Online Appendix

Reference Dependence and Attribution Bias: Evidence from Real-Effort Experiments

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B Supplemental Tables and Figures

In this appendix we provide additional empirical results that supplement the main text and provide robustness checks for our primary results.

Figure B1 shows the CDFs of WTW for the *control* and *coin-flip* treatments from Experiment 1, aggregated over all payment levels (and smoothed using the Epanechnikov kernel). As a validation of our basic setup, a Kolmogorov-Smirnov equality-of-distributions test verifies that control participants were more willing to work on the noiseless task than the noisy one ($D = .1225; p < .001$).[1] Speaking to our main hypotheses, the figure highlights that WTW in the *contol + no noise* group was lower than the *coin flip + no noise* group—the latter almost first-order stochastically dominates the former. By contrast, the cumulative distribution of WTW in the *control + noise* group first-order stochastically dominates that of the *coin flip + noise* group.

We next show that dividing the Experiment 1 sample in half according to the total amount of time participants spent on the experiment (from the start of Session 1 to completion) does not have a large effect on our nonparametric results. This is demonstrated in Tables B1 and B2 below. However, these comparisons based on duration are limited due to unequal group sizes. Regression analysis (included in Table 3 in the main text) demonstrates that this effect does not alter the results of our parametric analysis.

We further show that the results of our parametric analysis are robust to changing the Stone-Geary background parameter that appears in the effort-cost function. Although our numerical estimates vary with this parameter, we show in Table B3 that our qualitative results hold for two

[1]While this test fails to account for redundancy in the data stemming from multiple observations from each individual, we calculated a more conservative version of the statistic by running individual K-S tests for each payment level. Three out of five payment levels showed significant differences between the cumulative distributions of WTW for *control + noise* and *control + no-noise*; the five p values were .024, .189, .041, .019, .090.

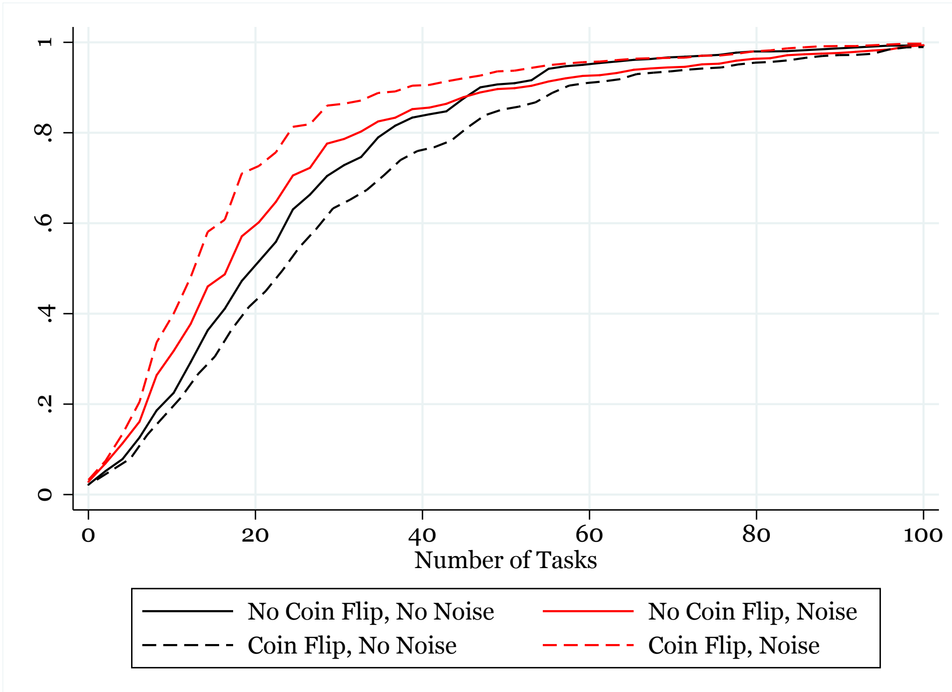

Figure B1: *Cumulative bid distribution by group.* Cumulative distribution curves are over all five payment levels and are smoothed using the Epanechnikov kernel.

alternative specifications of the background parameter which vary by an order of magnitude. (We omit such an analysis for Experiment 2.)

Next, we utilize a logit model to explore whether any observables predict attrition in Experiment 1 (Table B4). Although we have overall lower attrition in the high-probability treatment, we do not find that other factors influenced attrition. This effect is easily seen in Table 1 in the main text. We suspect this is due to the fact that we ran the high-probability session at a slightly different time of day.

We then turn to the Experiment 2. To address potential concerns about differential experience and learning, Table B5 presents non-parametric results for Experiment 2 (analogous to the final two columns of Table 4) in which we drop any participants who completed extra tasks in the first session. This analysis leaves far fewer participants in our sample, but our qualitative results hold. We then utilize the random numbers from the BDM in our experiment to instrument for whether a person completed extra tasks. This analysis verifies that, while doing extra tasks may have changed WTW in Session 2, our primary conclusions remain for those who did not complete extra tasks.

Finally, following the robustness exercise in Experiment 1 concerning attrition, we estimate a similar logit model for Experiment 2 (Table B6). We did not collect demographic information from participants in Experiment 2, and thus we have fewer potential explanatory variables. That said, we find no convincing link between observables and attrition.

Table B1:
EXPERIMENT 1. BASELINE RESULTS (LESS THAN MEDIAN TOTAL DURATION)

	Control		Coin Flip		High Prob.	
Variable	noise=0	noise=1	noise=0	noise=1	noise=0	noise=1
Willingness to Work (WTW)	22.43	20.91	28.19	16.88	23.66	21.79
	(1.480)	(1.952)	(2.081)	(1.675)	(2.211)	(2.771)
Observations	425	370	370	390	250	200

Notes: Willingness to work is averaged over five payment levels. Standard errors (in parentheses) are clustered at the individual level.

Table B2:
EXPERIMENT 1. BASELINE RESULTS (GREATER THAN MEDIAN TOTAL DURATION)

	Control		Coin Flip		High Prob.	
Variable	noise=0	noise=1	noise=0	noise=1	noise=0	noise=1
Willingness to Work (WTW)	28.26	24.03	29.15	18.73	24.51	21.28
	(2.814)	(2.569)	(2.598)	(2.292)	(1.605)	(1.423)
Observations	190	295	275	275	440	535

Notes: Willingness to work is averaged over five payment levels. Standard errors (in parentheses) are clustered at the individual level.

Table B3:
EXPERIMENT 1. ROBUSTNESS OF PARAMETRIC ANALYSIS

	Estimated via Tobit Regression	
	($\omega = 1$)	($\omega = 10$)
Cost curvature parameter, γ	1.335 (0.0180)	1.417 (0.0194)
$\hat{\theta}_1(\text{noise} \mid p = 0.5)$	0.0413 (0.00392)	0.0321 (0.00323)
$\hat{\theta}_1(\text{noise} \mid p = 0.99)$	0.0321 (0.00310)	0.0236 (0.00225)
$\hat{\theta}_1(\text{noise} \mid p = 1)$	0.0318 (0.00314)	0.0234 (0.00234)
$\hat{\theta}_1(\text{no noise} \mid p = 0)$	0.0250 (0.00230)	0.0190 (0.00180)
$\hat{\theta}_1(\text{no noise} \mid p = 0.01)$	0.0261 (0.00233)	0.0195 (0.00181)
$\hat{\theta}_1(\text{no noise} \mid p = 0.5)$	0.0209 (0.00209)	0.0155 (0.00158)
$H_0 : \hat{\theta}_1(\text{noise} \mid p = 0.5) = \hat{\theta}_1(\text{noise} \mid p = 0.99)$	$\chi^2(1) = 4.76$ $p = .029$	$\chi^2(1) = 6.56$ $p = .010$
$H_0 : \hat{\theta}_1(\text{no noise} \mid p = 0.5) = \hat{\theta}_1(\text{no noise} \mid p = 0.01)$	$\chi^2(1) = 4.08$ $p = .043$	$\chi^2(1) = 4.65$ $p = .031$
Observations	4015	4015
Clusters	803	803

Notes: Standard errors (in parentheses) are clustered at the individual level and recovered via delta method. 18 observations are left-censored and 43 are right-censored.

Table B4:

EXPERIMENT 1. DETERMINANTS OF RETURNING FOR SECOND SESSION

	Logit. Dependent variable: $\mathbb{1}$(return)					
	Raw	AMEs	Raw	AMEs	Raw	AMEs
$\mathbb{1}$(Noise)	-0.099	-0.007	-0.123	-0.009	-0.132	-0.009
	(0.251)	(0.018)	(0.253)	(0.018)	(0.255)	(0.018)
$\mathbb{1}$(Coin Flip)			0.003	0.000	0.031	0.002
			(0.277)	(0.020)	(0.279)	(0.020)
$\mathbb{1}$(High Probability)			1.065**	0.076**	1.101**	0.078**
			(0.364)	(0.027)	(0.371)	(0.027)
Constant	2.523***		2.271***		2.096***	
	(0.184)		(0.240)		(0.586)	
Demographics					X	X
Observations	886	886	886	886	886	886

Notes: Standard errors in parentheses. The control treatment forms the baseline comparison group; demographics includes dummies for income of respondent and gender, and age; none are significant.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B5:
EXPERIMENT 2. THE EFFECT OF EXTRA TASKS IN SESSION 1

	Dependent variable: $(e_{i,1} - e_{i,2})$		
	Drop Participants	*OLS*	*IV Using BDM*
$\mathbb{1}$(No Noise)	4.896	4.896	11.181*
	(2.685)	(2.681)	(4.428)
$\mathbb{1}$(Noise)	-5.443**	-5.443**	-8.010
	(1.885)	(1.883)	(4.629)
$\mathbb{1}$(Extra Tasks)*$\mathbb{1}$(Noise)		3.351	10.459
		(3.730)	(11.765)
$\mathbb{1}$(Extra Tasks)*$\mathbb{1}$(No Noise)		8.431	-12.137
		(5.164)	(14.176)
Observations	240	360	360

Notes: Standard errors (in parentheses) clustered at individual level. Instruments are random number from BDM and dummies for the randomly selected question (five such variables). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B6:
EXPERIMENT 2. DETERMINANTS OF RETURNING FOR SECOND SESSION

	Logit. Dependent variable: $\mathbb{1}$(return)			
	Raw	AMEs	Raw	AMEs
$\mathbb{1}$(Noise)	-0.134	-0.019	-0.129	-0.015
	(0.568)	(0.080)	(0.659)	(0.080)
Avg WTW, Session 1			-0.006	-0.001
			(0.014)	(0.003)
$\mathbb{1}$(Russian, Session 1)			0.436	0.052
			(0.674)	(0.092)
Constant	1.638***		0.803	
	(0.413)		(1.134)	
Session Dummies			X	X
Observations	87	87	87	87

Notes: Standard error in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

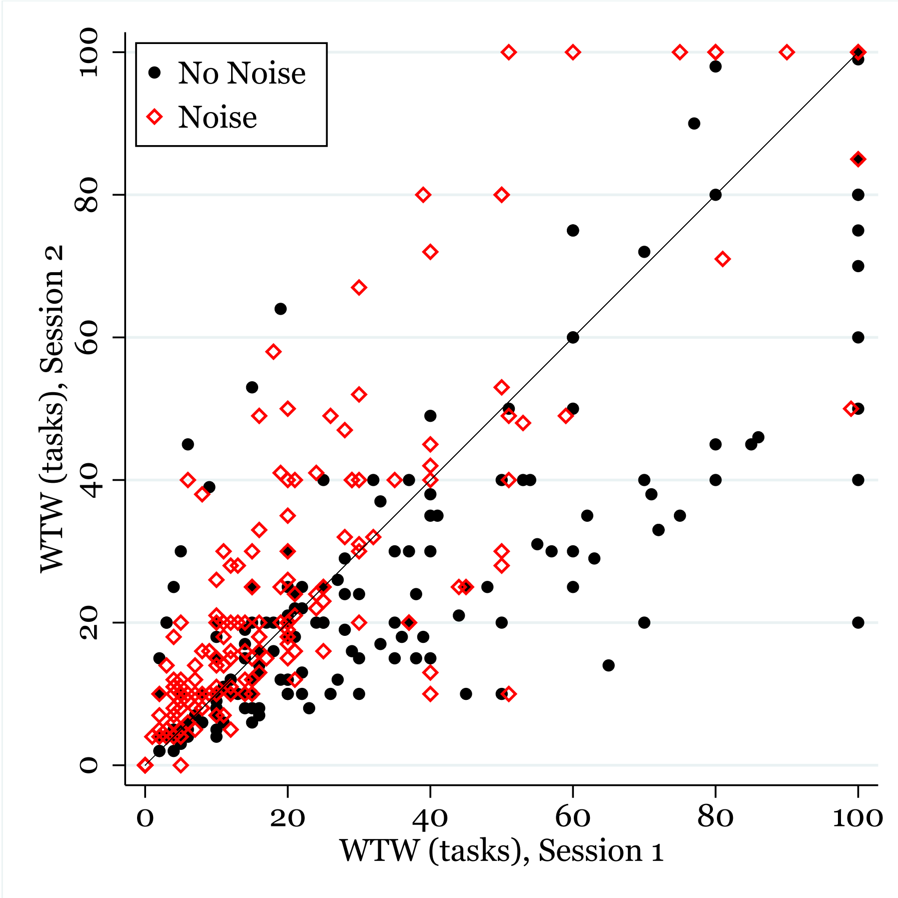

Figure B2: *Raw willingness to work (WTW) data from Experiment 2.* Each observation in this figure represents a participant's WTW for a fixed payment in sessions one and two of the experiment. Black dots represent participants who faced the no-noise task; red diamonds represent participants who faced the noisy task.

