ONLINE APPENDIX:
"An Experiment on Time Preference and Misprediction in Unpleasant Tasks"

9 Online Appendix

We now report a variety of robustness checks on specification choices, participant sample, and data sample. Many of these robustness checks were designed ex-post, in response to suggestions and our own realizations of problems. We do not report all specifications and robustness checks due to space constraints, but have not omitted any analyses because they yielded "unfavorable" conclusions.

9.1 Stability of parameters across the experiment

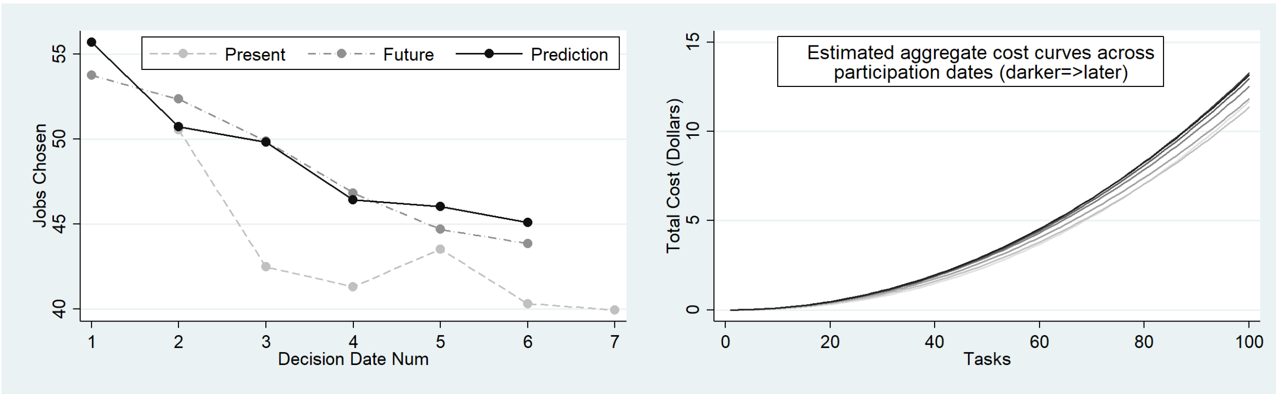
In our simple model, we assume that a participant's parameters are stable across time, such that participants make consistent decisions across time. However, in the main text, we note that participants' cost of completing tasks appears to be increasing over the course of the experiment, despite lowering task-completion times. In the left panel of Figure A1, we confirm this conclusion in the raw data by showing a downward trend in average wage-adjusted immediate-work, future-work and prediction decisions as the date of the decision increases, particularly in the first few dates. Recall that we control for this learning issue in the main analysis by including participation-date fixed effects on the cost slope parameters in Columns (3)-(5). In the right panel, we display the estimated total-cost curves from the specification in Column (3)—with darker colored lines representing later dates—affirming that we are capturing and controlling for these increasing costs.

While we allow the cost curve to vary in the main analysis, we do not let the main parameters of interest—β, β_h, and $\widetilde{\alpha}$—vary over time. Yet as a robustness check, we ran specifications in which these parameters too are allowed to vary across dates. We visually present the results in Figure A2. Our main parameter estimates remain largely stable, with one exception: The value of $\widetilde{\alpha}$, which is relatively stable over several weeks, dips near zero for date 6 and rises to over 10 for date 7–a result for which we have no explanation or interpretation.

9.2 Internal-Consistency Rewards

As we discuss in the paper, when making immediate-work decisions for which they previously stated a prediction, participants act somewhat inconsistently with our simple model of monetary payment utility and disutility from work. To understand the deviation, consider the potential outcomes of a participant's immediate-work decision given a previous prediction. If

Figure A1: Choice data and estimated aggregate cost curves across participation dates



Note: Left panel: Average present-work, future-work, and prediction choices across participation dates, controlling for wages. There is a downward trend, particularly in the early participation dates, suggesting that participants' relative costs are increasing. Right panel: In column (3) of Table (1), we use participation date fixed effects to allow the aggregate cost curve to vary over time. This graph shows the estimated cost curves for each participation date, with later dates in darker colors.

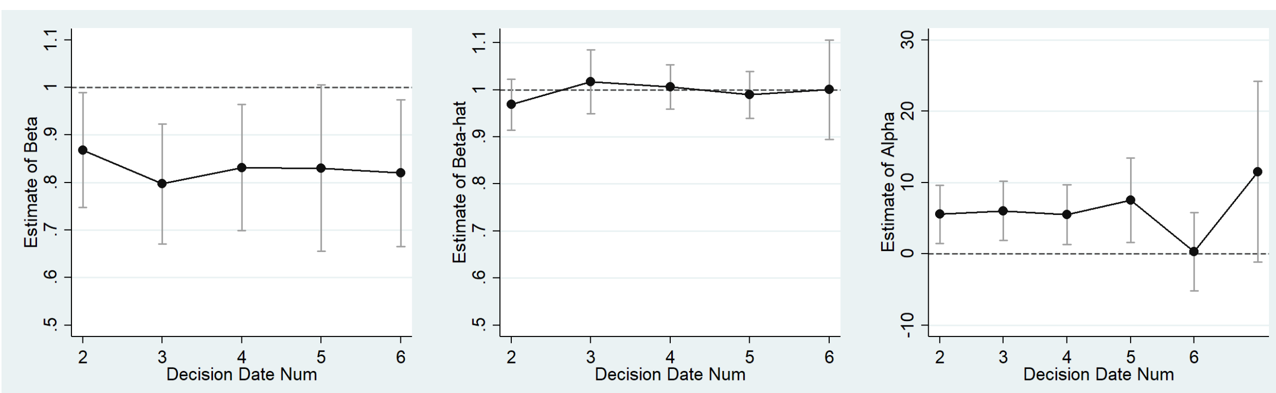


Figure A2: Aggregate parameter estimates across participation dates

Note: In the main analysis, we assume that our main parameters (beta, beta-hat, and alpha) are constant across participation dates. This figure plots the parameter estimates from a specification in which these parameters are allowed to vary over the decision date. Confidence intervals are created using standard errors clustered at the individual level.

her immediate work preference lies within the prediction interval, she will choose that level and receive the bonus. The situation is more complicated when her work preference is outside the interval. If the bonus is high enough, the participant will choose the closest work level in the interval (on one of the bounds) to receive the bonus. If the bonus is too low, however, she will choose her preferred level and forgo the bonus. Therefore, we expect some portion of decisions continuously spread across the decision interval, a large chunk of decisions at the lower bound, and some decisions far outside the interval. Because $\beta < 1$, we expect current preferences to fall below the prediction on average, leading the average immediate-work decision to be lower than the associated prediction. Furthermore, the model predicts that the difference will rises in wages. In the likely case that participants receive preference shocks to immediate-work preferences, these general predictions continue to hold.

Before turning to the data, we note that this analysis is made more complicated by the fact that we observe censored work decisions (between 0 and 100), which leads to censored predictions. For example, if the participant predicts that she would choose 150 tasks without constraints, she predicts that she will choose 100 tasks given the constraints. Then, if the day of work arrives and the participant's immediate-work preference is to complete 130 tasks, she is forced to choose 100 tasks. In this case, even though her immediate-work preferences differ from her unconstrained prediction, there is no observed difference due to censoring. This problem is clear in the data: for predictions of either 0 or 100, nearly 95% of the resultant work decisions perfectly match the prediction. As this effect is presumably due to censoring, we focus on predictions strictly between 0 and 100, where this confound does not exist.

With these corner predictions removed, the histogram plotting the difference between the immediate-work decision and the associated prediction are shown in Figure A3. As predicted, a significant chunk of the immediate-work decisions (36%) lie on the lower bound of the prediction interval. Furthermore, the average difference between immediate-work decisions—denoted on the histogram with a straight line—is negative (-1.53) and significantly lower than zero ($Z = 2.47$, $p = 0.017$), clustering standard errors at the participant-level. Finally, although not shown in the graph, this difference is marginally significantly rising in the wage level ($Z = 1.96$, $p = 0.056$).

However, there are important deviations from the predictions of the model. First, for 29% of the data, the immediate-work decisions perfectly matches the associated prediction. Based on our model, this should be a rare event, particularly given the likelihood of shocks to immediate-work preferences, as it is unlikely that a participant would end up preferring the exact work level in the prediction. Second, there are no cases in which participants choose outside the prediction interval. Given our estimated parameters, the size of estimated immediate-work preference shocks, the size of the bonuses, and an assumption that participants value the

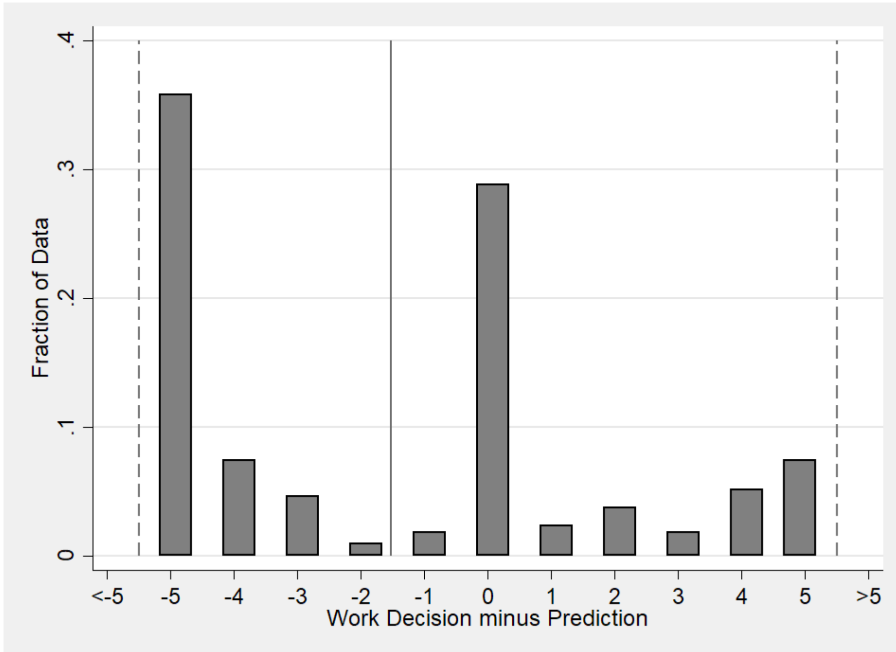


Figure A3: Analysis of immediate-work decisions given previous predictions

Note: This figure shows a histogram of the difference between immediate-work decisions following a previous prediction and the associated prediction. The prediction interval (+/- 5 tasks) is shown in dotted lines. Observations above and below the prediction interval are combined in the ">5" and "<-5" bins. The average of the data is shown in the vertical solid line.

monetary bonuses the same as monetary wages, rough simulations suggest that participants should forego the bonus rather than work within five of their prediction 20% of time, leading to 15% of the prediction-affected immediate-work decisions lying below the prediction interval and 5% lying above. It appears that, instead, participants have (1) a strong unmodeled preference to choose within the prediction interval and receive the monetary bonus and (2) a weaker desire to match previous predictions exactly.

Interestingly, these consistency preferences are surprisingly "local." To understand this finding, suppose that a participant previously made a prediction of 60 tasks given a wage $.20, but only desires to do 40 tasks for this wage when she arrives on the work day. Suppose that this participant desires to be consistent with her past preferences and consequently chooses 60 tasks when shown her previous prediction. What will this participant do when faced with a wage of $.18 (for which she prefers to do around 40 tasks)? One might imagine that the participant would recognize that her previous prediction did not just imply doing 60 tasks for $.20, but implied a general preference to do a higher level of work across other wages—for example, doing around 60 tasks for $.18. This does not appear to be the case. Immediate-work decisions with "similar" wages (but no past prediction for that wage) are between 6.7-9.0 tasks lower (Z ranging from $1.98 - 2.73$ and p from $0.001 - 0.05$) than those with the prediction, depending on the definition of "similar."

Potentially more pedestrian reasons might explain some of the behavior. For example, in our dataset, participants commonly appear to round their decisions. For example, 48% of non-corner predictions are divisible by 10 and 72% are divisible by 5. The tendency to round decisions makes it is far more likely that immediate-work decisions will end up matching predictions. Supporting this hypothesis, nearly twice the proportion of round predictions lead to perfectly matching work choices in comparison to non-round decisions (34% vs. 17% for predictions divisible by 5 and 39% vs. 20% for predictions divisible by 10), although there is still some perfect matching with no rounding.

9.3 Estimating the effect of uncertainty

The formal model that we estimate in the paper assumes no "structural" uncertainty, allowing only for error terms as a reduced-form way to rationalize the mismatch between the best-fit model predictions and observed noise. This error could correspond to measurement errors, random errors, model uncertainty, or as a heuristic way to allow for unmodeled preference heterogeneity. We implicitly assume that participants do not adjust their decisions to account for future uncertainty, a potentially unrealistic assumption. For example, a participant might be aware that she will sometimes feel unpredictably tired, while on other days, she will feel unpredictably refreshed. Knowing this, she will choose future-work and prediction decisions to maximize her expected utility given these shocks, leading to different decisions than suggested by our model.

