# Online Appendix

# for

# The Asymmetry in Responsible Investing Preferences and Beliefs

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**Online Appendix A: Derivation of the Main Result in the Theoretical Framework**

The investor maximizes expected utility with a strictly increasing and concave Bernoulli utility of the form $u(x+\lambda y)$, where $|\lambda| \ll 1$ and the wealth to be allocated is normalized to one.[1] Assume, first, that $\lambda$ is zero (as in the Neutral treatment). Let $\tilde{r}$ denote the *rate* of return on the risky asset. Because the risk-free return is zero, the investor's gain from investing $a$ in the risky asset is $1 - a + (1 + \tilde{r})a = 1 + \tilde{r}a$. The investor's optimization problem is therefore $\max_a \mathrm{E}[u(1 + \tilde{r}a)]$ and the first order condition is $0 = \mathrm{E}[u'(1 + \tilde{r}a_0)\tilde{r}]$, whose solution defines the optimal allocation $a_0$. Now consider the case of strictly positive $\lambda$. In the Positive/Negative treatments control the sign of the externality, which we denote as $\tau$. The investor's problem is

$$\max_a \mathrm{E}[u(1 + \tilde{r}a + a\tau\lambda(1 + \tilde{r}))]$$

To first-order in $\lambda$ this can be re-written as

$$\max_a \mathrm{E}[u(1 + \tilde{r}a) + a\tau\lambda(1 + \tilde{r})u'(1 + \tilde{r}a)].$$

The first-order condition becomes

$$0 = \mathrm{E}[u'(1 + \tilde{r}a^*)\tilde{r} + \tau\lambda(1 + \tilde{r})(u'(1 + \tilde{r}a^*) + a^*u''(1 + \tilde{r}a^*)\tilde{r})].$$

Defining $a^* \equiv a_0 + \Delta a$, and conjecturing that $\Delta a \sim \lambda$, one obtains, to first order in $\lambda$, that

$$0 = E[u'(1 + \tilde{r}a_0)\tilde{r} + u''(1 + \tilde{r}a_0)\tilde{r}^2\Delta a + \tau\lambda(1 + \tilde{r})(u'(1 + \tilde{r}a_0) + a_0u''(1 + \tilde{r}a_0)\tilde{r})].$$

Note that the expectation of the first term is zero because of the Neutral treatment first order condition. This results in the following linear equation for $\Delta a$

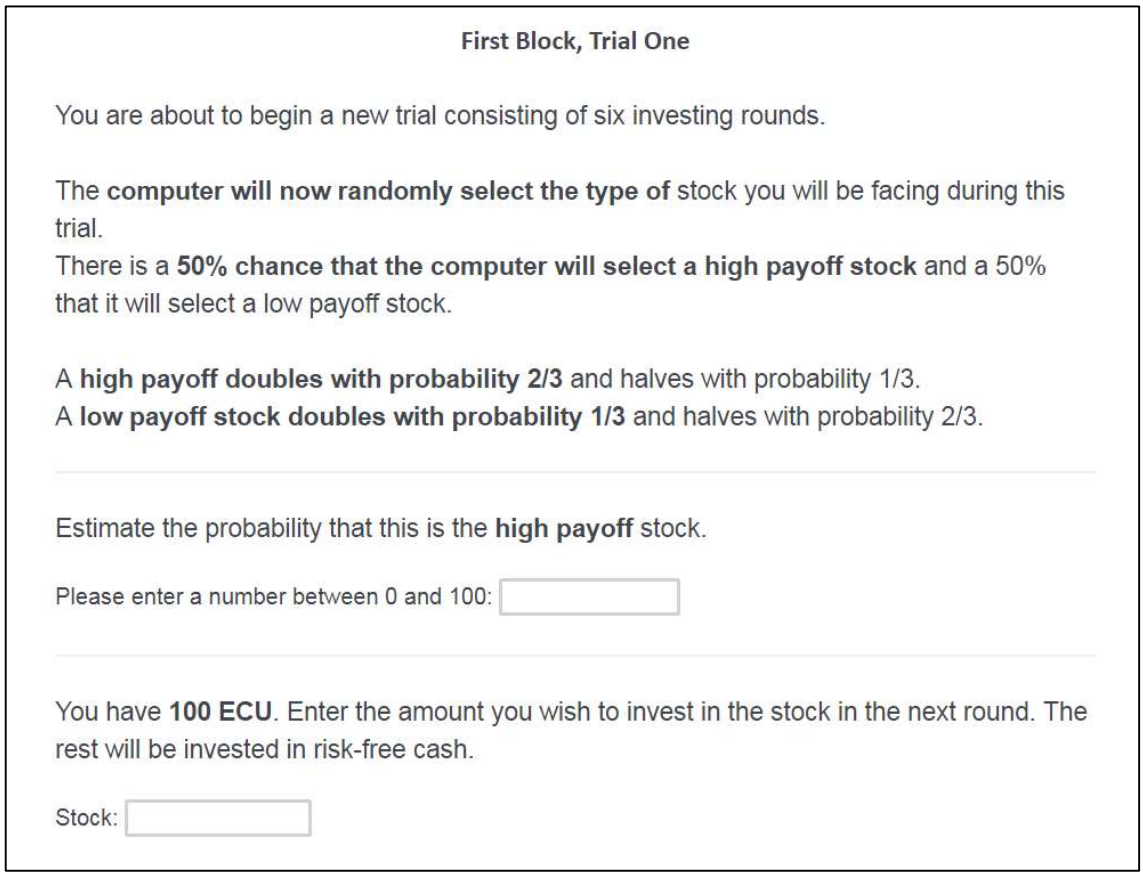
$$\Delta a = \tau\lambda \frac{E[(1 + \tilde{r})(u'(1 + \tilde{r}a_0) + a_0u''(1 + \tilde{r}a_0)\tilde{r})]}{-E[u''(1 + \tilde{r}a_0)\tilde{r}^2]} \equiv \tau\lambda\phi(a_0).$$

