"De Gustibus" and Disputes about Reference Dependence

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Abstract

Existing tests of reference-dependent preferences assume universal loss aversion. This paper examines the implications of heterogeneity in gain-loss attitudes for such tests. In experiments on labor supply and exchange behavior we measure gain-loss attitudes and then study a canonical treatment effect that distinguishes different models of reference dependence. We document substantial heterogeneity in gain-loss attitudes and evidence against universal loss aversion. We then document heterogeneous treatment effects over gain-loss attitudes consistent with formulations of expectations-based reference points. Assuming homogeneous preferences would lead to different and possibly incorrect conclusions in these tests. Our findings provide foundational support for reference points derived from expectations, and reconcile inconsistencies across prior exercises.

1   Introduction

Models of reference-dependent preferences are regarded as a major advance in behavioral economics, rationalizing a range of observations at odds with the canonical model of expected utility over final wealth (Camerer et al., 1997; Kahneman, J. L. Knetsch, et al., 1990; Odean, 1998; Rabin, 2000). The predictions of any reference-dependent model hinge on two model components: the reference point governing the location around which gains and losses are encoded; and gain-loss attitudes encapsulating how individuals weigh gains and losses relative to the reference point.

Recent tests of reference-dependent models focus on hypotheses about the first model component, the location of the reference point—distinguishing backward-looking factors such as the status quo posited by Kahneman and Tversky (1979) from the forward-looking expectations-based mechanisms proposed by Bell (1985), Kőszegi and Rabin (2006, 2007), and Loomes and Sugden (1986). As the reference point represents a powerful degree of freedom in application, these tests have been valuable for understanding how to discipline reference-dependent models (Abeler et al., 2011; Cerulli-Harms et al., 2019; Ericson and Fuster, 2011; Gneezy et al., 2017; Heffetz and List, 2014; Smith, 2019). Importantly, all prior exercises have been conducted under a specific *homogeneity* assumption on gain-loss attitudes: universal loss aversion, where all individuals weigh losses more severely than commensurate gains. This strikingly strong assumption —a form of the classic *De Gustibus Non Est Disputandum* assumption (Stigler and Becker, 1977)—is an unstated centerpoint of the prior tests. Thus, prior tests have effectively ignored variation in the second model component, gain-loss attitudes.

In this manuscript, we examine the possibility that individuals are *heterogeneous* in their gain-loss attitudes—i.e., individuals are differentially "loss averse", weighing losses more than gains to varying degrees, and some individuals may even be "gain-seeking",

weighing gains more than losses to varying degrees—and explore the implications of this heterogeneity for identifying models of the reference point.[1]

Permitting heterogeneity in gain-loss attitudes in tests of reference-dependent models may be important for two reasons. First, within experimental designs used to identify expectations-based reference dependence (EBRD), different predictions are generated depending on the extent of loss-averse or gain-seeking preference. In the extreme, gain-seeking subjects should react to key experimental treatments in exactly the opposite way as loss-averse subjects. Second, heterogeneity in gain-loss attitudes reflects an empirical realism: a recent literature has noted that even with loss aversion on average, there is substantial variation around the mean with sizable minorities of subjects in lottery choice experiments even appearing to be gain-seeking (Chapman, Snowberg, et al., 2018).[2] If individuals are heterogeneous in their gain loss-attitudes and behave in theoretically predicted ways, then prior exercises have aggregated different effects without any way to disentangle heterogeneity in attitudes from the corresponding test of the reference point.[3] The combination of these two issues may explain the inconclusive, and at times contradictory, findings in the study of EBRD models without accounting for heterogeneity.[4]

We implement two pre-registered laboratory experiments with a total of 1524 subjects to investigate the relevance of heterogeneous gain-loss attitudes for testing models of ref-

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[1]The concept of gain-seeking behavior is not merely a theoretical notion; rather, it aligns with observable behavior in specific contexts such as speculative investing and lottery buying, much like the concept of loss aversion.

[2]Chapman, Snowberg, et al. (2018) evaluate seven prior studies from lottery choice along with one of the experiments in this manuscript and report a weighted average of 22% gain-seeking subjects. They also document nearly 50% gain-seeking subjects in a lottery choice experiment with a representative sample. Additional evidence of heterogeneity in gain-loss attitudes is documented in Brown et al. (2021), Chapman, Dean, et al. (2017), Erev et al. (2008), Fehr and Goette (2007), Harinck et al. (2007), J. Knetsch and Wong (2009), Nicolau (2012), Sokol-Hessner et al. (2009), and Sprenger (2015)

[3]In Appendices A.2 and B.4 we demonstrate this point concretely. We show that predicted KR treatment effects are not necessarily linear in gain-loss attitudes. Hence, the average treatment effect may not coincide with the treatment effect of the average preference. Indeed, average treatment effects can differ dramatically and even have a different sign from the treatment effect at the average preference.

[4]While early experimental applications showed treatment effects in line with the EBRD formulation of reference points (Abeler et al., 2011; Ericson and Fuster, 2011), other exercises have shown more limited or contradictory effects (Cerulli-Harms et al., 2019; Gneezy et al., 2017; Heffetz and List, 2014; Smith, 2019).

erence dependent preferences. Our baseline designs and treatment manipulations closely follow existing work on the two main paradigms used to test the EBRD formulation: labor supply (e.g., Abeler et al., 2011; Gneezy et al., 2017) and exchange (e.g., Cerulli-Harms et al., 2019; Ericson and Fuster, 2011; Heffetz and List, 2014). Each experiment consists of two stages. Stage 1 measures each participant's gain-loss attitudes in the specific context of the experiment. Stage 2 tests EBRD by changing subjects' expectations between a Low expectations and a High expectations condition. Under EBRD models, such manipulations change the location of the reference point, and so should change behavior. Under alternative formulations of reference points, no such effects are predicted. Hence, these designs constitute tests of the expectations-based formulation of the reference point.

The EBRD predictions in these two leading paradigms depend on gain-loss attitudes. Aggregating different effects can lead heterogeneity in gain-loss attitudes to confound the test of EBRD in both settings. Our key experimental innovation is the addition of Stage 1 in order to measure gain-loss attitudes in specific ways that do not interfere with the theoretical predictions and experimental manipulations in each context. These measures allow us to evaluate the extent of heterogeneity in gain-loss attitudes, account for heterogeneity when testing the EBRD formulation of the reference-point, and examine the heterogeneous treatment effects over gain-loss attitudes predicted by EBRD models. In this sense, we explore whether heterogeneous preferences, *gustus*, can help resolve the outstanding dispute on the nature of reference dependence.

Our two studies generate two very similar results. First, we find substantial heterogeneity in gain-loss attitudes. While subjects in both studies exhibit loss aversion on average, we estimate substantial variation around the mean and sizable minorities of gain-seeking subjects. Both studies show around three quarters loss-averse, and one quarter gain-seeking subjects. These are the first findings documenting the distribution of gain-loss attitudes in labor supply and exchange settings. Furthermore, we document a similar heterogeneity using monetary lottery decisions. The findings from these three different techniques reinforce prior results on heterogeneous gain-loss attitudes in lottery choice (Chapman, Snowberg,

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et al., 2018), and clarify that homogeneous loss aversion would be an incorrect assumption to maintain in tests of reference-dependent models. Our analyses leverage both reduced-form and structural approaches to infer gain-loss attitudes from the data and accommodate potential uncertainty in measurement in various ways.

Second, in each study, gain-loss attitudes from Stage 1 are highly predictive of the treatment effects observed in Stage 2. We document heterogeneous treatment effects over gain-loss attitudes. Higher values of the key loss aversion parameter are associated with larger treatment effects on average. We also document that negative treatment effects are more frequently associated with gain-seeking individuals. Though in one of our studies the average treatment effect for gain-seeking individuals is slightly positive, in the other one it is significantly negative. Differentially loss-averse and gain-seeking subjects respond quite differently to the manipulation of expectations. Without accounting for heterogeneity, we would draw very different conclusions from our studies, finding more limited, or even no, aggregate support for EBRD. However, accounting for it, we find strong evidence for EBRD. This represents the first experimental test of EBRD accounting for heterogeneous gain-loss attitudes, and the first experimental findings of heterogenous EBRD treatment effects over gain-loss types.

Our empirical results indicate that mixed evidence on EBRD is likely not driven by a failure of the expectations-based formulation of reference points, but rather by a failure of the second component of the joint hypothesis inherent to prior tests: that gain-loss attitudes are homogeneously loss averse. Without accounting for heterogeneous gain-loss attitudes, prior tests suffer from both aggregation and power issues: the average treatment effect need not be the treatment effect of the average individual (which we discuss in detail in Appendices A.2 and B.4), and potentially muted theoretical average effects require larger sample sizes for appropriately-powered experiments. In a simple and reproducible way, we show that the predictions of EBRD are reliably recovered once one accounts for heterogeneity in gain-loss attitudes.

While our evidence provides strong arguments in favor of EBRD, there are also aspects of the data that cannot be fully explained by the model. EBRD posits that both the levels of behavior and the treatment effects in our experiment are exclusively determined by expectations and their influence on reference points. In neither of our studies can EBRD provide a complete explanation of the exact quantitative effects for every level of gain-loss attitudes. The quantitative deviations from the model that we observe hint at additional potential determinants of reference points beyond expectations. The existing literature puts forward a variety of sources—including status quo-based, attention-based, and anchoring-based reference points—that may affect behavior. We thus view this evidence as pointing at the potential multiplicity of determinants for behavior, motivating future work that aims to disentangle them.

Above all, this paper highlights the need to account for heterogeneity in gain-loss attitudes in order to use and test models of reference-dependence. Besides tests of expectations-based models, our results also have implications for other applications of gain-loss attitudes, including Rabin's (2000) explanation for risk aversion in the small and in the large, insurance for small losses (Slovic et al., 1977), and preferences for bunched resolution of uncertainty (Kőszegi and Rabin, 2009). The explanations for these phenomena rely on loss aversion. Admitting heterogeneity in gain-loss attitudes will lead to more nuanced predictions in each of these settings. Future work on these phenomena is now equipped with a methodology for investigating and controlling for the influence of heterogeneity in gain-loss attitudes.

The manuscript proceeds as follows. In Section 2, we discuss our two-stage labor supply experiment ($N = 500$), building upon the original designs of Abeler et al. (2011) and Gneezy et al. (2017). In Section 3, we discuss our two-stage exchange experiment ($N = 1024$), building on the designs of Cerulli-Harms et al. (2019), Ericson and Fuster (2011), and Heffetz and List (2014). Section 4 provides additional discussion and concludes.

2　Labor Supply Experiment

2.1　Experimental Design

The labor supply experiment consists of two stages. In Stage 1, we present subjects with a number of decisions that elicit how much effort they are willing to provide at various piece rates, both fixed and uncertain. The objective is to recover each individual's gain-loss attitudes. In Stage 2, we present subjects with a set of choices that manipulate the implied expectations-based reference point while holding other potential reference points constant, constituting a test of the EBRD formulation.

Stage 1: Measuring Gain-Loss Attitudes.　Subjects were informed about the experiment's various parts and the task they would be asked to complete—transcribing a row of blurry Greek text.[5] They went on to complete two practice tasks to familiarize themselves with the process.

Next, subjects used a slider to indicate how many of these transcription tasks they were willing to complete at a given piece rate. They were shown the earnings associated with a given number of tasks, as well as an estimate of the corresponding completion time. Each piece rate offering was either fixed, e.g., $w = \$0.20$ per completed task, or uncertain, e.g., a 50% chance of $w_h = \$0.30$ per task and a 50% chance of $w_l = \$0.10$ per task. Subjects made decisions for a total of 30 piece rates, 10 of which were fixed. Each uncertain piece rate was linked to a fixed piece rate with the same mean, i.e., $0.5w_h + 0.5w_l = w$. We rely on these two types of piece rates to identify gain-loss attitudes for each individual accounting for auxiliary parameters such as the shape of their cost function.

On each decision screen, subjects made choices for five different piece rates. On a given decision screen, all offered piece rates were fixed, or all were uncertain. Subjects completed a total of six decision screens which appeared in random order. Similar to Augenblick and

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[5]The task is borrowed from Augenblick and Rabin (2019).

Rabin (2019), we selected (expected) piece rates between \$0.05/task and \$0.3/task (an hourly wage rate between approximately \$4.00 and \$26.00, according to subjects' average time of completion).

Stage 2: Experimental Manipulation of Expectations.   After completing the Stage 1 choices, we informed subjects that they would make two additional effort decisions with slightly different earnings structures. In these additional decisions, subjects were informed that there would be a 50% chance of a per task piece rate of \$0.20, a $p\%$ chance that a fixed payment \$20 would be paid regardless of the number of completed tasks, and a $q\%$ chance that a fixed payment \$0 would be paid regardless of the number of completed tasks.[6] Subjects chose a number of tasks to complete in two conditions: Condition Low, where $p = 0.05$ and $q = 0.45$; and Condition High where $p = 0.45$ and $q = 0.05$. Each subject made both decisions in different screens, which were displayed in random order.

In both conditions subjects received a piece rate with 50% chance. With complementary chance, their earnings were unrelated to the number of tasks completed, and were either Low or High in expectation across the two conditions. [7] Within EBRD models, the Low and High conditions induce different expectations of earnings and so induce different reference points. This, in turn, leads to different willingness to work across the two conditions. In the neoclassical model and in models with exogenous reference points, this manipulation should have no effect on optimal choice.

Lottery Elicitation, Incentives, and Questionnaire.   Following the real-effort decisions, subjects evaluated two risky lotteries using Multiple Price Lists (MPLs), a common elicitation technique to measure gain-loss attitudes in the monetary lottery domain.

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[6]These instructions remained purposefully vague about the amounts of money involved as well as any variation over the two choices because our aim was to obtain within-individual comparisons.

[7]This structure allows us to study both within-subject treatment effects by comparing a given subject's answers across conditions and between-subject treatment effects by restricting the sample to only the first condition subjects saw. We pre-registered predictions about within-subject treatment effects in order to maximize statistical power. Appendix Table A3 provides the between-subject results for comparison. While the estimates are noisier, the results are qualitatively similar regardless of the method of analysis.

Subjects made a total of 42 monetary lottery choices in two probability equivalent tasks (following Sprenger, 2015) in which we held fixed a sure payoff of \$5 [\$0] and offered the lottery $(p, \$10; 0)$ [or $(p, \$3; -\$3.5)$] with p ranging from 0% to 100% in increments of 5% as the alternative.[8]

Both the labor supply and lottery choices were incentivized. The experimental earnings were based on one of the 32 effort choices or the 42 monetary lottery choices, with each choice having the same chance of being randomly selected to be the *decision-that-counts*. Regardless of which decision or how many tasks were selected, each subject had to complete a minimum of 10 transcriptions. If the decision-that-counts was one of the monetary lottery choices, the computer generated a random number and determined the outcome of the lottery, and the subjects received their payment upon completion of the mandatory tasks and an ensuing survey. If one of the effort decisions was selected for payment, subjects first completed the mandatory 10 tasks and then the additional number they indicated in that decision; if the relevant wage was stochastic, uncertainty in wages was not resolved until after they had completed all of the additional tasks.[9]

After all the tasks were completed, subjects were presented with a series of Raven's matrices (John Raven and Jean Raven, 2003) to obtain a measure of cognitive skill, followed by a demographic survey (gender, major, age, parental income, and risk attitudes).

Procedures and Pre-Registration. Our sample for the labor supply experiment consists of 500 subjects recruited through the UC San Diego Economics Laboratory. The experiment was pre-registered at the AEA RCT Registry (Campos-Mercade et al. 2021, AEARCTR-0007277) and conducted between April and July 2021. On average, subjects earned \$15.5. The experiment was implemented in *oTree* (Chen et al., 2016). A full set of decision screenshots is provided in Appendix C.

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[8]Assuming subjects have monotonic preferences over money—e.g., they prefer \$5 for sure to a 0% chance of \$10 and prefer a 100% chance of \$10 to \$5 for sure—the p at which they switch from preferring one option to another informs us about their gain-loss attitudes. Within our elicitation, a single switch point was enforced for all subjects.

[9]All subjects had been informed of this procedure in the instructions.

2.2 Identifying Gain-Loss Attitudes and Heterogeneous Theoretical Predictions

We derive theoretical predictions of the leading Kőszegi and Rabin (2006, 2007) EBRD model in the labor supply context.[10] A reader familiar with the Kőszegi and Rabin (2006, 2007) model may wish to skip this section and proceed directly to the predictions spelled out at the end of Section 2.2.2 or the results presented in Section 2.3. We assume that individual i's utility function is represented by

$$u_i(w, e | r_w, r_e) = m(we) - c_i(e) + \mu_i(m(we) - m(r_w)) + \mu_i(c_i(e) - c_i(r_e)).$$

The first component of utility, $m(we) - c_i(e)$, is standard consumption utility obtained from working e tasks and earning we. Consumption utility is complemented with a reference-dependent, psychological component of utility, for which the utility from realized earnings $m(we)$ is compared to the utility of reference-point earnings $m(r_w)$ under a piece-wise linear gain-loss function μ_i, where

$$\mu_i(z) = \begin{cases} \eta z & z \geq 0 \\ \eta \lambda_i z & z < 0 \end{cases} .$$

Intuitively, if an outcome falls short of the reference point by a difference of z, this leads to a reduction of utility by $\eta \lambda_i$ times this difference. An outcome that exceeds the reference point increases utility by η times the difference, where $\eta > 0$. Thus, λ_i represents individual gain-loss attitude and can either exhibit loss-aversion where losses are felt more severely than commensurate gains, $\lambda_i > 1$, or gain-seeking where gains are felt more severely than commensurate losses, $\lambda_i < 1$. If $\lambda_i = 1$, the individual is considered "loss-neutral". Throughout the analysis, we assume that $m(we) = we$ and constant for all individuals,

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[10]Throughout, our theoretical analysis will use the Kőszegi and Rabin (2006, 2007) formulation. An earlier literature also provided formulations of reference dependence grounded in rational expectations, but without the equilibrium concepts we use to analyze behavior (Bell, 1985; Loomes and Sugden, 1986).

that $c_i(e)$ is an increasing, at least twice-differentiable, strictly convex function, $c_i''(e) > 0$, and normalize $\eta = 1$ for all individuals.

Kőszegi and Rabin (2006, 2007) propose that agents hold the entire distribution of expected outcomes as their referent. Each potential realization is compared to each potential reference point and weighted by the relevant densities. In order to close the model, Kőszegi and Rabin (2006, 2007) equip it with the rational expectations Choice-Acclimating Personal Equilibrium (CPE) concept. Intuitively, a choice is a CPE if the agent's expected utility from this choice given their expectation of this choice as the referent exceeds the expected utility of any alternative choice given the expectation of that alternative choice as the referent. We consider the CPE identification (and estimation) of gain-loss attitudes in Stage 1 of our experimental design, and the CPE comparative statics in Stage 2 of our experimental design.

2.2.1 Stage 1 Estimates of Gain-Loss Attitudes

In this subsection we develop our approach for empirically identifying a structural as well as a reduced-form measure of individual gain-loss attitudes.

Consider an uncertain piece rate condition in Stage 1, $(0.5, w_l; 0.5, w_h)$, $w_h > w_l$. The individual chooses effort, e_i, knowing that with 50% chance they will earn either $e_i \times w_l$ or $e_i \times w_h$. The associated CPE utility for such an effort choice, e_i, is

$$0.5 w_l e_i + 0.5 w_h e_i - 0.25(\lambda_i - 1)(w_h e_i - w_l e_i) - c_i(e_i).$$

If the individual faces a fixed piece rate, w, then CPE utility reduces to

$$u(w e_i | w e_i) = w e_i - c_i(e_i).$$

In choosing a functional form for the cost of effort, our pre-registered analysis follows Augenblick and Rabin (2019) by assuming $c_i(e_i) = \frac{1}{\alpha_i \gamma_i}(e_i + 10)^{\gamma_i}$ with $\gamma_i > 1$, where 10

represents the required minimum number of tasks that all subjects must complete.[11] Note that this formulation permits individual variation in γ_i and α_i, the parameters of the cost function.

The optimal effort choice, e_i^*, in these two cases thus satisfies the marginal condition

$$\frac{1}{\alpha_i}(e_i^* + 10)^{\gamma_i - 1} = \overline{w} - 0.25(\lambda_i - 1)\Delta w, \tag{1}$$

where $\overline{w}$ is the average wage, such that $\overline{w} = 0.5w_l + 0.5w_h$ for uncertain piece rates, and $\overline{w} = w$ for fixed piece rates; and Δw is the spread in the wage, such that $\Delta w = w_h - w_l$ for uncertain piece rates, and $\Delta w = 0$ for fixed piece rates.

This provides an intuitive formulation for identifying gain-loss attitudes from the sensitivity of behavior to wage spreads, Δw. Loss neutral individuals with $\lambda_i = 1$ make their effort decisions only as a function of the average wage, $\overline{w}$, and, thus, choices are invariant to Δw. Loss-averse individuals with $\lambda_i > 1$ lower their effort in response to increases in Δw, all else equal. Conversely, gain-seeking individuals with $\lambda_i < 1$ will increase their effort in response to increases in Δw, all else equal.[12]

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[11] As Augenblick and Rabin (2019) point out: "The parameter α is necessary and represents the exchange rate between effort and the payment amount. If instead $c_i(e_i) = \frac{1}{\gamma_i}(e + 10)^{\gamma_i}$, a requirement such as linear marginal costs (which necessitates $\gamma_i = 2$), would also imply that the marginal cost of e_i tasks is exactly e_i monetary units, regardless of the task type or the payment currency." (P. 955)

[12] Our formulation assumes that utility of money, $m(\cdot)$, is linear. If individuals had diminishing marginal utility of money, one would expect a potential deviation between $e_{i,U}^*$ in the uncertain condition and $e_{i,F}^*$ in the fixed wage condition even if $\lambda = 1$. Indeed, if $m(\cdot)$ were concave, the optimal responses with $\lambda = 1$ would be calculated from marginal conditions

$$m'(we_{i,F}^*)w = \frac{1}{\alpha_i}(e_{i,F}^* + 10)^{\gamma_i - 1}$$

and

$$0.5m'(w_l e_{i,U}^*)w_l + 0.5m'(w_h e_{i,U}^*)w_h = \frac{1}{\alpha_i}(e_{i,U}^* + 10)^{\gamma_i - 1}.$$

These two values will differ to the extent that marginal utility changes over the range $[w_l * e, w_h * e]$. For values of e around 40 tasks and a range of $w_h - w_l \approx 0.1 - 0.2$ this corresponds to a \$4-8 range. Changes in marginal utility over such ranges would have to be dramatic to deliver perceptible effects on behavior and would deliver calibrational implausibilities at larger stakes. Moreover, if one were to attribute differences between $e_{i,U}^*$ and $e_{i,F}^*$ to changes in marginal utility, one would predict null effects (and no heterogeneity) in Stage 2 of our design.

This intuition on identification motivates a simple methodology for estimation of gain-loss attitudes. Specifically, taking logs of equation (1), one obtains

$$log(e_i + 10) = \frac{log(\alpha_i)}{\gamma_i - 1} + \frac{1}{\gamma_i - 1}log(\overline{w}) + \frac{1}{\gamma_i - 1}log\left[1 + 0.25(1 - \lambda_i)\frac{\Delta w}{\overline{w}}\right]. \qquad (2)$$

Noting that for small values of $0.25(1-\lambda_i)\frac{\Delta w}{\overline{w}}$, the first-order approximation $log\left[1 + 0.25(1 - \lambda_i)\frac{\Delta w}{\overline{w}}\right] \approx 0.25(1 - \lambda_i)\frac{\Delta w}{\overline{w}}$ holds, one can write

$$log(e_i + 10) \approx k_i + g_i log(\overline{w}) - l_i\frac{\Delta w}{\overline{w}}, \qquad (3)$$

where

$$k_i = \frac{log(\alpha_i)}{\gamma_i - 1}, \quad g_i = \frac{1}{\gamma_i - 1}, \quad \text{and } l_i = \frac{0.25(\lambda_i - 1)}{\gamma_i - 1}.$$

This formulation is linear in the experimentally-varied parameters $log(\overline{w})$ and $\frac{\Delta w}{\overline{w}}$. Moreover, $l_i \geq 0$ if and only if $\lambda_i \geq 1$, such that l_i provides a sufficient statistic for whether an individual is loss-averse or gain-seeking.[13] We will refer to l_i as the reduced form and to λ_i as the structural measure of gain-loss attitudes.

Assuming equation (3) is satisfied with equality subject to a mean zero independent disturbance term, this formulation can be estimated with linear least squares techniques. The corresponding regression estimate for $\hat{l}_i$ captures the response of labor supply to wage uncertainty, and maps closely to a quantitative estimate for λ_i. Indeed, one can give this reduced form estimate a structural interpretation by considering the value $1 + 4 \cdot (\frac{\hat{l}_i}{\hat{g}_i}) \equiv \hat{\lambda}_i$. Within our data the maximal value of $\frac{\Delta w}{\overline{w}}$ is 2. Hence, without the linearity approximation of equation (3), any values of $\lambda_i \geq 3$ could not be estimated as they would deliver undefined values of $log\left[1 + 0.25(1 - \lambda_i)\frac{\Delta w}{\overline{w}}\right]$ in these cases. Recognizing this, we topcode estimates

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[13]To see this, note that for $x \in (-1, \infty)$, $log(1 + x) \geq 0 \iff x \geq 0$, with $x = 0.25(1 - \lambda_i)\frac{\Delta w}{w}$.

of $\hat{\lambda}_i$ from the linear procedure at 3. Additionally, because values of $\hat{\lambda}_i < 0$ are difficult to interpret, we bottcomcode such values at zero.[14]

2.2.2 Heterogeneous Effects of Stage 2 Low vs. High Conditions

In the following we develop our empirical approach for identifying the individual-level treatment effect of our Stage 2 manipulation of expectations.

We consider how individuals behave when offered an earnings structure $(p, X; q, Y; 0.5, w)$ where $X > Y$; that is, individuals have a 50% chance of earning a piece-rate, w, per unit of effort, a $p\%$ chance of earning $\$X$ regardless of effort, and a $q = (50 - p)\%$ chance of earning $\$Y$ regardless of effort. Following the development of Gneezy et al. (2017), we study the effects of an increase in p when $Y \leq we_i^* \leq X$.[15] In Appendix A.1 we derive the CPE choice, e_i^*, in this case satisfying marginal condition

$$0.5w\left[1 + (p - q)(\lambda_i - 1)\right] = c_i'(e_i^*), \tag{4}$$

and the effect of increasing the probability of the high outcome, p, while keeping $p+q = 0.5$ as

$$\frac{\partial e_i^*}{\partial p}\Big|_{p+q=0.5} = \frac{(\lambda_i - 1)w}{c_i''(e_i^*)}.$$

As the outside possibility unrelated to effort, $(p, X; q, Y)$, increases in expectation, individuals should change their level of effort. The change in effort is governed by λ_i, with $\frac{\partial e_i^*}{\partial p}\big|_{p+q=0.5}$ increasing in λ_i provided strictly convex costs, $c_i''(e) > 0$. This effect contrasts with that of alternative models of the reference point, where $\frac{\partial e_i^*}{\partial p}\big|_{p+q=0.5} = 0$. Moreover,

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[14]In order to provide a structural estimate of $\hat{\lambda}_i$ without relying on the linearity approximation of equation (3), one could simply estimate the partially linear regression equation implied by equation (2) via non-linear least squares. We conduct these estimates and compare them to our estimated values of $\hat{\lambda}_i$. The correlation between the values of $\hat{\lambda}_i$ from linear and non-linear procedures is 0.97 for the 443 subjects for whom both are estimable.

[15]For all other rank cases, there is no predicted treatment effect (see Appendix A.1 for details).

the direction of the response is also governed by λ_i with

$$\lambda_i > 1 \implies \frac{\partial e_i^*}{\partial p}\big|_{p+q=0.5} > 0$$
$$\lambda_i < 1 \implies \frac{\partial e_i^*}{\partial p}\big|_{p+q=0.5} < 0.$$

In our implementation we set $X = \$20$, $Y = \$0$, $w = 0.20$, and vary p from 0.05 in the (L)ow condition to 0.45 in the (H)igh condition. Under the assumed functional form $c_i(e_i) = \frac{1}{\alpha_i \gamma_i}(e_i + 10)^{\gamma_i}$, where 10 represents the required tasks, these conditions are associated with solutions

$$e_{i,L}^* + 10 = (\alpha_i 0.10\,[1 - 0.4(\lambda_i - 1)])^{\frac{1}{\gamma_i - 1}}$$
$$e_{i,H}^* + 10 = (\alpha_i 0.10\,[1 + 0.4(\lambda_i - 1)])^{\frac{1}{\gamma_i - 1}},$$

such that the theoretical treatment effect can be expressed in percentage terms as the log difference in effort across the two conditions:

$$TE_i^* \equiv log(e_{i,H}^* + 10) - log(e_{i,L}^* + 10) = \frac{1}{\gamma_i - 1}log\left[\frac{1 + 0.4(\lambda_i - 1)}{1 - 0.4(\lambda_i - 1)}\right]$$

Our second stage focuses on measuring $e_{i,H}$ and $e_{i,L}$ for each subject, thus delivering an empirical analog for this theoretical treatment effect, TE_i^*. Similarly, our first stage provides both reduced form and structural measures of the key behavioral parameter λ_i: $\hat{l}_i$, and $\hat{\lambda}_i$. The theoretical formulation above thus leads to the following empirical predictions.