To study the effect of anticipated preference shocks on participants' decisions, we modify our model such that a participant faces zero-mean normally-distributed preference shocks η_γ with standard deviation $\sigma_\gamma(\eta_\gamma)$ to her cost-curve parameter γ. We focus on the effects of this change on future-work decisions and the estimate of β; the effect on β_h is ambiguous and depends heavily on the precise form of the error term.[71] The agent's future-work decision at time $t < k$ given the anticipated preference shock maximizes expected utility is then

$$\max_e \; E[\, \varphi \cdot \delta^{(T-k)} \cdot e \cdot w - \frac{1}{\overline{\gamma} + \eta_\gamma}(e+10)^{\overline{\gamma}+\eta_\gamma}], \tag{13}$$

[71] We conjecture (but have not proven) that adding uncertainty given convex costs leads to lower predictions. Intuitively, positive shocks lead to smaller drops in chosen effort than the corresponding rises in chosen effort from equivalent negative shocks. Therefore, lower predictions lead to a higher probability of drawing a parameter that leads to effort chosen within five tasks of the prediction. However, the bias on the estimate of β_h from not accounting for this uncertainty is unclear: β_h is identified in the comparison of predictions and future-work decisions, and—as we show shortly—these decisions are also lower due to uncertainty.

with $\overline{\gamma}$ representing the mean of the realized parameter γ. Simplifying and solving for the first-order condition yields an implicit solution for observed effort

$$\varphi \cdot \delta^{(T-k)} \cdot w = E[(e+10)^{\overline{\gamma}-1+\eta_\gamma}]. \tag{14}$$

Given convex costs and this symmetric error, anticipated preference shocks will lead to lower future-work decisions than in our baseline model, because the agent desires to insure herself against positive shocks in effort costs. Not taking this effect into account biases our main estimates of β upward, as β increases with the difference between future-work and immediate-work decisions.

To demonstrate this effect empirically, we estimate our model taking this anticipated uncertainty into account. Note that, as this anticipated error will not lead to any variation in future-work decisions for a given wage, we still require a reduced-form way to account for the mismatch between decisions and model predictions. We therefore add the reduced-form error term ε_γ, with standard deviation $\sigma_\gamma(\varepsilon_\gamma)$, to both present and future decisions. Given this, the likelihood of observing immediate-work decision e_j becomes:

$$L(e_j) = \frac{\gamma^*_{present} - \gamma}{\sigma_\gamma(\varepsilon_\gamma) + \sigma_\gamma(\eta_\gamma)} \tag{15}$$

where $\gamma^*_{present} = \frac{\ln(\varphi \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w) + \ln(e_j+10)}{\ln(e_j+10)}$. For reference, $\gamma^*_{present}$ is derived in Equation 25 of Appendix Subsection 9.15. The likelihood of observing future work decision e_j becomes:

$$L(e_j) = \phi\left(\frac{\gamma^*_{future}(\eta_\gamma) - \gamma}{\sigma_\gamma(\varepsilon_\gamma)}\right) \tag{16}$$

where: $\gamma^*_{future}(\eta_\gamma)$ maximizes 13 given $\eta_\gamma \sim N(0, \sigma(\eta_\gamma))$.

Column (1) of Table A1 first presents the results of this model with both anticipated and reduced-form error, but assuming that participants do not change their future work decisions to take this error into account. The estimates $\widehat{\sigma}(\varepsilon_\gamma)$ and $\widehat{\sigma}(\eta_\gamma)$ are presented, showing that there is additional dispersion in present effort decisions—captured in $\widehat{\sigma}(\eta_\gamma)$—compared to future-effort decisions. Column (2) presents the same results under the assumption that participants take this uncertainty into account when making future work decisions. As expected, the estimate of β is lower when taking uncertainty into account.

9.4 Projection Bias

We add projection bias to the model by assuming that the agent will (mistakenly) project her current marginal disutility–the marginal cost from the next task she completes, which we label

Table A1: Estimation given preference shock to parameter gamma with participants taking this uncertainty into account in decisions

	(1) Shock on γ No Reaction	(2) Shock on γ Optimal Reaction
Present Bias $\hat{\beta}$	0.817	0.766
	(0.029)	(0.030)
Cost Curvature $\hat{\gamma}$	2.420	2.330
	(0.054)	(0.022)
Decision Error $\widehat{\sigma}(\varepsilon_{\gamma})$	0.212	0.217
	(0.011)	(0.013)
Preference Shock $\widehat{\sigma}(\eta_{\gamma})$	0.131	0.123
	(0.016)	(0.006)
Observations	8049	8049
Participants	72	72
Log Likelihood	-641	-699
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.09	p= 0.00

Note: These specifications assume that participants face preference shocks to the parameter gamma on the day of work, in addition to a standard reduced-form error term to capture deviations from model predictions and observed choices on all decisions. Column (1) assumes that participants do not take preference shocks into account when making future-work decisions. Column (2) assumes that participants do optimally take these shocks into account. Standard errors are clustered at the participant level.

$C'(e_{done})$ given she has just done e_{done} previous tasks–onto her marginal costs from the e^{th} task $C'(e)$. Under the simple parameterization in Loewenstein, O'Donoghue, and Rabin (2003), where $\alpha \in [0,1]$ measures the severity of projection bias, her perceived marginal cost would be $\widetilde{C}'(e) = (1-\alpha) \cdot C'(e) + (\alpha) \cdot C'(e_{done})$. Consequently, a person who has completed more work (such as the ten mandatory tasks) just before the time of decision will perceive that her marginal costs from all subsequent tasks are higher, leading to lower work decisions for a given wage.

There are other (potentially less natural) models which lead to similar qualitative predictions. For example, an agent who has just performed e_{done} tasks could be modeled as perceiving the cost from completing a fresh set of tasks as if she had already completed e_{done} tasks. That is, with the linear parameterization: $\widetilde{C}(e) = (1-\alpha) \cdot C(e) + (1-\alpha) \cdot C(e + e_{done})$.

Tables A2 and A3 estimate these two models using nine different specifications of the sort used elsewhere in the paper. The estimates of α are between .27 and .73, with seven of the nine between 0.4 and 0.6. All but one are statistically significantly different than the full-rationality value of $\alpha = 0$. However, worrisomely (and one of our reasons for our caution for the structural estimation), the more theoretically grounded model has convergence issues, leading to large or non-reported standard errors in two specifications.

9.5 Additional Specifications without Projection Bias

For completeness, Table A4 replicates the main table in the paper without the estimation of the projection bias parameter. There is virtually no impact on the other parameters.

As we note in the conclusion, it is possible to imagine experiments that confound projection bias and present bias because people are asked future-work preferences when in one mental state (such as feeling fresh) while being asked present-work preferences when in another state (such as feeling tired). Using our data, we can simulate the results of this type of experiment by only including future-work decisions that occur before the ten mandatory tasks and only including present-work decisions that occur after the ten mandatory tasks. Table A5 replicates the main table in the paper with these restrictions. Broadly, the parameters are noisier given the large reduction in the number of observations, but are lower (not including those with prediction-accuracy sophistication). However, contrary to our expectations, the estimates in column (3), which include both participant and decision-date fixed effects and might be considered our preferred specification, are largely unchanged.

Table A2: Structural estimation of projection bias - based on marginal cost projection

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.833	0.811	0.833	0.833
	(0.040)	(0.042)	(0.104)	(0.041)
Naive Pres. Bias β_h	0.999	1.013	1.005	1.003
	(0.013)	(0.011)	(0.082)	(0.009)
Discount Factor δ	1.003	1.006	1.003	1.003
	(0.003)	(0.002)	(0.009)	(0.002)
Cost Curvature γ	2.186	2.163	2.132	1.972
	(0.067)	(0.091)	(0.467)	(0.079)
Cost Slope φ	402	440	431	270
	(85)	(146)	(683)	(86)
Proj Bias α	0.533	0.430	0.407	0.267
	(.)	(0.079)	(0.349)	(0.067)
Participant FE		X	X	X
Day FE			X	X
Prediction Soph.				
Later Decisions				X
Observations	8049	8049	8049	5539
Participants	72	72	72	64
Log Likelihood	-28409	-25075	-24834	-16524
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p= 0.109	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.92	p= 0.24	p= 0.95	p= 0.73
$H_0(\widehat{\alpha}=0)$	p= .	p<0.001	p= 0.242	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.43	p= 0.01	p= 0.75	p= 0.08

Note: This table structurally estimates the projection bias parameter using the model of marginal-cost projection. Standard errors are clustered at the participant level.

Table A3: Structural estimation of projection bias - based on task level projection

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.835	0.812	0.833	0.833	0.825
	(0.038)	(0.042)	(0.040)	(0.041)	(0.041)
Naive Pres. Bias β_h	0.999	1.014	1.006	1.003	1.004
	(0.011)	(0.011)	(0.010)	(0.009)	(0.003)
Discount Factor δ	1.003	1.005	1.003	1.003	1.003
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)
Cost Curvature γ	2.145	2.142	2.118	1.971	2.126
	(0.070)	(0.084)	(0.081)	(0.079)	(0.081)
Cost Slope φ	724	710	687	367	720
	(252)	(266)	(244)	(127)	(257)
Proj Bias α	0.730	0.526	0.527	0.407	0.521
	(0.260)	(0.128)	(0.129)	(0.126)	(0.127)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	8049	8049	8049	5539	8049
Participants	72	72	72	64	72
Log Likelihood	-28412	-25079	-24838	-16522	-24837
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.93	p= 0.23	p= 0.58	p= 0.74	p= 0.11
$H_0(\widehat{\alpha}=0)$	p= 0.005	p<0.001	p<0.001	p= 0.001	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.37	p= 0.01	p= 0.06	p= 0.08	p= 0.07

Note: This table structurally estimates the projection bias parameter using the model of task-level projection. Standard errors are clustered at the participant level.

Table A4: Structural estimation without projection bias parameter

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.859	0.830	0.841	0.830	0.839
	(0.036)	(0.042)	(0.040)	(0.042)	(0.041)
Naive Pres. Bias β_h	1.001	1.015	1.007	1.006	1.004
	(0.010)	(0.012)	(0.010)	(0.003)	(0.009)
Discount Factor δ	1.002	1.005	1.003	1.003	1.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Cost Curvature γ	2.066	2.085	2.058	2.069	1.929
	(0.070)	(0.082)	(0.080)	(0.079)	(0.077)
Cost Slope φ	482	530	496	529	294
	(166)	(194)	(172)	(183)	(99)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.				X	
Later Decisions					X
Observations	8049	8049	8049	8049	5539
Participants	72	72	72	72	64
Log Likelihood	-28438	-25112	-24872	-24870	-16539
$H_0(\hat{\beta}=1)$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$
$H_0(\widehat{\beta_h}=1)$	p= 0.94	p= 0.20	p= 0.50	p= 0.07	p= 0.66
$H_0(\widehat{\delta}=1)$	p= 0.48	p= 0.02	p= 0.05	p= 0.06	p= 0.07

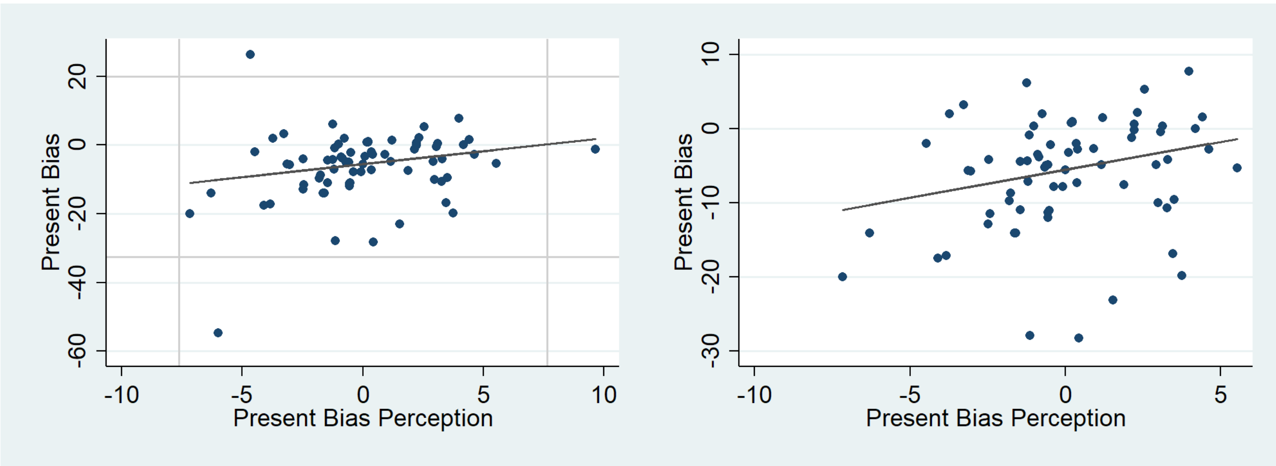
Note: This table replicates the main estimation table in the paper without the inclusion of the projection bias parameter. Standard errors are clustered at the participant level.

Table A5: Structural estimation simulating an alternative experiment in which future-work preference are only elicited in "cold" state and present-work preferences only in "hot" state

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.780	0.752	0.833	0.829	0.865
	(0.062)	(0.055)	(0.053)	(0.054)	(0.054)
Naive Pres. Bias β_h	1.001	1.009	1.006	1.001	1.030
	(0.039)	(0.023)	(0.022)	(0.005)	(0.022)
Discount Factor δ	1.001	1.009	1.000	1.000	1.000
	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Cost Curvature γ	2.057	1.972	1.973	1.975	1.878
	(0.076)	(0.086)	(0.087)	(0.088)	(0.084)
Cost Slope φ	498	320	365	371	248
	(190)	(120)	(142)	(145)	(92)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.				X	
Later Decisions					X
Observations	2858	2858	2858	2858	2153
Participants	72	72	72	72	64
Log Likelihood	-10015	-8602	-8548	-8549	-6238
$H_0(\hat{\beta}=1)$	$p<0.001$	$p<0.001$	p= 0.002	p= 0.001	p= 0.012
$H_0(\widehat{\beta_h}=1)$	p= 0.98	p= 0.71	p= 0.77	p= 0.85	p= 0.18
$H_0(\widehat{\delta}=1)$	p= 0.91	p= 0.00	p= 0.87	p= 0.87	p= 0.98

Note: This table replicates the main estimation table in the paper focusing on a subset of the choices. Using our data, we simulate the effects of only asking questions and predictions for future work when the participants hadn't yet started working (i.e. before the ten mandatory tasks), and only asked present-work questions only after they had started working (i.e. after the ten mandatory tasks).