Note, first, that this verifies the conjecture that $\Delta a \sim \lambda$. In addition, as claimed in the text, note that $\phi(a_0)$ depends only on $a_0$, $\tilde{r}$, and the shape of the utility function.

[1] The subject's actual wealth, prior to the experiment, can be viewed as part of the utility function. The only requirement on the utility function is that it is smooth.

# Online Appendix B: Experiment Snapshots

## Panel 1: Initial Round Allocation Screen



**Panel 2: Outcome Screen after Three Rounds**

**Trial: 1**

The stock outcome for Round 3 is: Halve (↓)

History of Decisions and Outcomes

| Round Number | Probability Estimate Prior to Outcome | Stock Allocation Prior to Outcome | Outcome | Winnings from Round |
|---|---|---|---|---|
| 1 | 20 | 50 | Halve (↓) | 75 |
| 2 | 30 | 50 | Double (↑) | 150 |
| 3 | 40 | 40 | Halve (↓) | 80 |
| 4 | | | | |
| 5 | | | | |
| 6 | | | | |

Recall that **high payoff** stocks will double with a probability of 2/3 and halve with a probability of 1/3.

**Low payoff** stocks will double with a probability of 1/3 and halve with a probability of 2/3.

Estimate the probability that this is the **high payoff** stock.

Please enter a number between 0 and 100:

You have **100 ECU**. Enter the amount you wish to invest in the stock in the next round. The rest will be invested in risk-free cash.

Stock:

**Panel 3: Social Issues**

**What Social Issues Are Important to You?**

Below are a number of current corporate social issues, listed in alphabetical order. Please rank these issues from 1 to 6 in terms of how much you care about each issue. A ranking of 1 means you care the most and a ranking of 6 means you care the least. You can rank by clicking and dragging. If you would like to keep the current ranking simply click and slightly drag any of the options.

Gender discrimination (example: not hiring women for jobs for which they are qualified)

Human Trafficking (example: forcing children to work as slave labour in factories or on farms)

Refugees (example: trading with dictatorial regimes which have resulted in mass fleeing from the country)

Poverty (example: underpaying workers in developing countries)

Animal welfare (example: infecting laboratory monkeys with diseases to test pharmaceutical drugs)

Environment (example: releasing carbon dioxide into the atmosphere)

**What Social Issues Are Important to You?**

You selected environment as your top social issue. Below is a description of two environmental non-profits.

**The Rainforest Alliance works to conserve biodiversity and ensure sustainable livelihoods by transforming land-use practices, business practices and consumer behaviour.**

**Conservation Strategy Fund sustains natural ecosystems and human communities through strategies powered by conservation economics. Our trainings, analyses and timely expertise make development smarter, quantify the benefits of nature, and create enduring incentives for conservation.**

Please select a non-profit organization to link to your trading profits:

- ○ The Rainforest Alliance
- ○ The Conservation Strategy Fund

**Panel 4: Positive Block Instruction Screen and Outcome Screen**

**The Conservation Strategy Fund gains by your stock investment**

You are about to begin a block of two trials. Each trial consists of six investment rounds. You will be asked to make the same decision as in the practice trial.

At the beginning of each of the two trials the computer will randomly choose whether the stock for that trial is a high or low payoff stock. You will then face the series of six investment rounds.

In each investment round you will be asked how much you wish to allocate to the stock and to cash. After the stock outcome is determined, you will be asked to indicate the probability that you are facing a high payoff stock and how much you trust your probability estimate.

One round may be randomly chosen as your actual payoff round. If that round is chosen as your payoff round, in addition to paying you, **the researchers will DONATE the same amount of money as your payoff from your stock investment to your designated non-profit**. For example, if you earn 135 ECU from investing including 70 ECU from your stock investment, your chosen non-profit will receive 70 ECU.

**The payment to the non-profit will come out of the researchers' funding, not from your trading payoff.** You will be sent an email documenting our payments to the various non-profit organizations involved in this experiment in a few days.