Prediction 1. The empirical treatment effect, TE_i, in the labor supply experiment increases in loss aversion, $\hat{l}_i$ and $\hat{\lambda}_i$.

Prediction 2. The empirical treatment effect, TE_i, in the labor supply experiment is positive for loss-averse individuals, $\hat{l}_i > 0$ or $\hat{\lambda}_i > 1$.

Prediction 3. The empirical treatment effect, TE_i, in the labor supply experiment is negative for gain-seeking individuals, $\hat{l}_i < 0$ or $\hat{\lambda}_i < 1$.

2.3 Results From The Labor Supply Experiment

2.3.1 Stage 1: The Distribution of Gain-Loss Attitudes in Labor Supply

In Stage 1, our 500 subjects each make 30 effort choices, 10 for fixed piece rates and 20 for uncertain piece rates. In Appendix Table A1, we present the mean, median, and interquartile range for each choice. Overall, subjects exhibit increasing labor supply, being willing to complete more tasks for greater fixed piece rates. Importantly, subjects are willing to complete fewer tasks under uncertain piece rates relative to fixed rates of equal mean. Within the context of our KR analysis, this implies loss aversion on average. Appendix Table A1 also documents substantial heterogeneity. At every piece rate, whether fixed or uncertain, the interquartile range covers a wide portion of the choice space. This, in turn, suggests substantial heterogeneity in both costs and gain-loss attitudes.

In order to evaluate the extent of heterogeneity, we estimate the linear regression implied by equation (3). Because this formulation is identical for all subjects with individual values of k_i, g_i, and l_i, we fit the standard random coefficients model of Swamy (1970), which delivers individual estimates of each parameter. Of our 500 subjects, 5.4% (27 subjects) have zero variation in e_i across their 30 effort choices and so no estimates can be obtained. Additionally, 4% (20 subjects) have estimated values of $\hat{g}_i \leq 0$ implying non-convex costs. Removing these observations that cannot be estimated or are prima-facie inconsistent with our pre-registered theory removes a total of 9.4% (47 subjects) of observations, leaving a final sample of 453 subjects.

Panel A of Figure 1 plots the distribution of the reduced form loss aversion measure, $\hat{l}_i$, for our 453 observations. The average estimate of $\hat{l}_i$ is 0.090, while the average estimate of $\hat{g}_i$ is 0.520, and the average estimate of $\hat{k}_i$ is 4.54. Of the 453 subjects, 70.6% exhibit $\hat{l}_i > 0$, indicating loss aversion, while 29.4% exhibit $\hat{l}_i < 0$, indicating gain seeking. Panel
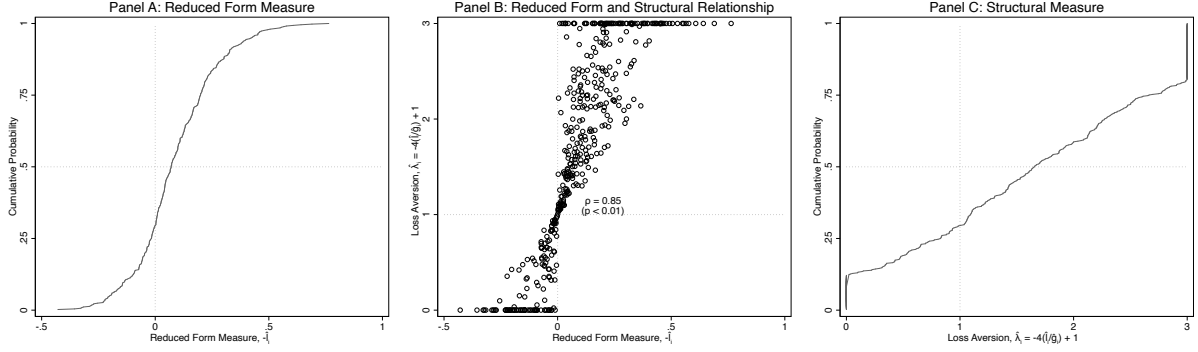
Figure 1: Stage 1: Gain-loss attitudes in the labor supply experiment

Notes: Panel (a) and (c) show CDFs of the reduced form and structural measures of gain-loss attitudes, respectively. Panel (b) displays the relationship between the two measures ($\rho = 0.85$, $p < 0.01$)

B provides the mapping between the reduced form $\hat{l}_i$ and the structural $\hat{\lambda}_i$. The raw correlation between the two values is $\rho = 0.85$ ($p < 0.01$). Additionally, as the theory requires, $\hat{l}_i > 0$ is perfectly diagnostic for $\hat{\lambda}_i > 1$, and so the taxonomy of loss-averse and gain-seeking is identical: 70.6% exhibit $\hat{\lambda}_i > 1$, indicating loss aversion, while 29.4% exhibit $\hat{\lambda}_i < 1$, indicating gain seeking. Panel C plots the distribution of the structural measure, $\hat{\lambda}_i$, with an average value of 1.65 and a median value of 1.66. Roughly 12.1% of $\hat{\lambda}_i$ estimates are censored at zero and 19.7% are censored at three, despite the smoothness of the reduced form distribution, $\hat{l}_i$. Individuals with very little or very much sensitivity to the average wage, $\overline{w}$, yield estimates of $\hat{g}_i$ that are either very large or close to zero, respectively, and correspondingly extreme measures of $\hat{\lambda}_i = 1 + 4 \cdot (\frac{\hat{l}_i}{\hat{g}_i})$.

Our findings of substantial heterogeneity in gain-loss attitudes in the labor supply setting echo findings from lottery choice with similar samples. Chapman, Snowberg, et al. (2018)'s analysis of prior data indicates median values of $\hat{\lambda}$ between 1.5 and 2.5 and an average of 22% gain-seeking subjects. Having reproduced these heterogeneities, we now turn to the second stage of our design and the examination of EBRD treatment effects.

2.3.2 Stage 2: Heterogeneous Treatment Effects of Low vs. High

We now examine whether individual gain-loss attitudes (estimated from Stage 1 choices) are predictive of individual-level treatment effects (estimated from Stage 2 effort choices).[16]

Analyses of Prediction 1. Figure 2 illustrates the relationship between $\hat{\lambda}_i$ from Stage 1 and treatment effects from Stage 2. We construct fifteen equally sized bins of $\hat{\lambda}_i$ and calculate the average behavior in each bin. Panel A provides an analysis corresponding to Prediction 1, plotting the relationship between $\hat{\lambda}_i$ and individual treatment effects, TE_i. Individuals with greater values of $\hat{\lambda}_i$ have systematically larger treatment effects, consistent with Prediction 1. The raw correlation between TE_i and $\hat{\lambda}_i$ is $\rho = 0.18$ ($p < 0.01$).

Column (1) of Table 1 provides corresponding regression analyses for Prediction 1, controlling for additional factors. The log effort level $log(e_i+10)$ is regressed on an indicator for Condition High, providing an estimate of TE_i. Without accounting for gain-loss attitudes, Condition High is associated with a treatment effect of approximately 0.26 (individual clustered s.e. $= 0.03$). This corresponds to a roughly 26% increase in effort in Condition High relative to Condition Low, reproducing the findings of Abeler et al. (2011). Importantly, however, the value $R^2 = 0.03$ indicates that much of the variation in behavior is not accounted for in this aggregate analysis.

Panel A of Figure 2 indicates that the aggregate analysis in column (1) of Table 1 masks substantial heterogeneity in treatment effects. In columns (2) and (3), we provide estimates of heterogeneous treatment effects. We interact the indicator for Condition High with the reduced form measure of loss aversion, $\hat{l}_i$, and the structural measure, $\hat{\lambda}_i$, respectively. We additionally control for the other estimated parameters, $\hat{g}_i$ and $\hat{k}_i$ along with their interactions with Condition High. In both columns (2) and (3), we find that within

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[16]Our main (pre-registered) analysis exploits the within feature of the experiment, leveraging each subject's answers to both Condition Low and Condition High. Appendix Table A3 provides between-subjects analysis using either each subject's first or second choice. As expected, the estimates are noisier. Heterogeneous treatment effects are more pronounced when examining each subject's second choice, but they move in the predicted direction when examining only first choices as well.

Panel A: Heterogeneous Treatment Effects (Prediction 1)

Panel B: Directional Effects (Predictions 2 and 3)
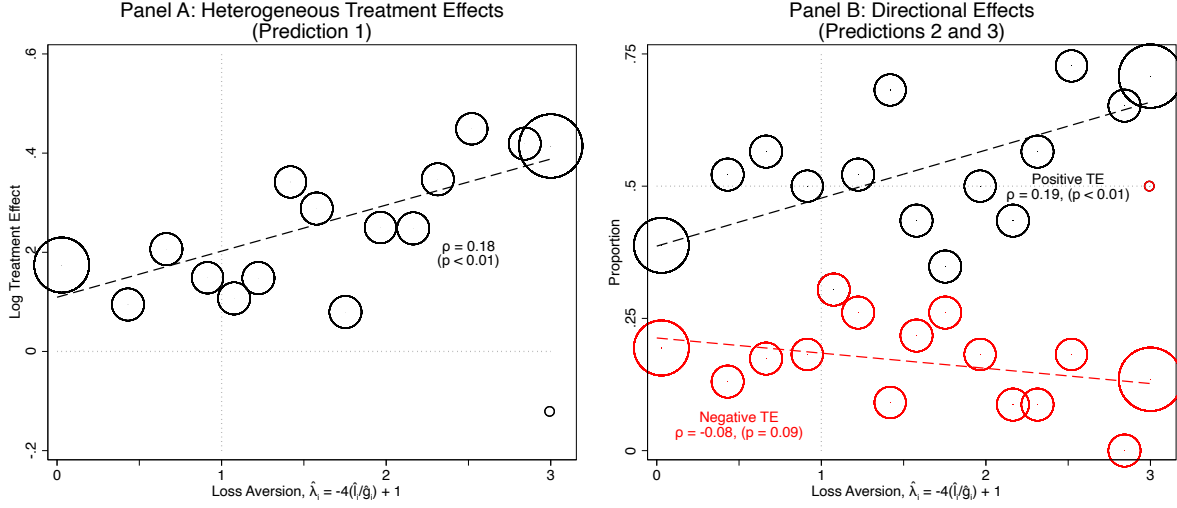
Figure 2: Stage 2: Heterogeneous treatment effects in the labor supply experiment

Notes: Panel A shows the relationship between $\hat{\lambda}_i$ and individual treatment effects, TE_i, in fifteen equally sized bins of $\hat{\lambda}_i$. Panel B plots the relationship between $\hat{\lambda}_i$ and the empirical probability of having either a positive (black markers) or negative (red markers) value of TE_i.

Condition Low, there is a substantial negative correlation between gain-loss attitudes and effort levels: more loss-averse individuals state lower effort levels in Condition Low. This finding is consistent with theoretical predictions laid out in section 2.2.2 in the formula for $e_{i,L}^*$. In both columns (2) and (3), we document a sizable and significant degree of heterogeneity in treatment effects depending on loss aversion. More loss aversion is associated with greater values of TE_i, consistent with Prediction 1. Importantly, when accounting for heterogeneous treatment effects over gain-loss attitudes, along with the additional parameters $\hat{g}_i$ and $\hat{k}_i$, a substantially greater proportion of behavior is explained; the R^2 values increase by more than a factor of 10.[17]

In addition to the standard regressions presented in columns (2) and (3) of Table 1, we also present bootstrap analyses to account for the potential issue of using the values $\hat{l}_i$, $\hat{\lambda}_i$,

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[17]Much of this additional explanatory power derives from the levels of $\hat{g}_i$ and $\hat{k}_i$. Interestingly, consistent with the formula for TE_i, $\hat{g}_i$ (representing the convexity of the cost function, γ_i) is correlated with treatment effects, whereas $\hat{k}_i$ (capturing the level of α_i) is not. For completeness, Appendix Table A2 provides the full table of estimates for Table 1 including those for $\hat{g}_i$ and $\hat{k}_i$ and corresponding interactions with Condition High.

$\hat{g}_i$, and $\hat{k}_i$ generated from a prior estimation procedure as regressors. This classic 'generated regressor problem' (Murphy and Topel, 2002) could intuitively lead to flawed inference as it treats preference parameters that should be recognized as quantitatively imprecise as ideal data. To overcome this issue, we bootstrap the entirety of Stage 1 estimation and the evaluation of heterogeneity in Stage 2 treatment effects.[18] The resulting average bootstrap coefficient and its standard deviation are presented in brackets in Table 1, columns (2) and (3). The conclusions drawn are identical to those derived from the standard regression analysis. Recognizing the potential for uncertainty in estimated preference parameters is an important factor when conducting exercises of this form, but the conclusions drawn in this setting are not altered.

Analyses of Predictions 2 and 3. Panel B of Figure 2 and columns 4 and 5 of Table 1 provide analyses associated with Predictions 2 and 3: that loss averse individuals will be more likely to have positive treatment effects and gain-seeking individuals will be more likely to have negative treatment effects. Panel B plots the relationship between $\hat{\lambda}_i$ and the empirical probability of having either a positive (black markers) or negative (red markers) value of TE_i. Individuals with $\hat{\lambda}_i > 1$ are systematically more likely than those with $\hat{\lambda}_i < 1$ to exhibit a positive TE_i. The correlation between $\hat{\lambda}_i$ and positive TE_i is $\rho = 0.19$ ($p < 0.01$). In contrast, individuals with $\hat{\lambda}_i < 1$ are somewhat more likely than those with $\hat{\lambda}_i > 1$ to exhibit negative TE_i. The raw correlation between $\hat{\lambda}_i$ and negative TE_i is $\rho = -0.08$ ($p = 0.09$). Using ordered logit regressions, columns (4) and (5) of Table 1 show that both $\hat{l}_i$ and $\hat{\lambda}_i$ are highly predictive of the sign of TE_i (i.e. $\{-1, 0, 1\}$) in both standard and bootstrapped analyses. These findings are directionally consistent with theoretical Predictions 2 and 3.

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[18]In each iteration of the bootstrap we follow this procedure: 1) sample with replacement to arrive at a data set of the same size as the original (a required 30 observations per subject for all 453 subjects); 2) conduct the estimation to arrive at individual values of $\hat{l}_i$, $\hat{\lambda}_i$, $\hat{g}_i$, and $\hat{k}_i$; 3) run the linear regressions associated with Table 1, columns (2) and (3); 4) record coefficients. In each iteration of the bootstrap we may have $\hat{g}_i \leq 0$ or insufficient response variation for some subjects. In such cases, these subjects' observations are dropped. The average bootstrap has observations from 445 subjects.

Table 1: Heterogeneous treatment effects in the labor supply experiment

Dependent Variable:	Panel A: Prediction 1 $log(e + 10)$			Panel B: Predictions 2 and 3 *Sign of Treatment Effect*	
	(1)	(2)	(3)	(4)	(5)
Condition High	0.26	0.06 [0.05]	-0.10 [-0.11]		
	(0.03)	(0.15) [(0.04)]	(0.15) [(0.04)]		
Gain-loss attitude: Reduced form ($\hat{l}_i$)		-1.22 [-1.12]		1.55 [1.22]	
		(0.18) [(0.07)]		(0.53) [(0.19)]	
Condition High $\times$ Reduced form ($\hat{l}_i$)		0.64 [0.53]			
		(0.19) [(0.06)]			
Gain-loss attitude: Structural ($\hat{\lambda}_i$)			-0.19 [-0.18]		0.33 [0.25]
			(0.03) [(0.01)]		(0.09) [(0.05)]
Condition High $\times$ Structural ($\hat{\lambda}_i$)			0.10 [0.08]		
			(0.03 [(0.01])		
Constant (Condition Low)	3.50	0.92 [0.98]	1.23 [1.32]		
	(0.03)	(0.18) [(0.05)]	(0.17) [(0.05)]		
Controlling for $\hat{g}_i$ and $\hat{k}_i$	No	Yes	Yes	Yes	Yes
R-Squared	0.03	0.40	0.39		
# Observations	906	906	906	453	453
H_0 : Zero TE (High-Low)	$F_{1,452} = 102.6$	$F_{1,452} = 0.17$	$F_{1,452} = 0.48$		
	$(p < 0.01)$	$(p = 0.68)$	$(p = 0.49)$		
H_0 : Gain-Loss $\perp$ Effort in Low		$F_{1,452} = 44.01$	$F_{1,452} = 49.14$		
		$(p < 0.01)$	$(p < 0.01)$		
H_0 : Gain-Loss $\perp$ TE		$F_{1,452} = 11.27$	$F_{1,452} = 15.23$	$\chi^2(1) = 8.65$	$\chi^2(1) = 12.61$
		$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$	$(p < 0.01)$

Notes: Panel A: Ordinary least squares regression explaining each subject's effort choice. Each subject provides two observations: one with their effort in Condition Low, and one with their effort in Condition High. Panel B: Ordered logit regression for sign of treatment effect. Each subject provides one observation based on the difference between Condition High and Condition Low. Clustered standard errors at the individual level in parentheses. Values in brackets correspond to bootstrapped values from 500 bootstraps re-estimating gain-loss attitudes and reconducting regression in each bootstrap. Each regression also controls for values of $\hat{g}_i$, $\hat{C}_i$, and interactions of each with Condition High. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i = 0$); 4) constant treatment effect over gain-loss attitudes (Condition High$\cdot_i$ or Condition High$\cdot_i = 0$). F-statistics, χ^2-statistics and two-sided p-values reported.

Limitations. One critical observation to note in Panel B of Figure 2 is that even for $\hat{\lambda}_i < 1$, positive treatment effects are more likely than negative treatment effects. Similarly, in Panel A of Figure 2 the average treatment effects for individuals with $\hat{\lambda}_i < 1$ is slightly positive. These facts are inconsistent with the EBRD formulation, which predicts negative treatment effects for such individuals. More broadly, we can assess the consistency of the data with precise theoretical predictions. To do so we calculate the value of $\hat{TE}_i = TE^*(\hat{\lambda}_i)$ for each individual and compare it to its empirical counterpart. Though the two measures are significantly correlated ($\rho = 0.25$, $p < 0.01$), the empirical treatment effects for gain-seeking individuals exceed the theoretical predictions, and the empirical treatment effects for loss-averse individuals fall short of theoretical predictions. Overall, individuals are simply not as sensitive to the difference between Conditions High and Low as their gain-loss estimates would theoretically imply. One possibility is that this lack of sensitivity is driven by the presence of noise: all of our constructs are subject to measurement error, which can attenuate the estimated relationship between them. However, the EBRD formulation of the reference point may also be substantively incomplete, so that our formulation misses some determinants of subjects' behavior, such as issues related to attention and salience. We interpret our findings as showing that while expectations-based reference points are quantitatively important drivers of effort choices, there are likely additional determinants of behavior in our study.

Gain-loss Attitudes Across Domains. Prior work has documented linkages between gain-loss attitudes measured with and without risk, coupling measures of small-stakes risk aversion with exchange behavior in standard endowment effect experiments (see, e.g., Dean and Ortoleva, 2015; Gächter et al., 2022). This work documents sizeable correlations between different measures, ranging from 0.3 to 0.6.

Appendix Figure A2 provides the distribution of gain-loss attitudes calculated using CPE from subjects' lottery choices. The mean and median λ are 1.48 and 1.42, respectively. As in the labor supply setting, we find substantial heterogeneity in gain-loss attitudes

across subjects. We classify a sizable minority of 28 percent as gain-seeking. We find that gain-loss attitudes estimated from lottery choices are correlated with the structural estimates of gain-loss attitudes based on labor supply decisions, but not dramatically so (Pearson's $r = 0.091$, $p = 0.03$; Spearman's $\rho = 0.084$, $p = 0.075$). And, we find that our lottery measure of gain-loss attitudes has no predictive power for treatment effects in Stage 2. These findings suggest that though heterogeneity is similar across domains, gain-loss attitudes at the individual level are potentially more domain-specific than generally appreciated.

3 Exchange Experiment

3.1 Experimental Design

The basic structure of the exchange experiment closely follows that of the labor supply experiment. Stage 1 serves to elicit gain-loss attitudes at the individual level. Stage 2 features a manipulation of expectations adapted to the exchange setting.

Stage 1: Measuring Gain-Loss Attitudes. At the beginning of the experiment, participants saw equally-sized pictures and descriptions of two objects. They were then randomly assigned a private cubicle in which they found one of the two objects. We informed them that the object in front of them was in their possession.[19] After three minutes allotted for inspection of the object, we asked subjects three questions. First, for each object subjects were asked "How much do you like this object?" with a Likert response scale ranging from 0="Not at all" to 8="Very much". Second, for each object they were asked "How much would you want to have this product?" using the same response scale. Third, they were asked "If you had to choose one of the objects, which one would you prefer to

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[19]Crucially, we did not say that they "own" the object, and we asked them to not remove the packaging yet.

keep?". These three unincentivized preference statements are the raw data from which our estimates of gain-loss attitudes are constructed.[20]

After subjects provided their preference statements, the experimenter randomly selected half of all subjects in the session based on a draw from a lotto drum that was clearly visible to all subjects. The experimenter replaced the endowed good with the alternative good for each of the selected subjects. This random replacement of Stage 1 objects was conducted to provide subjects with an experience of probabilistic exchange and to generate exogenous variation in the objects obtained in Stage 1. We informed subjects at the end of Stage 1 that they now own the object in their possession.

Stage 2: Experimental Manipulation of Expectations. The procedures in Stage 2 were purposefully similar to those in Stage 1. In a separate room, subjects saw pictures and descriptions of two objects—different from those used in Stage 1. Upon returning to their private cubicle they would find one of the two new objects, which we again assigned randomly. We study two between-subjects conditions, with randomization at the session level.[21] In both conditions, subjects decide whether they would like to retain their assigned object or exchange it. The two conditions differ in the probability that exchange will be forced regardless of their statement. In Condition Low, subjects face a 0% chance that exchange will be forced. That is, this condition is equivalent to a standard exchange setting common to endowment effect experiments. In Condition High, subjects are forced to exchange their object with 50% chance regardless of choice. The chance of forced exchange was based on a draw from a lotto drum that was visible to all subjects. Within EBRD models, the Low and High conditions induce different expectations of the final

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[20]Our design decision to use unincentivized preference statements for estimating Stage 1 gain-loss attitudes was motivated by a desire to focus on just a single experimental choice in Stage 2. Analytically this avoids subjects considering their suite of experimental choices in both stages as their CPE strategy. One may worry about the reliability of unincentivized preference statements. However, given the predictive power of these preference statements for predicting choices over other objects, these worries are allayed by the data.

[21]We present our analysis with robust standard errors in the main text and Appendix Table A9 reproduces our results with standard errors clustered at the session level. Statistical significance is enhanced with clustering, and so we decided to provide the more conservative values in the main text.

object to be obtained and so induce different reference points. This, in turn, leads to different willingness to exchange across the two conditions. In the neoclassical model or models with backwards looking reference points, the probability of forced exchange should have no effect on optimal choice.

Procedures and Pre-Registration. The objects used for the exchange experiment were a USB stick, a set of three erasable pens, a picnic mat, and a thermos.[22] We selected these four objects on the basis of a pre-experimental survey evaluation of 12 candidate objects. We put particular emphasis on ruling out complementarities between items across rounds. The former two (USB stick and pens) and the latter two objects (picnic mat and thermos) each constituted a pair. Across the two stages, each subject encountered each pair of objects exactly once. The use of each pair as the Stage 1 pair was counterbalanced at the session level.

The total sample for the exchange experiment consists of 1024 subjects recruited from the BonnEconLab at University of Bonn in Germany. In total, 59 percent (603 of 1024 subjects) were randomly assigned to Probabilistic Forced Exchange. An initial sample of 607 subjects participated in June and July 2015, and a pre-registered replication sample of a further 417 subjects participated in July 2018 (Goette et al., 2018, AEARCTR-0003124).[23] Subjects received a participation fee of 6 euros and also two of the four objects used in the experiment according to their endowments, choices, and chance. A full set of screenshots for our experiment, implemented in *ztree* (Fischbacher, 2007), can be found in Appendix D.

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[22]Pictures and information presented to subjects are reproduced in Appendix D.

[23]While the experiment carried out in June and July 2015 was not pre-registered, the one carried out in July 2018 was pre-registered. In the main body of the paper we pool the results from both experiments, but Appendix Table A8 shows that the main results replicate in both samples. There were a few very minor differences between the original sessions and those in the replication, which are also described in Appendix B.6.

3.2 Identifying Gain-Loss Attitudes and Heterogeneous Theoretical Predictions

We again derive theoretical predictions using the Kőszegi and Rabin (2006, 2007) EBRD model, now applied to the exchange setting with two objects. A reader familiar with the Kőszegi and Rabin (2006, 2007) model may wish to skip this section and proceed directly to the predictions spelled out at the end of Section 3.2.2 or the results presented in Section 3.3. We consider individual i's two-dimensional utility function over object X and object Y,

$$u_i(\mathbf{c}|\mathbf{r}) = m_X + m_Y + \mu_i(m_X - r_X) + \mu_i(m_Y - r_Y),$$

where $\mathbf{c} = (m_X, m_Y)$ refers to consumption utility associated with the quantity of each object, and $\mathbf{r} = (r_X, r_Y)$ similarly refers to reference utility. Thus, an individual's utility function consists of two components: consumption utility, $m_X + m_Y$, and gain-loss utility, $\mu_i(m_X - r_X) + \mu_i(m_Y - r_Y)$. We let $m_X, r_X \in \{0, X\}$, and $m_Y, r_Y \in \{0, Y\}$ denote both the outcome and the corresponding utility of zero or one unit of object X, and zero or one unit of object Y, respectively. For our primary analysis we assume utilities, X and Y to be homogeneous in the population, but we also investigate heterogeneity in valuations in Appendix B.2.[24] As before, we assume piecewise linear gain-loss attitudes, with potential heterogeneity in loss-aversion or gain-seeking, λ_i, and $\eta = 1$ for all individuals. We consider the estimation of gain-loss attitudes in Stage 1 of our experimental design, and the CPE comparative statics in Stage 2 of our experimental design.

3.2.1 Stage 1 Estimates of Gain-Loss Attitudes

In Stage 1 of our design subjects are explicitly endowed with an object and then asked to provide preference statements about that object and an alternative. These statements are made without knowledge of any possibility of actual exchange. Hence, theoretically,

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[24]The exercise elaborated in Appendix B.2 assumes homogeneous gain-loss attitudes and heterogeneous valuations as the source of variation in behavior in Stage 1. This formulation is clearly rejected by the heterogeneous treatment effects observed in Stage 2 of our exchange study.

the reference point is fixed at the endowed object.[25] An individual endowed with X will state a preference in the form of a higher liking value for X, higher wanting value for X, or hypothetical choice of X if $u_i(X, 0 | X, 0) - u_i(0, Y | X, 0) > \delta$, where δ captures the possibility of equal rating levels.[26] Under our functional form assumptions such a preference statement occurs if

$$(1 + \lambda_i) - 2\frac{Y}{X} - \delta_X > 0,$$

where $\delta_X \equiv \frac{\delta}{X}$. Similarly, an individual endowed with X would state a preference for Y if

$$2\frac{Y}{X} - (1 + \lambda_i) - \delta_X > 0.$$

An individual would state equal preferences if neither inequality were satisfied. These two equations provide an intuitive formulation for identifying gain-loss attitudes. Controlling for the relative utility of the two objects, $\frac{Y}{X}$, an individual with a greater value of λ_i should be more likely to prefer their endowment and less likely to prefer the alternative.

This simple intuition on identification motivates a reduced-form measure of gain-loss attitudes based on residual preference for endowed objects. First, we conduct a principal components analysis on the three preference statements in Stage 1 and reduce the data to the first principal component. Within our data the first component captures around 70 percent of the variation in relative wanting, relative liking, and hypothetical choice statements. We then regress this component on Stage 1 object assignment. The residuals of this regression summarize a residual preference for the endowed or the alternative object accounting for the average preference. An individual who disproportionately likes their assigned object relative to average preferences is plausibly more loss averse than one who

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[25]Though implausible given our design, potential alternative formulations might be to assume that subjects believe they can change their reference point from X to Y or to assume subjects consider retaining their endowed object, X, *and* gaining the alternative, Y (evaluating utility of Y as $X + (1 + \eta)Y$). Importantly, both of these formulations would imply that Stage 1 statements reveal no information on gain-loss attitudes, λ_i. Hence, both would yield null predictions for heterogeneous treatment effects in Stage 2. As such, the results we document invalidate these formulations.