Figure A4: Inclusion of all participants in scatterplots of measures of present bias and sophistication



Note: These graphs plot the individual non-parametric measures of present bias and sophistication. The right graph, included in the paper, removes three participant who have measures which are more than 2.56 standard deviations from the mean. The left graph includes these participants.

9.6 Scatterplots of Present Bias and Sophistication Measures

Figure 6 removes three outliers for visual ease. The left panel of Figure 9.6 includes these outliers (as well as lines for both axes which are 2.58 standard deviations from the mean), while the right panel reproduces the right panel of Figure 6 for comparison.

9.7 Estimating Separate Monetary and Effort Discount Factors

In the paper, we assume that the discount factor for money δ_m and effort δ_e are equal, labeling each as δ. Without this assumption, equation (8) requires a replacement of $\delta^{(T-t)}$ with $\delta_m^{(T-k)}$ and $\delta^{(k-t)}$ with $\delta_e^{(k-t)}$. Table A6 estimates these separate parameters under different assumptions and specifications. Columns (1), (2), and (3) do not include any fixed effects (mirroring column (1) in Table 1), while columns (4), (5), (6) include participant and decision-day fixed effects (mirroring column (3) in Table 1). Columns (1) and (4) constrain $\delta_m = \delta_e$, replicating the results in columns (1) and (3) of Table 1, respectively. Columns (2) and (5) estimate the parameters δ_m and δ_e separately. As with the estimate of δ in the main paper, these estimates are slightly above 1, with δ_m close to statistically different from 1[a.2] in column (5) ($p = .060$). In both cases, the separate estimates are far from statistically different from each other ($p = .500$ and $p = .939$, respectively). None of the other parameters estimates vary in any meaningful way. Finally, columns (3) and (6) constrain $\delta_m = 1$ (the daily borrowing interest rate at the time of the paper was likely at most 20% per year, yielding a daily discount rate of 0.9995), again yielding no meaningful difference in the other parameters.

9.8 Participants Not Included in the Main Sample

In the main text, we focus on a primary sample of 72 participants for whom we are able to estimate individual structural parameters. The removed participants appear very similar to those in the primary sample with respect to the main non-parametric measures discussed in the paper. Removed participants chose an average of 5.06 ($Z = 2.07$, $p = 0.048$) fewer tasks when making decisions about immediate work than future work, 0.25 ($Z = 0.31$, $p = 0.76$) more tasks for future-work decisions than predictions (and consequently 5.31 ($Z = 2.25$, $p = 0.03$) fewer tasks for immediate-work decisions than predictions).

In Figure A10, we present the raw data of the 28 removed participants. The participants are ordered by the coefficient obtained from a linear regression of decisions on wages, with the estimated regression line shown in the plots. There is only one participant (ID:90, top left of graph), who has a negative relationship between wages and choices. For a large set of the removed participants, there is very little variation in decisions given different wages, including four participants with no variation. There are a few participants with seemingly reasonable decisions, but for which the estimation routine did not converge for whatever reason, potentially because the number of decisions was too small due to attrition.

Figures A5-A9 reproduce the five main non-parametric figures in the paper for the full 100 participant sample. The graphs are all extremely similar to those presented in the text for our main sample of 72 participants.

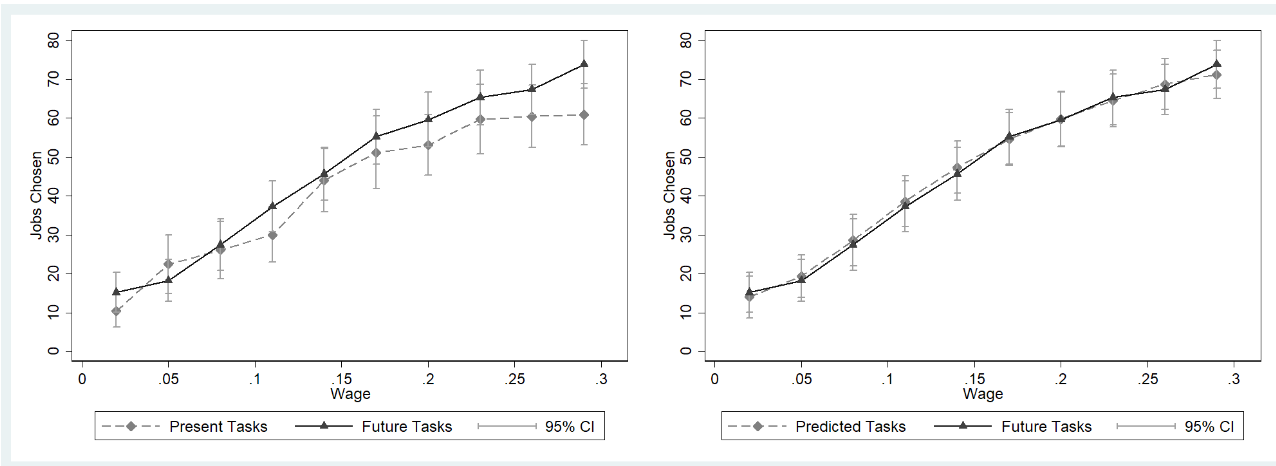
Table A7 replicates our main aggregate specification in Table 1 for the full 100 participant sample. For completeness, Table A8 replicates it for the full sample with attritors removed. As we cannot commonly identify a fixed-effect for each of the remove participants, one common fixed-effect is used for these participants. The qualitative results are unchanged, although the estimate of the present-bias parameter β is moderately lower.

Table A6: Allowing Different Monetary and Effort Discount Factors

	(1) Initial Estimation δ_m=δ_e	(2) Initial Estimation δ_m, δ_e	(3) Initial Estimation δ_m=1, δ_e	(4) Decision Day FE δ_m=δ_e	(5) Decision Day FE δ_m, δ_e	(6) Decision Day FE δ_m=1, δ_e
Present Bias β	0.835	0.854	0.862	0.833	0.834	0.862
	(0.038)	(0.040)	(0.036)	(0.040)	(0.040)	(0.039)
Naive Pres. Bias β_h	0.999	0.998	0.998	1.006	1.005	1.004
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Money Discount δ_m	1.003	1.001	1.000	1.003	1.003	1.000
	(0.003)	(0.004)	(.)	(0.001)	(0.001)	(.)
Effort Discount δ_e	1.003	1.003	1.003	1.003	1.004	1.002
	(0.003)	(0.003)	(0.003)	(0.001)	(0.012)	(0.012)
Cost Curvature γ	2.145	2.147	2.147	2.118	2.117	2.119
	(0.070)	(0.070)	(0.070)	(0.081)	(0.080)	(0.080)
Cost Slope φ	724	703	698	687	667	678
	(252)	(250)	(249)	(244)	(326)	(335)
Proj Task Reduct. $\tilde{\alpha}$	7.304	7.361	7.347	5.269	5.274	5.317
	(2.597)	(2.604)	(2.596)	(1.290)	(1.287)	(1.289)
Participant FE				X	X	X
Work Day FE				X	X	X
Prediction Soph.						
Later Decisions						
Observations	8049	8049	8049	8049	8049	8049
Participants	72	72	72	72	72	72
Log Likelihood	-28412	-28411	-28411	-24838	-24838	-24841
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.93	p= 0.86	p= 0.84	p= 0.58	p= 0.58	p= 0.69
$H_0(\widehat{\alpha}=0)$	p= 0.005	p= 0.005	p= 0.005	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\delta_m}=1)$	p= 0.375	p= 0.844		p= 0.059	p= 0.060	
$H_0(\widehat{\delta_e}=1)$	p= 0.375	p= 0.319	p= 0.302	p= 0.059	p= 0.762	p= 0.850
$H_0(\widehat{\delta_m}=\widehat{\delta_e})$		p= 0.500			p= 0.939	

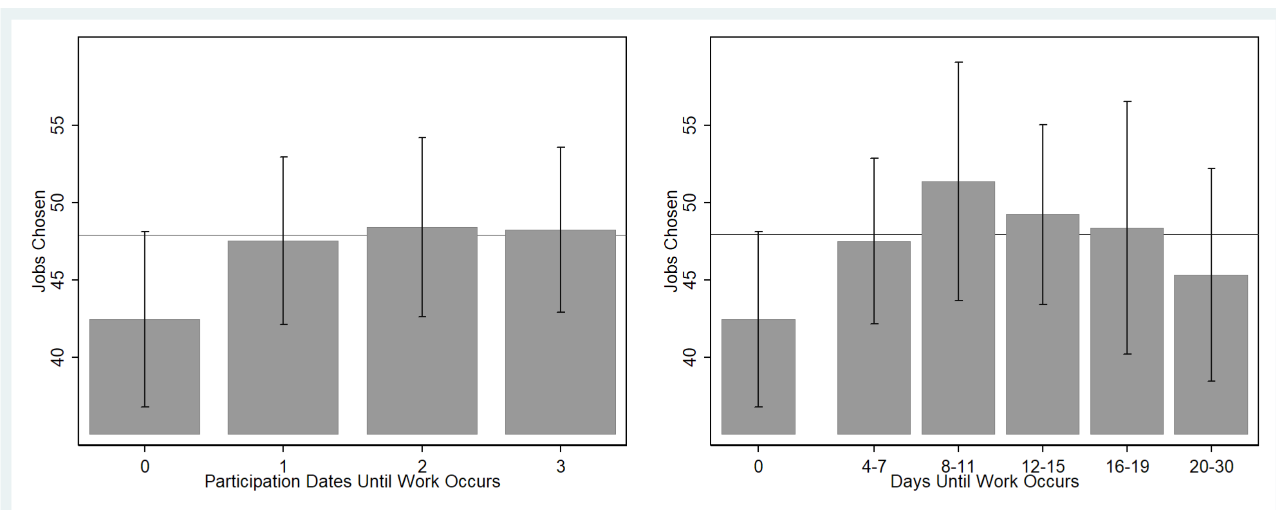
Note: Aggregate structural estimations for our primary sample of 72 participants, allowing for separate monetary and effort discount factors. Columns (1) and (4) force δ_m=δ_e, matching the results in the main estimation table. Columns (2) and (5) estimate separate parameters δ_m, δ_e. Columns (3) and (6) force δ_m=1 and estimate δ_e. When fixed effects are added, the parameter presented is the average of the fixed effects. Standard errors are clustered at the participant level.

Figure A5: Full Sample: Present vs. future decisions (left) and predictions vs. future decisions (right)



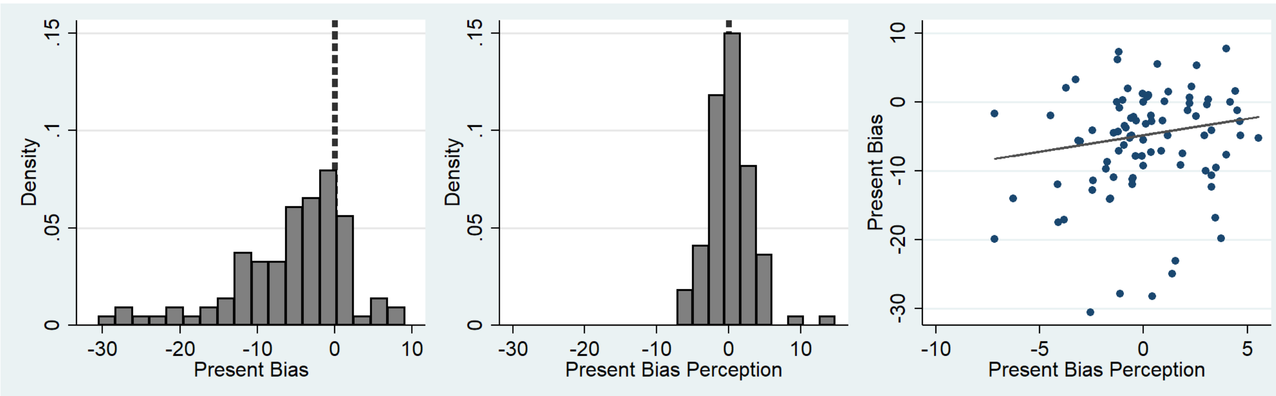
Note: This Figure replicates that in Figure 2 for the entire sample with any variation in decisions.

Figure A6: Full Sample: Work decisions given different delays to the time of work



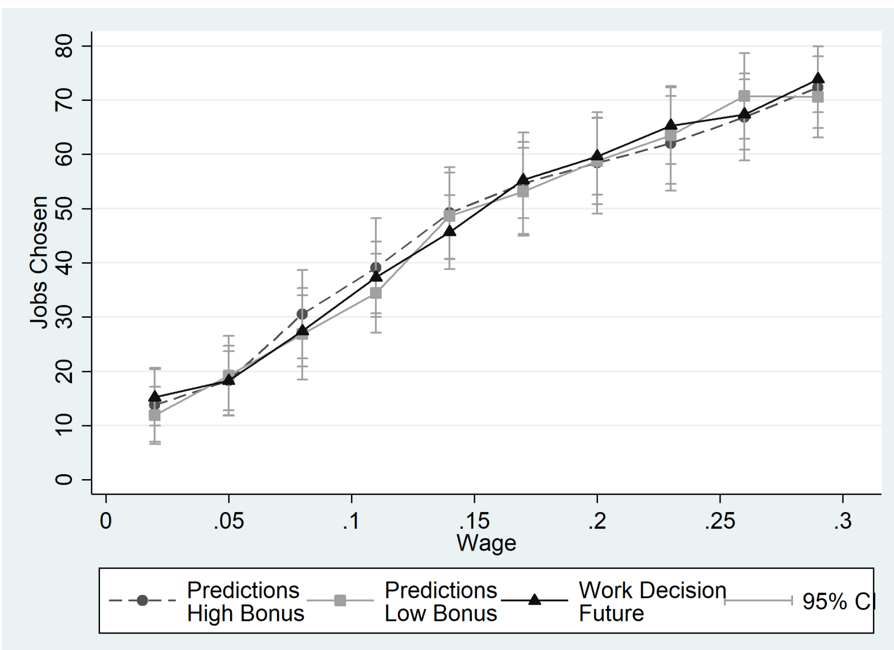
Note: This Figure replicates that in Figure 3 for the entire sample with any variation in decisions.