Your designated non-profit for this block of three trials is: The Conservation Strategy Fund

**Non-profit gains by your stock investment**

**Trial: 1**

The stock outcome for Round 3 is: Double (↑)

**History of Decisions and Outcomes**

| Round Number | Probability Estimate Prior to Outcome | Stock Allocation Prior to Outcome | Outcome | Winnings from Round (if round is selected) | Payment to The Conservation Strategy Fund (if round is selected) |
|---|---|---|---|---|---|
| 1 | 40 | 60 | Double (↑) | 160 | 120 |
| 2 | 60 | 45 | Halve (↓) | 77.5 | 22.5 |
| 3 | 50 | 50 | Double (↑) | 150 | 100 |
| 4 | | | | | |
| 5 | | | | | |
| 6 | | | | | |

Recall that **high payoff** stocks will double with a probability of 2/3 and halve with a probability of 1/3.

**Low payoff** stocks will double with a probability of 1/3 and halve with a probability of 2/3.

Estimate the probability that this is the **high payoff** stock.

Please enter a number between 0 and 100:

You have **100 ECU**. Enter the amount you wish to invest in the stock in the next round. The rest will be invested in risk-free cash.

Stock:

**Panel 5: Negative Block Instruction Screen and Outcome Screen**

**Block: SPCA International loses by your stock investment**

You are about to begin a block of two trials. Each trial consists of six investment rounds. You will be asked to make the same decision as in the practice trial.

At the beginning of each of the two trials the computer will randomly choose whether the stock for that trial is a high or low payoff stock. You will then face the series of six investment rounds.

In each investment round you will be asked how much you wish to allocate to the stock and to cash. After the stock outcome is determined, you will be asked to indicate the probability that you are facing a high payoff stock and how much you trust your probability estimate.

One round may be randomly chosen as your actual payoff round. If that round is chosen as your payoff round, in addition to paying you, **the researchers will DEDUCT from funds allocated to the non-profit the same amount of money as your payoff from your stock investment**. For example, if you earn 135 ECU from investing including 70 ECU from your stock investment, your chosen non-profit will have 70 ECU deducted from their balance.

**The deduction from the non-profit will have no effect on your trading payoff.** You will be sent an email documenting our payments to the various non-profit organizations involved in this experiment in a few days.

Your designated non-profit for this block of three trials is: SPCA International

**Block: Non-profit loses by your stock investment**

**Trial: 1**

The stock outcome for Round 3 is: Double (↑)

History of Decisions and Outcomes

| Round Number | Probability Estimate Prior to Outcome | Stock Allocation Prior to Outcome | Outcome | Winnings from Round (if this round is selected | Deduction from SPCA International (if this round is selected) |
|---|---|---|---|---|---|
| 1 | 50 | 30 | Halve (↓) | 85 | -15 |
| 2 | 20 | 40 | Halve (↓) | 80 | -20 |
| 3 | 15 | 30 | Double (↑) | 130 | -60 |
| 4 | | | | | |
| 5 | | | | | |
| 6 | | | | | |

Recall that **high payoff** stocks will double with a probability of 2/3 and halve with a probability of 1/3.

**Low payoff** stocks will double with a probability of 1/3 and halve with a probability of 2/3.

Estimate the probability that this is the **high payoff** stock.

Please enter a number between 0 and 100:

You have **100 ECU**. Enter the amount you wish to invest in the stock in the next round. The rest will be invested in risk-free cash.

Stock:

## Online Appendix C: Comparison of the Two Studies

The analysis reported in the main text pooled two distinct studies. One was run in 2018 using 160 subjects recruited at the University of Texas, Austin. In that study, the Neutral treatment was presented to subjects before social preferences were elicited and, therefore, before the Positive or Negative treatments were presented (the order of the Negative and Positive blocks was randomized). The second study, run in 2025 using Prolific, used a subject pool of 160 adults more representative of the US population. The order of all three treatments in that study was randomized. Naturally, that subject pool tilted younger in the 2018 study, with a median age of 20.

Aside from the above differences, it is worth noting that late 2018 was a period with heightened interest in ESG in the US. For example, according to Morningstar, US-domiciled sustainable funds took in nearly $5.5bn in 2018, the third straight year of record inflows and a stark contrast to the broader US fund universe, which had its weakest flows since 2008. Judging by mutual fund investors, the sentiment had changed with 2023 recording the first year with net outflow from US sustainable funds; 2024 brought in an even worse net outflow.

Tables C-1 and C-2, identical in structure to Table 1, report the treatment effects on allocations and probability estimates in the two studies. While the overall level of allocation in the 2018 study is lower than the 2024 study, the key results are intact: large and asymmetric effect on allocations in the Negative compared with the Positive treatments, and only a marginal effect on subjective probabilities.[2]

It is important to note that the effect in 2018 does not appear stronger than we observe with a current, and more representative sample of US adults. Thus, the main results of the paper appear to be robust to replication and to the shifting sentiment surrounding ESG investment.