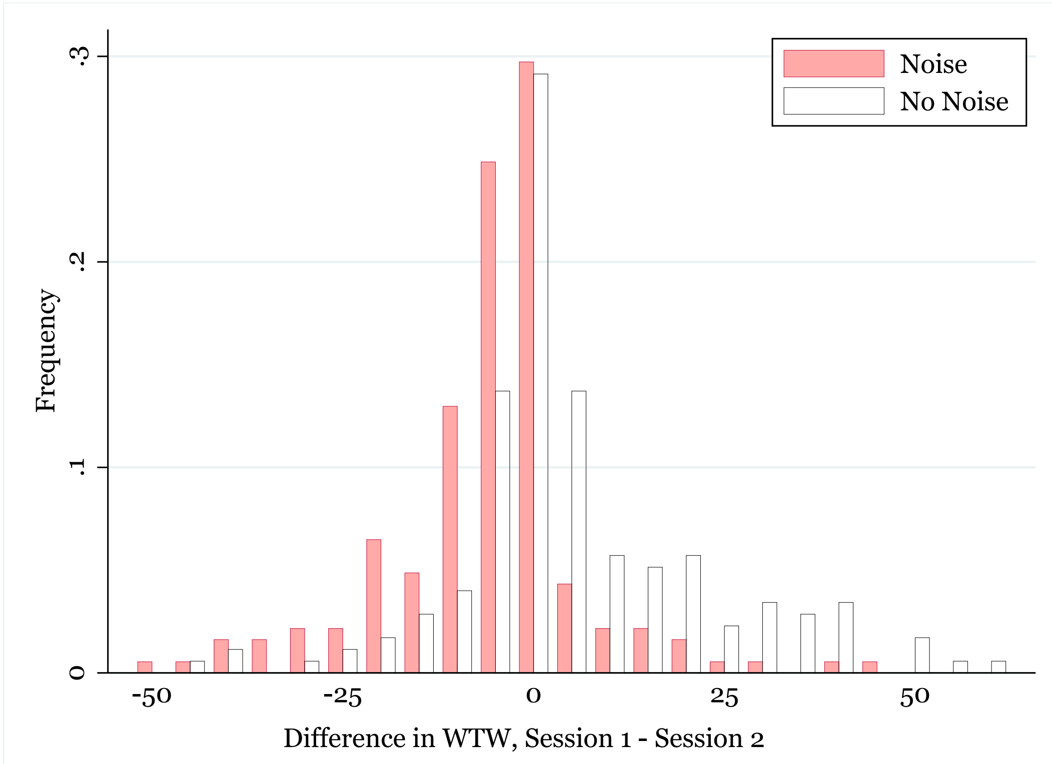

Figure B3: *Histogram of the difference in willingness to work (WTW) between the first and second sessions in Experiment 2.* Each observation in this figure represents the change in a participant's WTW for a fixed payment between sessions one and two of the experiment. Clear bars represent participants who faced the no-noise task; solid red bars represent participants who faced the noisy task.

C Experiment 1: Derivation of Optimal Effort

In this appendix we show that, under reasonable assumptions, a rational participant with reference-dependent utility will choose an effort level in Experiment 1 that is decreasing in her expected value of her cost parameter, $\theta_i(a)$. This analysis formalizes the predictions regarding effort stated in Observations 1 and 2.

Recall that the predicted effort of a participant with reference-dependent utility assigned to task a solves Equation 7 in the main text: indifference between completing $e_i^*(a|p_i)$ tasks for m dollars and not working at all implies that $e_i^*(a|p_i)$ is the value of $e_{i,2}$ that solves

$$\widehat{\mathbb{E}}_{i,1}\left[u_{i,2}|e_{i,2}\right] = m + \widehat{\mathbb{E}}_{i,1}\left[V_{i,2}^e\right] + \eta\widehat{\mathbb{E}}_{i,1}\left[n\left(V_{i,2}^e \mid \widehat{\mathbb{E}}_{i,1}\left[V_{i,2}^e\right]\right)\right] = 0$$

$$\Rightarrow \quad \widehat{\mathbb{E}}_{i,1}\left[u_{i,2}|e_{i,2}\right] = m - \hat{\theta}_{i,1}(a)c(e_{i,2}) + \eta\widehat{\mathbb{E}}_{i,1}\left[n\left(V_{i,2}^e \mid \hat{\theta}_{i,1}(a)c(e_{i,2})\right)\right] = 0. \tag{C.1}$$

Recall that, conditional on $e_{i,2}$, the participant's effort cost in period 2 is a random variable $V_{i,2}^e = -[\theta_i(a) + \epsilon_{i,2}]c(e_{i,2})$. Define the random variable $X_{i,2}(a) = \theta_i(a) + \epsilon_{i,2}$ and let $\widehat{F}_{i,1}$ denote the participant's subjective CDF over $X_{i,2}$ conditional on any information obtained in period 1. Let $x_{i,2}$ denote the realization of $X_{i,2}$. Furthermore, note that $n\left(V_{i,2}^e \mid \hat{\theta}_{i,1}(a)c(e_{i,2})\right) = -[x_{i,2}(a) - \hat{\theta}_{i,1}(a)]c(e_{i,2})$ if $x_{i,2}(a) \leq \hat{\theta}_{i,1}(a)$, and otherwise $n\left(V_{i,2}^e \mid \hat{\theta}_{i,1}(a)c(e_{i,2})\right) = -\lambda[x_{i,2}(a) - \hat{\theta}_{i,1}(a)]c(e_{i,2})$. Thus,

$$\begin{aligned}\widehat{\mathbb{E}}_{i,1}\left[n\left(V_{i,2}^e \mid \hat{\theta}_{i,1}(a)c(e_{i,2})\right)\right] = -c(e_{i,2})\Big(&\widehat{F}_{i,1}\big(\hat{\theta}_{i,1}(a)\big)\widehat{\mathbb{E}}_{i,1}\big[X_{i,2}(a) - \hat{\theta}_{i,1}(a) \mid X_{i,2}(a) \leq \hat{\theta}_{i,1}(a)\big] \\ &+ \lambda\big[1 - \widehat{F}_{i,1}\big(\hat{\theta}_{i,1}(a)\big)\big]\widehat{\mathbb{E}}_{i,1}\big[X_{i,2}(a) - \hat{\theta}_{i,1}(a) \mid X_{i,2}(a) > \hat{\theta}_{i,1}(a)\big]\Big),\end{aligned} \tag{C.2}$$

and thus

$$\begin{aligned}&\widehat{\mathbb{E}}_{i,1}\left[n\left(V_{i,2}^e \mid \hat{\theta}_{i,1}(a)c(e_{i,2})\right)\right] = \\ &\qquad - c(e_{i,2})(\lambda - 1)\big[1 - \widehat{F}_{i,1}\big(\hat{\theta}_{i,1}(a)\big)\big]\widehat{\mathbb{E}}_{i,1}\big[X_{i,2}(a) - \hat{\theta}_{i,1}(a) \mid X_{i,2}(a) > \hat{\theta}_{i,1}(a)\big].\end{aligned} \tag{C.3}$$

Substituting Equation C.3 back into Equation C.1 yields:

$$\begin{aligned}\widehat{\mathbb{E}}_{i,1}\left[u_{i,2}|e_{i,2}\right] &= m - \hat{\theta}_{i,1}(a)c(e_{i,2}) \\ &\quad -\eta(\lambda - 1)\big[1 - \widehat{F}\big(\hat{\theta}_{i,1}(a)\big)\big]\widehat{\mathbb{E}}_{i,1}\big[X_{i,2}(a) - \hat{\theta}_{i,1}(a) \mid X_{i,2}(a) > \hat{\theta}_{i,1}(a)\big]c(e_{i,2}) \\ &= m - h\big(\hat{\theta}_{i,1}(a)\big)c(e_{i,2}),\end{aligned} \tag{C.4}$$

where

$$h\big(\hat{\theta}_{i,1}(a)\big) \equiv \hat{\theta}_{i,1}(a) + \eta(\lambda - 1)\big[1 - \widehat{F}_{i,1}\big(\hat{\theta}_{i,1}(a)\big)\big]\widehat{\mathbb{E}}_{i,1}\big[X_{i,2}(a) - \hat{\theta}_{i,1}(a) \mid X_{i,2}(a) > \hat{\theta}_{i,1}(a)\big]. \tag{C.5}$$

As noted in the main text, we assume the participant's prior over $\theta_i(a)$ and the distribution over $\epsilon_{i,2}$ are both normal. Thus, according to the participant, $X_{i,2}$ is normally distributed with mean $\hat{\theta}_{i,1}(a)$; let ξ^2 denote the variance of $X_{i,2}$. We can then write $X_{i,2} = \hat{\theta}_{i,1}(a) + \delta$ where $\delta \sim N(0, \xi^2)$.

Substituting this into Equation C.5 yields

$$h\big(\hat{\theta}_{i,1}(a)\big) = \hat{\theta}_{i,1}(a) + \eta(\lambda - 1)\frac{1}{2}\mathbb{E}[\delta\big|\delta > 0], \tag{C.6}$$

where we have additionally used the fact that $\widehat{F}_{i,1}(\hat{\theta}_{i,1}(a)) = \frac{1}{2}$ given that $X_{i,2}$ is symmetric about $\hat{\theta}_{i,1}(a)$. It is well known that $\mathbb{E}[\delta|\delta > 0] = 2\xi\phi(0) = 2\xi/\sqrt{2\pi}$, where ϕ is the standard normal PDF (see, e.g., Greene 2003). Hence,

$$h\big(\hat{\theta}_{i,1}(a)\big) = \hat{\theta}_{i,1}(a) + \eta(\lambda - 1)\frac{\xi}{\sqrt{2\pi}}. \tag{C.7}$$

From Equation C.7, it is immediate that h is increasing in $\hat{\theta}_{i,1}(a)$. Given that e_i^* is chosen such that $\widehat{\mathbb{E}}_{i,1}[u_{i,2}|e_i^*] = 0$, Equation C.4 implies that the participant will select e_i^* such that $h(\hat{\theta}_{i,1}(a))c(e_i^*) = m$. Therefore, e_i^* is decreasing in $\hat{\theta}_{i,1}(a)$. It then follows that if $\hat{\theta}_{i,1}(h)$ tends to be higher than $\hat{\theta}_{i,1}(l)$, then participants assigned the noisy task will exhibit lower effort levels than those assigned the noiseless task (i.e., fixing p, $e^*(h|p) < e^*(l|p)$ on average).

D Reference Points that Incorporate the BDM Mechanism

In this appendix we consider how our theoretical predictions of Experiment 1 extend when a participant's reference point incorporates the uncertainty introduced by the BDM mechanism. In particular, we show that the the optimal effort of a participant with reference-dependent utility is still decreasing in her estimate of the effort-cost parameter, $\hat{\theta}_{i,1}(a)$. Consider participant i who has been assigned to task a. Her willingness to work (WTW) on additional trials is elicited via a BDM mechanism: the participant announces $e_i \in [0, 100]$ and then a number e is uniformly drawn from $[0, 100]$ at random. If $e < e_i$, the participant completes e tasks in exchange for a bonus of m dollars. Otherwise, she does no additional work and does not earn a bonus. Thus, conditional on submitting e_i to the mechanism, the participant will do additional work with probability $G(e_i)$, where G denotes the CDF of a uniform random variable on $[0, 100]$ (and g denotes the associated PDF). Furthermore, upon submitting e_i, the participant's expected consumption utilities on the money and effort dimensions are, respectively, $r^m(e_i) \equiv G(e_i)m$ and $r^e(e_i; \hat{\theta}_{i,1}(a)) \equiv G(e_i)\widehat{\mathbb{E}}_{i,1}[V_{i,2}^e|e < e_i]$ where $\widehat{\mathbb{E}}_{i,1}[V_{i,2}^e|e < e_i] = \hat{\theta}_{i,1}(a) \cdot \int_0^{e_i} c(e)\frac{g(e)}{G(e_i)}de$. Thus, the values $r_i^m(e_i)$ and $r_i^e(e_i; \hat{\theta}_{i,1}(a))$ serve as the participant's reference points along each dimension in period 2. As such, she chooses e_i^* to maximize

$$\widehat{\mathbb{E}}_{i,1}[u_{i,2}|e_i] = G(e_i)\Big\{\widehat{\mathbb{E}}_{i,1}\big[V^e_{i,2} + \eta n\left(V^e_{i,2}\,\middle|\, r^e(e_i;\hat{\theta}_{i,1}(a))\right)\big|e<e_i\big] + m + \eta\left(m - r^m(e_i)\right)\Big\}$$
$$+ [1-G(e_i)]\Big\{\eta\left(0 - r^e(e_i;\hat{\theta}_{i,1}(a))\right) + \eta\lambda\left(0 - r^m(e_i)\right)\Big\}, \quad \text{(D.1)}$$

where the expectation $\widehat{\mathbb{E}}_{i,1}$ is with respect to the random number e drawn by the mechanism, $\epsilon_{i,2}(a)$, and the participant's updated beliefs over $\theta_i(a)$. The first term in braces in Equation D.1 is the participant's expected utility conditional on the BDM assigning additional work. In this contingency, her disutility of effort will (on average) come as a loss relative to her expected value on this dimension, $r^e(e_i;\hat{\theta}_{i,1}(a))$, since this expectation incorporates a chance of no extra work and hence zero effort. Similarly, the monetary bonus comes as a gain relative to her expected monetary gain, $r^m(e_i)$, which incorporates a chance of no extra work and hence no bonus. The second term in braces is the participant's expected gain-loss utility conditional on the BDM assigning no additional work. In this contingency, she experiences a gain on the effort dimension but a loss on the monetary dimension.