[26]Note that $\delta = 0$ for our hypothetical choice data as there was no possibility of stating indifference.

exhibits a residual in the opposite direction. Hence, we consider these residuals as a reduced form measure of gain-loss attitudes, $\hat{l}_i$.[27]

In order to provide a structural estimate of the parameter, λ_i, we make the following assumptions. First, rather than assuming deterministic choice, we posit that an individual endowed with X will state a relative preference for X with probability

$$\pi_{X|X} = Prob((1 + \lambda_i) - 2\frac{Y}{X} - \delta_X > \epsilon),$$

a relative preference for Y with probability

$$\pi_{Y|X} = Prob(2\frac{Y}{X} - (1 + \lambda_i) - \delta_X > \epsilon),$$

and, where appropriate, would provide equal ratings for the two objects with probability $\pi_{E|X} = 1 - \pi_{X|X} - \pi_{Y|X}$. Symmetric formulations are assumed for individuals endowed with object Y. Within this structure, ϵ can be interpreted as capturing idiosyncratic variation in the $\frac{Y}{X}$ parametrically, or noise in response. We assume $Prob(\cdot)$ is the logistic function, leading to logit choice. Second, we assume that λ_i is drawn from a log-normal distribution with $log(\lambda_i) \sim N(\mu_\lambda, \sigma_\lambda^2)$, leading to a mixed logit formulation. Third, we assume the deterministic portion of relative utility, $\frac{Y}{X}$, is homogeneous in the population, and a parameter to be estimated. And fourth, we assume $\delta_X = 0.55$, a value that our prior research indicated to be an appropriate aggregate value.[28] These assumptions permit us

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[27]Residual preference for assigned objects could also partially reflect heterogeneity in the intrinsic utilities, $\frac{Y}{X}$. Because subjects are assigned new objects in Stage 2, heterogeneity in $\frac{Y}{X}$ in Stage 1 is orthogonal to any subsequent treatment effects. Hence, the interpretation of Stage 1 measures as being driven by heterogeneity in $\frac{Y}{X}$ is rejected by the heterogeneous treatment effects observed in Stage 2.

[28]See Appendix B.6 for these prior estimates. We found some sensitivities of the value σ_λ^2 to attempting to estimate δ_X alongside the other parameters. The challenge is intuitive: a larger value of δ_X implies individuals should more frequently give the two objects equal ratings. All else equal, a higher variance of gain-loss attitudes is required to justify the relative infrequency of such observations. Appendix Table A5 provides analysis setting δ_X at several different values and demonstrating corresponding sensitivity for the variance of gain-loss attitudes.

to estimate the parameters of the distribution of gain-loss attitudes $N(\hat{\mu}_\lambda, \hat{\sigma}_\lambda^2)$ based on Stage 1 data.[29]

Moving from the estimated distribution of gain-loss attitudes to an expected value of $\hat{\lambda}_i$ for each individual is a straightforward step. As proposed in Train (2009), from the estimated distribution, $N(\hat{\mu}_\lambda, \hat{\sigma}_\lambda^2)$, we simulate the distribution of gain-loss attitudes and the corresponding distributions of preference statements. We then calculate the expected simulated value of loss aversion for each possible combination of Stage 1 preference statements and use this as our measure of $\hat{\lambda}_i$ for all subjects who make a given combination of Stage 1 statements. Appendix B.2 provides additional details and Appendix Table A6 provides examples of the corresponding mappings from preference statements to $\hat{\lambda}_i$.

3.2.2 Heterogeneous Effects of Stage 2 Low vs. High Conditions

Consider Condition Low, in which subjects are asked whether endowed with object X they prefer X or Y. In this setting, the two potential CPE selections are $\{(X,0), (0,Y)\}$ (the first reflecting the choice to keep, and the second the choice to exchange). The individual can support keeping their endowed object in a CPE if $u_i(X, 0|X, 0) \geq u_i(0, Y|0, Y)$. Given our assumptions, this condition is satisifed for all values of X at or above a Low condition threshold $X \geq X_{Low,i} = Y$. That is, the individual can support keeping their endowed object if it has weakly greater consumption utility than the alternative.[30]

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[29]It is also straightforward to alter the assumptions of this formulation to estimate heterogeneity in intrinsic utilities, $\frac{Y}{X}$, rather than gain-loss attitudes. Such an exercise is presented in Appendix B.2, and yields estimates of aggregate loss aversion and substantial variation in object valuations. As noted above, interpreting Stage 1 measures as being driven by heterogeneous utilities rather than heterogeneous gain-loss attitudes leads to the prediction of no heterogeneous treatment effects in Stage 2, and thus is rejected by the data.

[30]It has been noted before that the CPE formulation predicts that individuals exchange in standard endowment effect designs only on the basis of consumption utility, and so fails to predict an endowment effect. The Kőszegi and Rabin (2006, 2007) EBRD model is also equipped with several alternative equilibrium concepts and refinements, Personal Equilibrium (PE) and Preferred Personal Equilibrium (PPE), the former of which can rationalize and endowment effect. Importantly, PE, PPE, and CPE all share common comparative statics for the change from Low to High conditions: loss-averse individuals should grow more willing to exchange in High relative to Low, while gain-seeking individuals should grow less willing to exchange in High relative to Low. Appendix B.1 presents all three forms of the Kőszegi and Rabin (2006, 2007) model's application to this design for completeness.

Next, consider the environment in Condition High. With probability 0.5, the agent, assumed endowed with X, will be forced to exchange X for Y regardless of their choice. If the individual wishes to retain their object, they are subject to a stochastic reference point, as with probability 0.5 their object will be exchanged regardless of their choice. Now, the potential CPE selections for someone endowed with X are $\{0.5(X,0) + 0.5(0,Y), (0,Y)\}$, with the first element reflecting attempting to keep the endowed object and the second reflecting exchange, as before. They can support attempting to keep their object as a CPE if

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

which, under our functional form assumptions, requires that X be at or above a revised threshold

$$X \geq X_{High,i} = \frac{1 + 0.5(\lambda_i - 1)}{1 - 0.5(\lambda_i - 1)} Y.$$

The manipulation of probabilistic forced exchange changes the CPE threshold for not exchanging from $X_{Low,i} = Y$ in Condition Low to $X_{High,i} = \frac{1+0.5(\lambda_i-1)}{1-0.5(\lambda_i-1)}Y$ in Condition High.

Note that the value of λ_i determines the difference between the thresholds in Low and High conditions. If individuals are loss-averse, $\lambda_i > 1$, then $X_{Low,i} < X_{High,i}$. If higher values for object X are required to support not exchanging in Condition High, this implies that loss-averse individuals should be more willing to exchange in High than in Low. In contrast, if individuals are gain-seeking $\lambda_i < 1$, then $X_{Low,i} > X_{High,i}$, and gain-seeking individuals are less willing to exchange in High than in Low. The empirical analogs for these theoretical relationships are the focus of our experiment.

We define the *Treatment Effect (TE)* as the percentage of individuals who exchange in Condition High minus those who exchange in Condition Low. The development above leads to the following empirical predictions for heterogeneous treatment effects.

Prediction 4. The empirical treatment effect, TE, in the exchange experiment increases in loss aversion, $\hat{l}_i$ and $\hat{\lambda}_i$.

Prediction 5. The empirical treatment effect, TE, in the exchange experiment is positive for loss-averse individuals, $\hat{l}_i > 0$ or $\hat{\lambda}_i > 1$.

Prediction 6. The empirical treatment effect, TE, in the exchange experiment is negative for gain-seeking individuals, $\hat{l}_i < 0$ or $\hat{\lambda}_i < 1$.

3.3 Results From The Exchange Experiment

3.3.1 Stage 1: The Distribution of Gain-Loss Attitudes in Exchange.

Fifty-seven percent of subjects state that they would hypothetically choose their endowed object, 45 percent provide a higher liking rating for their endowed object compared to 33 percent for the alternative, and 45 percent provide a higher wanting rating for their endowed object compared to 32 percent for the alternative. The different preference statements are remarkably correlated within individual. The pairwise Pearson correlations between hypothetical choice, relative liking, and relative wanting statements all exceed 0.7.

Given random assignment of endowed objects and the counterbalanced design, the distributions of preference statements should, in principle, be identical between endowed and alternative objects. Instead, all three distributions show a clear preference for the subject's endowed object relative to the alternative. For each measure we reject the null hypothesis that stated preferences are equal over the endowed and alternative objects.[31] These collected preference statements show a clear endowment effect, and so are indicative of loss aversion on average. However, we also document substantial heterogeneity. Thirty-eight percent of subjects (385 of 1024) state that they would hypothetically choose, strictly like,

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[31] Two sided t-tests comparing "Endowed>Alternative" to "Alternative>Endowed" are significant for all statements (Liking: $t = 5.48$, Wanting: $t = 5.86$, Hypothetical Choice: $t = 6.06$, $p < 0.01$ for all comparisons).
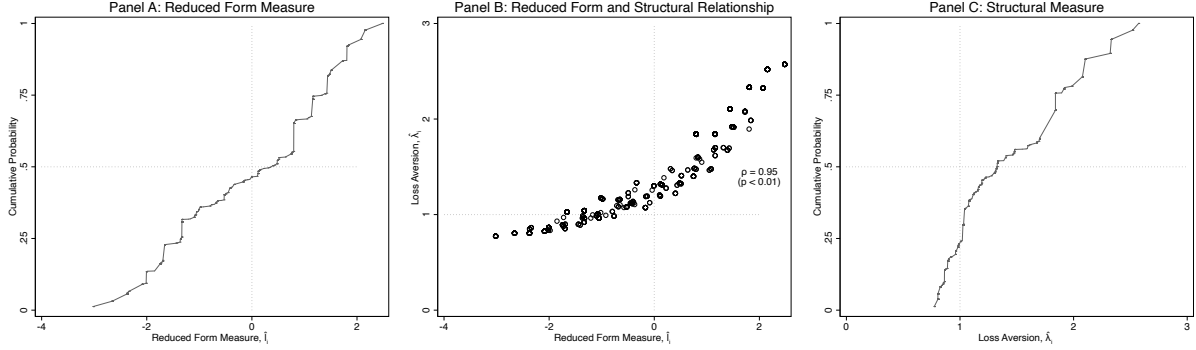
Figure 3: Stage 1: Gain-loss attitudes in the exchange experiment

Notes: Panel (a) and (c) show CDFs of the reduced form and structural measures of gain-loss attitudes, respectively. Panel (b) displays the relationship between the two measures ($r = 0.95$, $p < 0.01$)

and strictly want their endowed object. And, twenty-six percent of subjects (262 of 1024) exhibit the opposite pattern of hypothetically choosing, strictly liking, and strictly wanting the alternative object. While this heterogeneity in statements likely partly reflects variation in valuations for the different objects, the predictive power of these Stage 1 statements for Stage 2 behavior with different randomly assigned objects demonstrates that an important component is driven by heterogeneous gain-loss attitudes.

Figure 3 shows the distributions of our reduced form and structural measures of gain-loss attitudes associated with the heterogeneity in Stage 1 preference statements, along with the relationship between the two. As in the labor supply study, we document substantial variation in gain-loss attitudes, irrespective of which measure we rely on. Appendix Table A4 provides the structural estimates for the distribution of gain-loss attitudes, $N(\mu_\lambda, \sigma_\lambda^2)$, alongside the auxiliary parameters for relative utilities, $\frac{X}{Y}$, for each pair of objects; and Appendix Table A6 provides the mapping from preference statements to individual estimates of $\hat{\lambda}_i$ under these estimates. Within our sample, $\hat{\lambda}_i$ has mean 1.49 and median 1.34. In line with our labor supply findings, we calculate that 76% of subjects are loss-averse, $\hat{\lambda}_i > 1$, while 24% are gain-seeking $\hat{\lambda}_i < 1$. Also as in our labor supply experiment, we observe a strong correlation between the reduced form and structural measures of gain-loss attitudes (Pearson's $r = 0.95$, $p < 0.01$).

3.3.2   Stage 2: Heterogeneous treatment effects of Low vs. High

Stage 1 behavior, measured with one pair of objects for each subject, delivers estimates of gain-loss attitudes that can be used to analyze Stage 2 choices in the Low and High conditions measured with a different pair of objects. Figure 4 provides a visual illustration of the connections between Stage 1 gain-loss attitudes and Stage 2 behavior. In both panels, we construct 15 equally spaced bins of Stage 1 $\hat{\lambda}_i$ and connect this measure of gain-loss attitudes to a relevant choice or treatment effect in Stage 2 to test Predictions 4-6.

Analyses of Prediction 4.   Figure 4 Panel A documents the relationship between $\hat{\lambda}_i$ and estimated treatment effects: we estimate larger treatment effects among subjects with greater values of $\hat{\lambda}_i$. This connection between gain-loss attitudes and treatment effects is closely in line with the theoretical implications of EBRD and Prediction 4.

Table 2 provides corresponding regression results for Prediction 4. In column (1), we regress the likelihood of exchanging in Stage 2 on an indicator for Condition High without accounting for heterogeneous gain-loss attitudes. In Condition Low, 38 percent of subjects choose to exchange. Comparing this value to the neoclassical benchmark of 50 percent indicates a significant endowment effect in Condition Low, $F_{1,1022} = 25.66$, $(p < 0.01)$. The estimated coefficient on the indicator for Condition High is 0.00 (clustered s.e. $= 0.03$), showing that the substantial endowment effect observed in Condition Low is unaffected by probabilistic forced exchange on average. In contrast to the prediction of EBRD models with universal loss aversion (which would predict a positive treatment effect), we fail to reject that this treatment effect is different from zero.

The precisely estimated aggregate null effect in Table 2 column (1) masks substantial heterogeneity in treatment effects over gain-loss attitudes. Without accounting for heterogeneous gain-loss attitudes, the average treatment effect reported in column (1) potentially aggregates different-signed effects of loss-averse and gain-seeking subjects. This aggrega-

Panel A: Heterogeneous Treatment Effects
(Predictions 4)

Panel B: Directional Effects
(Predictions 5 and 6)
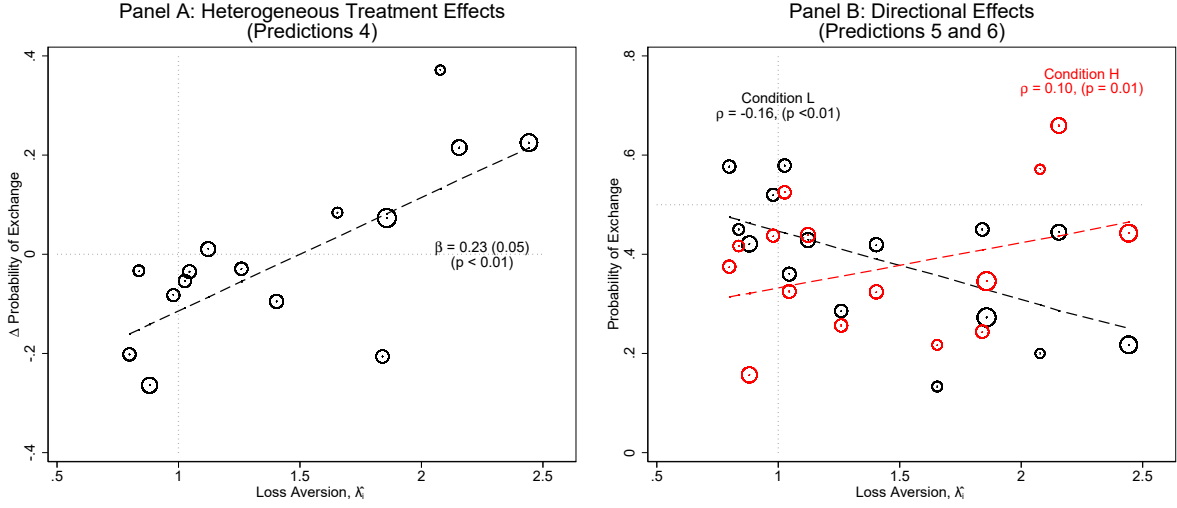
Figure 4: Stage 2: Heterogeneous treatment effects in the exchange experiment

Notes: Panel A shows the relationship between $\hat{\lambda}_i$ and treatment effects in fifteen equally sized bins of $\hat{\lambda}_i$. Panel B plots the relationship between $\hat{\lambda}_i$ and willingness to exchange in Condition Low (black markers) and Condition High (red markers).

tion creates a number of theoretical issues challenging reliable identification.[32] Columns (2) and (3) accommodate the heterogeneous treatment effects suggested by Figure 4: we interact treatment with reduced form and structural measures of gain-loss attitudes. Both measures are highly positively correlated with the effect of treatment, consistent with Prediction 4. More loss averse subjects have greater increases in their willingness to exchange as they move from the Low to the High condition. Consistent with EBRD, individuals respond to the change in expectations across Low and High conditions, and differentially so depending on their gain-loss attitudes. Alternative formulations of the reference point predict zero treatment effect and zero heterogeneity therein, and, thus, are rejected by our exchange study results. Importantly, as in the labor supply experiment, when account-

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[32]In Appendix B.4, we show that in the exchange setting the relationship between λ_i and treatment differences for exchange probability can be concave, with the negative effects for gain-seeking individuals being of greater absolute magnitude than the positive effects for loss-averse individuals. This leads to substantial aggregation issues in our setting as the average treatment effect may be substantially understated relative to the treatment effect of the average preference. This may help to explain why the average treatment effect is indeed null.

ing for heterogeneous treatment effects over gain-loss attitudes, a substantially greater proportion of behavior is explained; the R^2 values increase by more than a factor of 10.

In addition to the standard regressions presented in columns (2) and (3) of Table 2, we also present bootstrap analyses to account for the potential issue of using the values $\hat{l}_i$ and $\hat{\lambda}_i$, generated from prior estimation procedures as regressors. As in the labor supply study, we bootstrap the entirety of Stage 1 estimation and the evaluation of heterogeneity in Stage 2 treatment effects. The resulting average bootstrap coefficient and its standard deviation are presented in brackets in Table 2, columns (2) and (3).[33] The conclusions from the bootstrap analyses are qualitatively similar to the original analysis.

Analyses of Prediction 5 and 6.   Panel A of Figure 4 also provides analyses associated with Predictions 5 and 6: that the level of the treatment effect is positive for loss-averse individuals but negative for gain-seeking individuals. We find that individuals with $\hat{\lambda}_i > 1$ are systematically more likely than those with $\hat{\lambda}_i < 1$ to exhibit a positive treatment effect. Panel A shows negative estimated treatment effects for all bins with $\hat{\lambda}_i < 1$, and positive treatment effects for 55% (6 out of 11) of the bins with $\hat{\lambda}_i > 1$.

To shed light on the drivers of the heterogeneous treatment effect in Panel A, Panel B of Figure 4 plots the empirical frequency of exchanging separately for the High and Low conditions, for the 15 different bins of $\hat{\lambda}_i$. First, we observe a negative relationship in Condition Low: more loss-averse subjects are less likely to exchange their endowment for the alternative, $\rho = -0.16$ ($p < 0.01$). Second, this relationship reverses in Condition High: willingness to exchange increases in $\hat{\lambda}_i$, $\rho = 0.10$ ($p < 0.01$). Within the Kőszegi and Rabin (2006, 2007) model's CPE construct, the positive correlation between $\hat{\lambda}_i$ and willingness to exchange in Condition High is predicted. However, the negative correlation between $\hat{\lambda}_i$ and willingness to exchange in Condition Low lies outside the CPE formulation; exchange

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[33]Given the computational intensity of the task, we limit the analysis to 500 bootstrap iterations. Not every bootstrap for the mixed-logit estimation converged, and some bootstraps delivered extreme outlier regression coefficients for the Condition High treatment effect. Column (3) thus presents bootstrapped coefficients and standard errors winsorized at 5th and 95th percentile for the Condition High treatment effect (conditional on converging), yielding 425 total bootstraps.

Table 2: Heterogeneous treatment effects in the exchange experiment

Dependent Variable:	Exchange $(= 1)$		
	(1)	(2)	(3)
Condition High	0.00	0.00 [0.00]	-0.34 [-0.37]
	(0.03)	(0.03) [(0.03)]	(0.09) [(0.14)]
Gain-loss attitude: Reduced form $(\hat{l}_i)$		-0.05 [-0.05]	
		(0.02) [(0.02)]	
Condition High $\times$ Reduced form $(\hat{l}_i)$		0.08 [0.08]	
		(0.02) [(0.02)]	
Gain-loss attitude: Structural $(\hat{\lambda}_i)$			-0.14 [-0.15]
			(0.04) [(0.08)]
Condition High $\times$ Structural $(\hat{\lambda}_i)$			0.22 [0.25]
			(0.05) [(0.11)]
Constant (Condition Low)	0.38	0.38 [0.38]	0.58 [0.60]
	(0.02)	(0.02) [(0.02)]	(0.07) [(0.09)]
R-Squared	0.03	0.40	0.39
# Observations	1024	1024	1024
H_0 : Zero TE (High-Low)	$F_{1,1022} = 0.01$	$F_{1,1020} = 0.02$	$F_{1,1020} = 15.12$
	$(p = 0.91)$	$(p = 0.90)$	$(p < 0.01)$
H_0 : Gain-Loss $\perp$ Exchange in Low		$F_{1,1020} = 10.69$	$F_{1,1020} = 11.23$
		$(p < 0.01)$	$(p < 0.01)$
H_0 : Gain-Loss $\perp$ TE		$F_{1,1020} = 14.65$	$F_{1,1020} = 17.25$
		$(p < 0.01)$	$(p < 0.01)$

Notes: Ordinary least squares regression explaining each subject's decision to exchange their object. Values in brackets correspond to bootstrapped values from 500 bootstraps re-estimating gain-loss attitudes and reconducting regression in each bootstrap. Not every bootstrap for the mixed-logit estimation converged, and some bootstraps delivered extreme outlier regression coefficients for the Condition High treatment effect. Column (3) thus presents bootstrapped coefficients and standard errors winsorized at 5th and 95th percentile for the Condition High treatment effect (conditional on converging), yielding 425 total bootstraps. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i = 0$); 3) constant treatment effect over gain-loss attitudes (Condition High $\times$ $\hat{\lambda}_i$ or Condition High $\times$ $\hat{l}_i = 0$). F-statistics and two-sided p-values reported.

in Condition Low should be independent of gain-loss attitudes under CPE. Interestingly, however, in their model's alternative Personal Equilibrium (PE) construct, this correlation is admitted (see Appendix B.1.3 for details). Given that some portion of our observed heterogeneous treatment effects falls outside of the CPE framing, our results may speak to the relevance of this alternative equilibrium construct.

Limitations. One important observation to note in Panel A of Figure 4 is that we document negative treatments even for some bins of $\hat{\lambda}_i > 1$. This is inconsistent with the EBRD formulation and Prediction 5, which predicts positive treatment effects for all loss-averse individuals. By contrast, we document slightly negative levels of treatment effects for individuals with low levels of loss aversion, i.e. those that are estimated to be close to gain-loss neutrality. The linear fit shown in Panel A suggests a crossing point from negative to positive treatment effect at a level of loss aversion of $\hat{\lambda}_i \approx 1.5$, rather than at 1 as predicted by the theory. Similar to our findings on labor supply, one possibility is this reflects the inherent noisiness of our estimates of loss aversion and empirical estimates of treatment effects. Another possibility that we openly embrace is that the EBRD formulation of the reference point is incomplete, and that there are additional drivers of behavior in our study for which we cannot account.

In sum, the results on the heterogeneity of gain-loss attitudes and its predictive power for the behavioral effect of a shift in the expectations-based reference point closely mirror those of the labor supply experiment. This is despite the fact that the two sets of findings rely on entirely distinct experimental paradigms and leverage different approaches for identifying gain-loss attitudes.

4   Conclusion

Prior work testing reference-dependent preferences assumes universal loss aversion. This paper studies the role of heterogeneity in gain-loss attitudes, and explores its implications

for identifying models of the reference point. Failing to acknowledge heterogeneity in gain-loss attitudes is critical both because comparative statics used to test different formulations of the reference point can change sign depending on the level of gain-loss attitudes and because such heterogeneity is an empirical reality. In two laboratory experiments, we show that once one accounts for heterogeneity in gain-loss attitudes, experimental tests are strikingly supportive of Expectations-Based Reference Dependence (EBRD) formulations of reference points.

Our large-sample pre-registered experiments show that the existing body of evidence on heterogeneity in gain-loss attitudes is not a mere artifact of measurement error or behavioral noise. Instead, by showcasing its out-of-sample predictive power, we document that gain-seeking behavior has a substantive interpretation that can be productively used in theory testing. The consistency of our findings across our two experimental settings attests to the robustness and importance of recognizing heterogeneity.

Conceptually, the importance of recognizing parameter heterogeneity in identifying behavioral predictions hinges on two issues: non-linearity in aggregation and statistical power. First, treatment effects need not aggregate linearly over the dimension of heterogeneity, so ignoring heterogeneity can confound inference. The severity of this concern differs by model and context, and we, ourselves, show a potentially more pronounced aggregation problem in our study of exchange behavior than in our study of labor supply. Similar concerns have been highlighted in other decision domains such as intertemporal choice (Weitzman 2001; Jackson and Yariv 2014). Second, even under linear aggregation, heterogeneity influences power considerations. An empirical study that is theoretically well-powered under the assumption of preference homogeneity may be under-powered if there is actual heterogeneity, which may lead to false conclusions from null findings. Both issues are of first-order importance for interpreting empirical tests of theories that likely feature parameters with real-world heterogeneity.

There is no universally accepted measurement of gain-loss attitudes, and each candidate has unique advantages and potential drawbacks. In the two designs presented in this

manuscript, we elicit gain-loss attitudes in markedly different ways. In our labor supply study, we estimate gain-loss attitudes both from a large number of incentivized labor supply decisions and lottery choices. We treat each decision as isolated for the purposes of estimating gain-loss attitudes. Such approaches facilitate estimation, but fail to account for the possibility that the reference point (EBRD or otherwise) depends upon the entire body of choice problems. In our exchange behavior study, by contrast, we estimate gain-loss attitudes from hypothetical non-choice data, circumventing this challenge but creating the concern that the measures are not incentivized. Importantly, regardless of these differences in domain and measurement technique, we find quite similar distributions of gain-loss attitudes in our two studies. Whether measured using incentivized labor supply, lottery choices, or hypothetical exchange choices, around three quarters of subjects are measured to be loss averse and one quarter gain seeking.

Though we provide results on the role of EBRD in the two main paradigms used to test models of reference-dependent preferences, the considerations that motivate this paper equally apply to the role of gain-loss attitudes in other classes of theories and applications. Heterogeneity matters not only for tests of non-expectations-based forms of reference dependence, such as current or backward-looking elements (e.g., Bowman et al. 1999), but also for other field settings in which loss aversion has been shown to play a role, such as job search (DellaVigna et al. 2017), insurance choice (Barseghyan et al. 2013) or tax compliance (Engström et al. 2015).

Beyond the context of gain-loss attitudes, our work contributes to a growing literature in behavioral economics that acknowledges the importance of (structurally) recognizing heterogeneity in behavioral parameters (see DellaVigna 2018 for a recent review). Our paper shows that taking the theoretical implications of heterogeneity seriously—instead of treating it as a nuisance—can deliver more comprehensive tests of behavioral theories and potentially reconcile conflicting evidence.

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Appendix For Online Publication

Appendix Table of Contents

Appendix A Additional Development, Analysis, and Results for Labor Supply Study

This Appendix provides additional theoretical development and analysis for the labor supply study. Appendix A.1 presents theoretical considerations applicable to the labor supply study. Appendix A.2 discusses theoretical treatment effects and aggregation thereof over gain-loss attitudes. Appendix A.3 provides a reconciliation report with pre-analysis plan. Finally, Appendix A.4 presents additional results noted in the text.

A.1 Theoretical Considerations for Labor Supply

We present the theoretical framework of the Kőszegi and Rabin (2006, 2007) EBRD formulation as applied to an individual's labor supply decision. An agent's utility consists of two components: 1) consumption utility derived from earned wages and the (negative) cost of exerting effort, and 2) psychological utility derived from comparing the realized wage and effort level to the agent's expectations. Formally, this is represented by

$$u_i(w, e | r_w, r_e) = m(we) - c_i(e) + \mu_i(m(we) - m(r_w)) + \mu_i(c_i(e) - c_i(r_e)).$$

The first component of utility, $m(we) - c_i(e)$, is standard consumption utility obtained from working e tasks and earning we. Consumption utility is complemented with a reference-dependent, psychological component of utility, for which the utility from realized earnings $m(we)$ is compared to the utility of reference-point earnings $m(r_w)$ under a piece-wise linear gain-loss function μ_i, where

$$\mu_i(z) = \begin{cases} \eta z & z \geq 0 \\ \eta \lambda_i z & z < 0. \end{cases}$$

Intuitively, if an outcome falls short of the referent by a difference of z, this leads to a reduction of utility by $\eta\lambda_i$ times this difference. An outcome that exceeds the reference point increases utility by η times the difference, where $\eta > 0$. Thus, λ_i represents individual gain-loss attitude and can either exhibit loss-aversion where losses are felt more severely than commensurate gains, $\lambda_i > 1$, or gain-seeking where gains are felt more severely than commensurate losses, $\lambda_i < 1$. If $\lambda_i = 1$, there is the individual is considered 'loss-neutral'. Throughout the analysis, we assume that $m(we) = we$ and constant for all individuals, that $c_i(e)$ is an increasing at least twice-differentiable convex function, and normalize $\eta = 1$ for all individuals.