[2] A more thorough comparison of the various tables with those in the main text can be made by examining an earlier version of this paper available at https://www.nber.org/papers/w29288.

**Table C-1: Stock Investment Allocations and Probability Estimates—2018 Study**

This table reports the means, standard deviations, and ranges of the participants' stock investment allocations under each condition in Panel A, along with their probability estimates that they face a high-payoff stock in Panel C. In Panels B and D the table includes the results from tests for whether the allocations and estimates differ significantly across the treatments. In Panel E are the results of a test for the effect asymmetry through calculating the ratio of allocation between the Neutral minus Negative treatments and Positive minus Neutral treatments ("asymmetry multiplier"). All *t*-tests are based on matched samples at the subject-treatment level; *p*-values for these tests are reported in Panels B, D and E.

Panel A: Stock Allocation in ECU

| | Negative (N=160) | Neutral (N=160) | Positive (N=160) | Total (N=480) |
|---|---|---|---|---|
| Mean (SD) | 28.104 (17.817) | 36.651 (20.557) | 39.044 (21.739) | 34.600 (20.606) |
| Range | 0.000 - 100.000 | 4.167 - 95.833 | 2.833 - 100.000 | 0.000 - 100.000 |

Panel B: *p*-values from Matched Sample *t*-tests on Stock Allocation

| | Negative=Neutral | Negative =Positive | Positive = Neutral |
|---|---|---|---|
| Probability | 0.0% | 0.0% | 7.1% |

Panel C: Probability Estimates

| | Negative (N=160) | Neutral (N=160) | Positive (N=160) | Total (N=480) |
|---|---|---|---|---|
| Mean (SD) | 46.713 (13.039) | 48.976 (11.492) | 48.618 (12.327) | 48.102 (12.316) |
| Range | 9.667 - 75.917 | 5.833 - 77.417 | 8.833 - 81.667 | 5.833 - 81.667 |

Panel D: *p*-values from Matched Sample *t*-tests on Probability Estimates

| | Negative=Neutral | Negative =Positive | Positive = Neutral |
|---|---|---|---|
| Probability | 8.8% | 12.3% | 76.4% |

Panel E: Asymmetry in Stock Allocation ECU

| | Neutral - Negative (N=160) | Positive - Neutral (N=160) | Asymmetry Multiplier | Test: Multiplier = 1 (prob) |
|---|---|---|---|---|
| Mean (SD) | 8.547 (18.570) | 2.392 (16.630) | 3.5727 | 0.81% |

**Table C-2: Stock Investment Allocations and Probability Estimates—2025 Study**

This table reports the means, standard deviations, and ranges of the participants' stock investment allocations under each condition in Panel A, along with their probability estimates that they face a high-payoff stock in Panel C. In Panels B and D the table includes the results from tests for whether the allocations and estimates differ significantly across the treatments. In Panel E are the results of a test for the effect asymmetry through calculating the ratio of allocation between the Neutral minus Negative treatments and Positive minus Neutral treatments ("asymmetry multiplier"). All *t*-tests are based on matched samples at the subject-treatment level; *p*-values for these tests are reported in Panels B, D and E.

Panel A: Stock Allocation in ECU

| | Negative (N=160) | Neutral (N=160) | Positive (N=160) | Total (N=480) |
|---|---|---|---|---|
| Mean (SD) | 34.671 (25.793) | 45.782 (24.899) | 48.060 (25.605) | 42.838 (26.049) |
| Range | 0.000 - 100.000 | 0.000 - 100.000 | 0.000 - 100.000 | 0.000 - 100.000 |

Panel B: *p*-values from Matched Sample *t*-tests on Stock Allocation

| | Negative=Neutral | Negative =Positive | Positive = Neutral |
|---|---|---|---|
| Probability | 0.0% | 0.0% | 11.22% |

Panel C: Probability Estimates

| | Negative (N=160) | Neutral (N=160) | Positive (N=160) | Total (N=480) |
|---|---|---|---|---|
| Mean (SD) | 45.986 (13.65) | 48.591 (12.776) | 49.861 (12.566) | 48.146 (13.080) |
| Range | 1.000 - 78.333 | 13.833 - 83.000 | 19.083 - 97.417 | 1.000 - 97.417 |

Panel D: *p*-values from Matched Sample *t*-tests on Probability Estimates

| | Negative=Neutral | Negative =Positive | Positive = Neutral |
|---|---|---|---|
| Probability | 5.3% | 0.8% | 23.3% |

Panel E: Asymmetry in Stock Allocation ECU

| | Neutral - Negative (N=160) | Positive - Neutral (N=160) | Asymmetry Multiplier | Test: Multiplier = 1 (prob) |
|---|---|---|---|---|
| Mean (SD) | 11.111 (23.296) | 2.279 (18.047) | 4.8761 | 0.14% |

## Online Appendix D: Main Treatment Effects on Filtered Sample

Table D-1, below, replicates the main, non-parametric analysis in Table 1, including only the subjects who exhibited weakly rational behavior in the Neutral treatment. This is the set of subjects used for most of the paper's analysis. In short, the results using this subsample are remarkably similar to those reported in Table 1, with the allocation asymmetry being 5.9 (up from 4.2 in Table 1).

