Appendices

Online - Not for publication

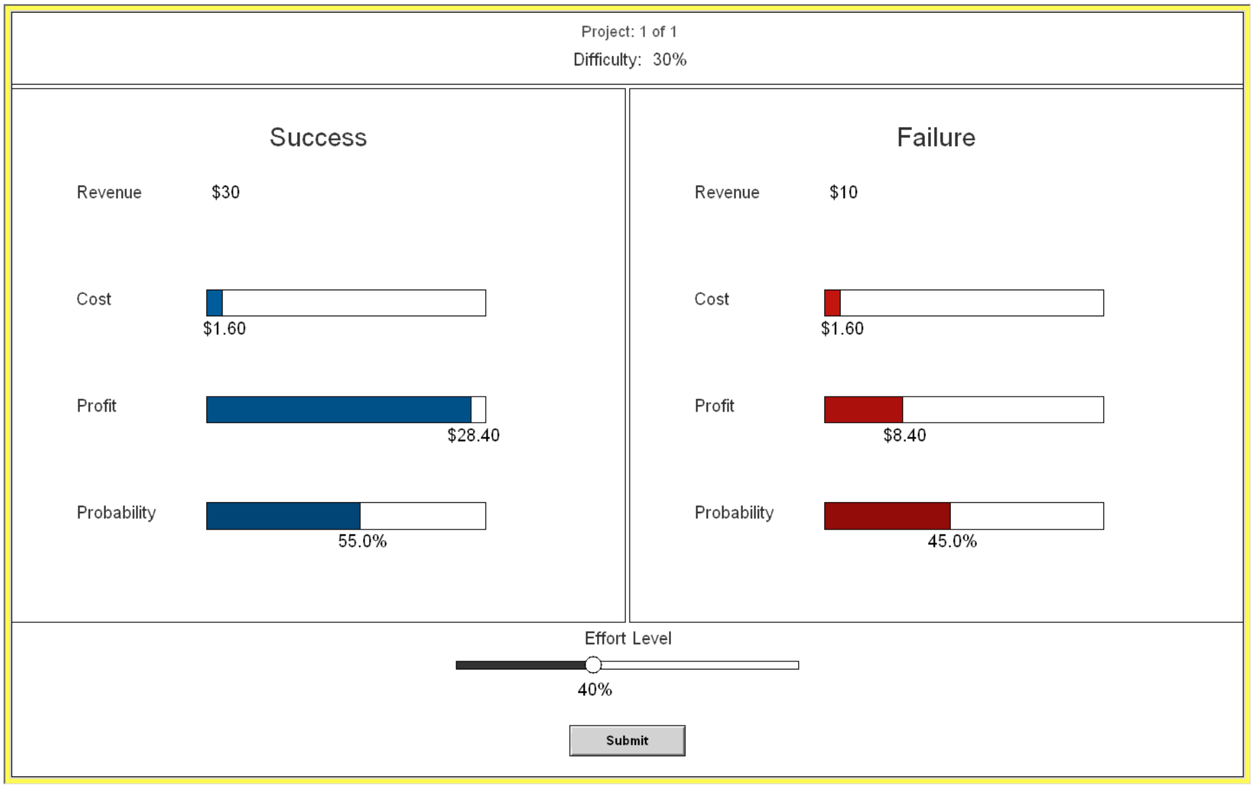
A Design of the Effort Task

Table A.1: Summary of Treatments

id	θ	w	z	k	5/21/15	5/28/15	6/2/15	6/3/15	6/4/15	6/5/15	$\bar{a}$
1	0	1	2	1	1	1	1	1	1	1	0.59
2	0	1	4	1	1	1	1	1	1	1	0.66
3	0	2	2	1	1	1	1	1	1	1	0.57
4	0	2	2	2	1	1	1	1	1	1	0.39
5	0	2	4	1	1	1	1	1	1	1	0.65
6	0	2	4	2	1	1	1	1	1	1	0.57
7	0.25	1	2	1	1	1	1	0	0	0	0.61
8	0.25	2	2	1	0	0	0	1	1	1	0.7
9	0.25	2	2	2	0	0	1	0	0	0	0.55
10	0.25	2	4	1	0	0	0	1	1	1	0.68
11	0.5	1	2	1	1	1	1	0	0	0	0.64
12	0.5	2	2	1	0	0	1	1	1	1	0.59
13	0.5	2	2	2	0	0	1	0	0	0	0.6
14	0.5	2	4	1	0	0	0	1	1	1	0.75
15	0.75	1	2	1	1	1	0	0	0	0	0.54
16	0.75	2	2	1	0	0	1	1	1	1	0.57
17	0.75	2	2	2	0	0	1	0	0	0	0.56
18	0.75	2	4	1	0	0	0	1	1	1	0.71
19	1	1	2	1	1	1	1	1	1	1	0.45
20	1	1	4	1	1	1	1	1	1	1	0.62
21	1	2	2	1	1	1	1	1	1	1	0.46
22	1	2	2	2	1	1	1	1	1	1	0.41
23	1	2	4	1	1	1	1	1	1	1	0.7
24	1	2	4	2	1	1	1	1	1	1	0.59

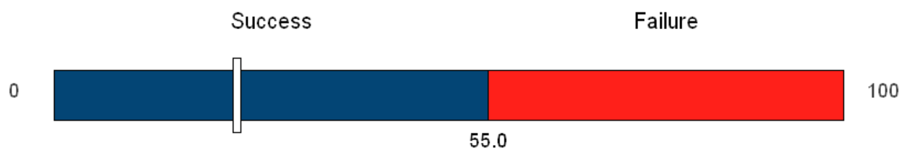
Note: The first column is an id of a treatment. The next four columns show the values of the treatment variables for that treatment. The next six columns correspond to the six sessions and indicate whether a treatment was (1) or was not (0) used in a session. The last column shows the mean effort level for a treatment across all sessions.

Figure A.1: Choice Screen for the Effort Task



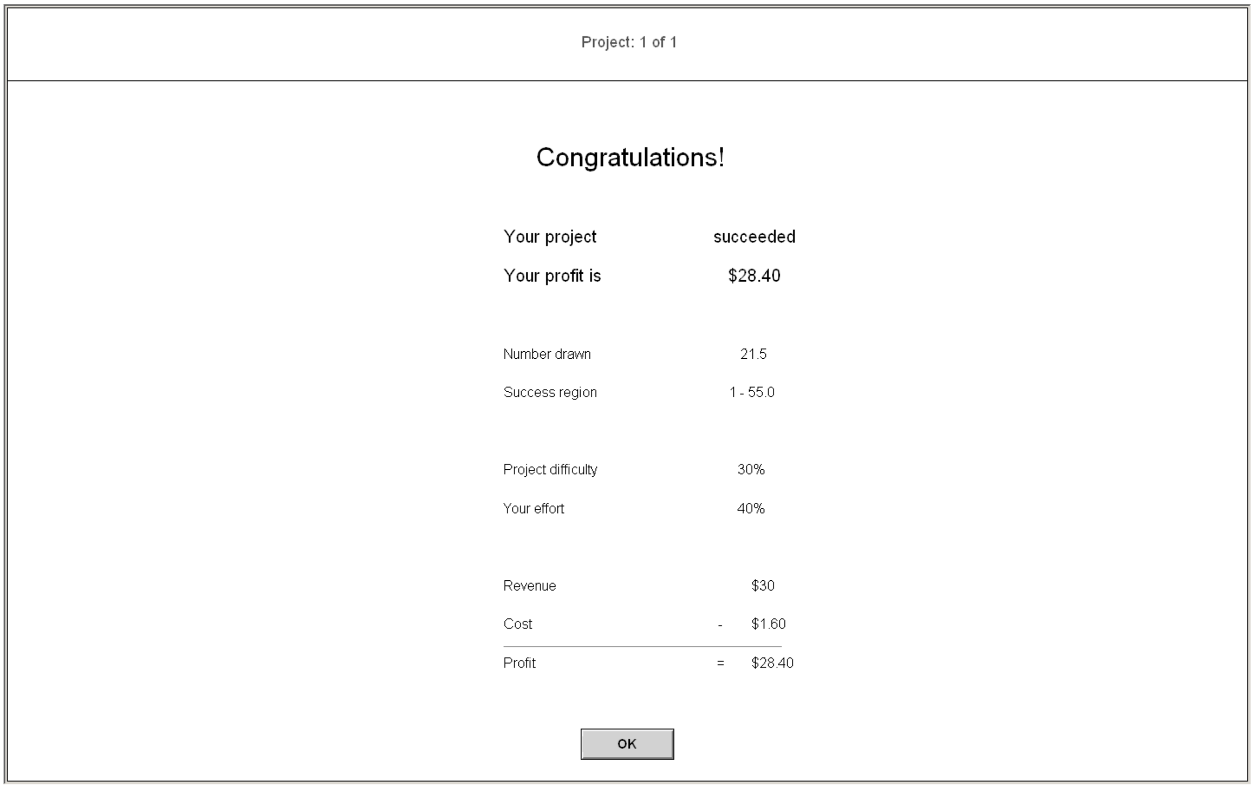
Note: The figure shows the graphical interface of the decision screen. The top of the screen showed the current round and a current project's difficulty. The middle of the screen was split into the Success and Failure regions that showed the corresponding values of revenue, cost, profit, and probability for each outcome. Subjects could choose their effort level by dragging a slider at the bottom of the screen. The slider could take one of 101 positions from a set $\{0, 1, 2, \ldots, 100\}$%. Subjects could observe how the values of probabilities, costs, and profits were changing as they experimented with the effort level. These variables were represented both numerically and graphically as colored bars.