Kőszegi and Rabin (2006, 2007) propose that agents hold the entire distribution of the outcome space as their expectation. Each potential realization is compared to every other potential realization and weighted by the relevant densities. In the labor supply context, decision-makers face a potentially stochastic schedule of wages and must commit to an effort level prior to the realization of wages. Thus, when considering the utility of an effort level e', the agent computes the expected consumption utility given the known wage distribution as well as the expected gain-loss utility. Mathematically, this is represented as a double integral over the stochastic reference points ($\mathbf{r} = (r_w, e')$) and the stochastic consumption realizations ($\mathbf{c} = (w, e')$):

$$U_i(F|G) = \int \int u_i(\mathbf{c}|\mathbf{r})dG(\mathbf{r})dF(\mathbf{c}),$$

where F, G represent the lotteries over the wage-outcome space at a fixed level of effort.

A.1.1 Choice Acclimating Personal Equilibrium (CPE)

In order to close the model, Kőszegi and Rabin (2006, 2007) equip it with the rational equilibrium concept known as CPE:

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Choice Acclimating Personal Equilibrium (CPE): A choice $F \in \mathcal{D}$, where $\mathcal{D}$ is the possible outcome space, is a choice-acclimating personal equilibrium if

$$U_i(F|F) \geq U_i(F'|F') \ \forall \ F' \in \mathcal{D}.$$

In our context, the effort level e_i^* is a CPE if its associated ex-ante utility—given the distribution of wages it induces—is the largest of all the possible effort choices given the ex-ante distributions they respectively induce. In deriving comparative static predictions throughout the following sections, we will assume that agents seek to maximize their CPE utility.

A.1.2 CPE Comparative Statics

We consider how CPE individuals behave when offered a wage $(p, X; q, Y; 0.5, w)$ where $Y < X$; that is, individuals have a 50% chance of earning a piece-rate, w per unit of effort, a $p\%$ chance of earning $\$X$, and a $q = (0.5 - p)\%$ chance of earning $\$Y$ regardless of effort. The CPE utility induced by a prospective effort level, e_i is given by

$$U((p, X; q, Y; 0.5, we_i)|(p, X; q, Y; 0.5, we_i)) =$$

$$
\begin{cases}
pX + qY + 0.5we_i + (1 - \lambda_i)\left[pq(X - Y) + 0.5p(X - we_i) + 0.5q(Y - we_i)\right] - c_i(e_i) & we_i < Y < X \\
pX + qY + 0.5we_i + (1 - \lambda_i)\left[pq(X - Y) + 0.5p(X - we_i) + 0.5q(we_i - Y)\right] - c_i(e_i) & Y < we_i < X \\
pX + qY + 0.5we_i + (1 - \lambda_i)\left[pq(X - Y) + 0.5p(we_i - X) + 0.5q(we_i - Y)\right] - c_i(e_i) & Y < X < we_i.
\end{cases}
$$

Following the appendix of Gneezy et al. (2017), we study the effects of an increase in p by signing the derivative $\frac{\partial e_i^*}{\partial p}|_{p+q=0.5}$ when $Y \leq we_i \leq X$. When the considered level of effort yields earnings between Y and X, the optimal level of effort can be found by

studying the first order condition of

$$0.5w\left[1 + (p - q)(\lambda_i - 1)\right] = c_i'(e_i^*).$$

Defining $\bar{P} = p + q = 0.5$ and $p - q = 2p - \bar{P} = 2p - 0.5$, we can sign the partial derivative as

$$\frac{\partial e_i^*}{\partial p}|_{p+q=0.5} = (c_i'^{-1})'(0.5w[1 + (2p - 0.5)(\lambda - 1)]) * (\lambda - 1)w.$$

By the inverse function theorem, $(c'^{-1})'(0.5w[1 + (2p - 0.5)(\lambda_i - 1)]) * (\lambda_i - 1)w = \frac{1}{c_i''(e_i^*)}$ where $0.5w[1 + (2p - 0.5)(\lambda_i - 1)] = c'(e_i^*)$. Thus,

$$\frac{\partial e_i^*}{\partial p}|_{p+q=0.5} = \frac{(\lambda_i - 1)w}{c''(e_i^*)}$$

and by the assumed convexity of $c_i(\cdot)$, we know $c_i''(e^*) > 0$ so that

$$\lambda_i > 1 \implies \frac{\partial e_i^*}{\partial p}|_{p+q=0.5} > 0$$
$$\lambda_i < 1 \implies \frac{\partial e_i^*}{\partial p}|_{p+q=0.5} < 0.$$

Thus, under CPE, loss-averse individuals are predicted to increase their effort whereas gain-seeking individuals are predicted to decrease their effort in response to an increasing in p, holding fixed $p + q = 0.5$.

For completeness, we also discuss the other two cases: $we_i < Y < X$ and $Y < X < we_i$. First, consider $we_i < Y < X$. The first order condition yielding optimal effort is

$$0.5w\left[1 + (p + q)\eta(\lambda - 1)\right] = c'(e),$$

and because $c_i'(e_i)$ is continuous and differentiable, $c_i'^{-1}(e_i)$ exists and the optimal e_i^* is

$$e_i^* = c_i'^{-1}\left(0.5w\left[1 + (p + q)(\lambda_i - 1)\right]\right).$$

Turning back to $\frac{\partial e_i^*}{\partial p}|_{1-p-q=0.5}$, let $p + q = \bar{P} = 0.5$—since changes in p must leave $p + q$ constant, we have that $\frac{\partial e_i^*}{\partial p}|_{1-p-q=0.5} = 0$ in this case. Next, consider $Y < X < we_i$. Again, we examine the first order condition given by

$$0.5w\left[1 - (p + q)(\lambda_i - 1)\right] = c'(e_i),$$

and

$$e_i^* = c_i'^{-1}(0.5w[1 - (p + q)(\lambda_i - 1)]),$$

again yielding $\frac{\partial e_i^*}{\partial p}|_{1-p-q=0.5} = 0$.

A.2 Non-Linear Aggregation of Labor Supply Treatment Effects and Statistical Power

Having established an individual's theoretical treatment effect,

$$TE_i^*(\lambda_i, \gamma_i) \equiv log(e_{i,H}^* + 10) - log(e_{i,L}^* + 10) = \frac{1}{\gamma_i - 1} log \left[\frac{1 + 0.4(\lambda_i - 1)}{1 - 0.4(\lambda_i - 1)} \right],$$

we can consider aggregation of treatment effects into an average theoretical treatment effect,

$$\overline{TE^*(\lambda_i, \gamma_i)} = \frac{1}{N} \sum TE^*(\lambda_i, \gamma_i).$$

When will the average treatment effect deviate from the treatment effect of the average gain-loss attitude, $\overline{\lambda}_i$? Note that for quadratic costs, $\gamma_i = 2$, the marginal cost function is linear, and so treatment effects are a function of λ_i alone

$$TE_i^*(\lambda_i, 2) = log \left[\frac{1 + 0.4(\lambda_i - 1)}{1 - 0.4(\lambda_i - 1)} \right],$$

In such a case, an alternate expression for the difference in treatments, $e_{i,H}^* - e_{i,L}^* = \alpha_i 0.10[0.8(\lambda_i - 1)]$, would be linear in λ_i and α_i. If λ_i and α_i were independent then averaging over these two linear dimensions of heterogeneity would not lead to deviations between the average value of $e_{i,H}^* - e_{i,L}^*$ and its value at the average λ_i.

Of course, aggregation of the relevant treatment effect of interest, TE_i^*, will not generally be linear. Holding γ fixed across individuals, Figure A1 plots $TE^*(\lambda_i, \gamma)$ for $\gamma \in \{1.5, 2, 2.5, 3\}$. In all cases, the average treatment effect would not necessarily correspond to the treatment effect of the average preference. Moreover, the relationship between λ_i and theoretical treatment effects illustrated in Figure A1 may lead average treatment effects to overstate the case for loss aversion. Naturally, much depends on the distribution of gain loss attitudes and the shape of costs, but if the average preference is loss averse, then due to the convexity apparent in Figure A1 for some values of γ one could obtain substantially upwards-biased average treatment effects.

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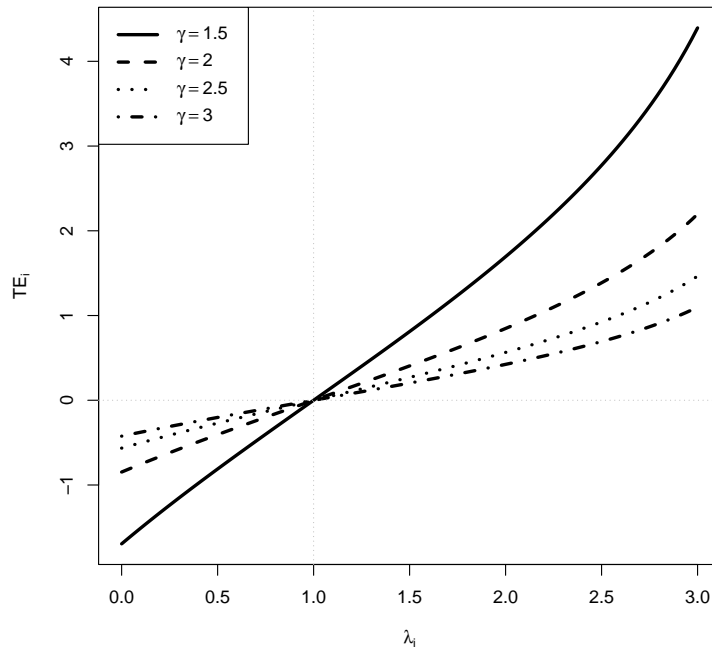
Figure A1: Predicted treatment effects by gain-loss attitudes

Notes: This figure represents predicted treatment effects for different values of λ (x-axis) and γ (different curves).

In our estimation exercise, we obtain an average estimate of $\hat{g}_i = 0.520$, implying an average $\hat{\gamma}_i = (1/0.520) + 1 = 2.92$. Examining the curve for the nearby value of $\gamma = 3$ suggests limited non-linearity in treatment effects over λ_i. Nonetheless, even if the average treatment effect is approximately the treatment effect of the average preference, aggregating over different gain-loss types can affect the power of any conducted experimental test.

To illustrate a simple example where linear aggregation is theoretically appropriate, assume $\gamma = 2$ and homogeneous α, and consider the alternate average difference measure,

$$\overline{e_{i,H}^*(\lambda_i, 2, \alpha) - e_{i,L}^*(\lambda_i, 2, \alpha)} = \kappa\overline{\lambda_i} - \kappa,$$

where $\kappa = \alpha \cdot 0.10 \cdot 0.8$. The theoretical standard deviation of this difference is thus

$$sd(e_{i,H}^*(\lambda_i, 2, \alpha) - e_{i,L}^*(\lambda_i, 2, \alpha)) = \kappa \cdot sd(\lambda_i).$$

Our average estimate is $\hat{k}_i = 4.54$. Recall that $k_i = log(\alpha_i)/(\gamma_i - 1)$, such that with γ fixed at 2, this would correspond to a value $\alpha = exp(4.54) = 93.7$, and thus $\kappa = 0.1 * 0.8 * 93.7 \approx 7.5$. We estimate an average value of $\hat{\lambda}_i = 1.65$ with a standard deviation of 1.04. Absent any other source of variation, we would thus expect an average difference of 4.9 with a standard deviation of 7.8 under our estimated distribution of gain-loss attitudes.

A study that is theoretically powered assuming homogeneous gain-loss attitudes and straightforward sampling variation will have different power considerations when accounting for this additional source of variation introduced by heterogeneity. Consider an EBRD labor supply experiment conducted with approximately 50 subjects. Absent heterogeneity in gain-loss attitudes, the above difference of 4.9 would be powered at 80% with 50 subjects if the standard deviation of the difference due to sampling variation alone were approximately 11.5. If heterogeneity and sampling variation were independent (and thus additive in variance to yield standard deviation $\sqrt{(11.5^2 + 7.8^2)} \approx 13.9$), this same difference would require approximately 70 observations to appropriately power accounting for the above heterogeneity. Hence, as illustrated in this simple example, accounting for

heterogeneity in gain-loss attitudes can substantially alter the power considerations associated with testing average treatment effects in labor supply designs, even when linear aggregation is theoretically appropriate for the object of interest.

A.3 Reconciliation with Pre-Analysis Plan of the Labor Study

In this section we report the methodology and corresponding analyses that we pre-registered for the labor supply study (Campos-Mercade et al. 2021, AEARCTR-0007277). By and large, the main text of the paper closely follows the pre-analysis plan. There are however two key points to discuss in order to reconcile the analyses in the main text with the pre-analysis plan: the number of subjects and the estimation of gain-loss attitudes (Stage 1). We discuss each of these points below.

A.3.1 Sample size

Our power analyses showed that a sample between 500 and 600 subjects would give us enough power to detect the hypothesized heterogeneous treatment effects of the gain-loss attitudes. We hence pre-registered that we would gather between 500 and 800 subjects. The reason why we pre-registered a range is that we were unaware of how many subjects we would be able to recruit using the UC San Diego Economics Laboratory, online, and in the middle of the COVID-19 pandemic. Once we started collecting data we found out that recruiting subjects was harder than anticipated, with very few subjects signing up for our last sessions. We hence decided to stop as soon as we hit the pre-registered lower bound of 500 subjects. This decision was made prior to downloading the data and performing the first analysis.

A.3.2 Identifying Gain-Loss Attitudes

As in the main text of the paper (Section 2.2), we pre-registered that we would use a maximum likelihood tobit method using $c_i(e_i) = \frac{1}{\gamma_i}(e+10)^{\gamma_i}$ to estimate gain-loss attitudes. In the main text of the present paper, however, we go one step further and develop a simple methodology for estimation of gain-loss attitudes that allows us to retrieve $\hat{\lambda}_i$ using a linear formulation.

This new measure not only helps our analysis conceptually but also computationally: since in order to account for estimation uncertainty we bootstrap the Stage 1 estimation (Murphy and Topel 2002), the linear formulation allows us to perform this analysis much more efficiently. Importantly, we initially performed different analyses using maximum likelihood (which could not account for estimation uncertainty) and all our results were qualitatively and quantitatively similar.

A.4 Additional Tables and Figures for Labor Supply Study
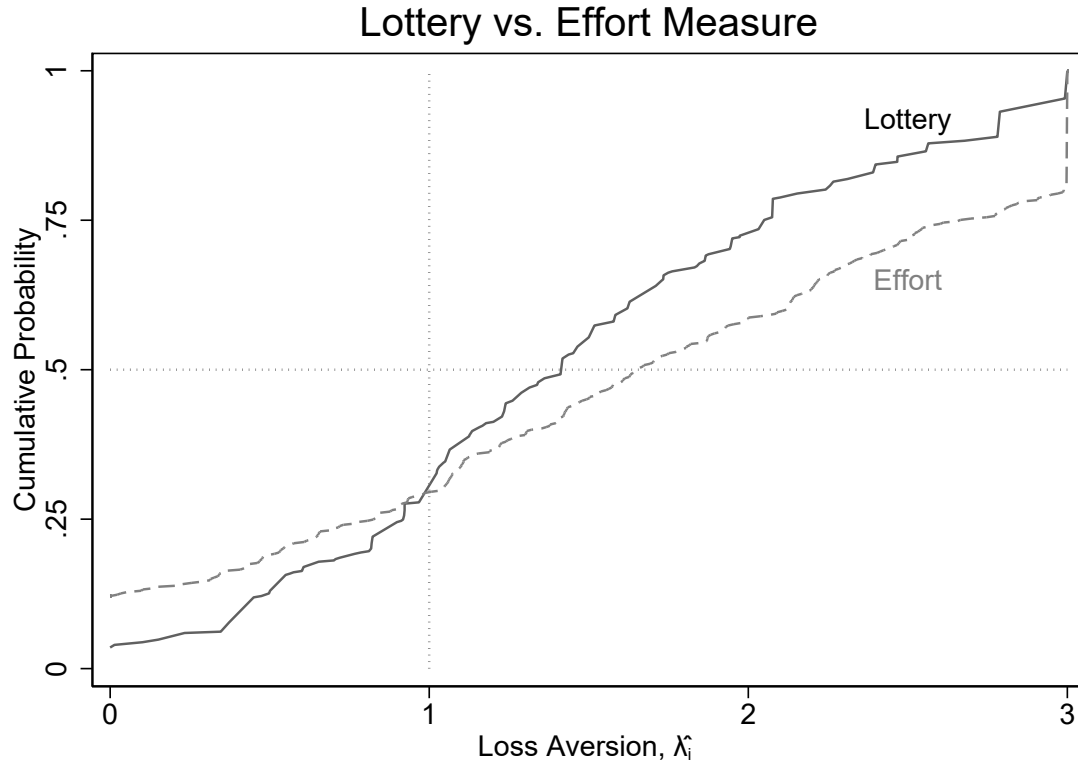
Figure A2: Distribution of $\hat{\lambda}_i$ estimated from subjects' effort and lottery choices

Table A1: Descriptive statistics in the labor supply study

Decision	Fixed w.	Low w.	High w.	Mean	SD	Q25	Q50	Q75	Fr. 100	Fr. 0
1	0.05			19.43	27.49	0	8.5	26.25	0.06	0.37
2	0.1			25.1	29.47	0	14	40	0.07	0.28
3	0.125			31.55	30.94	5	21	50	0.08	0.2
4	0.15			38.68	33.45	10	30	61	0.12	0.15
5	0.175			48.83	34.22	20	45.5	80	0.2	0.06
6	0.2			39.05	35.27	9	28	65	0.16	0.15
7	0.225			42.85	35.15	11	36.5	71	0.16	0.14
8	0.25			46.6	35.37	14	42	80	0.19	0.12
9	0.275			51.59	34.81	20	50	85	0.21	0.09
10	0.3			61.7	32.99	34	60	100	0.31	0.01
11		0	0.1	18.59	27.45	0	6	25.25	0.06	0.38
12		0	0.2	23.89	29.44	0	11.5	36	0.07	0.3
13		0.025	0.225	31.74	30.4	8	21.5	50	0.09	0.17
14		0.05	0.25	38.52	31.72	12	31	56	0.12	0.12
15		0.075	0.275	48.82	32.82	20	43	73.5	0.19	0.04
16		0.1	0.3	35.71	32.12	10	28	50	0.13	0.14
17		0.125	0.325	41.01	32.52	12.75	35	60	0.14	0.11
18		0.15	0.35	45.72	33.23	17	42	71	0.16	0.1
19		0.175	0.375	51.73	33.94	21	50	83.25	0.2	0.08
20		0.2	0.4	60.79	32.78	30	60	100	0.3	0.01
21		0.025	0.275	31.27	30.51	7	20	50	0.09	0.16
22		0	0.3	27.39	30.12	2	16.5	45	0.08	0.22
23		0.025	0.325	36.88	31.15	10	30	55.25	0.1	0.11
24		0.05	0.35	43.95	32.71	16	40	64	0.16	0.08
25		0	0.4	36.84	32.87	10	25	56	0.13	0.12
26		0.075	0.375	38.96	32.87	10	30	60	0.15	0.1
27		0.05	0.45	40.51	32.24	13	32.5	60	0.13	0.09
28		0	0.5	32.29	31.71	6	20	50	0.1	0.17
29		0.1	0.5	49.54	33.33	20	44	79.25	0.2	0.04
30		0	0.6	39.74	33.47	11	30	61.25	0.15	0.1

Notes: This table shows the decisions that subjects faced in the labor supply study, with their respective descriptive statistics. The first ten decisions consisted of a fixed wage (Fixed w.), and decisions 11 to 30 consisted of a stochastic wage (with a low wage, Low w., and a high wage, High w.). For each decision, this table shows the average number of tasks that subjects decide to solve (Mean), the standard deviation (SD), the 25-percentile effort choice (Q25), the median effort choice (Q50), the 75-percentile effort choice (Q75), the fraction of decisions to solve 100 tasks (Fr. 100), and the fraction of decisions to solve 0 tasks (Fr. 0).

Table A2: Heterogeneous treatment effects in the labor supply experiment

Dependent Variable:	Panel A: Prediction 1 $log(e+10)$			Panel B: Predictions 2 and 3 *Sign of Treatment Effect*	
	(1)	(2)	(3)	(4)	(5)
Condition High	0.26 (0.03)	0.06 [0.05] (0.15) [(0.04)]	-0.10 [-0.11] (0.15) [(0.04)]		
Gain-loss attitude: Reduced form ($\hat{l}_i$)		-1.22 [-1.12] (0.18) [(0.07)]		1.55 [1.22] (0.53) [(0.19)]	
Condition High × Reduced form ($\hat{l}_i$)		0.64 [0.53] (0.19) [(0.06)]			
Gain-loss attitude: Structural ($\hat{\lambda}_i$)			-0.19 [-0.18] (0.03) [(0.01)]		0.33 [0.25] (0.09) [(0.05)]
Condition High × Structural ($\hat{\lambda}_i$)			0.10 [0.08] (0.03 [(0.01)])		
Constant (Condition Low)	3.50 (0.03)	0.92 [0.98] (0.18) [(0.05)]	1.23 [1.32] (0.17) [(0.05)]		
$\hat{g}_i$		-1.69 [-1.58] (0.14) [(0.05)]	-1.80 [-1.64] (0.14) [(0.06)]	-0.16 [-0.17] (0.44) [(0.15)]	0.12 [-0.02] (0.46) [(0.17)]
$\hat{k}_i$		0.79 [0.76] (0.05) [(0.01)]	0.77 [0.73] (0.05) [(0.02)]	0.08 [0.09] (0.15) [(0.03)]	0.04 [0.08] (0.15) [(0.04)]
Condition High × $\hat{g}_i$		0.23 [0.17] (0.11) [(0.05)]	0.29 [0.19] (0.12) [(0.05)]		
Condition High × $\hat{k}_i$		0.01 [0.02] (0.05) [(0.01)]	0.01 [0.03] (0.01) [(0.02)]		
R-Squared	0.03	0.40	0.39		
# Observations	906	906	906	453	453
H_0 : Zero TE (High-Low)	$F_{1,452} = 102.6$ ($p < 0.01$)	$F_{1,452} = 0.17$ ($p = 0.68$)	$F_{1,452} = 0.48$ ($p = 0.49$)		
H_0 : Gain-Loss ⊥ Effort in Low		$F_{1,452} = 44.01$ ($p < 0.01$)	$F_{1,452} = 49.14$ ($p < 0.01$)		
H_0 : Gain-Loss ⊥ TE		$F_{1,452} = 11.27$ ($p < 0.01$)	$F_{1,452} = 15.23$ ($p < 0.01$)	$\chi^2(1) = 8.65$ ($p < 0.01$)	$\chi^2(1) = 12.61$ ($p < 0.01$)

Notes: Panel A: Ordinary least squares regression explaining each subject's effort choice. Each subject provides two observations: one with their effort in Condition Low, and one with their effort in Condition High. Panel B: Ordered logit regression for sign of treatment effect. Each subject provides one observation based on the difference between Condition High and Condition Low. Clustered standard errors at the individual level in parentheses. Values in brackets correspond to bootstrapped values from 500 bootstraps re-estimating gain-loss attitudes and reconducting regression in each bootstrap. Each regression with loss aversion also controls for values of $\hat{g}_i$, $\hat{k}_i$, and interactions of each with Condition High. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i = 0$); 4) constant treatment effect over gain-loss attitudes (Condition High* $\hat{\lambda}_i$ or Condition High* $\hat{l}_i = 0$). F-statistics, χ^2-statistics and two-sided p-values reported.

Table A3: Between subjects analysis of labor supply experiment

Dependent Variable:	$log(e + 10)$					
	Panel A: First Choice			Panel B: Second Choice		
	(1)	(2)	(3)	(4)	(5)	(6)
Condition High	0.17	-0.06	-0.15	0.35	0.14	-0.08
	(0.07)	(0.35)	(0.32)	(0.07)	(0.34)	(0.33)
Gain-loss attitude: Reduced form $(\hat{l}_i)$		-0.88			-1.44	
		(0.27)			(0.24)	
Condition High $\times$ Reduced form $(\hat{l}_i)$		0.23			0.93	
		(0.35)			(0.35)	
Gain-loss attitude: Structural $(\hat{\lambda}_i)$			-0.15			-0.22
			(0.04)			(0.04)
Condition High $\times$ Structural $(\hat{\lambda}_i)$			0.03			0.16
			(0.05)			(0.05)
Constant (Condition Low)	3.58	1.00	1.24	3.42	0.88	1.24
	(0.05)	(0.25)	(0.23)	(0.05)	(0.25)	(0.24)
R-Squared	0.01	0.40	0.40	0.06	0.41	0.39
# Observations	453	453	453	453	453	453
H_0 : Zero TE (High-Low), $F_{1,451/445}$	6.39	0.03	0.20	26.51	0.16	0.06
	$(p = 0.01)$	$(p = 0.86)$	$(p = 0.65)$	$(p < 0.01)$	$(p = 0.69)$	$(p = 0.81)$
H_0 : Gain-Loss $\perp$ Effort in Low, $F_{1,445}$		10.71	13.99		34.67	36.32
		$(p < 0.01)$	$(p < 0.01)$		$(p < 0.01)$	$(p < 0.01)$
H_0 : Gain-Loss $\perp$ TE, $F_{1,445}$		0.43	0.41		6.90	9.91
		$(p = 0.51)$	$(p = 0.52)$		$(p = 0.01)$	$(p < 0.01)$

Notes: Ordinary least squares regression explaining each subject's effort choice. Each subject provides a single observation: either their effort in Condition Low, or their effort in Condition High. Columns (1) to (3) correspond to the first choice that each subject did in the experiment, columns (4) to (6) correspond to the second one. Robust standard errors at the individual level in parentheses. Each regression with loss aversion also controls for values of $\hat{g}_i$, $\hat{k}_i$, and interactions of each with Condition High. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i = 0$); 4) constant treatment effect over gain-loss attitudes (Condition High* $\hat{\lambda}_i$ or Condition High* $\hat{l}_i = 0$). F-statistics and two-sided p-values reported.

Appendix B Additional Development, Analysis, and Results for Exchange Study

This appendix provides additional theoretical development and analyses for the exchange study. Appendix B.1 provides an expanded theoretical treatment of both the Choice-Acclimating Personal Equilibrium treatment used in the text as well as Personal Equilibrium and Preferred Personal Equilibrium. Appendix B.2 covers estimation of the distribution of gain-loss attitudes and calculation of individual values. Appendix B.3 and B.4 provide an assessment of theoretical treatment effects and aggregation of treatment effects over heterogeneous types. Appendix B.5 presents additional results noted in the text. Finally, Appendix B.6 provides a recap of a prior methodology for analysis used in a working paper related to the exchange study and presents a reconciliation report for our pre-analysis plan.

B.1 Theoretical Considerations for Exchange Study

We examine the predictions of the Kőszegi and Rabin (2006, 2007) EBRD formulation in simple exchange settings with two objects, recognizing heterogeneity of gain-loss attitudes. Consider a two-dimensional utility function over two objects of interest, object X and object Y. Let $\mathbf{c} = (m_X, m_Y)$ and $\mathbf{r} = (r_X, r_Y)$ represent vectors of intrinsic utility and reference utility, respectively. As described in Section 3.2.1, overall utility is described by

$$u_i(\mathbf{c}|\mathbf{r}) = m_X + \mu_i(m_X - r_X) + m_Y + \mu_i(m_Y - r_Y),$$

where

$$\mu(z) = \begin{cases} \eta z & \text{if } z \geq 0 \\ \eta \lambda_i z & \text{if } z < 0. \end{cases}$$

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In this piece-wise linear gain-loss function, the parameter η captures the magnitude of changes relative to the reference point, and λ_i captures individual gain-loss attitudes. If $\lambda_i > 1$, the individual is loss-averse, experiencing losses more than commensurately-sized gains. If $\lambda_i < 1$, the individual is gain-seeking, experiencing gains more than commensurately-sized losses. We normalize $\eta = 1$ for all individuals and restrict consumption utilities, X and Y to be homogeneous. We explore heterogeneity of consumption utilities in our estimation exercises of Appendix B.2.

B.1.1   Choice Acclimating Personal Equilibrium (CPE)

Unless exogenously determined, the vector $\mathbf{r}$ is established as part of a consistent forward-looking plan for behavior. Kőszegi and Rabin (2006, 2007) posit a reference-dependent expected utility function $U_i(F|G)$, taking as input a distribution F over consumption outcomes, $\mathbf{c}$, which are valued relative to a distribution G of reference points, $\mathbf{r}$. That is

$$U_i(F|G) = \int \int u_i(\mathbf{c}|\mathbf{r})dF(\mathbf{c})dG(\mathbf{r}).$$

A *Personal Equilibrium* is a situation where, given that the decision-maker expects as a referent some distribution, F, they indeed prefer F as a consumption distribution over all alternative consumption distributions, F'. Ex-ante optimal behavior has to accord with expectations of that behavior. Formally, given a choice set, $\mathcal{D}$, of lotteries, F, over consumption outcomes $\mathbf{c} = (m_X, m_Y)$, KR's *Personal Equilibrium* states the following:

Personal Equilibrium (PE): A choice $F \in \mathcal{D}$, is a personal equilibrium if

$$U_i(F|F) \geq U_i(F'|F) \ \forall \ F' \in \mathcal{D}.$$

Regardless of endowment, if object X is to be chosen in a PE, then $\mathbf{r} = (X, 0)$, and if object Y is to be chosen in a PE then $\mathbf{r} = (0, Y)$.

