simulated log likelihood,

$$\mathcal{SL} = \sum_{i=1}^{N} log(\check{L}_i).$$

This simulated log likelihood is maximized to deliver estimates of $\mu_{\frac{X}{Y}}$ and $\sigma^2_{\frac{X}{Y}}$ alongside the homogeneous gain-loss parameter, λ.

Operationally for implementing both of our simulated likelihood techniques we use 1000 Halton draws for each heterogeneous parameter and implement the code in Stata. The code for our procedure estimating the distribution of gain-loss attitudes is presented below.

```
/* Estimator with MSL Portion for Distribution of Lambda */

capture program drop MSL_hetlambda
program define MSL_hetlambda
    * specifiy the arguments for the program
    args lnf l ratio12 ratio34 d12 d34 ln_sd

    * declare temporary variables
    tempvar choice choicetype endowed2 endowed3 endowed4 lambda delta firstval secondval sim_f sim_avef


    quietly {
        * initialize the data
        generate int `choice' = $ML_y1
        generate int `choicetype' = $ML_y2
        generate int `endowed2' = $ML_y3
        generate int `endowed3' = $ML_y4
        generate int `endowed4' = $ML_y5


        * initiate simulation average likelihood
        generate double `sim_avef' = 0

        * set seed equivalent to prior seed
        set seed 10101

        * simulate likelihood at each draw of lambda
        forvalues drawnum = 1/1000 {

            * draw lambda
            generate double `lambda' = exp(`l' + (exp(`ln_sd')*invnormal(draws1_`drawnum')))

            * evaluate the utilities
            generate double `firstval' = (1 + `lambda')
            replace `firstval' = (1 + `lambda')*`ratio12' if `endowed2' == 1
            replace `firstval' = (1 + `lambda') if `endowed3' == 1
            replace `firstval' =  (1 + `lambda')*`ratio34' if `endowed4' == 1

            generate double `secondval' =  2*`ratio12'
            replace  `secondval' =  2  if `endowed2' == 1
            replace  `secondval' = 2*`ratio34'  if `endowed3' == 1
            replace  `secondval' = 2  if `endowed4' == 1

            *indifference value
            generate double `delta' = exp(`d12')
            replace `delta' = exp(`d34')  if (`endowed3' == 1 | `endowed4' == 1)

            * construct simulated likelihood at current draw for ratings statements
            gen `sim_f' =   invlogit(`firstval' - `secondval' - `delta') if `choice' == 1  & (`choicetype'
== 1 | `choicetype' == 2)
            replace `sim_f' = invlogit(`secondval' - `firstval' - `delta')  if `choice' == -1 & (
`choicetype' == 1 | `choicetype' == 2)
            replace `sim_f' =  1- invlogit(`firstval' - `secondval' - `delta')  - invlogit(`secondval' -
`firstval' - `delta')    if `choice' == 0 & (`choicetype' == 1 | `choicetype' == 2)


            * construct simulated likelihood  for hypothetical choice
            replace `sim_f' = invlogit(`firstval' - `secondval')   if `choice' == 1  & `choicetype' ==3
            replace `sim_f' =  1- invlogit(`firstval' - `secondval')  if `choice' == -1  & `choicetype' ==3

            *update average simulated likelihood
            replace `sim_avef' = `sim_avef' + (`sim_f'/1000)

            drop `lambda'  `firstval' `secondval' `sim_f' `delta'

            }

        * Establish log simulated likelihood

        replace `lnf' = ln(`sim_avef')

    }
end
```