Figure A.2: Project Outcome



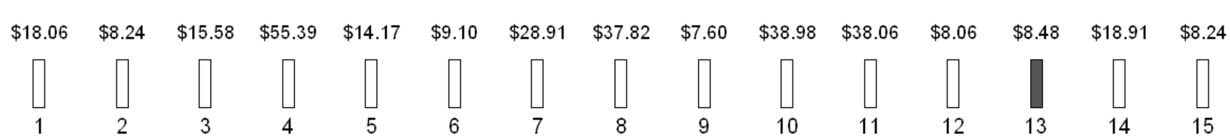
Note: The figure shows the graphical representation of a project's outcome. An outcome screen featured a bar with the success and failure regions, which corresponded to the success and failure probabilities determined by a subject's choice of effort. Along this horizontal bar, a white slider was moving quickly. The slider's position at each fraction of a second was determined by a draw from a uniform random distribution. After three seconds, the needle stopped either in the success or failure region, which determined whether the project succeeded or failed.

Figure A.3: Project Summary



Note: The figure shows a summary screen. The screen presented the outcome of a project and the realized profit, along with the details on the random draw, the characteristics of a project, realized revenue and cost.

Figure A.4: Payoff for the Effort Task



Note: The figure shows the final screen that determined the payoff for the effort task. The screen showed all the past rounds and profits made in those rounds. Every fraction of a second a random bar was highlighted, and after three seconds the highlighting stopped, which determined the payoff for the effort task.

B Subject Instructions

Introduction

Welcome and thank you for participating! This is an experiment in individual economic decision-making. Please, mute/turn off all of your electronic devices for the duration of the experiment.

Payment

Your total payment will consist of a participation payment of $5 and the sum of the payments from the two decision tasks. Your payment can be considerable and will depend on your decisions and chance. You will be paid in cash privately at the end of the session.

Time

Today's session will consist of a quiz on probabilities, two decision tasks and a demographic survey.[B.1] The session will take up no more than 2 hours.

Payment Protocol

Each of the 2 decision tasks will have several rounds. At the end of each task we will randomly select one of the decision rounds to determine your payment. It is worthwhile to think carefully about each decision, since you don't know which decision round will be picked.

Privacy

You will not interact with other participants. Please, do not reveal your identity to anyone. You must not talk to other participants during the experiment.

Final Notes

Please read these instructions carefully. You are welcome to ask questions at any point. Just raise your hand and we will answer your question in private.

Task 1

In this task you will choose an effort level for a project (Figure 1). A project has two possible outcomes: success or failure. In case of success the project will yield you a high revenue (i.e., payoff), in case of failure it will yield you a low revenue. The exact values of high and low revenues will be shown on the screen. The task is to select the level of effort you prefer the most. There are no right or wrong answers, just pick whatever suits you the most.

Effort

By choosing a higher effort level you increase the chances that the project will be successful. Equivalently it means that the chances of failure are reduced, because the probability of success and failure must add up to 100%. Effort is costly to you: the higher is the effort level, the higher

[B.1] In each session subjects also participated in a supplementary incentivized risk elicitation task, the results of which are not reported here.

is the cost. The cost will be subtracted from the revenue of the project. On the screen you can observe how chances of success/failure, cost of effort and the profit (=revenue minus cost) change as you change the effort level.

Example

On the Figure 1 you can see a project that gives you a revenue of $30 if it's successful and $10 if it fails. Suppose you chose an effort level of 40%, which leads to a 55% probability of success (45% probability of failure) and costs you $1.60. In case of success your profit will be: $30 (revenue) - $1.60 (cost of effort) = $28.40 (profit). If the project fails your profit will be: $10 (revenue) - $1.60 (cost of effort) = $8.40 (profit). Note that you bear the cost of effort regardless of whether the project succeeds or fails.

Each additional unit of effort will increase the probability of success by the same amount but will cost you more than the previous one.

Example

Increasing effort from 0% to 1%, or from 1% to 2%, or from 2% to 3% (and so on) increases the probability of success by the same amount. Increasing effort from 99% to 100% costs more than an increase from 98% to 99%, which in turn costs more than an increase from 97% to 98% (and so on).

Difficulty

Another important characteristic of the project is its difficulty. Difficulty affects the chances of success, just like effort, but in the opposite way. A more difficult project is less likely to succeed than an easier one, for any given level of your effort. The difficulty of the project will appear on the top of the choice screen.

Example

In the previous example, suppose the difficulty was 30%. Now imagine that the project's difficulty increased to 70%. Given the same effort level as before, 40%, the probability of success might decrease to 25% (equivalently, the probability of failure might increase to 75%). Note that difficulty does not affect revenues or cost of effort, only the chances of success/failure.

Payoff

The outcome of the project will be determined right after you submit your choice. You will see a bar with a success region, a failure region and a randomly moving white needle (Figure 2). The regions are determined by your choice of effort. The needle is equally likely to appear at any position along the bar. It will stop after 3 seconds. If it ends up in the success region the project will succeed, if it ends up in the failure region the project will fail (Figure 3). The next screen will show you the summary of the current round (Figure 4).

Example

On the Figure 2 the probability of success is 55% and the probability of failure is 45%. If at the moment you stop the needle it is in the region 0–55, the project will succeed (Figure 3). If it is in *the region 55.1–100, it will fail.*

There will be 15 rounds, as well as 5 practice rounds. Rounds will differ in the project difficulty, costs and possible revenues. After you complete all the rounds, one of them will be randomly picked for payoff. You will see bars with rounds' numbers and their results (Figure 5). These bars will be randomly highlighted. Each bar is equally likely to be highlighted at any given moment. It will stop after 3 seconds and the payoff will be determined.

C Demographic Survey

1. What is your age?
2. What is your gender?
   - Male
   - Female
3. What is your racial or ethnic background?
   - White or caucasian
   - Black or African American
   - Hispanic
   - Asian
   - Native American
   - Multiracial
   - Other
   - Prefer not to answer
4. What is your marital status?
   - Married
   - Single
   - Divorced
   - Widowed
   - Other
   - Prefer not to answer
5. What is your major/field of study?
   - Accounting
   - Economics
   - Finance
   - Business Administration
   - Education
   - Engineering
   - Health and Medicine
   - Biological and Biomedical Sciences
   - Math, Computer Sciences, or Physical Sciences
   - Social Sciences or History
   - Law
   - Psychology
   - Modern Languages and Cultures