Given the potential for the multiplicity of PE selections, the KR model is constructed with a notion of equilibrium refinement, *Preferred Personal Equilibrium* (PPE), and an alternate non-PE criterion, *Choice-Acclimating Personal Equilibrium* (CPE). In both of these constructs, ex-ante utility is used as a basis for selection and, hence, for making more narrow predictions. For ease of explication, we focus our analysis on the CPE criterion. We also provide theoretical analyses under the PE and PPE approaches. Importantly, all three formulations share common comparative statics, and therefore make qualitatively similar predictions, for our KR test.

Given a choice set, $\mathcal{D}$, of lotteries, F, over consumption outcomes $\mathbf{c} = (m_X, m_Y)$, *Choice-Acclimating Personal Equilibrium* states the following:

Choice-Acclimating Personal Equilibrium (CPE): A choice $F \in \mathcal{D}$, is a choice-acclimating personal equilibrium if

$$U_i(F|F) \geq U_i(F'|F') \ \forall \ F' \in \mathcal{D}.$$

Under CPE, an individual selects between options like $[\mathbf{c}, \mathbf{r}] = [(X, 0), (X, 0)]$ and $[\mathbf{c}, \mathbf{r}] = [(0, Y), (0, Y)]$.[34]

B.1.2 CPE Comparative Statics

The CPE concept noted above requires consistency between the distributions of $\mathbf{c}$ and $\mathbf{r}$. We consider a baseline simple exchange condition, Condition Low, for an individual endowed with object X. We focus on the choice set consisting of pure strategy choices $\mathcal{D} = \{(X, 0), (0, Y)\}$, with the first element reflecting choosing not to exchange and the second choosing to exchange.

In this setting, there are two potential CPE 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 CPE if

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

---

[34]Note that a selection need not be PE in order to be CPE. The alternate concept, PPE requires F and F' to be PE, rather than simply elements of $\mathcal{D}$.

which, under our functional form assumptions, becomes

$$X_{L,CPE,i} \geq Y. \tag{5}$$

Figure A3 graphs the Condition Low CPE cutoff, $\underline{X}_{L,CPE} = Y$, the smallest value of X at which the individual can support not exchanging, which is constant for all values of the gain-loss parameter, λ. The value $\underline{X}_{L,CPE} = Y$ implies that choice in Condition Low is governed only by intrinsic utility. This represents the inability of CPE to rationalize the standard endowment effect. This prediction is not shared by the PE formulation, wherein the value of gain-loss attitudes tunes the set of permissible PE choices and can lead to an endowment effect (see below). Nonetheless, the critical comparative static shared by both formulations is delivered by comparing exchange behavior in this baseline Condition Low with Condition High's probabilistic forced exchange.

Now, consider an environment of probabilistic forced exchange, Condition High. As shown in Section 3.2.1, agents can support attempting not to exchange as a CPE if

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

which, under our functional form assumptions, becomes

$$0.5X + 0.5Y + 0.25(1 - \lambda_i)(X + Y) \geq Y$$
$$X_{H,CPI,i} \geq \frac{1 + 0.5(\lambda_i - 1)}{1 - 0.5(\lambda_i - 1)}Y.$$

The manipulation of probabilistic forced exchange changes the CPE threshold from $\underline{X}_{L,CPE,i} = Y$ to $\underline{X}_{H,CPE,i} = \frac{1+0.5(\lambda_i-1)}{1+0.5\eta(1-\lambda)}Y$. Figure A3 illustrates the changing CPE cutoff values associated with not exchanging. In Condition High, the individual can support attempting to retain X in CPE on the basis of both intrinsic utility and gain-loss attitudes.

The gain-loss parameter, λ_i, tunes precisely how behavior should change between Conditions Low and High. Figure A3 is partitioned into four regions. Two critical regions of
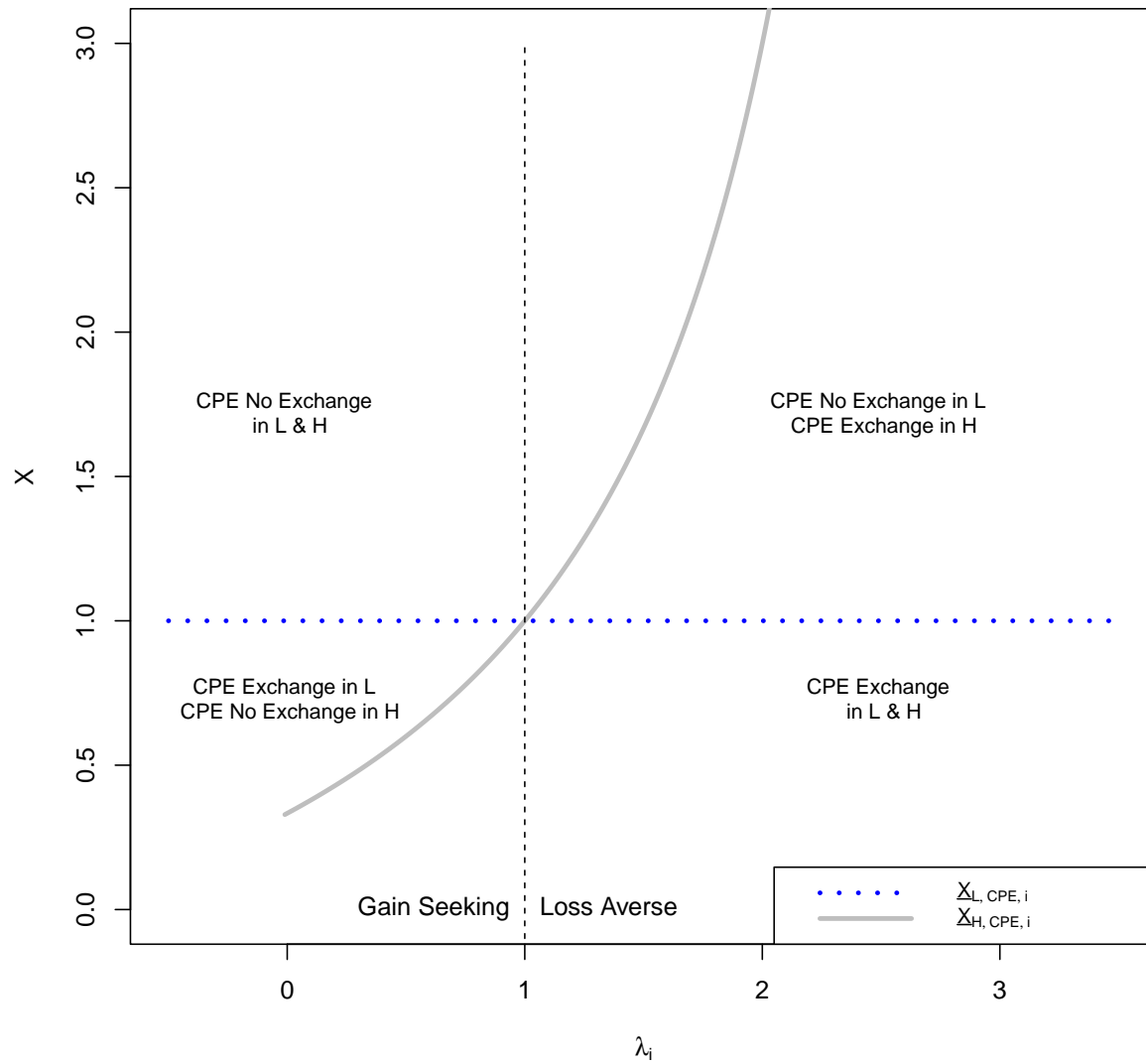
Figure A3: Gain-Loss Attitudes and Theoretical CPE Strategy Thresholds

Notes: Threshold values for CPE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

changing CPE choice are identified. For $X > Y$ and $\lambda_i > 1$, it is CPE to not exchange in Condition Low, and CPE to exchange in Condition High. This region has been the basis of prior experimental tests under the assumption of universal loss aversion; such individuals become more willing to exchange when probabilistically forced. Ignored to date is the region where $X < Y$ and $\lambda_i < 1$. In this region, it is CPE to exchange in Condition Low, and CPE to not exchange in Condition High. In contrast to the loss-averse prediction, such gain-seeking individuals become less willing to exchange when probabilistically forced. The KR comparative static for the difference between Condition Low and Condition High changes sign at $\lambda_i = 1$.

B.1.3 Additional Theoretical Analysis: PE and PPE

We now provide 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 $X, Y, \lambda_i, \eta > 0$. We begin with the restrictions on behavior implied by PE. To begin, we focus on Condition Low 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

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

or

$$X_{L,PE,i} \geq \frac{2}{1 + \lambda_i} Y. \tag{6}$$

Note that the smallest value of X at which the individual can support not exchanging, $\underline{X}_{L,PE,i} = \frac{2}{1+\lambda_i} Y$, is inferior to Y if $\lambda_i > 1$. As such, loss-averse individuals with $\lambda_i > 1$ 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, $[\mathbf{c}, \mathbf{r}] =$

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$[(0, Y), (0, Y)]$, if

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

or

$$X_{L,PE,i} \leq \frac{1 + \lambda_i}{2} Y.$$

The highest value of X at which the agent can support exchanging, $\overline{X}_{L,PE,i} = \frac{1+\lambda_i}{2} Y$, increases linearly with λ. For $\underline{X}_{L,PE,i} \leq X \leq \overline{X}_{L,PE,i}$, there will be multiple equilibria, with the agent able to support both exchanging and not exchanging as a PE.

Note that for gain-seeking individuals with $\lambda_i < 1$ it is also possible for $\overline{X}_{L,PE,i} < X < \underline{X}_{L,PE,i}$, 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 A4 provides the pure strategy PE cutoffs associated with exchanging and not exchanging in Condition Low.
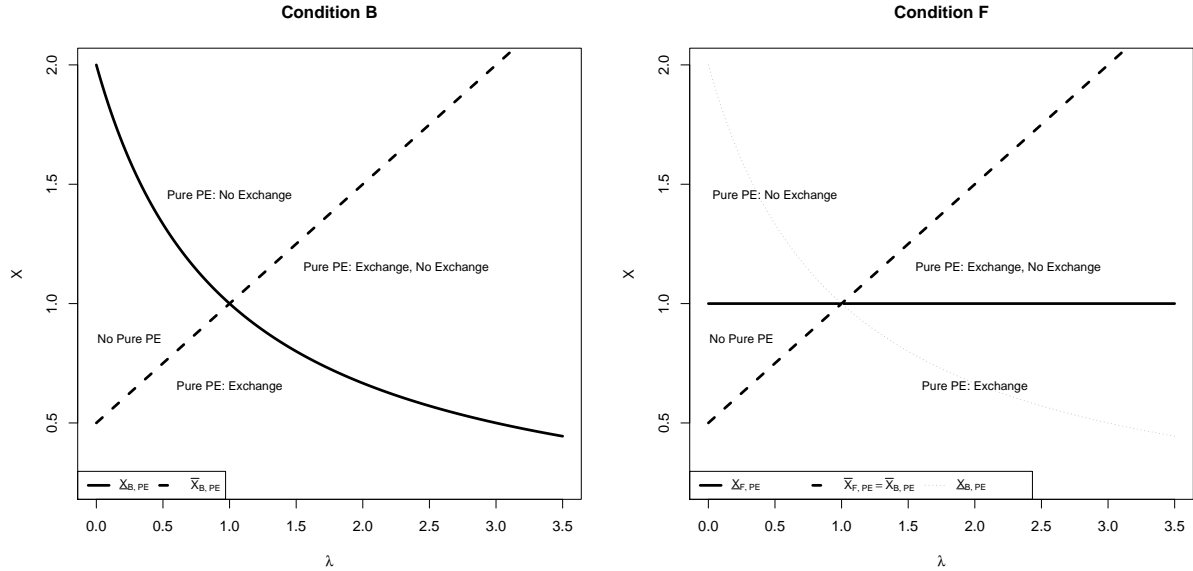
Figure A4: Gain-Loss Attitudes and Theoretical Pure PE Strategy Thresholds

Notes: Threshold values for pure strategy PE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

Now, consider Condition High. 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

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

or

$$X_{H,PE,i} \geq Y. \tag{7}$$

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

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

which as before is

$$X_{H,PE,i} \leq \frac{1 + \lambda_i}{2} Y.$$

Hence, $\overline{X}_{H,PE,i} = \overline{X}_{L,PE,i}$.

The manipulation of probabilistic forced exchange changes the PE cutoff for not exchanging from $\underline{X}_{L,PE,i} = \frac{2}{1+\lambda_i}Y$ to $\underline{X}_{H,PE,i} = Y$. 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 $\lambda_i > 1$ and valuation $\underline{X}_{L,PE,i} < X < \underline{X}_{H,PE,i}$ moves from a position of multiple PE in Condition Low, to having a unique PE to exchange in Condition High. Such an individual plausibly grows more willing to exchange when moving from Condition Low to Condition High. Similarly, a gain-seeking individual with $\lambda_i < 1$ and valuation $\underline{X}_{H,PE,i} < X < \underline{X}_{B,PE,i}$ moves from a position of no pure strategy PE in Condition Low

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to having a unique PE of exchange in Condition High. Such an individual plausibly grows less willing to exchange when moving from Condition Low to Condition High. Figure A4, illustrates these changing pure strategy PE considerations from Condition High to Condition Low. The direction of these comparative statics is identical to that of our CPE analysis in the main text.

B.1.4 PE Mixed Strategy Analysis

To provide a 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 Low, 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

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

or

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

For a given p, let $\mathbf{q}^*(p) \equiv \{argmax_q U_i(q,p)\} \equiv \{argmax_q U_i(q(X,0)+(1-q)(0,Y)|p(X,0)+(1-p)(0,Y))\}$. 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

$$
\begin{aligned}
\frac{\partial U_i(q,p)}{\partial q} &= X - Y - p(Y - \lambda_i X) + (1-p)(X - \lambda_i Y) \\
&= 2X - (1+\lambda_i)Y - p(1-\lambda_i)(Y + X)
\end{aligned}
$$

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

$$
2X - (1+\lambda_i)Y - (1-\lambda_i)(Y + X) \geq 0,
$$
$$
X \geq \frac{2}{(1+\lambda_i)}Y,
$$

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

$$
2X - (1+\lambda_i)Y \leq 0
$$
$$
X \leq \frac{(1+\lambda_i)}{2}Y,
$$

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

$$
\frac{2}{(1+\lambda_i)}Y \leq X \leq \frac{(1+\lambda_i)}{2}Y,
$$

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

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

candidate mixture

$$p \in (0,1) \ s.t \ p = \frac{2X - (1 + \lambda_i)Y}{(1 - \lambda_i)(Y + X)}$$

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 $\frac{2X - (1+\lambda_i)Y}{(1-\lambda_i)(Y+X)} \in (0,1)$. For such a proper mixture probability to exist for $\lambda_i > 1$, it must be that

$$\frac{2}{(1 + \lambda_i)}Y < X < \frac{(1 + \lambda_i)}{2}Y.$$

That is, if $\lambda_i > 1$, 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 $\lambda_i < 1$, it must be that

$$\frac{(1 + \lambda_i)}{2}Y < X < \frac{2}{(1 + \lambda_i)}Y.$$

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

Figure A5 summarizes the PE considerations in Condition Low 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 A4, for $\lambda_i < 1$ within the bounds $\frac{(1+\lambda_i)}{2)}Y < X < \frac{2}{(1+\lambda_i)}Y$, there is now a mixed strategy PE. Further, for $\lambda_i > 1$ and $\frac{2}{(1+\lambda_i)}Y < X < \frac{(1+\lambda_i)}{2}Y$ there are three equilibria when accounting for potential mixtures.

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

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Condition Low

Condition High

Figure A5: Gain-Loss Attitudes and Theoretical PE Strategy Thresholds

Notes: Threshold values for mixed strategy PE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

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

$$U_i(p(X,0) + (1-p)(0,Y)|p(X,0) + (1-p)(0,Y)) \geq$$

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

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

$$\frac{\partial U_i(q, 0.5)}{\partial q} = 2X - (1 + \lambda_i)Y - 0.5(1 - \lambda_i)(Y + X) \geq 0$$

$$(1 + 0.5(1 + \lambda_i))X \geq (1 + 0.5(1 + \lambda_i))Y$$

$$X \geq Y,$$

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

$$\frac{\partial U(q, 0)}{\partial q} = 2X - (1 + \lambda_i)Y \leq 0$$

$$X \leq \frac{(1 + \lambda_i)}{2}Y,$$

which corresponds to the pure strategy threshold, $\overline{X}_{H,PE,i} = \overline{X}_{L,PE,i}$.

Again strict mixtures, $p \in (0, 0.5)$, for which $\frac{\partial U_i(q,p)}{\partial q} = 0$, $p \in \mathbf{q}^*(p)$, 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

$$p \in (0, 0.5) \ s.t \ p = \frac{2X - (1 + \lambda_i)Y}{(1 - \lambda_i)(Y + X)}$$

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 $\frac{2X-(1+\lambda_i)Y}{(1-\lambda_i)(Y+X)} \in (0, 0.5)$. For such a proper mixture probability to exist for $\lambda_i > 1$, it must be that

$$Y < X < \frac{(1 + \lambda_i)}{2}Y$$

That is, if $\lambda_i > 1$, 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 $\lambda_i < 1$, it must be that

$$\frac{(1 + \lambda_i)}{2}Y < X < Y.$$

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

Figure A5 summarizes the PE considerations in Condition High recognizing the possibility of mixed strategy equilibria with the corresponding value of the mixture proba-

bility noted. Moving from Condition Low to Condition High all mixed strategy PE with $p \in (0.5, 1)$ are eliminated from the choice set. Individuals with $\lambda_i > 1$ and multiple equilibria, $PE = \{0, p > 0.5, 1\}$ in Condition Low have a unique $PE = \{p = 0\}$ in Condition High. Such individuals may exchange less than 100 percent of the time in Condition Low and do so 100 percent of the time in Condition High, growing more willing to exchange. In contrast, individuals with $\lambda_i < 1$ and a unique $PE = \{p > 0.5\}$ in Condition Low, have a unique $PE = \{p = 0.5\}$ in Condition High. Such individuals would attempt to retain their object less than 100 percent of the time in Condition Low and would do so 100 percent of the time in Condition High, 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.1.5   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 A5, it is straightforward to identify the selection, p, with the highest value of $U_i(p(X, 0) + (1 - p)(0, Y)|p(X, 0) + (1 - p)(0, Y)) = pX + (1 - p)Y + p(1 - p)\eta(1 - \lambda_i)(X + Y)$. In the case of Condition Low, there is a region of multiplicity for $\lambda_i > 1$ 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 $p(1 - p)(1 - \lambda_i)(X + Y) < 0$ for $\lambda_i > 1$. Following this logic, in Condition Low, multiplicity is resolved via PPE by selecting either $p = 1$ if $X > Y$ or $p = 0$ if $X < Y$.

Condition B — **Condition F**
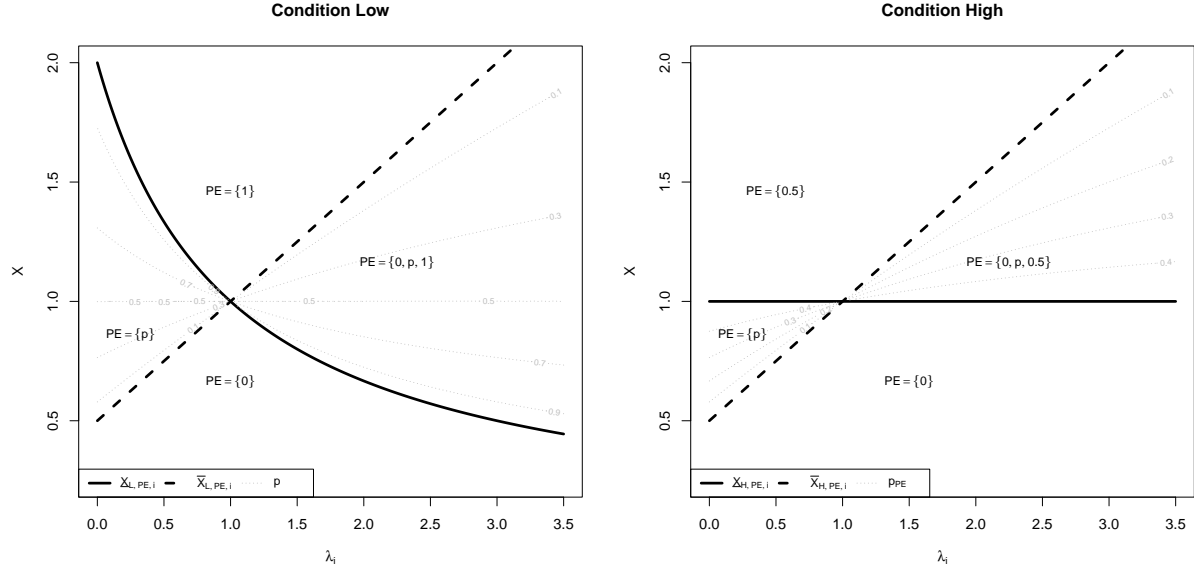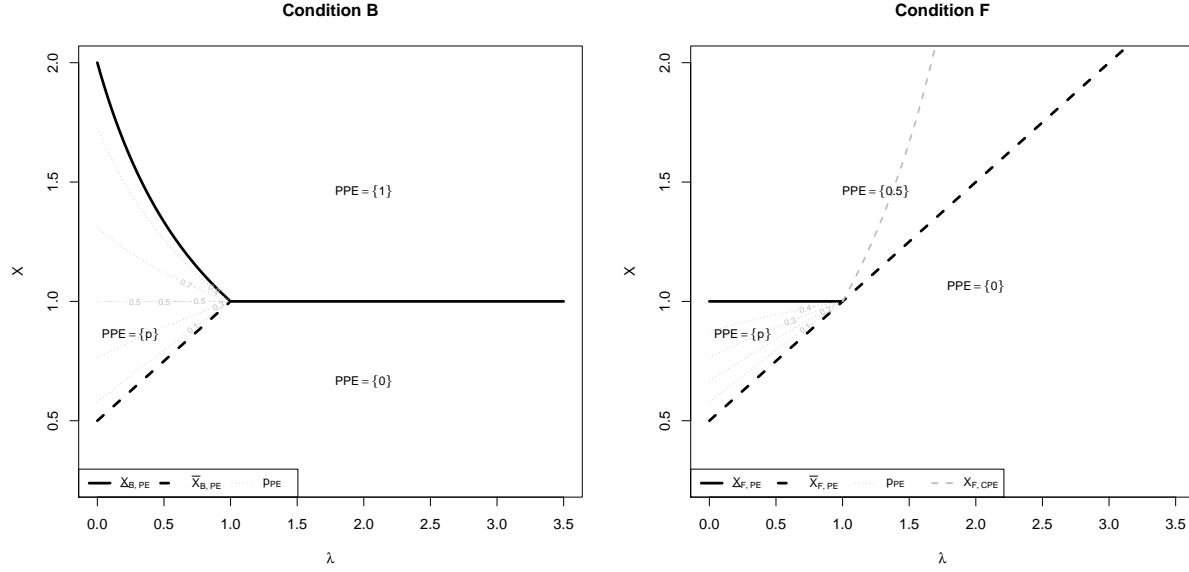
Figure A6: Gain-Loss Attitudes and Theoretical PPE Strategy Thresholds

Notes: Threshold values for PPE for agent endowed with X, assuming $Y = 1$ and $\eta = 1$.

Similarly, in Condition High, there is a region of multiplicity for $\lambda_i > 1, Y < X < \frac{(1+\lambda_i)}{2}Y$ where the set of $PE = \{0, p \in (0, 0.5), 0.5\}$. Note that for $\lambda_i > 1$, if $X < \frac{(1+\lambda_i)}{2}Y$, then $X < \frac{(1+0.5(\lambda_i-1))}{(1+0.5(1-\lambda_i))}Y = \frac{(1+\lambda_i-0.5(\lambda_i+1)}{(2-0.5(\lambda_i+1))}Y$. That is, in this region of multiplicity, X is below the $X_{H,CPE,i}$ 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 $\{0, p = \frac{2X-(1+\lambda_i)Y}{(1-\lambda_i)(Y+X)} \in (0, 0.5)\}$ provide higher utility. For this key mixture,

$$p = \frac{2X - (1 + \lambda_i)Y}{(1 - \lambda_i)(Y + X)}$$
$$(1 - p) = \frac{(1 - \lambda_i)(Y + X)}{(1 - \lambda_i)(Y + X)} - \frac{2X - (1 + \lambda_i)Y}{(1 - \lambda_i)(Y + X)}$$

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The PPE selection will be $p = 0$ provided

$$Y > pX + (1 - p)Y + p(1 - p)(1 - \lambda_i)(X + Y)$$

$$Y > X + (1 - p)(1 - \lambda_i)(X + Y)$$

$$Y > X + \left[\frac{(1 - \lambda_i)(Y + X)}{(1 - \lambda_i)(Y + X)} - \frac{2X - (1 + \lambda_i)Y}{(1 - \lambda_i)(Y + X)} \right] (1 - \lambda_i)(X + Y)$$

$$Y > X + [(1 - \lambda_i)(Y + X) - 2X + (1 + \lambda_i)Y]$$

$$Y - (1 + \lambda_i)Y - (1 - \lambda_i)Y > X + (1 - \lambda_i)(X) - 2X$$

$$-Y > -\lambda_i X$$

$$X > \frac{1}{\lambda_i} Y,$$

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

Figure A6 summarizes the PPE considerations in Conditions Low and High recognizing the possibility of a mixed strategy PPE with the corresponding value of the mixture probability noted. Also graphed in Figure A6 is the relevant CPE cutoff for $\lambda_i > 1$ in Condition High 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 $\lambda_i > 1$ should grow more willing to exchange moving from Condition Low to Condition High, while individuals with $\lambda_i < 1$ should grow less-so.

B.2   Estimation and Calculation of Gain Loss Attitudes in the Exchange Study

In this appendix section, 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, $Prob_{w_i, X}$,

$$
\begin{aligned}
Prob_{w_i, X} &= G((1 + \lambda_i) - 2\tfrac{Y}{X} - \delta_X) & if\ w_i = 1 \\
Prob_{w_i, X} &= G(2\tfrac{Y}{X} - (1 + \lambda_i) - \delta_X) & if\ w_i = -1 \\
Prob_{w_i, X} &= 1 - G((1 + \lambda_i) - 2\tfrac{Y}{X} - \delta_X) - G(2\tfrac{Y}{X} - (1 + \lambda_i) - \delta_X) & if\ w_i = 0,
\end{aligned}
$$

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

$$
\begin{aligned}
Prob_{w_i, Y} &= G(2 - (1 + \lambda_i)\tfrac{Y}{X} - \delta_X) & if\ w_i = -1 \\
Prob_{w_i, Y} &= G((1 + \lambda_i)\tfrac{Y}{X} - 2 - \delta_X) & if\ w_i = 1 \\
Prob_{w_i, Y} &= 1 - G(2 - (1 + \lambda_i)\tfrac{Y}{X} - \delta_X) - G((1 + \lambda_i)\tfrac{Y}{X} - 2 - \delta_X) & if\ w_i = 0.
\end{aligned}
$$

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

$$
\begin{aligned}
Prob_{l_i, X} &= G((1 + \lambda_i) - 2\tfrac{Y}{X} - \delta_X) & if\ l_i = 1 \\
Prob_{l_i, X} &= G(2\tfrac{Y}{X} - (1 + \lambda_i) - \delta_X) & if\ l_i = -1 \\
Prob_{l_i, X} &= 1 - G((1 + \lambda_i) - 2\tfrac{Y}{X} - \delta_X) - G(2\tfrac{Y}{X} - (1 + \lambda_i) - \delta_X) & if\ l_i = 0,
\end{aligned}
$$

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

$$Prob_{l_i,Y} = \qquad\qquad G(2 - (1 + \lambda_i)\frac{Y}{X} - \delta_X) \qquad\qquad if\ l_i = -1$$

$$Prob_{l_i,Y} = \qquad\qquad G((1 + \lambda_i)\frac{Y}{X} - 2 - \delta_X) \qquad\qquad if\ l_i = 1$$

$$Prob_{l_i,Y} = \ 1 - G(2 - (1 + \lambda_i)\frac{Y}{X} - \delta_X) - G((1 + \lambda_i)\frac{Y}{X} - 2 - \delta_X) \quad if\ l_i = 0.$$

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

$$Prob_{h_i,X} = \ G((1 + \lambda_i) - 2\frac{Y}{X}) \quad if\ w_i = 1$$

$$Prob_{h_i,X} = \ G(2\frac{Y}{X} - (1 + \lambda_i)) \quad if\ w_i = -1,$$

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

$$Prob_{h_i,Y} = \ G(2 - (1 + \lambda_i)\frac{Y}{X}) \quad if\ w_i = -1$$

$$Prob_{h_i,Y} = \ G((1 + \lambda_i)\frac{Y}{X} - 2) \quad if\ w_i = 1.$$

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_i is drawn from a log-normal distribution with $log(\lambda_i) \sim N(\mu_{\lambda_i}, \sigma^2_{\lambda_i})$.