Figure A7: Full Sample: Participant-level non-parametric measures of actual and perceived present bias



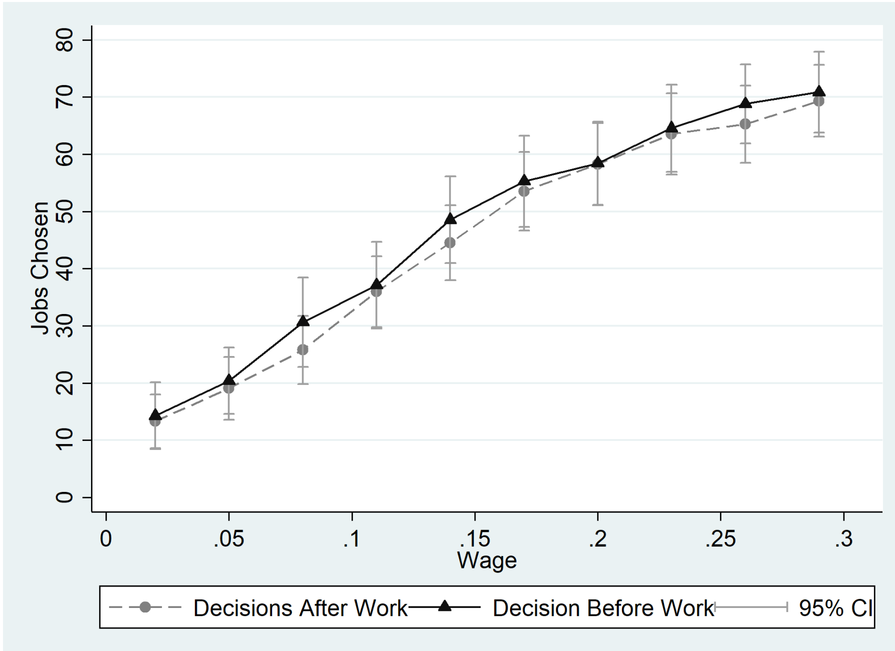
Note: This Figure replicates that in Figure 4 for the entire sample with any variation in decisions.

Figure A8: Full Sample: The variation of predictions given different bonus amounts



Note: This Figure replicates that in Figure 5 for the entire sample with any variation in decisions.

Figure A9: Full Sample: Comparison of decisions made before and after 10 mandatory tasks.



Note: This Figure replicates that in Figure 7 for the entire sample with any variation in decisions.

9.9 Curvature in Utility from Monetary Payments

Throughout the paper, we parameterize the monetary utility function $U(\cdot)$ to be linear in payments. In this section, we instead parameterize this function to be the standard CARA utility function and show that monetary curvature has very little effect on our main parameter estimates. We start by modifying equation 7 to be:

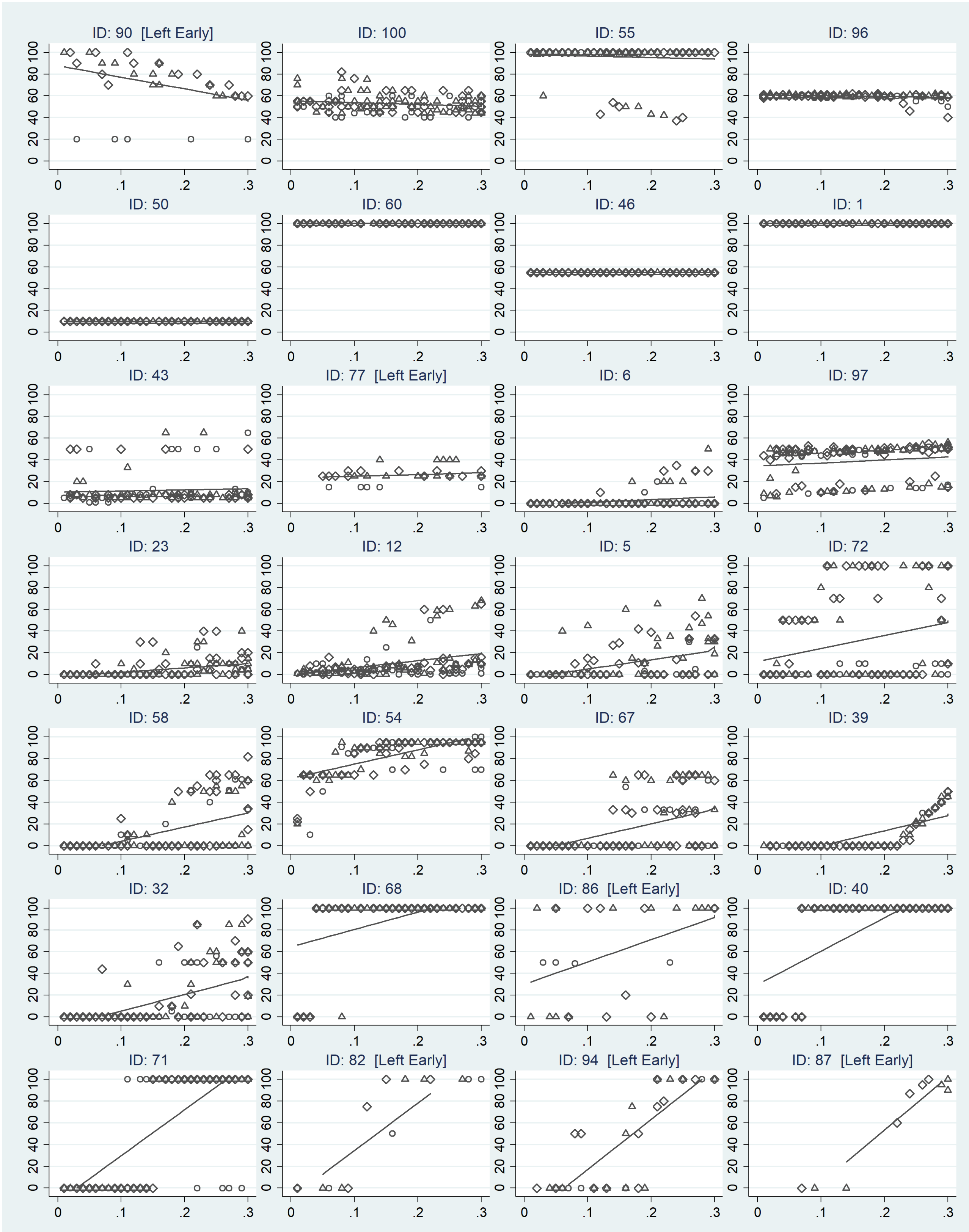
$$e^* = \arg\max_e \quad \delta^{T-k} \cdot \exp(-a(y + e \cdot w)) - \frac{1}{\beta^{\mathbf{1}(k=t)}} \cdot \frac{1}{\beta_h^{\mathbf{1}(p=1)}} \cdot \delta^{t-k} \cdot \frac{1}{\varphi \cdot \gamma}(e + 10)^{\gamma}. \qquad (17)$$

where y is the initial wealth of the participants and a used instead of the traditional α to differentiate from the projection-bias parameter α. Solving for the optimal choice yields:

$$e^* = \frac{(\gamma - 1)}{a \cdot w}\mathbb{W}(\frac{a \cdot w(\varphi \cdot \exp(-a \cdot y) \cdot w \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{T-k} \cdot \exp(10 \cdot a \cdot w))^{\frac{1}{\gamma-1}}}{\gamma - 1} - 10, \quad (18)$$

where $\mathbb{W}(z)$ represents principle value of the Lambert W function (the principal solution for $\mathbf{w}$ in the implicit equation $z = \mathbf{w} \cdot \exp(\mathbf{w})$). As in the main text, it is possible to estimate

Figure A10: Scatter of all decisions of 28 removed participants



Note: In our main analysis, we focus on a primary sample of 72 participants. This graph shows scatter plots of task decisions (y-axis) given a wage (x-axis) of all of the removed participants, as well as the linear regression line. The plots are ordered by the regression slope coefficients. "ID" is the assigned id of the participant and "[Left Early]" represents attrition. Present, future, and prediction decisions are represented by circles, diamonds, and triangle respectively.

Table A7: Robustness: primary aggregate estimation using full sample

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.768	0.775	0.734	0.723	0.731
	(0.042)	(0.043)	(0.064)	(0.068)	(0.065)
Naive Pres. Bias β_h	1.003	1.017	1.010	1.006	1.000
	(0.012)	(0.013)	(0.012)	(0.013)	(0.003)
Discount Factor δ	1.008	1.009	1.012	1.013	1.011
	(0.003)	(0.003)	(0.007)	(0.008)	(0.007)
Cost Curvature γ	2.254	2.161	2.117	1.943	2.117
	(0.104)	(0.113)	(0.112)	(0.111)	(0.111)
Cost Slope φ	995	757	609	304	612
	(492)	(386)	(300)	(148)	(302)
Proj Task Reduction $\tilde{\alpha}$	8.123	5.715	5.217	4.908	5.212
	(2.847)	(2.103)	(2.174)	(2.487)	(2.167)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	10919	10919	10919	7489	10919
Participants	100	100	100	86	100
Log Likelihood	-38025	-35661	-35524	-23707	-35525
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.83	p= 0.18	p= 0.42	p= 0.62	p= 1.00
$H_0(\widehat{\alpha}=0)$	p= 0.004	p= 0.007	p= 0.016	p= 0.048	p= 0.016
$H_0(\widehat{\delta}=1)$	p= 0.02	p= 0.00	p= 0.09	p= 0.09	p= 0.09

Note: This table replicates Table 1 for the full sample of 100 participants. Participant fixed effects are only calculated for participants in primary sample as the maximum likelihood routine does not converge otherwise. Standard errors are clustered at the participant level.

Table A8: Robustness: primary aggregate estimation using full sample minus attritors

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.761	0.783	0.730	0.721	0.729
	(0.045)	(0.047)	(0.071)	(0.073)	(0.072)
Naive Pres. Bias β_h	1.006	1.022	1.012	1.006	0.998
	(0.013)	(0.014)	(0.013)	(0.013)	(0.004)
Discount Factor δ	1.010	1.009	1.013	1.014	1.013
	(0.004)	(0.003)	(0.008)	(0.009)	(0.008)
Cost Curvature γ	2.318	2.188	2.141	1.962	2.137
	(0.123)	(0.130)	(0.127)	(0.122)	(0.126)
Cost Slope φ	1310	949	744	344	734
	(759)	(557)	(418)	(184)	(410)
Proj Task Reduction $\tilde{\alpha}$	8.910	6.070	5.326	4.812	5.355
	(3.090)	(2.298)	(2.347)	(2.619)	(2.342)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	9799	9799	9799	7044	9799
Participants	79	79	79	79	79
Log Likelihood	-34012	-31959	-31834	-22452	-31834
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.65	p= 0.11	p= 0.34	p= 0.63	p= 0.58
$H_0(\widehat{\alpha}=0)$	p= 0.004	p= 0.008	p= 0.023	p= 0.066	p= 0.022
$H_0(\widehat{\delta}=1)$	p= 0.01	p= 0.00	p= 0.10	p= 0.10	p= 0.10

Note: This table replicates Table 1 for the sample of 79 non-attritor participants. Participant fixed effects are only calculated for participants in primary sample as the maximum likelihood routine does not converge otherwise. Standard errors are clustered at the participant level.

all parameters given an assumed level of curvature a, although φ and $\exp(-a \cdot y)$ cannot be separately identified from their product $\varphi \cdot \exp(-a \cdot y)$.

Table A9 replicates our main aggregate specification minus the sophistication column for a monetary curvature parameter a equal to .01. This parameter implies that the ratio of the marginal utility of an additional dollar at the start of the experiment in comparison to the end of the experiment (after receiving ~$100) is nearly three. Even this somewhat extreme level of curvature has almost no impact on our main parameters.

While our data is not designed to separately identify monetary curvature a and effort-cost curvature γ, random bonus payments provide variation which can be used to identify diminishing sensitivity to wages given (slightly) higher levels of wealth. We find little evidence of this sensitivity: a linear regression—including fixed effects for decision date, participants, and wages—suggests that participants reduce task decisions by 0.183 for each additional previously-received dollar in bonus payments, which is far from statistically significant ($Z = 0.68$, $p = 0.501$).

9.10 Different Functional Form for the Cost Curve

In order to identify the main structural parameters, we assume that the cost function takes a power form with two parameters such that $C(e) = \frac{1}{\varphi \cdot \gamma}(e+10)^{\gamma}$. In this section, we assume the cost function is a more flexible third-degree polynomial and show it has virtually no impact on the estimates of our main parameters. We start by modifying equation 7 to be:

$$\begin{aligned} e^*_{3rd} &= \arg\max_e \ \delta^{T-k}(e \cdot w) - \frac{1}{\beta^{\mathbf{1}(k=t)}} \cdot \frac{1}{\beta_h^{\mathbf{1}(p=1)}} \cdot \delta^{t-k} \cdot C(e+10) && (19) \\ \text{where } C(e+10) &= \psi_1 \cdot (e+10) + \psi_2 \cdot (e+10)^2 + \psi_3 \cdot (e+10)^3 && (20) \end{aligned}$$

Solving for the optimal choice yields:

$$\begin{aligned} e^*_{3rd} &= \arg\max_e \ \frac{\sqrt{D \cdot (\psi_2^2 - 4\psi_1\psi_3) + D \cdot (4w\psi_3)} - D \cdot \psi_2}{2D \cdot \psi_3} - 10 && (21) \\ \text{where } D &= \frac{1}{\beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{T-k}} && (22) \end{aligned}$$

Table A10 replicates our main aggregate specification minus the sophistication column with the three polynomial variables. The change in the cost curve specification has virtually no impact on our main parameter estimates.

