Reference-Dependent Effort Provision under Heterogeneous Loss Aversion: Pre-Analysis Plan

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1 Introduction

The goal of this experiment is to study Kőszegi and Rabin (2006)'s (KR) expectations-based reference dependence model in the domain of effort provision, paying careful attention to the issue of heterogeneity in gain-loss attitudes. Existing tests of the KR model in this domain typically elicit real effort according to two payment schemes: subjects are either paid a piece-rate wage per task, or earn a fixed fee for all of the tasks they complete (Abeler et al., 2011; Gneezy et al., 2017). Random manipulations of the fixed fee (from low to high) yields the key comparative static prediction these experiments aim to test. Under the assumption of loss aversion – that agents dislike losses more than commensurate gains – the KR model predicts that a larger probability on the high fixed fee should shift the agent's stochastic reference point up, thus inducing more effort. However, the results of the prior studies were inconclusive, with Abeler et al. (2011) finding strong support for KR but Gneezy et al. (2017) finding null effects.

One potential explanation lies in heterogeneity of gain-loss types; recent work by Chapman et al. (2018) suggests that, in a sample representative of the U.S. population, roughly 50% of the population is gain loving – enjoying gains more than commensurate losses. For these types, we show that the KR comparative static prediction reverses in this context so that a larger chance of the higher fixed fee is predicted to lead to lower effort provision. Moreover, new research by Goette et al. (2018) has shown that, due to nonlinearities in the aggregation of predicted treatment effects, aggregate tests of KR treatment effects are severely underpowered. In light of this, we propose a pre-analysis plan for an experiment designed to test the KR model in the real effort domain with an eye towards the issues introduced by heterogeneity.

2 Experiment Design

After subjects enter the lab, consent to be part of the experiment, and read instructions, they will perform a series of sample tasks – transcribing greek letters as shown in Figure 1, borrowed from Augenblick and Rabin (2018) – in order to get a sense of how many they might be willing to do. Our experimental protocol follows the existing literature closely, specifically adopting a version of Gneezy et al., 2017 (described in more detail below). Importantly, because we are interested in the testing the interaction between treatment and gain-loss preferences, our design requires two stages – the first designed to measure gain-loss attitudes and the second to administer the treatment.

Following Goette et al. (2018), we plan to structurally measure gain-loss attitudes in the real effort domain in Stage 1, asking participants how many tasks they are willing to do at various wages. These pre-selected wages are common across all subjects, and come from our fixed set of 30 rates. Similar to Augenblick and Rabin (2018), we select (expected) wages from between \$0.05/task and \$0.3/task (an hourly wage rate between approximately \$4.00 and \$26.00, according to their average time of completion); this range was able to generate sufficient variation in exerted effort to identify a reasonable cost of effort function in their study (see Figure 5). To ensure incentive compatibility, we remind subjects that each choice they make is equally likely to be selected as the *decision-that-counts*. They are explicitly reminded several times throughout the experiment that they may be asked complete the number of tasks they indicate.

The fixed set of 30 wages is made up of two distinct types of rates: deterministic and stochastic. As a simple example, imagine two contracts, one offering 20 cents per task completed (deterministic) and another offering a 50% chance of 30 cents per task and a 50% chance of 10 cents per task (stochastic – a mean-preserving spread of the first wage). We rely on these two types of wages to jointly identify a cost of effort function and gain-loss preferences for each individual. Intuitively, applying the KR model equipped with Choice-Acclimating Personal Equilibrium (CPE), the agent optimizes by choosing the number

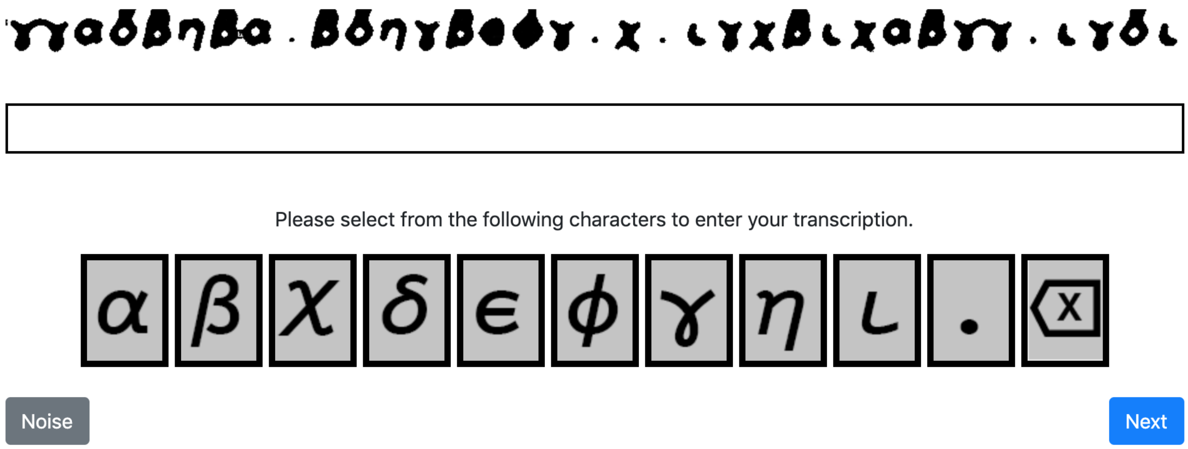


Figure 1: **Greek Letter Transcription Task**

of tasks that equates marginal costs to marginal benefits – which is either deterministic or stochastic depending on the wage. By offering a menu of wages (with stochastic and deterministic rates on separate pages) and comparing the decisions, we can estimate the gain-loss attitude parameters as well as parameters for a cost of effort function. The mathematical details are described in a later section. These decisions made in stage 1 of our study will be used to compute estimates of gain-loss attitudes and cost of effort.

After the subjects make these choices, we offer each subject our two main treatment conditions. Following Gneezy et al. (2017), we ask subjects how many tasks they would like to complete when their payment is a 50% chance they will earn a piece-rate of 20 cents per task, a q% chance they will earn a fixed fee of \$0, and a p% chance of \$20 regardless of the number of tasks they complete. By varying p, q between $(0.45, 0.05)$ and $(0.05, 0.45)$, we create our low and high probability treatment conditions for the high fixed fee. We will refer to $p = 0.45$ as Treatment and $p = 0.05$ as Baseline, so that a Treatment Effect is the difference between these two. Note that subjects will see each of the treatment conditions separately and in a randomized order, so that we are able to perform both between and within subject analysis.