Similar to the analysis in the main text, the treatment probability p may influence e_i is through its affect on the participant's perception of $\theta_i(a)$ (i.e., via misattribution). Thus, we will examine how the optimal effort choice, e^*_i, depends on this perception, $\hat{\theta}_{i,1}(a)$. To simplify the analysis below, we assume the participant forms certain beliefs about $\theta_i(a)$ following period 1, and thus the contingency in which she is assigned additional work necessarily comes as a loss on the effort dimension.

First consider the case without reference dependence (i.e., $\eta = 0$). The objective function in Equation D.1 reduces to

$$\widehat{\mathbb{E}}_{i,1}[u_{i,2}|e_i] = G(e_i)\left(\widehat{\mathbb{E}}_{i,1}\big[V^e_{i,2}\big|e<e_i\big] + m\right) = \hat{\theta}_{i,1}(a)\cdot\int_0^{e_i} c(e)g(e)de + G(e_i)m, \quad \text{(D.2)}$$

and the first-order condition implies an optimal choice of $e^*_i = c^{-1}\big(m/\hat{\theta}_{i,1}(a)\big)$. Clearly e^*_i is decreasing in $\hat{\theta}_{i,1}(a)$.

We now consider the case with reference dependence (i.e., $\eta > 0$). It is helpful to rewrite the objective function in Equation D.1 as the sum of two components: the expected monetary benefit from statement e_i, which we denote by

$$B(e_i) \equiv G(e_i)\Big\{m + \eta\left(m - r^m(e_i)\right)\Big\} - \eta\lambda[1-G(e_i)]r^m(e_i), \quad \text{(D.3)}$$

and the expected effort cost from e_i, which we denote by

$$K(e_i;\hat{\theta}_{i,1}(a)) \equiv -G(e_i)\widehat{\mathbb{E}}_{i,1}\left[V^e_{i,2} + \eta n\left(V^e_{i,2}\,\middle|\, r^e(e_i;\hat{\theta}_{i,1}(a))\right)\middle| e < e_i\right] + \eta[1-G(e_i)]r^e(e_i;\hat{\theta}_{i,1}(a)). \tag{D.4}$$

Thus, the objective in Equation D.1 reduces so that the person chooses e_i to maximize

$$\widehat{\mathbb{E}}_{i,1}[u_{i,2}|e_i] = B(e_i) - K(e_i;\hat{\theta}_{i,1}(a)). \tag{D.5}$$

Given the objective above, we now analyze when the optimal effort choice, e_i^*, is a decreasing function of $\hat{\theta}_{i,1}(a)$. Let $L(e_i;\hat{\theta}_{i,1}(a))$ denote the first derivative of the objective function with respect to e_i:

$$L(e_i;\hat{\theta}_{i,1}(a)) \equiv \frac{\partial B(e_i)}{\partial e_i} - \frac{\partial K(e_i;\hat{\theta}_{i,1}(a))}{\partial e_i}, \tag{D.6}$$

so the first-order condition (FOC) requires $L(e_i^*,\hat{\theta}_{i,1}(a)) = 0$. Using the Implicit Function Theorem,

$$\frac{\partial e_i^*}{\partial \hat{\theta}_{i,1}(a)} = -\left(\frac{\partial L(e_i^*;\hat{\theta}_{i,1}(a))}{\partial e_i^*}\right)^{-1}\frac{\partial L(e_i^*;\hat{\theta}_{i,1}(a))}{\partial \hat{\theta}_{i,1}(a)}. \tag{D.7}$$

Thus, so long as the second-order condition (SOC) holds and the FOC thus describes the optimum, then $\frac{\partial L(e_i^*;\hat{\theta}_{i,1}(a))}{\partial e_i^*} < 0$ and

$$\operatorname{sgn}\left(\frac{\partial e_i^*}{\partial \hat{\theta}_{i,1}(a)}\right) = \operatorname{sgn}\left(\frac{\partial L(e_i^*;\hat{\theta}_{i,1}(a))}{\partial \hat{\theta}_{i,1}(a)}\right). \tag{D.8}$$

Furthermore, since only the cost component of the objective depends on $\hat{\theta}_{i,1}(a)$, we have

$$\frac{\partial L(e_i^*;\hat{\theta}_{i,1}(a))}{\partial \hat{\theta}_{i,1}(a)} = -\frac{\partial^2 K(e_i^*;\hat{\theta}_{i,1}(a))}{\partial \hat{\theta}_{i,1}(a)\partial e_i^*}. \tag{D.9}$$

From Equation D.4 and the definition of $r^e(e_i;\hat{\theta}_{i,1}(a))$ (along with our assumption that the participant has resolved uncertainty over $\theta_i(a)$), we have

$$\begin{aligned} K(e_i;\hat{\theta}_{i,1}(a)) =& -G(e_i)\left\{\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e<e_i] + \eta\lambda\left(\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e<e_i] - G(e_i)\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e<e_i]\right)\right\} \\ & - \eta[1-G(e_i)]G(e_i)\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e<e_i]. \\ =& -\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e<e_i]G(e_i)\left\{1+\eta(\lambda-1)[1-G(e_i)]\right\}. \end{aligned} \tag{D.10}$$

Note that $\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e<e_i] = -\hat{\theta}_{i,1}(a)\frac{1}{G(e_i)}\int_0^{e_i} c(e)g(e)de$. Since g is a uniform PDF, it is constant. We denote this constant by $\bar{g}$, and thus $G(e) = \bar{g}e$. (Given that our experiment uses

$e \sim$ Uniform$[0, 100]$, $\bar{g}$ in this case is $\frac{1}{100}$.) Furthermore, let $\bar{c}(e_i) \equiv \int_0^{e_i} c(e)de$, so $\widehat{\mathbb{E}}_{i,1}[V^e_{i,2}|e < e_i] = -\hat{\theta}_{i,1}(a)\frac{\bar{g}}{G(e_i)}\bar{c}(e_i)$. From D.10, we thus have

$$K(e_i; \hat{\theta}_{i,1}(a)) = \hat{\theta}_{i,1}(a)\bar{g}\bar{c}(e_i)\left\{1 + \Lambda[1 - G(e_i)]\right\}, \tag{D.11}$$

where $\Lambda \equiv \eta(\lambda - 1)$. Similar simplification of $B(e_i)$ in Equation D.3 yields

$$B(e_i) = mG(e_i)\left\{1 - \Lambda[1 - G(e_i)]\right\}. \tag{D.12}$$

From Equations D.11 and $D.12$, it is immediate that the solution depends on the reference-dependence parameters only through the "composite" parameter $\Lambda = \eta(\lambda - 1)$. Furthermore, for any η, $\lambda = 1$ implies $\Lambda = 0$ and K and B reduce to the standard cost and benefit functions absent reference dependence, and hence the objective function reduces to the one in Equation D.2. Thus, without loss aversion, the optimal choice e_i^* is same regardless of whether the participant has reference-dependent utility or not; therefore, e_i^* is clearly decreasing in $\hat{\theta}_{i,1}(a)$.

We now consider the case with loss aversion, so $\Lambda > 0$. Together, Equations D.8 and D.9 imply that e_i^* is decreasing in $\hat{\theta}_{i,1}(a)$ if $\frac{\partial^2 K(e_i^*;\hat{\theta}_{i,1}(a))}{\partial\hat{\theta}_{i,1}(a)\partial e_i^*} > 0$. From D.11, $\frac{\partial^2 K(e_i^*;\hat{\theta}_{i,1}(a))}{\partial\hat{\theta}_{i,1}(a)\partial e_i^*} > 0$ iff

$$\begin{aligned} c(e_i^*)\left\{1 + \Lambda[1 - G(e_i^*)]\right\} - \bar{g}\Lambda\bar{c}(e_i^*) > 0& \\ \Leftrightarrow \left\{1 + \Lambda[1 - G(e_i^*)]\right\} > \bar{g}\Lambda\frac{\bar{c}(e_i^*)}{c(e_i^*)}&. \end{aligned} \tag{D.13}$$

Furthermore, using Equations D.12 and D.11, the SOC implies that

$$\begin{aligned} \left.\frac{\partial^2 B(e_i)}{\partial e_i^2}\right|_{e_i=e_i^*} - \left.\frac{\partial^2 K(e_i;\hat{\theta}_{i,1}(a))}{\partial e_i^2}\right|_{e_i=e_i^*} < 0& \\ \Leftrightarrow 2m\bar{g}\Lambda < \hat{\theta}_{i,1}(a)\left[c'(e_i^*)\left\{1 + \Lambda[1 - G(e_i^*)\right\} - 2\bar{g}\Lambda c(e_i^*)\right]&. \end{aligned} \tag{D.14}$$

Maintaining our implicit assumption that $\hat{\theta}_{i,1}(a) > 0$, Condition D.14 then holds only if

$$0 < c'(e_i^*)\left\{1 + \Lambda[1 - G(e_i^*)]\right\} - 2\bar{g}\Lambda c(e_i^*) \Leftrightarrow \left\{1 + \Lambda[1 - G(e_i^*)]\right\} > 2\bar{g}\Lambda\frac{c(e_i^*)}{c'(e_i^*)}. \tag{D.15}$$

Substituting inequality D.15 into D.13 establishes that $\frac{\partial^2 K(e_i^*;\hat{\theta}_{i,1}(a))}{\partial\hat{\theta}_{i,1}(a)\partial e_i^*} > 0$ if

$$2\frac{c(e_i^*)}{c'(e_i^*)} > \frac{\bar{c}(e_i^*)}{c(e_i^*)} \quad \Leftrightarrow \quad 2c(e_i^*)^2 > c'(e_i^*)\bar{c}(e_i^*). \tag{D.16}$$

Condition D.16 holds, for instance, for any $c(\cdot)$ that is a power function, as we assume in our parametric estimation. Under our specification of $c(e) = e^{\gamma}$ for $\gamma > 1$ (see Section II.C), Condition D.16 is equivalent to

$$2e^{2\gamma} > \frac{\gamma}{\gamma+1}e^{2\gamma}. \tag{D.17}$$

We have therefore shown that, with a power-function cost specification (or any other specification that meets Condition D.16), the optimal action e_i^* is a decreasing function of $\hat{\theta}_{i,1}(a)$ when the participant's reference point is the expected value of the lottery induced by the BDM mechanism. Given that e_i^* is a decreasing function of $\hat{\theta}_{i,1}(a)$, the predictions of Observations 1 and 2 carry over to this setting. Namely: p does not directly influence a participant's objective function, but, under misattribution, $e_i^*(a|p)$ is an increasing function of p because $\hat{\theta}_{i,1}(a)$ is a decreasing function of p.

E Experiment 2: Predictions of Reference Dependence

In this appendix we consider the predictions of the reference-dependent model absent misattribution in Experiment 2. In particular, we show that expectations-based reference dependence with a "forward looking" reference point (a la Kőszegi and Rabin) generates an effect that pushes effort in our experiment in the opposite direction as misattribution. Namely, reference-dependence causes participants assigned the noiseless task to (on average) increase effort across periods, and those assigned the noisy task to (on average) decrease effort across periods. In Section III.B we discussed how sufficiently strong misattribution generates the opposite pattern: participants assigned the noiseless task tend to *decrease* effort across periods, while those assigned the noisy task tend to increase it.

The analysis in this section builds on Appendix D, where we described how a participant with reference-dependent utility optimally chooses effort when her reference point incorporates the uncertainty introduced by the BDM mechanism. We now extend that analysis to the two-period setting of Experiment 2.

The key differentiating feature of Experiment 2 is that the participant's reference point when making her first effort decision might still reflect the lottery induced by the coin flip. That is because a participant's decision about effort comes roughly 10 minutes after the resolution of the coin flip, and this may be too little time for the participant's reference point to fully adapt to her assigned task. If her reference point does not adapt, then her expected utility on each dimension *prior* to the coin flip determines her reference point on that dimension. Thus, her reference point—and hence her behavior—depends on the utility she expects from *each* of the tasks, not just the one she is ultimately assigned. This contrasts with Experiment 1: in that design, a participant chooses effort only once, and that choice happens well after she learned her task assignment. This allows ample time for her reference point to adapt to her assigned task. Thus, in Experiment 1, a person's reference point at the time of choice depends solely on her realized task assignment and not on what "could have been" if the coin landed differently.

Before analyzing the case where the participant's reference point does not adapt to the assigned task by the time of her first effort decision, it is worth noting predictions for the case where it *does* adapt before the first decision. With a quickly adapting reference point, effort in each period is described by the single-decision solution derived in Appendix D. Thus, if we assume that, on average, participants have unbiased priors about $\theta(a)$—implying that the average of participants' expectations over $\theta(a)$ does not move in a systematic direction over time—then the average effort of those facing a given task is constant across periods. Fixing participants average beliefs over $\theta(a)$, this effort level is given by the value $e^*(a)$ that maximizes Objective D.5 in Appendix D. As we showed there, $e^*(l) > e^*(h)$—effort by those assigned the noiseless task is predicted to be greater than those assigned the noisy task.