Table A9: Robustness: Primary Aggregate Estimation Fixing Monetary Curvature

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.851	0.833	0.865	0.862
	(0.036)	(0.036)	(0.034)	(0.035)
Naive Pres. Bias β_h	0.999	1.014	1.009	1.006
	(0.010)	(0.009)	(0.009)	(0.008)
Discount Factor δ	1.002	1.006	1.002	1.002
	(0.003)	(0.002)	(0.001)	(0.001)
Cost Curvature γ	1.870	1.839	1.835	1.717
	(0.069)	(0.080)	(0.078)	(0.074)
Cost Slope*Wealth $\varphi \cdot exp(-a \cdot y)$	258	215	228	138
	(82)	(74)	(77)	(44)
Proj Task Reduction $\tilde{\alpha}$	6.669	3.742	3.806	2.736
	(2.633)	(1.180)	(1.225)	(1.223)
Participant FE		X	X	X
Day FE			X	X
Prediction Soph.				
Later Decisions				X
Observations	8049	8049	8049	5539
Participants	72	72	72	64
Log Likelihood	-28369	-24945	-24733	-16452
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.96	p= 0.13	p= 0.34	p= 0.41
$H_0(\widehat{\alpha}=0)$	p= 0.011	p= 0.002	p= 0.002	p= 0.025
$H_0(\widehat{\delta}=1)$	p= 0.37	p= 0.00	p= 0.07	p= 0.10

Note: Aggregate structural estimations for our primary sample of 72 participants, where the risk aversion parameter a is constrained to be .01. Standard errors are clustered at the participant level.

Table A10: Robustness: Primary Aggregate Estimation with Third-Degree Polynomial Cost Curve

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.830	0.820	0.830	0.844
	(0.041)	(0.037)	(0.039)	(0.043)
Naive Pres. Bias β_h	1.001	1.012	1.004	1.004
	(0.012)	(0.010)	(0.009)	(0.009)
Discount Factor δ	1.004	1.007	1.005	1.003
	(0.003)	(0.002)	(0.003)	(0.002)
Poly Var 1 ψ_1	0.027	0.012	-0.006	0.015
	(0.007)	(0.007)	(0.011)	(0.007)
Poly Var 2 ψ_2	0.0014	0.0031	0.0035	0.0033
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Poly Var 2 ψ_3	0.000013	0.000006	0.000003	0.000002
	(0.000002)	(0.000002)	(0.000001)	(0.000001)
Proj Task Reduction $\tilde{\alpha}$	3.991	3.921	4.469	2.872
	(2.304)	(1.506)	(1.446)	(1.362)
Participant FE		X	X	X
Day FE			X	X
Prediction Soph.				
Later Decisions				X
Observations	7919	7919	7919	5444
Participants	71	71	71	63
Log Likelihood	-28114	-24872	-24699	-16460
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.94	p= 0.25	p= 0.66	p= 0.68
$H_0(\widehat{\alpha}=0)$	p= 0.083	p= 0.009	p= 0.002	p= 0.035
$H_0(\widehat{\delta}=1)$	p= 0.27	p= 0.00	p= 0.08	p= 0.24

Note: Aggregate structural estimations with a third-degree polynomial cost curve specification. This table uses our primary sample with one additional participant removed (this participant's individual cost curve parameter does not converge). Standard errors are clustered at the participant level.

9.11 Sample Robustness

We check robustness of our results to eliminating choices that might be distorted for various reasons. Recall that the main analysis does not include any immediate-work decisions for which participants had made a previous prediction because prediction-accuracy payments might distort these work decisions. In Table A11, we additionally remove entire *decision sets* for which a previous prediction was made for *any* wage in the set. Recall that we often asked participants to make two future-work or prediction decision sets on one date. To remove any consistency effects across these decision sets, Table A12 removes the second decision set of a given type. Finally, to remove consistency effects across decision sets of different types (immediate work, future work, and predictions), Table A13 only includes the first decision set made by the participant on a given date. Our conclusions are largely stable, except for the non-statistically significant β coefficient of 0.915 for the later dates in the most restrictive data sample. As a result of the restrictions, this specification only uses 32% of the sample, leading to relatively erratic estimates - for example, in this specification, β_h is estimated at 1.09.

9.12 Predictions-As-Commitment

In the majority of our main estimation table (Table 1), we assume that participants make straightforward predictions and do not use prediction-accuracy payments for soft commitments. In Column (5), we show that assuming this use of predictions in the specification in Column (3) does not change the results. In Table A14, we perform this exercise for the first four columns in Table 1 (consequently replicating Column (5) of Table 1 as Column (3) of Table A14). There is very little quantitative change in the results.

9.13 Location of Fixed Effects

In our original analysis plan, we expected to display one specification in which we allowed the slope φ and cost curvature γ parameters to vary arbitrarily for each participant. However, due to the large number of fixed effects, this specification does not converge when decision-date fixed effects are also added. Consequently, in the main paper, we were required to use an alternative specification: using participant fixed effects for the slope φ parameter. In Columns (1)-(6) of Table A15, we show that the estimates are robust to other possibilities. The parameters are largely consistent with two fixed-effects specifications in the paper (Columns (2) and (3) of Table 1), with some estimates above and some below: however, the specification which adds only decision-date fixed effects to the φ parameter (Column (3)) leads to a higher β estimate of 0.907, which is borderline statistically significant ($p = 0.073$).

Table A11: Robustness: primary aggregate estimation using a restricted data sample

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.851	0.785	0.808	0.790	0.798
	(0.048)	(0.051)	(0.050)	(0.058)	(0.051)
Naive Pres. Bias β_h	0.999	1.014	1.006	1.004	1.006
	(0.011)	(0.011)	(0.010)	(0.009)	(0.003)
Discount Factor δ	1.003	1.006	1.003	1.003	1.003
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)
Cost Curvature γ	2.149	2.154	2.128	1.970	2.139
	(0.072)	(0.086)	(0.082)	(0.076)	(0.083)
Cost Slope φ	734	744	713	366	758
	(259)	(285)	(258)	(120)	(277)
Proj Task Reduction $\tilde{\alpha}$	6.835	5.137	5.099	3.615	5.016
	(2.729)	(1.341)	(1.344)	(1.356)	(1.320)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	7550	7550	7550	5040	7550
Participants	72	72	72	64	72
Log Likelihood	-26675	-23562	-23335	-15026	-23333
$H_0(\hat{\beta}=1)$	p= 0.002	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.93	p= 0.22	p= 0.53	p= 0.68	p= 0.05
$H_0(\widehat{\alpha}=0)$	p= 0.012	p<0.001	p<0.001	p= 0.008	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.40	p= 0.01	p= 0.06	p= 0.08	p= 0.08

Note: This table replicates Table 1, but removes observations in which present-work decision have any prediction bonus in the decision set. Standard errors are clustered at the participant level.

Table A12: Robustness: primary aggregate estimation using a restricted data sample

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.842	0.829	0.858	0.853	0.849
	(0.037)	(0.041)	(0.039)	(0.040)	(0.040)
Naive Pres. Bias β_h	1.004	1.021	1.010	1.002	1.003
	(0.019)	(0.015)	(0.013)	(0.013)	(0.003)
Discount Factor δ	1.003	1.006	1.002	1.002	1.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Cost Curvature γ	2.129	2.116	2.083	1.931	2.089
	(0.071)	(0.086)	(0.082)	(0.079)	(0.081)
Cost Slope φ	660	621	591	309	615
	(226)	(236)	(213)	(106)	(221)
Proj Task Reduction $\tilde{\alpha}$	6.951	4.805	4.684	3.686	4.642
	(2.657)	(1.330)	(1.329)	(1.286)	(1.313)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	6559	6559	6559	4499	6559
Participants	72	72	72	64	72
Log Likelihood	-23119	-20511	-20304	-13427	-20303
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.82	p= 0.17	p= 0.46	p= 0.89	p= 0.29
$H_0(\widehat{\alpha}=0)$	p= 0.009	p<0.001	p<0.001	p= 0.004	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.29	p= 0.01	p= 0.34	p= 0.27	p= 0.37

Note: This table replicates Table 1, but removes the second future and prediction decision sets made on a decision date. Standard errors are clustered at the participant level.

Table A13: Robustness: primary aggregate estimation using a restricted data sample

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.851	0.875	0.878	0.915	0.851
	(0.044)	(0.053)	(0.056)	(0.063)	(0.050)
Naive Pres. Bias β_h	1.035	1.096	1.074	1.093	0.997
	(0.057)	(0.059)	(0.051)	(0.052)	(0.009)
Discount Factor δ	1.003	1.006	1.003	1.001	1.003
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Cost Curvature γ	2.077	2.109	2.062	1.909	2.060
	(0.074)	(0.093)	(0.088)	(0.084)	(0.089)
Cost Slope φ	519	572	517	271	527
	(182)	(238)	(206)	(101)	(215)
Proj Task Reduction $\tilde{\alpha}$	5.110	4.990	4.738	4.380	4.812
	(2.766)	(1.690)	(1.734)	(1.625)	(1.741)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	3639	3639	3639	2559	3639
Participants	72	72	72	64	72
Log Likelihood	-12712	-11388	-11250	-7608	-11254
$H_0(\hat{\beta}=1)$	p<0.001	p= 0.018	p= 0.030	p= 0.175	p= 0.003
$H_0(\widehat{\beta_h}=1)$	p= 0.54	p= 0.10	p= 0.15	p= 0.07	p= 0.73
$H_0(\widehat{\alpha}=0)$	p= 0.065	p= 0.003	p= 0.006	p= 0.007	p= 0.006
$H_0(\widehat{\delta}=1)$	p= 0.31	p= 0.01	p= 0.31	p= 0.79	p= 0.31

Note: This table replicates Table 1, but removes all but the first decision set of any kind made on a decision date. Standard errors are clustered at the participant level.

Table A14: Robustness: assuming predictions used for commitment

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.825	0.799	0.825	0.828
	(0.038)	(0.043)	(0.041)	(0.043)
Naive Pres. Bias β_h	1.006	1.005	1.004	1.003
	(0.004)	(0.003)	(0.003)	(0.003)
Discount Factor δ	1.003	1.005	1.003	1.003
	(0.003)	(0.002)	(0.001)	(0.002)
Cost Curvature γ	2.156	2.151	2.126	1.976
	(0.069)	(0.084)	(0.081)	(0.076)
Cost Slope φ	769	752	720	377
	(261)	(284)	(258)	(125)
Proj Task Reduction $\tilde{\alpha}$	7.236	5.191	5.207	4.025
	(2.582)	(1.254)	(1.270)	(1.243)
Participant FE		X	X	X
Day FE			X	X
Prediction Soph.	X	X	X	X
Later Decisions				X
Observations	8049	8049	8049	5539
Participants	72	72	72	64
Log Likelihood	-28411	-25078	-24837	-16522
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.09	p= 0.08	p= 0.11	p= 0.33
$H_0(\widehat{\alpha}=0)$	p= 0.005	p<0.001	p<0.001	p= 0.001
$H_0(\widehat{\delta}=1)$	p= 0.38	p= 0.01	p= 0.07	p= 0.08

Note: This table replicates the main table, but consistently assumes that participants use prediction-accuracy payments for commitment. Standard errors are clustered at the participant level.

Table A15: Robustness: differing location of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Present Bias β	0.810	0.907	0.817	0.865	0.813	0.851
	(0.045)	(0.052)	(0.041)	(0.047)	(0.043)	(0.043)
Naive Pres. Bias β_h	1.013	1.005	1.010	1.007	1.009	0.997
	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.009)
Discount Factor δ	1.005	0.996	1.004	0.999	1.003	1.000
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Cost Curvature γ	2.239	2.162	2.135	2.235	2.231	2.266
	(0.099)	(0.083)	(0.084)	(0.098)	(0.099)	(0.095)
Cost Slope φ	873	930	702	954	852	11668
	(369)	(355)	(265)	(408)	(360)	(14316)
Proj Bias $\tilde{\alpha}$	5.910	5.754	4.777	5.720	5.384	6.538
	(1.381)	(1.313)	(1.282)	(1.418)	(1.409)	(1.423)
γ Participant FE	X			X	X	X
φ Participant FE		X	X			
γ Day FE			X		X	X
φ Day FE		X		X		X
Observations	8049	8049	8049	8049	8049	8049
Participants	72	72	72	72	72	72
Log Likelihood	-25161	-24948	-25048	-25116	-25129	-24848
$H_0(\hat{\beta}=1)$	$p<0.001$	$p=0.073$	$p<0.001$	$p=0.004$	$p<0.001$	$p<0.001$
$H_0(\widehat{\beta_h}=1)$	$p=0.30$	$p=0.66$	$p=0.38$	$p=0.58$	$p=0.47$	$p=0.76$
$H_0(\widehat{\alpha}=0)$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$
$H_0(\widehat{\delta}=1)$	$p=0.03$	$p=0.12$	$p=0.04$	$p=0.65$	$p=0.10$	$p=0.99$

Note: In the main Table in the paper, we run two fixed-effects specifications. In this table, we display the results given a variety of different locations for the fixed effects. Standard errors are clustered at the participant level.