Once these critical choices for our experiment have been made, we present subjects with Multiple Price Lists (MPLs), a commonly used protocol to estimate gain-loss preferences in the monetary risk domain (Sprenger, 2015). More specifically, we implement two Probability Equivalent tasks through MPLs, in which we hold fixed a sure payoff of \$5 [\$0] as Option B and offer the gamble $(p, \$10; 0)$ [or $(p, \$3; -3.5)$] for p ranging from 0% to 100% in increments of 5% as Option A. Assuming subjects have standard preferences over money at both extremes – 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 Option B to Option A informs us about their gain-loss preferences. As is standard when using KR to measure gain-loss attitudes in this context, we must assume that the fixed option (here, Option B) acts as the reference point.[1]

These measurements are intended to shed light on the relationships between gain-loss preferences across different contexts, and will thus be incentivized. Although we are interested in exploring whether these gain-loss measurements are predictive of our heterogenous treatment effects in the effort domain, we recognize that we are potentially underpowered to test this hypothesis depending on the correlation between the measurements in each domain. For this reason, analysis from these measures will be purposefully separated from our main analysis using the stage 1 measurements of gain-loss preferences. Despite coning after the effort elicitation, subjects are made aware of this separate MPL task in the first set of instructions and are informed that each decision across the Stage 1, Treatment, and MPL tasks are equally likely to be the *decision-that-counts.* [2] We opt to implement these MPLs at the end of the effort choices so as to not affect any of the effort responses, which are the core of our experiment.

Finally, we randomly select the *decision-that-counts* for each subject. Once they have learned of the selected decision, regardless of which decision or how many tasks were selected, each subject will complete a mandated 10 transcriptions. If the decision is from one of the MPLs, the computer will generate a random number and determine the outcome of the lottery, and the subject will receive their payment upon completion of the mandatory

[1]We describe how these preferences in a later section, see Sprenger (2015) for additional details.

[2]As described in the following paragraph, all subjects will be asked to complete a mandatory 10 tasks regardless of the nature of the *decision-that-counts.*

tasks. If one of the effort decisions is selected, subjects first complete the mandatory 10 tasks and then the additional number they indicated in that decision; if the relevant rate is stochastic, we do not resolve the uncertainty in wages until after the subjects have completed all of the additional tasks.[3] This does lead to differential levels of uncertainty when completing both the mandatory task and the additional tasks; those with MPL decisions know their payment, those with deterministic wages know their payment, but those with stochastic wages do not. This is intentional, and aimed to mitigate the risk that subjects strategically indicate a large amount of tasks at a highly uncertain wage of $(0.5, \$0.00; 0.5, \$0.60)$ with the intention of leaving if the rate is determined to be \$0.00.[4]

For each task, subjects have 3 chances to enter the correct transcription – if they fail all three attempts, they are simply presented a new set of greek characters and their tally does not increase toward their goal. After all the tasks are completed, participants are presented a series of Raven's matrices (John Raven and Jean Raven, 2003) to measure cognitive ability, followed a demographic survey (gender, major, age, parental income, risk attitudes). Finally, we resolve any remaining wage lotteries, and pay subjects privately.

3 Hypotheses

Our hypothesis of interest is that subjects previously measured to be loss averse will respond to the treatment in the directionally opposite way compared to those measured as gain loving. Specifically, when the probability of receiving the high fee increases (p goes from

[3]They will have been informed of this in the instructions.

[4]When considering the implications of this asymmetric uncertainty, we weighed the tradeoffs between the current approach and alternatives – most obviously resolving all uncertainty prior to the mandatory tasks. The cost of our asymmetric uncertainty approach is that one could argue we misinterpret selections of 0 effort under stochastic wages as loss aversion when in fact it stems from the desire to resolve uncertainty. Because the duration of the experiment is relatively short (30-120 minutes depending on the decision-that-counts), we are not as worried about this potential confound. Moreover, we can compare behavior under these wages (where uncertainty resolution is delayed by a brief amount) to behavior in the MPLs, where we have stochastic earnings but no delay in resolution of uncertainty; although this comparison may be hard to interpret because there is no established correlation across the two measures of gain-loss preferences, the existence of loss averse subjects in the MPL task helps verify that the choices under stochastic wages meaningfully reflect gain-loss attitudes.

0.05 to 0.45), we predict (according to the KR model outline below) that loss averse subjects will increase their effort on average while gain loving subjects will decrease their effort on average. This hypothesis follows directly from the KR model when using the CPE solution concept. Letting w be the piece rate wage, e stand for effort (number of tasks), $L, H > L$ the fixed fees, and fixing $1 - p - q = 0.5$, we can write the CPE utils of an agent expecting payment $(p, H; q, L; 1 - p - q, w)$ as:

$$U((p, H; q, L; 0.5, we)|(p, H; q, L; 0.5, we)) =$$

$$\begin{cases} pH + qL + 0.5we + \eta(1-\lambda)\left[pq(H-L) + 0.5p(H-we) + 0.5q(L-we)\right] - c(e) & we < L < H \\ pH + qL + 0.5we + \eta(1-\lambda)\left[pq(H-L) + 0.5p(H-we) + 0.5q(we-L)\right] - c(e) & L < we < H \\ pH + qL + 0.5we + \eta(1-\lambda)\left[pq(H-L) + 0.5p(we-H) + 0.5q(we-L)\right] - c(e) & L < H < we. \end{cases}$$

Following the math in the appendix of Gneezy et al. (2017), we study the effects of an increase in p by considering each of the three cases and signing the derivative $\frac{\partial e^*}{\partial p}|_{1-p-q=0.5}$.

3.0.1 Case 1: $we < L < H$

Assume first that $we < L < H$, so that the considered level of effort falls below the low fixed fee.The first order condition yielding optimal effort is

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

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

$$e^* = c'^{-1}\left(0.5w\left[1 + (p+q)\eta(\lambda - 1)\right]\right).$$

Turning back to $\frac{\partial e^*}{\partial p}|_{1-p-q=0.5}$, let $p+q=\bar{P}=0.5$ – since changes in p must leave $p+q$ constant, we have that $\frac{\partial e^*}{\partial p}|_{1-p-q=0.5}=0$ in this case.[5]

3.0.2 Case 2: $L < we < H$,

Next, assume that $L < we < H$, so that the considered level of effort falls between the low and high fixed fees. Here, solving for optimal effort results in a first order condition of

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

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

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

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

$$\frac{\partial e^*}{\partial p}|_{1-p-q=0.5}=\frac{\eta(\lambda-1)w}{c''(e^*)}$$

[5]For a more concrete example, consider the cost function used in Augenblick and Rabin (2018): $c_i(e_i)=\frac{1}{\alpha\gamma_i}(e_i+10)^{\gamma_i}$. In this case, we can solve for

$$e^*=\left(\alpha 0.5w\left[1+(p+q)\eta(\lambda-1)\right]\right)^{\frac{1}{\gamma-1}}.$$