In contrast, even with unbiased priors (on average), reference dependence absent misattribution can generate systematic aggregate changes in effort across periods when participants' reference points do not adapt prior to the first decision. The basic intuition is as follows. Let $e_t^*(a)$ denote the optimal effort level a participant reports to the BDM mechanism in period t when assigned to task a.[2] In period 2—when the participant's task is fully anticipated—her optimal effort choice $e_2^*(a)$ will follow the derivation in Appendix D: she exhibits a high WTW if assigned the noiseless task, and a low WTW if assigned the noisy task. In period 1, however, her optimal strategy involves less effort on the noiseless task relative to period 2 (i.e, $e_1^*(l) < e_2^*(l)$), and *more* effort on the noisy task relative to period 2 (i.e,. $e_1^*(h) > e_2^*(h)$). In other words, the difference in effort across tasks is more compressed in period 1 than it is in period 2 (i.e., $e_1^*(l) - e_1^*(h) < e_2^*(l) - e_2^*(h)$).

The strategy described above is optimal because it mitigate losses. In particular, the participant chooses to work less on the noiseless task in period 1 (relative to what she would do in period 2) so that her expected payment and effort cost from the noiseless task in period 1 are more similar to what she expects to earn from the noisy task. By equalizing expected payments and effort costs across the tasks, neither assignment will generate large sensations of loss. For example, if the participant instead planned to work as much on the noiseless task in the first period as she would in the second period, then being assigned to the noisy task would come with a substantial loss on the money dimension: she would have earned more if she were assigned the noiseless task because she planned to work a substantial amount on that task. By planning to initially work less on the noiseless task (and more on the noisy task) relative to period 2, she can reduce such sensations of disappointment stemming from her assignment. Notice that this loss-mitigation strategy is only relevant when the participant compares her realized outcome to the expected outcomes from

[2]The remainder of the analysis focuses on a single participant, and we will therefore drop subscripts denoting the participant's label (e.g., i) in order to reduce notational clutter.

each possible task assignment—that is, when the participant's reference point has not adjusted to her assigned task. This is why such a strategy is irrelevant for our analysis of effort choices in Experiment 1 and in period 2 of Experiment 2.

We now formalize the intuition described above. As in Appendix D, we simplify the analysis by assuming the participant forms degenerate beliefs about $\theta(h)$ and $\theta(l)$ following the initial learning session; we denote these beliefs by $\hat{\theta}(h)$ and $\hat{\theta}(l)$, respectively.[3] Our approach follows the "person equilibrium" concept introduced by Kőszegi and Rabin (2006): prior to her task assignment, the participant forms effort plans for each possible assignment outcome and period, denoted by $e_t(a)$, and these plans determine her expectations in each period. A personal equilibrium requires that these plans are *consistent*: given the reference points induced by her plans, it is optimal for the participant to follow through with these plans. Furthermore, we will focus on the participant's *preferred* personal equilibrium, which is the consistent plan that provides the highest expected utility out of all consistent plans.

Reference Points. Let r_t^m and r_t^e denote the participant's reference point in period t over money and effort, respectively. We assume that these reference values are equal to the participant's expected monetary payment and effort cost in each round. In a personal equilibrium, these values are therefore endogenously determined by the participant's effort plans. To clarify, recall from our analysis of Experiment 1 (Appendix D) that the chance of working in period t conditional on announcing $e_t(a)$ to the BDM mechanism is $G(e_t(a)) = \bar{g}e_t(a)$ (where $\bar{g} = \frac{1}{100}$ since our experiment uses $e \sim \text{Uniform}[0, 100]$). Furthermore, the expected disutility of effort from task a conditional on announcing $e_t(a)$ is $G(e_t(a))\widehat{\mathbb{E}}_t[V_t^e | e < e_t(a)] = -\bar{g}\hat{\theta}(a)\bar{c}(e_t(a))$, where $\bar{c}(e) = \int_0^e c(x)dx$. These formulae allow us to write r_t^m and r_t^e in terms of the participant's effort plans:

- In period 1, we assume the participant's reference point along each dimensions matches the expectations she forms *prior* to the coin flip. Thus, her expected disutility of effort is the average disutility she expects to face from the noiseless and noisy task, and her expected payment is the average earnings she expects from each task. These ex-ante expectations depend on the participant's effort plan contingent on each outcome of the coin-flip. Thus, if she plans to report $e_1(a)$ to the mechanism conditional on being assigned to task a, then her reference points are given by:

$$r_1^m = \frac{\bar{g}}{2}[e_1(h) + e_1(l)]m \quad \text{and} \quad r_1^e = -\frac{\bar{g}}{2}[\hat{\theta}(h)\bar{c}(e_1(h)) + \hat{\theta}(l)\bar{c}(e_1(l))]. \tag{E.1}$$

- In period 2, we assume the participant's reference point along each dimension has adapted

[3] This allows us to derive predictions by focusing on a single participant. We could instead allow for uncertainty over $\theta_i(a)$ and derive aggregate predictions. Given our previous assumption that an individual's priors are unbiased on average (i.e., $\mathbb{E}[\hat{\theta}_{i,0}(a)|\theta_i(a)] = \theta_i(a)$), the average population beliefs should remain constant over time under rational updating.

to her task: she expects to work on task a, and therefore she forms her expectations over her disutility of effort and payment conditional on working on task a. This matches our assumption for the reference point in the single-period analysis of Experiment 1. Thus, conditional on being assigned to task a, her reference points are given by:

$$r_2^m(a) = m\bar{g}e_2(a) \;\text{ and }\; r_2^e(a) = -\hat{\theta}(a)\bar{g}\bar{c}(e_2(a)), \tag{E.2}$$

We next analyze the optimal effort plans given these reference points they induce.

Objective Function. As in our analysis of Experiment 1, we can break down the objective function in each period into the expected monetary benefit and expected effort cost. Following Equation D.3 from Appendix D, the expected monetary benefit from task a in period t is

$$\begin{aligned} B_t^a(e_t(a)|r_t^m) &\equiv G(e_t(a))\Big\{m + \eta\,(m - r_t^m)\Big\} - \eta\lambda[1 - G(e_t(a))]r_t^m \\ &= (1+\eta)\bar{g}e_t(a)m - \eta\bar{g}e_t(a)r_t^m - \eta\lambda[1 - \bar{g}e_t(a)]r_t^m \\ &= (1+\eta)\bar{g}e_t(a)m - \eta r_t^m - \Lambda[1 - \bar{g}e_t(a)]r_t^m, \end{aligned} \tag{E.3}$$

where $\Lambda \equiv \eta(\lambda - 1)$. Following Equation D.4 from Appendix D, the expected effort cost from task a in period t is

$$\begin{aligned} K_t^a(e_t(a)|r_t^e) &\equiv -G(e_t(a))\Big\{\widehat{\mathbb{E}}_t\big[V_t^e|e < e_t(a)\big] + \eta\lambda\left(\widehat{\mathbb{E}}_t\big[V_t^e|e < e_t(a)\big] - r_t^e\right)\Big\} \\ &\qquad\qquad\qquad\qquad + \eta[1 - G(e_t(a))]r_t^e \\ &= (1+\eta\lambda)\hat{\theta}(a)\bar{g}\bar{c}(e_t(a)) + \eta\lambda\bar{g}e_t(a)r_t^e + \eta[1 - \bar{g}e_t(a)]r_t^e \\ &= (1+\eta\lambda)\hat{\theta}(a)\bar{g}\bar{c}(e_t(a)) + \eta r_t^e + \Lambda\bar{g}e_t(a)r_t^e. \end{aligned} \tag{E.4}$$

Optimal Effort in $t = 1$. In period $t = 1$, the optimal effort choices, $e_1^*(h)$ and $e_1^*(l)$, jointly maximize $\frac{1}{2}[B_1^h(e_1(h)|r_1^m) - K_1^h(e_1(h)|r_2^e)] + \frac{1}{2}[B_1^l(e_1(l)|r_1^m) - K_1^l(e_1(l)|r_2^e)]$. The FOC with respect to $e_1(h)$ is thus

$$\begin{aligned} &(1+\eta)\bar{g}m - \{2\eta + \Lambda[2 - \bar{g}(e_1(h) + e_1(l))]\}\frac{\partial r_1^m}{\partial e_1(h)} + \Lambda\bar{g}r_1^m \\ &\qquad - (1+\eta\lambda)\hat{\theta}(h)\bar{g}c(e_1(h)) - \{2\eta + \Lambda\bar{g}(e_1(h) + e_1(l))\}\frac{\partial r_1^e}{\partial e_1(h)} - \Lambda\bar{g}r_1^e = 0, \end{aligned} \tag{E.5}$$

and the FOC with respect to $e_1(l)$ is

$$(1+\eta)\bar{g}m - \{2\eta + \Lambda[2-\bar{g}(e_1(h)+e_1(l))]\}\frac{\partial r_1^m}{\partial e_1(l)} + \Lambda\bar{g}r_1^m \\ -(1+\eta\lambda)\hat{\theta}(h)\bar{g}c(e_1(l)) - \{2\eta + \Lambda\bar{g}(e_1(h)+e_1(l))\}\frac{\partial r_1^e}{\partial e_1(l)} - \Lambda\bar{g}r_1^e = 0. \quad \text{(E.6)}$$

From the definitions of r_1^m and r_1^e in Equation E.1, we have

$$\frac{\partial r_1^m}{\partial e_1(a)} = \frac{m\bar{g}}{2} \quad \text{and} \quad \frac{\partial r_1^e}{\partial e_1(a)} = -\frac{\bar{g}}{2}\hat{\theta}(a)c(e_1(a)). \quad \text{(E.7)}$$

Hence, two FOCs above can be written, respectively, as

$$m\{1-\Lambda+\Lambda\bar{g}[e_1(h)+e_1(l)]\} - \hat{\theta}(h)\{1+\Lambda-\Lambda\frac{\bar{g}}{2}[e_1(h)+e_1(l)]\}c(e_1(h)) \\ + \Lambda\frac{\bar{g}}{2}[\hat{\theta}(h)\bar{c}(e_1(h)) + \hat{\theta}(l)\bar{c}(e_1(l))] = 0, \quad \text{(E.8)}$$

and

$$m\{1-\Lambda+\Lambda\bar{g}[e_1(h)+e_1(l)]\} - \hat{\theta}(l)\{1+\Lambda-\Lambda\frac{\bar{g}}{2}[e_1(h)+e_1(l)]\}c(e_1(l)) \\ + \Lambda\frac{\bar{g}}{2}[\hat{\theta}(h)\bar{c}(e_1(h)) + \hat{\theta}(l)\bar{c}(e_1(l))] = 0. \quad \text{(E.9)}$$

Let $L_1^h(e_1(h), e_1(l))$ and $L_1^l(e_1(h), e_1(l))$ denote the functions defined by the left-hand side of Equations E.8 and E.9, respectively. Restricting attention to interior solutions, the optimal effort plans in period 1, $e_1^*(h)$ and $e_1^*(l)$, must solve the system of equations given by $L_1^h(e_1^*(h), e_1^*(l)) = 0$ and $L_1^l(e_1^*(h), e_1^*(l)) = 0$. Notice, however, that if $L_1^h(e_1^*(h), e_1^*(l)) = L_1^l(e_1^*(h), e_1^*(l)) = 0$, then it is immediate from Equations E.8 and E.9 that $\hat{\theta}(h)c(e_1^*(h)) = \hat{\theta}(l)c(e_1^*(l))$; that is, the optimal effort levels are chosen to equalize the "consumption utility" of effort across the two tasks. To summarize:

Lemma E.1. *Given the setup formalized above, the optimal effort choices in period 1, $e_1^*(h)$ and $e_1^*(l)$, are such that the participant's effort cost is the same regardless of her task assignment; that is, $\hat{\theta}(h)c(e_1^*(h)) = \hat{\theta}(l)c(e_1^*(l))$. Furthermore, given that $\hat{\theta}(h) > \hat{\theta}(l)$, the participant's initial effort on the noiseless task exceeds her initial effort on the noisy task; that is, $e_1^*(l) > e_1^*(h)$.*

Optimal Effort in $t=2$. In period $t=2$, the optimal effort choice conditional on being assigned to task a, $e_2^*(a)$, maximizes $B_2^a(e_2(a)|r_2^m(a)) - K_2^a(e_2(a)|r_2^e(a))$, and thus solves the following

FOC:

$$(1+\eta)\bar{g}m - \{\eta + \Lambda[1-\bar{g}e_2(a)]\}\frac{\partial r_2^m(a)}{\partial e_2(a)} + \Lambda\bar{g}r_2^m(a)$$
$$- (1+\eta\lambda)\hat{\theta}(a)\bar{g}c(e_2(a)) - \{\eta + \Lambda\bar{g}e_2(a)\}\frac{\partial r_2^e(a)}{\partial e_2(a)} - \Lambda\bar{g}r_2^e(a) = 0. \quad \text{(E.10)}$$

From the definition of $r_2^m(a)$ and $r_2^e(a)$ in Equation E.2, we have

$$\frac{\partial r_2^m(a)}{\partial e_2(a)} = m\bar{g} \text{ and } \frac{\partial r_2^e(a)}{\partial e_2(a)} = -\hat{\theta}(a)\bar{g}c(e_2(a)), \quad \text{(E.11)}$$

and thus the FOC in Equation E.10 can be written as

$$m\{1 - \Lambda + 2\Lambda\bar{g}e_2(a)\} - \hat{\theta}(a)\{1 + \Lambda - \Lambda\bar{g}e_2(a)\}c(e_2(a)) + \hat{\theta}(a)\Lambda\bar{g}\bar{c}(e_2(a)) = 0. \quad \text{(E.12)}$$

Let $L_2^a(e)$ denote the function on the left-hand-side of the FOC above. Thus, $e_2^*(a)$ is such that $L_2^a(e_2^*(a)) = 0$.