9.14 Date-of-Work Fixed Effects

In multiple specifications in the paper, we control for participant learning by including *date-of-decision* fixed effects on cost curve parameters. However, these fixed effects do not control for consistent changes in the cost curve for a given *date-of-work*. These changes might occur if participants shared a common event on the same participation date, such as a midterm on date four. Given that participants choose their own calendar dates for each of the final six "participation dates," this coordination would be unexpected. However, as a formal check, table A16 mirrors our main estimation Table, but includes date-of-work rather than date-of-decision fixed effects where appropriate. There is little effect on the estimates.

9.15 Location of Error Term

Throughout the paper, we assume that observed effort choices e are composed of predicted effort choice and an additive reduced-form normally-distributed error term ε. In this section, we show that our results are robust to different assumptions about the location and form of the error term. First, we calculate the likelihood functions given three alternative error specifications, and then we structurally estimate the relevant parameters given these specifications.

In our first alternative specification, we assume that the error term on effort choices is distributed log-normally, rather than normally. In this case:

$$L(e_j) = \phi_{LN}\left(\frac{(\varphi \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w)^{\frac{1}{\gamma-1}} - e_j}{\sigma}\right),$$

where $\phi_{LN}(\cdot)$ is the log-normal probability distribution function. In our second alternative specification, we assume that there is a normally-distributed error which occurs on the parameter γ. In this case, observed effort would be equal to:

$$e = (\varphi \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w)^{\frac{1}{\gamma+\varepsilon_\gamma-1}} - 10, \tag{23}$$

with ε_γ distributed normally with mean zero and standard deviation σ_γ. Given this,

$$\frac{\ln(\varphi \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w) + \ln(e+10)}{\ln(e+10)} \sim N(\gamma, \sigma_\gamma^2), \tag{24}$$

which leads the likelihood of observation i to become:

$$L(e_j) = \phi\left(\frac{\frac{\ln(\varphi \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w) + \ln(e_j+10)}{\ln(e_j+10)} - \gamma}{\sigma_\gamma}\right). \tag{25}$$

Table A16: Robustness: Using date-of-work rather than date-of-decision fixed effects

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.835	0.812	0.805	0.815	0.800
	(0.038)	(0.042)	(0.038)	(0.044)	(0.040)
Naive Pres. Bias β_h	0.999	1.014	1.003	1.007	1.002
	(0.011)	(0.011)	(0.011)	(0.009)	(0.003)
Discount Factor δ	1.003	1.005	1.010	1.004	1.010
	(0.003)	(0.002)	(0.008)	(0.005)	(0.008)
Cost Curvature γ	2.145	2.142	2.116	1.967	2.120
	(0.070)	(0.084)	(0.079)	(0.074)	(0.078)
Cost Slope φ	724	710	576	361	589
	(251)	(268)	(227)	(120)	(231)
Proj Task Reduction $\tilde{\alpha}$	7.302	5.257	4.700	3.857	4.682
	(2.597)	(1.278)	(1.237)	(1.326)	(1.223)
Participant FE		X	X	X	X
Work Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	8049	8049	8049	5539	8049
Participants	72	72	72	64	72
Log Likelihood	-28412	-25079	-24937	-16545	-24936
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.93	p= 0.23	p= 0.77	p= 0.42	p= 0.42
$H_0(\widehat{\alpha}=0)$	p= 0.005	p<0.001	p<0.001	p= 0.004	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.37	p= 0.01	p= 0.20	p= 0.47	p= 0.20

Note: This table replicates Table 1, but uses work-date rather than participation-date fixed effects in Columns (3)-(5). Standard errors are clustered at the participant level.

In our third alternative specification, we assume that there is a log-normally-distributed error which occurs on the parameter φ. In this case, observed effort would equal to:

$$e = ((\varphi + \varepsilon_{\varphi}) \cdot \beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w)^{\frac{1}{\gamma-1}} - 10, \tag{26}$$

with ε_{φ} distributed log-normally with mean zero and standard deviation σ_{φ}.[72] Given this,

$$\frac{(e+10)^{\gamma-1}}{\beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w} \sim LogN(\varphi, \sigma_{\varphi}^2), \tag{27}$$

which leads the likelihood of observation i to become:

$$L(e_j) = \phi_{LN}\left(\frac{\frac{(e_j+10)^{\gamma-1}}{\beta^{\mathbf{1}(k=t)} \cdot \beta_h^{\mathbf{1}(p=1)} \cdot \delta^{(T-k)} \cdot w} - \varphi}{\sigma_{\varphi}}\right). \tag{28}$$

Replicating our main results given these three different specifications are presented in Tables A17,A18, and A19, respectively. Comparison of the columns suggests that the location of the error term does not have a large effect on any of the coefficients, although the β parameter in the Table A19 is higher than in our main table (but still statistically significantly different from 1).

9.16 Effect of Tobit Estimation

In the estimations of the paper, we account for the censored nature of the data by correcting the likelihood function following a standard Tobit specification. Table A20 presents the results without using a Tobit, using a likelihood of Equation (9) rather than Equation (10). The main parameters are largely stable (with β slightly higher in the later specifications) and the main conclusions continue to hold. The cost-curvature and slope parameters do increase, presumably to account for the fact that participants' tasks decisions level out at 100 tasks, regardless of wage.

9.17 Endogeneity of Participation-Date Choice

Recall that we allowed participants to choose their own dates, with the restriction that each participation date was within 4 to ten days of the previous date and the final date occurred

[72] It is possible to write down a model with a normally-distributed error term on φ, but this assumption is hard to rationalize with the observed data. In particular, there are many instances in the data where a person chooses to a large amount of work (for example, 100 tasks) for a very low wage (like \$.01). Rationalizing these data points requires an extremely high φ parameter that is hard to justify given a normally-distributed error on the ϕ parameter. As a result, estimations with this form do not converge.

Table A17: Robustness: error on the log of effort

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.806	0.766	0.816	0.823
	(0.040)	(0.039)	(0.038)	(0.038)
Naive Pres. Bias β_h	1.000	1.008	1.003	1.008
	(0.013)	(0.012)	(0.011)	(0.010)
Discount Factor δ	1.004	1.011	1.005	1.003
	(0.003)	(0.002)	(0.002)	(0.002)
Cost Curvature γ	1.662	1.657	1.658	1.573
	(0.051)	(0.067)	(0.066)	(0.063)
Cost Slope φ	73	72	81	60
	(16)	(18)	(21)	(15)
Proj Task Reduction $\tilde{\alpha}$	3.187	3.042	3.076	2.442
	(1.048)	(0.733)	(0.746)	(0.761)
Participant FE	X	X	X	X
Day FE			X	X
Prediction Soph.				
Later Decisions				X
Observations	8049	8049	8049	5539
Participants	72	72	72	64
Log Likelihood	-9437	-6919	-6784	-4586
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 1.00	p= 0.49	p= 0.76	p= 0.44
$H_0(\widehat{\alpha}=0)$	p= 0.002	p<0.001	p<0.001	p= 0.001
$H_0(\widehat{\delta}=1)$	p= 0.22	p= 0.00	p= 0.00	p= 0.08

Note: Main estimation with the first alternative error specification discussed in the paper, with a normal error on the log of effort. Standard errors are clustered at the participant level.

Table A18: Robustness: error on parameter gamma

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.816	0.753	0.888	0.863
	(0.029)	(0.031)	(0.046)	(0.053)
Naive Pres. Bias β_h	0.994	1.006	0.999	1.009
	(0.020)	(0.021)	(0.021)	(0.025)
Discount Factor δ	1.006	1.016	1.001	1.001
	(0.003)	(0.002)	(0.002)	(0.003)
Cost Curvature γ	2.420	2.673	2.711	2.757
	(0.054)	(0.046)	(0.046)	(0.057)
Cost Slope φ	1481	3511	5530	6370
	(336)	(647)	(1027)	(1429)
Proj Task Reduction $\tilde{\alpha}$	3.367	2.209	2.602	2.227
	(0.961)	(0.587)	(0.625)	(0.587)
Participant FE		X	X	X
Day FE			X	X
Prediction Soph.				
Later Decisions				X
Observations	8049	8049	8049	5539
Participants	72	72	72	64
Log Likelihood	-666	908	1069	654
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p= 0.015	p= 0.009
$H_0(\widehat{\beta_h}=1)$	p= 0.77	p= 0.79	p= 0.95	p= 0.72
$H_0(\widehat{\alpha}=0)$	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.08	p= 0.00	p= 0.74	p= 0.71

Note: Main estimation with the first alternative error specification discussed in the paper, with a normal error on the parameter γ. Standard errors are clustered at the participant level.

Table A19: Robustness: error on parameter phi

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions
Present Bias β	0.909	0.819	0.935	0.918
	(0.028)	(0.027)	(0.033)	(0.037)
Naive Pres. Bias β_h	1.007	1.009	1.002	1.015
	(0.016)	(0.016)	(0.015)	(0.019)
Discount Factor δ	1.004	1.013	1.001	1.000
	(0.003)	(0.002)	(0.002)	(0.002)
Cost Curvature γ	2.155	2.472	2.513	2.543
	(0.068)	(0.051)	(0.050)	(0.057)
Cost Slope φ	518	1629	2483	2771
	(158)	(351)	(516)	(663)
Proj Task Reduction $\tilde{\alpha}$	2.897	0.919	0.426	0.570
	(1.252)	(0.677)	(0.659)	(0.611)
Participant FE		X	X	X
Day FE			X	X
Prediction Soph.				
Later Decisions				X
Observations	8049	8049	8049	5539
Participants	72	72	72	64
Log Likelihood	-6501	-4960	-4816	-3178
$H_0(\hat{\beta}=1)$	p= 0.001	p<0.001	p= 0.049	p= 0.026
$H_0(\widehat{\beta_h}=1)$	p= 0.66	p= 0.57	p= 0.88	p= 0.44
$H_0(\widehat{\alpha}=0)$	p= 0.021	p= 0.174	p= 0.518	p= 0.351
$H_0(\widehat{\delta}=1)$	p= 0.17	p= 0.00	p= 0.65	p= 0.98

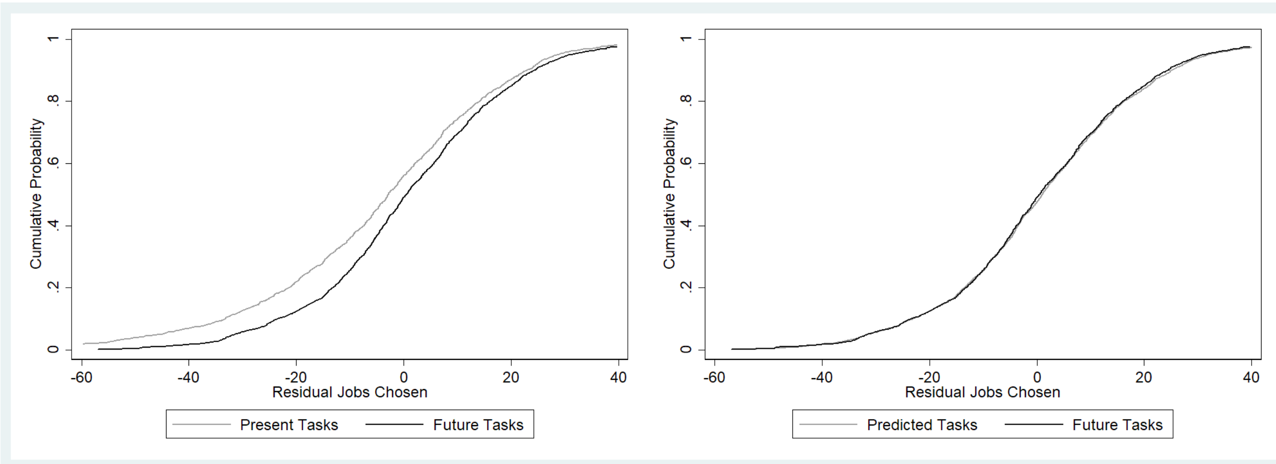
Note: Main estimation with the first alternative error specification discussed in the paper, with a normal error on the parameter φ. Standard errors are clustered at the participant level.

Table A20: Robustness: primary aggregate estimation without using a Tobit correction

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.826	0.836	0.888	0.887	0.883
	(0.038)	(0.032)	(0.030)	(0.033)	(0.030)
Naive Pres. Bias β_h	1.000	1.013	1.006	1.011	1.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.001)
Discount Factor δ	1.003	1.007	1.001	1.000	1.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Cost Curvature γ	2.606	2.713	2.697	2.589	2.701
	(0.095)	(0.120)	(0.115)	(0.106)	(0.116)
Cost Slope φ	4552	6693	7039	4368	7208
	(2074)	(3513)	(3591)	(2067)	(3697)
Proj Task Reduction $\tilde{\alpha}$	2.721	2.548	2.998	2.338	2.996
	(1.617)	(0.701)	(0.732)	(0.744)	(0.734)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	8049	8049	8049	5539	8049
Participants	72	72	72	64	72
Log Likelihood	-38549	-35309	-35044	-23899	-35044
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.99	p= 0.25	p= 0.59	p= 0.30	p= 0.43
$H_0(\widehat{\alpha}=0)$	p= 0.092	p<0.001	p<0.001	p= 0.002	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.32	p= 0.00	p= 0.21	p= 0.79	p= 0.24

Note: This table replicates Table 1, but without using a Tobit correction for the censored nature of the data Standard errors are clustered at the participant level.