The ratio of effort under two different treatment conditions, P' and Q' is then

$$\frac{e_1^*+10}{e_2^*+10}=\frac{(\alpha 0.5w)^{\frac{1}{\gamma-1}}\left(1+(P')\eta(\lambda-1)\right)^{\frac{1}{\gamma-1}}}{(\alpha 0.5w)^{\frac{1}{\gamma-1}}\left(1+(Q')\eta(\lambda-1)\right)^{\frac{1}{\gamma-1}}},$$

so that the α terms disappear.

and by the assumed convexity of $c(\cdot)$, we know $c''(e^*) > 0$ so that – fixing $\eta = 1$ (any positive number would also hold)

$$\lambda > 1 \implies \frac{\partial e^*}{\partial p}|_{1-p-q=0.5} > 0$$
$$\lambda < 1 \implies \frac{\partial e^*}{\partial p}|_{1-p-q=0.5} < 0.$$

That is to say, loss averse agents are predicted to increase their effort whereas gain loving subjects ($\lambda < 1$) should decrease their effort in this case as the probability of the high fee (p) increases.

3.0.3 Case 3: $L < H < we$

Lastly, we can consider the case when $L < H < we$, so that the considered effort is above the high fixed fee. Again, we examine the first order condition given by

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

and

$$e^* = c'^{-1}(0.5w[1 - (p+q)\eta(\lambda - 1)]),$$

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

3.0.4 Combined Predictions

Thus, our predicted treatment effects of increasing the probability of the high fixed fee on effort will go in opposite directions for gain loving and loss averse types when $L < we < H$, and should otherwise be zero. The range in which the treatment bites is informative for our design – by setting $L = 0, H = 20, w = 0.20$ with effort choices $e \in [0, 100]$, we ensure that our two conditions have the potential to generate predicted differences for all considered effort levels. Moreover, the derived sensitivity of treatment effects on λ suggest it is important to properly measure λ using the preliminary wage menus, which we describe next.

4 Structural Estimation

4.1 Stage 1 Data

As previously mentioned, the decisions made in Stage 1 of our experiment will be used to estimate the gain-loss parameters for individual participants; specifically, we build a structural model assuming that agents behave according to KR's CPE concept and estimate the parameters of interest (cost of effort function, gain-loss attitudes) using MLE. Under CPE, the agent facing a deterministic piece-rate maximizes the following utility function:

$$u(we_i|we_i) = we_i - c_i(e_i),$$

so that the optimal effort choice $e_i^*((1,w))$ satisfies the first order condition $w = c_i'(e_i)$. Note that this is the same as a neoclassical agent, and is clearly independent of the gain-loss attitude, λ. As a result, we can trace out the cost of effort function by offering a number of different deterministic wages w_j and eliciting the agent's optimal effort given the wage.

In choosing a functional form, we follow Augenblick and Rabin (2018) and assume that $c_i(e_i) = \frac{1}{\alpha\gamma_i}(e_i + 10)^{\gamma_i}$, where 10 represents the required number of tasks that all subjects must complete in order to receive their completion fee, regardless of how many they choose to work at the various rates (0-100 is the range).[6] Thus, the marginal consideration is

$$\frac{1}{\alpha}(e_i + 10)^{(\gamma_i - 1)} = w.$$

By introducing stochastic piece-rates, we are able to identify the gain-loss parameter λ_i as we vary the wages. To see this, consider the piece-rate $(0.5, w_l; w_h)$, $(w_h > w_l)$, which represents a contract under which the agent exerts 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 utils for such an effort choice, e_i, is then

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

where $c_i(e_i)$ is as described above. The optimal effort choice under this wage structure, e_i^*, must then satisfy the first order condition

$$0.5w_l + 0.5w_h - 0.25\eta(\lambda_i - 1)(w_h - w_l) = \frac{1}{\alpha}(e_i + 10)^{\gamma_i - 1}.$$

Following standard practice when estimating λ in the KR06 model, we fix $\eta = 1$.

Using the variation in both deterministic and stochastic wages, as well as the functional form assumptions, we estimate individual level parameters $(\hat{\alpha}, \hat{\gamma}_i, \hat{\lambda}_i)$ using standard MLE methods. Let e_i^* be the optimal level of effort for an agent facing the wage bundle W, which solves the first order conditions described in the prior sections (depending on whether W is deterministic or stochastic).[7] As in Augenblick and Rabin (2018), assume that the experimentally observed level of effort is distributed around e_i^* with a Normal$(0, \sigma)$ noise

[6]Quoting from Augenblick and Rabin (2018), " 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."

[7]For deterministic wages, $e_i^* = (\alpha w)^{\frac{1}{\gamma_i - 1}} - 10$; for stochastic wages,

$$e_i^* = (\alpha(0.5w_l + 0.5w_h - 0.25\eta(\lambda_i - 1)(w_h - w_l))^{\frac{1}{\gamma_i - 1}} - 10.$$

term, ϵ. Then we have the likelihood of observing effort e_i:

$$L(e_i) = \phi(\frac{e_i^* - e_i}{\sigma}),$$

where ϕ is the pdf of a standard normal random variable.[8]

However, because of the imposed limitations on task choices (that they fall within 0 and 100 tasks), we can adapt the typical normal MLE using a Tobit correction to account for the fact that the choice of a corner solution may not satisfy the standard tangency conditions of the utility maximization problems. The resulting, corrected likelihood of observing e_i is

$$L^{tobit}(e_i) = \mathbf{1}(0 < e_i < 100)\phi(\frac{e_i^* - e_i}{\sigma}) + \mathbf{1}(e_i = 100)\Phi(\frac{e_i^* - 100}{\sigma}) + \mathbf{1}(e_i = 0)(1 - \Phi(\frac{e_i^*}{\sigma})).$$

To compute the estimates, we follow standard protocol by searching for the parameters that optimize the sum over the log-likelihoods. Note that these methods are not guaranteed to converge for every subject, particularly if the subject's choices display no variation across the wages, or appear inconsistent according to our KR specification. As a result, we anticipate needing to drop a small fraction of our population. This is taken into account and further described in our later Power Calculations section.

We also consider other likelihood formulations, eyeing different computational methods to identify the individual parameters. In particular, estimation using Hamiltonian Monte Carlo from *rstan* (Stan Development Team, 2020) would follow much the same procedure but under a Bayesian framework, wherein we specify additional priors on the distributions of our parameters.[9]

[8]Note that there are important interactions between the CPE assumption and the cost of effort assumption. In particular, $\lambda > 3$ is ruled out under CPE since it has unrealistic implications – including violations of First Order Stochastic Dominance (see Masatlioglu and Raymond (2016) for more details). If we did not rule this out, we would have computational issues in our estimation as $\lambda \geq 3$ produces NA values (root of a negative) unless $\gamma = 2$.