Let $\theta \equiv (\mu_{\lambda_i}, \sigma^2_{\lambda_i})$, represent the parameters of this distribution, and let $f(\lambda_i|\theta)$ be the distribution of λ_i given these parameters. A single individual's choice probabilities are thus

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

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

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

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_i} and $\sigma^2_{\lambda_i}$ alongside the homogeneous utility ratio $\frac{X}{Y}$.

When considering the possibility of heterogeneous utility rather than heterogeneous gain-loss attitudes, 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 rth simulant.

We simulate L_i as

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

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_i. Operationally for implementing both of our simulated likelihood techniques we use 100 Halton draws for each heterogeneous parameter and implement the code in Stata. Table A4 provides the corresponding estimates from this exercise. One important point to note is that these estimates are provided with discernibility parameter δ_X fixed to be 0.55 (as noted in the text). Table A5 provides estimates corresponding to alternate values of δ_X to assess sensitivity of the estimated distribution of gain-loss attitudes to variation in this parameter.

B.2.1 Classifying Individual Gain-Loss Attitudes Accounting for Errors

Moving from the distribution of gain-loss attitudes to an expected value of λ for each individual is a straightforward step after estimation. As proposed by Train (2009), we simulate the distribution of λ, and calculate the expectation of $\hat{\lambda}_i$ for each possible Stage 1 statement profile. For example, under the estimated log-normal density, $g(\lambda)$, one simulates $Prob_{X|X}(\lambda)$, and the expected value given a preference for X when endowed with X as

$$\hat{\lambda}_i = \int \lambda \frac{Prob_{X|X}(\lambda)g(\lambda)}{\int Prob_{X|X}(\lambda)g(\lambda)d\lambda}d\lambda.$$

For each endowment, subjects could provide one of two hypothetical choice statements, one of three relative liking statements, and one of three relative wanting statements, yielding 18 potential statement profiles. With four endowments, there are 72 potential profiles, each

36

Table A4: Method of Simulated Likelihood Estimates

	(1)	(2)	(3)	(4)
	Estimate	(Std. Error)	Estimate	(Std. Error)
	Heterogeneous λ		*Heterogeneous $\frac{Y}{X}$*	
Gain-Loss Attitudes:				
$\hat{\lambda}$	1.37	(0.08)	1.32	(0.05)
$\hat{\mu}_\lambda$	0.17	(0.07)	-	-
$\hat{\sigma}^2_\lambda$	0.30	(0.22)	-	-
Pair 1 Utilities (USB Stick (X) - Pen Set (Y)) *:*				
$\frac{\hat{Y}}{X}$ (Initial)	0.62	(0.04)	0.62	(0.03)
$\frac{\hat{Y}}{X}$ (Replication)	0.61	(0.04)	-	-
$\hat{\mu}_{\frac{Y}{X}}$	-	-	-0.56	(0.09)
$\hat{\sigma}^2_{\frac{Y}{X}}$	-	-	0.17	(0.13)
Pair 2 Utilities (Picnic Mat (X) - Thermos (Y)):				
$\frac{\hat{Y}}{X}$ (Initial)	1.11	(0.04)	1.03	(0.03)
$\frac{\hat{Y}}{X}$ (Replication)	0.88	(0.04)	-	-
$\hat{\mu}_{\frac{Y}{X}}$	-	-	-0.03	(0.04)
$\hat{\sigma}^2_{\frac{Y}{X}}$	-	-	0.12	(0.08)
Discernibility:				
δ_X	0.55	-	0.55	-
# Observations	3,072		3,072	
Log-Likelihood	-2743.25		-2752.35	
Akaike's Information Criterion (AIC)	5498.49		5514.70	

Notes: Method of simulated likelihood estimates. Standard errors in parentheses.

Table A5: 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)	1.65	(0.21)
$\hat{\mu}_\lambda$	0.26	(0.03)	0.17	(0.07)	0.04	(0.08)
$\hat{\sigma}^2_\lambda$	0.00	(0.02)	0.30	(0.22)	0.92	(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	(0.04)	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.

with an implication for the value of $\hat{\lambda}_i$.[35] We extend the above example to construct the probability of each such profile assuming independence between the simulated probabilities for hypothetical choice, liking, and wanting statements. We simulate statement profiles at around 30,000 draws from the estimated distribution of gain-loss attitudes assuming logit errors on choice probabilities. This exercise of mapping from preference statements to a conditional expectation of gain-loss attitudes takes into account the possibility of noise as the preference statements are simulated assuming the model's logit errors.

In Table A6, we provide the calculation of $\hat{\lambda}_i$, averaged over the initial and replication study, for eight common statement profiles (accounting for 647 of 1024 (63.1 percent) of observations). Consider an endowment of the USB stick: if a subject stated a preference for the USB stick in all three statements they would have $\hat{\lambda}_i = 1.86$, while if they stated a preference for the pen set in all three they would have $\hat{\lambda}_i = 0.76$. Providing the same profiles when endowed with the pen set leads to $\hat{\lambda}_i$ of 1.03 and 2.58, respectively. The values exhibited in Table A6 are intuitive: stating a preference for one's endowed object indicates loss aversion, while stating a preference for the alternative indicates gain seeking.

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[35]Note that because we allow for different utilities in our initial study and replication, there are 72 such values for each.

The magnitudes of $\hat{\lambda}_i$ are tuned by the intrinsic values of the two objects reported in Table A4.

Table A6: Preference Statements and Individual Gain-Loss Classifications

Endowed USB Stick			
HC(USB Stick) > HC(Pen Set)		HC(USB Stick) < HC(Pen Set)	
L(USB Stick) > L(Pen Set)	$\hat{\lambda}_i = 1.86$, (N=161)	L(USB Stick) < L(Pen Set)	$\hat{\lambda}_i = 0.76$, (N = 32)
W(USB Stick) > W(Pen Set)		W(USB Stick) < W(Pen Set)	
Endowed Pen Set			
HC(USB Stick) > HC(Pen Set)		HC(USB Stick) < HC(Pen Set)	
L(USB Stick) > L(Pen Set)	$\hat{\lambda}_i = 1.03$, (N=111)	L(USB Stick) < L(Pen Set)	$\hat{\lambda}_i = 2.58$, (N= 57)
W(USB Stick) > W(Pen Set)		W(USB Stick) < W(Pen Set)	
Endowed Picnic Mat			
HC(Mat) > HC(Thermos)		HC(Mat) < HC(Thermos)	
L(Mat) > L(Thermos)	$\hat{\lambda}_i = 2.25$, (N=84)	L(Mat) < L(Thermos)	$\hat{\lambda}_i = 0.85$, (N= 67)
W(Mat) > W(Thermos)		W(Mat) < W(Thermos)	
Endowed Thermos			
HC(Mat) > HC(Thermos)		HC(Mat) < HC(Thermos)	
L(Mat) > L(Thermos)	$\hat{\lambda}_i = 0.84$, (N=52)	L(Mat) < L(Thermos)	$\hat{\lambda}_i = 2.17$, (N= 83)
W(Mat) > W(Thermos)		W(Mat) < W(Thermos)	

Notes: Implications for $\hat{\lambda}_i$ for 8 key statement profiles, depending on endowment. HC: Hypothetic Choice; L: Liking Rating Score; W: Wanting Rating Score. $\hat{\lambda}_i$ averaged over relevant observation number, N, between initial and replication study.

Figure A7 provides the distribution of $\hat{\lambda}_i$ implied by Stage 1 preference statements as the solid black line. This distribution has mean 1.49, median 1.34, with 24 percent of subjects exhibiting $\hat{\lambda}_i < 1$. The distribution of $\hat{\lambda}_i$ is similar in shape and key statistics to the underlying log-normal estimates. However, the distribution of $\hat{\lambda}_i$ does exhibit fewer extreme gain-seeking and loss-averse observations than its underlying distribution. Individual heterogeneity in $\hat{\lambda}_i$ in hand, we are equipped to analyze heterogeneous treatment effects.

B.3 Predicting Heterogeneous Treatment Effects in Exchange

Section 3.2.1 establishes the two critical CPE thresholds,

$$X_{L,i} = Y,$$

$$X_{H,i} = \frac{1 + 0.5(\lambda - 1)}{1 - 0.5(\lambda_i - 1)} Y.$$
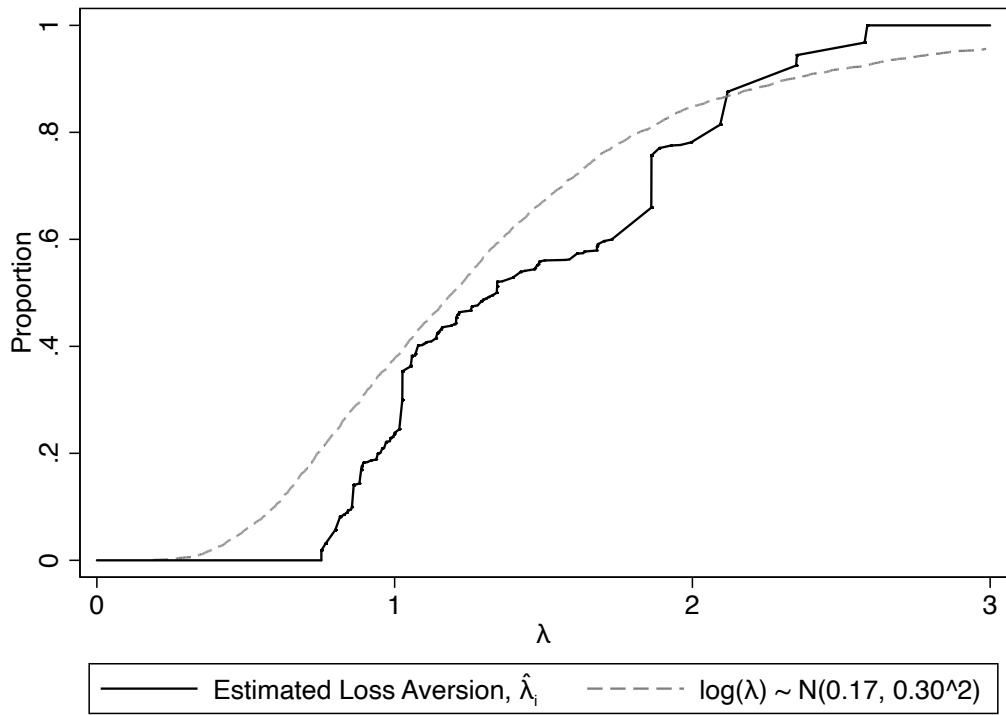
Figure A7: **Estimated and Calculated Distributions of Gain-Loss Attitudes**

Notes: The dashed line represents estimated distribution $log(\lambda) \sim N(0.17, 0.30^2)$. Solid line represents the expected value of λ conditional on the Stage 1 statements, $\hat{\lambda}_i$, as described above.

Under deterministic choice, these CPE thresholds would map to choice probabilities 0 and 1 depending on the relative values of X and Y and the value of λ_i. In such an environment individual treatment effects on choice probabilities are either 1, 0, or -1 depending on the values of the these same parameters.

We do not assume deterministic choice, but rather stochastic choice. Hence, an individual will choose the alternative Y over their endowed object X in Condition Low, when

$$X + \varepsilon \leq Y$$

or

$$\epsilon \leq \frac{Y}{X} - 1$$

where $\epsilon = \frac{\varepsilon}{X}$ is a draw from mean zero distribution $F(\cdot)$. Hence, the probability of exchange in Condition Low is

$$Prob(Exchange_L) = Prob(\epsilon \leq \frac{Y}{X} - 1) = F(\frac{Y}{X} - 1).$$

Similarly, an individual will exchange in Condition High, when

$$X + \varepsilon \leq \frac{1 + 0.5(\lambda_i - 1)}{1 - 0.5(\lambda_i - 1)} Y,$$

and

$$Prob(Exchange_H) = F(\frac{1 + 0.5(\lambda_i - 1)}{1 - 0.5(\lambda_i - 1)} \frac{Y}{X} - 1).$$

This yields an individual treatment effect as a function of the parameters of interest,

$$
\begin{aligned}
TE(\lambda_i, X, Y) &= Prob(Exchange_H) - Prob(Exchange_L) \\
&= F(\frac{1 + 0.5(\lambda_i - 1)}{1 - 0.5(\lambda_i - 1)} \frac{Y}{X} - 1) - F(\frac{Y}{X} - 1).
\end{aligned}
$$

The analysis of Figure 4 in the main text presents predictions of $TE(\lambda_i, Y, X)$ for each individual at their value of $\hat{\lambda}_i$ and at the estimated value of $\frac{Y}{X}$ for their assigned condition with $F(\cdot)$ assumed to be logistic.

B.4 Non-Linear Aggregation of Exchange Treatment Effects and Statistical Power

Having established the theoretical treatment effect,

$$
\begin{aligned}
TE(\lambda_i, X, Y) &= Prob(Exchange_H) - Prob(Exchange_L) \\
&= F(\frac{1 + 0.5(\lambda_i - 1)}{1 - 0.5(\lambda_i - 1)}\frac{Y}{X} - 1) - F(\frac{Y}{X} - 1).
\end{aligned}
$$

we can consider aggregation of treatment effects in an average treatment effect,

$$
\overline{TE(\lambda_i, X, Y)} = \frac{1}{N}\sum_{i=1}^{N} TE(\lambda_i, X, Y).
$$

When will the average treatment effect deviate from the treatment effect of the average gain-loss attitude, $\overline{\lambda_i}$? Note that there are two dimensions of non-linearity in λ_i that influence aggregation. First, the CPE threshold determining behavior in Condition High,

$$
X_{H,i} = \frac{1 + 0.5(\lambda - 1)}{1 - 0.5(\lambda_i - 1)}Y,
$$

is non-linear in λ_i. Second, given standard functional forms for $F(\cdot)$ like logistic or normal, the probability of exchange is plausibly non-linear in its arguments. Both of these forces will lead to deviations between the average treatment effect and the treatment effect of the average preference. Figure A8, plots $TE(\lambda_i, X, Y)$ with $F(\cdot)$ assumed to be logistic as above with various values for the relative utility $\frac{Y}{X}$.

The non-linear relationships illustrated in Figure A8 may lead average treatment effects to deviate dramatically from the treatment effect of the average preference. Overall the

nature of the aggregation problem depends on the relative utility value, $\frac{Y}{X}$. When the alternative good is better than the endowment, $\frac{Y}{X} > 1$, gain-seeking individuals have more extreme negative treatment effects than loss-averse individuals. When $\frac{Y}{X} < 1$ the opposite is true. For $\frac{Y}{X} = 1$, both concave and convex regions of $TE(\lambda_i, X, Y)$ exist and the extent of aggregation problems depends importantly on the underlying distribution of λ_i. Even with loss aversion on average, the average treatment effect is plausibly muted relative to the treatment effect of the average preference. Given our distributional estimates for λ noted in Table A4, and assuming $\frac{X}{Y} = 1$, the average treatment effect would be approximately 0.08 and the treatment effect of the average preference, $\lambda = 1.37$, would be approximately 0.11.

In addition to muted average treatment effects, heterogeneity in gain loss attitudes can influence the power of any conducted experimental test. Given our distributional estimates for λ noted in Table A4, and assuming $\frac{X}{Y} = 1$, the average treatment effect would be 0.08 and the standard deviation of treatment effects would be 0.12. As noted above, the treatment effect of the average preference noted in Table A4 is 0.11. A study that is theoretically powered assuming homogeneous gain-loss attitudes and straightforward sampling variation will have different power considerations when accounting for this additional source of variation.

Absent heterogeneity in gain-loss attitudes, a treatment effect of 0.08 or 0.11 on exchange probability (assuming all subjects participate in *both* Low and High conditions, and Low condition exchange probability of 0.5) would be powered at 80% with approximately 600 or 320 subjects, respectively (one mean, standard deviation calculated as sum of independent binomial variances $\sqrt{p(1-p) + (p+TE)(1-(p+TE)))}$). This shows a first challenge to power associated with non-linear aggregation of treatment effects: an average treatment effect that is below the treatment effect of the average preference requires a larger sample to appropriately power. Absent heterogeneity, the standard deviation of a 0.08 treatment effect on exchange probability is $\sqrt{0.5(1-0.5) + 0.58(1-0.58)} \approx 0.7$. If heterogeneity were to be recognized, the expected standard deviation of treatment effects
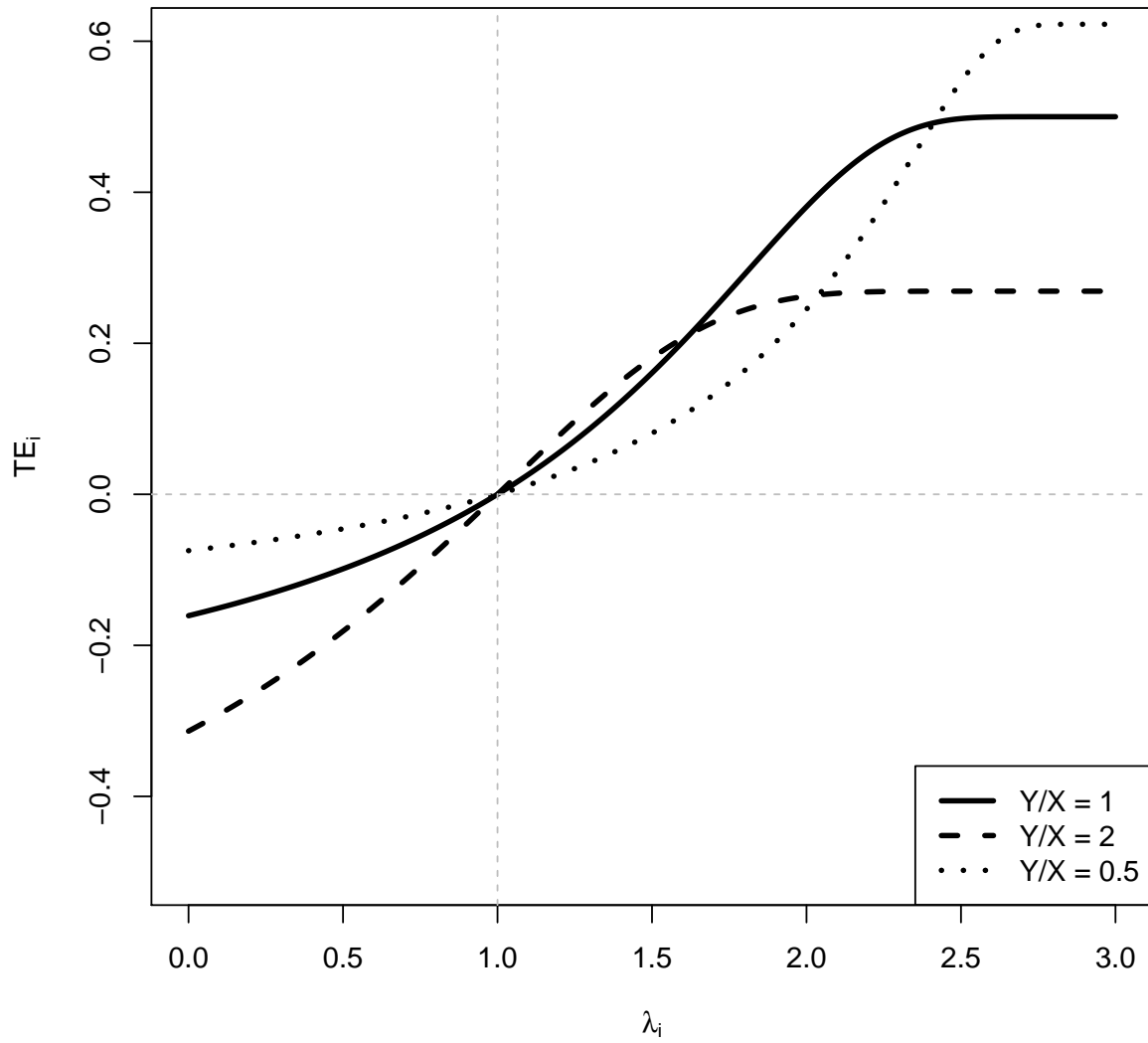
Figure A8: Gain-Loss Attitudes and Predicted Treatment Effects

Notes: Figure plots $TE(\lambda_i, X, Y)$ against λ_i for various values of $\frac{X}{Y}$ and a logistic distribution of errors, independent and identically distributed in Condition Low and Condition High.

would grow. Assuming an independent effect of the heterogeneity described above would increase the standard deviation slightly to $\sqrt{0.7^2 + 0.12^2} \approx 0.71$, and the required sample size for 80% power would increase to approximately 620 subjects in a within-subject design. Hence, the combined effects of heterogeneity through non-linear aggregation and increased variability of treatment effects can lead to substantially different power calculations than those conducted assuming homogeneous preferences.

B.5 Additional Results for Exchange Study

Complementarities Between Stages. Our results indicate that gain-loss attitudes measured with one pair of objects in Stage 1 are predictive of exchange behavior for a distinct counterbalanced pair of objects in Stage 2. Though we attempted to choose Stage 1 and Stage 2 objects that would have no plausible complementarities, if some un-modeled, unintentional complementarity did exist it might spuriously appear as predictive power across stages. For example, a subject might state a preference for or against both of their endowed objects in order to consume both endowed objects or both alternatives together. Note that this mechanism cannot explain the Stage 2 treatment effect, but could perhaps provide a rationale for the correlations documented between Stage 1 gain-loss attitudes and exchange in Stage 2, Condition Low.

Importantly, our Stage 1 design was constructed with one piece of random variation that serves to break complementarities between objects across stages. After providing their preference statements, half of subjects have their endowed object replaced with the alternative. If our results are reproduced both for subjects who have their endowed object replaced and those who do not, then explanations based upon accidental complementarities cannot be relevant for our results. To explore this possibility, Table A7 reproduces the structural results of Table 2 separately by individuals who do and do not have their Stage 1 endowed object replaced. For both groups, our results are maintained.

Table A7: Stage 2 Behavior and Stage 1 Experience

| | Dependent Variable: Exchange (=1) | | | | | |
| | Stage 1 Object Not Replaced | | | Stage 1 Object Replaced | | |
	(1)	(2)	(3)	(4)	(5)	(6)
Condition High	0.013	0.010	-0.252	-0.019	-0.013	-0.415
	(0.044)	(0.044)	(0.125)	(0.043)	(0.043)	(0.121)
Reduced form $(\hat{l}_i)$		-0.041			-0.060	
		(0.022)			(0.022)	
Condition High * Reduced form $(\hat{l}_i)$		0.050			0.102	
		(0.029)			(0.028)	
Structural $(\hat{\lambda}_i)$			-0.120			-0.155
			(0.057)			(0.058)
Condition High * Structural $(\hat{\lambda}_i)$			0.175			0.271
			(0.077)			(0.077)
Constant (Condition Low)	0.386	0.388	0.567	0.374	0.372	0.601
	(0.033)	(0.033)	(0.094)	(0.034)	(0.033)	(0.094)
R-Squared	0.000	0.008	0.011	0.000	0.025	0.024
# Observations	511	511	511	513	513	513
H_0 : Zero Treatment Effect (High-Low)	$F_{1,509} = .08$	$F_{1,507} = 0.05$	$F_{1,507} = 4.05$	$F_{1,511} = 0.19$	$F_{1,509} = 0.09$	$F_{1,509} = 11.73$
	$(p = 0.77)$	$(p = 0.82)$	$(p = 0.05)$	$(p = 0.67)$	$(p = 0.77)$	$(p < 0.01)$
H_0 : Gain-Loss Attitudes $\perp$ Exchange in L		$F_{1,507} = 3.68$	$F_{1,507} = 4.45$		$F_{1,509} = 7.49$	$F_{1,509} = 7.15$
		$(p = 0.06)$	$(p = 0.04)$		$(p < 0.01)$	$(p < 0.01)$
H_0 : Gain-Loss Attitudes $\perp$ Treatment Effect		$F_{1,507} = 2.92$	$F_{1,507} = 5.22$		$F_{1,509} = 13.13$	$F_{1,509} = 12.52$
		$(p = 0.09)$	$(p = 0.02)$		$(p < 0.01)$	$(p < 0.01)$

Notes: Ordinary least square regression. Robust standard errors in parentheses. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i$ coefficient = 0); 3) constant treatment effect over gain-loss attitudes (Condition High * $\hat{\lambda}_i$ or Condition High * $\hat{\imath}$ coefficient= 0). F-statistics and two-sided p-values reported.

Replication consistency. Our results to here have combined the data from our initial and replication exchange studies. Table A8 reproduces the structural results of Table 2 separately for the two samples, clustering standard errors at the session level. The null aggregate treatment effect and heterogeneous treatment effects over gain-loss attitudes are produced in both our initial and replication studies. Quantitatively the observed relationships between gain-loss attitudes and exchange behavior are broadly consistent, though the replication has less precise estimates due to the smaller sample size.

Table A8: Replication Consistency, Clustered SE

| | *Dependent Variable: Exchange (=1)* | | | | | |
| | Initial Study | | | Replication Study | | |
	(1)	(2)	(3)	(4)	(5)	(6)
Condition High	0.004	-0.001	-0.409	-0.010	-0.007	-0.232
	(0.034)	(0.034)	(0.110)	(0.044)	(0.044)	(0.101)
Reduced form ($\hat{l}_i$)		-0.064			-0.034	
		(0.022)			(0.016)	
Condition High * Reduced form ($\hat{l}_i$)		0.100			0.046	
		(0.027)			(0.021)	
Structural($\hat{\lambda}_i$)			-0.160			-0.102
			(0.052)			(0.052)
Condition High * Structural ($\hat{\lambda}_i$)			0.268			0.157
			(0.065)			(0.064)
Constant (Condition Low)	0.365	0.373	0.616	0.399	0.394	0.541
	(0.028)	(0.027)	(0.092)	(0.030)	(0.029)	(0.080)
R-Squared	0.000	0.022	0.024	0.000	0.006	0.008
# Observations	607	607	607	417	417	417
H_0 : Zero Treatment Effect (High-Low)	$F_{1,30} = .01$	$F_{1,30} = 0$	$F_{1,30} = 13.74$	$F_{1,21} = 0.05$	$F_{1,21} = 0.03$	$F_{1,21} = 5.27$
	($p = 0.90$)	($p = 0.98$)	($p < 0.01$)	($p = 0.82$)	($p = 0.87$)	($p = 0.03$)
H_0 : Gain-Loss Attitudes $\perp$ Exchange in L		$F_{1,30} = 8.15$	$F_{1,30} = 9.44$		$F_{1,21} = 4.72$	$F_{1,21} = 3.84$
		($p < 0.01$)	($p < 0.01$)		($p = 0.04$)	($p = 0.06$)
H_0 : Gain-Loss Attitudes $\perp$ Treatment Effect		$F_{1,30} = 13.73$	$F_{1,30} = 16.99$		$F_{1,21} = 4.87$	$F_{1,21} = 6.07$
		($p < 0.01$)	($p < 0.01$)		($p = 0.04$)	($p = 0.02$)

Notes: Ordinary least square regression. Standard errors clustered at the session level in parentheses. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i$ coefficient = 0); 3) constant treatment effect over gain-loss attitudes (Condition High * $\hat{\lambda}_i$ or Condition High *$\hat{i}$ coefficient= 0). F-statistics and two-sided p-values reported. F-statistics and two-sided p-values reported.

Our replication study was conducted to assure confidence in our previously obtained heterogeneous treatment effects. The registration of our pre-analysis plan, including power calculations, can be found at `https://www.socialscienceregistry.org/trials/3124`. The analysis proposed there carries one important difference to that conducted here: our proposed methodology for identifying gain-loss attitudes was based on standard logit,

rather than mixed logit methods. This was the methodology used in a previous draft of the results of the exchange experiment posted at `https://papers.ssrn.com/sol3/papers.cfm?abstractid=3170670`. Advice from an anonymous referee highlighted the value of the mixed logit methods that we currently conduct. For completeness, in Appendix B.6 we provide the pre-registered replication analysis. There, as well, we find a striking consistency between the results obtained in our initial and replication samples.