Given that this FOC takes the same form as the one in Appendix D, the analysis from Appendix D implies that $e_2^*(a)$ is decreasing in $\hat{\theta}(a)$. Thus, given that $\hat{\theta}(h) > \hat{\theta}(l)$, we have that $e_2^*(l) > e_2^*(h)$: similar to period 1, the optimal plan in period 2 calls for greater effort when facing the noiseless task than the noisy one.

Changes in Optimal Effort Across Periods. We have so far shown that a participant who believes $\hat{\theta}(h) > \hat{\theta}(l)$ will, within each period, exert more effort if she's assigned the noiseless task rather than the noisy one. But, fixing the task she ultimately faces, how will her effort change *across* periods? The final step of our analysis compares $e_1^*(a)$ with $e_2^*(a)$ for each $a \in \{h, l\}$. For this step, we will simplify matters by assuming—as in previous sections—that effort costs follow a power function; that is, $c(e) = e^\gamma$ for some $\gamma > 1$. We will first consider changes in effort for the noiseless task ($a = l$) and then consider the noisy task ($a = h$).

1. *Willingness to Work on the Noiseless Task Increases Across Periods.* We now show that $e_1^*(l) < e_2^*(l)$. From Lemma E.1, we have $\hat{\theta}(l)c(e_1^*(l)) = \hat{\theta}(h)c(e_1^*(h))$ and thus

$$e_1^*(h) = c^{-1}\left(\frac{\hat{\theta}(l)}{\hat{\theta}(h)}c(e_1^*(l))\right) = \left(\frac{\hat{\theta}(l)}{\hat{\theta}(h)}\right)^{\frac{1}{\gamma}} e_1^*(l) = \psi_L e_1^*(l), \quad \text{(E.13)}$$

where $\psi_L \equiv \left(\frac{\hat{\theta}(l)}{\hat{\theta}(h)}\right)^{\frac{1}{\gamma}} < 1$. In light of Equation E.13, we can write the FOC $L_1^l(e_1^*(h), e_1^*(l))$ characterizing effort in period 1 entirely in terms of $e_1^*(l)$ by substituting the expression for

$e_1^*(h)$ from Equation E.13 into Equation E.9, which yields[4]

$$m\{1-\Lambda+\Lambda\bar{g}[1+\psi_L]e_1^*(l)\} - \hat{\theta}(l)\{1+\Lambda-\Lambda\frac{\bar{g}}{2}[1+\psi_L]e_1^*(l)\}c(e_1^*(l)) \\ + \Lambda\frac{\bar{g}}{2}[1+\psi_L]\hat{\theta}(l)\bar{c}(e_1^*(l)) = 0. \quad \text{(E.14)}$$

Letting $\widetilde{L}^l(e_1(l);\psi)$ denote the left-hand side of the equation above as a function of $e_1(l)$ and the parameter ψ, we have that $e_1^*(l)$ must satisfy $\widetilde{L}^1(e_1^*(l);\psi_L) = 0$. Notice, however, that the FOC characterizing $e_2^*(l)$ (Equation E.12) is identical to the FOC above except the parameter ψ takes value 1 instead of $\psi_L < 1$; that is, $e_2^*(l)$ solves $\widetilde{L}^l(e_2^*(l);1) = 0$. Thus, to show that $e_1^*(l) < e_2^*(l)$, it suffices to show that the solution to $\widetilde{L}^l(e^*;\psi) = 0$ is increasing in ψ. Using the implicit function theorem,

$$\frac{\partial e^*}{\partial \psi} = -\left(\frac{\partial \widetilde{L}^l(e^*;\psi)}{\partial e^*}\right)^{-1} \frac{\widetilde{L}^l(e^*;\psi)}{\partial \psi}. \quad \text{(E.15)}$$

Focusing on interior solutions, the second-order condition implies that $\frac{\partial \widetilde{L}^l(e^*;\psi)}{\partial e^*} < 0$, and hence $\frac{\partial e^*}{\partial \psi} > 0 \Leftrightarrow \frac{\widetilde{L}^l(e^*;\psi)}{\partial \psi} > 0$. From Equation E.14, we have

$$\frac{\widetilde{L}^l(e^*;\psi)}{\partial \psi} = m\Lambda\bar{g}e^* + \Lambda\frac{\bar{g}}{2}\hat{\theta}(l)[e^*c(e^*)+\bar{c}(e^*)] > 0, \quad \text{(E.16)}$$

which therefore establishes that $e_2^*(l) > e_1^*(l)$.

2. *Willingness to Work on the Noisy Task Decreases Across Periods*. We now show that $e_1^*(h) > e_2^*(h)$. The argument is symmetric to the one above. Namely, from Lemma E.1, the optimal effort in period 1 must satisfy $e_l^*(l) = \psi_H e_1^*(h)$, where $\psi_H = 1/\psi_L > 1$. Substituting this expression for $e_l^*(l)$ into the FOC in Equation E.8 implies that $e_1^*(h)$ must solve

$$m\{1-\Lambda+\Lambda\bar{g}[1+\psi_H]e_1^*(h)\} - \hat{\theta}(h)\{1+\Lambda-\Lambda\frac{\bar{g}}{2}[1+\psi_H]e_1^*(h)\}c(e_1^*(h)) \\ + \Lambda\frac{\bar{g}}{2}[1+\psi_H]\hat{\theta}(h)\bar{c}(e_1^*(h)) = 0. \quad \text{(E.17)}$$

Again letting $\widetilde{L}^h(e_1(h);\psi)$ denote the left-hand side of the equation above as a function of $e_1(h)$ and the parameter ψ, we have that $e_1^*(h)$ must satisfy $\widetilde{L}^h(e_1^*(h);\psi_H) = 0$. Equation E.12 reveals, however, that $e_2^*(h)$ must solve $\widetilde{L}^h(e_1^*(h);1) = 0$. The implicit-function-

[4] Recall that $\bar{c}(e) = \frac{e^{\gamma+1}}{\gamma+1}$. Hence, $e_1(h) = \psi_L e_1(l)$ implies that $\hat{\theta}(h)\bar{c}(e_1(h)) = \hat{\theta}(h)\left(\frac{\hat{\theta}(l)}{\hat{\theta}(h)}\right)^{1+1/\gamma} e_1(l)^{\gamma+1}/(\gamma+1) = \hat{\theta}(h)\frac{\hat{\theta}(l)^{1/\gamma}}{\hat{\theta}(h)^{1+1/\gamma}}\bar{c}(e_1(l)) = \psi_L\bar{c}(e_1(l))$.

theorem argument from the previous part implies that the solution to $\widetilde{L}^h(e^*;\psi) = 0$ is also increasing in ψ. Thus, since $\psi_H > 1$, we have that $e_2^*(h) < e_1^*(h)$.

F Additional Theoretical Details

In this appendix we provide details on how misattribution interferes with belief updating when a participant misencodes signals but otherwise follows Bayes' Rule. These details provide a more formal derivation of the predictions generated by misattribution described in Sections II.B and III.B. We consider two rounds of learning; that is, the participant receives two signals in sequence. We examine beliefs and behavior after the first round to address predictions for Experiment 1, and then consider both the first and second round to address predictions for Experiment 2. Regarding Experiment 1, we demonstrate that a misattributing participant i will form a systematically distorted estimate of her underlying effort-cost parameter, $\theta_i(a)$. This estimate undershoots the true value when she is assigned the noiseless task and overshoots it when she is assigned the noisy one. We then demonstrate that the second signal is likely to move the participant's estimate in the *opposite* direction of her initial error: her estimated cost of the noiseless task following the second round tends to increase while that of the noisy task tends to decrease.

As in previous sections, we assume that each participant i has prior beliefs over $\theta_i(a)$ that follow a normal distribution: $\theta_i(a) \sim N\left(\hat{\theta}_{i,0}(a), \rho^2\right)$, where $\hat{\theta}_{i,0}(h) > \hat{\theta}_{i,0}(l)$. We also assume that participants' initial estimates of $\theta_i(a)$ are unbiased in the population so that for all i and a, $\mathbb{E}[\hat{\theta}_{i,0}(a)|\theta_i(a)] = \theta_i(a)$; hence, the initial estimates of $\theta_i(a)$ averaged across individuals is equal to the true value. A participant's signals about $\theta_i(a)$ stem from either the single initial learning session in Experiment 1, or from both learning sessions in Experiment 2.[5] Assuming the participant is assigned task a, each learning session $t \in \{1, 2\}$ provides a signal $X_{i,t}(a) = \theta_i(a) + \epsilon_{i,t}$, where $\epsilon_{i,t} \sim N(0, \sigma^2)$.[6] Let $x_{i,t}(a)$ denote the realized signal and let $\hat{x}_{i,t}(a)$ denote the misattributor's encoded value of this signal.

Recall that $\hat{\theta}_{i,t}(a)$ denotes the participant's estimate of $\theta(a)$ entering period $t = 1, 2$. Given our normality assumptions, a participant who is Bayesian (aside from misencoding signals) updates her beliefs as follows:

$$\hat{\theta}_{i,t}(a) = \hat{\theta}_{i,t-1}(a) + \alpha_t \left[\hat{x}_{i,t}(a) - \hat{\theta}_{i,t-1}(a)\right], \tag{F.1}$$

where $\alpha_t = \frac{\rho^2}{t\cdot\rho^2+\sigma^2}$. The encoded signal, $\hat{x}_{i,t}$, is defined by Equation 3, and thus depends on

[5] We focus on a participant who is not assigned to do additional work in the first session of Experiment 2. Hence, the initial learning sessions comprise the participant's only experience with the task.

[6] Notice that $X_{i,t}(a) = -V^e_{i,t}(a)/c(e_{i,t})$, where $V^e_{i,t}(a)$ is defined in Equation G.1 and $e_{i,t}$ is the required number of trials the participant must complete in learning-session t.

how the true signal, $x_{i,t}(a)$, compares to the participant's expected effort cost entering round t. This expectation in turn depends on the participant's treatment group: those who are initially uncertain which task they will work on will hold different expectations about their eventual effort cost than those who are certain. We will therefore examine how updating differs depending on the participant's treatment group, p, where where p denotes the participant's ex ante likelihood of being assigned the noisy task. Recall that $p = 1$ and $p = 0$ correspond to the control group, and $p = 1/2$ corresponds to the coin-flip group.

We now analyze the encoded signal that a misattributing participant forms based on her assigned task and treatment group. For this exercise, we fix the true signal the participant receives in a given period, $x_{i,t}(a)$, and consider how she would encode this signal if she were in the coin-flip group versus the control group. We let $\hat{x}_{i,t}(a|p)$ denote this misencoded signal as a function of the treatment, p. Once we establish the direction in which signals are biased across treatment groups, the updating rule in Equation F.1 will then immediately reveal how the average estimate of the cost parameter in a given period should differ across treatments under misattribution.

Biased Updating in Period 1. We begin by analyzing how the treatment distorts signals in the first period. The predictions we obtain here primarily relate to Experiment 1. Consider participant i whose treatment group is such that she expects to face the noisy task with probability p. Her expected cost signal entering period 1 is thus $\widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p] \equiv p\hat{\theta}_{i,0}(h) + (1-p)\hat{\theta}_{i,0}(l)$. Upon realizing signal $x_{i,1}(a)$, Equation 3 implies that her misencoded signal is

$$\hat{x}_{i,1}(a|p) = \begin{cases} x_{i,1}(a) + \left(\frac{\eta-\hat{\eta}}{1+\hat{\eta}}\right)\left(x_{i,1}(a) - \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p]\right) & \text{if} \quad x_{i,1}(a) \leq \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p] \\ x_{i,1}(a) + \lambda\left(\frac{\eta-\hat{\eta}}{1+\hat{\eta}\lambda}\right)\left(x_{i,1}(a) - \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p]\right) & \text{if} \quad x_{i,1}(a) > \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p]. \end{cases} \tag{F.2}$$

Letting $\kappa^G \equiv \left(\frac{\eta-\hat{\eta}}{1+\hat{\eta}}\right)$ and $\kappa^L \equiv \lambda\left(\frac{\eta-\hat{\eta}}{1+\hat{\eta}\lambda}\right)$, we can define the following random variable that measures the extent to which a signal is misencoded:

$$K_{i,1}(a|p) \equiv \begin{cases} \kappa^L & \text{if} \quad x_{i,1}(a) > \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p] \\ \kappa^G & \text{if} \quad x_{i,1}(a) \leq \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p]. \end{cases} \tag{F.3}$$

Thus, we can write the misencoded signal in Equation F.2 more simply as

$$\begin{aligned} \hat{x}_{i,1}(a|p) &= x_{i,t}(a) + k_{i,1}(a|p)\left[x_{i,1}(a) - \widehat{\mathbb{E}}_{i,0}[X_{i,1}(a)|p]\right] \\ &= x_{i,t}(a) + k_{i,1}(a|p)\left[x_{i,1}(a) - p\hat{\theta}_{i,0}(h) - (1-p)\hat{\theta}_{i,0}(l)\right], \end{aligned} \tag{F.4}$$

where $k_{i,1}(a|p)$ is the realization of $K_{i,1}(a|p)$. Notice that if the participant does not suffer misattribution (i.e., $\hat{\eta} = \eta$), then $k_{i,1}(a|p)$ is always equal to zero. Furthermore, if the participant does suffer missatribution and is loss averse, then $\kappa^L > \kappa^G$, implying that high cost signals are distorted upward more than low cost signals are distorted downward.[7]

First consider how signals about the noiseless task in particular are differentially distorted depending on whether the participant is in the coin-flip group (i.e., $p = 1/2$) or the control group (i.e., $p = 0$). From Equation F.4, we have

$$\begin{aligned} &\hat{x}_{i,1}(l|p = 1/2) - \hat{x}_{i,1}(l|p = 0) \\ &\qquad = k_{i,1}(l|1/2)\big[x_{i,1}(l) - .5\hat{\theta}_{i,0}(h) - .5\hat{\theta}_{i,0}(l)\big] - k_{i,1}(l|0)\big[x_{i,1}(l) - \hat{\theta}_{i,0}(l)\big] \end{aligned} \tag{F.5}$$

There are three cases to consider, depending on the values of $k_{i,1}(l|1/2)$ and $k_{i,1}(l|0)$:

i. $x_{i,1}(a) > .5\hat{\theta}_{i,0}(h) + .5\hat{\theta}_{i,0}(l)$, in which case $k_{i,1}(l|1/2) = k_{i,1}(l|0) = \kappa^L$;

ii. $x_{i,1}(a) \in \big[\hat{\theta}_{i,0}(l), .5\hat{\theta}_{i,0}(h) + .5\hat{\theta}_{i,0}(l)\big]$, in which case $k_{i,1}(l|1/2) = \kappa^G$ and $k_{i,1}(l|0) = \kappa^L$;

iii. $x_{i,1}(a) < \hat{\theta}_{i,0}(l)$, in which case $k_{i,1}(l|1/2) = k_{i,1}(l|0) = \kappa^G$.