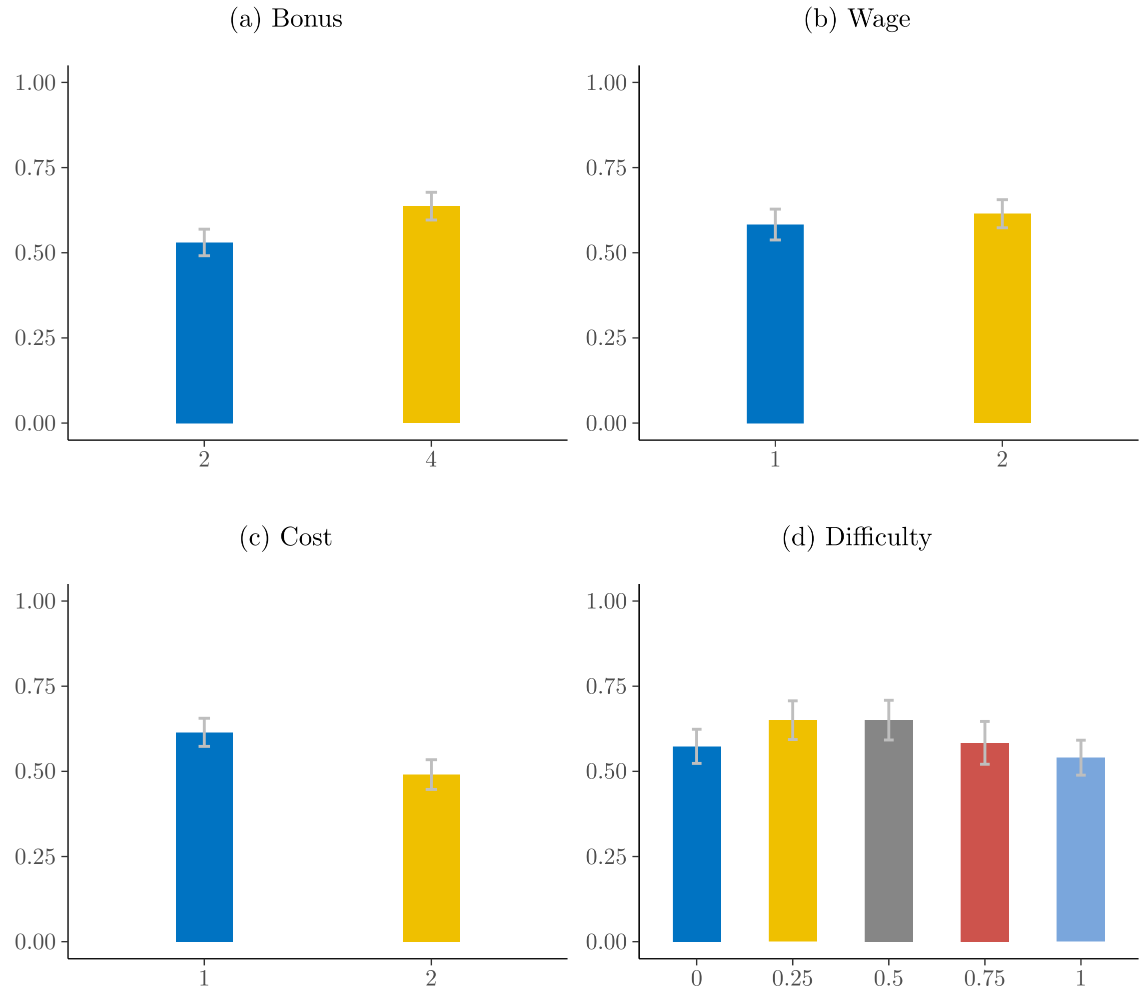
- Other

6. What is your GPA?
7. What is your year in school?
    - Freshman
    - Sophomore
    - Junior
    - Senior
    - Masters
    - Doctoral
8. What is the number of people in your household?
9. What is the total income of your household?
    - Under $5000
    - $5000—$15000
    - $15001—$30000
    - $30001—$45000
    - $45001—$60000
    - $60001—$75000
    - $75001—$90000
    - $90001—$100000
    - Over $100001
    - Prefer not to answer
10. What is the total income of your parents?
    - Under $5000
    - $5000—$15000
    - $15001—$30000
    - $30001—$45000
    - $45001—$60000
    - $60001—$75000
    - $75001—$90000
    - $90001—$100000
    - Over $100001
    - Don't know
    - Prefer not to answer

D Additional Analysis

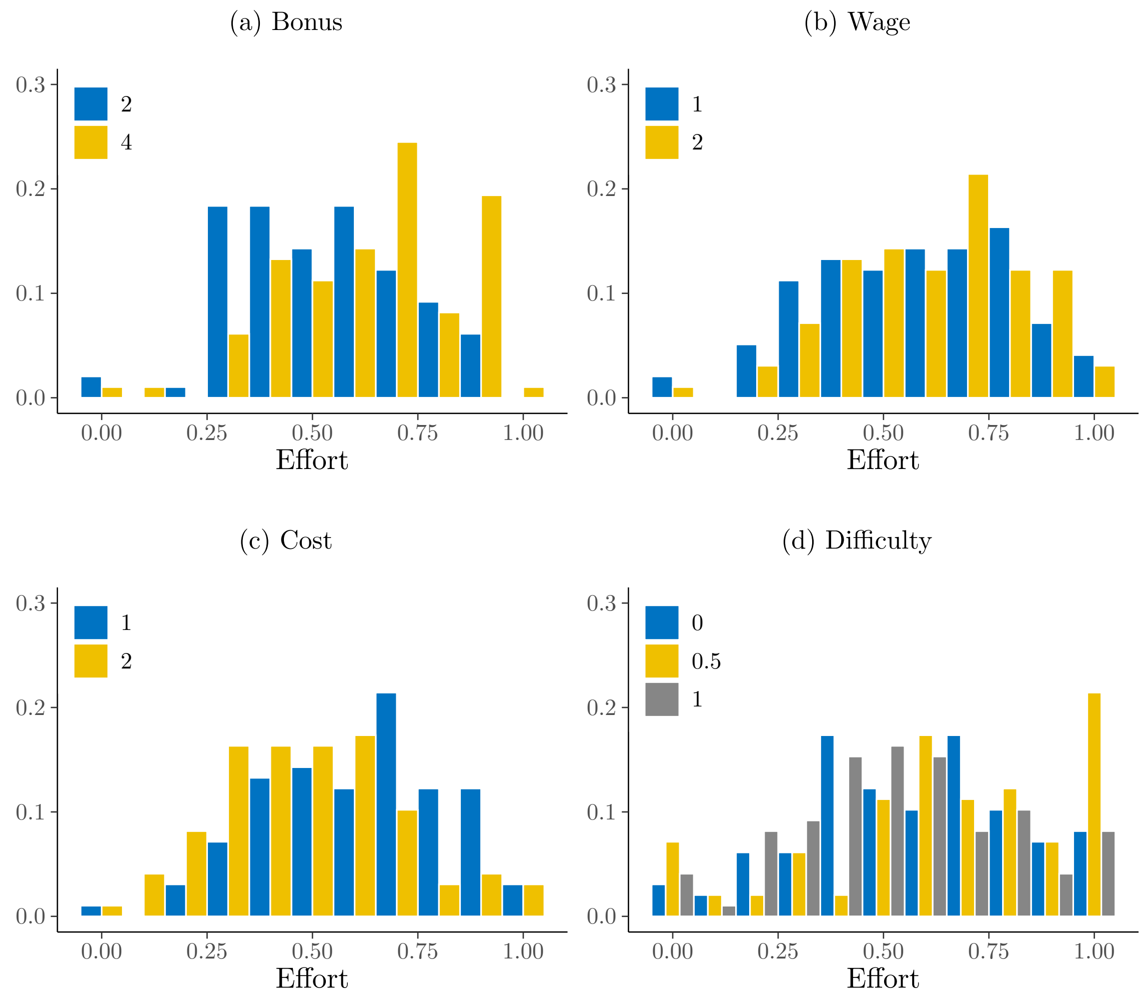
D.1 Additional Graphs

Figure D.1: Means of Effort by Treatment Variable



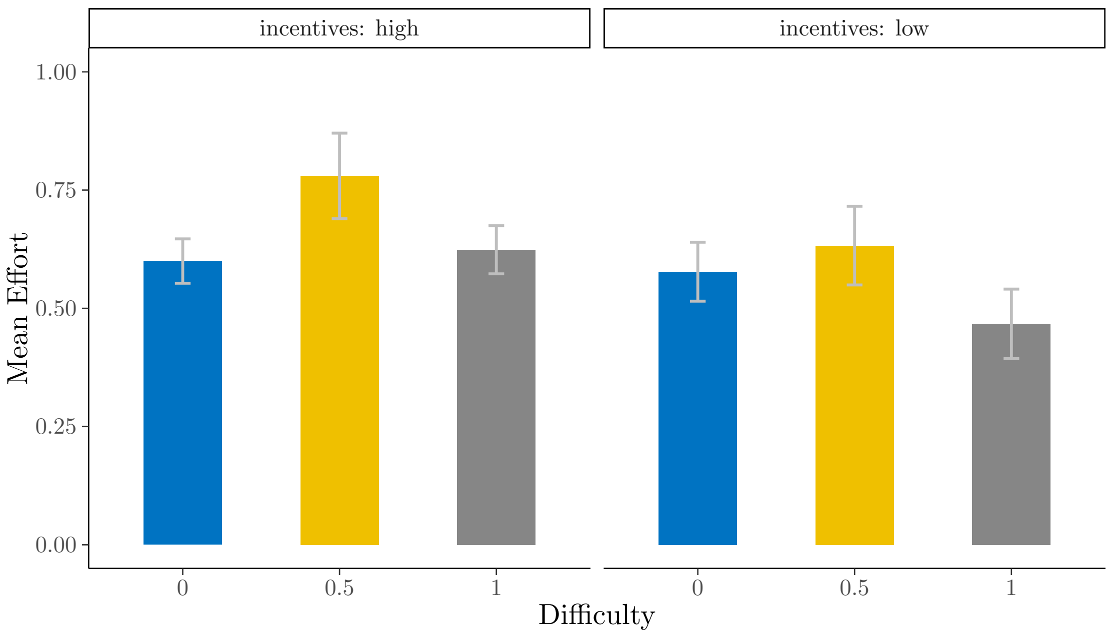
Note: The graph shows the means of effort levels broken down by a treatment variable and a value of the variable. Effort levels used to plot the means are subject-level mean effort levels for each value of a treatment variable. Vertical grey error bars show the 95% confidence intervals from a $t-$test.

Figure D.2: Histograms of Effort by Treatment Variable



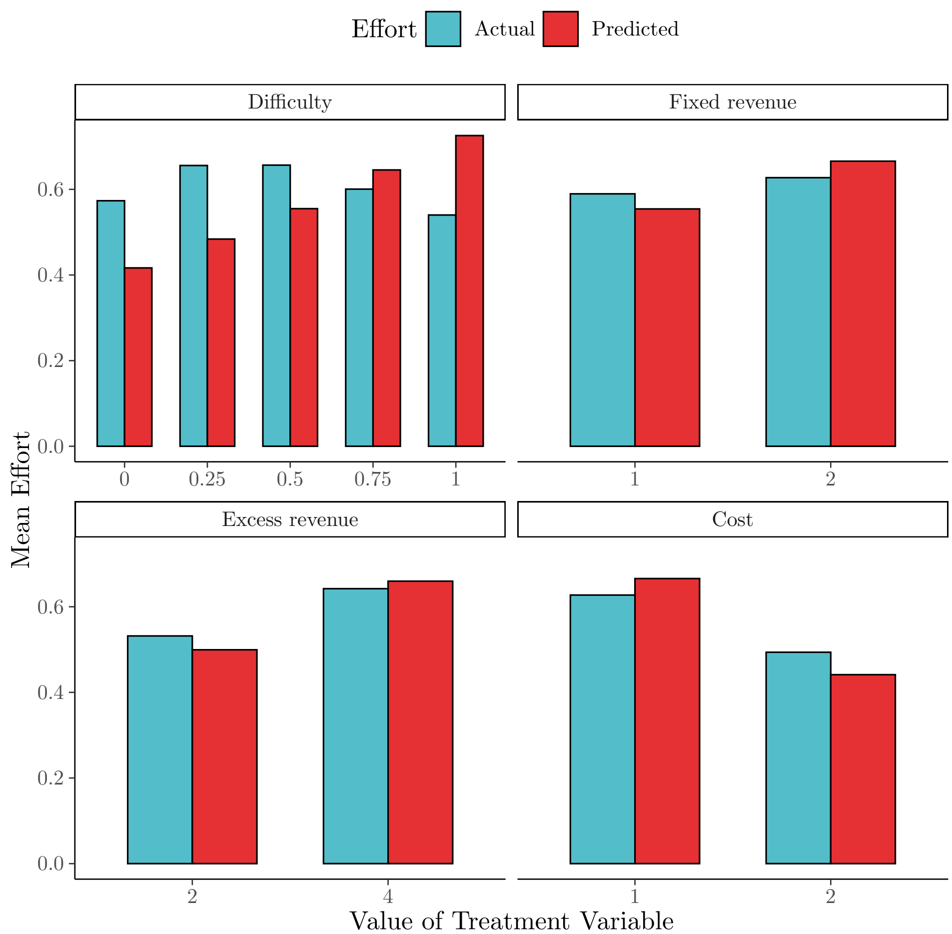
Note: The graph shows the histogram of effort levels broken down by a treatment variable and a value of the variable. Effort levels used to plot the means are subject-level mean effort levels for each value of a treatment variable. The vertical axis is scaled to show the relative proportions of observations falling into the bins within each value of the variable.