Table A9: Exchange Behavior and Probabilistic Forced Exchange, Clustered SE

| | Dependent Variable: Exchange (=1) | | |
	(1)	(2)	(3)
Condition High	-0.004	-0.004	-0.337
	(0.027)	(0.026)	(0.075)
Reduced form ($\hat{l}_i$)		-0.050	
		(0.014)	
Condition High *Reduced form ($\hat{l}_i$)		0.077	
		(0.018)	
Structural ($\hat{\lambda}_i$)			-0.136
			(0.036)
Condition High * Structural ($\hat{\lambda}_i$)			0.224
			(0.046)
Constant (Condition Low)	0.380	0.380	0.583
	(0.020)	(0.019)	(0.060)
R-Squared	0.000	0.014	0.017
# Observations	1024	1024	1024
# Clusters	53	53	53
H_0 : Zero Treatment Effect (High-Low)	$F_{1,52} = .02$	$F_{1,52} = .02$	$F_{1,52} = 20.02$
	$(p = 0.89)$	$(p = 0.89)$	$(p < 0.01)$
H_0 : Gain-Loss Attitudes $\perp$ Exchange in Low		$F_{1,52} = 13.19$	$F_{1,52} = 14.33$
		$(p < 0.01)$	$(p < 0.01)$
H_0 : Gain-Loss Attitudes $\perp$ Treatment Effect		$F_{1,52} = 19.48$	$F_{1,52} = 24.01$
		$(p < 0.01)$	$(p < 0.01)$

Notes: Ordinary least square regression. Standard errors clustered at session level in parentheses. Null hypotheses tested for 1) zero treatment effect (Condition High coefficient= 0); 2) no relationship between gain-loss attitudes and behavior in Condition Low behavior ($\hat{\lambda}_i$ or $\hat{l}_i$ coefficient = 0); 3) constant treatment effect over gain-loss attitudes (Condition High * $\hat{\lambda}_i$ or Condition High * $\hat{}_i$ coefficient= 0). *F*-statistics and two-sided *p*-values reported.

B.6 Replication Exchange Study and Reconciliation with Pre-Analysis Plan

In this section we report the methodology and corresponding analyses from an earlier working paper analyzing only the results of the exchange experiment (`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 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`.

B.6.1 Stage 1: Identifying Gain-Loss Attitudes

Our previous methodology relied on the same preference statements that we introduced in Section 3.1, but focused only on the liking preference statements. Instead of residualizing the first principal component of the preference statements as described in Section 3.2.1, in our previous analyses we constructed 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

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$U(0, Y|X, 0)$. 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.[36] We normalize one of the good's values to be $Y = 1$, and estimate the remaining parameters via maximum likelihood.

Table A10 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 slightly less pronounced in our replication study.

Table A10: 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.

---

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

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

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

$$P(R(X) = R(Y)) = 1 - P(R(X) > R(Y)) - P(R(Y) > R(X)).$$

B.6.2 Stage 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 $\hat{\lambda} < 1.30$,[37] 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.[38] 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-seeking. 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-seeking. These are the taxonomies of individual gain-loss types used in our previous analysis.

B.6.3 Stage 2: Heterogeneous Treatment Effects

Table A11 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. All of these results leverage our initial methodology described above that only relies on the liking preference statements. Beginning with the initial study, we find a null average treatment effect in column (1). In Condition Low, 36.5 percent of subjects choose

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

[38]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.

to exchange, demonstrating a significant endowment effect relative to the null hypothesis of 50 percent exchange, $F_{1,605} = 18.32$, $(p < 0.01)$. Probabilistic forced exchange in Condition High 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-seeking, based on their Stage 1 liking statements. Panel A of Table A11 shows a dramatic heterogeneous treatment effect. Loss-averse subjects exhibit a statistically significant endowment effect in Condition Low, and grow more approximately 16 percentage points more willing to exchange in Condition High. Gain-seeking subjects exhibit no endowment effect in Condition Low, and grow approximately 25 percentage points less willing to exchange in Condition High. The heterogeneous treatment effect over gain-seeking 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-seeking and loss-averse subjects noted above. Based on these power analyses, the replication targeted 400 subjects. Panel B of Table A11 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-seeking 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-seeking 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 as

Table A11: Prior Analysis: Exchange Behavior and Probabilistic Forced Exchange

	(1)	(2)	(3)	(4)
	Dependent Variable: Exchange (=1)			
	Full Sample	Loss Averse	Loss Neutral	Gain Seeking
Panel A: Initial Study				
Condition High	0.004	0.158	0.027	-0.248
	(0.034)	(0.067)	(0.066)	(0.078)
Constant (Condition Low)	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 (High-Low)	$F_{1,605} = 0.01$	$F_{1,215} = 5.64$	$F_{1,238} = 0.17$	$F_{1,148} = 10.18$
	$(p = 0.90)$	$(p = 0.02)$	$(p = 0.68)$	$(p < 0.01)$
H_0: Constant (col. 2) = Constant (col. 4)				$F_{1,363} = 1.44$
				$(p = 0.23)$
H_0: Condition High (col. 2) =Condition Low (col. 4)				$F_{1,363} = 15.76$
				$(p < 0.01)$
Panel B: Replication Study				
Condition High	-0.010	0.206	-0.073	-0.160
	(0.044)	(0.085)	(0.075)	(0.094)
Constant (Condition Low)	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 (High-Low)	$F_{1,415} = 0.05$	$F_{1,122} = 5.79$	$F_{1,183} = 0.95$	$F_{1,106} = 2.92$
	$(p = 0.83)$	$(p = 0.02)$	$(p = 0.33)$	$(p = 0.09)$
H_0: Constant (col. 2) = Constant (col. 4)				$F_{1,228} = 5.22$
				$(p = 0.02)$
H_0: Condition High (col. 2) =Condition Low (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 endowment effect in Condition Low, regression (Constant = 0.5); 2) zero treatment effect (High-Low); 3) Identical Condition Low behavior across loss-averse and gain-seeking subjects (Constant (col. 2) = Constant (col. 4)); 4) Identical treatment effects of forced exchange across loss-averse and gain-seeking subjects (High condition (col. 2) = High condition (col. 4)). Hypotheses 3 and 4 tested via interacted regression with observations from columns (2) and (4).

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

Appendix C   Instructions - Labor supply experiment

The following set of screenshots demonstrates a demo version of our experiment, designed on oTree (Chen et al., 2016).

Welcome

Hello and thank you for taking the time to participate in this study. This experiment consists of several parts. Each part will include self-contained instructions about the relevant choices. If you're not sure about something at any time throughout the study, please feel free to contact your host for this session.

This study has been approved by the IRB at UCSD, and a copy of the consent form is attached below. By clicking next, you agree to take part in the experiment.

University of California, San Diego
Consent to Act as a Research Subject

Economics Experiment

Who is conducting the study, why you have been asked to participate, how you were selected, and what is the approximate number of participants in the study?
Alexandre Kellogg (Economics PhD candidate) and Professor Charles Sprenger are conducting a research study to find out more about economic decision-making. You have been asked to participate in this study because you are over the age of 18 and a student at UCSD. In your session today there will be 10 to 24 participants. Over the entire research project, there will be approximately 800 participants.

Why is this study being done?
The purpose of this study is to get precise and reliable measures of the foundational preferences of economic decision-making.

What will happen to you in this study and which procedures are standard of care and which are experimental?
If you agree to be in this study, the following will happen to you:
You will be paid for your earnings. You and the other participants will make a series of decisions, and your earnings will depend on the decisions that you make.

☐ I consent to be a participant in this study.

Next

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Receiving Payment and Your Identity

All payments will be sent to you via Venmo/Zelle. In order to receive payment, we will need to collect an email address linked to this form of payment. This information will only be seen by the PIs in this study. As soon as your payments are made, the link between the choices you made and your payment will be destroyed, and the record with your email address will be deleted. Your identity will not be a part of the subsequent data analysis.

Please enter the email associated with your Zelle account:

Next

Experiment Overview

In the main part of this experiment, you will have the possibility to earn money by completing a number of tasks. Each task consists of transcribing a line of blurry Greek letters from a Greek text. The experiment is divided into five parts, which we will explain in turn.

Part 1

In **Part 1**, you will make 32 decisions. In each decision, you will be offered a rate for each task that you complete, and you will be asked to decide how many tasks you want to complete at that rate. For example, in one of the decisions you could be offered $0.20 for every task that you complete, and you will have to decide how many tasks (from 0 to 100) you want to complete at that rate.

Before you make any decisions about the number of tasks you wish to complete for each rate, you will be asked to complete 2 practice tasks. This will allow you to become acquainted with the task and give you a sense of how long a task takes you to complete.

Part 1 takes approximately 20 minutes.

Part 2

In **Part 2**, you will make 42 decisions. In each decision, you will be presented with two options: Option A will be a lottery, paying (for example) $10 with 20% chance and $0 with 80% chance and Option B will be a sure amount of $5. For each choice, the probabilities in Option A will vary, and you will be asked to indicate which option you prefer.

Part 2 takes approximately 10 minutes.

Part 3

After you have made your decisions in **Part 1** and **Part 2**, a computer will randomly determine which decision from **Part 1** or **Part 2** is chosen to be the *decision-that-counts*. The *decision-that-counts* will determine which of your prior choices will be implemented, and will thus determine part of your earnings for this study. Each of the choices you make are equally likely to be selected.

Next, everyone will be required to complete 10 tasks. Completing these mandatory tasks is required in order to earn your completion fee of $7.00 as well as the earnings determined from the *decision-that-counts*.

Part 3 can take anywhere from 5 minutes to 20 minutes, depending on how long it takes you to complete a task. On average, it takes about 42 seconds to complete one task.

Part 4

Once you have completed the 10 tasks, you may be asked to complete additional tasks as determined by your prior choices from the *decision-that-counts*.

Part 4 may take anywhere from 1 minute to 2 hours depending on which decision was selected as the *decision-that-counts*, the number of tasks that you selected, and the time it takes you to complete each task.

Part 5

Once you have finished with **Part 4**, you will then be asked to solve a few puzzles and answer a few demographic questions. There are a total of 5 puzzles to solve within 10 minutes. For each correct answer you submit, you will receive an additional $1.

After filling out your responses, you will receive your final payment via the account information you provided in the previous page. Your final payment will consist of a $7.00 completion fee + your earnings from completing each of the parts. If you do not complete all of the tasks you had previously chosen during **Part 4**, you will not receive the completion fee nor payment for any of the tasks, and will instead receive a show-up fee of $5.00.

Summary

To review, this experiment consists of 5 distinct parts. In **Part 1** and **Part 2**, you will make a series of choices, each of which is equally likely to determine your payment. In **Part 3**, the *decision-that-counts* will be revealed and you will be asked to complete the required 10 tasks. In **Part 4**, you will be asked to complete any additional tasks determined by your prior choices (if relevant). Finally, **Part 5** has a brief set of puzzles and survey questions prior to concluding the experiment.

More detailed instructions will be presented prior to each part. If you have questions or want clarification, remember that you can always contact your host for this session. On the next page, you will learn more about the Greek transcription tasks you will be asked to complete.

Next

The Task

To complete a task, you will have to transcribe a line of blurry letters from a Greek text. For each task, Greek text will appear on your screen. You will be asked to transcribe these letters by finding and clicking on the corresponding letter, which will insert that letter into the completion box. If you would like to delete the most recently added character, please click on the backspace image. One task is one row of Greek text. For the task to be complete, your transcription must be 80% accurate or better. The following is an example of a row of blurry Greek text and the row of letters you will be asked to select from, along with its solution:

Please select from the following characters to enter your transcription.

The correct transcription for the example task is provided above; recall, however, that you do not need to be 100% accurate. If you submit a transcription that is 80% accurate or better (defined as requiring 7 or fewer insertions, deletions, or substitutions to achieve the perfect transcription), you will have completed the task. If your answer is incorrect (less than 80% accurate), you will have 2 more tries (for a total of 3) to submit a correct answer, after which you will be presented with a new task and the incorrect submissions will not be counted as a completed task.

As part of the task, several auditory "beeps" will sound randomly while you are completing the tasks. Please put on your headphones and/or turn your volume up so that you can hear the beeping noises. After each time you hear this beeping noise, you must press the "Noise" button at the bottom left of the screen. If you do not press the "Noise" button within five seconds of hearing the beeping noise, your transcription will be reset. If you press the noise button erroneously (when there was no beeping sound), your transcription will be reset. Note that resetting the transcription does not count as a try; your current progress will simply be deleted and you will have to re-enter the transcription.

The time it takes to complete a task will vary from person to person. **On average, however, each task takes about 42 seconds to complete.**

Before you make your decisions, we will present you with 1 tasks so that you better understand what it means to complete a task as you make your choices. This will also provide you a chance to ensure that you can hear the beeping noises correctly. If you have any trouble with the task or any questions about it, please contact your host!

Next

Sample of Task

Please transcribe the row of Greek letters by selecting the appropriate letters. Press **Next** when you wish to submit your response. Remember to press the **Noise** button within 5 seconds of hearing the beeps, otherwise your responses will be removed and you will have to start over. You have 3 chances to complete each task. If you fail to complete the task within three tries you will simply be shown a different one.

Number completed 0/1. Attempt: 1 of 3.

γηαα . βγααιι . χε . αφαβ . ε . ββγηχ . βφ . γγ . ι

Please select from the following characters to enter your transcription.

| α | β | χ | δ | ϵ | φ | γ | η | ι | . | ⌫ |

Noise

Next

Part 1

Throughout the following screens, you will make a total of 32 decisions. We will begin by explaining the kind of decisions that you will make for the first 30 decisions of the study. After you make these 30 decisions, you will receive a new set of instructions regarding the last 2 decisions.

Decisions 1 to 30

In the next six screens, you will have to decide how many tasks you are willing to complete for a given rate. *As a reminder, one task means a correct transcription of a blurry line of Greek text*. The rates will be presented in lists of 5 at a time, and all rates within a list will either be *deterministic*, for example $0.15/task, or *stochastic*, for example a 50% chance of $0.10/task and a 50% chance of $0.20/task. The rates per task will range from $0.00 to $0.60 per task.

An example of your choice environment is provided below.

Low Wage (50%)	High Wage(50%)		Chosen Tasks	
$0.0/task	$0.1/task	(50% Chance of $0.00 50% Chance of $2.20)	22 tasks (~16mins)	

Each rate will have a corresponding slider where you can choose, for that rate, how many tasks you are willing to complete. As you move the slider, you will see a subtotal next to the rate, as well as the estimated time to complete the number of Greek tasks indicated. This time is estimated based on the average of 42 seconds per task at the bottom of the page, but you may enter your own estimated time given what you learned in the practice tasks.

Recall that each of the decisions that you will make throughout **Part 1** and **Part 2** of this study is equally likely to be the decision that counts. **Thus, it is very important that you think carefully about each decision you make, as it could be the one selected for payment.** If one of these 30 decisions is randomly selected to be the *decision-that-counts*, you will be asked to complete the number of Greek tasks that you indicated and you will be compensated at the rate specified by the *decision-that-counts*. Recall that everyone will be required to complete their 10 tasks before continuing on to the number of tasks that you indicated in the *decision-that-counts*.

If the rate for the *decision-that-counts* is deterministic, say $0.15/task, and you said you would work 50 tasks at that rate, you will be paid a $7.00 completion fee + $7.50 for your tasks for a total of $14.50 (plus an additional $1 for each puzzle you correctly solve in **Part 5**).

If the *decision-that-counts* involves a stochastic rate, say $0.10/task with 50% chance and $0.20/task with 50% chance, and you chose to work 50 tasks, then you will be asked to complete the 50 tasks after the mandatory 10. After you have completed all of these tasks, the computer will reveal which of these two rates applies by flipping a coin. Once the rate is determined, say the computer selects $0.20/task ($0.10/task), you will be paid a total of $17.00 ($12.00), $7.00 for the completion fee + $10.00 ($5.00) for your 50 tasks (plus an additional $1 for each puzzle you correctly solve in **Part 5**).

Over the next six pages, you will be presented with a series of 5 wages per page and asked to indicate the amount of tasks you wish to complete at the given rates.

Next

Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that, in addition to the number of tasks you select here, everyone will be required to complete 1 tasks paid for by the completion fee. There is an equal chance that each of these wages will be selected as the decision-that-counts, so please make your decisions carefully. **Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.**

Low Wage (50%)	High Wage(50%)		Chosen Tasks	
$0.0/task	$0.1/task	(50% Chance of $0.00 50% Chance of $2.20)	22 tasks (~16mins)	──●──────────
$0.0/task	$0.2/task	(50% Chance of $0.00 50% Chance of $13.40)	67 tasks (~47mins)	──────────●──
$0.025/task	$0.225/task	(50% Chance of $0.48 50% Chance of $4.28)	19 tasks (~14mins)	──●──────────
$0.05/task	$0.25/task	(50% Chance of $3.65 50% Chance of $18.25)	73 tasks (~52mins)	───────────●─
$0.075/task	$0.275/task	(50% Chance of $1.95 50% Chance of $7.15)	26 tasks (~19mins)	────●────────

Hourly wage and time computed using task time of (sec): [42]   ☐ I confirm my final choices for all 5 sliders.

[Next]

Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that, in addition to the number of tasks you select here, everyone will be required to complete 1 tasks paid for by the completion fee. There is an equal chance that each of these wages will be selected as the decision-that-counts, so please make your decisions carefully. **Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.**

Wage	Chosen Tasks
$0.2/task	
$0.225/task	
$0.25/task	
$0.275/task	
$0.3/task	

Hourly wage and time computed using task time of (sec): 42   ☐ I confirm my final choices for all 5 sliders.

Next

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Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that, in addition to the number of tasks you select here, everyone will be required to complete 1 tasks paid for by the completion fee. There is an equal chance that each of these wages will be selected as the decision-that-counts, so please make your decisions carefully. **Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.**

Wage	Chosen Tasks
$0.05/task	
$0.1/task	
$0.125/task	
$0.15/task	
$0.175/task	

Hourly wage and time computed using task time of (sec): `42`   ☐ I confirm my final choices for all 5 sliders.

Next

Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that, in addition to the number of tasks you select here, everyone will be required to complete 1 tasks paid for by the completion fee. There is an equal chance that each of these wages will be selected as the decision-that-counts, so please make your decisions carefully. **Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.**

Low Wage (50%)	High Wage(50%)	Chosen Tasks	
$0.1/task	$0.3/task		●—————
$0.125/task	$0.325/task		●—————
$0.15/task	$0.35/task		●—————
$0.175/task	$0.375/task		●—————
$0.2/task	$0.4/task		———●———

Hourly wage and time computed using task time of (sec): [42]   ☐ I confirm my final choices for all 5 sliders.

[Next]

Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that, in addition to the number of tasks you select here, everyone will be required to complete 1 tasks paid for by the completion fee. There is an equal chance that each of these wages will be selected as the decision-that-counts, so please make your decisions carefully. **Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.**

Low Wage (50%)	High Wage(50%)	Chosen Tasks	
$0.075/task	$0.375/task		●————
$0.05/task	$0.45/task		●————
$0.0/task	$0.5/task		●—————
$0.1/task	$0.5/task		●————
$0.0/task	$0.6/task		●————

Hourly wage and time computed using task time of (sec): [42]   ☐ I confirm my final choices for all 5 sliders.

[Next]

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Part 1 Continued

Decisions 31 and 32

Next, you will be asked to make your final two decisions for **Part 1** of this study. Each of the two decisions will be presented on their own page, so **please make sure you carefully review the rates for each decision**. As in the previous decisions, you will have to decide how many tasks to complete at different rates. The only difference in these two decisions is the structure of the rates: with 50.0% chance, you will get $0.20/task, with 5.0% chance you will get a fixed payment of $X *regardless of the number of tasks that you decided to do*, and with 45.0% chance you will get a fixed payment of $Y *regardless of the number of tasks that you decided to do*. For example, if you select to complete 30 tasks, then after you complete the 30 tasks you will either be paid $0.20/task, $X, or $Y.

Recall that at the end of the study, one of the 32 decisions you've made in **Part 1**, including these final two, may be randomly selected for payment. This means that each decision is equally likely to be the decision-that-counts. **Thus, it is very important that you think carefully about each decision you make, as it could be the one selected for payment.**

Next

Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that there is an equal chance that each of these wages will be selected as the decision-that-counts. Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.

Fixed (L) (5.0%)	Fixed (H) (45.0%)	Wage (50.0%)		Chosen Tasks	
$0	$20	$0.2/task	(50% Chance of $3.20 5% Chance of $0.00 45% Chance of $20.00)	16 tasks (~12mins)	

Hourly wage and time computed using task time of (sec): 42   Next

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Effort Choices

Please indicate the number of tasks you are willing to do at each of the following wages by adjusting the slider below. Recall that there is an equal chance that each of these wages will be selected as the decision-that-counts. Make sure to adjust all the sliders before continuing, otherwise you will be asked to re-enter your choices.

Fixed (L) (45.0%)	Fixed (H) (5.0%)	Wage (50.0%)	Chosen Tasks
$0	$20	$0.2/task	

Hourly wage and time computed using task time of (sec): 42   Next

Instructions for Part 2

On the following pages, you will be asked to make 21 choices per page. In each choice, you will be presented with two options -- "Option A" and "Option B" -- and asked to indicate which of the two you prefer.

"Option A" will be a lottery that pays either $10.00 ($3.00) with probability varying from 0.0% to 100.0%, or $0.00 (-$3.50) otherwise; "Option B" yields a payoff of $5.00 ($0.00) for sure, i.e. with a probability of 100%.

On each page, the first and last choice will be selected by default to help demonstrate that Option B is initially the preferred option, but Option A grows more desirable in each row; by the last choice, Option A should clearly be preferred. You will not be able to change these choices.

For the remaining choices, please select your preference between Option A and Option B. Once you have switched from Option B to Option A, all subsequent choices will be automatically switched to Option A. This is intended to help maintain consistency due to the ordering of the choices: if you prefer Option A to Option B in choice number 10 (for example), then you should prefer Option A to Option B in choice 11, 12, and so on. An example of this for a set of potential choices is shown below. Someone who prefers a 10% chance of $10 (and 90% chance of $0) to $5 for sure should also prefer a 15% chance of $10 (and 85% chance of $0) to $5 for sure, because a 15% chance is strictly better than a 10% chance and the $5 for sure never changes.

Option A		Option B
$10.00 with a probability of 0.0%, $0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 5.0%, $0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 10.0%, $0.00 otherwise	● Option A ○ Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 15.0%, $0.00 otherwise	● Option A ○ Option B	$5.00 with a probability of 100.0%

After you have made all of your choices, please review the page prior to submitting these decisions. Recall that one of these decisions may be randomly chosen for your payment.

If you indicated that you prefer Option A (the lottery) for the relevant decision, a random number between 1 and 100 will be generated to determine the outcome of the lottery. For instance, if the **decision-that-counts** is $10.00 with 20% chance and $0.00 with 80% chance, a random number between 1-80 will result in payment of $0.00, but a random number between 81-100 will result in payment of $10.00.

If you indicated that you prefer Option B for the relevant decision, you would receive $5.00 in this example.

Recall that, along with your choices from **Part 1**, each of the choices you make in **Part 2** are equally likely to be the *decision-that-counts*. Please carefully consider each choice as they are all equally likely to determine your final payment.

Next

Part 2 Decisions

Option A		Option B
$3.00 with a probability of 0.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 5.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 10.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 15.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 20.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 25.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 30.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 35.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 40.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 45.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 50.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 55.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 60.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 65.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 70.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 75.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 80.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 85.0%,-$3.50 otherwise	○ Option A ● Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 90.0%,-$3.50 otherwise	● Option A ○ Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 95.0%,-$3.50 otherwise	● Option A ○ Option B	$0.00 with a probability of 100.0%
$3.00 with a probability of 100.0%,-$3.50 otherwise	● Option A ○ Option B	$0.00 with a probability of 100.0%

Next

Part 2 Decisions

Option A		Option B
$10.00 with a probability of 0.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 5.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 10.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 15.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 20.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 25.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 30.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 35.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 40.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 45.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 50.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 55.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 60.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 65.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 70.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 75.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 80.0%,$0.00 otherwise	○ Option A ● Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 85.0%,$0.00 otherwise	● Option A ○ Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 90.0%,$0.00 otherwise	● Option A ○ Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 95.0%,$0.00 otherwise	● Option A ○ Option B	$5.00 with a probability of 100.0%
$10.00 with a probability of 100.0%,$0.00 otherwise	● Option A ○ Option B	$5.00 with a probability of 100.0%

Next

Results

The following decision was randomly chosen for your payment:

	Option A			Option B
	$10.00 with a probability of 85.0%, $0.00 otherwise	●	○	$5.00 with a probability of 100.0% (sure payoff)

As shown above, you indicated that you prefer Option A in this decision.

For the lottery, one of the two possible outcomes has been randomly realized based on the corresponding probabilities.

Your payoff in this task equals **$10.00**.

Next

The Task

Recall that for each task, you will have to transcribe a line of blurry Greek letters from a Greek text. One task is one row of Greek text. For the task to be complete, your transcription must be 80% accurate or better. The following is an example of a row of blurry Greek text and the dictionary:

δηιφα . βαιδφι . ηβεχφηφιεδ . γηειφφγφαγ .

δηιφα.βαιδφι.ηβεχφηφιεδ.γηειφφγφαγ.

Please select from the following characters to enter your transcription.

α β χ δ ϵ φ γ η ι . ⌫

The correct transcription for the example task is provided; recall, however, that you do not need to be 100% accurate. If you submit a transcription that is 80% accurate or better (defined as requiring 7 or fewer insertions, deletions, or substitutions to achieve the perfect transcription), you will have completed the task. If your answer is incorrect (less than 80% accurate), you will have 2 more tries (for a total of 3) to submit a correct answer, after which you will be presented with a new task and the incorrect submissions will not be counted as a completed task.

As part of the task, several auditory "beeps" will sound randomly throughout the transcription process. Please put on your headphones and/or adjust the volume so that you can hear the beeping noises. After each time you hear this beeping noise, you must press the "Noise" button at the bottom left of the screen. If you do not press the "Noise" button within five seconds of hearing the beeping noise, your transcription will be reset. If you press the noise button erroneously (when there was no beeping sound), your transcription will be reset. Note that resetting the transcription does not count as a try; your current progress will simply be deleted and you will have to re-enter the transcription.

Once you click the next button, you will be presented with the 1 required tasks. After you complete these, you will be continue onto **Part 5** and attempt to solve several puzzles ($1 per correct submission) and answer a few demographic questions. Then, you will receive compensation based on your *decision-that-counts*. Recall that you were randomly selected to be paid $10.00 from the lottery task.
Once you finish all of these tasks, you will receive a completion fee of $7.00 in addition to your lottery payout, for a total of $17.00 (plus $1 per correct puzzle entry).

Next

Mandatory Tasks

Please transcribe the row Greek letters by selecting the appropriate letters. Press **Next** when you wish to submit your response. Remember to press the **Noise** button within 5 seconds of hearing the beep, otherwise your responses will be removed and you will have to start over. You will have 3 chances to complete each task. If you fail to complete the task within three tries you will simply be shown a different one.

Number completed 0/1. Attempt: 1 of 3.

$$\chi\alpha\phi\gamma\eta\beta\alpha \cdot \chi\chi\eta\delta\iota\chi\delta \cdot \epsilon\chi\phi\eta\chi\alpha\delta\gamma\chi\iota \cdot \delta\eta\iota\gamma\phi\gamma\alpha\gamma$$

Please select from the following characters to enter your transcription.

α β χ δ ε φ γ η ι . ⌫

Noise

Next

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Part III Solving puzzles

Instructions

You will be presented with 5 problems, each showing a pattern with a bit cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns, BUT NOT THE DIAGONALS.

You will be paid $1 for each correct problem you solve. You have 10 minutes to complete all problems.

For example, for the following matrix, the correct pattern is 8.
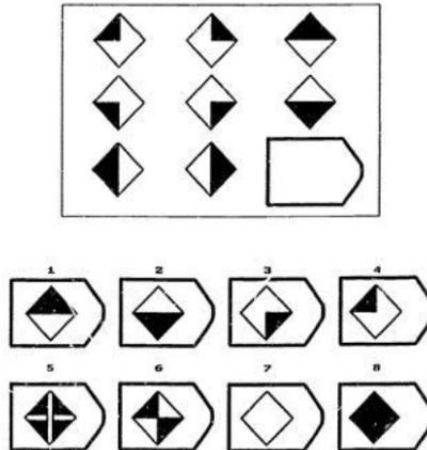
Click next to start solving the problems.

Next

Make your choice

Question 1 of 5

Instructions

You will be presented with 5 problems, each showing a pattern with a bit cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns, BUT NOT THE DIAGONALS.

You will be paid $1 for each correct problem you solve. You have 10 minutes to complete all problems.
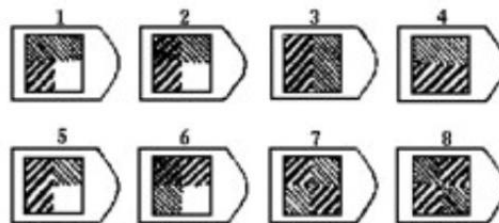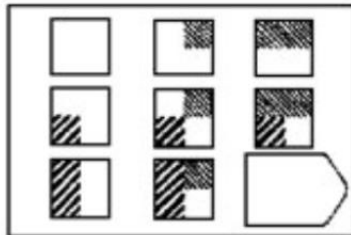
Please choose an item that best fits the pattern:

--------- ⌄
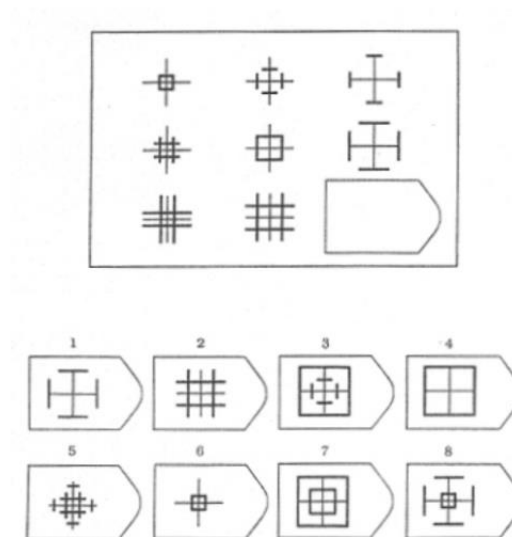
Next

Make your choice

Question 2 of 5

Instructions

You will be presented with 5 problems, each showing a pattern with a bit cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns, BUT NOT THE DIAGONALS.