In cases (i) and (iii), $k_{i,1}(l|0)$ and $k_{i,1}(l|1/2)$ are both equal to the same $\kappa^j \in \{\kappa^G, \kappa^L\}$, and hence F.5 reduces to

$$\hat{x}_{i,1}(l|p = 1/2) - \hat{x}_{i,1}(l|p = 0) = -\frac{\kappa^j}{2}[\hat{\theta}_{i,0}(h) - \hat{\theta}_{i,0}(l)] < 0. \tag{F.6}$$

In case (ii), $k_{i,1}(l|0)$ and $k_{i,1}(l|1/2)$ differ, leading to

$$\begin{aligned} \hat{x}_{i,1}(l|p = 1/2) - \hat{x}_{i,1}(l|p = 0) &= \kappa^G[x_{i,1}(l) - .5\hat{\theta}_{i,0}(h) - .5\hat{\theta}_{i,0}(l)] - \kappa^L[x_{i,1}(l) - \hat{\theta}_{i,0}(l)] \\ &< \kappa^G[x_{i,1}(l) - .5\hat{\theta}_{i,0}(h) - .5\hat{\theta}_{i,0}(l)] - \kappa^G[x_{i,1}(l) - \hat{\theta}_{i,0}(l)] \\ &= -\frac{\kappa^G}{2}[\hat{\theta}_{i,0}(h) - \hat{\theta}_{i,0}(l)] \\ &< 0, \end{aligned} \tag{F.7}$$

where the first inequality follows because $x_{i,1}(l) - \hat{\theta}_{i,0}(l) > 0$ given that $x_{i,1}(a) \in [\hat{\theta}_{i,0}(l), .5\hat{\theta}_{i,0}(h) + .5\hat{\theta}_{i,0}(l)]$.

All three cases together imply that participant i facing task l will always encode a lower signal if she were in the coin-flip group rather than the control group. An entirely symmetric argument (omitted) implies that participant i facing task h will always record a *higher* signal if she

[7] Recall that $x_{i,t}(a)$ reflects the participant's *cost* in period t. Hence, the participant experiences a positive surprise when her signal is *less* than expected; she experiences a negative surprise when it is greater than expected. This is why the signs in Equation F.2 are flipped relative to 3—the latter was written in terms of benefits rather than costs.

were in the coin-flip group rather than the control group. Thus, assuming participants update according to Equation F.1, the preceding results imply that $\hat{\theta}_{i,1}(l|p = 1/2) < \hat{\theta}_{i,1}(l|p = 0)$ and $\hat{\theta}_{i,1}(h|p = 1/2) > \hat{\theta}_{i,1}(h|p = 1)$, where $\hat{\theta}_{i,1}(a|p)$ denotes a participant's predicted expectation of $\theta_i(a)$ conditional on her treatment group, p.[8] The results of our parametric estimation in Section II.C mirror these predictions (see Table 3). Furthermore, given this ordering of beliefs across treatment groups, the analysis of Appendices C and D shows that these beliefs generate the predicted differences in aggregate effort described Observation 2.

Biased Updating In Period 2. We now demonstrate how misattribution generates a predictable change in beliefs between periods 1 and 2 depending on a participant's task assignment. The predictions we obtain here relate exclusively to Experiment 2 since Experiment 1 had only one round of experience prior to the sole effort decision. Recall that in Experiment 2, each participant was assigned her task via a coin flip. Thus, in this analysis, a participant's period 1 beliefs, $\hat{\theta}_{i,1}(a)$, correspond to $\hat{\theta}_{i,1}(a|1/2)$ derived above.

We examine how these beliefs change after another round of learning. We maintain our assumption that the participant's reference point in the second period adjusts to her assigned task. That is, $\widehat{\mathbb{E}}_{i,1}[X_{i,2}(a)] = \hat{\theta}_{i,1}(a)$. Thus, the participant's encoded signal is

$$\begin{aligned} \hat{x}_{i,2}(a) &= x_{i,2}(a) + k_{i,2}(a)\left[x_{i,2}(a) - \widehat{\mathbb{E}}_{i,1}[X_{i,2}(a)]\right] \\ &= x_{i,2}(a) + k_{i,2}(a)\left[x_{i,2}(a) - \hat{\theta}_{i,1}(a)\right], \end{aligned} \tag{F.8}$$

where $k_{i,2}(a)$ is the realization of

$$K_{i,2}(a) \equiv \begin{cases} \kappa^L & \text{if} \quad x_{i,2}(a) > \widehat{\mathbb{E}}_{i,1}[X_{i,2}(a)] \\ \kappa^G & \text{if} \quad x_{i,2}(a) \leq \widehat{\mathbb{E}}_{i,1}[X_{i,2}(a)]. \end{cases} \tag{F.9}$$

From the updating rule in Equation (F.1) and the expression above for the misencoded signal, the participant's expected change in beliefs between periods 1 and 2 (from an ex-ante perspective) is thus equal to

$$\begin{aligned} \mathbb{E}[\hat{\theta}_{i,2}(a) - \hat{\theta}_{i,1}(a)] &= \alpha_2 \mathbb{E}[\widehat{X}_{i,2}(a) - \hat{\theta}_{i,1}(a)] \\ &= \alpha_2 \mathbb{E}[(1 + K_{i,2}(a))(X_{i,2}(a) - \hat{\theta}_{i,1}(a))], \end{aligned} \tag{F.10}$$

where $\mathbb{E}[\cdot]$ denotes expectations with respect to the true underlying distributions. Notice that Equation F.10 is positive iff $\mathbb{E}[X_{i,2}(a)] > \mathbb{E}[\hat{\theta}_{i,1}(a)]$. Given that signals are independent across periods

[8]This prediction invokes our assumption that a participant's priors over the cost parameters are independent of their treatment assignment.

with mean $\theta_i(a)$, the previous condition holds iff $\theta_i(a) > \mathbb{E}[\hat{\theta}_{i,1}(a)]$. As we argued above, assignment to the noiseless task via the coin-flip implies that $\hat{\theta}_{i,1}(l)$ is biased downward.[9] Hence the previous inequality holds and thus, in expectation, $\hat{\theta}_{i,2}(l) > \hat{\theta}_{i,1}(l)$: the perceived effort cost of the noiseless task tends to increase across periods, reducing the participant's WTW on that task. Similarly, assignment to the noisy task via the coin-flip implies that $\hat{\theta}_{i,1}(h)$ is biased upward. Hence the inequality above *fails* to hold, and thus, in expectation, $\hat{\theta}_{i,2}(h) < \hat{\theta}_{i,1}(h)$: the perceived effort cost of the noisy task tends to decrease across periods, increasing the participant's WTW on that task. This pattern in beliefs generated by misattribution clearly runs against the predictions of reference-dependence absent misattribution (explored in Appendix E), where effort on the noiseless task tends to increase across periods while effort on the noisy task tends to decrease.

G Back-of-the-Envelope Parameter Estimates

This appendix presents the simple calculations that underlie our parameter estimates discussed at the end of Section II.C.

We build from the belief-formation model presented in Section II.B. Recall that Table 3 presents estimates of participants' perceptions of the cost parameter $\theta(a)$ for each task across the various treatment groups. The model in Section II.B can deliver a system of equations that characterize the predicted perceptions of $\theta(a)$ across groups of as a function of the underlying reference-dependence parameters, (η, λ), and the degree of misattribution, $\hat{\eta}$. Here, we substitute our estimated perceptions of $\theta(a)$ from Table 3 into this system of equations and solve for the implied values of η, λ, and $\hat{\eta}$.

This approach implicitly assumes that the values in Table 3 reflect the perceptions that a fixed representative agent would form in each of the treatment groups. This exercise therefore calculates the preference and bias parameters of this representative agent. Accordingly, we drop the participant label i from the subsequent notation.

Recall from Section II.B that the agent's consumption utility in the initial session is

$$v_1^e = -\left[\theta_i(a) + \epsilon_1\right] c(8). \tag{G.1}$$

As above, we assume the agent believes that $\theta(a) \sim N\left(\hat{\theta}_0(a), \rho^2\right)$ and $\epsilon_t \sim N(0, \sigma^2)$, which

[9] Our assumption that priors are unbiased in the population is relevant here: this assumption implies that, on average, $\hat{\theta}_{i,1}(l) < \theta_i(a)$; that is, that the average expectation among participants regarding $\theta(l)$ after one round of learning is lower than the true parameter value.

implies that her updated perception of $\theta(a)$ is

$$\hat{\theta}_1(a) = -\alpha\left(\frac{\hat{v}_1^e}{c(8)}\right) + (1-\alpha)\hat{\theta}_0(a) \;\text{ where }\; \alpha \equiv \frac{\rho^2}{\rho^2+\sigma^2}, \tag{G.2}$$

where $\hat{v}_1$ is agent's (mis)encoded consumption value. We simplify matters in two ways: (i) we consider the limit in which $\sigma \to 0$, and (ii) we assume that the agent's prior expectations match the true values, so $\hat{\theta}_0(a) = \theta(a)$ for $a = h, l$. The first simplification implies that the agent's consumption utility is approximately $v_1^e = -\theta(a)c(8)$, and that the agent's updated perception of $\theta(a)$ is approximately $\hat{\theta}_1(a) = -\hat{v}_1^e/c(8)$. The second simplification implies that the agent's beliefs are unbiased to begin with, and thus the perceptions we estimate from the control conditions reveal the agent's priors.

We take the estimated values in Table 3 to represent the values of $\hat{\theta}_1(a)$ resulting from each possible treatment condition. To derive equations that characterize these values, we must consider the agent's misencoded consumption value in each condition. Using Equation 3, the $\hat{\theta}_1$ is given by

$$\hat{v}_1^e = \begin{cases} -\hat{\theta}(a)c(8) + \kappa^G\left(-\hat{\theta}(a)c(8) - \widehat{\mathbb{E}}[V_1]\right) & \text{if} \quad -\theta(a)c(8) \geq \widehat{\mathbb{E}}[V_1] \\ -\theta(a)c(8) + \lambda\left(\frac{\eta-\hat{\eta}}{1+\hat{\eta}\lambda}\right)\left(-\hat{\theta}(a)c(8) - \widehat{\mathbb{E}}[V_1]\right) & \text{if} \quad -\theta(a)c(8) < \widehat{\mathbb{E}}[V_1], \end{cases} \tag{G.3}$$

where $\kappa^G \equiv \frac{\eta-\hat{\eta}}{1+\hat{\eta}}$ and $\kappa^L \equiv \lambda\left(\frac{\eta-\hat{\eta}}{1+\hat{\eta}\lambda}\right)$. While we are not able to obtain separate estimates of η, λ, and $\hat{\eta}$, we will be able to solve for implied values of κ^G and κ^L. The magnitude of these two summary statistics help describe the extent of misencoding—since they would be both be zero absent misattribution—and the difference between them reveals the extent of asymmetric encoding of gains and losses due to loss aversion.