D Additional Tables

Table A3: **Method of Simulated Likelihood Estimates: Sensitivity Analysis**

	(1)	(2)	(3)	(4)	(5)	(6)
	Estimate	(Std. Error)	Estimate	(Std. Error)	Estimate	(Std. Error)
	Heterogeneous λ		*Heterogeneous λ*		*Heterogeneous λ*	
Gain-Loss Attitudes:						
$\hat{\lambda}$	1.29	(0.04)	1.37	(0.08)	1.64	(0.21)
$\hat{\mu_\lambda}$	0.26	(0.03)	0.17	(0.07)	0.04	(0.08)
$\hat{\sigma^2_\lambda}$	0.00	(0.00)	0.29	(0.21)	0.91	(0.39)
Pair 1 Utilities (USB Stick (X) - Pen Set (Y)) *:*						
$\frac{\hat{Y}}{X}$ (Initial)	0.64	(0.03)	0.62	(0.04)	0.57	(0.04)
$\frac{\hat{Y}}{X}$ (Replication)	0.64	(0.04)	0.61	(0.04)	0.57	(0.05)
Pair 2 Utilities (Picnic Mat (X) - Thermos (Y))*:*						
$\frac{\hat{Y}}{X}$ (Initial)	1.10	(0.03)	1.11	(0.03)	1.13	(0.04)
$\frac{\hat{Y}}{X}$ (Replication)	0.90	(0.04)	0.88	(0.04)	0.87	(0.05)
Discernibility:						
δ_X	0.50	-	0.55	-	0.60	-
# Observations	3,072		3,072		3,072	

Notes: Maximum likelihood estimates. Standard errors in parentheses.

Table A4: **Exchange Behavior and Probabilistic Forced Exchange, Clustered SE**

	Dependent Variable: Exchange (=1)		
	(1)	(2)	(3)
Condition F	-0.004	-0.340	-0.004
	(0.027)	(0.076)	(0.026)
$E[\lambda]$		-0.136	
		(0.036)	
Condition F * $E[\lambda]$		0.225	
		(0.046)	
Reduced Form Measure			-0.050
			(0.014)
Condition F * Reduced Form			0.077
			(0.018)
Constant (Condition B)	0.380	0.584	0.380
	(0.020)	(0.061)	(0.019)
R-Squared	0.000	0.017	0.014
# Observations	1024	1024	1024
# Clusters	53	53	53
H_0 : Zero Endowment Effect in B	$F_{1,52} = 34.96$	$F_{1,52} = 1.87$	$F_{1,52} = 38.26$
	$(p < 0.01)$	$(p = 0.18)$	$(p < 0.01)$
H_0 : Zero Treatment Effect (F-B)	$F_{1,52} = .02$	$F_{1,52} = 20.07$	$F_{1,52} = 0.02$
	$(p = 0.89)$	$(p < 0.01)$	$(p = 0.89)$
H_0 : Gain-Loss Attitudes $\perp$ Exchange in B		$F_{1,52} = 13.98$	$F_{1,52} = 13.19$
		$(p < 0.01)$	$(p < 0.01)$
H_0 : Gain-Loss Attitudes $\perp$ Treatment Effect		$F_{1,52} = 24.03$	$F_{1,52} = 19.48$
		$(p < 0.01)$	$(p < 0.01)$

Notes: Ordinary least square regression. Standard errors clustered at session level in parentheses. Null hypotheses tested for 1) zero baseline endowment effect regression (Constant coefficient = 0.5); 2) zero treatment effect (Condition F coefficient= 0); 3) no relationship between gain-loss attitudes and behavior in Condition B behavior ($E[\lambda]$ or Reduced Form Measure coefficient = 0); 4) constant treatment effect over gain-loss attitudes (Condition F * $E[\lambda]$ or Condition F * Reduced Form coefficient = 0). F-statistics and two-sided p-values reported.

Table A5: **Stage 2 Behavior and Stage 1 Experience, Clustered SE**

	Dependent Variable: Exchange (=1)			
	Stage 1 Object Not Replaced		Stage 1 Object Replaced	
	(1)	(2)	(3)	(4)
Condition F	0.013	-0.255	-0.019	-0.418
	(0.035)	(0.120)	(0.044)	(0.124)
$E[\lambda]$		-0.121		-0.153
		(0.053)		(0.064)
Condition F * $E[\lambda]$		0.176		0.272
		(0.071)		(0.077)
Constant (Condition B)	0.386	0.569	0.374	0.600
	(0.027)	(0.092)	(0.032)	(0.104)
R-Squared	0.000	0.011	0.000	0.024
# Observations	511	511	513	513
# Clusters	53	53	53	53
H_0 : Zero Endowment Effect in B	$F_{1,52} = 17.82$	$F_{1,52} = 0.57$	$F_{1,52} = 15.78$	$F_{1,52} = 0.92$
	($p < 0.01$)	($p = 0.45$)	($p < 0.01$)	($p = 0.34$)
H_0 : Zero Treatment Effect (F-B)	$F_{1,52} = 0.13$	$F_{1,52} = 4.51$	$F_{1,52} = 0.18$	$F_{1,52} = 11.31$
	($p = 0.72$)	($p = 0.04$)	($p = 0.67$)	($p < 0.01$)
H_0 : Gain-Loss Attitudes $\perp$ Exchange in B		$F_{1,52} = 5.25$		$F_{1,52} = 5.81$
		($p = 0.03$)		($p = 0.02$)
H_0 : Gain-Loss Attitudes $\perp$ Treatment Effect		$F_{1,52} = 6.19$		$F_{1,52} = 12.62$
		($p = 0.02$)		($p < 0.01$)