Figure D.3: Mean Effort Levels by Difficulty and Incentive Levels



Note: The graph shows the means of effort levels broken down by the value of difficulty. The left panel shows the mean effort levels for the low level of incentives with $w = 1$ and $z = 2$. The right panel shows the mean effort levels for the high level of incentives with $w = 2$ and $z = 4$. Vertical grey error bars show the 95% confidence intervals from a $t-$test.

Figure D.4: Actual and Predicted Mean Effort Levels from EU model



Note: The figure plots actual mean effort and mean effort predicted from the estimated EU model by treatment variable.

D.2 Additional Tables

Table D.1: Panel Regression Results with Interactions

Variable	Coefficient	SE	Statistic	p-value
Bonus = 4	0.084	0.027	3.108	0.002
Wage = 2	-0.006	0.027	-0.234	0.815
Cost = 2	-0.137	0.03	-4.567	<0.001
Difficulty = 0.5	0.052	0.037	1.401	0.162
Difficulty = 1	-0.109	0.04	-2.694	0.007
Bonus = 4 x Difficulty = 0.5	0.099	0.056	1.752	0.08
Bonus = 4 x Difficulty = 1	0.081	0.028	2.861	0.004
Wage = 2 x Difficulty = 0.5	-0.021	0.055	-0.385	0.7
Wage = 2 x Difficulty = 1	0.038	0.032	1.215	0.225
Cost = 2 x Difficulty = 0.5	0.097	0.061	1.585	0.113
Cost = 2 x Difficulty = 1	0.028	0.034	0.826	0.409
Bonus = 4 x Wage = 2	0.001	0.039	0.035	0.972
Bonus = 4 x Cost = 2	0.024	0.036	0.662	0.508

Notes: Number of observations: 1333, number of groups: 98, adjusted R^2: 0.02.
The table reports the estimation results of a panel regression with subject fixed effects and interaction terms. The dependent variable is effort. The independent variables are the indicators for the specified values of treatment variables and their interactions. The interaction between cost and wage is not included because of collinearity. The sample excludes observations where difficulty takes the values of 0.25 and 0.75. The standard errors are heteroskedasticity-robust (HC1) and clustered on the subject level.

D.3 Stochastic Choice

The model considered so far assumes that the agent's choices are deterministic, even though she makes them in a stochastic setting. For a fixed set of parameters $\bar{\pi}$, the agent always chooses $a^* = \arg\max U(a \mid \bar{\pi})$. However, a large body of experimental evidence shows that subject's choices are stochastic (Starmer and Sugden, 1989; Camerer, 1989; Ballinger and Wilcox, 1997) and a large and growing theoretical literature rationalizes this behavior (Matêjka and McKay, 2015; Gul, Natenzon, and Pesendorfer, 2014). It is natural to ask whether and how the predictions change if one allows the agent's choices to be stochastic.

The main difference between a deterministic and a stochastic model of choice is that the stochastic model can only make predictions about *expected* effort, since choice is now a random variable for an outside observer. To illustrate the point, consider a simple case when the choice set consists of only two elements, full effort and no effort, $A = \{1, 0\}$. Assign probabilities q and $1 - q$ to choices of full and no effort, respectively, according to the usual multinomial logit formula (Luce, 1959)

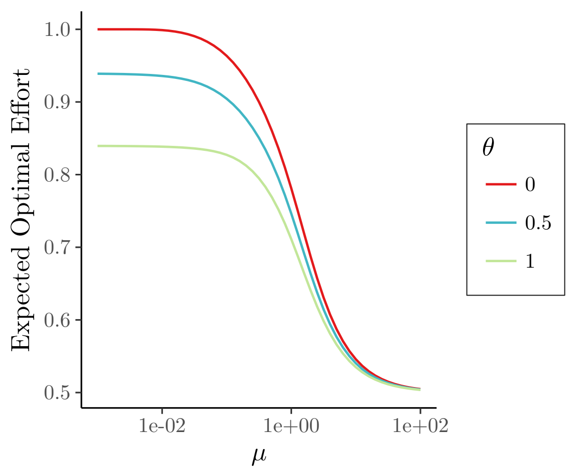
$$q = \frac{\exp(U(1 \mid \pi)/\mu)}{\exp(U(1 \mid \pi)/\mu) + \exp(U(0 \mid \pi)/\mu)} = \Lambda\left(\frac{U(1 \mid \pi) - U(0 \mid \pi)}{\mu}\right),$$

where Λ denotes the logistic cdf and μ is the noise parameter: higher values of μ make choices more "random" in the sense of not taking into account the respective utilities.

Suppose that under some set of parameters $\bar{\pi}$ the utility of full effort is higher than the utility of no effort, $\Delta U(\bar{\pi}) \equiv U(1 \mid \bar{\pi}) - U(0 \mid \bar{\pi}) > 0$. In this case, the deterministic model would predict that the choice will always be the full effort. In the stochastic model, we would have that the choices *on average* will be closer to the full effort, because $\mathbb{E}(a) = q$ and $\Delta U(\bar{\pi}) > 0$ implies that $p = \Lambda(\Delta U(\bar{\pi})/\mu) > 1/2$. In the limit, as noise goes to zero, one would have that $\lim_{\mu \to 0} \mathbb{E}(a) = 1$: small noise values would push the expected effort towards the prediction of the deterministic model, as the difference in utilities becomes more salient. As noise increases, the difference between utilities becomes less salient and the expected effort is sucked towards $1/2$, since $\lim_{\mu \to \infty} \Lambda(\Delta U(\bar{\pi})/\mu) = 1/2$: effort choice becomes uniformly distributed. The deterministic model is therefore a special case of a stochastic model with zero noise.

Figure D.5 demonstrates the result in a general case when the agent's choice set is $[0, 1]$ for three levels of difficulty. I use the monetary cost of effort specification with the CRRA utility of money function $u(x) = x^{1-\gamma}/(1-\gamma)$ with $\gamma = 0.2$ and no probability weighting with the cost of effort and probability of success functions defined as before. Proposition 1.A predicts declining effort levels in response to higher difficulty. The picture confirms that the ordering of optimal choices in the deterministic case is preserved for the expected choices in the stochastic case.

Figure D.5: Expected Effort as a Function of Noise



D.4 Individual Heterogeneity

Figure D.6 shows the distributions of the average treatment effects for each treatment variable computed at a subject level. Colors highlight the probability masses of the negative (blue) and positive (red) ATE's. The subjects are typed based on the sign of their ATE as either Decreasing (negative ATE) or Increasing (positive ATE) for bonus, wage, and cost. The typing for difficulty is more complicated and explained below.

Bonus

The distribution of the ATE's for bonus is unlikely to be normal (Shapiro-Wilk test, $p = 0.02$). The majority of subjects, 81%, increase their effort in response to higher bonus. The proportion of Increasing types is significantly higher than the proportion of Decreasing types (test for equality of proportions, $p < 0.001$). The behavior of Decreasing types is hard to rationalize (it would imply that those subjects prefer less money to more money), and thus is probably due to confusion. While the proportion of Decreasing types is non-negligible, the mean ATE for them is only -0.059. Excluding the subjects who make errors would increase the mean effect size to 0.147 from the unconditional average of 0.107.

Wage

The ATE's for wage are well approximated by a normal distribution (Shapiro-Wilk test, $p = 0.621$). The increase in wage results in higher effort for 62% of the subjects. The remaining 38% reduce their effort on average by 0.14, which is comparable to the mean effect size for Increasing types, 0.136. The proportion of Increasing types is significantly higher than the proportion of Decreasing types (test for equality of proportions, $p = 0.02$), but the mean effect size across all the subjects, 0.032, is close to zero. The behavior of Decreasing types, given their strong presence in the distribution, is unlikely to be entirely driven by errors and might reflect actual preferences.