**Table D-1: Stock Investment Allocations and Probability Estimates**

This table reports the means, standard deviations, and ranges of the participants' stock investment allocations under each condition in Panel A, along with their probability estimates that they face a high-payoff stock in Panel C. In Panels B and D the table includes the results from tests for whether the allocations and estimates differ significantly across the treatments. In Panel E are the results of a test for the effect asymmetry through calculating the ratio of allocation between the Neutral minus Negative treatments and Positive minus Neutral treatments ("asymmetry multiplier"). All *t*-tests are based on matched samples at the subject-treatment level; *p*-values are reported in Panels B, D and E.

Panel A: Stock Allocation in ECU

| | Negative (N=256) | Neutral (N=256) | Positive (N=256) | Total (N=768) |
|---|---|---|---|---|
| Mean (SD) | 29.48 (21.24) | 40.60 (23.40) | 42.50 (23.91) | 37.53 (23.56) |
| Range | 0.00 - 100.00 | 0.00 - 100.00 | 0.00 - 100.00 | 0.00 - 100.00 |

Panel B: *p*-values from Matched Sample t-tests on Stock Allocation

| | Negative=Neutral | Negative =Positive | Positive = Neutral |
|---|---|---|---|
| Probability | 0.00% | 0.00% | 7.35% |

Panel C: Probability Estimates

| | Negative (N=256) | Neutral (N=256) | Positive (N=256) | Total (N=768) |
|---|---|---|---|---|
| Mean (SD) | 46.39 (12.68) | 48.47 (11.78) | 48.64 (11.55) | 47.83 (12.04) |
| Range | 10.00 - 77.83 | 13.83 - 83.00 | 19.33 - 82.58 | 10.00 - 83.00 |

Panel D: *p*-values from Matched Sample t-tests on Probability Estimates

| | Negative=Neutral | Negative =Positive | Positive = Neutral |
|---|---|---|---|
| Probability | 3.8% | 2.3% | 85.3% |

Panel E: Asymmetry in Stock Allocation ECU

| | Neutral - Negative (N=131) | Positive - Neutral (N=131) | Asymmetry Multiplier | Test: Multiplier = 1 (prob) |
|---|---|---|---|---|
| Mean (SD) | 11.12 (20.47) | 1.90 (16.87) | 5.87 | 0.0% |

## Online Appendix E: Survey to Establish External Validity

Below is an example of a survey question eliciting subjects' preference for "reducing good" versus "causing harm".

A local town council debates the use of municipal funds to house and support people experiencing homelessness. Because of the limited funds available for all of the city needs, the council is evenly split on the measure, and the final vote resides with the elected mayor who is undecided (but will have to decide one way or another in a week). It is impossible to know which way the Mayor currently leans.

If you had to make a choice between the following alternatives, which would you choose

- **Donate** $1,000 to a firm that will lobby the Mayor to vote **against** helping people experiencing homelessness.
- **Cut** $1,000 of funding from a charity that will lobby the Mayor to vote **for** helping people experiencing homelessness.
- The choices are equally bad.

## Online Appendix F: Structural Examination of Subject Heterogeneity

This appendix develops the stimulus-response model used to estimate individual-level allocation parameters, addressing the limitations of a naïve subject-by-subject regression approach. In a naïve approach we would regress allocations on subjective probabilities separately for each subject and treatment, but this presents two major challenges. First, with only 12 decisions per subject per treatment, subject-level regressions lack statistical power. Second, subject responses reflect experimental error for a variety of reasons.[3] Because allocations are bounded between 0 and 100 ECU, experimental noise can bias observations away from the boundaries and correspondingly bias inferences about individual allocation responses to perceived probabilities.[4] To address these issues, we adopt a reduced-form model relating noisy optimal allocations to subjective probabilities. We then estimate individual-level parameters as random effects. This approach allows us to efficiently quantify individual preferences while controlling for the edge biases that arise from noise.

Most utility models predict an optimal allocation that roughly follows a sigmoid function of subjective probability.[5] Consistent with this prediction, we assume that noisy individual allocations, in a given treatment, can be described in reduced form as follows:

$$ECU_i^T = a_i + b_i f(Prob_i) + e_i, \tag{F1}$$

where the transformed allocation, $ECU^T \in \Re$, is unbounded and related to the allocation choice via the sigmoid transformation,

$$ECU = 100/(1 + \exp(-ECU^T)). \tag{F2}$$

[3] Subjects make mistakes, get confused, or simply find it difficult to maintain the same level of engagement throughout the rounds of an experiment. There is also the possibility that they enjoy injecting a random component to their choices. Holding constant the subjective probability and treatment, the average filtered subject exhibited a standard deviation of 11 ECU in their allocations.