Notes: Ordinary least square regression. Standard errors clustered at session level in parentheses. Null hypotheses tested for 1) zero baseline endowment effect regression (Constant coefficient = 0.5); 2) zero treatment effect (Condition F coefficient= 0); 3) no relationship between gain-loss attitudes and behavior in Condition B behavior ($E[\lambda]$ coefficient = 0); 4) constant treatment effect over gain-loss attitudes (Condition F * $E[\lambda] = 0$). F-statistics and two-sided p-values reported.

Table A6: **Replication Consistency and Additional Controls, Clustered SE**

	Dependent Variable: Exchange (=1)				
	Initial Study		Replication Study		
	(1)	(2)	(3)	(4)	(5)
Condition F	0.004	-0.409	-0.010	-0.239	-0.805
	(0.034)	(0.111)	(0.044)	(0.102)	(0.411)
$E[\lambda]$		-0.159		-0.103	-0.116
		(0.053)		(0.053)	(0.053)
Condition F * $E[\lambda]$		0.266		0.161	0.174
		(0.065)		(0.064)	(0.064)
Constant (Condition B)	0.365	0.616	0.399	0.542	0.917
	(0.028)	(0.093)	(0.030)	(0.081)	(0.343)
Additional Controls	No	No	No	No	Yes
Additional Interactions	No	No	No	No	Yes
R-Squared	0.000	0.023	0.000	0.008	0.060
# Observations	607	607	417	417	417
# Clusters	31	31	22	22	22
H_0 : Zero Endowment Effect in B	$F_{1,30} = 23.85$	$F_{1,30} = 1.53$	$F_{1,21} = 11.73$	$F_{1,21} = 0.26$	$F_{1,21} = 1.48$
	$(p < 0.01)$	$(p = 0.23)$	$(p < 0.01)$	$(p = 0.61)$	$(p = 0.24)$
H_0 : Zero Treatment Effect (F-B)	$F_{1,30} = 0.01$	$F_{1,30} = 13.44$	$F_{1,21} = 0.05$	$F_{1,21} = 5.51$	$F_{1,21} = 3.84$
	$(p = 0.90)$	$(p < 0.01)$	$(p = 0.82)$	$(p = 0.03)$	$(p = 0.06)$
H_0 : Gain-Loss Attitudes $\perp$ Exchange in B		$F_{1,30} = 9.09$		$F_{1,21} = 3.79$	$F_{1,21} = 4.78$
		$(p < 0.01)$		$(p = 0.07)$	$(p = 0.04)$
H_0 : Gain-Loss Attitudes $\perp$ Treatment Effect		$F_{1,30} = 16.61$		$F_{1,21} = 6.32$	$F_{1,21} = 7.47$
		$(p < 0.01)$		$(p < 0.01)$	$(p = 0.01)$

Notes: Ordinary least square regression. Standard errors clustered at session level in parentheses. Null hypotheses tested for 1) zero baseline endowment effect regression (Constant coefficient = 0.5); 2) zero treatment effect (Condition F coefficient= 0); 3) no relationship between gain-loss attitudes and behavior in Condition B behavior ($E[\lambda] = 0$); 4) constant treatment effect over gain-loss attitudes (Condition F * $E[\lambda]$ = 0). The number of clusters in replication data does not permit test for effect of additional controls or interactions (all coefficients = 0), which would require. Additional controls include: gender, age, educational status, monthly income bracket, knowledge of economics, composite Raven matrices score, composite CRT score, and fixed effects for experimental assistant. Interactions include all controls interacted with Condition F. F-statistics and two-sided p-values reported.