Cost

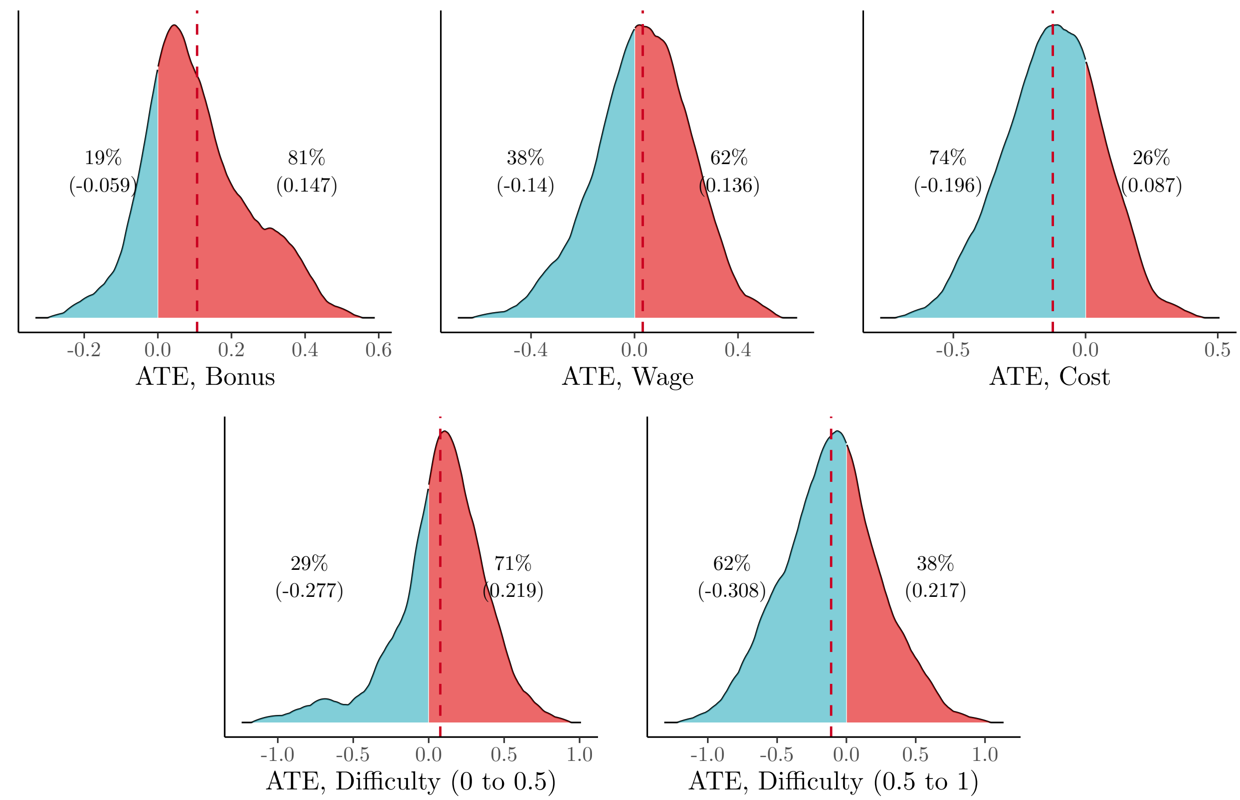
The ATE's for cost are also well approximated by a normal distribution (Shapiro-Wilk test, $p = 0.794$). The effect of increasing cost is negative for 74% of the subjects. The proportion of Decreasing types is significantly higher than the proportion of Increasing types (test for equality of proportions, $p < 0.001$). The proportion of Increasing types is non-negligible, but the mean effect size for them, 0.087, is relatively small. Their behavior is likely to be caused by errors. Excluding them would reduce (increase in absolute terms) the mean effect size from -0.124 to -0.196.

Difficulty

The first increase in difficulty results in higher effort for 71% of the subjects. The mean effect size for those subjects is 0.219. The distribution of the ATE's for the first increase in difficulty is unlikely to be normal (Shapiro-Wilk test, $p = 0.001$). The second increase in difficulty leads to lower effort for 62% of the subjects, with the conditional mean effect size of -0.308. The ATE's for the second increase are well approximated by a normal distribution (Shapiro-Wilk test, $p = 0.968$). The subjects who increase their effort initially are not necessarily the same subjects who then reduce their effort (e.g., some of them increase their effort even further). The response to difficulty is thus characterized by Increasing, Decreasing, U, or Inverse-U types,[D.2] which requires

[D.2] Specifically, Increasing types increase their effort on both intervals of difficulty (from 0 to 0.5 and 0.5 to 1), Decreasing types reduce their effort on both intervals, U types reduce their effort on the first interval and increase knowing the full response path and cannot be shown on a distributions picture like in Figure D.6. The dominant type is Inverse-U, with 50% of subjects conforming to it (see Figure D.7). The equality of proportions of each type is clearly rejected (test for equality of proportions, $p < 0.001$). The subjects are split roughly equally among the three other types, with Increasing type being the second largest group after Inverse-U type.

Figure D.6: Individual Heterogeneity in ATEs



Note: The figure plots the ATEs computed at a subject level. The vertical bars represent the means of distributions. The numbers are the percentages of subjects with negative and positive ATE, with the conditional ATEs for each type in parenthesis.

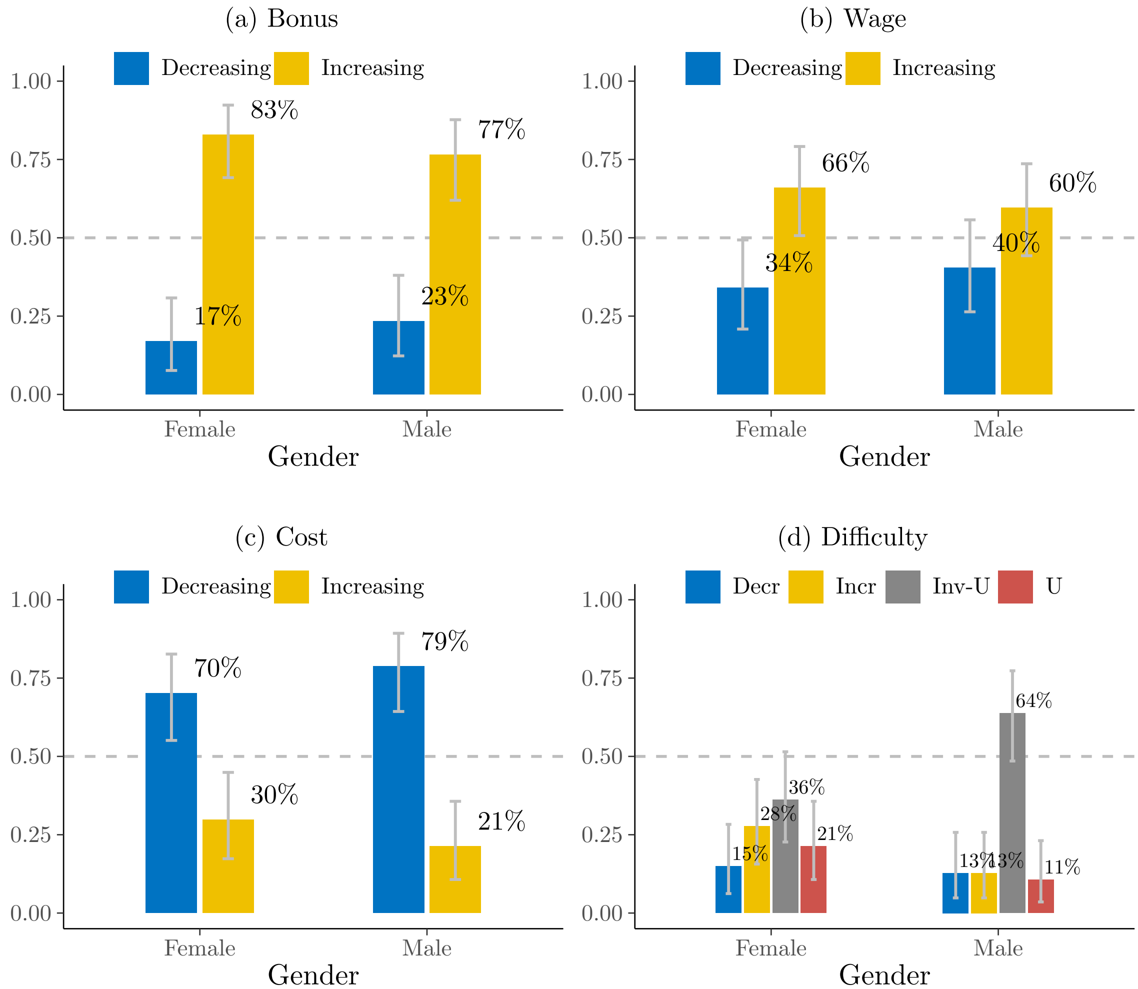
Individual Heterogeneity and Gender

An important question is whether the differences between the types can be attributed to the observable subjects' characteristics, such as gender. In the cases of bonus and cost, this amounts to asking whether females or males are more likely to make errors. Figure D.7 shows the proportions of subjects who exhibit a given type of a treatment effect broken down by gender. For bonus (Figure D.7a), the proportion of females belonging to a decreasing type, 17%, is lower than the corresponding proportion of males, 23%, however, this difference is not statistically significant (Fisher's exact test, $p = 0.608$). A similar result holds for wage (Figure D.7b), the proportion of females belonging to a decreasing type, 34%, is slightly lower than the corresponding proportion

their effort on the second interval, and Inverse-U types increase their effort on the first interval and reduce their effort on the second interval. I omit the intermediate values of difficulty 0.25 and 0.75 to simplify the classification of types.

of males, 40%, but not significantly so (Fisher's exact test, $p = 0.67$). The proportion of females who decrease their effort in response to higher cost, 70%, (Figure D.7) is slightly lower than the corresponding proportion of males, 79%, with no significant difference (Fisher's exact test, $p = 0.478$). The effect of difficulty (Figure D.7d), however, does reveal a marginally significant association between gender and response type (Fisher's exact test, $p = 0.048$).[D.3] The proportion of males belonging to the Inverse-U type, 64%, is higher than the corresponding proportion of females, 36%. The females are more likely than males to exhibit the U and Increasing effort response to difficulty.