[4] While this bias can also impact the estimates in Table 2, within-subject estimates are more sensitive to the noise-induced bias. Indeed, consistent with a bias-driven deviation from the regression model, the residuals in Regression (2) of Table 2 exhibit a U-shape magnitude with respect to the perceived probability (roughly highest at the boundaries).

[5] A sigmoid function takes the form, $y = A\ (1 + \exp(a - bx))^{-1}$ with $b \geq 0$.

In Equation (F1), *i* refers to the subject, *f*() is an increasing function specified below, $a_i$ and $b_i$ are subject-specific constants, and $e_i$ captures experimental noise. A standard sigmoid corresponds to the case where *f* is linear. Because $ECU$ is convex in $ECU^T$ at low values and concave at high values, this formulation models how experimental noise biases allocations away from the boundaries of [0,100].[6] The choice of *f*() reflects behavior in the absence of noise. For instance, if $f(p)$ is finite at $p=0$, then the decision maker would be risk-loving because the allocation to the stock (an actuarially fair gamble at $p$=0) would be greater than zero. Because $b$ is a measure of the sensitivity of allocation to a first-degree stochastically dominating shift in the payoff distribution of the stock, one can interpret $b$>0 as a measure of local risk tolerance with higher $b$ signifying higher risk tolerance. We model

$$f(p) = \ln\left(\frac{p}{1-p}\right). \tag{F3}$$

Our modeling choice implies global risk aversion and that, absent noise, the allocation tends to the full endowment of 100 ECU as the subjective probability approaches one. This lends parsimony to modeling the dependence of allocation on subjective probability.[7]

To address the issue of statistical power, we adopt a random effects framework estimated to allow for treatment differences. That is, we allow each subject to have a different average level of investment (intercept, $a_i$) and a different allocation sensitivity to probabilities (slope, $b_i$) in each of the treatments. In a random effects framework, the subject-level coefficients are assumed to be drawn from a distribution whose mean and standard deviation are estimated. A benefit of this approach over individual regressions is the joint estimation of covariance of distinct random effects. The estimated model is

[6] This is an implication of Jensen's Inequality.

[7] To avoid infinities in expressions (2) and (3), extreme allocations of 0 or 100 ECU are adjusted to 0.1 or 99.9 ECU, respectively, and extreme reported probabilities of 0 or 1 are adjusted to 0.001 or 0.999. The qualitative conclusions of our analysis are robust to simply excluding these observations. They are also robust to alternative specifications such as, $f(p) = p$, or $f(p) = ln(p)$, or $f(p) = c\,ln(p) + dp$, or $f(p) = c\,ln(p) + ln(1-p)$.

$$ECU^{T}_{\tau,i,n} = a_{\tau,i} + b_{\tau,i} f\left(Prob_{\tau,i,n}\right) + e_{\tau,i,n}. \quad \text{(F4)}$$

where τ denotes the treatment, *i,* the subject ID (corresponding to the random effect), *n,* the round number for the given treatment, and $Prob_{\tau,i,n}$, the probability reported by the subject in round *n* of the given treatment.

Results are reported in Table F-1, which presents the estimated means and standard deviations of the random coefficient distributions for each treatment together with the residual standard deviation.[8] Consistent with the main results, both the baseline allocation, mean(*a*), and the probability sensitivity, mean(*b*), are significantly lower in the Negative treatment, relative to the Neutral treatment. By contrast, the two Positive treatment mean coefficients do not allow for a simple ranking relative to the Neutral treatment estimates.

**Table F-1: Random Effects Regression of Transformed Allocation on Reported Probabilities**

The table reports random-effect regressions of transformed allocations on reported probabilities estimated as specified in Equation (F4). *a* refers to intercept and *b* to sensitivity to probabilities. The error term is assumed to be i.i.d. across subjects and rounds, within treatment. Standard errors are in parentheses. Asterisks denote the probabilities for statistical tests of differences from zero (**p*<0.1; ***p*<0.05; ****p*<0.01).

| Treatment | mean(*b*) | sd(*b*) | mean(*a*) | sd(*a*) |
|---|---|---|---|---|
| Negative | 0.874*** | 0.953 | -1.532*** | 2.476*** |
| | (0.075) | (0.125) | (0.161) | (0.146) |
| Neutral | 1.207*** | 0.801 | -0.338* | 2.172*** |
| | (0.064) | (0.094) | (0.141) | (0.153) |
| Positive | 1.009*** | 0.922 | -0.0887 | 2.354*** |
| | (0.073) | (0.085) | (0.152) | (0.155) |
| | sd($e_{Neg}$) | sd($e_{Neu}$) | sd(*ePos*) | *N* |
| | 2.004*** | 2.271*** | 2.012*** | 9,216 |
| | (0.132) | 0.173 | 0.141 | |

[8] The random effects model estimates correlations between the *a'*s and *b'*s, some of which are found to be statistically different from zero. In the interest of brevity, we omit these results.