[9]Priors would come from work in Goette et al. (2018), under the assumption that λ is LogNormally distributed in the population.

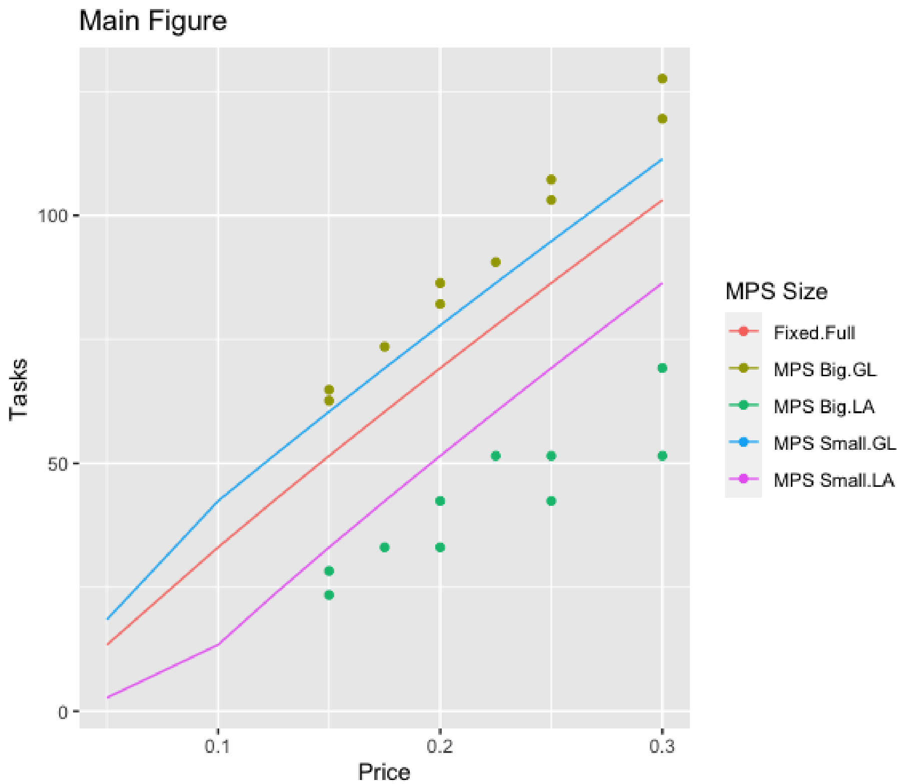


Figure 2: **First Stage Effort by Wage** Price represents the wage: it can either be Fixed (piece rate), MPS Small (a stochastic wage with EV=Price) if the spread is less than \$0.1 around the mean, or MPS BIG if the spread is $\geq$\$0.1. This plot was created with fixed parameter values of $\gamma = 2.138,\ \alpha = 724,\ \lambda = 2$ for loss averse and $\lambda = 0.5$ for gain lovers. In the paper, we will aggregate all those classified as gain loving or loss averse, and take the mean task choice at each expected wage.

These estimates in hand, we can generate something like Figure 2 to depict the differences in first stage behavior between gain-lovers and loss averse individuals. Specifically, the curves plot out the way the gain-loss attitudes interact with wage uncertainty in relation to the number of tasks individuals are willing to complete for a given Expected Wage.

4.2 Structural Estimation: MPLs

Following Sprenger (2015), we briefly outline the process by which we estimate gain-loss preference parameters from choices in the MPLs. Unlike the prior sections in which we discussed choices in the framework of CPE, we require a distinct equilibrium concept known as Personal Equilibrium (PE) to identify λ_i in these tasks.

Let r represent the fixed amount, and $F(p, x_1; x_2)$ represent the p-gamble over $x_1 > x_2$. Because $r > x_2$ is the fixed decision element, we assume that subjects prefer the fixed amount to the 0% gamble; similarly, with $x_1 > r$ we assume that subjects prefer the 100% gamble to r. However, for a specific p, subjects will choose by comparing the utility of the fixed amount, $U(r|r) = r$ and the utility of the p-gamble,

$$U(F|r) = p[x_1 + \eta(x_1 - r)] + (1 - p)[x_2 + \eta\lambda_i(x_2 - r)].$$

Call p_i^* the particular decision at which they switch so that $U(F^*|r) = U(r|r)$. Given the observed p_i^*, we solve

$$\begin{aligned} r &= p_i^*[x_1 + \eta(x_1 - r)] + (1 - p_i^*)[x_2 + \eta\lambda_i(x_w - r)] \\ \hat{\lambda}_i &= \frac{p_i^*(x_1 + \eta(x_1 - r)) + (1 - p_i^*)x_2 - r}{(1 - p_i^*)\eta(r - x_2)}. \end{aligned}$$

Typically, we set $x_2 = 0$ for convenience, which yields

$$\hat{\lambda}_i = \frac{p_i^*(x_1 + \eta(x_1 - r)) - r}{(1 - p_i^*)\eta r}.$$

We may also use the Bayesian approach to model both the population distribution as well as the individual λ_i. In particular, we structure our estimator assuming Logit Choice, where individuals compare the CPE KR utils of options A and B in each row of the MPL, and choose with logit noise. We can then model the decision to choose A as coming from a *Bernoulli*(p), where p is the inverse logit of the difference in KR CPE utils between options A and B – itself a function of the MPL parameters and λ_i.

5 Analysis Plan

In order to test our between-subject hypothesis that loss averse and gain loving agents react differently to our treatment of increasing the fixed payment, we run a standard differences-in-differences design using our estimated value of the gain-loss parameter (λ_i), a treatment indicator for the high probability of fixed payment choice $(0.5, we; 0.45, 20; 0.05, 0)$, as well as an interaction between the treatment indicator and the gain-loss parameter:

$$e_i = \beta_0 + \beta_1 \times \lambda_i + \beta_2 \times Treatment_i + \beta_3(Treatment \times \lambda_i) + \epsilon_i.$$

The differences-in-differences regression allows us to easily retrieve the statistical significance of our coefficient of interest, the interaction of the gain-loss measure and treatment indicator (null hypothesis that $\beta_3 = 0$). We will also run the following regressions to test whether there are treatment effects in the predicted direction within the gain-loss types:

$$e_i = \gamma_0 + \gamma_{1,c_i} \times Treatment_i + \nu_i,$$

for $c_i \in \{LA, LN, GL\}$. The simple t-test on γ_{1,c_i} provides a test of the aforementioned comparative static predictions – which the theory suggests should result in $\hat{\gamma}_{1,LA} > 0, \hat{\gamma}_{1,GL} < 0, \hat{\gamma}_{1,LN} = 0$.