Figure D.7: Association Between Gender and Treatment Effect by Treatment Variable



Note: The graph shows the proportion of subjects who exhibit a given type of a treatment effect broken down by gender. The error bars show the 95% confidence intervals.

[D.3] Adjusting for multiple hypothesis testing by controlling for the false discovery rate (Benjamini and Hochberg, 1995) yields the following p-values: 0.67, 0.67, 0.67, 0.1912 in the four tests, respectively, thus making the association between the effect of difficulty and gender not statistically significant.

Individual Heterogeneity in Parameter Estimates

To explore individual heterogeneity in preference parameters, I re-estimate the model allowing the parameters to depend on demographic characteristics. I assume that each behavioral parameter β^j can be written as a linear combination of demographic indicators for gender and race, with Black male being the base category:[D.4]

$$\begin{aligned} \beta^j = \beta^j_{Constant} + \beta^j_{Female}\,\mathbb{I}(Gender_i = Female) + \\ + \beta^j_{White}\,\mathbb{I}(Race_i = White) + \beta^j_{Asian}\,\mathbb{I}(Race_i = Asian). \end{aligned} \tag{D.1}$$

Table D.2 presents the estimation results, which reveal preference differences between demographic groups. Females tend to have a higher estimate of the coefficient of CRRA than males, while Whites tend to have a lower estimates than Blacks or Asians. There are no significant differences in the coefficient of CRRA between Blacks and Asians. Turning to the estimates of the probability weighting function, females tend to have a slightly higher estimate of the shape parameter α than males, though the difference is not statistically significant. Similarly, there are no statistically significant differences in the estimates of α between racial groups. The estimates of the scale parameter ψ show that females tend to have lower estimates than males, while Whites tend to have higher estimates than Blacks. There are no statistically significant differences in the estimate of ψ between Asians and Blacks or Asians and Whites.

Figure D.8 interprets these estimates graphically by showing the estimated probability weighting functions and implied decision weights from equiprobable lotteries for males and females separately. For males, the probability weighting function is clearly S-shaped, while for females, it is closer to being simply concave. As a result, males tend to overweight outcomes between the extremes, while females tend to overweight best outcomes. Figure D.9 presents similar results for race. The differences between races are less pronounced than the differences between genders, which results in similar S-shaped probability weighting functions and similar decision weights.

[D.4] To account for individual heterogeneity, it would be desirable to allow each subject have their own $\beta_{constant}$, as in a fixed-effects model. Unfortunately, estimating a fixed-effects model is not feasible in the present design. Fixed effects in the present structural framework would imply that every subject has their own vector of structural parameters (risk aversion, shape and scale of probability weighting). This is equivalent to estimating the structural model for each subject individually. There is not enough data for each subject to perform such estimation. Using the fixed effects (within) estimator is not possible here, because fixed effects enter the regression equation non-linearly and cannot be differenced out.

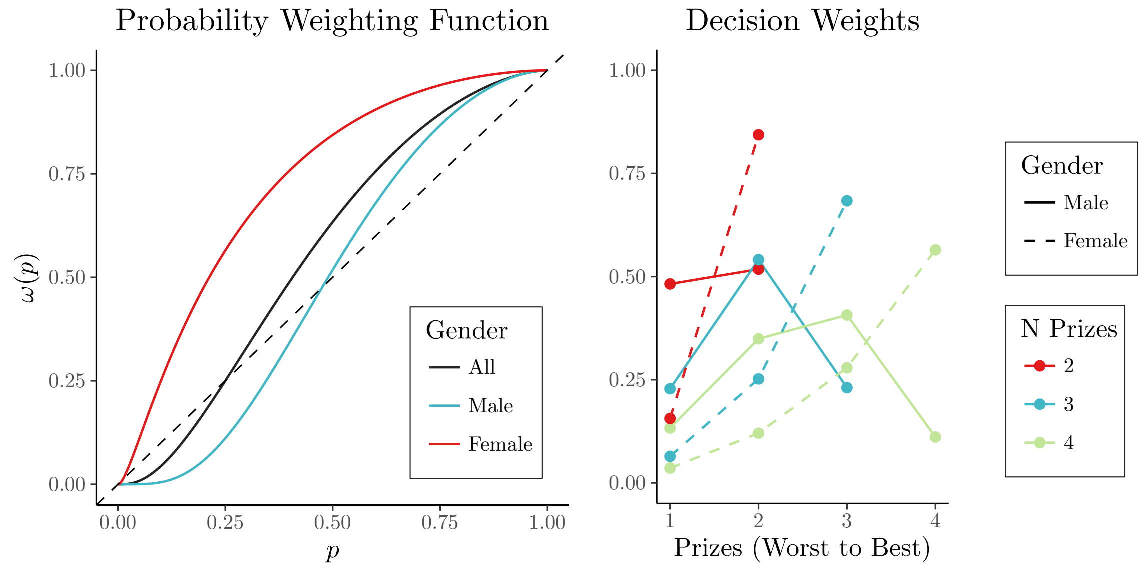
Table D.2: Estimates of the Model with Demographic Covariates

Parameter	Estimate	SE	2.5%	97.5%
γ				
Constant	0.528	0.150	0.234	0.821
Female	1.339	0.388	0.577	2.100
White	−1.375	0.486	−2.327	−0.422
Asian	0.250	0.193	−0.129	0.629
α				
Constant	1.479	0.084	1.314	1.644
Female	0.121	0.174	−0.219	0.461
White	−0.204	0.195	−0.586	0.178
Asian	0.034	0.148	−0.256	0.325
ψ				
Constant	1.075	0.079	0.921	1.230
Female	−0.796	0.095	−0.982	−0.611
White	0.615	0.161	0.300	0.930
Asian	0.222	0.114	−0.001	0.446

N obs = 1625.

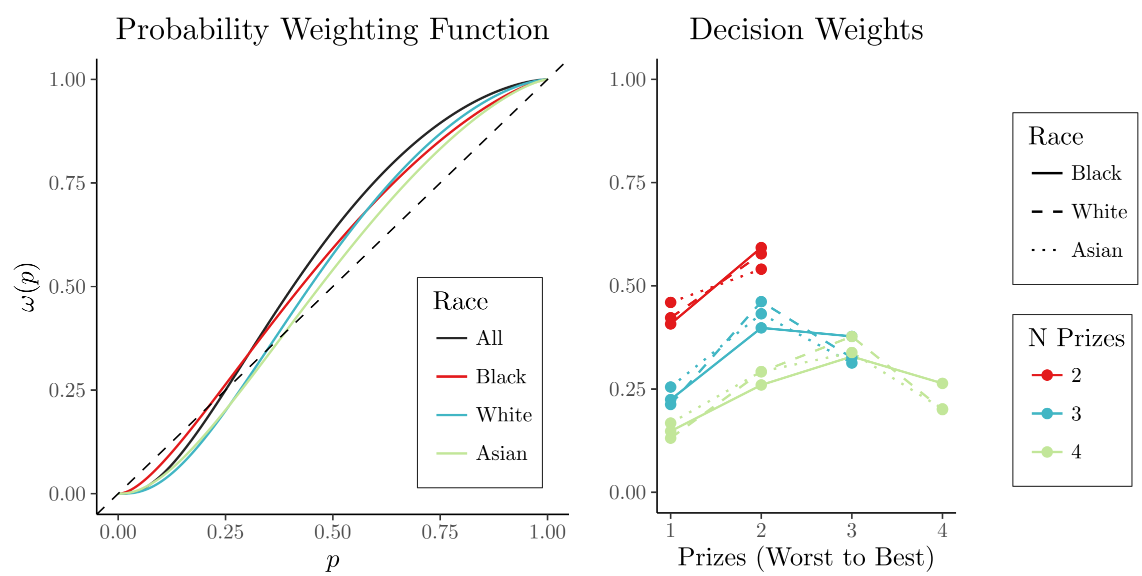
Notes: The table reports the estimation results of the model specified in equations (8), (9), (10), and (D.1). The table reports the point estimates, standard errors, as well as 95% confidence intervals. The estimated parameters are the risk aversion (γ), the shape parameter of the probability weighting function (α), and the scale parameter of probability weighting function (ψ). The base category (constant) is Black male.

Figure D.8: Estimated Probability Weighting Functions and Implied Decision Weights by Gender



Notes: The left panel shows the estimated probability weighting function for males and females (solid lines) together with 45-degree line (dashed) that represents the case of no weighting (as in EU model). The right panel shows the implied decision weights (solid lines) from the estimated probability weighting functions for males and females for equiprobable lotteries with a varying number of outcomes (2, 3, 4).