The table also shows that the slope and intercept coefficient dispersions across subjects, sd($a$) and sd($b$), are estimated to be larger in the Negative treatment, compared with the Positive and Neutral treatments. This result suggests pronounced heterogeneity in treatment effects in the Negative treatment. Finally, we observe large and heterogeneous levels of residual variation across the treatments. The residual magnitudes justify our effort to adjust for edge-induced biases.[9]

To compare model predictions to the simple statistics from Table 1, Panel A, we use the model estimates of each subject's intercept and slope parameters to calculate that subject's *expected allocations* in the treatment without experimental noise. We do this using the theoretical distribution of objective stock probabilities in the six rounds.

Table F-2 reports the average over subjects of their predicted expected allocation in each of the treatments. Consistent with the results of Table 1, the expected allocations are lower in the Negative treatment (0.304) relative to the Neutral treatment (0.431) which, in turn, is not far from the expected allocation in the Positive treatment (0.459). The magnitude of the treatment effect is similar to that documented in Table 1 and corresponds to a reduction of nearly 30% in allocations in going from the Neutral to the Negative treatment.

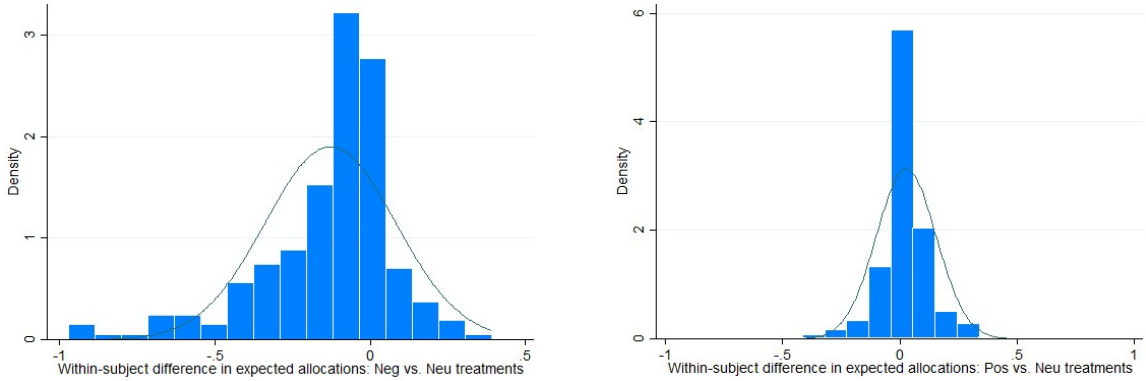
**Table F-2: Average of Expected Allocations in Each Treatment**
The table reports the expected allocation averaged across subjects in each of the treatments based on subject-level coefficient estimates of the mixed regression in Equation (F4) and assuming no experimental noise (the residual is set to zero). Allocations are normalized to be between 0 and 1.

| Treatment | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Negative | 256 | 0.304 | 0.233 | 0.001 | 0.998 |
| Neutral | 256 | 0.431 | 0.233 | 0.002 | 0.999 |
| Positive | 256 | 0.459 | 0.249 | 0.002 | 0.999 |

[9] The random effects model estimates correlations between the *a*'s and *b*'s, some of which are found to be statistically different from zero. In the interest of brevity, we omit these results.

To examine the heterogeneity of the treatment effect across subjects, for each subject we compute the difference in expected allocation between the Negative and the Neutral treatments, and again the difference in expected allocation between the Positive and the Neutral treatments. This analysis allows us to compute two relative treatment effect measures per subject. We plot the distribution of these relative treatment effects in Figure F-1. Under the null that differences in behavior across treatments are noise, the distribution of relative treatment effects should be symmetric about zero. The histograms in Figure 4 suggest that this roughly holds for the Positive treatment but that the same is not true for the Negative treatment.

**Figure F-1: Distribution of Allocations - Histograms**
The figure reports the distribution of subjects' expected allocations in the two treatments relative to their expected allocation in the Neutral treatment. Expectations are calculated using subject-level coefficient estimates of the mixed regression in Equation (F4) and assuming no experimental noise (the residual is set to zero). Allocations are normalized to be between 0 and 1.




To quantify treatment-dependent heterogeneity across subjects, we estimate a 2-component finite mixture model of normal distributions to each of the histograms. The results, reported in Table F-3, suggest that about three quarters of subjects are drawn from a population that expects to allocate only two more ECUs in the Positive treatment (component 1) than in the Neutral treatment, while the remaining part of the population does not allocate more in the Positive treatment than in the Neutral one (the mean of component 2 is modest but not statistically different from zero). By contrast, approximately half of the subjects are drawn from

a population that expects to allocate 20 ECUs *less* in the Negative treatment (relative to the Neutral treatment), while the remaining expect to allocate 4 ECU less. This analysis demonstrates that the treatment effect is not just strong in aggregate but also pervasive across subjects. The finding that approximately half the subjects are highly sensitive to the Negative treatment is consistent with the survey finding by Bauer et al. (2021) that two out of three Dutch pension plan participants were in favor of RI mandates.