6 Power Calculations

6.1 Approach 1: Perfect Recovery

To get a sense of the number of observations required for adequate power, we simulate treatment effects by bootstrapping $\lambda_i, \alpha, \gamma_i$ values based on existing experimental evidence. Specifically, we draw λ_i from the lognormal distribution estimated from data in Goette et al. (2018) ($\lambda_i \sim lognorm(meanlog = 0.17, sdlog = \sqrt{0.29})$), from which 38%

are categorized as gain loving and 62% as loss averse. For the cost of effort, we use the individual structural estimates from the identical task computed by Augenblick and Rabin (2018) (Table 2) – drawing the requisite number of observations for the cost curvature with $\gamma_i \sim \mathcal{N}(2.138, 0.619^2)$ and α fixed at 724.[10] We draw 10,000 observations using the parameters described above and, for each set, we solve for the optimal Stage 2 effort (restricted between 0-100) by finding the level of effort that maximizes CPE utils given the sample parameters. Then, we run the differences-in-differences specification to get a sense of the magnitude of these theoretical treatment effects – presenting the results in Table 1.

Table 1: **Simulated Differences in Differences Results**

	(AR18) Effort Choice	(Aggregate) Effort Choice
Constant	63.68	46.70
	(1.207)	(0.608)
λ	-12.48	
	(0.770)	
Treatment	-12.42	5.14
	(1.717)	(0.863)
$\lambda \times$ Treatment	12.90	
	(1.102)	
Observations	10000	10000
R^2	0.028	0.00

Notes: Notes: OLS regression with robust standard errors in parentheses. AR18 represents the base simulation results, using Augenblick and Rabin (2018)'s estimated parameters. Aggregate represents the regression of effort on a constant and a treatment indicator (over all gain-loss types). Thus, the constant in column 3 represents the average number of tasks chosen when facing the low condition, and the treatment coefficient represents the aggregate treatment effect – how much the average number of tasks chosen changes when the fixed amount rises.

[10] Augenblick and Rabin (2018) do not estimate individual distributions for this parameter, so we fix it at the mean of the aggregate structural estimate. Moreover, each specification in Table 2 has slightly different estimates, so we use Column 1 for this section.

Next, we generate a minimum detectable effect curve as a function of the bootstrapped sample size to get a sense of what treatment effects we are adequately powered to discern at the 5% level (two-sided) with 80% power. For each simulated sample size, we run 200 regressions (as represented in Table 1), from which we use the mean of the estimated standard error of β_3 to compute the minimum detectable effect, $MDE = (t_{\alpha/2} + t_{1-\kappa})\sigma_{\hat{\beta}}$, under 80% power ($\kappa = 0.8$), and $\alpha = 0.05$. As we vary the size of the bootstrapped sample, the precision of our estimates will change, allowing us to plot a MDE curve as a function of the bootstrapped sample, presented in Figure 3.[11] According to Table 1, the treatment effect of interest is expected to converge to about 12.9, which would require a sample of roughly 600 observations to be adequately powered.

Because the treatment effect can vary a bit with a sample of 600 subjects, we take an additional verification step and bootstrap 10,000 samples of 600 individuals from our simulated data and estimate the interaction effect therein. This yields 10,000 estimates of the treatment effect from our simulated population, from which we extract that the 25^{th} and 75^{th} as roughly 9.4 and 15.1. We could be a bit more conservative and take a sample of closer to 700 subjects given this information.

However, we've obtained this sample estimate by assuming that the λ we measure in our first stage for each individual is identical to the λ that generates the data; when we instead recover the $\hat{\lambda}_{MLE}$ from first stage behavior, there will be some noise in our measurements, which will affect the magnitude of the treatment effect as shown in the next section.

6.2 Approach 2: Noisy Recovery

The above analysis pre-supposes that we are perfectly measuring individual's gain-loss attitudes; by using the true λ to generate the effort predictions as well as classify the

[11] Note that the N presented is the total sample size of the experiment – 50% of which are in the treatment condition, and the distribution of gain-loss attitudes among this sample is drawn as described from that in Goette et al. (2018).

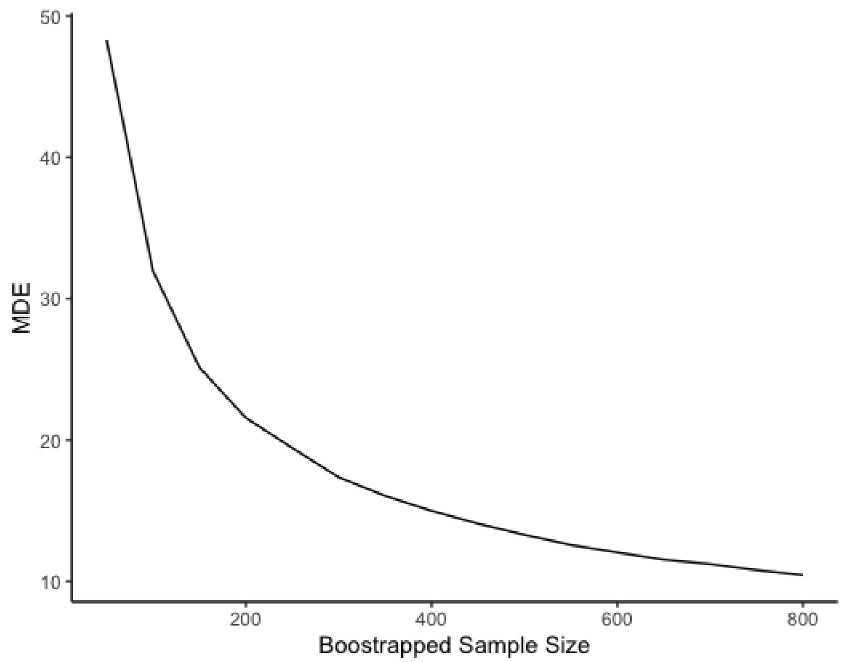


Figure 3: **Bootstrapped MDE by N**. Minimum detectable effect, computed as $MDE = (t_{\alpha/2}+t_{1-\kappa})\sigma_{\hat{\beta}} = 2.8\sigma_{\hat{\beta}}$, is plotted by running the differences-in-differences specification and using the associated standard error of $\hat{\beta}_3$ for various bootstrapped sample sizes, incremented by 20 from 50 to 1000. Here, we use the parameters as given in Augenblick and Rabin (2018)

individual, we ignore the attenuation bias that arises from mismeasured λ.[12] In this section, we study how measurement error affects these simulations with an eye to the number of observations we require after considering this additional noise.