Figure A11: Cumulative distribution: Present vs. future decisions (left) and predictions vs. future decisions (right)



Note: These graphs display the cumulative density for different types of decisions of the residuals of a regression of jobs chosen on wage and participant fixed effects. Left graph: Comparison between residuals from decisions about work in the future and decisions made about work in the present given different wages. Right graph: Comparison between residuals from decisions about work in the future and predictions made about work in the future given different wages.

within six weeks of the start of the experiment. This flexibility was designed to allow participants to avoid dates with previous commitments, such as classes, exams, or social events. However, this endogeneity could potentially bias our results: for example, if participants with high exponential discount factors ($\delta = 1$) choose their dates in close succession, while those with lower discount factors choose to space their dates as far as possible, our estimate of δ might be potentially biased, which could in turn bias our other estimates. Table A21 replicates our main results with the distance between each payment date forced to match the average distance between payment dates across all participants. There is very little quantitative change between the results in this table and that in the paper.

9.18 Distribution of Decisions

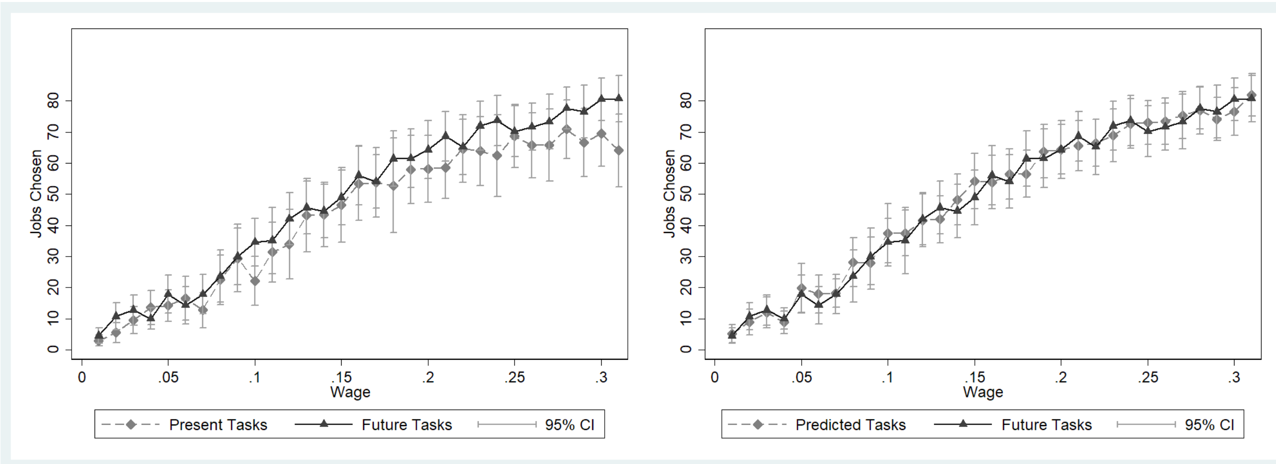
Figure 2 shows the average task decisions given different wages for work decisions and predictions. To demonstrate the distribution of different types of decisions, Figure A11 presents the cumulative densities of the residuals of a regression of task decisions on participant and wage fixed effects. The left panel suggests that the distribution of decisions made about future work first-order stochatiscally dominates the distribution from present work. The right panel shows almost no difference between the distributions derived from future work and predictions.

Table A21: Robustness: primary aggregate estimation using average participation date choice

	(1) Initial Estimation	(2) Participant FE	(3) Decision Day FE	(4) Later Decisions	(5) Pred. Soph.
Present Bias β	0.820	0.808	0.825	0.833	0.817
	(0.040)	(0.043)	(0.042)	(0.044)	(0.043)
Naive Pres. Bias β_h	1.000	1.013	1.005	1.003	1.004
	(0.011)	(0.012)	(0.010)	(0.009)	(0.003)
Discount Factor δ	1.005	1.006	1.004	1.003	1.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cost Curvature γ	2.154	2.145	2.117	1.971	2.125
	(0.072)	(0.084)	(0.081)	(0.075)	(0.081)
Cost Slope φ	710	710	676	367	708
	(244)	(265)	(237)	(120)	(252)
Proj Bias α	7.646	5.384	5.277	4.080	5.214
	(2.610)	(1.293)	(1.287)	(1.277)	(1.266)
Participant FE		X	X	X	X
Day FE			X	X	X
Prediction Soph.					X
Later Decisions				X	
Observations	8049	8049	8049	5539	8049
Participants	72	72	72	64	72
Log Likelihood	-28396	-25070	-24837	-16523	-24836
$H_0(\hat{\beta}=1)$	p<0.001	p<0.001	p<0.001	p<0.001	p<0.001
$H_0(\widehat{\beta_h}=1)$	p= 0.97	p= 0.26	p= 0.59	p= 0.77	p= 0.11
$H_0(\widehat{\alpha}=0)$	p= 0.003	p<0.001	p<0.001	p= 0.001	p<0.001
$H_0(\widehat{\delta}=1)$	p= 0.01	p= 0.01	p= 0.03	p= 0.11	p= 0.03

Note: This table replicates our main results but with the distance between each payment dates forced to match the average distance between payment dates across all participants. Standard errors are clustered at the participant level.

Figure A12: Present vs. future decisions (left) and predictions vs. future decisions (right)



Note: Left graph: Comparison between decisions make about work in the future and decisions made about work in the present given different wages. The difference is a reduced-form measure of present bias. Right graph: Comparison between decisions make about work in the future and predictions made about work in the future given different wages. The difference is a reduced-form measure of sophistication about present bias. Standard errors bars are clustered at the individual level.

9.19 Main Non-Parametric Graph with No Wage Bins

In the paper, we present results with wages combined into ten categories for visual ease. Figure A12 shows the same graph without the wage bin allocation. Not surprisingly, the graph is noisier, although the same qualitative features continue to hold.

9.20 Experimental Instructions

Welcome:

Thank you for participating in the study. We will begin shortly.

Eligibility for this study:

To continue in this study, you need to meet these criteria: You must be willing to participate for seven (7) separate days over the next six weeks. Each participation day will require at least 20 minutes of your time. You can choose participate for additional time each day to receive supplementary payments. The first day (today) will occur in the xlab. All other days will occur at any computer that has access to the Internet.

You must be willing to receive your payment from this study as one single payment by check at the end of the study. Payments will be made seven weeks from today, on December 7th, 2012. You will return to the xlab to receive this payment.

If you do not meet these criteria, please inform us of this now.

Informed Consent

Placed in front of you is an informed consent form to protect your rights as a participant. Please read it. If you would like to choose not to participate in the study you are free to leave at this 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.

Anonymity

Your anonymity in this study is assured. Your name will never be recorded or connected to any decision you make here today. Your email will be collected solely in order to send reminder emails. After the study, your email information will be destroyed and will not be connected to your responses in the study.

Rules

Please turn your cell phones off. Please put away any books, papers, computers, etc. If you have a question at any point, just raise your hand. There will be a quiz once we have finished with the instructions. If it is clear that you do not understand the instructions when we review your answers, you will be emailed and removed from the study.

Your Earnings

You will be paid a one-time completion payment of $50 for completing the minimum requirements of the study. Furthermore, you will have the chance to earn a supplementary payment of between $2-$25/hour for further participation. You will also have the chance to earn additional bonuses.

It is very important for the study that you participate on your chosen participation days. Therefore, as we discuss below, you will be allowed to your modify a participation date if needed (up to 5pm the day before). You cannot modify participation dates after that point. Unfortunately, if you do not modify a date and you miss one of your participation dates, *you will forgo the $50 completion payment and will be immediately removed from the study* (you will receive any supplementary payments and additional payments you have already earned). There will be absolutely no exceptions to this rule, regardless of the reason.

All payments (completion, supplementary, bonus) will be made as one single payment by check at the end of the study, regardless of if you are removed from the study. All payments will be made seven weeks from today, on December 7th, 2012. You will return to the xlab to receive this payment.

Choosing Future Participation Days

As stated above, you will participate in the study for 7 days over the next 6 weeks. Today is your first participation day. Today, you will choose a set of 6 future participation dates that occur within the next 6 weeks. Participation dates must between 4 and ten days apart. That is, if you choose November 12th as you third participation date, your fourth participation date must lie between November 16th and November 22nd.

For future participation dates, you will be emailed an online study link the day before your participation date. This link will be active on 4am (Pacific Time) on the participation date. You simply click on the link and follow the instructions. You must complete the study for that day in one sitting *by midnight*. If you fail to complete the study for that day, you will be immediately removed from the study and will forgo the $50 completion payment.

You will have the ability to modify your participation dates over the course of the study if needed. For example, if chose November 12th as your third participation date, but later learn that you will have a test on that day, you can change the third participation date to November 14th. There is a small fee of $.25 each time you modify your participation dates. You may modify a participation date up to 5pm the day before the participation date. That is, if your third participation date is November 12th, then you can modify this date anytime up to 5pm on November 11th.

The Study

This study examines people's decisions about doing work for monetary payments. For the study, we have designed a task (discussed below) that you can choose to do for different wages. The task has no value to us beyond understanding these decisions.

We are interested in these work decisions at different points in time. For example, in the study, you might be asked on Monday how many tasks you want to do next Thursday for different wages. Then, when next Thursday arrives, you be asked how many tasks you want to do on that day for different wages. Note that the answers about work in the future may be the same or may be different than the eventual answers about work when the day arrives. You will actually have to do the tasks specified in one of the decisions, so it is in your interest to answer truthfully.

We are also interested in people's perceptions about their future work decisions. For example, in the study, you might be asked on Monday how many tasks *you think* you will want to do when you answer work questions next Thursday. That is, we want to know your prediction of your future answers. Note that these predictions may be the same or may be different than the answers about future work. You may be rewarded for accurate predictions, so it is in your interest to answer truthfully.

Greek Transcription Job

As we just discussed, we have designed a task involving transcribing a line of blurry letters from a greek text for this study.

We will now spend a few minutes practicing this job on the computer. Before we continue, you will be asked to register using your email by clicking "register" once you open the computer shortcut. Make sure that you enter a valid email address as this is the email we will use to contact you about future participation days.

In the task, Greek text will appear in a Transcription Box on your screen. For each letter you will need to find and select the corresponding letter and enter it into the Completion Box on your screen. *One task is one row of greek text.* For the task to be complete your accuracy must be 80% or better.

As part of the task, an auditory "beep" will sound randomly throughout the transcription process. Please put on your headphones so that you can hear the beeping noise. After you hear this beeping noise, you must press the "noise" button at the bottom left of the screen. If you do not press the "noise" button within five seconds of hearing the beeping noise, your transcription will be reset. If you press the noise button erronously (when there was no beeping noise), your transcription will be reset.

On average, people with some experience complete a task in about 52 seconds (about 70/hour).

Each day of participation, you will have to complete 10 *mandatory tasks* (10 lines of greek text). Furthermore, you will 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 choices in the study.

Participation Date: Timeline

Each participation date will involve a series of steps, which we will discuss now. The order of these steps might be different on different days. Today, we will complete only a subset of the following steps. In future participation dates, you will complete all of the following steps.

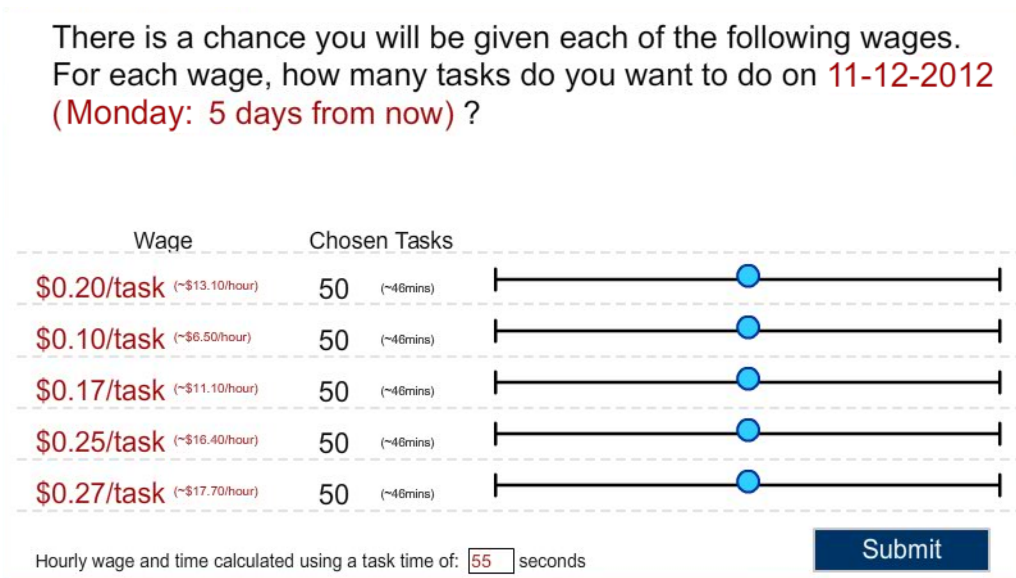
Completion of Mandatory Tasks

Recall that you are required to complete 10 mandatory tasks on each participation date. These mandatory tasks will ensure that you participate for at least 20 minutes for each participation date.

Question Type 1: Work Decisions

Recall that we are interested in people's decisions about doing work for monetary payments. Therefore, you will be asked a series of questions concerning your preference about completing additional supplementary tasks. Note that the supplementary tasks are in addition to the 10 mandatory tasks.