**Table F-3: Distribution of Allocations: Finite-mixture Model Analysis**
The table reports a decomposition of each histogram in Figure F-1 into a mixture of two normal distributions. Means, standard deviations, and mixture probability are estimated for the data depicted in each of the histograms. Allocations are normalized to be between 0 and 1. Asterisks denote the probabilities for statistical tests of differences from zero (*$p$<0.1; **$p$<0.05; ***$p$<0.01).

| Within-subject difference in expected allocations relative to the Neutral treatment | | |
|---|---|---|
| | Negative treatment | Positive treatment |
| Mean of component 1 | -0.205*** | 0.0192*** |
| | (0.027) | (0.005) |
| Mean of component 2 | -0.0410*** | 0.0505 |
| | (0.008) | (0.028) |
| Var of component 1 | 0.0676*** | 0.00245*** |
| | (0.009) | (0.001) |
| Var of component 2 | 0.00305** | 0.0518*** |
| | (0.001) | (0.012) |
| | | |
| Probability of component 1 | 0.529 | 0.726** |
| | 0.061 | 0.061 |
| N | 256 | 256 |

To contextualize these estimates, consider that, based on the estimates from Table F-3, the approximately half the subjects with Type 1 tendencies in the Negative treatment will exhibit an average asymmetry multiplier of 8.9. The remaining subjects with Type 1 tendencies in the Negative treatment will exhibit a smaller average asymmetry multiplier of 1.8. Thus the

population that is estimated to exhibit a significantly high asymmetric multiplier accounts for approximately half the subject pool.

Finally, to obtain further confirmation that a Negative treatment effect is pervasive among participants, we plot the model-based expected allocation in the Negative treatment against the Positive treatment, by subject, and relative to a 45-degree line (see Figure F-2). First, the figure shows that most subjects fall under the 45-degree line, consistent with allocations in the Negative treatment being lower than in the Positive treatment, even when accounting for differences in baseline levels of allocations. Second, the asymmetry in distribution relative to the 45-degree line is observed for virtually all levels of Positive treatment allocations. Thus, the sensitivity to negative externalities is found among most subjects, whether they appear to care about positive externalities or not.

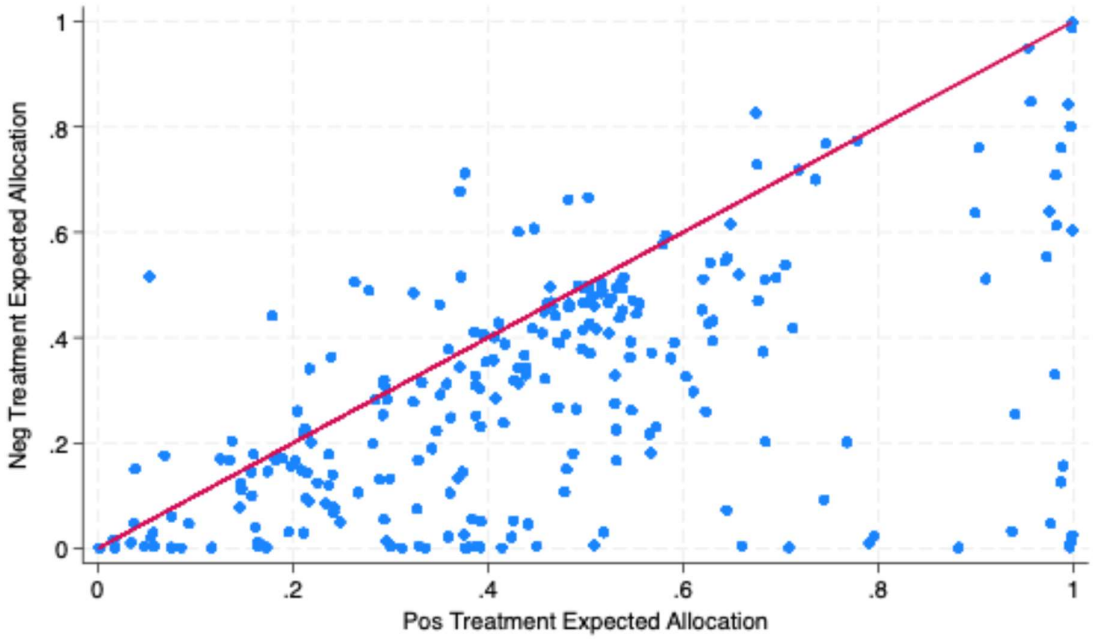



**Figure F-2: Expected Allocations in Positive and Negative Treatments**
The figure reports the expected allocations in the Positive and Negative treatments based on model estimates (see Table F-1). Each dot corresponds to a subject.