Figure D.9: Estimated Probability Weighting Function and Implied Decision Weights from Equiprobable Lotteries by Race (Effort Task)



Notes: The left panel shows the estimated probability weighting functions for Asian, Black, and White subjects (solid lines) together with 45-degree line (dashed) that represents the case of no weighting (as in EU model). The right panel shows the implied decision weights (solid lines) from the estimated probability weighting functions for Asian, Black, and White subjects for equiprobable lotteries with a varying number of outcomes (2, 3, 4).

E Ceteris Paribus Analysis of Treatment Effects

Let δ denote the vector of values of the treatment variables. Each treatment $j \in J$ represents a particular combination of the values of treatment variables from the set of all treatments J, $\delta_j \equiv (z_j, w_j, k_j, \theta_j)$. Set J_x is the set of all *CP*-pairs for a treatment variable x and is defined as

$$J_x = \left\{ (j_1, j_2) \mid j_1, j_2 \in J, x_{j_1} = x^1, x_{j_2} = x^2, x^1 < x^2, (\delta_{-x})_{j_1} = (\delta_{-x})_{j_2} \right\},$$

where δ_{-x} denotes the vector of values of treatment variables except x, and for convenience the first index corresponds to a treatment with a lower value of the treatment variable. Let k index the elements of J_x and $K_x \equiv ||J_x||$ be the number of elements in this set. For every *CP*-pair $k = 1, \ldots, K_x$ the two samples used in the *ceteris paribus* tests are

$$\left\{ a_{i,(j_1)_k} \right\}_{i=1,\ldots,n}, \left\{ a_{i,(j_2)_k} \right\}_{i=1,\ldots,n}, (j_1, j_2)_k \in J_x,$$

where $a_{i,j}$ denotes effort chosen by a subject i in a treatment j, and n is the total number of subjects in the experiment.

Table E.3: Summary Results for the *Ceteris Paribus* Analysis

		p-values		
CP-pair	ATE	t	Wilcoxon	sign
		z		
1	0.083	0.003	<0.001	<0.001
2	0.05	0.153	0.042	0.007
3	0.146	<0.001	<0.001	<0.001
4	−0.002	0.971	0.765	0.856
5	0.174	0.004	0.001	
6	0.174	0.016	0.006	
7	0.167	<0.001	0.001	0.014
8	0.202	<0.001	<0.001	0.001
9	0.154	<0.001	<0.001	0.001
		w		
1	0.011	0.7	0.463	1
2	−0.022	0.407	0.598	0.902
3	0.077	0.187	0.245	
4	−0.027	0.634	0.558	
5	0.035	0.617	0.714	
6	0.015	0.688	0.835	0.815
7	0.05	0.304	0.25	0.228
		k		
1	−0.173	<0.001	<0.001	<0.001
2	−0.077	0.019	0.001	<0.001
3	−0.15	0.024	0.089	
4	−0.007	0.93	0.654	
5	−0.01	0.926	0.876	
6	−0.073	0.036	0.112	0.336
7	−0.121	0.002	0.002	<0.001
		θ (0 to 0.5)		
1	0.055	0.292	0.25	
2	0.018	0.729	0.816	
3	0.183	0.039	0.042	
4	0.142	0.015	0.038	
		θ (0.5 to 1)		
1	−0.165	0.004	0.004	
2	−0.123	0.023	0.028	
3	−0.189	0.036	0.045	
4	−0.096	0.105	0.394	

Notes: The first column is an index of a *CP*-pair, the second column shows the average treatment effect of a treatment variable in a given pair, the last three columns show the p-values from either a) the paired t test, the Wilcoxon signed rank test, and the sign test, or b) the unpaired t test and the Wilcoxon rank sum test. The *CP*-pairs with an empty value in the column for the sign test are the non-paired samples. All the tests are two-sided.

F Derivations and Proofs

Consider the derivative of $U(a \mid \pi)$ w.r.t. a:

$$U' = \sum_{x=0}^{1} \big(u(w+zx,a) f_a(x \mid a,\theta) + u_a(w+zx,a) f(x \mid a,\theta)\big) \tag{F.1}$$

$$= \sum_{x=0}^{1} u(w+zx,a) \frac{f_a(x \mid a,\theta)}{f(x \mid a,\theta)} f(x \mid a,\theta) + \sum_{x=0}^{1} u_a(w+zx,a) f(x \mid a,\theta) \tag{F.2}$$

$$= \mathbb{E}\, u(Y,a) \frac{f_a(X \mid a,\theta)}{f(X \mid a,\theta)} + \mathbb{E}\, u_a(Y,a). \tag{F.3}$$

At the maximum point a^* the FONC must hold:

$$\mathbb{E}\, u(Y,a) \frac{f_a(X \mid a,\theta)}{f(X \mid a,\theta)} = -\,\mathbb{E}\, u_a(Y,a). \tag{F.4}$$

The LHS of this equation is

$$\mathbb{E}\, u(Y,a) \frac{f_a(X \mid a,\theta)}{f(X \mid a,\theta)} = \sum_{x=0}^{1} u(y,a) f_a(x \mid a,\theta) \tag{F.5}$$

$$= u(w,a)(-p_a(a,\theta)) + u(w+z,a) p_a(a,\theta) \tag{F.6}$$

$$= p_a(a,\theta)[u(w+z,a) - u(w,a)] \tag{F.7}$$

$$= p_a(a,\theta) \Delta u(w,z,a) \tag{F.8}$$

$$= z p_a(a,\theta) u_y(\bar{y},a), \tag{F.9}$$

where the last equality follows from the Mean Value Theorem and $\bar{y} \in [w, w+z]$. The RHS of the FONC is

$$-\,\mathbb{E}\, u_a(Y,a) = -[u_a(w,a)(1-p(a,\theta)) + u_a(w+z,a) p(a,\theta)] \tag{F.10}$$

$$= -[u_a(w,a) + p(a,\theta)(u_a(w+z,a) - u_a(w,a))] \tag{F.11}$$

$$= -[u_a(w,a) + z p(a,\theta) u_{ya}(\bar{y},a)], \tag{F.12}$$

where the last equality follows from the Mean Value Theorem and $\bar{y} \in [w, w+z]$.

Consider the second derivative of U w.r.t. a:

$$U'' = \sum_{x=0}^{1} \big(u(w+zx,a) f_{aa}(x \mid a,\theta) + 2u_a(w+zx,a) f_a(x \mid a,\theta) + u_{aa}(w+zx,a) f(x \mid a,\theta)\big) \tag{F.13}$$

$$= \sum_{x=0}^{1} u_{aa}(w+zx,a) f(x \mid a,\theta) + \sum_{x=0}^{1} 2u_a(w+zx,a) \frac{f_a(x \mid a,\theta)}{f(x \mid a,\theta)} f(x \mid a,\theta) \tag{F.14}$$

$$+ \sum_{x=0}^{1} u(w+zx,a) \frac{f_{aa}(x \mid a,\theta)}{f(x \mid a,\theta)} f(x \mid a,\theta) \tag{F.15}$$

$$= \mathbb{E}\, u_{aa}(Y,a) + 2\,\mathbb{E}\, u_a(Y,a) \frac{f_a(X \mid a,\theta)}{f(X \mid a,\theta)} + \mathbb{E}\, u(Y,a) \frac{f_{aa}(X \mid a,\theta)}{f(X \mid a,\theta)}. \tag{F.16}$$

The first term is the expectation of u_{aa}, which is negative by assumption. The last term can be rewritten as

$$\sum_{x=0}^{1} u(w+zx,a) f_{aa}(x \mid a,\theta) = u(w,a)(-p_{aa}(a,\theta)) + u(w+z,a)p_{aa}(a,\theta) \tag{F.17}$$

$$= p_{aa}(a,\theta)\Delta u(w,z,a) \tag{F.18}$$

$$= zp_{aa}(a,\theta)u_y(\bar{y},a), \tag{F.19}$$

where the last equality follows from the Mean Value Theorem and $\bar{y} \in [w, w+z]$. This term is also negative, since the utility gain Δu is positive and p_{aa} is negative by assumption. The middle term is

$$\sum_{x=0}^{1} 2u_a(w+zx,a) f_a(x \mid a,\theta) = 2\big(u_a(w,a)(-p_a(a,\theta)) + u_a(w+z,a)p_a(a,\theta)\big) \tag{F.20}$$

$$= 2p_a(a,\theta)\big(u_a(w+z,a) - u_a(w,a)\big) \tag{F.21}$$

$$= 2zp_a(a,\theta)u_{ya}(\bar{y},a), \tag{F.22}$$

where the last equality follows from the Mean Value Theorem and $\bar{y} \in [w, w+z]$. While $p_a > 0$ by assumption, the term u_{ya} cannot be signed without an additional assumption about the cross-partial derivative of u. If u is submodular, $u_{ya} \leqslant 0$, the expected utility function U is strictly concave and the first-order condition is sufficient. If u is supermodular, $u_{ya} \geqslant 0$, however, one needs to check the second-order condition as well.