To address this, we continue with our initial approach of drawing bootstrapped samples from prior data, sampling $\gamma_i \sim \mathcal{N}(2.138, 0.692^2)$, $\phi = 724$, as well as $\lambda_i \sim lognorm(meanlog = 0.17, sdlog = \sqrt{0.29})$. With these parameters, we solve for the optimal CPE effort in each of the Stage 1 choices, as well as for the Baseline and Treatment conditions in Stage 2. Crucially, we generate "Observed Effort" by adding normally distributed noise (mean zero, and standard deviation ranging from 0.5 to 12) to the optimal CPE effort, from which we estimate individual Maximum Likelihood Estimates of λ_i using the simulated Stage 1 data.

Next, we compute the treatment effects replacing the true value of the gain-loss parameter in the original differences-in-differences specification with the (MLE) value of λ:

$$e_i = \beta_0 + \beta_1 \times \hat{\lambda}_i + \beta_2 \times Treatment_i + \beta_3(\hat{\lambda}_i \times Treatment_i) + \epsilon_i.$$

To understand how noise interacts with the attenuation of β_3, we iterate over the standard deviation of our normal error (from 0.5 to 12.5) and, for each error value, take the average of $\hat{\beta}_3$ and $se(\hat{\beta}_3)$ over 100 iterations.

Ultimately, this exercise reassures us that we are able to adequately recover values of λ_i yielding regression estimates of our treatment effect in line with the perfect recovery exercise. It also reminds us that there can be substantial heterogeneity on the treatment effects across noise levels, with standard errors on our treatment, echoing the results from drawing repeated samples of 600 observations from our population.

[12] Measurement error in the cost of effort parameters is of less concern to us here, because the treatment effect of interest is a differences-in-differences estimate that crucially relies on gain-loss attitudes as opposed to effort cost.

6.3 Cost of Effort Curvature

There is one particular complication we would like to mention. The wide distribution of $\gamma_i \sim \mathcal{N}(2.138, 0.692^2)$ we adopt in this pre-analysis plan causes some reason for concern both in our MDE simulations and in our recovery of λ_i using the MLE procedure. First, when bootstrapping the MDE, this distribution leads to a staggering number of corner cases in our setting (because of the interaction with λ_i), which affects our power calculations. This can be seen in the histogram below (4), which demonstrates the (constrained) optimal effort choices in our simulated treatment conditions. We therefore conduct our analysis again with a more restricted distribution of $\gamma_i \sim \mathcal{N}(2.138, 0.15^2)$, with Stage 2 choices reflected in the second histogram below. Under this distribution, the bootstrapped heterogeneous treatment effect with 10000 draws from our population is shown in Table 2. MDE analysis suggests that heterogeneous treatments will typically fall between 28.55 and 32.07, which would require much fewer observations for adequate power (closer to 100).

On the MLE front, this wide distribution on γ_i similarly leads to corner choices in the Stage 1 data, which results in identification issues for λ. This is predominantly because some of these simulated individuals are assigned combinations of λ_i and γ_i that yield no variation across the Stage 1 choices (the corners). While we suspect that our subject pool will have some fraction of individuals with similar difficulties, we do not expect it to be of a similar magnitude as under the wide γ_i distribution. There, we recover about 80-95% of the $\hat{\lambda}$ values as non-missing, and 90% of our recovered $\hat{\lambda}$ values represent the same gain-loss type as the true λ.

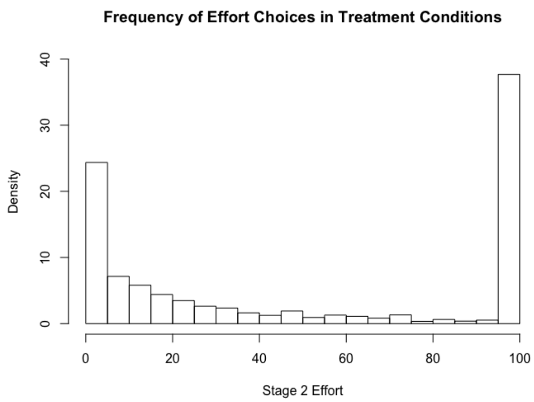
7 Conclusion

This document has outlined our experimental design, tying it closely to theoretical derivations of KR preferences in the real-effort domain. In particular, we have derived heterogeneous treatment effects over gain-loss preferences, and used simulated data to demonstrate

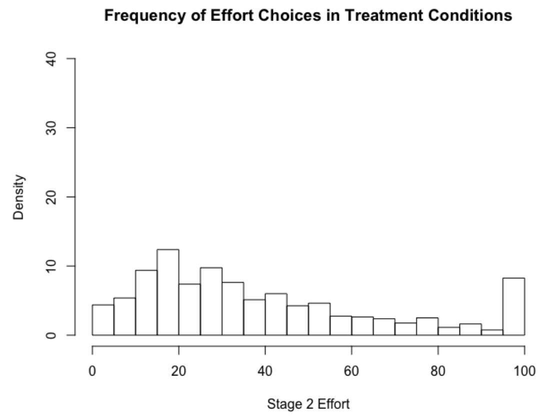
Table 2: **Simulated Differences in Differences Results**

	(New γ_i) Effort Choice	(Aggregate) Effort Choice
Constant	55.62	33.42
	(0.6821)	(0.379)
λ	-16.20	
	(0.430)	
Treatment	-27.88	12.62
	(1.000)	(0.541)
$\lambda\times$ Treatment	29.94	
	(0.647)	
Observations	10000	10000
R^2	0.224	0.052

Notes: Notes: OLS regression with robust standard errors in parentheses. New γ_i represents the base simulation results, using Augenblick and Rabin (2018)'s estimated parameters but reducing the standard deviation on γ_i. Aggregate represents the regression of effort on a constant and a treatment indicator (over all gain-loss types). Thus, the constant in column 3 represents the average number of tasks chosen when facing the low condition, and the treatment coefficient represents the aggregate treatment effect – how much the average number of tasks chosen changes when the fixed amount rises.