As a first step toward calculating κ^G and κ^L, note that $\widehat{\mathbb{E}}[V_1]$ in Equation G.3 varies across conditions. Given our assumption that priors are unbiased, the coin-flip condition induces $\widehat{\mathbb{E}}[V_1] = -.5c(8)(\theta(l) + \hat{\theta}(h))$. In contrast, the control condition facing task a induces $\widehat{\mathbb{E}}[V_1] = -\hat{\theta}(a)c(8)$. It is thus apparent from Equation G.3 that the control conditions involve no misencoding. Hence, the estimated value of $\hat{\theta}_1(\text{noise}|p = 1) = .049$ reported in Table 3 gives us $\theta(h)$. Similarly, the estimated value of $\hat{\theta}(\text{no noise}|p = 0) = .038$ gives us $\theta(l)$.[10]

Turning to the coin-flip condition, let $\hat{\theta}_1(a|p = .5)$ denote the agent's updated perception of $\theta(a)$ after facing task a in the coin-flip condition. Recall that $\hat{\theta}_1(a|p = .5) = -\hat{v}_1^e/c(e)$, where $\hat{v}_1^e$ is the misencoded value induced by the coin-flip condition; this value is obtained by substituting our expression for $\widehat{\mathbb{E}}[V_1]$ in coin-flip case into Equation G.3. This yields

[10]For the calculations in this section, we use estimates from Column 2 of Table 3, which uses the full sample and includes controls.

$$\hat{\theta}_{i,1}(a|p=.5) = \begin{cases} \theta_i(l) - .5\kappa^G\left(\theta_i(h)-\theta_i(l)\right) & \text{if} \quad a=l \\ \\ \theta_i(l) + .5\kappa^L\left(\theta_i(h)-\theta_i(l)\right) & \text{if} \quad a=h. \end{cases} \tag{G.4}$$

As described above, the control conditions yield numerical estimates of $\theta_i(a)$. And the two coin-flip estimates from Table 3 provide numerical estimates for the left-hand side of Equation G.4; namely, $\hat{\theta}_1(l|p = .5) = 0.032$ and $\hat{\theta}_1(h|p = .5) = 0.063$. Thus, the only unknowns in System G.4 are κ^G and κ^L. Solving these two equations for these values yields $\kappa^G = 1.140$ and $\kappa^L = 2.635$.

H Experimental Instructions

In this section, we provide the full text of our experimental instructions. We use brackets to denote alternative instructions corresponding to different treatments. All instructions commenced with an informed consent form. The research in this study was reviewed by the Human Research Protection Program at Harvard University (protocol numbers: IRB15-0365 and IRB16-0944).[11] The replication was determined exempt by the Human Research Protection Program at Michigan State University.

H.1 Sample Reviews, Experiment 1

For a full text of the reviews used in Experiment 1, please contact the authors.

"To read this book is to go on a journey to places at once unexpected yet familiar; for example, one point is supported by reference to a diagram of nose shapes and sizes. His books teach rather than exposit; they do not lack for a direct thesis–they make arguments and reach conclusions."

Score: 5; Positive Review

"Sometimes you don't go out and find a book; the book finds you. Facing an impending loss without a foundation of faith to fall back on, I asked myself: 'What is the meaning of life if we're all just going to die?' The author answers that question in the most meaningful way possible."

Score: 5; Positive Review

"To be sure, this is a very quick read. The book is already very tiny, and the inside reveals large font and double spacing. It took me about two hours to finish this book. I believe I am an somewhat

[11]The Nock Lab at Harvard generated the noise used in our experiments. They used the stimuli in work unrelated to our own. In their studies, this sound was played at modest volume (slightly louder than we played the noise). Participants in their (more extensive) studies found the sound unpleasant, but with no lasting effects (e.g., ringing ears).

slow reader compared to other bookworms. On the other hand, I found many other books to be much more compelling and memorable takes on the meaning of life."

Score: 1; Negative Review

"Sometimes books like this are a real bore. Even worse, sometimes the science is terrible or inconsistent. I was pleased to find that this book is consistent with the established literature while also providing new insight."

Score: 5; Positive Review

"This book is nothing you expect it to be. I was looking forward to fun, witty tales of some of the author's romances. But no. He teamed up with a sociologist, and wrote a sociology textbook. It's bland and it's boring, with research percentages and the odd pie chart thrown in to liven things up."

Score: 1; Negative Review

H.2 Complete Experiment Instructions: Experiment 1

Session 1

We will begin with some simple demographic questions.

What is your gender?
☐ Male ☐ Female
What is your annual income?
☐ less than $15,000
☐ $15,000 - $29,999
☐ $30,000 - $59,999
☐ $60,000 - $99,999
☐ $100,000 or more
What is your age (in years)?
What is your zip code? [Format: 00000]

We will not deceive you whatsoever in this experiment. All of the instructions provide examples and guidance for the actual tasks you will do. There will be no surprises or tricks. This study will consist of two sessions. You will do the first session now. You will sign in to do the second session later. In each session, you will do a simple job that takes roughly 3 to 5 minutes. You will earn a fixed payment of $4 for completing both sessions. In the second session, you will have the chance to earn extra pay if you elect to do extra work. You must complete both sessions to earn any pay for this study. There will be absolutely no exceptions to this rule. All payments will be credited to your MTurk account within one week of completing the study.

The second session will be unlocked 8 hours after the first session. In order to unlock the second session, a link will be emailed to you. We ask that you complete the second session as soon as you are able to. You must complete the second session within one week of the email in order to receive payment.

Your task in both sessions will be listening a series of audio recordings of book reviews (from Amazon) to determine whether each review is generally positive or negative.

You must wait at least 10 seconds before any buttons will appear. You must then decide if the review is positive or negative. A positive review means that the reviewer generally liked the book and is providing a recommendation. A negative review means that the reviewer generally disliked the book and is cautioning against reading it.

We will now give you a sample task to practice. Once you have listened to the review and correctly determined if it is a positive or negative review, please close the pop-up window and click the arrow below to continue. Please click the link below for a sample of the task. [LINK]

During each of the two participation sessions, you will have to complete eight tasks. Note: the average time of each recording is about 20 seconds.

During the eight required reviews, you cannot get more than two answers wrong. If you get more than two answers wrong, you will be dropped from the study and will not receive payment. However, if you listen to the entire audio recording, the answers should be quite easy.

During the second session, we will ask you about your willingness to do additional reviews for extra pay. Your job in this first session is to learn about the difficulty of the task and think about your willingness to do additional reviews next session.

[*Coin flip*: Depending on chance, a background noise may be played on top of the audio review. We'll describe what determines whether you hear the noise in a moment. However, we'd like to make sure you know what the sound will be. Please click the play button below for a sample of the noise. When you are finished listening to the sample noise, click the arrow below to continue.]

[*Coin flip*: In a moment, you will begin the eight initial reviews. Before that, however, we must determine if you will have to hear the annoying noise over the audio review.In order to do this, you will flip a (digital) coin. If the coin lands Heads, you will not have to hear the noise. If it lands Tails, you will have to hear the noise.]

[*Coin flip*: Importantly, your flip today determines what you'll do on the second session of the experiment. If the coin flip lands Tails and you hear the annoying noise today, you will also hear it next session. If the coin flip lands Heads and you do not hear the annoying noise today, you will not hear it next session. So the result of this coin flip really matters!]

Click the button below to flip the coin: [BUTTON]

Sorry [Congratulations]. You will [not] have to hear the noise while you listen to the audio reviews. We will now begin the eight initial tasks. At the end of the task, you will see a code. You will need that code to continue. Click the words below to begin. [BEGIN TASK]

Remember - this experiment has two parts. The link to the second session will be emailed to you in 8 hours.

Since you heard [did not hear] the annoying noise today, you will also hear it next session. Please click the arrow to submit your work.

Modified Script for High-Probability Treatment

The *high probability* treatment used the same instructions as above for Session 1, except the paragraphs labeled *Coin flip* were replaced with the following:

[*High Probability:* In a moment, you will begin the eight initial reviews. Before that, however, we must determine if you will have to hear the annoying noise over the audio review. In order to do this, we will draw a random number from 1-100. If the random number is 100, you will not have to hear the noise. If it is any other number, you will have to hear the noise.]

[*High Probability*: Importantly, the random number today determines what you'll do on the second session of the experiment. If the number is 1-99 and you hear the annoying noise today, you will also hear it next session. If the random number is 100 and you do not hear the annoying noise today, you will not hear it next session. So the result of this random draw really matters!]]

Session 2

Welcome to the second session of the experiment.

As with the first session, if you choose not to participate in the study, you are free to exit. You must finish this session in order to receive payment. As a reminder: we will not deceive you whatsoever in this experiment. All of the instructions provide examples and guidance for the actual tasks you will do. There will be no surprises or tricks.

As with last session, you will listen to an audio recording of a review and must determine whether the reviewer is giving a generally positive or negative review. Be careful to listen to the whole review!

You heard [did not hear] the noise on top of the audio last session, and you will [not] hear it again this session. [*Noise only*: If you need a reminder of the noise, there is a sample below. To play, click the play button twice.]

As before you will have to complete eight reviews. However, this session you will have the option to complete extra reviews for additional payments. These extra tasks will come after the eight initial reviews. You will first decide how many extra reviews you would like to do on top of the eight initial reviews. You will then do the first eight reviews. Finally, you will have a chance to complete extra reviews if you were willing to do so. We will describe how this is determined on the next slides.

The method we use to determine whether you will complete extra reviews may seem complicated. But, we'll walk through it step-by-step. The punchline will be that it's in your best interest to just answer truthfully. First, we will ask you how many additional reviews you are willing to do for a fixed amount of money. For instance, we might ask: "What is the maximum number of extra reviews you are willing to do for $0.40?" This question means that we will give you $0.40 in exchange for you completing some amount of additional work.

On the decision screen, you will be presented a set of sliders that go between 0 and 100 tasks. You will also see an amount of money next to each slider. You will move each slider to indicate the maximal number of reviews you'd be willing to do for each amount of money. That is, if you would be willing to do 15 additional reviews but not 16, then you should move the slider to 15.

You will make five decisions, but only one will count for real. We will choose which decision counts for real using a random number generator. Therefore, it is in your best interest to take each question seriously and choose as if it were the only question.

Once we determine which question counts for real, we will draw a random number between 0 and 100. If your answer is less than that random number, you will not do additional reviews. However, if your answer is greater than or equal to that random number, you will do a number of additional tasks equal to the random number.

Example: Suppose you indicated you were willing to do 15 additional reviews for $0.40 and this question was chosen as the one that counts. If the random number was 16 or higher, you would do no additional tasks. However, if the random number was 12, you would do 12 additional reviews.

The next pages have a short quiz to help clarify how this works.

Suppose you were asked ”What is the maximum number of additional reviews you are willing to do for $0.80?” and you responded 60. If the random number is 17, how many reviews will you complete?

☐ 0 and I will be paid $0 in supplementary payments

☐ 60 and I will be paid $0.80 in supplementary payments

☐ 17 and I will be paid $0.80 in supplementary payments

☐ 17 and I will be paid $2.67 in supplementary payments

[On answering correctly] Correct. You will earn the extra payment if the random number is less than the number you indicated, and you will complete a number of additional reviews equal to the random number.

Suppose you were asked ”What is the maximum number of additional reviews you are willing to do for $0.80?” and you responded 60. If the random number is 76, how many additional reviews will you complete?

☐ 0 and I will be paid $0 in supplementary payments

☐ 76 and I will be paid $0.80 in supplementary payments

☐ 60 and I will be paid $0.80 in supplementary payments

☐ 76 and I will be paid $0 in supplementary payments

[On answering correctly] Correct. If the random number is greater than your choice, you will complete zero reviews and you will not receive an extra payment.This method of selecting how many additional reviews you will do might seem very complicated, but as we previously highlighted, there’s a great feature to it: your best strategy is to simple answer honestly. If, for example, you’d be willing to do 20 reviews for $0.40 but not 21, then you should answer 20. You may very well do less than 20 reviews (depending on the random number) but you certainly will not do more than 20. Put simply: just answer honestly.

Remember, you will decide whether to do additional reviews, then complete the eight initial reviews. Then we will draw a random number which determines if you will do extra reviews.

We will now ask you the questions about your willingness to do additional reviews for additional payment. Remember, we are using the method just described, so answer honestly. These are the real questions. One of the sliders will count for payment, so pay close attention.

What is the maximal number of additional reviews you’re willing to complete for:

$2.50? [SLIDER]

$2.00? [SLIDER]

$1.50? [SLIDER]

$1.00? [SLIDER]

$0.50? [SLIDER]

We will determine whether you will do additional reviews after you complete the eight initial tasks. We will begin those on the next page.

Like last session, you will [not] have to hear the noise during the audio reviews. We will now begin the eight initial reviews. When you have completed these eight reviews, you will see a code. You will need that code to continue. Click the words below to begin. [BEGIN TASK]

We’ll now draw the random number that determines which question counts for payment.

The random number selected the question where you were asked the maximum number of tasks you would do for [AMOUNT]. You answered [RESPONSE]. We’ll now draw a second random number that determines whether you do additional tasks and, if so, how many.

The random number is: [RANDOM NUMBER]. You answered: [RESPONSE].

[*Random number too high*: Since the random number was higher than the number you were willing to do, you will not complete any extra reviews and you will not receive any extra payments.] Since the random number was lower than the number you were willing to do, you will complete extra reviews. You will do [RANDOM NUMBER] extra reviews and receive [AMOUNT]. In order to verify that you completed all the additional reviews, we will give you a code when you finish. [BEGIN SUPPLEMENTAL TASKS]

Thank you for participating. Your MTurk code is on the screen that follows. Payments will be processed within one week. Please click the final button below to submit your work.

H.3 Complete Experiment Instructions: Experiment 2

Session 1

In front of you is an informed-consent form to protect your rights as a participant. Please read it. If you choose not to participate in the study, you are free to leave at any point. If you have any questions, we can address those now. We will pick up the forms after the main points of the study are discussed.