Consider the special case when $u(y,a) = v(y) - c(a)$, $p(a,\theta) = 1/2(a+1-\theta)$, $c(a) = ka^2$. Then $p_a(a,\theta) = 1/2$, $\Delta u(w,z,a) = v(w+z) - v(w)$, $u_a(y,a) = -c'(a) = -2ka$, and $u_{ya}(y,a) = 0$. Plugging these values into the FONC yields

$$1/2\big(v(w+z) - v(w)\big) = -(-2ka^*) \tag{F.23}$$

$$a^* = \frac{v(w+z) - v(w)}{4k}. \tag{F.24}$$

Assume now that $u(y,a) = -e^{-\gamma(y-c(a))}$, $p(a,\theta) = 1/2(a+1-\theta)$, $c(a) = ka^2$. Then at $a = a^*$

$$\Delta u(w,z,a) = -e^{-\gamma(w+z-c(a))} + e^{-\gamma(w-c(a))} = e^{-\gamma(w-c(a))}(-e^{-\gamma z} + 1), \tag{F.25}$$

$$u_a(y,a) = -\Big(e^{-\gamma(y-c(a))}(-\gamma)(-2ka)\Big) = -2ak\gamma e^{-\gamma(y-c(a))} \tag{F.26}$$

and

$$u_a(w+z,a) - u_a(w,a) = -2ak\gamma e^{-\gamma(w+z-c(a))} + -2ak\gamma e^{-\gamma(w-c(a))} \tag{F.27}$$

$$= -2ak\gamma e^{-\gamma(w-c(a))}(-e^{-\gamma z} + 1). \tag{F.28}$$

Plugging these values into the FONC yields

$$\frac{1}{2}e^{-\gamma(w-c(a))}(-e^{-\gamma z}+1) = -\left(-2ak\gamma e^{-\gamma(w-c(a))} + \frac{a+1-\theta}{2}2ak\gamma e^{-\gamma(w-c(a))}(-e^{-\gamma z}+1)\right) \tag{F.29}$$

$$\frac{1-e^{-\gamma z}}{2} = 2ak\gamma - a^2k\gamma(1-e^{-\gamma z}) - ak\gamma(1-\theta)(1-e^{-\gamma z}) \tag{F.30}$$

$$\frac{1}{2k\gamma} = \frac{2a}{1-e^{-\gamma z}} - a^2 - ak(1-\theta) \tag{F.31}$$

$$\frac{1}{2k\gamma} = -a^2 + a\left(\frac{2}{1-e^{-\gamma z}} - 1 + \theta\right) \tag{F.32}$$

$$\frac{1}{2k\gamma} = -a^2 + a\left(\underbrace{\frac{1+e^{-\gamma z}}{1-e^{-\gamma z}}}_{A} + \theta\right) \tag{F.33}$$

$$a^2 - (A+\theta)a + \frac{1}{2k\gamma} = 0. \tag{F.34}$$

The roots of this quadratic equation are

$$a_{1,2} = \frac{A+\theta \pm \sqrt{(A+\theta)^2 - 2/(k\gamma)}}{2}. \tag{F.35}$$

Note that the negative root, a_1, is less than $(A+\theta)/2$, while the positive root, a_2, is greater than $(A+\theta)/2$. The first derivative of U can be written as

$$U' = k\gamma(1-e^{-\gamma z})e^{-\gamma(w-c(a))}\left((a-a_1)(a-a_2)\right). \tag{F.36}$$

It is easy to see that the first derivative changes its sign from positive to negative at a_1 and from negative to positive at a_2, hence a_2 is a local minimum, while a_1 is a local maximum, $a^* = a_1$.

Consider the optimality condition at $a = a^*$

$$a^2 - (A+\theta)a + \frac{1}{2k\gamma} = 0. \tag{F.37}$$

Differentiate w.r.t. θ to get

$$2a\frac{\partial a}{\partial \theta} - (A+\theta)\frac{\partial a}{\partial \theta} - a = 0 \tag{F.38}$$

$$\frac{\partial a}{\partial \theta}(2a - (A+\theta)) = a \tag{F.39}$$

$$\frac{\partial a}{\partial \theta} = \frac{a}{2a-(A+\theta)}. \tag{F.40}$$

Since $a^* < (A+\theta)/2$, the sign of the partial derivative is negative.

To derived the general comparative statics, consider again the general FONC:

$$zp_a(a^*,\theta) + u_a(w,a^*) + zp(a^*,\theta)u_{ya}(\bar{y},a^*) = 0. \tag{F.41}$$

It defines an implicit function $F(a^*, \theta) = 0$. Using the Implicit Function Theorem, we get

$$\frac{da^*}{d\theta} = -\frac{F_\theta}{F_a} = -\frac{z p_{a\theta}(a^*, \theta) u_y(\bar{y}, a^*) + z p_\theta(a^*, \theta) u_{ya}(\bar{\bar{y}}, a^*)}{U''(a^*)} \tag{F.42}$$

$$= -\frac{z \left[p_\theta(a^*, \theta) u_{ya}(\bar{\bar{y}}, a^*) + p_{a\theta}(a^*, \theta) u_y(\bar{y}, a^*)\right]}{U''(a^*)}. \tag{F.43}$$

Proposition 1.A

Proof. Consider the terms in the square brackets. Since $p_\theta < 0$ and $u_y > 0$, the terms u_{ya} and $p_{a\theta}$ must have the opposite signs (with the possibility that one or both of them are zero) to unambiguously determine the effect of difficulty on optimal effort. Hence, the condition $\operatorname{sgn}(u_{ya}) \operatorname{sgn}(p_{a\theta}) < 1$ must hold. If the condition holds, the sign of the effect of difficulty on optimal effort will coincide with the sign of u_{ya}, if $u_{ya} \neq 0$, or be the opposite of the sign of $p_{a\theta}$, if $p_{a\theta} \neq 0$. If both $u_{ya} = 0$ and $p_{a\theta} = 0$, difficulty will have no effect on optimal effort. □

Under the probability weighting assumption, the FONC is

$$z\tilde{p}_a(a^*, \theta) u_y(\bar{y}, a^*) + u_a(w, a^*) + z\tilde{p}(a^*, \theta) u_{ya}(\bar{\bar{y}}, a^*) = 0 \tag{F.44}$$

$$z\omega'(p(a^*, \theta)) p_a(a^*, \theta) u_y(\bar{y}, a^*) + u_a(w, a^*) + z\omega(p(a^*, \theta)) u_{ya}(\bar{\bar{y}}, a^*) = 0. \tag{F.45}$$

Using the Implicit Function Theorem yields (the points at which functions are evaluated are dropped to improve readability)

$$\frac{da^*}{d\theta} = -\frac{z\left[\omega' p_\theta u_{ya} + u_y\left(\omega'' p_\theta p_a + \omega' p_{a\theta}\right)\right]}{U''(a^*)} \tag{F.46}$$

Proposition 1.B

Proof. Consider the terms in parentheses. The sign of $p_\theta p_a$ is negative, since $p_\theta < 0$ and $p_a > 0$. The sign of ω' is positive, since the probability weighting function is a strictly monotonically increasing transformation. Hence, for the expression in parentheses to have an unambiguous sign, one must have that ω'' and $p_{a\theta}$ are of the opposite signs (with the possibility that $p_{a\theta} = 0$), or $\operatorname{sgn}(\omega'') \operatorname{sgn}(p_{a\theta}) < 1$. Consider now the remaining terms in square brackets. Since $u_y > 0$, to sign the expression in brackets unambiguously, one must have that the expression in parentheses has an unambiguous sign and that this sign is the opposite of the sign of u_{ya} (with the possibility that $u_{ya} = 0$). Hence the condition $\operatorname{sgn}(u_{ya}) \operatorname{sgn}(p_{a\theta}) < 1$. If both conditions hold, the effect of difficulty on optimal effort will have the sign opposite to the sign of ω''.

□

To derive the comparative statics w.r.t. bonus, consider the FONC written as

$$p_a(a^*, \theta)\left(u(w + z, a^*) - u(w, a^*)\right) + u_a(w, a^*) + p(a^*, \theta)\left(u_a(w + z, a^*) - u_a(w, a^*)\right). \tag{F.47}$$

Implicit differentiation w.r.t. z yields

$$\frac{da^*}{dz} = -\frac{p_a(a^*, \theta) u_y(w + z, a^*) + p(a^*, \theta) u_{ya}(w + z, a^*)}{U''(a^*)} \tag{F.48}$$

Proposition 2

Proof. Consider the numerator of da^*/dz. The terms p_a, u_y, and p are non-negative, but the sign of u_{ya} is undetermined. Hence, to unambiguously sign the effect of bonus, one must have $u_{ya} \geqslant 0$ in which case the effect of bonus will be non-negative. □

To derive the comparative statics w.r.t. wage, consider the FONC written in the form

$$p_a(a^*, \theta)\left(u(w + z, a^*) - u(w, a^*)\right) + \mathbb{E}\, u_a(w + zX, a^*). \tag{F.49}$$

Implicit differentiation w.r.t. w yields

$$\frac{da^*}{dw} = -\frac{p_a(a^*, \theta)\left(u_y(w + z, a) - u_y(w, a)\right) + \mathbb{E}\, u_{ya}(w + zX, a^*)}{U''(a^*)} \tag{F.50}$$

$$= -\frac{zp_a(a^*, \theta)u_{yy}(\bar{y}, a^*) + \mathbb{E}\, u_{ya}(w + zX, a^*)}{U''(a^*)}, \tag{F.51}$$

where the last equality follows from the Mean Value Theorem and $\bar{y} \in [w, w + z]$.

Proposition 3

Proof. Consider the numerator of da^*/dw. The first term is non-positive, since $z \geqslant 0$, $p_a \geqslant 0$, and $u_{yy} \leqslant 0$. The sign of the second term is undetermined, since the sign of u_{ya} is undetermined. Hence, in order to unambiguously sign the effect of wage, one must have $u_{ya} \leqslant 0$ in which case the effect of wage will be non-positive. □