(a) $\gamma_i \sim \mathcal{N}(2.138, 0.619^2)$



(b) $\gamma_i \sim \mathcal{N}(2.138, 0.15^2)$

Figure 4: Distributions of Stage 2 Effort under Assumptions on γ_i

the magnitude of these effects under various assumptions. The key assumptions revolve around the distributions of gain-loss preferences and the shape of the cost of effort function; ultimately, while we are confident that $\lambda_i \sim lognorm(meanlog = 0.17, sdlog = \sqrt{0.29})$ represents a reasonable assumption, the results vary quite dramatically based on the cost of effort curvature γ_i. Under one set of very conservative assumptions, we would require roughly 700 observations to power heterogeneous treatment effects on the order of 12 tasks. However, if we assume a tighter distribution ($\gamma_i \sim \mathcal{N}(2.138, 0.15^2)$), around 100 subjects would be required for adequate power on treatment effects of around 30 tasks. Moreover, we are aware that some fraction of subjects (potentially between 5% and 20%) will have to be removed from our sample due to identification issues (if they only ever select a corner).

We therefore opt to recruit around 500-600 subjects to err on the side of caution. Importantly, our first session will allow us to gauge whether our wages generate reasonable variation in effort choices – if in fact the plurality of our subjects choose to complete 100 tasks at all wage offerings, then we can re-assess our assumptions on the cost of effort curvature. More likely, if many subjects consistently opt for 0 tasks, we can raise our wage offerings to induce variation.

8 Blank Tables

Table 3: **Aggregate Parameter Estimates**

	(1)	(2)
	Estimate	(Std. Error)
	$c(e) = \frac{1}{\alpha\gamma}(e+10)^{\gamma}$	
Gain-Loss Parameter:		
$\hat{\lambda}$		()
Cost of Effort:		
$\hat{\alpha}$		()
$\hat{\gamma}$		()

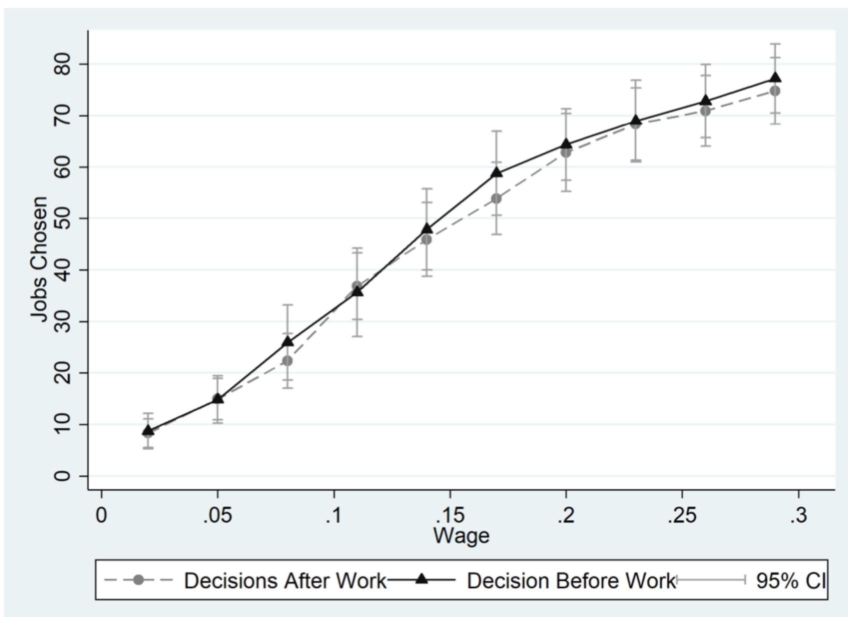
Notes: Maximum likelihood estimates. Robust standard errors in parentheses. $c_i(e)$ refers to the cost of effort assumption made.

Table 4: **Between Subject Comparative Static Test**

	(1)	(2)	(3)	(4)
	Dependent Variable: e			
	Full Sample	Loss Averse	Loss Neutral	Gain Loving
Structural Bounds Taxonomy				
Treatment (= 1 if)				
	()	()	()	()
Baseline (Constant)				
	()	()	()	()
R-Squared				
# Observations				
H_0: No Treatment Effect	F=	F=	F=	F=
	(p =)	(p =)	(p =)	(p =)
H_0: Treatment Effect (col. 2) = Treatment Effect (col. 4)				F =
				(p =)

Notes: Ordinary least square regression. Robust standard errors in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Null hypotheses tested for 1) zero between subject treatment effect, ($\beta_{F=14} = 0$); 2) Identical treatment effects across loss averse and gain loving agents ($\beta_{F=14}$ (col. 2) = $\beta_{F=14}$ (col. 4));. Hypotheses 2 tested using a differences-in-differences specification, $e_i = \beta_0+\beta_1\times\mathbf{1}(LA)+\beta_2\times\mathbf{1}(LN)+\beta_3\times Treatment+\beta_4(Treatment\times\mathbf{1}(LN))+\beta_5(Treatment\times\mathbf{1}(LA))+\epsilon$, and reporting the statistics associated with β_5. Taxonomy of types based on structural bounds. Loss Neutral types are such that the 95% CI on the lambda include 1.

Figure 7: Comparison of decisions made before and after 10 mandatory tasks.

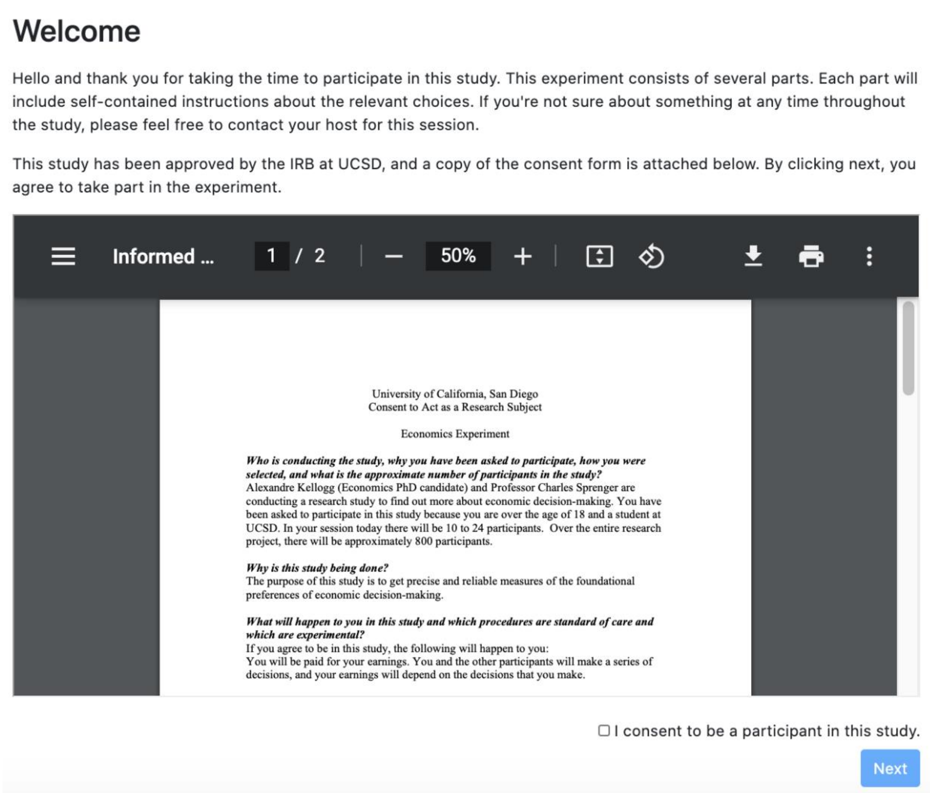


Note: For readability, wages are grouped into 10 bins. Confidence intervals are created using standard errors clustered at the individual level.