You will be paid $1 for each correct problem you solve. You have 10 minutes to complete all problems.

Please choose an item that best fits the pattern:

--------- ▼

Next
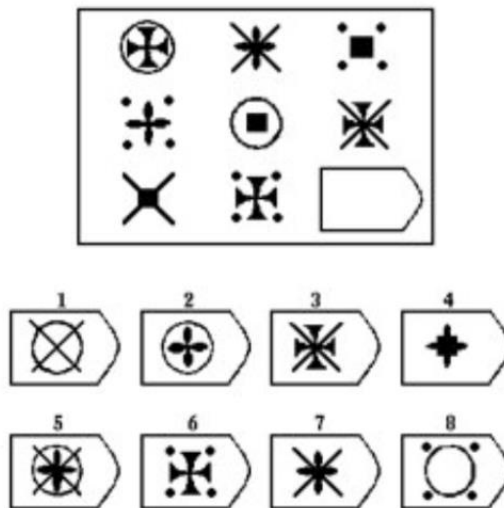
Make your choice

Question 3 of 5

Instructions

You will be presented with 5 problems, each showing a pattern with a bit cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns, BUT NOT THE DIAGONALS.

You will be paid $1 for each correct problem you solve. You have 10 minutes to complete all problems.

Please choose an item that best fits the pattern:
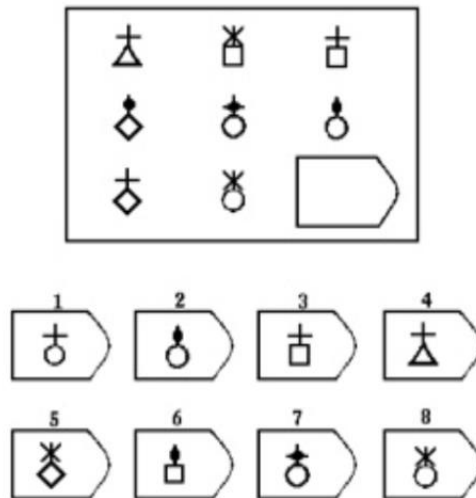
4 ⌄

Next

Make your choice

Question 4 of 5

Instructions

You will be presented with 5 problems, each showing a pattern with a bit cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns, BUT NOT THE DIAGONALS.

You will be paid $1 for each correct problem you solve. You have 10 minutes to complete all problems.

Please choose an item that best fits the pattern:

--------- ▾

Next

Make your choice

Question 5 of 5

Instructions

You will be presented with 5 problems, each showing a pattern with a bit cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns, BUT NOT THE DIAGONALS.

You will be paid $1 for each correct problem you solve. You have 10 minutes to complete all problems.
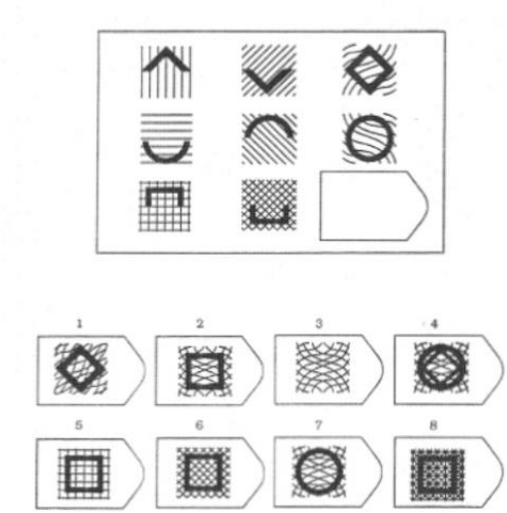
Please choose an item that best fits the pattern:

--------- ⌄

Next

Results

You have completed all problems.

You have correctly solved 0 problems.

Your total payment for this part is $0.

Next

Thank You for Participating

Before we finalize your earnings, please answer the following short survey.

What year of your undergraduate education are you in?

○ First   ○ Second   ○ Third   ○ Fourth   ○ Other

What is your major or intended major?

[   ]

What is your gender?

○ Male   ○ Female   ○ Other   ○ Decline to Answer

Which of the following income brackets do your parents fall into?

○ Below 50k   ○ 50k to 100k   ○ Above 100k   ○ Decline to Answer

How do you evaluate yourself: Are you in general a more risk-taking (risk-prone) person (10) or do you try to avoid risks (0, risk-averse)?

○ 0 (Risk averse)   ○ 1   ○ 2   ○ 3   ○ 4   ○ 5   ○ 6   ○ 7   ○ 8   ○ 9   ○ 10 (Fully prepared to takes risks)

<div align="right">

Next

</div>

Thank You for Participating

As a reminder, your lottery payoff was randomly determined to be $10.00.
Your total earnings, including the completion fee of $7.00 and the earnings from the Raven Matrices of $0.00, are $17.00.

Next

Appendix D Instructions - Exchange experiment

D.1 Images of Objects Presented to subjects

The following images were projected to the wall of the lecture room at the beginning of the respective stage. For the displayed example, the Stage 1 pair consisted of the USB stick and erasable pens, but this was counter-balanced at the session level.
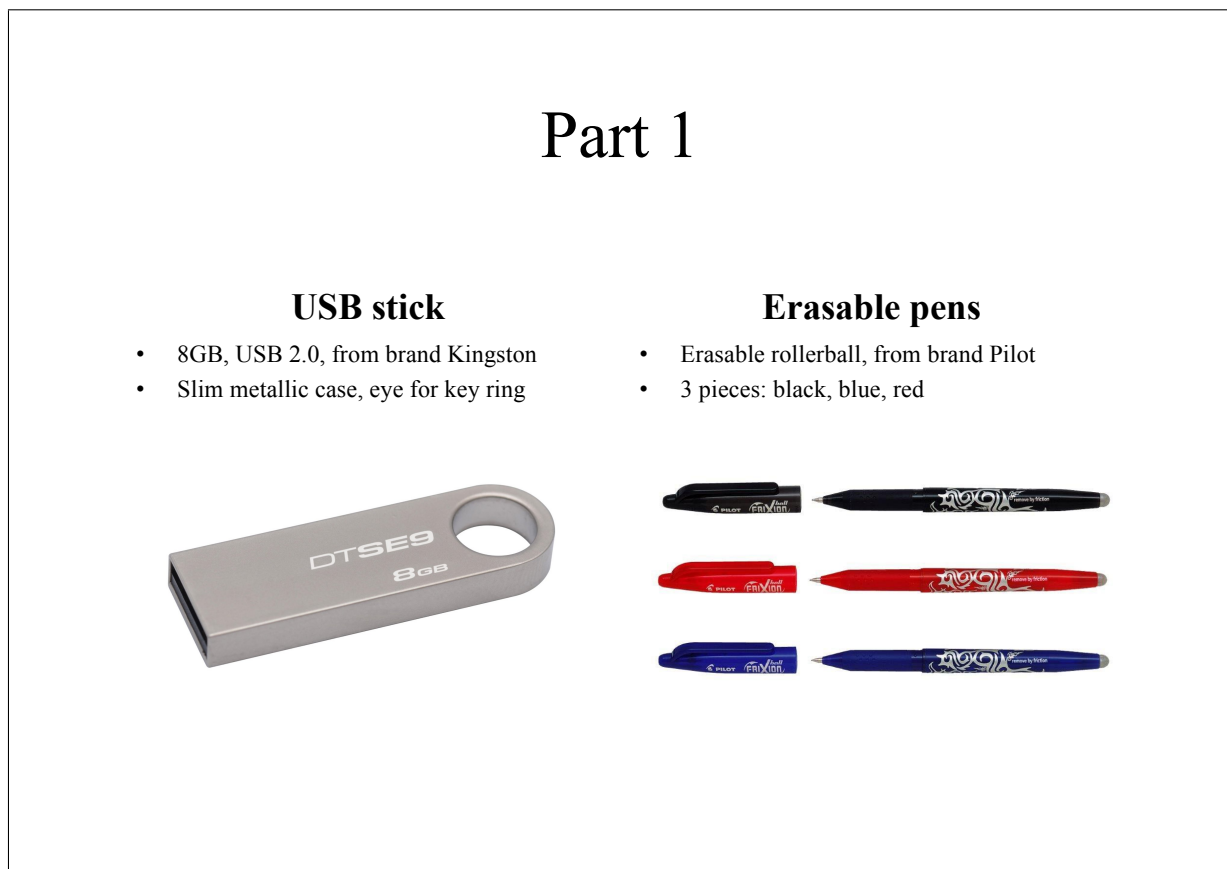

Figure A9: Image 1 Projected on the Wall to Present Objects.
For Stage 1 with objects pair consisting of USB stick and erasable pens.

D.2 Original instructions in German (computer-based)

Willkommen in Teil 1 von 2 in diesem Experiment!

Part 2

Thermos bottle

- Stainless steel, 500ml, double-wall insulated
- For warm and and cold drinks

Picnic mat

- Foldable, water-resistant PVC bottom side
- Ca. 120x140cm, with Velcro fastener

Figure A10: Image 2 Projected on the Wall to Present Objects.
For Stage 2 with objects pair consisting of thermos and picnic mat.

Bitte schließen Sie den Vorhang Ihrer Kabine und lesen die folgenden Informationen. Alle Eingaben, die Sie in diesem Experiment am Computer machen, sind völlig anonym und können nicht mit Ihrer Person in Verbindung gebracht werden. Es geht an keiner Stelle in diesem Experiment um Schnelligkeit. Bitte nehmen Sie sich stets ausreichend Zeit, um die Anweisungen zu lesen und zu verstehen.

Sie besitzen nun das Produkt vor Ihnen. Sie können es jederzeit anfassen und inspizieren. Bitte öffnen Sie jedoch noch nicht die Verpackung und benutzen das Produkt nicht.

Die beiden Ihnen vorgestellten Produkte wurden zufällig und in gleichen Mengen auf die Kabinen verteilt. Ihre Kabinennummer hat sich ebenfalls rein zufällig aus der Wahl Ihres Sitzplatzes im Präsentationsraum ergeben.

Klicken Sie OK, wenn Sie diese Informationen gelesen haben. Falls Sie Fragen haben, rufen Sie bitte den Leiter des Experiments.

Bitte beantworten Sie die Fragen.

[USB stick / Thermoskanne]

Wie gut gefällt Ihnen das Produkt?

Wie gern würden Sie dieses Produkt mitnehmen?

[Radierbare Kugelschreiber / Picknick-Matte]

Wie gut gefällt Ihnen das Produkt?

Wie gern würden Sie dieses Produkt mitnehmen?

Wenn Sie sich für ein Produkt entscheiden müssten, welches würden Sie lieber behalten?

[USB stick / Thermoskanne] [Radierbare Kugelschreiber / Picknick-Matte

Bitte lesen Sie die folgenden Informationen aufmerksam.

Der Leiter des Experiments wird gleich mit einer Bingo-Trommel eine Zufallszahl zwischen 1 und 20 ziehen.Die gezogene Zahl wird danach laut durchgesagt. Wenn die gezogene Zahl eine Zahl [von 11 bis 20 / von 1 bis 10] ist, werden/wird [Ihr USB-Stick / Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] weggenommen und Sie erhalten stattdessen eine/einen [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne]. Wenn die gezogene Zahl eine Zahl [von 1 bis 10 / von 11 bis 20] ist, behalten Sie [Ihr USB-Stick / Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und es passiert nichts. Nachdem die Zahl gezogen wurde und gegebenenfalls ein Austausch der Produkte vollzogen wurde, passiert nichts mehr in diesem Teil des Experiments. Sie können das Produkt dann endgültig behalten.

Bitte bestätigen Sie erst, wenn Sie alles verstanden haben. Falls Sie Fragen haben, rufen

Sie bitte den Leiter des Experiments und warten, bis er zu Ihnen kommt.

[Mood elicitation 1]

Bitte beantworten Sie die folgenden Fragen dazu, wie Sie sich gerade fülen. Welche Ausdrücke treffen auf Sie jetzt im Moment eher zu? Positionieren Sie den Schieberegler entsprechend. "Unglücklich, Wütend, Unzufrieden, Traurig, Verzweifelt"—"Glücklich, Begeistert, Zufrieden, Frühlich"

Es ist soweit! Bitte warten Sie, bis die Zahl gezogen wurde.

Zur Erinnerung: Wenn die gezogene Zahl [von 11 bis 20 / von 1 bis 10] ist, verlieren Sie [Ihr USB-Stick / Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und erhalten stattdessen eine/einen [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne]. Wenn die gezogene Zahl [von 1 bis 10 / von 11 bis 20] ist, behalten Sie [Ihr USB-Stick / Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne].

Die gezogene Zahl ist [1 / 2 / ... / 20].

Dies ist eine Zahl [von 1 bis 10 / von 11 bis 20]. Daher [verlieren Sie [Ihren USB-Stick / Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und erhalten stattdessen eine/einen [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] / können Sie [Ihren USB-Stick"/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] behalten]. Bitte warten Sie, während der Leiter des Experiments den Austausch in den Kabinen durchführt.

[Mood elicitation 2 and control question.]

Bitte beantworten Sie die folgenden Fragen dazu, wie Sie sich gerade fülen. Welche

Ausdrücke treffen auf Sie jetzt im Moment eher zu? Positionieren Sie den Schieberegler entsprechend. "Unglücklich, Wütend, Unzufrieden, Traurig, Verzweifelt"—"Glücklich, Begeistert, Zufrieden, Frühlich"

In der Lottoziehung die eben stattgefunden hat: Wie hoch war die Wahrscheinlichkeit (in Prozent), dass Sie Ihr ursprüngliches Produkt verlieren würden? Bitte geben Sie eine Zahl zwischen 0 und 100 ein. Please enter a number between 0 and 100.

Teil 1 des Experiments ist vorbei!

Bitte befolgen Sie die Anweisungen.

- Prägen Sie sich die Nummer Ihrer Kabine ein.

- Sie können jetzt zurück in den Präsentationsraum gehen.

- Bitte lassen Sie [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] in der Kabine liegen. Sie werden in wenigen Minuten zurück in der gleichen Kabine sein.

- Zur Erinnerung: Das Produkt gehört nun endgültig Ihnen und Sie werden es mit aus dem Experiment nehmen.

Willkommen in Teil 2 in diesem Experiment!

Bitte schließen Sie den Vorhang Ihrer Kabine und lesen die folgenden Informationen.

Sie besitzen nun den/die [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] vor Ihnen. Sie können es jederzeit anfassen und inspizieren. Bitte öffnen Sie jedoch noch nicht die Verpackung und benutzen das Produkt nicht.

Die beiden für Teil 2 vorgestellten Produkte ([USB Stick und radierbare Kugelschreiber] / [Thermoskanne und Picknick-Matte]) wurden erneut zufällig und in gleichen Mengen auf die Kabinen verteilt.

Klicken Sie OK, wenn Sie diese Informationen gelesen haben. Falls Sie Fragen haben, rufen Sie bitte den Leiter des Experiments.

[Instructions Stage 2—ONLY BASELINE (p=0.0)]

Bitte lesen Sie die folgenden Informationen aufmerksam. Der/Die [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] aus Teil 2 des Experiments gehört nun Ihnen und Sie können es behalten. Wenn Sie möchten, können Sie [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] freiwillig gegen ein/eine [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] tauschen. Wie auch immer Sie sich entscheiden, Ihre Wahl ist endg¸ltig und Sie werden Ihr gewähltes Produkt danach mit aus dem Experiment nehmen. Bitte bestätigen Sie erst, wenn Sie alles verstanden haben. Falls Sie Fragen haben, rufen Sie bitte den Leiter des Experiments und warten, bis er zu Ihnen kommt

[Instructions Stage 2—ONLY FORCED EXCHANGE (p=0.5)]

Bitte lesen Sie die folgenden Informationen aufmerksam. Sie haben ein neues Produkt in Teil 2 des Experiments erhalten ([einen USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne]).

Sie erhalten gleich die Gelegenheit, [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] freiwillig gegen [einen USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] zu tauschen. Wenn Sie sich für einen Tausch entscheiden, erhalten Sie wie gewüscht [einen USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] für [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und können [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] endgültig behalten. Das Experiment ist damit abgeschlossen.

Wenn Sie sich gegen einen Tausch entscheiden, besteht danach eine Wahrscheinlichkeit von 50%, dass der Austausch dennoch erzwungen wird und sie trotzdem tauschen müssen.

Folgendes passiert konkret im Fall, dass Sie sich gegen einen freiwilligen Tausch entscheiden: Der Leiter des Experiments wird (wie in Teil 1 des Experiments) mit einer Bingo-Trommel eine Zufallszahl zwischen 1 und 20 ziehen. Die gezogene Zahl wird danach laut durchgesagt. Wenn die gezogene Zahl eine Zahl [von 11 bis 20 / von 1 bis 10] ist, wird/werden Ihnen [Ihr USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] weggenommen und Sie erhalten stattdessen [einen USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne]. Wenn die gezogene Zahl eine Zahl [von 1 bis 10 / von 11 bis 20] ist, behalten Sie [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und es passiert nichts. Nachdem die Zahl gezogen wurde und gegebenenfalls ein Austausch der Produkte vollzogen wurde, passiert nichts mehr in diesem Teil des Experiments. Sie können das Produkt dann endgültig behalten.

Bitte bestätigen Sie erst, wenn Sie alles verstanden haben. Falls Sie Fragen haben, rufen Sie bitte den Leiter des Experiments und warten, bis er zu Ihnen kommt

[Mood elicitation 3]
Bevor Sie die Möglichkeit erhalten, Ihr Produkt zu tauschen, beantworten Sie bitte die folgenden Fragen dazu, wie Sie sich gerade fülen. Welche Ausdrücke treffen auf Sie jetzt im Moment eher zu? Positionieren Sie den Schieberegler entsprechend. "Unglücklich, Wütend, Unzufrieden, Traurig, Verzweifelt"—"Glücklich, Begeistert, Zufrieden, Frühlich"

Möchten Sie [Ihren USB-Stick/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] gegen [einen USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] tauschen?

Ja, ich möchte tauschen.

Nein, ich möchte nicht tauschen.

[ONLY BASELINE (p=0.0)]

Sie haben sich [für / gegen] einen freiwilligen Tausch enschieden. Bitte warten Sie, während der Leiter des Experiments den Austausch in den Kabinen durchführt.

[ONLY FORCED EXCHANGE (p=0.5)]

Sie haben sich [für / gegen] einen freiwilligen Tausch enschieden. Bitte warten Sie, während der Leiter des Experiments den Austausch in den Kabinen durchführt.

[ONLY NON-TRADERS] Danach entscheidet sich, ob Sie trotzdem tauschen müssen.

[ONLY TRADERS] Bitte warten Sie, bis das Experiment weitergeht. Es wird nun eine Zufallszahl für diejenigen gezogen, die sich gegen den freiwilligen Austausch entschieden haben. Danach geht das Experiment für Sie weiter.

[ONLY NON-TRADERS] Zur Erinnerung: Wenn die gezogene Zahl [von 11 bis 20 / von 1 bis 10] ist, verlieren Sie [Ihr USB-Stick"/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und erhalten stattdessen eine/einen [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne]. Wenn die gezogene Zahl [von 1 bis 10 / von 11 bis 20] ist, behalten Sie [Ihr USB-Stick"/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne].

[ONLY NON-TRADERS]

Die gezogene Zahl ist [1 / 2 / ... / 20].

Dies ist eine Zahl [von 1 bis 10 / von 11 bis 20]. Daher [verlieren Sie [Ihren USB-Stick / Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] und erhalten stattdessen eine/einen [USB-Stick / radierbare Kugelschreiber / eine Picknick-Matte / eine Thermoskanne] / können Sie [Ihren USB-Stick"/ Ihre radierbaren Kugelschreiber / Ihre Picknick-Matte / Ihre Thermoskanne] behalten]. Bitte warten Sie, während der

Leiter des Experiments den Austausch in den Kabinen durchführt.

[Mood elicitation 4]

Bitte beantworten Sie die folgenden Fragen dazu, wie Sie sich gerade fülen. Welche Ausdrücke treffen auf Sie jetzt im Moment eher zu? Positionieren Sie den Schieberegler entsprechend. "Unglücklich, Wütend, Unzufrieden, Traurig, Verzweifelt"—"Glücklich, Begeistert, Zufrieden, Frühlich"

Das Experiment ist zu Ende!

Sie können beide Produkte behalten. Zudem erhalten Sie gleich eine Teilnahmevergütung von 4 Euro. Bitte warten Sie noch kurz in Ihrer Kabine, bis Sie der Experimentator herausruft. Vielen Dank für Ihre Teilnahme!

D.3   English translation of instructions

Welcome to part 1 of 2 in this experiment!

Please close the curtain of you cabin and read the following information. All computer entries that you make in this experiment are fully anonymous and cannot be traced back to you. Speed is not important at any point in this experiment. Please always take sufficient time to read and understand the instructions.

You are currently in possession the product in front of you. You may touch it and inspect it anytime. However, please do not open the packaging and do not use the product The two objects presented to you ([USB stick and erasable pens / thermos and picnic mat]) have been randomly allocated to the cabins in equal quantities. Your cabin number was also randomly determined based on your choice of seat in the presentation room.

Please click on OK when you have read these information. If you have questions, please call an experimenter.

Please answer the questions.

[USB stick / thermos]

How much do you like this product?

How much would you want to have this product?

[Erasable pens / picnic mat]

How much do you like this product?

How much would you want to have this product?

If you had to choose one of the objects, which one would you prefer to keep?

[Erasable pens / picnic mat] [USB stick / thermos]

Please read the following information carefully.

The experimenter will soon draw a random number between 1 and 20 using a lotto drum. The drawn number will then be announced loudly. If the drawn number is a number [from 11 to 20 / from 1 to 10], your [USB stick / erasable pens / thermos / picnic mat] will be taken away from you and you instead receive [USB stick / erasable pens / thermos / picnic mat]. If the drawn number is a number [from 1 to 10 / from 11 to 20], you will keep your [USB stick / erasable pens / thermos / picnic mat] and nothing happens. After the number has been drawn and the exchange of objects has taken place (if applicable), nothing else happens in this part of the experiment. You can then keep your object for good.

Please only confirm below once you have understood everything. If you have questions, please call the experimenter and wait until he comes to your cabin.

[Mood elicitation 1]

Please answer the following questions about how you currently feel. Which expressions

better apply to you at the moment?

"Unhappy, Angry, Unsatisfied, Sad, Desperate"—"Happy, Thrilled, Satisfied, Content, Hopeful"

The time has come. Please wait until the number has been drawn.

Remember: If the drawn number is a number [from 11 to 20 / from 1 to 10], your [USB stick / erasable pens / thermos / picnic mat] will be taken away from you and you instead receive [USB stick / erasable pens / thermos / picnic mat]. If the drawn number is a number [from 1 to 10 / from 11 to 20], you will keep your [USB stick / erasable pens / thermos / picnic mat].

The drawn number is [1 / 2 / ... / 20].

This number is a number [from 1 to 10 / from 11 to 20]. Therefore [you can keep your [USB stick / erasable pens / thermos / picnic mat] / your [USB stick / erasable pens / thermos / picnic mat] will be taken away from you and you instead receive [USB stick / erasable pens / thermos / picnic mat]]. Please wait while the experimenter carries out the exchange in all cabins.

[Mood elicitation 2 and control question.]

Please answer the following questions about how you currently feel. Which expressions better apply to you at the moment?

"Unhappy, Angry, Unsatisfied, Sad, Desperate"—"Happy, Thrilled, Satisfied, Content, Hopeful"

Regarding the lottery draw, that has just taken place: What was the probability (in percent) that you would lose your initial object? Please enter a number between 0 and 100.

Part 1 of the experiment is over!

Please follow the instructions.

- Memorize your cabin number.

- You can no go back to the presentation room.

- Please leave your [USB stick / erasable pens / thermos / picnic mat] in the cabin. You will be back in the same cabin in a few minutes.

- Remember: The object now belongs to you for good and you will take it away from this experiment.

Welcome to part 2 in this experiment!

Please close the curtain of you cabin and read the following information. You are now also in possession of the [USB stick / erasable pens / thermos / picnic mat] in front of you. You can touch and inspect it at any time. However, please do not yet open the packaging and do not use the object yet. The two objects presented to you for part 2 ([USB stick and erasable pens / thermos and picnic mat]) have again been randomly allocated to the cabins in equal quantities.

Please click on OK when you have read these information. If you have questions, please call an experimenter.

[Instructions Stage 2—ONLY BASELINE (p=0.0)]

Please read the following information carefully. The [USB stick / erasable pens / thermos / picnic mat] from part 2 of the experiment now belongs to you and you can keep it for good. If you like, you can exchange your [USB stick / erasable pens / thermos / picnic mat] voluntarily for [USB stick / erasable pens / thermos / picnic mat]. Whichever way you decide, your choice is final and you will take your selected object with you from this

experiment.

Please only confirm below once you have understood everything. If you have questions, please call the experimenter and wait until he comes to your cabin.

[Instructions Stage 2—ONLY FORCED EXCHANGE (p=0.5)]

Please read the following information carefully. You have received a new object in part 2 of the experiment ([USB stick / erasable pens / thermos / picnic mat]). You will soon get the opportunity to exchange your [USB stick / erasable pens / thermos / picnic mat] voluntarily for [USB stick / erasable pens / thermos / picnic mat].

If you decide to exchange, you will receive [USB stick / erasable pens / thermos / picnic mat] as requested for your [USB stick / erasable pens / thermos / picnic mat] and you can then keep your [USB stick / erasable pens / thermos / picnic mat] for good. The experiment is then finished.

If you decide against an exchange, there will be a probability of 50 percent that the exchange will be forced anyways and you have to exchange nevertheless.

Concretely, the following happens in the case that you decide against a voluntary exchange: The experimenter will draw a random number between 1 and 20 using a lotto drum (as in part 1 of the experiment). The drawn number will then be announced loudly. If the drawn number is a number [from 11 to 20 / from 1 to 10], your [USB stick / erasable pens / thermos / picnic mat] will be taken away from you and you instead receive [USB stick / erasable pens / thermos / picnic mat]. If the drawn number is a number [from 1 to 10 / from 11 to 20], you will keep your [USB stick / erasable pens / thermos / picnic mat] and nothing happens. After the number has been drawn and the exchange of objects has taken place (if applicable), nothing else happens in this part of the experiment. You can then keep your object for good.

Please only confirm below once you have understood everything. If you have questions, please call the experimenter and wait until he comes to your cabin.

[Mood elicitation 3]

Before you get the opportunity to exchange your object, please answer the following questions about how you currently feel. Which expressions better apply to you at the moment? "Unhappy, Angry, Unsatisfied, Sad, Desperate"—"Happy, Thrilled, Satisfied, Content, Hopeful"

Do you want to exchange your [USB stick / erasable pens / thermos / picnic mat] for a [USB stick / erasable pens / thermos / picnic mat]?

Yes, I want to exchange.

No, I do not want to exchange.

[ONLY BASELINE (p=0.0)]

You have decided [for / against] a voluntary exchange. Please wait while the experimenter carries out the exchange in all cabins.

[ONLY FORCED EXCHANGE (p=0.5)]

You have decided [for / against] a voluntary exchange. Please wait while the experimenter carries out the exchange in all cabins.

[ONLY NON-TRADERS] After this, it will be determined whether you have to exchange anyways.

[ONLY TRADERS] Please wait until the experiment continues. A random number will now be drawn for those who decided against a voluntary exchange. After that the experiment continues for you.

[ONLY NON-TRADERS] Remember: If the drawn number is a number [from 11 to 20 / from 1 to 10], your [USB stick / erasable pens / thermos / picnic mat] will be taken

away from you and you instead receive [USB stick / erasable pens / thermos / picnic mat]. If the drawn number is a number [from 1 to 10 / from 11 to 20], you will keep your [USB stick / erasable pens / thermos / picnic mat].

[ONLY NON-TRADERS]

The drawn number is [1 / 2 / ... / 20]

This number is a number [from 1 to 10 / from 11 to 20]. Therefore [you can keep you [USB stick / erasable pens / thermos / picnic mat] / your [USB stick / erasable pens / thermos / picnic mat] will be taken away from you and you instead receive [USB stick / erasable pens / thermos / picnic mat]. Please wait while the experimenter carries out the exchange in all cabins.

[Mood elicitation 4]

Please answer the following questions about how you currently feel. Which expressions better apply to you at the moment?

"Unhappy, Angry, Unsatisfied, Sad, Desperate"—"Happy, Thrilled, Satisfied, Content, Hopeful"

The experiment is over!

You can keep both your objects. You will also receive a show-up fee of 4 euros. Please wait shortly in you cabin until the experimenter calls you out. Thank you for your participation!