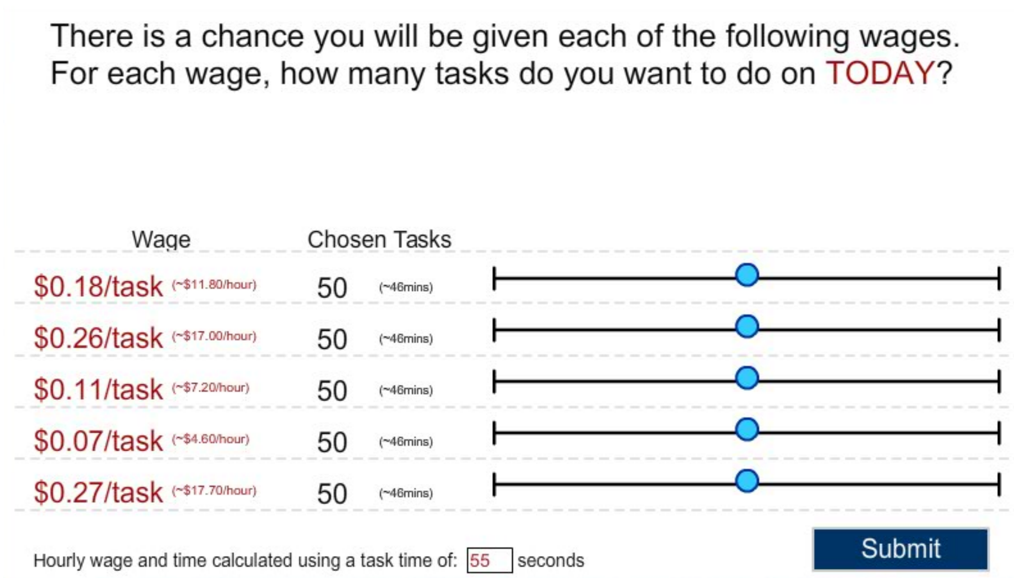
We are interested in these work decisions at different points in time. Therefore, you will be asked questions about how many tasks you want to do in the future as well as questions about how many tasks you want to do today. For example, you might see the following screen on the computer:



In this screen, you are asked to choose the number of tasks that you want to complete on November 12th, 2012 for five different wages. For example, on the first line, you are asked the number of tasks you would like to complete for $.20/task. You will use the slider bar to choose a number between 0 and 100. You will also do this for the other 4 wages.

As another example, you might see the following screen on the computer:

In this screen, you are asked to choose the number of supplementary tasks that you want to complete today. For example, on the first line, you are asked the number of tasks you would like to complete for $.18/task. You will use the slider bar to choose a number between 0 and 100. You will also do this for the other 4 wages.



The hourly wage estimates and time-to-completion estimates have been calculated using a task time of 55 seconds. Notice that the box in the bottom of the screen allows you to enter a different task time if you want a different estimate of the hourly wage and time-to-completion.

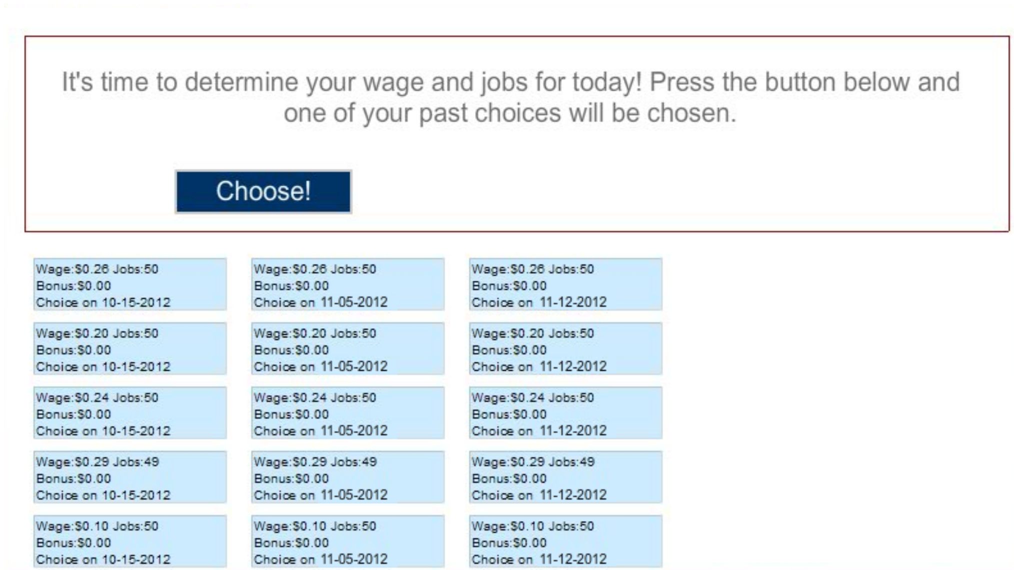
The wages in each question have been chosen at random from a set of wages from $.01/task to $.31/task. Your decisions cannot in any way affect the choice of future wages—**the wages for this study have already been randomly chosen by a random number generator.**

Each one of these decisions could be randomly chosen as the **decision-that-counts** (the process for choosing that decision-that-counts is discussed below). If a decision is chosen as the decision-that-counts, you must complete that amount of supplementary tasks for the supplementary wage. Therefore, **it is in your own interest to answer honestly about your work preferences**, because you might actually have to complete the work you specify for the given wage. For example, if given a wage of $.12/task, you would like to do 50 tasks (and make an extra $6.00), you should answer "50."

Recall that you can modify participation dates. If you modify a date, then the decisions about that date will be transfered to the new date. For example, if your third decision date is November 12th and you change it to November 14th, all of the decisions you made about November 12th will then have the potential to be chosen as the decision-that-counts on November 14th.

Random Selection of the "Decision-That-Counts"

You will be asked questions about how many tasks you want to do in the future and how many tasks you want to do on that day. Therefore, when a given participation date arrives, you will have answered many questions about work on that date. We will collect all of those decisions and randomly choose **one** as the decision-that-counts. This is the screen that collects all of the past decisions:



When you press the “choose” button, one of these decisions will be randomly chosen as the decision-that-counts. The decision-that-counts **has already been chosen by a random number generator in the computer**. You cannot affect how the decision-that-counts is chosen with your choices.

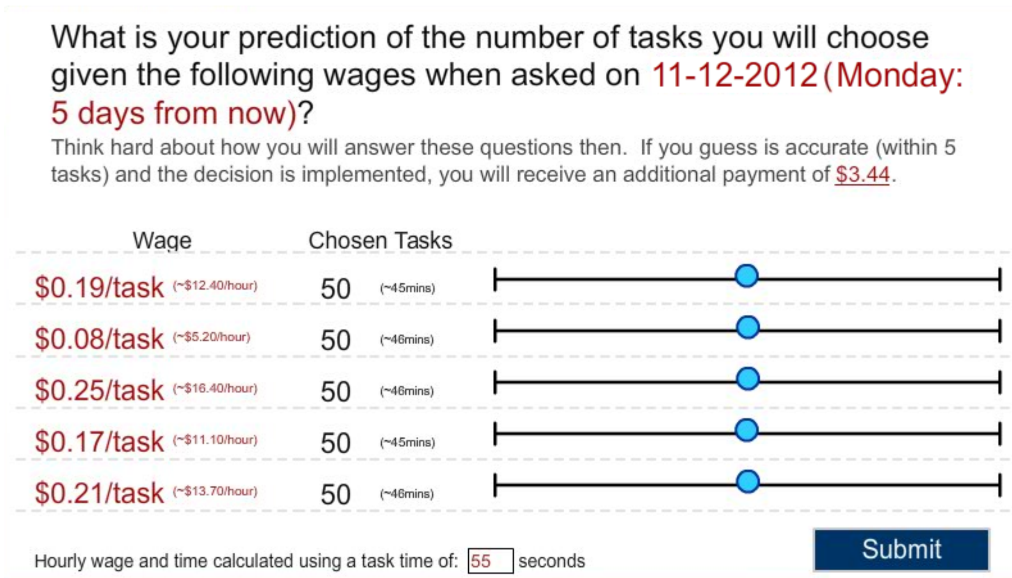
Completion of Supplementary Work

Once the decision-that-counts is chosen, you must complete the amount of supplementary tasks you chose for the wage in the decision-that-counts. For example, if you answered “40” to the question: *“For \$.18/task, how many tasks do you want to complete TODAY?”,* and this decision is chosen as the decision-that-counts, you would complete 40 supplementary tasks and make a supplementary payment of 40·\$.18=\$7.20.

Question Type 2: Predictions

Recall that we are also interested in people’s perceptions about their future work decisions. Therefore, you will be asked a series of questions concerning your predictions about how many tasks *you think* you will want to do when you answer work questions in the future. For example, you might see the following screen on the computer:

The first line asks for your prediction of your own answer on November 12th to a question about the number of tasks you want to complete for a wage of \$.19. For example, if you predict that you would answer 62 to this question on November 12th, you should answer “62.” Furthermore, the question gives a bonus amount if your answer is within 5 tasks of your



eventual answer on that day (in the example above, it is $3.44). Again, the wage and bonus **have already been chosen by a random number generator** and you cannot affect this choice with your decisions.

On November 12th, when you are in the step of the study that asks questions of type 1, there is some chance that the computer will ask you the set of questions you made a prediction about, such as "*For $.19/task, how many tasks do you want to complete today?"*. If this occurs, you will be reminded about your previous predictions about your own answers (for example, "62") and be reminded about the bonus if you answer within 5 tasks of this amount. If you answer such that your previous prediction is accurate (for example, you choose a number between 57-67) and this decision is chosen as the decision-that-counts, you will receive the bonus. If you do not answer such that the previous prediction is correct (for example, you choose "10") or this decision is not chosen as the decision-that-counts, you will not receive any bonus.

As there is a chance that the question you are making predictions about will be asked and chosen as the decision-that-counts, **it is in your interest to make your predictions as accurate as possible.**

Recap:

- This is a study about work decisions. We are interested in *decisions* about work for different wages at different points in time. We are also interested in *predictions* about future decisions.

- The study requires participation for seven days over the next six weeks. Today is the first participation date.

- You will choose your participation dates today. They can be modified in the future for a small fee. You cannot modify a date after 5pm the day before.
- You will be paid a one-time-completion payment of $50 for completing the minimum requirements of the study on each day. Furthermore, you will have the chance to earn anywhere from $2-$25/hour for further participation and the chance to earn additional bonuses. You will return to the xlab on December 7th to receive your payment by check.
- If you choose to no longer participate, or do not complete the jobs you chose, you will forgo the completion payment of $50 and be removed from the study. You will return to the xlab on December 7th to receive your payment by check.
- You will be asked to complete tasks involving transcription of greek letters.
- Each week, you will be asked to complete a minimum requirement of tasks.
- Each week, you will be asked questions about how many supplementary tasks you would like to complete for different wages on different days.
- Each week, one of the decisions you make about supplementary work will be randomly chosen as the decision-that-counts and you will complete your chosen supplementary number of tasks for the chosen supplementary wage.
- Each week, you will make predictions about your future answers to questions about supplementary tasks given different wages. If the question you make a prediction about is chosen as the decision-that-counts and your prediction is accurate, you will receive a bonus payment.
- On December 7th, you will receive a payment consisting of your completion payment of $50, plus any supplementary earnings you made during the study, plus any bonuses made during the study. You will return to the xlab to receive your payment by check.

Consent

Now that we have explained the study, you are free to leave if you would like to choose not to participate in the study. Otherwise, please sign the consent form and we will pick these up now.

Choosing Dates

Please choose 6 future participation dates using the calendar on the computer. Once you choose a date today, it cannot be amended until tomorrow. Recall that participation dates must between 4 and 10 days apart. You will have the ability to modify these dates over the course of the study for a fee of $.25. You may modify a participation date up to 5pm the day before the participation date.

Mandatory Work

Now you will complete your minimum work of 10 tasks for the first participation date. When this is completed, please fill out the quiz at your table.

Quiz

Once you have completed the minimum work, you may answer the questions on the quiz. You are free to consult these instructions when answering questions. Recall that if your answers suggest that you do not understand the study, you will be emailed and removed from the study. Please sit quietly once the quiz has been completed.

Question Type 1: Work Decisions

You will answer questions about your preferences about work on your second participation date. On the screen, you see five different wages, with five different sliders. For each wage, choose the number of tasks that you want to do on that date.

Once you are done, you will answer questions about your preferences about work today. On the screen, you see five different wages, with five different sliders. For each wage, choose the number of tasks that you want to do today. Because we do not have time today to complete the tasks, you will not have to complete these tasks. These questions are used solely for you to get practice with the computer interface. This is the only set of practice questions in the entire study.

Please stop when you have finished these decisions.

Question Type 2: Predictions

You will now answer a set of five questions about *your predictions* about work decisions on the third participation date. On the screen, you see five different wages, with five different sliders. For each wage, choose the number of tasks that you predict you will want to do when you answer questions on your third participation date.

Random Selection of the "Decision-That-Counts"

The decision-that-counts will now be chosen. You have made five decisions about work today. These decisions have been collected and one will be chosen randomly. Press "choose" to randomly choose the decision-that-counts.

Completion of Supplementary Work

On a normal day of the study, you would now have to complete the supplementary work chosen in the decision-that-counts. As we do not have time today, you do not have to complete these tasks. The computer has been set to require only one task. Please complete it now. On future days, you will have to do the number of tasks chosen in the decision-that-counts for the wage chosen.

Future Participation Dates

You will receive an email the night before each participation date. This email contains a personalized link to access the study. You will also receive a reminder email the night of each participation date. If you have any questions, please email: experiment@haas.berkeley.edu.

Feel free to take these instructions for future reference. This concludes today's portion of the experiment.

Quiz

Please complete the quiz in order to make sure that you understand the study.

Participant #: ____

Session Date and Time: ____________

1. Including today, how many participation dates are required in the study?
2. How many mandatory tasks are you required to participate on each participation date?
3. When can you modify participation dates? What is the fee for modification?
4. You will make many decisions about how many tasks you want to do on a date. Only one of the decisions will be chosen as the decision-that-counts. How is this decision chosen?
5. You will be paid a bonus if your prediction for a given wage is within ____ tasks of your eventual decision
6. True / False: The wages and decisions-that-count are chosen randomly. There is no way that you can affect the random choice with your decisions.