Figure 5: **Jobs Chosen by Wage**. Augenblick and Rabin (2018)

9 Instructions and Material Presented to Participants

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.

Informed ... 1 / 2 50%

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

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.

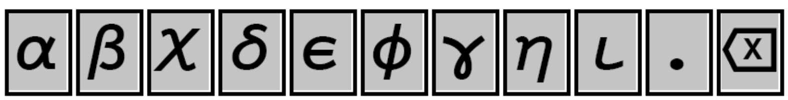
Next

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:

δηιφα.βαιδφι.ηβεχφηφιεδ.γηειφφγφαγ.

Please select from the following characters to enter your transcription.



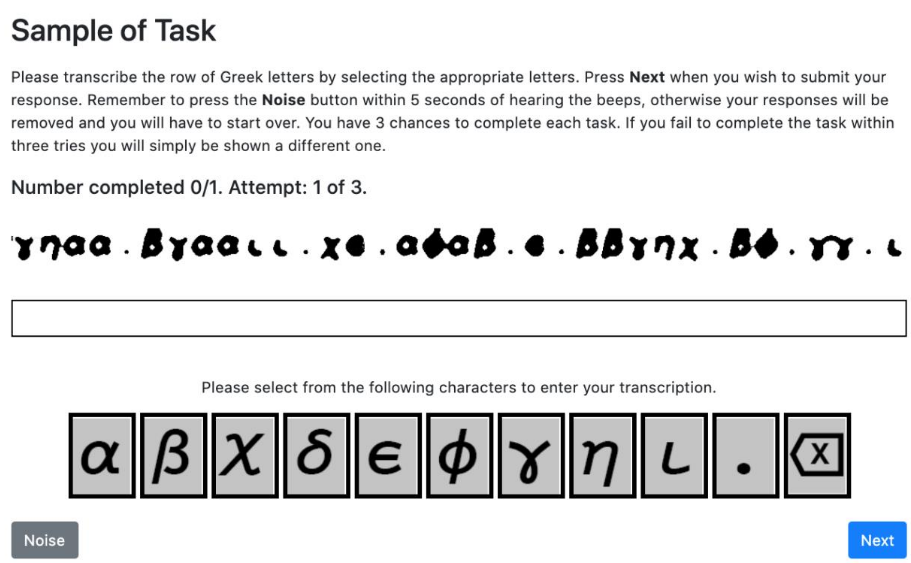
The correct transcription for the example task is provided above; recall, however, that you do not need to be 100% accurate. If you submit a transcription that is 80% accurate or better (defined as requiring 7 or fewer insertions, deletions, or substitutions to achieve the perfect transcription), you 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

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

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

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.

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.

χαφγηβα . χχηδιχδ . εχφηχαδγχι . δηιγφγαγ

Please select from the following characters to enter your transcription.

α	β	χ	δ	ϵ	ϕ	γ	η	ι	.	⌫

Noise

Next

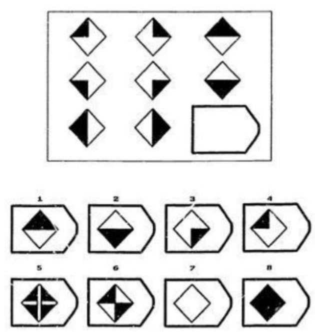
Part III Solving puzzles

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

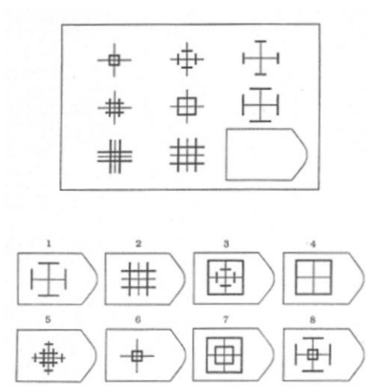
Time left to complete this section: **9:52**

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

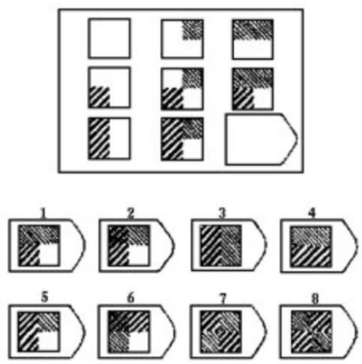
Time left to complete this section: **9:37**

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

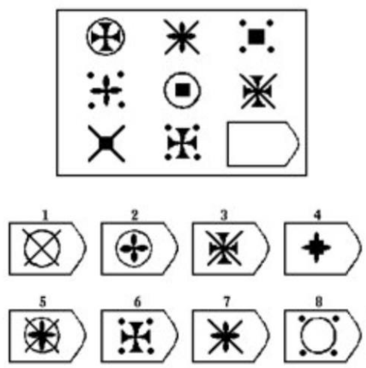
Time left to complete this section: **9:21**

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

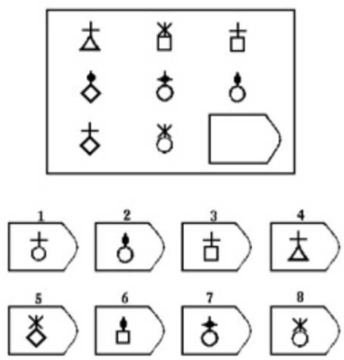
Time left to complete this section: **9:06**

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

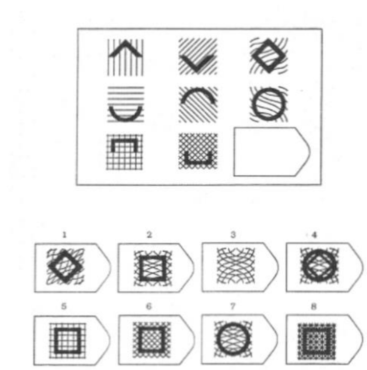
Time left to complete this section: **8:43**

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)

Next

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

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