We will not deceive you whatsoever in this experiment. All of the instructions provide examples and guidance for the actual tasks you will do. There will be no surprises or tricks. If you have any questions at any time, please raise your hand and we will do our best to clarify things for you.

In this experiment, you will have the chance to earn supplemental payments ranging from $2-$25/hour. It is very important for the study that you participate in both days. Unfortunately, if you miss one of your participation dates, you will forgo any completion payments and supplemental payments and will be removed from the study (you will receive the show-up fee). There will be absolutely no exceptions to this rule, regardless of the reason. Completion and supplemental payments will be made as one single payment in cash at the end of the study.

Your task will be transcribing a line of handwritten text in a foreign language. We will explain the task and then allow you to spend a few moments practicing this job on the computer. Note that the example text may not exactly match what you will face in the experiment.

Letters will appear in a Transcription Box on your screen. For each handwritten letter, you will need to enter the corresponding letter into the Completion Box. In order to enter a letter into the Completion Box, simply click the letter from the provided alphabet. We refer to one row of text is one task. In order to advance to the next task, your accuracy must be above 90%.

We will now give you a sample task to practice. You will see handwritten characters and must enter the corresponding character into the Completion Box by clicking on the appropriate button. When you have transcribed a whole row, press "Submit". You may spend as much time as you like transcribing the text. If you succeed, a new line of text will appear. Once you have transcribed one row successfully, please close the pop-up window and click the arrow below to continue. Please click the link below for a sample of the task. [SAMPLE TASK]

During each of the two participation days, you will have to complete five tasks (five lines of foreign text). Note: the average time to complete a similar task in a different experiment was about 52 seconds (about 70 tasks/hour).

After completing five initial tasks, you will have the option to complete additional supplementary tasks for supplementary payments. The number of supplementary tasks you must complete on each participation day and the supplementary payment will depend on your own willingness to work. The supplementary tasks will come shortly after the five initial tasks.

In order to determine whether you will complete additional tasks, we will ask you how many additional tasks you are willing to do for a fixed amount of money. For instance, we might ask: ”What is the maximum number of additional tasks you are willing to do for $5?” This question means that we will give you $5 in exchange for you completing some amount of additional work. The next few screens describe a pretty complicated system that will determine how many additional tasks you actually do. But the point of this system is simple: there is no way to game the system. It is in your best interest to answer honestly.

On the decision screen, you will be presented a set of sliders that go between 0 and 100 tasks. You will also see an amount of money next to each slider. You will move each slider to indicate the maximal number of tasks you'd be willing to do for each amount of money. That is, if you would be willing to do 15 additional tasks but not 16, then you should move the slider to 15. For example (you need not enter anything) What is the maximal number of additional tasks you're willing to complete for:

$1? [SLIDER]
$2? [SLIDER]
$3? [SLIDER]
$4? [SLIDER]
$5? [SLIDER]

You will make five decisions, but only one will count for real. We will choose which decision counts for real using a random number generator. Therefore, its in your best interest to take each question seriously and choose as if it was the only question.

Once we determine which question counts for real, we will draw a random number between 0 and 100. If your answer is less than that random number, you will do no additional tasks. However, if your answer is greater than or equal to that random number, you will do a number of additional tasks equal to the random number.

Example: Suppose you indicated you were willing to do 15 additional tasks for $5 and this question was chosen as the one that counts. If the random number was 16 or higher, you would do no additional tasks. However, if the random number was 12, you would do 12 additional tasks. The next page has a short quiz to help clarify this system.

Suppose you were asked ”What is the maximum number of additional tasks you are willing to do for $10?” and you responded 30. If the random number is 8, how many tasks will you complete?

☐ 0 and I will be paid $0 in supplementary payments
☐ 30 and I will be paid $10 in supplementary payments
☐ 8 and I will be paid $10 in supplementary payments
☐ 8 and I will be paid $2.67 in supplementary payments

Correct. You will be paid the full amount regardless of the random number, and if the random number is less than the number you indicated, you will only need to complete a number of additional tasks equal to the random number.

Suppose you were asked ”What is the maximum number of additional tasks you are willing to do for $10?” and you responded 30. If the random number is 46, how many additional tasks will you complete?

☐ 0 and I will be paid $0 in supplementary payments
☐ 46 and I will be paid $10 in supplementary payments

☐ 0 and I will be paid \$10 in supplementary payments

☐ 30 and I will be paid \$0 in supplementary payments

Correct. If the random number is greater than your choice, you will complete zero tasks and you will not get paid. This method of selecting how many additional tasks you will do might seem very complicated, but as we previously highlighted, there's a great feature to it: your best strategy is to simple answer honestly. If you'd be willing to do 20 tasks for \$5 but not 21, then you should answer 20. You may very well do less than 20 tasks (depending on the random number) but you certainly will not do more than 20. Put simply: just answer honestly.

Depending on chance, a background noise may be played throughout the transcription process. We'll describe what determines whether you hear the noise in a moment. However, we'd like to make sure you know what the sound will be. Please click the play button below twice for a sample of the noise. When you are finished listening to the sample noise, click the arrow below to continue.

In a moment, you will begin the five initial tasks. Before that, however, we must determine if you will have to hear that annoying noise during the whole transcription process. In order to do this, you will flip a coin. If the coin lands Heads, you will not have to hear the noise. If it lands Tails, you will have to hear the noise.

Importantly, your flip today determines what you'll do on the second day of the experiment. If the coin flip lands Tails and you hear the annoying noise today, you will also hear it next week. If the coin flip lands Heads and you do not hear the annoying noise today, you will not hear it next week. So the result of this coin flip really matters!

When you reach this screen, please put your hand up. You may remove your headphones for this stage of the instructions. One of the experimenters will come by and help you. We are using a standard U.S. Quarter. This is not a trick coin and we're going to ask you to flip it. Please flip it and let it land on the table in front of you. If the coin does not flip more than twice, we will ask you to flip again. You'll be asked to flip a practice flip, and then you'll flip the one that counts. Reminder: Heads → No Noise. Tails → Annoying Noise

The experimenter will the answer this question.

☐ Tails

☐ Heads

Enter Code to Advance

[*Noise*: You will have to hear the noise. Please put your headphones back on. We will now begin the five initial tasks.] You will not have to hear the noise. However, we ask that you please put your headphones on so that you do not hear others. At the end of the task, you will see a code. You will need that code to continue. Click the words below to begin. [BEGIN TASK] Please enter the code below to continue

We will now ask you some questions about your willingness to do additional tasks for additional payment. Remember, we are using the system described earlier, so answer honestly.One of the sliders will count for real payment, so pay close attention.

What is the maximal number of additional tasks you're willing to complete for:

\$20? [SLIDER]

\$16? [SLIDER]

\$12? [SLIDER]

\$8? [SLIDER]

\$4? [SLIDER]

We'll now draw a random number to determine which question counts for payment.

The random number selected the question where you were asked the maximum number of tasks you would do for [AMOUNT]. You answered [RESPONSE]. We'll now draw a second random number that determines whether you do additional tasks and, if so, how many.

The random number is: [RANDOM NUMBER]. You answered: [RESPONSE].

[*Random number too high*: Since the random number was higher than the number you were willing to do, you will not complete any extra reviews and you will not receive any extra payments.] Since the random number was lower than the number you were willing to do, you will complete extra reviews. You will do [RANDOM NUMBER] extra reviews and receive [AMOUNT]. In order to verify that you completed all the additional reviews, we will give you a code when you finish. [BEGIN SUPPLEMENTAL TASKS]

Thank you for participating. [*Noise*: REMINDER: Since you heard the annoying noise today, you will also hear it in a week.]

REMINDER: Since you did not hear the annoying noise today, you will not hear it in a week.

Day 1 of the experiment is complete. Please return at the same time one week from now.Please click the arrow to submit your work. When you have finished, you may exit the lab.

Session 2

Welcome to the second day of the experiment.

Please turn your cell phones off. If you have a question at any point in the experiment, please raise your hand and a lab assistant will be with you to help. There will be a short quiz once we have finished the instructions. If you do not understand the instructions after both the instruction period and the quiz, please raise your hand and ask for help.

As with the first day, if you choose not to participate in the study, you are free to leave at any point. If you have any questions, we can address those now.

As a reminder: we will not deceive you whatsoever in this experiment. All of the instructions provide examples and guidance for the actual tasks you will do. There will be no surprises or tricks.

Like last week, your task is to transcribe a line of handwritten letters from a foreign language. This week, you will do a different language. You will the task under the same conditions as last week.

[*Noise*: You heard the noise last week, and you will hear it again this week. If you need a reminder of the noise, there is a sample below. To play, click the play button twice.]

You did not hear the noise last week, and you will not hear it again this week.

As with last week, letters will appear in a Transcription Box on your screen. For each handwritten letter, you will need to enter the corresponding letter into the Completion Box. In order to enter a letter into the Completion Box, simply click the letter from the provided alphabet. We refer to one row of text is one task. In order to advance to the next task, your accuracy must be above 90%.

As before you will have to complete five tasks (five lines of foreign text) and then you will have the option to complete additional supplementary tasks for supplementary payments. The supplementary tasks will come shortly after the five initial tasks.

In order to determine whether you will complete additional tasks, we will ask you how many additional tasks you are willing to do for a fixed amount of money. For instance, we might ask: "What is the maximum number of additional tasks you are willing to do for $5?" This question means that we will give you $5 in exchange for you completing some amount of additional work. It is in your best interest to answer these questions honestly.

Recall we used a random number system to determine how many additional tasks you did (if any). We'll provide a quick reminder of that system now.

On the decision screen, you will be presented a set of sliders that go between 0 and 100 tasks. You will also see an amount of money next to each slider. You will move each slider to indicate the maximal number of tasks you'd be willing to do for each amount of money. That is, if you would be willing to do 15 additional tasks but not 16, then you should move the slider to 15.

You will make five decisions, but only one will count for real. We will choose which decision counts for real using a random number generator. Therefore, its in your best interest to take each question seriously and choose as if it was the only question.

Once we determine which question counts for real, we will draw a random number between 0 and 100. If your answer is less than that random number, you will do no additional tasks. However, if your answer is greater than or equal to that random number, you will do a number of additional tasks equal to the random number.

Example: Suppose you indicated you were willing to do 15 additional tasks for $5 and this question was chosen as the one that counts. If the random number was 16 or higher, you would do no additional tasks. However, if the random number was 12, you would do 12 additional tasks. The next page has a short quiz to help clarify this system.

Suppose you were asked "What is the maximum number of additional tasks you are willing to do for $10?" and you responded 60. If the random number is 17, how many tasks will you complete?

☐ 0 and I will be paid $0 in supplementary payments
☐ 60 and I will be paid $10 in supplementary payments
☐ 17 and I will be paid $10 in supplementary payments
☐ 17 and I will be paid $2.67 in supplementary payments

Correct! You will be paid the full amount regardless of the random number, and if the random number is less than the number you indicated, you will complete a number of additional tasks equal to the random number.

Suppose you were asked "What is the maximum number of additional tasks you are willing to do for $10?" and you responded 60. If the random number is 76, how many additional tasks will you complete?

☐ 0 and I will be paid $0 in supplementary payments
☐ 76 and I will be paid $10 in supplementary payments
☐ 60 and I will be paid $10 in supplementary payments
☐ 76 and I will be paid $0 in supplementary payments

Correct. If the random number is greater than your choice, you will complete zero tasks and you will not get paid.This method of selecting how many additional tasks you will do might seem very complicated, but as we previously highlighted, there's a great feature to it: your best strategy is to simple answer honestly. If you'd be willing to do 20 tasks for $5 but not 21, then you should answer 20. You may very well do less than 20 tasks (depending on the random number) but you certainly will not do more than 20. Put simply: just answer honestly.

[*Noise*: Like last week, you will have to hear the noise. Please put your headphones back on.] Like last week, you will not have to hear the noise. However, we ask that you please put your headphones on so that you do not hear others. We will now begin the five initial tasks. At the end of the task, you will see a code. You will need that code to continue. Click the words below to begin. [BEGIN TASK] Please enter the code below to continue:

We will now ask you some questions about your willingness to do additional tasks for additional payment. Remember, we are using the system described earlier, so answer honestly.One of the sliders will count for real payment, so pay close attention.

What is the maximal number of additional tasks you're willing to complete for:

$20? [SLIDER]

$16? [SLIDER]

$12? [SLIDER]

$8? [SLIDER]

$4? [SLIDER]

We'll now draw a random number to determine which question counts for payment.

The random number selected the question where you were asked the maximum number of tasks you would do for [AMOUNT]. You answered [RESPONSE]. We'll now draw a second random number that determines whether you do additional tasks and, if so, how many.

The random number is: [RANDOM NUMBER]. You answered: [RESPONSE].

[*Random number too high*: Since the random number was higher than the number you were willing to do, you will not complete any extra reviews and you will not receive any extra payments.] Since the random number was lower than the number you were willing to do, you will complete extra reviews. You will do [RANDOM NUMBER] extra reviews and receive [AMOUNT]. In order to verify that you completed all the additional reviews, we will give you a code when you finish. [BEGIN SUPPLEMENTAL TASKS]

Thank you for participating. As you know, the experiment consisted of two days. Our main hypothesis was whether the chance of getting a different task on the first day changed your perceptions of the task difficulty that day. We did not highlight this specific hypothesis during the experiment in order to maintain the external validity of the study. We're excited to analyze the data and thank you again for your participation. Click the arrow to submit your work.